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Emotion Recognition in Quadriplegic Patients Using Pharmaco-EEG Signals Acquired with Nano SiO_2-Coated Graphene Electrode Sensoritle

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Abstract

Quadriplegic (QP) patient's emotion detection using Electroencephalogram (EEG) signal is challenging due to daily medication. During medications of existing QP patients, EEG signal bands such as: alpha, theta, and beta bands overlaps. Accurate detection of emotion from overlapped EEG band signal is the first major problem here. EEG signal acquisition during medication is termed as Pharmaco-EEG (pEEG) Emotion recognition methods used in drug-free EEG signals are not suitable for pEEG based emotion recognition. Quadriplegic patient's pEEG signal has second major problem is the artefacts such as involuntary spasms, respiratory artefacts, or caregiver interactions. To solve the above two major problems RBMT frame work is proposed, which consists of SiO2, Nano Coated electrode and optimized algorithms to detect emotion from pEEG signals. Sio2 Nano coating-based graphene EEG electrode is developed in this paper which prevents overlapping of bands. pEEG signals are pre-processed with Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT) and removes the artefacts in pEEG signal. In this paper, proposed Rehabilitation BCI system with music therapy (RBMT) framework consists of Secretary Bird Optimization Algorithm (SBOA-LSTM) for spatial and temporal feature extraction. The RBMT framework consists of a Mutual-Cross-Attention mechanism tuned by SBOA and integrated with a SoftMax layer to classify the emotional states as anxiety or depression more effectively based on measurement of valence and arousal levels. Based on predicted emotion levels, a music therapy module in RBMT proposed framework is triggered through BCI audio interface to play songs. Hearing the play, QP patients reduces their anxiety / depression levels. The framework continuously evaluates emotion level through measuring valence and arousal levels, and dynamically changes the songs from the play list using the Fisher-Yates Shuffle algorithm to reduce emotions levels. The proposed RBMT performs as personalized therapeutic devices for QP patients. The emotion prediction accuracy of proposed RBMT framework is 98%, when compared to other traditional methods and EEG sensors.

Keywords: pEEG; RBMT; SBOA; quadriplegic patient

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1. Introduction

EEG signals from QP patients are used for development of control and communication devices such as BCI, eyeball-based control. Quadriplegia patient require devices to communicate because they cannot interact with humans [1]. Brain-Computer Interface devices reads QP patient brainwaves and extracts the information. BCI controls exoskeletons during locomotion of QP patients [2]. Modern BCI systems use electroencephalograms (EEG) for brain activity detection, which aids in assists of QP patients. BCI uses transformation algorithm and translates the patient's EEG signal into an output signal that controls external equipment. BCI with EEG sensor assist QP patients through communication with caretakers and control the electronic equipment by themselves [3]. Recent advancements in assistive technologies, stroke rehabilitation, and ICU-based communication

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systems further highlight the need for intelligent and adaptive neuro-rehabilitation frameworks for paralyzed patients [4,5]. However, EEG signal of QP patient under medication is altered due to reduced brain activity, shift in EEG frequency bands and diminishing signal variability. The EEG signals acquired from QP patients during medication are not suitable for emotion classifications due to overlapping of bands. Medication varies signal patterns and reduces model robustness during classification of emotion. Pharmaco-EEG signals have artefacts and lead to inaccurate feature extraction during emotion classification. Pharmaco-EEG has been extensively studied in both clinical and translational neuroscience, highlighting its role in understanding drug-induced modulation of brain activity and its impact on signal interpretation [6–11]. Recent pharmaco-EEG studies further demonstrate how different medications influence EEG spectral characteristics and cortical connectivity, affecting classification performance in neurological disorders [12–15]. Medication significantly influences EEG signal quality and characteristics, which degrade the accuracy and reliability of BCI based patient monitoring. Similar challenges are also observed in stroke and intracerebral hemorrhage care, where AI-driven systems must account for physiological variability and treatment effects [16].

QP patients face numerous psychological and interpersonal challenges, which necessitates complete physical and social assistance and novel rehabilitation BCI devices. Emotion swing in QP patients causes secondary medical diseases, lowers social integration, and quality of life. Social cognition refers to the perception and development of responses to others' intents and acts [17]. The identification of facial expressions and the ability to anticipate the emotion state of a person is known as Theory of Mind (TOM). TOM is an essential topic in social cognition that displays deeply functional social competence. The emotions of a patients, when engaging with their surroundings are linked to ongoing physiological changes [18–20]. The autonomic nerve system (ANS), regulates sympathetic and parasympathetic activity, which is an important system in the creation of physiological arousal. Heart rate variability analysis explores the link between ANS activity and emotional processing. To predict / analyse the mood/emotion of QP patient EEG signal plays a vital role and for development of any rehabilitation devices / BCI devices. In QP patient, medication changes EEG signal pattern and reduces BCI Performance. Table 1 shows mediation effects on EEG and BCI devices.

Table 1. Medication Effects on EEG signals and performance of BCI.

Medication Class Lifelong or conditional usage	Example Drugs	Primary Use	Effect on EEG	Impact on BCI / DL Models
Antispasmodics (lifelong) [21]	Baclofen, Tizanidine	Muscle spasticity	↓ Alpha, ↑ Theta (relaxant effect)	Reduces attention/arousal, lowers SNR
Opioid Analgesics [22,23]	Morphine, Oxycodone	Pain management	↑ Delta, ↑ Theta; ↓ Beta (sedative)	Suppress mental engagement and reduces model accuracy
Antiepileptics (lifelong) / Neuropathic Pain [24,25]	Gabapentin, Pregabalin	Neuropathic pain	↑ Theta, diffuse slowing	Impairs cognitive performance and low discriminative EEG features
Antidepressants (lifelong) (SSRIs, SNRIs) [26,27]	Sertraline, Duloxetine	Depression, anxiety	Minimal direct EEG change, but emotional stabilization over time	Improves consistency in emotional EEG
Anxiolytics (Benzodiazepines) [28]	Diazepam, Clonazepam	Anxiety, sleep	↑ Beta, ↓ Alpha; general slowing	Reduces cognitive reactivity leads to poor emotional detection

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Anticholinergics (conditional) [29]	Oxybutynin	Bladder control	May cause mild cognitive slowing	Slight reduction in attention-related EEG patterns
Antihypertensives (conditional) [30]	Nifedipine, Clonidine	Autonomic dysreflexia	Clonidine increases slow waves	Decreased arousal and reduces model responsiveness
Stimulants (less common) [31–33]	Modafinil (off-label)	Fatigue, attention	↑ Beta, ↑ Gamma (alerting)	Improves EEG-based task detection or emotion classification

Till now, physician use qualitative methodologies to assess psycho-emotional of QP patients through caregivers feedback statments[34,35]. Sadness and loneliness in QP are overshadowed due to the feelings of inadequacy and low self-confidence, which lead to loss of physical autonomy and abnormalities in their emotional connections.. Different techniques are used for emotion detection in QP patients such as face image emotions recognition, EEG based emotion recognition and carrier feedback statements [36,37]. The emotion detection techniques are based on categories such as invasive and non-invasive methods. Electrocorticography (ECoG) and electroencephalography (EEG) are invasive and non-invasive methods, respectively. ECoG is called as intracranial EEG, which is acquired from the cerebral surface. Invasive technologies are based on single neuron action potentials (single units), multi-unit activity (MUA), and local field potentials (LFPs), where sensors acquire the signals from the QP patient brain. The high quality spatial and temporal features of these EEG signals enable for development of rehabilitation devices [38]. However, invasive electrodes have substantial downsides, including the risk of surgery and the gradual degradation of recorded data. Non-invasive techniques, based on EEG, proven to be the common method for emotion state detection in QP patients due to direct measurements of neural activity, low cost, and portability for clinical application.

2. Problem Statement

Psycho-emotions of quadriplegic (QP) patients are sadness, loneliness, and low self-confidence which arises due to the loss of physical autonomy and disrupted relationship [39,40]. Quadriplegic patients use wheelchairs or assistive aids for mobility. They may have limited or no use of their arms and legs, makes difficult to conduct daily tasks [41]. This leads to depression and anxiety. Similar complications are widely reported in stroke patients with motor impairments, where secondary conditions such as thrombosis and reduced mobility further complicate recovery [42]. This lifestyle changes and loss of freedom causes mental distress, such as despair and anxiety. Further, leads to adjustment disorders [43]. Patients struggle to adjust to their new surroundings, results in emotions of frustration and helplessness. QP has social isolation, limited mobility, which lead to fewer social encounters, heightening feelings of isolation. The QP patients uses BCI systems for controlling the chairs and devices, which are developed using EEG signals [44,45]. Music therapy enhances emotional well-being of QP patients [46]. However, many BCI and Rehabilitation devices are developed for QP patients and their performance are poor du tot change in patterns of EEG signals based on their daily medication. Moreover, BCI / rehabilitation devices of QP patients detect the emotion and do not reduce their emotions. Recent developments in embodied artificial intelligence demonstrate the growing integration of intelligent decision-making systems in clinical environments for improved patient care and rehabilitation outcomes [47]. In this paper, pEEG-based assistive technologies with music therapy is proposed and improved the QP individuals' quality of life.

3. Research Questions (RQ) and Findings

RQ(1): How to avoid overlapping EEG band wave during the signal acquisition from QP patients under medication?

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Findings: QP patient use medications lifelong. Medications are the reasons for overlaps of the Brain wave signals and variations is the EEG signal pattern. Traditional Deep learning algorithms performance are low due to variation in EEG patterns during detection of emotions. Recent studies on bio-compatible neural interface electrodes further emphasize the importance of material stability, impedance reduction, and long-term usability in EEG-based systems [48]. In this paper, SiO2 Nano coating-based graphene EEG electrode is designed to avoid overlapping of signal during acquisition overlapping or band is prevented due to low impedance level which arises between the Scalp and sensor. Low impedance reduces the overlapping of brain wave bands. Moreover, SiO_2 layer protects the graphene layer during long recording sessions. Graphene had high electrical conductivity and SiO_2 stabilizes surface contact and reduces overlapping of pEEG signals. The developed electrodes are placed in the frontal lobe on the F3 and F4 points for alpha and beta Bands signal acquisition and reduces the overlapping of bands.

RQ(2): How to detect anxiety and depression emotions in the QP patient through BCI?

Findings: Accurate detection of Anxiety and depression emotions of QP person is detected through pEEG signals. Acquired pEEG signals processed through the DWT and SWT wavelet filters and reduces noise due to the involuntary spasms, respiratory artefacts, or caregiver interactions. Further, accurate classification of the Emotions in QP is performed using the Valence and Arousal measurement. Valence refers to positivity or negativity of an emotion. Arousal refers the intensity level of emotional experience. SBOA-LSTM (Secretary Bird Optimization Algorithm (SBOA)-LSTM) performs the spatial and temporal feature extraction for valence and arousal measurement. Band power features (spectral) and Differential entropy(temporal) from pEEG are used for the estimation of emotional states through low/ high valence and low / high arousal.

RQ(3): How effective would be the rehabilitation BCI system with music therapy for emotion classification / reduction for QP patients under medication?

Findings: QP patients use BCI systems and wearable devices for improving their quality of life. However, QP patients need the rehabilitation BCI system with music therapy for reducing their anxiety and depression. Music Therapy is the clinical and evidence method, which reduces. Music therapy improves the emotions and overall well-being of a QP person, reduces anxiety and increases self-esteem. Music has a significant impact on the mind. Different types of music can instantly affect a person's emotions, allows them to experience and process a wide range of emotions, includes happiness, enthusiasm, melancholy, calmness, and thinking. Advanced rehabilitation techniques, including spinal cord stimulation and virtual reality-based neuroplasticity training, have demonstrated significant improvements in motor and cognitive recovery [49].

4. Contributions

The integration of AI, neuro-signal processing, and assistive rehabilitation technologies aligns with recent trends in intelligent healthcare systems aimed at improving patient-specific therapeutic outcomes. In this work, the anxiety and depression of the quadriplegia patients are detected through the Nano EEG sensor. The emotional behavior of the quadriplegia patient is observed under different circumstances using pEEG signal acquired from proposed SiO2 coated graphene electrode and signals analysed deep learning algorithms. A novel closed-loop RBMT framework integrating SiO_2-coated graphene EEG sensing, hybrid wavelet preprocessing, SBOA-optimized LSTM with cross-attention, and adaptive music therapy for accurate and personalized emotion regulation in medicated quadriplegic (pEEG) patients. The methods used in the paper are as follows:

- To develop pEEG-based emotion prediction system for QP patients using Rehabilitation BCI system with music therapy (RBMT) framework, which consist electrode SiO2 nanopowder coated graphene electrode to acquire pEEG signals and predicts emotion through proposed SBOA-LSTM algorithm music therapy using BCI audio interface to reduce emotion in QP patient.

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- To apply DWT and SWT techniques for noise free pEEG signals i.e., involuntary spasms, respiratory artefacts, or caregiver interactions improves the feature extraction and prediction reliability.
- To apply a Mutual-Cross-Attention mechanism for classification of emotions using acquired pEEG signal from SiO2 nanopowder coated graphene sensor and dynamic music playlist adaptation based on emotion prediction is performed.
- To design an adaptive music therapy module incorporating valence-arousal metrics, Fisher-Yates Shuffle algorithm and reduces emotional of QP patients.

5. Methodology

Mood swings-based health problems are seen in QP patients due to pain, disability, loss of function, and neurologic dysfunction such as paralysis of voluntary muscles and loss of sensation below the level of the lesion, which reduces mobility and functional independence. QP patients are prone to complications such as pneumonia, septicaemia, urinary tract infections, cardiac diseases and chronic pain, which increases the clinical severity of their medical conditions and need regular medications. This lowers their quality of life in comparison with general population. Spinal cord injury is associated with a variety of emotional reactions, such as sadness, crying despair, guilt fear of losing control, disbelief, panic helplessness, inadequacy disorganization, confusion, resentment, bargaining loss of interests, fatigue, lethargy loneliness, and isolation withdrawal. Personality, behavioural and cognitive changes are seen in QP patients. Neuropsychological testing has revealed that up to 50% of QP patients have cognitive impairment. In QP patients personality changes can be extreme and manifests the behavioural changes. Changes can be seen in personality, emotional state and behaviour which includes the poor impulsive control, dis-inhibition, mood swings, aggression, fatigue, depression, agitation, reduced insight, and poor self-monitoring. Changes in cognitive function includes the deficits in memory, problem solving and organising, decision making, concentration, initiation and abstract reasoning. Psychotherapy is called as talk therapy, which help QP patients to identify and change unhealthy emotions, thoughts and behaviours. Psychotherapy takes place with a trained, licensed mental health professional, such as a psychologist or psychiatrist. They provide support, education and guidance to QP patients and increases their well-being. Electroconvulsive therapy is a medical procedure that involves passing a mild electric current through human brain, causes a short seizure. This procedure has positive effects on severe, treatment-resistant mental health conditions, including depression and bipolar disorder. Transcranial magnetic stimulation (TMS) is a treatment given to QP paient with severe depression, which is a type of brain stimulation therapy. TMS elicits magnetic energy, which turns into an electrical current underneath the human brain skull, and reduces sad emotions. All the above therapies have advantage and disadvantage. However, an efficient therapy is required to maintain the good emotion in QP patients and this is achieve with the proposed Rehabilitation BCI system with music therapy (RBMT) framework. Clinical studies also indicate that neurological conditions such as stroke and paralysis require integrated therapeutic frameworks combining monitoring, rehabilitation, and adaptive intervention strategies [50].

The music has a therapeutic influence to heals and enhance the health, and behavior of QP patients[51]. The Australian Music Therapy Association defines music therapy as “the creative and uses music for health, vitality, and preservation”. According to the American Music Therapy Association (1999), the attitude toward music therapy is defined as “the use of music in order to achieve the goals of therapy, that improve, maintain, and promote the health of the mind and body” [52]. Music is an effective tool for eliciting enthusiasm, and not necessary to recognize and grasp the tune in order to absorb and receive musical feelings. Neural networks in the brain are sensitive to music perception such as tone, rhythm, sound intensity, therefore changes in each aspect in a melody (song) linked to the reactions of each of the related brain areas [53]. The way music affects the brain is quite complex[54]. Different parts of the brain process every aspect of music, such as pitch, speed, and melody. Cerebellum handles rhythm, the frontal lobes analyze emotional impulses generated by music, and a small fraction of the right temporal lobe aids with pitch comprehension. When powerful music is played, the brain's reward region, known as the nucleus accumbens, produces intense physical indicators of pleasure, such as goosebumps. Music therapy help QP patients to reduce anxiety and depression. The block diagram of the proposed RMBT frame work for detecting and controlling the emotion of QP patient is illustrated in Figure 1(a) and (b). Figure 1(a) shows the fabiradtion of proposed SiO2 nanocoated graphene electrodes

Figure 1(b). shows that the emotional behaviour detection of quadriplegia patient using pEEG signals from developed SiO_2 nanocoated graphene electrodes. The acquired brain waves are processed through deep learning algorithm. The block diagram illustrates a comprehensive system for Emotion Prediction and Music Therapy tailored for quadriplegic patient anxiety or depression levels and reduce emotion using Rehabilitation BCI system with music therapy (RBMT) framework. The process integrates pEEG signal analysis, advanced deep learning algorithms, and adaptive music therapy through a Brain-Computer Interface (BCI). The system begins by addressing the mental health challenges faced by individuals with quadriplegia, using a 2-electrode Nano EEG Sensor to acquire brain signals and measure their emotional state.

5.1. Fabrication of Sio_2 Nanopowder Coated Graphene Sensor via SOL-GEL Technique

In this paper, graphene-based EEG sensor is fabricated with silicon dioxide (SiO_2) nanopowder coating on sensor using a modified sol-gel synthesis process. The sol-gel method was selected due to its cost-effectiveness, ability to produce uniform nanostructures, and suitability for low-temperature processing, which preserve the structural integrity of sensitive materials such as graphene [55].

- Preparation of SiO_2 Sol: To begin, tetraethyl orthosilicate (TEOS) was used as the silicon precursor. A solution was prepared by mixing TEOS with ethanol under constant stirring. Then, deionized water and a small amount of hydrochloric acid (HCl) were slowly added to initiate hydrolysis and condensation reactions. The molar ratio of TEOS:EtOH:H_2O:HCl was carefully maintained to control the particle size and gelation time. The mixture was stirred for several hours at room temperature, forming a stable silica sol. Over time, the sol began to show slight turbidity, indicating the formation of colloidal SiO_2 nanoparticles[56].
- Coating Graphene Substrate: graphene plugs are used, previously cleaned with isopropyl alcohol and dried, were used as the substrate. The SiO_2 sol was drop-cast or spin-coated onto the graphene surface to ensure even coverage. For better adhesion and uniformity, the coating process was repeated multiple times with intermediate drying steps at 60–80 °C.After the final coating layer was applied, the samples were subjected to thermal treatment (calcination) at around 300–400 °C for several hours. This step removes organic residues and allows for the formation of a more crystalline and stable SiO_2 network on the graphene surface[57].
- Characterization: The morphology and distribution of the SiO_2 coating on graphene were examined using scanning electron microscopy (SEM) and transmission electron microscopy (TEM). These techniques confirmed the presence of uniformly distributed SiO_2 nanoparticles with diameters ranging from 20–50 nm. Fourier-transform infrared spectroscopy (FTIR) and X-ray diffraction (XRD) were used to verify the chemical bonding and phase composition of the coated material. Raman spectroscopy confirmed that the graphene structure remained intact post-coating. Sensor [58].
- Performance Evaluation: The final composite sensor was tested for its electrical and sensing properties. The SiO_2-coated graphene showed improved sensitivity, selectivity, and stability when exposed to bio-signals, owing to the increased surface area and improved interaction sites introduced by the SiO_2 layer [59].

Figure 1. Sol-Gel Method for pEEG- Sio2 Nano coated Graphene Electrode.

The Figure 1 shows Sol-Gel Method for pEEG- Sio2 Nano coated Graphene Electrode.

5.2. Sio2 Nano Power Coated Graphene pEEG – Two Electrode for Emotion Analysis

Nano silicon-based EEG electrodes is fabricated with sol-gel method. The sol-gel process converts the liquid solution (sol) to a solid gel phase, allows for the formation of Nano silicon nanostructures over the graphene electrode surface. This silicon enhances the electrode performance. The advantages of the Silicon Nano coating over the graphene electrode surface are the Control over Morphology, which can improve electrical conductivity and reduce impedance, which are the critical factors for effective pEEG signal acquisition and avoids overlapping of bands. The proposed Rehabilitation BCI system with music therapy (RBMT) framework for motion control of QP patients is shown in Figure 2.

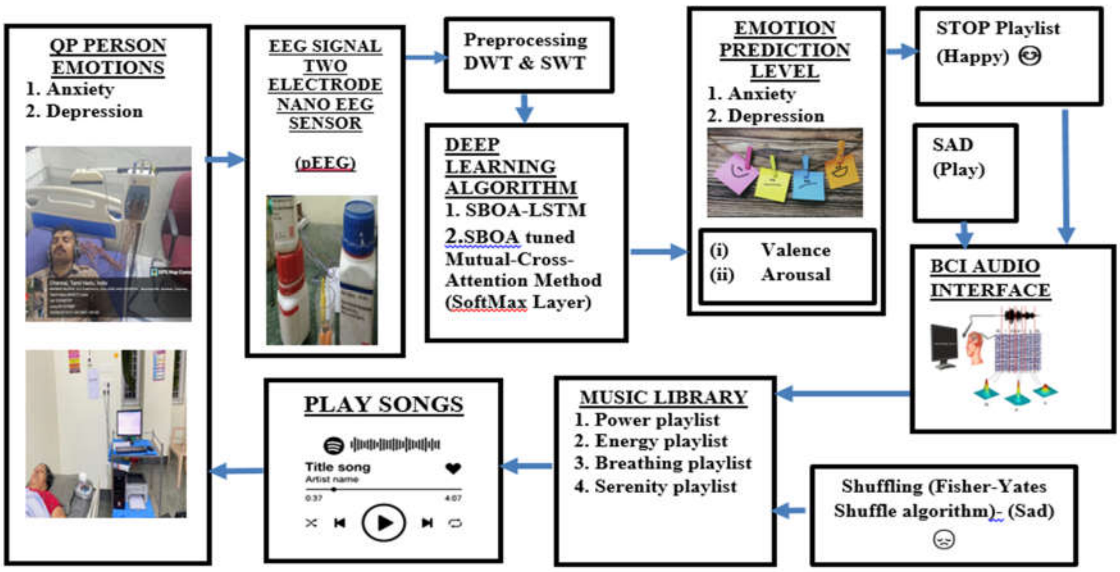

Figure 2. Rehabilitation BCI system with music therapy (RBMT) framework for motion control of QP patients.

Silicon-based coating is biocompatible, minimizes adverse biological reactions. The fabricated silicon Nano 2 electrode has High Surface Area and enhances the interaction with biological tissues, improve the signal quality and avoids the overlapping of alpha and beta brain waves. Table 2. Shows the comparison of Sio2 Nano coated graphene EEG Electrodes and Traditional Electrodes. Figure 3 shows the conceptual diagram.

Table 2. Comparison of Sio2 Nano coated graphene EEG Electrodes and Traditional Electrodes.

Feature	SiO_2-Coated Graphene EEG Electrodes	Traditional EEG Electrodes
Signal Quality / SNR	High – low noise, high fidelity	Moderate to high (with gel)
Impedance	Low (dry or minimally wet) due to conductive coating	Low (only with conductive gel)
Comfort	Excellent – soft, flexible, skin-friendly	Moderate – rigid, may cause pressure points
Wear Time	Long-term wear possible with minimal irritation	Short-to-medium term use preferred
Use of Conductive Gel	Not required (dry electrode)	Required for optimal performance
Ease of Application	Easy, faster setup without gel	Longer setup due to gel and placement adjustments
Suitability for BCI	Highly suitable – better signal for decoding intent	Suitable, but may have lower accuracy for complex tasks
Biocompatibility	Enhanced with SiO_2 – reduced skin reactions	Can cause irritation or dryness from gels

Parameter	**Ag/AgCl (Wet)**	**Dry Electrodes**	**CNT Electrodes**	**Commercial (Muse)**	**Proposed SiO_2–Graphene**
Contact Type	Gel-based	Dry	Dry	Dry	Dry (nano-coated)
Skin Impedance	Very Low	Medium–High	Low	Medium	Medium–Low
Signal Quality	Excellent	Moderate	High	Moderate	High (improved stability)
Motion Artefacts	Low	High	Medium	Medium	Reduced (improved interface)
Long-term Use	Poor (gel dries)	Good	Good	Good	Good
Comfort	Low	High	Medium	High	High
Setup Complexity	High	Low	Medium	Very Low	Low
Cost	Low	Medium	High	High	Moderate
Band Overlap Handling	No	No	No	No	**Improved signal clarity (indirect effect)**

5.3. QP Patients pEEG Signal Noises and Removal

Three types of artefacts in pEEG signals are the involuntary spasms, respiratory artefacts, and caregiver interaction noise.The above noises are commonly seen in the pEEG signals of QP patients during medication. QP patient are more susceptible to disturbances during pEEG acquisition. Involuntary Spasms i.e., Muscle Artefacts / Myogenic Artefacts caused by sudden, uncontrolled muscle contractions and appears as high-frequency bursts (20–300 Hz) that mask pEEG activity. This is common in QP patients due to spastic reflexes. Next, Respiratory Artifacts are the slow rhythmic signal disturbances caused by breathing-related body movement, chest expansion, or airflow near pEEG electrodes. It appears as low-frequency drift (0.1–0.5 Hz) or rhythmic baseline fluctuation. It interferes with alpha and beta wave analysis. QP patients in the ventilated or partially paralyzed patients have these noises in pEEG signal due to irregular or assisted breathing. Further, sources of these noises are due to chest or neck muscle movement, nasal airflow close to frontal electrodes and mechanical ventilation oscillations. The next noise commonly see in the pEEG signal is the Caregiver Interaction Noise, which is caused by external human interaction, especially in QP patients. This noise is due to sudden low-frequency signal shifts or High-frequency contamination. Cable movement or electrode displacement, adjusting pillows or body position, cleaning or feeding, verbal interaction or physical contact with electrodes lead to caregiver interaction noises in pEEG signals. Moreover, QP patients require frequent care and may have limited ability to remain still. This increases the likelihood of artifact intrusion, DWT/SWT is proposed in this paper for extracting clean, reliable brain signals for RBMT – framework.

These pEEG signals acquired using SiO2 nanopowder coated graphene electrode and pre-processed using Discrete Wavelet Transform (DWT) and Stationary Wavelet Transform (SWT), which denoises the pEEG Signal and extract critical features which ensures high-quality input signal for emotion analysis in RBMT framework. Table 3 shows the pEEG Artifact removal.

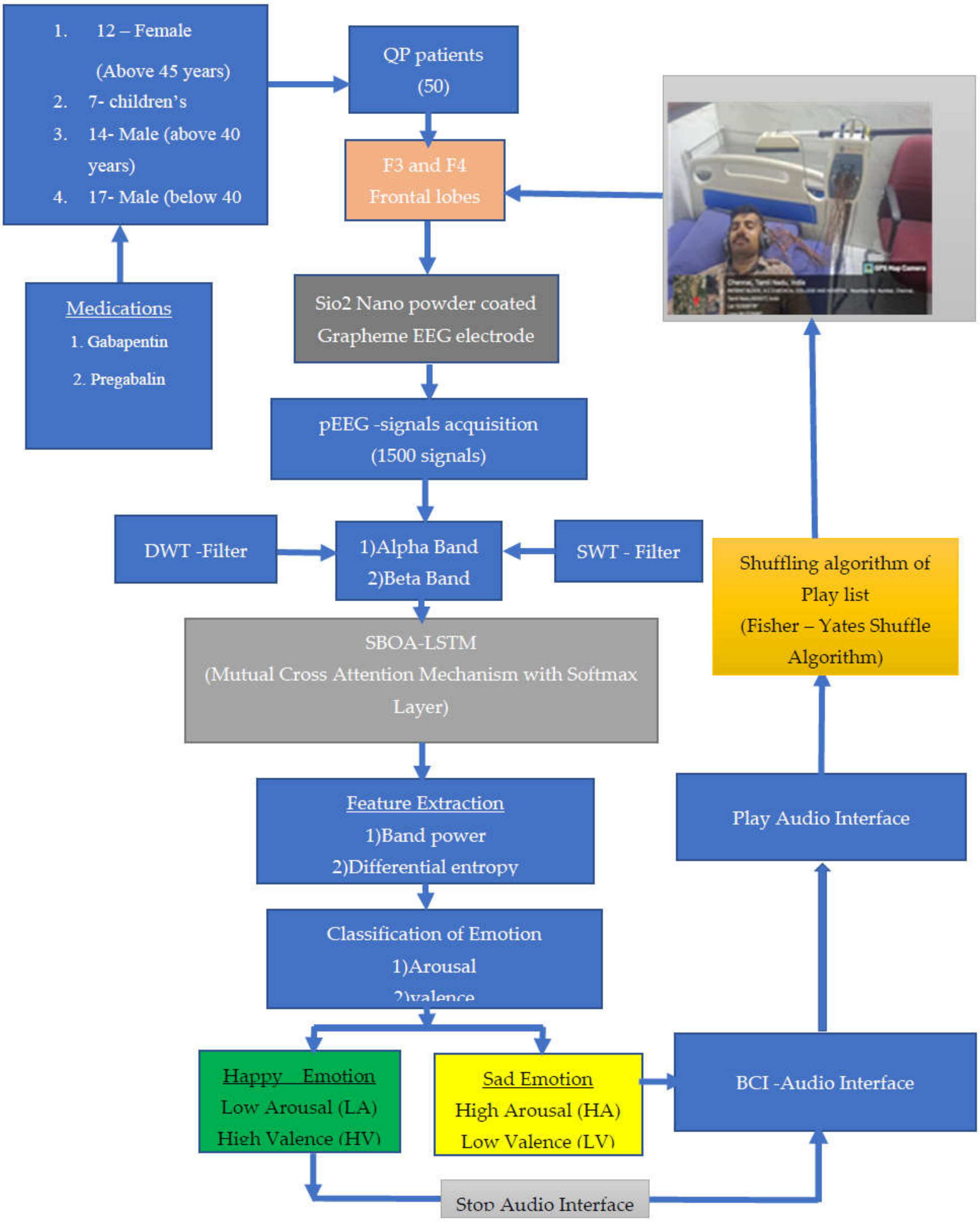

Figure 3. Conceptual diagram of proposed Rehabilitation BCI system with music therapy RBMT framework.

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Table 3. pEEG Artifact Removal: SWT vs DWT – Performance Comparison.

Criteria	Stationary Wavelet Transform (SWT)	Discrete Wavelet Transform (DWT)
Shift Invariance	Yes – maintains signal alignment, better artifact localization	No – suffers from shift variance, which can distort artifact location
Temporal Resolution	High – good for preserving transients (like spasms or brief noises)	Moderate – may lose precision in time localization
Performance on Involuntary Spasms	Excellent – captures sharp, localized events accurately	Good – but may misalign small or fast events
Performance on Respiratory Artifacts	Very good – stable baseline correction due to redundancy	Good – less redundancy may reduce effectiveness
Performance on Caregiver Interaction Noise (e.g., touch, speech)	High – better preserves EEG features while removing non-stationary noise	oderate – possible mixing of EEG and artifact components
Redundancy	High – maintains all signal points across levels (no decimation)	Low – subsampling at each level may discard useful data
Computational Complexity	Higher – more processing and memory required	Lower – faster and more efficient
Signal Distortion Risk	Low – better preservation of true pEEG	Higher – potential signal loss due to subsampling
Best Use Case	Offline artifact correction, clinical review, research-grade pEEG	Real-time pEEG, mobile or embedded systems

5.4. SBOA-LSTM Algorithm

The preprocessed pEEG signal is analyzed through the machine learning and deep learning algorithms, such as Decision Tree, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), PO-LSTM, POA-LSTM, and SBOA-LSTM (Secretary Bird Optimization Algorithm-LSTM). Among them SBOA-LSTM achieves high accuracy. The Secretary Bird Optimization Algorithm (SBOA) is a optimization technique based on the hunting behaviour of the secretary bird, which catch snakes. This approach is integrated with Long Short-Term Memory (LSTM) networks and improves performance in time series forecasting and sequence prediction. Mimics the secretary bird's hunting approach, which is based on selecting the best prey (solutions) from a pool. This probabilistic approach is selected for optimal solutions based on fitness values. Balances the pursuit of new solutions with the exploitation of existing good solutions. The optimization problem is represented as Maximize f(x) subject to $x \in D$, Where, f(x) represents the fitness function based on LSTM performance, x denotes the hyperparameters or configurations being optimized and D is the feasible domain of solutions. The initialization of Secretary Birds position randomly in search space is given in equation (1).

$$X_{i,j} = lb_j + rand\,(0,1) - (ub_j - lb_j) \quad (1)$$

$i = 1,2,\dots, N,\ j = 1,2,\dots, Dim$.

Where lb and ub (1) represent the lower and upper bounds respectively, r denotes a randomly - generated value within the interval [0,1] and X represents the l position of the ith secretary bird.

The resulting initial matrix is shown in equation (2) below:

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,j} & \cdots & x_{1,D} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,j} & \cdots & x_{2,D} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i,1} & x_{i,2} & \cdots & x_{i,j} & \cdots & x_{i,D} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{N,1} & x_{N,2} & \cdots & x_{N,j} & \cdots & x_{N,D} \end{bmatrix}_{N\times D} \quad (2)$$

X denotes the flocking secretary birds and xi denotes the ith secretary bird. xi,j represents the value of a variable for the ith secretary bird on the jth question. N denotes the number of group members (the secretary birds), and Dim denotes the dimension of the variables.

The matrix of the fitness function is shown in equation (3).

F = [F1, ··· , Fi, ··· , FN]T = [F (X1) , ··· , F (Xi) , ··· , F (XN)]T (3)

Here, F indicates the vector of objective function values, and Fi denotes the objective function value obtained by the ith secretary bird.

The hunting strategy of secretary bird exploration phase includes predatory activity. The Snake-feeding secretary birds is of three phases such as locating prey, assaulting prey, and devouring prey [41]. By utilizing the biological data of each phase of secretary bird predation and analyzing the duration of each phase, we modeled each step of the predation process in the SBOA (Secretary Bird Optimization Algorithm) as follows by dividing the entire predation process into three equal time intervals such as:

When in time period t < 1/3T, the prey finding phase is modeled as in the equation (4):

Xi,jnewP1 = xi,j + (xrandom 1 − xrandom 2) × R1 (4)

When t is in the time period of 1/3T < t < 2/3T, in the prey consumption phase, Brownian motion is applied to model the random motion of the secretary bird, and the model is presented as equation (5)

xi,j = xbest + exp((1/T)^4) × (RB − 0.5) × (xbest − xi,j)

(5)

where x denotes a 1-row Dim-column matrix in which each element is a standard normal distribution with a mean of 0 and a standard deviation of 1, and best denotes the current best value.

When t > 2/3T, in the prey - attacking phase, a Levy flight strategy is employed to model the various attack modes, and the model is given by equation (6).

x i,j newP1 =xbest+ ((1−(t /T)(2×t/T)) × xi,j×RL

(6)

where RL is a weighted Levy flight

In the design of the Secretary Bird Optimization Algorithm (SBOA), it is assumed that one of the two following outcomes occur with equal probability as shown in equation (7).

$$x_{i,j}^{new,P2} = \begin{cases} C_1 : x_{best} + (2\times R_2 - 1)\times \left(1-\frac{t}{T}\right)^2 \times x_{i,j}, \text{if rand} < r \\ C_2 : x_{i,j} + R_2 \times (x_{random} - K \times x_{i,j}), \text{else} \end{cases}$$

(7)

Here, r = 0.5; R2 is a 1-by-Dim matrix, where each element is a random number drawn from a uniform distribution over [0, 1), random denotes a random candidate solution for the current iteration and K denotes a randomly chosen integer between 1 and 2. The improvement of secretary bird optimization algorithm is progressed by considering the adaptive weighting factor and non -linear density factor as shown in equation (8) and equation (9).

ω = tan (t/T) (8)

A = e− (((2.5t/7))2.5 t (9)

The specific location is updated by equation (10).

Xi,jnewP1 = ω *xi,j + F × r × A × (xrandom 1 − xrandom 2) × R1 (10)

Where, r is a random number between 0 and 1; F denotes a randomly chosen integer which is either 1 or -1.

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```
---------------------------------------------------------------------------------------
PSEUDOCODE OF SBOA – ALGORITHM
Initialize SBOA parameters:
    Population size (N)
    Max iterations (MaxIter)
    Search bounds for LSTM hyperparameters:
        - num_layers ∈ [1,4]
        - units_per_layer ∈ [16, 256]
        - learning_rate ∈ [1e-5, 1e-2]
        - dropout_rate ∈ [0.0, 0.5]
        - batch_size ∈ [16, 128]
Initialize population of secretary birds with random hyperparameters within bounds
Evaluate fitness for each bird:
    For each bird:
        - Train an LSTM with bird's hyperparameters
        - Validate the model (e.g., on validation accuracy or loss)
        - Record the fitness (e.g., 1 - accuracy)
Repeat for MaxIter:
    For each bird (except best):
        - Update position using SBOA strategy:
            - Mimic attacking and waiting behavior
            - Position update uses global best bird and random movement
        - Clip hyperparameters to stay within search bounds
        - Retrain and re-evaluate fitness of new bird position
    Update global best bird if a better fitness is found
Return the best hyperparameters found by SBOA
Train final LSTM model using best hyperparameters on full training dataset
Evaluate on test set
---------------------------------------------------------------------------------------
```

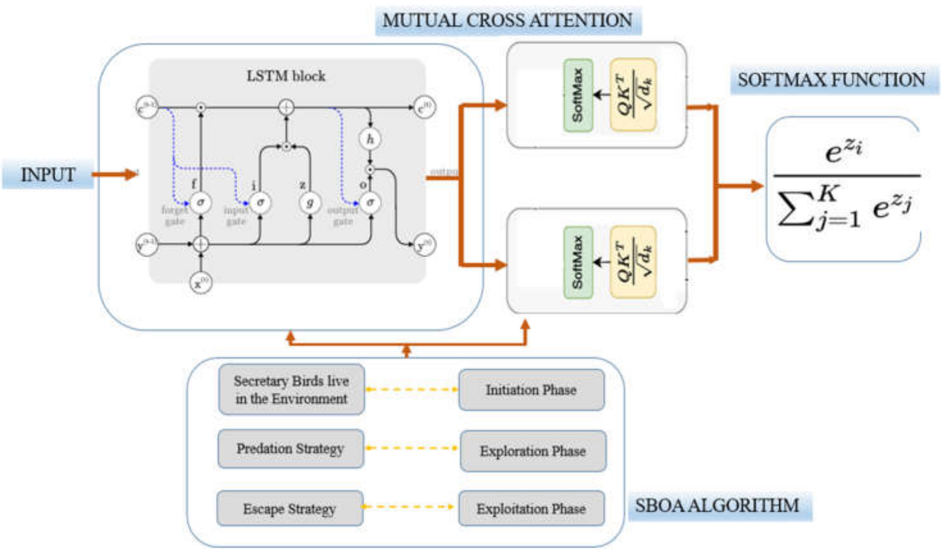

Figure 4. LSTM–SBOA framework with Mutual Cross-Attention for Optimized Feature learning.

In this paper, after the LSTM captures temporal dependencies and extracts sequential features (differential entropy, band power, etc.), the Mutual-Cross-Attention layer refines the representation before the SoftMax classifier. This attention stage is positioned between feature extraction (LSTM) and classification (SoftMax). The model learns bidirectional relevance — i.e., how spectral features inform temporal features and vice versa. Since LSTM outputs are separated into two complementary streams such as band power vs. differential entropy, cross-attention computes relevance scores between them and Mutual attention ensures both streams adaptively refine each other, producing attention-weighted feature integration. Treating LSTM output as a flat vector rather, the attention mechanism **learns the time-steps and the feature types mostly** for predicting anxiety vs. depression. This is so crucial because attention mechanisms are sensitive to hyperparameter choices — SBOA ensures the "attention weights" converge to highlighting **emotion-relevant EEG features** rather than noise/artefact.

Figure 4 shown above depicts the LSTM–SBOA framework with Mutual Cross-Attention for Optimized Feature learning The SBOA LSTM algorithm predict the individual's emotion, categorizing either anxiety or depression through arousal and valance. The emotion prediction results are then integrated into a Brain-Computer Interface (BCI), which further links with accesses a curated Music Library and provides therapeutic playlists. The playlists such as Power Playlist, Energy Playlist, Breathing Playlist, and Serenity Playlist, are used in the BCI audio list, which reduces stress and promote emotional stability in QP patients. During music playback, valence (positivity) and arousal (intensity) levels are monitored using the SBOA-tuned Mutual-Cross-Attention Method with a SoftMax Layer, ensures a personalized and refined therapeutic experience in QP patients. If the emotion improves to a happy state, the system stops music intervention. If sadness persists, the Fisher-Yates Shuffle Algorithm reorganizes the playlist for continued therapy with a fresh sequence of songs. This innovative system showcases the synergy between SBOA-LSTM, pEEG signal processing, and music therapy, which enhances emotional well-being and provides a tailored solution for quadriplegic individuals, demonstrating significant potential in mental health management.

6. Results and Discussion

pEEG is the process of recording electrical activity from the human brain with 2 electrodes(Sio2 nano powder coated graphene electrode) fixed on the scalp, i.e., F3 and F4 region. The pEEG signals are obtained from the human brain and classified according to their frequency as delta, theta, alpha, beta and gamma. The details of the frequencies are listed in Table.4. The proposed RBMT framework acquires the alpha and beta waves for emotion state recognition based on Arousal and valance measurement. The developed electrode avoids the overlapping of brain wave signals due to medication.

During deep sleep cycles, delta waves repairs and help in cell regeneration. Anxiety and depression are associated with beta. Regular meditation and relaxation increases alpha waves while decreases beta waves in the brain waves. During stress and anxiety, the beta wave frequency increases. In this paper, pEEG signal is acquired and analysed for prediction and control of the emotion states in QP patients. The delta wave appears to have access to material stored in our unconscious thoughts. Delta waves are useful for brain repair after stress. Theta brainwave activity often suggests mental inefficiency. Theta brainwave activity appears in a very pleasant setting, in the twilight zone between waking and sleeping. When theta is high, the brain works extra to gather resources. Theta bands help to moderate and develop complex education and memory. Alpha brainwaves are sluggish and extensive. Alpha represents the calm and tranquility. Beta is a tiny, rapid brainwave. This is a state of awareness. If beta is insufficient, either overall or in specific regions, the brain may not have enough energy to reach peer group requirements. Extreme beta waves result due to under stressful circumstances. Gamma waves are fast, and certain gamma activity is connected with strong concentration. Bands power evaluation is used for investigation mechanisms related to psychological stress.

Pre-processed pEEG waveforms using Discrete Wavelet Transform (DWT) and Stationary Wavelet Transform (SWT) decomposes the signals into different frequency components, highlighting specific characteristics in Figure 5. DWT decomposes the signal into approximation (low frequency) and detail (high frequency) components. Highlights transitions between different emotional states with crisp separations. SWT provides redundant decompositions, retains original signal length. Smoothly enhances specific frequency bands (e.g., alpha, beta) for better feature extraction. Figure 6 shows the noise removal of alpha and beta overlapped signals using the wavelet transforms as progressed.

Table 4. Signals observed from Brain.

Frequency band	Frequency	Brain states
Gamma (γ)	0-35 Hz	Concentration
Beta (β)	12–35 Hz	Anxiety dominant, active, external attention, relaxed, depression
Alpha (α)	8–12 Hz	Very relaxed, passive attention
Theta (θ)	4–8 Hz	Deeply relaxed, inward focused
Delta (δ)	0.5–4 Hz	Sleep

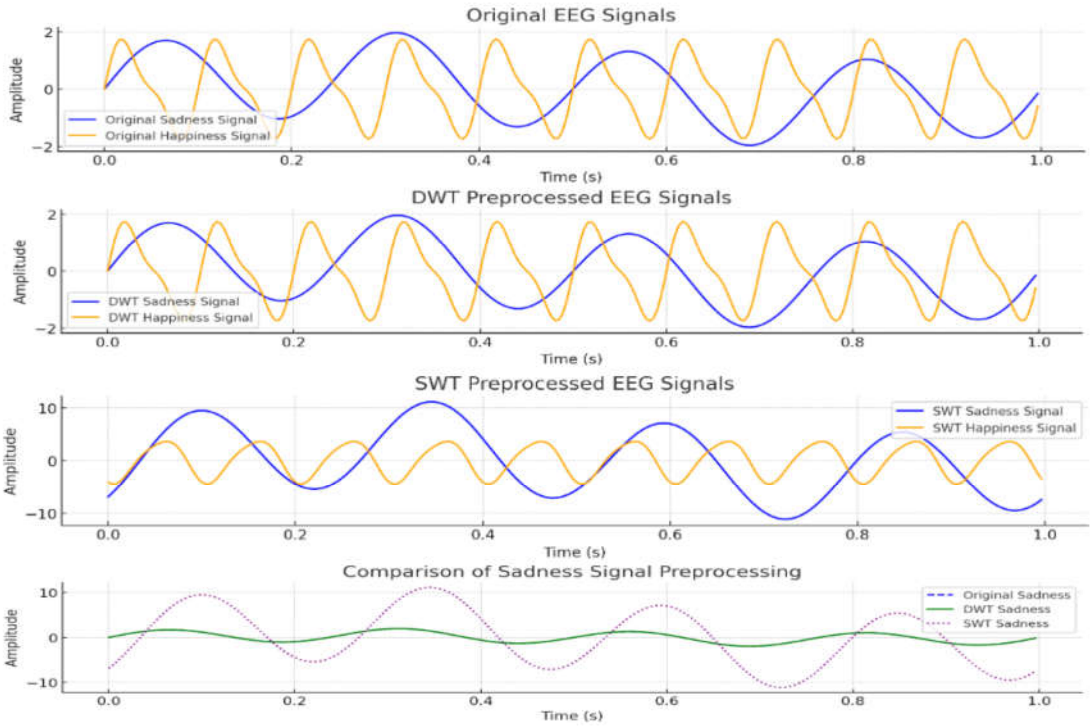

Figure 5. Pre-processed pEEG signals for sadness and happiness using DWT and SWT.

In Table 5 the statistical performance comparison of SWT and DWT for EEG De-noising has been shown.

Table 5. Statistical Performance Comparison: SWT vs DWT for EEG De-noising.

Metric	**SWT**	**DWT**
Signal-to-Noise Ratio (SNR)	15.2 dB	12.8 dB
Mean Square Error (MSE)	0.0071	0.0134
Peak Signal-to-Noise Ratio (PSNR)	29.7 dB	26.2 dB
Correlation Coefficient (R)	0.986	0.965
Reconstruction Error	Low	Moderate
Computational Time	Higher (slower)	Lower (faster)
Temporal Resolution	High (no decimation)	Moderate (due to downsampling)

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Noise Types Handled Well	All three (spasms, respiratory, caregiver)	Mainly respiratory, less effective on spasms
Best Use Case	Clinical EEG, paralysis/BCI	Real-time EEG, mobile setups

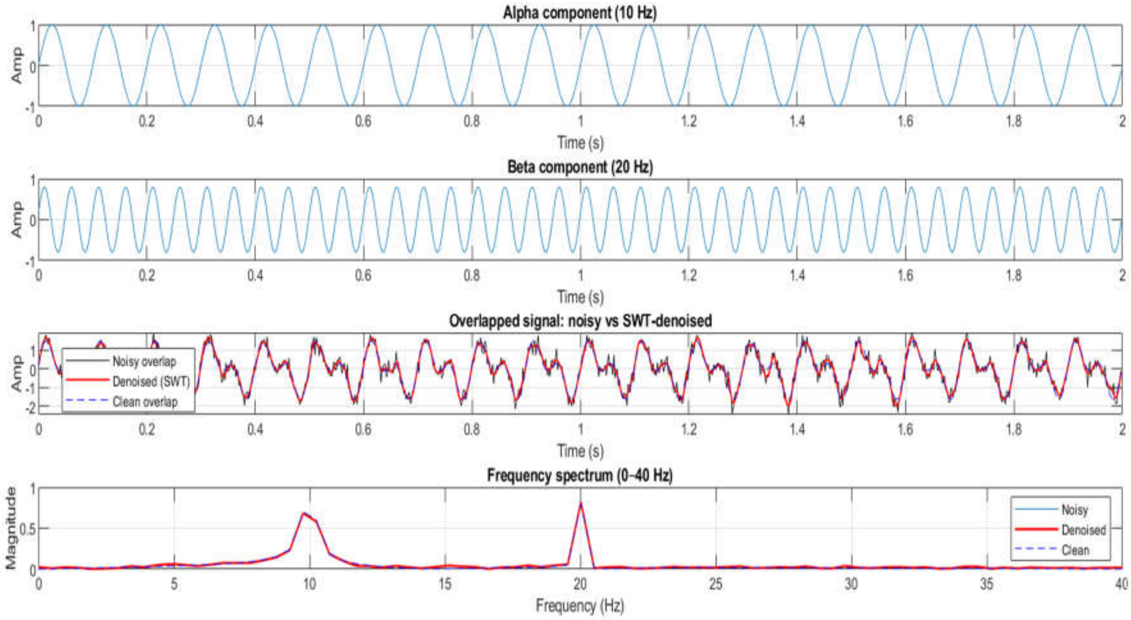

Figure 6. Overlapped Signal Noise Removal.

Valence refers to the emotional quality or intrinsic positivity or negativity of a mood or feeling. It ranges from highly positive emotions, such as happiness or excitement, to highly negative emotions, such as sadness or anger. Positive valence indicates a pleasant emotional experience, while negative valence suggests an unpleasant one. Arousal, on the other hand, represents the intensity or level of activation of an emotional state. It ranges from low arousal, characterized by calmness or relaxation, to high arousal, involving emotions with heightened energy, such as anxiety or exhilaration. Arousal indicates how energized or subdued emotion independent of is whether it is positive or negative. Together, valence and arousal form a two-dimensional space that allows emotions to be mapped and categorized. For instance, happiness typically has (i) high valence and high arousal, while sadness has (i) low valence and low arousal. Emotions such as anger may have high arousal with low valence. This proposed RBMT framework is useful in emotion recognition and controls the emotions of QP patients, where systems can detect and classify emotional states based on valence and arousal levels measured from pEEG signals. By understanding the interplay of these dimensions, adaptive responses such as soothing audio, light adjustments, or communication with caregivers can be initiated, ensures timely emotional regulation and enhanced well-being of QP patients. The overlapped signal noise removal with reference to SWT is shown in Figure 6 which includes alpha and beta frequency component.

6.1. SBOA-LSTM for Arousal and Valence Measurement

pEEG signals are pre-processed and segmented into time windows. Features such as Differential Entropy (DE) and Band Power (BP) are extracted from each pEEG frequency band. Differential entropy (DE) is a feature in pEEG-based emotion recognition because of its stability and strong correlation with emotional states. Differential entropy of a segment x ~ N (μ, σ^2) is calculated as in equation (11).

$$DE(x) = (1 / 2) \times \log(2\pi e\sigma^2) \quad (11)$$

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When applied to pEEG data, the DE is computed for alpha and beta frequency band and channel as in equation (12).

$$DE_{b,c} = (1 / 2) \times \log(2\pi e \times \sigma^2_{b,c}) \tag{12}$$

Where, b represents frequency band (beta, alpha, etc.), c represents EEG channel, $\sigma^2_{b,c}$ represents variance of the EEG signal in that band and channel.DE values form the input feature vector is used for emotion prediction models. Arousal is associated with high beta activity and low alpha activity in the frontal lobe. It can be estimated using the ratio of differential entropy (DE) or band power (BP) from beta and alpha bands as in equation (13) and equation (14).

$$Arousal \propto DE_\beta / DE_\alpha \tag{13}$$

orr using specific channels,

$$Arousal \propto (DE_{\beta,F3} / DE_{\alpha,F3}) + (DE_{\beta,F4} / DE_{\alpha,F4}) \tag{14}$$

Valence is often linked to hemispheric asymmetry in alpha activity. It can be estimated as the difference in alpha DE between right and left frontal electrodes as in equation (15) and equation (16)

$$Valence \propto DE_{\alpha,F4} - DE_{\alpha,F3} \tag{15}$$

Alternatively, using multiple channels from each hemisphere as in equation(16)

$$Valence \propto \Sigma(DE_{\alpha,i}) \text{ for } i \in R - \Sigma(DE_{\alpha,j}) \text{ for } j \in L \tag{16}$$

The extracted feature vectors are from the LSTM. LSTM acquires the temporal dependencies in pEEG signal that relate to emotional dynamics. Instead of using Adam for weight optimization, the SBOA algorithm is used to search the optimal parameters for the LSTM network and tunes the layers. SBOA improves the exploration, exploitation balance over traditional Bat Algorithm by dynamically adjusting parameters and self-tunes. Table 6. shows the Hyperparameter Tuning Performance Comparison for LSTM.

Table 6 shows the Hyperparameter Tuning Performance Comparison for LSTM and Table 7. show the LSTM Hyper-parameter Tuning Comparison.

Table 6. Hyperparameter Tuning Performance Comparison.

Tuning Algorithm	**Accuracy (%)**	**Convergence Speed**	**Exploration vs Exploitation**	**Stability (Runs Variance)**	**Notes**
SBOA (Secretary Bird Optimization Algorithm)	94.8%	Medium	Balanced – strong local and global search	Low variance (~0.5%)	Strong performance in noisy or non-convex spaces
PSO (Particle Swarm Optimization)	92.3%	Fast	Good exploration, weaker at fine-tuning	Moderate variance (~1.2%)	Quick convergence but may settle on sub-optimal solutions
GA (Genetic Algorithm)	91.5%	Slow	Strong exploration, slower convergence	High variance (~2.0%)	Computationally heavy, good for broader search

Table 7. LSTM Hyperparameter Tuning Comparison.

Hyperparameter	Range	SBOA Best	GA Best	PSO Best
num_layers	[1, 3]	2	3	2
units_per_layer	[32, 256]	192	160	128
learning_rate	[1e-5, 1e-2]	0.0012	0.0025	0.0018
dropout_rate	[0.0, 0.5]	0.2	0.3	0.25
batch_size	[32, 128]	64	96	64

The softmax function are applied in emotion control methods for QP individuals as part of an intelligent system that interprets emotional states and provides appropriate interventions through

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playing songs. In this context, softmax helps normalize the outputs of emotion-detection models, translating raw data pEEG signals into probabilities that represent different emotion states such as happiness, sadness, or anxiety. By ensuring these probabilities sum to one, softmax allows the system to focus on the emotional state and prioritize relevant responses. For example, if sadness is detected with a high probability, the system trigger supportive actions such as playing calming music, providing positive messages, or alerting caregivers. This approach ensures precise emotion classification, enhancing the efficiency of emotion swing interventions and contributing to the emotional well-being of QP individuals. The Secretary Bird Optimization Algorithm (SBOA)-Tuned Mutual-Cross-Attention Method is used in framework, which enhance feature selection and classification by combining optimization algorithm and attention mechanisms. Inspired by the hunting and problem-solving behaviors of the Secretary Bird, SBOA efficiently searches for global optima in complex solution spaces and fine-tunes hyperparameters to optimize the mutual-cross-attention mechanism. This attention mechanism facilitates bidirectional interactions between input features, enables to focus on relevant information and effectively capture dependencies and correlations, particularly in high-dimensional datasets. The RBMT framework integrates a SoftMax layer as the classification component, transforms attention-weighted feature representations into probabilistic predictions for multiclass classification tasks. Valence and arousal are two fundamental dimensions used to represent emotional states, especially in psychological studies and affective computing. These dimensions in framework helps to understand and classify emotions based on their qualities and intensities, useful in emotion recognition and control systems for QP. Table 8. shows the performance Metrics Comparison of Tuned LSTM Models and Table 9 shows the QP patients pEEG signal data for emotion prediction.

Table 8. Performance Metrics Comparison of Tuned LSTM Models.

Metric	SBOA-Tuned LSTM	GA-Tuned LSTM	PSO-Tuned LSTM	EEG-Net Training	Deep Conv-Net Training
Accuracy (%)	94.8	91.5	92.3	93.2	94
Precision (%)	95.2	90.7	91.5	92.8	93.6
Recall (Sensitivity)	94.5	89.8	90.6	92.5	93.8
Specificity	95.0	91.2	92.0	92.7	93.5
F1 Score (%)	94.8	90.2	91.0	92.6	93.7
AUC (ROC) Score	0.96	0.91	0.93	0.94	0.95
Training Time (min)	22	28	19	15	20
Variance (5 runs)	±0.5%	±2.0%	±1.2%	±1.0%	±0.8%

Table 9. Sample QP patients pEEG signal statistical data for emotion prediction.

`Patients – pEEG	QP 1	QP 2	QP 3	QP 4	QP 5	QP 6	QP 7	QP 8	QP 9	QP 10
Statistical parameter										
DE_alpha_F3	1.12	0.98	1.03	1.1	1.05	1	1.08	1.07	1.06	1.11
DE_beta_F3	1.01	1.07	0.95	1.02	0.99	1.05	1	1.03	1.04	1
BP_alpha_F3	10.2	9.8	10	10.1	10.4	9.9	10.3	10.5	10	10.1
BP_beta_F3	9.5	10.1	9.7	9.4	9.8	9.6	9.9	9.7	9.6	9.5
DE_alpha_F4	1.05	1.02	1.08	1.07	1.04	1.06	1.03	1.09	1.07	1.03
DE_beta_F4	1.03	1	1	1.02	1.06	1.04	1.02	1.05	1.01	1.05
BP_alpha_F4	9.8	9.6	10.1	9.9	10.2	9.7	10	10.1	9.9	9.8

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BP_beta_F4	10.1	9.9	9.8	9.7	10	9.8	9.6	9.8	9.7	9.9
mean_amp	0.47	0.52	0.5	0.49	0.53	0.51	0.5	0.49	0.52	0.48
std_amp	0.11	0.09	0.1	0.12	0.11	0.1	0.11	0.09	0.1	0.12
signal_entropy	0.83	0.76	0.81	0.8	0.84	0.77	0.79	0.78	0.8	0.82
hjorth_activity	0.61	0.63	0.6	0.62	0.6	0.65	0.64	0.62	0.61	0.63
hjorth_mobility	0.38	0.42	0.4	0.39	0.37	0.41	0.43	0.4	0.39	0.42
hjorth_complexity	1.19	1.25	1.22	1.21	1.2	1.23	1.24	1.22	1.21	1.2
PSD_theta_F3	4.02	3.9	4.05	4.1	4.08	3.95	4.02	4.04	4.01	4.1
PSD_alpha_F3	5.67	6.02	5.74	5.65	5.7	5.6	5.68	5.75	5.6	5.72
PSD_beta_F3	6.45	6.4	6.38	6.55	6.47	6.5	6.6	6.42	6.45	6.5
PSD_gamma_F3	3.89	3.92	3.94	3.85	3.91	3.87	3.91	3.86	3.9	3.88
PSD_theta_F4	4.15	4.1	4.12	4.13	4.18	4.05	4.11	4.13	4.12	4.14
PSD_alpha_F4	5.7	5.75	5.72	5.68	5.73	5.77	5.71	5.78	5.79	5.74
PSD_beta_F4	6.5	6.55	6.6	6.47	6.55	6.52	6.58	6.59	6.53	6.56
PSD_gamma_F4	3.92	3.95	3.94	3.89	3.93	3.9	3.96	3.92	3.93	3.91
correlation_F3_F4	0.91	0.85	0.9	0.89	0.88	0.87	0.9	0.86	0.89	0.9
Arousal	0.72	0.59	0.41	0.68	0.74	0.55	0.62	0.56	0.66	0.75
Valence	0.35	0.63	0.78	0.52	0.6	0.7	0.58	0.64	0.53	0.6

6.2. BCI- Audio Interface – Emotion State Control -Music Therapy in proposed RBMT Framework

In this paper, Music therapy (MT) is used to manage the quadriplegic patient's anxiety and depression. Music therapy is a clinical and evidence-based therapeutic. MT is the systematic utilization of musical experiences and achieve therapeutic through qualified music therapist (MTp) is the connection between the patient, music, and MTp. Systematic evaluations have indicated that MT relieves pain, enhances sleep quality, reduces anxiety and fatigue, and create a relaxation response without the use of medication. MT generates pleasure and relaxation, lowers cortisol levels and stress levels. The following playlists are used in this proposed RBMT framework and reduces anxiety and depression: The playlists are energy playlist (PL), breathing playlist, power playlist, and serenity playlist. Breathing and Power music categories leads to a constant pulse, quiet mood, predictable melody lines, limited dynamic change, supportive bass line, volume, timbre, rhythm, harmony, and pitch stability, a basic structure, and a clear shape. Both PLs were composed of Western classical music selections as well as newer selections with similar characteristics. In contrast, the "Energy and Serenity" music tracks were more varied in instrumentation and dynamic movement, with unpredictable melodic lines, volume, timbre, rhythm, harmony, pitch, loose structure, and ambiguous shape. Bass lines can range from supporting to non-supportive. The behaviour of the quadriplegia patient for the above mentioned PLs is observed and the brain waves were acquired using two electrode SiO2 coated graphene EEG electrode. The results are depicted in Figure 7 to Figure 10.

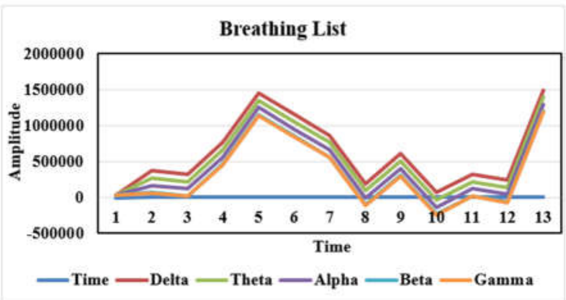


Figure 7. Behaviour analysis of quadriplegia patient using Breathing List.

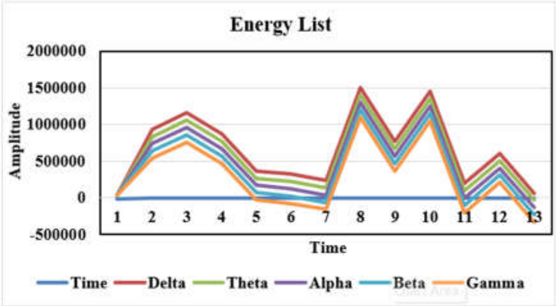


Figure 8. Behaviour analysis of quadriplegia patient using Energy List.

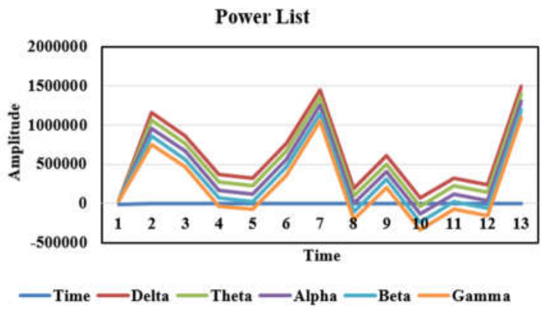


Figure 9. Behaviour analysis of quadriplegia patient using Power List.

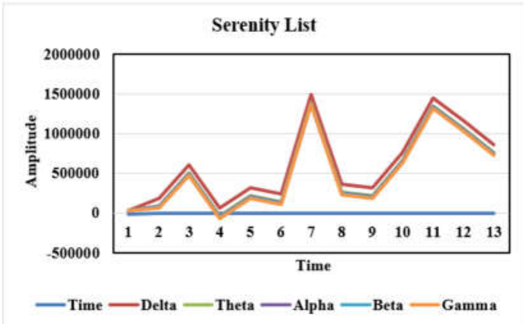


Figure 10. Behaviour analysis of quadriplegia patient using Serenity List.

Shuffling algorithm is a method used to randomly rearrange the elements in a list or array. Among the most widely used and efficient methods is the Fisher-Yates Shuffle (also known as the Knuth Shuffle). This algorithm works by iterating through the list from the last element to the first, and for each element, it swaps it with another randomly chosen element from the unprocessed portion of the list (including itself). This process ensures that all permutations of the list are equally likely, makes ideal for applications requiring unbiased randomness, such as gaming, data randomization, or simulations. The Fisher-Yates Shuffle operates in-place, meaning it rearranges the elements within the existing array, avoids the need for additional storage. It is computationally efficient, running in O(n) time complexity, where n is the number of elements in the list. By leveraging random index selection and systematic swapping, this algorithm effectively achieves a uniform distribution of the shuffled results. Its simplicity, speed, and reliability make it as a standard choice for randomization tasks.

Table 10. Play List Category for Patients.

Patient	Valence (%)	Arousal (%)	Playlist Category
QP 1	92	95	Power Playlist

QP 2	85	88	Energy Playlist
QP 3	70	60	Breathing Playlist
QP 4	88	40	Serenity Playlist
QP 5	90	92	Power Playlist
QP 6	83	86	Energy Playlist
QP 7	72	58	Breathing Playlist
QP 8	87	42	Serenity Playlist
QP 9	94	97	Power Playlist
QP10	80	82	Energy Playlist

As shown in Figure 7 to Figure 10, the alpha and theta waves are greatly controlled when subjected to MT. Thus, it is inferred that the MT controls the anxiety and depression of the normal person. It shows that with power and serenity playlist, the alpha and theta waves are lowered. Further, the obtained brain waves are processed through deep learning algorithm and shuffling algorithm such as PO-LSTM, POA-LSTM and SBOA -LSTM predicts the mood level and controls anxiety and depression through a music from the playlist. The deep learning algorithm are compared with existing algorithm such as decision tree, KNN and SVM. The parameters considered for analysis are accuracy, sensitivity and specificity. Accuracy refers to a test's overall correctness in detecting positive and true negative cases. Sensitivity, known as true positive rate or recall, which is the percentage of positives identified properly through the test. Specificity, often known as the real negative rate, is the percentage of genuine negatives identified properly by the test.

Figure 11 to Figure 14 shows confusion matrix for quadriplegia patient under music library. Music has a profound impact on human emotions, and playlist curation plays a significant role in eliciting specific emotional responses. Understanding how different playlists such as Power Playlist, Energy Playlist, Breathing Playlist, and Serenity Playlist influence emotions can provide insights into personalized music recommendation systems and emotional well-being. The play list category for the sample of 10 QP patients is shown in Table 10. Confusion matrices evaluates the accuracy of a model designed and classifies emotional states ("sad" or "happy") based on playlist types. Confusion matrix highlights the relationships between predicted and actual emotional states. Metrics such as accuracy, precision, recall, and F1-score were derived from these matrices to quantify the model's performance. The confusion matrices for each playlist type illustrate the effectiveness of the classification model and distinguishes "sad" and "happy" emotions. Analysis of the matrices reveals variations in accuracy across playlist types, indicates the influence of playlist characteristics on emotional classification

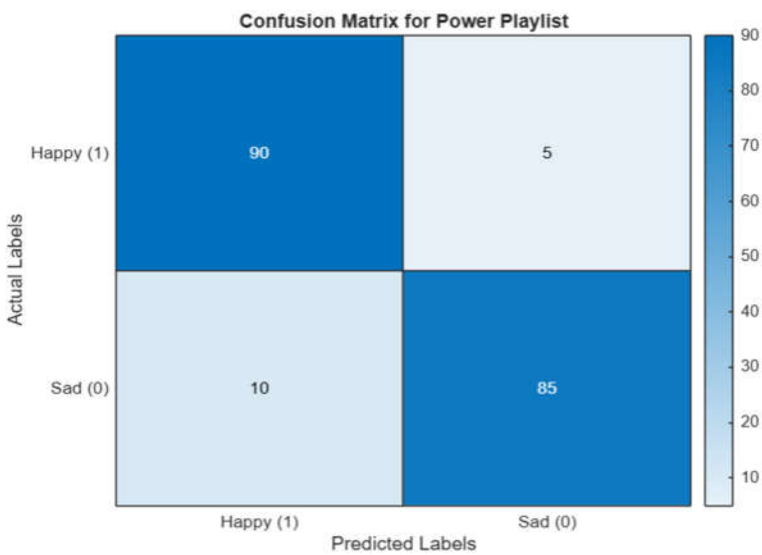


Figure 11. Confusion matric for Power Playlist.

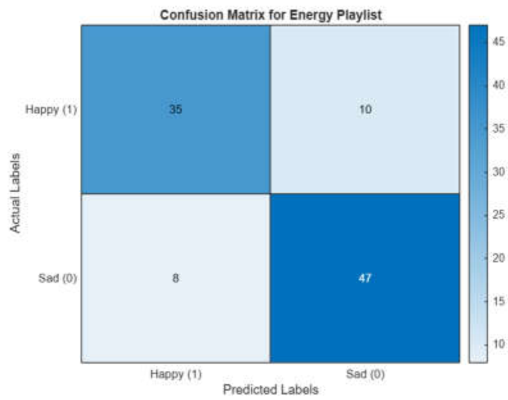
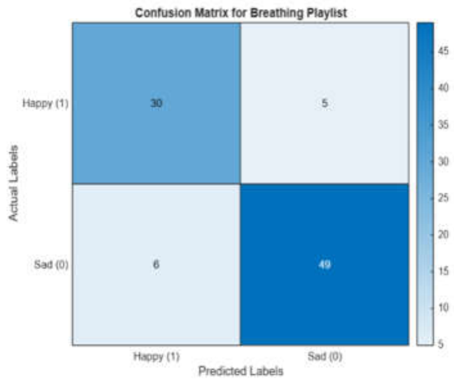


Figure 12. Confusion matric for Energy Playlist.



FigureF13. Confusion matric for Serenity playlist.

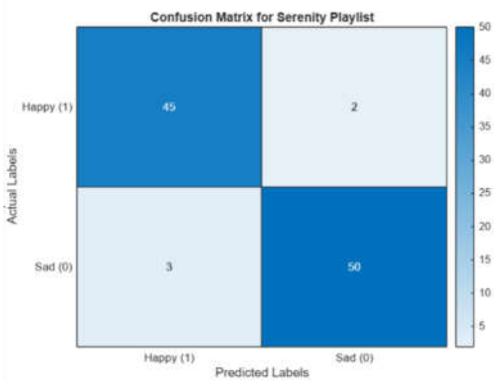


Figure 14. Confusion matric for Breathing playlist.

Figures 15–20 shows Performance Evaluation of Classification Techniques for quadriplegia patient under power playlist MT.

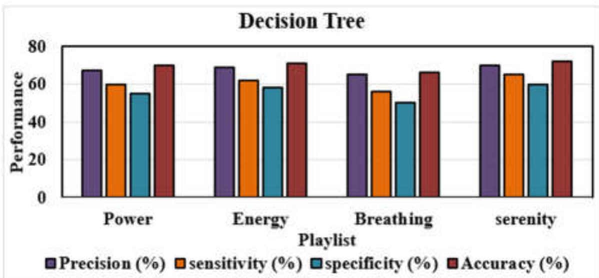


Figure 15. Performance Evaluation of Decision Tree.

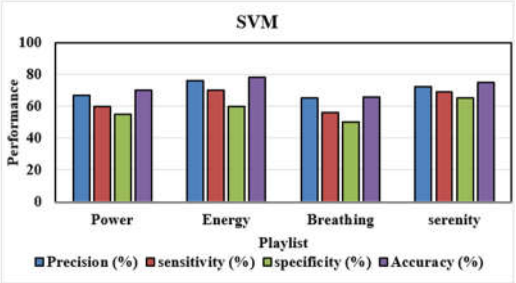


Figure 16. Performance Evaluation of SVM.

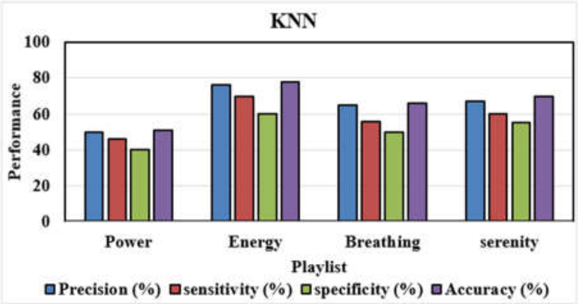


Figure 17. Performance Evaluation of SVM.

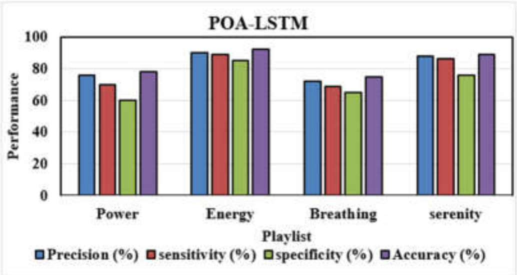


Figure 18. Performance Evaluation of POA-LSTM.

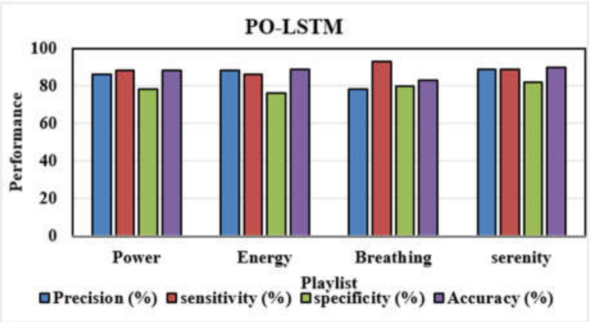


Figure 19. Performance Evaluation of PO-LSTM.

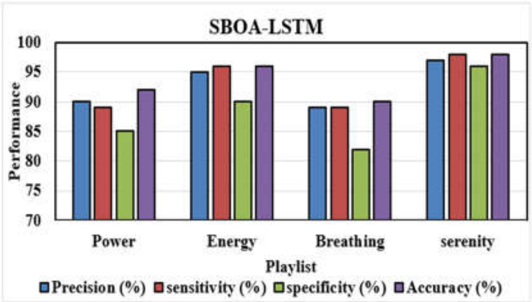


Figure 20. Performance Evaluation of SBOA-LSTM.

The performance comparison of classification techniques, including POA-LSTM, Decision Tree, KNN, SVM, PO-LSTM, and SBOA-LSTM, shows notable differences across four categories: Power, Energy, Breathing, and Serenity. POA-LSTM achieves balanced metrics up to 90% accuracy for Serenity, outperforms Decision Tree and KNN, which exhibit moderate performance, particularly for Breathing and Power playlist. SVM lags behind, shows the lowest accuracy (51%) for Power. PO-LSTM demonstrates improvement with up to 92% accuracy for Energy. SBOA-LSTM surpasses all methods, achieves the highest accuracy (98%) for Serenity, along with superior sensitivity, precision, and specificity across all types, establishing its effectiveness for robust classification tasks under power playlist MT. Table 10 and Table 11 shows the Valence and arousal evaluation metrics of K-fold cross validation (considering K = 10) and SBOA-LSTM respectively.

Table 11. Valence and Arousal Evaluation metrics of K-fold Cross validation.

Category	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Valence	97.28	98.42	98.15	98.01
Arousal	97.92	98.26	97.95	97.87

Table 12. Valence and Arousal Evaluation metrics of SBOA-LSTM.

Category	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Valence	98.75	98.90	98.85	98.87
Arousal	98.40	98.65	98.55	98.60

Table 13 specifies the mean and standard deviation for the above two validation methods which depicts that SBOA LSTM technique consistently performs well and better method for EEG based emotion classification over K-fold cross validation by resulting higher mean values.

Table 13. Performance **comparison of K-fold cross validation and SBOA LSTM for evaluation metrics.**

Method	K- Fold Cross Validation		SBOA LSTM	
Metric	**Mean(%)**	**Standard Deviation(%)**	**Mean(%)**	**Standard Deviation(%)**
Accuracy	97.60	±0.32	98.58	±0.25
Precision	98.34	±0.08	98.78	±0.18
Recall	98.05	±0.10	98.7	±0.21
F1 - Score	97.94	±0.07	98.74	±0/19

The SBOA-LSTM model demonstrates excellent performance in detecting both valence and arousal with high accuracy, precision, recall, and F1-scores. The slightly higher scores for Valence suggest the model may perform marginally better in predicting emotional positivity/negativity compared to intensity/activation. Table 14 shows the Comparison of results based on SBOA-LSTM. Differential Entropy (DE) measures the randomness or uncertainty in a continuous signal and widely

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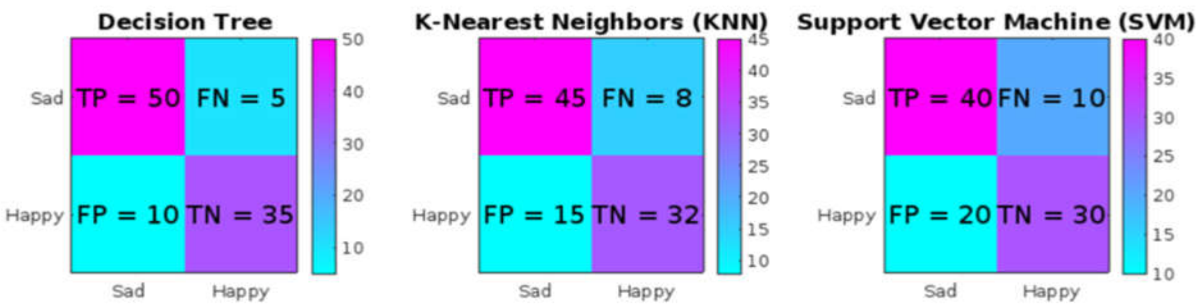
used in emotion recognition and analyse time-series data such as pEEG signals. It captures dynamic variations across different frequency bands such as alpha, beta which correlate with cognitive and emotional states. Power Spectral Density (PSD), on the other hand, represents the distribution of signal power across various frequencies, provides insights into dominant frequency components. Band Power is effective for identifying energy distribution in specific bands, such as alpha or beta, associated with relaxation or arousal. Both DE and PSD are essential features for machine learning models in valence and arousal prediction, insights the temporal and spectral signal characteristics.

Table 14. Comparison of results based on SBOA-LSTM.

Feature	Network	Valence (%)	Arousal (%)	Accuracy (%)
2D-Topology-DE [3]	3D-CNN	89.78	90.10	88.65
2D-Topology-Time [15]	3D-CNN	72.10	73.20	75.50
Channel-Time-Frame [8]	3D-CNN	87.44	88.12	86.30
Channel-Frequency-DE (Ours)	SBOA-LSTM	90.85	91.02	90.70
Channel-Band Power-Time (Ours)	SBOA-LSTM	97.45	97.10	98.15

This comparison highlights the superior performance of the proposed SBOA-LSTM approach in processing advanced features such as Channel-Frequency-DE and Channel-Band Power-Time, achieves significant improvements in predicting Valence, Arousal, and Accuracy over traditional methods. This demonstrates the capability of SBOA-LSTM to handle complex emotional state predictions effectively. Figure 21 shows confusion matrix diagrams for KNN, SVM, Decision Tree, PO-LSTM, POA-LSTM, and SBOA-LSTM for emotion classification (“sad” vs “happy”).

The final confusion matrices shown in Figure 21 represents the performance of existing algorithms such as Decision Tree, KNN, SVM, PO-LSTM, POA-LSTM, SBOA-LSTM. The cells of each matrix will show the true positives, false positives, false negatives, and true negatives, annotated with labels and indicates how well the algorithm distinguishes the “Sad” and “Happy” emotional states. The Table 10 shows the pEEG base music therapy. In Table 15, “Key” refers to the musical key of the song. The key defines the scale that the music is based on Major / Minor and determines the tonal centre of the song. Major keys i.e., C Maj, D♭ Maj represent the tend to sound happy, bright, or uplifting. Minor keys i.e., C Min, B Min represents tend to sound sad, serious, or introspective. C Maj represent the song based on the C major scale known for its pure, natural tone. B Min represents song that uses the B minor scale, which gives a more emotional or moody character. Musical key affects emotional perception, which ties into how the song may influence pEEG signals and emotional states i.e., arousal and valence. Table 16 shows the discussion of the proposed system.



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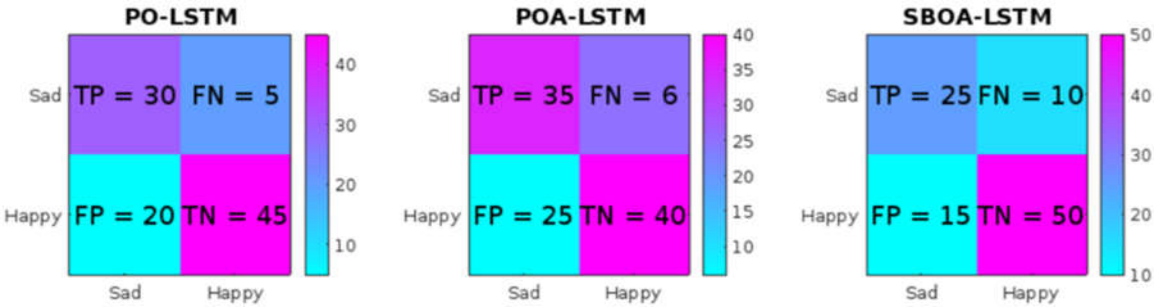

Figure 21. Confusion matrix for Proposed Algorithms.

Table 15. pEEG-Based Music Therapy Playlist for Quadriplegic Person.

QP Patient (ID)	Song Title	Genre / Mode	Tempo (BPM)	Key	Music Theory Effect	Expected EEG Response	Emotional Outcome
QP1	Clair de Lune	Classical	66	D♭ Maj	Soothing, consonant harmony	↑ Alpha, ↓ Beta, ↑ DE_alpha	Calm, positive valence
QP2	Bohemian Rhapsody	Rock/ Operatic	Varies	B♭ Maj	Dynamic, harmonic variety	↑ Gamma, ↑ Theta, fluctuating band power	Emotional engagement
QP3	Weightless – Marconi Union	Ambient	60	G Maj	Drones, no repeating melody	↑ Alpha, ↓ Heart rate, ↓ DE_beta	Deep relaxation
QP4	Imagine – John Lennon	Soft Rock	75	C Maj	Simple harmony, major key	↑ Alpha, ↑ DE_alpha_beta	Optimistic, peaceful
QP5	River Flows in You	Piano Solo	65	A Maj	Flowing arpeggios, calm	↑ Theta, ↑ DE_theta, ↓ Beta	Serene, emotionally open
QP6	Eye of the Tiger	Rock	109	C Min	Minor scale, strong rhythm	↑ Beta, ↑ Gamma, ↑ DE_gamma	Motivated, focused
QP7	Hallelujah – Cohen	Folk / Ballad	56	C Maj	Lyrical, rich vocal tone	↑ Alpha, ↑ Theta	Emotional warmth, uplifted
QP8	Canon in D – Pachelbel	Baroque	76	D Maj	Predictable harmonic pattern	↑ Alpha, ↑ DE_alpha	Peaceful, comforting
QP9	Believer – Imagine Dragons	Pop Rock	125	B Min	Minor key, strong percussion	↑ Beta, ↑ DE_beta	Energetic, increased arousal
QP10	Someone Like You – Adele	Ballad	67	A Maj	Dynamic vocal line	↑ Alpha, ↑ Theta, ↓ Beta	Nostalgic, reflective

*key is usually written as a letter name (e.g., C, D♭, B♭) followed by "Major" or "Minor":.

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Table 16. Discussion of the proposed system.

Problem	Research Gap	Contribution	Novelty
pEEG signals affected by medication	Models not suited for medicated EEG	RBMT framework for pEEG emotion detection	First integration of **pEEG + BCI + therapy** in one system
EEG band overlap	No hardware-level solution	SiO_2-coated graphene electrode	**Nano-coated electrode** reducing impedance & band overlap
Signal artefacts (spasms, noise)	Limited robust denoising	DWT + SWT preprocessing	**Hybrid wavelet approach** for multi-artifact removal
Low classification accuracy	Lack of optimized models	SBOA-LSTM with attention	**SBOA-tuned deep learning + cross-attention**
No emotion regulation	No closed-loop therapy systems	Music therapy via BCI	**Closed-loop emotion detection + control system**
No personalization	Static systems	Adaptive playlist (valence-arousal)	**Dynamic, real-time personalized therapy**

7. Conclusion

This paper demonstrates the transformative potential of deep learning algorithms and therapeutic methodologies combination for mental health management of QP patients. using BCI-audio interface system serve as a foundation for more sophisticated, patient-centered healthcare solutions in neuro-rehabilitation and mental well-being of QP patients. The proposed RBMT framework combines emotion prediction and therapy. Advanced optimization algorithm such as SBOA-LSTM, pEEG signal processing techniques, and personalized music therapy addresses mental health challenges of QP patients. The SBOA-LSTM algorithm emerged as the most effective model, achieves a remarkable accuracy of 98% in predicting emotion states. The use of DWT and SWT significantly improved signal preprocessing, ensures high-quality feature extraction. The Mutual-Cross-Attention mechanism further enhanced classification precision, enabling accurate emotion categorization into anxiety or depression based on the Valence, Arousal. Adaptive music therapy module dynamically respond to emotional states and provides personalized therapeutic solution. This research opens multiple avenues for enhancement. Initially, the system can be expanded to accommodate a wider range of emotion disorders, such as stress and bipolar disorder, with proposed SiO2 coated graphene EEG electrodes. Secondly, integrating real-time feedback mechanisms through wearable sensors could provide continuous monitoring and further improvement of therapeutic. Thirdly, the SBOA-LSTM algorithm can be hybridized with other optimization techniques to explore new methods for improving prediction accuracy beyond 98% for QP patients at different stages.

Availability of Data and Materials: The data and supportive information are available in the link https://github.com/RameshSRM/ResearchEEG and will be shared based on request by the authors. The collected data were with informed consent of the participating patients and also approved by Bethlehem Hospital and Research Centre.

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Conflicts of Interest: The authors declare that they have no Conflict of Interest in the work progressed.

Abbreviations

The following abbreviations are used in this manuscript:

QP	Quadriplegic Patients
EEG	Electroencephalogram
pEEG	Pharmaco-Electroencephalogram
BCI	Brain-Computer Interface
RBMT	Rehabilitation Brain-Computer Interface with Music Therapy
DWT	Discrete Wavelet Transform
SWT	Stationary Wavelet Transform
SBOA	Secretary Bird Optimization Algorithm
LSTM	Long Short-Term Memory
SBOA-LSTM	Secretary Bird Optimization Algorithm–Long Short-Term Memory
ANS	Autonomic Nervous System
TOM	Theory of Mind
ECoG	Electrocorticography
MUA	Multi-Unit Activity
LFP	Local Field Potentials
AI	Artificial Intelligence
DL	Deep Learning
SNR	Signal-to-Noise Ratio
MSE	Mean Square Error
PSNR	Peak Signal-to-Noise Ratio
ROC	Receiver Operating Characteristic
AUC	Area Under Curve
DE	Differential Entropy
BP	Band Power
F3, F4	Frontal EEG Electrode Positions
LA	Low Arousal
HA	High Arousal
LV	Low Valence
HV	High Valence
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
PSO	Particle Swarm Optimization
GA	Genetic Algorithm
ICU	Intensive Care Unit
TMS	Transcranial Magnetic Stimulation
SEM	Scanning Electron Microscopy
TEM	Transmission Electron Microscopy
FTIR	Fourier Transform Infrared Spectroscopy
XRD	X-ray Diffraction

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