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The treatment of complex PTSD in a refugee woman through the integration of neurofeedback with trauma-informed therapy: A case study

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Abstract

Objective: The case of Fay, a 40-year-old Syrian refugee woman who has experienced both developmental and refugee trauma was chosen to demonstrate the potential of neurofeedback in treating complex PTSD symptoms.

Methods: Outlines pre and post assessments, and the use of neurofeedback protocols for stabilisation of arousal, their rationale and how they were integrated into trauma-informed therapy.

Results: Pre and post comparisons indicate changes in resting EEG patterns as well as significant reductions in post-traumatic symptoms, depression and anxiety symptoms.

Conclusions: Stabilisation of arousal via neurofeedback may contribute to the establishment of safety that promotes emotional regulation and ability to undergo painful trauma processing. Neurofeedback as an adjunct to trauma-informed therapy may be particularly warranted in cases of complex PTSD.

Keywords: Neurofeedback, complex PTSD, refugee trauma, developmental trauma & protocols

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1. Introduction

This paper describes the case of Fay, a refugee woman who has experienced developmental trauma and presents with complex PTSD symptoms. It outlines her treatment using neurofeedback as an adjunct to psychological therapy and her progress.

2. Background

2.1. Complex PTSD

Refugees may be up to 10 times more likely to meet criteria for post-traumatic stress disorder (PTSD) compared to the general population (Fazel et al., 2005). A subset of this group is also likely to qualify for the ICD-11 diagnosis of complex PTSD (cPTSD) (11th ed,; ICD-11; World Health Organization, 2020). In addition to re-experiencing, avoidance and hypervigilance symptoms, cPTSD also includes criteria related to disturbances of self-organisation (DSO) including emotional dysregulation, interpersonal difficulties and negative self-concept (Jowett et al., 2020). Complex PTSD typically involves multiple or repeated traumas of an interpersonal nature, and produces more complex, chronic symptoms with greater functional impairment (Brewin et al., 2017; Cloitre, et al., 2013; Cloitre, 2020). In particular, it has been found that childhood trauma was predictive of increasing symptom complexity in adults (Cloitre, et al., 2009). Indeed, adverse childhood experiences have been established to have a linearly cumulative effect on symptoms (Felitti, et al., 1998).

NSW Service for the Treatment and Rehabilitation of Torture and Trauma Survivors (STARTTS), encounters clients who have experienced earlier adverse life events or developmental trauma along with war-related or refugee trauma later in adulthood. According to the cPTSD diagnostic criteria, in addition to experiencing the core PTSD symptoms, these clients would be more likely to experience DSO disturbances and have greater functional impairment. Heightened physiological instability seen in PTSD (Ge et al, 2020; Begic., et al., 2001; Giesbrecht, et al., 2006; Wahbeh & Oken, 2013) as well as heightened interpersonal instability suggests the need for the establishment of both physiological and interpersonal safety without which therapy work would be precluded. Indeed, the establishment of safety is the cornerstone of trauma work (Herman, 1992) and according to polyvagal theory, co-regulation with the therapist is a fundamental way to establish this safety (Porges, 2001). However, for clients who have experienced complex trauma, interpersonal trust needed for the establishment of safety may take time and be more difficult (Lawson, et al., 2013). Hence, promoting physiological stability may be a useful tool that contributes to the development of therapeutic trust and safety, and consequently, greater receptivity to therapy in general.

2.2. Physiological markers in PTSD

Physiological instability in PTSD has been demonstrated in several studies. Namely, a recent meta-analysis has confirmed that individuals with PTSD exhibit lower HRV (Ge et al, 2020). Studies have also shown EEG abnormalities in PTSD sufferers, although results from these studies are heterogeneous. For instance, it has been found that beta and theta are elevated in veterans with PTSD (Begic et al., 2001) and that theta is linked to higher levels of dissociation (Giesbrecht et al., 2006). It has also been found that peak alpha frequency is elevated in a PTSD group, potentially reflecting their increased vigilance to their surroundings (Wahbeh & Oken, 2013). It can be speculated that the differences in these groups may be partially explained by the differences in predominant PTSD symptoms - for instance, hyperarousal vs. hypoarousal, however further research into this area is needed to elucidate these heterogeneous results. Nonetheless, these studies suggest the potential for the use of biofeedback modalities for establishing physiological stability, which may in turn contribute to interpersonal therapeutic safety.

2.3. Neorofeedback

Neurofeedback is a biofeedback modality that has been successfully used in the treatment of both developmental trauma (Fisher, 2014) and refugee trauma (Askovic & Gould, 2009; Askovic et al., 2017; Askovic et al., 2020). Neurofeedback trains brainwave patterns in response to real-time EEG and is based on operant conditioning principles (Sherlin et al., 2011). During neurofeedback, an individual is rewarded for amplifying certain brainwaves, while simultaneously inhibiting others. Protocols used to decide which brainwaves to reward and inhibit are based on a thorough clinical assessment and often accompanied by a qEEG assessment. Clients 'play' a game or watch a video and receive visual and auditory feedback in response to their performance.

Neurofeedback in the traumatised population primarily works to reduce/address arousal (Fisher, 2014). A review investigating the effects of neurofeedback in the treatment of PTSD indicates that neurofeedback is 'probably efficacious' (Reiter et al., 2016) and more recent reviews are also showing promising results (Chiba et al., 2019; Steingrimsson et al., 2020; Panisch & Hai, 2020). More specifically, van der Kolk (2016) demonstrated that neurofeedback is useful in regulating emotional arousal and reducing chronic PTSD symptoms. It can be argued that this stabilisation of physiological arousal allows the nervous system to move away from fight/flight/freeze responses and into the social engagement system, which according to Porges (2011) would be required for successful co-regulation with the therapist. Hence, for clients with cPTSD, this physiological stability may be the building block to the establishment of therapeutic trust and therefore increasing receptivity to therapy in general.

3. Methodology

3.1. Case Introduction

Fay is a 40-year-old Syrian woman who arrived to Australia alone. Fay had experienced typical war-related trauma as a result of the ongoing conflict in her country. Fay had also experienced displacement and separation from her family, as well as an incident of attempted sexual assault during her time in a neighbouring country. In addition to the traumatic events experienced in her adulthood, Fay also experienced several incidences of childhood sexual assault from a family member, followed by a traumatic medical procedure as a result of this assault. Upon arrival to Australia, Fay found herself alone, and without the support of her family who were overseas. In addition, she faced settlement challenges that all refugees face upon arrival to a new country including learning a new language, finding work, engaging in additional study and navigating the socio-political-economic environment. Whilst there existed established communities from Fay's culture, she did not feel she belonged there and felt discriminated against as an unmarried woman of 40. Normal life challenges of finding a partner and having a family also contributed to Fay's distress.

Fay had received approximately one year of trauma-informed supportive counselling, psychoeducation, elements of CBT and Motivational Interviewing as well as focusing on managing physiological and affective dysregulation through grounding, diaphragmatic breathing and progressive muscle relaxation. Fay was referred for neurofeedback to address continuing issues with severe sleeping difficulties, nightmares, panic / anxiety attacks, memory and concentration issues, anger outbursts, emotional dysregulation and depressed mood. She was taking a SNRI (50 mg) daily.

3.2. Case Formulation

Overwhelming emotional dysregulation was the most visible feature of Fay's presentation. She often presented to sessions distressed and easily triggered into an emotional outburst. She reported crying easily and having anger outbursts outside of sessions. The cascade of emotions included fear, anger, sadness and shame that led to dissociative experiences. These included going blank in sessions, as well as withdrawal behaviours such as oversleeping and avoidance of situations, persons and confrontations. These dissociative experiences and avoidant behaviours disrupted processing of emotional trauma. Indeed, dissociation has been found to be a major contributing factor in maintaining PTSD symptoms (Briere et al., 2005). Fay's most common triggers were interpersonal interactions with adult males, particularly those she suspected may have intentions of engaging her on an intimate level. These triggers led to flashbacks of childhood sexual abuse and a general sense of vulnerability and lack of autonomy to protect herself. Her inability to uphold boundaries and trust herself led to a deep sense of shame, which reinforced core dysfunctional beliefs developed in childhood. These included beliefs about being weak, being blameful and being unlovable.

Fay's sense of being unprotected and vulnerable was likely exacerbated by her current circumstances of being recently separated from her family and having to adjust to a new country, culture and language. This likely lowered the threshold for stress, meaning that she was triggered into emotional dysregulation with greater frequency and intensity. Fay's EEG results indicated slow widespread alpha, particularly temporally, occipitally and along the midline. Additionally, hypercoherent alpha was present frontally. These EEG patterns could relate to FA's emotional dysregulation, dissociation and memory issues (Fingelkurts et al., 2007; Hassan et al., 2020; Klimesch, 1997). The combination of classical symptoms of PTSD including hypervigilance, re-living and avoidance, with additional issues of emotional dysregulation, negative self-concept and interpersonal difficulties, suggests the likelihood that Fay had cPTSD, as differentiated by the ICD-11 (11th ed.; ICD-11; World Health Organization, 2020).

Despite these challenges and significant emotional dysregulation issues, Fay engaged well in therapy and developed good rapport with the therapist. Fay is a bright and resourceful woman who learnt English very fast and developed an understanding of the Australian socio-economic system quickly. Fay was also psychologically minded and when felt safe enough shared deep insights into her issues with courage and clarity.

3.3. Assessment

Written consent for use of client data was obtained at the time of their EEG assessment.

Table 1. Diagnostic tools

Assessment	**Description**
Clinical Interview	*Clinical interview assessing client's presenting issues, developmental history and current lifestyle factors*
Harvard Trauma Questionnaire (HTQ-S) (Mollica et al, 1992)	*A cross-cultural instrument measuring torture, trauma and post-traumatic stress.*
Hopkins Symptom Checklist – Depression (HSC-D) (Mollica et al, 1987)	*A cross-cultural instrument measuring depression.*
Hopkins Symptom Checklist – Anxiety (HSC-A) (Mollica et al, 1987)	*A cross-cultural instrument measuring anxiety.*
DASS-21 (Lovibond & Lovibond, 1995)	*Depression Anxiety Stress Scales*
GSE (Schwarzer & Jerusalem, 1995)	*General Self-Efficacy Scale*
Digit Span (Wechsler, 2008)	*A subtest examining attention and working memory from the Wechsler Adult Intelligence Scale – IV.*
Quantitative Electroencephalogram (qEEG)	*Resting-state EEG activity for eyes open and eyes closed conditions*

3.4. Treatment

Fay received 37 neurofeedback sessions in total, as an adjunct to psychological therapy. Approximately, half of each session was spent on neurofeedback and the other half on psychological therapy.

3.4.1. Stage 1 –Safety

The initial stage of therapy focused on the establishment of safety which included physiological stabilisation through neurofeedback. This was reflected in the choice of initial neurofeedback protocol, which aimed at stabilising symptoms through use of interhemispheric training (T3-T4/C3-C4) (Gapen et al., 2016; Othmer, 2005). This was in conjunction with grounding techniques including diaphragmatic breathing, naming affect and identifying triggers to emotional distress.

3.4.2. Stage 2 –Development and trauma attachment

The next stage of treatment focused on delving deeper into Fay's developmental trauma and attachment relationships – a client led, organic progression, which was accompanied by the addition of right-hemisphere training (T4-P4), found to be particularly useful for reduction in PTSD symptoms (Gapen, et al., 2016).

3.4.3. Stage 3 –Experimental

The final stage involved experiential exercises including imaginal exposure. This allowed Fay to confront some of her fears but more importantly, gave Fay more insight and clarity into who was to blame for these events, as well as to process her relationships to her parents. During this last stage, an additional Fz-Pz protocol was added, targeting frontal lobe functioning, to assist with more cortical control over limbic dysregulation as well as help with executive functioning and decision making (Viviani & Vallesi, 2021).

Please note that the stages in therapy and the accompanying protocols were not linear but rather, dynamic, and protocols and frequencies were adjusted based on client feedback within sessions or at follow-up. However, the general progression of therapy and accompanying protocols are adequately summarised in this manner.

Table 2. Neurofeedback Protocols

Neurofeedback Protocol	Frequency range	Rationale
T3-T4/C3-C4	Alpha enhancement	*Assist with headaches, panic, anxiety, nightmares and general stabilization of symptoms*
T4-P4	Alpha enhancement	*Assist with further calming and emotional regulation*
Fz-Pz	SMR	*Enhance inhibitory abilities, executive functioning and attention*

4. Results and Discussion

Following 37 neurofeedback sessions, Fay's scores improved on all measures.

4.1. Harvard and Hopkins

Pre-treatment, Fay's trauma symptoms score was extremely high (HTQ-S) (Mollica et al, 1992), however on re-assessment her score was subclinical (<2.5). Fay's score for anxiety (HSC-A) (Mollica et al, 1987) also decreased to below cut-off (<1.75). Her score for depression (HSC-D) (Mollica et al, 1987) was just above cut-off for clinical significance (>1.75).

Table 3. Psychometric comparisons of trauma symptoms, depression, and anxiety symptoms

Comparison	HTQ-S	HSC-A	HSC-D
PRE	3.88	3.20	3.67
POST	2.06	1.7	1.8

4.2. DASS-21

Pre-treatment, Fay's scores on DASS-21 (Lovibond & Lovibond, 1995) were all in the extremely severe range. On re-assessment, her score for stress was in the normal range and her scores for depression and anxiety were in the mild range.

Table 4. Psychometric comparisons of DASS-21 scores

DASS Comparison	Depression	Anxiety	Stress
PRE	18	15	21
POST	**5**	**4**	**7**

4.3. GSE

Fay's scores on the GSE (Schwarzer & Jerusalem, 1995) increased from 10 to 18, indicating an increase in Fay's belief in her own self-efficacy. This correlated with Fay's own reports of increased trust in herself and her ability to set appropriate boundaries.

4.4. Digit Span (DS), WAIS Subset

Fay's total score for the Digit Span improved from pre to post assessment. Fay was unable to complete the sequential part of the task in the initial assessment. This was a reflection of her compromised cognitive functioning, which may have been partly a result of her inability to regulate. Following treatment, she performed in the average range for this component.

Table 5. Comparisons of Digit Span scores

DS Comparison	DS Forwards	DS Backwards	DS Sequential
PRE	***2***	**5**	**1**
POST	**3**	**3**	**8**

4.5. EEG Results

Fay's pre-post treatment EEG comparison in both eyes open and eyes closed condition showed a significant increase in the organised posterior alpha rhythm suggesting that the client's brain has become better regulated (Bazanova & Vernon, 2014). A reduction in slow alpha activity recorded over the right temporo-parietal region indicated an improvement in the social engagement system (Felmingham et al, 2003; Dalili et al, 2017; Chu et al, 2017). A reduction in slow front-central rhythm and an increase in higher alpha frequency may be indicative of an improvement in Fay's cognitive functioning, as reflected in the enhanced performance on the Digit Span. This is in line with research demonstrating sensorimotor rhythm (SMR) training to increase attention and working memory components of executive functioning (Vernon et al., 2003).

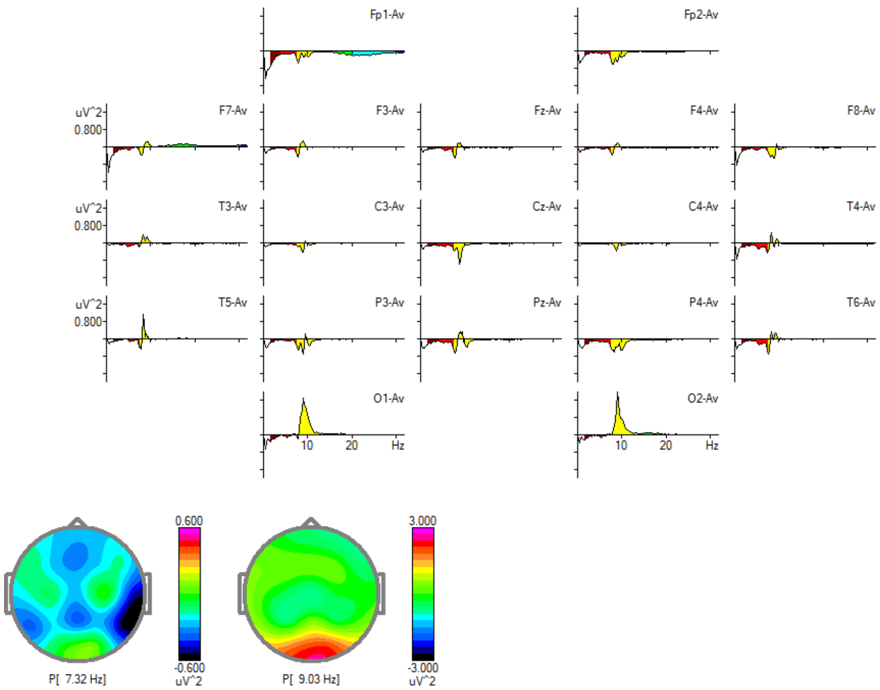

Fig. 1. Graphs of EEG power spectra; fragment: Eyes opened 12:32:41, Offset: 0.00 s, Length: 601.48 s, Number of epochs 1. Eyes open quantitative EEG generated comparison of Alpha frequency (7.32Hz and 9.03Hz) power (uV^2) at pre- and post-therapy assessment. Red-purple colour indicates an increase in power and dark blue colour indicates a decrease in power of Alpha rhythms in different brain locations.

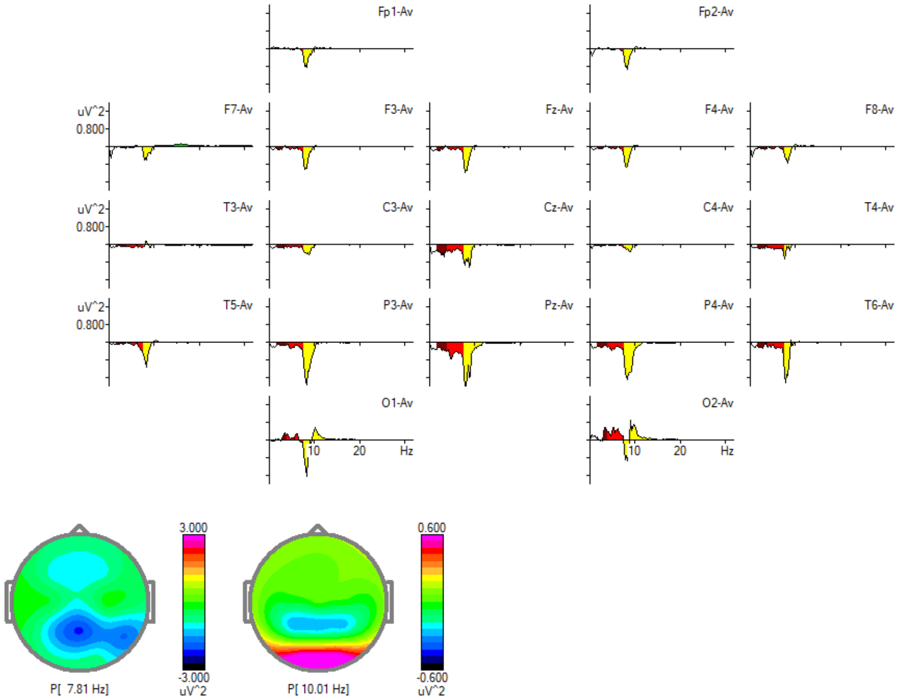

Fig. 2. Graphs of EEG power spectra; fragment: Eyes closed 12:42:49, Offset: 0.00 s, Length: 601.02 s, Number of epochs 1. Eyes closed quantitative EEG generated comparison of Alpha frequency (7.81Hz and 10.01Hz) power (uV^2) at pre- and post-therapy assessment. Red-purple colour indicates an increase in power and dark blue colour indicates a decrease in power of Alpha rhythms in different brain locations.

Fay's case was chosen because she represented a subgroup of clients seen at STARTTS who present with PTSD symptoms along with interpersonal and self-related vulnerabilities. These clients tended to have experienced early childhood trauma in addition to later war-related, refugee trauma and displacement and hence, generally present with more complex PTSD. This was evident for Fay in that she was still highly symptomatic following a year's worth of trauma-informed therapy. Following 37 neurofeedback sessions, Fay's symptoms decreased significantly, and she gained meaningful functional improvements. This suggests there may be a need for interventions that can target physiological instability and arousal dysregulation as part of the general goal of establishing safety and that this in turn will contribute to improved emotional regulation. Indeed, this is consistent with previous findings that demonstrated a significant reduction in PTSD symptoms and improvements in affect regulation following neurofeedback training (van der Kolk, et al., 2016).

Fay showed clinically significant reductions in her post-traumatic symptoms, anxiety and depression. Fay became progressively more stable in sessions, was less prone to emotional dysregulation and dissociation, and she reported improvements in sleep. These improvements suggest that a level of stability and safety was attained, which had not occurred until the addition of neurofeedback as an adjunct to therapy. Importantly, neurofeedback also gave Fay insight into previously unknown areas of her nervous system (i.e., her brainwaves), which helped place some of her symptoms in context. It also gave her a sense of control and empowerment in knowing that her brain was able to learn and change. Her improved emotional regulation was also evident in Fay's ability to withstand imaginal exposure exercises and undergo painful emotional processing relating to parental attachment. It is our hypothesis that this was achieved through the establishment of safety that allowed Fay to move away from the habitual fight/flight/freeze responses and to access the social engagement system (Porges, 2001). Lastly, Fay showed functional improvements in social and occupational spheres – she was able to make new social connections, to interview for a job and enrol in a study course. In her last session, Fay remarked how her memories which had caused her significant emotional pain were now better managed.

5. Conclusion

This case study highlights the potential use of neurofeedback as an adjunct to therapy, specifically by establishing a sense of safety through physiological stability, which may assist clients in their ability to process painful traumatic material and may be especially warranted in cases of complex and chronic trauma. A limitation of this study is the difficulty in differentiating the effects of neurofeedback from psychological therapy itself, although the fact that Fay had trauma-informed therapy as a standalone treatment for a year reduces this limitation somewhat. Another consideration is therapeutic alliance – it cannot be ruled out that a change in therapist produced these effects and therapeutic alliance has been shown to be a moderate contributing factor to therapy outcome (Martin, et al., 2000). Hence, further research is needed to investigate these factors and to generalise these results. Nonetheless, this case study highlights the importance of considering neurofeedback treatment as an adjunct to psychological therapy for trauma.

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EEG based Epileptic data classification using Long Short Term Memory (LSTM)

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Abstract

This study aims to analyze the Epileptic Electroencephalography (EEG) signals. The goal is to differentiate EEG patterns of epilepsy and non-epilepsy in subjects. The EEG of the subjects was recorded during and before the seizure occurred. Next, the features are automatically extracted from raw EEG data; later, these features are used for classification. Here, the long short-term memory (LSTM) algorithm was implemented as a classifier. The classification accuracy of more than 0.98 is achieved for both classes. These promising results make our model reliable for practical implementations.

Keywords: EEG, LSTM, deep learning, epilepsy.

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1. Introduction

There are 65 million people in the world that are affected by epilepsy. Epilepsy is the most severe neurological disease. It is also recognized as the most common chronic disease (Thurman et al., 2011). Epileptic patients usually suffer from misunderstanding, discrimination, and social stigma (Quintas et al., 2012) (Meyer et al., 2010). It is not easy to live with an unpredictable chronic disease as it can disrupt autonomy for daily life activities. With advances in medical science, epilepsy can be treated successfully in many cases. Still, the treatment is long-term, which affects the treatment process, especially in middle-income and low-income countries (Cameron et al., 2012). Furthermore, all patients do not respond to the medical treatment; sometimes, surgery is required, and other treatments such as neurostimulation to treat the disease. Therefore, looking at brain patterns can help in the treatment of epilepsy.

Electroencephalography (EEG) signals can be used for the identification of brain abnormalities associated with epilepsy seizures. These are represented as sharp spikes in EEG data. EEG epilepsy signals can be classified into four main categories: 1) interictal, 2) postictal, 3) seizure, and 4) preictal. Preictal is the time before a seizure occurs (Rahman et al., 2021). It remains activated in the brain for about fifteen minutes and can go up to one hour. Postictal is the time just after the seizure occurs. Interictal is the time between the two states, that is, postictal and preictal. Seizure depicts the phase where an actual seizure occurs (Rahman et al., 2021). However, many methods exist in the literature for epilepsy classification using EEG. The drawback of these EEG based epileptic seizure detection methods include low sensitivity and specificity. Sensitivity is usually ranging from 26 to 56%. Specificity is a bit better but still not reliable enough as, in some cases, it's as low as 78% (Asadzadeh et al., 2020). One possible reason is the diversity of patients in clinical settings (Benbadis et al., 2003). This paper uses the BONN university dataset to classify epilepsy and control groups.

2. Materials and Methods

2.1. Block Diagram

We propose using a deep learning algorithm called long short-term memory (LSTM) to recognize epileptic brain activity. The block diagram of the system is shown in figure 1. Here the input is the EEG dataset of the Control group and epileptic group. For the pipeline, the EEG dataset is given as input from the given data; features are extracted automatically and then classified into the two classes epilepsy and non-epilepsy.

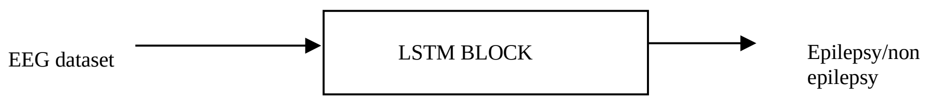

Figure 1. Block diagram of the system.

2.2. Dataset (EEG)

We utilize the publicly available Bonn epileptic database. Bonn dataset is categorized into five subsets (A - E). Data from 5 patients were recorded, and each subgroup contained 100 single-channel EEG signals of 23.6 seconds. The sampling frequency for the EEG recording was 173.61 Hz, and the signal resolution was 12-bits. The raw EEG dataset E contained epileptic seizure activity.

2.3. Recurrent Neural Network (RNN)

The significance of a Recurrent Neural Network (RNN) is that it utilizes sequential information, especially the time series data. If all the inputs and the corresponding outputs are independent of each other, then a traditional neural network can be used. However, this assumption of independence is not valid for the EEG time-series data, and hence for many tasks, that is not a good approach to follow. For example, consider a task that looks at the words in a sentence and then performs a prediction for the next word in that sentence. In order to achieve a good prediction of the upcoming word, it is better to have the knowledge and memory of the words preceding it. Here, for this example, RNN can be employed because they are recurrent in the sense that they perform the same task for every word of the sentence. The output depends on the previous computations, and it is already known that they have a "memory" that is involved in capturing and holding information about the previous computations. Issues of RNN include vanishing problem and exploding gradient problem. In this paper, we propose to use LSTM, which is a type of RNN.

2.4. Long short-term memory (LSTM)

1. Using LSTM for classification

LSTM is a type of RNN and RNN is a type of Neural Network. Therefore, just as a neural network can be used for classification, both RNN and LSTM can be used as classifiers. For the proposed LSTM scheme as a classifier, in addition to the input from the current time step, a hidden state is also used to hold the information from the previous time step. Hence, LSTM can perform classification with better results than RNN and Neural Network because of LSTM's good performance for EEG time series data. Since the Bonn dataset contains EEG time series data, LSTM is chosen among all other deep learning techniques.

2. Working Principle of LSTM

Traditional neural networks do not have persistence, and that is their major shortcoming. A recurrent neural network addresses this problem by having loops in them, which makes the information persist. The problem of RNN is long-term dependencies and hence LSTM is proposed to be used to address these dependencies. As mentioned above, the Long short-term memory (LSTM) deep learning networks are a type of RNN and they are involved in learning long-term dependencies. By default, LSTM remembers information because it has memory and can retain it for a long duration. The chain-like structure of LSTM with four layers is similar to RNN, though RNN has one layer only. The LSTM has gate structures, and this empowers LSTM to manipulate information by adding or removing them. Here, in this paper, the LSTM-based deep learning model has been proposed for the classification of epileptic and non-epileptic states using EEG brain waves. There are many techniques that can be used for further encoding, but this paper proposes to use one-hot encoding. Similarly, for the implementation of LSTM, tensor flow is used. The performance of the proposed method is evaluated using a confusion matrix. Figure 2 shows the LSTM architecture used in this paper. In figure 2, X_{t+1} is the input vector, H_t is the hidden state vector, W_f Is the weight vector, $tahh$ is the gate function, C_t is the Cell input activation vector, and finally σ is the forget gate activation function.

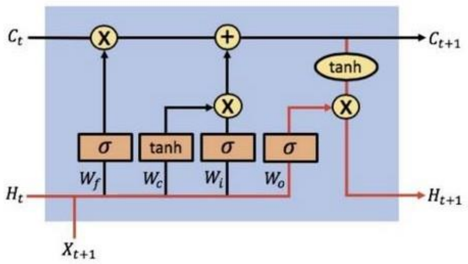

Figure 2. The LSTM architecture

3. Results

The dataset is split into 80% for training and 20% for testing. The labels are converted into one hot encoder as:

0 >> [1,0] and 1 >> [0,1].

The model is trained using the following parameters, and figure 3 shows the learning curve of the model.

- Batch size: which is the number of training examples defined in one iteration,
- Number of epochs: is a hyperparameter that explains how many times the learning algorithm works through the entire training dataset,
- Hidden size: It's the number of hidden units,
- Optimizer: It optimizes the attributes of the deep learning network.

For the implementation of the proposed method, following values are used for the above-mentioned parameters:

- Batch size: 16,
- Number of epochs: 25,
- Hidden size: 128,
- Optimizer: Adam optimizer is used for optimizing.

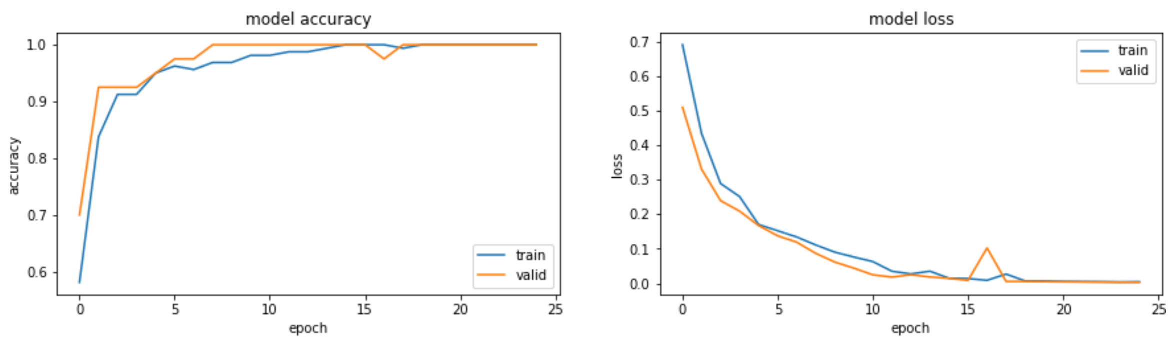

Figure 3. The learning curve of the LSTM model

The model is evaluated using the standard evaluation metrics of precision-recall and F-score using the formula stated is equation 1 to equation 3. Table 1 shows the confusion matrix and Figure 3 shows the ROC curve.

$$Precision = \frac{TP}{TP+FP} \qquad (1)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (2)$$

$$F1 = 2 * \frac{Precision*Recall}{Precision+Recall} \quad (3)$$

Table 1: Confusion matrix of the model

	precision	recall	f1-score	support
normal	1.00	1.00	1.00	20
epileptic	1.00	1.00	1.00	20
accuracy			1.00	40
macro avg	1.00	1.00	1.00	40
weighted avg	1.00	1.00	1.00	40

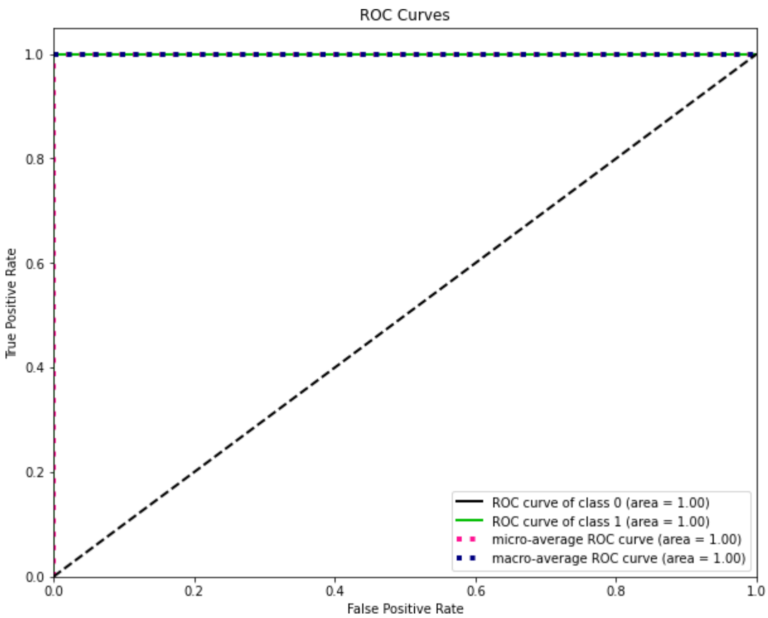

Figure 4. ROC curve of LSTM classifier

This study analysed epileptic and normal classes using EEG signals and Long short-term memory (LSTM) as a deep learning classifier. Participants were classified as epileptic or normal. The EEG signals were recorded from normal subjects and from subjects with epilepsy. Using EEG signals to identify epilepsy is important as it can help subjects with epilepsy in the future to predict seizures before time so that necessary preventive measures can be taken. However, this is just proof of concept with one subject only. This classification accuracy is expected to decrease with more subjects. As the dataset is small, overfitting is possible, which is the reason for obtaining100% accuracy. Including more subjects in the dataset will resolve overfitting and it is expected that the accuracy will be decreased from 100% to 95%-98%.

4. Conclusions

We have proposed a deep-learning model to distinguish epileptic EEG signatures from the Control in this work. EEG is recorded from 21 scalp sites using EEG electrodes. In this paper, we have proposed to use LSTM deep learning algorithm for classification. High classification accuracy was recorded for epilepsy and Control. The above results conclude that LSTM has good potential for classifying the EEG time-series signals.

References

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