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TOPICAL REVIEW

Application of Artificial Intelligence Techniques for Brain–Computer Interface in Mental Fatigue Detection: A Systematic Review (2011–2022)

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ABSTRACT Mental fatigue is a psychophysical condition with a significant adverse effect on daily life, compromising both physical and mental wellness. We are experiencing challenges in this fast-changing environment, and mental fatigue problems are becoming more prominent. This demands an urgent need to explore an effective and accurate automated system for timely mental fatigue detection. Therefore, we present a systematic review of brain-computer interface (BCI) studies for mental fatigue detection using artificial intelligent (AI) techniques published in Scopus, IEEE Explore, PubMed and Web of Science (WOS) between 2011 and 2022. The Boolean search expression that comprised (((ELECTROENCEPHALOGRAM) AND (BCI)) AND (FATIGUE CLASSIFICATION)) AND (BRAIN-COMPUTER INTERFACE) has been used to select the articles. Through the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) methodology, we selected 39 out of 562 articles. Our review identified the research gap in employing BCI for mental fatigue intervention through automated neurofeedback. The AI techniques employed to develop EEG-based mental fatigue detection are also discussed. We have presented comprehensive challenges and future recommendations from the gaps identified in discussions. The future direction includes data fusion, hybrid classification models, availability of public datasets, uncertainty, explainability, and hardware implementation strategies.

INDEX TERMS Brain-computer interface (BCI), electroencephalogram (EEG), mental fatigue detection, PRISMA.

I. INTRODUCTION

Mental fatigue sometimes referred to as cognitive fatigue or brain fatigue, is characterized by a sense of tiredness or exhaustion that impairs a person's capacity to focus and think effectively. Many people have it, and it can be caused by a variety of reasons such as stress, insomnia, workload, and continuous mental activity [1]. The detrimental effects of mental fatigue have been frequently reported as a major risk factor in the occurrence of automobile accidents [2]. It is alarming to note that fatigue is responsible for 20 to 30 percent of all motor vehicle collisions [3], where 5 to 15 percent of these accidents end in fatality.

In the workplace, mental fatigue increases the risk of errors. It was observed that mental fatigue caused a decline in typing performance although employees were permitted breaks at work [4]. Therefore, several studies have been conducted to investigate the use of keystroke dynamics features in the recognition of mental fatigue [5], [6].

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Mental fatigue among healthcare professionals is a major concern. The ability of healthcare providers to do their jobs has a significant impact on other people's lives. A national study conducted in Portugal in 2021 reported 66 percent of physicians had high levels of emotional exhaustion, 33 percent had high levels of feeling self-disconnected or detached, and 39 percent had high levels of reduction in self-accomplishment due to excessive and prolonged stress when performing duties at the workplace [7].

Recently, the correlation between mental fatigue on physical endurance was studied. In addition to the psychobiological state that is brought on by long durations of mentally taxing activities and is characterized by feelings of fatigue and an inability to muster up sufficient amounts of energy [1], [8] mental fatigue affects athletic performance in longer-duration sports where continual management of effort is required. It was reported that mental fatigue has a negative impact on an individual's ability to run [9], cycle [10] and swim [11]. Similarly, it was demonstrated that mental fatigue leads to a decline in a soccer player's physical and technical performance [12], as well as an impairment in both their precision and speed of decision-making [13].

From the clinical perspective, mental fatigue can cause psychomotor deficits, which subsequently lead to other health problems, in particular neurodegeneration [14], [15]. In the early stages of Parkinson's disease, patients were reported to exhibit higher levels of physical and mental fatigue compared to healthy persons [16]. Moreover, fatigue is one of the most disabling symptoms for patients with Parkinson's disease [17], [18]. Thus, making it difficult for these patients to participate in daily life activities.

In a nutshell, mental fatigue can lead to a reduction in productivity and worsening quality of life. If left untreated, it may eventually cause serious complications. The symptoms of mental fatigue might not be apparent during the early stages, thus making it difficult to detect until it is too late. Many instruments have been devised to identify mental fatigue, such as the NASA Task Load Index [19], Karolinska Sleepiness Scale [20], Epworth Sleepiness Scale [21], Checklist Individual Strength (CIS) [22] and Chalder Fatigue Scale (CFS) [23]. However, these techniques are based on subjective judgments and are prone to errors and biases. Furthermore, mental fatigue is a cumulative process that develops over a period of time [24], thus delaying its detection and increasing the risks brought about by mental fatigue.

Research on brain-computer interface (BCI) began in the 1970s [25]. BCI aims to explore the potential of using brain signals as the source of instructions to perform tasks through computer systems. BCI is a hardware and software framework that allows machines and other communication devices to be controlled based on brain signals. Different forms of brain activation signals have been analyzed to perform mental fatigue detection, including electroencephalogram (EEG) [26]. Based on the type of brain activation, a BCI system using EEG can be categorized as either active BCI, passive BCI, or reactive BCI [27].

In recent years, there has been a growing interest in applying artificial intelligence techniques to brain-computer interfaces for the detection of mental fatigue, with studies extending to sleep analysis and drivers' behaviors. Specifically, for sleep-related investigations, researchers have proposed a multi-modal approach based on the Squeeze-and-Excitation Network with Domain Adversarial Learning (SEN-DAL) to effectively capture features from electroencephalogram (EEG) and electrooculogram (EOG) signals for sleep staging [28]. Additionally, a novel Sleep Heterogeneous Graph Neural Network (SleepHGNN) has been introduced, leveraging the interactivity and heterogeneity of physiological signals [29]. In a separate study, a novel Bayesian spatial-temporal relation inference neural network, known as the Bayesian spatial-temporal transformer (BSTT), has been proposed for adaptive inference of brain spatial-temporal relations during sleep, enabling the extraction of spatial-temporal features [30]. Moreover, mental fatigue analysis extends beyond sleep and also encompasses the analysis of drivers' behaviors [31]. These advancements hold promise for further advancements in mental fatigue detection and understanding human factors related to sleep and driving.

This paper presents a systematic review of studies published between 2011 and 2022 on mental fatigue detection using BCI. In the following section, the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) method used in this review is described. The various machine learning and deep learning models employed for automated fatigue detection are discussed. Also, the challenges faced and future directions are presented.

II. METHODOLOGY

The PRISMA guideline 2020 [32] was used to analyze the most relevant studies on mental fatigue detection using BCI. The search consisted of several sequential processes which include identification, screening and inclusion, as depicted in the PRISMA flowchart in Fig. 1.

In the identification stage, all publications up to 13th September 2022 were compiled from searches made in Scopus, IEEE Explore, PubMed and Web of Science (WOS) databases. The retrieval was performed using the following Boolean search expression for all articles and journal papers:

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(((ELECTROENCEPHALOGRAM) AND (BCI))
AND (FATIGUE CLASSIFICATION)) AND
(BRAIN-COMPUTER INTERFACE)
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Related articles written in English from 2011 to 2022 were downloaded, not limited to the country or region of the author. A total of 562 publications were extracted, 310 were obtained from Scopus, 168 were retrieved from IEEE Explore, 38 were retrieved from PubMed and 46 were retrieved from Web of Science (WOS). The number was reduced to 429 after removing 133 publications with duplicated titles.

In the screening stage, 1 review paper was further excluded and another 14 were not accessible. Upon further screening

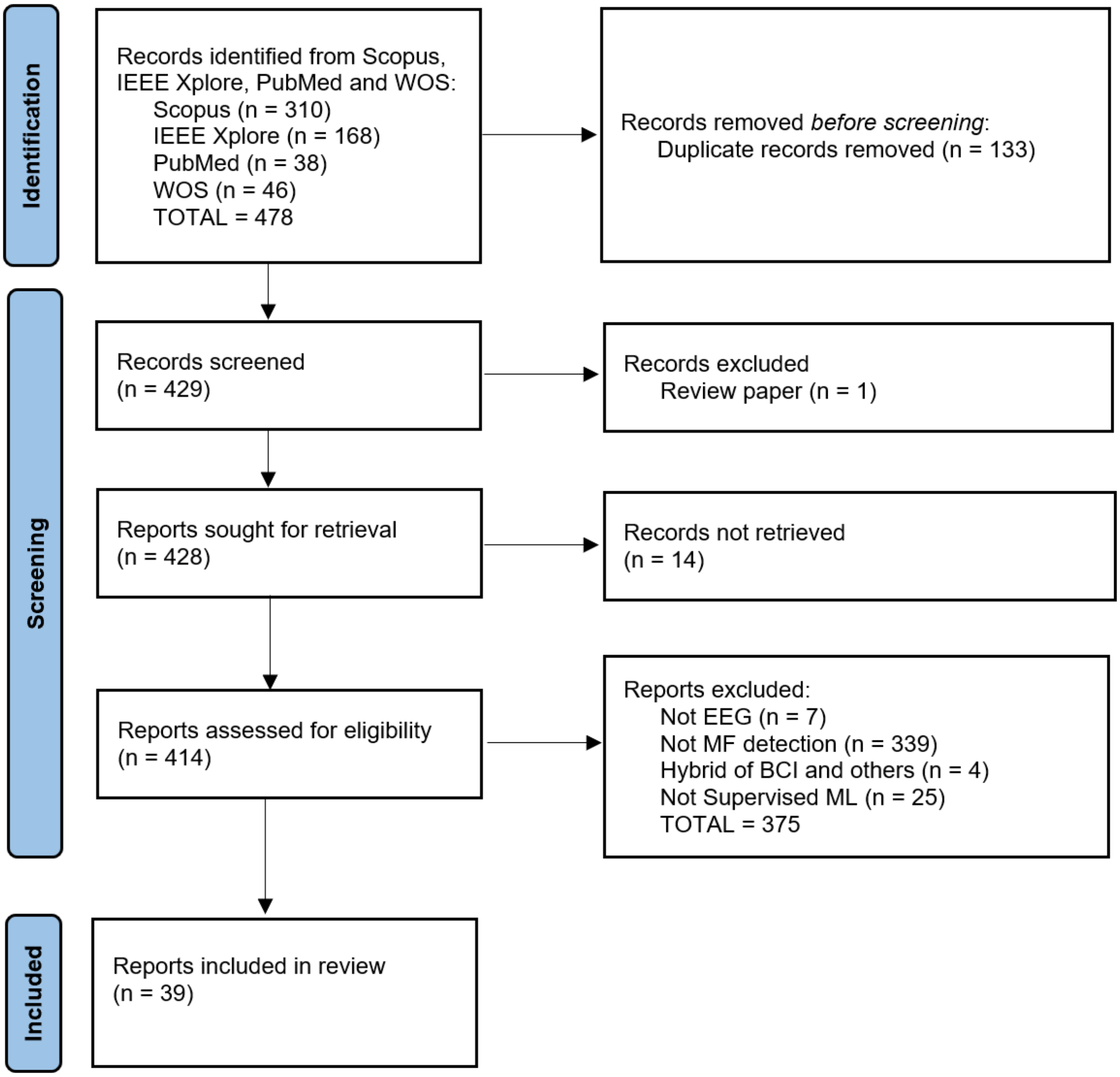

FIGURE 1. PRISMA 2020 flow diagram used for BCI studies on automated mental fatigue detection.

of the articles, 375 were excluded from the list due to the different study scopes. This included 7 articles that did not address the implementation of BCI using EEG, 339 articles that did not cover mental fatigue, 4 articles that presented the integration of BCI with other modalities, and 25 articles that did not include the implementation of supervised machine learning (ML) for mental fatigue detection. As a result, only 39 publications were selected for this review.

III. MENTAL FATIGUE DETECTION USING BRAIN COMPUTER INTERFACE

EEG refers to the recording of electrical waves emitted at the scalp due to neuronal activations in the brain. EEG is non-invasive, where electrodes are placed on the scalp at specific locations to record brain activities. Moreover, EEG is more portable, relatively cheaper and easy to use compared to other neuroimaging machines such as functional magnetic resonance imaging (fMRI) [33], positron emission tomography (PET) [34], single-photon emission computerized tomography (SPECT) [35], [36] and near-infrared spectroscopy (NIRS) [37], [38]. In addition, EEG produces signals with excellent temporal resolution. In other words, recorded EEG signals contain details of brain activities up to the order of milliseconds time instances. Therefore, EEG has been widely used to study the cognitive and affective states of mind. This includes mental fatigue detection.

Using the supervised ML approach, many models have been proposed to detect mental fatigue from EEG signals. It involves four fundamental steps which are signal acquisition, pre-processing, feature extraction, and classification [39], as depicted in Fig. 2. The ML and DL approaches used for automated mental fatigue detection is shown in

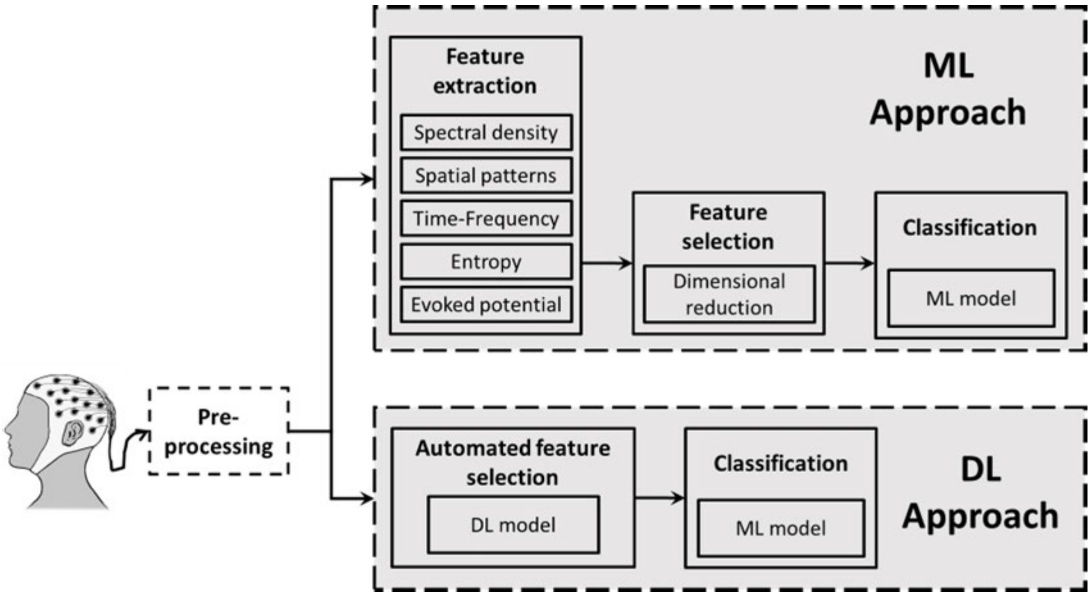

FIGURE 2. Illustration of ML and DL approaches used for automated mental fatigue detection.

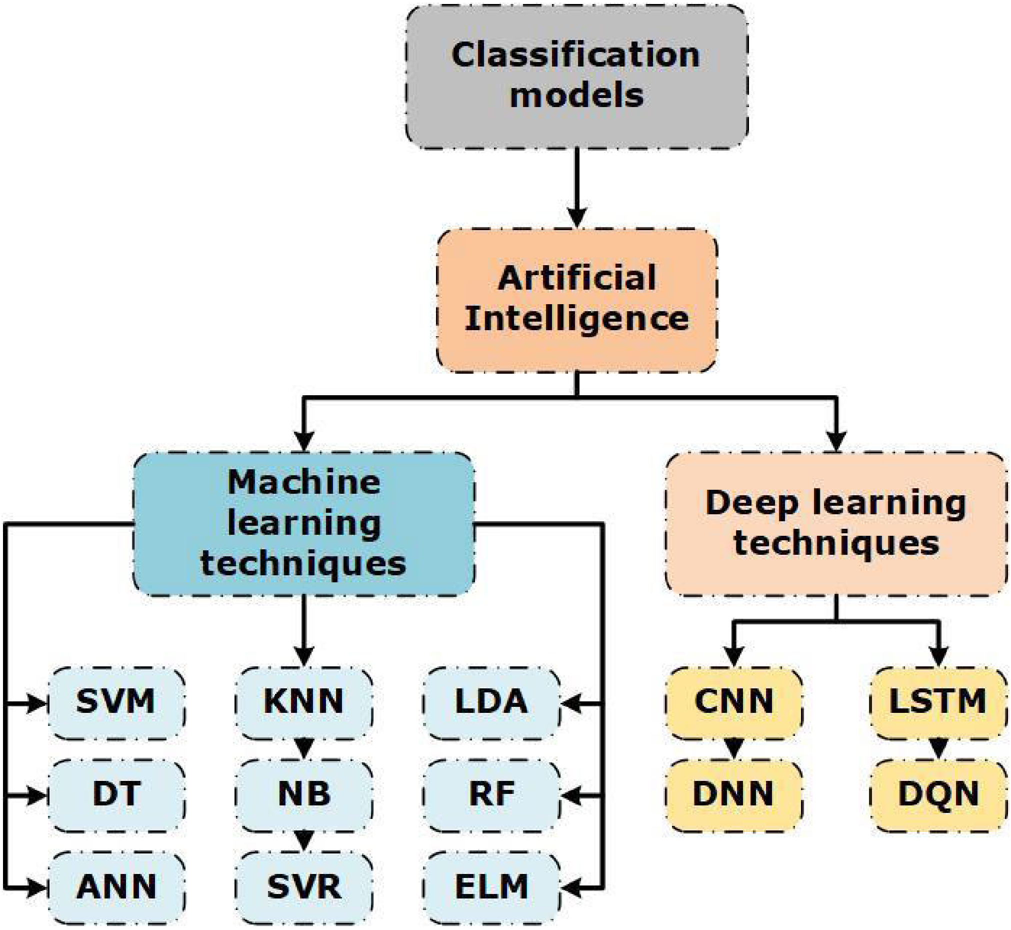

FIGURE 3. Classification models comprised of artificial intelligence.

Fig. 2 and 3. The EEG signal acquisition is governed by the (i) electrode placements and (ii) frequency bands. In the preprocessing phase, artifacts are detected and removed from the data. The feature extraction step helps transform

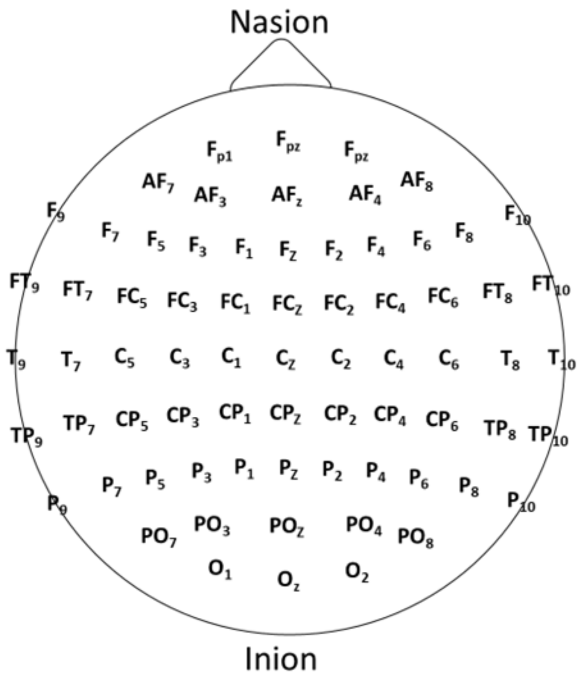

FIGURE 4. 10 -20 EEG electrodes positioning system.

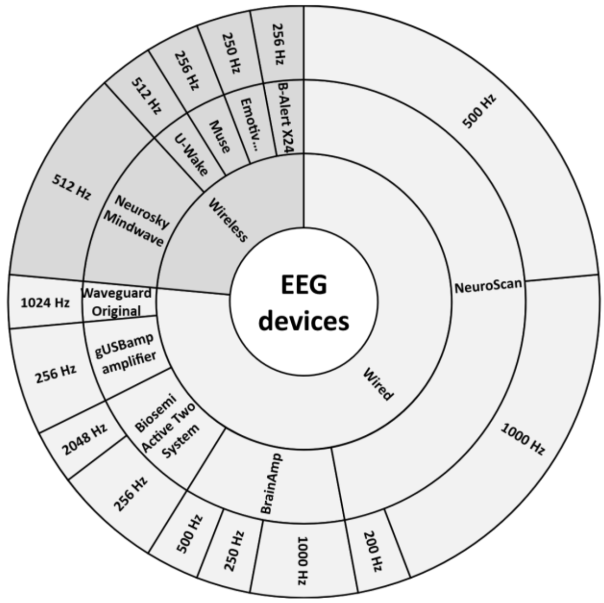

FIGURE 5. Sunburst plot of EEG devices. The first, second and third levels indicate transmission, neuro headset, and sampling rates, respectively.

the data into a format that allows classification algorithms to describe the phenomenon. Finally, the classification algorithm differentiates the normal and fatigue states by classifying the input features.

A. EEG SIGNAL ACQUISITION

EEG signal acquisition involves the recording of electrical signals emitted from electrodes placed on the scalp following the 10-20 international standard EEG electrode placements [40], as depicted in Fig. 4. With the advancement of technology, various EEG models of different designs and functionalities are now available. Fig. 5 shows the different EEG devices used in mental fatigue detection studies. Device details such as the manufacturers, types and number of electrodes are further elaborated below.

1) B-ALERT X24

B-Alert X24 is a medical-grade EEG system with a 20-channel headset. It has an optional channel for electrocardiogram (ECG), electrooculogram (EOG), or electromyogram (EMG). B-Alert X24 is produced by Advanced Brain Monitoring, Carlsbad, CA, USA and is connected to the computer using Bluetooth [41], [42].

2) BIOSEMI ACTIVE TWO SYSTEM

The Biosemi Active Two system is a wired EEG system manufactured by Biosemi, the Netherlands. It includes 64 active electrodes mounted on a cap. For signal recording, electrolyte gel is filled into each of the pre-amplified Ag/AgCl electrodes [43].

3) BRAINAMP

BrainAmp is a series of products produced by Brain Products GmbH, German. It is a signal amplifier that can measure up to 30 EEG channels (Fp1, Fp2, F3, F4, Fz, FC1, FC2, FC5, FC6, T7, T8, C3, C4, Cz, CP1, CP2, CP5, CP6, TP9, TP10, P3, P4, P7, P8, Pz, PO9, PO10, O1, O2, and Oz). It is also equipped with 4 EOG channels [44].

4) EPOC+

EPOC+ is a wireless neuroheadset produced by Emotiv. It consists of 14-channel wet Ag/AgCl electrodes including AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4. In a study by Bin and Pan [45], the sampling rate was set to 250 Hz.

5) GUSBAMP AMPLIFIER

The gUSBamp amplifier is manufactured by Guger Technologies. A gUSBamp amplifier set supports up to 16 EEG channels using any compatible electrodes and headset. It can easily connect to a computer through a USB socket [46], [47].

6) LIVEAMP

LiveAmp is another series of products produced by Brain Products GmbH, German. It is a small, wireless EEG amplifier for mobile EEG applications. In a study by Massé et al. [48] on mental fatigue detection, LiveAmp was connected to an R-Net helmet with 32 passive electrodes. However, only 4 channels of Fz, Cz, Pz and Oz were analyzed in the study.

7) MUSE

MUSE is a consumer EEG system produced by InteraXon, Canada. It only contains 4 channels, i.e. AF7, AF8, TP9 and

TP10. It supports wireless connectivity through Bluetooth with a proprietary mobile app [41], [49].

8) NEUROSCAN

NeuroScan produces several total solutions consisting of hardware and software for EEG analysis. The components and platforms are not limited to a single field of study, allowing for frequent and reliable transitions between recordings in one field to another utilizing the same hardware setup. Tian et al. [50] used a SymAmp2 NeuroScan device to record 32 channels of EEG data, including two vertical-EOG and horizontal-l EOG, at a sample rate of 1000Hz. Gao et al. [51] and Li et al. [52] employed the NeuroScan system, which included 40 electrodes with a sampling frequency of 1000 Hz and was organized following the standard international 10/20 method. To record EEG data, Liu et al. [53] and Khare et al. [54] used a NeuroScan NuAmps Express system placed with 30 sintered Ag/AgCl EEG active electrode sites and a unipolar reference. The sampling rate was 500 Hz.

9) NEUROSKY

NeuroSky devices are well-known for their affordable cost, ease of use, and quick data processing. However, they have limited sensitivity and performance quality due to the use of only one electrode [55]. NeuroSky Mindwave employs a single-channel electrode that takes data from the Fp1 electrode using a 10/20 method. A1 electrode is utilized as a reference electrode and is clipped to the left ear. The device has a sampling rate of 512 Hz [56].

10) UWAKE

U-Wake is a mobile and wireless EEG device featuring one frontal EEG channel and one clip that includes a Ground channel (GND) and a Reference channel (REF). Bluetooth is used for transmission. EEG signals can be recorded at a 512 Hz sampling rate [57].

11) WAVEGUARD ORIGINAL

The Waveguard Original EEG cap is one of the products offered by ANT Neuro. It is designed to work in conjunction with ANT Neuro's EEG amplifiers and recording systems, ensuring compatibility and optimal performance. It is equipped with up to 256 Ag-AgCl surface electrodes that placed according to the international 10–20 system. In the study by Li et al. [58], 64 wired electrodes are used to capture EEG signals at the sampling rate of 1024 Hz.

B. EEG DATASETS

Many of the EEG datasets used were non-public data collected in situ for the studies. The publicly available datasets used for mental fatigue detection studies are summarized in Table 1.

1) EEG MOTOR MOVEMENT/IMAGERY DATASET

The dataset consists of EEG recordings from 109 subjects. The subjects performed various motor imagery tasks while 64-channel EEG was recorded using the BCI2000 system. The motor imagery tasks include opening and closing the left fist or right fist or both fists or feet, followed by visualizing the physical movements made [59], [60].

2) SEED-VIG

The SEED-VIG dataset was created to investigate driver's vigilance using EEG and forehead EOG. It contains EEG recordings of 12 channels (CP1, CPZ, CP2, P1, PZ, P2, PO3, POZ, PO4, O1, OZ, O2, FT7, FT8, T7, T8, TP7 and TP8) from 23 subjects. The SEED-VIG dataset was collected while subjects were in a simulated driving system, which has a massive screen showing a four-way highway scene positioned in front of a real vehicle. To induce fatigue in the participants, the road was straight and monotonous, and the experiments were conducted in the early afternoon after lunch. The duration of the experiment was approximately two hours [61].

3) SUSTAINED-ATTENTION DRIVING DATASET (SADD)

The dataset consists of 62 sessions of 32-channel EEG data from 27 subjects, who were instructed to maintain their vehicle in the center of the lane while driving on a simulated four-lane highway for 1.5 hours. Random lane-departure events were programmed to steer the vehicle away from its original path and into the left or right lane, hence inducing mental fatigue. A complete trial included deviation onset, response onset and response offset events. The next trial, which instructed the subject to return to the initial cruising lane, began 5–10 seconds after the conclusion of the previous trial [62].

C. EEG SIGNAL PRE-PROCESSING

EEG signals are made up of electrical waves ranging from 0.5 cycles per second to 60 cycles per second measured at the scalp. Mainly, the waves are identified based on the different bandwidths including delta, theta, alpha, beta and gamma [63]. Table 2 summarizes the frequency range of EEG waves. Raw EEG signals may contain unwanted noise and artifacts which come from various sources [64]. The noise may be captured from the amplifier, power line, or faulty setup of electrodes. Additionally, the artifacts are emitted from the heart (electrocardiogram - ECG or EKG), cornea-retinal (electrooculogram - EOG), and nerve's stimulation (electromyogram - EMG). Such noise and artifacts are removed at the pre-processing phase via filters.

In general, filters are grouped into 3 main categories, namely low-pass filter, high-pass filter and notch filter [65]. The low-pass filters, also known as high-frequency filters (HFF), attenuate high frequencies and allow low frequencies to "pass-through" with respect to the cutoff frequency. On the other hand, high-pass filters, also known as

TABLE 1. Summary of the dataset used for mental fatigue detection.

Dataset	Number of subjects	Number of EEG channels	Links
EEG Motor Movement/Imagery Datasets [59], [60]	109	64	https://physionet.org/about/database/
SEED-VIG [61]	23	12	https://bcmi.sjtu.edu.cn/~seed/seed-vig.html
Sustained-Attention Driving Dataset (SADD) [62]	27	32	https://figshare.com/articles/dataset/Multi-channel_EEG_recordings_during_a_sustained-attention_driving_task/6427334/2

TABLE 2. Frequency range of various EEG waves.

EEG Waves	Range
Delta	Below 4 Hz
Theta	4 Hz to 7 Hz
Alpha	8 Hz to 12 Hz
Beta	13 Hz to 30 Hz
Gamma	30 – 100 Hz

low-frequency filters (LFF), allow high frequencies to ''pass-through'' by filtering out the low pass frequencies. A notch filter discard signals at a specific frequency, rather than a range. Another type of filter is called the bandpass filter which typically combines a low-frequency filter and a high-frequency filter to limit the range of unwanted low-frequencies and high-frequencies signals from passing through.

Based on the articles reviewed, the bandpass filter is most commonly employed in the pre-processing of EEG signals for mental fatigue detection using supervised ML. Not all EEG frequency waves were analyzed in the articles reviewed. From the 35 articles in this review, only 2 studies reported using all frequency waves for mental fatigue detection [66], [67].

In addition to the frequency band selection, some studies have proposed different approaches to discard unwanted artifacts, mainly due to eye movement or eye blink and muscle noise contamination. For removing artifacts due to the eye blink movement, many of the studies apply independent component analysis (ICA) [42], [44], [56], [66], [68], [69]. Other techniques proposed were enhanced automatic wavelet ICA (EAWICA) [70], second-order blind identification (SOBI) [67], [71] and a combination of digital filters and a rule-based decision system [72]. Artifacts from muscle noise contamination were removed using Canonical correlation analysis [73], [74].

D. FEATURE EXTRACTION AND SELECTION

Feature extraction in supervised ML is extracting independent variables for the classification task. For EEG, the features or variables may not be apparent because the signals are dynamic, volatile, non-linear, and non-stationary. Thus, many feature extraction techniques have been proposed for mental fatigue detection.

Power spectral density (PSD) is a widely used feature extractor for classifying EEG signals. PSD is an average power of a signal in a selected frequency range. It can be calculated using different algorithms including fast Fourier transform (FFT) [42], [44], [53], [57], [75], [76], [77], Welch's periodogram method [50], [78], continuous wavelet transform (CWT) [52], [79] and power percentage [56].

Apart from power, the spatial patterns of EEG signal activations were also extracted as features for mental fatigue detection. This was carried out using an algorithm known as common spatial patterns (CSP) [66], [67], [80]. CSP is a technique that analyzes scatter plot spatial patterns of signal activations from several EEG electrodes. It designs a linear transform of spatial filters that maps the scatter plots into a new discriminative space. In another study, spatial features were combined with temporal features for mental fatigue detection [51]. Feature extraction was also performed through time-frequency analysis [69] and differential entropy (DE) [58], [81], [82], [83], [84] based on a representation of a random variable's average surprisal in continuous probability distributions. In addition to that, visual evoked potential (VEP) that was derived from EEG through steady-state VEP (SSVEP) [85] and steady-state motion VEP (SSMVEP) [86] were also used as features for mental fatigue detection.

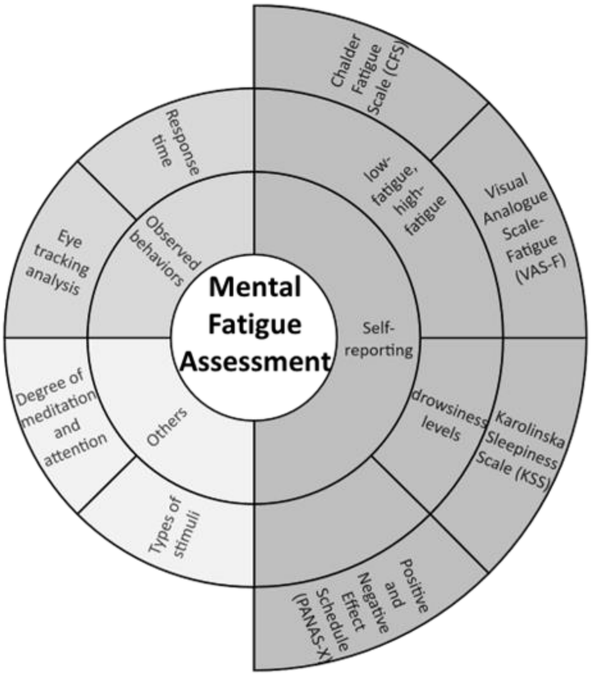

FIGURE 6. Sunburst plot of mental fatigue states assessment techniques. First, second and third levels indicate modalities, measurements, and self-reporting instruments, respectively.

E. CLASSIFICATION

Through a supervised ML method, various classification algorithms were used to create mental fatigue detection models from EEG. It entails training the models to minimize error rates between the target in the training set and the mental fatigue states estimated by the trained model. The methods for labelling the mental fatigue states and the various classification algorithms employed for mental fatigue detection are discussed in this section.

1) MENTAL FATIGUE STATES ASSESSMENT

The labelling of mental fatigue states on EEG recordings was determined using the self-reporting technique and observed behaviors, as summarized in Fig. 6. Through self-reporting, the target labels of mental fatigue were determined based on feelings, attitudes or opinions of the subjects.

For example, each subject was prompted to report their perceived levels of fatigue, frustration, and attention using a five-point Likert scale on the expanded positive and negative effect schedule (PANAS-X) [87]. The Karolinska sleepiness scale (KSS) spans 9 levels (1 = extremely alert, 2 = very alert, 3 = alert, 4 = rather alert, 5 = neither alert nor sleepy, 6 = some signs of sleepiness, 7 = sleepy, but no effort to keep awake, 8 = sleepy, some effort to keep awake, 9 = very sleepy, great effort keeping awake, fighting sleep) was also used to capture the subject's drowsiness levels [67], [88]. The KSS levels were also categorized differently in different studies. In a study by Lee et al. [44], out of the 9 levels, level 7 was excluded to make the categories more distinct. Levels 1 to 6 were considered normal state while levels 8 to 9 as fatigue. In other studies, KSS was divided into alert, mild fatigue, and fatigue states [51], [76]. By combining the output of the visual analogue scale-fatigue (VAS-F) [89] and Chalder fatigue scale (CFS) [90], the mental fatigue states were measured as low-fatigue and high-fatigue by Talukdar et al. [80] and Sharma et al. [91].

Other than self-reporting, mental fatigue states are also measured based on the observed behaviors of the respective subjects. The majority of studies that were carried out on drivers looked at the response time taken for a respective driver to get back on track once distractions were simulated [53], [68], [69], [75], [92]. Eye tracking analysis was also performed to determine mental fatigue detection based on vigilance [81].

Other than observed behaviors, the target labels of mental fatigue states were also determined based on the relative degree of meditation and attention [93]. Besides that, the target is also labelled based on the types of stimuli played during a driving simulation [66].

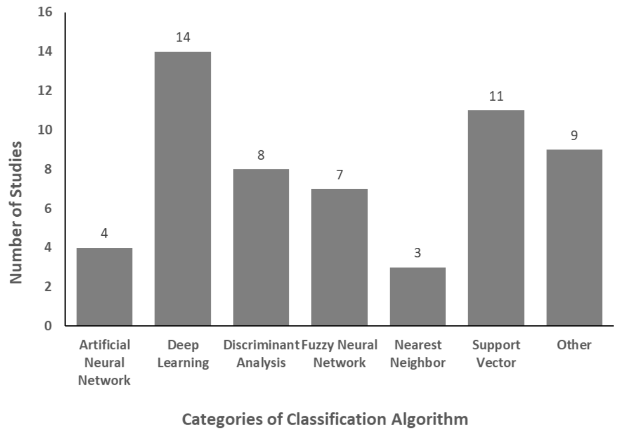

FIGURE 7. Graph of number of studies versus various AI studies.

2) CLASSIFICATION ALGORITHMS

The classification algorithms employed in mental fatigue detection can be categorized into several categories. They are artificial neural networks, deep learning, and discriminant analysis, fuzzy neural networks, nearest neighbor and support vector.

As shown in Fig. 7, deep learning algorithms are the most commonly used technique in performing mental fatigue detection. Besides the simple form of deep learning algorithm, namely deep neural network (DNN) [83], convolutional neural networks (CNN) have also been often utilized to address classification problems. CNN is typically used to analyze visual data [94] and has been applied for detecting mental fatigue from EEG images [74], [95], [96]. In other studies, customized CNN for EEG signals was proposed, namely EEG-based spatial-temporal CNN (ESTCNN) [51], [81]. It consists of two levels of feature extraction, the first is the extraction of temporal dependencies, followed by using dense layers to fuse the spatial from EEG data. A non-binary classification of mental fatigue detection was proposed by Lee et al. [44] using multiple features block-based CNN (MFB-CNN). In a study where dilated shuffle CNN (DSCNN) [52] was employed, multiple parallel expansion convolution layers were used to extract the multi-scale time-frequency domain features. DSCNN combines channel shuffle and group convolution procedures that extract sequence information to increase the efficiency of the entire network while decreasing the amount of computation. Using a parallel design, the multiharmonic linkage CNN (MHLCNN) [86] model was employed to learn the spectrum distribution features under a range of harmonic bands, that were attached to generate a string that was used for the classification of mental fatigue states. Aside from that, the simplified Bayesian CNN (SBCNN) was also proposed for performing mental fatigue detection [85]. It employs a variational inference approach to learn the posterior distribution of the weights of a neural network, from which weights can be sampled via backpropagation. In a separate study by Ming et al. [97], a deep Q-learning (DQN) algorithm was proposed based on the improvement of conventional reinforcement learning architecture involving the target network and experience replay. A 3D Convolutional Neural Network (3D CNN) primarily consists of the space-time stream and the space-frequency stream, which aim to capture and analyze discriminative features across the dimensions of space, time, and frequency was proposed in [78]. Each stream consists of 3D representations of EEG signals for spatial information, attention mechanisms for dynamic exploration of valuable dynamics, and 3D convolutions for learning spatial, temporal, and spectral dependencies.

In addition to that, an ensemble convolutional neural network is employed to perform the identification of mental fatigue levels in language understanding tasks by Ye et al. [98]. More traditional artificial neural networks were also used to classify mental fatigue states, such as annealed chaotic competitive learning network (ACCLN) [93] and radial basis function (RBF) network. Based on a recurrent neural network that is excellent at processing temporal data, a long short-term memory (LTSM) network was also proposed for mental fatigue detection [45], [99].

Fuzzy neural network classifiers are among the commonly used classifiers. Recurrent self-evolving fuzzy neural network (RSEFNN) was able to boost memory capability for adaptive noise cancellation when assessing drivers' mental states during a car driving task [53], [68], [92]. Besides RSEFNN, self-constructing neural fuzzy inference network (SONFIN) and Takagi-Sugeno-Kang (TSK)-type recurrent fuzzy network (TRFN) [53], [92] were also employed.

Other classifiers that have been used to perform mental fatigue detection were based on the generative domain adversarial neural network (GDANN) [100], k-nearest neighbor (KNN) [48], [83], [101], linear regression (LR) [50], [57],

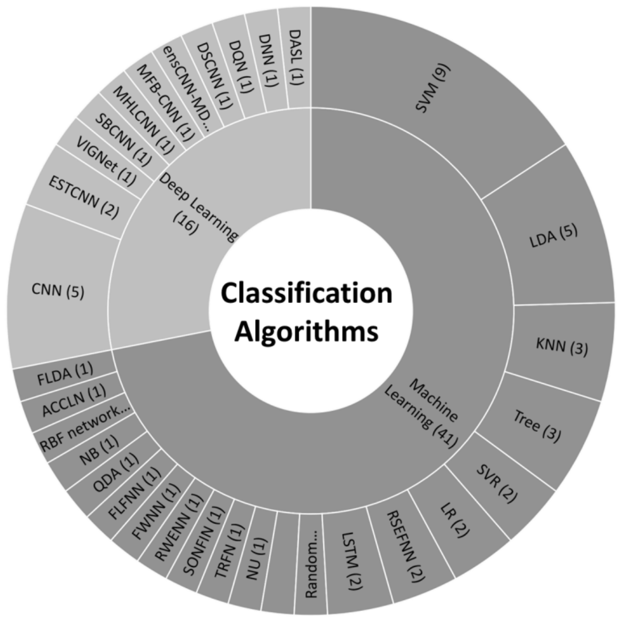

FIGURE 8. Sunburst plot of classification algorithms used for mental fatigue detection. First and second level indicate the supervised machine learning algorithms.

negative unlabeled (NU) learning [76], LightFD tree [66], bagged tree [74], random forest [84], Domain Adversarial Sparse Learning (DASL) [79] and hybrid of particle swarm optimization algorithm and extreme learning machine, namely (PSO-H-ELM) [101]. Support vector machine (SVM) [42], [48], [56], [75], [77], [81], [82], [83], [101] and support vector regression (SVR) [53], [92], [102] were also widely used for mental fatigue detection. Support vectors are normally employed to perform the classification of dichotomous states. Several variants of discriminant analysis algorithm were also employed to perform mental fatigue detection including linear Discriminant analysis (LDA) [42], [48], [56], [80], [103], Fisher's LDA (FLDA) [67], quadratic discriminant analysis (QDA) [56] and Naïve Bayes [42]. A summary of classification algorithms used for mental fatigue detection is shown in Fig. 8.

IV. DISCUSSION

In general, most BCI studies on mental fatigue detection using supervised ML were adapted from conventional ML sequential processes which include signal acquisition, pre-processing, feature extraction and classification. EEG signal acquisition involves the recording of electrical signals at the scalp based on the 10-20 international standard EEG electrodes positioning system, as shown in Fig. 4. In most studies, different types of electrodes, the number of electrodes, transmission types and the sampling rate of EEG devices produced by different manufacturers were used. Various versions of EEG devices with different numbers of electrodes ranging from 1 to 40 channels were used in the brain-computer interface for mental tiredness detection based on the compilation.

The typical sampling rates used in the studies reviewed were 256 Hz, 500 Hz, 512 Hz, and 1000 Hz. For pre-processing, bandpass filters were commonly used to eliminate and filter undesirable noise and artifacts in the EEG signals. All frequency waves of EEG (i.e. delta, theta, alpha, beta and gamma) were reported in different studies.

From our analysis, we have observed that very few research has been targeted on channel-wise analysis. Also, very few techniques have been developed that present a brain-region analysis. The majority of the research has been focused on rhythm-based analysis and frequency-based analysis. From our review, we have found that FFT-, filtering-, and wavelet-based analysis have been the most frequently used analysis models. Our analysis shows that spectral and entropy features are the most widely used features used for the detection of mental fatigue. Our analysis also revealed that wired-EEG monitoring devices are commonly used devices for fatigue analysis and detection. The highest number of subjects used in fatigue detection is thirty-seven, while the least number of subjects is six. The holdout validation technique is commonly used for fatigue detection and prediction, followed by Leave-One- Site-Out (LOSO) validation. Out of 39 articles included in our review, seven articles have used RMSE for detecting or predicting fatigue, twenty-five articles used accuracy predictor for fatigue detection, two articles included RMSE and accuracy measure for the detection or prediction for fatigue detection, and the status of one article is unknown. The overview from our systematic review of automated fatigue detection is shown in Fig. 9. The review analysis shows that fatigue detection with ML models is common, followed by deep learning-based classification. The neuroscan model has been widely used for EEG acquisition. FFT-based spectral features have been investigated the most for detection and prediction. RMSE is used for prediction, while classification-based models used accuracy to evaluate their model. SVM classifier has been most effective among ML-based classification. CNN-based classification has been widely used for fatigue detection. The analysis reveals that the highest accuracy of 100% has been obtained using FLDA-based classification with CSP-based feature extraction and tenfold cross-validation (CV) technique on twenty subjects [67]. On the other hand, the least accuracy of 60% has been obtained with FBCSB features and LDA classifier using holdout validation on thirty subjects [104]. The regression-based analysis has used SVR for their classification.

V. CHALLENGES

From our discussion, we have identified various research gaps and challenges which are briefly discussed below:

A. DATASET AVAILABILITY

The accessibility of public datasets is crucial for researchers and data scientists conducting studies, developing novel techniques, and building models. However, there may be a paucity of publicly accessible data sets in some circumstances, which can be a substantial problem for individuals working on the subject. From our review analysis, we have analyzed that the majority of the studies have used private datasets. Also, public EEG-based fatigue detection datasets are scarcely available for research. In addition, the number of subjects involved in current studies is fewer, making it less reliable for real-time implementation.

B. DATA IMBALANCE

A data imbalance occurs when the proportion of data among distinct classes within a dataset is not equal. As a result, certain classes may have many more or far fewer instances than others. Data imbalance can be a significant difficulty in ML because it can influence the correctness of a model's prediction. For example, if an algorithm for classification is developed on a set of data with an uneven class distribution, it may become biased toward the majority of the class and perform badly on the minority class. This is due to the possibility that the model will learn to prioritize the dominant class to improve its overall accuracy while negatively affecting the minority class.

C. BRAIN LOCALIZATION

The process of determining the precise location of a certain function or activity within the brain is referred to as brain area localization. This procedure is critical for comprehending how the brain functions as well as detecting and treating physiological conditions like fatigue. Current literature lacks the ability to identify or present the brain-region or channel-wise analysis [105]. This creates some opportunities for the researchers to develop techniques for identifying potential brain regions active during mental fatigue states.

D. ADAPTIVE ANALYSIS

EEG signals are highly nonlinear and non-stationary. To detect the spontaneous variations within EEG signals during fatigue states require adaptive analysis. The current techniques majorly depend on frequency-based analysis for feature extraction. However, to get a detailed insight into the spontaneous variations in the EEG during the fatigue state, it is necessary to have an adaptive analysis. Therefore, analysis of EEG signals using powerful techniques like time-frequency analysis (short-time Fourier transform, Wigner-Ville distribution, Cohen's class, etc.) [106], [107], adaptive nonlinear decomposition (tunable Q wavelet transform, variational mode decomposition, FAWT, etc.) [91], [108], [109] and their hybrid combinations.

E. FEATURE EXTRACTION AND SELECTION

Current studies have explored the limited utility of feature analysis and selection. Features play a crucial role in data analytics and classification. However, accurate analysis and appropriate selection of features are important to maximize the system performance [105]. The studies in our review reveal that feature extraction and analysis have not been

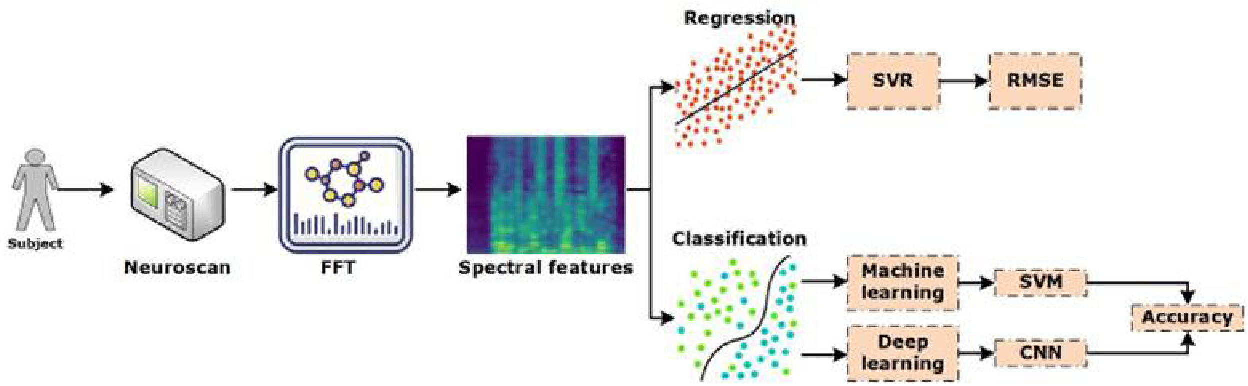

FIGURE 9. Overall observations of our systematic review for automated mental fatigue detection.

adopted to their full capacity. Therefore, there exists a huge scope for a broader analysis of features like spectral, time-frequency, nonlinear, statistical, and entropies for their role in fatigue detection.

F. UNIFORMITY OF VALIDATION

ML models are susceptible to various threats that can result in performance degradation. One such threat is the overfitting of a model, where the model does not learn from new data and thereby provides saturated decisions. The holdout validation technique is one such threat to the overfitting of the model. The existing research in our review reveals that the majority of the developed algorithms use holdout validation, therefore, the possibility of overfitting cannot be neglected. To make a classification model more robust, it is necessary to validate the performance on different scenarios with multiple trials. In addition, validation based on k-fold cross-validation and LOSO validation must be explored to their full capacity for real-time realization of the developed system.

VI. FUTURE DIRECTION

From the review analysis and discussion, we have identified the potential future directions and research recommendation as shown in Fig. 10 and discussed in detailed in the following subsections:

A. HYBRID AND EFFECTIVE CLASSIFICATION

In recent times, we have witnessed a boom in technological advancements. This has resulted in multi-dimensional data from different sources. This increase in data has brought several opportunities for the development of an effective fatigue detection system. Our analysis has shown that the majority of current systems employ ML-based classification models, especially using the SVM classifier. However, traditional ML-based classification is limited in their capacities to sustain its performance with an increasing amount of data. On the other hand, the deep learning models used for fatigue detection in this review use mostly CNN-based models. Though CNN is effective for handling big data and provides better performance, they are not utilized to its highest capacity and also requires huge computational time [106], [110]. To overcome this, there is an urgent need to develop an effective and lightweight model for the detection and prediction of fatigue. Therefore, a hybrid combination of lightweight transfer learning models (squeezeNet, ResNet, XceptionNet, InceptionNet, etc.) with feature selection and ML models can significantly enhance the system's performance with less training time.

B. MULTIMODAL DATASETS

Several factors cause a person to experience fatigue. Fatigue affects the functionality of important body organs like the heart, eyes, and brain, because of the autonomous nervous system. The sympathetic and parasympathetic nerve systems, which regulate blood pressure, heart rate, and other cardiovascular processes, convey signals from the brain to the heart. In reaction to stress or danger, the sympathetic nervous system, for example, activates the "fight or flight" response, which elevates heart rate and blood pressure. The heart, in turn, transmits signals to the brain via the vagus nerve, which gives sensory data about the heart's functioning to the brainstem and other areas of the brain. According to research, these signals can influence cognitive and emotional processes such as focus, recall, and emotion [111], [112]. Therefore, the analysis of multimodal data can reveal the changes in important organs during fatigue. In addition, exploring multimodal data may help the researchers to shift the paradigm from one electrophysiological analysis like EEG to other like Photoplethysmography (PPG) and ECG. In addition, acquiring EEG signals are difficult (due to multichannel analysis, artefacts, and low signal-to-noise ratio), costly, and requires special settings (dedicated room, presence of expert). Therefore, the use of multimodal data can open new research directions for shifting paradigms from one modality to other.

C. EXPLAINABLE AI (XAI)

The advancements in feature engineering and boost in ML techniques have resulted in significant improvements in system performance. However, clinicians offer their resistance to

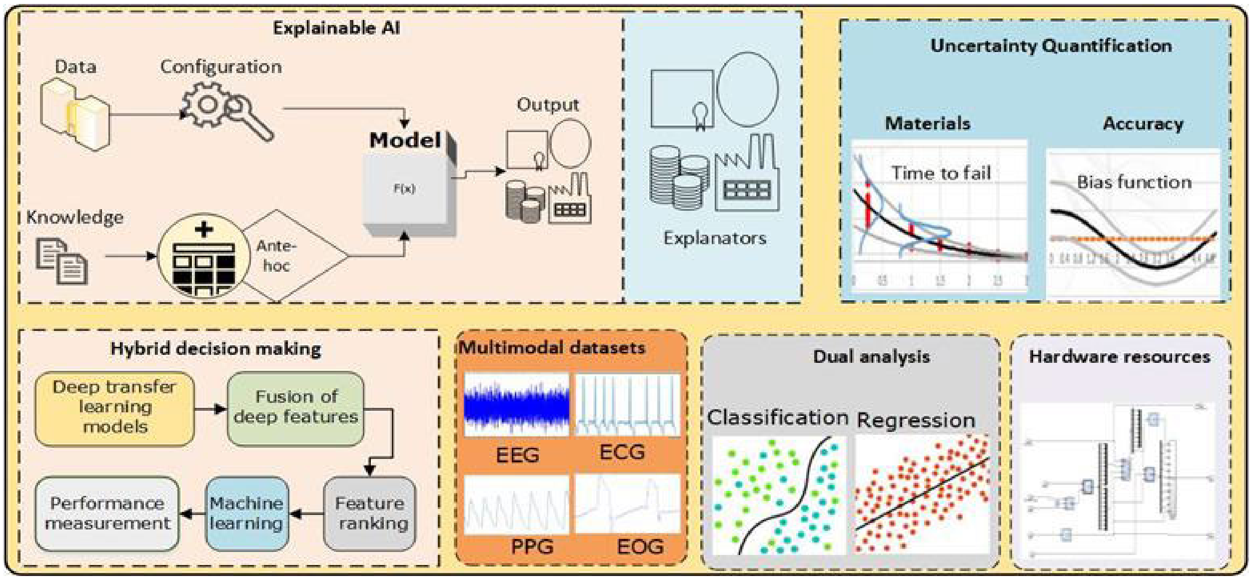

FIGURE 10. Graphical overview of the research recommendations and future directions.

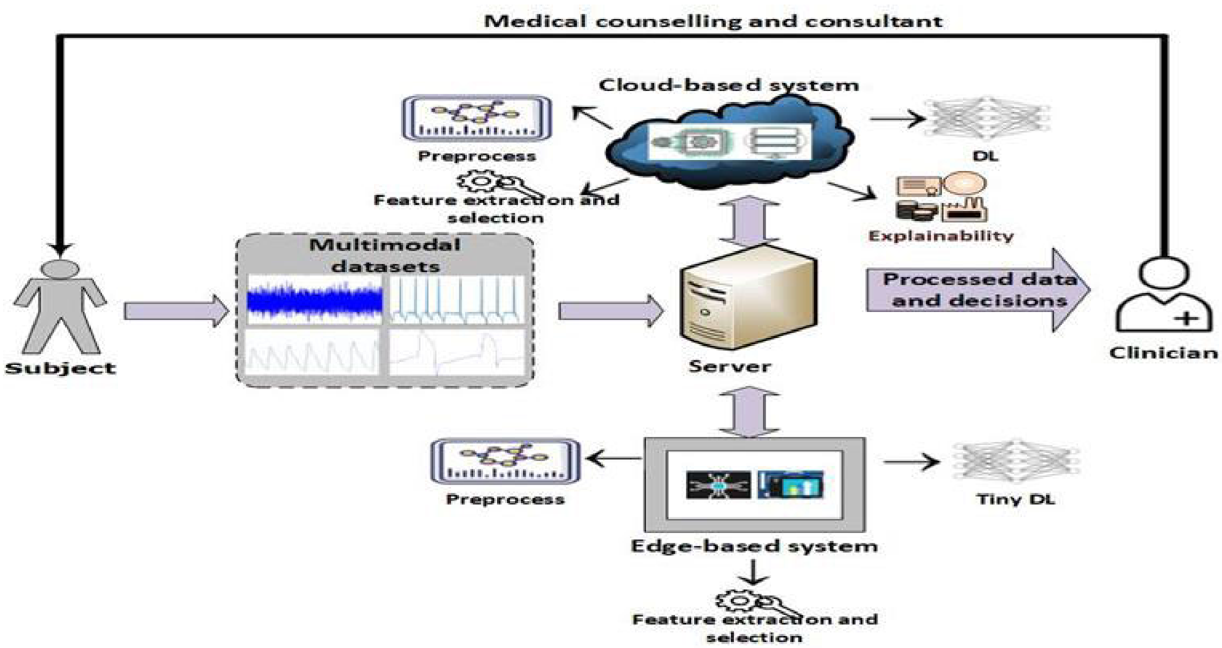

FIGURE 11. Snapshot of automated mental fatigue intervention edge- and cloud-based classification.

accepting the decision given by the automated classification models [105], [113]. Also, the variations in the data, system setting, and varying surrounding conditions affect the system's decision. These changes significantly affect the decisions of ML or DL models making them less reliable. To overcome this, explainable artificial intelligence (XAI) is required. XAI not only provides the reason for individual and overall decisions, but also enables the stakeholder to understand when to trust the model, when the model fails, and why the model has erred in the decisions. In addition, with the help of XAI one can localize the brain region or identify an effective channel that significantly reduces computational power [105]. Not only this, XAI helps to identify the contribution of individual feature in classification and their importance to reduce feature dimensionality.

D. UNCERTAINTY

The reliability and robustness of the classification model are crucial especially while deploying them in real-time scenarios. This demands the model to be trained and tested in different scenarios. However, our review show that the current automated fatigue detection models are developed on cleaned and pre-processed signals. In addition, the subjects included in the dataset of current studies are included from a single

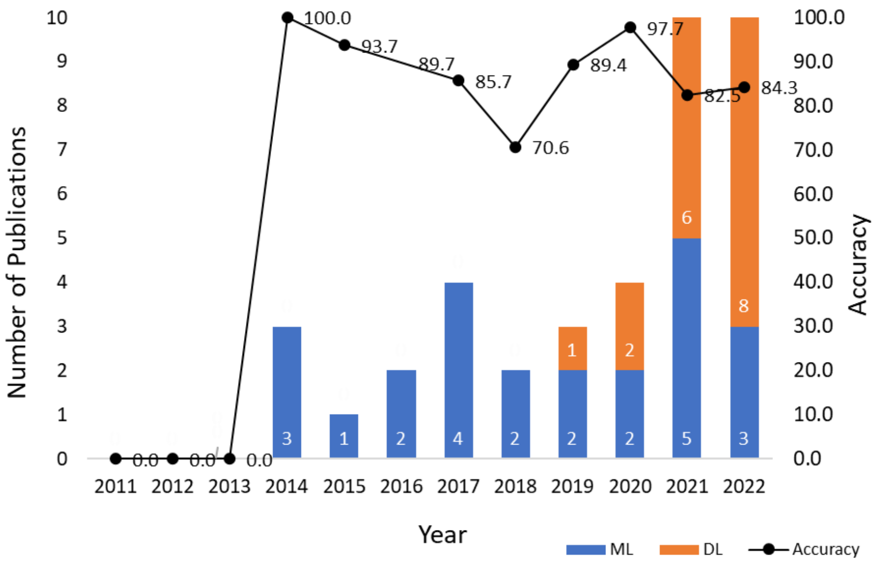

FIGURE 12. Trend on mental fatigue detection.

geographical area, making it local for a particular application. In real scenarios, such assumptions about cleaned data and subjects within one geographical area may not hold, thus negatively affecting the system's performance. This negative change in the system's performance due to artefacts within the data and change in geographical location or other factors can cause uncertainty in the model. The sources of uncertainty in data can be the result of the presence of noise in data, a mismatch between testing and training sets, a mismatch in geographical conditions, and variations in the acquisition system [114], [115]. Such uncertainty in data makes the developed classification model unreliable. Therefore, it is required to measure the uncertainty within the model using uncertainty quantification (UQ) [116], [117]. To investigate UQ, a few well-known models such as Bayesian inference, fuzzy systems, Monte Carlo simulation, rough classification, Dempster-Shafer theory, and imprecise probability can be used [117]. To resolve uncertainty, updating tuning parameters and noise reduction within the data is required.

E. DETECTION AND PREDICTION MODELS

Accurate detection and prediction of fatigue are crucial for a healthy lifestyle. But over review analysis shows that only two studies from one author group have explored fatigue detection and prediction [57], [81]. Since fatigue can occur at any instance due to a lack of rest and other factors, it is important to track periodic changes in physiology to detect and predict fatigue. Therefore, there still exists a vast scope for the researcher to develop and implement a robust and effective model for detecting and predicting fatigue in real scenarios. Such models can alert an individual about their current status and the probability of occurrence of fatigue in the near future.

F. HARDWARE REALIZATION

While proposing any system, it is important to consider the prototype and design realization of the proposed system. The current review explored the utilization of EEG in fatigue detection using supervised ML techniques. However, practically it is difficult to acquire EEG due to its acquisition constraints and signal strength. Also, as EEG signals are acquired from multi-channels, analyzing the data from these multi-channels is computationally expensive and difficult. To overcome this, brain-heart interaction due to the autonomous nervous system can help to identify variations in cardiac activities [111], [112]. As ECG can provide subtle variations in cardiac activities, it can be used as an effective measure for fatigue detection. Also, due to its high signal-to-noise ratio and ease it acquisition, analysis of ECG is easy and cost-effective. The variations in cardiac activities can also be tracked from PPG, such signals may bring a revolution in tracking neurological changes using ECG and PPG. PPG also offers ease in signal acquisition, cost-effective, portable, and provides a faithful representation of cardiac activities. Therefore, the realization of hardware using such effective and portable wearables can be of merit to study neurological conditions.

For future research, the model can be expanded to include a neurofeedback-based automatic mental fatigue intervention system. A snapshot of automated mental fatigue intervention edge- and cloud-based classification is shown in Fig. 11. It has two main processes: mental fatigue detection and mental fatigue intervention using edge- and cloud-based decisions. The mental fatigue detection process is performed continuously until the mental fatigue state is detected. Once detected, the mental fatigue intervention process takes place by sending an alert to the user to carry out mental fatigue

TABLE 3. Summary of list of BCI studies on mental fatigue detection using supervised machine learning that have been published from 2011-2022.

Author	Year	Model	Sampling Rate (Hz)	No. of channels	Transmission Type	Feature Extraction Technique	No. of Subjects	Validation	Classification Performance (Accuracy (%)/RMSE)
Li, X., Chen, P., Yu, X., & Jiang, N.[58]	2022	Waveguard Original	1024	64	Wired	Spectral	20	Holdout (80:20)	CNN (Acc: 70)
M. Li; C. Ma; W. Dang; R. Wang; Y. Liu; Z. Gao [52]	2022	Neuroscan	1000	40	Wired	CWT (Normal) CWT (Fatigue)	8	Holdout (80:10:10)	DSCNN (Acc.: 96.75) DSCNN (Acc.: 77.52)
Ren B., Pan Y. [45]	2022	Emotiv EPOC+	250	14	Wireless	TFMI	11	Holdout (70:30)	LSTM (RMSE: 3.5878) CNN-LSTM (RMSE: 3.5121)
Tabejamaat M., Mohammadzade H. [102]	2022	Neuroscan	1000		Wired	Wavelet decomposition (Logarithmic energy, Differential entropy)	23	Fivefold CV	SVR (RMSE: 0.1429) PPR (RMSE: 0.1054)
W. Dang; M. Li; D. Lv; X. Sun; Z. Gao [86]	2022	Not mentioned	1000	8		SSVEP (Normal) SSVEP (Fatigue) SSMVEP (Normal)	8	Holdout (80:10:10)	MHLCNN (Acc: 97.23) MHLCNN (Acc: 81.47) MHLCNN (Acc: 78.78)
Ye C., Yin Z., Zhao M., Tian Y., Sun Z. [98]	2022	Not mentioned	Not mentioned	14	Wireless	FFT (PSDs, temporal statistics, and entropies)	15	Holdout (90:10)	ensCNN-MD (87.69)
Zeng C., Mu Z., Wang Q. [101]	2022	Brain Vision Recorder	1000	32	Wired	STFT (PSD) EMD (ESD)	6	Holdout (83:17)	KNN (Acc: 83.33) SVM (Acc: 86.28) PSO-H-ELM (Acc: 88.83) KNN (Acc: 90.94)

intervention such as performing physical exercises to reduce mental fatigue [104]. Alternatively, an automated intervention can be performed by adjusting other parameters that may reduce mental fatigue, such as brightness [118], [119] and temperature [120], [121]. In other words, the system is able to teach the subject how to control his/her brain processes [122].

TABLE 3. ***(Continued.)*** **Summary of list of BCI studies on mental fatigue detection using supervised machine learning that have been published from 2011-2022.**

									SVM (Acc: 93.62) PSO-H-ELM (Acc: 94.24)
Caspar E.A., de Beir A., Lauwers G., Cleeremans A., Vanderborght B. [103]	2021	Biosemi Active Two System	2048	16	Wired	FBCSP	30	Holdout	LDA (Acc: 60)
H. Kuang; J. Qu [99]	2021	Neuroscan	500	32	Wired	STFT (PSD)	27	LOSO	EEGNet (Acc: 59) SVM (Acc: 71.67) LSTM (Acc: 78.84)
K. Chen; Z. Li; Q. Ai; Q. Liu; L. Wang [95]	2021	--	500	16		FFT (PSD) Time domain (Hjorth features) Feature fusion	8	Fivefold CV	CNN (Acc: 88.8) CNN (Acc: 89) CNN (Acc: 92.8)
Ko, L. W., Sandeep Vara Sankar, D., Huang, Y., Lu, Y. C., Shaw, S., Jung, T. P. [74]	2021	Neuroscan	500	32	Wired	Canonical correlation analysis	16	CV	Bagged tree (Acc: 81.59% - Offline) (Acc: 78.1% - Online)
Li M., Li F., Pan J., Zhang D., Zhao S., Li J., Wang F. [85]	2021	Neuroscan	1000	32	Wired	SSVEP (filtering)	10	Holdout	SBCNN (Acc: 90.70)
Paulo J.R., Pires G., Nunes U.J. [96]	2021	Neuroscan	500	30	Wired	Filtering (recurrence plots)	27	LOSO	CNN (Acc: 75.87)
Peng Y., Wong C.M., Wang Z., Rosa A.C., Wang H.T., Wan F. [82]	2021	gUSBamp amplifier	600		Wired	Wavelet transform (Sample entropy) Wavelet transform (wavelet entropy)	11	Tenfold CV	SVM (Acc: 65.1) SVM (Acc: 96.5)
S. Hwang; S. Park; D. Kim; J. Lee; H. Byun [83]	2021	Neuroscan	200	17	Wired	Filtering (differential entropy)	8	Holdout (66:17:17)	KNN (Acc: 86.02) SVM (Acc: 81.85) DNN (Acc: 91.38) Adversarial

TABLE 3. ***(Continued.)*** **Summary of list of BCI studies on mental fatigue detection using supervised machine learning that have been published from 2011-2022.**

									learning (Acc: 92.09)
Y. Ming; D. Wu; Y. -K. Wang; Y. Shi; C. -T. Lin [97]	2021	Neuroscan	500	3	Wired	Filtering	37	Holdout	DQN (RMSE: 1.15)
Zeng H., Li X., Borghini G., Zhao Y., Aricò P., Di Flumeri G., Sciaraffa N., Zakaria W., Kong W., Babiloni F. [100]	2021	Not mentioned	200	61		Filtering (PSD)	13	LOSO	DANN: (Acc: 81.82) GDANN (Acc: 91.63)
Sharma S, Khare S. K., Bajaj V., Ansari I A [91]	2021	--	250	3	--	FAWT (statistical measures)	18	Tenfold CV	Decision tree (Acc: 88.6) Naïve Bayes (Acc: 72.8) SVM (Acc: 75.8) KNN (Acc: 81.5) Bagged Tree (Acc: 90.2) ELM (Acc: 95.6)
Ko W., Oh K., Jeon E., Suk H.-I. [81]	2020	U-Wake	512	1	Wireless	Raw EEG (DE)	23	Fivefold CV	SVM (Acc: 92.0) ESTCNN (Acc: 74.0) VIGNet (Acc: 96.0) SVM (RMSE: 0.07) ESTCNN (RMSE: 0.22) VIGNet (RMSE: 0.04)
Z. Li, J. Wang, Z. Jia, Y. Lin [78]	2020	BrainAmp	250	22 (BCI IV 2a)	Wired	Space-time representation using PSD	9	5-fold	3D CNN (89.2)
				60 (BCI III 3a)			3		3D CNN (97.7)
Lee D.-H., Jeong J.-H., Kim K., Yu B.-W., Lee S.-W. [44]	2020	BrainAmp	1000	30	Wired	Filtering (ICA)	7	Holdout (50:50)	MFB-CNN (Acc: 75)

TABLE 3. *(Continued.)* **Summary of list of BCI studies on mental fatigue detection using supervised machine learning that have been published from 2011-2022.**

Talukdar U., Hazarika S.M., Gan J.Q. [80]	2020	Biosemi Active Two System	256	64	Wired	Adaptive CSP	11	--	Davies Bouldin index (Acc: --/RMSE: --) Fisher score (Acc: --/RMSE: --) Dunn's index (Acc: --/RMSE: --)
Khare, S. K., Bajaj, V., & Sinha, G. R. [54]	2020	--	250	3	--	Variational Nonlinear Chirp Mode Decomposition (statistical features)	6	Tenfold CV	Decision tree (Acc: 84.6) KNN (Acc: 75) SVM (Acc: 75.8) LR (Acc: 69.6) Bagged tree (Acc: 92.4)
Wu, Z., Zeng, H., Zhao, Y., Li, X., Zhang, J., Hattori, M. [79]	2020	--	--	61	--	PSD	14	CV	Domain Adversarial Sparse Learning (Acc: 97%)
Foong R., Ang K.K., Zhang Z., Quek C. [76]	2019	Muse	256	4	Wireless	Fast EMD and FFT (PSD)	29	Holdout (Training 28 subject: testing one subject)	NU (Acc: 93.77)
Z. Gao; X. Wang; Y. Yang; C. Mu; Q. Cai; W. Dang; S. Zuo [51]	2019	NeuroScan	1000	40	Wired	Filtering (Spatial-temporal features)	8	Tenfold CV	ESTCNN (Acc: 97.37)
Zeng H., Yang C., Zhang H., Wu Z., Zhang J., Dai G., Babiloni F., Kong W., Chuang L. [66]	2019	gUSBamp amplifier	256	16	Wired	CSP (regularized spatial covariance)	10	Holdout (80:20)	SVM (Acc: 90.1) LMNN (Acc: 88.1) GRU (Acc: 77.01) CNN (Acc: 84.37) LightFD tree (Acc: 95.31)

TABLE 3. ***(Continued.)*** **Summary of list of BCI studies on mental fatigue detection using supervised machine learning that have been published from 2011-2022.**

Hendrawan M.A., Pane E.S., Wibawa A.D., Purnormo M.H. [56]	2018	Neurosky Mindwave	512	1	Wireless	Savitzky Golayfilter (Power percentage using PSD)	7	Holdout	LDA (Acc: 72.86) QDA (Acc: 65.72) SVM (Acc: 62.86)
S. Tian; Y. Wang; G. Dong; W. Pei; H. Chen [50]	2018	NeuroScan	1000	32	Wired	Welch's periodogra m (PSD)	18	LOSO	LR (Acc: 81)
Hu, J. [84]	2017	Neuroscan	1000	32	Wired	Entropy features	12	LOSO	Random forest (Acc: 85.7%)
Myrden A., Chau T. [42]	2017	B-Alert X24	256	16	Wireless	FFT (total spectral power)	11	Tenfold CV	LDA (Acc: 74.8), SVM (Acc: 73.4) NB (Acc: 70.6)
Qin X., Deng J., Wang M., Wang P., Wang L., Zhang Y. [93]	2017	Neurosky Mindwave	512	1	Wireless	DWT (band energy)	30	Holdout	ACCLN (Acc: 98.4) dd RBF (Acc: 88.75)
Zhang X., Li J., Liu Y., Zhang Z., Wang Z., Luo D., Zhou X., Zhu M., Salman W., Hu G., Wang C. [77]	2017	Not mentioned	Not mentioned	Not mentione d	Wired	DWT (rhythms, PSD)	10	LOSO	SVM (Acc: 90.70)
Liu Y.-T., Lin Y.-Y., Wu S.-L., Chuang C.-H., Lin C.-T. [53]	2016	NeuroScan	500	30	Wired	FFT (PSD)	10	Holdout	RSEFNN (RMSE: 0.042), RWENN (RMSE: 0.042) SVR (RMSE: 0.042) SONFIN (RMSE: 0.046) FWNN (RMSE: 0.044) TRFN (RMSE: 0.043)
Y. Liu; S. Wu; Kuang-Pen Chou; Y. Lin; Jie Lu; Guangquan Zhang; Wen-Chieh Lin; C. Lin [68]	2016	NeuroScan	500	30	Wired	FFT (event-related spectral perturbatio n)	10	Holdout	RSEFNN (RMSE: 0.1197)
Ko L.-W., Lai W.-	2015	NeuroScan	1000	17	Wired	FFT (PSD)	15	LOSO	LR (Acc:

TABLE 3. *(Continued.)* **Summary of list of BCI studies on mental fatigue detection using supervised machine learning that have been published from 2011-2022.**

K., Liang W.-G., Chuang C.-H., Lu S.-W., Lu Y.-C., Hsiung T.-Y., Wu H.-H., Lin C.-T. [57]									93.7) LR (RMSE: 0.219)
Lin C.-T., Chuang C.-H., Huang C.-S., Tsai S.-F., Lu S.-W., Chen Y.-H., Ko L.-W. [75]	2014	Not mentioned	Not mentioned	Not mentione d	Wired	FFT (PSD)	15	Twofold CV	SVR (RMSE: 0.124)
Roy R.N., Charbonnier S., Bonnet S. C [67]	2014	BrainAmp	500	32	Wired	CSP (rhythms, relative power)	20	Tenfold CV	FLDA (Acc: 100)
Y. Liu; Y. Lin; S. Wu; C. Chuang; M. Prasad; C. Lin [69]	2014	NeuroScan	500	30	Wired	FFT (event-related spectral perturbatio n routine)	10	Tenfold CV	FLFNN (MSE: 0.067) LR (MSE: 0.25) MLP (MSE: 0.112) SVR (RMSE: 0.098)

Changes in brain activity that result in mental fatigue can be counteracted as soon as they are identified to avert more severe outcomes.

VII. CONCLUSION

This review looks at studies published between 2011 and 2022 on mental fatigue detection. As depicted in Fig. 12, the number of publications on the subject increases steadily over the years. As the topic is just beginning to gain traction, this review includes 39 studies on brain-computer interface implementations for detecting mental exhaustion using supervised machine learning. Mental fatigue detection using EEG signals can be performed through conventional machine learning using any common supervised machine learning algorithms for classification. With the recent developments in neuroimaging, studies can be expanded to real-time neurofeedback-based automatic mental fatigue detection for early intervention.

In summary, the significance of this review is as follows:

- Out of 562 studies, 39 have been selected for this review. The studies were categorized according to the EEG devices used for signal acquisition, the feature extraction techniques, labelling techniques and classifiers used for mental fatigue detection.
- As there was no common standard used by the various authors in the signal acquisition, feature extraction, labelling the targets and classification, this makes the comparison of results impossible.
- The classification performance of using either wireless or wired neuroheadset is comparable.
- The advantages of this review are:
- A systematic review of automated fatigue detection using EEG signals.
- Comprehensive analysis and discussion on developed automated systems.
- Identification of potential challenges in existing automated fatigue detection models.
- Important future directions and research recommendations of researchers for future development of effective fatigue detection systems.
- There are several limitations of this review:
- Only BCI studies that analyzed EEG as the acquired brain signals were reviewed. Studies employing other neuroimaging techniques were excluded. Studies using hybrid methods were also omitted.
- Only BCI studies on mental fatigue detection using supervised machine learning techniques are included in the review.
- The number of subjects involved in the recording of EEG for the studies was small.
- Difficulty in comparing the performance of each classifier due to the different number of subjects and tuning parameters involved in the studies.

APPENDIX

See Table 3.

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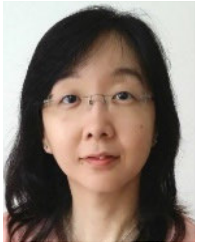

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