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Electroencephalogram (EEG)-based Systems to Monitor Driver Fatigue: A Review

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ABSTRACT

An efficient system that is capable to detect driver fatigue is urgently needed to help avoid road crashes. Recently, there has been an increase of interest in the application of electroencephalogram (EEG) to detect driver fatigue. Feature extraction and signal classification are the most critical steps in the EEG signal analysis. A reliable method for feature extraction is important to obtain robust signal classification. Meanwhile, a robust algorithm for signal classification will accurately classify the feature to a particular class. This paper concisely reviews the pros and cons of the existing techniques for feature extraction and signal classification and its fatigue detection accuracy performance. The integration of combined entropy (feature extraction) with support vector machine (SVM) and random forest (classifier) gives the best fatigue detection accuracy of 98.7% and 97.5% respectively. The outcomes from this study will guide future researchers in choosing a suitable technique for feature extraction and signal classification for EEG data processing and shed light on directions for future research and development of driver fatigue countermeasures.

Keywords: Driver fatigue, electroencephalogram (EEG), feature extraction, signal classification

1. INTRODUCTION

Driver distraction and inattention caused by fatigue are identified as the main causes of road accidents [1]. Fatigue is a feeling of extreme physical and mental tiredness [2]. Driver fatigue causes detrimental effects to attention, reaction time, recall, hand-eye coordination and vigilance, resulting in performance deterioration [3]. In addition, it contributed to 80.6% of road accidents in Malaysia in year 2016 [4]. According to the recent report by the Royal Malaysian Police (RMP), the number of road accidents in Malaysia has increased alarmingly with a record of 414,421 from 2010 to an increased number of 567,516 calamities in 2019 [5].

Previous studies have identified sleep disorders [6] and driving duration [7] as the main causes of traffic accidents . Ideally, most healthy adults require around 7.5 to 9 hours of good quality sleep every night. Those with less amount of sleep shall build up a sleep debt, hence, having the potential to fall asleep behind the wheel. These drivers are also prone to misjudge speed and distance and have impaired reaction time and decision making [8]. Meanwhile, over driving duration increases the steering error, reaction time [9], vehicles speed and diminishes driver awareness of pedestrians [10]. Road complexity is also correlated with driver fatigue. Driving in

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complex traffic conditions while performing different task demands surely cause a certain level of fatigue [11]. A study which investigated the brain activity of eight subjects, through EEG frequencies using a simulated driving task, found that brain activities of the straight sections are significantly different from curve sections [12]. The same trend was obtained as the drivers experienced high passive fatigue symptoms in low demand (straight) road than high demand (curvy) road through observation of lane positioning and steering wheel control [13].

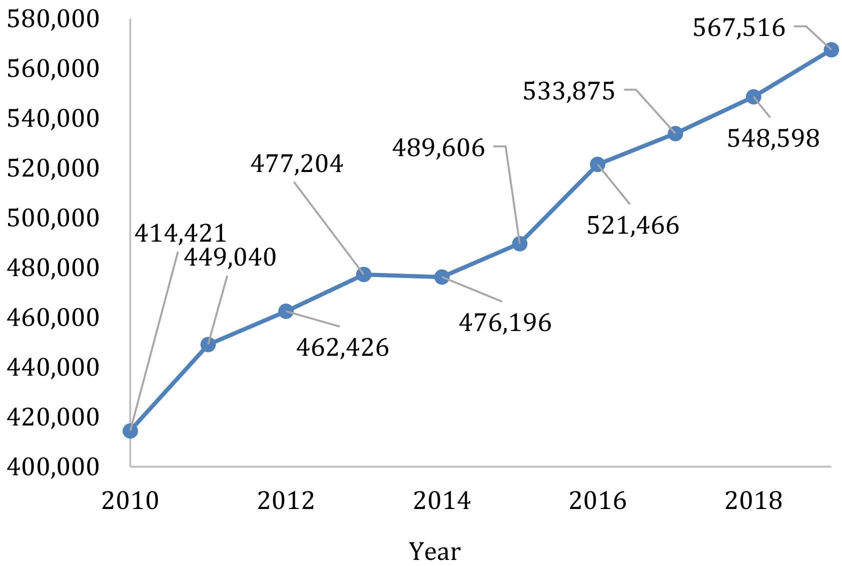

Figure 1. Malaysia Road Accident 2010 ~ 2019 [5].

Therefore, an immediate and reliable system that is capable to detect driver fatigue under different driving demands and conditions is urgently demanded to reduce fatigue related risks on the road [14]. As the drivers encounter difficulty in detecting fatigue, it is essential for the vehicle to be installed with a driving safety assistance system that can provide necessary warning. In the past few years, many researchers have shown interest in the development of fatigue detection and monitoring system. Numerous mechanisms and measures in detecting fatigue while driving have been proposed like (a) vehicle-based parameters using electronic sensors, for instance lane tracking [15] and steering rotation [16] (b) driver-based behaviour utilising video imaging techniques such as eye closure and blink rates [17] and facial expressions [18]; and (c) physiological-based parameter. Nevertheless, the computer vision based approaches like eye blinking are vulnerable to environmental factors like weather, brightness and road conditions, which could result in low detection accuracy [19]. Additionally, during the pandemic of COVID-19, it has become normal for drivers to wear masks, which is a challenge for driver fatigue detection.

In physiological measures, the researchers study the correlation of physiological bio-signal like electrocardiograms (ECG) to detect heart rate variability [20], electromyograms (EMG) to measure muscle activity [21], electrooculograms (EOG) to measure the eye movement [22], and electroencephalograms (EEG) to assess brain condition [23]. Recently, a great number of scholars conduct investigations on the benefits of physiological-based parameters due to its characteristics of detecting a driver's fatigue state in advance. Amongst them, EEG is considered to be the most significant and reliable method to asses driver fatigue [24] as this method can reflect ongoing reaction of the brain status [25].

2. ELECTROENCEPHALOGRAMS (EEG)

EEG is a test to record electrical activity in the brain, which is a result of excitatory and inhibitory post-synaptic potentials produced by cell bodies and dendrites of pyramidal neurons [26]. The recoding of the EEG signals is executed by attaching electrodes consisting of small metal discs on the subject scalp using the standardized electrode placement scheme (Figure 2) [27, 28].

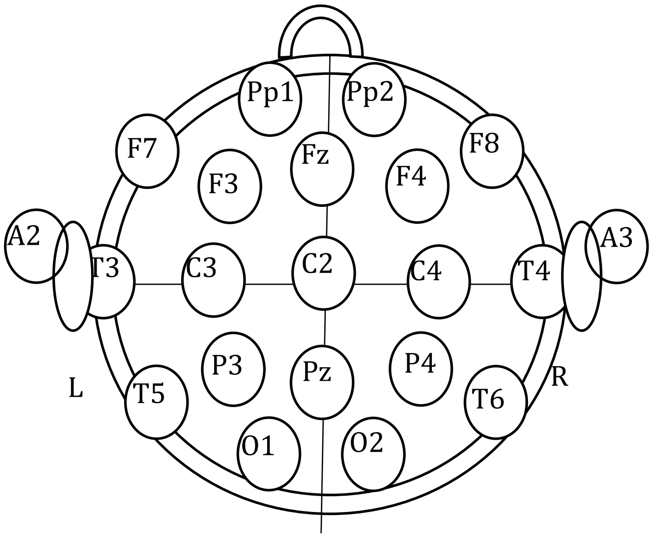

Figure 2. Standardized electrode placement scheme [28].

There are 4 stages involved in EEG signal processing (Figure 3). The first stage is pre-processing which involves signal acquisition, artifacts removal (noises that come from sources other than brain like eye blinking, muscle artifacts and deep breathing during the test), signal averaging, resulting in signal improvement, and edge detection[29]. The next stage is feature extraction to select the information or features deemed most useful for classification exercise [30]. The third stage is feature selection to select only the relevant features by discarding the features with little or no predictive information [31]. The final stage is signal classification which is to properly predict the labels for each class in the data.

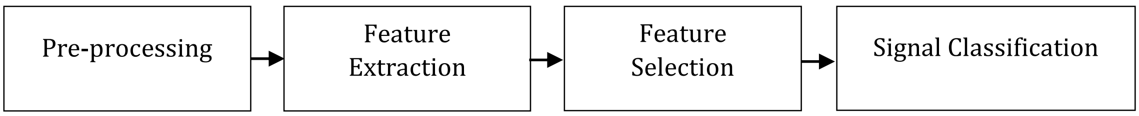

Figure 3. Stages of EEG processing [32].

Feature extraction and signal classification are the most critical stages in the process of EEG signal classification [33]. EEG signals contain vital information, and with the help of proper feature extraction methods, useful features can be obtained to express the brain conditions for different mental tasks and yield an exact classification of mental tasks. The selection of methods and algorithm for classification of EEG signals is also important to accurately classify these features to a particular class of brain conditions [34, 35]. Therefore, the selection and reliability of feature chosen and extraction play a crucial role and major challenge [36]. In this article, an overview of techniques for feature extraction and signal classification in the EEG signal analysis to detect fatigue was presented. Next, the pros and cons of the techniques for these two stages and their fatigue detection accuracy performance were discussed.

3. REVIEW METHOD

To determine relevant and high potential studies to be included into this study, a schematic approach was utilized by listing out the pertinent keywords and run databases, selecting of only applicable resources, determining other resources, and resources priority evaluation. A list of keywords related to fatigue detection and monitoring system were first identified. To acquire relevant search results, three basic Boolean operators: AND, OR and NOT were used by connecting the keywords in a logical way that the database will understand. Other commands include truncation, phrases and parentheses. This set of commands can be utilized in almost every search engine, online catalogue or database.

The command AND narrows a search by telling the database to present all search terms in the resulting records, for example a search on driver fatigue AND electroencephalograms (EEG). If one term is contained in the article and the other is not, the item will not appear in the search results list. Meanwhile, the command OR broaden the search by telling the search engine that any of the search terms must be presented in the results list, for example fatigue OR drowsiness. Hence, all the documents contain either fatigue of drowsiness will appear in the results list. The command NOT narrows a search by telling the search engine to search the first term and ignore any records containing the term after the NOT, for example signal classification NOT pre-processing. The search engine will only find documents that only contain the key phrase signal classification and will exclude all results that include the keyword signal classification.

Several academic research databases were used like Scopus, Web of Science, Google Scholar, IEEE Xplore and Research Gate. The example of well-defined logical string of search words used for searching are shown in Table 1. The database searching results to number of literature studies. To ensure only applicable resources are selected, the abstracts were read thoroughly. The bibliographies and references of the useful resources were examined to find other potential resources related to the topics. Next, the resources need to be prioritized by evaluating the credibility based on the information accuracy, author qualifications, research objectivity, content currency and coverage.

Table 1 Examples of Keywords and Phrases Used to Scaffold Relevant Articles for This Review

AND	Driver fatigue AND electroencephalograms (EEG)
OR	Fatigue OR drowsiness OR monotony OR tired
NOT	Signal classification NOT pre-processing

4. DISCUSSION

Table 2 presents a brief summary of previous studies related to driver fatigue detection and monitoring system utilising EEG technology. The literature table is comprised literature references and methods proposed for features extraction and signals classification. The percentage of fatigue detection accuracy using these approaches is also presented.

Table 2 Summary of Fatigue Monitoring System Using EEG

References	Feature(s) Extraction	Signal Classifiers	Fatigue Detection Accuracy, %
[37]	Principle Component Analysis	Radial Basis Function neural network	92.71
[38]	Principle Component Analysis Network	Support Vector Machine	95
[39]	Fast Fourier transform	Support vector machine	90.7
[40]	Combined entropy: Spectral Entropy+ Approximate Entropy+ Sample Entropy+ Fuzzy Entropy	Random Forest	97.5
	Spectral Entropy	Random Forest	81.2
	Approximate Entropy	Random Forest	83.4
	Sample Entropy	Random Forest	84.0
	Fuzzy Entropy	Random Forest	85.7
[41]	Combined entropy: Spectral Entropy+ Approximate Entropy+ Sample Entropy+ Fuzzy Entropy	Support Vector Machine	98.75
[42]	Combined entropy: Spectral Entropy+ Approximate Entropy	Support Vector Machine	91.3
[43]	Wavelet Entropy	Support Vector Machine	90.7
	Spectral Entropy	Support Vector Machine	81.3
[44]	Fuzzy Entropy	Support Vector Machine	85
[45]	Fuzzy Entropy	Random Forest	96.6
[46]	Autoregressive	Bayesian neural network	88.2

The pros and cons of techniques used for feature extraction and signal classification are illustrated in Tables 3 and 4.

Table 3 Summary of Pros and Cons of Features Extraction Techniques

Extraction Technique	Pro(s)	Con(s)
Principle Component Analysis	1) Low noise contamination as the maximum variation basis is selected and so the small variations in the background are disregarded automatically [47]. 2) Minimize overfitting problems caused by too many variables in the dataset through reduction of redundant features [47, 48]	1) The covariance matrix is hard to be analysed in an accurate manner [47]. 2) The reduction of data dimensionality might cause relative information disappearance [49].

	3) Require small storage database as only the trainee images are kept in the form of their projection on a reduced basis [47].	
Fast Fourier Transform	1) Able to capture waveform in a relatively short time [50]. 2) Appropriate tool for processing waves that are composed of some combination of cosine and sine waves [51]. 3) Able to minimize the calculations of redundant events [52].	1) Less useful tool for non- stationary signal processing (non-stationary signal is a signal that has property changes) [53]. 2) Sensitive to the existence of large noise in dataset, and it does not have shorter duration data record [54]. 3) Does not have fine spectral prediction and cannot be used for analysis of short signals like EEG [54].
Spectral entropy	1) Adapt to normal distributions [55].	1) Aggregation might cause data loss [56]. 2) No explanation regarding temporal relationships between different values extracted from a time series signal [57].
Approximate entropy	1) Able to withstand interference and noise [58]. 2) Stable estimation with short series of noisy data [59]. 3) Able to differentiate a number of systems like periodic and multiple periodic systems and chaotic systems [58]. 4) Good tool for random signal, certain signal and their combinations [60].	1) Heavily dependent on the input signal length. Short length signals result to a lower value than predicted [60]. 2) Susceptible to strong noises [59]. 3) Low calculation efficiency [59]. 4) Lack of results consistency for different values of phase space dimensions, *m* and similarity tolerance, *r* [59].
Sample entropy	1) Its usability on short data sets with noise [61]. 2) Its functionality to separate large system variations [61]. 3) Great performance in result consistency [60]. 4) Does not contain self-matches to calculate the probability [60]	1) Low calculation efficiency [62]. 2) Poor consistency of entropy values for the sparse data [63].
Fuzzy Entropy	1) Not sensitive to background noises [64]. 2)Great sensitivity to the dynamical changes in the information content [65].	1) Low calculation efficiency[62].
Wavelet entropy	1) Able to determine any fine change in a non-stationary signal [66]. 2) Good noise elimination [66]. 3) No pre-determined parameters [66].	Requires to select a proper mother wavelet [54].
Autoregressive	1) Able to distinguish short-term EEG spectrum with its sensible accuracy [67]. 2) Parameters are estimated by simple algorithms [67]. 3) Able to provide more details on spectrum data [67]. 4) Provides smooth interpretable power spectrum [67].	1) Difficult to select the model order in AR spectral estimation [54]. 2) Inappropriate estimated model and incorrect model's orders selection will cause bad spectral estimation [54].

Table 4 Summary of Pros and Cons of Signal Classifier Techniques

Extraction Technique	Pro(s)	Cons(s)
Random Forest	1) Reduce overfitting problem in decision trees and minimize the variance which is good to improve the accuracy [68]. 2) Automatically handle mixed types of missing data [68]. 3) The classification is robust to partial occlusions [69].	1) Complexity: Generate a large number of trees in a forest and combines their outputs. To accomplish this, this algorithm needs more computational power and resources [70].
Support Vector Machine	1) Efficient to obtain high generalization performance, as it uses an induction principle known as structural risk minimization (SRM) principle [71] 2) Able to handle large and dynamic data sets without suffering overfitting condition [72]. 3) Do not require features reduction to avoid overfitting [72]. 4) Provide a technique known as kernel function to fit the surface of the hyper plane to the 1704 data. [72].	1) Longer learning period for a large scale of data [73]. 2) Multi-class classification requires a combination of SVMs as it is originally a model for the binary-class classification [74].
Neural Network	1) Ability to work even when the input data set is corrupted due to missing values and noise. The trained network is capable to fill the values without affecting the prediction [75]. 2) Ability to exhibit a certain amount of fault tolerance. The presence of one or more corrupted cells does not affect its performance in defining task properly [76].	1) Need extra hardware to operate like processors with parallel processing power, in accordance with their structure [77]. 2) Does not provide details on why and how the network produces a probing solution [77]. 3) No specific rule for evaluating ANN structure. Proper network structure is achieved through 2 indictors; a) experience and b) trial and error [77].

4.1 Principle Component Analysis (PCA) and Radial Basis Function (RBF) neural network

A study presented a principle component analysis (PCA) to reduce a large EEG signals dataset and radial basis function (RBF) neural network to classify the data into two driving status (fatigue vs. alert) [37]. In the application of EEG signal processing, large datasets are increasingly common and difficult to interpret. PCA is one of the most promising tools to reduce the dimensionality of large datasets, allowing great features interpretability without causing information loss [78] and minimizing the complexity of signal feature extraction and classification [79].

RBF is a type of neural network [80]. Recently, a great number of researchers have investigated RBF as a meaningful classifier due to its linear-in-the-parameters network structure and great non-linear approximation ability. Few studies presented that the RBF-based classification approach outperforms competing techniques in terms of classification accuracy for epileptic seizure classification in comparison with other five classifiers [81, 82]. This result is in agreement with a study as the author acquired better performance in mental fatigue estimation utilising RBF kernel-based support vector regression in comparison with other kernel functions [83]. The RBF network is a single hidden layer feedforward neural network greatly dependent on several key parameters like the number of the hidden nodes, number of centre vectors, width and output weights. The parameters can be predicted by using the current global optimization technique [84, 85]. However, optimization of high number of network parameters require pricey computational cost and poor convergence and further result to bad classification accuracy. Therefore, the author developed a two-level learning hierarchy RBF neural network (RBF-TLLH) to optimize the key network parameters. The recommended techniques acquire a higher classification performance of 92.71% [37].

4.2 Principle Component Analysis Network (PCANet), Fast Fourier Transform (FFT) and Support Vector Machine (SVM)

A study proposed similar method by incorporating the PCA with the principle component analysis network (PCANet) technique as the feature extraction and support vector machine (SVM) as classifier in the classification of awake and fatigues states for six participants [38]. The experimental results demonstrated great classification performance of fatigue detection up to 95%. PCANet is excellent in classification task as it automatically extracts features from multichannel EEG data based on the deep learning method instead of extracting handcrafted features in conventional approaches [86]. However, large dimensionality of input data might cause dimension explosion which increases computation cost and complexity. Therefore, the author proposed to minimize the EEG sample dimensionality by employing PCA prior to the PCANet processing.

SVM is a supervised training algorithm that analyse data and recognize pattern for classification and regression analysis. The aim is to determine the optimal decision surface in space so that different sorts of data can be divided on both sides of the decision surface for classification [80]. A study investigated two disadvantages of SVM [74]. First, this classifier is originally a model for the binary-class classification, hence a combination of SVMs for the multi-class classification is recommended. However, it does not provide a significant improvement as much as in the binary classification. Second, other approximate algorithms are required as the SWM needs longer time to analyse large dataset. The use of approximate algorithms is effectively minimizing the computation time, yet deteriorating the classification performance. To encounter the problems, the author proposed to use a combination of several SVMs to enhance the classification performance. The SVM ensemble method was originally proposed by [87]. The author employed the boosting method to train each individual SVM and took another SVM for combining various SVMs. A study demonstrated a great classification accuracy as the proposed SVM ensemble with bagging or boosting outperforms a single SVM [74]. Meanwhile, another research investigated non-intrusive technique to monitor driver fatigue by exploiting the driver's facial expression by using SVM for classification purposes where high recognition rate of 95.2% was produced. The data were classified into two possible driver states; normal state and drowsy state [88].

A study investigated the fatigue accuracy detection system for high-speed train safety utilising SVM as the classifier and fast fourier transform (FFT) to extract the features, where 90.7% fatigue detection accuracy was obtained [39]. FFT is an extremely useful automated technique for EEG data analysis, as it categorizes the signals into five frequency bands; delta (0- 4Hz), theta (4-8Hz), alpha (8-13Hz), beta (13-30Hz) and gamma (30-100 Hz) that contain major characteristic waveforms of EEG spectrum [89] as shown in Table 5. A study successfully extracted the statistical features within the standard range of frequency bands; alpha (8-13Hz), beta (14-26Hz), delta (0.4- 4Hz) and theta (4-7Hz) [90]. A group of researcher used FFT to derive two statistical features (spectral entropy and spectral centroid) over four frequency bands namely alpha (8 Hz - 16 Hz), beta (16 Hz - 32 Hz), gamma (32 Hz - 60 Hz) and alpha to gamma (8 Hz - 60 Hz) [91].

Delta and theta bands are ignored in this study due to too low frequency range and insufficient information regarding emotional condition changes during wakeful states. Regardless of its capability to provide accurate and efficient result, this technique does not have excellent spectral resolution and is not recommended for analysis of short EEG signals [54, 92, 93]. A study compared the FFT and the autoregressive (AR) based on their power spectrum [92]. The author monitored two waves that indicated alertness condition; alpha wave (14 Hz) and beta wave (28 Hz), showing that AR technique outperforms the FFT in delineating the epilepsy region which can be visually observed and noticeable. In addition, the detection time in determining seizure onset by AR is far better than FFT method.

Table 5 Brain Wave Frequencies With Their Characteristics [94]

Type	Frequency, Hz	Physiological Condition
Delta, δ	0-4	Deep rest, sleep
Theta, θ	4-8	Deeply relaxed, inward focused
Alpha, α	8-13	Very relaxed, calm, passive attention
Beta, β	13-30	Alert, anxiety dominant active, focus

4.3 Entropy and Random Forest

Recently, a great number of researchers have studied the application of entropy-based algorithms for feature extraction method. Entropy is a nonlinear technique that evaluate the degree of regularity or predictability in a given system. This characteristic allows it to be used for measuring the level of chaos of nonlinear series data, and is deemed useful to determine the variation for normal and abnormal brain signals [95]. Lately, entropy has been widely employed in the analysis of EEG signals because EEG signal is an unstable, complex and nonlinear signal [96]. A number of information entropies are useful for EEG analysis, such as spectral entropy (PE), approximate entropy (AE), sample entropy (SE), wavelet entropy (WE) and fuzzy entropy (FE). These entropies are extensively used for quantification in the cognitive analysis of EEG signals in various mental and sleep conditions, making that entropy index a rather preferable technique for EEG analysis [41].

A study investigated the use of a single entropy of WE and PE to extract the EEG features and SVM for classification where they achieve 90.7% and 81.3% detection accuracy respectively [43]. Another research applied different entropy of FE and used same classifier of SVM [44]. The author successfully achieves 85% of detection accuracy. Recently, scholars studied the implementation of combined entropy analysis approach, which may be a promising application for improving the fatigue detection accuracy capability. A group of researchers studied the performance of multi entropies (PE+AE+SE+FE) to extract the feature and SVM as the classifier where great detection fatigue accuracy of 98.75% is achieved [41]. A study investigated the performance of multi entropies (PE+AE+SE+FE) and single entropy using random forest as the classifier based on O1 channel [40]. The result showed that combined entropies achieved best detection accuracy of 97.5% compared to the single entropy.

Random forest is an ensemble of decision trees, often trained with the bagging technique and utilized Ensemble Learning algorithm to make predictions. It builds numerous decision trees on the subset of the data and merges the trees outputs together to reduce overfitting problem and also minimizes the variance and therefore get a more accurate and stable prediction [97]. Selecting number of trees is one of the significant parameter optimization in random forest algorithm [98]. However, the related literature provides little or no directions on how many trees should be built to compose a Random Forest [70]. The general idea of the bagging technique is that a large number of trees must be built to obtain a better generalization performance [97]. However, a large number of trees require much more computational power and resources. A research investigated the effect of different number of trees (5, 10, 15, 20 and 25) on the dataset [98]. The author found that changing number of trees has no remarkable effects on mean accuracy of the Random forest, however, the computation time to train the model has increased significantly.

4.4 Autoregressive (AR) and Bayesian Neural Network

A study employed the combination of autoregressive (AR) to extract the EEG feature algorithms of forty-three healthy volunteers and Bayesian neural network (BNN) to classify the two-state outputs classification (fatigue state vs. alert state) [46]. The experimental results showed an excellent sensitivity of 89.7%, a specificity of 86.85 and an accuracy 88.2%. AR uses a parametric technique to estimate the power spectrum density (PSD) of the EEG, resulting to no spectral leakage issues and thus yield better frequency resolution unlike nonparametric method [54]. Therefore, AR method has been widely utilized in EEG analysis as an alternative to other nonparametric method like Fourier-based approach [99] due to its ability to model the peak spectra of EEG signals, efficient for resolving sharp changes in the spectra [46] and being applicable to short segments of EEG data [100]. However, determining correct AR's modelling order number in spectral estimation presents a critical problem [54, 100]. A proper selection of AR model order number will determine the signal complexity and sampling rate. Once the order is too low, the result will produce smooth spectra where the whole signal cannot be captured in the model. Meanwhile, too high model number will increase noise, resulting in unreliable representation of the signal [54, 100].

Hence, identifying AR's model order is a vital process as its performance can influence EEG signal analysis and classification. A study investigated the conventional method of AR order estimation in EEG-based BCI studies by assessing a hypothesis whether an appropriate mixture of multiple AR orders provide a better representative of the true signal compared to single modeling order [100]. The author used two mechanisms to determine appropriate mixture of modeling orders; (1) Evolutionary-based fusion (2) Ensemble-based mixture. The AR-mixtures are then assessed against three conventional methodologies to determine its classification performance: (1) modeling order (2,4,6,8,10,16 and 30) proposed by the literature on similar experimental conditions (2) conventional modeling order estimation methods which include Bayesian Information Criterion (BIC), Final Prediction Error (FPE) and Akaike Information Criterion (AIC) (3) blind mixture of AR features acquired by a series of well-known modeling orders [101]. The considered methodologies are then assessed by five-well-known datasets from BCI competition III that comprise 2,3 and 4 motor imagery tasks. The hypothesis was approved and ensemble-based modeling order and evolutionary-based order fusion methods were recommended to determine the adequate mixture of modeling orders.

The Bayesian is neural network type. This is a non-linear classification technique that is able to solve problems in domains where data are scarce, as a method to mitigate overfitting [102]. This network also acts as an excellent knowledge representation and reasoning technique under conditions of uncertainty [103]. This system is capable to reason on the basis of incomplete input data, hence, beneficial in resolving the issue of uncertainty knowledge representation and enhancing the validity for the expert system inference. Nevertheless, learning a Bayesian network from data within the domain is pricey due to consideration of large number of variables [104].

5. CONCLUSION

This paper presents a literature survey of existing integration techniques that are being used to analyze EEG signals at feature extraction and classification stages in fatigue monitoring and detection applications. A reliable technique for feature extraction is necessary to achieve robust classification of signal. Meanwhile, a robust method for classification stage will determine the accuracy to classify the features to a particular group of brain states. Comparison tables of pros and cons of each technique for both steps are presented to help future researchers to choose a suitable extraction technique and classifier for EEG data processing. The integration of combined entropy (feature extraction) with SVM and ANN (classifier) offers the highest fatigue detection accuracy of 98.7% and 96.5~99.5% respectively. Hence this combination technique can be further explored in extracting and classifying the EEG signal for driver fatigue detection and monitoring analysis.

Incidentally, most of the studies related to feature extraction and classification using EEG have been conducted by using driving simulators rather than on a real road. EEG is a method of high temporal resolution and its signals are prone to be spoiled by undesired noise which will result in various artifacts or inaccuracies. The presence of these artifacts shall deteriorate the EEG signal performance to evaluate the driver fatigue [105]. Ease of experimental control makes driving simulators an effective research tool compared to driving on a real road where the environmental and irrelevant traffic sounds will contaminate the EEG data [106]. Therefore, the methodology of extracting high-quality EEG signals and accurately classifying the EEG signals under real road conditions require further research.

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