Journal of Computer and Communications, 2024, 12, 218-245
https://www.scirp.org/journal/jcc
ISSN Online: 2327-5227
ISSN Print: 2327-5219

A State of the Art: EEG-Based Classification and Recognition Models of Mental Stress

Azleena Kamarul Bahrain, Zulkifli Mahmoodin, Muhammad Noor Nordin, Mohd Zubir Suboh

Medical Engineering Technology Section, Universiti Kuala Lumpur-British Malaysian Institute, Selangor, Malaysia
Email: azleena@unikl.edu.my

How to cite this paper: Bahrain, A.K., Mahmoodin, Z., Nordin, M.N. and Suboh, M.Z. (2024) A State of the Art: EEG-Based Classification and Recognition Models of Mental Stress. *Journal of Computer and Communications*, **12**, 218-245.
https://doi.org/10.4236/jcc.2024.1212013

Received: November 15, 2024
Accepted: December 27, 2024
Published: December 30, 2024

Abstract

Over the past several decades, numerous methods have been applied by research and professionals to detect and measure mental stress, varying from subjective methods such questionnaires and face-to-face interviews up to the objective methods using physiological signals and neuroimaging equipment such as salivary cortisol and functional magnetic resonance imaging (fMRI), respectively. Among those methods, an Electroencephalograph (EEG) is one of the utmost chosen non-invasive methods by professionals and researchers in recording real time brain signals. This paper highlights the state of art for each of the studies, by comparing and analyzing the method and protocol of EEG data collection, including the selection of electrodes and brain regions involving two major categories of mental stress: acute and chronic. Selection of EEG features, with the necessary signal pre-processing and processing techniques, and the classification models used in these studies have been summarized and discussed.

Keywords

Electroencephalograph (EEG), Mental Stress, Feature Extraction

1. Introduction

Regardless of age, gender or race, people worldwide are vulnerable to mental health issues or mental disorders. The World Health Organization (WHO) had identified depression as a leading cause of disability and around 280 million people globally experience this mental disorder. Pitiful depression can lead to worst case scenario such suicide. While suicide is fourth primary reasons of death for people in age 15 - 29 years old suicide. They also discovered people in severe mental health conditions have short life span due to inevitable physical conditions [1]. Thus, these alarming scenarios drive many people to study and focus on the prevention, screening, assessment, and treatment of mental health problems.

Mental stress is one of the main causes leading to physiological problems. It has interested numerous researchers in recent decades. This field has been discovered broadly in numerous studies from different angles, aspects, and points of view. Across all these studies, several types of stress, tools, methodology and approach involved. One of these kinds was the development of objective assessment in detecting or screening mental stress. Initially, mental stress can be measured both using subjective and objective techniques [2] [3]. Face-to-face medical interview by the psychologist and questionnaires (developed by the expertise) like Perceived Stress Scale (PSS) [4], The Ardell Wellness Stress Scale and Depression Anxiety Stress Scale (DASS) [5] are stress subjective detection techniques. As those are subjective techniques, the results may vary from one expert to another. In addition, the questionnaires required participant time to fill up, to understand and interpret the questions. One understanding and interpretation toward the questions may be different or wrong. This method may also trigger acute stress response [6]. In some cases, the participant overreaction to the question may also affect accuracy of the outcome. Furthermore, the questionnaires need further evaluation by an expert such counsellor or psychiatrist to validate the screening test.

In contrast, mental stress might also be detected, measured, and analyzed objectively via physiological measures or neuroimaging techniques. For physiological measures, various body parameters can be used to indicate mental stress condition including heart rate variability, blood pressure, pupil size and electrodermal activity [7]. However, those signals may easily be influenced by many factors such as the subject's physical activities and environmental changes [8]-[10]. While the Neuroimaging Techniques can be grouped into non-invasive and invasive techniques such Positron Emission Tomography (PET), Functional near-infrared spectroscopy (fNIRS) [11], Functional magnetic resonance imaging (fMRI) [12], and Electroencephalogram (EEG) [11]. Some of them are designed for structural imaging while the others are for functional. Among all these modalities, despite having certain disadvantages, EEG is the most common tool used in stress detection studies. In neuroscience field, EEG is the second most prevalent tool used [13]. The signals recorded by EEG are directly associated with the electrical activities occurring in the brain [14] [15]. In fact, they were many studies of related area tend to make EEG as their chosen tool.

2. Mental Stress

In general, a response to the perceived threat or stressor is called stress. Naturally, stress is a normal body response to stressors that prepare the body to deal with different conditions, such as during fight and flight situation or excitement by means of survival. When people are in a stressful situation, their mental, physical, and physiological systems are temporarily altered to prepare an individual to adapt with the situation. However, when people cannot handle the stress and the stress is persistent, their body will be physiologically, mentally, and emotionally affected [16]. Initially, it was an act of maintaining homeostasis and beneficial for survival. The three diverse types of stress are acute stress, episodic acute stress, and chronic stress (**Figure 1**). Acute stress is the most prevalent and normal type of stress that is experienced by everyone. While acute stress that occurs regularly is known as episodic acute stress. However, chronic stress is severe, prolonged stress response that leads to negative effects on the mental, physical, and physiological system [6] [17]. It has the potential to diminish the response efficiency of the central-peripheral regulatory system in sustaining health [18] as well as to produce aberrant autonomic nervous system functioning [19].

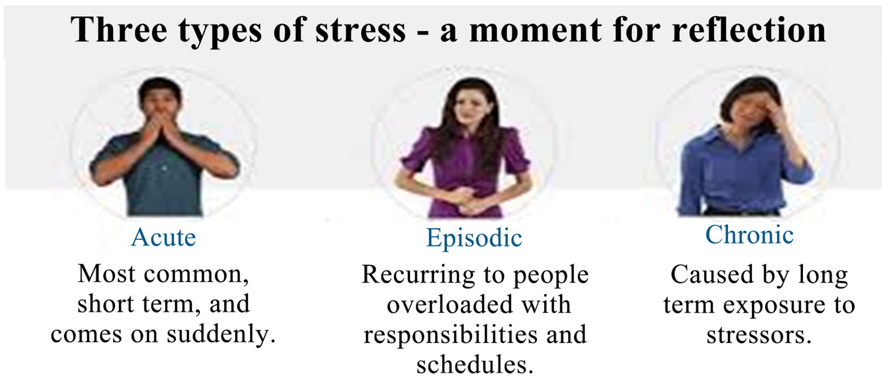

Figure 1. Types of stress (Anticancer Lifestyle Program).

3. EEG Based Classification and Recognition Models

Numerous techniques of data acquisition, data analysis and classifier have been chosen in various mental stress classification and recognition studies. The general methodology consists of standard stages which include data acquisition, pre-processing, extraction and classification of features, and evaluation (**Figure 2**). Yet, the data, techniques, protocols, equipment, software, programming languages and algorithms were all varied. Some studies focusing on the resting-state or baseline EEG signal, while in most studies the stress evoked EEG signal were recorded in their experiments. Some authors choose to collect their own EEG data while others preferably used the existing EEG database.

Figure 2. General block diagram.

3.1. EEG Data

In many studies, acute stress is more likely to be investigated than chronic stress or perceived stress as it can be simply induced by the stressors during experiments. However, in both type of stress studies, the researchers opt to healthy subjects as participants compared to those with any mental health history. The exclusion criteria usually have been shared earlier via different mediums such as social media, questionnaires, or telephone interview [20]. Usually, the subjects have been labelled into control and stressed by using stress test questionnaires [20]-[23].

In most works, various stressors have been applied to the subjects, to induce stress and to observe their stress response with the aim of discovering the affiliation to the brain. Those available methods are such Cold Pressor Stress (CPS), Montreal Imaging Stress Test (MIST), Trier Social Stress Test (TSST), CO_2 Challenge Test, Stroop Test, Paced Auditory Serial Addition Task (PASAT), Maastricht Acute Stress Test (MAST), Noise Stress, Mannheim Multicomponent Stress Test (MMST) and the Stroop Color & Word Test (SCWT) [24]. AlShorman, O. *et al.* [21] used 14 healthy participants among undergraduate university male students between age of 18 and 23 years old, which grouped them into control and stressed using DASS questionnaires. Acute stress was induced by CPS to the stressed subjects as painful sensation stimulated. Meanwhile in [20], a complex procedure was performed on 22 healthy participants consisting of 11 males and 11 females. For the whole data collection process that took more than 2 hours per participant, its involved of saliva sampling for the cortisol concentration test as stress biomarker, 3 different questionnaires that include of state trait anxiety inventory (STAI), life event scale (LES), self-rating depression scale (SDS) and followed by EEG data acquisition with TSST as stress induction method. Saliva sampling test and the 3 different questionnaires were performed twice in the beginning and in the final stage.

Authors of [22] used 4 movie clips containing stressed and non-stressed contents to elicit stress on 35 healthy subjects consisting of both genders between the age group of 23 to 55 years old. The effects on arousal and valence dimension were mapped to the stress response. At the end of the video watching, the State Anxiety Questionnaire (SAQ) attempted by the participants was used to label them as stressed and non-stressed subjects. Like other authors, [23] were also stimulated stress in a variety of conditions. The subjects were required to observe a black circle on a computer screen for 5 minutes, attempting mental arithmetic calculation for 5 minutes and finally performing mental arithmetic in distraction surrounding. The ideas were to create normal, less-stressed, and high-stressed conditions, respectively. In this study, 20 university students aged 18 to 25 years old were recruited based on the Thai version of 10-item PSS.

In [25], EEG was recorded from 14 students aged 17 to 21 years, consisting of 8 males and 6 females before and after examinations. The examination is also a stressor. Therefore, the first experiment was conducted in 12 minutes when the subjects, closing and opening their eyes, rested, and revised for the examination. The second experiment was conducted after they attempted the 1 hour 30 minutes examination in 3 minutes while performing mental arithmetic task of PSYTASK software. While authors in [26], recruited 50 students, comprises of 32 males and 18 females aged 19 to 38 years old in their study. The experiments involved baseline EEG recording with the eye-closed for 3 minutes in the first session and subjects wore Virtual Reality (VR) device containing of horror video for 3 minutes and 30 seconds in the next session. The experiments continued with the recording of another eye-closed resting state in 3 minutes, followed by the 40 questions of website IQ test in 20 minutes and again another eye-closed resting state in its 3 minutes final session. A quite large number of subjects used in [27] study. 90 students included 30 subjects for each grade; freshman, sophomore and junior were selected. However, no other details on the students' age and gender can be found in the paper. They attempted stress self-assessment form before deep sleep of EEG was recorded and next was when they were watched the provided videos. In [28], EEG data for 4 subjects in age of 21 to 26 years were recorded for 2 minutes each in three different scenarios: resting state, low stress inducing activity using simple arithmetic puzzles and high stress inducing activity using SCWT.

Unlike other studies in this paper, 9 healthy but visually impaired subjects, 3 males and 6 females in the age range of 22 to 53 years had been used in [29]. The EEG signals were recorded while they walked independently via a complex route containing seven different environments.

Rather than collecting their own data, many studies analyze existing EEG data from the available databases. Even though using public datasets is efficient, it risks standardizing procedures and outcomes, thereby restricting new contributions. Public datasets might lead to overfitting and poor generalization to new populations. Issa, S. *et al.* [30] knowingly used 2 public databases in their study known as DEAP and MAHNOB-HCI. The DEAP dataset contains of EEG and face expression video data of 16 male and 16 female participants aged 19 to 37 years old that were recorded while they were watching 40 one-minute-long music videos. Same goes for MAHNOB-HCI, it contains recorded EEG and other peripheral physiological signals of 27 participants from both genders aged 19 to 40 years old who were required to watch 20 music videos 43.9 to 117 second (about 2 minutes) long. Later, in both datasets the participants were required to rate the music videos based on certain dimensions. Authors in [31] analyzing existing dataset that containing of 7 male and 7 female subjects age ranging from 22 to 46 years old with normal vision ability in a complicated EEG protocol. The EEGs were recorded in 2 different tasks, namely categorization and recognition. Subjects were requested to watch a computer screen containing 10 blocks with 100 target and non-target (distractors) images and respond. While, [32] used data from PhysioBank. These 36 EEG data recorded while they were in baseline state for 182 seconds (about 6 minutes) and performing cognitive mental activity of a complex serial subtraction for 62 seconds. Raufi, B. *et al.* [33] choose the STEW (Simultaneous Task EEG Workload) dataset for their study. It contains raw EEG data for 48 subjects in resting state and when they did multitask SIMKAP test. A DREAMER dataset was used in [34] containing EEG data from 23 subjects. In this dataset, the subjects had been watching 18 clips consisting of audio and visual stimuli to evoke different emotions. The emotion in the category of Valence, Arousal and Dominance for each clip was self-evaluated by the subjects.

Table 1. EEG data in acute stress studies.

Author, Year [Ref]	Stressor	No of Subjects	Subject's Age (years old)	Gender	Stress Label Mechanism	Data Source
R. Fu *et al.*, 2022 [20]	TSST	22	23.05 ± 2.25	Both	Saliva, STAI, LES, SDS	Primary
O. AlShorman *et al.*, 2022 [21]	CPS	14	18 - 23	Male	DASS	Primary
N. Phutella *et al.*, 2022 [22]	Movie Clips	35	23 - 55	Both	SAQ	Primary
A. Hemakom *et al.*, 2022 [23]	Mental Arithmetic	20	18 - 25	Both	PSS	Primary
V.G Rajendran *et al.* 2022 [25]	Before sitting for the examination After sitting for the examination & while performing Mental Arithmetic test	14	17 - 21	Both	None	Primary
A.G. *et al.*, 2022 [26]	Horror Video, IQ Test	50	19 - 38	Both	None	Primary
L. Liu *et al.*, 2022 [27]	Videos	90	Not stated	Not Stated	Stress Self-Assessment	Primary
P. Singh *et al.*, 2022 [28]	Arithmetic Puzzle & SCWT	4	21 - 26	Both	None	Primary
M.S. Karim *et al.*, 2021 [29]	Complex and Different Walking Route	9	22 - 53	Both	None	Primary
S. Issa *et al.*, 2022 [30]	Listening to 40 one-minute-long music videos	32	19 - 37	Both	None	DEAP
	Listening to 20 music videos	27	19 - 40	Both	None	MAHNOB-HCI
R. Gupta *et al.*, 2022 [31]	Watching images on the computer screen	14	22 - 46	Both	None	Research Paper by A. Delorme *et al.*
T. Priya *et al.*, 2020 [32]	Complex Serial Subtraction	36	Not stated	Not Stated	None	PhysioBank
B. Raufi *et al.*, 2022 [33]	At rest and SIMKAP Test	48	Not stated	Male	None	STEW
D. Virmani *et al.*, 2021 [34]	Video Clips	23	Not stated	Not Stated	None	DREAMER

Nevertheless, the authors such [35]-[39] were investigating chronic stress or perceived stress in the study. In most of similar studies on chronic stress or perceived stress studies, they did not stimulate any acute stress to the subjects. Yet, in [38] healthy participants were used which involved of 20 males and 20 females in the age of 18 to 40 years old. In this study, the EEG signal has been acquired from them while their eyes opened and focused on the blank screen. The PSS questionnaire was a tool used to label them into non-stressed and various levels of stressed subjects. While the EEG signal in [39] and [35] were recorded from 28 subjects, age range 21 - 34 years old (10 females and 18 males) and 33 subjects respectively, in a closed eye for 3 minutes followed by filling of the PSS-10 questionnaire. However, for [35] the experimental procedure was later continued by an interview session with the psychologist. The same goes for [36], the EEG was recorded from 86 healthy participants containing of 47 males and 39 males aged 21 to 40 years old after they attempted PSS-10 stress questionnaires. Study by [37] use existing dataset from the Department of Neurology of Max Planck Institute which consists of EEG data and Perceived Stress Questionnaire (PSQ) of 202 healthy participants. The EEG was recorded for 16 cycles with 60 second each, of which 8 cycles with eyes closed and another 8 cycles with eyes opened. However, due to the small number of participants with severe perceived stress based on the PSQ results, only 50 subjects containing less stressed and more stressed were selected for further analysis. Meanwhile, the objective of the study for authors in [40] was to classify perceived stress but the experimental protocol consists of stressor to stimulate stress. They recruited 28 participants aged 18 to 40 years old with a history of non-medical illnesses and at least 12 years of education. All 13 males and 15 females subject in this study were asked to fill in the PSS-10 questionnaire to labelled them into several categories. Two EEG recordings were conducted afterwards that consist of pre-activity that required the subject to relax in sitting condition and eye open in 3 minutes and another one was post activity that recorded after the subject performed slide presentation in front of small group of audiences.

This section provides analysis on mental stress studies in two different objectives, on acute stress and chronic stress. **Table 1** and **Table 2** provide summaries of the EEG data specifications for the respective research works. According to the gender and demographic representation, most studies try gender-balanced sampling, although others focus solely on certain demographics (for example, young students), which may restrict generalizability. Distinct approach can be seen in both types of stress studies as stress was evoked in all acute stress studies by various stressors. The variety of stress-inducing procedures indicates versatility and adaptability. For example, CPS successfully elicits physiological stress reactions via pain stimuli, but TSST incorporates social evaluative factors to capture broader stress dimensions. These studies also frequently include biomarkers (e.g., cortisol levels) in addition to EEG, which improves the physiological validity of stress classifications [20]. While in the chronic stress studies the baseline or resting EEG was recorded. Still, there were also chronic stress studies comparing both EEG signal at rest and stimulated one as in [40]. Though, the study on the human acute stress seems preferable among researchers perhaps because the acute stress generated by the induced stressors are more likely to be detected and recorded using EEG. The EEG frequencies altered explicitly in response to the induced stressors. Further analysis of the EEG data able to expose the imperative findings [41]. Conversely, the study of chronic stress using EEG is seldom and is more challenging as specific techniques are required to extract and distinguish properties that correspond to the chronic stress of an individual in the EEG signals at rest. The introduction of stressors into mental stress studies should be avoided as it will induce fake stress that can interfere in the interested signal. As a result, these studies excel in ecological validity because they eschew artificial stressors and instead depend on baseline recordings that represent a subject's natural condition. Techniques such as the PSS-10 (Perceived Stress Scale) provide validated frameworks for assessing stress levels without producing acute reactions that may bias chronic stress-related EEG patterns. In the chronic stress experiments, the EEG signals of proven chronic stress subjects should be utilized. Most researchers prefer to use primary data as they can custom the sample characteristics as well as the experimental procedures though it requires more effort and sacrifice. Some use a small number of subjects, and those numbers varied. Nonetheless, an enormous number of subjects with correct criteria and selection can contribute substantially to the accuracy of the results. Ultimately, all the studies showed inconsistency in sample sizes. Acute stress research often employs small, homogenous groups, but chronic stress studies benefit from bigger datasets. Variability in sample procedures, such as age, gender, and demography, might make research less comparable. However, some studies fail to account for it or employ unbalanced samples, resulting in conflicting interpretations of stress reactions across genders. For example, [21] employed solely male participants, but [20] achieved gender balance, which might introduce biases. This mismatch influences the dependability of cross-study generalizations. Therefore in future, the study on this topic also need to have concern on gender as one of the dependent variables, since studies found several differences on the EEG waves and properties [42].

Table 2. EEG data in chronic stress studies.

Author, Year [Ref]	Stressor	No of Subjects	Subject's Age (years old)	Gender	Stress Label Mechanism	Data Source
S.M.U. Saeed *et al.*, 2020 [35]	No Stressor—Eyes closed	33	18 - 40	Both	PSS-10 & Interview	Primary
N. Hamid *et al.*, 2015 [36]	No Stressor	86	21 - 40	Both	PSS-10	Primary
H. Baumgartl *et al.*, 2020 [37]	No Stressor—Eyes closed (8 cycles) and opened (8 cycles)	50	Not stated	Not Stated	PSQ	Department of Neurology of Max Planck Institute Dataset
M. Majid *et al.*, 2022 [38]	No Stressors—Eyes opened and focused on the blank screen	40	18 - 40	Both	PSS	Primary
S.M.U. Saeed *et al.*, 2018 [39]	No Stressor—Eyes closed	28	21 - 34	Both	PSS-10	Primary
A. Arsalan *et al.*, 2019 [40]	Pre-activity—Eyes opened Post activity—Performed Slide Presentation	28	18 - 40	Both	PSS-10	Primary

3.2. EEG and Electrodes

Table 3. A summary of EEG and electrodes.

Author, Year [Ref]	EEG Model	No of Electrodes	EEG Positions
R. Fu *et al.*, 2022 [20]	LiveAmp 32	32	Fp1, Fz, F3, F7, FT9, FC5, FC1, C3, T7, TP9, CP5, CP1, Pz, P3, P7, O1, O2, P4, P8, TP10, CP6, CP2, Cz, C4, T8, FT10, FC6, FC2, F4, F8, Fp2, IO
O. AlShorman *et al.*, 2022 [21]	EGI's Geodesic EEG System	128	Undefined
N. Phutella *et al.*, 2022 [22]	Interaxon Muse	4	TP9, AF7, AF8, and TP10
A. Hemakom *et al.*, 2022 [23]	Asalab	8	Fp1, Fp2, F3, F4, P3, P4, T3, T4
V.G Rajendran *et al.* 2022 [25]	Enobio	8	FP1, FP2, P3, P4, O1, C4, T7, and T8
A.G. *et al.*, 2022 [46]	Undefined	2	Fp1, Fp2
L. Liu *et al.*, 2022 [27]	Undefined	Undefined	Undefined
P. Singh *et al.*, 2022 [28]	ANTNeuro	17	AF3, F3, F7, FC5, T7, P4, P7, Pz, P8, O1, O2, T8, FC6, F4, F8, AF4, and CPz
M.S. Karim *et al.*, 2021 [29]	Undefined	Undefined	Undefined
S. Issa *et al.*, 2022 [30]	Undefined	7	FP2, FP1, AF4, AF3, F4, F3, and F
R. Gupta *et al.*, 2022 [31]	SynAmps	32	Fp1, Fpz, AF3, AF4, F7, F3, Fz, F4, F8, FC5, Fc1, FC2, FC6, T7, C3, Cz, C4, T8, CP5, Cp1, CP2, CP6, P7, P3, Pz, P4, P8, PO3, PO4, O1, O2
T. Priya *et al.*, 2020 [32]	Undefined	19	Fp1, Fp2, F3, F4, F7, F8, Fz, C3, C4, Cz, P3, P4, Pz, T3, T4, T5, T6, O1, O2
B. Raufi *et al.*, 2022 [33]	Emotiv EPOC	14	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4
D. Virmani *et al.*, 2021 [34]	Undefined	14	AF3, AF4, F3, F4, F6, F7, FC5, FC6, T7, T8, P7, P8, O1, O2
S.M.U. Saeed *et al.*, 2020 [35]	EMOTIV Insight	5	AF3, AF4, T7, T8, Pz
N. Hamid *et al.*, 2015 [36]	G-Mobilab+	2	Fp1, Fp2
H. Baumgartl *et al.*, 2020 [37]	Undefined	62	Undefined
M. Majid *et al.*, 2022 [38]	MUSE	5	AF7, AF8, TP9, TP10, Fpz
S.M.U. Saeed *et al.*, 2018 [39]	Neurosky Mindset	1	FP1
A. Arsalan *et al.*, 2019 [40]	MUSE	5	AF7, AF8, TP9, TP10, Fpz

The number of electrodes applied in EEG test can be as many as 256 [43] or as few as a single channel [39]. It was found that the high-density EEG applications can reveal detailed brain information that correlated to the brain electrical activities generated by huge electro-cortical sources. However, signal-processing techniques such as Independent Component Analysis (ICA) are required in this scenario to differentiate electrocortical activity from artifact-contaminated EEG [43]. Nevertheless, a high number of electrodes may be inappropriate and impractical in certain neuro brain activities such if EEG being used as pre assessment tool in stress screening test. Furthermore, many electrodes are unlikely in this case due to the cost of high-density systems, longer time for the EEG preparation, susceptible to more noises and increase computational complexity [6] [44]. Consequently, the number of electrodes can be reduced according to the aims of the studies as well as due to the applications, but it is vital to identify the corresponding electrocortical sources involved to that study [43]. In contrast, the use of single electrode may decrease the correlation between the EEG features [45] and unable to create spatial maps of brain activity which leads to the missing of information details. Even though this low-cost device is easy to prepare and wireless [22] [36] [39] [46], the authors in [22] reported several of the data corrupted due to the loose connection between the electrodes and scalp using that device.

Table 3 summarizes the EEG's brands, the quantity of electrodes and the electrode positions used in several literatures. To the best of our knowledge, there is no robust model developed to accurately identify and classify stress. No agreement was made on the number of electrodes and the positions to scientifically represent stress response. However, the selection of the electrode position is crucial in any studies as the source of biological potential of each EEG signal recorded by each electrode is differ. The brain is a human central control system. Hence, various parts of the brain have divergent and specialized functional tasks. High-density EEG systems (such as EGI's Geodesic EEG System with 128 electrodes) can provide comprehensive spatial mapping of brain activity, catching subtle stress-related patterns. However, in general 32 and 64 channels are the most utilized in the standard EEG setting [47]. Whilst in the studies by [48], they found the significance of using 8 channels to classify mental stress level compared to 1, 5, 8, 9, 15, 19 and 32. Apparently, electrode counts (from 1 to 128) and placements vary, causes lack of unified protocol and making direct comparisons between research impossible. Thus, a uniform structure might improve repeatability. However, each work in this review was exceptional novel as they gained different findings for various performance accuracies.

3.3. Signal Pre-Processing

An EEG has been known susceptible to several noises and unwanted artifacts caused by environmental noise such power line interference, room lighting, electronic equipment, motion artifacts and due to physiological noise includes heart electrical signal, cardiac muscular activities, and eye movements [49]. A simple filtering technique able to remove all the noises but it tends to eliminate vital information from the signal. Nowadays, many techniques can be implemented to reduce or to remove noises and unwanted artifacts with the goal to increase Signal to Noise Ratio (SNR). It is also vital to consider several effective measures before, during and after the EEG recording for the similar goal [50].

Commonly, in many studies such [21] and [46] power line interference at 50/60 Hz was [50] rejected using a notch filter or also known as Band-stop filter. While, certain EEG has its built-in software to remove this noise such band reject filter of ENOBIO NIC1.4 software as in [25]. However, [35] was free from this noise as the EEG frequency response was set between 1 Hz to 43 Hz and its DC offset was removed by subtracting the average of the original signal.

In [20] [21] [33] and [37] studies, ICA was an effective method to separate individual EEG signal into independent components, to remove eye movement and muscle signal artifacts. Hence, the computation of z-scores for slope, gradient median, hurts exponent and spectral kurtosis were determined to identify bad components. The value that is out of range was considered artifacts. Finally, the Inverse ICA was used to convert the good components into time domain/original neural EEG signal in [33]. Instead, those noises were also removed in [20] study when the IO channel that encapsulates EEG signal representing eye movements was eliminated. V.G Rajendran *et al.* [25] applied EMG filter in ENOBIO NIC1.4 software to remove noises made by the eye movements. While [31] proposed Normalized Least Mean Square (NLMS) algorithm in their studies as adaptive filter to remove artifacts. Authors in [40] use on board driven right leg (DRL) feedback mechanism for noise cancellation as well as to enhance the EEG electrodes skin contact characteristic. As for MUSE EEG used in [22] and [38], its on-board noise cancellations can improve the EEG signals, thus Fast Fourier Transform (FFT) was employed to the original signal to obtain the frequency bands of interest.

Diverse thoughts and methodologies applied in each research design. Merely, various range of bandpass, high pass and other filters had been applied in those works to eliminate unwanted signals and to obtain specific range of frequency accordingly such as bandpass filter of 0.1 Hz - 30 Hz [21], 0.5 Hz - 30 Hz [46], 0.1 - 40 Hz [25], 0.5 Hz - 50 Hz [37], high pass filtering at 1 k Hz [23] and at 1 Hz [33].

Fu, R. *et al.* [20] used a zero-phase finite impulse response filter to obtain EEG signal between 0.5 to 40 Hz. Other steps such data segmentation can be seen applied in [32]. After both types of relaxed and stressed data became balanced, the data was segmented at certain points to make further analysis at ease. Raufi, B. *et al.* [33] applied new reference in their studies by averaging the electrical activity measured across all those 14 channels. However, to be considered as average reference, this technique shall engage with higher number of channels that cover wider area of the scalp to minimize bias towards any electrodes.

A variety of noise-reduction strategies such ICA, demonstrate the relevance of preprocessing in enhancing signal-to-noise ratio. Studies utilizing ICA show improved noise control and significant signal extraction.

3.4. Feature Extraction Technique of EEG Signal

The accuracy performance of any machine learning model can be improved with the application of feature selection methods by extracting the most useful and correct features to a model. Some EEG features might not or are less significant, some are redundant, and others might just be artifacts or there are also features that preferential but misleading due to unrelated biological and technical factors [51] [52]. Too large features may lead to the difficulty for the machine learning algorithm to differentiate signals. Regardless to that, the selection of EEG features must base on the type of brain studies and objectives of the research. Hence, optimizing the number of features did not only decrease computational cost but also increase the model performance accuracy [39] [45]. Certain features have better harmonization with the selected function used in that specific study to allow for preservation and enhancement of the frequency spectrum information [35]. The type of extracted features for any study is determined by the right choice of its mother wavelet function and order, which is highly reliant on the signal of interest [53] [54]. Differ techniques applied in those studies to extract features of interest as has been summarized in this section.

The most liked method chosen by the research is FFT due to its capability converting time domain signals to frequency domain, and the other way around [21] [22] [26]-[28] [32] [37]-[40]. AlShorman, O. *et al.* [21] is applying FFT to obtain and analyse the average power spectrum for 5 basic EEG bands from 16 electrodes taken from the frontal lobe of 14 healthy male participants meanwhile [22] analyse 20 Power Spectrum Density (PSD) of EEG basic bands from 4 fixed electrodes on the commercially EEG headbands. While [27], the features such hurst index, fluctuation index, sample entropy and permutation entropy were evaluated from 5 EEG bands extracted using FFT, where they found the fluctuation index had the best classification effect. However, distinctive features were further observed and analyzed in study such [28]. They were interested in the relative ratio of alpha and beta power beside the absolute power of the theta, alpha, and beta of the EEG, the Hjorth parameters and statistical features. Meanwhile, using the same method, several PSD were derived from the EEG signal inclusive of additional 56 features representing various power ratio in [32] where, the Fp1 channel recorded to have the best accuracy among the other 18 channels. The observation also shows that the PSD is higher during stress for delta, theta, and gamma bands. In [37] study, frequency bands which developed based on the fine-grained EEG spectrum have a higher information content. The sub-bands were extracted with a step width of 0.5 Hz. Four sub frequency bands in beta and delta ranges, 2.5 - 3 Hz (delta), 24.0 - 24.5 Hz (beta), 24.5 - 25.0 Hz (beta) and 26.0 - 26.5 Hz (beta) were found significantly higher related to the objective of study. Similarly, in [38], this method was utilized to extract features from 5 basic EEG bands such rational asymmetry, divisional asymmetry, correlation, and mean power. A specific selection algorithm was used to identify optimum EEG frequency bands that can produce the highest accuracy while the wrapper method was used to determine the features with good correlations. Saeed, S.M.U. *et al.* [39] applied correlation-based feature subset selection method with the intention to reduce feature vector length. Using this method, correlation was observed between features and between feature to class. Consequently, three vectors out of eight have been selected; comprised of low beta, high beta and low gamma that were considered as most significant neural oscillations in classifying human stress in this study. Although frequently employed for spectrum analysis, FFT's inability to capture temporal fluctuations restricts its effectiveness in dynamic stress detection.

Welch's method is another way to convert time into frequency domains based on the concepts of averaging the periodogram. However, in one of the steps, FFT is introduced as in [40]. All the frequency bands consisting of delta, theta, alpha, beta, and gamma for each electrode were extracted using this method analysed in terms of PSD, correlation, differential asymmetry, rational asymmetry, and power spectrum resulted to 40, 10, 10, 10 and 20 features, respectively. The same goes to [26], the PSD values of 3 selected EEG frequency bands consisting of theta, alpha and beta were extracted and studied where, they found the activity of beta frequency band shows significant changes in distinguishing between resting and stressful situations. In the case of [35], 45 features comprised of PSD for seven different sub frequency bands, relative gamma wave as well as alpha asymmetries, and alpha and beta asymmetries from 5 electrodes were extracted by using normal Welch method. Unlike the other papers, this study applied both for PSS and expert evaluation in subjectively classifying stress.

Next in [23], 7 EEG frequency bands between 0 Hz to 100 Hz for 8 electrodes signal were decompose using Discrete Wavelet Transform (DWT) as it excels in determining both time and frequency localization. Initially, 120 features that include of relative power and absolute power for the 7 frequency bands, plus with absolute and relative amplitude asymmetry in alpha bands between several selected electrodes were obtained. But later, the number of features were reduced using Filter, Wrapper and Hybrids methods to discover the most significance and yield the highest mean accuracy.

Such authors in [30] were interested in the emotional changes in different stimulated environments. They applied data selection strategies, to select the most significant electrode and choose to use either full-channel or middle-half channel data. Practically, the authors found that Fz electrode produces the best results in the feature extraction while the accuracy for middle-half channel data was significantly better than the full-channel data. A gray-scale image (GSI) that featured the Fz electrode signal has been calculated using continuous wavelet transform (CWT). Those images contain the EEG voltage variation during time and represent certain emotions.

In [31], a combination of Discrete cosine transformation (DCT) has been used to extract 22 most crucial features from the input signal. Next, 10 optimized features were selected using modified Binary Particle Swam Optimizer (MBPS) including the subject's stress level including of mean absolute deviation, skewness, spectral centroid, Wilson amplitude, zero crossing rate, spectral flux, mean and cross convolution.

The relative energies of 3 brain waves such as theta, alpha and beta as well as several EEG band ratios were evaluated in [25]. These features were analyzed using Wavelet Packet Transform method (Daubechies (db4) wavelet), which decomposed the EEG signals into 6 levels consisting of both low and high-frequency components. Relative energies, theta to alpha ratio and sum of alpha theta to beta ratio, were found higher, while lower for beta to alpha ratios, beta to sum of alpha theta ratio and beta to theta ratio during stressful conditions.

Meanwhile, [29] measured various crucial features consisting of absolute power, average band power, relative power, spectral entropy, and standard deviation from 5 common frequency bands using spectral estimation methods and achieved better outcomes compared to the several previous studies using the same dataset.

Raufi, B. *et al.* [33] focusing on the several EEG band ratios at certain brain regions. The electrodes in the frontal and parietal cortical regions were grouped into several clusters, consisting of three frontal clusters and one parietal cluster. Theta band was extracted from each frontal cluster while alpha band from the parietal cluster. Alpha-to-Theta and Theta-to-Alpha ratios were computed from the average PSD values of alpha band for electrodes in the parietal lobe and average PSD values of the theta band from electrodes in the frontal lobe. The other indexes were performed from the combination of different electrode clusters. The extraction of high-level features was carried out using Time Series feature Extraction Library (TSFEL) which offers numerous statistical properties from various domains.

In contrast to the others, [20] the generative network of in this model constructed by five deconvolutional layers works as feature extractor. Random noise was taken as input to the generator with the data format of the outputs was identical to the real EEG. Several features such band power, mean of PSD, variance of PSD, divisional asymmetry, rational asymmetry, correlation was employed from the data of each subject for every stress stage.

Unlike other works discussed earlier, an Intelligent Signal Processing Technique in the MATLAB Programming Toolbox was used to perform signal processing and analysis in [36]. Energy Spectrum Density (ESD) of all EEG bands was computed and analyzed offline. The correlation analysis results disclosed a significant relationship between the right alpha and beta of EEG, ESD value and the high stress subjects. Whereas several EEG band ratios from theta, Alpha dan Beta waves were calculated using MATLAB.

Optimizing feature selection improves classification accuracy while reducing computational complexity. In this paper, innovative techniques to feature extraction, such as the use of FFT and deconvolutional layers, demonstrate advances in dealing with EEG complexity. Later, creating adaptive feature extraction algorithms based on individual EEG variability and comparing classic methods (e.g., FFT, wavelet transform) to new approaches (e.g., generative adversarial networks) can improve related fields.

3.5. Classification of EEG Signal

Those studies discovered many types of classifiers to investigate level of mental stress such as Linear Discriminant Analysis (LDA), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Naïve Bayes (NV), Artificial Neural Network (ANN), Random Forest (RF), Linear Regressing (LR), Decision Tree (DT), Multi-layer perceptron (MLP), Convolutional Neural Network (CNN) and Neural Network (NN) based on the features extracted from the EEG signal [33] [55]. As shown in **Table 4**, various classifiers are being utilized in those studies and several similar ones are also chosen by those authors. Factors such having a huge and good data, relevant features, optimum hyperparameter set and proper signal processing resulting in higher accuracy.

Table 4. A summary of classifier types and performance.

Author, Year [Ref]	Type of Classifier	Classification Accuracy (%)	Stress Level Class
O. AlShorman *et al.*, 2022 [21]	SVM RBF Kernel, SVM Linear, SVM polynomial, SVM Sigmoid and NB	SVM and NB (Subject Wise) = 98 SVM Linear (Mix) = 90	Non-Stress and Stress
P. Singh *et al.*, 2022 [28]	SVM & KNN	SVM (Two-level) = 91.19 SVM (Three-level) = 76.71	Two-level (No stress & Stress) Three-level Stress (No stress, Low Stress, High Stress)
S.M.U. Saeed *et al.*, 2018 [39]	SVM	SVM = 78.57	Stress & Not Stress
S.M.U. Saeed *et al.*, 2020 [35]	SVM, NB, KNN, LR, and MLP	SVM = 85.20	Stress & Control
T.Y. Wen *et al.*, 2022 [26]	SVM	SVM = 98	Three-level Stress (Low Stress, Medium Stress, High Stress)
R. Gupta *et al.*, 2022 [31]	MPBSO + MWOA + SVM, MBPSO + WOA + SVM, PSO + MWOA + SVM, and MBPSO + SVM	SVM + MPBSO + MWOA = 96.36	Four-level Stress (No stress, Low Stress, Medium Stress, High Stress)
B. Raufi *et al.*, 2022 [33]	LR, SVM, DT	LR and SVM = 80++	Resting, SIMKAP
T. Priya *et al.*, 2020 [32]	Gaussian SVM, Polynomial SVM and KNN	KNN (M = 1) (Fp1) = 99.42 ± 0.36	Relax and Stress
A. Hemakom *et al.*, 2022 [23]	RF, KNN, SVM and RBF-SVM	KNN + Hybrid + 1 feature (absolute power of low gamma for T3) = 85	Non-Stress and Low Stress
	RF, KNN, SVM and RBF-SVM	KNN + Hybrid + 3 features (absolute power of theta for Fp1 & Fp2, normalized power of theta for Fp1) = 87.5	Non-Stress and High Stress

Continued

M.S. Karim *et al.*, 2021 [29]	RF, SVM, KNN and LDA	RF = 99	Three-level Stress (Low Stress, Mid Stress, High Stress)
S. Issa *et al.*, 2022 [30]	BLS, D CNN, CNN, KNN, SVM and LDA	BLS (Full Channel data) = 93.1 BLS (Middle Half Channel) = 94.4	Happy, Sad, Angry, Fear
A. Arsalan *et al.*, 2019 [40]	SVM, NB, MLP	MLP (leave-one-out) Two-classes = 92.85 Three-classes = 64.28	Two-classes (Non-Stressed, Stressed) and Three-classes Stress (Non-Stressed, Mild Stressed, Stressed)
M. Majid *et al.*, 2022 [38]	MLP, SVM, NB	MLP (Two-classes) = 95 (Three-classes) = 77.50	Two-classes (Non stress & stress) and Three-classes (Non stress, Mild stress, Stress)
D. Virmani *et al.*, 2021 [34]	KNN, DT	DT = 75	Non-stress and stress
R. Fu *et al.*, 2022 [20]	CNN + Adversarial Theory	Four classes = 86.89 Five classes = 80.30	Four Classes (Before-Stress, Medium-Stress, High-Stress, Stress Recovery) Five Classes (Before-Stress, Medium-Stress, High-Stress, Early Stress Recovery, Late-Stress Recovery)
N. Phutella *et al.*, 2022 [22]	MLP, 1—Layer LSTM, 2—Layer LSTM, and 3—Layer LSTM	2-Layer LSTM = 93.17	Non-Stress and Stress
L. Liu *et al.*, 2022 [27]	IELM, SVM, linear SVM, radial basis NN, RF and ELM	IELM = 87.28	Three-level Stress (Low Stress, Average Stress, High Stress)
H. Baumgartl *et al.*, 2020 [37]	RF	RF = 81.33	Less Stressed and More Stressed
N. Hamid *et al.*, 2015 [36]	None	None	Low Stress and High Stress
V.G Rajendran *et al.*, 2022 [25]	None	None	Before Examination and After Examination

Among all the classifiers, SVM is often selected as one of the algorithms by the researchers in their studies to classify mental stress. The reliability of SVM in detecting mental stress is undeniable as it has been proven in many previous studies. AlShorman, O. *et al.* [21] classify the EEG features into subject wise and mix containing of mental stress and control subjects using SVM RBF Kernel, SVM linear, SVM polynomial, SVM sigmoid and NB machine learning. Subject-wise classification accuracy using SVM and NB achieved up to 98% and subject mix using SVM linear classifier had the highest accuracy at 90%. However, the use of only one category of gender and a small number of subjects in this study might increase performance accuracy. Meanwhile in [28], the average classification accuracy was made on the two-level and three-level of stress using SVM and KNN. SVM outperforms KNN for the two-level and three-level stress classification at 91.19% and 76.71%, respectively. Obviously, the two-level classification yields better results in this study. While in [39], SVM has been used as the only classifier in their study.

As correlation-based feature subset selection method was applied, it did not only decrease computational cost as feature set is reduced but it also increases SVM accuracy up to 78.57% compared to their previous study in [56]. In 2020, the researchers in [39] made further improvements in various aspects that led to an increase in [35]. In this study, the data was fed into five different machine learning classifiers: SVM, NB, KNN, LR, and MLP. A better average accuracy was obtained by using SVM with accuracy of 85.20% compared to other classifiers. As for [46], features were grouped into 3 stress levels using k-means clustering before fed into SVM for the classification. 98% of SVM performance accuracy was obtained while using only beta band absolute power from the Fp2 electrode which is located at the right pre-frontal region. Henceforth, the combination of SVM with modified Binary Particle Swam Optimizer (MBPSO) to select significant features and modified Whale Optimization Algorithm (MWOA) to choose optimal kernel in the SVM classifier in [31] resulted on better accuracy, sensitivity, specificity, and F1 score with values of 96.36%, 96.84%, 90.8%, and 97.96% respectively compared to the other SVM combinations. Raufi, B. *et al.* [33] focusing on the several EEG band ratios at certain brain regions. However, the authors are interested in exploring the association between EEG bands and individual's mental workload rather than identifying mental stress. The electrodes in the frontal and parietal cortical regions were grouped into several clusters, consisting of three frontal clusters and one parietal cluster. The model was proposed using three different classifiers such LR, SVM and DT on the subjects while at rest and performing SIMPKAP task. In this study, LR and SVM can classify mental workload for accuracy by more than 80%.

However, in [32] the KNN classifying stress is better compared to SVM. All features in this study have been fed into 2 types of classifiers, SVM and KNN by Hold-out and 10-Fold cross validation techniques. The Gaussian and Polynomial were applied as kernel functions for the SVM in this study. Variety of SVM and KNN classifiers for different hyperparameters such Gaussian SVM with KS = 2.5, 9.9 and 90, Polynomial SVM with O-2 and O-3 and KNN with M = 1, M = 10, M = 100 being analyzed. As a result, the KNN (M = 1) using 10-fold cross validation techniques and KNN using Holdout technique had better performance and higher classification accuracy compared to other techniques and classifiers in this study with 96.96% +/− 0.10 and 96.10% +/− 0.55, respectively. While in [23], the authors analyzed the combination of various features with different classifiers which resulted in different accuracy and computational times. It consists of a cross match between 3 different feature selection methods and 4 classification algorithms consisting of KNN, RF, SVM and RBF-SVM which resulted in the development of 12 machine learning models. The 4 classification algorithms consisted of RF, KNN, SVM and RBF-SVM were used to classify features into non-stress and low stress, and between non-stress and high stress in four scenarios consisting of: without using feature selector, using Filter, Wrapper or Hybrid. This paper demonstrated the performance of each model in terms of the number of features involved, the classification accuracy calculated, and the computation times required. In the classification into non-stress and low stress periods, the KNN using Hybrid method and single feature provide highest classification accuracy of 85% with reasonable computational time of 2.28 seconds. While for the classification into non-stress and high stress periods, the KNN using Filter method, and 3 features provide highest classification accuracy of 87.5% with low computational time of 0.73 seconds.

Besides that, several studies also obtained good outcomes while utilizing different algorithms. Such in [29], the authors improvised the classification accuracy of stress detection method in their study. Their finding defeated previous studies made by the different authors using the same data set when certain classifiers and noteworthy features were matched. In this study, the RF classifier had the highest classification accuracy of 99% compared to other classifiers such SVM, KNN and LDA that reached average of 89% while classifying stress into three levels for 7 different environments using 10-fold cross validation approach. Henceforth, a few classifiers such Broad Learning System (BLS), Deep Convolutional Neural Network (D CNN), CNN, KNN, SVM and LDA had been used in [30]. BLS was found to be the best classifier when used on both types of databases DEAP and MAHNOB-HCL with accuracy of 93.1% in 0.7 s process time and 94.4% in 0.6 s for full-channel data and middle-half-channel data, respectively. EEG signals in [40] were recorded in two different scenarios, Pre-activity and post-activity for two-classes and three-classes. The selected data in this study were classified using SVM, NB and MLP. It was found that EEG signal recorded during pre-activity phase produced better outcome. The MLP classifier also obtained highest accuracy for two-classes and three-classes classification of 89.28% and 60.71% using 10-fold cross validation method and 92.85% and 64.28% using leave-one-out cross validation method, respectively while using theta signal surpass other classifiers, methods, and features.

Instead of EEG, the use of physiological modalities for mental stress detection can be found in numerous approaches. The use of multi-modal data enhances resilience, particularly in three-class stress categorization. It works in several cases, as the proposed model contains more detailed information that makes it more accurate and robust. In [38], three different physiological modalities include EEG, photoplethysmography (PPG) and galvanic skin response (GSR) were used to acquire data to classify perceived stress. All the features of EEG, GSR and PPG were classified using MLP, SVM and NB in various modalities combinations for two and three classes. It was found that the best performance was obtained when using MLP classifier with the combination of features from all modalities. Yet the results on the model performance showed that the two classes were more accurate than the three classes classification with accuracy of 95% and 77.50%, respectively as the classification of three classes was more challenging and required better technique. Whereas [34], acquired the brain and heart signals, using EEG and ECG respectively to detect stress. Thus, the EEG features were analyzed and classified using KNN and DT for which DT with the total accuracy of 75% was found slightly more accurate than KNN with 68% in this paper.

The usage of other types of classifiers can be seen in the following paragraphs. Mental stress classification into five-class and four-class classifications in [20] was performed using a deep neural network consisting of a combination of CNN and adversarial theory called symmetric deep convolutional adversarial network (SDCAN). The adversarial mechanism enhances subject generalization in the stress classification task by identifying invariant representation and discriminative features in the raw signal. The generator and discriminator of the model used were two symmetrical CNNs, the discriminative and generative networks that constructed into five layers of convolutional and deconvolutional layers. Random noise was taken as input to the generator with the data format of the outputs was identical to the real EEG. While the input to the discriminator was taken from the real EEG data of different stress stages and the generated input from the generator while the outputs was the probability distribution from the generated data or the real data. The proposed method has proven to increase classification accuracy compared to the other conventional CNN methods with an average accuracy of 86.89% and 80.30% for four-class and five-class stress classifications.

Long short-term memory (LSTM) is recurrent neural networks that work well with sequence data. The authors in [22] use different LSTM layers containing 8, 16 and 24 neurons and discovered LSTM with 16 neurons was the best model with accuracy of 93.17% in this study. All EEG bands from frontal and temporal brain regions were analyzed using small window size to capture the signal details. Initially, the small window size tends to increase processing speed thus allowing model to be trained faster.

The Extreme Learning Machine (ELM) model was known for its superiority over the training speed and better accuracy compared to the several models on classifying even number of samples. However, in case of uneven number of samples as in [27], authors had introduced label weighting and AdaBoost algorithms into the traditional ELM to improve model's performance known as Improved Extreme Learning Machine (IELM). Other than that, SVM, linear SVM, radial basis NN (RBFNN), RF and ELM also had been used to classify stress as comparison to IELM which achieved the highest accuracy of 87.28%.

Baumgartl, H. *et al.* [37], used RF as classifier and resulted in a balanced accuracy of 81.33% as reliable performance indicators for F_7 and AF_7 electrodes for those placed on the left pre-frontal cortex of the brain across other electrodes. The authors discovered that more stressed individuals have higher PSD in the left prefrontal cortex for mid delta band but lower power in beta band.

Unlike other works discussed earlier, no classifier was used in [36] and [25]. An Intelligent Signal Processing Technique in the MATLAB Programming Toolbox was used to perform signal processing and analysis in [36], while in [25] the stress prediction was made based on the statistical analysis on various EEG parameters.

Comparing classifiers might yield contradictory results. While SVM frequently outperforms others, some research indicates better performance with KNN [32] or RF [29], indicating a reliance on feature selection approaches and data quality. Two-class stress models (e.g., non-stress vs. stress) often obtain better accuracy (e.g., [26] reported 98%), whereas research adding multi-class models (e.g., mild, moderate, severe stress) encounter accuracy declines (e.g., [20], 80.30% for five classes). This reflects the difficulties of distinguishing overlapping stress levels. The implementation of multi-modal approaches show promise, but the findings remain inconsistent. Majid, M. *et al.* [38] found better accuracy using multi-modal features, although this was not generally supported by other investigations [34].

4. Discussion

The EEG signal provides information on the functioning of the brain. This information is used by the medical and health professionals to diagnose and detect neurological diseases and disorders. Apart from that, history recorded the crucialness of EEG in mental health study since the early 20's century. As the EEG exhibits complex behaviors with non-stationary and nonlinear dynamic properties signals, there are several methods involved to process the signal.

In this paper, we reviewed research works that associated with mental stress analysis based on the EEG signals. However, it is important to highlight that direct comparison may not be proper as the state of art of each of the works differs. Several discussions were made on the number and location of electrodes, the size of subject population, the signal preprocessing and processing methods and the features of interests. Machine learning was used in most of the works; hence similarity can be found in the methodology's framework.

In fact, those works can be diverted into two major categories: acute and chronic stresses. The study on acute stress is more common as physiological changes on the subjects can be observed in the present of stress inducers. But the utilization of stress inducers may also cause unnecessary discomfort that raises ethical concerns. These strategies may unintentionally generate diversity in stress reactions owing to individual coping processes. Acute stress can cause temporary physiological changes, making it challenging to apply findings to chronic stress situations. Meanwhile, stress is detected on the subjects without the presence of any stressors, reflecting chronic stress. Obviously, the acute stress studies using inducers tend to be more consistent as compared to chronic stress studies which seen suffer with baseline variability that overlapped with other mental states such fatigue or mild anxiety. Resting-state EEG is useful in chronic stress research, although its dependence on self-reported measurements (e.g., PSS-10) are relies on individual perception, without robust physiological markers that restrict physiological inference, introducing subjectivity and potential bias. This makes chronic stress categorization more difficult than acute stress detection. With respect to today's mental health issue [1], developing a system capable of identifying chronic stress accurately is a privilege to humankind. Episodic acute stress is less studied as it is always considered as a variant of either acute or chronic stress, contains blends elements of both major categories of stress.

Among the paperwork discussed were used a variety of sample sizes, in the range of 4 to 90 subjects consisting of healthy young and middle-aged adults between the ages of 17 to 55 years old. The effect of small sample size may cause the machine learning model to experience overfitting of data thus unable to conclude accurately. Therefore, an optimum and appropriate number of subjects as well as the decent quality of the data obtained in the machine learning research based may increase the prediction's accuracy [57]. But [28] obtained quite high classification accuracy for 2-level stress classification though they were using only 4 subjects. The utilization of fivefold cross validation to calculate accuracy is also disputable. However, it was noted that each subject in this study attempted several tests using SCWT and arithmetic and in addition, many features were analyzed.

In terms of the number of electrodes used, it is also disparate. Ranging from a single electrode up to 128 electrodes can be seen in those paper works. The selection of electrode was based on the findings from the other paperwork, the medical science perspective such from the Brodmann's area, and based on the objective of the studies as well as due to the fixed electrodes of the EEG head band. Most of them had chosen similar electrodes which were in the prefrontal and frontal area, the brain region that housing task in managing emotions and cognitive functions such Fp1, Fp2, AF3, AF4, F3, F4, F7, F8 and Fz. There is also a certain part in the temporal lobe that acts in the same way. While other electrodes located in the parietal, central and occipital also had been chosen by the researchers accordingly with respect to the objectives of the studies. Nevertheless, the use of a single electrode usually does not provide three-dimensional maps of brain activity which can reflects the association between EEG brainwaves and stress, or vast number of electrodes not necessarily required as it may also offers several drawbacks. The selection of the electrode position is crucial in any studies as the source of biological potential of each EEG signal recorded by each electrode differs. The brain is a human central control system. Hence, distinct parts of the brain have divergent and specialized functional tasks. In general, 32 and 64 channels are the most utilized in the standard EEG setting [47]. Whilst in the studies by Hag, A. *et al.* [48], they found the significance of using 8 channels to classify mental stress level compared to 1, 5, 8, 9, 15, 19 and 32. Those studies showed inconsistencies in the electrode configurations as the electrode counts and placements vary, making direct comparisons between research is impossible. Precisely, high-density layouts enhance spatial resolution while low-channel setups may overlook important stress-related activity. As for the electrode placement, some are concentrating on frontal areas and others taking a more comprehensive cortical approach. Perhaps, having a uniform structure of electrode configurations might improve repeatability.

Instead of that, numerous methods were used to extract features of interest from the raw EEG signal. The EEG signal contains detailed information and behaviors which are only visible in the frequency domain representation. Thus, we found that FFT is the most utilized method used to decompose EEG signals in most of the paper works, high due to its speed and memory efficiency as well as its competency in capturing insight time and frequency characteristics. Meanwhile, multiplicity of features extracted from the EEG signals and analyzed to determine the related stress. Yet, among them PSD and power ratios are the most common choices in those papers. The features from Theta and Beta bands were found significantly correlated with stress in several studies such in [23] [25] [26] [32] [38] [40] and [26] [36]-[39] respectively especially for the electrodes located in the prefrontal and frontal brain regions. Meanwhile, the association of stress for Alpha, Delta and Gamma were also discovered in a few studies. A wiser approach using Exploratory Data Analysis (EDA) shall be implemented to analyze and summarize data to get insights and better understanding on the data signal while using machine learning method.

Next, it was found that SVM is the most nominated classifier and surpasses other types, with a usage of 70%. It is a supervised learning algorithm, usually used to perform classification and regression activities. In those reviewed paper works, it was used to classify mental stress. The capability of SVM to handle both linear and non-linear data such EEG signals, classifying high dimensional data but also can effectively process any project with limited samples might be the factors as option by the researchers. SVM's persistent high accuracy (sometimes greater than 90%) in identifying stress levels has been validated in several investigations [35] [26]. It is the most effective classifier for stress detection, especially in two-class models. However, to bear in mind, not all SVM ended up as the classifier with the highest classification accuracy. Furthermore, a neural network is also a good option as shown in [20], works as end-to-end system without depending on the feature extraction to recognize multilevel mental stress efficiently. Novel techniques, such as CNN with adversarial processes [20] and LSTM [22], take use of deep learning's ability to represent complex EEG data, resulting in promising feature extraction and multi classification accuracies of up to 93.17%.

5. Conclusions

This publication composes a summary of plethora of methods and protocol of EEG data collection, including the selection of electrodes and brain regions, feature vectors and various application of classifiers. The differences between acute stress and chronic stress studies were also highlighted methodologically. There was a distinct difference in terms of number subjects, number of electrodes used, brain regions and the protocol while acquiring EEG data. It is also synthesis emphasizes EEG's benefits in acute stress detection while showing significant gaps in chronic stress techniques and multi-class classifications. Addressing these discrepancies is critical for furthering stress research and application. Nevertheless, in all the mentioned studies showed that there was no robust objective assessment as biomarker for recognizing and classifying stress.

Hence, several potential research trends and avenues are highlighted to be further investigated in EEG-based stress studies. First, is a trend toward developing standardization of protocols for acquiring, preprocessing, and extracting EEG data in stress research including electrode location and sample size as the standardization is crucial for consistent and reproducible results across investigations. Stress-induction methods (e.g., TSST, CPS) and stress-level categorization criteria should be standardized for acute stress with ethical considerations for a balance between reliable stress induction methods and participant comfort and well-being. Less intrusive stress-induction methods that nonetheless elicit valid EEG responses can be developed. One way to achieve that is by using participant comments to improve experimental design. While, to capture variability in chronic stress, the establishment of reliable resting-state techniques are essential. This includes multi-session recordings or longitudinal research to monitor EEG alterations in people with long-term stress. The trustworthy EEG biomarkers for long-term stress need to be find while resolving the issue of signals that overlap with those of moderate anxiety or exhaustion. The relationships that exist between EEG measures of chronic stress and other health indicators, such as immunological responses and cortisol levels also interesting to be examined. Meanwhile, linking acute stress EEG responses to chronic stress indicators improves knowledge of long-term stress physiology.

Research to determine the effect of different electrode configurations (e.g., 32 vs. 128 channels) on categorization accuracy is also vital for both types of stress studies. A part of that, since several studies found that uneven sample procedures hinder generalizability of their findings, a worldwide standard for gender-balanced and diversified demographic characteristics must be created. Any research that can investigate the effect of varying demographic characteristics and certain hormones on the stress-response disparities and EEG patterns should be conducted.

Integrating multi-modal physiological data, including EEG, ECG, GSR, and PPG, allows for a more thorough stress evaluation. Several studies found that multi-modal techniques increase stress classification accuracy, especially for complicated scenarios with many stress levels. Thus, investigation can be conducted to observe on how EEG and wearable sensors can work together to assess stress in real-time during ambulation and to discover the impact of each modality on stress classification accuracy to enhance feature selection. Real-time and ambulatory stress monitoring with portable EEG equipment is a growing trend, moving away from laboratory-based investigations. Many low-density systems with fewer electrodes with easier settings are available in the market. They are suitable for ambulatory monitoring, but improvement must be made to the signal quality and artifacts reduction. Thus, future research should demonstrate the efficacy of single-channel and low-density systems in larger, more diversified sample sizes. Investigate the integration of EEG with mobile health apps to measure stress levels continuously or integrate with VR or AR to evaluate stress in an immersive environment.

The applications of machine learning and deep learning using sophisticated algorithms such as CNNs, LSTMs, and hybrid architectures were able to improve classification accuracy and generalizability in this kind of field. Thus, future research that can develop AI models to better understand how various EEG variables contribute to stress detection will be awesome. Integrating EEG research with psychology, neuroscience, and AI can produce effective stress detection systems and usable stress management technologies (e.g., wearables, apps) can help both research and public health. Future studies that address these patterns and paths might not only improve EEG stress research but also widen its usefulness in clinical and daily settings.

Ultimately, as future directions, there are ideas that research can thoroughly explore such as running cross-dataset benchmarking that involves comparing findings across datasets using consistent preprocessing and feature extraction methods to assure dependability. Next, enhancing multi-modal approaches as combining EEG with additional physiological parameters (e.g., ECG, GSR) may improve stress categorization and overcome EEG constraints. Then, improve deep learning applications by prioritizing CNNs, LSTMs, and adversarial networks for accurate feature extraction and categorization. Other than that, is to examine gender and age variations in EEG responses to stress to improve EEG-based stress detection, it's important to include gender and demographics. Lastly, implementing longitudinal studies as the use of longitudinal data can validate and follow the effects of chronic stress over time as well as able to address variability in chronic stress markers. Based on Food and Drug Administration (FDA) definition, an ideal biomarker shall be designed for a particular disease or mental health problem and capable of discerning dissimilar physiological states. Apart from that, it needs to be safe, easy, and faster to use, the results must be accurate and consistent while used for different genders and various ethnic groups.

Acknowledgements

Authors would like to thank Universiti Kuala Lumpur-British Malaysian Institute for financially supporting this work through the Short-Term Research Grant (STRG) (STR20006).

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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