Study on the Prediction and Prevention of Falls Risk in the Elderly based on Neural Network

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Abstract. Objective: To improve the accuracy of fall risk prediction for the elderly, establish an efficient prediction model based on neural network, and thus reduce the number of fall events, improve the quality of life and safety level of the elderly. Methods: A comprehensive study of the sports, health and environmental data of 500 industry experts over a one-year time span was conducted. A multi-level perception analysis model, convolutional neural network (CNN) and long short-term memory network (LSTM) were used for comparative evaluation. Ten rounds of cross-validation and Adam algorithm were used to improve the model, and its precision, positive prediction accuracy, true positive rate and F1-score were estimated. Results: The long short-term memory network model performed well in many evaluation criteria, with an accuracy of 93%, a positive prediction rate of 91%, a detection rate of 92%, and an F1-score of 91%. Conclusion: The LSTM neural network has excellent performance in the identification of fall signs in the elderly population, and has the potential to be used for early warning and customized prevention plans to reduce the frequency of falls.

Keywords: component; Fall risk in the elderly, Neural network, Long short-term memory network, Prediction model

1. Introduction

As the challenges of global aging worsen, falls among the elderly have become a top priority for public health. Statistics show that falls are the leading cause of death among people over 65 years old. Every year, about 38,000 elderly people die from falls, and about 2.9 million people receive emergency treatment due to falls. Recently, the mortality rate and emergency room visit rate caused by falls among the elderly have increased significantly, increasing by 60% and 20% respectively [1]. This situation poses a challenge to the quality of life of the elderly, and puts pressure on the stability of the healthcare system and social welfare. Most of the existing methods for predicting the possibility of falls are based on basic statistical analysis, which is difficult to adapt to the volatility and variability of the risk of falls among the elderly. Neural networks are the core elements of the intelligent technology field and are good at handling complex non-linear challenges. They show great prospects in the field of medical prognosis [2]. The

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goal of this study is to use neural network technology to improve the accuracy of fall risk prediction for the elderly, and to establish an efficient fall risk prediction model by comprehensively evaluating the activity dynamics, health status and environmental data of the elderly. Explore and verify the fall prediction analysis system based on neural network, and evaluate its application environment, practicality, efficiency and accuracy in practice. Reference number 3. Through the application of the prediction model, the risk of falls in the elderly can be revealed in advance, and personalized preventive measures can be formulated, thereby significantly reducing the frequency of fall accidents and improving the quality of life and safety of the elderly.

2. Experimental Design

2.1 Experimental environment and tools

In terms of hardware facilities, this experiment is equipped with a high-efficiency computing station with built-in NVIDIA RTX 3090 graphics card, 24GB video memory and more than 10496 CUDA cores, which has the processing power to process big data and cultivate deep neural networks. In addition, the laboratory area is also equipped with Intel Xeon E5-2698 v4 processor and 128GB random access memory to ensure high speed and efficiency of data processing. In the field of sensing technology, it is equipped with three-dimensional acceleration sensors and angular velocity sensors. The data collection rate of these sensors reaches a collection frequency of 100 times per minute, which has the ability to accurately track and record the daily movement data of the elderly group. The experimental space is equipped with a number of high-resolution monitoring devices (1080p resolution, 30fps), which are designed to focus on closely monitoring the actions of senior researchers in the research site. These monitoring systems are connected to the central processing station via the network to transmit and save information in real time. The environmental tracking and observation device integrates a temperature detector (accuracy of $\pm 0.1°$ C), a humidity detector (accuracy of $\pm 2\%$ RH) and a light intensity sensor (measuring range of 0-100,000 lux), aiming to monitor fluctuations in the living environment of the elderly. In the programming world, Python programming tools are widely used, and the TensorFlow and Keras deep learning libraries are used to design and train neural network models. Data processing and analysis are implemented with the help of Pandas and NumPy libraries, Scikit-learn is used for feature selection and data preparation, and data storage is carried out with the help of the MySQL data management system. All data are encrypted and transmitted via the secure transport layer protocol to ensure data security. The visualization of experimental information is combined with the drawing toolkit and statistical mapping tools.

2.2 Data Collection

The research sample includes 250 female participants and 250 male participants who are over 65 years old, with an equal gender ratio. The data collection takes one year, throughout the year, covering seasonal changes and ecological evolution, aiming to collect comprehensive and typical data. Real-time information is collected using three-dimensional motion trackers and angular velocity sensors. These monitoring devices are fixed at the waist of the human body, with a collection rate of thousands of times per minute, recording walking methods, balance states and movement patterns. In addition, high-definition monitoring equipment is used for real-time supervision to record the daily life movements and fall events of the elderly. Environmental data is collected through temperature detectors, humidity monitors and light detectors. The temperature measurement range is -10° C to 50° C, with an accuracy of ±0.1° C; the measurement range of the humidity monitoring equipment is 0-100% RH, with an accuracy of ±2% RH; the sensing range of the brightness sensor is 0-100,000 lux. These data reveal the impact of changes in natural environmental factors on the possibility of falls. Medical information covers the basic medical health records and medical history of the elderly population, such as age information, gender information, weight data, height data, medical history and medication history, etc. Through collaboration with local medical centers and health insurance companies, a comprehensive health data assessment is conducted on each participant once a quarter to record the latest health status and possible falls.

2.3 Feature extraction and selection

This study uses a comprehensive multi-source data method to analyze and select the decisive factors affecting the risk of falls in the elderly. In the initial stage, dynamic attributes are extracted from the data collected from the three-axis motion sensor and the angular momentum rate sensor, covering the walking cycle characteristics, cadence frequency, stride length, acceleration change rate, angular velocity, etc. The gait cycle (T) is obtained by calculating the time difference between consecutive steps, the cadence (f) is the number of steps per unit time, and the step length (L) is calculated by multiplying the speed (v) and the gait cycle, and the formula is $L=v\times T$. The acceleration change rate (Δa) and angular velocity (ω) are calculated by the derivative of the sensor data. Secondly, environmental features are extracted from the environmental sensor data, including average temperature ($\overline{T}$), temperature fluctuation range (ΔT), humidity (RH), light intensity (I), etc. The temperature fluctuation range (ΔT) is calculated by the difference between the maximum temperature and the minimum temperature, and the humidity and light intensity are directly read from the sensor data. Thirdly, health features are extracted from health data, including age (A), gender (G), weight (W), height (H), BMI (body mass index, formula: $BMI=\frac{W}{H^2}$), medical history (M) and drug use (D), etc. These features are normalized so that their values are between 0 and 1 to eliminate the influence of features of different dimensions.

In terms of feature selection, a feature selection method based on correlation was used to analyze the relationship between each feature and the risk of falls through the Pearson correlation coefficient (ρ), and features with an absolute value of the correlation coefficient greater than 0.3 were selected. At the same time, the principal component analysis (PCA) technique was used to reduce the dimension of high-dimensional data and extract the principal component with the greatest explanatory power for the risk of falls. The formula is $Y=W^TX$: where Y is the principal component vector, W is the weight vector, and X is the feature vector.

2.4 Neural Network Model Design

2.4.1 Model selection

In the model screening phase, based on the results of preliminary feature screening and selection, this study implemented a variety of neural network models for comparative evaluation, including multi-layer perceptron (MLP), convolutional neural network (CNN) and long short-term memory network (LSTM). The deep neural network performs deep reinforcement transformation of features through dense layers. The input space scale includes 20 main screened features. The hidden layer is constructed by two levels, each layer contains 128 neural units, and the activation element uses ReLU (Rectified Linear Unit). The mathematical expression is written as:

$$f(x) = \max(0, x)$$

The output layer adopts the hyperbolic tangent function as the activation mechanism to predict the probability of falling. Subsequently, the convolutional neural network applies convolution filters to capture the local structure of features, which is suitable for processing the temporal and spatial characteristics of sensor data. The model includes several convolutional layers, the size of the convolution kernel is set to 3x3, the step size is set to 1, and each stage is equipped with 64 convolution kernels. The convolution is followed by the maximum pooling layer (Max-Pooling), and the size of the pooling layer is set to 2x2. The output result of the convolutional neural network arrives at the output node triggered by the Sigmoid function after being processed by the full connection layer.

In addition, as an efficient continuous data processing algorithm, the long short-term memory network is suitable for the evaluation and identification of the dynamic characteristics of the limb activities of the elderly. The LSTM unit includes an input gate, a forget gate, and an output gate. The formulas are: input gate $i_t = \sigma\left(W_i \cdot \left[h_{t-1}, x_t\right] + b_i\right)$, forget gate $f_t = \sigma\left(W_f \cdot \left[h_{t-1}, x_t\right] + b_f\right)$, output gate $o_t = \sigma(W_o [h_t - 1, x_t] + b_o)$, where σ is the Sigmoid activation function, W and b are the weight and bias parameters. The number of hidden units in the LSTM layer is set to 100, and finally the fully connected layer and the Sigmoid output layer are connected.

2.4.2 Model training and validation

The ten-fold cross-validation method was used in the model building and verification stage, and the data set was divided into multiple sections of training data (accounting for 90%) and verification data (accounting for 10%). The purpose was to ensure the universality of the model. In the training stage, the Adam algorithm adjuster was used to adjust the parameters. The initial learning rate was set to 0.001, the batch size was set to 64, and each algorithm model was trained for hundreds of rounds of iterations. The cost function used the binary cross-entropy loss for the binary classification problem, and the expression was:

$$L = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log\left(\hat{y}_i\right) + \left(1 - y_i\right)\log\left(1 - \hat{y}_i\right)\right]$$

Among them, is the actual label and is the predicted probability [4] .

At the end of each training phase, the performance of the algorithm in the validation set is evaluated, and indicators such as correctness, retrieval rate, precision and F1-score are calculated. The calculation formula for accuracy is:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Among them, TP is a true positive example, TN is a true negative example, FP is a false positive example, and FN is a false negative example. Recall rate (Recall) represents the ability of the model to identify the risk of falling, and the formula is:

$$\text{Recall} = \frac{TP}{TP + FN}$$

Precision reflects the accuracy of model prediction, and the formula is :

$$\text{Precision} = \frac{TP}{TP + FP}$$

F1-score is the harmonic mean of precision and recall, and the formula is:

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

In the learning process, in order to avoid overfitting, an early stopping mechanism was implemented, which ended the training process immediately when the accuracy of the validation set no longer improved.

3. Results Analysis

In the training and verification phase of the model, the ten-fold cross-validation method was implemented to evaluate three models: multi-layer perceptron (MLP), convolutional neural network (CNN) and long short-term memory network (LSTM). The performance of each model on the test set is shown in the following table:

TABLE I. PERFORMANCE OF THE MODEL ON THE TEST SET

Model	**Accuracy**	**Recall**	**Accuracy**	**F1-score**
MLP	0.88	0.85	0.87	0.86
CNN	0.91	0.89	0.90	0.89
LSTM	0.93	0.91	0.92	0.91

As can be seen from Table 1, the recurrent neural network model is significantly superior under many evaluation criteria, with an accuracy of 93%, an actual positive detection rate of 91%, a true positive prediction rate of 92%, and an F1-score of 91%. Relatively speaking, the performance of the convolutional neural network and multi-layer perceptron models is slightly insufficient, with the recognition accuracy of the CNN model being 91% and the recognition accuracy of the MLP model being 88%. By studying the change paths of the loss functions of various models, it is observed that the training efficiency of the long short-term memory network model is relatively high, and the error rate of the validation set gradually stabilizes after about 20 rounds of training iterations, and is lower than that of other models, showing that it has obvious advantages in processing sequence data information. In addition, the implementation of the timely stop strategy effectively curbs the problem of overfitting of the model and ensures the generalization ability of the model. In the process of in-depth discussion, the classification performance of the LSTM model was evaluated through the confusion matrix. The results show that the LSTM model performs well in identifying fall events and can accurately distinguish between real falls and fake falls. Table 2 is the confusion matrix of the LSTM model:

TABLE II. CONFUSION MATRIX OF LSTM MODEL

Actual/Forecast	fall	Non-fall
fall	820	80
Non-fall	90	1010

The above data analysis indicates that deep intelligent recurrent neural networks can more accurately predict the risk of falls among the elderly during practical application. Based on the predicted results, corresponding preventive measures can be implemented in advance to reduce the incidence of falls, improve the quality of life of the elderly and ensure their safety.

4. Discussion

4.1 Research Findings

This study used three models, multi-layer perceptron (MLP), convolutional neural network (CNN) and long short-term memory network (LSTM), to evaluate. The experimental results showed that the LSTM deep learning algorithm showed the highest accuracy in predicting the risk of falls in the elderly. Specifically, the LSTM architecture surpassed other model architectures in terms of accuracy, recall, precision and F1-score, reaching 93%, 91%, 92% and 91% respectively. This outstanding performance is largely due to the ability of the LSTM network to process time series data, which enables it to more accurately track the dynamic movement patterns of the elderly population over time. By analyzing the error matrix, the LSTM network showed a high accuracy in the fall behavior, with 820 actual fall cases and 80 misidentified non-fall cases, indicating that it can accurately identify real fall events, and also has a high accuracy in identifying non-fall behaviors, with 1010 actual non-fall cases and 90 misidentified fall cases. In addition, the implementation of an early termination mechanism during the training phase effectively avoided over-optimization of the model and improved the wide applicability of the model. These data illustrate that the fall risk prediction model based on long short-term memory networks has demonstrated excellent applicability and effectiveness in real-world applications. It can predict the risk of falls in the elderly in advance and assist in the formulation of individualized fall prevention strategies. It can therefore effectively reduce the occurrence of falls and improve the quality of life and safety of the elderly.

4.2 Study limitations

Although the long short-term memory network algorithm has shown excellent performance in the prediction of fall risk in the elderly, this study still has constraints. In the initial stage, the scope of data collection was limited to 500 elderly people in a specific area. The number of samples and geographical restrictions may lead to the applicability of the model. After further review, although many ecological factors and health indicators were taken into account during the experimental planning period, some subtle factors such as mental health and social support were not fully evaluated. In addition, the model showed excellent accuracy and stability during the training and verification period, but it may encounter more complex real-life situations in actual use. The robustness and real-time performance of the model need to be further tested. In the final stage, although an early termination plan was adopted to prevent overfitting, changes in data distribution and their effects may still affect the accuracy of model predictions during the application process.

4.3 Future Research Directions

Future exploration needs to focus on increasing sample size and variability to enhance the applicability and robustness of the model. For example, the data collection area should be expanded to cultural diversity in various places, and the sample size should be increased to obtain a more comprehensive fall factor. At the same time, many potential influencing factors must be considered, such as psychological status, social support, and medication status, to thoroughly evaluate the risk of falls in the elderly, aiming to improve the response speed and adaptability of the model. Consider the experiment of integrating multi-sensory information and real-time observation framework, and improve the calculation method to shorten the response time. In this process, the verification of actual application should be carried out in more complex and changeable scenarios to ensure the robustness and reliability of the model. In addition, the research needs to study the construction of an interactive platform and early warning information system that is easy for users to operate, so that family members and care workers can obtain the health status and danger warning of the elderly in real time, so as to formulate more efficient protection strategies. These suggestions are expected to promote the efficiency of the fall precursor analysis program and provide a more stable safety line for the elderly population.

5 Conclusion

This study used a comparative analysis of three models, namely, multi-layer perceptron (MLP), convolutional neural network (CNN) and long short-term memory network (LSTM), to confirm the superiority of LSTM model in the prediction of fall risk in the elderly. The recurrent neural network model performed well in accuracy, completeness, recall rate and F1-score, indicating that it has significant advantages in processing sequence data and capturing time series changes. Then, the survey also revealed limitations such as insufficient sample capacity and data types, and incomplete consideration of potential variables. Future academic research should broaden the scope of data collection, increase the number of samples, incorporate other hidden influencing factors, test the toughness and credibility of the model in a more complex and changeable real environment, and carry out in parallel to build an intuitive and convenient operation platform and a preemptive alarm system, which will help enhance the value of effectiveness and help the elderly, their relatives and care workers to implement protective behaviors immediately, thereby significantly reducing the frequency of fall accidents and improving the quality of life and safety standards of the elderly. Through continuous improvement and refinement, the fall prediction detection system relying on neural networks has the potential to show more outstanding effectiveness in the field of public health.

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