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## ORIGINAL

# EFFECTS OF ATTENTION AND CONCENTRATION ON PERFORMANCE AND TRAINING METHODS IN ATHLETES

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## ABSTRACT

Athletes have to receive a large amount of complex and variable information at all times during training and competition, especially in high-level events, where the processing of clinical stimuli directly determines victory or defeat when athletes are of comparable abilities. Therefore, it is particularly important to improve the attention and executive function of high-level athletes, and the traditional way is to improve the attention of sports through the perspective of sports training, while neglecting the analysis of sports EEG characteristics. Therefore, this paper proposes a deep learning-based EEG signal classification method. In the data processing stage, z-score normalization is used for feature data and one-hot coding is used for label data. After that, the pre-processed EEG data are divided into three parts: training set, validation set and test set. The training set is mainly used for the training stage of the model, the validation set is mainly used for the setting of hyper-parameters, and the test set is used for the evaluation of the model performance. In the model training stage, two recursive structures, Long Short-term Memory (LSTM) and Gated Recurrent Unit (GRU), were used as the base predictor, and the AdaBoost algorithm was used to integrate the prediction of the results obtained after the training of the base predictor, and the four states of the athlete's brainwave were finally classified and identified. The four states of the athlete's brain waves were finally classified and identified. The experiments in this paper are carried out on the dataset provided by Physio Net, and the experimental results show that this scheme has better effectiveness and accuracy, and can improve the performance and training effect of athletes.

**KEYWORDS:** Attention and Concentration in Athletes; Attention; Concentration on Performance; Athletes; Deep Learning

## 1. INTRODUCTION

In today's sports competitions, mental quality plays an increasingly important role, but what determines the outcome of a match is not only the competition between participants in terms of technical and physical qualities, but more importantly, the competition in terms of mental quality. In many competitions, the competition between excellent athletes, the important factor affecting the outcome of the game is the athlete's mentality (Dewi, 2018; Mujika, 2017). In actual competitions, many athletes perform abnormally, often caused by emotional tension. In order to solve this problem, many researches on methods such as psychological suggestion and self-counselling have been conducted. However, it is not uncommon for athletes and coaches to pay enough attention to psychological training to explore relevant psychological monitoring in daily training. Moreover, it is not uncommon to see abnormal behaviours during competitions due to athletes' excessive stress on the field of play. It can be seen that psychological factors have a great impact on athletes' training and competitive status, and attention ability is an important part of it, which has an irreplaceable role in athletes' training and competition performance. Athletes find problems in habitual training. It is particularly important to find solutions to these problems (Boni & Abremski, 2022; Mujika, 2017; Welhaf & Kane, 2023).

Attention is very complex and its manifestations take several different forms, including focused, sustained, selective, alternating and distracted attention. In sport psychology, attentional processes, such as concentration, or the ability to focus mental effort on the task at hand and ignore distractions, are recognised as important determinants of successful athletic performance. Concentration of attention, which is essentially the concentration of consciousness, refers to the ability to focus on a target task for a prolonged period of time, excluding distractions, in any given situation. The ability to concentrate effectively is considered important and necessary for competitive success in all sports. The ability of top athletes to focus on a task throughout a competition may help them to mitigate the adverse effects of sub-optimal conditions, such as ambient noise and inclement weather, or those that come from internal sources such as memories and imaginations unrelated to the competition (Andre & Clement Darling, 2019; Kotseruba & Tsotsos, 2020).

Concentration is the ability to focus on one thing free from external distractions. Psychologists have analysed the power of concentration in a comprehensive and systematic way. He pointed out that through meticulous research, concentration is a way of life. Good concentration tends to bring peace of mind to people, thus enabling them to deal with various things in their lives more effectively. Things like memory, comprehension, listening, studying, working, etc. Concentration on internal performance so-called external, is the state of looking at a wide variety of things and interacting with people, not only that, but also drives thinking and promotes potential developmental abilities in forms that are invisible to the naked eye. In addition, attention is a basic function of human cognitive abilities, and higher cognitive abilities are regulated through attention (Schuetz & Venkatesh, 2020). In order to examine attention, it is necessary to systematically examine that person's sustained attention, selective attention, ability to switch attention, etc.

In the field of competitive sports, the question of how to improve the attentional capacity of athletes has been one of the key issues of research for a long time. Regardless of the type of sport activity, focusing attention can greatly contribute to their skill development and help them achieve ultimate success. However, due to the uniqueness of various sports, the attentional capacity they require may vary. In recent years, more and more academics are exploring ways to enhance attention in order to more effectively realise their potential (Ouyang, Yu, Cai, & Ye, 2024). This is especially true for sports that require a great deal of attentional input to excel, such as archery and football, which require high levels of attention to achieve outstanding results. According to the latest research, accurate visual perception and proper attention allocation can enable athletes to quickly and accurately acquire effective information on the field of play. In the field of sports, there are many well-established attention training methods today, such as: mental skills training, attention training. The 7-Step Mental Training Method guidebook provides training in 7 areas: relaxation training, anxiety suppression, development of positive thinking skills, self-regulation, imagery, concentration, and control of energy expenditure. Although psychologists differ in their understanding of mental training, the importance of concentration or focus training cannot be ignored. Based on the importance of attention, in the study of sport psychology, researchers have been exploring training methods that are effective in enhancing athletes' ability to pay attention.

However, few have analysed the EEG characteristics of athletes, Electroencephalography (EEG) is a non-invasive method to measure brain activity by recording electrical activity on the skull and scalp of athletes. Often the electrical activity of the brain displays distinctly complex behaviour with strong non-linear and dynamic properties. Communication in brain cells occurs through electrical impulses, which are measured by placing electrodes on the subject's scalp, and EEG signals are generated by inhibitory and excitatory postsynaptic potentials in cortical nerve cells. These postsynaptic potentials accumulate in the cortex and extend to the surface of the scalp where they are recorded as EEG. Therefore in this paper we propose a deep learning based EEG signal recognition method for athletes (Jiang & He, 2023; C.-H. Wang, Liang, & Moreau, 2020). The main contributions are as follows:

(1) In this paper, a deep learning-based EEG signal classification method

is proposed. In the data processing stage, z-score normalisation is used for feature data, and one-hot coding is used for label data to enhance feature expression.

(2) In this paper, two recursive structures of LSTM and GRU are used as the base predictor, and the AdaBoost algorithm is used to integrate the prediction of the results obtained after the training of the base predictor, and the four states of the athlete's brainwave are finally recognised in order to assist the training of the athlete's attention and concentration.

## 2. Methodology

In competitive sports, athletes need to have excellent concentration in order to perform at their best in competitions. Events such as archery, hurdling, and fencing all require athletes to remain calm and be able to concentrate effectively. Therefore, in the competitive arena, athletes are competing not only in terms of skill, but also in terms of concentration during the game. Athletes need to focus their attention on playing the game, but also need to reasonably allocate their attention to various things, therefore, this paper proposes a deep learning-based EEG signal recognition method for athletes for attention and concentration enhancement.

### 2.1 Attention and Concentration

Scholars define attention as the psychological process in which an individual selectively pays attention to a certain stimulus and ignores other stimuli around him, which mainly contains two dimensions of focus and selectivity, as shown in Figure 1. Attention is the direction and concentration of mental activity on a certain object, individual perception, thinking, memory and other psychological characteristics can be mobilised in the process of attention, directionality means that the object of attention is selective and targeted. Concentration is the intensity with which attention stays on an object. Attention includes selection; vigilance; and the ability to control, plan, and co-ordinate activities, with three separate but interacting components. Overall, although definitions of attention vary slightly in description, they all refer to the process by which an individual point to and selects a particular thing and inputs, processes, and integrates information about that thing.

The classification of attention is gradually comprehensive and multidimensional in the process of continuous development, in the theoretical model of attention divided attention into five dimensions are: concentration, selectivity, persistence, alternation and distribution. Some researchers classify attention into selective attention, focused attention and sustained attention according to the different functions of attention, and into attention distribution, attention transfer, attention breadth and attention stability according to the quality of attention.

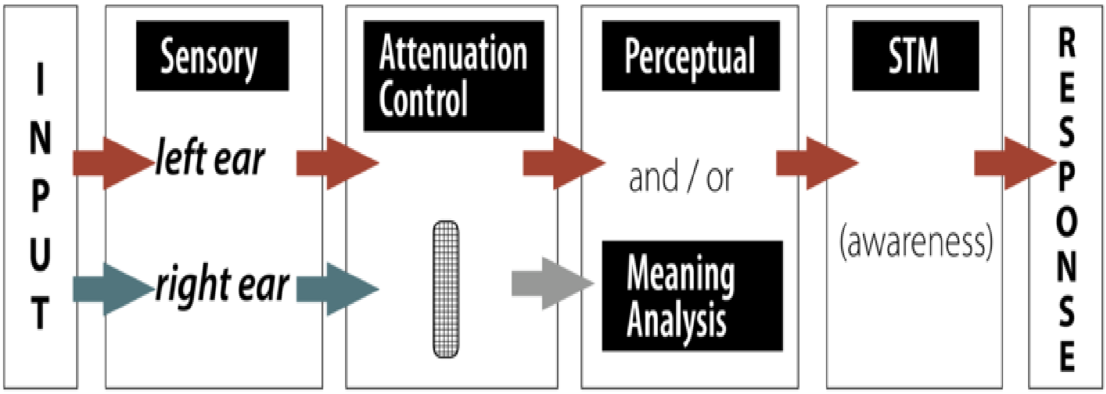


**Figure 1:** Schematic diagram of the attention.

The nature of attention determines its importance to all cognitive processes of an individual, which in turn influences the entire behavioural process. In training and competition, athletes face an ever-changing environment and need to receive a large amount of complex and variable information, all of which takes up cognitive resources, making the concentration of attention particularly important. The information received by athletes can be divided into internal and external, which includes both what athletes need and irrelevant information that they want to suppress and exclude. Therefore, for attention, ignoring the irrelevant information and seizing the key and valuable information can help athletes to eliminate the interference, implement the techniques and tactics, and give full play to their own level to win the game in the complex competition. Some psychologists believe that attention is an important factor for athletes to get excellent performance in the game. Some scholars show that, among the many factors that have an impact on the game, as the "foundation" and "bridge" of the material is not attention, in the high level of athletes competing on the same field, excellent attention to the ability to win. Some scholars believe that attention is a part of mental skills, and athletes must strengthen their ability to control attention through continuous training and learning. Whereas concentration is mainly about being very focused on something and maintaining a certain level of intensity or tension for a certain period of time. For shooting and archery athletes, it is important not only to have the ability to resist distractions, but also to focus on training goals over a longer period of time.

## 2.2 The relationship between athlete attention and performance

In competitive sports, athletes need to have excellent concentration in order to achieve the best results in a competition. Events such as archery, hurdling and fencing require athletes to remain calm and be able to concentrate effectively, as shown in Figure 2. Therefore, in the competitive arena, athletes are competing not only in terms of skill, but also in terms of concentration during the game. Athletes in the game not only need to focus on the game, but also need to reasonably allocate attention to various things, therefore, in the daily training should not only pay attention to technical and tactical training, but also pay attention to psychological skills training. In the psychological training methods, general psychological training methods are focused attention training, thinking ability training and specialised perception training, etc.; pre-game psychological training methods are self-suggestion and relaxation training, simulation training, biofeedback training and representation reproduction training.

At present, there are many mature attention training methods in the field of sports. Researchers conducted a 10-week attention training intervention in a laboratory and a real sports situation. Both results indicated that cognitive training in the laboratory and team training in a real-world situation had a positive effect on the expansion of athletes' attentional windows, and that athletes' training in the laboratory and on the sports field contributed equally to attentional performance. Resting eye movement is a well-regarded visual gaze strategy that helps movement performers to maintain prolonged gaze prior to movement initiation, which improves skill learning and contributes to the maintenance of athletic performance under the pressure of competition.

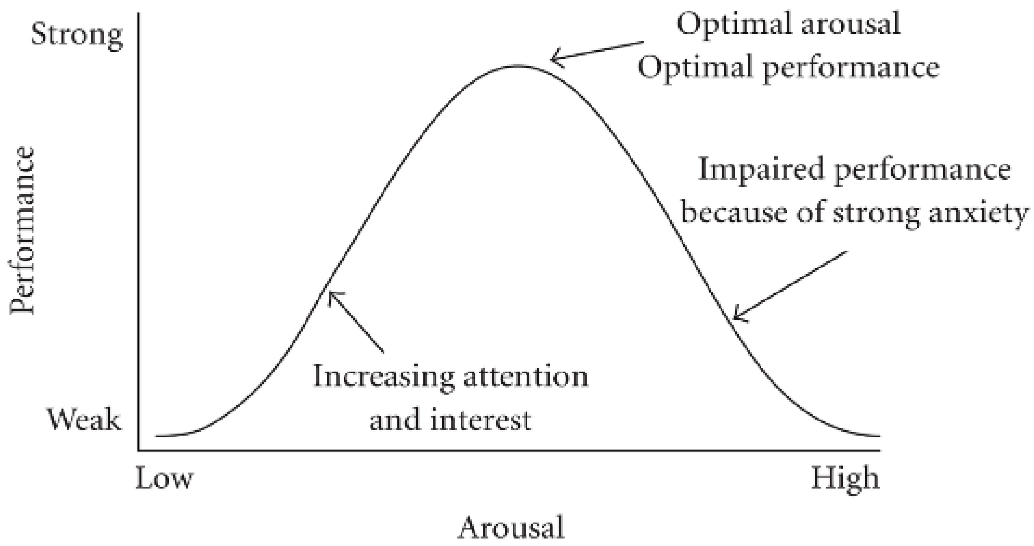


**Figure 2:** Schematic diagram of multi-head self-attention mechanism calculation.

EEG-based neurofeedback training, also known as EEG-biofeedback training, is a special kind of biofeedback training and is also the most commonly used method in neurofeedback training. In the field of sports, EEG-based neurofeedback training is also used. Neurofeedback training can cultivate athletes' self-understanding and regulation ability of physical physiological activities and brain neural activities, and can help cultivate athletes' ability to be alert and focused, manage their emotions, fear and attention, so as to focus more on Focus on the key factors to complete a certain movement skill, as shown in Figure 3.

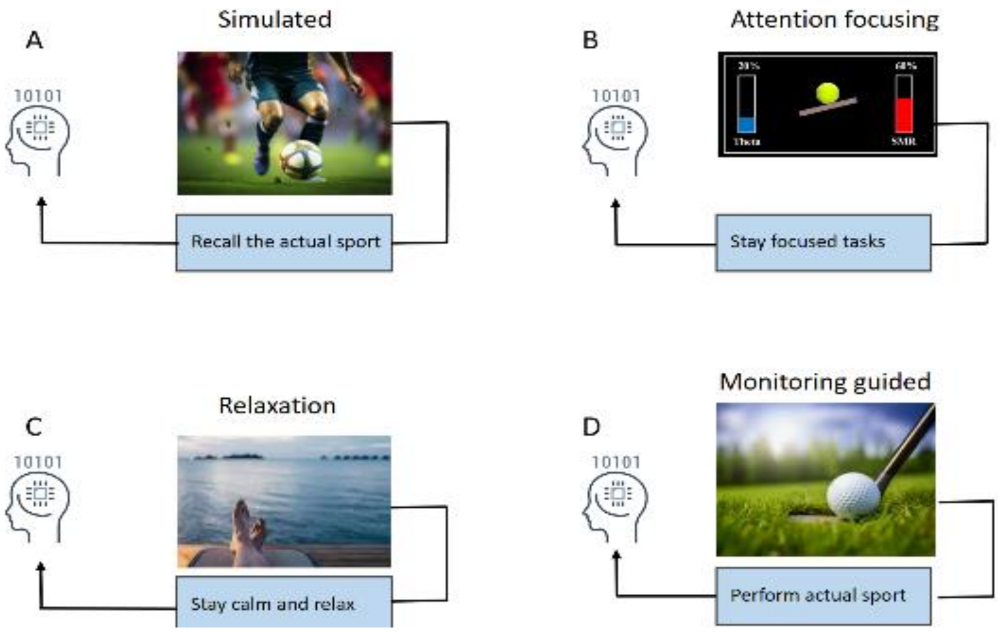


**Figure 3:** Schematic diagram of EEG and attention.

## 2.3 Recurrent Neural Network

In traditional neural network models (Huang, Zhang, Liu, & Li, 2023; S. Wang & Li, 2023) (such as densely connected networks and convolutional neural networks), they all go from the input layer through the hidden layer, and then to the output layer. The nodes between each layer are not connected. No status information is saved. In contrast, RNN traverses all sequence elements, and the output of each current layer is related to the output of the previous layer. That is, the nodes between each layer are connected, and the state information of the previous layer is retained. In theory, RNN should be able to process sequence data of any length, but in order to reduce a certain complexity, in practice only the previous state information is usually selected. First, the principle of RNN is briefly introduced, as shown in Figure 4.

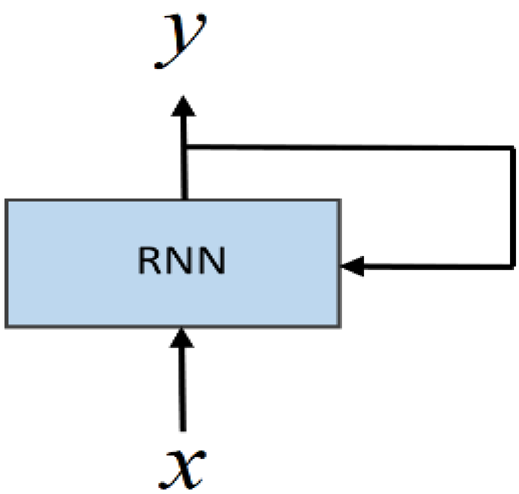


**Figure 4:** Schematic diagram of the RNN

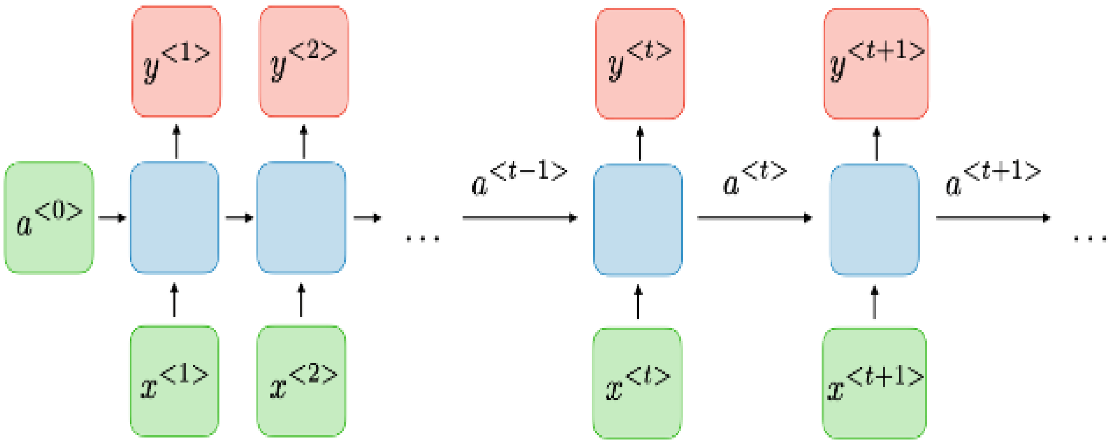


**Figure 5:** Schematic diagram of the unfolding of recurrent neurons.

We can also expand this neural network in the form of time series, as shown in Figure 5. The output of each neuron is determined based on the current input $x(t)$ and the previous moment $y(t-1)$. Their corresponding weights are $W_x$ and $W_y$. Then, the output of a single neuron is calculated as follows:

$$y_t = \phi\left(x_t^T \circ W_x + y_{t-1}^T \circ W_y + b\right) \qquad (1)$$

If you expand the middle hidden layer, you will get the result shown in Figure 6. Usually, the state of an RNN unit at time *t* is denoted as $h_t$. *U* represents the weight of the input at this moment, *W* represents the weight of the previous output, and *V* represents the weight of the output at this moment. At time $t = 1$, generally $h_0$ means that the initial state is 0, and the values of *U*, *W* and *V* are randomly initialized and calculated using the following equation:

$$h_1 = f\left(Ux_1 + Wh_0 + b_h\right) \qquad (2)$$

$$O_1 = g\left(Vh_1 + b_0\right) \qquad (3)$$

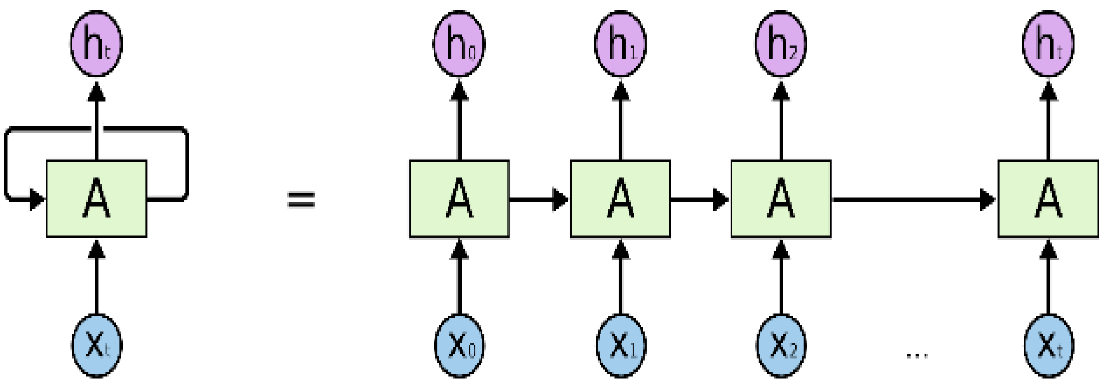


**Figure 6:** Schematic diagram of hierarchical expansion of hidden layer

## 2.4 LSTM

The basic flow of the LSTM unit (shown in Figure 7) is as follows: as the short-term memory $c_{(t-1)}$ is traversed across the whole network from left to right, it first passes through a forgetting gate to discard some memories, and then passes through an input threshold to selectively add some new memories, and finally outputs $c_{(t)}$ directly. In addition, in this part of the operation of adding memories, the long-time memories are first passed through the tanh function and then filtered by the output threshold, which produces the short-time memory $h_t$. In conclusion, the LSTM recognises important inputs (the role of the input threshold) and stores this information in the long term memory, retaining the needed part through the forgetting gate, as well as being able to extract it when it is needed, which is computed in the following equations:

$$i_{(t)} = \sigma\left(w_{xi}^T \circ x_{(t)} + w_{hi}^T \circ h_{(t-1)} + b_i\right) \quad (4)$$

$$f_{(t)} = \sigma\left(w_{xf}^T \circ x_{(t)} + w_{hf}^T \circ h_{(t-1)} + b_f\right) \quad (5)$$

$$o_{(t)} = \sigma\left(w_{xo}^T \circ x_{(t)} + w_{ho}^T \circ h_{(t-1)} + b_o\right) \quad (6)$$

$$g_{(t)} = \tanh\left(w_{xg}^T \circ x_{(t)} + w_{hg}^T \circ h_{(t-1)} + b_g\right) \quad (7)$$

$$c_{(t)} = f_{(t)} \otimes c_{(t-1)} + i_{(t)} \otimes g_{(t)} \quad (8)$$

$$y_{(t)} = h_{(t)} = o_{(t)} \otimes \tanh\left(c_{(t)}\right) \quad (9)$$

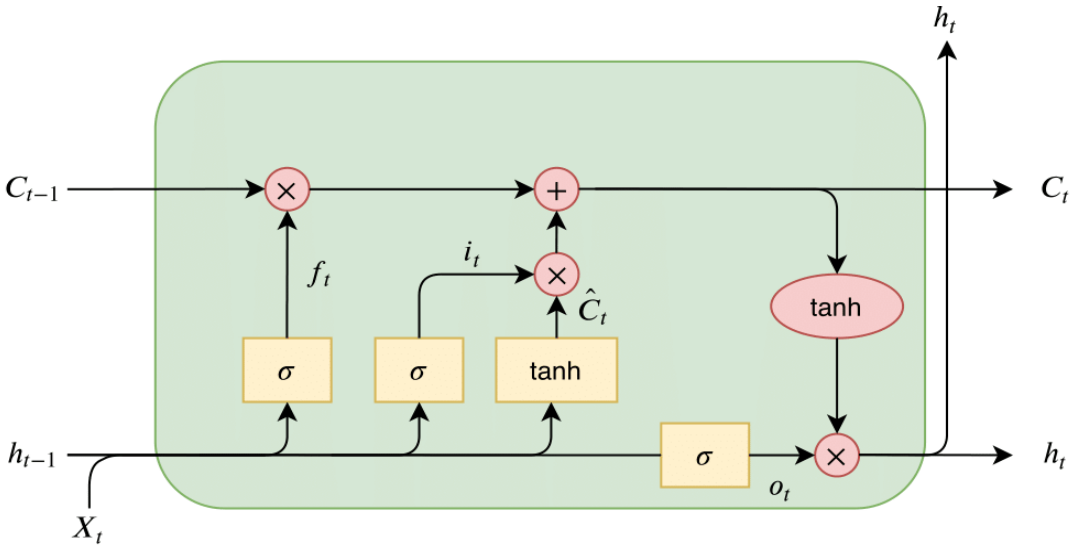


**Figure 7:** Schematic diagram of the LSTM

## 2.5 GRU

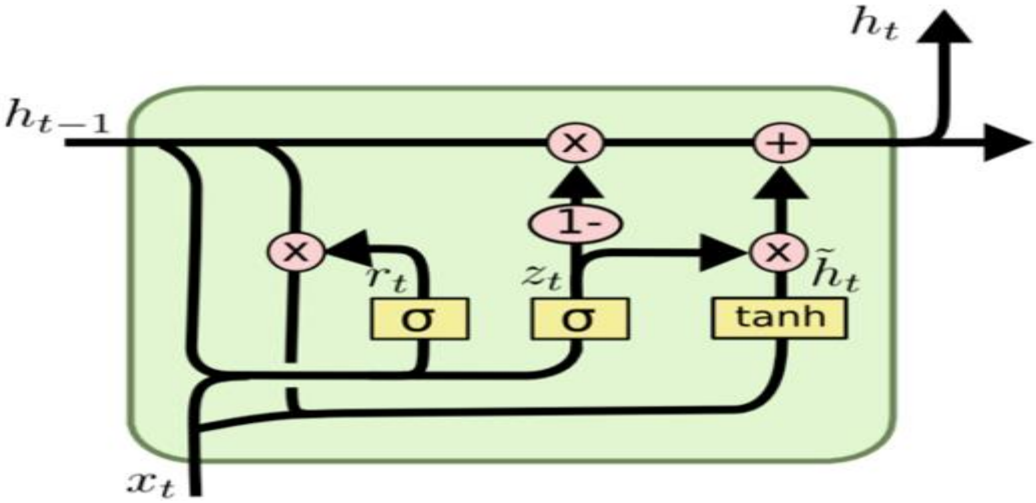


**Figure 8:** Schematic representation of the GRU

There are three threshold controllers in the LSTM unit structure: input threshold, forget threshold and output threshold, these three gate functions control the input value, memory value and output value, respectively, but there is no output threshold in the structure of the GRU unit (shown in Figure 8), there are only two gates: reset gate and update gate. The reset gate is in charge of $r_{(t)}$ and is used to control which parts of the state information from the previous moment are available to be displayed to the main layer. If the value of the reset gate is smaller, then less state information is written. The update gate is the responsibility of $z_{(t)}$ and is used to control how much of the state information from the previous moment is brought into the current state. If the value of the update gate is larger, then more state information from the previous moment is brought in, and the equations for the calculation of the GRU are as follows:

$$z_{(t)} = \sigma\left(w_{xz}^T \circ x_{(t)} + w_{hz}^T \circ h_{(t-1)}\right) \qquad (10)$$

$$r_{(t)} = \sigma\left(w_{xr}^T \circ x_{(t)} + w_{hr}^T \circ h_{(t-1)}\right) \qquad (11)$$

$$g_{(t)} = \tanh\left(w_{xg}^T \circ x_{(t)} + w_{hg}^T \circ \left(r_{(t)} \otimes h_{(t-1)}\right)\right) \qquad (12)$$

$$h_{(t)} = \left(1 - z_{(t)}\right) \otimes \tanh\left(w_{xg}^T \circ h_{(t-1)} + z_{(t)} \otimes g_{(t)}\right) \qquad (13)$$

## 2.6 AdaBoost

The basic idea of the AdaBoost algorithm is as follows: To build an AdaBoost classifier, you first need to train a base classifier) and use it to make classification predictions on the training set. Then increase the weight of misclassified sample instances. Then, the samples with updated weights will be used again to train the next new weak classifier, and then predict the training set again, continue to update the weights, and continue to recurrent forward. In each round of training, the population (sample population, that is, the training set) is used to train the weak learner, generate new sample weights, and iterate until the predetermined error rate is reached or the set maximum number of iterations is reached. The AdaBoost algorithm first initializes the weight of each sample, normalizes the weight, calculates the weighted error rate of each feature classifier, selects the best weak classifier, and adjusts the weight according to the best weak classifier. The weight update rules are iterated, and finally a strong classifier is trained. When predicting, the AdaBoost algorithm calculates the prediction results of all classifiers, weights them using the classifier's weight $a_j$, and finally obtains the prediction results through voting. The calculation equation is as follows:

$$\hat{y}(x) = \arg\max \sum_{j=1}^{N} a_j \tag{14}$$

## 2.7 Integrated recognition model

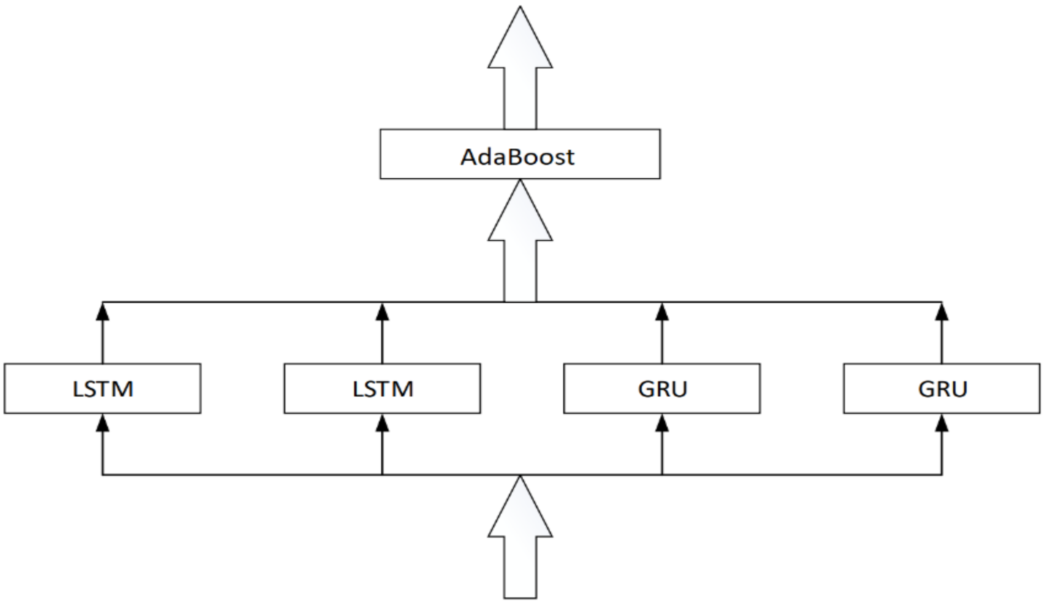


**Figure 9:** Schematic representation of the proposed model.

Since LSTM and GRU can well solve problems such as long dependencies in recurrent neural networks, and the prediction results obtained by ensemble learning are much better than the best single predictor, this article proposes an EEG prediction based on integrated recurrent neural networks model. The model is shown in Figure 9. The recurrent neural network in Figure 9 is mainly composed of LSTM and GRU. As the base predictor of the AdaBoost ensemble learning algorithm, they will classify and predict the sample set, continuously update the weights of the sample instances during the algorithm iteration, and then use it for the next step. A training session. Therefore, we integrate their respective prediction results and obtain better prediction results than a single classifier through weighted voting.

## 3. Experiment and Results

### 3.1 Datasets

Physio Bank ATM consists of four parts: Input, Output, Toolbox, and Navigation; Input is used to select the public dataset, select the subject and which movement the subject is imagining, and select the electrode channel; Output is used to select the length of output, the time format, and the data format; Toolbox is used to select the specific data format, such as CSV, TXT, EDF, and .mat files used in matlab. Output is to select the output length, time format, and data format, while Toolbox is to select the specific data format, such as CSV, TXT, EDF, and .mat file for matlab. Finally, Navigation is used to select which record is to be used, either the current record, the previous record or the next record.

The dataset uses 64-channel EEG data recorded on the BCI2000 system (http://www.bci2000.org), with approximately 26.4 million samples collected from 109 volunteers, and is composed of 1-minute and 2-minute EEG recordings. The EEG dataset consists mainly of feature data and labelled data, which need to be processed before training the model. The feature data will have various ranges of values when unprocessed, some are negative, some are floating point numbers, and some are relatively large integers, so these feature data need to be processed. In this paper, z-score standardized processing method is used for feature data, which is the data preparation stage in the whole framework.

### 3.2 Experimental setup

The experimental setup consists of two parts, the experimental environment setup used during the experiment and the hyper parameter setup of the model used, as shown in Tables 1 and 2.

**Table1:** Experimental environment setup.

| TYPE | PARAMETERS |
|---|---|
| OS | Ubuntu 16.04 |
| GPU | Nvidia RTX 4090 |
| RAM | 24G |
| PYTHON | 3.6.5 |
| TRANSFORMERS | 3.0.2 |
| PYTORCH | 1.4.0 |

**Table2:** Hyper parameter settings

| HYPERPARAMETER | VALUE |
|---|---|
| BATCH_SIZE | 32 |
| DROPOUT | 0.4 |
| OPTIMIZER | Adam |
| LEARNING RATE | 3e-5 |
| EPOCH_NUM | 2000 |

### 3.3 Experimental results and analysis

In this paper, a total of 38000 samples from 20 subjects were selected for multiple experiments and analyses, and in order to determine the number of base predictors for the integrated model, 11 experiments were done in this paper and the results of the experiments were compared and analysed as shown in Table 3.

**Table 3:** Results of the comparison of the effects of integration experiments

| ID | LSTM | GRU | ACC |
|---|---|---|---|
| **1** | 1 | 0 | 0.8435 |
| **2** | 0 | 1 | 0.8560 |
| **3** | 1 | 1 | 0.8612 |
| **4** | 2 | 0 | 0.8652 |
| **5** | 2 | 1 | 0.8720 |
| **6** | 1 | 2 | 0.8867 |
| **7** | 2 | 2 | 0.8827 |
| **8** | 3 | 0 | 0.8804 |
| **9** | 3 | 1 | 0.8732 |
| **10** | 3 | 2 | 0.8685 |
| **11** | 3 | 3 | 0.8622 |

In Table 3, the numbers in the LSTM and GRU columns represent the number of their respective base predictors, and the first seven experiments show that the accuracy of the model prediction increases with the increase of the number of base predictors, while the accuracy of the model prediction begins to decrease when the number of LSTMs is increased to three. Therefore, the number of both LSTMs and GRUs in this scheme is set to 2.

It can also be seen that there is a significant improvement in the results compared to other single RNN layer models. The predictions obtained are also much better than a single predictor as the strategy used for integrated learning is a majority weighted voting method. In order to further prove the effectiveness and superiority of the scheme proposed in this paper, it is compared with other methods and the results are shown in Table 4.

**Table 4:** Results of comparison of related methods

| ID | MODEL | FEATURE PROCESSING | ACC |
|---|---|---|---|
| **1** | SVM | Coif4+MAV | 0.7497 |
| **2** | K-means | DWT | 0.8330 |
| **3** | LDA | CSP | 0.7470 |
| **4** | ANN | FFT | 0.7496 |
| **5** | CNN | - | 0.8649 |
| **6** | Ours | - | 0.9230 |

As can be seen from Table 4, most of the current schemes for EEG signal classification research use machine learning algorithms, which basically need to carry out the feature extraction process of EEG, and most of them ignore the characteristics of the EEG time series, which leads to the experimental results are not ideal. Compared with other schemes, the integrated recurrent neural network proposed in this paper can make full use of the characteristics of the time series, does not need to carry out feature extraction, and can carry out end-to-end training experiments, and then finally through the integration of the prediction, so it can get better results.

## 4. Conclusion

In this paper, we propose a deep learning-based EEG signal classification method. In the data processing stage, the z-score standardization method is used for feature data, and the one-hot encoding method is used for label data. Then the preprocessed EEG data is divided into three parts: training set, verification set and test set. The training set is mainly used for the training phase of the model, the validation set is mainly used for setting hyper parameters, and the test set is used for evaluating model performance. The model training phase mainly uses two recursive structures, Long Short-term Memory (LSTM) and Gated Recurrent Unit (GRU), as the base predictor, and uses the AdaBoost algorithm to train the base predictor. Make integrated predictions and finally classify and identify the four states of athletes' brain waves. The experiments in this article were conducted on the data set provided by Physio Net. The experimental results show that the scheme has good effectiveness and accuracy and can improve athletes' performance and training effects.

## REFERENCES

Andre, R., & Clement Darling, R. I. (2019). Acute Type B Dissection. *Vascular & Endovascular Review, 2*(1).

Boni, A. A., & Abremski, D. (2022). Commercialization Challenges and Approaches for Digital Health Transformation. *Journal of Commercial Biotechnology, 27*(1). doi:https://doi.org/10.5912/jcb1024

Dewi, E. M. P. (2018). *The Implementation of Mental Training Method in Sport* *to Increase Athlete's Mentality at Student Education and Exercise (PPLP) Makassar.* Paper presented at the 3rd ASEAN Conference on Psychology, Counselling, and Humanities (ACPCH 2017).

Huang, Z., Zhang, P., Liu, R., & Li, D. (2023). An Improved YOLOv3-Based Method for Immature Apple Detection. *IECE Transactions on Internet of Things, 1*(1), 9-14.

Jiang, P., & He, H. (2023). EEG Signal Analysis based on machine learning in psychological balance detection of athletes. *Evolutionary Intelligence, 16*(5), 1533-1538.

Kotseruba, I., & Tsotsos, J. K. (2020). 40 years of cognitive architectures: core cognitive abilities and practical applications. *Artificial Intelligence Review, 53*(1), 17-94.

Mujika, I. (2017). Quantification of training and competition loads in endurance sports: methods and applications. *International journal of sports physiology and performance, 12*(s2), S2-9-S2-17.

Ouyang, Y., Yu, M. Y., Cai, X., & Ye, H. (2024). The impactof workplace marginalization on organizational citizenship behavior of property management personnel in public health emergencies. *IECE Transactions on Social Statistics andComputing, 1*(1), 9–14.

Schuetz, S., & Venkatesh, V. (2020). The rise of human machines: How cognitive computing systems challenge assumptions of user-system interaction. *Journal of the Association for Information Systems, 21*(2), 460-482.

Wang, C.-H., Liang, W.-K., & Moreau, D. (2020). Differential modulation of brain signal variability during cognitive control in athletes with different domains of expertise. *Neuroscience, 425*, 267-279.

Wang, S., & Li, J. (2023). Facial expression recognition of aerobics athletes based on CNN and HOG dual channel feature fusion. *International Journal of Information and Communication Technology, 22*(3), 281-293.

Welhaf, M. S., & Kane, M. J. (2023). A combined experimental–correlational approach to the construct validity of performance-based and self-report-based measures of sustained attentio n. *Attention, Perception, & Psychophysics*, 1-37.