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Classification of Mental Stress on a Sports Person Using EEG

A Abhishek[1], Dr. G Nallavan[2]
Department of Sports Technology, Tamilnadu Physical Education and Sports University (TNPESU), Melakkottaiyur, Chennai- 600127, India.

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Abstract: *The biological response to stress originates in the brain but involves different biochemical and physiological effects. Many common clinical methods to assess stress are based on the presence of specific hormones and on features extracted from different signals, including electrocardiogram, blood pressure, skin temperature, or galvanic skin response. The aim of this work is to assess stress using EEG based variables obtained on 4 sportsmen during their activity. In this work, deep neural networks are used to identify stress in a sportsman by analyzing electro-encephalography (EEG) signals. The performance of the proposed method is evaluated using the Database for Emotion Analysis using Physiological Signals (DEAP). A feature set is extracted in 32 EEG channels, which consists of statistical features, Hjorth parameters, band power, and frontal alpha asymmetry. To further consolidate, the effectiveness of the proposed method is compared with that of a state-of-the-art principle method. MATLAB tool has been used to evaluate existing and proposed system performance*

Key Word: *EEG Analysis, MATLAB, Stress Classification, Electro-Encephalography, DEAP*

I. INTRODUCTION

Given the competitive nature of professional sports, it is well understood that athletes are continuously in need of innovative technologies and modalities to gain an edge to optimize their performance and health. There has been a large and growing shift in the athletic community towards the use of wearable devices as a means to monitor training progress and recovery. This is evidenced by an ever-growing sports performance technology market which offers smart watches, bands, garments, and patches with inbuilt sensors. Despite this, there are limited peer reviewed validation studies for wearable in spite of their increased incorporation in sports as a means of monitoring athletes' workload. With the advent of miniaturized sensors, integrated computing, and artificial intelligence, it is expected that the emerging data-driven health and performance technologies will be of increased relevance in the field of sports performance. Given the well-established link between sleep and athletic performance, as well as sleep and traumatic brain injury (TBI), many sports practitioners turn to brain imaging and neurophysiologic measures in the hopes of improving the recovery capacity and sports performance of their athletes. Under normal physiological conditions, exercise is thought to have a positive impact on sleep. However, high training load or injury may jeopardize sleep, and consequently impair recovery. It has been noted that heavy competition schedules, stress, brain injury, commute, academic demands, circadian misalignment, and overtraining have been all identified as potential obstacles to obtaining proper sleep. Furthermore, previous studies have demonstrated that athletes are particularly susceptible to sleep loss around competition time, further highlighting the need for a reliable way of monitoring sleep in this demographic (O'Donnell et al., 2018; Walsh et al., 2021; Watson, 2017)

II. EEG PROCESSING FOR STRESS DETECTION

Electroencephalography is one of the easiest, cheapest and most widely used ways for recording the electrical activity in the brain. Since its discovery, there is a high interest in associating the recorded signals of the brain with the cognitive processes or the physical/psychological condition of the person at the time of recording. A usual way of studying the relation between a person's cognitive processes and the recorded, electroencephalographic (EEG) signals is through "oddball" experiments. During an oddball experiment a person monitors a screen, where various stimuli are presented, and has to respond by pressing a button upon the presentation of a specific type of stimulus. In this thesis we propose ways of using a person's EEG signals in order to "predict" their performance in such an experiment.

III. THE ELECTROENCEPHALOGRAM

Electroencephalography is the first and most popular way of non-invasively observing the activity of the human brain. EEG is recording of electrical signals naturally produced by one's brain, by using electrodes placed on the subject's scalp. The recorded electrical potentials are produced by extracellular synaptic trans-membrane currents in neuronal dendrites 9 The standard system for placing the electrodes on the scalp is the 10-20 system. According to it, the anion, inions, left and right pre-auricular points are used as reference points.

IV. EG FREQUENCY BANDS

As any waveform, the EEG recorded in each channel can be analyzed in terms of its frequency components. It has been found that the energy of the EEG in the frequency domain is concentrated in specific bands depending on the mental state and the cognitive processes that the subject undergoes. This is because of the synchronous depolarization of cells of neurons, involved in the aforesaid mental state or cognitive processes, which results in the generation of rhythmical electric activities. The above frequency bands are named natural rhythms in the brain and their relation with various cognitive processes is summarized briefly as follows Delta (0.5-3.5 Hz): It is related to signal detection and decision making processes. • Theta (4-7 Hz): It is highly correlated with associative processing. It is present in oddball experiments 300 msec after the target of interest is shown and contributes to the formulation of the P300 component. • Alpha (8-13 Hz): It is associated with memory related processes. In oddball experiments the energy of the alpha rhythm before the stimulus onset strongly affects the N100 and P200 components. 10 • Beta (13-40 Hz): It is related to a wide range of mental activities such as integrated thinking, computing mathematical problems, planning and high level processing of information.

V. DIGITAL SIGNAL PROCESSING

DSP manipulates different types of signals with the intention of filtering, measuring, or compressing and producing analog signals. Analog signals differ by taking information and translating it into electric pulses of varying amplitude, whereas digital signal information is translated into binary format where each bit of data is represented by two distinguishable amplitudes. Another noticeable difference is that analog signals can be represented as sine waves and digital signals are represented as square waves. DSP can be found in almost any field, whether it's oil processing, sound reproduction, radar and sonar, medical image processing, or telecommunications, essentially any application in which signals are being compressed and reproduced.

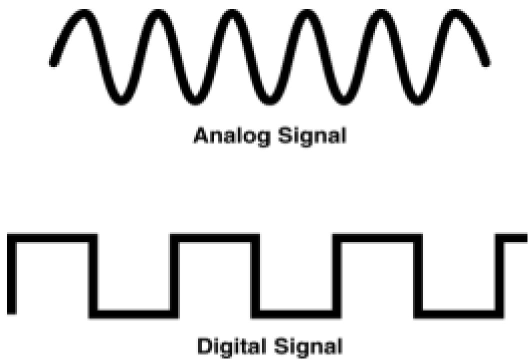

Fig.1 Types of Signals

Below is a figure of what the four components of a DSP look like in a general system configuration.

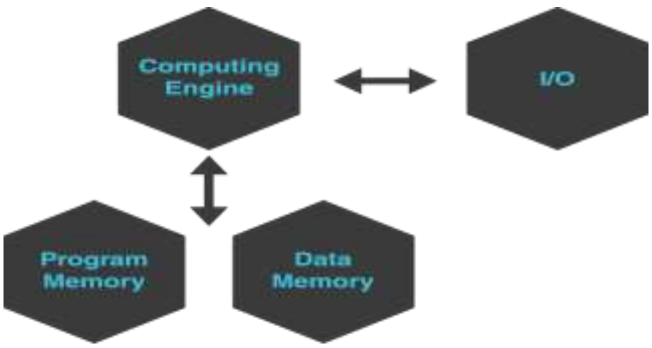

Fig.2 General System

VI. VARIOUS CLASSIFICATION TECHNIQUES

SVM, KNN, and CT are the widely used classification algorithms in the majority of the EEG related studies. In the present study, we evaluated the performance of these classifiers (SVM, KNN, and CT) plus the Artificial Neural Network (ANN) classifier in the depression detection process. All classifications and 10-fold cross validations have been implemented using the MATLAB software (version R2014a).

VII. PROPOSED SYSTEM

The world of competitive sport is exciting, intense and increasingly fast-paced. Athletes and coaches alike often find themselves working overtime to identify ways to sharpen individual skills, maximize team talent, and develop mental toughness, all to stay one step ahead of the competition and achieve performance excellence. In truth, working hard and striving to be the best are hallmark goals of many competitors. However, if not properly balanced with necessary rest and down time, this quest to “be the best” can result in athletes and coaches experiencing increased feelings of pressure or stress that instead of propelling them toward their goal, can in fact be detrimental to performance. Knowing the signs and symptoms as well as effective stress management strategies can help people better manage their own stress. This can help coaches in providing more assistance and support to their athletes and staff to create an overall healthier sport environment.

VIII. CNN ARCHITECTURE

CNN model is employed with the number of neurons in each layer, filter size, and stride summarized in Table 2. A convolution operation is performed in the input layer with a filter size of 5 (stride 1) to obtain the 1st layer (output neurons of 1996 x 5). Then a max-pooling operation is performed in the first layer to reduce the number of neurons to 998 x 5 in layer 2. After which, 27 another round of convolution is performed to form the next layer (layer 3). The max-pooling operation is once again applied after the convolution to obtain layer 4 with 497 x 5 neurons. Similarly, 3 more convolution and max pooling operations are performed alternately to produce layers 5, 6, 7, 8, 9, and 10. Layer 10 is connected to 80 neurons in the first fully-connected layer, layer 11, which is in turn connected to 40 full-connected neurons in layer 12. Lastly, layer 12 is connected to the final layer with 2 output neurons that represent normal and depressed.

The authors can acknowledge any person/authorities in this section. This is not mandatory.

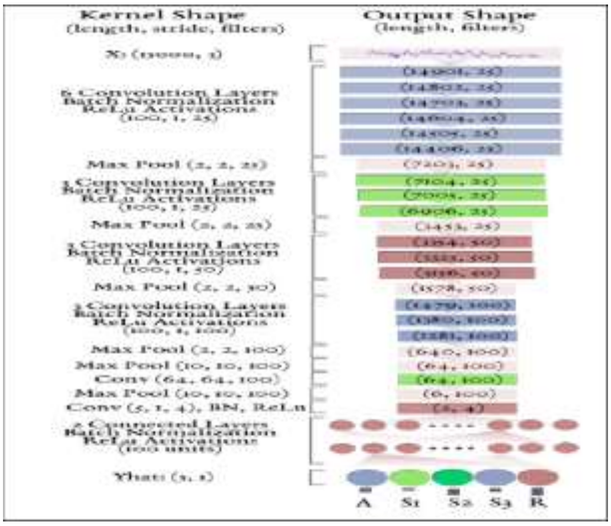

Fig.3 CNN Architecture

IX. SYSTEM IMPLEMENTATION

Investigation of the current system and its constraints on implementation, design of methods to achieve the changeover, and evaluation of change over methods.

1 Testing the developed software with sample data.
2 Debugging of any errors if identified.
3 Creating the files of the system with actual data.
4 Making necessary changes to the system to find out errors.
5 Training of our personnel.

Apart from planning, major tasks of preparing the implementation are education and training of users. The more complex system being implemented, the more involved will be the system 30 analysis and the design effort required just for implementation. An implementation coordinating committee based on policies of individual organizations has been appointed. The implementation process begins with preparing the plan for the implementation for the system. According to this plan, the activities are to be carried out, discussion made regarding the equipment and resources and the additional equipment as to be acquired to implement the new system. The implementation is the final and important phase. The most critical stage in achieving a successful new system and in giving the user confidence that the new system will work and be effective. The system can be implemented only after thorough testing is done and if it is found to work according to the specification.

X.RESULTS AND DISCUSSION

The proposed network was trained and tested to detect depression. It required approximately 6 minutes 12 seconds to finish 5000 epochs of training the EEG data. Then, an overall performance is computed by averaging the results from all 5000 iterations. Power spectral density (PSD) is computed from the preprocessed time-domain EEG signal in order to know the functional characteristics of the signal using a fast Fourier transform (FFT). In equation 1, the factor '2' is multiplied for the purpose of the removal of negative energies. Here we do not consider this part of power spectral density. The computed PSD is divided into Delta (0-3.9)Hz, Beta (4-7.9)Hz, Alpha I (8-9.9)Hz, Alpha II (10-13.9)Hz, Beta I (14-21.9)Hz, Beta II (22- 29.9)Hz and Gamma I (30-46.9)Hz, Gamma II (47-65)Hz bands

$$PSD(f) = 2 \times \frac{|FFT(X(n))|^2}{F_S \times N}$$

The features of theta (4-7Hz) and beta (12-30Hz) waves can calculate the stress. The theta can record the difficult task of the brain [3, 4] and beta can notice the body movements such as limp and hind limbs of Hand and Leg [5, 6]the sad emotion is considered as the stress state of human beings.

The power spectral density of all features above and below the threshold is used to calculate the state conditions.

The power in delta band	$P_\Delta = \sum_{f=0}^{3.9} PSD(f)$
The power in Theta band	$P_\Theta = \sum_{f=4}^{7.9} PSD(f)$
The power in Alpha I band	$P_{\alpha 1} = \sum_{f=8}^{9.9} PSD(f)$
The power in Alpha II band	$P_{\alpha 2} = \sum_{f=10}^{13.9} PSD(f)$
The power in Beta I band	$P_{\beta 1} = \sum_{f=14}^{21.9} PSD(f)$
The power in Beta II band	$P_{\beta 2} = \sum_{f=22}^{29.9} PSD(f)$
The power in Gamma I band	$P_{\gamma 1} = \sum_{f=30}^{46.9} PSD(f)$
The power in Gamma II band	$P_{\gamma 2} = \sum_{f=47}^{65} PSD(f)$

PERSON - 1

Fig 4.1 shows the representation of the ALPHA band after the feature extraction process.

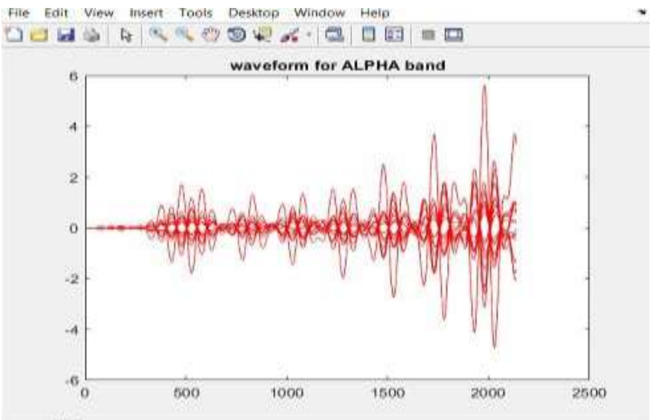

Fig 4.1 Representation of ALPHA band for person 1

Fig 4.2 shows the representation of BETA band after feature extraction process

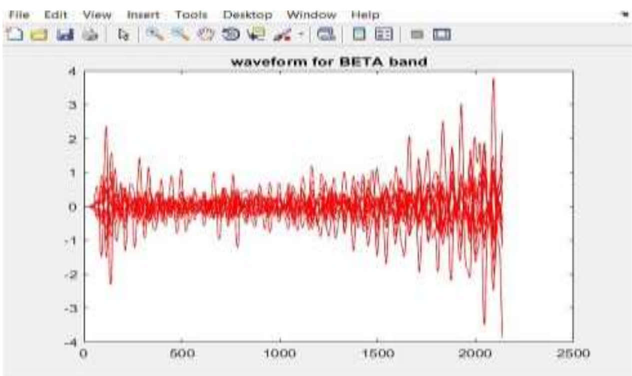

Fig.4.2 Representation of BETA band Person I

Fig 4.3 shows the representation of THETA band after the feature extraction process.

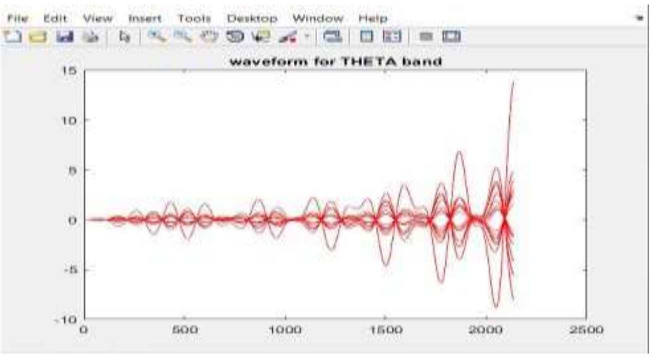

Fig.4.3 Representation of THETA band

Fig 4.4 shows the representation of the DELTA band after the feature extraction process.

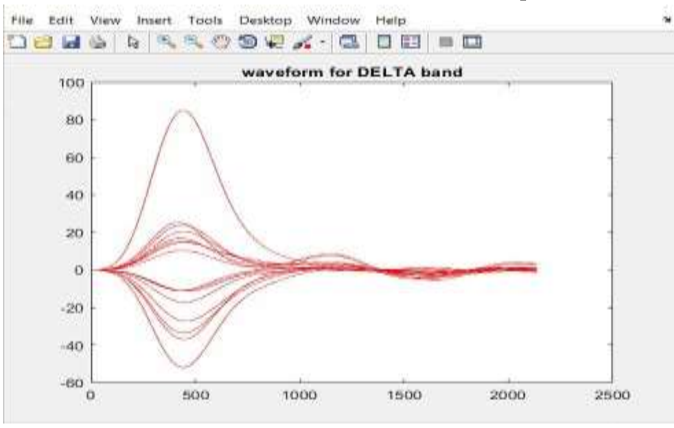

Fig.4.4 Representation of DELTA band

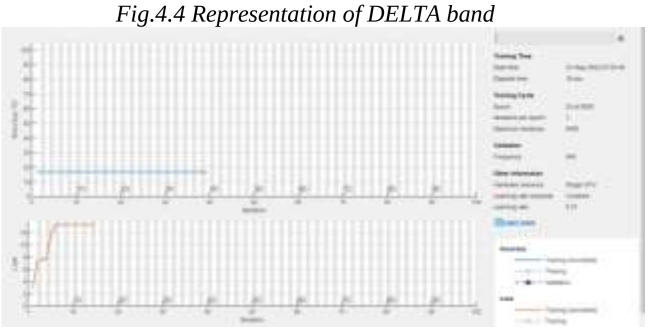

Fig.4.5 Training Process

Fig 4.5 represents the training process of proposed convolution neural networks. After completing the training process, the network is tested and validated using the test dataset.

Fig.4.6 Trained Output

Fig 4.6 shows the mental status (Normal/Depressed) of a test input data which is shown by the dialog box format. Here, the subject is depressed.

PERSON -II

Fig 4.7 shows the representation of the ALPHA band after the feature extraction process.

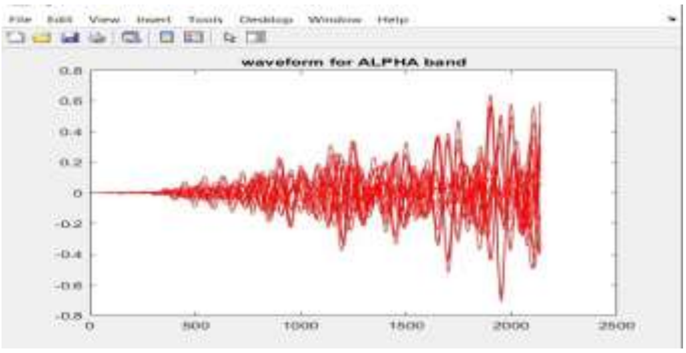

Fig.4.7 Representation of ALPHA band for person 2

Fig 4.8 shows the representation of the BETA band after the feature extraction process.

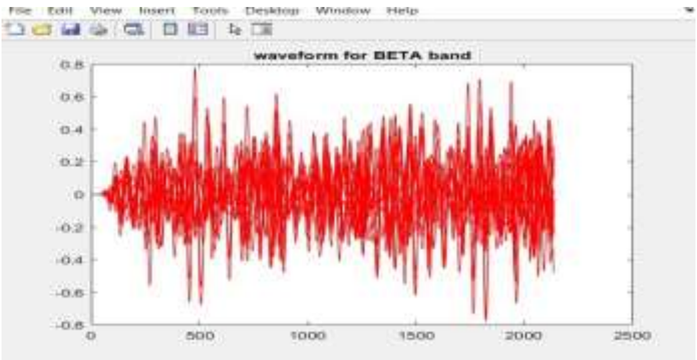

Fig.4.8 Representation of BETA band for person 2

Fig 4.9 shows the representation of THETA band after the feature extraction process

Fig.4.9 Representation of THETA band for person 2

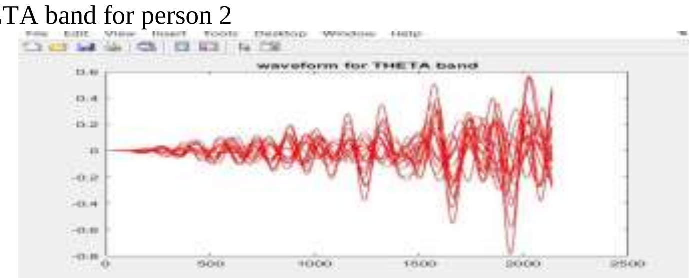

Fig 4.10 shows the represent ation of the DELTA band after the feature extraction process.

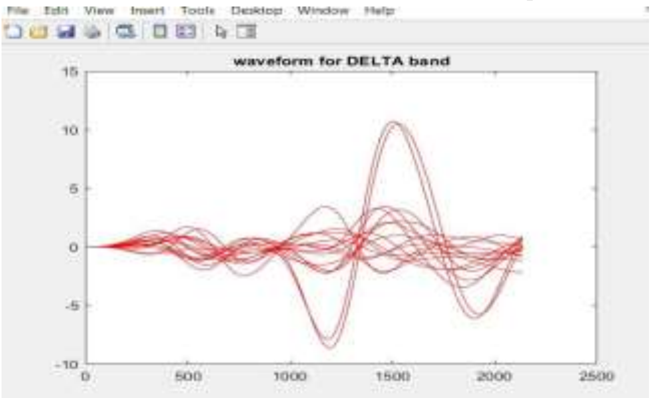

Fig.4.10 Representation of DELTA band for person 2

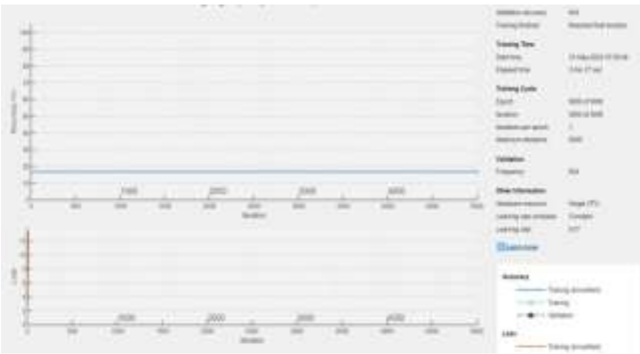

Fig.4.11 Training Process

Fig 4.11 represents the training process of proposed convolution neural networks. After completing the training process, the network is tested and validated using the test dataset.

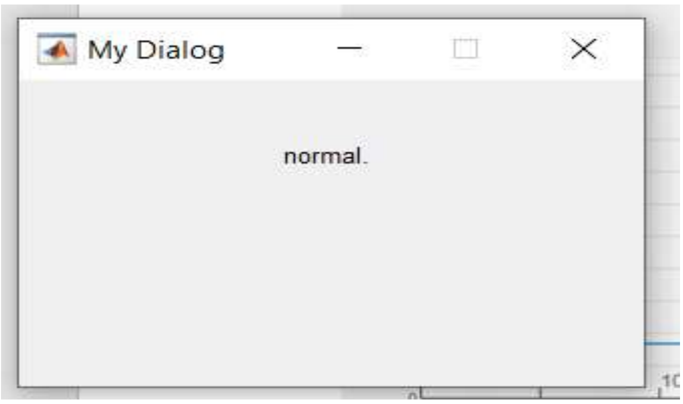

Fig.4.12 Trained Output

Fig 4.12 shows the mental status (Normal/Depressed) of a test input data which is shown by the dialog box format. Here, the subject is depressed.

From above the method the other players are absorbed.

CLASSIFICATION	ACCURACY (%)	SENSITIVITY (%)	SPECIFICITY (%)
SVM	0.8216±0.0429	0.7711±0.0354	0.8721±0.0518
KNN	0.8565±0.0601	0.8218±0.0410	0.8912±0.0516
CNN	0.9211±0.0323	0.8996±0.0101	0.93±0.0966

Table 1 Overall Performance Values

Table 1 shows the performance (accuracy, sensitivity, specificity) obtained by the proposed network. It represents the variations of performance over the existing and proposed work.

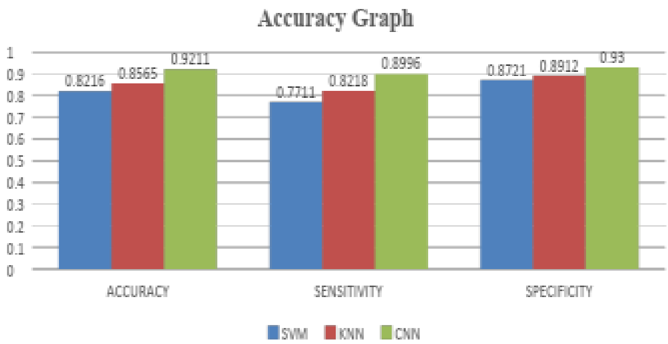

Fig. 5 Accuracy Graph

Fig. 5 shows the data in those tables and the variations of performance analysis over the existing and proposed algorithms.

XI. CONCLUSION

Diagnosis of stress is important for a sportsman lifestyle. Since EEG is a non-invasive, simple, relatively inexpensive, and potentially mobile brain imaging technology with high temporal resolution, it seems to be a natural candidate as a diagnostic tool for mental state detection. Numerous studies indeed confirm the great potential of EEG for diagnosing stress detection .In this work, we have proposed a novel Deep learning method for stress state identification with EEG signal. To improve model interpretability and identification accuracy, FFT based preprocessing and accurate features of alpha, beta, theta and delta are extracted. These findings suggest that our approach provides new ideas for automatically identifying neurological diseases from the perspective of functional networks using MATLAB.

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