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A Deep Learning-Based Model for Stroke Rehabilitation Assessment

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Abstract—**The in-depth research on wearable sensor networks and machine learning technologies has greatly facilitated their application and development in the field of rehabilitation assessment of stroke patients. In the face of the large amount of data generated by wearable sensors, the current mainstream machine learning-based research methods require human experience to select and extract features from the raw data, which is difficult and insufficient for feature extraction. In addition, given that upper limb motor dysfunction is the most prevalent and severe among stroke patients, current research on stroke rehabilitation assessment also mainly focuses on the assessment of upper limb motor function, and lacks quantitative assessment protocols that combine the upper and lower limbs. To solve the above problems, this paper proposes a stroke rehabilitation assessment model incorporating upper and lower limb features, and extensive experiments on a self-constructed dataset show that this end-to-end deep learning method outperforms machine learning with a single research perspective as well as traditional deep learning methods.**

Index Terms—**deep learning, rehabilitation assessment, stroke, upper and lower limb data**

I. Introduction

Stroke is characterised by high morbidity, high mortality, high disability and high recurrence rates [1], the patient will suffer a huge financial burden and psychological pain as a result. Studies have shown that more than 50% of stroke patients have a reduced quality of life due to motor dysfunction. For post-stroke patients, early implementation of rehabilitation therapy can significantly improve their clinical performance and promote the recovery of their motor function and daily activity ability [2]. Rehabilitation assessment is a fundamental and important part of stroke rehabilitation therapy. Rehabilitation assessment refers to the collection and analysis of patient data to evaluate the degree of recovery of dysfunction in a multidimensional manner, so as to form a quantitative or qualitative assessment of the patient's functional status, which providing support for the identification of rehabilitation treatment plans [3]. In clinical medicine, a scale-based assessment method is generally adopted for the rehabilitation assessment of stroke patients. Although this type of scale assessment method is widely used in clinical practice, it still suffers from the problems of long duration, subjective influence and difficulty in community and family settings, which are not conducive to guiding the clinical development of individualised and refined rehabilitation treatment plans [4]. In order to improve the effectiveness of stroke rehabilitation treatment, reduce healthcare costs, and lessen the burden on physicians, there is an urgent need to address the intelligence of the stroke rehabilitation process.

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II. Related work

In recent years, the development of wearable sensor networks, machine learning, and other technologies has provided a new way for fine assessment of rehabilitation in stroke patients [5]. In terms of motor function assessment, some studies have been conducted to obtain patient motor data based on wearable devices and use machine learning methods to predict patient function scale scores. Li et al [6] used RGBD sensors and force-sensitive resistive sensors together to collect patients' movement information, combined machine learning and rule-based logical classification for assessment scoring, and proposed an automated Fugl-Meyer upper limb assessment system that covers all 30 voluntary items of the scale. Clinical validation of the system in 20 hemiplegic stroke patients demonstrated that the system was able to generate reliable FMA scores. Song et al [7] proposed an automated method based on data collected from a mobile phone, where the patient performs FMA exercise with a mobile phone in hand, extracts features from the mobile phone exercise data and automatically scores the FMA test items using a decision tree. 10 stroke patients with upper limb dysfunction participated in a validation trial comparing automated FMA scores with traditional FMA scores from trained therapists. The results showed that the FMA scores of the mobile phone-based automated system were highly correlated with the FMA scores of trained therapists. In existing research, machine learning algorithms require human experience to select and extract features from raw data, and there are cases of insufficient feature extraction. In addition, because upper limb motor dysfunction is the most common and severe in stroke patients, most studies have only modelled the upper limb part of the patient's body, and there is a lack of quantitative assessment methods for the lower limb or the combination of the upper and lower limbs. To fill these gaps, this paper proposes a deep learning model that incorporates a dual attention mechanism [8]. This end-to-end deep learning architecture fuses upper and lower limb features and introduces a dual attention mechanism for the first time in the field of stroke rehabilitation assessment, which improves the feature extraction capability as well as enhances the basic convolution to produce discriminative features in a wearable sensor scenario. Objective assessment of motor function in stroke patients was achieved, providing interpretable clinical results.

III. MODEL

This paper explores an end-to-end lightweight network and further proposes a dual-attention module to help the network focus on more informative temporal and channel features that can further improve classification accuracy. The network structure is shown in Fig. 1. The upper and lower limb time series data collected by the inertial sensors are first preprocessed using a sliding window technique to divide them into consecutive fixed-length samples with overlap rates, and then fed into the network in order to extract feature representations. In this paper, we utilise residual networks as a backbone to enhance the feature representation. To prevent overfitting, the residual network contains only 3 sets of convolutional layers, each consisting of 2 building blocks composed of ordinary convolutions. There are 6 convolutional layers in total, and each building block has a shortcut connection that serves to skip blocks for identity mapping and to add the residual mapping of the block to become the final underlying mapping. The residual network is implemented with a two-layer skip, which contains ReLU, batch normalisation, and a dual-attention module between the two layers. Finally, rehabilitation assessment of stroke patients was completed through the full connectivity layer.

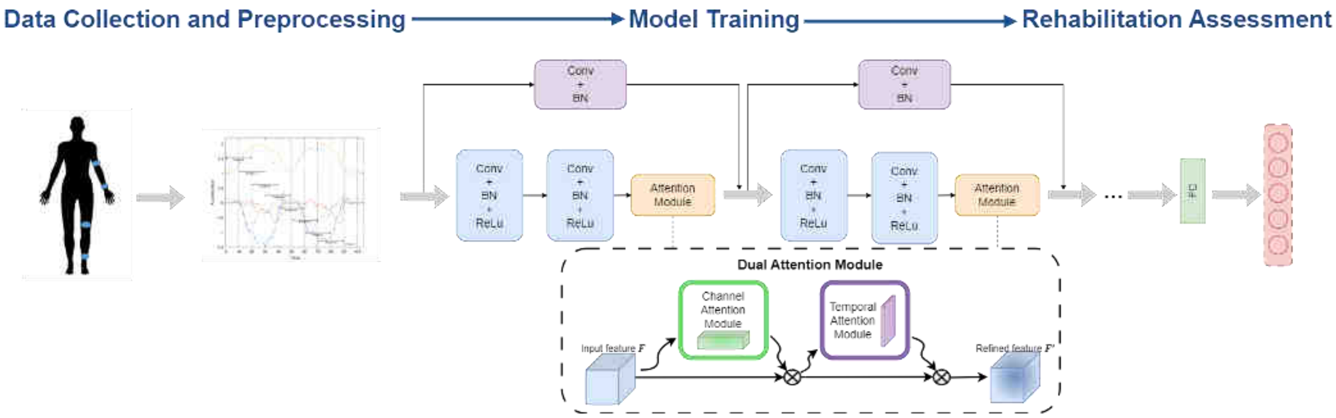


Fig.1 Overview of the proposed method

In the dual-attention module, for more efficient feature aggregation, for a given input feature, both mean pooling and max poolimg features are used. Let us consider a CNN layer and its corresponding feature map $A \in R^{C\times H\times W}$, where C, H and W are channel (number of filters), width (temporal axes) and height (sensor axes) dimension. The weight of channel attention can be calculated as:

$$W_c = \sigma(f_{(w_1,w_2)}(g_1(A)) + f_{(w_1,w_2)}(g_2(A))) \tag{1}$$

where $g_1 = \frac{1}{WH}\sum_{i=1,j=1}^{W,H} A_{ij}$ and $g_2 = \max_{i=1,j=1}^{W,H} A_{ij}$ are channel-wise global average-pooling and max-pooling. σ is sigmoid function. Since the two FC layers are designed to capture nonlinear cross-channel interactions, (1) can be further expressed as:

$$W_c = \sigma(w_2 \mathrm{ReLU}(w_1 g_1(A)) + w_2 \mathrm{ReLU}(w_1 g_2(A))) \tag{2}$$

where ReLU denotes the rectified linear unit used between the two FC layers. To reduce parameters, the size of w_1 and w_2 are set to $C\times(C/r)$ and $(C/r)\times C$ respectively where r is reduction ratio.

In a similar way, temporal attention can be computed by applying average pooling and max pooling operations to aggregate the channel information of the feature map. We join the two pooled features in order to aggregate the information along the channel index.The cascaded merged features are then convolved by a standard convolutional layer which can be formulated as:

$$W_T = \sigma(f^{n\times 1}([g_1(A); g_2(A)])) \tag{3}$$

where σ is sigmoid function. $n\times 1$ denotes the convolution filter size, g_1, g_2 denotes average pooling and max pooling. Finally, these two attention submodules are combined by elementwise multiplication, and then each attention submodule is scaled to [0, 1].

IV. EXPERIMENTS

A. Dataset and Data preprocessing

In this paper, triaxial acceleration data from 50 volunteers were collected using inertial sensors, and the IMUs were bound as shown in Fig. 2, with the coordinate system X-axis pointing upwards, Y-axis horizontally to the left, and Z-axis vertically outwards. Using the Brunnstrom Evaluation Scale, which is used clinically in stroke, as the basis for the development of a rehabilitation assessment model [9]. All 50 volunteers recruited were required to complete a simulation of the motor process of the upper and lower limbs in stages II to VI Brunnstrom staging, and stage I patients were not considered because they did not have any motor performance.

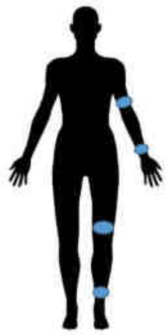


Fig.2 Wearing position of the IMU

Shoulder touch was selected as the data collection movement for the upper limbs, and heel-knee-shin test was selected as the data collection movement for the lower limbs, and each movement was completed 2 times without interruption. The collected data were first divided by a sliding window of size 100 with an overlap rate of 0.9, and then normalised by z-score to convert data of different magnitudes into a uniform measure score.

B. Experiments Setup

All models were run with the deep learning framework PyTorch on a computer with an Intel i5 7200U CPU and an NVIDIA GeForce 940MX GPU. Trained by Adam optimiser to minimize the cross-entropy loss function, for the proposed model, this paper sets the learning rate to 1e-4, training epochs to 100, and batch size to 256 to speed up the convergence of the model. In the experiments, the dataset was randomly divided into training, validation and test sets at a ratio of 0.8, 0.1 and 0.1.

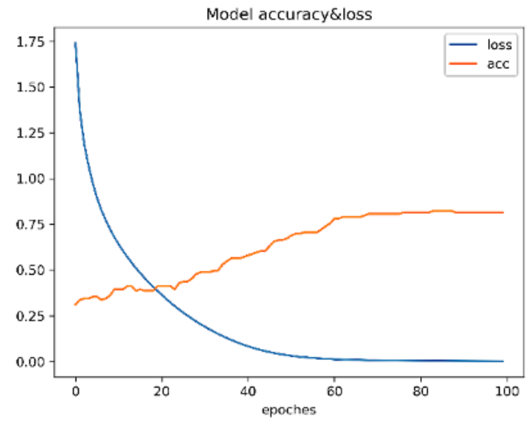
C. Experiments Results

In order to verify the validity of this paper from a whole-body perspective, comparative experiments were carried out on the proposed model using upper limb acquisition data, upper and lower limb acquisition data as inputs, respectively, and the specific model training process is shown in Fig. 3. The accuracy of the whole body perspective is 0.12 higher than that of the upper limb perspective, and after the 30th iteration, both the LOSS and ACC levelled off, which is a significant improvement in the performance of classification. This is due to the fact that the discriminative features are more adequately extracted for the model with upper and lower limb data as common inputs, and the training and testing results are significantly better than those of the model with a single angle input.

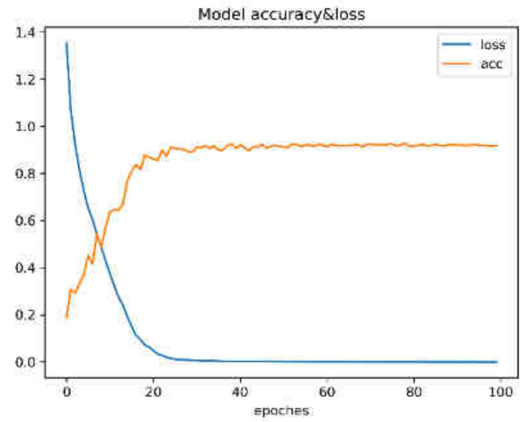
Table I

Model	Dataset	
	Upper	Upper&Lower
Logistic Regression	0.71	0.75
CNN	0.79	0.82
LSTM	0.78	0.81
Proposed Method	***0.84***	***0.93***

In addition, this paper also compares the proposed model with traditional machine learning and deep learning models, and the specific experimental results are shown in Table I. The results show that the accuracy of the models based on deep learning are all better than logistic regression [10], which is because deep learning methods are more parameterised and more complex than traditional machine learning methods, and can extract richer and more accurate features on their own. Moreover, compared with the commonly used CNN and ResNet methods, the proposed model achieves better results, which represents that the model possesses stronger feature extraction and classification capabilities, and further proves the effectiveness of the dual-attention mechanism.



(a) only upper limb data



(b) upper&lower limb data

Fig.3 Results on different dataset

V. CONCLUSION

In this paper, we propose an end-to-end deep learning model to address the inadequacy of relying on the use of machine learning methods for manual feature extraction and the problem of a single research perspective in the field of stroke rehabilitation assessment. The model incorporates upper and lower limb features to assess the degree of rehabilitation of the patient from a whole-body perspective, and introduces a dual-attention mechanism for the first time in the field, which improves the feature extraction capability. Various comparative experiments have proved that the proposed method is better than traditional machine learning models and some commonly used deep learning models in terms of research perspective and accuracy. It has good application prospects for automatic classification of the degree of recovery for stroke patients, which to some extent promotes the development of intelligent rehabilitation process.

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