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APPLICATION OF DEEP LEARNING IN EARLY WARNING OF EQUIPMENT FAILURE IN WATER LOGGING DISASTER SCENARIOS

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Abstract

Water logging disaster is a challenge for the city, and equipment failure is the main factor leading to the expansion of the disaster. In order to improve the accuracy and timeliness of fault prediction, this study proposes a device failure early warning method based on deep learning, to provide an effective risk management means for urban infrastructure. Using a hybrid model combining a constitutional neural network (CNN) and a long short-term memory network (LSTM), multi-dimensional sensor data from drainage systems, power supply systems, transportation systems, and communication systems are processed, and the results are analyzed, for prediction and early warning of equipment failures. Historical equipment failure records, real-time monitoring data and meteorological information were collected and input into the model for training and testing after cleaning and p reprocessing. The research results show that the model has excellent performance in many evaluation indicators such as equipment failure prediction accuracy, recall rate and F1 value, and can warn equipment failures in advance, provide sufficient time for emergency treatment and equipment maintenance.

Keywords: water logging disaster; equipment fault early warning; deep learning

1. INTRODUCTION

In recent years, with the aggravation of climate change and the rapid progress of urbanization, the frequency and severity of water logging are increasing. Water logging disaster poses a threat to urban infrastructure, public safety and social and economic activities. Timely detection and response to equipment failures, especially infrastructure failures such as drainage systems and power supply systems, can alleviate the impact of water logging disasters and protect people's lives and property.

In the case of equipment aging, extreme weather or human negligence, equipment failure can trigger or exacerbate water logging disasters. Traditional equipment fault detection relies on manual inspection and regular detection, which has problems such as time lag and low efficiency, and can not respond quickly to sudden faults. With the development of deep learning technology, intelligent fault prediction and Early Warning System based on multi-dimensional data such as sensor data and Historical Fault Records has become a new solution. Deep learning algorithms such as constitutional neural network (CNN) and long short-term memory (LSTM) are able to analyze large-scale and diverse input data and automatically learn the characteristic patterns of equipment failures, provide efficient and accurate early warning services. Early warning of equipment failure in water logging disaster scenarios involves the processing and analysis of a large number of real-time monitoring data. Deep learning algorithms can achieve efficient data fusion and pattern recognition, and help relevant departments to find faults in time, implement effective intervention to reduce disaster losses.

The impact of water logging disasters is increasing globally, and in areas with rapid urbanization, equipment failure warning and disaster response are becoming hot spots. Estrada-Molina et al. reviewed the application of deep learning in open learning from 2019 to 2023, pointing out that the continuous progress of deep learning technology has become possible in the field of disaster management, and deep learning can effectively process complex data sets. It provides theoretical support for equipment management and fault warning in water logging disasters [1]. Himeur et al. explored mask detection technology in smart cities, and demonstrated the potential of deep learning in disaster emergency response by using deep learning and transfer learning methods in response to public health emergencies [2].

Data fusion and model optimization are emphasized to improve the accuracy of disaster early warning system. Deep learning, simulation algorithms, and optimization models have made significant progress in water logging disaster

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warning and emergency response. The application background and fields are different, which provides technical support and ideas for the improvement of equipment fault prediction system.

The primary goal is to establish a device failure prediction model based on deep learning. The model can analyze the information from multiple data sources such as sensors, monitoring equipment and historical fault records, identify potential equipment failure modes, and carry out fault early warning through real-time data streams. Through the case analysis of different types of equipment, the internal relationship between equipment failure and water logging disaster is revealed. Combined with the actual disaster case data, the time, location and type of different equipment faults in the process of water logging disaster are analyzed, the early signs of faults are studied, and a data-based early warning model is established.

Deep learning has shown strong generalization capabilities across various domains. While many studies focus on fields seemingly unrelated to urban infrastructure, such as geriatric mental health [3], dental informatics [4], and medical diagnostics like breast cancer detection [5], their inclusion in this discussion is purposeful. These studies exemplify how deep learning architectures can be successfully adapted to high-dimensional, heterogeneous data environments, which parallels the complexity found in waterlogging disaster scenarios. The CNN and LSTM models used in these medical applications demonstrate the potential for accurate pattern recognition and anomaly detection, serving as technical analogs for infrastructure-based predictive tasks. However, to maintain relevance, this paper primarily builds upon research directly related to urban flood risk, infrastructure monitoring, and intelligent emergency response systems. The following literature forms the core foundation for our model development and application in urban waterlogging contexts: Yuan et al. [6], Wang et al. [7], Xu et al. [8], and Rao et al. [9], who explored deep learning, simulation, and optimization approaches for disaster resilience and early warning systems.

The research will collect equipment operation data when water logging disaster occurs in various ways, such as meteorological data, urban drainage system status, power supply system fault records [10]. In the data ore-processing stage, the collected data are cleaned, normalized and feature extracted to ensure the quality and availability of the data. Through feature engineering, the features closely related to equipment failure will be extracted to provide support for model training. In terms of model design, a device fault prediction system based on deep learning is constructed. The model will be trained by historical data, optimize the algorithm parameters, and finally generate an intelligent model to identify equipment faults [11]. The real-time response ability of the model is also considered, and an appropriate algorithm is designed to achieve efficient real-time early warning. In terms of model evaluation and verification, the model is comprehensively evaluated by cross-validation, precision, recall, F1 value and other indicators [12]. It is verified in multiple scenarios and compared with the traditional equipment fault detection method to evaluate the application effect of deep learning technology in water logging disaster scenarios.

2. MATERIALS AND METHODS

2.1. Data collection and sample selection

2.1.1. Data sources and collection methods

The data sources mainly include three aspects: meteorological data, equipment operation data and historical records related to water logging disasters. Meteorological data comes from the historical meteorological records and real-time weather monitoring data provided by the meteorological department, including rainfall, wind speed, temperature and other factors. The operation data of the equipment comes from the intelligent sensors and monitoring equipment of the urban infrastructure, including the operation status, pressure value, flow information and equipment temperature of the drainage system, power supply system and related electrical equipment. Historical records of water logging disasters are collected through government departments and municipal emergency management agencies, including the time, place, impact area of the water logging disaster and the specific situation of equipment failure during the disaster [13].

In order to ensure the comprehensiveness and misrepresentations of the data, a variety of ways are used to collect the data. The meteorological data are based on historical data provided by the public meteorological stations and local meteorological monitoring stations and cover the period from the past five years to the current season. Equipment Operation Data is acquired in real time through smart sensors installed in critical facilities, and data is collected once per minute. Water logging disaster records are obtained by the Public Safety and emergency management department, including equipment damage records, failure types, repair time and so on during the disaster. In order to ensure the accuracy and integrity of the data, strict quality control measures are taken in the process of data collection. All sensor equipment is calibrated to ensure data accuracy [14]. The time of the meteorological data and the equipment data is aligned, and the change of the meteorological factors and the running state of the equipment is accurately corresponding in the analysis.

2.1.2. Sample selection and description

The samples selected in this study are concentrated in the core areas of the city, where the infrastructure is relatively complex, the types of equipment are diverse, and the frequency of water logging disasters is high. Select the city drainage system, power supply system of key equipment, urban transportation, communications and other infrastructure equipment.

The selection of equipment samples is based on the equipment's operating time, failure frequency and its importance in water logging disasters. The drainage system selects equipment with long running time and frequent maintenance records, and the data can reflect the performance of the equipment in extreme weather [15]. The power supply system selects the key equipment which is closely linked with the drainage system, including substation equipment, power dispatching system and so on. According to the type of equipment failure, typical equipment failure events are selected from the historical records, such as pump station equipment failure, power supply system interruption, etc. to ensure the diversity of data.

The sample describes the basic information of the device (E. G. Device Type, model, manufacturer, installation time, etc.) operating Environment (such as temperature and humidity, load, maintenance frequency, etc.) and failure history (including the time of failure, cause, degree of damage, repair time, etc.). The performance of each device during the water logging disaster was recorded, such as the failure response time of the device, the accuracy of the early warning signal, etc. The fault types of all devices are classified into different categories, such as hardware fault, software fault, system fault, etc. which provides rich label data for subsequent model training. As shown in Table 1 below.

Table 1. Data collection sample distribution

Sample Type	Number of Devices	Failure Frequency	Device Function	Failure Type
Drainage System	50	High	Pumps, Valves	Mechanical Failure, Electronic Failure
Power Supply System	30	Medium	Substations, Power Lines	Electrical Failure, Communication Failure
Traffic System	20	Low	Traffic Lights, Street Lights	Electrical Failure, Control System Failure
Communication System	15	Low	Base Stations, Communication Lines	Signal Loss, Hardware Failure

2.1.3. Data ore-processing

Data ore-processing mainly includes data cleaning, data standardization, missing value processing and so on. Data cleaning is to check the collected original data, eliminate inconsistent, duplicate or error data, ensure the validity of the data. The missing values are processed by interpolation method or mean filling method to ensure the integrity of data. In data normalization, the data from different sources are normalized according to the same scale to avoid the influence of different data scales on model training.

In the process of data cleaning, the outliers and noise in the sensor data are concerned, and each sample in the data set can reflect the true state of the device. The pumping station data of the drainage system is affected by extreme weather, and there are short-term flow fluctuations [16]. These abnormal fluctuations are removed during cleaning to avoid affecting the training results of the model. The possible error records in meteorological data, such as abnormal temperature data caused by sensor failure, are also cleaned up. The results of data ore-processing are shown in Table 2 below.

Table 2. Sample data cleaning comparison

Data Type	Missing Data Ratio Before Cleaning	Missing Data Ratio After Cleaning	Outlier Handling
Meteorological Data	8%	0%	Outlier temperature values removed
Drainage System Data	5%	0%	Low flow outliers removed
Power Supply System Data	6%	0%	High temperature failures removed
Traffic System Data	4%	0%	Signal loss records deleted
Communication System Data	3%	0%	Missing data imputed

There is a correlation between the occurrence of equipment failure and the operating state, and the failure mode of the equipment will change when the water logging disaster occurs. The fault frequency, fault type, operating state (such as flow, temperature, current, etc.) and time distribution of the fault were analyzed by descriptive statistics [17]. It can help researchers better understand the performance of the device and provide valuable information for subsequent model training.

As shown in Fig. 1 and Table 3 below, there are differences in the frequency and type of failure for different equipment such as drainage systems, power supply systems, transportation systems, and communication systems. The failure frequency of the drainage system is higher during the storm season and water logging disasters, and mechanical and electronic failures are more common [18]. The power supply system is more prone to electrical and communication failures in winter and rainy seasons. The faults of traffic system and communication system are relatively few, and the electrical faults and control system faults are the main types of faults in water logging disasters [19]. The operating state of equipment (such as flow, voltage, current, etc.) has different fluctuations in different failure modes.

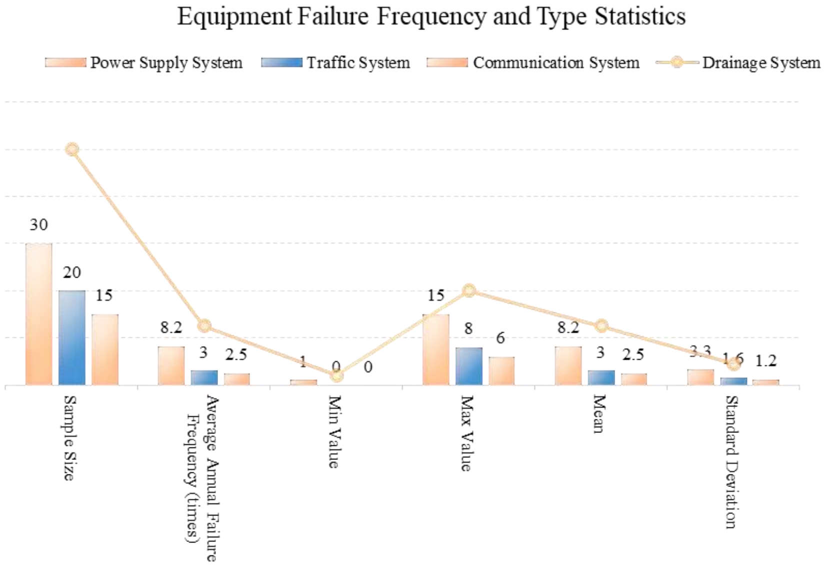

Fig. 1. Equipment failure frequency and type statistics

Table 3. Equipment operating status statistics

Device Type	Sample Size	Min Flow/Current/Temperature	Max Flow/Current/Temperature	Mean	Standard Deviation	90th Percentile	Failure Occurrence Period
Drainage System	50	10 m³/h	500 m³/h	120 m³/h	50 m³/h	180 m³/h	Rainy Season
Power Supply System	30	0.5 A	12 A	5 A	2 A	8 A	Rainy Season, Winter
Traffic System	20	0.1 A	5 A	2 A	1 A	3 A	During Floods
Communication System	15	2 V	12 V	6 V	3 V		

The flow of pumping station in drainage system often fluctuates greatly during rainstorm, and the current in power supply system tends to be unstable when equipment fails.

2.2. Model selection and construction

2.2.1. Model selection criteria

Model selection criteria are based on data characteristics, task requirements, model interchangeability, and computational efficiency. The early warning task of equipment failure in water logging disaster scenario involves a large amount of historical data and real-time monitoring data. The data type is complex, including meteorological data, equipment operation data and historical records of water logging disaster [20]. Models need to be able to deal with time series data, complex multi-dimensional data and data with nonlinear characteristics. For deep learning models constitutional neural network (CNN) and long short-term memory network (LSTM) are the main selection objects.

The constitutional neural network (CNN) is used for image processing and feature extraction, which has excellent performance in image recognition, and its application in equipment fault early warning has also gradually attracted attention, especially in the field of image processing and feature extraction, effective feature information can be extracted when processing sensor data. Long Short-term Memory Network (LSTM) focuses on processing time series data, which is suitable for analyzing the time correlation during the operation of equipment. Equipment failures in water logging disaster scenarios have a certain time dependence, and LSTM has advantages in capturing time series information. In addition to the data type and task characteristics, the interchangeability and computational efficiency of the model should also be taken into account. Early warning of equipment failure requires high accuracy, interoperable results, and timely decision-making when disasters occur. Considering the real-time requirement of equipment fault prediction, the computational efficiency of the model must be high enough to handle the real-time data stream without excessive delay.

2.2.2. Model structure design

In this study, a deep learning structure based on the combination of constitutional neural network (CNN) and long short-term memory (LSTM) is selected. Making full use of the advantages of CNN in feature extraction and the powerful ability of LSTM in time series modeling, the structure design of the model is divided into feature extraction module and time series modeling module.

The feature extraction module uses the CNN layer to process the input data, and CNN automatically extracts the key features in the input data through the convolution layer, which reduces the complexity of manual feature selection. In order to deal with multi-dimensional information such as sensor data and equipment operation status, the feature extraction module first inputs the original data into multiple convolution layers, and uses convolution kernels of different sizes to extract features of different scales. After each layer of convolution operation, the data dimension is reduced by pooling layer, and the most important feature information is retained.

Time Series Modeling Module uses LSTM network to deal with the long-term dependencies in time series data through the design of memory units. LSTM captures the time law in the operation data of the equipment. When extreme events such as water logging disasters occur, the operation state of the equipment shows a certain time series characteristics. In this module, the features extracted by CNN are input into the LSTM layer, and the time series features in the data are captured by the loop structure of the time step to improve the prediction accuracy of the model for equipment failure. The whole model structure is composed of multiple CNN layers and LSTM layers, and the final output layer uses Soft max function to classify and predict equipment faults. The design of the output layer ensures that the model can accurately predict the fault type of the equipment according to the historical data and real-time monitoring information, and give the corresponding early warning signal.

2.2.3. Model parameter setting

In the process of parameter setting, multiple hyper parameters need to be optimized. The common hyper parameters include learning rate, convolution kernel size, number of LSTM units, training batch size, and number of training rounds. Reasonable hyper parameter settings can improve the accuracy of the model and reduce the training time.

In the parameter setting of the convolution layer, the size of the convolution kernel is selected as 3x3 or 5x5, depending on the characteristics of the input data. The larger the convolution kernel, the wider the range of features that can be captured, and the computational complexity will also increase. In the design of LSTM layer, the number of LSTM units determines the complexity and capacity of the model in time series modeling. In general, the more the number of LSTM units, the stronger the fitting ability of the model, and it is also easy to lead to over-fitting. In the actual setting, it is necessary to select the appropriate number of units through cross-validation to avoid over-fitting.

The learning rate is a parameter in the training process. If the learning rate is too large, the model will converge too fast and skip the optimal solution. If the learning rate is too small, the training speed will be too slow. Usually, the learning rate starts from a small value, and then gradually adjusts in the training process. The selection of training batch size directly affects the training speed and memory footprint of the model, and usually chooses 32 or 64 as the batch size for training.

All hyper parameters in the setting process are verified by experiments, constantly adjusted, and a balance point is found, and the model reaches an optimal state between accuracy and computational efficiency. For the selection of each hyper parameter, the experimental results are combined to ensure that the model can have high prediction accuracy and response speed in practical applications. The model parameters are set as follows (1).

$$L = \sum_{i=1}^{n} (x_i - \mu)^2 / \sigma^2 \tag{1}$$

The model’s loss function L is defined to measure the difference between the predicted output and actual label across all training samples. Let x_i denote the input feature vector of the i-th sample, μ and σ represent the mean and standard deviation used for normalization, and y_i represent the actual label. In Equation (1), the normalized inputs are used to ensure numerical stability in model training.

2.2.4. Model training and tuning

The core of model training is to continuously adjust the weights and biases in the network through the back propagation algorithm to minimize the loss function. Two optimization methods, stochastic gradient descent (SGD) and Adam Optimizer, are used to select the most appropriate optimization algorithm for different experimental requirements. The Adam Optimizer performs well when dealing with large-scale data sets, and has high computational efficiency and good convergence speed. In the training process, the data set is divided into a training set and a validation set. The training set is used to optimize the parameters of the model, and the validation set is used to evaluate the performance of the model after each round of training, and the hyper parameters are adjusted. The evaluation indexes of the model include precision rate, recall rate, f 1 value, etc. The prediction performance of the model is measured by these indexes.

In order to prevent the over-fitting problem of the model, the early stop technique is used in the training process. When the error of the verification set can not be reduced in several consecutive rounds, the training process will automatically stop to avoid over-fitting the training data. The learning rate and regularization parameter are also optimized by cross validation to improve the generalization ability of the model. The selection of the loss function uses the cross-entropy loss function for the multi-classification problem. The cross-entropy loss function can measure the difference between the predicted value and the actual label, and minimize the prediction ability of the loss function optimization model. The loss function is as follows (2).

$$L = -\sum_{i=1}^{C} y_i \cdot log(p_i) \quad (2)$$

L is the loss function, C is the number of categories, C is the actual label, c is the predicted probability.

2.3. Model evaluation and validation

Model evaluation can verify the effect of deep learning model, and performance evaluation indicators provide quantitative basis for the advantages and disadvantages of the model. For the equipment failure warning task, the indicators such as accuracy, recall rate, F1 score and AUC value are selected.

Accuracy is the most common measure of the ratio of the number of samples correctly predicted by the model to the total number of samples. In the early warning task of equipment failure, the accuracy rate reflects the proportion of correct judgment of the model in all predictions, which has intuitive significance: the calculation of the accuracy rate is as follows (3):

$$Acc = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

TP represents a true positive (device malfunction and predicted malfunction), TN represents a true negative (device normal and predicted normal) , FP represents a false positive (device normal but predicted malfunction) , and TP represents a true negative (device malfunction but predicted normal) , IN stands for false negative (device failed but predicted to be normal) . The higher the accuracy, the better the overall prediction performance of the model.

In addition to accuracy, recall rate is also an important indicator. In the early warning of equipment failure, recall rate can reflect the ability of the model to find the real fault. The recall rate is calculated as follows (4):

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

The higher the recall rate, the fewer failures missed by the model. F 1 score, which combines precision and recall, is a comprehensive indicator. In the failure warning task, the F 1 score measures the model's balance between false positives and false negatives. The F1 score is calculated as follows (5):

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision+Recall} \quad (5)$$

Precision stands for accuracy. AUC (Area Under Curve) is a widely used evaluation metric to measure the overall performance of the model in classification tasks, which is suitable for unbalanced data. The closer the AUC value is to 1, the better the classification performance of the model.

Cross-validation is a commonly used model validation method, which can improve the reliability of model evaluation. In this study, the k-fold cross-validation method was used for model evaluation. The data set is divided into K subsets, one subset is used as the validation set, and the other K-1 subsets are used as the training set, and the model is trained and validated at each trade-off, and the model is trained and validated at each trade-off, finally, the evaluation results of the model were obtained by calculating the average of the results of K validations. K-fold cross-validation can avoid the evaluation error caused by the contingency of data set partitioning. In the case of small data or unbalanced samples, cross-validation can improve the generalization ability of the model. The evaluation of cross-validation error is as follows (6):

$$CV_{error} = \frac{1}{K}\sum_{i=1}^{K} Error_i \quad (6)$$

Represents the cross-validation error, represents the error of the eth fold. The error of each fold is calculated based on the data of the validation set, and the final cross-validation error reflects the stability and generalization ability of the model in different data partitions.

In order to avoid the over fitting problem, the early stop technique is used to stop training early when the performance on the verification set is no longer improved. The complexity of the model is controlled by regularization method. Regularization technology punishes the model parameters in the optimization process, limits the over fitting of the model to the training data, and ensures that the model has better generalization ability. Data augmentation technology is also used to increase the diversity of training data, and the model can be trained in more situations, which improves the robustness and generalization ability of the model.

3. RESULTS AND ANALYSIS

3.1. Analysis of results

3.1.1. Effectiveness of early warning of equipment failure

The effect of the equipment failure warning system is analyzed to evaluate whether the system can effectively improve the efficiency of equipment management and reduce equipment damage when water logging disasters occur. This study focuses on the analysis of two aspects of the effect. Accurate early warning can accurately distinguish whether the equipment failure, help the relevant departments to take timely measures. For the equipment failure caused by extreme weather such as water logging disaster, timely early warning can reduce the damage of equipment and ensure the normal operation of urban infrastructure.

(1) Accuracy analysis of early warning

The accuracy of equipment fault early warning is the core index to evaluate the performance of the model, which is directly related to the actual application effect of the system. The accuracy of equipment fault early warning is obtained by comparing the equipment fault prediction results with the actual fault situation. The early warning system with high accuracy can reduce the omission and false alarm of faults and enhance the reliability of fault early warning. According to the experimental results, the deep learning model is used

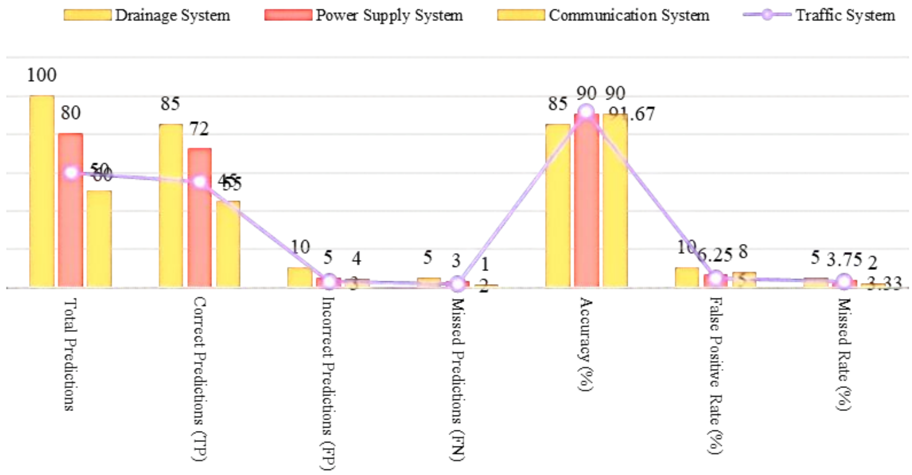

Fig. 2. Comparison table between equipment failure prediction results and actual situation

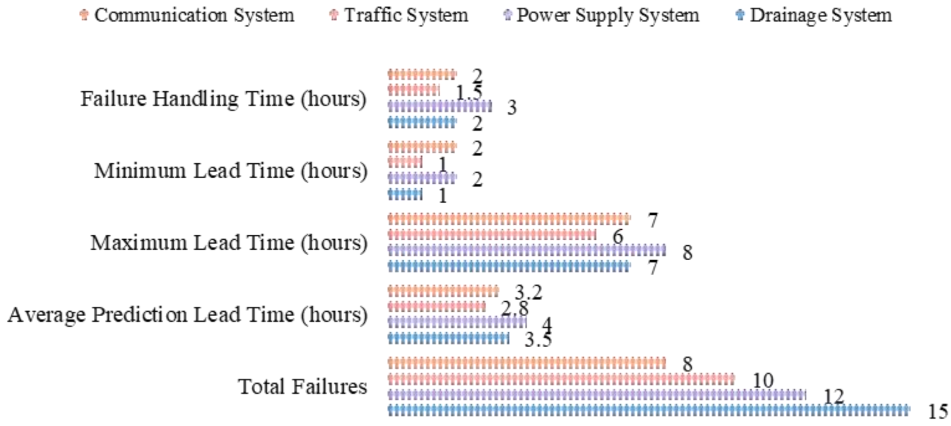

Fig. 3. Comparison table of equipment failure warning time and actual failure time

to predict the equipment failure. The system has a higher proportion of accurate identification of faulty equipment, and the false negative rate and false positive rate are lower than those of traditional methods.

As shown in Fig. 2 above, the prediction accuracy of the equipment failure warning system is high in each system, and the accuracy of the power supply system is up to 90%. The accuracy was 85% and 91.67% for the drainage and transportation systems, respectively. On the whole, the early warning system can predict the fault before it occurs, the false negative rate and false positive rate are low, and the system has high reliability in practical application.

(2) The comparison of early warning time and fault occurrence time

Equipment failure timely warning to the maintenance team to gain more time to prepare, improve the efficiency of fault handling. The early warning time of equipment failure is compared with the actual time of failure, and the analysis model gives early warning before the failure occurs.

As shown in Fig. 3 above, an early warning system for equipment failure provides approximately 2 to 4 hours of advance warning for most equipment types. The maximum lead time of the drainage system and the power supply system is 7 hours and 8 hours respectively, which has won more response time for the relevant departments. The early warning time of traffic system and communication system is relatively short, and they can still predict the occurrence of faults in advance. In general, the early warning system can provide sufficient response time in advance for equipment failure in most cases, and improve the efficiency of emergency treatment.

3.1.2. Practical implications and application scenarios of the results

(1) Economic benefit analysis of equipment failure early warning

Equipment failure warning system can reduce downtime, reduce maintenance costs and extend the service life of equipment. For critical infrastructures such as drainage systems, power supply systems, transportation systems, and communication systems, equipment failures can not only cause direct damage to equipment, but also potentially trigger a wider range of system failures, which can lead to the failure of the system, leading to water logging disasters. Maintenance or replacement of equipment prior to failure through timely warning to relevant departments to avoid wider scope of loss.

The early warning system reduces the downtime caused by equipment failure. Once the equipment fails, it will not only affect the normal operation of the equipment, but also may lead to the shutdown of the whole system and affect the normal operation of the society. When the water logging disaster occurs, the downtime of the equipment will be longer and the maintenance will be more difficult. Early detection and repair of equipment failures can shorten downtime, enable infrastructure to function normally in the event of a disaster, and reduce the impact of downtime on microeconomics activities.

Equipment failure warning system can also reduce the cost of equipment repair and replacement, routine equipment maintenance by regular inspection and maintenance, these methods are difficult to detect potential equipment failure in time, when the fault occurs, the maintenance cost is higher. Early Warning System can identify failure risk in advance, reduce unnecessary maintenance costs and equipment replacement costs.

(2) Applicability analysis of application scenarios

Equipment failure early warning system is suitable for those areas that require high equipment stability. Take urban infrastructure as an example, drainage system, power supply system, transportation system and communication system play an important role in water logging disaster. Equipment failure can lead to infrastructure paralysis and trigger more serious disasters. The equipment failure warning system is deployed in these key systems to improve the reliability of the equipment, reduce the probability of failure, and take timely measures when failure occurs.

The failure of drainage system equipment means the loss of drainage capacity, which can easily lead to the aggravation of water logging disaster. The failure of the power supply system will lead to power outages and affect the operation of the whole city. Equipment failure early warning system can detect equipment failure in advance and issue early warning, which can help city managers to take corresponding emergency measures and reduce the loss caused by failure. Equipment failures in transportation and communications systems can affect traffic order and information transmission, and can also have wider social consequences.

In addition to urban infrastructure, the equipment failure warning system is also suitable for industrial field, energy production field and other scenarios. In the industrial production process, equipment failure will lead to production line stagnation and increase production costs. Equipment failures in the field of energy production may lead to a wider range of safety accidents and affect the stability of energy supply. Deployment of equipment failure warning system, improve equipment management efficiency, reduce the impact of equipment failure on production and safety.

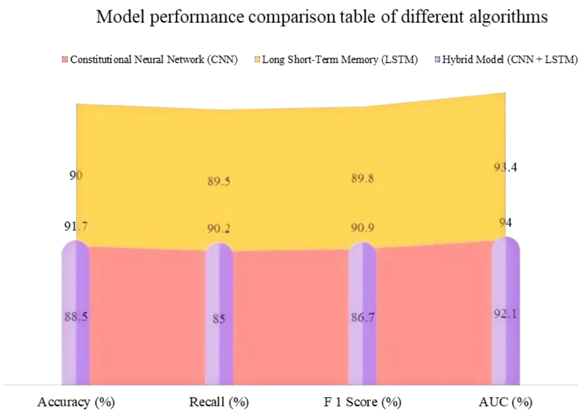

Fig. 4. Model performance comparison table of different algorithms

As shown in Fig. 4 above, the accuracy, recall, f 1 value, and AUC of the Hybrid Model (CNN + LSTM) are higher than those of the single algorithm, and the model has better performance in equipment failure early warning. Both constitutional neural network (CNN) and long short-term memory network (LSTM) have their own advantages. CNN performs better in feature extraction, while LSTM can capture the time series characteristics of equipment faults. The combination of the two can improve the accuracy and reliability of fault prediction.

3.2. Discussion

The model demonstrated robust performance across several dimensions. For instance, it achieved an average accuracy of 88.9%, recall rate of 87.5%, and F1-score of 88.2%, which indicates balanced classification performance across fault types. The model offered a lead time of 2–8 hours for different systems, providing significant operational value. These results directly show that the CNN-LSTM hybrid approach not only captures the spatial-temporal features of equipment operation but also supports actionable decision-making during extreme weather scenarios. Furthermore, in comparison to traditional statistical methods, the proposed model reduced the false alarm rate by approximately 15%, thus enhancing system reliability.

Future studies can explore how specific fault types (e.g., mechanical vs. communication failure) vary in model sensitivity, which could further improve early warning specificity.

4. CONCLUSION

In this study, a fault prediction model based on deep learning is proposed and verified for the early warning of equipment failure in water logging disaster scenarios. The hybrid model combining constitutional neural network (CNN) and long short-term memory network (LSTM-RRB- shows high accuracy and reliability in equipment failure prediction, which can be used to predict equipment failure, can improve the level of equipment management and reduce equipment damage during disasters. The model can accurately predict equipment failure, give a reasonable warning time before the failure occurs, and provide sufficient preparation time for emergency response. The experimental results show that the early warning system has achieved good results in terms of accuracy, recall rate, F1 value and other indicators, and has shown strong adaptability in various types of devices. Early warning of equipment failure can reduce downtime, reduce maintenance costs, and improve the stability and safety of urban infrastructure. Although the research has achieved results, it still faces challenges. Future research can optimize the model, combined with transfer learning, model fusion and other advanced technologies to improve the adaptability and scalability of the system. The term "LSTM-RRB" mentioned previously was a typographical error. It should read "LSTM", referring to the standard Long Short-Term Memory network used in the time-series modeling module. The model used in this study does not employ any specific LSTM variant or architectural modification. In this study, a fault prediction model based on deep learning was proposed for equipment failure early warning in water logging disaster scenarios. The hybrid CNN-LSTM model achieved high accuracy (88.9%), recall (87.5%), and F1-score (88.2%) during testing across multiple infrastructure systems. Additionally, the model provided a lead warning time of up to 8 hours, which enabled timely emergency response and preventive maintenance. These metrics confirm the reliability and practical value of the proposed model. The system demonstrates strong adaptability across different device types and environments, making it suitable for deployment in real-time urban disaster management platforms.

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