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Investigation of Machine Learning and Deep Learning Approaches for Detection of Mild Traumatic Brain Injury from Human Sleep Electroencephalogram*

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***Abstract*— Traumatic Brain Injury (TBI) is a highly prevalent and serious public health concern. Most cases of TBI are mild in nature, yet some individuals may develop following-up persistent disability. The pathophysiologic causes for those with persistent postconcussive symptoms are most likely multifactorial and the underlying mechanism is not well understood, although it is clear that sleep disturbances feature prominently in those with persistent disability. The sleep electroencephalogram (EEG) provides a direct window into neuronal activity during an otherwise highly stereotyped behavioral state, and represents a promising quantitative measure for TBI diagnosis and prognosis. With the ever-evolving domain of machine learning, deep convolutional neural networks, and the development of better architectures, these approaches hold promise to solve some of the long entrenched challenges of personalized medicine for uses in recommendation systems and/or in health monitoring systems. In particular, advanced EEG analysis to identify putative EEG biomarkers of neurological disease could be highly relevant in the prognostication of mild TBI, an otherwise heterogeneous disorder with a wide range of affected phenotypes and disability levels. In this work, we investigate the use of various machine learning techniques and deep neural network architectures on a cohort of human subjects with sleep EEG recordings from overnight, in-lab, diagnostic polysomnography (PSG). An optimal scheme is explored for the classification of TBI versus non-TBI control subjects. The results were promising with an accuracy of ∼95% in random sampling arrangement and ∼70% in independent validation arrangement when appropriate parameters were used using a small number of subjects (10 mTBI subjects and 9 age- and sex-matched controls). We are thus confident that, with additional data and further studies, we would be able to build a generalized model to detect TBI accurately, not only via attended, in-lab PSG recordings, but also in practical scenarios such as EEG data obtained from simple wearables in daily life.**

I. INTRODUCTION

Traumatic brain injury (TBI) is defined as an alteration in brain functioning or brain pathology initiated by external impacts, such as blunt trauma, penetrating objects, or blast waves. TBI can cause a wide range of functional short- or long-term changes affecting thinking, sensation, language, and emotion, and perhaps most prominently, sleep [3][8]. About 75% of TBIs that occur each year are concussions or mild TBI (mTBI) [2]. Not all instances of mTBI result in persistent disability, and currently there are no prognostic markers to predict individuals who are most at risk. Thus, novel approaches to the precise detection and prognostication of mTBI is of utmost importance.

The brain electrophysiological signal during sleep, namely sleep electroencephalogram (EEG) is highly stereotyped across mammals, owing to specific features present in different stages (e.g. rapid eye movement [REM] or non-REM sleep). Thus, any deviations from the stereotype may have profound implications for changes in brain physiology. We have previously shown that the sleep EEG is a promising modality to detect and study mTBI in both animal models and humans [4][11][12][9]. EEG reflects cortical neuronal activity, thus providing an indication of the neuronal changes in the brain with high temporal resolution, and changes in EEG can be detected and processed for further studies using advanced signal processing techniques [7]. However, even with the availability of advanced signal processing methods, detection of some neurological conditions is challenging when conditions are heterogenous (such as mTBI) or if little is known about underlying neurobiological mechanisms. In most cases, efficient signal processing requires prior information on the features which researchers have to extract from EEG for detection of the neurological condition. For detection of mTBI via EEG, there have been various studies trying to understand its effects on EEG [6][7][14]. These previous studies on mTBI primarily focused on spectral power and feature-driven approaches such as cross-frequency coupling using quantitative electroencephalogram (qEEG) analyses within different sleep stages. Nevertheless, promising methods such as non-linear dynamical analysis, complexity measures, analysis of causal interactions, graph theory, and information dynamics have received a limited application in the analysis of EEG, and allow the exploration of better and more advanced signal processing techniques.

To overcome the aforementioned limits, we investigated the use of machine learning algorithms and deep convolutional neural networks which have performed extremely well in learning directly from artifact removed clean datasets in data-intensive problems to produce great results. Complex

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machine learning algorithms learn non-linear relations between input data and output features. In situations when there is a lack of domain knowledge or when the exact relations between input data and output target labels are unknown, we leveraged the non-linear learning power of complex machine learning algorithms to learn the appropriate relations between them. While standard machine learning algorithms rely on manual features and generally are limited in the feature domain size, deep learning architectures tend to overcome these limitations with the cost of data driven nature. Among deep learning architectures, convolutional neural networks (CNNs) have proven to be capable of learning complex cognitive tasks like image recognition and speech processing. This learning capability comes with the cost of difficulty in designing proper architecture for a specific task. In this work, inspired from a CNN architecture used for sleep stage detection from raw EEG signal we designed a network and adopted it to the TBI detection task.

II. METHODS

A. Human EEG Data in Use

The source of the data for this cohort consisted of de-identified files from human subjects who underwent attended, in-laboratory diagnostic polysomnography in an American Academy of Sleep Medicine (AASM)-accredited sleep laboratory at a single site. Retrospective PSG records were obtained under IRB approval (Portland VA MIRB 4108, PI: Lim). PSG data included n=19 subjects, n=10 of whom had documented mTBI without other sleep disorders (e.g. no obstructive sleep apnea) and n=9 age- and sex-matched control subjects without mTBI or other sleep disorders. Subjects ranged in age from 26 years to 61 years (mean: 38.4 mTBI, mean: 43.22 Controls). Mild TBI status was confirmed by self-report and chart review.

Subjects completed an in-laboratory, technician-attended overnight polysomnogram (*i.e.*, Type I sleep study). Sleep studies were recorded using Polysmith® version 9.0 (Nihon Kohden; 2012). Sleep staging was performed by an American Academy of Sleep Medicine (AASM)-certified sleep technician and interpreted by a board-certified sleep medicine physician. Standard parameters as specified by the AASM were captured in the PSG recordings, including electroencephalography (EEG), electromyography (EMG) of the mentalis muscle, electrooculography (EOG; left and right eyes), electrocardiography (EKG), peripheral blood-oxygen saturation (SpO2), respiratory movement/effort (thorax and abdominal), airflow (nasal and oral), auditory (snoring), and body positioning (right side, left side, supine, prone).

Six EEG channels were obtained per standard sleep lab protocols and were used in this analysis. The electrode positions included F3, F4, C3, C4, O1, and O2 (**Fig. 1**). All electrodes were referenced to the average of A2 (right ear) and A1 (left ear).

B. Algorithms Used and Assessment

To investigate the problem of mTBI detection in human EEG, we employed two different classification approaches

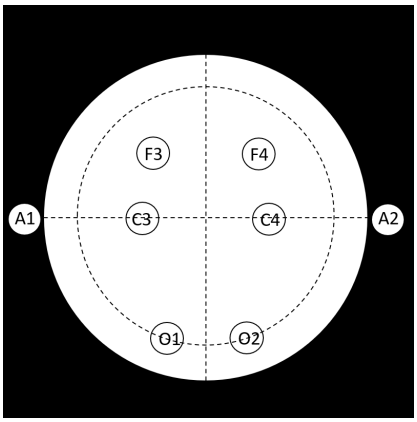

Fig. 1. EEG electrode positions.

or feature selection approaches and two different training/testing methodologies which are explained below.

1) Classification approaches: Classification algorithms used in this study can be broadly divided into two categories based on the way the features are extracted for classification purpose: The rule-based group such as decision trees (DT), random forest (RF), support vector machine (SVM), K-Nearest Neighbors (KNN) for which the features were extracted from the EEG and fed into the algorithms manually and the automatic feature selection group which used raw EEG data as input such as a deep convolutional neural network (CNN).

Rule-Based Machine Learning Approaches: In this methodology, different sections of raw EEG was extracted from the raw PSG data of each individual corresponding to various sleep stages - wake, N1, N2, N3, and REM and the analysis was done separately for different sleep stages. The extracted raw EEG was divided into 30 sec epochs which were then screened for artifacts using thresholding. Appropriate features were extracted from each EEG epoch based on the domain knowledge mentioned in previous sections. Relative power in delta (0.5 - 4 Hz), theta (4 - 8 Hz), alpha (8 - 12 Hz), sigma (13 - 16 Hz), beta (16 - 25 Hz), and gamma (30 - 35 Hz) bands were extracted from each epoch.

$$Relative\ Power = \frac{Power\ in\ freq\ band}{Total\ power} \tag{1}$$

Based on the literature, alpha:theta and beta:theta power ratios were also calculated as features from each epoch [4]. Previous studies have showed Hjorth parameters to be an effective feature to study group difference between concussion and control subjects [5]. Hjorth parameters such as activity, mobility and complexity were calculated using below equations.

$$Activity(x(t)) = var(x(t)) \tag{2}$$

$$Mobility(x(t)) = \sqrt{\frac{var\left(\frac{dx(t)}{dt}\right)}{var(x(t))}} \tag{3}$$

$$Complexity(x(t)) = \frac{Mobility\left(\frac{dx(t)}{dt}\right)}{Mobility(x(t))} \quad (4)$$

where x(t) denotes EEG signal. These features are fed to rule-based machine learning algorithms such as DT, KNN, SVM, and RF.

Automatic Feature Selection Approaches: Deep convolutional neural network was used in this methodology. Here the raw clean EEG epochs were given directly as inputs to the deep learning algorithms which learn to extract features automatically that best describes the relationship between input EEG and the target labels in the training dataset. This is achieved by stacking number of convolution layers on top of each other starting from raw input signal. The input signals convolves with each layer's weightings generating the input for the next layer. Finally we map the output of last convolution layer to the final labels using a couple of dense layers. The weights of convolutional and dense layers are being updated through back propagation calculated by the loss error computed for every mis-classified datapoint. This helps us to investigate features of EEG which do not directly correlate to neurobiology but still helps in our detection/classification problem. Unlike ruled-base algorithms deep architectures are capable of learning the features from the data during training. For instance, in this work we trained our CNN on the raw data signals without any defined features (such as power bands). Inspired by [10] architecture for sleep stage detection task using EEG, we used a similar network architecture in this work 2.

2) Training/Testing approaches: All algorithms were trained with two different types of data arrangements which evaluated pattern detection capability and generality of the trained model as explained below.

Random-Sampling (RS) Data Arrangement: In this arrangement, the features and the raw EEG epochs were fed to the machine learning and deep CNN algorithms respectively in 4:1 train:test ratio. Therefore, the training dataset comprised of 80% of the data or features from each subject, and the rest of the 20% of data or features from each subject was used as the testing set. For CNN, we set aside 20% of training dataset as development to select the best iteration to stop with early stop policy. This arrangement helps us to evaluate the power of pattern recognition of the algorithms as the data from each individual is not separated in train/test sets. It assumes that the data from all subjects are identical and that all EEG epochs are independent.

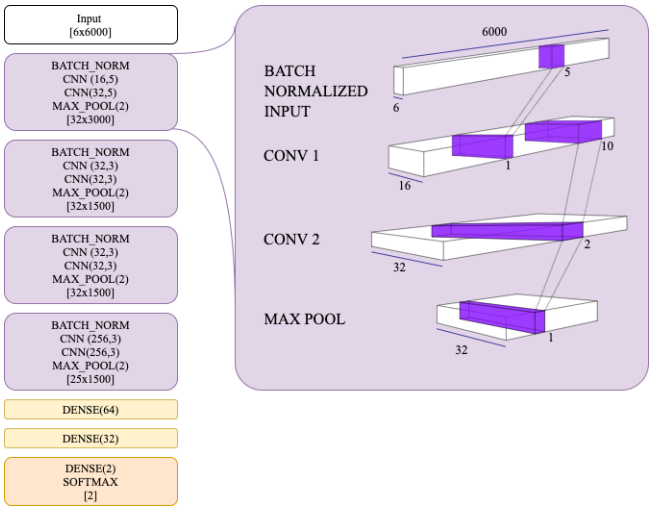

Fig. 2. CNN Architecture for TBI Detection. This is built of 4 blocks of Batch Normalization, 2 Convolutions and a max pooling stacked on top of each other delivering output to two dense layers collapsing to a prediction layer.

Independent-Validation (IV) Data Arrangement: In this arrangement data from one subject taken from each target class, that is, data from one mTBI subject and one control subject were kept aside for testing while the rest of the data were used in training the algorithms. This was carried out for all possibles combinations of training and testing sets. The IV data arrangement gives significant importance to differences in EEG from different subjects. This arrangement helps us study the trained model generality by predicting the class of new subjects whose data is not known to the algorithm beforehand. It does not assume a commonality of EEG patterns across subjects as done in RS.

III. RESULTS

Table I shows the 2-class classification accuracy obtained for all algorithms used in this study for random sampling arrangement and independent validation arrangement discussed in methods section. The accuracy is calculated for as the ratio of number of epochs classified correctly to the total number of epochs rather than as a ratio of number of subjects

TABLE I
CLASSIFICATION ACCURACY OF VARIOUS MACHINE LEARNING APPROACHES USING RANDOM-SAMPLING (RS) AND INDEPENDENT-VALIDATION (IV) DATA ARRANGEMENT (%)

Sleep stage	RS							IV						
	DT	RF	SVM	KNN			CNN	DT	RF	SVM	KNN			CNN
				3	5	7					3	5	7	
Wake	84.56	92.92	91.57	89.67	88.71	88.08	71.95	59.70	63.00	54.98	58.30	58.14	58.50	54.86
N1	87.85	94.32	91.32	86.07	85.39	84.93	77.59	67.70	69.39	54.14	48.96	49.16	49.00	55.26
N2	87.53	94.45	95.33	91.60	92.67	92.53	91.23	64.41	72.32	66.16	67.63	67.66	67.93	55.20
N3	84.21	96.09	95.94	93.91	94.92	95.43	84.44	55.32	56.20	55.44	54.68	54.32	54.04	54.82
REM	88.75	96.87	96.70	95.54	95.38	95.38	78.83	67.54	69.11	56.98	59.30	59.64	59.93	60.44

classified correctly to the total number of subject.

$$Accuracy = \frac{Number\ of\ epochs\ classified\ correctly}{Total\ number\ of\ epochs} \quad (5)$$

IV. DISCUSSION

The higher accuracy obtained in the RS data arrangement shows that the algorithms are able to learn the patterns which differentiate between 2 classes - mTBI and control subjects well using the extracted features. This scenario of accurately classifying subjects into the two classes once the prior information on the subject's EEG is known to the algorithm can be used to monitor subjects on a day to day basis in real-time. The potential of the above-discussed concept was showcased by our team in [1] using mice mTBI EEG obtained from a compelling mouse model [4]. It is worthwhile to mention that the same procedure can be translated to human EEG classification as well.

However, in the IV data arrangement, where the ML model does not have prior information on the subject's EEG during the training phase, the generality of the model learnt over the selected features was tested. As seen from the classification accuracy obtained in table I, this was not as good as compared to RS data arrangement. This may possibly be due to the low number of subjects on which the algorithm is trained on. As mentioned in the previous sections, deep learning algorithms perform best when they have huge amount of data to learn from and we have not been able to utilize the full potential of these algorithms due to availability of less number of subjects in the dataset used in this paper. In some cases, some subjects do not have any epochs from a particular sleep stage category, thereby further reducing the amount of data available for the ML algorithm to train. In almost all cases rule based algorithm outperforms CNN, reinforcing the data driven approach of deep learning models.

The results obtained in the current work remains preliminary and should be validated with a larger data set which we intend to do in our future analysis. When using a larger data we expect the classification accuracy obtained in IV data arrangement to converge to the results obtained in RS data arrangement thereby, indicating that the model has learnt more general parameters. However, recent studies on TBI EEG analysis consisting of larger datasets have shown similar results [13] which points towards the need for use of normalization between subjects' data or transfer learning/alignment techniques which can help generalize the ML model. With a larger sample size and better feature selection procedure, the system should be able to reach performance metrics achieved in the RS data arrangement.

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VI. REFERENCES

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