International Conference on Culture, Economy and Social Sciences (ICCESS 2026)

Application of Deep Learning in Risk Prediction of Cerebral Infarction

Wenjie Jia, Guohong Wang*

Department of Neurosurgery, The First People's Hospital of Jiayuguan City, Gansu, China

**Corresponding Author*

Abstract: Cerebral infarction is a global high incidence of cerebrovascular disease, with high disability rate, high mortality, high recurrence rate characteristics, serious threat to human health and quality of life. Traditional methods for predicting the risk of cerebral infarction are mostly based on static clinical data and classical statistical models, which are difficult to capture the dynamic temporal changes of patients' health status, and cannot fully explore the potential associations in long-term follow-up data, and the prediction accuracy is obviously limited. Deep learning technology shows significant advantages in the field of time series data processing, among which long-term memory recurrent neural network (LSTM-RNN) effectively solves the gradient disappearance problem of traditional recurrent neural network through gating structure, and can realize accurate extraction of long-term time series features and effective capture of long-term dependence relationship. In this paper, a cerebral infarction risk prediction model based on LSTM-RNN is constructed, standardized collection and systematic pretreatment of time series clinical data are completed, the overall framework of the model and the whole process training scheme are designed, and the prediction performance and generalization ability of the model are verified by multi-dimensional experiments. The experimental results show that the model shows excellent accuracy and robustness in the task of predicting cerebral infarction risk, and each core evaluation index is significantly better than that of traditional statistical model and other recurrent neural network models. It can provide reliable technical support for early screening, risk stratification and accurate prevention of cerebral infarction, and has important clinical application value and social significance.

Keywords: Cerebral Infarction; Risk Prediction; Deep Learning; Long-Term Memory; Recurrent Neural Network; Time Series Clinical Data

1. Introduction

Cerebral infarction is one of the most common cerebrovascular diseases in clinic. Its pathogenesis is cerebral blood supply disorder, which leads to ischemic and hypoxic necrosis of brain tissue, and then leads to neurological deficit. In recent years, influenced by aging population and lifestyle changes, the incidence of cerebral infarction in the world has been on the rise, and the age of onset has gradually become younger, which has become a major public health problem threatening human health. Cerebral infarction patients often leave sequelae such as limb paralysis and language disorder after onset, which not only seriously affects the quality of life, but also brings heavy burden to the social medical system and patients' families. Early screening and risk warning of cerebral infarction are the core links to reduce the risk of onset and improve the prognosis of patients. Therefore, building accurate and efficient risk prediction models has become a research hotspot in the field of cerebrovascular disease prevention and control.

Traditional methods for predicting cerebral infarction risk are based on static clinical data, and classical statistical methods such as Logistic regression and Cox proportional hazard model are used. They rely on artificial screening of risk factors and cannot fully mine nonlinear associations and potential laws in data [1]. At the same time, traditional methods can only predict based on static data at a single time point, and it is difficult to capture the dynamic time series changes of patients' health status, and it is difficult to make full use of long-term follow-up data. With the rapid development of artificial intelligence technology, deep learning is widely used in the field of medical data analysis, which can automatically extract high-level features without manual intervention, especially in time series data processing.

Recurrent neural network (RNN) is a deep learning model that specializes in processing time series data. It realizes time series information transmission through cyclic structure and can capture the dependency relationship between features. However, traditional RNN has gradient vanishing problem, which makes it difficult to deal with long time series data. Long-term memory recurrent neural network (LSTM-RNN) solves the gradient disappearance problem through the gating structure composed of input gate, forgetting gate and output gate, which can effectively retain the key information in long-term time series data, is suitable for processing the time-series clinical data generated by long-term follow-up of patients, and can accurately model the evolution process of cerebral infarction risk, providing a new technical path for risk prediction.

In this paper, systematic research on cerebral infarction risk prediction is carried out, and a prediction model based on LSTM-RNN is constructed. The overall framework and training scheme are designed, and the model performance is verified by experiments. The research results can provide technical support for early warning and precise prevention of cerebral infarction, promote the clinical transformation of deep learning technology in the field of cerebrovascular disease prevention and control, and provide new ideas for reducing incidence and improving patient prognosis.

2. Cerebral Infarction Risk Prediction Model Based on LSTM-RNN

2.1 Overall Framework Design

The cerebral infarction risk prediction model based on LSTM-RNN constructed in this paper takes patient time series clinical data as the core input and realizes accurate prediction through multi-module collaborative processing. The overall framework of the model is shown in Figure 1.

The core process of the model revolves around the whole process of time series data processing, and each module is closely connected to form a closed-loop system. First, input the patient's clinical data in multiple time steps, each time step corresponding to the health characteristics of a follow-up time point, covering physiological indicators, medical history information, living habits and other multi-dimensional content. Then the data enters the normalization processing module to eliminate the dimensional difference of different features, balance the influence of each feature on model training, and improve the training stability and convergence speed.

The normalized data is input into the LSTM core module, which receives the characteristic data of the current time step and the output hidden state ht of the previous time step to realize the cyclic transmission of timing information. LSTM module extracts key features of current time step through gating structure, screens information related to cerebral infarction risk, and eliminates irrelevant content. After feature extraction is completed, time series input integrity judgment is carried out, if not completed, time step t+1 is entered, normalization and feature extraction processes are repeated, and the current hidden state ht is transmitted to the next time step; if input is completed, extracted complete time series features are input to an output layer, mapping from features to prediction results is completed, and a final risk prediction result is output.

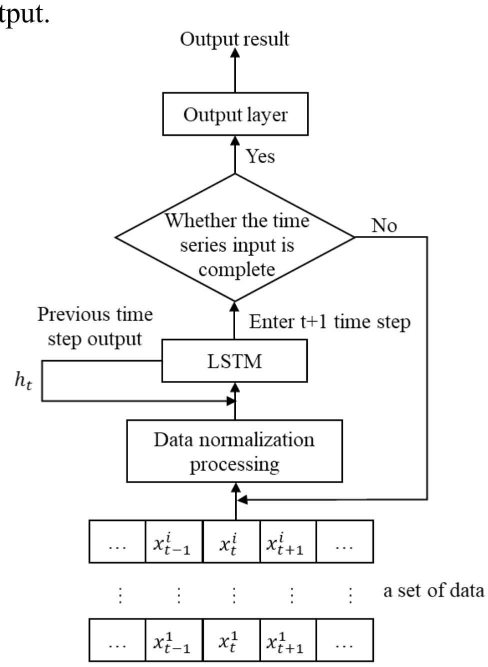

Figure 1. Cerebral Infarction Risk Prediction Model Based on LSTM-RNN

The framework design fully meets the characteristics of clinical time series data and prediction needs [2]. The LSTM gating structure can effectively retain key information of long time series, avoid the gradient disappearance problem of traditional RNN, and accurately model the dynamic changes of patient health status. The cyclic structure ensures the continuous transmission of time series information, so that the model makes full use of long-term follow-up data, comprehensively integrates health information at each time point, and improves prediction accuracy. Normalization module avoids training bias caused by index value difference, and output layer completes risk classification and evaluation according to prediction task requirements, providing support for clinical decision-making.

2.2 Data Acquisition and Pretreatment

Data is the basis of model training and prediction, and data quality directly determines the upper limit of model performance. Long-term follow-up data were collected from patients who met the inclusion criteria. The follow-up period covered the long-term health monitoring process to ensure the continuity of time series. The collected features cover basic physiological indicators, chronic disease history information, living habits, etc. All data are organized in time steps to form a continuous time series, and each time step corresponds to a complete feature vector of a follow-up point for model input [3].

Data preprocessing is the key to ensure data quality, which mainly includes data cleaning, normalization and time series data construction. Data cleaning For the missing values and outliers in the original data, reasonable methods are used to complete the missing values, ensure the integrity of the data, identify and eliminate outliers through statistical analysis, and eliminate interference to model training.

Data normalization adopts Min-Max normalization method, which linearly maps all feature data to [0,1] interval, eliminates dimensional differences, makes the influence of each index on model training at the same level, and improves training efficiency and convergence speed. Time series data construction arranges patient multi-time point data into sequence format suitable for LSTM input, determines sequence length according to follow-up time length, and aligns sequences to ensure uniform data format of different patients, which is convenient for batch training. The dataset undergoes preprocessing and is partitioned into training, validation, and test subsets via randomized stratified sampling; the training portion facilitates model parameter learning and refinement, the validation portion enables hyperparameter tuning and overfitting surveillance, and the test portion assesses the model's generalization capability, with each subset maintaining distributional alignment with the source data to guarantee evaluation reliability.

2.3 Training Process of the Model

The core of the LSTM-RNN model is the gating structure of the LSTM unit. The input gate regulates the proportion of current time-step data entering the cell state and filters effective information. The forgetting gate controls the proportion of the previous time-step cell state retained to the current step, preserving key information while eliminating irrelevant content. The output gate controls the proportion of cell state output to the current hidden state, generating ht and passing it to the next time step. The gating structure effectively solves the gradient disappearance problem of traditional RNN, and can accurately extract long-time series features, which is suitable for processing long-term follow-up data of patients [4].

Model training follows the standard process of deep learning. First, He initialization method is used to initialize parameters, and the initialization range is adjusted according to the input and output dimensions to avoid training non-convergence or gradient explosion. The preprocessed training set data are input into the model in batches, forward propagation calculation is carried out, current feature data and the previous time step ht are input at each time step, LSTM unit extracts feature through gating structure, updates cell state and ht, and transfers to the next time step [5].

After the forward propagation, the prediction error is measured by calculating the difference between the prediction result and the true label using cross-entropy loss function. The model parameters are updated by back propagation algorithm, and the Adam optimizer is used to realize adaptive learning rate update, which improves training efficiency and convergence speed. In the training process, reasonable training rounds and batch sizes are set, and an early stop mechanism is introduced to monitor the loss change of the validation set. If there is no decline in consecutive rounds, the training is stopped to avoid over-fitting and ensure the generalization ability of the model.

Time series information circulation transmission is the core of training. The continuous transmission of ht enables the model to make full use of the patient's historical health data, capture the dynamic changes of health status, and accurately predict the risk of cerebral infarction. LSTM gating structure selects key features to improve feature extraction efficiency and prediction accuracy. After training, the optimal parameters are saved for subsequent risk prediction to achieve model deployment and application [6].

3. Experimental Verification

3.1 Experimental Design

To comprehensively validate the performance of the LSTM-RNN-based cerebral infarction risk prediction model developed in this study, a multi-dimensional comparative experiment was designed to specify the experimental software and hardware configurations, evaluation metrics, and comparative models, ensuring the scientific rigor and reliability of the experiment. Leveraging the preprocessed time-series clinical data, the superiority and generalization capability of the proposed model are demonstrated through comparative analysis of prediction performance across different models.

The experimental software and hardware configuration directly affects the experimental efficiency and model training effect. The software and hardware configuration of this experiment is shown in Table 1. In hardware aspect, high-performance server is selected to ensure the smoothness of model training process and avoid training interruption or inefficiency caused by insufficient hardware performance. Python is selected as the software development language, LSTM-RNN model is constructed based on TensorFlow framework, Pandas and NumPy libraries are used for data processing, Matplotlib library is used for visualization of experimental results, so as to ensure the stability and compatibility of experimental environment.

Accuracy, precision, recall and F1 value were used as core evaluation indexes to evaluate the prediction performance of the model comprehensively. Accuracy rate reflects the correctness of the overall prediction of the model, accuracy rate reflects the true positive proportion of positive samples predicted by the model, recall rate reflects the proportion of true positive samples predicted correctly, F1 value combines accuracy rate and recall rate, reflecting the comprehensive performance of the model, the higher the value of each index, the better the prediction performance of the model.

To verify the superiority of this model, traditional statistical models and other deep learning models were selected as comparative models, including Logistic regression model, Cox proportional hazards model, traditional RNN model and GRU model. All models are trained and tested based on the same dataset, using the same evaluation index to ensure the fairness of the comparison experiment, focusing on comparing the core evaluation index of each model to clarify the performance advantages of the LSTM-RNN model in this paper.

Table 1 Experimental Software and Hardware Configuration

Category	Specific configuration
CPU	Intel Core i7-12700H, 2.7GHz, 14 cores, 20 threads
GPU	NVIDIA GeForce RTX 3060 with 6GB of RAM
memory	16GB DDR4 3200MHz
operating system	Windows 11 Pro
development language	Python 3.8
deep learning framework	TensorFlow 2.8.0
data processing library	Pandas 1.4.2,NumPy 1.22.3
visualization library	Matplotlib 3.5.1

3.2 Experimental Results and Analysis

The experiment was carried out strictly according to the above design scheme, and the pretreated data set was input into each model to complete model training and testing, and the core evaluation indicators of each model were recorded. The comparison results are shown in Table 2. Through the systematic analysis of the experimental results, the performance and superiority of the cerebral infarction risk prediction model based on LSTM-RNN constructed in this paper are verified.

Table 2 Performance Comparison of Different Models

Model	Accuracy rate	Precision rate	Recall rate	F1 value
Logistic regression model	0.782	0.765	0.758	0.761
Cox proportional hazards model	0.795	0.781	0.774	0.777
Traditional RNN model	0.823	0.815	0.809	0.812
GRU model	0.857	0.849	0.842	0.845
LSTM-RNN model	0.896	0.888	0.882	0.885

From the experimental results in Table 2, it can be seen that the LSTM-RNN model constructed in this paper is significantly better than other comparative models in all core evaluation indicators. The indicators of traditional statistical models (Logistic regression and Cox proportional hazards model) are relatively low, mainly because these models rely on manual screening features, cannot fully mine potential associations and nonlinear laws in time series data, and can only predict based on static data, which makes it difficult to capture dynamic changes in patients' health status, resulting in limited prediction accuracy. The traditional RNN model can not effectively retain the key information in the long time series data due to the gradient disappearance problem, and the feature extraction ability is insufficient. Therefore, the performance of the traditional RNN model is better than that of the traditional statistical model, but lower than that of the LSTM-RNN model and the GRU model in this paper.

GRU model and LSTM-RNN model belong to gated recurrent neural network, both of which can effectively solve gradient disappearance problem, but LSTM-RNN model has more perfect gating structure, through the synergy of input gate, forgetting gate and output gate, it can more accurately screen key features related to cerebral infarction risk, and more efficiently capture long-term dependence in long-term time series data, so it is better than GRU model in various evaluation indicators.

4. Conclusion

The model framework of cerebral infarction risk prediction based on LSTM-RNN designed in this paper realizes the whole process processing of time series clinical data and accurate prediction of cerebral infarction risk through the synergy of data normalization, LSTM feature extraction and output prediction modules. The gating structure of LSTM module effectively solves the gradient disappearance problem of traditional RNN, can accurately extract key features in long time series data, capture dynamic changes of patient health status, and provide reliable technical support for risk prediction.

The experimental results show that the LSTM-RNN model constructed in this paper shows excellent performance in the task of cerebral infarction risk prediction, and all core evaluation indicators are significantly better than traditional statistical models and other deep learning models. The accuracy, precision, recall and F1 value reach 0.896, 0.888, 0.882 and 0.885 respectively, with good accuracy and robustness. There are still some limitations in this study. In the future, the scale of data set can be expanded to include more dimensional clinical features, further optimize the model structure, improve the generalization ability and clinical applicability of the model, explore the application effect of the model in different populations and different regions, and provide a more perfect technical scheme for cerebral infarction prevention and control.

References

[1]Li X, Wang Y, Xu J. Development of a machine learning-based risk prediction model for cerebral infarction and comparison with nomogram model[J]. Journal of Affective Disorders, 2022, 314: 341-348.

[2]Abdulazim A, Heilig M, Rinkel G, et al. Diagnosis of delayed cerebral ischemia in patients with aneurysmal subarachnoid hemorrhage and triggers for intervention[J]. Neurocritical care, 2023, 39(2): 311-319.

[3]Dewi T, Mardiyati E N, Risma P, et al. Hybrid Machine learning models for PV output prediction: Harnessing Random Forest and LSTM-RNN for sustainable energy management in aquaponic system[J]. Energy Conversion and Management, 2025, 330: 119663.

[4]Zeng Z, Luo R, Xu W, et al. Prediction of first-onset cerebral infarction risk in patients with acute myocardial infarction: a retrospective cohort Study[J]. International Journal of General Medicine, 2025: 3501-3513.

[5]Arafa A, Kokubo Y, Sheerah H A, et al. Developing a stroke risk prediction model using cardiovascular risk factors: the Suita Study[J]. Cerebrovascular Diseases, 2022, 51(3): 323-330.

[6]Muehlen I, Sprügel M, Hoelter P, et al. Comparison of two automated computed tomography perfusion applications to predict the final infarct volume after thrombolysis in cerebral infarction 3 recanalization[J]. Stroke, 2022, 53(5): 1657-1664