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DETECTION OF MENTAL FATIGUE IN DRIVERS USING EEG APPLICATIONS

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Abstract

One of the most prevalent human illnesses is mental weariness, which is brought on by too much labour and too little sleep, both of which may deplete one's intellectual capacity. The detection of mental weariness has been researched using several EEG characteristics. In order to define mental exhaustion and provide an overview of prospective EEG aspects that may be connected to mental fatigue, this research analyses human EEG patterns for safe driving behaviour. A narrative review technique is used for explaining the neuronal activity of the human brain during mental exhaustion. Discussed are specific EEG characteristics related to driving activities, relationships with various EEG band waves, and feature extraction techniques. According to this early research, most studies tend to attribute the driver's mental tiredness to an increase in parietal alpha power. For our first analysis, we looked through public

EEG libraries to find prospective data sources. Finally, we provide a conceptual framework that may be used to recognise mental fatigue. Finally, future research may focus on identifying other EEG variables that are more crucial for generalisation across study circumstances.

Keywords: EEG, Modelling, Neural, Cognitive.

I. Introduction

According to World Health Organization (WHO) statistics, 1.2 million people died from traffic-related injuries in 2010, highlighting a major worldwide public health concern. When compared to other elements like vehicle conditions and environmental factors, such as exhaustion, previous research has shown that human factors like fatigue play a substantial role in traffic accidents. According to new research, physiological and psychological issues associated with exhaustion are among the things that might cause catastrophic accidents because they impair a driver's ability to see, hear, make decisions, and pay attention [1].

Physical and mental weariness may be distinguished in the literature on driving safety. Different fundamental systems control physical and mental energy. Overworking one's muscles may lead to physical exhaustion, stiffness, and tension in the muscles [2]. A person may be physically weary from high-intensity exercise and find it difficult to run, lift, or play, yet his alertness and focus may still be unaffected. In reality, the majority of studies have shown that exercise either improves mental ability or, more often, has little to no effect. On the other hand, mental fatigue could compromise physical capability [3]. Studies in the past have shown that cognitive load in the human brain may decrease efficacy in carrying out certain activities and result in diminished attention. Therefore, concentrating on mental exhaustion rather than physical fatigue is more beneficial [4].

Electroencephalogram (EEG) monitoring of brain signal activity may aid in explaining variances in the driver's performance. High temporal resolution, portability of the EEG equipment, and non-invasive recording are benefits of employing EEG for monitoring driver reactions. Due to the aforementioned benefits, EEG is often utilised in clinical and psychiatric research to examine patients' cognitive states, sleep patterns, and brain diseases. Recent EEG research has focused on neuromarketing and brain-computer interfaces, among other new EEG applications. The availability of suitable EEG devices and greater computational power for studying human EEG are the key drivers of these developments [5].

This essay identifies and discusses the signs of mental fatigue in the next section. It also explains the fundamental aspects of the human EEG and how these results might be examined in relation to traffic situations. Following these methods of study, reviews of EEG characteristics related to mental weariness are conducted. The paper's findings of comparable EEG patterns throughout the investigations serve as its conclusion.

II. Literature Survey

2.1 Occurrence of mental fatigue

One of the most prevalent human illnesses is mental weariness, which is brought on by too much labour and too little sleep, both of which may deplete one's intellectual capacity. The phrases "sleepiness," "drowsiness," and "tiredness" are commonly used interchangeably in the literature on road safety since they are all seen as signs of weariness [6].

Numerous driving fatalities brought on by mental exhaustion have been reported in previous studies. 3.9% of incidents involving 9,200 drivers in Norway were sleep-related, although almost 20% of night-time accidents involved drowsy drivers. In the United Kingdom, 7.3% of accidents had "tiredness" as their primary contributing cause [7].

One of the reasons that might cause catastrophic accidents, according to new research, is the physiological and psychological issues associated with exhaustion, which can impair a driver's eyesight, hearing, decision-making, and concentration. The efficiency of cognitive functioning will decrease with time, and this psychobiological condition is known as mental fatigue. According to seminal research, mental tiredness is a state that develops as a result of constant and cumulative mental strain that may result in lethargy, distraction, and poor focus [8].

Mental weariness also has an impact on how our brain processes information, which results in poor focus, a lack of mental control, and even choice or action mistakes. A person who is mentally exhausted has less desire to finish a task, has a disruption of cognitive abilities, and is more likely to feel bad emotions as a consequence of poor behaviour and decision-making [9].

These disabilities are more prevalent and have resulted in fatal accidents all around the globe . The signs and symptoms of mental weariness are shown in Figure 1.

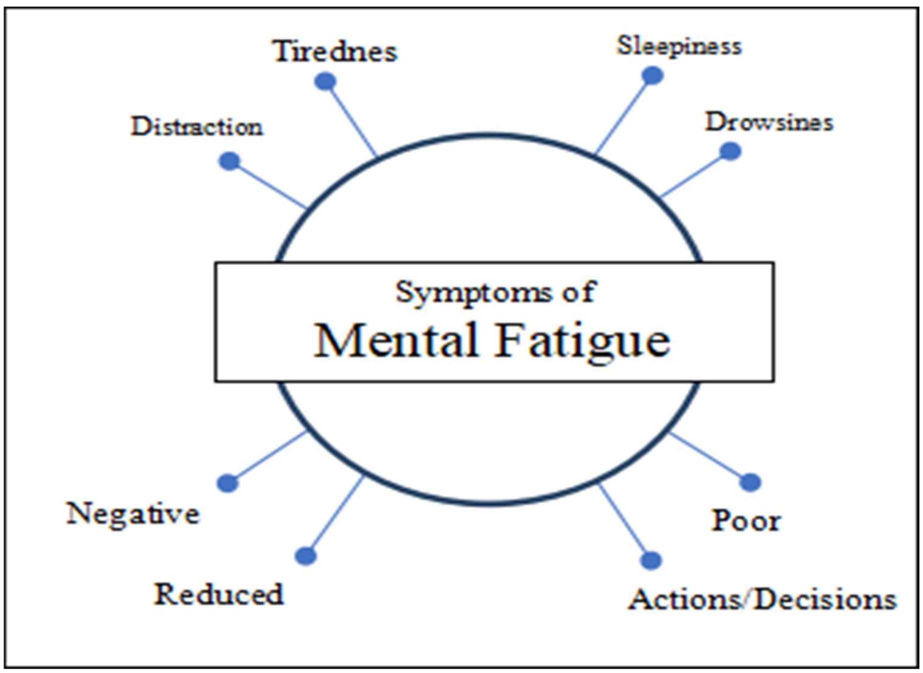

Figure 1. Symptoms

III. ELECTROENCEPHALOGRAM

One well-established method for identifying brain activity is an electroencephalogram. The foundation of EEG is the detection of the electrical activity of the human brain, which is brought on by neuronal firing during stages of cognition [10]. The brain is normally near to the sense organs at the top of an animate body. The cerebral cortex contains between 15 and 33 billion neurons, each of which is synoptically linked to thousands of other neurons [11]. These neurons may communicate with one another thanks to lengthy protoplasmic fibres called axons, which transport action potential trains to various locations throughout the body or brain and target certain recipient cells [12].

In essence, the human brain is a complicated structure that can link to and interact with various body systems, including the neurological system, the respiratory system, and the muscular system. Together, these systems make up the body's overall structure. In essence, the brain plays a critical role in assessing, coordinating, and directing human behaviour [13].
EEG is basically "the writing and drawing of electrical impulses emanating from the human scalp," according to researchers. Electrodes may be positioned on the scalp of a person to record these impulses. A typical EEG recording may be made using a variety of 16, 32, or 64 channel setups [14].
The rhythmic wave patterns of the alpha, beta, gamma, delta, theta, kappa, lambda, and mu waves may be used to describe EEG data. Theta, beta, delta, and alpha have all shown to be the most dependable and stable in terms of recurrence [15]. In a growing brain, as opposed to an adult brain, these wave patterns are characterised by a variety of frequencies and EEG activity [16]. The usual adult EEG frequency is 10 Hz, but the typical new-born frequency is between 3 Hz and 7 Hz [17].

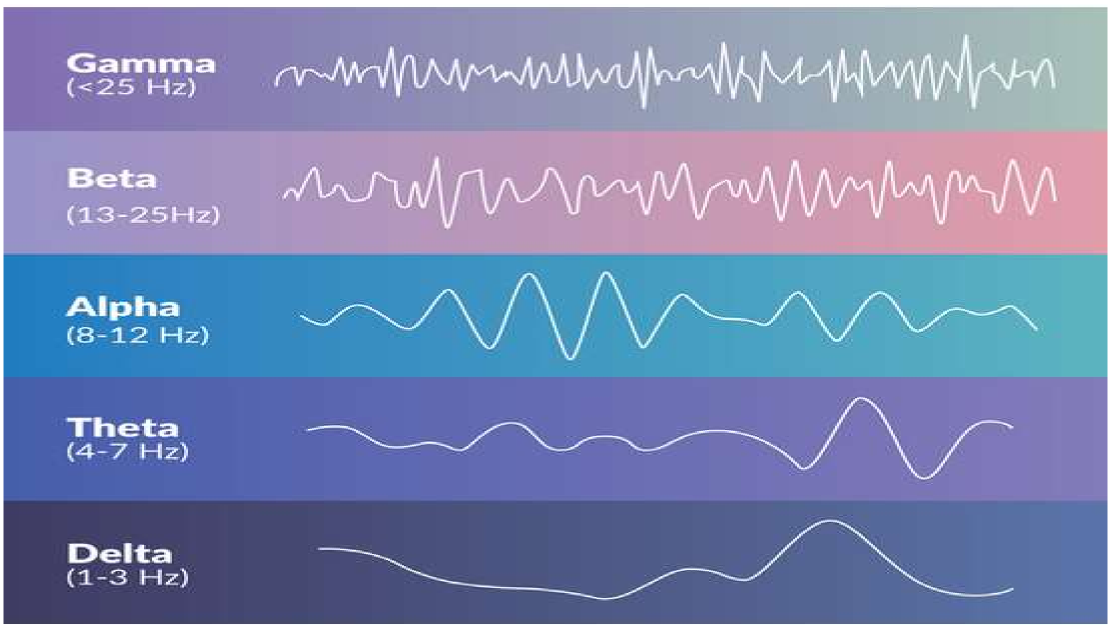

Figure 2. EEG Waveforms

By examining the human EEG, it is possible to comprehend the connection between different cognitive states and a subject's corresponding brain dynamics. Depending on the degree of mental weariness experienced by the driver, lower cognitive activity efficacy may be seen as task difficulty levels rise [18].
As a result, the effectiveness of Long-term cognitive activity use will somehow impair decision-making and information analysis, impairing drivers' ability to maintain focus and see clearly [19].

Analysis of mental fatigue

Both qualitative and quantitative techniques may be used to identify the EEG characteristics of mental weariness. Event-Related Potentials (ERPs), which are unique EEG measurements, are generated after eliciting events by sensory or cognitive stimuli, are used in qualitative EEG [20]. A skilled neurologist typically examines the ERP visually. Computers are used in more recent investigations to help with finer-grained ERP analysis. However, the fundamental drawback of ERP analysis remains to be the need for a longer data sweep for noise averaging [21].

Comparatively, quantitative EEG (qEEG) analyses EEG data using a variety of computational tools that include several mathematical and statistical methods. Spectral analysis and functional connectivity analysis are types of qEEG studies in mental fatigue [22]. "EEG characteristics" refers to values and novel patterns identified using qEEG collectively.

The link between EEG signals in various brain areas is examined via functional connectivity analysis. These connections are measured as synchronisation levels between various locations. Some of the metrics use statistical techniques like coherence analysis and the use of the clustering coefficient [23].

The most popular technique for analysis, known as spectral analysis, is breaking down EEG time series into the frequency domain to get the spectrum of the EEG signals [24]. In most cases, Fourier Transform (FT) application is necessary to provide the related frequency bands as mentioned in Section 3 above. A FT's main principle is that a complicated function, like the one shown in the unprocessed EEG waves, may be represented by the sum of many simple functions [25]. Each sub-spectral band's power at each sensor may be computed. One power value for each frequency band may be obtained by computing the total power value across all sensors [26]. As a result, the alpha band power at each sensor points or the alpha band power throughout the whole scalp may be recorded. Results may alternatively be shown in terms of absolute power or relative power [27]. The ratio of band power in a frequency band over all other bands is known as relative power. Machine learning methods were further utilised in several of the research to further examine the causal links between the retrieved characteristics and EEG readings 28].

IV. EEG Feature for Mental Fatigue Detection

In, brain signals were collected utilising a 64-channel, 10-20 International standards device. At first, the EEG's electrode impedance was set below 10 k, and the sampling frequency was 512 Hz. For faster processing, the signal was down sampled from 512 Hz to 256 Hz without significantly losing the essential data. The band-pass filtering between 1 and 40 Hz was done using a FIR filter. Later, using the Phase Lag Index, a weighted connection matrix was created (PLI). Graph theory seems to be the optimum method for the network, according to analysis findings, and the connection network build will be too complicated for useful biomarkers to be seen [29].

Another investigation aimed at identifying mental weariness used 64 channels of the 10-20 International system to assess EEG data. In this experiment, 10 K electrode impedances were maintained throughout all of the trials at a sampling rate of 512 Hz. The EEG signal was down-sampled from 512Hz to 256Hz. An FIR filter with a cut-off bandpass frequency of 1 to 40 Hz was used for filtering. Using FFT, the filtered data were recovered for the delta, theta, alpha, beta, and lower gamma frequency bands. The intensity of each feature in connection to tiredness was evaluated for the regression procedure using Random Forest (RF) [30].

According to the standardised placements of FP1, FP2, F7, F3, Fz, F4, F8, FC3, FCz, T3, C3, Cz, C4, T4, CP3, CPz, C4, T5, P3, Pz, C4, T6, O1, Oz, and O2 in [25], EEG signals were monitored using a 26-channel Quick cap. The average of A1 and A2 was used as the reference, and the sampling frequency was 500 Hz. To lessen the dimensionality of the data, Principal Component Analysis (PCA) was employed as the filter. Power spectral density (PSD) was used to extract EEG characteristics, which were then reported based on the delta, theta, alpha, and beta EEG frequency bands. The trapezoidal rule of numerical integration served as the foundation for the determination of the PSD value.

In the research investigation, a portable 16-channel signal amplifier with a USB amp was employed. 256Hz sampling rate and 24-bit quantization with active electrodes were employed for the signal acquisition. The placement of the electrodes on the scalp of the skull is based on 10–20 international placements of the electrodes O1, O2, P3, P4, P7, P8, OZ, FP1, FP2, CZ, FZ, T7, and T8. Fz served as the ground electrode, whereas A2 served as the reference electrode. In order to begin processing the EEG data, a bandpass filter between 0.5 and 60 Hz was used. The AC power frequency was afterwards removed by applying a notch filter to the signal. The absolute and relative powers of the alpha frequency band are calculated for the feature extraction using the Power Spectral Density (PSD) and Fast Fourier Transform (FFT) analysis approaches.

A comparable research by made use of the Emotiv Epoc headset and a 128 Hz sampling rate. The EEG was recorded on 14 channels, including AF3, F7, F3, FCS, T7, P7, 01, 02, P8, T8, FC6, F4, F8, and AF4.

De-noising was accomplished using an integrate pre-processing technique, and power line interference was eliminated using a Butterworth LP filer. Later, a wavelet analysis was performed to calculate the de-noising threshold using 7 layers of demy wavelet. A rhythm wave extraction based on wavelet packet transform was utilised to obtain EEG characteristics.

32 EEG channels were employed in [28] to capture the data at a sampling rate of 2048 Hz. The signal was pre-processed by being resampled to 256Hz. Only 12 channels—F3, F4, Fz, C3, C4, Cz, P3, P4, Pz, 01, 02, and Oz—cover the left and right midline, frontal, central, parietal, and occipital cortical areas of the head in this research. To get rid of movement artefacts, pre-processing was done using a high pass filter applied at 1 Hz. The research employed the S-transform, a Short Time Fourier Transform (STFT) and wavelet transform combination, for feature extraction.

Finally, the EEG Brain AMP system with 32 channels was used to capture the subject's mental tiredness. Signals from the EEG were captured at 500 Hz and referred to Acticap. In this experiment, a Common Spatial Patter (CSP) filter was employed to filter the bandpass, which is between 1 and 40 Hz. The average power in the EEG signal corresponding to five frequency bands—delta (1-4Hz), theta (4-8Hz), alpha (8-12Hz), beta (12-30Hz), and gamma—was estimated using Welch's power spectral density estimation (30–40 Hz).

V. DATASET OF EEG FOR MENTAL FATIGUE

At the time of our study, we were unable to locate any publicly available EEG dataset that was explicitly on EEG and driver mental tiredness. We looked through three data sources: Kaggle, UCI Machine Learning, and Physio bank. There was no result with the first keyword search for "(mental weariness) and (eeg or brain signal). In order to increase the percentage of the results, the keywords were condensed to "mental tiredness" based on the works of Petti crew and Roberts. The modified keywords produced no results from UCI Machine Learning or Physio bank, however three datasets from Kaggle were obtained. Further research revealed that none of the three datasets had EEG data or driving situations Burnout and resource allocation are two linked terms that should be further researched, according to the dataset descriptions.

Table 1. Data Repository

Data repository	**Keyword's search**	**No of results**
Kaggle	(Mental fatigue) and (EEG or brain signal)	0
	mental fatigue	3
UCI Machine Learning	(Mental fatigue) and (EEG or brain signal)	0
	mental fatigue	
Physio bank	(Mental fatigue) and (EEG or brain signal)	0
	mental fatigue	

Table 2. Dataset

Dataset descriptions	**Type of data**
Employees burnout during Covid-19	Psychometric questionnaires and scales
Mental fatigue, resource allocation, employee burnout	Psychometric questionnaires and scales
Covid-19 data	Psychometric questionnaires and scales

VI. Proposed Conceptual Mode

The conceptual model for our study, based on our early results, is shown in Figure 2. Various driving situations will be used to collect data using a 19-channel DABO EEG equipment. We use artefact rejection during the EEG pre-processing to get rid of eye and muscular movements. Next, we use a bandpass filter to extract EEG signals at different frequencies, including the delta, theta, alpha, beta, and gamma bands. We use signal averaging to get the event-related potentials during the feature extraction step (ERP). These characteristics will be put via binary logistic regression and SVM classification to determine if conditions exist for mental exhaustion or not.

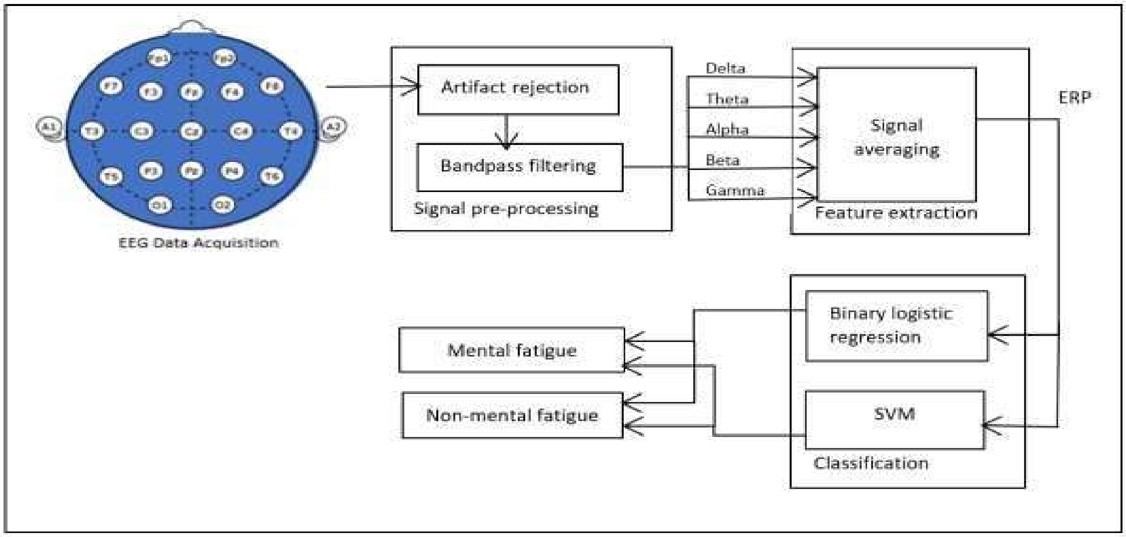

Figure 3. Conceptual Model

VII. Result analysis

EEG spectrum analysis seems to be the most often used method in the research under evaluation for identifying mental exhaustion in EEG drivers. The rise in alpha power or relative power, particularly in the parietal areas, is where the most consistent results are to be found. Even with only one sensor, spectral analysis is simple to perform and analyse.

However, as various research settings might have an impact on alterations in the alpha band, generalisation must be done with caution. Since just one research was included in this review, it is difficult to determine how distinct network regions and the reported signal of a tired brain relate in the context of functional connectivity. But it's fascinating to notice that, similar to spectral analysis, functional connectivity analysis identifies the parietal area as meriting more study.

Additionally, we searched three open EEG sources and discovered that all the datasets returned included psychometric tests and scales. As a result, the conceptual model that is being suggested includes the collecting of EEG data from human participants under various driving circumstances and activities. For the purposes of determining the circumstances of mental exhaustion and non-mental fatigue conditions, signal pre-processing, feature extraction, and binary classifications were suggested.

VIII. Conclusion

In conclusion, by detecting distinct EEG patterns in connection to mental exhaustion, the reviewed research provides intriguing insights into understanding the brain's cognitive functions. Although generalisations cannot yet be made because of technical issues including a particular research design used with small sample numbers, several patterns were specifically observed in the parietal alpha. Additionally, the majority of studies do not include any drug usage that can influence their EEG characteristics.

Numerous analytic techniques pointed to the great value of human EEG in detecting driver mental weariness. More EEG characteristics of greater relevance, according to the available literature, need to be studied. A novel EEG-based mental tiredness indicator that aids drivers in decision-making and ultimately lowers traffic fatalities may be developed with the use of new analytic techniques.

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