DETECTING COGNITIVE FATIGUE IN SUBJECTS WITH TRAUMATIC BRAIN INJURY FROM FMRI SCANS USING SELF-SUPERVISED LEARNING

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ABSTRACT

Understanding cognitive states from fMRI data have yet to be investigated to its full extent due to its complex nature. In this work, the problem of understanding cognitive fatigue among TBI patients has been formulated as a multi-class classification problem. We built a Spatio-temporal encoder model using convolutions and LSTMs as the building blocks to extract spatial features and to model the 4D nature of fMRI scans. To learn a better representation of the data and the condition, we used a self-supervised learning technique called "Contrastive Learning" to pretrain our encoder with a public dataset BOLD5000 and further fine-tuned our labeled dataset to predict cognitive fatigue. Furthermore, we present an fMRI dataset that contains scans from a mix of Traumatic Brain Injury (TBI) patients and healthy controls (HCs) while performing a series of standardized N-back cognitive tasks. This method establishes a state-of-the-art technique to analyze cognitive fatigue from fMRI data and beats previous approaches to solve this problem with different modalities. Besides, the ability of our models to take in raw fMRI scans (noisy images with artifacts output directly from the scanner) eliminates the need to implement a manual signal processing pipeline that varies based on the scanner used. Finally, we study the impact of different brain regions contributing to CF. The proposed technique outperforms the state-of-the-art method by over 13 percent on this dataset.

CCS CONCEPTS

• **Computing methodologies** → *Machine learning approaches*; • **Applied computing** → **Consumer health**.

KEYWORDS

cognitive fatigue, machine learning, fMRI brain imaging, self-supervised learning

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1 INTRODUCTION

Functional magnetic resonance imaging (fMRI) measures slight changes in blood flow that occur with activity in different brain regions. This imaging technique is completely safe and non-intrusive to the human brain. It is used to identify parts of the brain that handle critical functions and evaluate the effects of conditions such as stroke and other diseases. Some abnormalities can only be found with fMRI scans as it provides detailed access to activity patterns in a human brain.

Traumatic Brain Injury (TBI) is one of the most prevalent causes of neurological disorders in the US [14]. It is a condition that has been shown to affect working memory [5], and induce cognitive fatigue [25]. In this work, we focus on understanding cognitive fatigue that results from performing standardized cognitive tasks as it is one of the primary indicators of moderate-to-severe TBI.

Cognitive Fatigue (CF) is a subjective lack of mental energy perceived by an individual which interferes with everyday activities [9]. It is a common condition among people suffering from moderate to severe brain injury. Many researchers have tried to use different approaches to assess CF through various cognitive tasks and assessment tests by using objective measures such as response time (RT) and error rate (ER) [9]. However, these measures have certain limitations and do not correlate well with the self-reported scores during the tasks [42]. The inability to relate objective measures to self-reported cognitive fatigue led us to study the blood-oxygen-level-dependent (BOLD) signal associated with neural activation changes. The increased BOLD activation in TBI subjects signifies excessive cognitive work when compared to healthy subjects [42].

Raw fMRI scans are full of artifacts and noise due to several issues like central point artifacts, data clipping, data error artifacts, etc. These artifacts can differ based on the scanner used, and the settings applied during the scan. Thus, addressing and removing the unwanted noise is essential before analyzing the images. However, if a model can work directly on the raw data, it eliminates the painful process of pre-processing the images and saves time and effort. Hence, we prioritized training our models on raw data right out of the box and compared the performance with models learned from pre-processed data. With the self-supervised approach, our model outperformed supervised methods that were trained on images without any artifacts or noise.

With the advancements in deep learning techniques that can efficiently extract meaningful information from images/videos, we built a model that predicts self-reported CF scores based on neural activations captured through the fMRI scans. The main contributions of this work are:

- Identify multiple regions in the brain that contribute to cognitive fatigue and potentially comprise a fatigue network. The brain regions tested using Chaudhuri model of CF [3] and other fatigue-related brain areas [4, 10, 11, 42] are Caudate, Anterior Insula, Medial Prefrontal Cortex (mPFC), and Middle Frontal Gyrus (MFG).
- Develop machine learning (ML) models to detect and identify six levels of CF with the best accuracy of 86.84% using both pre-processed and raw fMRI brain scans. The models are trained and tested on different brain regions using masks and compared with their performance on the whole brain scan. Furthermore, they eliminate the need for a manual pre-processing pipeline based on the scanner used.
- A comprehensive dataset containing raw and pre-processed fMRI images collected from TBI subjects and Healthy Controls while performing CF inducing tasks
- Comparison of brain activity in the functional fatigue network in the brain between TBI and HC subjects. Our models and dataset indicate that TBI subjects undergo greater activity in the selected regions of the brain.

The rest of the paper is structured as follows: we start by discussing some of the previous works that have examined cognitive fatigue from different modalities and results that use deep learning for brain imaging. Then we explain the data collection, the preprocessing stage, and the system architecture. Finally, we present our experiments and results, followed by our conclusion on the work done and future directions at the end.

2 RELATED WORK

Previous researches have demonstrated that in people with Traumatic Brain Injury (TBI), the caudate nucleus of the basal ganglia shows a distinct pattern of activation over time than in healthy controls [25]. This finding was consistent with Chauduri and Behan's fatigue model [3], in which the basal ganglia played a crucial part in fatigue experience. On the other hand, Kohl et al. [25] inferred the presence of fatigue based on the pattern of brain activations across time. However, the study by Wylie et al. [42] was the first to look into state fatigue in people who have had a moderate-to-severe TBI. They investigated the involvement of the Caudate nucleus in fatigue by seeing if it changes its activity in direct proportion to the patients' instantaneous (state) fatigue experience [17].

While the Caudate nucleus and the Striatum as a whole were previously thought to be solely responsible for motor behavior control [29], recent evidence from animal and human research shows that this region is involved in a wide range of cognitive behaviors, including learning [12, 35, 38], outcome processing [7, 8], and working memory [1, 27]. Recent data indicate that fatigue caused by such cognitive tasks may manifest itself in Caudate nucleus activation [10]. In children who have suffered a TBI, cognitive fatigue has been linked to a network of areas in the Striatum and PFC, including the vmPFC, nucleus accumbens, and Anterior Cingulate Cortex (ACC) [34].

With the rapid increase in the availability of medical imaging datasets, deep learning has been adopted efficiently to process the data for diagnosing various diseases [15, 16, 33] and rehabilitation purposes [13, 23]. Researchers have also applied deep learning to identify early symptoms of various cognitive disorders [31, 45]. Specifically, works have been done in predicting diseases and subject traits using fMRI data with machine learning techniques [24, 32]. Further, convolutional neural networks (CNNs) [26], an approach that has been known to be very successful in solving computer vision tasks have been widely used to analyze the spatial features in fMRI images as well. A 4-layer convolutional neural network was proposed in [40] for classification from raw fMRI voxel values.

In [36], the authors used deep convolutional networks (DCNs) to encode fMRI images into low-dimensional feature space and decode them back for image reconstruction. Similarly, the authors in [30] proposed a large-scale bi-directional generative adversarial network called BigBiGAN to decode and reconstruct natural scenes from fMRI patterns. Furthermore, an architecture based on sparse convolutional autoencoder was used in [21] to learn high-level features from handcrafted time series derived from raw fMRI data.

There has also been a recent surge in the use of sequence models to process temporal fMRI data. Mao et al. [28] applied a specific type of RNN known as Long Short-Term Memory (LSTM) to process spatial features extracted from a CNN network. Another similar work in [37] used bi-directional LSTM along with a CNN.

Based on the previous works, deep learning has come a long way in understanding the structural and functional activities in the brain. However, work done in analyzing cognitive fatigue from fMRI scans has been severely limited and needs more attention. Hence, combining sequential models is essential to incorporate the temporal properties of 4D fMRI images and enhance the performance of CNN models that can only learn structural features from data. Furthermore, the addition of self-supervised learning methods helps in learning low-level brain fMRI features from similar public datasets. **To the best of our knowledge, we are the first ones to evaluate cognitive fatigue from fMRI brain scans.**

3 METHODOLOGY

We induced CF in healthy controls (HCs) and individuals with TBI using a working memory task during data collection. We assessed CF scores at multiple intervals through surveys and questionnaires and acquired fMRI data throughout the test. As the acquired raw data contains noise, a standard pre-processing pipeline was implemented to normalize and smoothen the data, as shown in Figure 2.

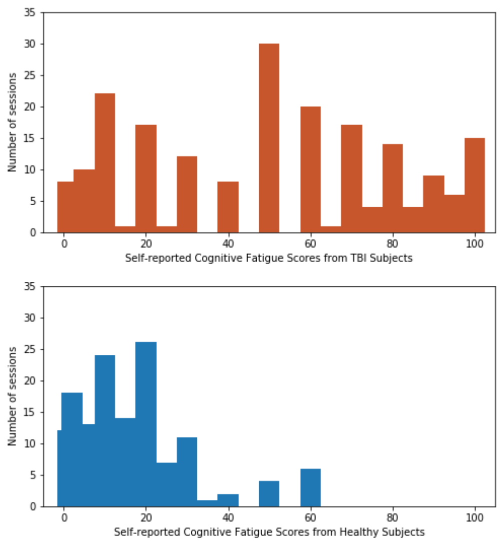


Figure 1: Distribution of self-reported cognitive fatigue scores after every N-back session from TBI subjects (top) and Healthy Controls (bottom). The score is a difference between the reported session score and the resting-state fatigue score recorded at the beginning of the first session.

The following subsections explain data collection, pre-processing, and system architecture to predict CF from fMRI data.

3.1 Data Collection and Pre-processing

For data collection, fMRI scans of the brain were recorded over a period where each subject was asked to perform a series of cognitive N-back tasks, as shown in Figure 2. The data was collected from thirty participants with moderate-severe TBI and 24 healthy controls (HCs). The average age of the subjects was 41 years (SD=12.7). Each participant performed four rounds of both 0-back and 2-back tasks. A baseline fatigue score was reported initially, followed by scores being reported after each round. Functional images were collected in 32 contiguous slices during eight blocks (four at each of two difficulty levels), resulting in 140 acquisitions per block (echo time = 30 ms; repetition time = 2000 ms; field of view = 22 cm; flip angle = 80°; slice thickness=4 mm, matrix = 64 × 64, in-plane resolution = 3.438 mm^2). Using the Visual Analog Scale of Fatigue (VAS-F), the subjects were asked to rate the amount of fatigue they experienced (in the range 0-100) after each round of the N-back task. The self-reported scores were mapped to six classes to make it a multi-class classification problem as represented in table 1.

On empirical inspection of the distribution (in Figure 1), we found that six categories strike a good balance/compromise between adequately describing the distribution of VAS-F scores in a limited set of categories while also maintaining sufficient complexity in the VAS-F data to allow for accurate modeling. Reducing the number of categories to five or increasing it to seven did not materially affect the model's performance. Additionally, the cognitive fatigue levels shown in table 1 are for reference only in order to quantify

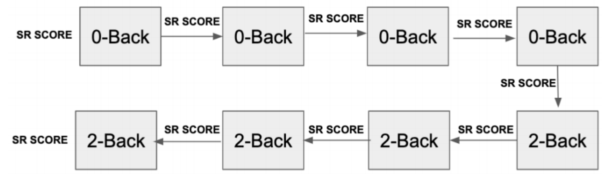


Figure 2: A flow diagram of a series of N-back tasks (some performed the 2-Back tasks first) performed during data collection (VAS-F Score: SR Score)

Table 1: Mapping self-reported (SR) Cognitive Fatigue scores to respective class labels. The fatigue levels are for references only and are not of any clinical significance.

Fatigue Score (SR)	Fatigue Level (Reference)	Class
0-10	No Fatigue	0
10-20	Very Low Fatigue	1
20-40	Mild Fatigue	2
40-60	Fatigue	3
60-80	High Fatigue	4
80-100	Extreme Fatigue	5

different levels of fatigue corresponding to the class label. The final 4D tensor acquired in NIfTI format was 140 x 32 x 64 x 64. The raw fMRI images were preprocessed using Analysis of Functional NeuroImages (AFNI) [6] and other standard techniques as discussed in previous works [42], shown in Figure 2.

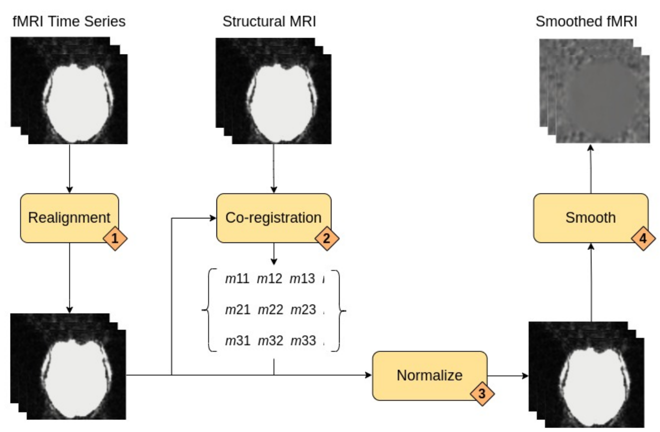


Figure 3: Pre-processing pipeline for fMRI scans to convert from raw noisy format to normalized and smoothed version.

3.2 System Architecture

fMRI scans are 4D in shape and are represented as (t, x, y, z), where 't' represents the timesteps of individual 3D brain volumes. The other three dimensions represent the intensity of voxels in the brain. The temporal relation between the scans recorded at different

Table 2: Performance results for different models on the cognitive fatigue classification task. Accuracies are calculated with 3-fold cross-validation. The encoder model used is CNN+LSTM and is the same for all three approaches. For the supervised approach, we add a linear layer at the end for classification.

Approach	Data Format	Dataset Used	Accuracy		
			HC only	**TBI only**	**Overall**
Supervised (Encoder + Linear)	Raw	Ours	71.72 ± 0.82	78.44 ± 1.71	74.35 ± 1.27
Supervised (Encoder + Linear)	Pre-processed	Ours	80.87 ± 0.63	84.91 ± 1.44	82.79 ± 0.73
Self-supervised + Fine-tuning	Raw	BOLD5000 + Ours	82.58 ± 0.53	92.39 ± 1.26	**86.84 ± 1.13**

time steps is captured using a Recurrent Neural Network (RNN) based architecture. We combined a CNN architecture with an LSTM [18] network for the encoder as shown in Figure 4. We used three layers of 2D convolution and batch normalization to learn the images' spatial (structural) features, whereas the LSTM network understands the temporal relation between the timesteps.

The encoder was pre-trained on a public dataset called BOLD5000 [2] using a self-supervised algorithm and was fine-tuned on our labeled dataset by adding a linear classifier layer at the end. Many researchers have opted BOLD5000 dataset as it is a large-scale, slow event-related human fMRI study incorporating 5,000 real-world images as stimuli. It also accounts for image diversity, overlapping with standard computer vision datasets, making it ideal for transfer learning tasks. Based on our experiment, the image representations learned by the encoder by first pre-training on the BOLD5000 dataset were more effective than training the models directly on the supervised dataset.

3.3 Self-supervised Pre-training

We used a self-supervised learning approach (contrastive learning [22]) to learn data representations from unlabelled samples, as it has been proven to work well with visual data. The methods utilize meta-data generated from the dataset that acts as pseudo-labels during training. With contrastive learning, models can effectively learn abstract features from images and videos. In this case, 4D fMRI data can be treated as a series of videos such that self-supervised methods [43] can be applied to it.

For pre-training the encoder, we use a contrastive-based approach. Two augmented versions are generated for every batch containing N samples, resulting in a total of $2N$. Every sample's augmented version is considered the positive candidate, and their similarity is encouraged to be maximum. In contrast, the model tries to minimize the positive and negative pair similarity. This condition is represented in Figure 5 with green and red double-headed arrows. We use cosine similarity to measure the closeness between two samples in a batch.

We apply extensive spatial and temporal augmentation during training. As part of spatial transformation, methods such as random affine, z-normalization, and re-scale intensity were used. One arbitrary transformation is also used among random blur, gamma, random motion, and random noise. Similarly, a random starting time t is selected for temporal augmentation, and n consecutive scans are extracted. Finally, the loss is calculated using a variant of the Noise Contrastive Estimation function (NCE) called InfoNCE, which is used when there is more than one negative sample present during the learning process and is defined by equation 1.

$$L_{infoNCE} = -log \frac{exp(sim(q,k_+)/\tau)}{exp(sim(q,k_+)/\tau) + \sum_{i=0}^{K} exp(sim(q,k_i)/\tau)} \quad (1)$$

In the equation 1, q represents the current sample, k_+ represents the positive sample (augmented version of q), and k_i represents the negative samples (other samples in the batch). τ represents the temperature coefficient, and sim represents the cosine similarity between two samples.

In this experiment, we used a contrastive learning method called MoCo [19] that includes negative samples as a dictionary queue and has been proven effective compared to other methods. Two encoders with the same architectural configuration are used; the main encoder Q (Query Encoder) is trained end-to-end on the sample pairs. The second encoder (Momentum Encoder) shares the same parameters as Q. The momentum encoder generates a dictionary as a queue of encoded keys with the current mini-batch enqueued and the oldest mini-batch dequeued. It gets updated based on the parameters of the query encoder using an update parameter called momentum coefficient as represented by equation 2. In equation 2, $m \in [0, 1)$ is the momentum coefficient. Only the parameters θ_q are updated by back-propagation.

$$\theta_k \leftarrow m\theta_k + (1 - m)\theta_q \quad (2)$$

3.4 Region of Interest Analysis and Cognitive Fatigue Interactions

With emerging tools of cognitive neuroscience to investigate cognitive fatigue, several fatigue-related brain areas have begun to emerge. Specifically, based on the studies in [3, 4, 10, 11, 42], the striatum of the basal-ganglia also known as caudate, the medial prefrontal cortex (mPFC), the anterior insula, and the middle frontal gyrus (MFG) as visualized in Figure 7 have been found to play a critical role in functional connectivity of the fatigue network in the brain. Therefore, these brain areas need to be analyzed thoroughly

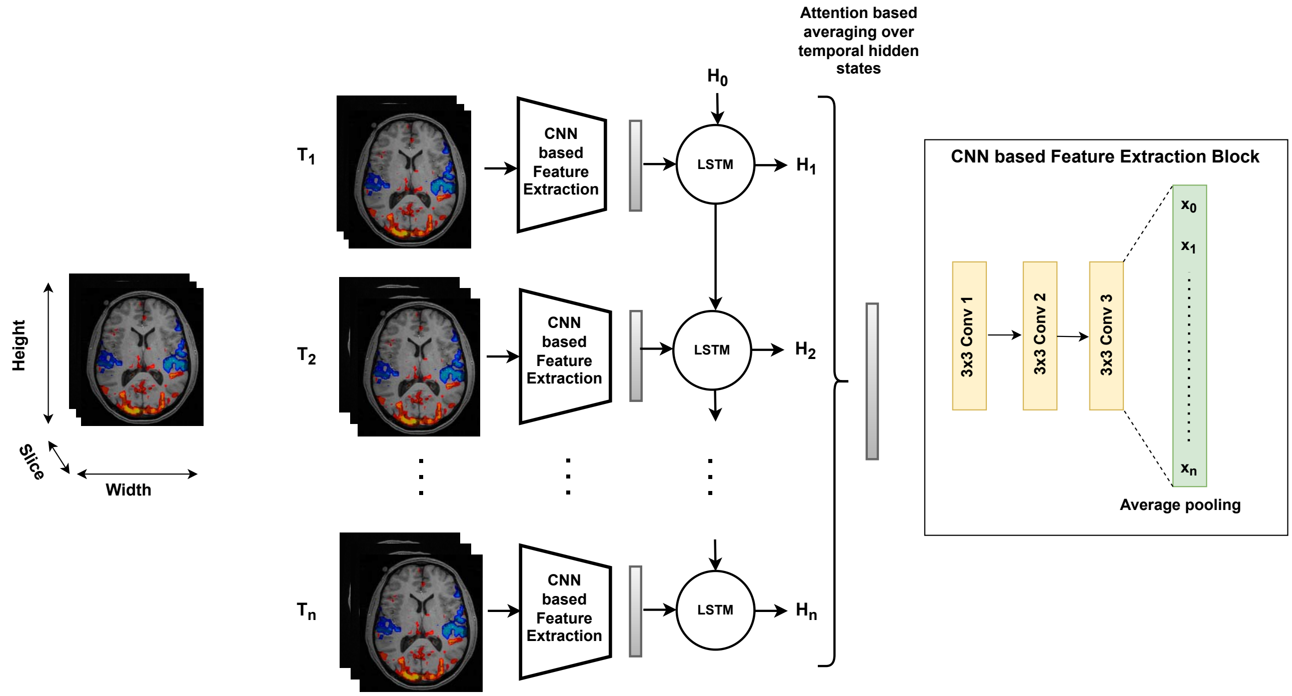


Figure 4: Spatio-temporal Model Architecture: CNN layers in the Encoder extract spatial features while LSTM layers model the temporal relation of the fMRI images followed by attention-based averaging over time.

Table 3: Performance comparison of methods using different modalities for cognitive/mental fatigue detection or prediction

Modalities	Methods Used	Accuracy	Reference
Physiological Sensors (ECG, RESP, EDA, SpO2)	LDA/SVM/DT	70%	Hirachan et. al [20]
Pre-processed fMRI	Logistic Regression	73%	Zadeh et. al [44]
Respiratory Signals	CNN	77.29%	Wang et. al [39]
EEG Channels	Signal Processing	80.0 %	Wei et. al [41]
Raw fMRI	**CNN+LSTM**	**86.84%**	**Ours**

to understand activation regions in the brain during cognitive fatigue.

Data analysis occurs in two steps. A whole-brain study is conducted first, followed by a fatigue-interaction (FI) analysis where cerebral activity in the brain is investigated in different regions of interest (ROIs). First, we train ML models for CF detection using the whole brain scan. Next, we apply several masks one at a time to the brain scans corresponding to different selected ROIs before training the same ML models. Finally, we compare the performance of the ML models for each region of interest against the whole brain scan.

4 EXPERIMENTS AND DISCUSSION

Most publicly available datasets are preprocessed with a standard pipeline for fMRI images. However, we used two different data versions to train the models: one using the **raw (unprocessed)** version and the other using **preprocessed** normalized version as obtained from the preprocessing pipeline in Figure 2. Furthermore, we used data from all four subjects in the publicly available **BOLD5000** dataset for self-supervised pre-training of the Encoder model as represented in Figure 5. In this case, we trained the encoder using MoCo [19] algorithm and Adam optimizer on the public dataset. The pre-training was carried out for a total of 200 epochs. The starting learning rate was set to 0.03 with a weight decay factor of 10^{-4} and a momentum parameter of 0.9. The learning rate was decayed by ten at 120 and 160 epochs, respectively.

We split our supervised labeled dataset into train, validation, and test sets to train the deep learning models. The train set contained 70% of the dataset, while the validation and the test datasets consisted of 15% each. The test set included a mix of TBI and HC subjects and constituted more than 300 reported instances during

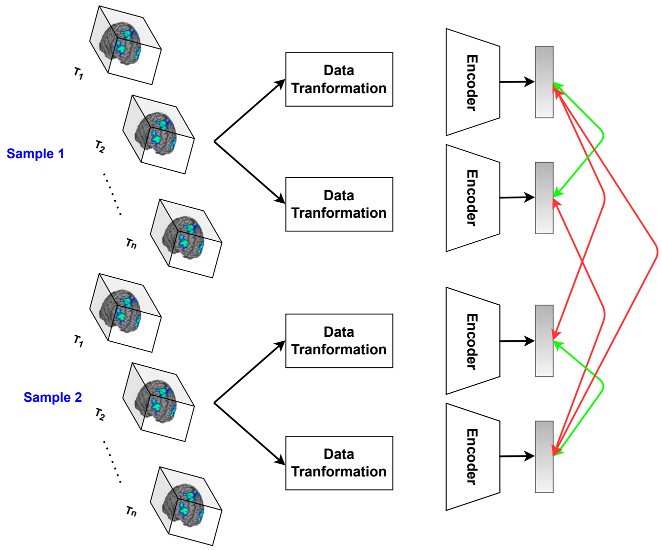
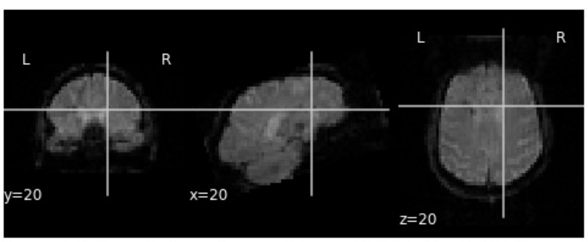
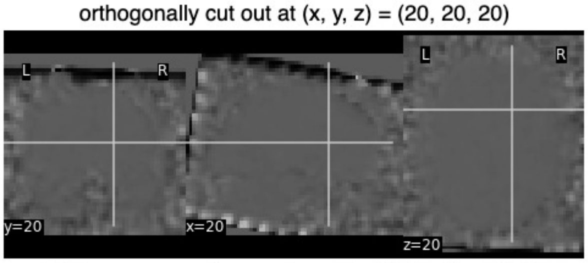


Figure 5: Self-supervised Pre-training Framework: MoCo algorithm for pre-training on BOLD5000 dataset. The green arrows represent positive pairs and red arrows represent negative pairs.



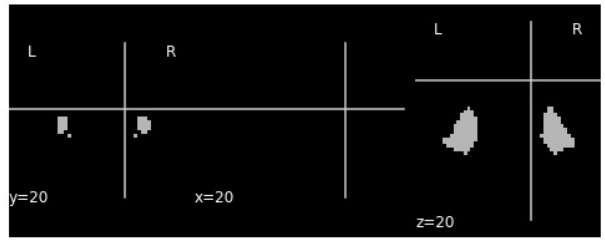
(a) Sample Raw Image from a TBI Subject #008, orthogonally cut out at (x, y, z) = (20, 20, 20)



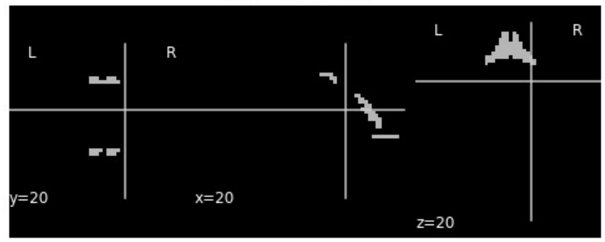
(b) Pre-processed Image from the TBI Subject #008, orthogonally cut out at (x, y, z) = (20, 20, 20)

Figure 6: Ortho visualization of a sample (a) Raw Image and the (b) Pre-processed version cut out at coordinates (x=20, y=20, z=20).

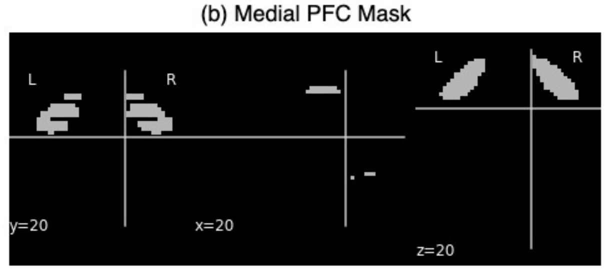
the N-back tasks. On the other hand, scans from all four subjects in the BOLD5000 dataset were used to pre-train the model using the self-supervised approach, as mentioned earlier. The primary encoder was initially trained on our collected dataset separately using a supervised approach for benchmarking. We used raw and



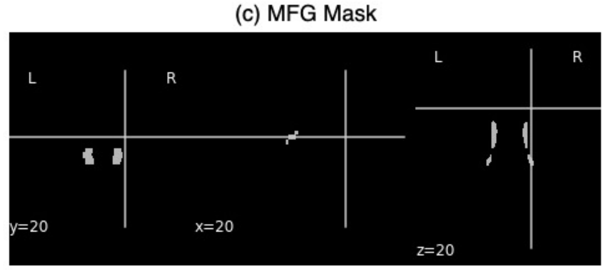
(a) Insula Mask



(b) Medial PFC Mask



(c) MFG Mask



(d) Caudate Mask

Figure 7: Ortho cut out visualization of (a) Insula Mask (b) MedialPFC Mask, (c) MFG Mask, and (d) Caudate Mask at coordinates (x=20, y=20, z=20).

preprocessed data for the supervised method to train two different models, as shown in table 2. Finally, once the encoder was pre-trained on the BOLD5000 dataset using the self-supervised algorithm, it was fine-tuned on our dataset. The performance of the different models is presented in table 2. The results show that the model pre-trained on the public dataset (BOLD5000) and later fine-tuned on our dataset outperformed other supervised methods.

Four NVIDIA GTX 1080 Ti GPUs were used to train the models, whereas, for testing, only one GPU was used. As shown in table 2, our method beats all previous approaches, including [44] in classifying cognitive fatigue from fMRI scans.

Table 4: CF Detection using Different Regions of Interest (ROIs) to identify areas with most brain activity. Supervised model refers to (Encoder + Linear) combination of layers trained on labeled data from our dataset where as SSL refers to Self-supervised Model initially trained on BOLD5000 dataset and later finetuned on our dataset.

Mask Used	Data Format	Model	Accuracy
Caudate	Pre-processed	Supervised	69.21%
	Raw	Supervised	62.33%
		SSL	**76.87%**
Insula	Pre-processed	Supervised	64.77%
	Raw	Supervised	62.12%
		SSL	67.94%
MedialPFC	Pre-processed	Supervised	73.78%
	Raw	Supervised	70.94%
		SSL	**78.92%**
MFG	Pre-processed	Supervised	75.29%
	Raw	Supervised	70.98%
		SSL	**79.13%**
NONE	Pre-processed	Supervised	82.79%
	Raw	Supervised	74.35%
		SSL	**86.84%**

4.1 Performance based on different ROIs using Masks

One of the main objectives of analyzing different brain regions is to understand and quantify the activity in those regions when a subject exerts effort in the brain and fatigue increases. The higher the activation in an area, the more significant its contribution towards the induction of CF. It can be made more evident by testing the ML models on each selected brain region separately. To achieve this, 3D binary masks of the same size as the original scan were generated that correspond to each brain region respectively. Next, they were applied to the input scans using multiplication to prepare them for training. In this way, each of the four areas mentioned above in the brain was used to train our ML models and evaluated based on its sole ability to detect CF.

Table 4 highlights the performance of different models on detecting cognitive fatigue when trained using scans from various regions in the brain. It is prominent that the models perform better when the whole brain scan is used than using only a part of the brain. However, it is interesting to note that some regions in the brain provide more information than others when detecting cognitive fatigue. In this case, the medial prefrontal cortex (mPFC) and the middle frontal gyrus (MFG) seem to contribute way higher than the insula and slightly more than the caudate. This indicates a higher functional activity in the brain's frontal portion during the fatigue induction process.

4.2 Performance on TBI vs HC Subjects

Since our dataset contains a mix of TBI and HC subjects, it is essential to understand the difference between the cerebral activity in the brain that induces cognitive fatigue in both groups. Therefore, we compare the performance of our ML models independently on data from each group. As shown in table 2, when testing TBI and HC subjects separately, the models seem to perform better on the TBI data. It could mean that the enhanced brain activations in the TBI subjects made it easier for the model to predict cognitive fatigue compared to the scans from healthy subjects. However, the difference in the performance is negligible, and the model seems to perform comparatively well on data from both subjects, which makes it robust for all cases. Also, based on the score distribution of TBI and HC subjects in Figure 1, TBI subjects seem to induce more fatigue than healthy subjects.

4.3 Comparison with Fatigue Detection Techniques using Different Modalities

Table 3 emphasizes a direct comparison of several cognitive fatigue detection and prediction techniques that use various input modalities. Our approach achieves the best results compared to other methods using different sensor-based modalities. One significant advantage of our procedure in the fMRI domain is that it eliminates the need to remove noise and artifacts from the raw images. Furthermore, as a future direction, we can work on identifying the region of interest in the brain that correlates to a specific fatigue level with the help of fMRI imaging. Finally, the advantages and the need to use fMRI scans to estimate cognitive fatigue accurately are well explained in our previous sections.

5 CONCLUSION

This paper presents a pre-trained Spatio-temporal architecture with self-supervised methods for processing 4D fMRI data that predicts cognitive fatigue in TBI and healthy subjects. Motivated by video classification, we use CNN layers to extract spatial features and an LSTM network for temporal data modeling. Additionally, we implemented a self-supervised algorithm to show that knowledge of fMRI data gained from other public datasets is helpful in downstream tasks. Unlike previous works that used the whole brain scan for binary prediction of cognitive fatigue, our method granulates the prediction into six different levels of CF with higher accuracy. Furthermore, we study the impact of essential brain regions that play a more significant role in the induction of CF. Finally, we observe that brain activations in TBI subjects are more prominent than HCs in the regions that we selected. Future works include exploring large-scale public datasets with improved self-supervised algorithms to enhance the overall performance and the granularity of cognitive fatigue prediction.

REFERENCES

[1] H. Akhlaghpour, J. Wiskerke, J. Y. Choi, Joshua P Taliaferro, Jennifer L. Au, and Ilana B. Witten. 2016. Author response: Dissociated sequential activity and stimulus encoding in the dorsomedial striatum during spatial working memory. *eLife* (2016).

[2] Nadine Chang, John A Pyles, Austin Marcus, Abhinav Gupta, Michael J Tarr, and Elissa M Aminoff. 2019. BOLD5000, a public fMRI dataset while viewing 5000 visual images. *Scientific data* 6, 1 (2019), 1–18.

[3] Abhijit Chaudhuri and Peter Behan. 2000. Fatigue and basal ganglia. *Journal of the neurological sciences* 179 (11 2000), 34–42. https://doi.org/10.1016/S0022-510X(00)00411-1

[4] Trevor T-J Chong, Matthew Apps, Kathrin Giehl, Annie Sillence, Laura L Grima, and Masud Husain. 2017. Neurocomputational mechanisms underlying subjective valuation of effort costs. *PLoS biology* 15, 2 (2017), e1002598.

[5] C Christodoulou, J DeLuca, JH Ricker, NK Madigan, BM Bly, G Lange, AJ Kalnin, WC Liu, J Steffener, BJ Diamond, et al. 2001. Functional magnetic resonance imaging of working memory impairment after traumatic brain injury. *Journal of Neurology, Neurosurgery & Psychiatry* 71, 2 (2001), 161–168.

[6] Robert W Cox. 1996. AFNI: software for analysis and visualization of functional magnetic resonance neuroimages. *Computers and Biomedical research* 29, 3 (1996), 162–173.

[7] M Delgado, H Locke, VA Stenger, and Julie Fiez. 2003. Dorsal striatum responses to reward and punishment: Effects of valence and magnitude manipulations. *Cognitive, affective and behavioral neuroscience* 3 (04 2003), 27–38. https://doi.org/10.3758/CABN.3.1.27

[8] M.R. Delgado, L.E. Nystrom, C. Fissell, Douglas Noll, and Julie Fiez. 2001. Tracking the Hemodynamic Responses to Reward and Punishment in the Striatum. *Journal of neurophysiology* 84 (01 2001), 3072–7. https://doi.org/10.1152/jn.2000.84.6.3072

[9] John DeLuca, Helen M Genova, Frank G Hillary, and Glenn Wylie. 2008. Neural correlates of cognitive fatigue in multiple sclerosis using functional MRI. *Journal of the neurological sciences* 270, 1-2 (2008), 28–39.

[10] Ekaterina Dobryakova, Helen Genova, John Deluca, and Glenn Wylie. 2015. The Dopamine Imbalance Hypothesis of Fatigue in Multiple Sclerosis and Other Neurological Disorders. *Frontiers in Neurology* 6 (03 2015). https://doi.org/10.3389/fneur.2015.00052

[11] Ekaterina Dobryakova, Hanneke E Hulst, Angela Spirou, Nancy D Chiaravalloti, Helen M Genova, Glenn R Wylie, and John DeLuca. 2018. Fronto-striatal network activation leads to less fatigue in multiple sclerosis. *Multiple Sclerosis Journal* 24, 9 (2018), 1174–1182.

[12] Ekaterina Dobryakova and Elizabeth Tricomi. 2013. Basal Ganglia Engagement during Feedback Processing after a Substantial Delay. *Cognitive, affective and behavioral neuroscience* 13 (07 2013). https://doi.org/10.3758/s13415-013-0182-6

[13] Farnaz Farahanipad, Harish Ram Nambiappan, Ashish Jaiswal, Maria Kyrarini, and Fillia Makedon. 2020. HAND-REHA: dynamic hand gesture recognition for game-based wrist rehabilitation. In *Proceedings of the 13th ACM International Conference on PErvasive Technologies Related to Assistive Environments*. 1–9.

[14] Mark Faul, Marlena M Wald, Likang Xu, and Victor G Coronado. 2010. Traumatic brain injury in the United States; emergency department visits, hospitalizations, and deaths, 2002-2006. (2010).

[15] Preetham Ganesh, Reza Etemadi Idgahi, Chinmaya Basavanahally Venkatesh, Ashwin Ramesh Babu, and Maria Kyrarini. 2020. Personalized system for human gym activity recognition using an RGB camera. In *Proceedings of the 13th ACM International Conference on PErvasive Technologies Related to Assistive Environments*. 1–7.

[16] Srujana Gattupalli, Ashwin Ramesh Babu, James Robert Brady, Fillia Makedon, and Vassilis Athitsos. 2018. Towards deep learning based hand keypoints detection for rapid sequential movements from rgb images. In *Proceedings of the 11th PErvasive Technologies Related to Assistive Environments Conference*. 31–37.

[17] Helen Genova, Venkateswaran Rajagopalan, John Deluca, Abhijit Das, Allison Binder, Aparna Arjunan, Nancy Chiaravalloti, and Glenn Wylie. 2013. Examination of Cognitive Fatigue in Multiple Sclerosis using Functional Magnetic Resonance Imaging and Diffusion Tensor Imaging. *PloS one* 8 (11 2013), e78811. https://doi.org/10.1371/journal.pone.0078811

[18] Alex Graves. 2012. Long short-term memory. *Supervised sequence labelling with recurrent neural networks* (2012), 37–45.

[19] Kaiming He, Haoqi Fan, Yuxin Wu, Saining Xie, and Ross Girshick. 2020. Momentum contrast for unsupervised visual representation learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 9729–9738.

[20] Niraj Hirachan, Anita Mathews, Julio Romero, and Raul Fernandez Rojas. 2022. Measuring Cognitive Workload Using Multimodal Sensors. *arXiv preprint arXiv:2205.04235* (2022).

[21] Heng Huang, Xintao Hu, Yu Zhao, Milad Makkie, Qinglin Dong, Shijie Zhao, Lei Guo, and Tianming Liu. 2017. Modeling task fMRI data via deep convolutional autoencoder. *IEEE transactions on medical imaging* 37, 7 (2017), 1551–1561.

[22] Ashish Jaiswal, Ashwin Ramesh Babu, Mohammad Zaki Zadeh, Debapriya Banerjee, and Fillia Makedon. 2021. A survey on contrastive self-supervised learning. *Technologies* 9, 1 (2021), 2.

[23] Rithik Kapoor, Ashish Jaiswal, and Fillia Makedon. 2022. Light-Weight Seated Posture Guidance System with Machine Learning and Computer Vision. In *Proceedings of the 15th International Conference on PErvasive Technologies Related to Assistive Environments*. 595–600.

[24] Meenakshi Khosla, Keith Jamison, Gia H Ngo, Amy Kuceyeski, and Mert R Sabuncu. 2019. Machine learning in resting-state fMRI analysis. *Magnetic resonance imaging* 64 (2019), 101–121.

[25] Alexander D Kohl, Glenn R Wylie, HM Genova, Frank Gerard Hillary, and J Deluca. 2009. The neural correlates of cognitive fatigue in traumatic brain injury using functional MRI. *Brain injury* 23, 5 (2009), 420–432.

[26] Yann LeCun, Yoshua Bengio, et al. 1995. Convolutional networks for images, speech, and time series. *The handbook of brain theory and neural networks* 3361, 10 (1995), 1995.

[27] S. Lewis, A. Dove, T. Robbins, R. Barker, and A. Owen. 2004. Striatal contributions to working memory: a functional magnetic resonance imaging study in humans. *European Journal of Neuroscience* 19 (2004).

[28] Zhenyu Mao, Yi Su, Guangquan Xu, Xueping Wang, Yu Huang, Weihua Yue, Li Sun, and Naixue Xiong. 2019. Spatio-temporal deep learning method for adhd fmri classification. *Information Sciences* 499 (2019), 1–11.

[29] Frank Middleton and Peter Strick. 2000. P.L. Basal ganglia and cerebellar loops: motor and cognitive circuits. *Brain research. Brain research reviews* 31 (04 2000), 236–50. https://doi.org/10.1016/S0165-0173(99)00040-5

[30] Milad Mozafari, Leila Reddy, and Rufin VanRullen. 2020. Reconstructing natural scenes from fMRI patterns using BigBiGAN. In *2020 International Joint Conference on Neural Networks (IJCNN)*. IEEE, 1–8.

[31] Hamza Reza Pavel, Enamul Karim, Mohammad Zaki Zadeh, Ashish Jaiswal, Rithik Kapoor, and Fillia Makedon. 2022. Automated System to Measure Static Balancing in Children to Assess Executive Function. In *Proceedings of the 15th International Conference on PErvasive Technologies Related to Assistive Environments*. 569–575.

[32] Francisco Pereira, Tom Mitchell, and Matthew Botvinick. 2009. Machine learning classifiers and fMRI: a tutorial overview. *Neuroimage* 45, 1 (2009), S199–S209.

[33] Ashwin Ramesh Babu, Mohammad Zaki Zadeh, Ashish Jaiswal, Alexis Lueckenhoff, Maria Kyrarini, and Fillia Makedon. 2020. A Multi-modal System to Assess Cognition in Children from their Physical Movements. In *Proceedings of the 2020 International Conference on Multimodal Interaction*. 6–14.

[34] Nicholas Ryan, Miriam Beauchamp, Richard Beare, Lee Coleman, Michael Ditchfield, Michael Kean, Timothy Silk, Sila Genc, Cathy Catroppa, and Vicki Anderson. 2016. Uncovering Cortico-Striatal Correlates of Cognitive Fatigue in Pediatric Acquired Brain Disorder: Evidence from Traumatic Brain Injury. *Cortex* 83 (08 2016). https://doi.org/10.1016/j.cortex.2016.07.020

[35] W. Schultz, P. Apicella, and T. Ljungberg. 1993. Responses of monkey dopamine neurons to reward and conditioned stimuli during successive steps of learning a delayed response task. In *The Journal of neuroscience : the official journal of the Society for Neuroscience*.

[36] Guohua Shen, Tomoyasu Horikawa, Kei Majima, and Yukiyasu Kamitani. 2019. Deep image reconstruction from human brain activity. *PLoS computational biology* 15, 1 (2019), e1006633.

[37] Armin W Thomas, Hauke R Heekeren, Klaus-Robert Müller, and Wojciech Samek. 2018. Interpretable LSTMs for whole-brain neuroimaging analyses. *arXiv preprint arXiv:1810.09945* (2018).

[38] Elizabeth Tricomi and Julie Fiez. 2008. Feedback signals in the caudate reflect goal achievement on a declarative memory task. *NeuroImage* 41 (08 2008), 1154–67. https://doi.org/10.1016/j.neuroimage.2008.02.066

[39] Jie Wang, Jilong Shi, Yanting Xu, Hongyang Zhong, Gang Li, Jinghong Tian, Wanxiu Xu, Zhao Gao, Yonghua Jiang, Weidong Jiao, et al. 2022. A New Strategy for Mental Fatigue Detection Based on Deep Learning and Respiratory Signal. In *Proceedings of the 11th International Conference on Computer Engineering and Networks*. Springer, 543–552.

[40] Xiaoxiao Wang, Xiao Liang, Yawen Zhou, Yanming Wang, Jin Cui, Huijuan Wang, Yu Li, Benedictor Alexander Nguchu, and Bensheng Qiu. 2018. Task state decoding and mapping of individual four-dimensional fMRI time series using deep neural network. *arXiv preprint arXiv:1801.09858* (2018).

[41] Chun-Shu Wei, Yu-Te Wang, Chin-Teng Lin, and Tzyy-Ping Jung. 2018. Toward drowsiness detection using non-hair-bearing EEG-based brain-computer interfaces. *IEEE transactions on neural systems and rehabilitation engineering* 26, 2 (2018), 400–406.

[42] GR Wylie, E Dobryakova, J DeLuca, N Chiaravalloti, K Essad, and H Genova. 2017. Cognitive fatigue in individuals with traumatic brain injury is associated with caudate activation. *Scientific reports* 7, 1 (2017), 1–12.

[43] Mohammad Zaki Zadeh, Ashwin Ramesh Babu, Ashish Jaiswal, and Fillia Makedon. 2020. Self-Supervised Human Activity Recognition by Augmenting Generative Adversarial Networks. *arXiv preprint arXiv:2008.11755* (2020).

[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] Mohammad Zaki Zadeh, Ashwin Ramesh Babu, Ashish Jaiswal, Maria Kyrarini, Morris Bell, and Fillia Makedon. 2021. Automated system to measure Tandem Gait to assess executive functions in children. In *The 14th PErvasive Technologies Related to Assistive Environments Conference*. 167–170.