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Research on a Fault Diagnosis Method of an A-Class Thermal Insulation Panel Production Line Based on Multi-Sensor Data Fusion

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Featured Application: Experimental results show that for the test dataset composed of A-class insulation board production line sensor data, the proposed method achieves better estimation results compared with a basic LSTM algorithm; its performance in each evaluation index is better.

Abstract: To detect the running state of an A-class thermal insulation board production line in real time, conveniently and accurately, a fault diagnosis method based on multi-sensor data fusion was proposed. The proposed algorithm integrates the ideas of Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM) and Attention Mechanism, and combines a Dilated Convolution Module (DCM) with LSTM to recognize complex signals of multiple sensors. By introducing an attention mechanism, the recognition performance of the network was improved. Finally, the real-time status information of the production line was obtained by integrating attention weight. Experimental results show that for the custom multi-sensor dataset of A-class insulation board production line, the proposed CNN-LSTM fault diagnosis method achieved 98.97% accuracy. Compared with other popular algorithms, the performance of the proposed CNN-LSTM model performed excellently in each evaluation index is better.

Keywords: A-class thermal insulation panel production line; fault diagnosis; deep learning; long short-term memory; attention mechanism

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Citation: Wang, Y.; Guo, X.; Liu, X.; Liu, X. Research on a Fault Diagnosis Method of an A-Class Thermal Insulation Panel Production Line Based on Multi-Sensor Data Fusion. *Appl. Sci.* **2022**, *12*, 9642. https://doi.org/10.3390/app12199642

Academic Editors: Yongbo Li, Qing Ni, Ke Feng, Yuejian Chen and Xiaoli Zhao

Received: 2 September 2022
Accepted: 23 September 2022
Published: 26 September 2022

1. Introduction

A-class insulation boards as one of the main materials of green environmental protection building insulation, are widely used in the construction industry because of their good thermal insulation properties. However, the manufacturing process of composite insulation board is very complex. A conventional insulation board production line consists of a rolling machine, molding machine, high pressure foaming machine, laminating machine, cutting machine and palletizing machines [1,2]. If one of the pieces of equipment fails, it affects the operation of the whole production line and results in the discontinuity of the process as well as other problems and various defects of the product. Therefore, effective fault diagnosis of the equipment can ensure the safe and stable operation of the insulation board production line.

The existing fault diagnosis methods for complex dynamic industrial systems include analytical methods, statistical methods and intelligent methods [3,4], and the technologies of distributed control systems, data storage, transmission have been widely used. However, in the face of massive data and control variables of production processes and equipment operation state, traditional analysis methods it has been difficult to fully extract the fault symptoms and causal logic relationship of data [5]. At the same time, complex systems contain the characteristics of dynamic randomness, multi-source uncertainty, high coupling and strong interference. Hence, it is difficult to establish accurate mathematical models and a complete or perfect expert knowledge system. The data-driven intelligent fault diagnosis method is more applicable because of data computational and modeling complexity in the era of big data [6]. Intelligent fault diagnosis methods have the advantages of direct and effective statistical analysis and information extraction of massive, multi-source and high-dimensional data. Based on the collected monitoring data of different sources and different types, intelligent fault diagnosis methods make use of various data mining techniques to obtain useful hidden information and achieve the purpose of detection and diagnosis [7].

An intelligent production line consists of multiple professional and automatic production lines and deploys a large number of intelligent sensors and components to the key link of product processing. Intelligent production lines are developing to provide high automation and integration. As the complexity of the production line increases, the possibility of module failures in the whole system increases [8,9]. Traditionally, this relies mainly on experienced workers to judge the running status of equipment. These methods make judgments on the state of equipment in the future based on general information recorded by the history of equipment maintenance, and may be limited due to the lack of complete analysis of equipment status and the influence of environmental factors [10]. In addition, the scheduled maintenance mode leads to insufficient or excessive maintenance and other problems. Compared with a traditional production line, an intelligent production line can monitor the running process and identify the running state of each component in the production process. Therefore, effective prediction of potential failures in the production line is essential to reduce maintenance and operation costs, and improve the overall performance of the production line.

Current production line fault diagnosis methods based on machine learning have problems of low prediction accuracy, slow response and high false alarm rate. Therefore, in view of the above problems, we propose a fault diagnosis method based on a recurrent neural network to accurately predict all kinds of faults that may occur in the production process of an A-class thermal insulation board production line.

A novel fault diagnosis method for an A-class thermal insulation panel production line based on deep learning is proposed. The main contributions of this paper are as follows:

(1) Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) are integrated in the proposed fault diagnosis method;

(2) Am attention mechanism is introduced to obtain special data and mask useless information, which improves the feature extraction ability of the proposed model;

(3) A Dilated Convolution Module (DCM) with LSTM is proposed in the CNN-LSTM model, which reduces the number of parameters while maintaining the ability of model feature extraction.

The rest of the paper is organized as follows. Section 2 introduces related work concerning fault diagnosis methods and the background of deep learning methods based on data fusion and LSTM. The proposed fault diagnosis method of an A-class thermal insulation panel production line is demonstrated in Section 3, and experiments and corresponding results are presented in Section 4. Finally, Section 5 shows the application of the detection system, and Section 6 concludes this paper and discusses future work.

2. Related Work

Fault diagnosis is an essential technique in reliability analysis of production equipment [11,12]. At present, fault diagnosis methods can be divided into three categories: model-based fault diagnosis methods, signal processing-based fault diagnosis methods and artificial intelligence-based fault diagnosis methods [13,14].

2.1. Fault Diagnosis Methods

Model-based fault diagnosis [15–18] methods need to establish accurate mathematical models for monitoring objects, such as differential equations, and diagnose faults by residual errors between model inputs and outputs [19]. Traditional fault diagnosis methods can be divided into three categories: analytical model-based approaches, qualitative empirical knowledge-based approaches, and data-driven approaches [20]. Xu [21] et al. combined improved composite multiscale fuzzy entropy and support vector machine (SVM) with particle swarm optimization (PSO) to diagnose rolling bearing faults. The disadvantage of this method is that it is very complicated and time-consuming to establish the model, and the accuracy of the model directly affects the performance of fault detection and diagnosis. A fault diagnosis method based on signal processing collects the sensor signals in the operation of the device, then extracts the features by observing and analyzing the hidden information in the sequence. Velasco-Gallego [22] proposed a fault diagnosis approach to identify the faults and malfunctions existing in marine systems. Zhao [23] et al. proposed a quality testing approach for the quality of transformer insulating oil based on fluorescent bicolor ratio and extraction of fluorescence characteristics of dual band information. The running transformer fault diagnosis model was established, through a custom filter and visible photoelectric detector, and allowed online real-time monitoring. However, this method can only analyze the characteristics of the signal itself, and is unable to dig deeper for hidden information. Fault diagnosis methods based on artificial intelligence using machine learning and deep neural networks can extract hidden features from a large number of datasets; the trained models are used to realize fault diagnosis, which achieves excellent results. A real-time anomaly detection intelligent system [24] was proposed to address the current gaps identified within the maritime industry. Zhang [25] et al. proposed a new intelligent defect detection framework based on time-frequency transform that trained sparse filtering model using the speed samples of agricultural machinery. Residual samples at different speeds were used to test its validity. This method can adaptively extract the existing fault features, which is an effective intelligent method for agricultural equipment fault detection. The performance of fault detection verifies that this method not only has strong fault classification ability at different speeds, but also has higher identification accuracy compared with other methods. Approaches based on Convolutional Neural Networks [26] or graph networks [27] have also been proposed to address the problem of fault diagnosis in industrial scenarios. Du [28] et al. proposed a fault diagnosis strategy based on Long Short-Term Memory to classify and determine different fault types for time-series data sequences. The method is useful to guarantee the operational safety of equipment, and can be used as a reference for fault detection.

2.2. Multi-Source Data Fusion Methods

In recent years, the demand for multi-source information fusion [29–31] in various applications has increased, and data fusion technology has been widely researched. The goal of data fusion is to alleviate the problem of weak recognition of single sensors and to obtain more accurate detection results. At the same time, deep learning has become a very attractive data processing method that can find higher-order abstract features that are difficult to be found by traditional feature extraction methods. Hence, it is widely used in massive multi-source data processing. Weiss S [32] et al. used extended Kalman filter (EKF) to fuse the camera information and IMU information. Pre-integration and visual information were used for state prediction and update. Li [33] et al. proposed a new integrated method based on convolutional neural network (CNN), a transfer learning method and support vector machine (SVM) to automatically identify flotation conditions. Compared with the existing recognition methods, the CNN-SVM model could automatically retrieve features from the original images and perform high-precision fault detection. Gu [34] et al. proposed a trend prediction method for large axial flow fans based on vibration signal-power information fusion to solve the problem of the insensitivity of measured signals to internal faults, poor timeliness and low sensitivity of online intelligent fault diagnosis. Extracted feature vectors were used as the input of particle swarm optimization and cross-validation optimized support vector machine to predict the operation trend of axial flow fan. Experimental results showed that the performance of this method was better than that of the benchmark method. Zhang [35] et al. proposed a reliability prediction method for satellite lithium battery. Bayesian model integrating binary performance degradation data and life data were used to predict the remaining life of satellite lithium battery. The results showed that the prediction accuracy of remaining life could be effectively improved by integrating binary performance degradation data and life data. Che et al. [36] proposed an aeroengine fault diagnosis fusion model based on deep learning that achieved high fault diagnosis accuracy under the influence of measurement error interference. Sun et al. [37] used a three-dimensional laser radar to obtain point cloud data of corn plants and the image data collected by the camera, automatically obtained a green feature binary image by using a super greening algorithm and the maximum interclass variance method, and then projected the point cloud data after clustering analysis onto the target edge frame of the image to build a multi-sensor data fusion support model for feature recognition. Sun et al. [38] proposed a mobile node location method of an underwater sensor array network based on multi-information fusion. The simulation results showed that the location performance of the fused location method was significantly improved.

2.3. Discussion

The models established by traditional fault diagnosis methods based on machine learning have been studied for many years. Since these methods are based on some assumptions, their classification accuracy still has the potential to be improved. Traditional fault diagnosis methods are not suitable in the case of multi-sensor fusion in this paper. The fault diagnosis methods based on data fusion make little use of multi-source data, which lead to insufficient feature extraction ability. Therefore, to address the above problems, a fault diagnosis method for an A-class thermal insulation board production line based on multi-sensor fusion is proposed, which can fully extract the useful information from multi-source sensor data and accurately classify the faults of an A-level thermal insulation board production line.

3. Fault Diagnosis Method Based on LSTM and Multi-Sensor Data Fusion

3.1. The Network Architecture of LSTM Based on Multi-Sensor Data Fusion

The architecture of a LSTM network is one kind of Recurrent Neural Network (RNN) network. Compared with basic version of RNN, LSTM can address the problem of exploding gradients and gradient vanishing and deal with relatively long-term data. The network architecture of LSTM is more complicated than of RNN, and the internal framework of LSTM adds three gated activation functions, i.e., input gate i_t, forgetting gate f_t and output gate o_t. The gated mechanism alleviates the problems of vanishing gradient and exploding gradient of RNN and solves the problem of long-term dependence relationship. The essential updating of LSTM can be described as follows:

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

$$f_t = \sigma\left(W_f \cdot [h_{t-1},\ x_t] + b_f\right) \tag{2}$$

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

where, i_t, f_t and o_t denote input gate, forget gate and output gate, respectively, h_{t-1} denotes last time output, W_* denotes the weight coefficient matrix, and b_* represents the offset vector. The network architecture of a basic LSTM block is displayed in Figure 1. According to characteristics of time sequence data and multi-factor correlation, a fault diagnosis method of an A-class thermal insulation panel production line is proposed based on LSTM and multi-sensor feature fusion. The detailed network architecture is shown in Figure 2. The outputs of LSTM block are concatenated along channels, which satisfy the requirements for subsequent attention and dilated convolution modules. Because of the implementation of a ResNet block, and attention and dilated Convolution modules, the proposed model can merge the outputs of the LSTM block and predict the state of the production line.

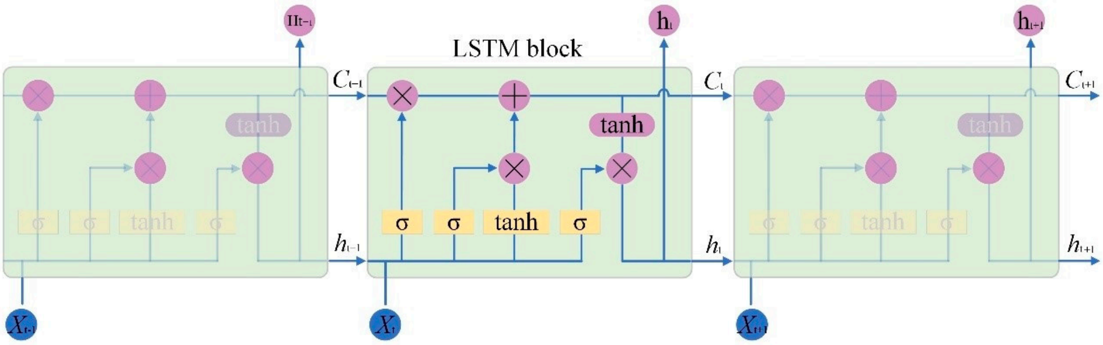

Figure 1. The schematic diagram of basic LSTM block.

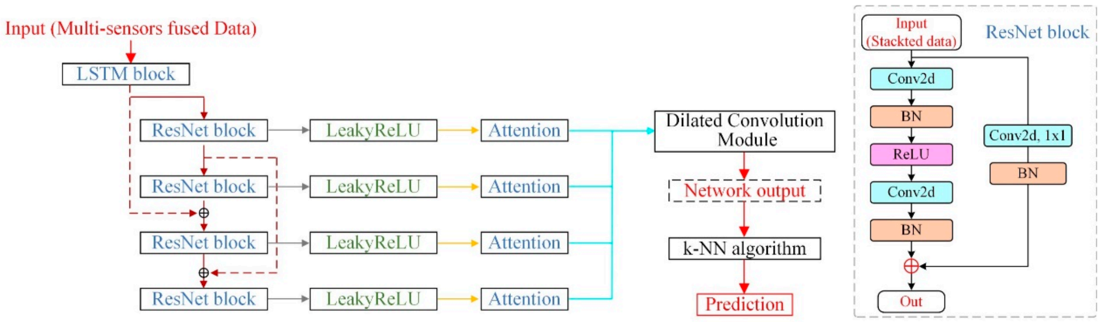

Figure 2. The network architecture of the proposed CNN-LSTM based on multi-sensor fusion.

The basic LSTM block has three main stages:

- Forget stage. This phase is mainly about selectively forgetting the input passed in by the previous node. That is, the network determines whether the intermediate information should be forgotten or remembered. Specifically, it controls information flow from the previous state, which needs to be retained or forgotten, by calculating the value of the forgetting gate.
- Memory stage. This stage is to decide what new information should be kept in the cell state. A sigmoid layer as the input gate layer decides which values should be updated. A tanh layer creates a vector of new candidate values, then combines above values to create an update to the state;
- Output stage. This is the final stage to decide which information is outputted. This output of the proposed CNN-LSTM contains prediction of each sensor deployed on equipment. Then, the network output is fed into the k-NN algorithm to obtain the final prediction.

The network output shown in Figure 2 is a ten-dimension tensor in which each dimension corresponds to the state of each sensor deployed in the A-class thermal insulation panel production line. Therefore, the output of the proposed CNN-LSTM model is a prediction of the current state of the production line. Finally, the fault diagnosis result is predicted by the k-NN algorithm, as further discussed in Section 4.

The proposed network structure of LSTM based on hierarchical residual connection is divided into three parts: the LSTM block, the ResNet module and the attention module. To enhance the feature expression ability of the current hidden layer state, the output of LSTM block is stacked by four residual connections and a LeakyReLU activation function. Then, the feature extraction capability of the network is improved by the attention module and the dilated convolution module. Finally, the predicted results are obtained by the Softmax function.

3.2. Dilated Convolution Module

Dilated convolution is proposed to solve some problems in image segmentation. For the task of image segmentation, the image fed into the convolutional network is filtered by convolutional layer before pooling layer. Image size can be reduced while the receptive field can be increased. Finally, the image size can be restored by up-sampling. However, in the process of downsampling or upsampling of the image, internal features and spatial hierarchical information are usually lost. Dilated convolution is proposed to alleviate the above problem. The dilated convolution module is shown in Figure 3, and can be described as:

$$r = \sum_i d_i(s_i - 1) \tag{4}$$

where, r is the receptive field, d_i represents dilation rate and s_i denotes filter size.

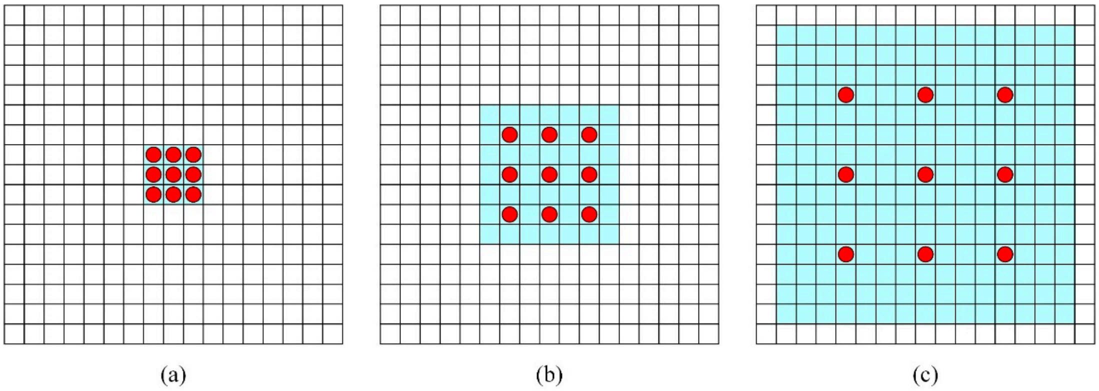

Figure 3. Dilated Convolution layer with different dilation rates. (**a**) Kernel size of Dilated Convolution is 3 × 3 and dilation rate is 1, which is same as the normal convolution process. (**b**) 2-dilated conv with kernel size is 3 × 3 and zero padding; (**c**) 4-dilated conv.

The advantage is that the receptive field of the dilated convolution module is increased while losing hardly any detail information. The original 3 × 3 convolution kernel has a 5 × 5 (dilated rate = 2) or larger receptive field with the same number of parameters and computation cost of a normal convolutional module. For LSTM network, dilated convolution can fuse feature information of different scales and establish the dependence between features of different time series, which improves the recognition ability of the LSTM network.

3.3. Attention Mechanism

For different types of input data, the feature extraction ability of the LSTM network is different. In other words, some components of the input data may dominate the network data. With the attention mechanism introduced, the proposed network can focus on essential hidden features. Therefore, the outputs from different depths of the residual module are fed into the attention layer, which extracts multiscale features and enhances the proposed network prediction accuracy efficiently. The details of the attention block are displayed in Figure 4.

After full feature extraction from CNN-LSTM module, the characteristics of multi-sensor information acquired are sent to the proposed attention mechanism to optimize feature extraction. In addition to improving the depth of feature extraction, the proposed model can effectively identify specific information and adaptively adjust channel characteristics, which independently learn the critical information of various sensor features in the fault diagnosis of an A-class insulation panel production line. Hence, the proposed attention block effectively enhances the feature extraction ability.

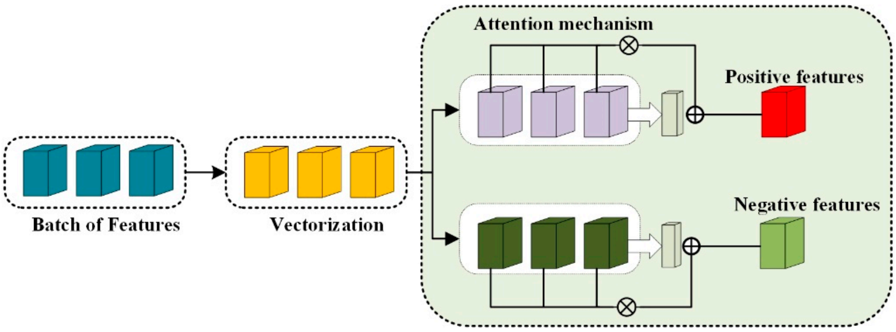

Figure 4. The attention block for the proposed CNN-LSTM network.

4. Experiments

4.1. Data Preprocessing

Data fill and timing alignment. Multiple sensors are installed in the fault diagnosis system of an A-class insulation panel production line for the mixing equipment, crawler Laminator and cutting equipment. Each sensor measures the corresponding key parameters, e.g., voltage, current or vibration signals, which are recorded in the form of time series. However, due to various reasons, the data collected by various sensors are missing on a small scale. In addition, because of different sensors, the data collected by different types of sensors has the problem of time inconsistency. Data loss and data synchronization affect the data quality, leading to a decrease in accuracy of prediction analysis. Therefore, it is necessary to perform the processing of data filling and time scale alignment for the collected original data. Data preprocessing is shown in Figure 5.

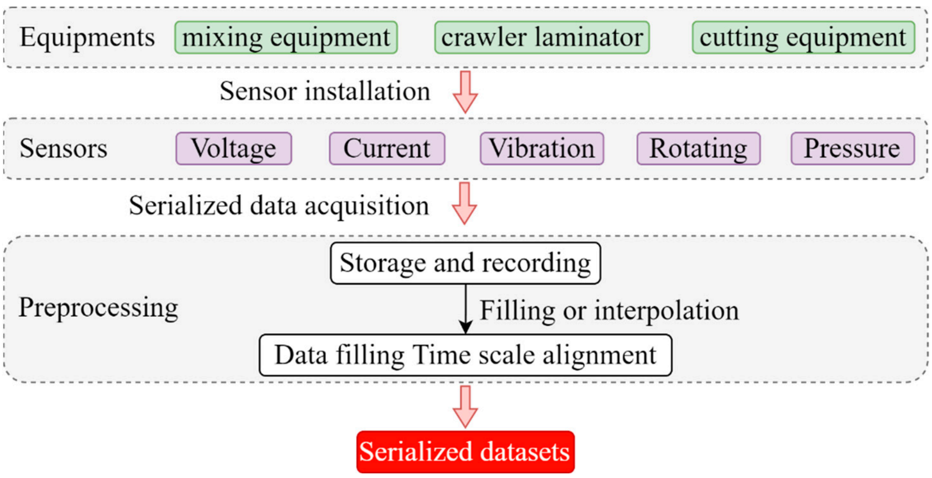

Figure 5. Acquisition and preprocessing of data fill and timing alignment.

To solve the problem of missing data values, when the missing data is small, the historical data of the previous moment (or the next moment) of the missing data can be used to make up the missing data by a filling or interpolation method. A data completion method based on quadratic interpolation can be introduced, since the missing data are few. A fitting curve by quadratic interpolation can estimate the overall trend of a small data gap. When there is a large amount of missing data, the above method is no longer applicable, so it is necessary to compare the data measured by sensors of adjacent measuring points or other relevant measuring points, and fill the missing data according to the data correlation. The preferred method is to find similar data at a similar time by data similarity analysis.

Principal component analysis (PCA) was used to perform data dimensionality reduction. The adjacent data whose similarity reached the threshold were used for data completion. If no similar data could be found, the entire segment of data with missing data were discarded. To solve the problem of time inconsistency of data collected by various sensors, it is necessary to transform the data. According to a uniform time interval, the mean value of all data values in the corresponding time period was taken to ensure the consistency of data collection frequency.

Time series data selection. In this paper, the data measured by a variety of sensors on the production line of an A-class insulation board were predicted and studied. According to a large number of relevant works, the data obtained from the actual measurement of A-class insulation board were selected. The signals of the LSTM-based multi-feature fusion prediction model adopted in this paper consisted of five parts, i.e., voltage, current, vibration, rotation and pressure, as listed in Table 1.

Table 1. Specification of different sensors installed on the production line.

Number	Device	Sampling Rate	Node Count	Range
1	Voltage sensors	600 Hz	3	0–450 V
2	Current sensors	450 Hz	2	0–300 A
3	Vibration	500 Hz	2	0–100 mm/s
4	Rotating	2 kHz	1	0–20 kHz
5	Pressure	2400 Hz	2	0–100 MPa

K-Nearest Neighbor algorithm. The output of the proposed CNN-LSTM model is a 10-dimension tensor, which can perform fault diagnosis by cascading a certain classification algorithm. Hence, K-Nearest Neighbor (K-NN) was introduced as the final classifier because of high accuracy and flexibility. The capacity of the custom multiple-sensor dataset is enormous, so, labeling the custom dataset is time-consuming and tedious. Therefore, the k-means algorithm was introduced to preprocess the custom dataset, and labeling and double-checking each cluster by experienced experts. The well-prepared custom dataset by k-means algorithm can be used as training dataset for the proposed CNN-LSTM model.

4.2. Experiments and Evaluation Method

Preparation. After the preprocessing of the data collected by various sensors in an A-class insulation panel production line, a complete time sequence signal dataset was established for training the CNN-LSTM network. Custom training and testing datasets acquired by above sensors are listed in Table 2. The running data of an A-class insulation panel production line at an average 16 h per day for 20 days were collected and preprocessed by a data filling algorithm. Data sampling rate was fixed at 1 kHz, and the mean of every 250 points was considered as a sample point. Therefore, the length of each sample in the custom multi-sensors dataset was 0.25 s, i.e., four samples per second.

Table 2. Detailed description of the custom dataset.

	Length of Each Sample	Proportion	Number of Samples
Train		70%	3225.6 k
Validation	0.25 s	20%	921.6 k
Test		10%	460.8 k
All	-	-	4608 k

The collected dataset of the operation status of an A-class insulation board production line includes the normal operation status of the production line and five failure states: abnormal pressure of air compressor, failure or abnormality of cutting equipment, abnormal state of raw material mixing equipment, main motor failure, and spindle failure of stirring kettle, as listed in Table 3. Since serious data imbalance existed in the custom multiple-sensor dataset, data augmentation was applied to alleviate the influence of data imbalance. The data augmentation algorithm was mainly implemented by randomly cropping and inserting. Target data segment, i.e., data of abnormal state were randomly cropped and inserted into data of normal state. An abnormal pressure of the air compressor may lead to serious production accidents, and was one of the key monitoring nodes. Failure or abnormality of other equipment may cause serious quality problems of A-class thermal insulation boards. Therefore, a data augmentation algorithm was mainly applied at the time periods when abnormal appearance was observed. The ratio of normal to abnormal (air compressor, cutting equipment, mixing equipment and stirring kettle) state was 65.4:34.6 (8:9.3:8.3:9), which is close to 65:35. The original data captured from each sensor is displayed in Figure 6. These abnormal data were caused by electromagnetic interference, load change or other reasons, and may revert to normal in a short time, and should not be treated as faults. Hence, the original data should be preprocessed. Part of the preprocessed training data is shown in Figure 7. Considering the high-sensitivity of deployed sensors, the average value and overall trend of each sensor are helpful to train the proposed model and predict the state of the production line. To give a rough impression, subplots (a) and (b) refer to the starting moment, and subplots (c) to (f) reflect the normal running state of corresponding equipment.

As can be seen from the figure, the preprocessed data have the same sampling frequency, which can effectively represent the operating status of each device.

Table 3. The possible state of each device in A-class insulation panel production line (Original dataset).

Device	Running State	Proportion
All devices	Normal	68.7%
Air compressor	Abnormal (pressure)	1.8%
Cutting equipment	Abnormal (voltage and current)	8.4%
Mixing equipment	Abnormal (rotation)	9.3%
Stirring kettle	Abnormal or breakdown (vibration)	11.8%

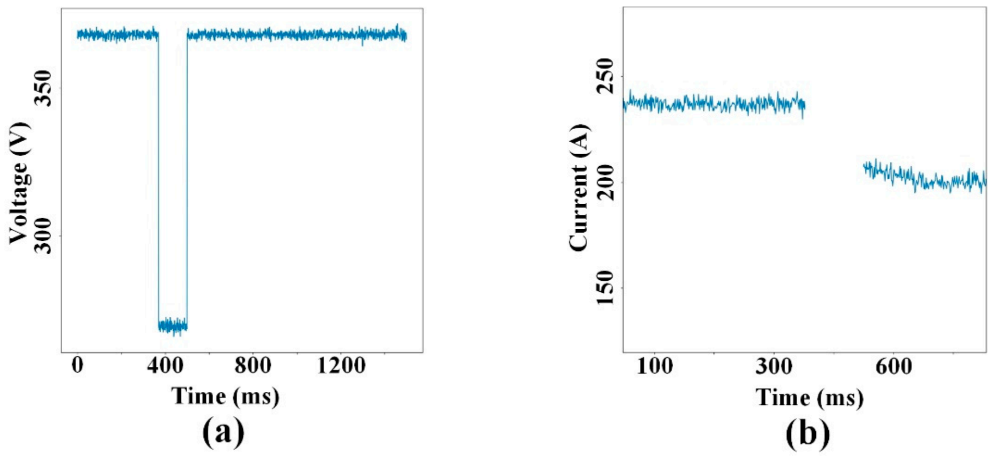

Figure 6. Original data captured from various sensors. Subplots (**a**,**b**) are curves of voltage and current, in which abnormal data exist.

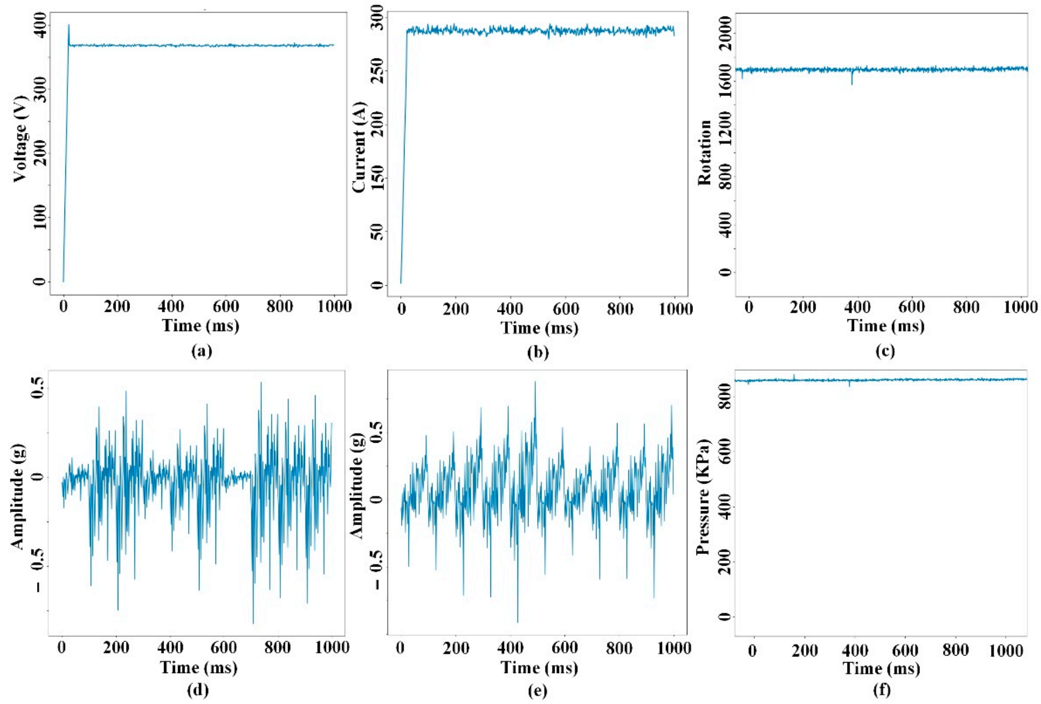

Figure 7. The preprocessed dataset of multi-sensor signals. Subplots (**a**–**f**) are signals of voltage, current, rotation, vibration-x, vibration-y and pressure, respectively. Subplots (**a**,**b**) refer to the starting moment, and subplots (**c**–**f**) reflect the normal running state of corresponding equipment.

Training. Adam was selected as the optimizer with a momentum of $\beta_1 = 0.95$, $\beta_2 = 0.997$ in the training process. Batch size was fixed to 128, and the learning rate was 0.0002 at the beginning. The decay ratio of learning rate was 0.98 per five epochs; hence, the final learning rate was $2e^{-4} \times 0.98^{40} \approx 8.9e^{-5}$. In the training process, the changes of mean square error (MSE) loss of the training and testing set are shown in Figure 8. In the first 30 epochs of training, the mean square error loss of the training set and test set showed a rapid decreasing trend, but after epoch 160, the decreasing trend became slower. As can be seen from Figure 8, in the training and testing set, MSE loss after training of epoch 180 are both minimum values. To select the model with the best performance, the model parameters after epoch 190 of training were selected as the final CNN-LSTM model parameters. At this time, the MSE loss of the training and testing set were about 0.4227 and 0.4213, respectively.

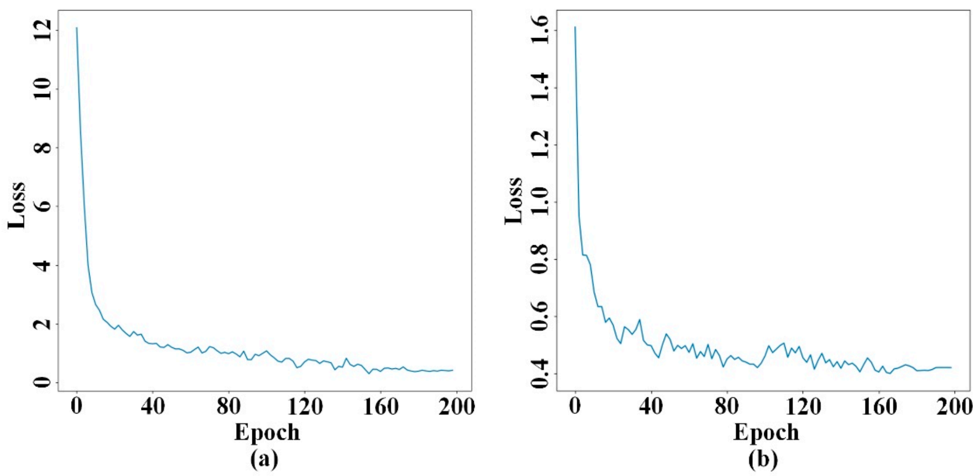

Figure 8. MSE loss curves of the proposed CNN-LSTM model. (**a**) Loss curve of the training dataset. (**b**) Loss curve of the testing dataset.

Testing. To verify the feasibility and effectiveness of the proposed CNN-LSTM model for the fault diagnosis method of an A-class thermal insulation board production line, four evaluation indexes, i.e., accuracy, precision, recall and F1-sore, were adopted to evaluate the prediction of the model and compare these with other algorithms, e.g., RNN [39], LSTM [40], SVM [33] and 1D-CNN [41]. In the same dataset, the proposed LSTM fault diagnosis model was used to train the multi-sensor dataset of an A-class insulation panel production line. The comparison is shown in Table 4, and the formulations can be described as follows:

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP}) \tag{5}$$

$$\text{Recall} = \text{TP}/(\text{TP} + \text{FN}) \tag{6}$$

$$\text{Accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{TN} + \text{FP} + \text{FN}) \tag{7}$$

$$\text{F}_1 = 2 \cdot (\text{Precision} \cdot \text{Recall})/(\text{Precision} + \text{Recall}) \tag{8}$$

where, TP, FP, TN and FN denote True Positive, False Positive, True Negative and False Negative. All algorithms involved in the comparison were slightly modified to fit the task, which was to predict the state of the production line in the next 10 s by the data of the last 100 s. Time consumption refers to the cost of time per prediction. The confusion matrix is shown in Figure 9 to provide further insights. The essential problem is how to predict if the production line is running properly or not. Although the output of the proposed CNN-LSTM model is multi-classification, false classifications among abnormal states of different equipment are not concerned. In other words, the multi-classification can be regarded as binary classification. Therefore, the left multi-classification confusion matrix in Figure 9 can be converted to a right matrix, which simplifies the fault diagnosis problem, in which 0 and 1 represent the normal and abnormal states, respectively.

Table 4. Comparison of results between the proposed network and other algorithms.

Algorithm	Accuracy	Precision	Recall	F1-Score	Time Consumption (s)
Proposed	98.97%	98.95%	99.47%	99.21%	0.437
RNN	71.58%	81.29%	73.16%	77.01%	0.583
LSTM	83.56%	88.48%	86.67%	87.56%	0.519
SVM	69.21%	72.77%	77.22%	74.93%	1.748
1D-CNN	78.07%	85.12%	81.38%	83.21%	0.364

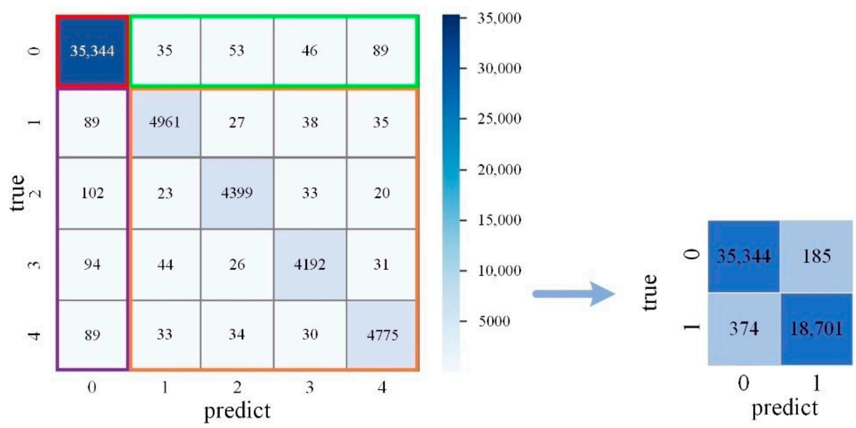

Figure 9. Confusion matrix of the proposed model, with 0 to 4 referring to normal and abnormal of states of the air compressor, cutting equipment, mixing equipment and stirring kettle, respectively.

In terms of fault diagnosis performance, the proposed CNN-LSTM model was obviously superior to other network based on RNN and SVM-based methods. Compared with typical deep RNN model and LSTM models applied in recent years, the proposed

CNN-LSTM model is better by all criteria, reaching 98% on average and meeting the needs of fault diagnosis in actual production.

5. Application

The proposed fault diagnosis system was applied in an actual production environment. The A-class insulation board production line consists of mixing equipment, a caterpillar laminating machine and cutting equipment. It is essential to keep each piece of equipment of an A-class insulation board production line normal and efficient in operation. Therefore, the voltage and current data of key nodes, vessel pressure and vibration signals of key motors of mixing equipment, crawler laminator and cutting equipment were sampled and monitored in real time. The production line of an A-class insulation board production line and its various sensors for key nodes are shown in Figure 10, and the specifications of deployed sensors are listed in Table 5. Data were acquired and sent to a computer by a PLC. All kinds of collected signals were preprocessed to ensure the integrity and credibility for each key node. Detailed procedures of signal preprocessing are described in Section 4. The training and testing datasets consisted of preprocessed multi-sensor data and were fed into the proposed CNN-LSTM network. The proposed CNN-LSTM network and datasets were sent to the server for training to obtain well-trained predictable models. The configuration of the high-performance server used for training is shown in Table 6.

Figure 10. The A-class insulation board production line and detailed pictures of various sensors. (**A**) Container pressure sensor. (**B**) Voltage sensor (AC). (**C**) Current sensor (DC). (**D**) Vibration sensor.

Table 5. Specifications of different sensors deployed in the production line.

Sensor	Input Voltage	Output	Resolution	Range
Voltage	-	RS485	600	0–450 V
Current	-		450	0–300 A
Vibration	12 or 24 V	4–20 mA	0.1 mm	0–100 mm/s
Rotation	24 V	0–10 V	0.3%	20–10,000 Hz
Pressure	12–36 V	4–20 mA	0.06 MPa	0.1–60 MPa

Table 6. Specification of the high-performance server.

No.	Device Name	Type
1	CPU	I9-10900kf
2	RAM	64G DDR4
3	Hard driver	512G SSD
4	GPU	RTX 2080s × 2

Data collected by each sensor were processed by a computer and fed into the proposed CNN-LSTM model. The output of the network contained the prediction of the next 10 s states of each piece of equipment, and was classified by the k-NN algorithm to obtain the final diagnosis. Days of industrial testing proved the prediction accuracy and stability of the proposed model. Prediction accuracy over 10 s reached 98.7%, and decreased by 6% when the prediction duration was increased to 15%. In general, a timely response, i.e., load reduction or shutdown, could be made with accurate prediction within 10 s. Hence, the proposed CNN-LSTM model satisfied the requirement of industrial production.

6. Conclusions and Future Works

In this paper, a fault diagnosis method for an A-class insulation panel production line based on multi-sensor fusion is proposed. A CNN-LSTM-based network, combined with an attention mechanism, improved hidden features extraction. Real-time data of an A-class insulation panel production line were collected by placing multiple sensors at key nodes. A well-trained model based on CNN-LSTM was validated by multiple sets of experiments. The experimental results showed that the prediction precision of the proposed fault diagnosis method reached 98.7%, could accurately predict different types of faults for an A-class insulation panel production line, and fully met the needs of industrial production. In future work, research on production line state prediction method for an A-class insulation board will be carried out to predict the production line state in real time and to improve production efficiency.

Author Contributions: Conceptualization, Y.W. and X.L. (Xiaowen Liu); methodology, Y.W.; software, Y.W.; validation, X.G. and X.L. (Xinhua Liu); formal analysis, X.G.; investigation, X.G.; resources, X.L. (Xinhua Liu); data curation, X.G.; writing–original draft preparation, Y.W.; writing-review and editing, X.L. (Xinhua Liu); visualization, Y.W.; supervision, X.L. (Xiaowen Liu); project administration, X.L. (Xiaowen Liu); funding acquisition, X.L. (Xinhua Liu). All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Postgraduate Research & Practice Innovation Program of Jiangsu Province, grant number SJCX22_1139.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Some or all data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare that there is no conflict of interest regarding the publication of this article.

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