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Construction of Prediction Model for Multi-Feature Fusion Time Sequence Data of Internet of Things Under VR and LSTM

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ABSTRACT The purpose of the study is to improve the utilization rate of time sequence data generated by the Internet of Things (IoT), and explore their hidden values. Based on the deep neural network of Long Short-Term Memory (LSTM), the prediction model of multi-feature fusion time sequence data under Virtual Reality (VR) is discussed. First, the application of VR in various fields and the application status of a deep learning algorithm to IoT are analyzed. Second, the preprocessing method of time sequence data of IoT and the demand of deep learning neural networks in predicting time sequence data are analyzed. Based on the above analysis, the prediction model for multi-feature fusion time sequence data of IoT based on the deep learning network of LSTM is proposed. Finally, the experiment are designed to test the performance of the model. The results show that the proposed model and the LSTM-based regression model show high accuracy in the prediction of electricity consumption data, while the Multi-Layer Perceptron (MLP) regression model has many errors in the prediction of the data. The mean absolute percentage error (Mape) of the proposed model is the lowest, with a percentage of only 2.49%, indicating that the difference between the predicted value and the real value of the proposed model is the smallest. The Mape of the LSTM regression prediction model is 2.57%, only slightly higher than the recommended model. The Mape of the MLP regression model is much higher, with a difference of 9% compared with the real value. The R^2 of the model is 0.873, which is the highest. This study provides a reference for the application of deep learning neural networks in IoT.

INDEX TERMS VR technology, LSTM neural networks, time sequence data, prediction model.

I. INTRODUCTION

In recent years, with the continuous progress of science and technology, virtual reality (VR) is widely used in various industries, showing great value and potential [1]. Lv *et al.* (2017) proposed an immersive glasses technology based on VR to obtain primary geographic information by integrating several latest information technologies, including HCI (Human-Computer Interaction), multimodal human-computer interaction, Geographic Information System (GIS), 3D GIS, and VR. Through VR glasses, geographical software can provide an immersive environment of the geographical structure [2]. Since the reform and opening-up, China's economy has developed rapidly, the national living standard

has been greatly improved, and the power demand has also increased, leading China's modern power system to embark on the road of rapid development. In addition, China has a vast territory and complex topography, so the structure of the power grid system is affected and is complex accordingly. With the continuous expansion of the capacity and scope of the power grid, it becomes more difficult for relevant staff to analyze the data and problems of the power grid, so a more comprehensive and realistic visual analysis tool is needed [3], [4]. A VR environment is more suitable for human-computer interaction and can provide greater human-computer information exchange bandwidth and a convenient and effective way for relevant personnel.

The development of IoT, big data technology, cloud computing, edge computing, and other emerging industries greatly promotes industrial automation and process, making

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people's lives into the Internet age. In the industrial production process, a large amount of information is collected, constituting big data through the Internet [5], [6]. These data are the multi-feature fusion time sequence data. The processing and prediction of these time sequence data are automated, performing effective supervision in the production process preventing hidden dangers, and promoting the improvement and development of industrial technology.

In the existing research, the research methods of the industrial sensor time sequence prediction can be divided into two categories. One is based on a classical statistical model, which is used to obtain a stable data sequence. This method requires a higher quality of the data itself because the model has poor adaptability and is not universal [7]. Therefore, it is not fully applicable in industrial applications with complex data. The other is based on the deep neural network prediction model under machine learning. This model has strong adaptability and a high degree of automation. It can independently learn and filter external information to form datasets, so it can flexibly process and deal with various complex information [8]. Common neural network prediction models include the (K-Nearest Neighbor) KNN regression prediction model, Back Propagation (BP) neural network model, and the convolution neural network (CNN) model.

The main task is to find a deep learning method to predict the time sequence data of IoT. First, the background and basic characteristics of the data of IoT are introduced and analyzed in detail. Second, the data are preprocessed and their functions are explored according to their characteristics. Then, the deep learning method from the feedforward neural network to the LSTM neural network model is studied based on the fusion model of multiple functions and Long short-Term Memory (LSTM). Finally, an improved prediction method of LSTM industrial sensor time sequence data based on multivariate is proposed, and the synchronous prediction data of IoT are obtained.

II. THEORY AND METHODS

A. APPLICATION STATUS OF DEEP LEARNING BASED ON IoT

Artificial intelligence (AI) as a tool is applied to various fields and gained more attention from scholars. Wang *et al.* (2021) analyzed the application of deep learning and related models to speech enhancement [9]. He believes that most of the existing deep learning methods use CNN to capture the time-frequency information of input features. However, compared with CNN, it is more reasonable to capture context information on the time axis of the feature using LSTM. And a LSTM-Convolutional-BLSTM encoder-decoder (LCLED) network for speech enhancement is proposed to relieve the heavy calculation load of LSTM, balance the complexity of the model, and improve its ability to capture time-frequency information. Two LSTM parts and convolution layers are used to model the context and features of frequency dimensions respectively. The results show that the proposed LCLED can simplify the complexity of the model, shorten

the training time, and improve the quality and intelligibility of enhanced speech. Füllsack *et al.* (2020) demonstrated the ability of LSTM neural networks to predict early warning signals (EWS) [10]. There are also many related studies on the application of CNN in IoT. ZI *et al.* (2020) proposed a heterogeneous processor for CNN-based AI applications on IoT equipment [11]. The heterogeneous processor includes an embedded RISC-V CPU, which is used as a general processor and an efficient CNN accelerator, and the accelerator supports various CNN models with macro instruction lists. Li *et al.* (2021) pointed out that IoT connecting the social system and the industrial system is promising [12]. With the help of the IoT, multi-modal and heterogeneous data from industrial equipment can be easily collected and analyzed to discover the underlying equipment maintenance and health-related potential knowledge. A new failure diagnosis method based on deep learning and fusion is proposed to process the heterogeneous data in the IoT environment where industrial equipment coexists.

In short, deep learning has many functions and is widely used in the IoT. However, the existing model for predicting the time sequence data of IoT has low prediction accuracy, and its prediction effect is dependent on the distribution of source data. The traditional machine learning method takes much time to analyze time sequence data, which will lead to low-accuracy prediction of time sequence data. In the feed-forward neural network, time window is created manually to simulate the time-related problems, but this method is only suitable for short-term time-related data of IoT. In this case, conventional feedforward neural networks are proposed and used to solve the above problems. However, the gradient disappears or the gradient tends to explode if the error propagation time is long, which will lead to a significant decline in efficiency.

B. APPLICATION STATUS OF DEEP LEARNING BASED ON IoT

In recent years, with the development of computer communication technology and sensor technology, society enters the era of IoT. More and more sensors are applied to different scenarios in various industries. The collected data are transmitted to the cloud network through the Internet, forming a huge IoT world [13]. The basic composition of IoT is shown in Figure 1.

IoT is different from traditional networks. It is usually composed of the discovery layer, network layer, and application layer. The data are collected through the layout of large-scale detection infrastructure, and then the collected data are sent to the remote cloud server of the organization for storage and processing. In recent years, IoT is widely used and studied in the food industry, smart cities, urban computing, and other fields [14], [15]. Statistics and analysis of the data generated by these large-scale sensors can obtain valuable information to realize the intelligent automation and intelligent decision-making of these IoT applications.

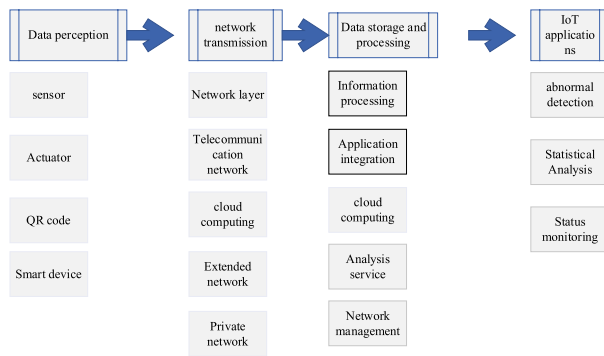


FIGURE 1. Basic structure of IoT.

The data collected by IoT have three characteristics: large scale, multiple types, and time dependence. The scale of data collection equipment is relatively large, so the amount of information is huge. The types of data are mostly reflected in the diversity of information collection equipment to produce different types of data. The time dependence is that the collected effective data usually need to be corresponding to time and follow certain temporal rules to obtain valuable information. Especially when the state of a future time point is predicted, timing is a very critical and necessary factor, which has a significant impact on the prediction effect [16].

As mentioned above, analyzing the data of sensors and equipment not only helps to understand their operation but also helps users make the best decisions. However, due to the complexity of computing and large-scale storage, data anomalies are inevitable. Therefore, it is necessary to set up the corresponding detection and processing system to diagnose and respond to failures. In the traditional IoT architecture, failure detection to be processed are generally divided into two categories, namely hardware failure and software failure. These failures will lead to various problems in the IoT system, such as equipment damage, data reading errors, and others, which may bring significant risks to IoT applications, especially for applications that are critical to security [17], [18]. Therefore, effective anomaly detection methods are needed to ensure the quality of data.

C. OVERVIEW OF TIME SEQUENCE CHARACTERISTICS OF IoT

IoT is originally known as the only coordinate object that can be identified by radio frequency identification (RFID). This concept is first produced in 1999. IoT has a certain self-configuration capability based on interoperable communication standards and protocols. It is usually defined as a dynamic, global network infrastructure [19], [20]. Smart interfaces can be used to contain information on the Internet, and IoT virtual devices and objects have identifiers and attributes. And IoT has a wide range of applications in various fields, including supply chain management, food and catering, manufacturing, health care, environmental monitoring, retail, logistics, tourism, intelligent shelf operation, and many other fields. At the same time, IoT has great economic and social significance.

The development of IT infrastructure plays an important role in accelerating IoT applications. In the prediction, IoT is helpful to solving social problems like medical monitoring and traffic congestion treatment [21]. Networks in IoT are expanding their influence.

The elements of the network must be interconnected, which is a necessary condition for IoT. The architecture of the IoT system should ensure normal operation and bridge the gap between the physical world and the virtual world. Network communication, the network model, and network security are factors that need to be considered in the design of the IoT architecture. In the design of IoT architecture, the scalability and interoperability between heterogeneous devices and their business models need to be considered [22], [23]. IoT needs to provide a real-time mode to interact with other objects, so the IoT architecture allows devices to dynamically interact with other objects and support clear communication of events. In addition, IoT must be decentralized and heterogeneous. In IoT, the service-oriented architecture includes four functions, namely, the data sensing layer, network layer, service layer, and interface layer. The time sequence data of IoT are taken as the research object. They are mainly produced in the data-oriented perception layer. The characteristics of time sequence data of IoT are large scale, high frequency, heterogeneous structure and strong time dependence [24].

D. CONCEPTS AND APPLICATIONS OF DEEP LEARNING ALGORITHM

With the continuous development of computer technology and AI (Artificial Intelligence), the deep neural network model is also applied to all aspects of life. Chen *et al.* (2020) studied a VR video tracking technology based on the You Only Look Once (YOLO) RNN (Recurrent Neural Network) model. Compared with the CNN model, the classification dataset pre-training model, and the YOLO algorithm, the accuracy and training speed of the model algorithm are verified, and the evacuation design simulation of subway station buildings is realized [25].

The technical basis of this study involves the application of a deep neural network, which is briefly introduced in this section.

When the neural network extracts and memorizes the samples, the general feed-forward neural network will construct multiple hidden layers and process the data through the hidden layer. When the summarized samples are analyzed, the feedforward operation method is needed. If the parameters in the hidden layer need to be adjusted, the backpropagation algorithm will be used. The application of various algorithms can help the neural network to adaptively learn various complex mathematical laws and relationships between input and output [26]. Even if new samples are added to the original data, they can be adjusted according to the learned rules. The feedforward neural network is the most basic neural network, and its architecture is shown in Figure 2.

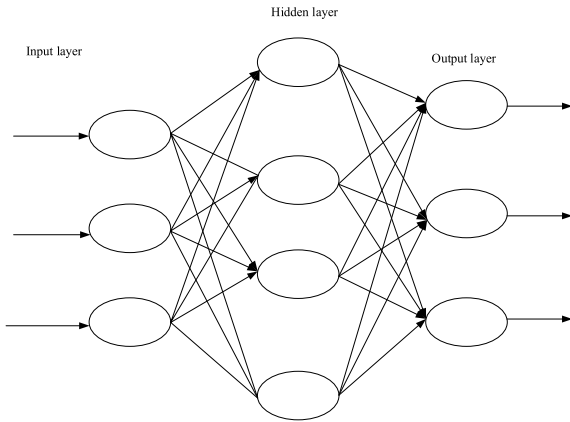


FIGURE 2. Basic structure of the feedforward neural network.

As shown in Figure 2, the composition of the feedforward neural network includes the input layer, the hidden layer, and the output layer. The neural network layer applied to the input dataset is regarded as the input layer, and the number of data features in the constructed dataset is represented by the number of neurons in the input layer. The hidden layer is a multi-layer neuron, which is sandwiched between the input layer and the output layer. The input and output of the parameters in the hidden layer are not visible and cannot be observed between developers, so it is called the hidden layer. The output layer is the last part of the neural network, and its number of neurons is determined by the function of the model. Only one neuron output layer is responsible for single point regression prediction, and multiple neurons are mainly responsible for multi-classification. The calculation forms of neural networks are divided into the forward calculation, the cost function, the back propagation algorithm, the gradient descent, and the activation function [27], [28].

The cyclic neural network is a new type of the network neural network to compensate for the fact that the feedforward neural network cannot capture time sequence data and extract their characteristics. The LSTM neural network is called the LSTM RNN, and it is an advanced version of RNN. The function of RNN is to process data in a logical sequence. It can only deal with data and save them all, and a lot of invalid data are produced as well. Because RNN neurons are limited, many data will be replaced by new data when they are full. If the processed data are too long, the previous data will be forgotten. Therefore, LSTM is used to solve the above problem. It has the function of processing logical sequence data, outputs and reads the data generated in the processing according to different needs, effectively identify the required data, and carries out long-term and short-term memory processing according to different data, which helps to improve the computational efficiency.

E. CONSTRUCTION OF THE MULTI-FEATURE FUSION IoT DATA PREDICTION MODEL BASED ON THE LSTM NEURAL NETWORK

The application of neural networks in data prediction is a hot topic at present. Xu *et al.* (2020) proposed a SE-stacking

model based on information fusion and ensemble learning for user purchase behavior prediction. After the integrated feature selection method is used to filter the purchase-related factors, the stack algorithm is used to predict the user's purchase behavior. Ten different types of models are selected as basic learners and the relevant parameters are specially modified to optimize the model [29].

However, the accuracy of traditional statistical methods according to the prediction results is not high, and it is too dependent on the distribution of source data. The traditional machine learning method does not consider the time dependence in the analysis of time sequence data, which will lead to the wrong prediction of time sequence data [30]. Under the feedforward neural network, the artificial time window is created to simulate the time relationship, but this method is only suitable for short-term time-related IoT data and not flexible enough. Conventional feedforward neural networks can usually solve time-related problems, but the gradient disappears or the gradient tends to explode if the error propagation time is long, which will lead to a significant decline in efficiency [31], [32]. Therefore, based on the characteristics of time sequence data of IoT, a time sequence prediction model of IoT based on LSTM is proposed, and the model architecture is shown in Figure 3.

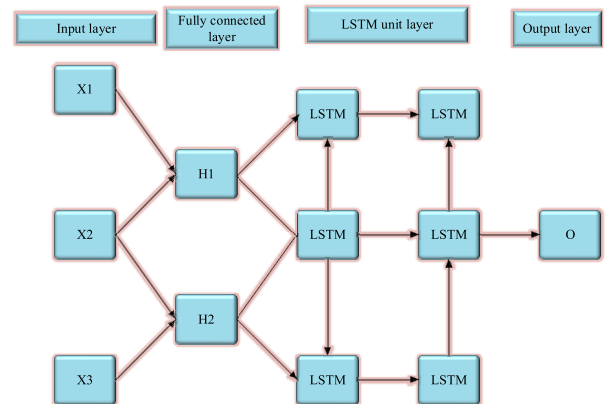


FIGURE 3. Architecture of IoT time sequence prediction model based on LSTM.

As shown in Figure 3, the LSTM network architecture training process based on the time sequence data of IoT is as follows. First, the number of samples is m and the step length of the time series is T , the data collected at the first T time points are predicted at the next time point. The least-square cost loss function and the L2 regularization representation of the model are used as the loss function of the model, as shown in Equation (1).

$$\text{loss}(a_1, a) = \frac{1}{2} \sum_{i=1}^z (a^{(i)} - a_1^{(i)})^2 + \frac{1}{2}c \sum \theta^2 \quad (1)$$

In equation (1), $a^{(i)}$ is the true value of the (i) -th sample, c is the regularization parameter, and θ is the parameter of the model. The gradient judgment equation is shown in

Equation (2):

$$f = \frac{\text{threshold}}{\|f\|^2} f \quad (2)$$

In equation (2), f is the gradient loss, and threshold is the threshold set in the model training.

III. RESEARCH METHODS AND EXPERIMENTAL DESIGN

A. DATA PREPROCESSING

Based on the four characteristics of large scale, high frequency, heterogeneous structure and strong time dependence, it is concluded that the original data may contain errors. Therefore, data preprocessing should be carried out to improve the accuracy and stability of the results. The preprocessing process of the data source is shown in Figure 4.

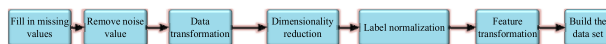


FIGURE 4. Data source preprocessing.

Figure 4 shows that the complete preprocessing process of data sources includes supplementing missing values, removing noise values, sample weight removal, dimension reduction, labeling normalization, feature transformation, and constructing datasets.

The first step is to supplement the missing value. There are three commonly used methods for it: (1) the filling of means, medians, and numbers. This method is suitable for continuous variables, and the mean or median of the target can be directly input in the column; (2) the interpolation method. This method completes data supplementation by using the average of the two points before and after the missing value; (3) implementing a model that matches the prediction. When there are many missing values, a mathematical model needs to be implemented. The disadvantage of this method is that it takes a lot of time to supplement the missing values. The second step is to remove the noise value. Since the collection device is sensitive to the external environment in the data collection process, it is easy to identify some abnormal values and noise. Therefore, the noise values can be identified easily and removed. There are three common methods to remove noise values, and the methods are the rule constraint method, the upper and lower quartile method and the 3 σ principle method. The rule constraint method is relatively simple and effective, and it is used to extract the feature of a data column. A constraint range is figured out after analysis, and the abnormal samples are filtered and removed. As the name implies, the upper and lower quartile method needs to find the value of the upper and lower quartiles, and then the graph is drawn. And the value is judged according to the graph. If it is beyond the edge range, the value may be a noise value. The 3 σ principle method is only applicable to the data or the data that conforms to the Gaussian distribution after the Log transformation. The method needs to find the average value and standard deviation of a certain column of eigenvalues that need to be judged. If the difference between a certain value and the average value is more than 3 times or more, it can

be preliminarily judged that the data are abnormal. The third step is to remove the sample weight. Sample deduplication is needed to avoid repeated samples in the collected data. There are many sample deduplication methods, like the direct comparison method. The fourth step is dimension reduction. Dimension reduction is to perform principal component analysis and downsampling on the original data with high dimensions, and reduce the dimensions of the original data to save the resources and time required for model training. The fifth step is data normalization. Data normalization is mainly aimed at the data whose eigenvalues are continuous variables because the continuous variation of eigenvalues may lead to a large difference in the dimension and order of data. Therefore, data need to be standardized. In addition, data normalization also has the effect of accelerating the convergence speed of the model. The sixth step is feature transformation. Feature transformation means that the features of data are changed to meet the training requirements of the input model. There are three common feature transformation methods, namely the Log transformation method, the one-hot coding method, and the box method. The seventh step is building a dataset. Building a dataset is the last step of data preprocessing. Its purpose is to generate a special dataset that contains the temporal relationship before and after data storage.

B. EVALUATION OF IoT TIME SEQUENCE PREDICTION MODEL BASED ON LSTM

The LSTM regression model and MLP regression model are used as comparison methods to verify the effectiveness of the proposed method. The most typical MLP includes three layers: the input layer, hidden layer, and output layer. The different layers of the MLP neural network are fully connected.

The LSTM regression model is constructed using an input layer, two hidden layers with LSTM memory blocks, and a regression layer [33]. At the same time, the least-squares loss function is used as the cost function of the model. The cost function of the MLP regression model is also the least-squares loss function.

The LSTM regression model and multilayer perceptron (MLP) regression model are used to verify the effectiveness of the proposed model. The LSTM regression model is built using the input layer, two hidden layers with an LSTM memory block, and a regression layer. The least square loss function is used as the cost function of the model. The MLP regression model is a typical feedforward neural network model, and it consists of an input layer, multiple hidden layers and the output layer. The cost function is also a least square loss function. Based on prior experience and the amount of experimental data, all models are trained on 80% of the dataset, tested on 10% of the dataset, and 10% of the dataset will be used as a validation set. The adaptive gradient algorithm (AdamgradM56) is used for training each model. And the maximum number of iterations is set to 10,000, and the model loss threshold is set according to the defined validation threshold so that the model training ends

early to avoid overlearning. The regularization and discarding techniques are used to reduce the complexity of these models [34]. At the same time, hyperparameters are selected for these models using validation sets. And all neurons in hidden layers of the model look for hyperparameters in the validation set. Since a bunch of parameters are involved in complex calculations, many hyperparameters in the model cannot be calculated accurately. Therefore, some conventional hyper-parameter optimization methods can only be used to select the appropriate hyper-parameters. The hyper-parameters of the improved prediction model for time sequence data of IoT based on LSTM proposed include the neurons in the fully connected layer, the time step of time sequence data, the LSTM units in the hidden layer, the threshold of the model, the small batches in sample training and the initial learning rate. First, the approximate range of this parameter is determined heuristically. Second, the grid search is used to select the parameter combination. Finally, the verification set of the model is used to test the effect and the best hyper-parameter combination is selected.

C. INTRODUCTION OF THE DATASET

The datasets used are real, and they include grid data, ring sensor traffic data and soil sensor data. The grid data and ring sensor traffic data are public datasets, while the soil sensor data are private data. Grid data are the electricity data of a user in the Netherlands for one year. They are collected every 15 minutes every day. The collection rule is that electricity consumption will be relatively high during the first five days of a week, and it will be relatively low at the weekend. The ring sensor traffic data are mainly composed of the number of vehicles detected near the stadium. The data are only collected on the day when there is a game. The characteristics of the original time sequence data are screened to analyze the data, and only the data of 1 hour before the game, during the game and 2 hours after the game are collected. The above two datasets are public datasets, and the link of the dataset is: <http://archive.ics.uci.edu/ml/datasets/Dodgers+Loop+Sensor>. The soil sensor dataset is mainly composed of soil data collected by soil sensors every hour. And the soil moisture data are only studied. Different from the first two datasets, this dataset have irregular time sequences.

D. EVALUATION INDEXES

The evaluation indicator of the prediction ability of the model is divided into two kinds, namely the average and the absolute percentage error of R2. The calculation equation is shown in equations (3) and (4).

$$Mape = \frac{1}{z} \sum_i^z \frac{|m_i - b_i|}{m_i} \tag{3}$$

In equation (3), m_i is the true value for a point, b_i is the predicted data value for a point, and z is the total number of samples.

$$R^2 = 1 - \frac{\sum_i^n (m_i - b_i)^2}{\sum_i^n (b_i - \bar{m}_i)^2} \tag{4}$$

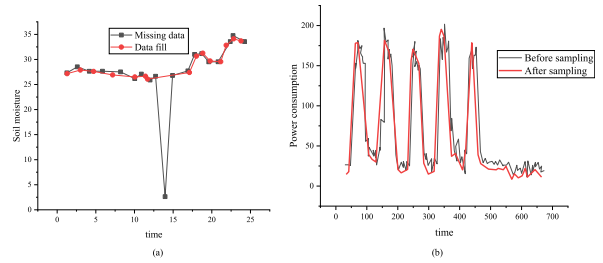


FIGURE 5. Comparison of data before and after preprocessing (a: the comparison of soil moisture data before and after preprocessing; b: the comparison of electricity consumption data before and after preprocessing).

In equation (4), m_i is the true data value for a point, b_i is the predicted data value for a point, \bar{m}_i is the average value of the real value, and n is the total number of samples.

IV. ANALYSIS AND DISCUSSION OF THE PREDICTION RESULTS OF LSTM TIME SEQUENCE DATA

A. PREDICTION RESULTS OF POWER DATA BASED ON LSTM TIME SEQUENCE PREDICTION MODEL OF IoT

Data preprocessing is carried out on the dataset, and the comparison of some data before and after preprocessing is shown in Figure 5.

Figure 5 shows that different types of raw data have different shortcomings, so their preprocessing methods are also different. For example, the missing data of the soil moisture data are supplemented and standardized, and then the invalid data are removed. The excessive data should be filtered or sampled according to the actual situation.

The prediction results of power data based on the LSTM time sequence prediction model of IoT performed by three models are shown in Figure 6.

From the comparison of the three models in Figure 6, it is found that the proposed model and the LSTM regression model show high accuracy in the prediction of power data, while the MLP regression model has many errors in the prediction of power data. From the number of eigenvalues, there is only one eigenvalue in the power quantity data. Therefore, the prediction results of the model based on LSTM and multi-feature fusion and the LSTM regression model proposed are the same.

Performance indicators for the three models are shown in Figure 7.

From the quantitative performance indicators of the three prediction models shown in Figure 7, the Mape of the proposed model is the lowest with a percentage of 2.49%, indicating that the relative error between the predicted value and the real value of the proposed model is the smallest. The Mape of the LSTM regression prediction model is 2.57%, only slightly higher than the recommended model. This result is also consistent with the intuitive trend shown in Figure 5. The Mape of the MLP regression model is much higher, reaching more than 9%. From the R^2 values, it is suggested that the model has the highest score of 0.873. In summary,

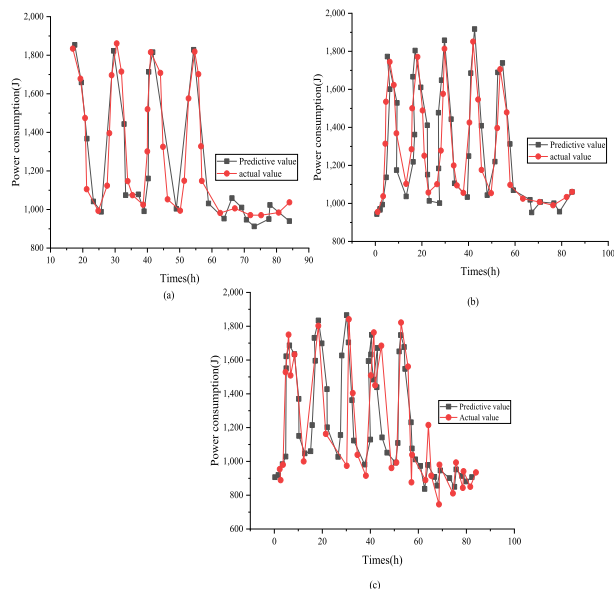


FIGURE 6. Comparison of the prediction results of the three regression models for electricity consumption (a) the prediction results of the proposed model for electricity consumption; (b) the prediction results of the LSTM regression model for electricity consumption; (c) the prediction results of the MLP regression model for electricity consumption.

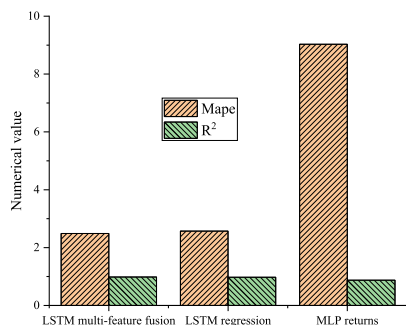


FIGURE 7. Comparison of performance indicators under three models of power.

it can be concluded that the MLP regression model has poor prediction in long-term time-dependent data.

B. PREDICTION RESULTS OF TRAFFIC DATASETS BASED ON LSTM TIME SEQUENCE PREDICTION MODEL OF IoT

The prediction results of three models for traffic datasets are shown in Figure 8.

Ring traffic data are short-term time-dependent time sequence data. After the data are preprocessed and modelled, the results of the three models shown in Figure 8 on this dataset are obtained. Through the comparison of the three models, it can be found that the model based on LSTM and the multi-feature fusion performs the best. The LSTM regression model is not as good as the improved LSTM model in some details, and the MLP regression model still performs poorly, and its prediction accuracy is low. Compared with the electricity consumption dataset, the number of features in the dataset meets the requirement of multiple features. Therefore, the model based on LSTM and multi-feature fusion are

theoretically superior to the LSTM regression model. The accuracy rates of the proposed model and the LSTM-based regression model are high in the prediction of the ring traffic data. Compared with the proposed model, the accuracy rate of the LSTM regression model is slightly lower in some details in the prediction of ring traffic data, while that of the MLP regression model is not stable.

The performance metrics for three models under annular traffic data are shown in Figure 9.

From the performance indicators of the three prediction models shown in Figure 9, the Mape of the proposed model is the lowest with a percentage of 6.75%, indicating that in the prediction of annular traffic data, the relative error between the predicted value and the real value of the proposed model is also the smallest among the three algorithms. The Mape of the LSTM regression prediction model is 9.68%. The comparison between the two models shows that the prediction accuracy and performance of the proposed model are better than those of the LSTM regression prediction model. The Mape of the MLP regression model is 11.36%, and the LSTM regression prediction model is slightly higher. From the R² value, the proposed model is 0.953 and closest to 1. This shows that the proposed model performs best in the prediction.

C. PREDICTION OF SOIL MOISTURE BASED ON LSTM TIME SEQUENCE MODEL OF IoT

The comparison of the prediction results of the three models on soil moisture is shown in Figure 10.

Figure 10 shows that the soil moisture data are weak time-dependent time sequence data. Figures 9(a), 9(b), and 9(c) show that the prediction accuracy of the proposed model is much higher than the other two models in the prediction of weak time-dependent time sequence data. In addition, the prediction effect of the LSTM regression model on time-dependent time sequence data is not high due to the influence of the external environment. Moreover, the difference between the predicted value and the actual value is close to 10%, and the prediction accuracy of the proposed model is higher. In short, in the prediction of weak time-dependent temporal data of soil moisture data, the prediction accuracy of the MLP regression model ranks the second, and it is higher than the that of LSTM regression model but still lower than the proposed model.

Performance indicators for data under three models on soil moisture are shown in Figure 11.

From the performance indicators of the three prediction models shown in Figure 11, the Mape of the proposed model is the lowest, and it is 0.92%, indicating that the relative error between the predicted value and the real value of the proposed model is still the smallest among the three algorithms in the prediction of soil moisture. The Mape of the MLP regression model is 1.29%, and that of the LSTM regression prediction model is 1.36%. The LSTM regression prediction model is not as good as the MLP regression prediction model in the prediction of soil moisture. From the R² value, the proposed

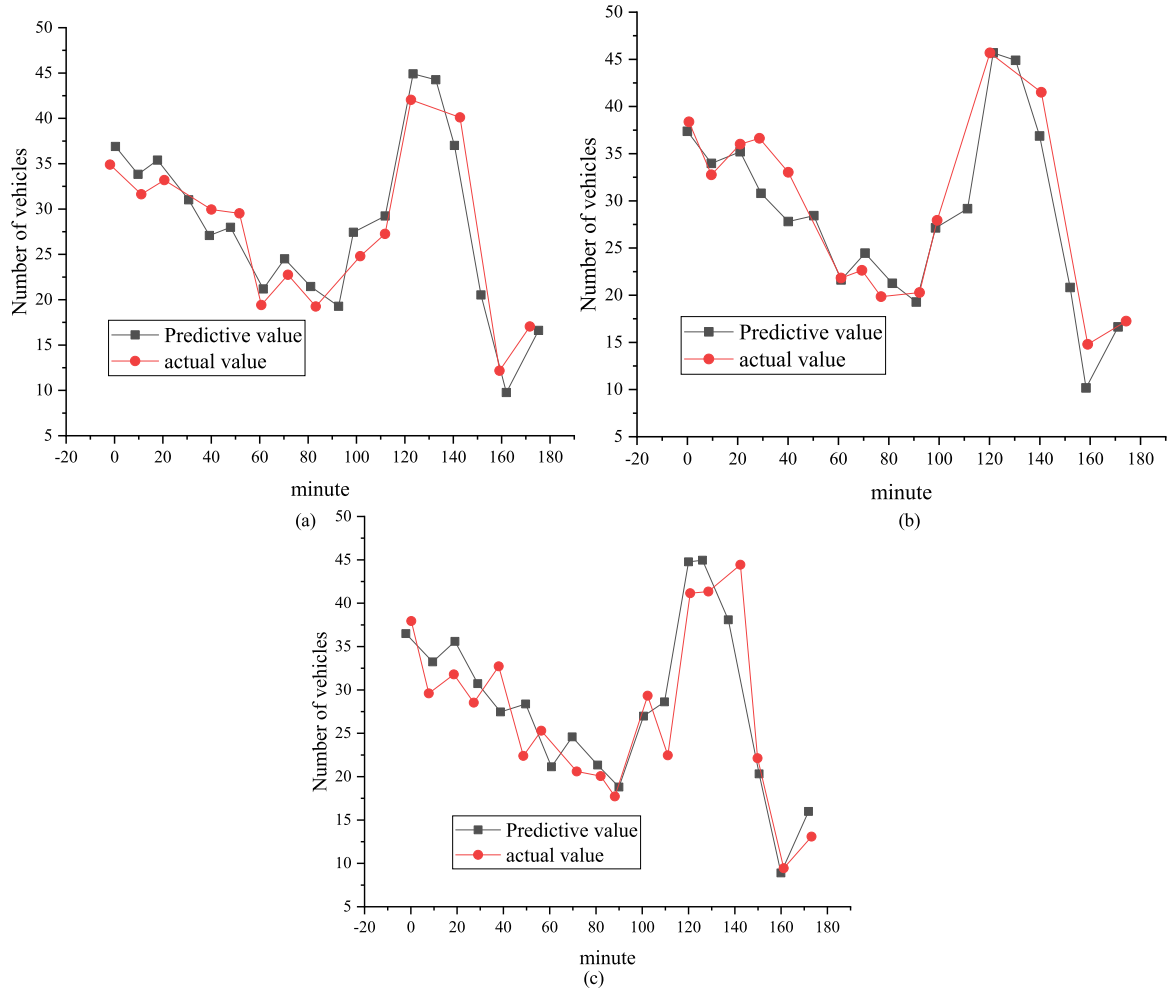


FIGURE 8. Comparison of the prediction results of the three models on the traffic dataset: (a) the prediction results of the proposed model on the traffic dataset; (b) the prediction results of the LSTM regression model on the traffic dataset; (c) the prediction results of the MLP regression model on the traffic dataset.

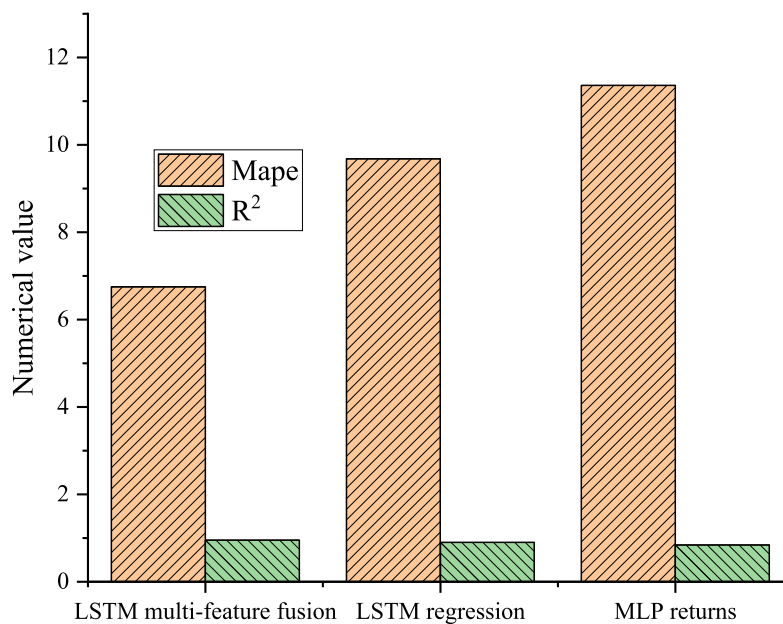


FIGURE 9. Comparison of performance indicators of three models on annual traffic data.

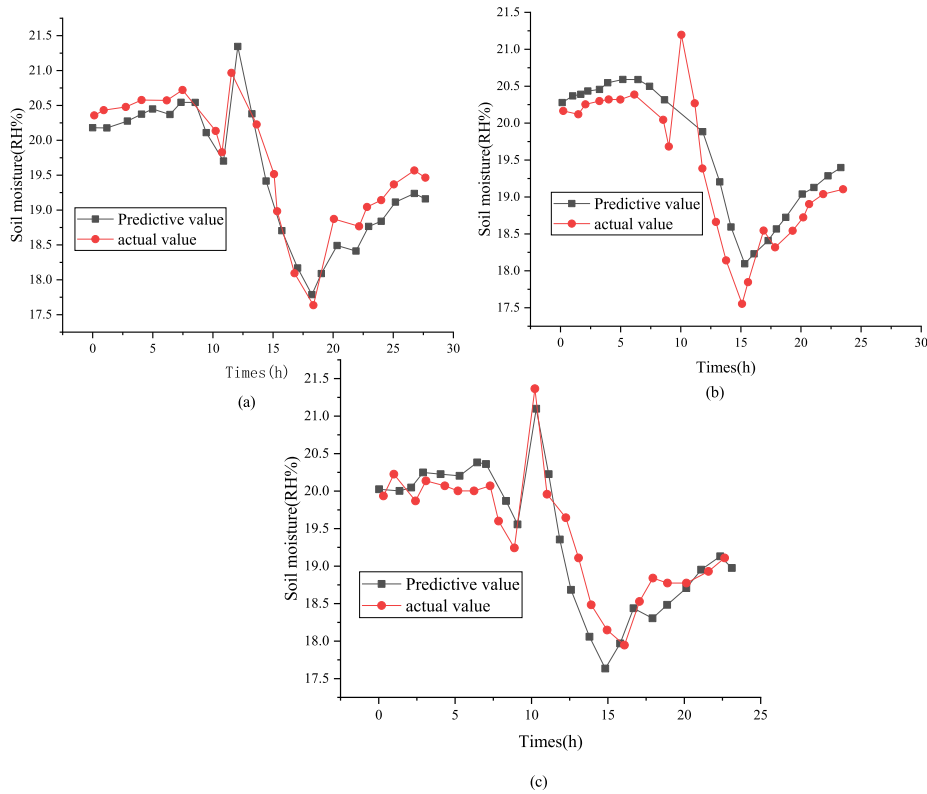


FIGURE 10. Comparison of the prediction results of the three models on soil moisture: (a) the prediction results of the proposed model soil moisture, (b) the prediction results of the LSTM regression model soil moisture, (c) the prediction results of the MLP regression model soil moisture.

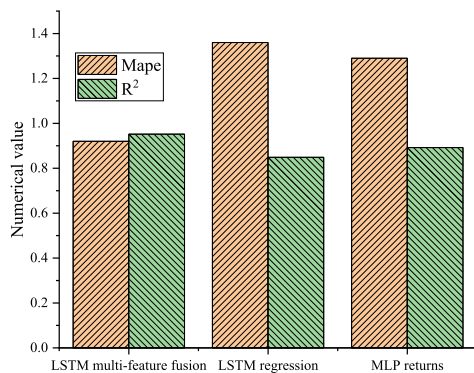


FIGURE 11. Comparison of performance indicators of three models on soil moisture.

model is still the highest, indicating that the proposed model has the best performance.

An prediction model based on LSTM is proposed to predict the time sequence data of IoT, so that it can extract features of the external, and completes the prediction of long-term, short-term and weak-time-dependent time sequence data of IoT. Then, the experimental evaluation of the model is carried out and the results are compared with the LSTM regression model and MLP regression model. The experimental results show that the model proposed performs better than the other two models under three different datasets. This proves that the model proposed can accurately predict the long-term, short-term and weak time-dependent time sequence data of

IoT. In short, the prediction model based on multi-feature fusion and LSTM has good performance in predicting the three kinds of data, and its prediction accuracy is high and stable with fewest errors.

V. CONCLUSION

The time sequence data prediction model of IoT is a hot topic. First, the characteristics of time sequence data of IoT are analyzed. The features of the time sequence data of IoT are obtained, and they are large-scale, multi-type, and time-dependence. Second, the general architecture of the traditional IoT and the preprocessing methods of time sequence data generated by different sensors are discussed. The deep learning algorithm is briefly introduced, and the shortcomings of statistical learning, traditional machine learning, and feedforward neural networks in the prediction of time sequence data of the traditional IoT are analyzed. Based on the above analysis, a multi-feature fusion IoT data prediction model based on the LSTM neural network is proposed, and the MLP regression model and LSTM regression prediction model are introduced for comparison to verify the performance of the proposed model. The experimental results show that the multi-feature fusion IoT data prediction model based on the LSTM neural network has an excellent performance in the prediction of long-term, short-term, and weak time-dependent time sequence data of

IoT, with the highest stability, the highest prediction accuracy, and the smallest error.

Due to the limitations of research experience and funds, the neural network of the multi-feature fusion data prediction model of IoT based on the LSTM neural network proposed has much room to be optimized, and the efficiency decreases when a large number of data are processed, which is also the deficiency of this study. In future research, multiple deep neural network algorithms should be integrated to improve the operation speed and efficiency of deep neural networks.

COMPLIANCE WITH ETHICAL STANDARDS

Conflict of Interest: All Authors declare that they have no conflict of interest.

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent was obtained from all individual participants included in the study.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

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