

Article

Investigating Brain Responses to Transcutaneous Electroacupuncture Stimulation: A Deep Learning Approach

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Abstract: This study investigates the neurophysiological effects of transcutaneous electroacupuncture stimulation (TEAS) on brain activity, using advanced machine learning techniques. This work analyzed the electroencephalograms (EEG) of 48 study participants, in order to analyze the brain's response to different TEAS frequencies (2.5, 10, 80, and sham at 160 pulses per second (pps)) across 48 participants through pre-stimulation, during-stimulation, and post-stimulation phases. Our approach introduced several novel aspects. EEGNet, a convolutional neural network specifically designed for EEG signal processing, was utilized in this work, achieving over 95% classification accuracy in detecting brain responses to various TEAS frequencies. Additionally, the classification accuracies across the pre-stimulation, during-stimulation, and post-stimulation phases remained consistently high (above 92%), indicating that EEGNet effectively captured the different time-based brain responses across different stimulation phases. Saliency maps were applied to identify the most critical EEG electrodes, potentially reducing the number needed without sacrificing accuracy. A phase-based analysis was conducted to capture time-based brain responses throughout different stimulation phases. The robustness of EEGNet was assessed across demographic and clinical factors, including sex, age, and psychological states. Additionally, the responsiveness of different EEG frequency bands to TEAS was investigated. The results demonstrated that EEGNet excels in classifying EEG signals with high accuracy, underscoring its effectiveness in reliably classifying EEG responses to TEAS and enhancing its applicability in clinical and therapeutic settings. Notably, gamma band activity showed the highest sensitivity to TEAS, suggesting significant effects on higher cognitive functions. Saliency mapping revealed that a subset of electrodes (Fp1, Fp2, Fz, F7, F8, T3, T4) could achieve accurate classification, indicating potential for more efficient EEG setups.

Keywords: EEG signal classification; EEGNet; saliency map; transcutaneous electroacupuncture stimulation (TEAS)



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1. Introduction

Transcutaneous electrical acupuncture (or ‘acupoint’) stimulation (TEAS) represents a significant advancement in integrative medicine, merging the principles of traditional acupuncture with modern electrical stimulation techniques. TEAS involves the application of electrical currents to acupuncture points on the skin surface, offering a non-invasive alternative to traditional manual acupuncture (MA) and electroacupuncture (EA) [1]. This

technique has garnered increasing attention for its potential therapeutic benefits, particularly in enhancing recovery and managing pain following surgical procedures. TEAS is notable for its ability to stimulate specific acupoints without needle insertion, which reduces the risk of infection and discomfort, making it a preferable option for many patients. Recent studies have highlighted the efficacy of TEAS in various clinical applications. Zhang et al. (2024) conducted a meta-analysis demonstrating that TEAS significantly improves postoperative recovery quality, as measured by Quality of Recovery-40 (QoR-40) scores, and that it reduces postoperative pain and nausea [2]. Similarly, another systematic review by Zhang et al. (2024) confirmed the effectiveness of TEAS in improving sleep quality and managing insomnia, especially in postoperative patients [3]. Additionally, Qin et al. (2023) demonstrated that TEAS effectively prevents postoperative nausea and vomiting (PONV) in high-risk patients undergoing laparoscopic gynecological surgery, reducing postoperative abdominal distension and pain, and improving overall recovery quality [4]. The safety profile of TEAS is well documented, with minimal adverse effects reported. Zhang et al. (2024) emphasized the method's safety in a meta-analysis, noting that TEAS not only improves postoperative QoR-40 scores but also reduces the incidence of postoperative nausea and vomiting without significant adverse reactions [2]. Moreover, the non-invasive nature of TEAS makes it suitable for patients who are contra-indicated for traditional acupuncture, due to needle phobia or bleeding disorders. Further supporting these findings, Liang et al. (2021) demonstrated the efficacy of TEAS in alleviating catheter-related bladder discomfort and improving overall postoperative comfort in patients undergoing transurethral resection of the prostate [5]. Moreover, Mi et al. (2018) found that TEAS improved the quality of recovery during the early period after laparoscopic cholecystectomy [6]. These studies collectively underscore the broad applicability and safety of TEAS in various surgical contexts. Investigation into the brain's specific reactions to acupuncture has garnered significant interest in recent times. Advanced neuroimaging tools, such as electroencephalogram (EEG) and functional magnetic resonance imaging (fMRI), have been extensively employed to unravel acupuncture's underlying processes. Researchers have utilized fMRI to explore how acupuncture modulates brain activities and to distinguish the effects elicited by various genuine and sham acupuncture points [7].

The physiological and psychological impacts of TEAS are influenced by various stimulus parameters, including the choice of acupuncture points, the intensity of stimulation, and the frequency at which stimulation is applied [8–10]. Research indicates that both low- and high-frequency stimulation are effective for analgesia, but through different mechanisms [11]. Low-frequency (2–4 Hz), high-intensity electrical stimulation resulting in muscle contractions and a sustained analgesic effect are particularly beneficial for neuropathic pain relief compared to high-frequency stimulations [12]. Conversely, high-frequency stimulation at low intensity is associated with muscle relaxation, which may also contribute to its analgesic properties [13]. Kim et al. [14] probed the impacts of EA on various biosignals, with a keen focus on EEG alongside bioimpedance and electrocardiogram (ECG) responses during the stimulation of two acupuncture points on the pericardium meridian, PC5 (Jianshi) and PC6 (Neiguan). To achieve a deeper understanding of time-based changes in brain activity, a continuous wavelet transform (CWT) with a Morlet wavelet was employed, allowing for the temporal localization of changes in the EEG signal. The study reported a generalized increase in EEG amplitude across all lobes during EA stimulation. Most significantly, the temporal lobe exhibited a pronounced increase in amplitude following stimulation at the PC5 point. Additionally, during the acupuncture point stimulation periods, there was a marked elevation in the power within the alpha wave band of the EEG. These alterations in EEG patterns suggest that specific acupuncture points, such as PC5 and PC6, may have broader neurophysiological implications, significantly influencing the temporal lobe of the brain. Zeng et al. [15] focused on cortical activities evoked by noxious somatosensory stimulation in humans, where they found significant modulatory effects. The study utilized a 64-electrode Neuroscan ESI-128 EEG system to measure the brain electrical activity of 24 healthy subjects, focusing

on somatosensory evoked potentials (SEPs) elicited by painful stimuli. The key results from the study indicated that EA at specific acupoints, as opposed to non-acupoints, leads to the emergence of a particular later-latency SEP component (P150) observed in the bilateral anterior cingulate cortex (ACC). This finding suggests that acupoint stimulation can specifically influence brain activity in regions associated with pain processing. In another related study, Lee et al. [16] investigated the effects of EA on brain waves by administering it at various frequencies and intensities to 15 healthy participants. The EA was applied at the bilateral ST36 (Zusanli) points in two modes: low frequency (2 Hz) at high intensity (5–6 mA) and high frequency (120 Hz) at low intensity (2–2.5 mA). The EEG data collected before (pre-stimulation) and during the EA stimulation using a 10–20 EEG system with eight electrodes were analyzed across theta, alpha, beta, and gamma bands using fast Fourier transformation. Statistical analysis was performed with the Wilcoxon signed-rank test, to compare EEG during EA stimulation with pre-stimulation EEG. The results indicated that high-frequency EA led to a significant decrease in theta power in most regions, an increase in alpha power in the posterior region, particularly significant at P3, and a decrease in beta and gamma power, with notable changes in the prefrontal and P4 regions, respectively. In contrast, low-frequency EA resulted in a significant decrease in theta power across all electrodes, while changes in alpha, beta, and gamma power were not significant. Li et al. [17] analyzed theta-band phase synchronization during the application of EA at the Neiguan (PC6) and Shenmen (HT7) acupoints. Recognized for its cognitive and consciousness-correlated activities, the theta band was scrutinized under acupuncture and resting states across hemispheres in 11 healthy subjects through multivariate EEG recordings using a 128-electrode neuron scan system. The researchers employed mean phase coherence to assess the synchronization between distinct cerebral regions, specifically between the parietal (P5, PO5), frontal (FP3, Fz, FC6), and occipital (POZ) areas. Their findings revealed a pronounced increase in phase synchronization between the parietal–frontal and occipital regions during and post-acupuncture when juxtaposed with resting conditions, highlighting a potential enhancement in functional brain connectivity. Contrarily, a decrease in phase synchrony was observed within the frontal regions, suggesting a modulatory effect of acupuncture on neural communication within those areas. Chen et al. [18] explored the neurophysiological underpinnings of TEAS's effects on brain activity. They employed EEG measurements to assess changes in the EEG power spectrum in response to acupuncture stimulation. The investigation specifically focused on the modulation of ongoing brain activity by acupuncture at the traditional Hegu acupoint compared to a mock point (non-acupoint) under high-frequency (100 Hz) and low-frequency (2 Hz) stimulation. The study recruited 12 healthy male volunteers and utilized a crossover design with two separate sessions. EEG recordings from a 124-electrode system were analyzed to evaluate power changes across various frequency bands. The findings revealed that high-frequency stimulation at the Hegu acupoint resulted in a significant decrease in theta power, particularly at the frontal midline electrodes, specifically Fz and FCz, as well as at electrodes over the contralateral right hemisphere frontal areas, including Fp2, F4, F8, and FC6. This suggests targeted modulation of neural activity in these regions during acupuncture treatment. This effect was absent during low-frequency stimulation and when stimulating the mock point. The attenuation in theta power was transient and observed only during the period of stimulation. Source localization techniques implicated the cingulate cortex and, more specifically, the ACC as the origin of the observed EEG changes. The results of the study suggest that high-frequency acupuncture at specific points can induce acute changes in cortical activity, with potential implications for modulating nociceptive processing. This modulation appears to be frequency- and location-specific, thereby supporting the concept of acupuncture's specificity and its measurable effects on brain function. The employment of a mock point serves as a control to underscore the specificity of the Hegu acupoint's effects, which has implications for the design of future studies examining the neural correlates of acupuncture.

In the realm of using deep learning algorithms to analyze the effects of TEAS on EEG signals at different frequencies, the study by Uyulan et al. [19] stands out as a pioneering effort. It is the only study to date that employs artificial intelligence (AI), specifically a hybrid convolutional neural network long short-term memory (CNN-LSTM) model, to investigate the effects of different TEAS stimulation frequencies on EEG. Using a 10–20 system with 19 electrodes, their research revealed that the most notable EEG changes from pre-stimulation occurred at higher TEAS frequencies, particularly at 80 and 160 pps. The study also found that different TEAS frequencies might selectively influence certain EEG frequency bands. With the use of the kappa statistic, the CNN-LSTM model demonstrated superior classification accuracy over traditional models like the multilayer perceptron neural network (MLP-NN). Using the same database as [19], this study introduced several novel approaches to classifying brain responses to TEAS and distinguishing between the various stimulation frequencies applied. EEGNet, a specialized CNN architecture designed for EEG-based tasks, was employed to implement a four-class classification approach corresponding to four different TEAS frequencies (2.5, 10, 80, and sham).

A key contribution of this work was the investigation of the time-based variation of EEG patterns across multiple stimulation phases—pre-stimulation, during-stimulation, and post-stimulation—and capturing the evolving nature of brain responses throughout each 40 min session. This phase-based analysis offered a more comprehensive understanding of how EEG signals modulate in response to different stimulation frequencies. Additionally, saliency maps were applied, to identify the most critical EEG electrodes for classification, enabling the optimization of the electrode setups and reducing the number of electrodes required without sacrificing accuracy. This approach improves system efficiency and will enhance patient comfort in practical, real-world applications. Furthermore, a detailed analysis of EEG frequency bands (delta, theta, alpha, beta, gamma) was conducted, to explore their sensitivity to TEAS stimulation, providing significant insights into how different frequencies affect various cognitive and neural processes. The robustness of the classification was also evaluated across a range of demographic and clinical factors, including sex, age, and psychological state, demonstrating the relevance of this work for personalized therapeutic applications. Overall, this study advances the field by providing a time-based, multi-phase, and frequency-band-specific analysis of EEG responses to TEAS, with potential implications for optimizing both therapeutic and clinical applications. The data collection for this study was designed as a methodological study at the University of Hertfordshire (UK) to investigate the cortical effects of TEAS. It was not a clinical trial; therefore, it included only healthy volunteers.

2. Materials and Methods

2.1. Study Design and Data Collection

The study received ethical clearance from the University of Hertfordshire's Health and Human Sciences Ethics Committee, which exercises Delegated Authority, under protocol number HSK/SF/UH/00124. The study was conducted with 48 participants, who each attended for four sessions. Sessions were structured into eight 5 min time slots, categorized as pre-stimulation (Slot 1), during stimulation (Slots 2–5), and post-stimulation (Slots 6–8). TEAS was administered using a charge-balanced Equinox E-T388 stimulator at frequencies of 2.5, 10, 80, or 160 pulses per second (pps), with the 160 pps frequency used as a 'sham' treatment because it had a very low amplitude and many participants were unable to feel it.

Exclusion criteria were carefully considered, to ensure the validity of the study. Participants were excluded if they had suffered a serious head injury, had epilepsy or diabetes, currently had cancer or a respiratory condition that impaired nasal breathing, or had an implanted electronic device. Individuals with impaired peripheral circulation (such as Raynaud's syndrome) or any shoulder, arm, or hand injury were also excluded. Additionally, those with severe physical or mental conditions or with learning disabilities that might prevent them from completing the study, or those dependent on prescribed or other psychoactive substances, were not included. Heavy users of caffeine, nicotine, or alcohol,

defined as consuming more than 400 mg of caffeine, 20 cigarettes, or two alcoholic drinks daily, were also excluded. Individuals undergoing non-routine non-pharmacological or complementary medical treatments, women who were pregnant, and those with minimal understanding of English were not eligible to participate.

The majority of the participants were local white British people from Hatfield in the United Kingdom, highlighting a limitation in sample diversity that may have influenced the results. The selection of the three TEAS frequencies used in this study—2.5, 10, and 80 pps—was guided by their prevalent use in clinical settings and the existing literature on TEAS [20]. The sequence of stimulation frequencies was semi-randomized across participants, to mitigate order effects.

Figure 1a displays the Equinox stimulator, and Figure 1b shows the arrangement of sensors and electrodes, featuring the fingertip photoplethysmography (PPG) sensor, an ECG electrode positioned on the right forearm, and TENS (transcutaneous electrical nerve stimulation) electrodes located at the LI4 (Hegu) acupoint and along the ulnar edge of the hands. The ECG electrodes placed on the left forearm are out of view, and the thermistor attached to the left middle finger is visible in the figure. The electrodes were round, with a diameter of 32 mm. A new set was used for each participant. The manufacturer was Schwa-Medico, Ehringshausen, Germany.

EEG data were recorded from 19 electrodes according to the international 10/20 system, with linked ears serving as the reference and a ground electrode placed anterior to Fz. Custom-fitted Electro Cap International (ECI) caps were used to ensure participant comfort and data quality. The EEG signals were amplified using a Mitsar EEG-202 amplifier and digitized at a sampling rate of 500 Hz. Preprocessing steps included the removal of noise and artifacts to produce clean EEG datasets for each participant, suitable for further analysis. The EEG slots were then divided into five 1 min segments, and each segment was split into two halves. Ten-second epochs were then extracted from the beginning of each half (at the 0 and 30 s marks). This method yielded ten epochs per slot, resulting in a comprehensive dataset that was used to assess the effects of the different TEAS frequencies on EEG activity. Figure 2 shows the first 1 s of each slot for better illustration, resulting in 8 s of data.

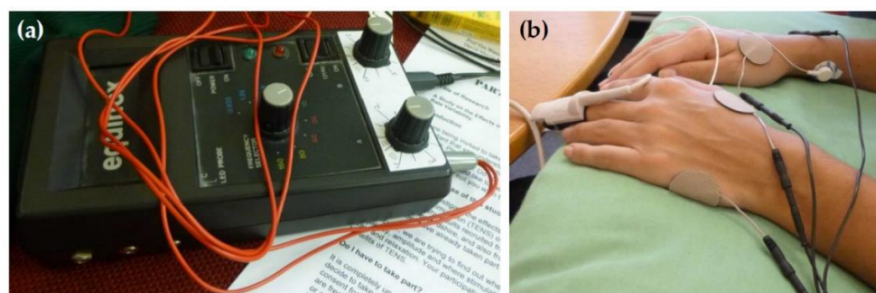


Figure 1. (a) The Equinox stimulator. (b) Sensor and electrode configuration, highlighting the fingertip PPG sensor, ECG electrode on the right forearm, and TENS electrodes at the LI4 acupoint and ulnar edge of the hands [19].

The demographic characteristics of the participants (age and sex), along with the clinical characteristics from the numerical rating scale for mood (NRS-M) measures before and after the TEAS sessions, are summarized as the means and standard deviations for all participants, not separated by sex, in Table 1. Additionally, the range of scores for each mood characteristic was between 0 and 100.

NRS-M was developed by two members of our team [21], to specifically target both negative and positive mood states. It consists of four negative subscales (anxious, confused, fatigued, and gloomy) corresponding to those in the widely used Brunel mood scale (BRUMS24) [22], and four positive subjective states (comfortable, lively, relaxed, and overall good mood), instead of solely emphasizing the pathological states highlighted by BRUMS24. By using fewer words, the aim was simplicity, to aid non-native English speakers and those with learning difficulties.

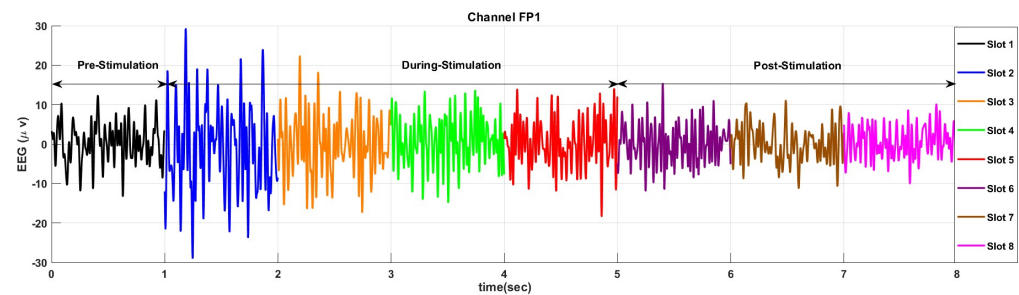


Figure 2. EEG data for Channel 1 across all slots, illustrating the pre-stimulation, during-stimulation, and post-stimulation phases. The slots are color-coded, and the horizontal axis indicates the first second of recording for each slot, for better illustration.

The means and standard deviations presented were calculated for all the participants, not separated by sex. Additionally, the range of scores for each clinical characteristic was between 0 and 100.

Table 1. Baseline demographic, pre-stimulation, and post-TEAS session clinical characteristics of the participants, based on the numerical rating scale for mood (NRS-M).

Demographic Features				
Feature	Male	Female		
Sex	18	30		
Age		Mean (SD) [Min, Max]		
		43.55 (16.98) [18, 69]		
Clinical Features				
Feature	Mean	SD	Min	Max
Pre-anxiety	15.70	19.61	1	100
Post-anxiety	8.74	14.87	3	80
Pre-comfort	67.17	21.71	0	101
Post-comfort	65.76	23.58	10	101
Pre-relaxation	68.31	20.66	0	100
Post-relaxation	70.91	22.60	1	101
Pre-liveliness	46.40	23.88	1	101
Post-liveliness	34.99	25.90	1	95
Pre-fatigue	31.11	23.70	2	89
Post-fatigue	37.53	26.31	3	100
Pre-gloominess	12.91	16.24	2	76
Post-gloominess	9.71	17.07	3	80

2.2. Data Preprocessing

The preprocessing pipeline began with band-pass filtering the data to isolate the frequency range of interest, specifically between 0.5 and 45 Hz, using second-order Butterworth filters implemented in MATLAB (Version: R2024a). This choice was made due to the Butterworth filter's maximally flat frequency response, ensuring minimal amplitude distortion and efficient computational performance. This filter effectively attenuates frequencies outside this range, including the interference from the UK's 50 Hz power supply. Following the initial filtering, an independent component analysis (ICA), utilizing the extended Infomax algorithm, was employed to identify and remove non-neural artifacts from the EEG data [23].

This step was complemented by the use of the multiple artifact rejection algorithm (MARA), to further enhance the artifact rejection process [24]. The identification of artifactual components was refined using ICLabel [25], an EEGLAB plugin [26], which facilitated the labeling and subsequent removal of these components.

ICLabel leveraged a pre-trained neural network to classify independent components into categories such as brain, muscle, eye, heart, line noise, channel noise, and others, based on their spatial, spectral, and temporal characteristics. Subsequently, those marked

artificial components were mathematically subtracted from the data, and the remaining components, primarily reflecting brain activity, were projected back to the scalp electrode space to reconstruct the EEG signals. This resulted in a cleaned dataset with reduced artifact contamination, suitable for further analysis.

Epochs exhibiting significant deviations in amplitude were identified and trimmed using the TrimOutlier EEGLAB plugin. The threshold for outlier removal was set at ± 3 standard deviations from the mean amplitude across all electrodes [19]. The final stage of preprocessing involved re-referencing the data, using a current source density (CSD) transformation, implemented via the CSD Toolbox in MATLAB, to apply a Laplacian montage, which provides a more localized representation of scalp electrical activity [27].

To augment the database, each 10 s epoch was divided into 1 s trials, with each trial having dimensions of 19 electrodes by 500 time samples. The number of trials for each distinct stimulation frequency across the eight slots was approximately as follows: for 2.5 pps, it ranged from 4740 to 4800 trials; for 10 pps, from 4750 to 4800 trials; for 80 pps, from 4750 to 4800 trials; and for the Sham condition, from 4750 to 4800 trials. The number of trials for each frequency remained relatively stable across the slots, ensuring a balanced dataset for subsequent analysis.

2.3. Applying EEGNet to TEAS Data

EEGNet, a compact convolutional neural network architecture specifically designed for EEG-based brain–computer interfaces (BCIs) [28], was employed for the classification of the EEG data. The choice of EEGNet over other models was well justified by its architecture, which efficiently manages the unique temporal and spatial dynamics of EEG signals through depthwise and separable convolutions. This specialization has been shown to enhance performance in EEG classification tasks, as reported by Lawhern et al. (2018) [28]. Furthermore, EEGNet offers high classification accuracy while maintaining a compact size, which is essential for handling computationally intensive analysis of EEG data. It achieves competitive or superior results compared to traditional models like SVMs and MLPs, while requiring fewer computational resources [28,29]. Additionally, EEGNet’s integration with saliency maps enhances interpretability by identifying critical EEG electrodes, allowing researchers to focus on significant brain regions. This capability aligns with recent advancements in deep learning for EEG analysis [30]. Figure 3 illustrates the architecture of EEGNet as adapted to our TEAS dataset.

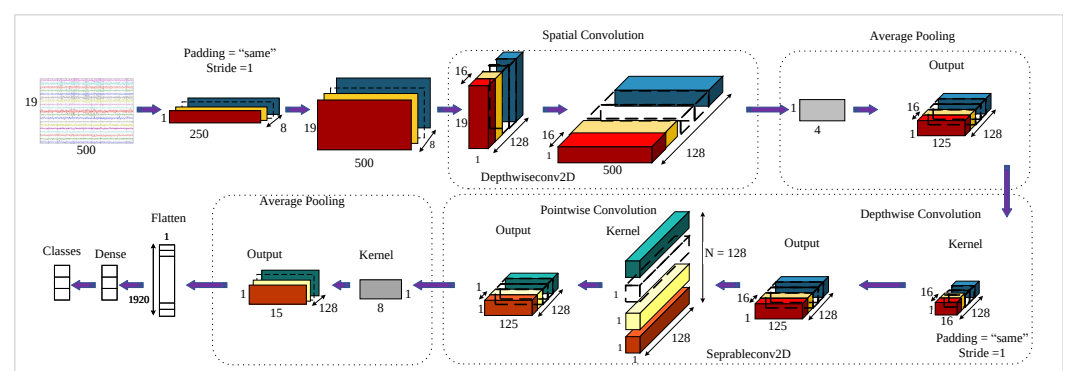


Figure 3. Block diagram of the customized EEGNet architecture.

EEGNet processed the input data through a series of convolutional and pooling layers. The key components of this process are explained below, with a detailed description of the variables involved.

First, consider the temporal convolution, which is defined as

$$Y_{ij} = \sum_{k=1}^K X_{ik} W_{kj} + b_j, \quad (1)$$

where Y_{ij} represents the output feature map at position i for the j -th feature. The input signal at position i for the k -th time sample is denoted by X_{ik} , and W_{kj} is the weight of the convolutional filter connecting the k -th input time sample to the j -th output feature. The bias term for the j -th output feature is denoted by b_j , and K represents the kernel size of the convolution.

Next, the depthwise convolution is described by the following equation:

$$Y_{ijk} = X_{ijk} * W_k, \quad (2)$$

where Y_{ijk} is the output feature map at position (i, j) for the k -th depthwise filter. The input signal at position (i, j) for the k -th depthwise filter is denoted by X_{ijk} , and W_k is the weight of the depthwise convolutional filter applied to the k -th input channel.

Finally, the separable convolution is expressed as

$$Y_{ijkm} = \sum_l (X_{ijkl} * W_{klm}), \quad (3)$$

where Y_{ijkm} represents the output feature map at position (i, j) after applying the separable convolution. The input signal at position (i, j) for the l -th input channel is represented by X_{ijkl} , and W_{klm} is the weight of the separable convolutional filter connecting the k -th depthwise filter to the m -th pointwise filter. The index l is used to iterate over the input channels for the depthwise convolution.

The EEGNet model processed the EEG data with an input layer configured for (19 electrodes, 500 samples, 1), matching the electrode setup and temporal data length. The first convolutional block utilized a 2D convolution with 8 filters and a kernel length of 250 to effectively capture the temporal features. This was followed by a depthwise convolution with a depth multiplier of 16, enabling the network to learn spatial filters specific to each electrode. To prevent overfitting, L2 regularization with a rate of 0.1 was applied, and the ELU activation function enhanced the training process. Average pooling reduced the data dimensionality, and a dropout rate of 0.5 further mitigated overfitting. The second block used separable convolutions with 128 filters, chosen to reduce computational complexity while efficiently learning spatial and pointwise features. This block also included batch normalization and ELU activation, followed by average pooling and dropout. A dense layer, with units corresponding to the number of classes, incorporated L2 regularization and a max-norm constraint to ensure stable learning. The output layer employed a softmax activation function to provide class probabilities. The key hyperparameters included a kernel length of 250, filter counts of 8 and 128, a normalization rate of 0.25, and a learning rate of 0.0001. These parameters were carefully selected to balance the model's capacity to learn complex patterns while maintaining generalization, ensuring effective capture of both temporal and spatial features for EEG classification tasks.

A 5-fold stratified cross-validation approach was implemented. By this method, the dataset was partitioned into five distinct subsets, with each fold consisting of 80% training data and 20% test data. This split was performed using stratification to maintain consistent proportions of classes across both the training and the test sets. Importantly, samples from all participants were included in each fold, ensuring that our model captured the general effects of TEAS on EEG signals rather than being influenced by individual subject variability. This approach reflected our objective to assess the generalized impact of TEAS on EEG activity. Several key metrics were utilized to evaluate the performance of the EEGNet classifier for multi-class classification tasks, tailored to assess the model's ability to accurately identify instances across multiple classes. These metrics included accuracy, sensitivity (recall), specificity, precision, and F1 score. The results from each fold were then aggregated to report the average values of these parameters. Additionally, the standard deviation ($\pm$ Value) for the accuracy across all folds is reported.

Accuracy was defined as the proportion of true results (true positives and true negatives) across all classes among the total number of cases examined. It provided an overall measure of the classifier's correctness across all classes and was calculated as follows:

$$\text{Accuracy} = \frac{\sum_{c=1}^C TP_c + \sum_{c=1}^C TN_c}{\sum_{c=1}^C (TP_c + FP_c + FN_c + TN_c)}, \quad (4)$$

where C is the number of classes, and TP_c , TN_c , FP_c , and FN_c are the true positives, true negatives, false positives, and false negatives for class c , respectively.

Sensitivity (recall) measures the proportion of actual positives for each class that are correctly identified by the classifier. Sensitivity is crucial in applications where the omission of a condition can have serious consequences. Sensitivity for class c was calculated as

$$\text{Sensitivity}_c = \frac{TP_c}{TP_c + FN_c}. \quad (5)$$

Specificity for a multi-class classification assesses the model's ability to correctly identify instances that do not belong to each particular class. For class c , specificity was calculated as

$$\text{Specificity}_c = \frac{TN_c}{TN_c + FP_c}. \quad (6)$$

Precision quantifies the number of correct positive predictions made by the classifier for each class. It was defined for class c as

$$\text{Precision}_c = \frac{TP_c}{TP_c + FP_c}. \quad (7)$$

The F1 score is the harmonic mean of precision and sensitivity for each class, providing a single score that balances the two metrics. It was calculated for class c as

$$\text{F1-Score}_c = 2 \times \frac{\text{Precision}_c \times \text{Sensitivity}_c}{\text{Precision}_c + \text{Sensitivity}_c}. \quad (8)$$

These metrics provided a comprehensive view of the classifier's performance in a multi-class scenario.

2.4. Saliency Map Computation

To interpret the decision-making process of the neural network model, saliency maps were utilized to extract the influential features within the EEG data for classification. Saliency maps are a well established technique in model interpretability, highlighting the sensitivity of the output to changes in the input [30]. This section explains the approach required to interpret the spatial significance of individual electrodes for particular class scores in an EEG classification task using EEGNet. The class score function of EEGNet, $S_c(\mathbf{I})$, is investigated for an input EEG signal, $\mathbf{I}_0$, and a specific class, c , to identify the influence of electrode readings on the score of class c for $\mathbf{I}_0$. Saliency maps are employed to visualize the spatial support of the class within the EEG signal.

Due to the intricate non-linear mappings in EEGNet, direct inference of pixel (electrode) importance from the weights is not possible. Thus, the class score function $S_c(\mathbf{I})$ near $\mathbf{I}_0$ is approximated with a linear model using the first-order Taylor expansion:

$$S_c(\mathbf{I}) \approx \mathbf{w}^T \mathbf{I} + b, \quad (9)$$

where $\mathbf{W}$ represents the derivative of S_c with respect to the EEG signal at $\mathbf{I}_0$, computed as [31]

$$\mathbf{W} = \left. \frac{\partial S_c}{\partial \mathbf{I}} \right|_{\mathbf{I}_0}, \quad (10)$$

where $\mathbf{W}$ denotes the saliency map for class c . To ensure that the saliency map values fall within a suitable range for recognized practice in the field—thereby making the maps meaningful and useful for interpreting the decision-making process of neural network models—the saliency map is normalized as follows [31]:

$$\mathbf{W}'_c(\mathbf{I}) = \frac{\mathbf{W}_c(\mathbf{I}) - \min(\mathbf{W}_c(\mathbf{I}))}{\max(\mathbf{W}_c(\mathbf{I})) - \min(\mathbf{W}_c(\mathbf{I}))}. \quad (11)$$

Here, $\mathbf{W}'_c(\mathbf{I})$ represents the normalized saliency map for class c . For multiple samples, the saliency maps are aggregated to obtain a mean map for the class [32]:

$$\bar{\mathbf{W}}_c = \frac{1}{N} \sum_{j=1}^N \mathbf{W}'_{c,j}, \quad (12)$$

where $\bar{\mathbf{W}}_c$ is the mean saliency map for class c , N is the number of samples, and $\mathbf{W}'_{c,j}$ is the normalized saliency map for the j -th sample.

2.5. Electrode Importance Scoring

Once the mean saliency maps were computed for each class, the importance of each EEG electrode was quantified. This step was crucial for understanding which brain regions were most influential in the classification process. To achieve this, the saliency values were summed across the time dimension for each electrode, resulting in a single saliency value per electrode for each class:

$$E_{c,k} = \sum_t \bar{\mathbf{W}}_{c,k,t}, \quad (13)$$

where $E_{c,k}$ is the summed saliency value for class c at electrode k , and $\bar{\mathbf{W}}_{c,k,t}$ is the mean saliency value at time t for electrode k . The next step involved normalizing these values, to account for the different scales of saliency values across the electrodes:

$$E'_{c,k} = \frac{E_{c,k}}{\sum_j E_{c,j}}, \quad (14)$$

where $E'_{c,k}$ is the normalized importance score for electrode k in class c . This normalization allowed us to compare the relative importance of each electrode within the class.

To determine the overall importance of each electrode across all classes, the normalized importance scores for each electrode were aggregated:

$$E''_k = \sum_c E'_{c,k}, \quad (15)$$

where E''_k is the aggregated importance score for electrode k across all classes c . This aggregation provided a holistic view of each electrode's contribution to the classification task, irrespective of class.

The final step was to rank the electrodes based on their aggregated importance scores. Electrodes with higher scores were deemed more influential in the model's decision-making process:

$$R = \text{argsort}(-E''), \quad (16)$$

where R is the ranked list of electrodes, and the argsort function sorts the electrodes in descending order of importance.

The ranked list of electrodes R provided a clear indication of which EEG electrodes (and, thus, which corresponding brain regions) had the most significant influence on classifying different classes. This information is valuable for understanding the neural mechanisms underlying the effects of TEAS, and it could guide the placement of electrodes in future studies or clinical applications.

3. Results

3.1. Classification Performance Across TEAS Sessions

The first task involved using the EEGNet deep learning model to assess whether brain response varied with respect to the TEAS frequency. Table 2 shows the classification accuracy for classifying the four TEAS frequencies of 2.5, 10, 80, and sham using each time slot during stimulation. From Table 2, the classification accuracies across the time slots were more than 95%, indicating a high level of consistency in the model's ability to correctly identify the four classes of TEAS frequencies. The complete classification performance, including sensitivity, specificity, precision, and F1 score for each individual class, is provided in Table S1 (see Supplementary Material). From Table S1, the sensitivity was more than 94%, the specificity was more than 97%, the precision was more than 94%, and the F1 score was more than 95% for all cases. This suggests that TEAS at various frequencies may engage different neural mechanisms and pathways. Understanding these EEG differences could help tailor TEAS treatments to achieve specific therapeutic effects, optimize stimulation protocols for individual patients, and provide a better understanding of how acupuncture influences brain activity in real time.

Table 2. Total classification accuracy during the stimulation across different TEAS frequencies. All values are presented as mean accuracies, with the overall range of standard deviations being 0.2% to 0.62%.

Metrics\Slots	Slot 2	Slot 3	Slot 4	Slot 5
Total Accuracy	95.65	96.70	96.45	97.66

3.2. Assessing Various TEAS Frequencies in Each Time Slot

The second task involved investigating how the brain's activity fluctuated across different phases of the TEAS sessions. The classification accuracies for the pre-stimulation, during-stimulation, and post-stimulation phases are presented in Table 3, and the corresponding sensitivity, specificity, precision, and F1 score for each individual class are reported in Table S2 (Supplementary Material). These results, as summarized in Tables 3 and S2, indicate that the EEGNet model achieved high classification accuracies across all combinations of time slots at each TEAS frequency. The accuracies for all frequencies consistently exceeded 92%, demonstrating the model's robustness in distinguishing between brain activities across different phases of the TEAS sessions. This provides a view of how TEAS affects brain activity over time, by not only influencing brain activity during the stimulation period but also having lingering effects, which are crucial for optimizing therapeutic strategies and advancing knowledge of TEAS neurophysiological mechanisms.

Table 3. Classification accuracy for different TEAS frequencies across time slots. All values are presented as mean accuracies, with the overall range of standard deviations being between 0.18% and 0.70%. The column "Comb". denotes the combinations of time slots used for classification. Slot 1 corresponds to the pre-stimulation phase, slots 2 through 5 correspond to the during-stimulation phase, and slots 6 through 8 correspond to the post-stimulation phase.

Comb.	Phase Description	2.5 pps	10 pps	80 pps	Sham
1_2_6	pre-, during-, post-stimulation	94.65	96.12	96.65	96.24
1_2_7	pre-, during-, post-stimulation	95.67	96.68	94.84	92.40
1_2_8	pre-, during-, post-stimulation	98.08	97.83	95.78	96.09
1_3_6	pre-, during-, post-stimulation	97.45	97.21	95.84	94.51
1_3_7	pre-, during-, post-stimulation	96.86	97.32	94.94	95.75
1_3_8	pre-, during-, post-stimulation	98.22	96.38	97.14	92.68
1_4_6	pre-, during-, post-stimulation	96.59	96.13	96.85	95.78
1_4_7	pre-, during-, post-stimulation	95.51	97.25	94.23	94.83
1_4_8	pre-, during-, post-stimulation	97.80	97.39	96.23	93.60
1_5_6	pre-, during-, post-stimulation	96.23	97.17	97.84	96.38
1_5_7	pre-, during-, post-stimulation	96.26	97.21	96.90	95.47
1_5_8	pre-, during-, post-stimulation	97.59	96.83	94.91	95.04

3.3. Impact of Demographics and Clinical Factors on EEGNet's Performance During TEAS

The study further explored the impact of personal characteristics—specifically, sex, age, and psychological state—on the classification accuracy of EEGNet in differentiating brain activity across the pre-stimulation, during-stimulation, and post-stimulation phases. The classification accuracy of the EEGNet model across different demographic factors indicated a high level of robustness and consistency. Here are the key observations from the results:

For female participants, the classification accuracy ranged from 93% to 100% (Table 4). This high accuracy suggests that the model performs exceptionally well in classifying EEG signals for females. For male participants, the accuracy ranged from 90% to 95%. Although slightly lower than for females, the accuracy was still within a high range, demonstrating the model's reliability. The complete classification performance for these two groups is provided in Tables S3 and S4 in the Supplementary Material.

The influence of age on the classification accuracy of EEGNet was examined by dividing the participants into two equal age groups. The median age of the participant pool was determined to be 45 years, resulting in two cohorts: 25 participants aged over 45 and 23 participants aged under 45. The participants aged over 45 years showed classification accuracies between 92% and 98% (Table 4). This indicates that the model can effectively classify EEG signals in older adults. For participants under 45 years, the accuracy ranged from 90% to 99%, which is comparable to the older group, suggesting that age does not significantly impact the model's performance. The complete classification performance for these two groups is provided in Tables S5 and S6 in the Supplementary Material.

The study further investigated the impact of psychological states, specifically relaxation and anxiety levels, on the classification accuracy of EEGNet for different TEAS frequencies across time slots. To achieve this, participants were first grouped based on their self-reported relaxation and anxiety scores. The dataset was processed to calculate pre-stimulation and post-stimulation scores for relaxation and anxiety. The 'pre-stimulation relaxation' and 'post-stimulation relaxation' scores were computed by summing up the scores of specific items from the NRS-M that corresponded to the participant's state of liveliness, comfort, and relaxation before and after the stimulation, respectively. Similarly, the 'pre-stimulation anxiety' and 'post-stimulation anxiety' scores were calculated by summing up the items related to anxiety, fatigue, and gloominess. To quantify the change in relaxation and anxiety levels due to the stimulation, the percentage change for each participant was calculated as follows:

$$\text{Change} = \left(\frac{\text{Post} - \text{Pre}}{\text{Pre}} \right) \times 100. \quad (17)$$

The participants were then grouped into 'high' and 'low' categories based on whether their percentage change was above or below the value of 50%. Those with a relaxation percentage change of 50% or higher were placed in the 'relax high' group, indicating a significant increase in relaxation levels post-stimulation. Conversely, participants with less than a 50% change were categorized into 'relax low', suggesting a lower increase in relaxation. The same approach was applied to anxiety levels. Participants with a percentage change of 50% or higher in anxiety scores were assigned to the 'anx high' group, indicating a significant increase in anxiety post-stimulation. Those with less than a 50% change were placed in the 'anx low' group, reflecting a lower increase or a decrease in anxiety levels. With these groups established, the EEG data were then analyzed to determine whether the psychological state of relaxation or anxiety had any significant effect on the brain's response to TEAS frequencies.

High relaxation levels corresponded to classification accuracies between 90% and 100% (Table 4). This near-perfect accuracy indicates that the model performs well regardless of the relaxation state of participants. Low relaxation levels still maintained high accuracy, ranging from 90% to 97%, showing that the model is robust even when participants are less relaxed. High anxiety levels resulted in classification accuracies of between 90% and

100%, similar to the high-relaxation group, indicating that the model's performance is not adversely affected by anxiety. Low anxiety levels also maintained a high accuracy range of between 90% and 97%, further demonstrating the model's resilience to variations in psychological state. The complete classification performance related to clinical features is provided in Tables S7–S10 in the Supplementary Material.

Table 4. Summary of classification accuracy across time slots (pre-stimulation, during stimulation, and post-stimulation) for demographic and clinical factors.

Demographic Factors	
Factor	Classification Accuracy (%)
Sex (Female)	93–100
Sex (Male)	90–95
Age (>45)	92–98
Age (<45)	90–99
Clinical Factors	
Factor	Classification Accuracy (%)
High relaxation	90–100
Low relaxation	90–97
High anxiety	90–100
Low anxiety	90–97

These results highlight the effectiveness and reliability of the EEGNet model across various demographic and clinical factors, making it a robust tool for classifying EEG signals in diverse populations. The consistently high classification accuracies across different groups underscore the model's potential applicability in clinical and therapeutic environments.

3.4. Classification of TEAS Stimulation Phases Across Frequencies

The classification accuracies obtained from applying a four-class classification model during stimulation phases across slots 2, 3, 4, and 5 for different TEAS frequencies are presented, as illustrated in Table 5 (Table S11 in the Supplementary Material). It is noteworthy that the accuracies for all frequencies consistently exceeded 93%. This high level of accuracy across the board indicates the robustness of the EEGNet architecture in distinguishing between the various stimulation conditions during the stimulation sessions.

Table 5. Total classification accuracy during the stimulation phase across different TEAS frequencies.

Metric\Frequency	2.5 pps	10 pps	80 pps	Sham
Accuracy	95.98 ± 0.42	95.68 ± 0.18	96.36 ± 0.60	93.52 ± 0.52

3.5. Evaluating EEG Frequency Band Responsiveness to TEAS

For this section, EEGNet was employed to classify various phases, using each EEG frequency band: delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–50 Hz) to investigate the responsiveness of each frequency band to the stimulation. The classification accuracies were averaged across different EEG frequency bands during various phases of TEAS.

Figure 4 summarizes the averaged classification accuracies over all combinations of the phases for each frequency band under various TEAS frequencies (Table S12a–l in the Supplementary Material show the classification accuracies of each combination). As shown in Figure 4, in the delta (1–4 Hz) frequency band, the classification accuracies were relatively uniform across all TEAS frequencies, including the sham condition, with values ranging from approximately 39.82% to 41.21%. This uniformity suggests that the delta band may not be significantly affected by the variations in TEAS frequency.

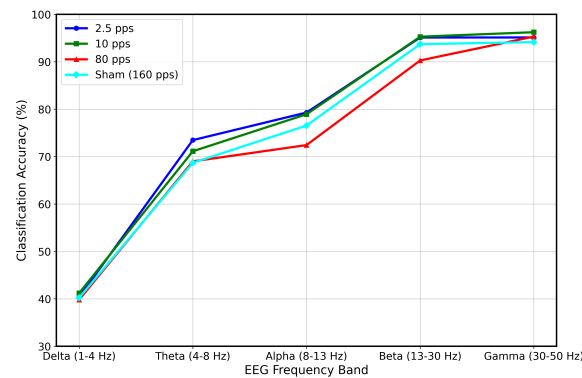


Figure 4. Averaged classification accuracy at each EEG frequency band for different TEAS frequencies across time.

For the theta (4–8 Hz) band, the classification accuracies were higher, indicating a greater sensitivity to TEAS. The accuracies ranged from approximately 68.69% to 73.48%, with the highest accuracy observed at 2.5 pps. This could indicate that the theta band is moderately responsive to TEAS. The alpha (8–13 Hz) band showed a more pronounced increase in classification accuracy with TEAS application, with values ranging from approximately 72.43% to 79.29%. The highest accuracy was again observed at 2.5 pps. The alpha band is often associated with a relaxed, yet alert state, and these results may suggest that TEAS has a more noticeable impact on this state.

In the beta (13–30 Hz) band, there was a significant increase in classification accuracy when TEAS was applied. The accuracies ranged from approximately 90.28% in the 80 pps condition to about 95% at 10 and 2.5 pps. Beta frequency is associated with active thinking, focus, and cognitive processing. Changes in beta frequency may indicate that TEAS enhances alertness and cognitive function, possibly by reducing anxiety and stress. Finally, the gamma (30–50 Hz) band exhibited the highest classification accuracies. The accuracies ranged from approximately 94.15% in the sham condition to 96.24% at 10 pps. Gamma frequency is linked to high-level cognitive functions, such as information processing, memory, and consciousness. Changes in gamma activity could suggest improved neural synchrony and integration of sensory information.

3.6. Optimizing Electrode Selection for EEG-Based TEAS Frequency Classification Using Saliency Maps

In this section, the goal was to refine the electrode selection for EEG-based classification of TEAS frequencies by identifying the optimal subset of electrodes that maintain high classification accuracy. The selection of electrode combinations was provided by a saliency map analysis, which identified the most salient electrodes for phase discrimination across four different stimulation frequencies of 2.5 pps, 10 pps, 80 pps, and Sham. The topographic distributions of aggregated saliency maps over all the 12 phase combinations for various TEAS frequencies are shown in Figure 5. From Figure 5, electrodes Fp1, Fp2, Fz, F8, F7, T4, and T3 had the highest scores, in terms of differentiating the three phases—pre-stimulation, during-stimulation, and post-stimulation—across all the TEAS frequencies. Beginning with the two most significant electrodes, Fp1 and Fp2, the accuracy scores for each TEAS frequency were determined for various combinations of sorted electrodes, as indicated in Table 6. The line chart of the accuracies versus the combinations is shown in Figure 6. From Figure 6, the first combination (comb1) included the prefrontal electrodes, Fp1 and Fp2, providing a pre-stimulation accuracy between 47.6% and 51.7% across the TEAS frequencies. By expanding this set to include the frontal midline electrode Fz (comb2), associated with the midline frontal cortex, there was a noticeable improvement in classification accuracy, highlighting the significance of this region in processing TEAS phases. Further additions of electrodes, such as F7 and F8 in comb3, which were over the left and right dorsolateral prefrontal cortex, and T3 and T4 in comb4, over the left and right temporal

areas, led to a substantial improvement in classification accuracy. Notably, the seven-electrode combination (comb4), which encompassed the prefrontal, midline frontal cortex, and temporal areas, achieved performance levels close to that of the full 19-electrode set (all electrodes), which spanned the entire scalp. This finding indicates that the additional electrodes beyond the seventh did not contribute significantly to the model’s performance, emphasizing the efficiency of the chosen subset of electrodes. This has profound implications for the application of EEG in clinical and research settings, suggesting that a reduced set of electrodes can provide efficient and reliable classification performance, potentially streamlining EEG protocols and improving patient comfort.

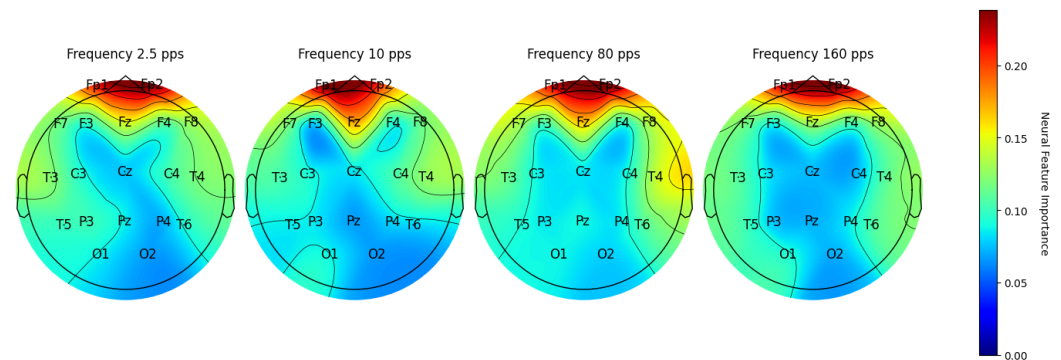


Figure 5. Topographic distribution of aggregated saliency maps for various TEAS frequencies. The color scale indicates the relative importance of each electrode’s signal in the model’s classification, with warmer colors indicating higher saliency.

Table 6. Electrode combinations and their corresponding electrode label; “comb” denotes the combinations of electrodes used for classification.

Name of Combinations	Combination	Name of Electrodes
comb1	1, 2	Fp1, Fp2
comb2	1, 2, 5	Fp1, Fp2, Fz
comb3	1, 2, 3, 5, 7	Fp1, Fp2, Fz, F8, F7
comb4	1, 2, 3, 5, 7, 8, 12	Fp1, Fp2, Fz, F8, F7, T3, T4
all electrodes	1–19	Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, O2

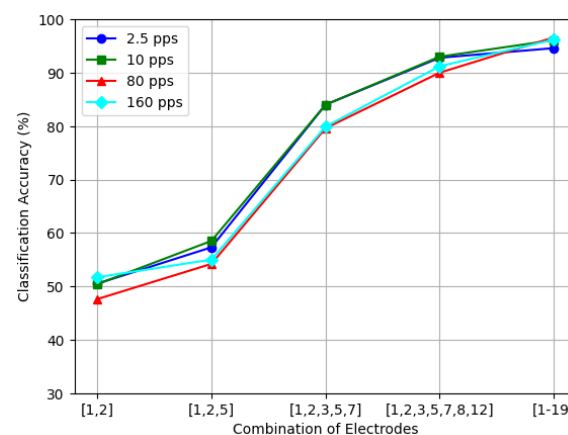


Figure 6. Aggregated classification accuracy of the three phases for incremental electrode combinations.

4. Discussion

The findings from our study verify and extend the work by Uyulan et al. [19], which pioneered the application of artificial intelligence (AI) to understand the effects of TEAS stimulation on EEG signals. Our research advances the field by not only employing a

cutting-edge convolutional neural network model, EEGNet, but also by achieving high classification accuracies. The EEGNet model achieved over 95% classification accuracy in detecting brain responses to various TEAS frequencies, with accuracies consistently high across different time slots during stimulation (95.65% to 97.66%). This high level of accuracy suggests that the model is proficient in distinguishing between the different TEAS frequencies, indicating that TEAS at various frequencies may engage different neural mechanisms and pathways. This knowledge could help tailor TEAS treatments to achieve specific therapeutic effects, such as pain management or cognitive enhancement.

Furthermore, the classification accuracies across the pre-stimulation, during-stimulation, and post-stimulation phases were consistently high (above 92%), demonstrating that EEGNet can effectively capture time-based brain responses throughout different stimulation phases. This provides a detailed view of how TEAS affects brain activity over time, which is crucial for optimizing therapeutic strategies and understanding the immediate and long-term neural effects of TEAS.

In terms of demographic and clinical factors, the study showed that EEGNet's classification accuracy remained high across different groups, including variations in sex, age, and psychological states. The accuracy for female participants ranged from 93% to 100%, while for male participants it ranged from 90% to 95%. Age groups also showed high accuracies, with older adults (over 45 years) ranging from 92% to 98% and younger adults (under 45 years) from 90% to 99%. Additionally, the model demonstrated that high relaxation states achieved accuracies between 90% and 100% and that low relaxation states ranged from 90% to 97%. Similarly, high anxiety levels corresponded to accuracies of 90% to 100%, while low anxiety levels ranged from 90% to 97%. This robustness across demographics and psychological states suggests that the model is reliable and could benefit a broad range of patients.

Additionally, the responsiveness of different EEG frequency bands to TEAS was investigated. The beta and gamma frequency bands exhibited the highest responsiveness, with classification accuracies exceeding 90%. This indicates significant effects on higher cognitive functions, aligning with previous studies suggesting that beta and gamma activities are associated with cognitive processing and neural synchrony.

Finally, the use of saliency maps revealed that a subset of electrodes (Fp1, Fp2, Fz, F7, F8, T3, T4) could achieve accurate classification. This finding is significant, as it suggests the potential for more efficient EEG setups, reducing the number of electrodes required without compromising accuracy. This could streamline EEG protocols, making them more patient-friendly and cost-effective. The electrodes identified as most significant in our analysis exhibited a strong correlation with those reported in prior studies. Wang et al. (2023) [33] conducted a study where EEG signals were collected during TEAS at PC3, PC5, PC7, and PC8 on the pericardial meridian in 21 healthy subjects. Their analysis using standard low-resolution electromagnetic tomography (sLORETA), phase-locking value (PLV), and complex network methods revealed activation in several cortical areas, including the prefrontal cortex (reflected in the signals recorded from the FP1 and FP2 electrodes), the orbitofrontal cortex (reflected in FP1, FP2, and Fz), the temporal gyrus and temporal pole (reflected in T3 and T4), and the triangular part and inferior frontal cortex (reflected in F7 and F8). These results demonstrate the broad cortical effects of TEAS, particularly in regions associated with higher cognitive functions.

Additionally, the study by Kong et al. (2015) [34] investigated neural activity during TEAS in 36 patients with left Bell's palsy. The study used a single-block fMRI design to detect neural activation across different phases of TEAS at acupoints LI4, Jiache (ST6), and a sham point. Their findings indicated increased activation in the pre-motor cortex and supplementary motor area (reflected in Fz) and in the prefrontal cortex (reflected in FP1 and FP2). The consistency of these findings with our electrode selection lends further credence to the notion that these brain areas are more susceptible to the influences of acupuncture and should be a focus in EEG-based studies in this domain.

Furthermore, the preferential influence of different TEAS frequencies on specific EEG frequency bands, as reported by Uyulan et al. [19] and Lee et al. [16], has been validated by our study, with the gamma and beta bands exhibiting the highest responsiveness to TEAS. This finding underlines the potential of TEAS in modulating higher-frequency brain functions, which could have significant implications for therapeutic applications.

5. Limitations

The data collection for this study took place under less-than-ideal conditions, within a laboratory environment that lacked soundproofing and regulated temperature control. However, efforts were made to reduce external noise as much as possible and to maintain a consistent, comfortable temperature throughout the year-long data collection period. Furthermore, our study was conducted with a relatively small sample size of 48 participants, which is limited for deep learning research. Despite this, the implementation of five-fold cross-validation was intended to mitigate the small sample size.

6. Conclusions

This study presents a significant advancement in understanding neurophysiological responses to transcutaneous electroacupuncture stimulation (TEAS) by employing cutting-edge deep learning techniques. Using EEGNet, a specialized convolutional neural network designed for EEG signal classification, the model demonstrated over 95% accuracy in detecting brain responses to various TEAS frequencies. The robustness of the model was evident across multiple phases—pre-stimulation, during-stimulation, and post-stimulation—with consistently high classification accuracies exceeding 92%, highlighting its effectiveness in capturing time-based brain responses. Moreover, the application of saliency maps provided valuable insights into the most critical EEG electrodes, suggesting that a subset of electrodes (Fp1, Fp2, Fz, F7, F8, T3, T4) is sufficient for accurate classification. This finding offers the potential for more efficient and streamlined EEG setups. The reduction in electrode use, without sacrificing accuracy, enhances the practicality and comfort of EEG-based procedures in clinical and therapeutic settings. The findings also underscore the importance of specific EEG frequency bands—particularly the beta and gamma bands, which exhibited the highest responsiveness to TEAS—indicating significant impacts on cognitive functions and neural synchrony. Additionally, the model's stability across various demographic and psychological factors, including sex, age, and anxiety or relaxation states, confirms its broad applicability.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/a17110477/s1>.

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