https://doi.org/10.33472/AFJBS.6.6.2024.6909-6922

African Journal of Biological Sciences

Journal homepage: http://www.afjbs.com

Research Paper Open Access

Towards Non-Invasive PTSD Diagnosis: Utilising EEG Based Emotion Recognition with the DEAP Database

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Article Info

Volume 6, Issue 6, June 2024

Received: 10 May 2024

Accepted: 17 June 2024

Published: 08 July 2024

doi: 10.33472/AFJBS.6.6.2024.6909-6922

ABSTRACT:

Post-Traumatic Stress Disorder (PTSD) poses a significant challenge in mental health diagnosis, necessitating innovative and non-invasive approaches. This paper explores the efficacy of emotion recognition through electroencephalography (EEG) as a potential diagnostic tool for PTSD. Leveraging the rich resource of the DEAP EEG database, this study focuses on employing statistical features, namely mean, standard deviation, kurtosis, and Hjorth parameters, to ascertain emotional states associated with PTSD. This work outlines the pressing need for effective and non-invasive PTSD diagnosis methods, emphasizing the potential of emotion recognition as a groundbreaking approach. EEG, with its ability to capture neural activity in real-time, emerges as a promising biomarker for decoding emotional responses associated with PTSD. The paper employs a 1D Convolutional Neural Network (1D CNN) as the classifier algorithm, demonstrating its efficacy in discriminating between valence, arousal, and liking associated with PTSD-related emotional responses. Results indicate a remarkable classification accuracy of 97.18%, highlighting the potential of the proposed approach for PTSD diagnosis. This research contributes a non-invasive diagnostic method, bridging the gap between neuroscience, emotion recognition, and mental health, ultimately paving the way for more effective and accessible PTSD assessment tools.

Keywords: 1D CNN, EEG, PTSD, Statistical Features.

1. Introduction

A person who has experienced a traumatic event may develop Post-Traumatic Stress Disorder (PTSD), a mental health disorder. A natural disaster, an accident, a battle, or an attack are examples of this kind of event. Some symptoms of post-traumatic stress disorder (PTSD) include reliving the event in their mind, avoiding situations that bring up memories of it, feeling afraid or depressed, and being easily agitated. Depending on factors including the length of time the traumatic event lasted and if they had support, each person may experience PTSD to varying degrees. Having healthy relationships and working might be difficult for some persons with PTSD. Physicians employ various techniques to diagnose PTSD. In order to find out what transpired and how the person feels, they may speak with them. To aid in the diagnosis of PTSD, tests exist that pose questions regarding symptoms. In order to gain further insight into PTSD, physicians may occasionally use devices to observe brain activity.

This research paper is structured according to the following format, with Section 1 providing an overview of the topic and laying the groundwork for the rest of the paper. A thorough review of the literature is the focus of Section 2, which arranges the research carried out into a coherent whole to set the proposed work in context. In the following Section 3, the conceptual framework in addition to explaining the theoretical foundations of the proposed work is given. In Section 4, results are presented along with a critical analysis that discerns the implications of the findings.

2. Literature Survey

In psychology, emotion is understood as a distinct facet of human thought processes. It includes people's subjective interpretations of the real world as well as their attitudes towards gratifying their basic desires. These psychological states have a real effect on people's work life and daily lives. According to neuroscientific studies, emotional regulation plays a crucial role in facilitating rational decision-making in situations involving complicated problem-solving. This highlights the effects of emotional experiences on cognition [1]. A thorough examination of emotional responses requires an interdisciplinary approach that incorporates concepts from cognitive science, biomedical engineering, and neuroscience due to the intricate relationship between emotions and cognitive functions.

Changes in environmental stimuli elicit changes in both physiological and behavioural indications simultaneously [2], highlighting the symbiotic link between emotional states and physiological markers. External manifestations of internal emotional feelings, like tone of voice, text, and facial expressions, serve as behavioural signals that obliquely provide affective information. On the other hand, physiological signals play the role of internal substrates that accurately represent the subtleties of human emotions. Examples of these signals include electrocardiography (ECG), electrodermal activity (EDA), electromyography (EMG), and pulse wave measurements [3]. Research and development efforts into creating new models, methods, algorithms, and systems for the identification and categorization of emotional states have increased dramatically in the past two years.

In order to obtain significant identification accuracy, Zhang et al. [4] presented a multimodal emotion detection model that makes use of convolutional neural networks and manifold learning. A self-supervised learning paradigm developed by Quispe et al. [5] makes it possible to extract representations from unlabeled signals, therefore boosting data efficiency. Dasdemir and colleagues [6] created a model that highlights the remarkable discriminatory efficacy of augmented reality systems in identifying emotional states during book reading activities. Empirical testing proved the efficacy of Hernandez-Melgarejo's [7] new feedback control schema, which modifies user states based on interactions within the user-virtual reality system. A self-supervised method for reliably obtaining representations from distinct physiological inputs was presented by Dissanayake et al. [8]. A bimodal structure was employed by Lee et al. [9] to enhance recognition performance, with noteworthy outcomes in the classification of arousal and valence. In order to extract emotion-related information from EEG data, Pusarla et al. [10] created a deep learning-based system that performed better than earlier methods. In order to obtain high accuracy in cross-subject emotion recognition, Moin et al. [11] developed a multimodal technique that combined facial gestures with EEG. A novel EEG dataset (WeDea) was presented by Kim et al. [12], showcasing its potential for emotion analysis. A machine learning framework was presented by Romeo et al. [13] to simulate time intervals that showed reliability in gold-standard conditions.

A novel method based on substructure-based joint probability domain adaptation was created by Fu et al. [15] to lessen the detrimental effects of noise on physiological inputs. Pusarla et al. [16] improved upon earlier approaches in terms of emotion identification accuracy by employing a local mean decomposition methodology for EEG signals. Katada and Okada [17] extensively addressed individual physiological differences to improve biosignal-based assessments of mood and personality. A multi-filtering augmentation technique was presented by Hasnul et al. [18], and it considerably increased the machine learning algorithms' classification accuracy. With adaptability and promising performance, Shi [19] suggested a universal technique appropriate for body sensor network scenarios including cross-domain information fusion.

Anuragi et al. [20] revealed an automated cross-subject emotion detection framework based on EEG data, which is distinct due to its split into four sub-band signals in the field of innovative systems. A novel paradigm for collecting physiological data in multi-sensory emotion detection was proposed by Asiain et al. [21]. In order to aid in the identification of stress, Zontone et al. [22] created a technique to gauge drivers' emotional reactions in a variety of driving situations. In order to evaluate car interior acceleration noises in conjunction with physiological inputs and produce precise sound quality judgements, Xie et al. [23] created a hybrid deep neural network.

Electroencephalography (EEG) is a tool that can be used to record the noticeable spatiotemporal fingerprints of human emotion dynamics, which are the result of a complex process. Because EEG is inexpensive and easy to record, it is considered a vital method for expressing in detail the coordinated activity of many neurons in the cerebral cortex. By introducing a novel approach to emotion image classification based on users' eye movements and EEG signals, Yang et al. [24] established a connection between psychological signals and anticipated emotional reactions. In their investigation on EEG-based emotion recognition and judgement, Yoon and Chung [25] accurately described emotions across two and three levels, accounting for valence and arousal features. In order to determine gamers' skill levels, Andreu-Perez et al. [26] created a multi-modal architecture that combined facial video recordings and functional near-infrared spectroscopy. They were able to achieve an impressive tri-class classification precision of 91.44%.

An improved radial basis function neural network method for analysing EEG signals was published by Zhang et al. [27]. This model outperformed earlier models in testing. Chew et al. [28] presented a novel preference-based assessment technique that classifies aesthetic preferences for virtual products with an astounding 80% accuracy by using EEG signals. By creating a comprehensive method for gathering physiological emotional databases, Chanel et al. [29] proved that employing EEG signals for arousal evaluation was feasible. Wagh and Vasanth [30] achieved maximum classification rates of 71.52% and 60.19% with decision tree and k nearest neighbour techniques, respectively, using a range of classifiers and a discrete wavelet transform to identify distinct emotions in EEG signals.

Using multi-channel EEG data converted into multi-spectral topological pictures, Ozdemir et al. [31] introduced a unique approach to emotion recognition with testing accuracies of 86.13% for arousal, 90.62% for valence, 88.48% for dominance, and 86.23% for like-unlike. Abadi et al.'s database, which is based on magnetoencephalograms, was created [32] with an emphasis on minimal scalp touch, real affective reactions, and fine-grained cognitive reaction analysis. An EEG-based art therapy evaluation approach was developed by Tang et al. [33], who emphasised the benefits of models with deep temporal elements of extended short-term memory over non-temporal features, especially in the high-frequency band.

Proposed Work

Based on the literature study, this research conducts an investigation into Post-Traumatic Stress Disorder (PTSD) diagnosis and proposes a simple and accurate method of diagnosing PTSD using the complexities of emotion recognition. The Fig. 1 shows the flow diagram of the proposed work.

This work approaches from the extraction of statistical features—specifically, mean, standard deviation, skewness, kurtosis, and Hjorth from the EEG signal obtained from the DEAP database, followed by the deployment of a 1D CNN classifier to classify the emotions. These carefully chosen statistical characteristics capture important aspects of emotional responses and provide the empirical basis for an accurate diagnostic approach.

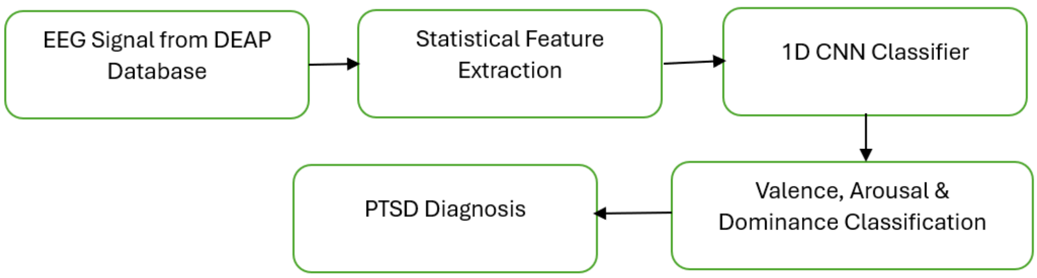


Fig. 1: Proposed Model Block diagram

1. Biomarker Used

As Electroencephalography (EEG) stands out as a leading method for identifying emotions and offers a unique insight into brain dynamics linked to emotional experiences, it has been utilised in this work. With its ability to capture real-time brain electrical activity, EEG provides precise measurements of cortical processes associated with emotions. Its non-invasive nature and high temporal resolution make it effective in analysing the quick and dynamic nature of emotional reactions. EEG's sensitivity to minute shifts in emotional states is a key advantage, as certain brain activity patterns correlate closely with emotions. Through frequency and amplitude analysis, researchers can categorize emotional states more precisely. EEG also records both conscious and unconscious emotional processes objectively, eliminating biases associated with self-reporting. Its adaptability allows for various experimental paradigms, supporting tailored trials to explore emotional correlates effectively. Recent advancements in machine learning and signal processing have further enhanced EEG's efficacy in identifying and classifying emotional states accurately. In summary, EEG's efficiency in emotion recognition stems from its real-time insight, sensitivity to subtle changes, objectivity, versatility, and compatibility with advanced analytical methods.

2. Database Used

The Database for Emotion Analysis using Physiological Signals (DEAP) dataset is invaluable for researchers in emotion analysis, providing a rich collection of physiological and EEG data. It features recordings from 32 subjects exposed to carefully selected audio-visual stimuli designed to elicit diverse emotional reactions. These stimuli, including videos and music samples, evoke emotions such as fear, grief, disgust, and joy. The database comprises recordings of EEG and peripheral physiological signals gathered from 32 participants during their exposure to music videos. With each participant undergoing 40 trials, the database encompasses a total of 1280 trials (32 participants * 40 trials).

The DEAP dataset is unique in that it captures a range of physiological reactions that are closely associated with emotional experiences. The Valence, Arousal and Dominance are the three categories wherein valence corresponds to whether the emotion is positive or negative while arousal is a measure of the emotional intensity or the strength that is associated with every emotion and dominance refers to the control. An emotional wheel comprising of 16 slices corresponding to 16 different emotions is what the DEAP dataset all about is. The participants having been made to watch 120 one-minute extracts of music videos were made to select slices of the emotion wheel and correspondingly the integers pertaining to each emotion viz., Pride, Elation, Joy, Satisfaction, Relief, Hope, Interest, Surprise, Sadness, Fear, Shame, Guilt, Envy, Disgust, Contempt and Anger. These emotions were broadly assessed under valence, arousal and dominance categories.

Specifically, the EEG data allows researchers to examine brainwave patterns in various frequency bands, which provides an unprecedented window into the neural bases of emotions. These physiological cues are then used to train models to identify and classify emotional states. This methodical approach makes it easier to examine in detail the complex relationship between mental activity and emotional processing. To sum up, the DEAP dataset is essential to improving our understanding of human emotions. Its abundance of multi-modal physiological data not only stimulates state-of-the-art research at the nexus of affective science and neuroscience, but also deepens our understanding of the relationship between emotions and physiological responses.

3. Features Extracted

The foundation of quantitative data analysis, statistical features, provide crucial measurements that reveal the underlying structure and properties of datasets. The mean, a key statistical characteristic that captures a dataset's central tendency, is at the vanguard of these measures. The mean, which is determined as the arithmetic average, serves as a crucial benchmark and represents the average value that data points tend to converge around. Its usefulness comes from its ability to provide a brief synopsis of the main trends in the dataset, making it easier to comprehend the dataset as a whole.

Standard deviation also is an important statistical feature that provides information about how data points are distributed or dispersed together with the mean. The standard deviation, which functions as a measure of variability, enables researchers to assess the dataset's consistency or volatility. While a smaller number indicates a more tightly clustered distribution, a higher standard deviation indicates a more scattered dataset, suggestive of greater variability among values.

Skewness, a distribution's asymmetry measure, adds even more usefulness to the statistical toolbox. Positive skewness denotes a longer right tail, suggesting a greater number of larger values; negative skewness denotes a longer left tail, suggesting a greater number of smaller values. Thus, skewness offers a detailed viewpoint on the distribution's form, revealing tendencies toward extreme values.

Kurtosis examines the tail behaviour of the distribution and the probability of extreme values, which enhances the study. A greater tendency for outliers or extreme values is indicated by a higher kurtosis, which indicates a more peaked distribution with heavier tails. On the other hand, a flatter distribution with lighter tails, denoting a more even distribution of values, is indicated by a lower kurtosis. By illuminating the relative concentration or dispersion of the distribution, this characteristic enhances the statistical story.

Hjorth parameters provide a specialised lens into physiological data and were originally developed for the examination of time-domain characteristics in biomedical signals. Hjorth parameters, which include activity, mobility, and complexity, explore the time dynamics of signals like EEG. Activity measures the total energy or amplitude of the signal, mobility the rate at which the signal varies, and complexity the irregularity of the signal. Hjorth parameters offer a deep layer of comprehension in the context of emotion recognition and biomedical signal processing by helping to interpret the complex temporal features underlying physiological responses.

4. Classifier Algorithm used:

A complex one-dimensional Convolutional Neural Network (1D CNN) technique is employed as the discriminating classifier in the composition of this diagnostic opera. The 1D CNN's inherent architectural strength is skilfully applied to interpret complex patterns in the statistical information that are extracted. The 1D CNN is the most popular classifier in the field of emotion classification, which is attributed to its exceptional ability to extract complex patterns from sequential data, like the EEG signals. By utilising convolutional operations to their fullest potential, 1D CNN surpasses traditional techniques by capturing hierarchical information nested within temporal sequences. The capacity of 1D CNN to identify minute details in time-domain data, which is vital for describing the temporal dynamics of emotional expressions, places it as a solid foundation for obtaining exceptional performance in emotion classification. The effectiveness of this architectural paradigm rests not only in its ability to automatically acquire discriminative characteristics but also in its ability to understand complex temporal linkages and abstract hierarchically, thus signalling a paradigm shift in the landscape of emotion classification through machine learning.

The block diagram of the 1D CNN used is displayed in Fig. 2.

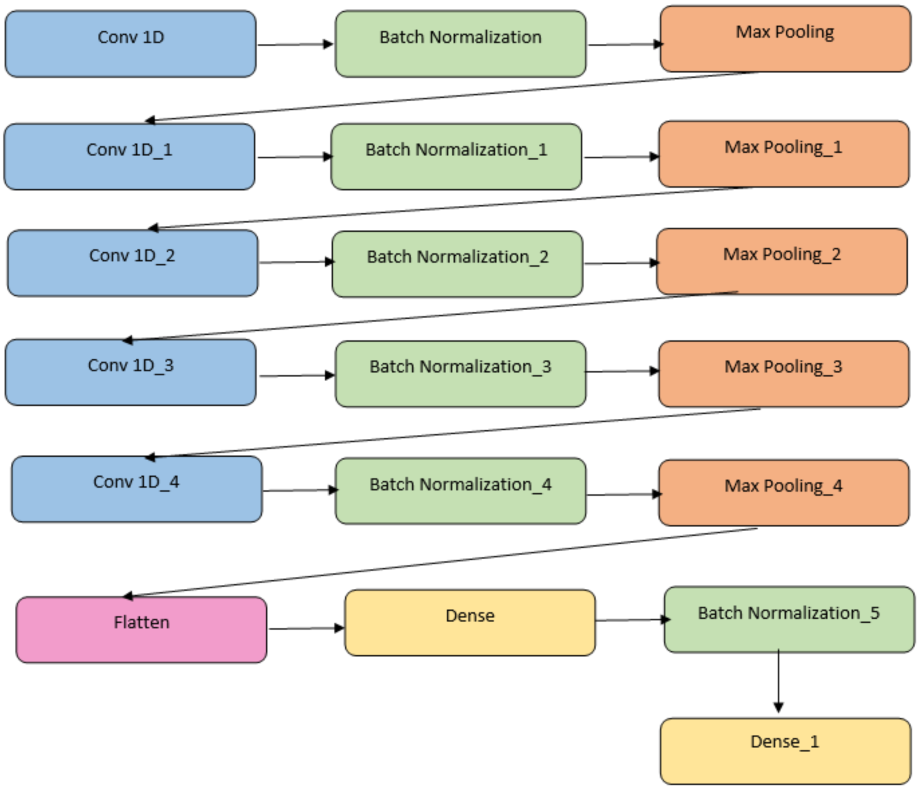
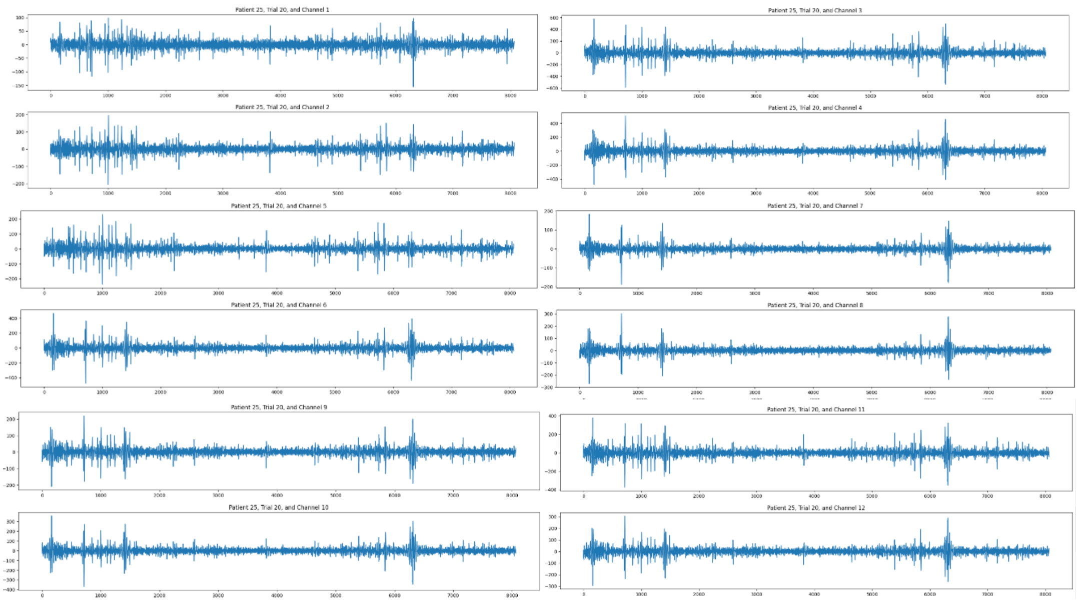


Fig. 2: Block diagram of 1D CNN

3. Resulte and Discussion

The samples of all the 32 participants with 40 trials are used in this work. The following Fig.3 displays a sample EEG plot pertaining to Patient 25, Trial 20, and Channels 1 to 32, that unveils the unique neural signatures of an individual during a particular experimental instance. The Trial 20 introduces a temporal dimension, capturing a snapshot of the patient's neural responses at a specific moment, while Channels 1 to 32 afford us the privilege of scrutinizing a broad spectrum of cortical regions.



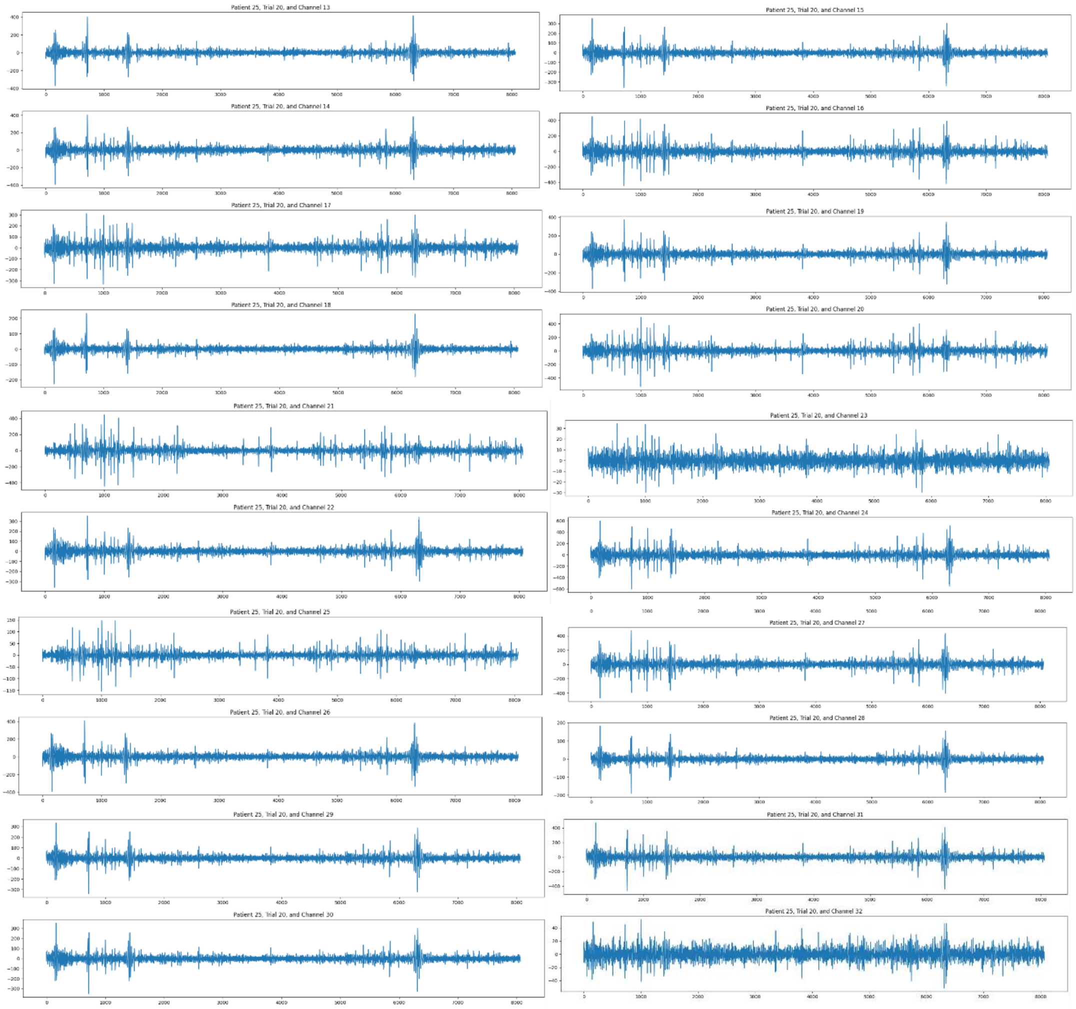


Fig. 3: Plots showing EEG signal for a chosen sample patient and a chosen trial.

For emotion recognition, the utilization of statistical features such as mean and standard deviation proves to be an efficient approach for classifying valence and arousal. The mean, representing the central tendency of a dataset, offers insights into the average level of emotional response. Meanwhile, the standard deviation, as a measure of variability, captures the extent to which emotional signals deviate from the mean. In the context of valence, mean values can indicate whether the emotional state leans towards positive or negative, while standard deviation provides a measure of the variability in these valence scores. Similarly, for arousal, the mean reflects the overall activation level, and standard deviation highlights the fluctuations or stability in arousal intensity.

The efficiency of mean and standard deviation lies in their simplicity and interpretability, making them valuable features in emotion classification models. These statistical measures encapsulate essential information about the distribution of emotional responses, providing a foundational understanding that can enhance the accuracy and interpretability of emotion recognition systems. The Fig. 4 gives the mean and standard deviation for valence and arousal of all the participants in the DEAP data set.

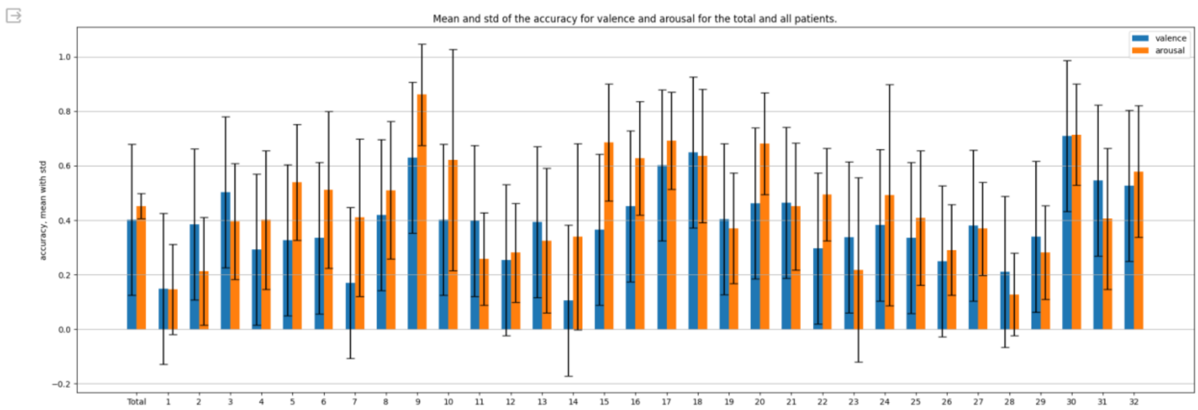


Fig. 4: Mean and standard deviation plots

Emotion categorization from EEG data is improved by utilising these statistical variables in conjunction with a one-dimensional Convolutional Neural Network (1D CNN). The model's ability to identify emotional states is enhanced by the CNN's capacity to extract hierarchical patterns, which mesh well with the intricate temporal correlations present in EEG signals. By combining statistical features with cutting-edge machine learning approach, emotion recognition is improved and the brain mechanisms underlying human emotions are identified. The confusion matrix shown in Fig. 5 stands as a crucial assessment tool in both machine learning and statistics, providing a condensed representation of a classification algorithm's performance through a four-cell table. The matrix includes True Positives (correct positive predictions), True Negatives (correct negative predictions), False Positives (incorrect positive predictions), and False Negatives (incorrect negative predictions). Derived from these components are key metrics like Accuracy, Precision (positive prediction accuracy), Recall (sensitivity or true positive rate), Specificity (true negative rate), and the F1 Score (harmonic mean of precision and recall). This matrix serves as a comprehensive evaluation framework, unveiling insights into the model's accuracy, strengths, and areas for improvement, facilitating the enhancement of its predictive capabilities. The Valence, Arousal and Dominance are the three categories indicated as “0”, “1” and “2” in the confusion matrix in Fig.5,

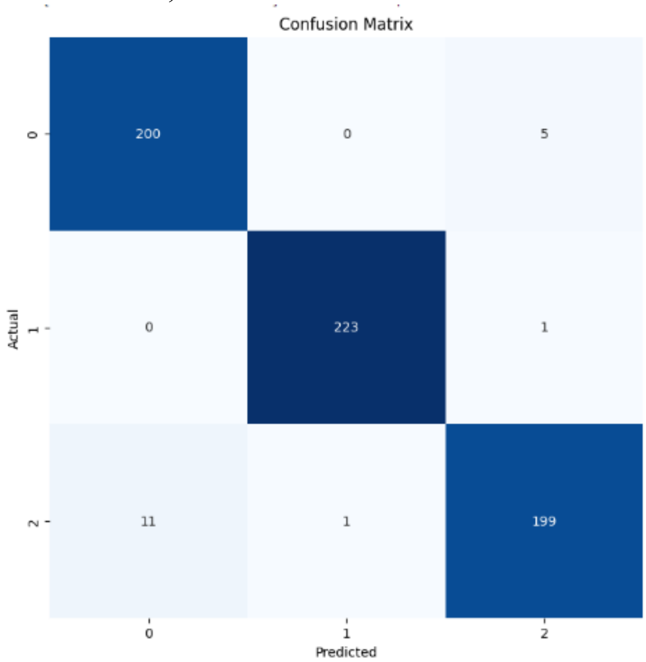


Fig. 5: Confusion matrix of the proposed work

The accuracy and loss plots of the classifier are shown in Fig. 6 and 7 respectively. These plots serve as integral visual tools for evaluating the training dynamics of a classifier model. The loss plot tracks the model's progress in minimizing the chosen loss function across epochs, depicting the optimization of predictive capabilities. A descending trend in the loss plot indicates improvement in the model's ability to make accurate predictions. Concurrently, the accuracy plot illustrates the model's classification performance over epochs by showcasing the percentage of correctly classified instances. An ascending accuracy plot ideally demonstrates the model's learning and adaptation to the training data. These visualizations are indispensable for diagnosing potential overfitting or underfitting issues, providing crucial insights into the model's convergence and efficacy in capturing underlying patterns within the training data.

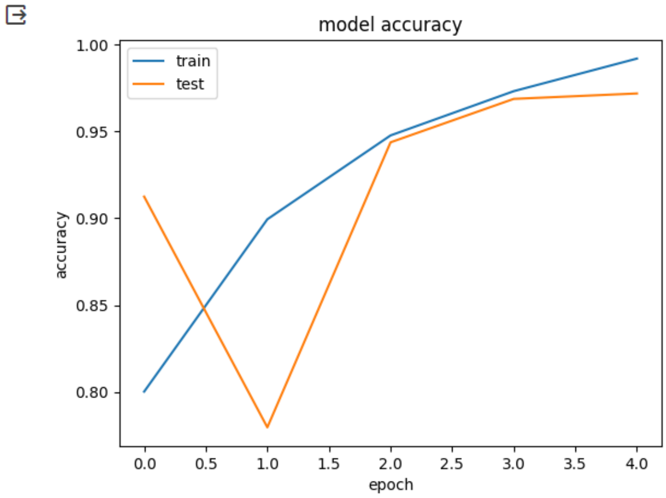


Fig. 6: Accuracy plot

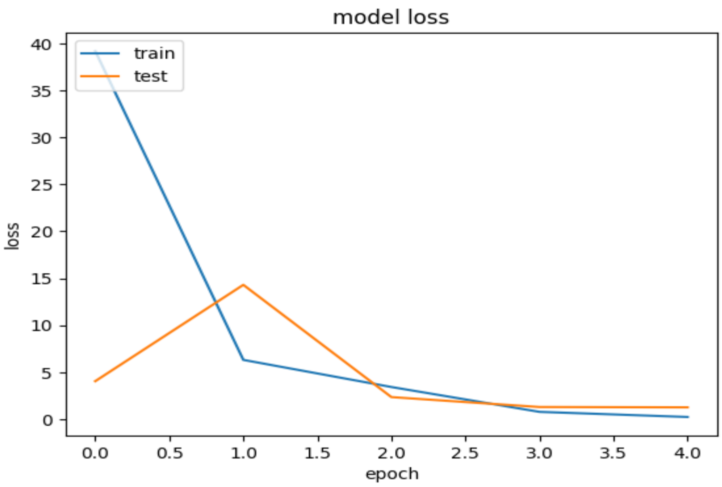


Fig. 7: Loss plot

In a classification task, precision, recall, and the F1 score serve as important metrics, providing better evaluation of a model's performance. Precision is often referred to as positive predictive value, serves as a crucial indicator of the accuracy of a model's positive predictions. Calculated as the ratio of true positives to the sum of true positives and false positives, precision illuminates the proportion of instances predicted as positive that are indeed true positives. A higher precision underscores the model's proficiency in minimizing false positives, underscoring its precision in identifying positive cases.

Table. 1: Classification report

Epoch	Loss	Accuracy	Validation Loss	Validation Accuracy
1/5	39.1818	0.8003	4.0448	0.9125
2/5	6.3109	0.8995	14.2986	0.7797
3/5	3.4242	0.9477	2.3507	0.9438
4/5	0.7784	0.9732	1.2941	0.9688
5/5	0.2335	0.9920	1.2585	0.9719

Recall, alternatively known as sensitivity or the true positive rate, assesses the model's effectiveness in capturing all positive instances. Computed as the ratio of true positives to the sum of true positives and false negatives, recall gauges the proportion of actual positive instances correctly identified by the model. Elevated recall values signify a reduced incidence of false negatives, emphasizing the model's adeptness in recognizing positive cases.

The F1 score regarded as the harmonic mean of precision and recall, offers a comprehensive metric that strikes a balance between false positives and false negatives. Calculated as 2 times the product of precision and recall divided by the sum of precision and recall, the F1 score provides a unified measure that accounts for both precision's focus on false positives and recall's emphasis on false negatives. This makes it particularly valuable in situations where a balanced evaluation is essential, and precision and recall have competing priorities.

Collectively, precision, recall, and the F1 score contribute to a holistic assessment of a classification model's capabilities, offering valuable insights into its capacity for accurate positive predictions, ability to capture all positive instances, and aptitude for maintaining a balance between false positives and false negatives. The selection of these metrics is contingent upon the specific priorities and requirements of the given application or problem at hand. Table 1 gives the overall Classification Report and Table 2 gives the values pertaining to each epoch.

<table>
<tr><th>Sl. No</th><th>Parameters</th><th>Classification category</th><th>Values</th></tr>
<tr><td>01</td><td>Accuracy</td><td colspan="2">97.188</td></tr>
<tr><td rowspan="3">02</td><td rowspan="3">Precision</td><td>0</td><td>0.95</td></tr>
<tr><td>1</td><td>1.0</td></tr>
<tr><td>2</td><td>0.97</td></tr>
<tr><td rowspan="3">03</td><td rowspan="3">Recall</td><td>0</td><td>0.98</td></tr>
<tr><td>1</td><td>1.0</td></tr>
<tr><td>2</td><td>0.94</td></tr>
<tr><td rowspan="3">04</td><td rowspan="3">F1 score</td><td>0</td><td>0.96</td></tr>
<tr><td>1</td><td>1.0</td></tr>
<tr><td>2</td><td>0.96</td></tr>
</table>

Table. 2: Loss and Accuracies per Epoch

Table. 3: Comparison with other related works

Reference	**Dataset used**	**Features Extracted**	**Classifier Employed**	**Accuracy (%)**
This work	DEAP	Statistical Features (mean, standard deviation, kurtosis, and Hjorth parameters)	1D CNN	97.19
Alhagry et al.[34]	DEAP	Not Mentioned	LSTM-RNN	85.55
Zhan et al.[35]	DEAP	Spectral Features	1D CNN	83.51
Eun Jeong Choi, Dong Keun Kim [36]	DEAP	Not Mentioned	LSTM	76.32
Chao et al.[37]	DEAP	Spatial Characteristics & Global Inter-channel Synchronization Features	SVM	71.03
Zhuang et al. [38]	DEAP	Intrinsic Mode Function by Empirical Mode Decomposition	SVM	70.54
Pandey and Seeja[39]	DEAP	Scalogram Image Features	1D CNN	60

Table. 3 above gives a comparison of the work in the literature with that of the proposed system. All having used the DEAP dataset have offered accuracies ranging from 60% to 85.55%, having extracted different sets of features, which is less when compared to the proposed model that offers a classification accuracy of 97.55%. Although the Zhan et al.[35] and Pandey and Seeja[39] have used CNN classifier, the proposed model using the statistical features, namely mean, standard deviation, kurtosis, and Hjorth parameters offers outstanding performance.

3. Conclusion

In conclusion, this work set out on a rigorous path towards PTSD diagnostic precision by utilising the large and complex DEAP database, which is well-known for its abundance of physiological information. An advanced 1D Convolutional Neural Network (CNN) classifier, was expertly utilised, yielding an accuracy peak of 97.18%. This high degree of accuracy demonstrates the powerful power of sophisticated machine learning paradigms, especially the 1D CNN framework, in revealing the subtleties hidden in EEG signals. It also attests to the discriminating powers of the selected statistical features in capturing soft emotional nuances. These results indicate an accurate method in psychiatric diagnostics, offering more precise and objective evaluation for the detection and comprehension of PTSD. This intersection of neuroscientific research, machine learning expertise, and mental health diagnostics, signals a paradigm change and an era in which EEG-based emotion detection becomes a powerful tool for improving the accuracy of psychiatric diagnosis.

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