An EEG-based Cognitive Fatigue Detection System

Enamul Karim*
Hamza Reza Pavel*
enamul.karim@mavs.uta.edu
hamzareza.pavel@mavs.uta.edu
University of Texas at Arlington
Arlington, USA

Ashish Jaiswal
University of Texas at Arlington
Arlington, USA
ashish.jaiswal@mavs.uta.edu

Mohammad Zaki Zadeh
University of Texas at Arlington
Arlington, USA
mohammad.zakizadehgharie@mavs.uta.edu

Michail Theofanidis
University of Texas at Arlington
Arlington, USA
michail.theofanidis@mavs.uta.edu

Glenn Wylie
Kessler Foundation
West Orange NJ, USA
gwylie@kesslerfoundation.org

Fillia Makedon
University of Texas at Arlington
Arlington, USA
makedon@uta.edu

ABSTRACT

Mental or Cognitive fatigue (CF) is the exhaustion of the neurological system brought on by prolonged cognitive tasks. It causes performance to decline in day-to-day life. Throughout this paper, we present an experimental setup where we artificially induce cognitive fatigue to participants. During the experimental process, we collected electroencephalogram (EEG) signals from the subjects that participated in the experiment. The goal of the study is to detect the presence or absence of cognitive fatigue. Our proposed solution was able to classify cognitive fatigue of the subjects with an accuracy of 88.17%.

CCS CONCEPTS

• **Computing methodologies** → **Machine learning**; • **Communication hardware, interfaces and storage** → *Signal processing systems*; *Sensors and actuators.*

KEYWORDS

Cognitive Fatigue Detection, Task engagement, N-back task, EEG, EEGNet, Deep Learning Approaches

ACM Reference Format:
Enamul Karim, Hamza Reza Pavel, Ashish Jaiswal, Mohammad Zaki Zadeh, Michail Theofanidis, Glenn Wylie, and Fillia Makedon. 2023. An EEG-based Cognitive Fatigue Detection System. In *Proceedings of the 16th International Conference on PErvasive Technologies Related to Assistive Environments (PETRA '23), July 05–07, 2023, Corfu, Greece.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3594806.3594848

1 INTRODUCTION

Cognitive fatigue is a common phenomenon caused by prolonged and demanding cognitive activity [12]. It is a weariness that develops over time and reduces an individual's energy, motivation, and concentration, leading to several issues, including human errors and a decline in performance in everyday life if not identified and dealt with effectively. Moreover, it has been demonstrated that mental fatigue has a detrimental impact on many aspects of one's life, including driving [9], athletic performance [32], decision-making [37], hazard perception in cyclists [45], and others. Furthermore, it is usually a primary symptom for multiple severe diseases like Multiple Sclerosis [26], Parkinson's Disease [20], Traumatic Brain Injury [11], etc. Hence, the need for detection of cognitive fatigue in our day-to-day lives is critical.

Most of the time, cognitive fatigue can occur due to intense mental activity that may result in decreased attention and high-level information processing [30]. Early detection of cognitive fatigue can help experts provide targeted interventions. This phenomenon has propelled a rise in the interest of cognitive fatigue detection. There have been several attempts to assess cognitive fatigue with various approaches. Most published research identifies cognitive fatigue using subjective user surveys instead of a well-defined objective measure [28, 35]. An emerging, alternative avenue for improving our ability to assess health-related quality of life (HRQoL) is to use objective data usually collected via sensors to create alternate measures of relevant characteristics and traits [14]. In the recent past, researchers have tried integrating physiological sensors in their experiments to understand and analyze cognitive fatigue [22, 23]. The efforts to automate the detection of fatigue using sensors have been promising as authors have tried to correlate the objective signals from the sensors to the self-report subjective scores from the participants.

This paper explores the relationship between self-reported, non-pathological cognitive fatigue and physiological multivariate time-series data acquired from a wearable commodity EEG sensor device in healthy subjects. Machine learning and deep learning approaches have been developed for time series classification such as Long short-term memory (LSTM), Recurrent Neural Network (RNN), and Convolutional Neural Networks (CNNs). The major contributions of our work are defined as follows:

- A novel experimental setup to induce cognitive fatigue while recording EEG data.
- A dataset collected from 21 healthy subjects.
- Analysis of existing ML models to classify whether a subject is cognitively fatigued or not using EEG signals.

*Both authors contributed equally to this research.

PETRA '23, July 05–07, 2023, Corfu, Greece

ACM ISBN 979-8-4007-0069-9/23/07.
https://doi.org/10.1145/3594806.3594848

The rest of the paper is organized as follows: Section 2 discusses the related work. Section 3 explains the experimental setup. Sections 4 and Section 5 deal with the steps involved in data collection and data annotation for the experiment, respectively. Section 6 addresses signal preprocessing, while Section 7 introduces the problem statement and methodology. Section 8 discusses the results followed by the conclusion and future work in Section 9.

2 RELATED WORK

Over the years, several human factors such as facial expressions [24], [34], speech [25], gait [33], physiological indicators like electroencephalogram (EEG) recordings, and dermal resistances [15] have been used to detect fatigue. However, non-physiological indicators such as facial expressions are not always reliable since they rely on people's lifestyles and ethnic origins. Moreover, vision-based fatigue detection from facial expressions presents certain difficulties such as the lighting conditions of the surroundings and tracking multiple non-rigid objects [18]. On the other hand, temperature and humidity can have an impact on physiological responses such as dermal resistance.

In the last few decades, a variety of techniques have been employed to detect cognitive fatigue. Some studies concentrate on predicting cognitive fatigue using the fMRI data that were gathered while patients were performing cognitive activity [44]. Many researchers have attempted to detect cognitive weariness in vehicle drivers. In [36], the authors have applied the K-means algorithm to detect cognitive fatigue of the drivers from the collected skin conductance (SC), oximetry pulse (OP), and respiration (RSP) data. Research has also been carried out to identify driver fatigue in real driving conditions using a hidden Markov model [16]. Moreover, variations in upper body posture to detect cognitive fatigue has been the subject of few studies [6]. Some researchers have also attempted to detect mental fatigue using eye-tracking data of the elder adults while they were watching videos [43]. Wearable devices have been used in some studies to identify mental fatigue [17]. In other cases, CNN and LSTM have been coupled together to detect cognitive fatigue [41]. However, due to its reputation for being more sensitive and reliable, several researchers have recently shown interest in using EEG data to detect and assess cognitive fatigue [10, 40].

EEG signals are frequently used in biomedical engineering and neurological science research due to their non-invasiveness and low cost. They have previously been utilized for the categorization of emotions [29], stress detection [19], body movement detection [38], and assessment purposes [4]. In the recent past, several EEG-based approaches have been proposed for detecting cognitive fatigue. EEG-based approaches have become one of the most popular methods for identifying CF due to its superior temporal resolution and information richness [21].

3 EXPERIMENTAL SETUP

An experiment was designed and conducted in a way to induce cognitive fatigue among the participants. The entire experimental setup is illustrated in Figure 1.

Our study involved 21 participants out of which 16 were male and 5 were female with an average age of 23.75 years and ages ranging from 21 to 35. The participants were asked to attend two sessions on two different days for the study. They attended a morning session and an evening session. We collected two sessions of data from 15 participants and one session of data from 6 participants.

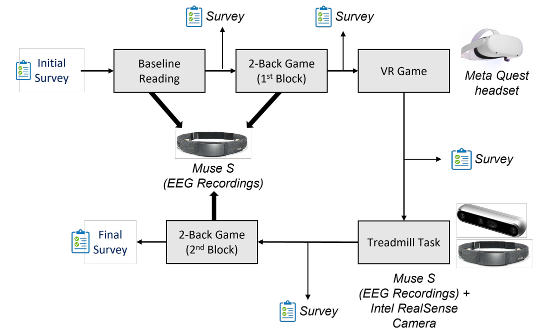

Figure 1: Overall Experimental Setup.

3.1 Human Factors

The initial survey was conducted to gather demographic information about the participants. At the end of each phase of the experiment, the participants were asked to complete surveys using the visual analog scale (VAS) to assess their current state of physical and mental fatigue. They were asked to assess their degree of fatigue on a scale of 1 to 10 depending on how tired/fatigued they felt, with 1 denoting the least and 10 the most amount of fatigue. In total, all the participants had to take part in VAS questionnaires four times. They completed a final assessment after the experiment to rate the different tasks based on how much they contributed to cognitive fatigue.

3.2 Fatigue Induction

In order to induce cognitive fatigue, the subjects were required to complete a number of tasks. The several cognitive fatigue inducing tasks that the participants had to perform are depicted in Fig 3.

The N-back task serves as a sequential cognitive test that evaluates the capacity of a person to hold, modify, and manipulate data in short-term memory. In an N-back task, stimuli are presented on a screen one at a time (Figure 2) and the participants need to determine if each stimulus is the same as the one presented N steps back in the sequence. It is acknowledged by therapists and specialists as a crucial tool for inducing cognitive fatigue since it provides an opportunity to manipulate working memory demand [8]. The 2-back task, which requires the subject to recall the stimulus that occurred two steps back, was used for the study. The participants were randomly displayed one letter at a time on a screen and instructed to respond by pressing the Space Bar of the keyboard as soon as they saw a letter that appeared two steps back. EEG recordings were measured as the subjects participated in the 2-back task.

Virtual Reality (VR) task was also introduced in the experiment to induce cognitive fatigue among the participants. As a part of the VR task, the participants were asked to play two rounds of the Beat Saber game wearing the Meta Quest headset. It is a Virtual Reality rhythm game where the subjects had to move through a

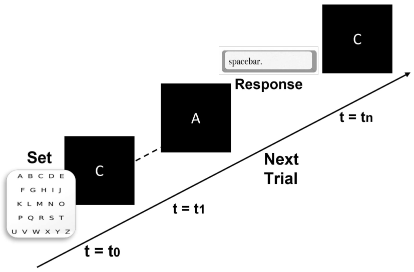

Figure 2: Demonstration of how N-back task is performed.

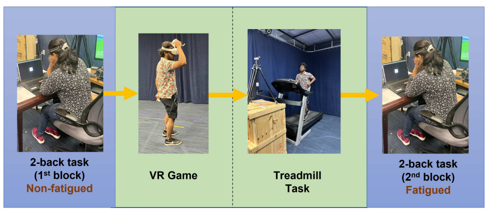

Figure 3: Different tasks performed by the participants to induce CF.

futuristic world [39]. While doing so, they had to slice blocks as they fly towards them unpredictably, and it is their job to destroy the blocks by slicing through them without getting struck.

In order to maximize the fatigue induced, subjects also ran on a treadmill (at a 15 degree incline) for three minutes. Physical fatigue is shown to be related to cognitive fatigue [42]. Finally, the participants had to take part in the second round of a 2-back task where the EEG signals were measured once again using the Muse S headband.

4 DATA COLLECTION

The EEG data were collected using a Muse-S [3] headband. It is a tool that can give feedback on brain activity in real-time. The electrodes in the Muse-S headband are positioned according to the 10–20 electrode positioning system (See Figure 4). It is an internationally recognized method for describing how the scalp electrodes are positioned during an EEG test. The position [7] for the data collection is defined by the designated head points from the left ear (**TP9**), left forehead (**AF7**), right forehead (**AF8**), and right ear (**TP10**), with **Fpz** serving as the reference point .

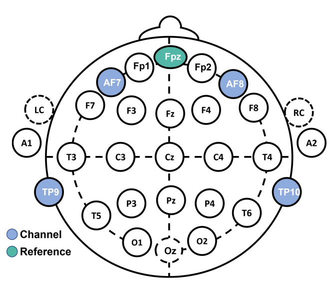

Figure 4: Muse S EEG headband electrodes placements [7].

5 DATA ANNOTATION

According to the findings of the surveys conducted at the end of each phase of the experiment, the participants were more cognitively fatigued after the second round of the N-back task than they were after the first round. The second round of the N-back task left them feeling more fatigued since they had to perform a physical task and play a VR game in between. Both the N-back task and the VR game are effective methods for inducing cognitive fatigue in participants. We labeled the EEG recordings collected during the first block of the N-back task as '*Non-Fatigued*' and those recorded during the second block as '*Fatigued*'. As a result, our task of detecting cognitive fatigue is simplified to a binary classification problem.

6 SIGNAL PREPROCESSING

Brainwaves are an indication of electrical activities happening in the brain. They are often described in terms of frequency bands. The different frequency bands are identified as δ (1–4 Hz), θ (4–8 Hz), α (8–12 Hz), β (12–30 Hz) and γ (30–80 Hz) which are illustrated in Figure 5 [1].

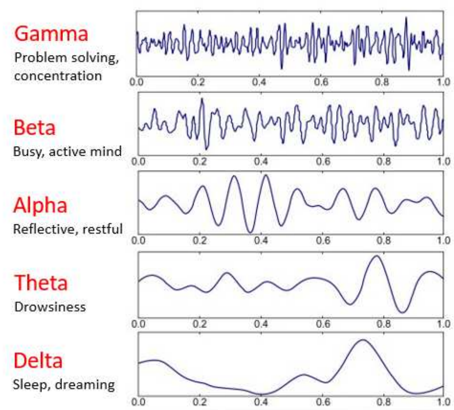

Figure 5: Different Brainwaves [1].

Different brainwaves are related to specific states and have particular functions. For example, delta waves are low-frequency waves that are produced in deep sleep or meditation and are necessary for natural healing and helping to feel completely rejuvenated. Theta brainwaves are also generated during sleep but they are associated with creativity and intuition and indicative of processes associated with memories, emotions, and feelings. Alpha brain waves are produced when the brain is in a relaxed and calm state and not focusing. Beta waves are linked with consciousness and active thinking. Higher brain processes like intellect, problem-solving, and concentration are linked to gamma waves.

We applied Fast Fourier Transform (FFT) to the collected raw data to convert the signals to individual spectral components. FFT is a discrete Fourier transform algorithm used in signal processing that provides useful information about the signals by reducing the complexity of DFT computations [31]. MuseLSL [5] library was utilized to transform EEG data from the four electrodes into values for each of the classic frequency bands (e.g. alpha, beta, delta, theta, and gamma).

7 PROBLEM STATEMENT AND METHODOLOGY

Raw EEG data were converted to individual spectral components using FFT. The EEG recordings were collected using the 4 electrodes connected to the Muse headset. The EEG data from each electrode contained different delta, theta, alpha, beta, and gamma frequency, creating a 20-dimensional input space. The main objective is to determine whether a person is cognitively fatigued or not using different classification techniques.

EEGNet [27] is a small CNN architecture for EEG-based BCIs that can be trained with very little data and used with a variety of BCI paradigms. It provides features that can be interpreted neurophysiologically. An EEG-specific network has been built using Depthwise and Separable convolutions that incorporates a number of well-known EEG feature extraction ideas, including optimal spatial filtering and filter-bank building, while also having fewer trainable parameters to fit. The key advantages of using this model:

- High performance with limited training data
- Limited number of parameters required

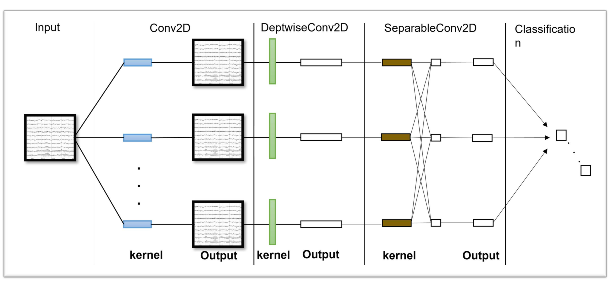

Figure 6: EEGNet architecture [27].

This model efficiently generalizes across several paradigms and performs well even with fewer parameters, indicating a more efficient use of model parameters. An overview of the model can be found in Figure 6. The network initially utilizes a temporal convolution to learn the frequency filters. Then a depthwise convolution, coupled to each feature map separately, is used to learn the frequency-specific spatial filter. The separable convolution that combines the depthwise convolution, is then used to learn a temporal summary for each feature map individually. Finally, a pointwise convolution is employed to classify the input data by learning how to combine the feature maps in an optimal way.

We used several other deep neural network models to see if they could accurately classify whether the participants were cognitively fatigued or not and compared the results to that of EEGNet. We began by implementing a Recurrent Neural Network (RNN) which is a type of neural network that allows prior outputs to be utilized as inputs [2]. Additionally we implemented a Long Short-Term Memory (LSTM) network, a sort of recurrent neural network that can learn long-term order dependencies in sequence prediction problems [13]. Furthermore, we tried to detect cognitive fatigue using a one-dimensional convolutional neural network (1D-CNN).

8 EXPERIMENTS AND RESULTS

The participants were asked to identify the task that caused the most cognitive weariness during the final survey. According to the data gathered from the participants, the VR task caused the highest cognitive fatigue, followed by the N-back and treadmill activities, respectively, as depicted in Figure 7.

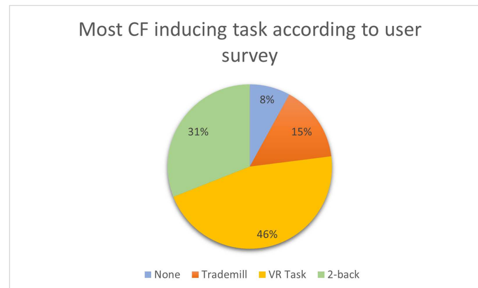

Figure 7: Percentage of CF inducing tasks according to user survey.

The different machine learning models were implemented and analyzed on a system with an Intel Core i7-8750 quad-core CPU, 16GB of RAM, and an NVIDIA GTX 1060 GPU with 120 Cuda cores and 14GB of graphics memory. The dataset was split in a way such that 85% of the data was used for training and the rest 15% for testing. The models were trained using the aforementioned dataset splits, and their accuracy is shown in Table 1.

A convolutional filter of size of (1,128) was used in the first block of EEGNet. The filter length was selected to be half of the sampling rate (here 256 Hz) of the data. The dropout probability in both blocks of the model was set to be 0.2 to avoid over-fitting when training on small sample sizes. The Adam optimizer with a learning rate of 0.0001 has been chosen for the classification. For training the dataset, a batch size of 16 and 100 epochs were used. For the experiment, we selected 16 pointwise filters and 8 temporal filters. Categorical Cross-entropy was used as the loss function. All other models were initially trained with the default hyper-parameters and later tuned to obtain better accuracy.

We compared the accuracy of EEGNet to that of other deep neural networks like RNN, LSTM, and 1D-CNN, which are used to categorize spatial or temporal data. Although RNN and LSTM are effective at extracting features from temporal data, the extracted spectral features from EEG signals contain both temporal and spatial components. As a result, LSTM and RNN exhibited low performance on our dataset. 1D-CNN also performed poorly on the given dataset. EEGNet outperformed all these models achieving an accuracy of 88.17%. It has achieved higher degree of accuracy due to its ability in performing well with little training data and extracting both spatial and temporal features efficiently.

9 CONCLUSION AND FUTURE WORK

In this paper, we have proposed a novel experiment to induce cognitive fatigue among the participants. Different machine learning models have also been implemented to help us identify signs of weariness from the EEG recordings. Results reveal that EEGNet

Method	Overall Accuracy
1D-CNN	63.62%
Recurrent Neural Network (RNN)	65.53%
Long Short-Term Memory (LSTM)	70.81%
EEGNet	88.17%

Table 1: Results Comparison.

performs significantly well even after having a small dataset. Our sample included more men than women, and it would therefore be valuable to replicate our results with a balanced sample in the future. Future research will also focus on identifying cognitive fatigue from EEG recordings collected from more than 4 electrodes, as opposed to the Muse-S headband, which is expected to produce better results.

ACKNOWLEDGMENTS

This work was partially supported by National Science Foundation grant 2226164. This material is based upon work by the authors. Any opinions, findings, conclusions, and recommendations expressed in this paper are those of the author(s) and do not necessarily reflect the views of the National Science Foundation (NSF).

REFERENCES

[1] 2016. Brain waves. "https://www.sciencedirect.com/topics/agricultural-and-biological-sciences/brain-waves"

[2] 2022. "Introduction to Recurrent Neural Network.". "https://www.geeksforgeeks.org/introduction-to-recurrent-neural-network/"

[3] 2023. Muse s: brain sensing headband - technology enhanced meditation. "https://choosemuse.com/muse-s/"

[4] Maher Abujelala, Cheryl Abellanoza, Aayush Sharma, and Fillia Makedon. 2016. Brain-ee: Brain enjoyment evaluation using commercial eeg headband. In *Proceedings of the 9th acm international conference on pervasive technologies related to assistive environments*. 1–5.

[5] Alexandrebarachant. 2021. Alexandrebarachant/Muse-LSL: Python script to stream EEG data from the Muse 2016 headset. https://github.com/alexandrebarachant/muse-lsl

[6] Shahzeb Ansari, Haiping Du, Fazel Naghdy, and David Stirling. 2022. Automatic Driver Cognitive Fatigue Detection based on Upper Body Posture Variations. *Expert Systems with Applications* (2022), 117568.

[7] Anum Asif, Muhammad Majid, and Syed Muhammad Anwar. 2019. Human stress classification using EEG signals in response to music tracks. *Computers in biology and medicine* 107 (2019), 182–196.

[8] A Bailey, S Channon, and JG Beaumont. 2007. The relationship between subjective fatigue and cognitive fatigue in advanced multiple sclerosis. *Multiple Sclerosis Journal* 13, 1 (2007), 73–80.

[9] Venkatesh Balasubramanian, K Adalarasu, and A Gupta. 2011. EEG based analysis of cognitive fatigue during simulated driving. *International Journal of Industrial and Systems Engineering* 7, 2 (2011), 135–149.

[10] Fiona Barwick, Peter Arnett, and Semyon Slobounov. 2012. EEG correlates of fatigue during administration of a neuropsychological test battery. *Clinical Neurophysiology* 123, 2 (2012), 278–284.

[11] A Belmont, N Agar, C Hugeron, B Gallais, and Philippe Azouvi. 2006. Fatigue and traumatic brain injury. In *Annales de réadaptation et de médecine physique*, Vol. 49. Elsevier, 370–374.

[12] Maarten AS Boksem and Mattie Tops. 2008. Mental fatigue: costs and benefits. *Brain research reviews* 59, 1 (2008), 125–139.

[13] Jason Brownlee. 2021. "A gentle introduction to long short-term memory networks by the experts.". "https://machinelearningmastery.com/gentle-introduction-long-short-term-memory-networks-experts/"

[14] Ieuan Clay. 2017. Impact of digital technologies on novel endpoint capture in clinical trials. *Clinical Pharmacology & Therapeutics* 102, 6 (2017), 912–913.

[15] Majid Fallahi, Majid Motamedzade, Rashid Heidarimoghadam, Ali Reza Soltanian, and Shinji Miyake. 2016. Effects of mental workload on physiological and subjective responses during traffic density monitoring: A field study. *Applied ergonomics* 52 (2016), 95–103.

[16] Rongrong Fu, Hong Wang, and Wenbo Zhao. 2016. Dynamic driver fatigue detection using hidden Markov model in real driving condition. *Expert Systems with Applications* 63 (2016), 397–411.

[17] Christos Goumopoulos and Nektaria Potha. 2022. Mental fatigue detection using a wearable commodity device and machine learning. *Journal of Ambient Intelligence and Humanized Computing* (2022), 1–19.

[18] Haisong Gu, Qiang Ji, and Zhiwei Zhu. 2002. Active facial tracking for fatigue detection. In *Sixth IEEE Workshop on Applications of Computer Vision, 2002.(WACV 2002). Proceedings.* IEEE, 137–142.

[19] Martijn Haak, Steven Bos, Sacha Panic, and Léon JM Rothkrantz. 2009. Detecting stress using eye blinks and brain activity from EEG signals. *Proceeding of the 1st driver car interaction and interface (DCII 2008)* (2009), 35–60.

[20] Peter Hagell and Lena Brundin. 2009. Towards an understanding of fatigue in Parkinson disease. *Journal of Neurology, Neurosurgery & Psychiatry* 80, 5 (2009), 489–492.

[21] James A Horne and Stuart D Baulk. 2004. Awareness of sleepiness when driving. *Psychophysiology* 41, 1 (2004), 161–165.

[22] Curtis S Ikehara and Martha E Crosby. 2005. Assessing cognitive load with physiological sensors. In *Proceedings of the 38th annual hawaii international conference on system sciences.* IEEE, 295a–295a.

[23] Ashish Jaiswal, Mohammad Zaki Zadeh, Aref Hebri, and Fillia Makedon. 2022. Assessing Fatigue with Multimodal Wearable Sensors and Machine Learning. *arXiv preprint arXiv:2205.00287* (2022).

[24] Mohsen Karchani, Adel Mazloumi, Gebraeil Nasl Saraji, Faramarz Gharagozlou, Ali Nahvi, Khosro Sadeghniiat Haghighi, Bahador Makki Abadi, and Abbas Rahimi Foroshani. 2015. Presenting a model for dynamic facial expression changes in detecting drivers' drowsiness. *Electronic physician* 7, 2 (2015), 1073.

[25] Jarek Krajewski, David Sommer, Thomas Schnupp, Tom Laufenberg, Christian Heinze, and Martin Golz. 2010. Applying nonlinear dynamics features for speech-based fatigue detection. In *Proceedings of the 7th International Conference on Methods and Techniques in Behavioral Research.* 1–5.

[26] Lauren B Krupp, Luis A Alvarez, Nicholas G LaRocca, and Labe C Scheinberg. 1988. Fatigue in multiple sclerosis. *Archives of neurology* 45, 4 (1988), 435–437.

[27] Vernon J Lawhern, Amelia J Solon, Nicholas R Waytowich, Stephen M Gordon, Chou P Hung, and Brent J Lance. 2018. EEGNet: a compact convolutional neural network for EEG-based brain–computer interfaces. *Journal of neural engineering* 15, 5 (2018), 056013.

[28] Glyn Lewis and Simon Wessely. 1992. The epidemiology of fatigue: more questions than answers. *Journal of epidemiology and community health* 46, 2 (1992), 92.

[29] Mu Li and Bao-Liang Lu. 2009. Emotion classification based on gamma-band EEG. In *2009 Annual International Conference of the IEEE Engineering in medicine and biology society.* IEEE, 1223–1226.

[30] Beat Meier, Nicolas Rothen, and Stefan Walter. 2014. Developmental aspects of synaesthesia across the adult lifespan. *Frontiers in human neuroscience* 8 (2014), 129.

[31] Henri J Nussbaumer. 1981. The fast Fourier transform. In *Fast Fourier Transform and Convolution Algorithms*. Springer, 80–111.

[32] Benjamin Pageaux and Romuald Lepers. 2018. The effects of mental fatigue on sport-related performance. *Progress in brain research* 240 (2018), 291–315.

[33] Hamza Reza Pavel, Enamul Karim, Ashish Jaiswal, Sneh Acharya, Gaurav Nale, Michail Theofanidis, and Fillia Makedon. 2023. Assessment of Cognitive Fatigue from Gait Cycle Analysis. *Technologies* 11, 1 (2023), 18.

[34] Mandalapu Saradadevi and Preeti Bajaj. 2008. Driver fatigue detection using mouth and yawning analysis. *International journal of Computer science and network security* 8, 6 (2008), 183–188.

[35] Steven R Schwid, MMSB Covington, Benjamin M Segal, and Andrew D Goodman. 2002. Fatigue in multiple sclerosis: current understanding and future directions. *Journal of rehabilitation research and development* 39, 2 (2002), 211–224.

[36] Manish Kumar Sharma and Mahesh Bundele. 2020. Cognitive fatigue detection in vehicular drivers using k-means algorithm. In *International Conference on Innovative Computing and Communications*. Springer, 517–532.

[37] Mitchell R Smith, Linus Zeuwts, Matthieu Lenoir, Nathalie Hens, Laura MS De Jong, and Aaron J Coutts. 2016. Mental fatigue impairs soccer-specific decision-making skill. *Journal of sports sciences* 34, 14 (2016), 1297–1304.

[38] J Stastny, Pavel Sovka, and A Stancak. 2001. EEG signal classification. In *2001 Conference Proceedings of the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Vol. 2. IEEE, 2020–2023.

[39] Ler Digital Studio. 2023. "Beat Saber - VR Rhythm Game.". "https://beatsaber.com/"

[40] Leonard J Trejo, Karla Kubitz, Roman Rosipal, Rebekah L Kochavi, Leslie D Montgomery, et al. 2015. EEG-based estimation and classification of mental fatigue. *Psychology* 6, 05 (2015), 572.

[41] Edmond Q Wu, Pengwen Xiong, Zhi-Ri Tang, Gui-Jiang Li, Aiguo Song, and Li-Min Zhu. 2021. Detecting dynamic behavior of brain fatigue through 3-d-CNN-LSTM. *IEEE Transactions on Systems, Man, and Cybernetics: Systems* 52, 1 (2021), 90–100.

[42] Xuejiao Xing, Botao Zhong, Hanbin Luo, Timothy Rose, Jue Li, and Maxwell Fordjour Antwi-Afari. 2020. Effects of physical fatigue on the induction of mental fatigue of construction workers: A pilot study based on a neurophysiological

approach. *Automation in Construction* 120 (2020), 103381.

[43] Yasunori Yamada and Masatomo Kobayashi. 2017. Fatigue detection model for older adults using eye-tracking data gathered while watching video: Evaluation against diverse fatiguing tasks. In *2017 IEEE International Conference on Healthcare Informatics (ICHI)*. IEEE, 275–284.

[44] Mohammad Zaki Zadeh, Ashwin Ramesh Babu, Jason Bernard Lim, Maria Kyrarini, Glenn Wylie, and Fillia Makedon. 2020. Towards cognitive fatigue detection from functional magnetic resonance imaging data. In *Proceedings of the 13th ACM International Conference on PErvasive Technologies Related to Assistive Environments*. 1–2.

[45] Linus HRH Zeuwts, Evelien Iliano, Mitchell Smith, Frederik Deconinck, and Matthieu Lenoir. 2021. Mental fatigue delays visual search behaviour in young cyclists when negotiating complex traffic situations: A study in virtual reality. *Accident Analysis & Prevention* 161 (2021), 106387.