Chronological overview and algorithmic analysis of EEG Signal Processing for Brain Response to Stimuli

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Abstract—The brain is one of the most complicated organs in the human body that controls the entire actions/reactions of the body by getting diverse stimuli via the nervous system. The stimulus that is stronger than the threshold stimulus is decoded by the sensory neurons counts creating information on the frequency and the stimulus of the action potentials. This work intends to plan a detailed survey on brain response to stimuli in EEG signal processing by reviewing about 35 papers selectively to determine the shortcoming of contributed works. The analysis is subjugated in terms of chronological review, and algorithmic analysis. This analysis determines the utilization of diverse models/approaches in the contributed papers. Moreover, the performance parameter analysis along with the best performance values is also stated clearly. Finally, the research gaps and challenges that rely on this topic are clearly described that paves the way for future research contributions.

Keywords—Stimuli; Brain Response; EEG signal processing; Algorithmic Analysis; Research Gaps

1. Introduction

The characterization of Human nature is based on its social communication. This communication comprised of other people emotions, social behavior, intentions, and identities. The emotional information encoding ability seemed to be difficult, towards determining possible threats and launching adaptive behavior. Emotions are considered as an episodic, biologically based perception pattern for particular stimulus. The research works on emotion recognition uses diverse stimulus types like sounds, pictures, and words.

Diverse aspects of brain network activity [36] [37] [38] are captivated by EEG and fMRI responses. EEG is initially termed as the sensitive synchronous cortical activity, while fMRI measures alter in blood oxygenation through the entire brain following neural activity. EEG offers the direct measure of neural activity having large temporal resolution, whereas, fMRI offers an indirect measure of neural activity having a large spatial resolution [43] [44] [45]. As every modality offers a sole picture of neural activity, consisting of (i.e., fusing) information between two modalities offers an enhanced spatiotemporal characterization of brain networks.

MMN studies have concluded that the perceptual deviance is recorded within the ERP signal in a comparatively earlier time window (~150 ms), with no requirements of active participants attending the deviant stimuli. The studies on Auditory MMN based on Granger causality models and source localization techniques have determined the generators of mismatch responses within the primary frontal cortex and auditory cortex. Corresponding learning on MEG and EEG [39] [40] [41] [42] responses to stimulus deviance have as well validated the cross-region phase synchronization and front temporal connectivity. Overall, these learning have recommended the organized learning of the local sensory cortex and frontal cortex in the form of innovative detection processes.

The contribution is summarized as:

- This survey exploits a review on brain response to stimuli in EEG, where several analyses are articulated about chronological review and algorithmic analysis from the contributed papers.
- Additionally, the performance measure with the best value is listed in detail.
- To the end, the research gaps and challenges regarding this topic are depicted for future advancement. The organized paper is detailed as follows: Section II explains the literature
survey on the contributed papers along with the chronological review. Section III defines the study on algorithms and performance measures. Section IV explicates the research gaps and their challenges for the future scope. Section V ends the paper.

**TABLE I:** Nomenclature table

| Acronym | Descriptions |
|---------|---------------|
| BSC     | Brain Signal Complexity |
| MSE     | Multi-Scale Entropy |
| SEM     | Structural Equation Modelling |
| GF      | Global Form |
| GM      | Global Motion |
| OR      | Orientation Reversal |
| EEG     | Electroencephalography |
| GSR     | Galvanic Skin Response |
| NREM    | Non-Rapid Eye Movement |
| ASSR    | Auditory Steady-State Responses |
| AM      | Amplitude Modulation |
| HRF     | Hemodynamic Response Function |
| fMRI    | Functional Magnetic Resonance Imaging |
| GLM     | General Linear Model |
| LSBN    | Large-Scale Brain Network |
| AUT     | Alternative Uses Task |
| DT      | Divergent Thinking |
| HGB     | High-Gamma frequency Band |
| VAS     | Visual Analog Scale |
| POMS    | Profiles Of Mood States |
| BSS     | Blind Source Separation |
| ROC     | Receiver Operating Characteristic |
| sLORETA | standardized Low-Resolution Brain Electromagnetic Tomography |
| ERN     | Error-Related Negativity |
| TRF     | Temporal Response Function |
| mTRF    | multivariate Temporal Response Functions |
| BCI     | Brain-Computer Interface |
| EMD     | Empirical Mode Decomposition |
| WT      | Wavelet Transform |
| MF DFA  | Multifractal De-trended Fluctuation Analysis |
| CWT     | Continuous Wavelet Transform |
| WCST    | Wisconsin Card Sorting Test |
| ICA     | Independent Component Analysis |
| ALNV    | Activity Learning Neural Vector |
| ASL     | American Sign Language |
| MLP     | Multi-Layer Perceptron |
| MMN     | Mismatch Negativity |
2. Literature Survey

A. Related Works

In 2019, Kaur et al. [1] have stated about the largely deployed marker of BSC at multiple temporal scales, which was named as MSE. Till now, the addressing of MSE’s psychometric reliability and quality was a challenging task. Hence, SEM was developed for this. Based on the EEG signal’s recording condition, the individual differences in BSC were decomposed as diverse factors using SEM. This work has estimated the average MSE differences across recording situations efficiently.

In 2017, Ahtola et al. [2] have evaluated a model for enhancing the consistency of determining EEG responses that induced using complicated visual stimuli for clinical use. This was made by incorporating an eye tracker over the setup of EEG and by optimizing the analysis protocol. For this purpose, the infants were offered continuous GF, GM and OR stimuli. In order to exclude epochs with disoriented gaze and control stimulus presentation, Eye tracking technique has been deployed. The estimation of spectral responses was made by Hoteling’s test statistic that indulged with the circular variant.

In 2020, Omam et al. [3] have experimented the correlation amongst the brain activity and human skin activity for the first time arithmetically using EEG signals and GSR. The fractal theory was deployed and the fractal dimensional variations of EEG and GSR signals were analysed while exposing the subjects to diverse olfactory stimuli in the pleasant odours structure. Thus, the statistical analysis outcomes have demonstrated the noteworthy stimulation effect on the complex variations of the GSR signal.

In 2018, Lustenberger et al. [4] have compared the auditory rhythmic stimuli effect at the time of NREM sleep and wake on EEG brain activity. Further, this work has examined the impact of dominant sleep rhythms presence on ASSR. Based on this, the topographical distribution of these modulations was depicted. On these conditions, this approach applied the AM white noise auditory stimuli at diverse frequencies. The review thus demonstrated that ASSR has been considerably modulated by vigilance state, sleep pressure and the availability of sleep spindles and slow-wave activity, which was based on the stimulation frequency applied, window/frequencies and electrode location.

In 2017, Tsolaki et al. [5] have examined the impact of neuronal activation over age and the response to diverse emotional stimuli. In this, the modulations in the early N170 event-related-potential component were studied by utilizing the Brain source localization. Moreover, in the neural activation for both emotional stimuli and the topographic maps, the age-induced differences were delineated. From the entire analysis, the limbic area and its implication to emotional processing were seemed to get affected by the aging process.

In 2019, Zhang et al. [6] have studied and analysed the recording of 128-channel EEG signals while the subjects have been listened to pseudo words and real in Mandarin. The dynamic brain connectivity patterns were analysed based on the sliding-window Granger causality analysis and EEG source reconstruction model. The overall analysis on this learning has thus recommended the speech representations that involved dynamic interactions between distributed brain regions that communicated via time-specific functional networks.

In 2019, Labounek et al. [7] have investigated the correlations among concurrent fMRI BOLD signals and EEG spatio-spectral pattern time courses based on canonical HRF. This was made regarding its 1st and 2nd temporal derivatives within voxel-wise GLM. The derivation of HRF shapes from EEG-fMRI time courses has been made at the time of visual oddball, “resting state”, and semantic decision paradigms. This work has shown the considerable correlation of time courses with fMRI dynamics that arranged within LSBN system.

In 2019, Zheng et al. [8] have introduced an automatic framework for visual classification, wherein the selection of multiple networks was guided based on the narrative analysis model (LSTMS-B) of EEG signals. This in turns directs the enhancement in the classification performance. In order to extract the category-dependent representations of EEG signal, this method named LSTMS-B was developed with the incorporation of ensemble learning and deep learning models. In this, the regression output was deployed as the features for classifying the images and at last, it was gained with 90.16% of average classification accuracy.

In 2019, Agnoli et al. [9] have examined the variations in alpha power at the time of structured version performance of the AUT, which needed for ideating the four alternatives that deployed for traditional objects in
sequential and distinct balanced time periods. A three-step approach was pursued by this data analysis process, which involves physiology aspects, behavior aspects, and their mutual relationship. A distinctive serial order impact at the time of DT production at the behavioral level was observed along with the raise in originality connected over the minimization in response percentage and maximization in ideational time for the four responses.

In 2019, Shen et al. [10] have investigated the neural oscillations included in the processing of tactile novelty. Particularly, explicating the physical categorization of diverse digits of the hand that equivalent to each other. The analysis on Time-frequency was evaluated by recording the EEG responses from a somatosensory mismatch protocol that involved the 1st, 3rd, and 5th digits stimulation. Further, the examination of EEG responses was made with two deviant stimuli and standard stimuli. The EEG response analyses have investigated the variation in phase as well as the power information. The discussions on these results were made regarding the emerging literature on neural processes included in the maintenance and generation of body representations.

In 2018, Völker et al. [11] have characterized the human brain’s error-related response on the basis of data that gained for HGB mapping with non-invasive EEG optimization. The resulting outcomes have thus validated the inclusive structure of local and global dynamics of error-related HGB activities within the brain of a human. The experimental analysis has furthermore explicated the fundamental spatio-temporal characteristics of HGB activity with complementing traditional error-related potential studies, a neural correlate of error processing.

In 2013, MURAO et al. [12] have examined the activity of electroencephalography and any anti-stress effects once after smelling the two green tea kinds. An auditory discrimination task and an arithmetic task have been deployed for testing the mental stress. The recording of EEG was facilitated before, after executing the mental tasks, before, and after smelling the tea samples. At the end of each task, the mental status of subjective was rated with the VAS and the POMS. The outcomes have thus represented that the ratings on subjective have obtained with increased electroencephalographic activities and relaxed feeling after smelling the green tea.

In 2018, Ndaro and Wang [13] have evaluated and explored the accuracy and efficiency impact of fatigue based on laparoscopic surgical training via EEG signal. The simulation of this modelled fatigue and data acquisition analysis modules were implemented using MATLAB. The EEG signals were recorded and transferred to the wireless personal computer using BrainLink concept via Bluetooth. The removal of artefacts from the captured EEG signals was made by BSS. Depending on Mahalanobis Distance (DC) and Regression Model, the evaluation of Fatigue was made and the investigational outcomes from ROC curve analysis determine their threshold value.

In 2017, Pauw et al. [14] have made a study for determining the straight link that existed among the brain and the nasal cavity. Four cognitive Stroop tasks have been carried out at each trail, and among these, two were the familiarization trials, and one-post and one-pre-NAS trails. Further, the determination of accuracy and reaction times for diverse stimuli has been detected. Moreover, sLORETA has been deployed for source localization.

In 2011, Brazil et al. [15] have deployed the Event-related potentials for unravelling the observation of matched healthy control subjects and one’s own and others’ incorrect and correct actions in psychopathic subjects. In a social flunker task, the investigation of ERN was made subsequent to own and other’s responses. The resultant outcomes have thus suggested that the action monitoring characteristics in psychopathy were bothered in social tactics and probably acts as a core role in the abnormal social behavior acquisition.

In 2020, Das et al. [16] have presented a data-driven model, which carried the knowledge benefit of developed stimulus for achieving a joint dimensionality reduction and noise reduction with no need for iterated trials. Based on the available stimulus, this model initially estimated the stimulus-driven neural response. Under the circumstance of speech stimulus neural tracking based on EEG, this approach has demonstrated the larger correlations among actual and predicted neural responses, more precise short-term TRF estimates, and larger attention decoding accuracies differentiated over traditional TRF-based decoding models.

In 2018, Lim et al. [17] have developed a narrative approach for tracking the EEG activity of diverse brain regions that included in the dispensation of non-target and target stimuli in oddball concept. Subsequently, the difference in the activation pattern for diverse oddball tasks was identified. Horn and Schunck Optical Flow
estimation approach were used for evaluating the activation flow among consecutive topo-maps. The comparative analysis regarding the subjective has demonstrated that this implemented approach was very much capable in tracking the activities of EEG.

In 2018, Tcheslavski et al. [18] have implemented a new technique based on EEG study for human colour perception by deploying mTRFs, which enumerated the spatiotemporal brain responses to sensory stimuli. The derivation of such functions was made from EEG observation over a subject; these subjects were rendered over the screen colour that varied along time. From the result analysis, it was clear that the prominent local extrema examined in mTRFs have to be attributed to the colours professed by the participant in spite of the post-stimulus latencies.

In 2016, Horki et al. [19] have introduced an investigational theory that facilitated the brainteaser’s performance, and in contrast, maximized the experimental protocol control. Subsequently, this work has exploited the same findings by mentally presenting to verbal performance of someone else’s brainteaser tasks and self-performed similar tasks for setting up an online BCI. This work has illustrated with selective attention of single auditory task, which has modulated either evoked or induced changes over EEG and has been utilized as a better communication factor in an auditory scanning concept.

In 2018, Lichtner et al. [20] have examined the impact of hypnotic drug propanol at doses equivalent to those in clinical practices affects the processing of somatosensory stimuli in primary and in the spinal cord and higher- order cortices. The result thus concluded that the variations in noxious stimuli processing at the time of propanol anesthesia can be associated to alterations in functional connectivity.

In 2014, Gonçalves et al. [21] have demonstrated EEG has deployed a linear modelling technique that formulates functional interest in sensory systems for quickly gaining spatiotemporally accurate responses to complex sensory stimuli. With this, narrative information was provided in human V6 on the timing of coherent motion processing. Simplifying, this technique poses the probability for facilitating the quick, economical spatiotemporal position of larger perceptual functions in acting humans.

In 2018, Shahabi et al. [22] have inspected the efficient brain networks connected with melancholic, neutral, and joyful music. Multivariate autoregressive modelling was used for extracting the connectivity patterns between EEG electrodes in diverse frequency bands when the subject listening to chosen Iranian and classical musical passage. The classification accuracies in differentiating familiar from unfamiliar, joyful from neutral and joyful from melancholic trials were estimated as $83.04\% \pm 1.47$, $93.7\% \pm 1.06\%$ and $80.43\% \pm 1.74\%$, correspondingly.

In 2015, Maity et al. [23] have executed the EEG over the subjective by an easier acoustical stimulus i.e., a ‘tanpura’ drone. In order to acquire raw EEG signals from blink and other muscular artefacts, EMD was applied. The theta and alpha waves from the de-noised EEG signal were segregated using the WT approach. The derived alpha and theta time series data were processed with non-linear analysis in the structure of MFDFA for studying their complexity variation.

In 2015, Jamal et al. [24] have applied an analysis technique based on CWT on EEG data that captivated at the time of face perception constraint from the onset of a stimulus to explore the temporal evolution of phase synchronization. These stable states were translated to complex networks of the brain, extracted few informative network measures to characterize the degree of information integration, and segregated processing in those synchro states, which directs to a novel technique to characterize information processing in the human brain. Themodelled methodology for the functional brain connectivity via these synchro states has been visualized as an innovative path for a quantitative description of the subject’s cognitive ability, stimuli, and segregation capability/information integration.

In 2019, Papousek et al. [25] have studied the recording of asymmetry responses of EEG alpha signals in psychology students (n=62). This was made regarding the course of a situation constructed for simulating a real examination, wherein needs the statistical concept’s oral explanation. Independent of momentary affective states and negative affect, trait positive affectivity has observed to be connected to employment of brain processes that support a more adaptive response in that matter.

In 2012, Díaz et al. [26] have explained the determination of the prefrontal EEG correlation at the time of working out the WCST and Tower of Hanoi. This study further described the impact of the subjects on earlier
experience of videos with aggressive or sexual content. The Pearson correlation has been used for determining the Prefrontal EEG coupling. The Self-Assessment Manikin Scale was estimated or measured using Valence and general arousal and the Sexual Arousal Scale was used for measuring the sexual arousal. Computerized editions of the WCST and Towers of Hanoi offered data on prefrontal executive functions.

In 2016, Mehmood et al. [27] have developed an adaptive model for feature extraction of emotion recognition in EEG-based human brain signals. The ICA has been used for neglecting the artefacts and it was done based on the pre-processing of raw brain signals. This research work has introduced a model for feature extraction based on LPP, and further developed a standard regarding frequency and statistical domain features. The experimental outcome has offered a way to advance a more specialized emotion recognition system using brain signals.

In 2018, Quandt and Kubicek [28] have presented a conclusion by recommending the sign sensorimotor characteristics that were summoned during Deaf signers read English words. This paper has made an analysis for the first time on neural oscillatory dynamics that occurred during this procedure, representing that beta and alpha EEG oscillations reflected sensorimotor features of ASL signs at the time of cross-linguistic, cross-modal translation. This work has thus represented the requirement of a complicated understanding of how English and ASL interact and overlap with one another in Deaf bilingual readers.

In 2016, Bhatti et al. [29] have determined the emotions like sad, anger, love and happy regarding the response of subjects listening to audio music tracks from rap, electronic, rock, metal, and hip-hop genres. This study mainly intends on determining the impact of diverse genres of music regarding the emotions of humans and signifying the respective age group that was influenced more by music. From the outcomes, it was evident that MLP has achieved superior accuracy in recognizing human emotion based on the subject’s response to audio music tracks under hybrid characteristics of brain signals.

In 2011, Stroganova et al. [30] have examined the power's temporo-spatial dynamics of the phase-linked component and the EEG alpha oscillation's total power on presenting a control non-illusory image and the illusory outline (Kanizsa square) for 16 healthy adult subjects. The oscillations of Alpha were determined based on wavelets; analysis of variance together with a novel nonparametric multifactorial analysis was done to study the dynamics statistical assessments of alpha power. This paper thus summarized that the initial maximization in alpha oscillations imitates activity modulation of neuron ensembles that contained in dealing with the overall patterns when associating the alpha rhythm blockade with orientation procedures.

In 2019, Vadivu and Sundararajan [31] have intended on recognizing the activity of the brain from EEG signal based on ALNV and Adaptive Wavelet Transform Classification approaches. The extraction of features was done by means of adaptive wavelet transform and the classification was carried out based on ANLV classification approach. The testing of this diverse brain activity EEG signals was done in MATLAB. This simulation results proved the betterment of proposed work with an accuracy of 95%.

In 2015, Yuvaraj et al. [32] have intended on investigating the impact of emotion processing on interhemispheric EEG coherence in PD. Seven homologous EEG computed from for beta, theta, gamma, alpha, and delta frequency bands. Additionally, the representation of emotional stimuli was gained based on subjective ratings. The findings thus stated that the PD patients were seemed to be impaired in identifying negative emotions like fear, sadness, disgust, and anger than the positive emotions like surprise and happiness. During emotion processing, these findings recommended that PD patients could suffer from functional impairment of inter-hemispheric connectivity.

In 2009, Schall et al. [33] have presented the continuously changing, temporally congruent and incongruent stimuli by investigating the audio-visual binding. The waveform and Spectro-temporal locking of neural activity were quantified by the Recorded EEG signals to stimulus dynamics. To be more specific, the modulation of this signal strength was made by the congruency of an associated auditory stream. Therefore, it was argued that these impacts replicate the interaction of audio-visual. This paper thus revealed that the waveform Spectro-temporal locking replicates diverse mechanisms contained in the dynamic audio-visual stimuli processing.

In 2013, Souza et al. [34] have examined the brain activity associated to auditory frequency discrimination learning for source localization based on a variation Bayesian technique, at the time of
instantaneous recording of EEG and fMRI. This framework mainly investigates on the activity of the stimulus-driven mechanism that determines the practice effects or the large-level attentional approaches connected to the perceptual task, control the learning process. The fMRI and EEG outcomes jointly recommended that the activity of gamma-band within the left IFG and right STG takes a major position at the time of perceptual learning.

In 2014, Smyrnis et al. [35] have examined the questioning function on spatial working memory associated to movement plans (motor working memory) and spatial working memory associated to perceptual processes and spatial attention (perceptual spatial working memory) takes on the similar neurophysiological substrate. Based on this, it employed evidence for perceptual working memory and a separate motor for streams processing. More specifically, in both gamma and beta bands, this work has examined a considerable improvement in the movement associated with differentiated over the perceptual-connected memory-specific amplitude spectrum signal in the central midline area. The outcomes thus offered a clear confirmation for the dissociation of motor and perceptual spatial working memory.

B. Chronological Review

Fig. 1 explicated the chronological analysis and the contribution percentage of the used papers on the topic brain response to stimuli in the EEG signal. The review is prepared on the contributed papers from 2009 to 2020. From this, the maximum contributed papers are from the year 2019, which has contributed about 22.86%. From 2018, 20% of the papers are taken and on the year 2016, 11.43% is taken for the review on this related topic. 8.57% is the contribution of the papers from the years 2015 and 2017. The papers from 2011, 2013, 2014, and 2020 are taken with the contribution of 5.71%. The rest of the papers from 2009 and 2012 have achieved the contribution of 2.86% from the overall papers.

1. Study on Algorithms and Performance measures

A. Algorithmic Analysis

Fig. 2 manipulates the algorithmic analysis towards different models used in the reviewed papers on brain response to stimuli in the EEG signal. Various methods or models are used in these contributed papers for this processing and are explicated as follows: SEM is the methodology used for the EEG signal processing in [1]. E prime software is deployed in the paper [2]. The author in [3] used the fractal theory. AM white noise auditory stimuli is the algorithm employed by the author in paper [4].

Brain source localization is utilized in [5]. MVAR is the methodology used by the author in [6]. Canonical HRF is deployed in [7] and the author in [8] uses the bagging theory concept. ICA is used in the two contributed papers of [9] and [28]. In [10], the author deploys ERSP. Bootstrap sampling is a well-known concept used in [11]. The features are extracted in [12] by the Kruskal-Wallis test. BSS algorithm is evaluated in paper [13]. The author in paper [14] uses the solera algorithm. GLM model is employed in the contribute papers [15] and [25].

TRF is the deployed concept in paper [16]. Horn and Schunck Optical Flow estimation method and Tikhonov regularization are used in [17] and [18], respectively. The author in paper [20] establishes the multilayer spectral estimation method for EEG processing. Linear least-squares regression approach is utilized in [21]. The author in papers [22] and [27] uses the SVM model for the precise recognition rate. EMD based EEG
processing is deployed in [23]. CWT is the assigned method in paper [24]. In [26], the Pearson correlation is employed. MLP is used in [29]. ANOVA concept is performed in papers [30] and [35]. ALNV is the deployed concept for estimation in [31]. Emotion elicitation protocol is utilized in [32]. IFFT is the arithmetical calculation used in [33]. Variation Bayesian approach is the performed concept by the author in [34].

![Fig. 2. Algorithmic Analysis Regarding Brain Response to Stimuli in EEG Signal](image)

**B. Analysis on Performance Measure**

Table II explains the performance analysis of the contributed papers with their best-attained values. The MSE, RMSE, and MAE are the error measures that need to be in minimum for effective processing, which is attained as 1.901, 0.134 and 0.08 in [1], [2] and [24], respectively. The recognition rate in [2] and [32] has attained the best value as 0.134, whereas the effect size in [3] achieves 0.5886.

The best performance of intensity is achieved with 0.17 in [5]. The frequent, target and distractor stimulus used in [7] has attained a better value as 2.5, 2.6 and -2.2, respectively. Accuracy measure has attained the contribution of 14.29% with the best value as 98.7, whereas precision and recall in [8] and [31] is achieved with 97.13 and 96.96, respectively. The F1-score contributed about 8.57% with the best-achieved value as 96.94. Mean is the most used measure in the contributed papers with the contribution of 17.14% and the best performance value of the mean is 38. Response or reaction time is achieved as 470ms in [12] and [35].

Slope and completion time in [13] gains superior value as 0.62 and 102s, respectively. GLUC and CAF in [14] achieve the performance value as 60 and 30, respectively. Similarly, the power ratio, hue, Hurst coefficient, threshold, burst suppression ratio and FDR is used respectively in papers [16], [18], [23], [34], [20] and [11], and is obtained with the best performance value as 0.543, 29.97Hz, 0.824, 17.5, 75.20% and 0.0215. The SD measure attains the best value as 9.3 and contributes to overall measure of about 11.43%.
| SL.No. | Measure          | Citation      | Best value |
|-------|------------------|---------------|------------|
| 1.    | MSE              | [1]           | 1.901      |
| 2.    | RMSE             | [1]           | 0.134      |
| 3.    | Recognition rate | [2] [32]      | 93.75      |
| 4.    | Effect size      | [3]           | 0.5886     |
| 5.    | Intensity        | [5]           | 0.17       |
| 6.    | Frequent stimulus| [7]           | 2.5        |
| 7.    | Target stimulus  | [7]           | 2.6        |
| 8.    | Distractor stimulus| [7]   | -2.2       |
| 9.    | Accuracy         | [8] [22] [27] [29] [31] | 98.7 |
| 10.   | Precision        | [8] [31]      | 97.13      |
| 11.   | Recall           | [8] [31]      | 96.96      |
| 12.   | F1-score         | [8] [29] [31] | 96.94      |
| 13.   | Mean             | [9] [15] [22] [24] [25] [32] | 38   |
| 14.   | FDR              | [11]          | 0.0215     |
| 15.   | Response/Reaction time | [12] [35] | 470ms |
| 16.   | Slope            | [13]          | 0.62       |
| 17.   | Completion time  | [13]          | 102s       |
| 18.   | GLUC             | [14]          | 60         |
| 19.   | CAF              | [14]          | 30         |
| 20.   | Power ratio      | [16]          | 0.543      |
| 21.   | Hue              | [18]          | 29.97Hz    |
| 22.   | Standard deviation| [22] [25] [32] [33] | 9.3 |
| 23.   | Hurst coefficient| [23]          | 0.824      |
| 24.   | MAE              | [29]          | 0.08       |
| 25.   | Threshold        | [34]          | 17.5       |
| 26.   | Burst suppression ratio | [20] | 75.20%   |
2. Research Gaps and Challenges

The EEG signal has a fascinating temporal resolution than other neuro imaging approaches, but it still falls low because of its lower spatial resolution. Furthermore, the EEG is faster and easier to utilize and is non-invasive. Additionally, it can differentiate the severity issues with low cost while comparing over other imaging devices. It can further popularly used for population screening to detect pre-clinical biomarkers due to its reduced cost. Availability of poor spatial resolution is the main drawback of this EEG signal. As the skull deforms the underlying brain electrical activity for a broad range area of the scalp, as it acts as a low-pass filter. Moreover, the changes in variables may also influence brain responses. Hence, there is a need for signal processing mechanisms to be developed for facilitating their analysis and interpretation in a quantitative way. However, the contributions concerning the brain response to stimuli in EEG signal processing is still in an infant stage. Since only few research contributions have been listed in the literature, future works are highly appreciated with advanced models.

3. Conclusion

This survey aimed on offering a detailed description of various contributions towards brain response to stimuli in EEG signal processing. Around 35 research papers related to brain response under the EEG signal has been reviewed. Firstly, the algorithm deployed in the different contributed papers was determined. Additionally, the analysis was extended over the used performance measures with their attained best values. To the end, the research gaps and challenges associated to this topic has been detailed to endure and rectify the future issues. We can say Electroencephalography (EEG) is an effective method for studying brain imaging, providing electrical activity in brain and time resolution is most important property of EEG as compared to other methods of brain imaging.

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