Traumatic Brain Injury Detection System using Machine Learning Models

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***Abstract*—Traumatic brain injury is a type of brain damage brought on by an external blow to the head. Numerous neurological conditions can develop as a result of this kind of injury, which is common. Accidents, falls, sports, and other injuries sustained during combat can all result in traumatic brain injury. Deficits in neurophysiology and cognition may eventually result, in addition to effects on sleep-wake function. It can eventually cause effects on sleep-wake function as well as neurophysiological and cognitive deficits. The most popular and minimally invasive method for identifying abnormalities in a patient's brain activity is EEG. Due to the fact that it manifests much earlier in people who have suffered a mild traumatic brain injury, it is much more effective at identifying craniocerebral injury. Inconsistencies are found more quickly as a result. In this paper, a method for analyzing electroencephalogram (EEG) signals to detect a traumatic brain injury is described. Deep learning techniques are used to preprocess and classify the EEG signals. To assess the effectiveness of the system, convolution neural networks (CNN) and XGBoost-based models are used.**

Keywords—EEG, TBI, feature extraction, classification

I. Introduction

Traumatic brain injury (TBI) is one of the most common injuries that affect the functioning of the brain. It is caused by an external jolt or collision to the human head, consequently resulting in the injury of the brain. This external impact can be due to vehicle accidents, falling, combat, and sports injuries. TBI symptoms include neurological complications such as behavioral, perceptional, sensorial, and sleep-wake disorders [2].

TBI is broadly classified into three categories based on their severity: mild TBI, moderate TBI, and severe TBI. Identifying severe TBI is easier since affected patients experience a duration of unconsciousness. However, differentiating between mild and moderate TBI can be difficult without clinical imaging inspection. The symptoms of mild TBI's physiological and pathological effects have not yet been recorded for medical analysis. Correspondingly, post-mild TBI patients have been reported to have experienced severe brief issues such as headaches, loss of attention, tiredness, and irritability. Hence, neuroimaging tools are needed to analyze the symptoms [4].

Currently, the common technologies that are used to detect mTBI are Computer Tomography (CT) and Magnetic Resonance Imaging (MRI). These tools demand specific operative expertise and expensive clinical systems which are often difficult to arrange for at the place of accident. A few positive mTBI cases also tested negative during the neuroimaging testing. Hence, it can be noted that medical neuroimaging can be expensive, time-consuming, and inefficient and new technology is required for an efficient classification [2].

Recent studies have indicated that electroencephalogram (EEG) can be used for the quick identification of TBI. This can be done by observing the alpha, beta, theta, and gamma frequency bands of quantitative EEG (qEEG). Manual analysis is, however, monotonous, and time expensive. Hence, there is a requirement for a computerized system that can execute the analysis efficiently. Many different machine-learning models have been proposed to analyze biomedical data [4].

In this paper, a machine learning-based methodology will be developed for the analysis of EEG to detect mTBI. CNN and XGBoost models will be used to identify mTBI by executing sleep staging on single-channel EEG signals. This model will help automate the process of analyzing EEG signals and will thus be able to classify TBI accurately [2].

II. Background Theory

A. Neurological Disabilities

Traumatic brain injury caused by an external mechanical impact may have a permanent or only temporary impact on a person's ability to think, interact with others, and move around. It has been referred to as a "silent epidemic" due to the high likelihood that it will result in disability [14]. The following signs and symptoms may indicate functional impairment: loss of consciousness (LOC), post-traumatic amnesia (PTA), focal neurological signs (such as seizures, dysphasia, reflex abnormalities, etc.), neuropsychological abnormalities, and intracranial lesions. After conducting a thorough review of the literature, it was determined that EEG abnormalities appear after mild traumatic brain injury before those seen in other neurological tests. EEG abnormalities are not uniform and depend on the severity of the injury.

B. EEG

EEG is effective, non-invasive, and crucial in detecting certain neurological disorders and recording the activity of brain neurons [16]. It is a non-destructive, side-effect-less, pain-free, and accurate representation of brain activity [17]. As accurate detections are key to preparing for treatment beforehand, EEG signals are preferred as they provide real-time data. The time-series EEG signal is generally categorized based on the signal frequency and characterized as alpha, beta, theta, gamma, and delta waves. Signal band analysis of the EEG signal with respect to different states and stimuli gives medical researchers an insight into the complex brain structure with respect to its functional and behavioral characteristics [17].

With the aid of software-assisted data analysis, these unprocessed signal recordings enable quantitative EEG interpretation (qEEG), which distinguishes between various patterns and types of EEG activity. Spectral analysis, absolute and relative amplitude, power, coherence, and symmetry between electrode pairs are a few of the frequent EEG measurements. [14]. The changes detected in the EEG are differentiated according to their severity:

1. Acute EEG changes:

These usually occur immediately after an mTBI. They show the high amplitude and frequency of waves. There is an immediate decrease in mean alpha frequency with an increase in theta and delta.

2. Subacute EEG changes:

These usually occur weeks or months after an mTBI. An increase in posterior alpha rhythm frequency of 1-2 Hz is observed.

3. Chronic EEG changes:

Patients who have persistent somatic, psychiatric, or cognitive complaints in the first weeks after mTBI show epileptiform and slow-wave abnormalities.

C. *Feature Extraction*

A feature is a characteristic or measurable property of an object or phenomenon. In Machine Learning, an attribute or feature represents a dimension and dimensions together create a data point. Generally, with the increase in the number of features and hence, data points, the ML algorithm would have more data to learn from improving its performance and accuracy but as concluded by Hughes (1968), with a fixed number of training samples, the performance measure of the classifier increases up to the point of an optimum number of dimensions and thereafter, the accuracy of calculating the output deteriorates. The model is no longer robust or able to generalize the amount of data accurately [18]. Feature extraction aims to reduce the number of features by creating new ones i.e transforming existing features that can be processed better while still preserving the original information [19].

D. Classification Models

Neural Networks (NN) can be used for many different applications and prediction models, one of which is a classifier. A classifier aims at predicting a discrete class label (y) for the given input variables (X). A predictive model is created that approximates a mapping function from input variables to output variables [20]. The classification problem at hand can be a binary classification or a multi-class classification problem. The inputs and output values can be continuous or discrete where continuous output values describe the probability of the label. Various classifiers based on different neural network (mathematical) models exist such as Support Vector Machines (SVM), Artificial NN (ANN), Naive Bayes, Convolutional NN (CNN), Multi-Layer Perceptron (MLP), XGBoost, Recurrent NN (RNN), etc.

III. Issues Involved In Existing Works

Despite the great progress in areas such as signal processing, feature extraction, and classification, there are still several limitations that hinder the development of medically accurate and robust models.

One major disadvantage includes the limited availability of appropriately sized datasets. Smaller datasets make it harder to achieve a good generalized model [5]. Authors in [1] highlighted that conventional methods are not as accurate and involve complicated feature extraction or selection of signals which can be computationally expensive as well. When tested, it was also seen that statistical methods for analysis were not very accurate and had low discriminatory power [4]. As noted in [4], the analysis of MRI and CTI scans to detect TBI has been a successful approach to its diagnosis but this method has mobility issues, is time-consuming, and has resource and accessibility restrictions.

With the aforementioned issues in mind, this work studies and implements the application of deep learning and signal processing techniques on EEG signals for the classification of TBI vs healthy.

IV. Literature Review

Numerous studies have been conducted on effective and efficient feature selection techniques and classification techniques to accurately detect neurological disorders such as seizures and TBI from EEG signals. This review aims to analyze the various techniques implemented on different datasets and study each methodology and its efficiency which help guide this work.

[1] proposed a CNN based supervised learning training model. The EEG signal is filtered, downsampled, and inputted into a 4-layer 1D Deep CNN to produce feature maps thereby performing feature extraction as well as classification. The model is deployed on Raspberry Pi to test simulated real-time data to evaluate the accuracy and computational abilities.

For multi-class classification of TBI mild vs moderate vs healthy samples, [4] preprocessed the EEG signal and fed it into an LSTM cell model which utilizes the temporal structure of EEG to perform feature extraction. The features are then used as training parameters for Error Correcting Output Coding SVM (i.e a Hamming Distance decoder SVM) for multiclass classification.

[5] made use of quantitative EEG biomarkers for the classification of mTBI-related pain and concussion vs healthy individuals. The raw data were preprocessed using Independent Component Analysis and the Infomax algorithm. The signal is then analyzed using the

Neurophysiological Biomarker Toolbox and MATLAB. Power spectral features are extracted using Welch's method. Both statistical methods and ML are applied to test discriminatory power. The latter using the SVM classifier portrayed higher accuracy and robustness.

For the detection of Epilepsy using EEG, paper [9] developed a 1D CNN based on deep learning that uses the models VGGNET and ResNet. The introduced technique was trained on 23 classes of the CHB-MIT dataset. The first step included the preprocessing of the EEG signals for the extraction of required features. The resulting accuracy for the models ResNet and VGGNet was achieved to be 97.60% and 97.32% respectively. It was concluded that ResNet is more proficient in the detection of epileptic seizure detection. The authors concluded by proposing a model with ResNet and VGGNet combined as their future scope of work.

A hybrid model was proposed by the paper [10] for the accurate detection of epileptic seizures. It involved the use of CNN for the application of automated feature extraction of EGG signals and the use of SVM for the classification of epileptic seizures. The introduced methodology was assessed using the CHB-MIT dataset. The results demonstrated the proficiency of the hybrid model compared to its individual constituent models.

The authors of the paper [11] also proposed a hybrid model to analyze the epileptic EEG datasets, Bonn and Hauz Khas. The model combined the use of a CNN model for the process of feature extraction and the use of RF and SVM for the purpose of classifying the seizure and normal states in an EEG. The model has exceeded its accuracy of 99.7% and 98.00% compared to the conventional models SVM and RF models. The paper thus concluded that the use of CNN models for the extraction of features can remarkably improve the accuracy of the use of conventional ML models.

In recent studies, machine learning has attracted much attention in the clinical field because it is a cost-effective method for detecting diseases using various data. The analysis of EEG data has greatly benefited from machine learning. Traditionally, feature extraction and classification have been accomplished using a multi-layer architecture. The EEG/ERP data from individual trials were processed by a deep learning network called TRauma ODdball Net in [3]. This was made up of various convolutional layers that distinguished between various ERPs (event-related potentials) in the evaluation of acute or post-acute concussions.

26 people with a recent diagnosis of concussion but no neurological or auditory issues were the subjects of [3], and data from them were gathered. Using electrodes made of Ag/AgCl and secured with an elastic cap, EEG data were captured in 10–20 systems. The acquired signal was processed and filtered using a bandpass filter that operated between 0.01 and 100 Hz. It underwent a notch at 60 Hz and a bandpass filter between 0.1 and 30 Hz for processing. Brain Vision Analyzer was used to preprocess the EEG data. [3] An EEG ConvNet and EEGNet form the foundation of the architecture used here. TRODNet used a 4-layer convolution: Linput for the input layer, L1 for the tensor input layer, L2 was the max-pooling layer, L3 was the feedforward layer, and Loutput for the output layer.

Aside from the pure software component, some research papers also discuss the use of microcontrollers and converters for data acquisition and subsequent processing of the data using ML models. An Analog Front End (AFE) ADS1299 EEGFE-PDK-based data acquisition system using the Raspberry Pi is presented in [15]. Four AFEs connected in a daisy chain configuration make up the low-power, low-noise system. A serial peripheral interface (SPI) that was programmed in the C programming language is used for communication between the Raspberry Pi and the AFE. MATLAB was used in this system to process the EEG signals after they were acquired using the AFE. MATLAB was used to implement a Butterworth bandpass filter with a frequency range of 0.5 to 50 Hz. In essence, this paper outlines a technique for data acquisition using a few hardware tools. An EEG simulator by the name of NETECH MiniSim EEG was used to calibrate the system.

[6] highlights the importance of having quantitative EEG methods coupled with multivariate machine learning techniques of quantitative EEG over a univariate method for identifying, classifying, and tracking individual subjects with mTBI. The study developed objective biomarkers for mild mTBI in the chronic period, more than five months after the injury. Resting-state, eyes-closed EEG data were collected from 71 individuals with military-related mTBI and 82 normal comparison subjects without traumatic brain injury.Metrics were used to measure differences in the delta, theta, alpha, beta, high beta, and gamma bands, and interhemispheric coherence in each band. A combination of a multivariate approach with machine learning methods yielded a composite metric that provided an overall predictive accuracy of 75% for correctly classifying individual subjects as coming from control vs mTBI groups.

The discussion of automatic detection of an epileptic seizure based on CNN methods [7] discusses how a deep learning-based approach is used to detect epileptic seizure onset and offset in multi-channel EEG signals. The approach involves two models, the epoch-based classification model, and the onset-offset detection model. The epoch-based classifier predicts seizure probability in each windowed EEG signal, and the onset-offset detector determines the seizure onset and offsets from the probability sequence. The model uses CNN to extract features and identify ictal patterns from segments of multi-channel EEG signals. The onset-offset detector groups detect epochs and neglect those that do not meet the criteria for ictal. The model was tested on the CHB-MIT Scalp EEG database and achieved a GDR of over 90% and F1 of 64.40%, with absolute onset and offset latencies of 5.83 and 10.12 seconds, respectively.

[8] discusses detecting mTBI with Topological Graph Embedding and 2D CNN. The project creates a model that combines an embedding feature extraction algorithm with a CNN model to predict whether brain networks belong in the normal category or mTBI category groups.they constructed a functional network from the cortical activity of the subject mice which is recorded with widefield imaging.This reading is taken and formulated in two sessions, before the injury, and after the injury. Node embedding features are then extracted from brain functional networks using the Node2vec algorithm. Embedding vectors are then used to construct images for the brain functional networks which are processed through a CNN classifier to classify brain

networks into normal and mTB. Experimental results portray that this method is providing high accuracy for mTBI classification.

V. DATA COLLECTION

An online dataset is used to train the model. Data were collected by the Centre for Brain Recovery and Repair at the University of New Mexico Health Sciences Centre.[21] The data was collected from 91 patients between the ages of 18 and 55 years. The subjects had a Glasgow Coma Scale between 13 and 15, a measure of their state of consciousness that includes three different types of consciousness; eye-opening, verbal response, and motor responses. This score in itself indicates mild brain injury or minimal impairment of consciousness. Data collection took place in several sessions: Session 1 took place 3-14 days after injury, Session 2 after 2 months, and Session 3 after 4 months after Session 1. These data were then preprocessed in Matlab. The segregation of the data between mTBI and healthy subjects is done by using 0 and 1 respectively.

VI. METHODOLOGY

The proposed method is a three-step process containing signal preprocessing, feature extraction, and classification. Finally, the results are evaluated by accuracy, specificity, and sensitivity metrics.

A. Signal Preprocessing

The raw EEG signals obtained from the dataset are contaminated with noise. Signal preprocessing results in a transformed signal with low noise/redundant features. The EEG data has been preprocessed as mentioned in the dataset, however, a bandpass filter needs to be applied to retrieve/obtain signals of only required frequencies.

Bandpass filtering is applied to the transformed signal to extract frequency components within a specific frequency range. This is done to capture important signals useful in differentiating between a brain injury and normal brain activity [25]. Simultaneously, it enables denoising and the removal of small amplitude components of the signal regardless of frequency resulting in a low signal-to-noise ratio [26].

A bandpass filter works by combining a low-pass and a high-pass filter into a single filter to filter out frequencies that are too low or too high thereby only allowing frequencies within a certain range to remain [27]. By filtering out frequencies, we are aiming at eliminating noise and artifacts such as removing heart signals related to pulse artifacts and low-frequency noise, such as building vibrations and nearby electromagnetic field noise, and AC powerline high frequency [28].

The Butterworth filter is popularly used as a bandpass filter and is an analog filter design producing the best output response with no ripple in the pass or stop band resulting in a maximally flat filter response. Additionally, by design, the Butterworth filter can simultaneously denoise [29].

This work began by reducing the number of datapoints in the set by setting max datapoints for a given sampling frequency as the mean number of datapoints from all EEG channel readings. The samples were also downsampled from a sampling frequency of 500Hz to a frequency of 125Hz. This downsampling was done to reduce the use of computational and time resources while training [2]. Then, this work made use of a Butterworth filter of order 2, and lower frequency limit of 1Hz, and an upper-frequency limit of 40 Hz as suggested by previous works.

B. Feature Extraction and Discrete Wavelet Transform

In this work, Discrete Wavelet Transform (DWT) is applied to the preprocessed EEG signal. While Convolution Neural Network (CNN) can be directly used on raw EEG signals as a feature extractor, the noise generated during recording would affect classification accuracy [30]. Wavelet transforms are widely used to efficiently extract features for interpretation from transient signals. Two methods of wavelet transform include the Continuous Wavelet Transform (CWT) and the DWT but the drawback of the CWT is that it generates a lot of redundant information making DWT a better choice as a wavelet transform [30].

Additionally, the ability of DWT to find patterns in signals and to be applied to non-stationary EEG signals has proved it to be suitable for localizing transient events which can occur as spikes [31]. DWT converts the time-series signal into a time-frequency domain signal [32] and provides a good trade-off between time and frequency localization [33]. The signal is decomposed into frequency components in different scales [34]. Features are then extracted from various sub-bands generated [35]. These features are statistical and entropy-based features in the time domain, frequency domain, and time-frequency domain [36]. The coefficients calculated in these scales are selected to perform single-scale signal reconstruction and feature extraction [34].

This work implements Daubechies wavelet of order 4 (db4). The order 4 (or also 2) of the Daubechies wavelet is better suited for signals with sharper, more abrupt changes which matches the property of EEG signals for mTBI identification [37]. A level 5 decomposition is used which gives a good resolution [38]. After applying DWT, to reduce the total amount of data processed and increase computational and training efficiency, Principal Component Analysis was applied to reduce the number of channels in each EEG signal to 4 most impactful channels (dimensionality reduction).

C. Classification of the EEG Signals

For the classification of the EEG Signals of healthy and of mTBi patients, we implemented CNN and XGBoost. The results of the two classification algorithms were then compared with respect to the evaluation metrics.

1. CNN

A Convolutional Neural Network, commonly abbreviated as CNN or ConvNet, is a type of neural network that extracts information from data in a grid-like format such as images, or graphs. Each neuron in a CNN, similar to neurons in a human brain, analyses data only in its responsive area. It has layers organized in such a way that it can identify both smaller and more complex features [22]. Every CNN model mainly consists of 4 layers namely the Convolutional layer, the Relu layer, Pooling Layer, and a fully connected layer.

a. Convolutional Layer:

It is the key layer of every CNN operation. This layer consists of various feature maps where every neuron extracts regional characteristics of distinct locations in the previous ones. The input is firstly convolved through the activation functions to acquire new features.

b. ReLu Layer:

The two ways to type an input x with its output function f are f(x) = (1-e-x) or f(x) = tanh(x). Using the ReLu function helps the CNN to train much faster when compared to a tanh activation function. It changes all negative values to 0 for a given input by using the formula: f(x) = max(x,0).

c. Pooling Layer:

This layer decreases the dimension of the feature maps computed which helps improve the power of feature extraction. The two types of pooling layers available are the mean-pooling layer and the max pooling layer.

d. Fully Connected Layer

All features created are finally passed through the fully connected layer to output the probability of distribution for each class. It incorporates all neurons produced by previous layers into a single layer. The accuracy and loss metrics are then calculated [23].

For the classification of the EEG signals, CNN here was used to spontaneously extract relevant features. The CNN architecture is using reference from [30], where we have added an additional dropout layer: Conv1D layer, used to prevent overfitting by dropping out some of the neurons randomly. This is the first layer of the CNN and it is responsible for detecting local patterns in the input data. The layer has 11 filters, each of size 5, and uses the ReLU activation function.

2. XGBoost

XGBoost is a Machine Learning algorithm that uses decision trees in a gradient-boosting structure. Decision tree-based algorithms such as RF, SVM, and XGBoost are regarded as one of the best models to evaluate structured or tabular data. Unlike trees in Gradient Boosting Decision Trees where the trees are built sequentially, trees in XGBoost are built in parallel, allowing it to be more accurate and reducing computational complexity. It scans gradient values in a level-wise manner while utilizing the partial sums to compute the efficiency of splits at every recorded split in a training part of the dataset [24].

XGBoost was implemented using the XGBoost package of Python (XGClassifier) to extract spectral features from the EEG Signals. XGBoost was optimal for extracting varied patterns from the signals, which helped in the efficient classification of the EEG signals in a reliable way [2].

VII. RESULTS

The metrics we have used to calculate the quality of our results are as follows:

- Accuracy measures the overall correctness of a model's predictions. It is the ratio of correctly predicted instances to the total number of instances.

Accuracy = (True Positives + True Negatives) / (True Positives + True Negatives + False Positives + False Negatives)

- Error Rate is the complement of accuracy and represents the overall incorrectness of a model's predictions. It is the ratio of incorrectly predicted instances to the total number of instances.

Error Rate = (False Positives + False Negatives) / (True Positives + True Negatives + False Positives + False Negatives)

- Sensitivity measures the proportion of actual positive instances correctly identified by the model.

Sensitivity = True Positives / (True Positives + False Negatives)

- Specificity measures the proportion of actual negative instances correctly identified by the model.

Specificity = True Negatives / (True Negatives + False Positives)

- Precision measures the proportion of predicted positive instances that are actually positive.

Precision = True Positives / (True Positives + False Positives)

- F1 score is a combined measure of precision and sensitivity. It provides a single value that balances the trade-off between precision and sensitivity.

F1 Score = 2 * (Precision * sensitivity) / (Precision + sensitivity)

	accuracy	error	sensitivity	specificity	precision	F1
XG	0.66	0.333	1.0	0.0	0.666	0.8
CNN	0.66	0.333	1.0	0.0	0.666	0.8

The test size for the model is kept as 0.2, which indicates that 20% of the data is allocated for testing and the remaining 80% is allocated for training the models. The continuous EEG data is divided into multiple smaller segments known as epochs. Here we have taken the epochs as 20 with a batch size of 16 for CNN. For XGBoost, the number of estimators or decision trees in the ensemble were taken as 200 with a default max depth of 6. The results portray that both the classification models i.e. CNN and XGBoost perform similarly with no significant advantage over one another. more computational prowess to process more data and having extended epochs would have increased the accuracy of said results.

VIII. CONCLUSION

Machine Learning techniques have shown promising results in analyzing EEG data for detecting various neurological disorders. Different models have been proposed for the detection of TBI and Epilepsy, and some models have used hybrid techniques like combining CNN with SVM or RF. Additionally, the use of quantitative EEG methods and multivariate machine learning techniques has also shown promising results for identifying, classifying, and tracking individuals with mTBI. Furthermore, some studies have also discussed the use of microcontrollers and converters for data acquisition and processing. The studies demonstrate the potential of these techniques in EEG analysis for the detection of various neurological disorders.

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