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ORIGINAL

EFFECTS OF PSYCHOLOGICAL STRESS AND ANXIETY ON PERFORMANCE AND COPING STRATEGIES IN ATHLETES

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ABSTRACT

Competitive sports are social sports activities with the main goal of winning competitions, which require athletes' physical and psychological abilities to be extremely high. Therefore, paying attention to the psychological health of outstanding athletes and improving their comprehensive quality are crucial to improving their sports performance. Traditional measures of psychological stress and anxiety mainly measure subjective stress feelings through stress perception scales, which ignores objective physiological indicators, while electroencephalogram (EEG), as an objective physiological data, has a strong correlation with different psycho-physiological conditions. Traditional feature extraction algorithms combined with machine learning require a large amount of a priori knowledge, while deep learning does not require a priori knowledge to deeply mine the deep features of the data. Therefore, this paper identifies and analyses psychological stress and anxiety in athletes based on deep learning by combining physiological data obtained from EEG signals and subjective data obtained from stress perception scales. Specifically, a stress EEG signal recognition model based on Transformer is proposed, the Transformer model in deep learning is explored, the encoder module in the Transformer model is applied to EEG signal analysis, and adaptive improvements are made and parameter optimization is carried out to be suitable for EEG signal analysis. Then experiments were carried out on two EEG signal public datasets, and the simulation experiment results proved the effectiveness of the proposed method.

KEYWORDS: Psychological Stress; Psychological Anxiety; Coping Strategies;

Neural network; Deep Learning

1. INTRODUCTION

Competitive sport refers to scientific and systematic training and competition to maximise individual and collective potential in terms of physical fitness, physical ability, psychology, intellect and athleticism, and to achieve outstanding athletic performance. Athletes' long and arduous training can only be recognised and rewarded if they excel in the arena. In the past, athletes were distinguished by their strong physique and sturdy muscles; today, with the rapid development of competitive sports, the difference in physiological functions of high-level athletes has become more and more minute, and the potential of athletic ability has been tapped to a certain limit (Du & Yuan, 2021; Won, Gopinath, & Hodgins, 2021). High-level athletes, coaches and sports researchers are all aware to different degrees that the key to victory or defeat in a match of equal strength depends on the psychological factors. An important factor affecting the performance of high-level athletes is the psychological factor (Chang et al., 2020a, 2020b). When a high-level athlete stands on the field of play, his physical qualities have already been determined, his technical movements have been automated, and his technical tactics have been programmed; only the psychological factor has the greatest variability and is the most unstable. From the analysis of international competitions, it can be found that among the high-level athletes who played badly in the competition, about 70% of them failed due to insufficient psychological preparation, and only about 20% of them failed due to insufficient technical and tactical preparation. It can be seen that good psychological quality is the most important thing for athletes to be able to play their techniques and tactics stably and fully and to win the competition (Akman, Arriola, Schroeder, & Ghosh, 2023; AMICK, 2021).

Theoretical and practical studies have shown that athletes (especially high-level athletes), as a special group of people, often face a variety of pressures in weekday training, athletic competitions, and daily life, such as sports injuries and diseases, competition targets, and media attention and so on. Long-term pressure will not only seriously affect the physical health of athletes, but also cause psychological burdens and disturbances to the athletes, resulting in the difficulty of normal performance of the competitive level (Ferioli, 2020; Solli, Sandbakk, Noordhof, Ihalainen, & Sandbakk, 2020). Throughout all kinds of sports competitions, there are examples of high-level athletes making mistakes in major competitions. Although the reasons are different, most of them are caused by excessive pressure. Therefore, how to correctly and effectively cope with various kinds of pressure is particularly important in today's high-level athletes with similar levels of competition. Numerous studies have shown that excellent athletic performance is inseparable from effective coping strategies, whereas ineffective and incorrect coping is detrimental to athletes' performance and satisfaction. Athletes who have good coping skills and experience in using them perform better when faced with pressure, training demands and intense competition. Thus, training athletes to respond correctly and effectively to various kinds of pressure, cultivating athletes with excellent psychological qualities, enabling athletes to overcome sports fatigue and devote themselves in hard training, and giving normal and extraordinary performance in major competitions are not only the goals pursued by every coach and athlete, but also an important direction of research for contemporary sports psychologists.

Stress is a state of tension in an individual's body and mind when they feel threatened. The earliest research on stress originated from European physiologists. On the basis of their research, physiologists in the early 20th century proposed a physiological theoretical model of stress, emphasising the individual's tension response and attempting to measure the individual's stress level by physiological indicators (such as cardiorespiratory indicators, blood pressure, respiratory status, etc.); after that, some researchers started from the physics of the stimulus-response model to study the stress of the external stimulus - the stressor, which promoted the development of stress research; by the 5th century, the development of stress research was promoted. external stimulus - stressor, promoting the development of stress research; to the fifties and sixties, the American psychologist from the psychological point of view of stress in-depth study, put forward the cognitive evaluation theory model. He believed that stress response is the result of individual cognitive evaluation of stressful situations or stressful events, especially emphasised the role of cognitive factors in stress response and focused on the influence of individual's subjective initiative on the stress process. Different groups have different social life environments, and thus have different stress characteristics. Existing research on psychological stress mainly focuses on the following special groups of people: research on the stress of teachers, research on the stress of students (junior high school students, senior high school students and college students mostly), research on the stress of nurses, research on the work stress of people in the workplace, research on the stress of patients with various chronic diseases and their families, and research on the stress of athletes, and so on. From the perspective of psychological stress, athletes belong to a high stress group. They face a lot of problems and challenges in their daily life, training and especially in competitions: loss of competitions, uproar from spectators, training injuries, performance indicators and so on. Especially for high-level athletes, the more intense the competition, the more comparable the strength of the opponents, the greater the psychological pressure generated, and even beyond the athlete's tolerance, triggering adverse consequences. In addition, if the individual is under a high level of stress for a long time, it will cause both physical and mental damage (Castaldelli-Maia et al., 2019).

Moderate pressure makes athletes highly concentrated, especially when the opponent's strength is not to be underestimated, resulting in a strong sense of collective belonging and enhancing group cohesion. However, when the pressure is too high, athletes will have anxiety, irritability, nervousness, irritability or low mood, which will interfere with the athletes' ability to think on the spot, reduce the speed of reaction and sensitivity of movement, and seriously affect the athletes' mental health and physical function. In addition, when athletes face overload pressure, their cognitive ability will be affected, resulting in decreased attention, narrower perceptual range, thus affecting intellectual function, and the adaptability of thinking will be reduced, thus affecting the performance of sports technology and tactical use. Moderate pressure allows athletes to follow the coach's arrangements and effectively restrain their own behaviour, which is conducive to enhancing team spirit and stimulating fighting spirit. However, when the pressure is too high, athletes in training and competition will experience slow footwork, reduced coordination of movement, reduced quality of movement, motor sensory disorders, increased errors, slow reaction and judgement, etc., and in life, they will experience symptoms such as rambling, insipid diet, sleep disorders, etc., which will lead to a reduction in the effect of training, and it is difficult to play the game to the normal level. From the above analysis, we can see that the relationship between athletes' psychological pressure and sports performance can be expressed by the inverted "U" curve. Too little pressure is difficult to wake up the attention of the athletes, and excessive pressure will make the athletes have adverse reactions, thus affecting the performance of the game, only moderate pressure is the most conducive to the performance of the athletic level (Endo, Sekiya, & Raima, 2023).

Although stress is an inevitable part of life, if it persists for a long time or exceeds an acceptable level, it can affect well-being and quality of life. Even during breaks during work, stress can prevent athletes from returning from a state of nervous system activation to a relaxed state. Therefore, we must pay attention to the psychological needs of modern residents, conduct timely stress assessments and provide corresponding psychological guidance to relieve stress before psychological stress causes serious physical and mental harm, and prevent psychological stress from having a negative impact on physical and mental health, which is good for athletes to maintain physical and mental health is of great significance. Scholars' research on psychological stress is also increasing year by year. It can be seen that stress issues are being paid attention to by more and more people. In the future, more people will pay attention to mental health issues and stress relief issues. Studying the identification and relief of stress is of great significance to promoting the physical and mental health development of athletes. In addition, this paper finds that traditional psychological stress and anxiety measures mainly measure subjective stress feelings through stress perception scales, which ignores objective physiological indicators, whereas electroencephalogram (EEG) (Babiloni et al., 2009; Del Percio et al., 2008), as an objective physiological data, is strongly associated with different psychophysiological conditions. Traditional feature extraction algorithms combined with machine learning require a large amount of a priori knowledge, while deep learning does not require a priori knowledge to deeply mine the deep features of the data. Therefore, the main contributions are as follows:

(1) In this paper, based on deep learning, physiological data obtained from EEG signals and subjective data obtained from stress perception scales are combined to identify and analyse psychological stress and anxiety in athletes.

(2) In this paper, a stress EEG signal recognition model based on Transformer is proposed, and the Transformer model in deep learning is explored, and the encoder module in the Transformer model is applied to EEG signal analysis, and adaptive improvements are made and parameter optimisations are carried out to apply to EEG signal analysis.

2. Methodology

This paper identifies and analyses athletes' psychological stress and anxiety based on deep learning combining physiological data obtained from EEG signals and subjective data obtained from stress perception scales, in order to explore the effects of athletes' psychological stress and anxiety on performance and coping strategies.

2.1 Mental health

With regard to the concept of mental health, the United Nations World Health Organization (WHO) defines mental health as "not only the absence of mental illness or abnormality, not only good social adaptation of the individual, but also the perfection of personality and the full development of mental potential, and also the optimal fulfilment of the individual's state of mind under a certain set of objective conditions". Specifically speaking, mental health has two meanings: one is normal psychological function, no mental illness, and the other is to be able to actively mediate their own psychological state, adapt to the environment, and effectively and constructively improve their personal lives and have a certain positive development of the state of mind. In summary, it can be found that most scholars believe and emphasise the internal coordination and external adaptation of the individual, and they all regard mental health as a state of good psychological functioning with internal and external coordination. We believe that mental health refers to the individual in the process of adapting to the environment, physiological and social aspects to achieve coherence, to maintain a good state of psychological functioning.

Stress theory suggests that stress is an internal psychological state of tension or arousal, an interpretive, emotional, and defensive coping process that occurs within the human body and is the adaptation and response of the individual when faced with, or perceived to perceive, or evaluated to be threatened or challenged by, a stressor of environmental change. It generally consists of three components, i.e., the stressor, the mediating variable, and the psychophysiological response. Stress theory suggests that the ability of stress to cause health damage is related to individual factors, the intensity of the stressor, social support and coping styles, and mental health can be calculated by the following equation:

$$S_i = \frac{M_i+B_i}{C_i+SC_i+SO_i} \qquad (1)$$

where S_i represents the state of mental health, M_i represents psychological stress, B_i represents physical and mental illness, C_i represents coping skills, SC_i represents self-confidence, and SO_i represents social support. According to stress theory (as shown in Figure 1), the main moderating variables of mental health are social support and coping styles. Social support refers to the material or moral support that an individual receives from others through social contacts. In stress theory, social support is often regarded as an important external resource. To date, many studies have demonstrated the link between social support and individual mental health. Whether from a holistic perspective, applying sociological and social epidemiological methods to the macro-analysis of the relationship between social support and individual mental health, or from an individual perspective, using clinical or experimental methods to the micro-study of the relationship between social support and a particular mental illness, have shown the beneficial effects of social support on individual mental health, social support has been widely recognised as a mental health function. Among them, the "buffer theory model" of social support holds that social support can buffer the negative effects of stressful events on physical and mental conditions under stressful conditions and maintain and improve the physical and mental health of individuals.

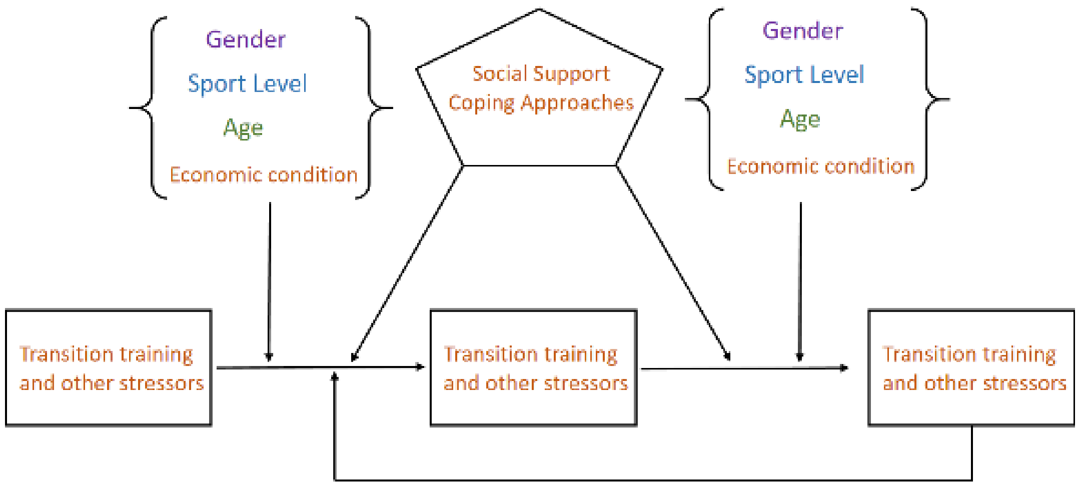

Figure 1: Schematic diagram of the mental health model

2.2 Overview of EEG signals

EEG is the most widely used non-invasive medical imaging technique, which records scalp electrical activity generated by brain structures with high temporal resolution and is capable of tracking changes in electrical activity within milliseconds, and has been widely used in neuroscience, cognitive science, cognitive psychology and psychophysiology research for understanding the mechanisms of brain activity, human cognitive processes, emotion detection, and diagnosis and treatment of brain disorders, such as epilepsy prediction , fatigue monitoring, sleep monitoring, attention deficit hyperactivity disorder detection and so on. The post-synaptic potential theory suggests that EEG signals are the sum of post-synaptic potentials during the synchronous activity of groups of neurons in the cerebral cortex and are some spontaneous rhythmic neuroelectric activity. The slow-wave activity of neurons in the brain originates in the cerebral cortex and is associated with the activity of parietal dendrites, and the generation of EEG signals in an individual is parallel to the morphology of parietal dendrites. Neural signals are transmitted as local currents to unexcited segments on the same cell, and as jumps in myelinated nerve fibres forward between different Langfeld's ganglia, as shown in the neuronal structure diagram in Figure 2.

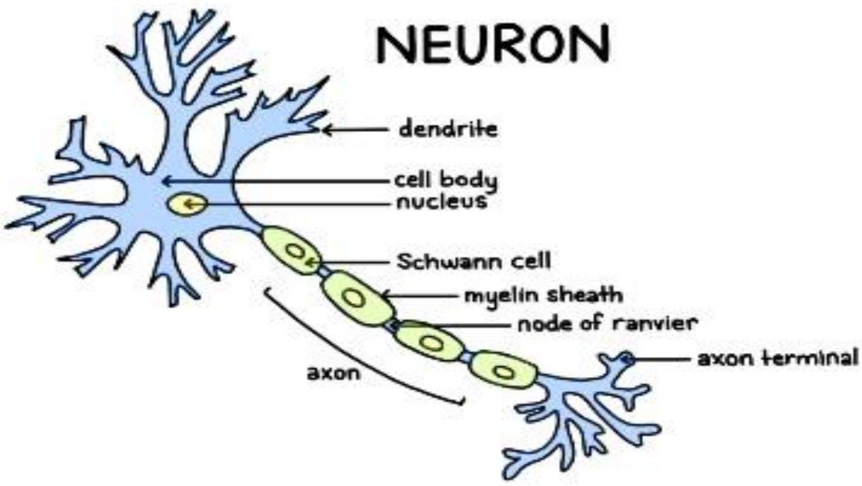

Figure 2: Schematic diagram of the structure of a neuron.

Nerve signals are transmitted between cells via synapses. When a nerve impulse reaches the presynaptic membrane, the presynaptic membrane releases a chemical transmitter that travels through the synaptic gap and eventually acts on special receptors on the postsynaptic membrane. The postsynaptic membrane opens certain ion channels, causing a change in the membrane potential and generating a postsynaptic potential. EEG reflects the electrophysiological activity of brain nerve cells in the cerebral cortex and contains a large amount of physiological information. Noise located between the signal generating source and the sensor can interfere with the EEG signals generated by the brain, and therefore, EEG signal channels tend to be highly spatially correlated. EEG signals can directly reflect the state and changes of the brain's nervous system, and then reflect the physiological and psychological state of the human body. EEG signals are characterized by time sensitivity and spatial ambiguity, high inter-subject specificity, and poor anti-interference. Low signal-to-noise ratio, nonlinearity and non-stationarity, etc. EEG signals are very weak in amplitude, typically ranging from 0.5 to 100 μV. The frequency range of the EEG signal is 0.5 - 50Hz. It is divided into the following four bands according to frequency. The schematic diagram and characteristics of the four bands are shown in Table 1 and Figure 3.

Table 1: Four bands and characteristics of EEG signals.

BAND	HZ	MV	MENTAL STATE
β	>13	5-20	CORTICAL EXCITEMENT
A	8-13	20-100	WAKE UP, RELAX
θ	4-8	100-150	SLEEP, EMOTIONAL STRESS
δ	0.5-4	20-200	DEEP SLEEPING

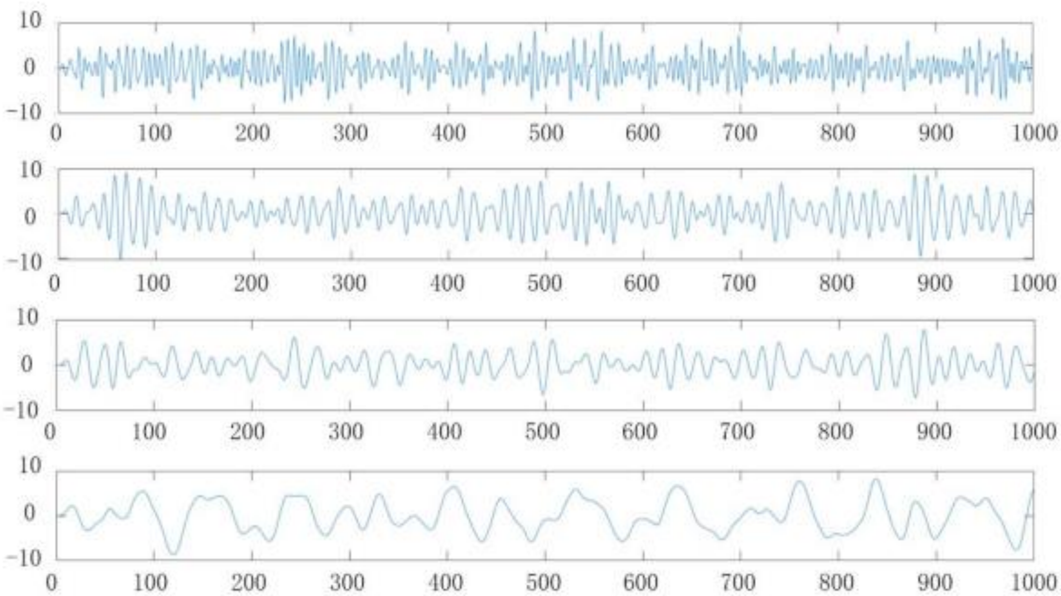

Figure 3: Schematic diagram of the four bands of EEG signals.

Symptoms of stress are rapid heartbeat, excessive sweating, indigestion, poor sleep and endocrine disorders. This method of stress assessment requires trained personnel to perform the assessment. In addition, various physiological signal measurements such as heart rate variability analysis, blood pressure, electromyography and electrocardiography can be used to analyse the state of stress in order to differentiate between the characteristics of a stressed state and those of a normal state. However, these physiological indicators are not easily detected, and with the development of EEG technology, portable EEG monitoring devices will be more widely used in areas such as stress detection.

Since the brain is the central part of stress generation, recording brain activity through EEG is considered to be one of the most reliable tools for stress detection and analysis. The spectral features are strongly correlated with different psycho-physiological conditions, so the power of different EEG signal bands is considered to be one of the most reliable indicators for analysis, and EEG power spectral features are correlated with stress levels, and power spectroscopy is a commonly used method in stress analysis. Studies have shown that α and β waves are markers of stress level identification, and stress is positively correlated with β -band power and negatively correlated with α -band power. FAA index is a measure of stress, and its calculation equation is as follows:

$$FAA = ln(\alpha_{right}) - ln(\alpha_{left}) \quad (2)$$

2.3 Transformer-based Psychological Stress and Anxiety Recognition

2.3.1 Transformer

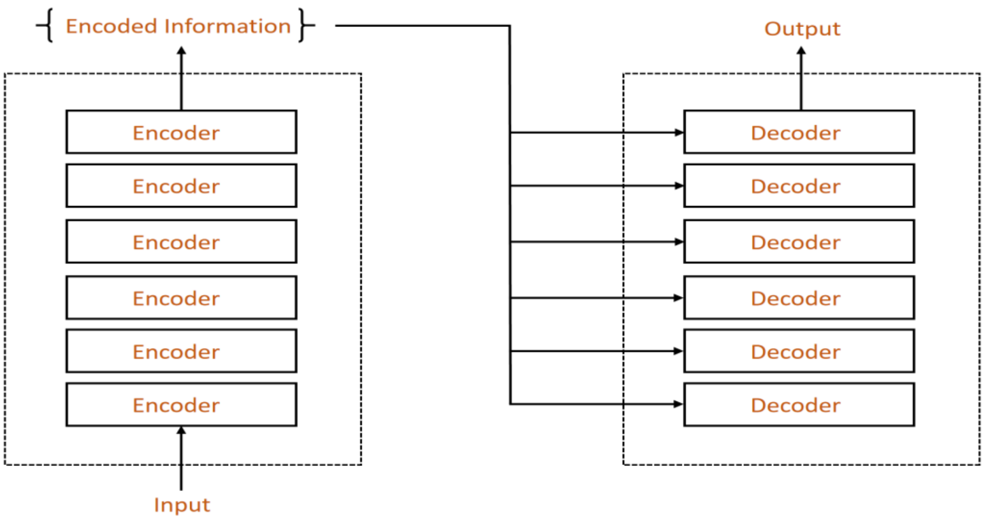

Figure 4: Schematic diagram of the structure of a neuron.

The Transformer model uses a self-attention mechanism that weights the importance of each part of the input data according to different weights, compressing all the necessary information into a single vector to generate an efficient representation. Unlike recurrent neural networks, Transformer processes the entire input at once and uses a multi-head attention mechanism to compute the relationships between positions in the sequence in parallel, thus requiring less training time, high parallelism, and high model efficiency. The model is a simple and extensible framework that is widely used in the field of natural language processing. For example, it is used in machine translation to achieve the translation of input text from one language to another; in text generation to generate text according to given rules; in text classification to classify text into different categories; and in sound recognition to recognise words and utterances in speech. In addition, it has also achieved great success in computer vision, such as image classification, target detection, etc. The Transformer model has been widely used in several fields due to its excellent ability to handle long sequences and is becoming a more general framework for learning sequential data, and the Transformer model framework is shown in Figure 4.

The Transformer model (Lee & Lee, 2022) uses an encoder-decoder architecture. The encoder is used to encode the input data, which maps the input data into a fixed size coding space, generating an efficient representation of the sequence that allows the computer to recognise something objectively present in the human world in a more rational way for further subsequent processing. The purpose of the encoder is to capture important information about the data and simplify the representation of the data to improve the efficiency of the model. Since the encoder side is computed in parallel, the time for training is greatly reduced. The decoder receives the output of the encoder and generates the final output.

2.3.2 Model Structure

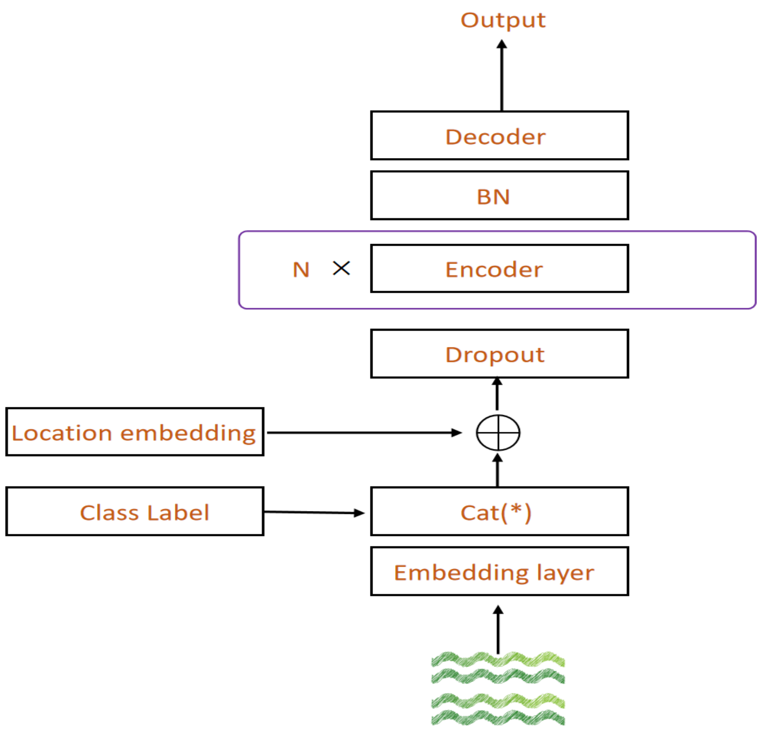

Figure 5: Transformer-based psychological stress and anxiety identification model structure

Cognitive behaviour in the human brain does not occur in an instantaneous response. The stress state occurs over a period of time, rather than a transient response, and there may be a connection between impulses that occur over a short period of time. EEG signals can be better analysed if the model takes the past into account. Convolutional neural networks (Huang, Zhang, Liu, & Li, 2023), which are local networks determined by the size of the kernel and the respective step size, are difficult to model long sequences, require complex connectivity operations if the sampling points are far apart and the convolution operation destroys the spatial properties of the EEG signal. Long and short-term memory networks may also be unable to account for such long-term dependencies due to forgetting factors. However, the self-attention mechanism used in Transformer is one that freely selects contextual information as a reference. The key to the self-attentive mechanism is to establish dependencies that are not constrained by long distances in the sequence, and all data can be seen at the same time. On the other hand, the mixed multiplication and addition operations of convolution disrupt the spatial nature of the EEG signal. It has been shown that it may be more beneficial to use multiple heads of attention in spatial coordinates to encompass representational similarity between regions. The Transformer model applies the self-attention mechanism exclusively to map global dependencies between inputs and outputs, avoids recursion, and relates different locations of a sequence to compute a representation of that sequence, essentially a metric similarity mechanism. Therefore, this chapter proposes a Transformer-based stress EEG signal recognition model for EEG signal analysis, which is entirely based on the self-attention mechanism, abandoning recursion and convolution. The model architecture is shown in Fig. 5. The model follows the overall architecture of an embedding layer, a random inactivation layer, an encoder, a normalisation layer and a linear layer, where the encoder consists of N modules of the same structure.

First, the EEG signal is input into the embedding layer to obtain the embedding and generate class labels for classification. This model does not use recursion and convolution, and completely uses the self-attention mechanism. Therefore, this model does not have the ability to learn sequence information like a recurrent neural network. In order to make full use of the sequence and spatial structure of EEG signals, it is necessary to actively provide sequence information to the model to help the model learn position information. Therefore, this model injects position information into the EEG signal, that is, adds position embedding. Position embedding and embedding have the same dimension $d_{mod\,el}$, so they can be added together. This article uses Gaussian embedding, which is defined as:

$$\psi(t,x) = \exp\left(-\frac{\|t-x\|^2}{2\sigma^2}\right) \quad (3)$$

There are N encoders with the same structure in the stress EEG signal recognition model based on Transformer. Each encoder contains two sub-layers, which can be expressed by the equation:

$$x + Sublayer(x) \quad (4)$$

The normalization layer of the encoder is to prevent overfitting, ensure the stability of the data feature distribution, and accelerate the convergence of the model. Its calculation equation is as follows:

$$y = \frac{x - E[x]}{\sqrt{Var[x] + \varepsilon}} * \gamma + \beta \quad (5)$$

3. Experiment and Results

3.1 Datasets

(1) OpenNeuro: OpenNeuro is a free and open-source neuroimaging database sharing platform created by Poldrack and his team, providing a large number of MRI, MEG, EEG, iEEG, ECoG, ASL and PET data sets available for sharing. As of now (May 2021) Month), there are already 540 publicly available data sets on OpenNeuro, and a total of 18,108 scientific researchers have joined the database contribution work on this platform.

(2) MODMA: The EEG dataset includes not only data collected using the traditional 128 electrode-mounted elastic cap, but also the new wearable 3-electrode EEG collector for universal applications. Speech data were recorded during interviews, readings and picture descriptions. Detailed descriptions of each sub-dataset are listed accordingly in the download section. In the future, more data will be added on a regular basis to cover not only more psychiatric disorders, such as schizophrenia, anxiety disorders, and bipolar disorder, but also more mental illnesses. There are additional data types such as eye tracking, facial expression recordings and MRIs. We encourage other researchers in the field to use it to test their own methods of analysing mental disorders.

3.2 Experimental setup

To identify and alleviate stress, this article designed a stress induction experiment. This article chooses Neuroscan electroencephalograph and Greentech's EEG cap for non-invasive EEG signal collection, uses a mental arithmetic task as a psychological stress source, and uses a stress perception scale based on the State-Trait Anxiety Scale to obtain subjective pressure data. The collection methods of EEG signals are divided into invasive and non-invasive collection. Invasive EEG signal collection involves implanting sensors into the brain through surgery. The collected EEG signals are highly accurate and have low noise. Non-invasive EEG signal collection collects EEG signals by placing electrodes on the brain scalp, which is highly safe. Therefore, a non-invasive EEG signal collection method was used in this experiment. Non-invasive EEG collection equipment generally collects EEG signals from the brain scalp through electrode patches on the EEG cap. Since the EEG signal is relatively weak, it is necessary to increase the amplitude of the EEG signal through an amplifier, filter part of the noise through filtering, and finally convert the data from analog signals to digital signals, display and store them on a computer or other terminal. This article uses a Neuroscan 64-lead electroencephalograph to record EEG signals and collects EEG signals through the Scan 4.5 software platform with a sampling rate of 512 Hz and an EEG cap from Greentech, as shown in Figure 6.

Figure 6: Schematic diagram of experimental setup.

3.3 Experimental results and analysis

The experimental results are shown in Table 2. In the experimental dataset, dichotomous classification of EEG signals with and without stress, i.e., Task I and Task II, using the Transformer-based Stress EEG Signal Recognition Model, achieved an accuracy of 93.78%. In one group, i.e., task two and task three, 64.38% accuracy was obtained in dichotomising EEG signals; in the second group, i.e., task two and task four, 67.62% accuracy was obtained in dichotomising EEG signals.

Table 2: Classification accuracy of Transformer-based stress EEG signal recognition model.

METHOD	OPENNEURO			MODMA	
	TASKS 1 & 2	TASKS 3 & 4	TASKS 2 & 4	B	G
RNN	0.8698	0.5205	0.6123	0.8125	0.7562
OURS(TRANSFORMER)	0.9378	0.6438	0.6762	0.8436	0.7887

In addition to the experimental data, in order to demonstrate the validity of the model on other datasets, it was tested on the public dataset of EEG signals during the mental arithmetic task, which contains EEG signals before and during the execution of the mental arithmetic task by the subjects. Each sample in this public dataset consisted of 180 seconds of EEG signal data during the resting state task and 60 seconds of EEG signal data during the completion of the mental arithmetic task, which was a 4-minute continuous subtraction operation. The sample size of this dataset is 36 subjects, divided into Groups B and G. The sample size of this dataset is 36 subjects. On this public dataset, the Transformer-based stress EEG signal recognition model binary classified the EEG signals before and during the mental arithmetic task, and obtained 84.36% accuracy on the EEG signals of group "B", 84.36% accuracy on the EEG signals of group "G", and 84.36% accuracy on the EEG signals of group "B". An accuracy of 84.36 per cent was obtained for group "B" and 78.87 per cent for group "G" EEG data.

In addition, Table 3 shows that the detection rate of psychological problems of excellent athletes is relatively high, in which the detection rate of 60<T<70 (considered to have mild psychological problems) reached 21% for the excitement and depression factors, 19% and 16% for the somatisation and pathological personality factors respectively, and the detection rate of the other three factors also reached 14%. The detection rate of T>70 (considered to have serious psychological problems) in the somatisation and excitation state factor reached 8% and 7%, respectively, in addition to the detachment from reality factor is 0, the other factors of the lowest 3%, which suggests that athletes' psychological stress and anxiety on the performance of the performance of the impact is large, through the method of this paper can be identified in advance, as well as timely intervention and treatment.

Table 3: Detection rates of factors of mental health in show athletes

	SOMATIZATION	DEPRESSION	ANXIETY	PATHOLOGICAL PERSONALITY	SUSPICION	OUT OF TOUCH WITH REALITY	EXCITED STATE
60 < T <70	19	21	14	16	14	14	21
T > 70	8	3	3	5	4	0	7

4. Conclusion

In this article, we consider that traditional psychological stress and anxiety measurement methods mainly measure subjective stress feelings through the stress perception scale, which ignores objective physiological indicators, and electroencephalography (EEG), as an objective physiological data, is closely related to There are strong correlations between different psycho-physiological conditions. The traditional feature extraction algorithm combined with machine learning requires a large amount of prior knowledge, while deep learning can deeply mine the deep features of the data without prior knowledge. Therefore, this article uses deep learning to combine the physiological data obtained from EEG signals and the subjective data obtained from the stress perception scale to identify and analyze athletes' psychological stress and anxiety. Specifically, a Transformer-based stress EEG signal recognition model was proposed, the Transformer model in deep learning was explored, the encoder module in the Transformer model was applied to EEG signal analysis, and adaptive improvements were made, the parameters were optimized to be suitable for EEG signal analysis. Experiments were then conducted on two public EEG signal data sets, and the simulation experimental results demonstrated the effectiveness of the proposed method.

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