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A Routine Electroencephalography Monitoring System for Automated Sports-Related Concussion Detection

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Abstract

Cases of concussions in the United States keep increasing and are now up to 2 million to 3 million incidents per year. Although concussions are recoverable and usually not life-threatening, the degree and rate of recovery may vary depending on age, severity of the injury, and past concussion history. A subsequent concussion before full recovery may lead to more-severe brain damage and poorer outcomes. Electroencephalography (EEG) recordings can identify brain dysfunctionality and abnormalities, such as after a concussion. Routine EEG monitoring can be a convenient method for reducing unreported injuries and preventing long-term damage, especially among groups with a greater risk of experiencing a concussion, such as athletes participating in contact sports. Because of the relative availability of EEG compared to other brain-imaging techniques (e.g., functional magnetic resonance imaging), the use of EEG monitoring is growing for various neurological disorders. In this longitudinal study, EEG was analyzed from 4 football athletes before their athletic season and also within 7 days of concussion. Compared to a control group of 4 additional athletes, a concussion was detected with up to 99.5% accuracy using EEG recordings in the *Theta-Alpha* band. Classifiers that use data from only a subset of the EEG electrodes providing reliable detection are also proposed. The most effective classifiers used EEG recordings from the *Central* scalp region in the *Beta* band and over the *Temporal* scalp region using the *Theta-Alpha* band. This proof-of-concept study and preliminary findings suggest that EEG monitoring may be used to identify a sports-related concussion occurrence with a high level of accuracy and thus reduce the chance of unreported concussion.

Keywords: EEG; EEG monitoring; electrode networks; non-patient-specific; sports-related concussion; SVM

Introduction

Traumatic brain injury (TBI) is the fourth-most prevalent neurological disorder after stroke, Alzheimer's disease, and epilepsy.¹ Approximately 80% of TBIs are classified as mild TBI (mTBI), and persons who ex-

perience mTBI generally do not show any evidence of impairments in the nervous system.² Although the terms mTBI and concussion are often used interchangeably, concussion is a subset of mTBI and characterized by an absence of primary brain injury as

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identified in traditional computed tomography/magnetic resonance imaging scans and more favorable outcome.^{3,4} The three most common causes of concussion are falls, motor vehicle accidents, and sports-related injuries. Falls are more common in elderly patients, and sports-related concussions (SRCs) are observed with increasing frequency in youth and college-age contact-sport athletes, such as boxing, football, ice hockey, and soccer.⁵⁻⁹

Incidence of concussion injuries is ~4 million per year in the United States and >75 million around the world.^{4,10,11} SRCs result in sequelae of symptoms (e.g., headaches, dizziness, and difficulty concentrating), cognitive disruption, and imbalance that typically resolve within 1–2 weeks in college-athletes.¹²⁻¹⁴ After a concussion, athletes are advised to carefully return to daily routines and activities under the supervision of their health provider or a certified trainer to prevent another concussion before full recovery from the previous incident. A TBI that occurs before the symptoms associated with the previous concussive injury have fully cleared is defined as second impact syndrome (SIS). Although recovery from a concussion is usually complete, it is believed that SIS can result in critical brain injuries or diffuse cerebral swelling.^{4,15,16} Based on the SRC data from the National Collegiate Athletic Association (NCAA) Injury Surveillance Program during the 2009–2010 to 2013–2014 academic years, incidence of SRC among NCAA athletes is estimated to be >10,000 per year, with 9.0% recurrent SRCs.¹⁷ Annual reported SRC incidence among collegiate men's football players has been estimated to be ~3500, including 5% recurrent concussions.¹⁷

The number of unreported SRCs is estimated to be ~30–50% of SRCs every year. The unreported case rate among collegiate athletes is estimated to be one third of total SRC cases.¹⁸⁻²⁰ Unreported concussive athletes are at a greater risk of SIS because of the lack of clinical management of the initial injury. Repeated concussions prolong post-concussion recovery and can result in long-term brain damage and perhaps more-severe neurological and cognitive impairments. Such long-term effects can reduce quality of life, resulting in an increase in emotional distress, sleeping impairments, and depression.²¹

Although post-concussion symptoms usually resolve within 7–10 days post-injury in 85% of cases,^{12,22} there is growing evidence that neural alterations caused by mTBI may persist for months after a concussion.²³ Diagnosing concussions requires trained and certified

clinical expertise and the availability of experts to evaluate concussions. Such skill requirements make such detection techniques less accessible to large segments of our population. An objective monitoring system may facilitate concussion detection in this critical window, to minimize the number of unreported concussion incidences, encourage injured athletes to seek proper medical attention effectively, and prevent further damages.

Brain-imaging techniques, such as functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), and diffusion tensor imaging, provide brain biomarkers of cerebral alterations after TBI and provide a higher spatial resolution compared to electroencephalography (EEG). However, because access to fMRI and MEG technology and training are not widely available, and are time-consuming and relatively costly,²⁴⁻²⁶ their clinical utility in concussion monitoring may be limited. In contrast, EEG methods are more accessible, more time- and cost-effective, and have a history of clinical monitoring in sleep disorders and epilepsy. These properties make EEG an attractive application for concussion monitoring and detecting possible concussions to facilitate clinical diagnosis.

Studies of brain activity in the frequency domain can identify brain regions active during specific mental and physical tasks. Simultaneous EEG-fMRI studies can show positive or negative correlations of the frequency characteristics of EEG signals with neurovascular processes in specific regions.²⁷ EEG power and network-based approaches have been investigated in frequency domain studies to distinguish between concussed and control groups.²⁸⁻³⁵ These studies examined differences in power in the EEG signal and active networks between athletes with concussion and controls for distinct frequencies and in particular regions of the brain. Most EEG studies monitor resting-state EEG. However, approaches that monitor task-related EEG recordings and elicit event-related brain potentials (ERPs), such as those recorded during attention or working memory tasks, can more accurately capture the neurocognitive processing differences associated with concussion.^{36,37}

A routine brain-monitoring system shortly after concussion can provide information to help prevent further damage to the brain of a concussed patient by guiding treatment and management of concussion symptoms before a player returns to activities that pose a risk to brain functioning. Short-term monitoring can objectively identify altered EEG dynamics and thus minimize the potential for a recurrent concussion. In the present study, EEG was recorded from college



football athletes while completing a 2-back task of working memory. Athletes participated before their primary athletic season and again within 7 days after concussion. Athletes who did not experience a concussion served as matched controls and were also tested at pre-season and within a similar time window as concussion participants.

A routine EEG-monitoring system is proposed to automatically detect any recent concussion based on features from the working memory task recorded at pre-season and post-injury. The goal of this approach is to capture the connectivity and variation in network coherency of brain signals in the frequency domain of different brain regions before and after a concussion. Networks are established based on pair-wise distance measurements between electrodes. The distances are calculated and extracted as coherency measurements in different frequency bands using a variety of distance metrics, including previously used metrics for detecting and localizing seizures.³⁸ The metrics investigated include some that combine measures of connectivity as well as measures of power in the frequency bands (the metrics are described in the Supplementary Materials). All coherencies in the frequency domain are studied over different scalp regions of the brain to capture any significant spatial differences between regions in classifying participants with a concussion and those without concussion. By combining sessions of a participant from before and after a possible concussion, the classifier captures any functional alteration caused by the concussion on the brain-activity networks and uses this to differentiate between the presence or absence of a recent concussion.

Methods

Data preparation

The data reported hereinafter come from a larger study investigating the influence of concussion on cognitive, electrophysiological, oculomotor, and vestibular outcomes in college athletes.^{36,37,39} The present study involves 6 collegiate American football athletes who participated before their athletic season and again after an in-season concussion, in addition to 6 age-matched teammates as control athletes. All concussions were diagnosed by a board-certified team physician and self-reported concussion history reviewed by a clinical vestibular audiologist. After experiencing a concussion, participants attended the second session within 7 days post-injury. Control participants attended their second data-collection session within a matching time win-

dow. Previous studies suggested that concussion recovery time varies between 5 and 14 days on average.^{12,22} Others have reported a significant reduction of EEG measures after the seventh post-concussion day.²³ Therefore, this study analyzed data of athletes who were tested before their athletic season and again within 7 days post-concussion (mean = 3.25 and standard deviation [SD] = 2.5 days post-injury). All procedures were approved by the host institutional review board before data collection. Data-collection sessions were held across three consecutive seasons from the 2012–2013 to 2014–2015 seasons.

Although at the time of recruitment control participants in the study were matched *a priori*, 2 concussion participants were excluded from the present analysis, 1 participant because of poor EEG quality and the other because of post-concussion follow-up >7 days. In addition, 2 control participants were discarded as the control group's outlier to have balanced distribution of sample size, resulting in a final data set that included 8 participants (4 concussions, 4 controls). Table 1 contains group-level demographic information such as age, concussion history, time gap between their sessions, and 2-back performance. The majority of the sample was White and Not Hispanic (87.5%). One participant in the concussion group reported a history of learning disability. Relative to controls, participants in the concussion group tended to be slightly older and the time

Table 1. Group Comparison of Participants

	Group	
	Concussion (n = 4)	Control (n = 4)
Age ^a	20.69 (1.04)	19.25 (0.74)
Days between sessions ^b	46.25 (14.97)	155 (94.32)
Concussion history ^c	4	2
Baseline		
Match Acc ^d	0.80 (0.11)	0.80 (0.10)
Match RT ^e	647.20 (169.15)	769.72 (41.77)
Non-match Acc ^f	0.92 (0.04)	0.93 (0.08)
Non-match RT ^g	655.29 (119.57)	781.36 (57.43)
Follow-up		
Match Acc	0.83 (0.06)	0.90 (0.07)
Match RT	589.46 (128.37)	657.82 (125.66)
Non-match Acc	0.93 (0.05)	0.96 (0.04)
Non-match RT	594.40 (83.55)	762.18 (80.80)

^aThe age of the participant at first testing session.

^bDays between the first and second testing sessions.

^cNumber of participants who reported a history of concussion, excluding the in-season concussions experienced for the concussion group.

^dResponse accuracy on match trials.

^eAverage response to match trials.

^fResponse accuracy on non-match trials.

^gAverage response time non-match trials.

Acc, accuracy; RT, response time.



between sessions shorter; however, these differences were not statistically significant ($p > 0.05$). Details about the demographic information of participants are provided in Supplementary Table S1 (Supplementary Materials).

Unfiltered EEG was recorded from a 256-channel Ag/AgCl electrode array using NetStation software (version 4.4.2; Electrical Geodesics Inc. [EGI], Eugene, OR) while participants completed a 2-back task of visual working memory. Details regarding the 2-back task and EEG/ERP processing parameters are reported elsewhere.³⁶ In brief, participants viewed individual presentations of uppercase English letters on a computer screen and were instructed to use two different buttons to indicate whether the current letter matched or mismatched the letter presented two letters previously. There were a total of 100 trial presentations, half of which were matches and the other half were mismatches. Data were manually reviewed for the final validation of the pre-processing steps. Trials in which the majority of the electrodes had faulty signals attributable to muscle or eye movements, along with high variance attributable to high potential shifts (>50 to $150 \mu\text{V}$), were removed from the data set.

Network-based features extraction

To build a balanced data set for each participant and reduce the number of faulty segments, the 50 trials with the lowest SD within a session were chosen for further analysis. The number of accurate segments for participants was between 77 and 97 (average = 85.75; SD = 6.299802) segments from 100 total trials in a session (50 matched and 50 unmatched). On average, 12.5 segments were removed as faulty segments, and 73.25 segments remained in the data set after removing the faulty segments. Therefore, to standardize the number of segments we used in this study, 50 segments per participant were chosen from the acceptable segments. To obtain the frequency domain representation of the EEG signal, a Tukey window was first applied.⁴⁰ Frequency components were computed using the fast Fourier transform (FFT) applied to the windowed data. FFT components were partitioned into the *Delta* (0.5–4.0 Hz), *Theta* (4–8 Hz), *Alpha* (8–14 Hz), and *Beta* (14–30 Hz) frequency bands. In addition to these frequency bands, combinations of these frequency bands were also defined to increase the resolution of the frequency bands and investigate the use of wider frequency ranges in the classifier. Combined bands were defined as *Delta-Theta* (0.5–8.0 Hz), *Theta-Alpha* (4–

14 Hz), and *Alpha-Beta* (8–30 Hz). The *All* band was defined to be the entire spectrum (0.5–30.0 Hz).

Pair-wise distance between the FFT components in a frequency band from different electrodes was calculated and used to develop indicators for the status of neural networks based on scalp recordings. If the distance between two channels is low (or they have strong coherence), it indicates neural communication between those electrode locations. Thus, the pair-wise distances between electrodes provided a measure of the brain-network dynamics. Previous studies generally focused on changes in the power of the signals in different bands. Studies using graph-theory-based coherence measures also have been studied with occasionally contradictory results.⁴¹ In addition to Euclidean (*Euclid*), cosine (*Cos*), and correlation coefficient (*Corr*) distance metrics, a combination of distance metrics and the power of frequency coefficients in channels are used to obtain three combined features: *Po3Euclid2*, *Po3cos2*, and *Po3Corr2*. These combined metrics were previously used for detecting seizures.^{38,42} Each feature provides a different view of brain-network interactions.

To capture the overall characteristics of a network of electrodes, two other features are defined: *AllFeat* and *AllFeatwPo*. *AllFeat(A,B)* is the combination of all the different measures of pair-wise distance between two channels A and B in a particular frequency band, and *AllFeatwPo(A,B)* is a similar extracted feature to *AllFeat(A,B)* along with the average power of the signal from each electrode in a specific frequency band. All described features are computed for different sets of electrodes as representors of different scalp regions of the brain to study the performance of the proposed model in scalp regions. Sets of electrodes chosen are illustrated in Figure 1, and their corresponding electrodes are described in Supplementary Table S2. Detailed equations and calculations of features are described in the Supplementary Materials.

Pair-wise distances of electrodes for each trial were calculated using the defined metrics. Pair-wise distances are representations of networks of electrodes and the synchronicity in each frequency band. A participant data set in a scalp region with N electrodes and a frequency band of interest forms a rank 3 tensor feature, with 50 ($2N \times N$) feature matrices. The data sets for athletes who experienced a concussion before their second sessions are labeled “Concussed,” and those who did not experience a concussion were labeled “Control.” Figure 2 depicts the steps for generating the feature data sets for a participant. The classifier used



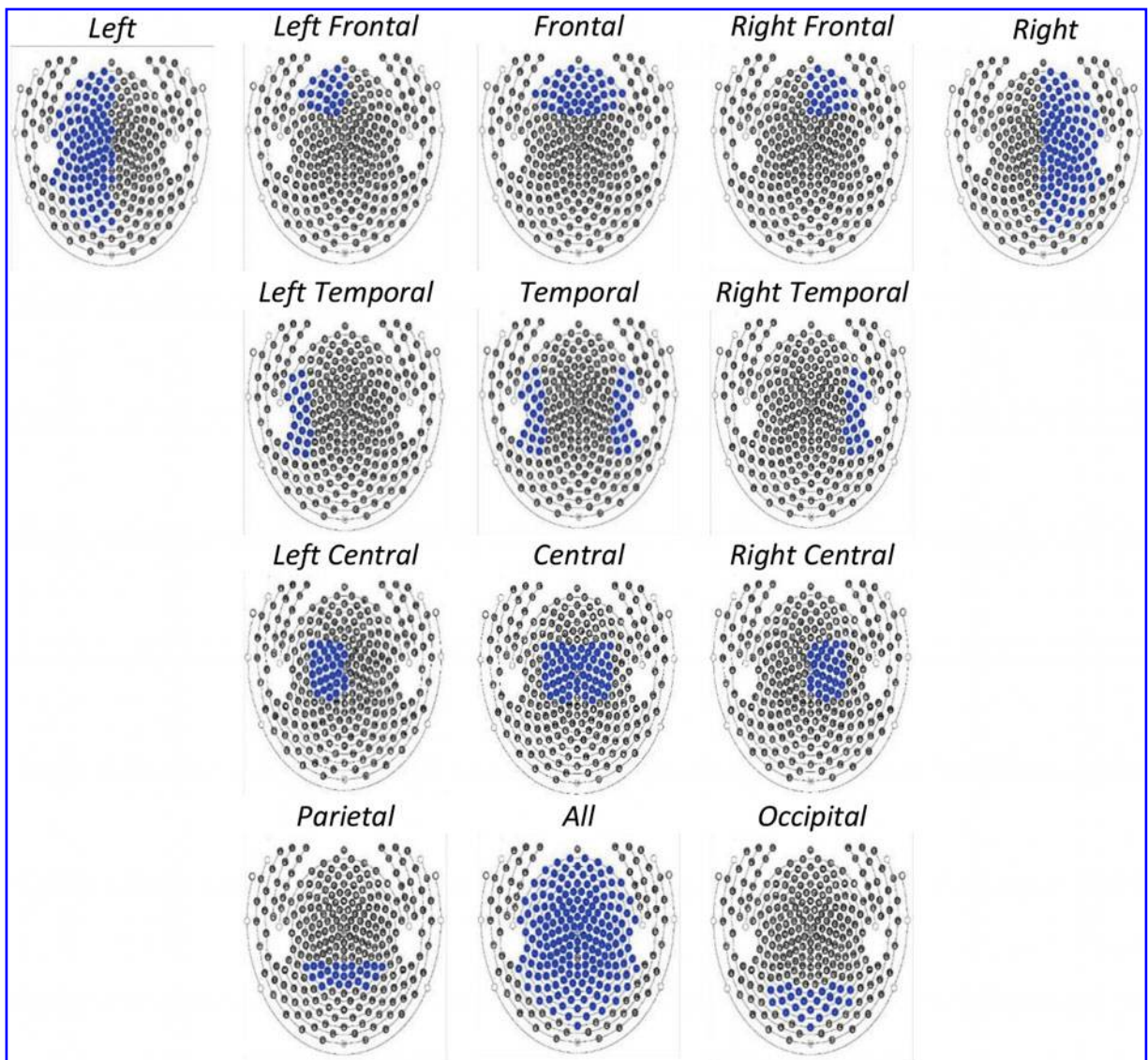


FIG. 1. Sets of electrodes mapped on the scalp regions. Associated electrodes of a selected area are highlighted in blue.

was a linear support vector machine (SVM), which was trained for each frequency band in all defined regions, separately for each of the feature metrics. To build a non-participant-specific model, 1 participant at a time was excluded from the training data for testing, whereas the rest were used for training the classifier model, also known as the leave-one-out cross-validation.

Membership of each trial of the isolated testing data set was predicted by fitting the extracted features of the trial to the trained classifier model. Based on the pre-

dicted class of trials and the group membership of the isolated participant (Concussion or Control), accuracy of the trained model was calculated by the number of correctly labeled segments from the 50 isolated trials of the testing data sets (Fig. 3). This process repeats for each participant as the isolated test data set, and the classifier is modeled with the other 7 participants.

Results

Concussion and control groups did not differ in 2-back accuracy or response time at baseline ($t_{(6)} < 1.91$,



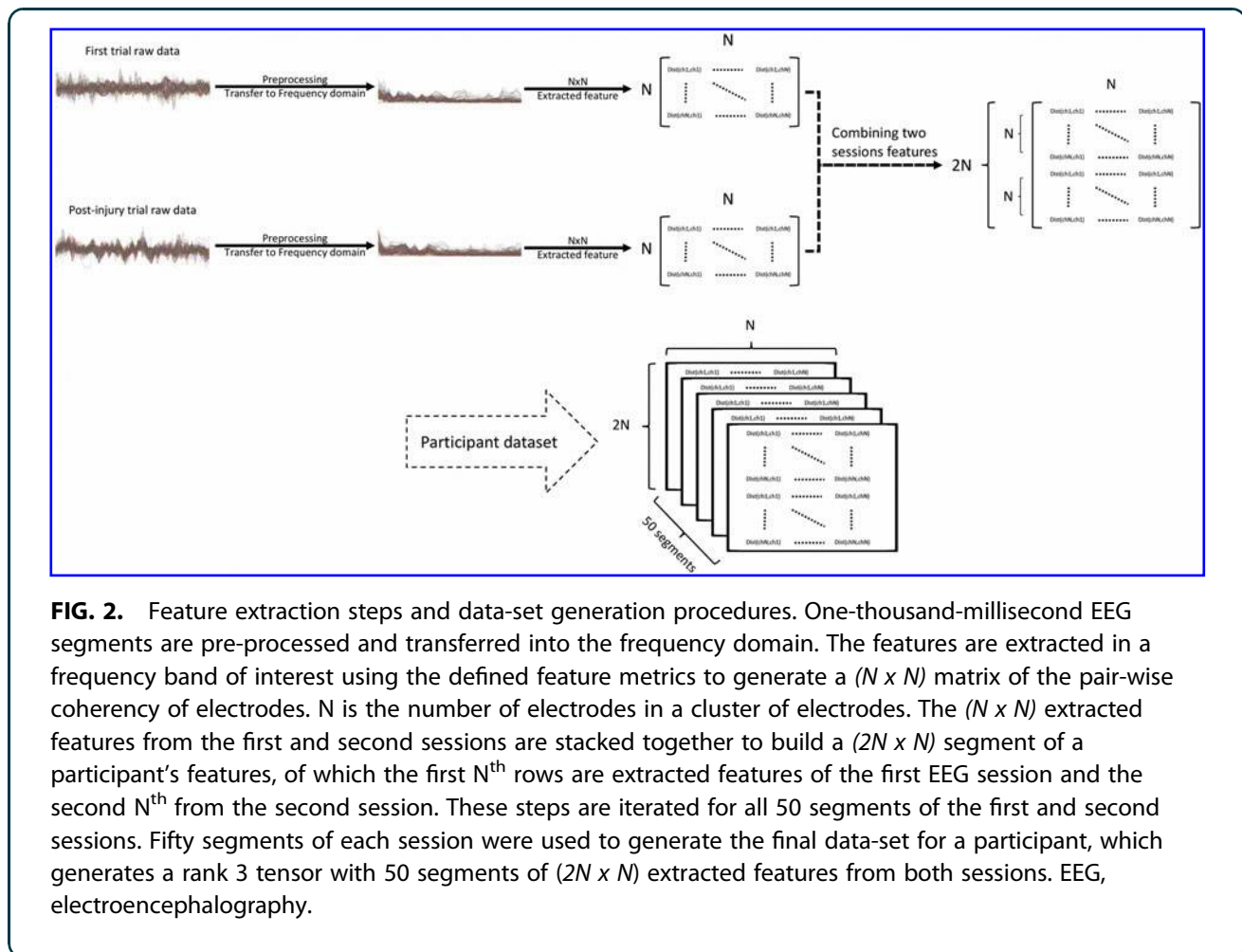


FIG. 2. Feature extraction steps and data-set generation procedures. One-thousand-millisecond EEG segments are pre-processed and transferred into the frequency domain. The features are extracted in a frequency band of interest using the defined feature metrics to generate a $(N \times N)$ matrix of the pair-wise coherency of electrodes. N is the number of electrodes in a cluster of electrodes. The $(N \times N)$ extracted features from the first and second sessions are stacked together to build a $(2N \times N)$ segment of a participant's features, of which the first N^{th} rows are extracted features of the first EEG session and the second N^{th} from the second session. These steps are iterated for all 50 segments of the first and second sessions. Fifty segments of each session were used to generate the final data-set for a participant, which generates a rank 3 tensor with 50 segments of $(2N \times N)$ extracted features from both sessions. EEG, electroencephalography.

$p > 0.05$; see Table 1). At follow-up, the concussion group responded more quickly to non-match trials than the control group ($t_{(6)} = 2.887$, $p = 0.028$); however, this failed to survive Bonferroni's correction. To examine the change in 2-back performance from baseline to follow-up session, difference scores between the two sessions were calculated for each participant on the accuracy and response-time metrics. The two groups did not differ in their change in performance between the two sessions ($t_{(6)} < 1.47$, $p > 0.05$).

Model results were analyzed first by comparing the performance of the classifier models in different frequency bands to identify the frequency bands that delivered the best performance in classifying concussed and control athletes. We then used signals from clusters of electrodes to determine whether a subset of electrodes was sufficient to provide accurate classification. In practical terms, if only a subset of the electrodes

could provide accurate detection of a concussion, this could reduce the cost of automated monitoring.

Figure 4 illustrates the average performance of concussed, control, and total average (average of all participants) in each frequency band using the pair-wise distances of electrodes in the *All* region. Using the signals in the *Theta-Alpha* band results in the best performance and shows consistent performance in both the Concussed and Control groups, with a median accuracy of 96.3%. The *Theta-Alpha* band contains the lowest variance range of performances for all features, of which the first- to third-quartile performances are all above 90% (Fig. 4).

To determine how well the classifier performed when only a subset of electrodes representing different scalp regions was used, the performance of the classifier in each region was compared using the features extracted from the *Theta-Alpha* band. The *Theta-*



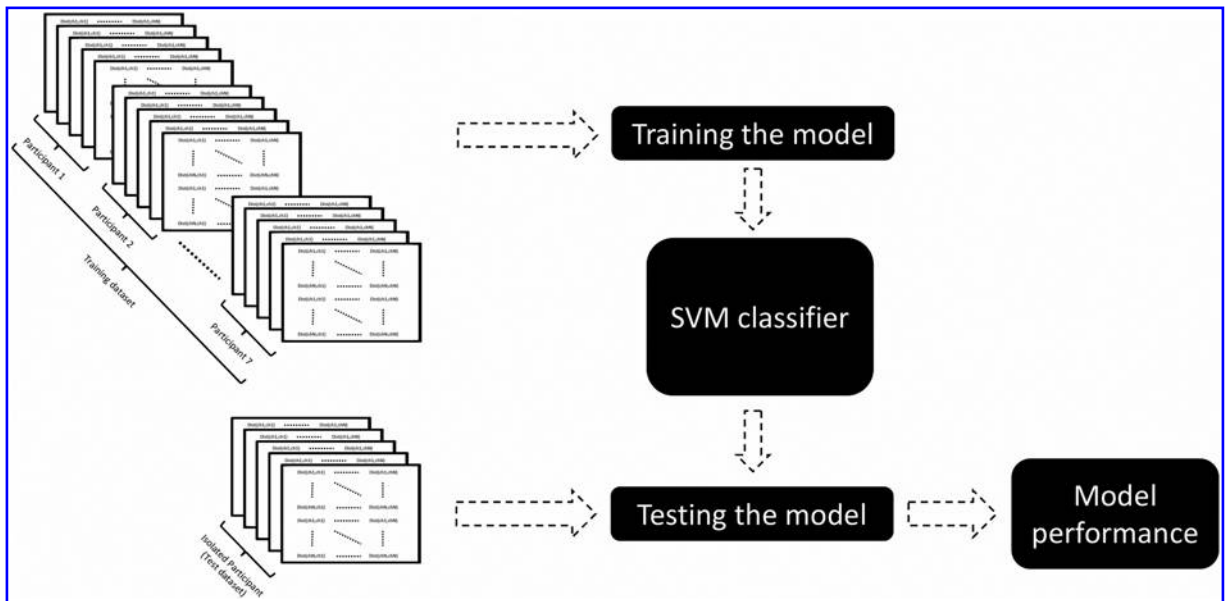


FIG. 3. Classifier model. Extracted features of a participant are excluded for training the classifier model as the test data set. After training the SVM classifier using extracted features of the other 7 participants, the model is evaluated on the isolated testing dataset (i.e., participant). Model performance reports the accuracy of the modeled classifier on predicting the correct label of the 50 segments of the test data set. SVM, support vector machine.

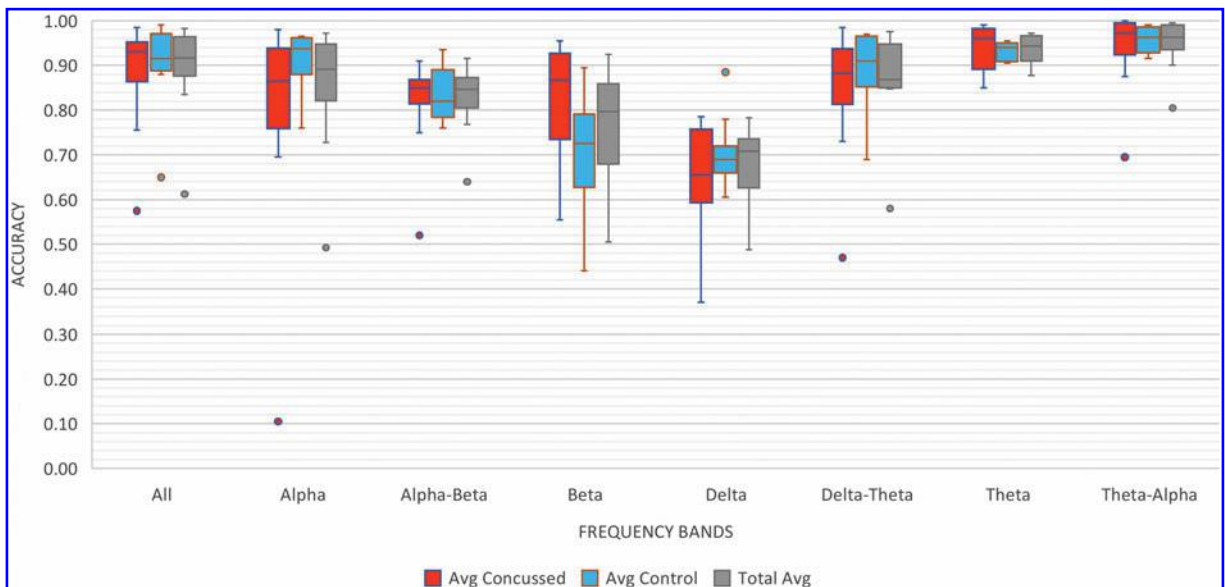


FIG. 4. Frequency bands performances. Box plots contain the average performance of modeled classifiers on concussed, control groups, and the total average (average of both groups) in each frequency band using all the defined metrics using the set of electrodes in the *All* region. Accuracies are in the range of [0 to 1]. Red, blue, and gray boxes are the average performance of the classifiers tested on the concussion, control, and both groups, respectively.



Alpha band had previously been identified as the most discriminative frequency band. Figure 5 demonstrates the performance of the classifiers using each set of electrodes over scalp regions for each group of participants. Clearly, using all the electrodes results in the best performance, with a total median accuracy of 96.25% across all participants for all features. However, looking at the performance of the classifier using a restricted set of electrodes can identify the scalp region with electrodes that are most responsive to the occurrence of a recent concussion. Using the electrodes from the *Frontal*, *L-Frontal*, *R-Frontal*, *Parietal*, and *Occipital* regions results in the poorest performance. Using electrodes from the *Temporal*, *Left*, and *Central* regions gives us the best overall performances, with 94.12%, 92.8%, and 90.12% median average accuracy, respectively.

The *Theta-Alpha* band and the *Temporal* region were selected as the best frequency band and region, on average, over all the defined feature metrics. To compare the performance of the distance metric on which to best capture the effect of changes caused by concussion, the top 10 results for each metric were compared. Supplementary Table S3 (Supplementary

Materials) contains the 10 modeled classifiers with best performances for each modeled classifier using the different feature metrics, using the defined subsets of electrodes and using the partitioned signal in different frequency bands. These results are shown in graphical form in Figure 6.

Three metrics (*AllFeat*, *Corr*, and *Cos*) show the best performance, with 96.87%, 96.37%, and 96.87% median accuracies, respectively. Among these three features, the median accuracy using *AllFeat* for both Concussed and Control groups is 96.75%. Although the median of the average performances for classifying both groups for *Cos* and *Corr* metrics are equal and close (0.5% lower) to the *AllFeat* model, the differences between the classification accuracies for the Concussed or Control groups using *Cos* and *Corr* metrics are slightly greater than the *AllFeat* metric. As mentioned before, the difference of median accuracies for the Concussed and Control groups using the *AllFeat* metric is 0 (96.75% [Concussed] – 96.75% [Control]). For the *Cos* metric, this difference is 1 (97.5% [Concussed] – 96.5% [Control]) and for the *Corr* metric it is 1.25 (97.5% [Concussed] – 96.25%

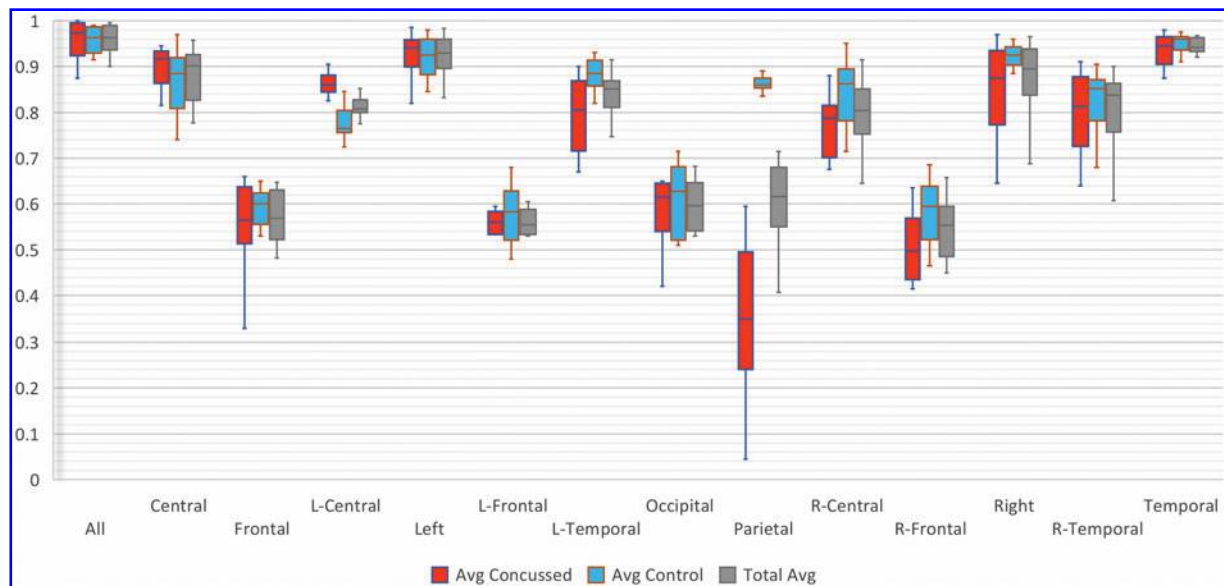


FIG. 5. Performances of clusters of electrodes in the *Theta-Alpha* frequency band. Performances of classifiers trained on all the defined feature metrics individually in the *Theta-Alpha* frequency band are illustrated for groups of electrodes. Accuracies are in the range of [0 to 1]. Red, blue, and gray boxes are the average performance of the classifiers tested on the concussion, control, and both groups, respectively. R-Frontal, right frontal; L-Frontal, left frontal; R-Temporal, right temporal; L-Temporal, left temporal; R-Central, right central; L-Central, left central.



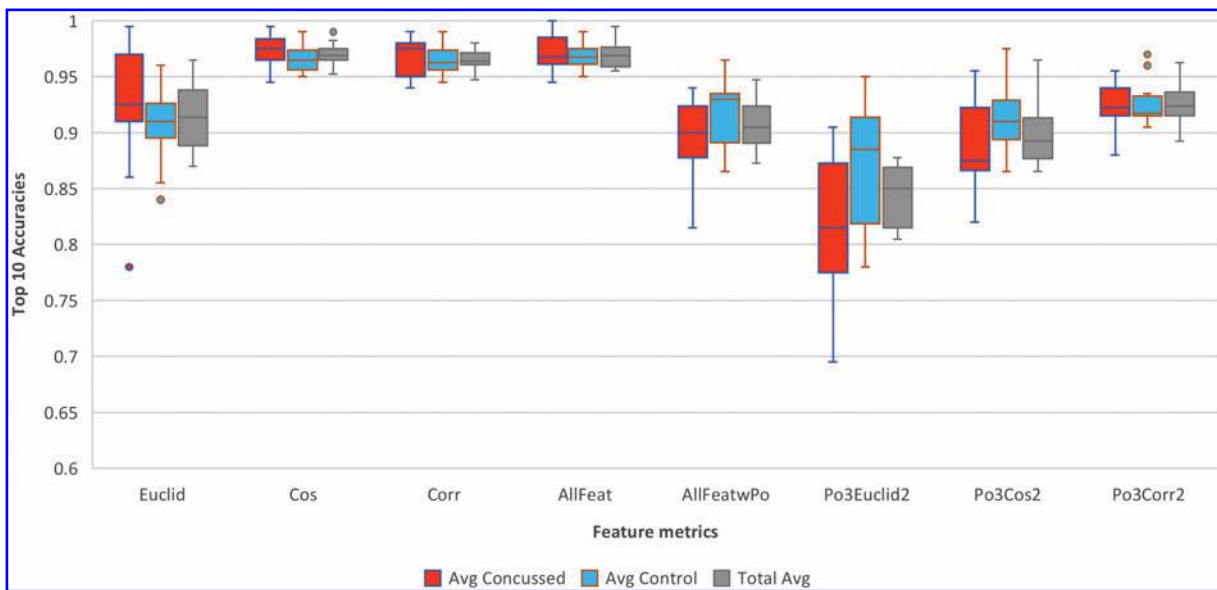


FIG. 6. Top 10 performances of feature metrics. Average accuracies of the top 10 models with the best performances for each feature metric, regardless of the frequency band and subset of electrodes for training the model, are illustrated for participants in concussion and control groups and overall performance of models for both groups (total average). Accuracies are in the range of [0 to 1]. Red, blue, and gray boxes are the average performance of the classifiers tested on the concussion, control, and both groups, respectively.

[Control]). Having a classifier with a balanced performance across both categories is preferred.

By looking at the overall performance of the classifier using frequency bands across each region separately, the scalp regions that contain distinguishable changes resulting from concussion can be investigated. The classifier operating in the *Theta-Alpha* band performs better than the other bands in the top 10 results across all metrics models (Supplementary Table S3). The classifier also works well in the *Beta* band in the *Central* region, which is among the four highest accuracy results in each metric category except for the *Euclid* and the *Po3Euclid3* metrics. Supplementary Figure S1 demonstrates the overall performance of frequency bands in different regions using all the feature metrics. Although the classifier operating on the data from the *Theta-Alpha* band in the *Temporal* region shows the best performance, the classifier model from the *Beta* band in the *Central* region also has a noticeably high accuracy, with a median accuracy of 93.9%.

Supplementary Table S4 contains the overall performance of modeled classifiers trained in each of the eight frequency bands, each of the eight feature metrics,

and over the 14 electrode clusters separately (896 models). The three best models are developed using the *Allfeat* metric in the *Theta-Alpha* band in the *All*, and *Temporal*, and in *Beta* band among the *Central* region, with an area under the curve (AUC) of 0.9986, 0.9895, and 0.9786, respectively. The receiver operating characteristic (ROC) of the three models with best performance are illustrated in Figure 7.

Discussion

The structure of the brain changes continuously across the human life span, and the functional connections within the brain may change as well.⁴³ Any neurophysiological alteration in the brain caused by disorders, such as stroke, dementia, or the experience of a concussion, is believed to change the way the different regions of the brain communicate, which, in turn, is a broad manifestation of neuronal communication in the brain. These abnormal and atypical alterations of the development of functional connectivity in the brain are rapid compared to the natural alterations in brain plasticity. These distortions are more significant if they are compared within a patient before and after



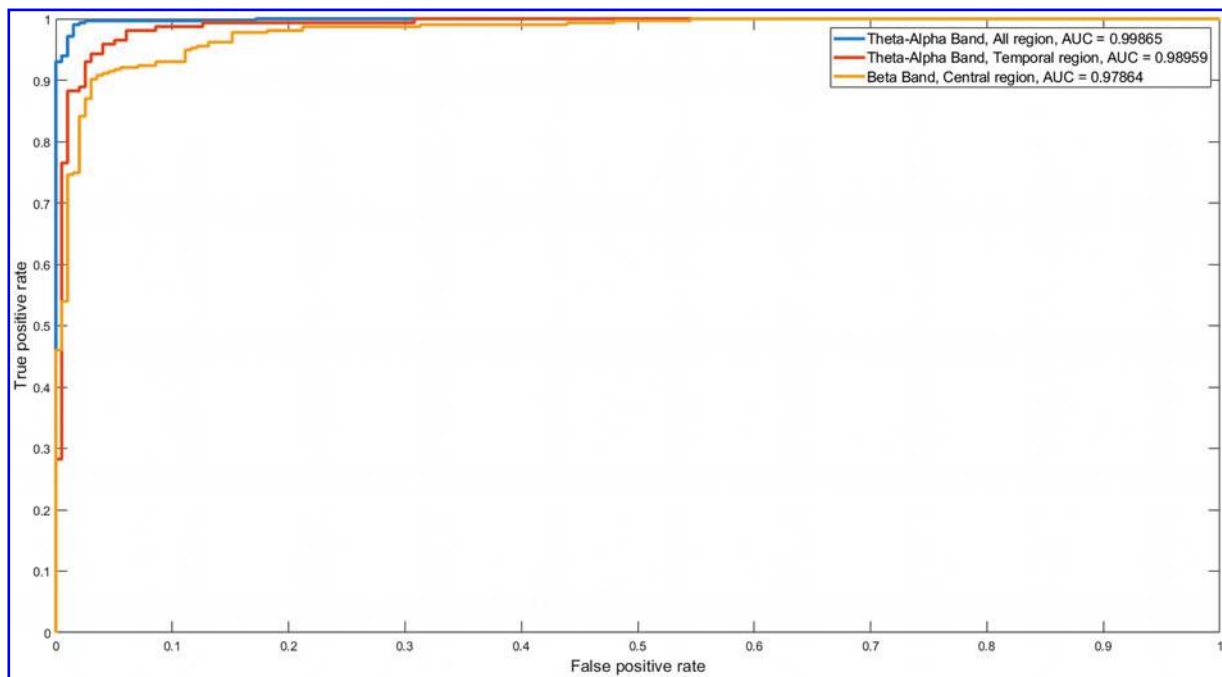


FIG. 7. ROC of models with best performances. ROC curves of the three best models are developed using the *Allfeat* metric in the *Theta-Alfa* band in the *All* (blue), *Temporal* (red), and *Beta* band among the *Central* region (yellow). The AUC of each ROC is provided in the legends. AUC, area under the curve; ROC, receiver operating characteristic.

an incident. In this study, alteration in the brain network was investigated in the frequency domain to capture the effect of concussion on networks in different regions of the brain.

Previous studies reported differences in the power in different frequency bands of the EEG signal in concussed groups compared to controls; however, none of these studies focused on differences in the same patient before and after a concussion. For example, Thompson and colleagues reported significantly reduced power in the *Delta* to *Beta* bands in concussed athletes compared to a control group.³⁰ More specifically, power in the *Alpha* and *Beta* bands was reduced more in frontal regions, and *Theta* power was decreased in the parietal regions. Teel and colleagues²⁹ also showed that there was a significant reduction in *Theta* and *Beta* powers in the concussed group compared to controls within 8 days of injury, and Gosselin and colleagues³³ reported a significant increase in *Delta* power and reduction in *Alpha* power among concussed athletes. Considering the different conditions of the tri-

als in these studies, they all showed a reduction in power in the *Theta*, *Alpha*, and *Beta* bands.

The results from the present pilot study suggest that classifiers that use changes in the brain of the same participant using features that include the power in the frequency bands result in lower accuracy than features that do not take into account the power in the frequency bands. It should be noted that unlike the work cited above, the current work did not use the difference in power between the two states. Instead, the average power was used to weight the pair-wise distance; the more power in the band, the more important the pair-wise distance. Our results seem to indicate that power weighting tends to hide the effect of the pair-wise distance and thus reduces the classifier performance. However, in accordance with findings from previous studies, the signal in the *Theta*, *Alpha*, and *Beta* bands was more discriminative between concussed and control groups. The best frequency bands for use in classification, described in the Results section, are the *Theta-Alfa* and *Beta* Bands using the



AllFeat feature. The *AllFeat* feature represents the coherency in the region, albeit without considering the signal power. Our results indicate differences in the pre- and post-concussion network connectivity at the *Temporal* and *Central* electrode sites.

Past studies in network coherence using graph-based approaches after concussion provided seemingly contradictory results. For instance, Cao and Slobounov³⁴ reported a significant decrease in frontocentral connectivity and a significant increase in parieto-occipital connectivity among concussed athletes, and Virji-Babul and colleagues³⁵ found reduced parieto-occipital connectivity and increased connectivity on the right pre-frontal cortex in the concussed group relative to the control group.

There are a limited number of studies focusing on automated classifiers for concussion. Cao and colleagues²⁸ used an SVM and obtained 77.1% accuracy for classifying asymptomatic participants at day 30 post-injury. Wickramaratne and colleagues⁴⁴ used a deep learning approach for classifying concussed groups. They proposed a long short-term memory model with 92.86% accuracy for classifying participants who suffered at least two concussions previously. These two studies examined concussion and the matched normal sessions individually. The proposed approach in this article looked for alteration with the occurrence of a concussion in a participant by taking into account brain-region networks from pre- and post-injury sessions of the participant. SVM classifiers generated in the *Theta-Alpha* frequency band classified concussed and control groups with 99.5% accuracy. Using a subset of the electrodes in specific regions still resulted in reliable classifiers with 97.25% and 96.75% accuracies using the *Beta* band in the *Central* area and *Theta-Alpha* band in the *Temporal* region, respectively.

Previous studies examined the concussion and the normal groups separately to identify markers for concussion. The proposed model uses alterations in the EEG network attributable to the occurrence of a concussion in a participant as a marker of concussion. Comparing pre- and post-sessions within 7 days results in an accurate classifier, which is essential for helping to detect concussion. Regular weekly or biweekly EEG monitoring may help prevent the likelihood of unreported concussions and SIS by identifying recent abnormal brain activity using the proposed approach. The proposed model can be a helpful aid to report potential concussion incidents for further investigation by certified technicians or neurologists for final diagnosis.

When recording from surface electrodes, particularly those within close proximity, it is always possible that volume conduction artifacts may influence coherence metrics, such as the pair-wise distance between FFT components used in the present study. Our use of an average reference, rather than ear or mastoid reference, in part was used to mitigate volume conduction effects.⁴⁵ Although we are unable to eliminate the potential for volume conduction effects, their contributions to our modeled data are assumed to be relatively constant between participants (and groups), particularly given our sample's homogeneity in age and sex, such that our model results, which discriminated between concussion and control groups, are unlikely to be biased by volume conduction effects.

The major limitation of this study is its small sample size. Although the research design was unique in examining longitudinal EEG changes from before to after concussion compared to a control group, a replication in a larger sample and including different sexes is warranted before generalizing these findings. Although previous studies like Zuckerman and colleagues⁴⁶ reported no difference in sex-based acute response to concussive injuries, studies on sex and age differences on concussive injuries are limited. Additionally, the lack of systematic routine monitoring hinders the obtaining of a larger data set that contains data from both pre-season and post-injury sessions of participants. Future studies require a collaborative data collection, with a larger initial participant sample size.

Conclusion

Long-term brain damage may be observed in adults who have participated in contact sports with a higher risk of concussion incidents, such as football, boxing, and soccer. Recurrence of concussions and especially recurrence of them before a full recovery from a previous concussion may lead to prolonged recovery times and severe long-term brain damage. In this pilot study, a regular EEG-monitoring technique is proposed, which can identify persons who have recently experienced a concussion with an accuracy of 99.5%. Although the difference between a concussed and normal brain can be captured months or years post-injury, it is important to identify the injury as early as possible to manage the injury and prevent any premature return to contact sport with the risk of another concussion incident before recovery. Future research with a larger sample size is encouraged in order to establish the clinical utility of SVM classifiers for routine concussion



monitoring. A weekly to biweekly routine monitoring, using a relatively inexpensive and portable modality such as EEG, may facilitate the diagnosing and monitoring of a recent concussion as early as possible to prevent severe and long-term damage to the brain.

Authors' Contributions

Conception and design of the study: A. Mansouri, K. Sayood, D.L. Molfese. Acquisition of data: P. Ledwidge, D.L. Molfese. Analysis and interpretation of data: A. Mansouri, K. Sayood. Drafting the manuscript: A. Mansouri. Revising the manuscript critically for important intellectual content: A. Mansouri, K. Sayood, P. Ledwidge, D.L. Molfese. Approval of the version of the manuscript to be published: A. Mansouri, K. Sayood, P. Ledwidge, D.L. Molfese.

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Author Disclosure Statement

No competing financial interests exist.

Supplementary Materials

Supplementary Table S1
Supplementary Table S2
Supplementary Table S3
Supplementary Table S4
Supplementary Figure S1
Supplementary Material

References

1. Patterns, P.S. (2018). Incidence and prevalence of major neurologic disorders. *US Pharm.* 43, 24.
2. Servadei, F., Teasdale, G., and Merry, G. (2001). Defining acute mild head injury in adults: a proposal based on prognostic factors, diagnosis, and management. *J. Neurotrauma* 18, 657–664.
3. Iverson, G.L., and Lange, R.T. (2011). Mild traumatic brain injury. In *The Little Black Book of Neuropsychology: A Syndrome-Based Approach*. M.R. Schoenberg and J.G. (eds). Springer: Boston, MA, pps. 697–719.
4. Harmon, K.G., Drezner, J., Gammons, M., Guskiewicz, K., Halstead, M., Herring, S., Kutcher, J., Pana, A., Putukian, M., and Roberts, W.; American Medical Society for Sports Medicine. (2013). American Medical Society for Sports Medicine position statement: concussion in sport. *Clin. J. Sport Med.* 23, 1–18.
5. Centers for Disease Control and Prevention. (2020). Heads Up. Brain Injury Basics: What Is a Concussion? www.cdc.gov/headsup/basics/concussion_what.html (Last accessed December 5, 2021).
6. Zhang, A.L., Sing, D.C., Rugg, C.M., Feeley, B.T., and Senter, C. (2016). The rise of concussions in the adolescent population. *Orthopaed. J. Sports Med.* 4, 2325967116662458.
7. Gavett, B.E., Stern, R.A., and McKee, A.C. (2011). Chronic traumatic encephalopathy: a potential late effect of sport-related concussive and subconcussive head trauma. *Clin. Sports Med.* 30, 179–188.
8. Daneshvar, D.H., Riley, D.O., Nowinski, C.J., McKee, A.C., Stern, R.A., and Cantu, R.C. (2011). Long-term consequences: effects on normal development profile after concussion. *Phys. Med. Rehabil. Clin.* 22, 683–700.
9. Hootman, J.M., Dick, R., and Agel, J. (2007). Epidemiology of collegiate injuries for 15 sports: summary and recommendations for injury prevention initiatives. *J. Athl. Train.* 42, 311–319.
10. Langlois, J.A., Rutland-Brown, W., and Thomas, K.E. (2006). Traumatic brain injury in the United States; emergency department visits, hospitalizations, and deaths. Centers for Disease Control and Prevention, National Center for Injury Prevention and Control: Atlanta, GA.
11. McCrea, M., Hammeke, T., Olsen, G., Leo, P., and Guskiewicz, K. (2004). Unreported concussion in high school football players: implications for prevention. *Clin. J. Sport Med.* 14, 13–17.
12. McCrory, P., Meeuwisse, W.H., Aubry, M., Cantu, R.C., Dvořák, J., Echemendia, R. J., Lars Enggebretsen, L., MD, PhD, Karen M. Johnston, K.M., MD, PhD, Jeffrey S. Kutcher, J.K.S., MD, Martin Raftery, M., MBBS, Allen Sills, A., MD, Brian W. Benson, B.W., MD, PhD, Gavin A. Davis, G.A., MBBS, Richard Ellenbogen, R., MD, Kevin M. Guskiewicz, K.M., PhD, Stanley A. Herring, S.A., MD, Grant L. Iverson, G.L., PhD, Barry D. Jordan, B.D., MD, James Kissick, J., MD, Michael McCrea, M., PhD, Andrew S. McIntosh, A.S., PhD, David L. Maddocks, D.L., LLB, PhD, Michael Makdissi, M., MBBS, PhD, Laura Purcell, L., MD, Margot Putukian, M., MD, Kathryn Schneider, K., PhD, Charles H. Tator, C.H., MD, PhD, ... & Turner, M. (2013). Consensus statement on concussion in sport—the 4th International Conference on Concussion in Sport held in Zurich, November 2012. *PM&R* 5, 255–279.
13. McCrea, M., Broglio, S. P., McAllister, T. W., Gill, J., Giza, C. C., Huber, D. L., Harezlak, J., Cameron, K.L., Houston, M.N., McGinty, G., Jackson, J.C., Guskiewicz, K., Mihalik, J., Brooks, M.A., Duma, S., Rowson, S., Nelson, L.D., Pasquina, P., Meier, T.B., CARE Consortium Investigators; Foroud, T., Katz, B.P., Saykin, A.J., Campbell, D.E., Svoboda, S.J., Goldman, J., and DiFiori, J. (2020). Association of blood biomarkers with acute sport-related concussion in collegiate athletes: findings from the NCAA and Department of Defense CARE Consortium. *JAMA Netw. Open* 3, e1919771.
14. Williams, R.M., Puetz, T.W., Giza, C.C., and Broglio, S.P. (2015). Concussion recovery time among high school and collegiate athletes: a systematic review and meta-analysis. *Sports Med.* 45, 893–903.
15. Cantu, R.C. (1998). Second-impact syndrome. *Clin. Sports Med.* 17, 37–44.
16. Cantu, R.C., and Gean, A.D. (2010). Second-impact syndrome and a small subdural hematoma: an uncommon catastrophic result of repetitive head injury with a characteristic imaging appearance. *J. Neurotrauma* 27, 1557–1564.
17. Zuckerman, S.L., Kerr, Z.Y., Yengo-Kahn, A., Wasserman, E., Covassin, T., and Solomon, G.S. (2015). Epidemiology of sports-related concussion in NCAA athletes from 2009–2010 to 2013–2014: incidence, recurrence, and mechanisms. *Am. J. Sports Med.* 43, 2654–2662.
18. Kerr, Z.Y., Register-Mihalik, J.K., Kroshus, E., Baugh, C.M., and Marshall, S.W. (2016). Motivations associated with nondisclosure of self-reported concussions in former collegiate athletes. *Am. J. Sports Med.* 44, 220–225.
19. Llewellyn, T., Burdette, G.T., Joyner, A.B., and Buckley, T.A. (2014). Concussion reporting rates at the conclusion of an intercollegiate athletic career. *Clin. J. Sport Med.* 24, 76–79.
20. Meehan, W.P. III, Mannix, R.C., O'Brien, M.J., and Collins, M.W. (2013). The prevalence of undiagnosed concussions in athletes. *Clin. J. Sport Med.* 23, 339–342.
21. Committee on Sports-Related Concussions in Youth; Board on Children, Youth, and Families; Institute of Medicine; National Research Council; Graham, R., Rivara, F.P., Ford, M.A., and Spicer, C.M. (eds). (2014). Consequences of repetitive head impacts and multiple concussions, in: *Sports-Related Concussions in Youth: Improving the Science, Changing the Culture*. National Academies Press: Washington, DC.
22. McCrea, M., Guskiewicz, K.M., Marshall, S.W., Barr, W., Randolph, C., Cantu, R.C., Onate, J.A., Yang, J., and Kelly, J.P. (2003). Acute effects and recovery time following concussion in collegiate football players: the NCAA Concussion Study. *JAMA* 290, 2556–2563.
23. Slobounov, S., Gay, M., Johnson, B., and Zhang, K. (2012). Concussion in athletics: ongoing clinical and brain imaging research controversies. *Brain Imaging Behav.* 6, 224–243.
24. Chen, J.-K., Johnston, K., Frey, S., Petrides, M., Worsley, K., and Ptito, A. (2004). Functional abnormalities in symptomatic concussed athletes: an fMRI study. *Neuroimage* 22, 68–82.



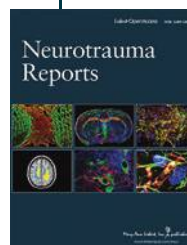
25. Lee, R.R., and Huang, M. (2014). Magnetoencephalography in the diagnosis of concussion, in: *Concussion*, Vol. 28. Karger: Basel, Switzerland, pps. 94–111.
26. Asken, B.M., DeKosky, S.T., Clugston, J.R., Jaffee, M.S., and Bauer, R.M. (2018). Diffusion tensor imaging (DTI) findings in adult civilian, military, and sport-related mild traumatic brain injury (mTBI): a systematic critical review. *Brain Imaging Behav.* 12, 585–612.
27. Michels, L., Bucher, K., Lüchinger, R., Klaver, P., Martin, E., Jeanmonod, D., and Brandeis, D. (2010). Simultaneous EEG-fMRI during a working memory task: modulations in low and high frequency bands. *PLoS One* 5, e10298.
28. Cao, C., Tutwiler, R.L., and Slobounov, S. (2008). Automatic classification of athletes with residual functional deficits following concussion by means of EEG signal using support vector machine. *IEEE Trans. Neural Syst. Rehabil. Eng.* 16, 327–335.
29. Teel, E., Ray, W., Geronimo, A., and Slobounov, S. (2014). Residual alterations of brain electrical activity in clinically asymptomatic concussed individuals: an EEG study. *Clin. Neurophysiol.* 125, 703–707.
30. Thompson, J., Sebastianelli, W., and Slobounov, S. (2005). EEG and postural correlates of mild traumatic brain injury in athletes. *Neurosci. Lett.* 377, 158–163.
31. Tysvaer, A.T., and Løchen, E.A. (1991). Soccer injuries to the brain: a neuropsychologic study of former soccer players. *Am. J. Sports Med.* 19, 56–60.
32. Munia, T.T., Gendreau, J.L., Verma, A.K., Johnson, B.D., Romanick, M., Tavakolian, K., and Fazel-Rezai, R. (2016). Preliminary results of residual deficits observed in athletes with concussion history: combined EEG and cognitive study, in: *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE: New York, pps. 41–44.
33. Gosselin, N., Lassonde, M., Petit, D., Leclerc, S., Mongrain, V., Collié, A., and Montplaisir, J. (2009). Sleep following sport-related concussions. *Sleep Med.* 10, 35–46.
34. Cao, C., and Slobounov, S. (2009). Alteration of cortical functional connectivity as a result of traumatic brain injury revealed by graph theory, ICA, and sLORETA analyses of EEG signals. *IEEE Trans. Neural Syst. Rehabil. Eng.* 18, 11–19.
35. Virji-Babul, N., Hilderman, C.G., Makan, N., Liu, A., Smith-Forrester, J., Franks, C., and Wang, Z. (2014). Changes in functional brain networks following sports-related concussion in adolescents. *J. Neurotrauma* 31, 1914–1919.
36. Hudac, C.M., Cortesa, C.S., Ledwidge, P.S., and Molfese, D.L. (2018). History of concussion impacts electrophysiological correlates of working memory. *Int. J. Psychophysiol.* 132, 135–144.
37. Ledwidge, P.S., and Molfese, D.L. (2016). Long-term effects of concussion on electrophysiological indices of attention in varsity college athletes: an event-related potential and standardized low-resolution brain electromagnetic tomography approach. *J. Neurotrauma* 33, 2081–2090.
38. Mansouri, A., Singh, S.P., and Sayood, K. (2019). Online eeg seizure detection and localization. *Algorithms*, 12, 176.
39. Ledwidge, P.S., Patterson, J.N., Molfese, D L., and Honaker, J.A. (2019). Clinical utility of oculomotor and electrophysiological measures in identifying concussion history. *Clin. J. Sport Med.* 29, 292–297.
40. Bloomfield, P. (2004). *Fourier Analysis of Time Series: An Introduction*. John Wiley & Sons: New York.
41. Conley, A.C., Cooper, P.S., Karayanidis, F., Gardner, A.J., Levi, C.R., Stanwell, P., Gaetz, M.B., and Iverson, G.L. (2018). Resting state electroencephalography and sports-related concussion: a systematic review. *J. Neurotrauma*. doi: 10.1089/neu.2018.5761.
42. Mansouri, A., Singh, S., and Sayood, K. (2017, May). Hierarchical online temporal and spatial EEG seizure detection, in: *2017 IEEE International Conference on Electro Information Technology (EIT)*. IEEE: New York, pps. 416–421.
43. Betzel, R.F., Byrge, L., He, Y., Goñi, J., Zuo, X.N., and Sporns, O. (2014). Changes in structural and functional connectivity among resting-state networks across the human lifespan. *Neuroimage*, 102, 345–357.
44. Wickramaratne, S.D., Mahmud, M.S., and Ross, R.S. (2020, June). Use of brain electrical activity to classify people with concussion: a deep learning approach, in: *ICC 2020-2020 IEEE International Conference on Communications (ICC)*. IEEE: New York, pps. 1–6.
45. Nunez, P.L., Srinivasan, R., Westdorp, A.F., Wijesinghe, R.S., Tucker, D.M., Silberstein, R.B., and Casuch, P.J. (1997). EEG coherency I: statistics, reference electrode, volume conduction, Laplacians, cortical imaging, and interpretation at multiple scales. *Electroencephalogr. Clin. Neurophysiol.* 103, 499–515.
46. Zuckerman, S.L., Solomon, G.S., Forbes, J.A., Haase, R.F., Sills, A.K., and Lovell, M.R. (2012). Response to acute concussive injury in soccer players: is gender a modifying factor? *J. Neurosurg. Pediatr.* 10, 504–510.

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Abbreviations Used

AUC	= area under the curve
Corr	= correlation coefficient
Cos	= cosine
EEG	= electroencephalography
ERPs	= event-related brain potentials
Euclid	= Euclidean
FFT	= fast Fourier transform
fMRI	= functional magnetic resonance imaging
MEG	= magnetoencephalography
mTBI	= mild TBI
NCAA	= National Collegiate Athletic Association
ROC	= receiver operating characteristic
SD	= standard deviation
SIS	= second impact syndrome
SRCs	= sports-related concussions
SVM	= support vector machine
TBI	= traumatic brain injury

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