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Neurostressology: A systematic review of EEG-based automated mental stress perspectives

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ABSTRACT

Presently, mental stress is a significant contributor to physical and psychological health issues, making its early detection and monitoring a public health priority. Among various neuroimaging methods, Electroencephalography (EEG) has emerged as a promising tool due to its ability to capture fine-grained temporal dynamics associated with cognitive stress responses. This paper presents a systematic review of 275 peer-reviewed studies published between 2003 and January 2025, focused on EEG-based mental stress quantification. While previous stress reviews primarily emphasized signal processing pipelines and psychological stress methods, this study emphasizes the potential of fusion-centric approaches. It systematically analyzes and compares studies across multiple dimensions, including EEG datasets, stressor categories, key electrodes, brain regions, feature correlations, and classifier performance, to identify methodological trends, inconsistencies, and gaps in standardization. The review underlines multiple levels of fusion, including multimodal fusion such as EEG with speech-based features, algorithmic fusion, and fusion of transfer learning and feature extraction using multimodal foundation models. It also examines key challenges in reproducibility, dataset availability, differences in brain region selection, experiment duration, and EEG processing approaches. Among classifiers, SVM, random forest, and decision tree are identified as the most effective AI methods for stress classification, with CNN and LSTM showing superior performance in capturing spatiotemporal patterns. This review concludes by highlighting the importance of fusing cortical activation patterns with EEG-based connectivity measures and deep learning techniques to enhance the accuracy of mental stress detection.

1. Introduction

Numerous research studies have stated that psychological stress is directly related to the physiological consequences that lead to various health disorders and illnesses, such as speech disorders, cognitive problems, stroke, depression, and cardiovascular disease [1,2]. Furthermore, mental stress indirectly impacts the human body in various ways, namely inadequate sleeping, skin conditions, decision-making, and eating habits [3–5]. Accordingly, researchers have illuminated distinctive methodologies to quantify stress levels in their initial phases to mitigate the harmful consequences on health and performance.

This review investigation scrutinizes mental stress methodologies' structured, coherent, and systematized patterns throughout stress-related circumstances. The growing interest in EEG-based stress research is evident from the increasing number of publications over the decades. Notably, there has been a significant rise in publications in the last decade, highlighting advancements in EEG and an increased focus on stress research. Furthermore, stress-related methodologies are explored by expressing their magnitude in:

(i) Validity, stability, and uniformity throughout diverse studies/situations.
(ii) And its effectiveness in terms of productivity for automated stress detection.

Previously, researchers evaluated stress using the Perceived Stress Scale (PSS) based questionnaire method. PSS is the most promising measurement, based on questionnaires, for assessing the stress intensity observed in individuals under various stressful situations. PSS was

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established and explained by *Cohen* et al., while initially aiming towards evaluating stress among high school junior students [6]. The score-based questionnaire method of stress evaluation became astoundingly popular during the COVID-19 situation. While assessing the mental stress of healthcare contributors during the pandemic circumstances of COVID-19, the results imply higher-level stress-relevant anxiety among the workers [7]. Along with PSS, other score-based questionnaires are also available, such as the Workability Index (WAI) and the Trans-theoretical Model (TTM). The TTM model delivers better results for mental stress evaluation among working employees than other questionnaires, such as WAI and PSS [8]. Aslan et al. investigated a higher degree of perceived stress among undergraduate college students during the pandemic situation of COVID-19 [9]. The WAI indexing method is primarily used in clinical health research, where workability is assessed during health examinations. In addition to this review, Lee et al. provide better insight while comparing the variants of PSS methods such as PSS-14, PSS-4, and PSS-10 [10]. It shows that PSS-10 is a superior method when compared to PSS-4 and PSS-14.

However, psychological questionnaires alone cannot comprehensively assess stress, as it is a dynamic "fight or flight" response that originates in the brain and involves multiple physiological processes. Therefore, to achieve a more holistic understanding, researchers often supplement subjective self-reported assessments with a range of objective physiological markers, including EEG [11], Heart Rate Variability (HRV) [12], skin conductance (EDA) [13], salivary cortisol [14], and Blood Pressure (BP) [15]. Physiological signals such as HRV, EDA and BP mainly indicate the stress response driven by the Autonomic Nervous System (ANS). In contrast, the regulation of stress itself is governed by the Sympathetic Nervous System (SNS) [11,16–19]. SNS activates the "fight or flight" response through key brain regions, including the Hypothalamus, Pituitary gland, and Adrenal cortex, collectively known as the HPA axis [17–19]. Brain regions highlighted in Fig. 1 provide the interplay between sensory processing via the thalamus and neuroendocrine responses via the hypothalamus and pituitary gland, which is fundamental to understanding stress-related neural dynamics [16,20]. Given the crucial role of SNS in stress regulation, EEG is regarded in this study as a robust biomarker for comprehending the neural dynamics associated with stress. Additionally, among other neuroimaging techniques such as fNIRS, PET, and fMRI, EEG stands out as the most prominent method to analyze numerous mental states including stress with pronounced advantages such as low cost, user-friendliness, high temporal resolution, detection of event-related potential and moment-by-moment variations of multiple brain regions [17,18].

A conventional EEG stress evaluation process involves two foremost components: feature extraction and stress classification. The EEG features have been distinctively categorized into time-domain, spectral-domain, connectivity, and statistical features as described in the remaining paper [11,21–27]. However, the findings of these studies are

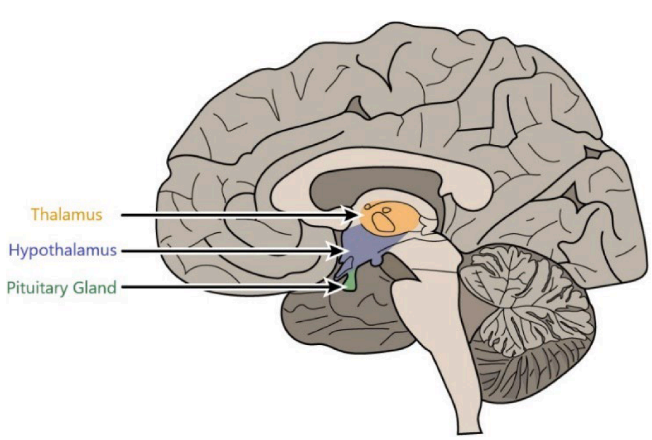

Fig. 1. Key brain structures are involved in stress processing.

based on the utility, practicality, and effectiveness of

EEG signal analysis approaches in estimating psychological stress have been incongruous and dissonant, obstructing and hindering further research and development.

For instance, some studies emphasize the dominance of frontal EEG regions, particularly channels such as AF3, AF4, F3, F4 in stress detection [28,29], whereas others report increased alpha activity in parietal regions or elevated beta power in temporal and occipital lobes [30,31]. Additionally, stress-induction protocols vary widely, ranging from short arithmetic tasks lasting 4–5 min [32] to extended multimodal assessments up to 80 min [29], with several studies adopting intermediate protocols of 30 min [33]. These inconsistencies present challenges for methodological standardization and comparative analysis across studies.

To frame this complex research landscape, we introduce the term "Neurostressology" as a research foundation for this review. Neurostressology refers to an emerging interdisciplinary research direction focused on quantifying mental stress through EEG-based neural dynamics, supported by machine learning, deep learning, and brain connectivity analysis. This research emphasizes the convergence of neuroscience, signal processing, and AI-based methods to advance real-time stress monitoring.

To overcome these hurdles, this research aims to orchestrate a broad review of the state-of-the-art EEG techniques for analyzing psychological stress while presenting prospective future research dispositions. In summary, the contributions of this paper are listed as follows.:

- Multimodal fusion-based stress detection: Integrates EEG with speech and wearable devices for real-time stress monitoring.
- Feature-level fusion: Utilizes fusion of TVEC and FEC feature maps.
- Large foundation models and transfer learning fusion: Utilizes fusion of pre-trained models (ResNet, AlexNet) and large foundation (ChatGPT, Gemini) for stress analysis.
- Innovative Algorithmic fusion for future research: Suggests CNN-INFO, LSTM-ALO, and haptic feedback integration for enhanced stress classification and intervention.

2. Materials and methods

This study follows PRISMA guidelines for a systematic literature review, ensuring rigorous data collection and analysis [34]. Fig. 2 outlines the inclusion and exclusion criteria used in the review process.

2.1. Search strategy

A systematic literature survey was conducted using PubMed, Google Scholar, IEEE Xplore, and ScienceDirect (up to January 2025). Keywords included "mental stress," "cognitive stress," "mental stress quantification," "EEG stress classification," and "EEG stress quantification." This search yielded 554 articles, from which 275 relevant studies were selected. Additionally, reference lists were reviewed to identify any overlooked significant publications.

2.2. Inclusion criteria

The inclusion requirement for this literature review benchmark is comprised of the following:

(i) Publication date-specific articles were selected that were publicized between 2003 and 2025.
(ii) Publication categories, such as research journals, book chapters and conference articles, were considered.
(iii) Significance, applicability, title of the articles, and abstracts were investigated.

The articles focused on psychological stress detection using wearable

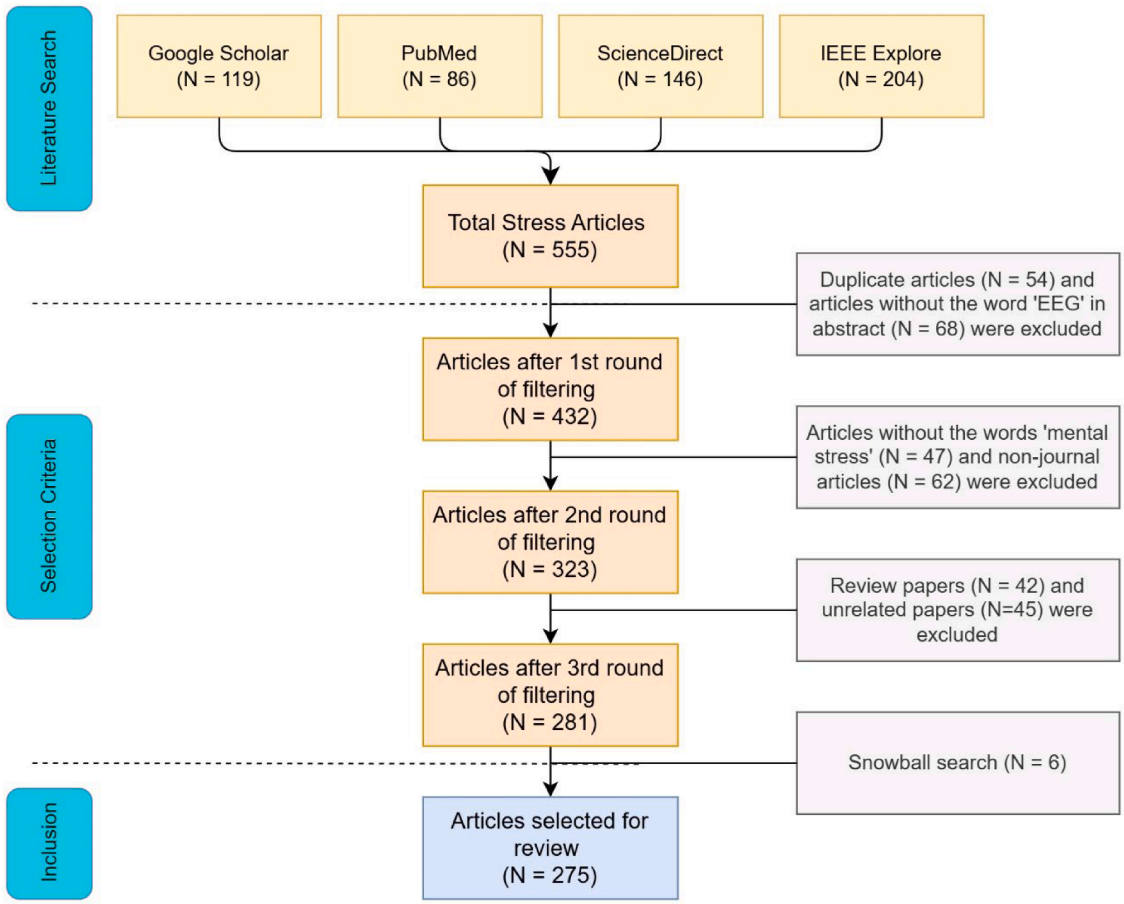

Fig. 2. Flow chart of search strategy and identification of relevant stress studies.

sensors and off-the-shelf devices for data acquisition alongside machine learning and deep learning algorithms for stress quantification.

2.3. Exclusion criteria

This review included manuscripts that are in English, including EEG experimental studies, while excluding those involving animals to eliminate potential influences of cognitive impairments. Identically matched and inappropriate articles were rejected. Various articles were accessible other than one research database. Therefore, those correspondingly matched articles were eliminated. It has been found that, even after examining the headings and abstract summaries of the articles, numerous articles were unrelated and unconnected. So, a total of 275 papers were selected for the literature review. Table 1 provides a comparative analysis of recent EEG-based mental stress review papers with this study.

Table 1
Comparative analysis of recent EEG-based mental stress review papers with this study.

	EEG-based mental stress review aspects										
Review papers (Year) [Ref.]	Stress tasks	Key electrodes/ regions	Pre-processing methods	Dataset Analysis	EEG bands	Spectrality in brain regions	Feature types	Feature correlations	Classifiers	Classification performances	Future directions
Katmah et al. (2021) [35]	✔	�	✔	�	✔	�	✔	�	✔	✔	✔
Rajendran et al. (2022) [36]	�	�	�	�	�	�	✔	�	✔	✔	�
Singh et al. (2024) [37]	�	�	�	�	�	�	✔	�	✔	✔	✔
Badr et al. (2024) [38]	✔	�	✔	�	✔	�	✔	�	✔	✔	✔
Vos et al. (2024) [39]	�	✔	✔	�	✔	�	�	�	✔	✔	✔
This study	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔

2.4. Variables of interest

The key variables investigated in each study are:

(i) Stressor categorization.
(ii) Number of participants.
(iii) Stress experiment duration.
(iv) EEG frequency bands.
(v) EEG electrodes.
(vi) EEG feature types.
(vii) Classifier types.
(viii) Classification performance.
(ix) Results summarized before and after stress induction.
(x) Observation of the findings.

3. EEG data analysis

EEG data analysis interprets electrical brain activity patterns from EEG data to extract meaningful insights about neural states and physiological conditions. EEG data analysis begins with pre-processing, which is essential for removing noise, artifacts, and other unwanted interferences from raw signals to ensure data quality. This is followed by feature extraction, where key characteristics of the brain's activity are identified, such as temporal, spectral, or connectivity features. These steps enable the analysis of neural dynamics and provide insights into underlying cognitive processes.

3.1. EEG pre-processing

EEG signals require extensive pre-processing to eliminate random noise, environmental interference, and physiological artifacts—particularly eye blinks and head movements—to ensure reliable analysis. As highlighted by Jiang et al., a thorough understanding of artifact types is essential, as physiological artifacts are the most common and significantly impact EEG data [40]. These artifacts can imply a significantly biased analysis. To mitigate this, EEG signals are often segmented into short epochs (e.g., 3 s) for visual inspection and artifact rejection.

Previously, various pre-processing methods, such as Blind Source Separation (BSS), wavelet transform techniques, notch filters, high pass, band pass, adaptive & wiener filtering, Empirical Mode Decomposition (EMD), and Independent Component Analysis (ICA) [41]. Pre-processing methods reviewed in recent stress studies are listed in Table 2. Despite these advancements, there remains a lack of standardized pre-processing protocols applicable across all EEG research studies.

The 'Dataset Used' section in Table 2 distinguishes between publicly available datasets, such as the STEW dataset [47], and custom-built datasets collected by the original studies. While these custom datasets are not publicly accessible, they can be reconstructed using well-documented and replicable task-based protocols such as N-back, mathematical tasks (MAT), Stroop task, and driving simulations. This supports potential dataset reconstruction under similar experimental conditions and partially mitigates the limitations associated with data accessibility. In EEG-based stress research, reviewing, cleaning, transforming, and modelling signals are essential for extracting meaningful insights and facilitating decision-making. While numerous analysis methods exist, selecting the most appropriate approach is important to minimize processing costs, storage demands, and dimensional complexity. The following section reviews key EEG feature analysis techniques applied in mental stress studies.

3.2. EEG feature analysis

EEG signals originate from the synchronized activity of nerve cells in the cerebral areas, and their analysis can provide insight into brain function and activity. EEG features are the characteristic properties of the electrical activity measured on the scalp using EEG electrodes. These features are obtained through signal processing and analysis techniques applied to the raw EEG signals, allowing the extraction of meaningful information about the brain activity [28].

Nowadays, numerous feature extraction approaches have been recognized to determine the present condition of brain activity by evaluating samples, progressions and distortions found in EEG signals. The feature extraction method is employed to select parametric characteristics or evidential data that are highly critical and significant for stress classification [52–54]. Scientifically, a feature exemplifies a distinctive characteristic parameter, an identifiable quantity, or a functioning module acquired from a derived model. It is highly essential to decrease the implementational complexity, diminish the data processing toll, and lastly, revoke the possible requirement of data compression. Current research trends provide several feature extraction methods broadly employed to obtain features from EEG signals. These methods have been stratified into four distinctive potential types of feature extraction methods, namely time domain features, power spectral features, connectivity features and statistical features.

Table 2
Pre-processing methods in reviewed stress studies.

Ref. (Year)	Pre-processing methods	Deep learning models	Dataset used	Accuracy
[42] (2018)	ICA band pass, normalized z-score.	EEG-ConvNet	Custom (Driving)	82.95 %
[43] (2018)	Band pass.	Hybrid ConvNet + LSTM ConvNet + LSTM + 1conv ConvNet + Bi-LSTM	Custom (N-back)	84.48 % 87.68 % 92.50 %
[44] (2019)	ICA, low pass (60 Hz), high pass (0.5 Hz), cut-off notch (60 Hz).	Deep CNN	Custom (Construction)	64.20 %
[45] (2019)	Normalized z-score.	Deep CNN	Custom (Driving)	96.00 %
[46] (2020)	High pass, low pass, and band pass.	Dual-layer LSTM EEGNet (CNN)	Custom (MAT + Breathing)	93.27 % 60.21 %
[47] (2020)	Band pass (4–32 Hz).	GWO + Hybrid deep BLSTM-LSTM	STEW Dataset (MAT)	82.57 %
[48] 2021	High pass, low pass, and band pass.	Dual-layer LSTM EEGNet (CNN) ConvNet Deep ConvNet LSTM-FCN	Custom (MAT + Breathing)	93.27 % 61.18 % 62.84 % 58.80 % 62.97 %
[49] 2021	Downsampling, high pass (3 Hz), low pass (45 Hz), ICA.	2D AlexNet CNN 3D AlexNet CNN	Custom (Audio Stimuli)	84.77 % 86.12 %
[50] 2021	Band pass, mean filter, ICA.	CNN LSTM	Custom (Healthcare – Aptitude)	77.90 % 94.40 %
[51] 2021	High pass (0.2 Hz), low pass (45 Hz), ICA, normalized z-score.	CNN	Custom (VR Stroop)	87.50 %

3.2.1. Time domain features

While quantifying mental stress, the most extensively used temporal feature is Hjorth parameters. Hjorth parameters are defined as statistical parameters that are used to characterise and explain the time-domain EEG signal. In some cases, Hjorth parameters are correspondingly depicted as normalized slope descriptors. These parameters are often described as Activity, Complexity and Mobility. The Mobility parameter estimates the mean frequency, whereas the Complexity parameter estimates the overall bandwidth of the EEG signal [55,56]. Furthermore, the Activity parameter illustrates the signal power that indicates the power spectrum in the frequency domain. Even though these parameters deliver numerous facts regarding the frequency spectrum of the EEG signal, they depend upon the time domain [57]. Nevertheless, the Hjorth parameters are vulnerable to signal noise. The mathematical definition of Hjorth parameters is explained in the following article [58]. These parameters require a briefer computation time to obtain frequency-based information and a significant substitute for Short-Time Fourier Transform (STFT). In a research article, Oh et al. reported that combining band-pass filtering with Hjorth parameters produces higher classification results than using the standard Hjorth parameters [59]. Other variant methods can be applied to approximate the time-domain complexity of EEG signals, such as entropies. A very common entropy that is used to estimate the unpredictability, along with quantifying the energy distributions of the power spectrum by investigating the time-series EEG signal, is Shannon's Entropy (SE). It advances to explore the information regarding the behaviour of the human brain throughout a no of states to distinguish mental stress [60]. In the research article, it was found that the participant group that obtained the high mental stress is inclined towards the lowest alpha-based entropy. Zhu et al. showed that Virtual Reality (VR) installed relaxation psychotherapy can alleviate mental stress by assessing the variations of SE [61]. The researchers testified that SE had an elevated drift towards the alpha band of the EEG signal in the prior and consequent immersion of VR. A different type of entropy observed among stress studies is Approximate Entropy (ApEn). ApEn is utilised in conjunction with time-series data to explore variations in the irregularity and regularity of EEG signals. Wang et al. support that the system complexity is accountable for resolving the data length while evaluating ApEn [62]. In the meantime, the study demonstrated that the induced Mental Arithmetic Tasks (MAT) show a substantial escalation of ApEn at the insular cortex and the anterior cingulate [62]. The primary benefit of using ApEn is its capability of handling noise and its feasibility in using deterministic, chaotic, and stochastic signals. Furthermore, Hasan et al. show that utilising the wavelet sum of entropy as a distinct feature can detect stress from the recorded EEG signals [55]. It signifies the summation of entropy for each estimated wavelet band. These wavelet bands are observed due to splitting the EEG signal into separate EEG spectral bands and deploying the Discrete Wavelet Transform (DWT) [55]. Lastly, another entropy, namely self-entropy, is utilised in unravelling the information network amongst the brain sectors by approximating the dynamic activity of the EEG signal [63,64]. The referenced research study contains detailed mathematical definitions of all entropies [61].

To this end, Higuchi's Fractal Dimension (FD) is another evaluation of the complexity, nonlinearity & unpredictability characteristics of EEG-based brain signals, where low values and high values of FD are linked with regular and irregular waveforms, respectively [65]. The referenced research article contains the mathematical definition of FD [66]. Higuchi's FD provides an essential assessment of stress classes, which has real-time effectiveness in testing irregular brain behaviour during chronic stress [67]. Numerous studies have shown that incorporating statistical features with FD eventually outperforms frequency-domain features [65,68]. A higher level of EEG complexity is observed in the frontal lobe when participants are immersed in the MAT stressors [68]. However, Khosrowabadi et al. report lower precision in Higuchi's FD when compared to Magnitude Squared Coherence (MSC) and Gaussian Mixture Model (GMM) for respective classifiers such as K-Nearest Neighbour (kNN) and Support Vector Machine (SVM) [67]. FD is independent of high efficiency and the nature of the signal, whereas it's inclined towards noise and spectral bands and will have low performance while only FD is being used [69].

3.2.2. Power spectral features

The power spectral features in EEG analysis refer to the frequency-domain characteristics of the EEG signals. These characteristics or features illustrate how the energy or the power of the EEG signal is distributed across different frequency bands. The power spectral analysis of EEG data is effective for conceptualizing the frequency composition of brain activity and can deliver an understanding of various cognitive and neurological processes. Therefore, some of the most commonly used spectral features and processing methods are illustrated in this sub-section.

The most basic frequency-domain feature is the Power Spectral Density (PSD) of the EEG signal, which is a measure that represents the distribution of power for time-domain EEG signals across different frequency bands and delivers important information to study brain activity patterns. PSD is particularly beneficial in estimating short data recordings and illustrating stochastic processes of the signal [70]. It could be estimated by utilising various non-parametric and parametric procedures. The non-parametric procedures are well-identified techniques since there is no need for parameter sections, namely the model's order.

Some non-parametric approaches include the Fast Fourier transform (FFT) [71], the Thompson multi-taper method [72], or Welch's method [73]. The EEG spectrum is allocated in 5 spectral bands, which are referred to as delta (0.5 – 4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13 – 30 Hz), and gamma (30–70 Hz) [28]. According to the spectrum, some commonly used EEG spectral features are EEG band activities, Relative Power (RP) of alpha, beta, theta, delta, gamma, Absolute Power (AP), mean power, Asymmetry Index (ASI) [74], Band power ratio such as beta/alpha [75], theta/alpha [75], (theta + alpha)/(alpha + beta) [76], theta/beta [76], (theta + alpha)/beta [76], (gamma + beta)/(delta + alpha) [77] and gamma/delta [77]. Multiple studies have elaborated on the effectiveness of PSD in estimating stress levels. In a research article, scientists observed a decrement in PSD in the alpha band of EEG while participants were immersed in a stressful situation [78]. Similarly, in another study, a significant drop in alpha rhythm was observed when the stress level was increased from level 1 to level 2 and again from level 2 to level 3 [19].

Researchers have used Spectral Moments (SM) in detecting psychological stress [32]. These moments provide information about the shape and properties of the spectral content. SM provides valuable information about the shape and properties of the spectral content for characterizing the spectral content of signals, including EEG signals. By computing these moments, researchers can gain insights into the central frequency, spread, and overall shape of the spectral distribution of a signal. Attallah et al. confirmed the efficiency of SM in distinguishing multiple stress levels and testified high accuracy with Linear Discriminant Analysis (LDA) while using SM as an EEG feature [32]. The referenced research study contains a detailed mathematical definition of SM methodology [79].

Some researchers have used AP as an EEG feature in detecting stress [80]. The AP at a specific frequency band is estimated by dividing the absolute value of the FFT of the EEG signal by the length of the EEG signal [80]. In the meantime, other researchers have utilised RP to examine the EEG rhythm by obtaining the ratio between the power of each band and the power of the whole spectrum band [81,82]. The referenced research article contains detailed mathematical definitions of AP and RP [83]. While detecting stress using AP, Arsalan et al. [84] and Subhani et al. observed a significant difference in the theta band in contrast to other EEG bands; on the contrary, RP was reduced when the stress levels were increased [83]. Subsequently, despite RP's sensitivity to memory recall and noise, RP indicated a better performance measure than AP [80].

Other studies have used power measures from Wavelet Transform (WT) coefficients to obtain features that are positively correlated with psychological stress [21,78]. The researchers have observed that the mean power of the alpha band substantially declined when the stress level was increased. Besides, WT has been used in many studies for multiresolution time-frequency analysis [85]. This analysis can be performed by breaking down the EEG signal into its constituent frequency bands, keeping the information both in the time domain and the frequency domain. After that, the AP can be estimated from the wavelet coefficients. The referenced research study contains the mathematical definition of the applied WT [85]. While the Fourier Transform (FT) stipulates a frequency-domain representation of the signal, WT provides fast access to the localized information of the EEG signal in time-frequency representation. Since EEG is a non-stationary signal, employing FT might result in minor modifications in the EEG spectrum. Still, the analysis might alter depending on the length of the EEG data. Hence, WT is a better choice than FT [86].

Previously, the Gaussian mixture of EEG spectrograms has been utilised in distinguishing stress by investigating the variations of the spectral density of the EEG signals relating to the time domain. Furthermore, researchers have used STFT as a data analysis method to estimate the spectrogram of the time-domain signal. After the computation of the spectrogram, the GMM, a linear combination of Gaussian Probability Distribution Functions (PDF), can be evaluated to obtain the density [67,87]. However, researchers have reported various drawbacks of this model, such as its symmetric nature and infinite range [88].

3.2.3. Connectivity features

EEG-based research aims to link brain rhythms to neural states underlying human behaviour and cognition [89]. EEG signals result from overlapping neural sources, varying associations based on source direction, position, and electrode placement [90]. This complexity has driven interest in functional and effective connectivity, evaluated using diverse data types that vary in spatial, temporal, and neural activity representation. Additionally, computational methods for connectivity analysis differ among researchers, even when using similar data.

The complexity of EEG arises from its association with various facets of brain activity, as the signals encapsulate vast amounts of information generated by intricate and interconnected neural networks. Therefore, investigating cerebral connectivity might deliver an accurate template of the brain while explaining in what manner the cerebral regions communicate and influence each other. Typically, two varieties of brain connectivity exist, namely Functional and Effective Connectivity [91]. Brain Functional Connectivity (BFC) refers to the statistical dependency of the synchronized activity among diverse cerebral areas, which allows them to communicate and work together to perform various functions. Numerous techniques for evaluating BFC might result in various inferences depending upon the analytical characteristics such as the strength of the cerebral synchronization, no of electrodes, placement of electrodes and stressor type. Utilising various versions of interpreting the BFC may point to inconsistent conclusions [91]. However, Effective Connectivity (EC) empirically illustrates how the cerebral regions influence each other [92]. Hence, in a nutshell, while BFC defines the non-directional synchronized activity among the cerebral cortexes, EC defines the directional influences among the different cerebral cortexes [93].

The analysis of coherence endeavours to detect cerebral synchronization and BFC among distinct cerebral areas. These conjoint associations are observed by investigating the phase and amplitude of the EEG signals [29,83]. The researchers, Xia et al., assessed the coherence in quantifying stress and observed a substantial elevation in all brain frequencies, excluding beta at frontal and parietal lobes [29]. Furthermore, profound coherence for delta wave was identified in the Pre-Frontal Cortex (PFC) and Temporal lobes at elevated stress levels. In the meantime, a research article reports having investigated an elevated delta and theta-based interhemispheric connectivity, while alpha and beta-based coherence interconnections spread throughout the scalp [94]. The referenced research article contains a detailed mathematical definition of coherence [95]. Another assessment of BFC in stress-related studies is MSC. Scientists have observed a substantial decrease in BFC among interhemispheric PFC and intrahemispheric PFC when the experiment shifts from a control condition to a stress condition [96]. Alonso et al. showed a reduced MSC for the alpha band in the frontal region and improved beta coherence throughout the scalp in EEG connectivity maps when sleep deprivation is employed as a stressor [74]. Nevertheless, a different brain manner was observed, such as an increased beta coherence in the sagittal sections of the brain when the Stroop Colour-Word Task (SCWT) was applied as a stressor. The referenced article provides the mathematical definitions of MSC [97].

Darzi et al. showed that MSC features have achieved the highest accuracy when compared to Power Spectral Density (PSD), Phase–Slope Index (PSI), Canonical Correlation Analysis (CCA), and Directed Transfer Function (DTF) features when SVM is applied as a classifier [28]. Similarly, Khosrowabadi et al. stated that the accuracy, sensitivity, and specificity of MSC are way higher than FD and GMM features when kNN and SVM are applied [67]. Subsequently, the primary benefit of using Coherence-based EEG analysis in quantifying stress is that it is not impacted by the amplitude oscillations for diverse cerebral regions. Nonetheless, a significant downside of utilising Coherence is its high sensitivity to power variations and phase couplings [94,98].

Consequently, Mutual Information (MI) is utilised to identify parallel correspondence of joint PDF and dynamic concatenation among different EEG signals [28,63]. Hence, MI aims to analyse the EEG signal in diverse frequency bands to discover the statistical dependencies among the signals [99]. In one research study, when the SCWT was employed among the participants, MI was not able to attain any noticeable increment in the EEG connectivity maps, but when sleep deprivation was applied; MI exhibited a prevalent reduction in linear cerebral regions in contrast to a substantial increment in non-linear regions such as frontal, temporal, and parental cerebral regions [74]. At the same time, another research investigation showed that the distributed information among cerebral regions was low throughout the relaxing phase, but a noteworthy elevation of MI was reported for alpha, theta, and delta bands in the frontal cortex when MAT was applied [100]. On the contrary, while contrasting MI with other connectivity features, MI takes less time to process and is not constrained to the real-valued variables; hence, MI can be utilised on diverse types of variables [101]. The referenced article describes the mathematical definitions of MI [30].

Phase lag is another connectivity feature utilised to identify delay or lag among two or more EEG signals associated with diverse cerebral areas. The referenced article provides detailed mathematical expressions for analysing phase lag [102]. Xia et al. have successfully identified phase lag in differentiating controlled and stressed situations for multiple levels [29]. However, Subhani et al. described reduced accuracy when phase lag is used, while other features such as Absolute Power (AP), Amplitude Symmetry and Coherence [83]. The major drawback of phase lag is that it delivers non-directional connectivity among brain regions [103].

PSI is an alternative connectivity feature that measures the phase synchronization among EEG signals. Research investigations have testified to diverse cerebral connectivity patterns throughout the chronic stress stimuli. However, the synchronization concerning the right temporal and left parietal regions displayed a 55 % significant reduction among stressed individuals [28]. Darzi et al. reported high-performing PSI measures in their study. At the same time, Khosrowabadi et al. provided low performance of PSI in contrast to the performances of Partial Directed Coherence (PDC) and DTF features [104]. The primary benefit of utilising PSI is to overcome independent background activity produced among two or more EEG electrodes and the capability to provide valuable directions for the non-linear phase spectrum [104]. Nevertheless, PSI cannot provide the directivity of the EEG signals [105]. The referenced investigation can deliver the mathematical expressions of PSI approaches [106].

PDC is a frequency-specific connectivity feature utilised to measure the magnitude and the direction of information flow among the diverse brain regions. Hence, frequency-specific directional influence amongst two channels incorporates various aspects such as Granger Causality (GC) and Akaike Information Criterion (AIC) [31]. Some research articles reported that, for reasons of stress, the fatigue level gets elevated, and the functional coupling gets reduced in theta, alpha and beta frequency bands for frontal and parietal areas of the brain [31,107].

Generalized PDC (gPDC) is an essential category of PDC that is used to measure BFC in multi-channel EEG analysis. The referenced article contains the mathematical definition of PDC [108]. Khosrowabadi et al. have utilised gPDC in discriminating stress, and the researchers have testified low accuracy and medium accuracy in contrast to DTF and PSI features [104].

DTF is another connectivity method used to measure the directional influences among diverse brain regions. Yu et al. have confirmed elevated DTF values in alpha and beta bands when the participants were immersed in MAT [109]. Precisely, the results of Yu et al. provide an escalating information flow from the central brain regions to occipital and parietal regions in beta and alpha frequency bands, respectively [109]. According to Khosrowabadi et al., DTF delivered the highest accuracy in quantifying stress in comparison to gPDC and PSI [104]. The referenced article can provide the mathematical definitions of DTF [110]. Although in research investigations, DTF has confirmed better performance compared to PSD, MSC, PSI and CCA [28], its major drawback is its vulnerability to brain-heart functional coupling [109].

3.2.4. Statistical features

This category of features has been observed by employing essential statistical functions on the EEG signals in the time domain to classify stress perception levels. Therefore, statistical methods are straightforward, convenient, and frequently used to provide a more comprehensive and informative understanding of brain activity [111]. Among these features, the most used for EEG data analysis are mean, standard deviation, kurtosis, skewness, root mean square, shape factor, impulse factor, and first & second differences [32,55,57,112].

Several studies have applied feature selection and dimensionality reduction techniques to mitigate feature redundancy and improve classification performance in EEG-based stress recognition. Methods such as Principal Component Analysis (PCA) [113], Minimum Redundancy Maximum Relevance (mRMR) [114], and Pearson correlation filtering [97] have been widely adopted to reduce high-dimensional feature sets by retaining only the most informative and non-redundant variables. For instance, mRMR prioritizes features that show high relevance to the output class while maintaining low mutual information among inputs, thereby improving generalization and reducing overfitting [114]. Similarly, correlation-based filters have been employed to remove multicollinear features prior to classifier training [97].

PCA has been frequently used as a dimensionality reduction strategy to extract orthogonal components from complex EEG feature vectors [113]. Deshmukh et al. demonstrated that PCA helped reduce dimensionality before classification [115]. Furthermore, another study has confirmed that it improved the separability of stress and non-stress classes in principal component space [116]. Shon et al. compared PCA to a genetic algorithm for feature selection, reporting that the genetic algorithm achieved a higher classification accuracy (71.76 %) than PCA (65.30 %), highlighting the impact of optimized feature selection on model performance [57]. In a related finding, Hou et al. showed that combining statistical features with power features and FD enhanced stress classification outcomes [65]. Other statistical features, such as variance, were found to be elevated during resting states, while kurtosis appeared to increase during stress across all frequency bands [117]. However, a known drawback of statistical features is their higher computational complexity, which can lead to longer processing times.

Despite these benefits, a notable number of studies reviewed did not specify whether feature redundancy was addressed, which indicates a methodological gap. Hence, this highlights a standardization in feature selection practices within EEG-based stress classification pipelines is required.

Table 3. Concluded that, despite contradictory outcomes involving a few EEG features, the alpha asymmetry index consistently correlates negatively with stress across various EEG feature investigations. The negative correlation of alpha activity and the positive correlation of beta activity are responsible for being consistent stress evaluators.

From an accuracy perspective, as shown in Fig. 3, the analysis evaluates the classification performance of different EEG feature types—spectral, temporal, connectivity, and statistical—using mean and standard deviation from previous stress studies. Classification accuracies were aggregated for each feature type, with the mean accuracy representing overall performance and the standard deviation reflecting variability across studies. The results indicate that spectral and statistical features achieved the best performance (~90 %) across studies, demonstrating their robustness in capturing stress-related neural characteristics. While slightly lower at over 85 %, the temporal and connectivity features still provided reliable contributions to stress classification.

These findings emphasize the effectiveness of spectral and statistical features as primary tools for stress detection, with temporal and connectivity features offering valuable complementary information.

Similarly, the analysis provided in Fig. 4 evaluates the classification accuracy based on EEG frequency bands—delta, theta, alpha, beta, and gamma—in stress detection. For each band, the mean accuracy was calculated to represent its overall contribution to stress classification, while the standard deviation highlights variability across studies. The results show that the alpha band achieved the highest performance (~90 %) across studies, indicating its strong association with stress-related cortical activity and prominence during task engagement. The beta band also demonstrated high accuracies, reflecting its role in increased alertness, cognitive activity, and arousal during stress phases. The theta band performed moderately well, highlighting its involvement in emotional regulation and cognitive processing under stress conditions. In contrast, delta and gamma bands exhibited lower accuracies, indicating their limited role in stress detection, as delta is primarily associated with deep relaxation or sleep states, and gamma reflects higher-order cognitive integration, which may not be strongly tied to stress-specific neural dynamics. This analysis highlights the critical importance of alpha, beta, and theta bands in effective stress classification while demonstrating reduced sensitivity for delta and gamma bands.

To this end, integrating spectral and connectivity-based EEG features can improve stress quantification by capturing localized power fluctuations and inter-regional brain interactions. Spectral features provide insights into frequency-specific neural oscillations, while connectivity measures reveal functional communication and effective causal

Table 3
List of popular EEG features and significant correlations.

EEG Features	No. of Studies [Ref.]	+ve	-ve	none
Delta activity	3 [118–120]	2	2	0
Theta activity	6 [74,118–122]	3	3	0
Alpha activity	8 [17,74,113,118–123]	2	7	0
Beta activity	7 [17,74,113,118,120,121,124]	5	2	0
Gamma activity	2 [74,121]	1	0	1
Beta/alpha ratio	3 [118,121,125]	2	0	1
Asymmetry index	10 [74,118,120,121,125,126]	1	9	1
Coherence	3 [74,118,120]	1	2	0
Beta coherence	1 [74]	1	0	0
Alpha Coherence	1 [74]	0	1	0
Brain Load Index	1 [127]	1	0	0
ApEn	1 [74]	0	1	0
Linear CMIF	1 [74]	0	1	0
Non-linear CMIF	1 [74]	1	0	0

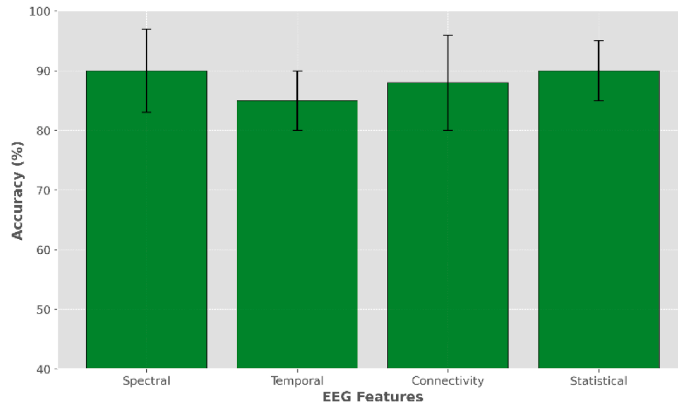

Fig. 3. Stress classification accuracy based on EEG features.

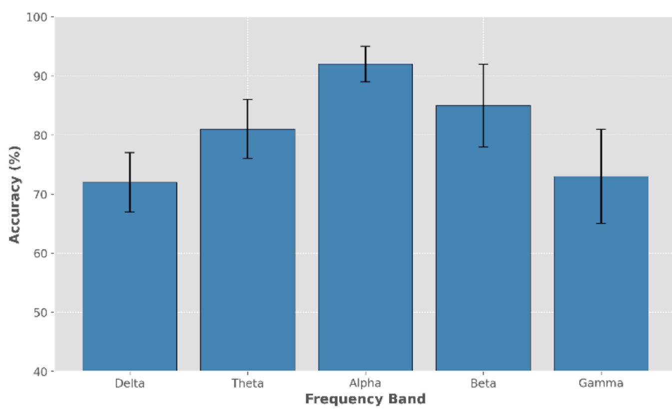

Fig. 4. Stress classification accuracy based on EEG frequency bands.

influences between brain regions. This combination allows for a more comprehensive characterization of stress-induced neural dynamics, leading to higher classification accuracy.

4. Classification methods

Stress studies have investigated diverse classifiers to assess the level of mental stress. The following section presents popular AI classifiers in EEG-based stress studies, with a comparative analysis of various EEG-based stress classification algorithms provided in Table 4.

SVM is a classification model built into a feature vector to discover the hyperplane that optimizes the margin between input data classifications. Several studies used SVM to differentiate between stress levels. For example, the studies in [67] and [128] have applied SVM to measure two stress levels and achieved accuracy levels of 75 % and 90 %, respectively. On the other hand, in one article, researchers utilised SVM to classify three stress levels [160]. Meanwhile, researchers have applied SVM by combining it with an error-correcting output code and reported that the average classification accuracy of these mental stress levels is declining from 97.61 % to 95.37 % and 91.40 % with the increased stress level [30]. Furthermore, Gaikwad et al. have shown an accuracy of 72.30 % in real time by using a trained algorithm as a reference [160]. According to Hou et al., increasing the number of stress levels (from two levels up to four) decreased the SVM accuracy [65].

Few researchers have applied NB to categorize stress perception levels. NB is a straightforward and table probabilistic algorithm that is utilised whilst the dimension of input is substantial [84]. Its algorithm is based on Bayes' theorem, which presumes that the obtained features are not dependent on one another. Subhani et al. stated that NB had detected mental stress with the highest accuracy of 94.0 %, 94.6 %, and 91.7 % for 1-level, 2-level, and 3-level, respectively [83]. *Darzi* et al. have classified 2 levels of mental stress by utilising SVM and NB and described that SVM performs better than NB. However, NB was 5 times faster than SVM [28]. Hence, NB is much more appropriate for handling online tasks, and it delivers faster classification since complicated optimization parameters are not essential. On the contrary, *Arsalan* et al. conveyed poor performance when NB was employed to classify 2-levels of stress and 3-levels of stress in the theta frequency band with accuracies of 75 % and 50 %, respectively [84]. Furthermore, *Saeed* et al. reported that they achieved high performance while classifying mental stress with a precision of 80.79 % [129]. Another research article has described a reduced performance of 71.40 % accuracy in quantifying mental stress while employing NB as a classifier and utilising feature vectors of low beta rhythms [161].

Alternatively, some researchers have employed LDA, another technique to categorize mental stress by discovering the linear mixture of EEG characteristics [162]. However, *Minguillon* et al. have employed LDA to classify cognitive stress in 3-levels by utilising the feature of average relative γ band and observed that adding further physiological markers might deliver better performance, where its achieved accuracy is 50 % [33]. On the other hand, *Vanitha* et al. have classified stress responses among students and reported LDA's poor performance with an accuracy of 70.16 % in contrast to other high- performance-based algorithms such as SVM with 89.07 % and kNN with 72.67 % [162]. Subsequently, the major limitation of LDA is the presumptions and constraints of linear restrictions, which are essential to accomplish the algorithm [33].

Additionally, stress studies have used LR to discriminate perceived stress [64]. LR can be defined as a statistical model that employs logistic functions to depict a determined binary variable in its fundamental structure. This algorithm is utilised to scrutinize the association between 1 opposing dependent variable and 1 continual independent variable [83]. Although LR showed few faults in identifying resting states, *Zanetti* et al. have classified 3-levels of psychological states by using LR with a high performance of 84.30 % accuracy [64]. In the meantime, when LR was utilised to categorize multiple stress levels using MAT, it showed high performance equivalent to RF and SVM [83]. *Saeed et al.* reported the highest accuracy of 85.15 % while using LR in quantifying stress with alpha asymmetry when contrasted to other algorithms such as Multilayer Perceptron (MLP), kNN and NB [129].

Likewise, kNN can be utilised to classify cognitive stress as a nonparametric learning technique [55]. The algorithm of kNN rests on evaluating the distance among the neighbours and selecting the k-closest neighbours. Therefore, two significant features to be recognised are the neighbouring distance and the optimum estimate of k [55, 129]. *Saeed* et al. have utilised kNN to classify chronic stress with alpha asymmetry, beta rhythm and gamma rhythm [129]. The researchers have achieved a 65.96 % accuracy by combining the following features.

Table 4
A comparative analysis of various EEG-based stress classification algorithms.

Classification Algorithms	No. of Papers [Ref.]	Advantages	Disadvantages	Maximum A_{cc} Achieved
SVM	25 [83, 112,116, 127–149].	1. It provides better results for semi-organized and unorganized data while scaling high-dimensional EEG data. 2. With a suitable kernel function, it can resolve any complicated difficulty, while its memory is effective compared to other methods.	1. It takes a longer time for a large EEG dataset training. 2. It doesn't function fairly in the presence of noise in EEG signals, and it also doesn't provide transparency and precision in results.	99.75 %
kNN	12 [112, 129,130, 134–136, 138–140, 150–152].	1. Detects outliers efficiently while the classes are not linearly distinguishable. 2. Provides simplicity and high accuracy during EEG methods and implementation. 3. No need for presumptions about the EEG data, while it can be used for both classification and regression problems.	1. Due to high space and time complexity, it is not appropriate for high-dimensional EEG data. 2. The presence of noise and artifacts in EEG fails to provide significant distance numbers. 3. Costly testing for every instance in EEG implementation.	99.93 %
LR	7 [83,129, 136,147, 148,153, 154].	1. No need to make presumptions regarding the dissemination of classes in feature space, as it makes it simpler for interpretation and implementation. 2. Capable of fast classification of unspecified EEG data as it expands to several classes, while the datasets are not linearly distinguishable. 3. Provides higher training efficacy with EEG data, is less susceptible to overfitting and reflects regularization to avert it.	1. The ability to assemble linear limits, which may lead to overfitting. 2. Prediction of discrete functions only. 3. Not efficient in solving linear problems. 4. It is not efficient in capturing complicated associations in EEG, while it is outlier sensitive.	85.15 %
Fuzzy Logic	2 [155, 156]	1. No requirement for accurate EEG inputs as it uses less memory space due to the small code size. 2. Due to its simple construction, it can resolve complicated EEG-based classification. 3. Exceedingly valuable for the unclear and imprecise EEG datasets.	1. It entails plenty of testing for confirmation and authentication with hardware. 2. Dependent on programmers' skills. 3. Not recognized for most of the cases, due to its inability to provide accurate results.	99.00 %
NB	7 [129, 142,147, 150,151, 156,157].	1. Ability to solve problems faster, even for multivariate EEG in class prediction problems. 2. Requires a reduced amount of EEG data for training, while its presumptions for feature-level independence are true. 3. More appropriate for explicit EEG input variables.	1. Presumes all the predictors to be independent, which is hardly seen in real life. 2. The ability to provide wrong estimations in certain circumstances, which makes the probability output unreliable.	94.60 %
DT	5 [131, 133,134, 150,157].	1. It provides simplicity in the visualization and interpretation of EEG. 2. It is effective in both regression and classification problems. 3. It automatically deals with outliers and missing values. 4. Less duration for EEG training.	1. It is not appropriate for large-scale EEG datasets due to the presence of overfitting. 2. Becomes unstable in the presence of noises in EEG, which leads to incorrect predictions. 3. High variance in outputs leads to higher inaccuracies in the concluding evaluation.	90.00 %
RF	6 [136, 142,147, 148,151, 158].	1. Through cross-validation, this method delivers high precision. 2. Overfitting decreases in decision trees as it works well with continuous EEG signals. 3. It performs well for both EEG-based regression and classification problems.	1. Requires more resources and computation to construct various trees to merge their output. 2. Requires additional time duration for training with EEG data. 3. Vague interpretation due to its construction of decision trees.	88.30 %

(continued on next page)

Table 4 (*continued*)

Classification Algorithms	No. of Papers [Ref.]	Advantages	Disadvantages	Maximum A_{cc} Achieved
		4. Automatically deals with missing values as it utilizes a rule-based approach, which isn't required for normalization of the data.	4. Fails to ascertain the outcomes of each variable.	
ANN	3 [133, 141,159].	1. Instead of storing the EEG-based information on its record, it stores it throughout the entire network. 2. After the training session, the data may provide an outcome yet with inadequate EEG data.	1. Highly hardware dependent. 2. Network functions are unsolved while delivering the solution. 4. Network duration unknown.	91.17 %

Legends: SVM: Support Vector Machine; kNN: K-Nearest Neighbor; LR: Logistic Regression; NB: Naïve Bayes; DT: Decision Tree; RF: Random Forest; ANN: Artificial Neural Network.

Another stress study utilised SVM, kNN and Bayesian classification algorithms, while kNN achieved the highest accuracy of 90 % [28]. The major benefit of using kNN in classifying stress is its minimal computation complexity while trading off with small data [28,55]. On the contrary, kNN's high vulnerability to local data structure is its major limitation.

Lastly, among the deep learning techniques, Convolutional Neural Networks (CNN) have shown high performance in quantifying stress [44]. CNN is considered a controlled MLP, and it delivers a substitute structure to simulate the cerebral functionalities in classifying cognitive stress [20]. In contrast to other classifiers, CNN can be utilised for substantial non-linear datasets, and it delivers noteworthy feature classification [163]. The major benefit of utilising CNN is that it neither depends upon individual endeavour nor on preceding data. Various stress investigations have utilised CNN; in particular, *Jebelli* et al. have categorized 3-levels of mental stress among workers and produced high performance of 79.26 % accuracy, which betters the SVM's performance of 79.12 % accuracy [164]. Another stress investigation has yielded 86.62 % accuracy in utilising CNN [44]. The researchers have reported that the optimal network setting to measure workers' mental stress requires 2 hidden layers, along with 83 neurons for the 1st hidden layer and 23 neurons for the 2nd hidden layer [164]. Hence, it can be stated that CNN eases the requirement for EEG feature extraction, whereas this takes a lot of time in the case of supervised learning techniques [44].

Performance metrics such as Accuracy, specificity, and sensitivity are commonly used as evaluation metrics in stress classifiers to assess the performance and effectiveness of the classification model [28,29,83].

- *Sensitivity (S_e):* It is provided by the ratio of the number of events that are accurately identified, T_P (true positive), to the total no of events, as expressed as,

$$S_e = \frac{T_P}{T_P + F_N}$$

Where F_N (false negative) is the no of missed events.

- *Specificity (SP_+):* It is provided by the ratio of the number of events that are accurately identified, T_P and the total no of events, expressed as,

$$SP_+ = \frac{T_P}{T_P + F_P}$$

Where F_P (false positive) is the no of events that detection comprises errors.

- *Accuracy (A_{cc}):* It is computed by the percentage of peaks identified among the total no of peaks.

$$A_{cc} = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \times 100\%$$

Some commonly used classifiers investigated in this review are illustrated in Table 4**,** along with their advantages, disadvantages, and highest accuracies in stress detection.

5. Results

Each EEG band signifies an individual's state of mind [17]. Most reviewed studies report that heightened beta activity correlates with increased alertness and arousal. In contrast, elevated alpha activity is associated with relaxation compared to stress, and theta waves are characteristic of sleep states [165]. Beta activity shows a significant increase during stress phases, indicating a strong positive correlation with stress [17,74,118,121,166–169]. In contrast, gamma activity demonstrates varied responses but generally decreases in both relaxed and stressful states, suggesting limited sensitivity to stress level variations [121,170].

XGBoost's built-in functionality importance score is used in this section to quantify the contribution of specific EEG features, brain regions, spectral bands, stress-inducing tasks and EEG datasets to stress classification [171]. The importance scores are based on model-based weight and gain metrics and do not reflect statistical significance.

5.1. Spectrality in brain regions

The analysis of spectral band contributions across brain regions, as provided in Fig. 5, further revealed distinct patterns of frequency-specific activity. Features were grouped by spectral bands (e.g., alpha, beta) and brain regions (e.g., Frontal, Temporal), and XGBoost was trained on these grouped features. The importance scores were calculated using the gain and weight metric, which measures the relative contribution of a feature to the reduction in prediction error. Features that result in higher gain and weights are more frequently selected for splits [171]. By summing up the weights and gains associated with each feature, XGBoost can compute the importance score, normalizing it between 0 and 1 [171].

It is important to distinguish between model-derived feature importance scores and statistical significance measures, as they represent fundamentally different types of information. The importance scores are based on multivariate, non-linear relationships captured by the XGBoost model and are optimized for improving classification performances [171]. In contrast, statistical significance measures such as p-values assess distributional differences across predefined classes, which are typically based on univariate tests (e.g., *t*-test, ANOVA) [74]. As a result, a feature might show statistical significance across classes but have low predictive power in the model [172]. Conversely, a feature with high predictive utility may not show strong univariate statistical differences [171]. Because of this fundamental disconnect, statistical

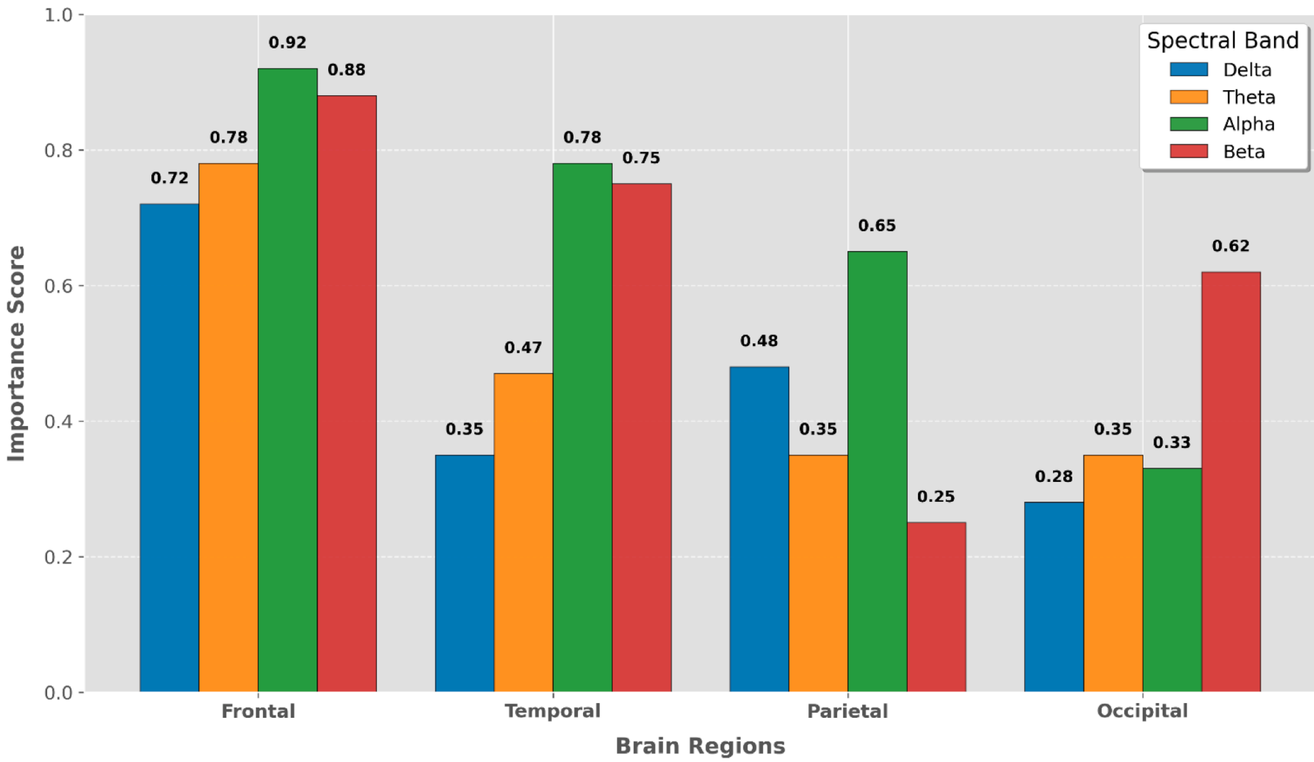

Fig. 5. Spectrality in brain regions.

significance-based p-values were not annotated to the values in Fig. 5.

Feature contributions within each region-band group were summed to compute overall importance scores, using the gain metric to reflect how effectively each feature improved model split decisions during training. The frontal region showed strong dominance in alpha (0.92), indicating its roles in neural relaxation and beta (0.88) bands associated with task engagement. The temporal region showed slightly lower but still prominent importance in alpha (0.78) and beta (0.75), indicating involvement in emotional and auditory stress processing. In the parietal region, alpha (0.65) was most important, linked to attention and sensory integration, followed by theta (0.35) and beta (0.48), and minimal delta (0.25), reflecting memory-related and low-frequency activity during stress. In contrast, the occipital region was characterized by dominant beta activity (0.62), including moderate alpha (0.35), theta (0.28), and delta (0.33), associated with visual attention and cognitive load. This analysis underscores the complementary contributions of distinct brain regions across spectral bands in stress processing particularly the frontal dominance of alpha and beta activity, which emphasizes its central role in higher-order cognitive and emotional regulation, while theta and delta activity in posterior regions provide further insight into stress-induced neural dynamics.

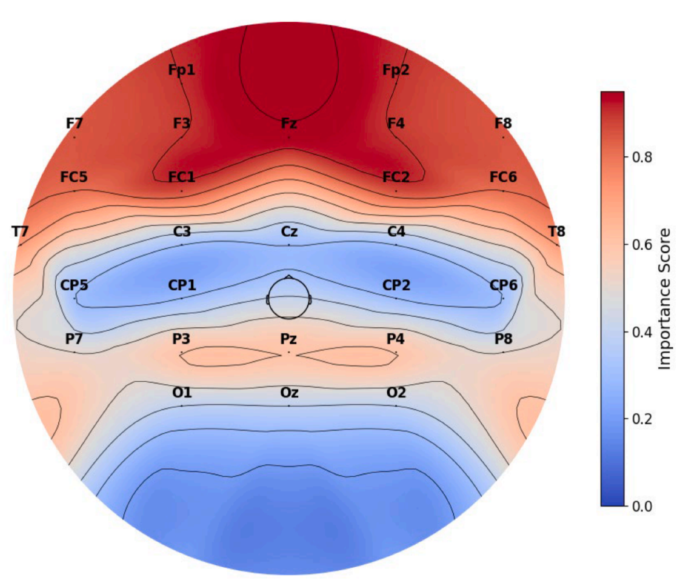

Fig. 6. Key EEG electrodes in stress studies.

5.2. Stress-specific EEG electrodes

Similarly, importance scores were computed to quantify each EEG channel's contribution to reducing the model's prediction error, reflecting its relevance in distinguishing stress from non-stress states.

The result as provided in Fig. 6 denotes that the frontal region channels such as Fz, Fp1, F3, F4, and FC1 exhibited the highest importance scores, underscoring their key role in stress detection, aligned with the prefrontal cortex's involvement in stress regulation. Central channels such as Cz, C4, and CP1 showed moderate relevance, suggesting a secondary role in stress processing, while occipital channels such as O1, Oz, and O2 had the lowest scores, reflecting their primary function in visual processing rather than stress response. Furthermore, the spatial patterns of importance scores suggest potential hemispheric differences, with slightly higher scores observed in left-hemisphere channels. This observation may reflect the asymmetry in stress processing, as the left hemisphere has been implicated in regulating positive emotions and coping strategies. These insights provide a robust foundation for selecting critical regions of interest in future stress classification studies.

5.3. Spectral importance among EEG features

Followingly this, a comparison of the importance of EEG frequency bands in stress feature analysis based on prior studies is presented. To compute XGBoost's importance scores for EEG features across frequency bands, features from each frequency band were extracted and grouped. Then, XGBoost was trained on those grouped features, and importance scores were calculated using weight and gain metrics based on how frequently and significantly each band's features were used in the model's decision trees to reduce error. Fig. 7 illustrates the comparative importance of feature types—PSD and connectivity—across EEG frequency bands. Connectivity features consistently outperformed PSD features, particularly in the beta band, with a score of 0.88.

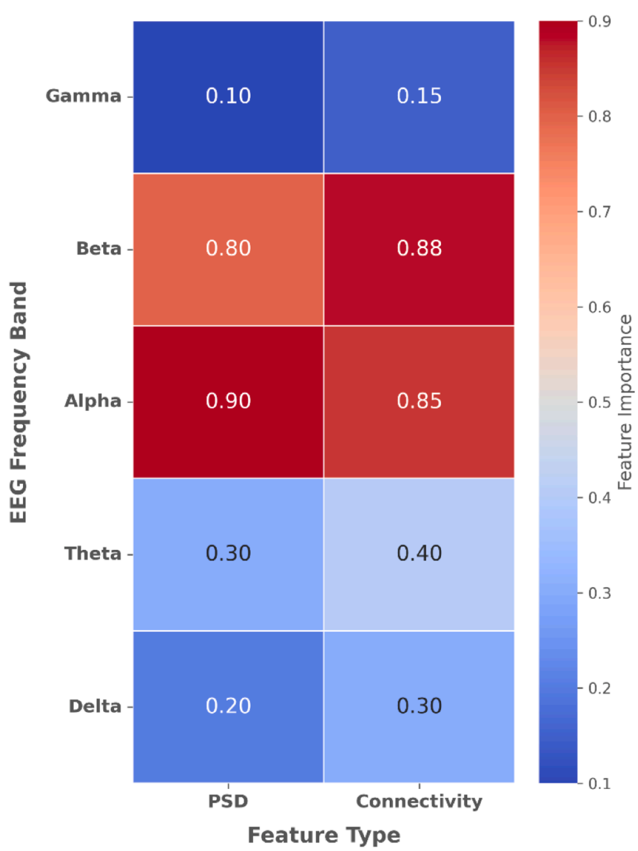

Fig. 7. Feature importance across EEG bands in stress studies.

This finding suggests that connectivity metrics, which capture the statistical dependency and information flow between brain regions, provide a more nuanced representation of stress-induced neural dynamics compared to standalone PSD measures. Interestingly, gamma band activity demonstrated the lowest feature importance across both feature types, with PSD and connectivity scores of 0.10 and 0.15, respectively. It indicates that gamma activity, while important in cognitive and attentional tasks, is less relevant in the context of stress detection. The moderate scores observed for the theta and delta bands highlight their utility in capturing slower, large-scale oscillatory activity associated with stress. These findings emphasize the need for integrating connectivity measures into stress classification frameworks, particularly for capturing complex inter-regional dynamics in the EEG bands.

5.4. Diagnosis of stressors

Previous studies provided task-specific EEG data, which were grouped into cognitive, emotional, and physiological stress categories. To compute XGBoost's importance scores, grouped features derived from each task category were used to train the model, with scores reflecting the contribution of task-specific features to improving model predictions. The stressor analysis, as provided in Fig. 8, delivers valuable insights into the relative influence of different stress-inducing scenarios on EEG-based stress detection. Cognitive stressors (e.g., MAT, SCWT) exhibited the highest importance score (0.78), emphasizing their robust impact on stress-related neural activity. These tasks often demand sustained attention and working memory, eliciting pronounced engagement of the frontal and temporal regions, as observed in the channel and spectrality analysis. Emotional stressors (e.g., IAPS, emotional audio/video), with an importance score of 0.62, ranked second, reflecting their ability to trigger significant neural responses in limbic and prefrontal regions. Social stressors (e.g., public speaking) also showed a strong contribution (0.66), highlighting the interplay between cognitive and emotional processing during interpersonal challenges. In contrast, physiological stressors (e.g., cold pressor tests) scored moderately (0.45), and game-based stressors had the lowest score (0.38), suggesting less usage due to these paradigms may elicit more localized neural responses.

This comparative analysis underscores the need for selecting appropriate stressor types in EEG studies to optimize the detection and classification of stress. Cognitive and social stressors provide robust paradigms for eliciting stress-related EEG patterns. In contrast, game-based and physiological stressors may require supplementary features or processing to enhance their effectiveness.

5.5. Public EEG datasets

The analysis of EEG datasets, as presented in Fig. 9, reveals notable variations in importance scores across different sources, indicating their relative effectiveness in EEG-based stress detection. In this context, XGBoost's weight metric refers to the number of times a feature derived from those datasets is used to split the data across all decision trees in the XGBoost model, indicating its relative frequency of use. On the other hand, gain measures the improvement in accuracy contributed by features from these datasets to the branches it is used on, reflecting its contribution to the model's predictive power.

Among the datasets, DREAMER exhibited the highest importance score (0.76), closely followed by DEAP (0.75) and SEED (0.72), while SAM 40 [173] showed a comparatively lower score (0.53). The high importance scores for DREAMER [174], DEAP [175], and SEED [176] suggest that features extracted from these datasets are mostly utilized EEG features relevant to stress classification.

In contrast, the limited number of studies utilizing the SAM 40 dataset could explain its lower importance score, suggesting that further exploration is needed to uncover its usage and effectiveness in stress detection. This approach of applying XGBoost's importance scores to

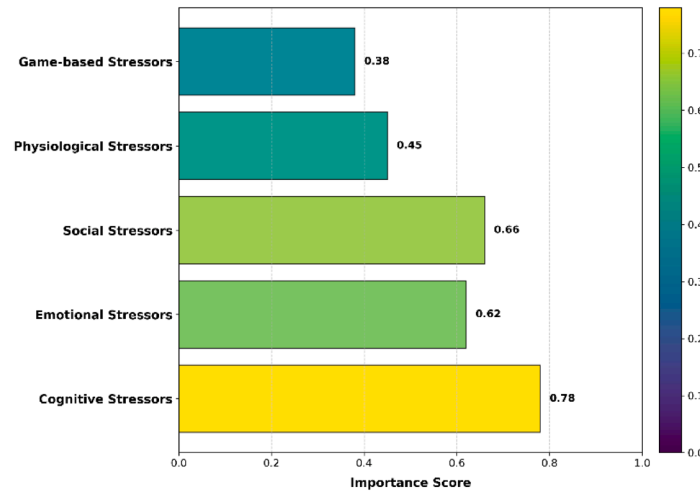

Fig. 8. Importance of various types of stressors.

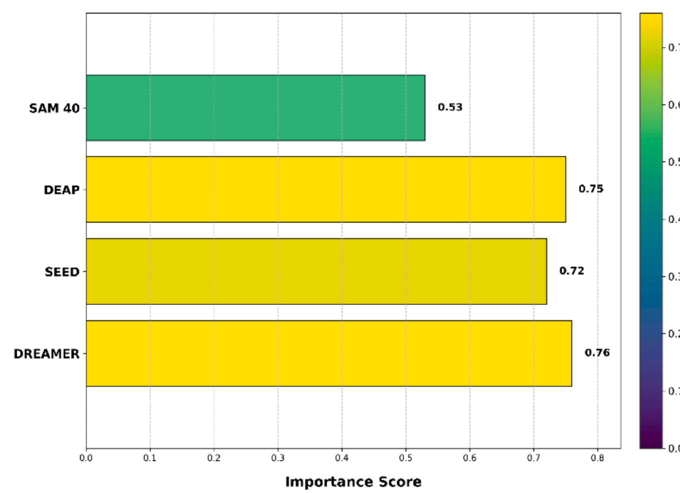

Fig. 9. Importance of various EEG-based public datasets.

assess EEG datasets offers a quantitative measure for determining the selection of datasets in stress recognition studies.

The complete XGBoost's hyperparameter settings used for all feature importance analysis presented in Fig. 5 through Fig. 9 are provided in Table 5. In this table, each figure column corresponds to a different XGBoost model trained on a specific grouping of features derived from the studies. Each model was implemented using the Scikit-learn compatible XGBClassifier interface, with integrated hyperparameter tuning performed separately for each analysis using GridSearchCV and 10-fold cross-validation to ensure consistent training across all tests.

Table 5
XGBoost's hyperparameter settings.

Hyperparameters	Fig. 5	Fig. 6	Fig. 7	Fig. 8	Fig. 9
n_estimators	300	250	200	350	400
learning_rate	0.05	0.07	0.10	0.03	0.04
max_depth	6	5	4	6	7
subsample	0.8	0.9	0.8	0.85	0.9
colsample_bytree	0.8	0.7	0.9	0.75	0.85
gamma	0.1	0.2	0.15	0.05	0.1
lambda (L2 reg.)	10	8	5	7	9

6. Discussion

Mental stress has turned into an expanding problematic issue in everyday life, having a detrimental effect on people and society. Various human body systems, for instance, the cardio-vascular [177], nervous [109], gastrointestinal (GI) [178], and immune systems [179] are adversely influenced by stress. This straightforwardly affects the cerebral area of the hippocampus despite stress [180]. Stressed individuals' decision-making and memory-based abilities are impaired by the reasons of this [3]. Stress also harms hormone secretion, which is most significant for processing a regular immune system [179]. Mental stress triggers cardiac arrhythmias by reducing blood pressure and heartbeats while initiating instability in the cardiovascular system [177]. At the same time, stress has a detrimental impact on the GI system, namely, disturbance in regular GI activity, irritable bowel syndrome, and reduced appetite [178]. Therefore, psychological stress detection, evaluation and assessment are essential to avoid serious health problems.

A comprehensive review of preceding EEG-based mental stress classification studies is provided in Table 6 of the **Appendix**. This comprehensive review focused on the various techniques utilised for EEG data analysis and classification algorithms for quantifying mental stress.

Particularly, it has been observed that picking the appropriate

Table 6
A comprehensive review of preceding EEG-based mental stress classification studies.

Papers (Year) [Ref.]	No. of participants	Brain regions	No. of EEG channels	Stressors/ tasks	Total task durations	Brain frequencies	Features	Classifiers	Stress levels (Classes)	Maximum $A_{cc\ a}$chieved
Khosrowabadi et al. (2011) [67]	26	Whole scalp	8	Exam stress	6. 30 min	Delta, theta, alpha, beta	FD, gaussian mixtures of EEG spectrogram, MSC	SVM, kNN	2 (Relax, Stress)	90.00 % (Both)
Saidatul et al. (2011) [20]	5	Whole scalp	19	MAT	11 min	Delta, theta, alpha, beta	Yule-Walker, Welch, and Burg methods.	ANN	2 (Relax-Stress)	91.17 %
Al-Shargie et al. (2015) [17]	12	PFC	8	MIST	60 min	Delta, theta, alpha, beta, noisy gamma.	AP, PSD	SVM	3 (Low-Medium-High)	94.00 %
Hou et al. (2015) [65]	9	Frontal & occipital lobes	14	SCWT	12 min	Theta, alpha, beta	PSD, FD, 6 statistical features.	SVM, kNN	2 (Low, High)	85.17 % (SVM)
Al-Shargie et al. (2015) [78]	5	PFC	7	MIST	17 min	Alpha	Alpha-based PSD	SVM	2 (Control-Stress)	95.00 %
Vanitha et al. (2016) [162]	6	PFC, frontal lobes	14	MAT	20 min	Delta, theta, alpha, beta, gamma	Instantaneous frequency, IMF	SVM, kNN, LDA	4 (Neutral-Low-Medium-High)	89.07 % (SVM)
Jun et al. (2016) [112]	10	Frontal & occipital lobes	14	MAT, SCWT	18 min	Theta, alpha, beta	RP difference of alpha and beta.	SVM	2 (Rest-Stress)	96.00 %
Al-Shargie et al. (2016) [113]	22	PFC	7	MIST	25 min	Delta, theta, alpha, beta	Mean powers	SVM	2 (Control-Stress)	91.70 %
Saeed et al. (2017) [161]	28	Frontal lobe	1	Psychological labelling	3 min	Low beta, high beta.	Liner regression, low beta.	NB	2 (Rest-Stress)	71.40 %
Subhani et al. (2017) [83]	22	Whole scalp	128	MIST	80 min	Delta, theta, low alpha, high alpha, low beta, beta, high beta, low gamma, gamma, high gamma	Amplitude asymmetry, AP, RP, coherence, and PL.	NB, SVM	2 (Control-Stress)	94.60 % (NB)
Secerbegovic et al. (2017) [181]	9	Forehead	1	Mental workload, public speaking	NA	Delta, theta, alpha, beta	Mean amplitude, RMS, Maximum amplitude, Weighted mean frequency.	SVM, NB	3 (Low-Medium-High)	83.33 % (NB)
Betti et al. (2017) [116]	15	Forehead	1	MAST	65 min	Low alpha, high alpha, low beta, high beta.	Attention, PSD	SVM	2 (Relax-Stress)	86.00 %
Al-Shargie et al. (2017) [166]	25	PFC	7	MIST	10 min	Delta, theta, alpha, beta	CCA	SVM	2 (Control-Stress)	89.80 %
Khosrowabadi et al. (2018) [104]	26	PFC	9	Audio-visual stimuli	10 min	Theta, alpha, beta	DTF, PSI, gPDC.	kNN, SVM	2 (Relax-Stress)	90.62 % (Both)
Jebelli et al. (2018) [182]	11	Frontal & occipital lobes	14	Work/field stress	Variable hours	Delta, theta, alpha, low beta, beta, high beta, gamma.	17 time-domain features & 7 frequency-domain features,	kNN, GDA, SVM	2 (Low, High)	75.90 % (SVM)
Saeed et al. (2018) [183]	28	Frontal lobe	1	Psychological labelling	3 min	Low beta, high beta, low gamma.	Neural oscillatory features	SVM	2 (Rest-Stress)	78.57 %
Papers (Year) [Ref.]	No. of participants	Brain regions	No. of EEG channels	Stressors/ tasks	Total task durations	Brain frequencies	Features	Classifiers	Stress levels (Classes)	Maximum A_{cc} achieved
Zanetti et al. (2018) [63]	1	Frontal lobe	14	MAT	31 min	Delta, theta, alpha, beta	MI, conditional MI	RF	2 (Rest-Stress)	97.50 %

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Table 6 (*continued*)

Papers (Year) [Ref.]	No. of participants	Brain regions	No. of EEG channels	Stressors/ tasks	Total task durations	Brain frequencies	Features	Classifiers	Stress levels (Classes)	Maximum A_{cc} achieved
Xia et al. (2018) [29]	22	PFC	128	MIST	80 min	Delta, theta, alpha, beta, gamma	Coherence, AP, RP, PL, Amplitude asymmetry	SVM	3 (Low-Medium-High)	79.54 %
Minguillon et al. (2018) [33]	10	PFC	4	MIST	30 min	Theta, alpha, gamma	Average relative gamma.	LDA	3 (Relax-Stress-Neutral)	50.00 %
Shon et al. (2018) [57]	32	Frontal lobe	32	Music videos	40 min	Delta, theta, alpha, beta, gamma	6 statistical features, Hjorth parameters, alpha frontal asymmetry, PSD.	kNN	2 (Relax-Stress)	67.08 %
Zanetti et al. (2019) [64]	17	Frontal & occipital lobes	14	MAT, playing games, watching videos.	31 min	Delta, theta, alpha, beta	MI, Shannon Entropy, covariance.	RF, LR.	2 (Relax-Stress)	84.30 % (both)
Lotfan et al. (2019) [184]	23	Frontal, parietal, temporal lobes	30	TSST	13 min	Delta, theta, alpha, beta	Transitivity, path length, modularity, efficiency.	SVM	2 (Relax, Stress)	93.62 %
Hasan et al. (2019) [55]	32	Frontal lobe	32	Music videos	NA	Delta, theta, alpha, beta, gamma	9 statistical features, PSD, Hjorth parameters, SD, Wavelet sum of entropy.	kNN	2 (Relax-Stress)	73.38 %
Darzi et al. (2019) [28]	26	Whole scalp	9	Long-term psychological task	8 min	Theta, low alpha, high alpha, low beta, high beta, low gamma	PSD, LI, CCA, PSI, GC, DTF, MI, MSC.	SVM, kNN, NB	2 (Relax-Stress)	94.00 % (SVM)
Masood et al. (2019) [185]	24	Frontal lobe	2	SCWT	11 min	Delta, theta, alpha, beta	PSD	CNN	2 (Relax-Stress)	85.00 %
Ahn et al. (2019) [12]	14	Left and right hemisphere	3	MAT, SCWT.	34 min	Low delta, high delta	Power asymmetry and normalized band power.	SVM	2 (Relax-Stress)	77.90 %
Saeed et al. (2020) [129]	33	Temporal, frontal lobes	5	Psychological labelling	39–58 min	Delta, theta, alpha, beta, low beta, gamma	Alpha asymmetry, beta asymmetry, and neural oscillatory features.	SVM, NB, kNN, LR, MLP	2 (Rest-Stress)	85.15 % (LR)
Attallah et al. (2020) [32]	66	Temporal, frontal, central, occipital, parietal	19	MAT	4 min	Delta, theta, alpha, beta	MDF, MFMD, SM, RMS, AR	Linear SVM, Cubic SVM, kNN, LDA.	2 (Relax-Stress)	99.94 % (LDA)
Zhang et al. (2020) [186]	25	PFC	4	MIST	24 min	Theta, alpha, beta, high gamma.	Alpha frontal asymmetry, beta power, and gamma power.	LDA	2 (Relax-Stress)	85.60 %
Halim et al. (2020) [187]	86	Frontal, occipital lobes	16	Driving task	45 min	Theta, alpha, low beta, high beta, gamma	6 Time-domain features 3 PSD-based features.	SVM, NN, RF	2 (Relax-Stress)	90.55 %
Papers (Year) [Ref.]	No. of participants	Brain regions	No. of EEG channels	Stressors/ tasks	Total task durations	Brain frequencies	Features	Classifiers	Stress levels (Classes)	Maximum A_{cc} achieved
Devi et al. (2020) [188]	20	Frontal, occipital lobes	14	Cognitive task	30 min	Alpha	DWT	CNN	2 (Low-High)	93.00 %
Baumgartl et al. (2020) [189]	227	PFC	62	Psychological labelling	16 min	Delta, theta, alpha, beta	PSD	RF	2 (Relax-Stress)	81.33 %
Al-Shargie et al. (2021) [190]	25	PFC	7	MAT	15 min	Alpha	Alpha PSD, coherence	NA	2 (Control-Stress)	NA
Liu et al. (2022) [191]	35	Whole scalp	64	Academic-related tasks	NA	Delta, theta, alpha, beta, gamma	Hurst index, fluctuation index, sample entropy, permutation entropy	IELM, RBF-NN, SVM, Linear SVM, RF, ELM	3 (Low-Average-high)	87.28 % (IELM)
Al-Saggaf et al. (2022) [192]	1213	Frontal, temporal, parietal, occipital	19	MIST-based task.	NA	Delta, theta, alpha, beta, gamma	PSD, coherence, asymmetry, relative power ratios of	CNN, SVM, DT, LR.	3 (Low-Moderate-high	96.00 % (CNN)

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Table 6 (*continued*)

Papers (Year) [Ref.]	No. of participants	Brain regions	No. of EEG channels	Stressors/ tasks	Total task durations	Brain frequencies	Features	Classifiers	Stress levels (Classes)	Maximum $A_{cc\ a}$chieved
							delta/theta, alpha/ beta.			
Fu et al. (2022) [193]	20	Whole scalp	32	TSST	5 min	Delta, theta, alpha, beta, gamma	Mean, std dev, Hjorth parameters, skewness, kurtosis, RMS, PSD, RP, coherence, frontal alpha asymmetry	Hybrid CNN+GAN	2 (Stress-Non stress)	93.20 %
Saffari et al. (2023) [194]	41	Frontal, central, parietal	9	watching videos, digit span, pattern recognition tasks	65 min	Alpha	ITPC, PLI	RF	3 (Low-Medium-High)	83.78 %
Konar et al. (2023) [195]	38	Frontal lobe	19	MAT	15 min	Delta, theta, alpha, beta	Skewness, kurtosis, mean, absolute, std dev, PSD	SVM, kNN, NB,	4 (Relax-Low-Moderate-High)	93.85 % (Combined SVM, kNN, NB)
Badr et al. (2023) [196]	22	Whole scalp	64	SCWT	19 min	Delta, theta, alpha, beta	Mean PSD using FFT	SVM, NB, DT, kNN, DA	2 (Control-Stress	99.98 % (SVM)
Hag et al. (2023) [197]	32	Frontal, central, parietal lobes	32	IAPS, MAT	20 min	Theta, low alpha, high alpha, low beta, high beta	Hjorth parameters, RP, wavelet energy, spectral entropy	SVM, RLDA, kNN	2 (Relax-Stress)	85.68 % (SVM)
Fernandez et al. (2024) [79]	40	Frontal, parietal lobes	32	TSST	15 min	Delta, Theta, Alpha, Beta	PSD, frontal alpha asymmetry	SVM, RF, LR	2 (Relax-Stress)	87.00 % (RF)
Bakare et al. (2024) [198]	15	Frontal, temporal lobes	14	MAT	22 min	Delta, Theta, Alpha, Beta, Gamma	PSD	SVM, RF	2 (Low-High)	93.50 % (SVM)
Premchand et al. (2024) [199]	40	Frontal, temporal lobes	4	Vigilance & Multi-Modal Integration Task,	40 min	Delta, Theta, Alpha, Beta, Gamma	PSD, FD, sample entropy, Hjorth parameters	SVR with majority voting	2 (Relax-Stress)	81.00 %
Afify et al. (2025) [200]	40	Frontal, temporal, parietal lobes	32	SCWT, MAT, mirror image recognition	5 min	Delta, Theta, Alpha, Beta, Gamma	Spectrogram features	CNN-VGG	4 (Relax-Mild-Moderate-High)	99.25 %

Legends: SCWT: Stroop Color-Word Task; MIST: Montreal Imaging Stress Task; MAST: Maastricht Acute Stress Test; DWT: Discrete Wavelet Transform; GDA: Gaussian Discernment Analysis; PL: Phase Lag; PFC: Prefrontal Cortex; MDF: Median Frequency; MFMD: Modified Frequency Mean; RMS: Root Mean Square; TSST: Trier Social Stress Test; LI: Laterality Index; PSI: Phase-Slope Index; CCA: Coefficient Analysis; GC: Granger Causality; AR: Autoregression; PDC: Partial Directed Coherence; DTF: Directed Transfer Function; FD: Fractal Dimension; SM: Spectral Moments; MSC: Magnitude Squared Coherence; AP: Absolute Power; RP: Relative Power; IMF: Intrinsic Mode Function; IAPS: International Affective Picture System; MI: Mutual Information; LDA: Linear Discriminant Analysis; DT: Decision Tree; RBF: Radial Basis Function; MLP: Multilayer Perceptron; CNN: Convolutional Neural Network; IELM: Improved Extreme Learning Machine; GAN: Generative Adversarial Network; ITPC: Intertrial Phase Clustering; VGG: Visual Geometry Group.

analysing procedure is difficult since there are a variety of factors implemented in stress experiments. These factors incorporate sample size, EEG head cap, stress task duration, stressor type, experiment time, suitable EEG processing, no of features, feature type, and suitable type of classification algorithm. Hence, the most important section for psychological stress quantification is picking the most significant features. Another concern is the considerable inconsistency among participants and their stress responses. Several stress responses might be acquired for a specific individual depending on their sociality, emotional state, health, and psychology.

The review has underlined the significant differences perceived among the research findings and observed that the dissimilarity of the EEG data analysis methods could lead to numerous inconsistent results. However, obtaining the EEG features associated with brain connectivity displayed an obvious model for quantifying mental stress since communications and influences among the cerebral regions in stressful circumstances will provide more real-time and dynamic data for analysis. Therefore, investigating the EEG-based brain connectivity features provides a clear model for assessing mental stress.

Furthermore, a no of variable experiment lengths have been observed in the discussed comprehensive review. A 30-min duration is observed in a research study that incorporates resting state, relaxation interval, 3 questions regarding self-assessment stress level questionnaire, MIST task & training, and maximum voluntary contraction [33]. In the meantime, some research article provides an 80-minute data acquisition period coming from 2 conditions of stress and control, where each is comprised of 40 min of habituation, 4-levels of the main condition, recovery time and resting state [29,83]. *Al-Shargie* et al. produced an experiment protocol, where 60 60-min sessions consist of an introduction, training, primary experiment and resting, and about 40 min for 3-levels of MAT tasks [17]. Likewise, a research study produced an experiment protocol that consisted of 18 min of introduction, training, and data recording for controlled and stressed conditions, where 3 min of counting numbers and 1 min of serial subtraction were when EEG signals were recorded [32]. *Saeed* et al. accomplished an elevation of beta power and a reduction in alpha power in the PFC cerebral cortex with a recording duration of 25 min [129]. However, to evade the influence of time and circadian rhythm on an individual's cognitive capability and stress performance, *Xia* et al. have favoured performing the EEG recordings of every individual concurrently at the same time of the day [29].

The nature of the task and no of participants (sample size) have a straightforward effect on the classification accuracy, for instance, the time constraints in performing MAT, which indicates moderate performance accuracy [83], and there are diversified results obtained with a considerable number of participants with the articles in [29] in contrast to [33]. It's noteworthy that most of the stress investigations had a constrained sample size; in simple words, the number of individuals involved was insufficient in controlling prejudgment brought on by individual differences. Hence, a larger number of participants is required as the sample size to confirm statistical power and to strengthen research outcomes. On the contrary, a reduced no of EEG channels asserts real-time psychological stress classification, nevertheless, this could elevate and facilitate the system's mobility. Thus, using 1 or 2 EEG electrodes from the frontal lobes might be adequate to recognize the stressed phase and controlled phase.

However, it's beneficial to use a higher number of EEG electrodes to classify stress at multiple levels, as recommended by the researchers [18]. As stated in the EEG pre-processing section, the EEG signals go through numerous filtering processes that might reduce redundant and unnecessary peaks and artifacts, and only the smaller residual noises could malform the data of the analysed EEG.

Finally, the EEG sensor utilised for recording the data and classifying psychological stress has a big influence on the number of existing EEG electrodes. The no of electrodes in a general EEG headgear can range from 1 to 256. The 10/20 international system for electrode placement has been followed in most of the studies. The advantages of utilising multichannel EEG equipment are that it records the EEG signal without losing any data as the EEG electrode network enlarges to added channels (instigated when electrodes become more separated while fewer are positioned), as well as in detecting EEG signals. This implies that practical therapeutic applications require higher-resolution EEG networks to record the brain signals.

6.1. Limitations

Most studies have induced psychological stress in controlled laboratory environments. Still, a more practical approach would be to design protocols that simulate real-world scenarios, such as designing them in VR. Additionally, many of these studies did not establish a correlation between physiological responses, like cortisol levels, and behavioural reactions, such as changes in facial expressions, speech patterns, or task performance. It's crucial because EEG measures electrical brain activity, but it does not capture hormonal or biochemical stress markers. Most reviewed research has been conducted in offline settings, whereas developing an online system for real-time stress recognition is highly recommended. Another crucial factor influencing stress assessment is the reliability of ground truth labels, essential for training classifiers to distinguish between stress and non-stress conditions. Typically, studies have relied on self-reported questionnaire scores, psychologist interviews, or a combination of both for labelling. However, these methods are limited as they heavily depend on participants' subjective perceptions, which may lead to inaccurate stress classification due to subconscious biases. Unlike controlled experimental settings, labelling stress in real-world scenarios presents a significant challenge.

6.2. Research gaps and future recommendations

This study has provided valuable insights into the relationship between AI-based models and EEG features for mental stress classification. Moving forward, several research gaps remain open for further research and exploration.

6.2.1. Feature-level fusion of diverse connectivity maps for deep learning models

From this review investigation, it has been observed that CNNs perform optimally when EEG signals are transformed into spectral images, whereas LSTM models are primarily applied to raw EEG data. However, most prior research has relied on BFC connectivity maps or spectrograms as input representations for CNNs. To further improve EEG-based classification, we propose investigating the fusion of Time-varying Effective Connectivity (TVEC) and Frequency-specific Effective Connectivity (FEC) spatial-temporal maps, such as alpha-PDC and beta-DTF. Converting EEG-based TVEC and FEC features into feature maps could enhance the interpretation of spatial and temporal dynamics, potentially leading to more accurate classification outcomes.

6.2.2. Multimodal fusion in stress-based behavioral neurology

Future advancements in stress assessment could leverage the multimodal fusion of speech and EEG-based features to improve accuracy and robustness. Speech characteristics, such as prosody, pitch variations, Mel-Frequency Cepstral Coefficients (MFCCs), and voice intensity, are known to reflect emotional and cognitive states [201,202]. When combined with EEG-based TVEC features, this fusion approach could capture neurological signals while linking them with behavioral indicators of stress.

The integration of these modalities into next-generation wearable devices, such as smart EEG headbands with built-in microphones and AI-driven processing units, could enable continuous and real-time stress monitoring [203]. These wearables can utilize on-device machine learning algorithms to process EEG and speech signals locally, minimizing latency and enhancing privacy [204]. Additionally, cloud-based platforms could support these devices by aggregating and analyzing multimodal data to generate personalized stress profiles [205]. Furthermore, fusing haptic feedback mechanisms into these wearables could allow for immediate stress management interventions, such as breath-pacing alerts or calming audio prompts when elevated stress levels are detected [206].

Future research could explore multimodal fusion strategies that combine EEG signals with complementary modalities such as speech or peripheral physiological signals. These approaches can enhance model robustness, as complementarity allows models to capture both internal neural states and external behavioral expressions of stress, thereby improving generalization by linking neurological dynamics with behavioral or affective markers [207]. However, multimodal fusion introduces its challenges, such as cross-modal alignment, heterogeneous data preprocessing requirements, and computational overhead [206]. Addressing these challenges is crucial for the development of real-time, wearable, and scalable stress detection systems that can operate reliably in naturalistic environments.

6.2.3. Advanced fusion of deep learning techniques

There is considerable potential in fusing attention-based deep learning models and Graph Convolutional Networks (GCNs) for EEG-based stress classification. GCNs are particularly valuable in analyzing cognitive connectivity features while enhancing classification accuracy, especially for non-Euclidean data structures like EEG signals. Additionally, attention-based models could improve classification outcomes by identifying the most relevant connectivity patterns within the data. Although some initial studies have explored these techniques, further research is needed to fully exploit their potential across various EEG classification tasks [208–210].

6.2.4. Fusion of transfer learning with multimodal foundation models

To extract deeper insights from the high-dimensional TVEC and FEC feature maps, a fusion of pre-trained deep neural networks such as ResNet, AlexNet [211,212], and multimodal foundation models such as ChatGPT, Gemini, DeepSeek and Claude can be employed to identify complex connectivity patterns [213]. These extracted feature embeddings can then be utilized in lightweight machine learning models such as SVM, RF, and DT, ensuring efficient and interpretable stress classification. This dual-stage pipeline—leveraging deep learning for feature extraction and ML for classification—could enhance the accuracy of stress quantification, highlighting the potential of fusing transfer learning with multimodal foundation models in neuroscience-based stress research.

6.2.5. Innovative algorithmic fusion for advanced stress detection

Recent studies have explored innovative hybrid algorithmic fusion strategies that combine deep learning with metaheuristic optimization to further enhance the interpretability and performance of EEG-based stress classification. Notably, models such as CNN-INFO and LSTM-ALO have been proposed in related biomedical applications [214, 215]. While these models are not implemented in this review, they are potential future directions for future algorithm-level fusion strategies aimed at enhancing feature selection and model optimization in EEG-based stress analysis.

CNN-INFO integrates CNNs with the Weighted Mean of Vector Optimizers (INFO), enabling both feature subset selection and hyperparameter tuning to enhance classification performance [214]. Additionally, LSTM-ALO combines Long-Short-Term Memory (LSTM) networks with the Ant Lion Optimizer (ALO) to optimize learning rates and accelerate convergence in time-series tasks [215]. These hybrid architectures are well-suited to the complex, high-dimensional nature of EEG signals in stress classification.

These frameworks demonstrate how different feature domains, such as spatial activations from CNNs and temporal dynamics from LSTMs, can complement optimization-driven parameter tuning to create more discriminative and generalizable EEG stress classifiers [214,215]. CNNs are effective in extracting spectral-spatial features from 2D EEG maps, while optimization methods identify discriminative subsets or tune deep network parameters to improve generalization, thereby utilizing complementary information across feature domains [44,164].

However, the practical implementation of these hybrid models poses challenges, including computational complexity, model interpretability, and real-time applicability, particularly for deployment in wearable EEG devices [215]. Efficient resource allocation, low-latency inference, and interpretability of fused architectures remain open research directions that must be addressed before widespread adoption in real-world stress monitoring scenarios.

To conclude, this review distinctly advances prior literature by systematically covering a broader spectrum of EEG-based stress perspectives, as detailed in Table 1. In contrast with earlier reviews, which selectively discussed aspects such as stress tasks or classifier performance, this work provides a comprehensive evaluation across nine principal perspectives, such as:

a) *Stressors:* This study categorizes five major stressors, such as cognitive, emotional, physiological, social, and game-based and ranks them using model-derived importance scores as provided in Fig. 8. The assessment shows that cognitive stressors (e.g., MAT, SCWT) exhibited the highest importance score, showing the strongest discriminative power. This granularity enhances stressor selection with importance-based assessment.
b) *Key electrodes:* Followingly this review identifies and ranks the EEG channels which are most relevant to stress classification based on model-derived importance scores. As shown in Fig. 6, frontal electrodes such as Fz, F3, F4, FC1 demonstrate noteworthy contributions, while enabling topographic localization of stress-responsive regions. This analysis emphasizes EEG sensor-level specificity, which is crucial for spatial targeting in stress monitoring.
c) *Pre-processing methods:* As summarized in Table 2, this review catalogues a range of pre-processing techniques serving as a consolidated reference point for EEG artifact handling approaches used in stress classification studies. Beyond just listing methods, the review highlights the inconsistencies in their application and underscores the lack of standardized pre-processing protocols in EEG-based stress analysis.
d) *EEG bands:* This review offers an in-depth analysis of canonical EEG bands by evaluating their discriminative potential in stress classification. As depicted in Fig. 4, the alpha and beta bands consistently demonstrated the highest classification accuracies across reviewed studies, highlighting their strong association with stress-related cognitive processes. In contrast, delta and gamma bands exhibited comparatively lower discriminative power. Additionally, Fig. 7 further supports the prominence of alpha and beta bands across PSD and connectivity feature types.
e) *Feature types:* This review provides a comprehensive analysis of EEG features across multiple domains, including statistical, spectral, temporal, and connectivity-based measures and evaluates their contribution to stress classification performance. Fig. 3 presents an aggregated analysis of classification performance across these EEG feature domains, revealing that spectral and statistical features achieved the highest average accuracy across stress studies, while temporal and connectivity features also contributed reliably to classification outcomes. Furthermore, Fig. 7 demonstrates that connectivity-based features, particularly those derived from alpha and beta bands, exhibit stronger contributions when compared to conventional spectral features such as PSD. This cross-domain evaluation emphasizes methodological diversity and identifies impactful feature types, distinguishing this work from prior reviews that typically focus on one or two isolated domains.
f) *Feature correlation:* Consequently, this review investigates the correlation between extracted EEG features and stress level variations. As shown in Table 3**.** alpha activity and alpha asymmetry index exhibit strong negative correlations with increasing stress, aligning with prior neurophysiological findings on frontal alpha suppression during stress. In contrast, the beta activity in frontal and temporal regions shows a strong positive correlation with stress, reflecting heightened arousal and task engagement. These findings reinforce the validity of spectral markers and provide empirical support for feature selection strategies based on correlation. In addition, Fig. 5 supports these findings by showing region-specific relevance of frequency bands.
g) *Spectrality in brain regions:* Subsequently, this review provides a novel lobe-specific spectrality profiling, which provides a refined view of EEG signal localization, a dimension that is rarely quantified in previous stress reviews. As illustrated in Fig. 5, frontal and temporal lobes exhibit the highest spectral relevance particularly in the alpha and beta bands, reflecting its involvement in stress regulation. In contrast, the parietal and occipital regions show lower spectral relevance, consistent with their primary roles in sensory integration and visual processing rather than stress modulation.
h) *Classifiers and their performances:* This review presents a synthesized performance-driven evaluation of AI-based classifiers, which enables a practical comparison of classifiers' strengths and trade-offs. Table 4 summarizes the classifier's suitability for EEG-based stress classification. Traditional classifiers such as SVM, RF, and DT consistently demonstrate strong performance across various EEG feature types. Among deep learning models, CNN and LSTM show superior classification performance by capturing spatial and temporal patterns.
i) *Public dataset analysis:* Lastly, this review explores an empirical framework for assessing dataset suitability and benchmarking future studies, by quantitatively ranking publicly available EEG datasets using model-derived importance scores. As illustrated in Fig. 9, DREAMER, DEAP, and SEED datasets consistently produced high importance scores, indicating their stronger contribution to stress classification performance across studies. In contrast, SAM 40 showed comparatively lower scores, potentially due to its smaller size and limited exploration in feature diversity.

7. Conclusion

This review systematically examines EEG-based mental stress quantification perspectives, emphasizing the future role of FEC and TVEC feature maps and the potential of fusion-based approaches. The integration of transfer learning, optimization-enhanced deep learning architectures, and large language models shows promising directions for improving EEG-based stress classification performance. The research findings highlight that spectral and statistical EEG features provide the highest classification performance, while connectivity-based features offer valuable informational insights. However, challenges such as inconsistent ground truth labelling, lack of real-world stress scenarios, and methodological variations across studies limit generalizability. Future studies could explore the fusion of hybrid architectures for incorporating 3D spatiotemporal EEG connectivity maps while optimizing the transfer learning approach for feature-level fusion connectivity-based analysis, as well as fusing multi-modal large foundation models for more robust stress detection. By addressing these gaps through fusion-centric strategies, EEG-based stress research can transition into real-time, real-world applications, enhancing both mental health monitoring and early stress intervention systems.

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Sayantan Acharya: Writing – original draft, Visualization, Validation, Software, Resources, Methodology. **Abbas Khosravi:** Writing – original draft, Visualization, Supervision, Formal analysis, Data curation. **Douglas Creighton:** Writing – original draft, Project administration, Formal analysis, Data curation, Conceptualization. **Roohallah Alizadehsani:** Writing – original draft, Supervision, Resources, Conceptualization. **U Rajendra Acharya:** Writing – original draft, Supervision, Project administration, Methodology, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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