ORIGINAL ARTICLE

Frontal Medial Theta-Based Intelligence System for Verifying Mild Traumatic Brain Injury

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Abstract

Purpose: The purpose of this study was to create an Intelligence System (IS) to analyze the Electroencephalogram (EEG) characteristics of patients with mild Traumatic Brain Injury (mTBI) and healthy volunteers. Generally, mTBI research demonstrates that patients suffer from Working Memory (WM). The frontal cortex is involved in the clinical physiology of mTBI and is crucial for delayed memory.

Materials and Methods: The Frontal-Medial Theta (FMT) is one of the most critical factors in mTBI verification. The oscillatory strength of FMT (4-8Hz) over the Frontal-Medial Cortex (FMC) or Supplementary Motor Area (SMA) and the medial-Sensory Motor Cortex (mSMC) is associated with efficient WM performance. The designed IS accesses the FMT of mTBI and healthy subjects by FCz and Cz electrodes placed in FMC or SMA and mSMC, respectively. The Multi-level Discrete Wavelet Transformation (MDWT) of EEG (FCz and Cz) is suggested here to investigate the mTBI. The FMT rhythms of EEG of FCz and Cz channels are extracted through 3-level-DWT. Then, 1768 features [712 features of healthy subjects + 1056 features of mTBI patients] for both the FCz and Cz electrodes were calculated via their FMT using eight statistical feature computations.

Results: The study found that the FMT strength of FCz and Cz electrodes is similar. The Bagging Classifier achieved 83.3333% accuracy with the 5% split for the FCz electrode.

Conclusion: The strength of the FMT-FCz and FMT-Cz electrodes is approximately the same, and both are equally crucial to investigating mild Traumatic Brain Injury.

Keywords: Multi-Level Discrete Wavelet Transformation; Frontal-Medial Theta; Frontal-Medial Cortex; Supplementary Motor Area; Medial-Sensory Motor Cortex; Mild Traumatic Brain Injury.

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1. Introduction

Traumatic Brain Injuries (TBIs) must still be identified and adequately evaluated if treatment and prognosis are to be successful. TBIs include initial damage induced by a mechanical insult, which can be death in the worst possible circumstances. In crucial cases, the well-known principle of the golden hour, which states that rehabilitation must be administered within the first 60 minutes for a trauma patient outside of the hospital, could influence the patient's medical condition [1]. The consequences of delayed treatment may include cerebral Dysautoregulation, Oedema, and high intracranial pressure [2]. As a result, early detection is critical for the ensuing treatment approach. TBI severity can be determined using various grading systems. The Glasgow Coma Scale (GCS) is a standard evaluation [3]. The GCS evaluates the severity of a TBI relying on the "motor response," "eye-opening reaction," and "verbal response" [4]. The GCS ratings for mild, moderate, and severe TBI patients are 14-15, 9-13, and 3-8, respectively. The GCS isn't perfect because it's a qualitative test that's very subjective and prone to bias. Additionally, an injured eye likely won't be able to perform the eye-opening response [5].

In medical research, Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) are the two clinical methods most frequently employed to identify brain dysfunctions. Nevertheless, they often fail to identify enduring abnormalities in patients with mTBI [6]. Furthermore, studies found that sleep-wake disturbances are widespread following a TBI based on Electroencephalogram (EEG) patterns [7]. Quick radiation scans are also a potential health risk for patients, which is a concern [8]. Magnetoencephalography (MEG), among numerous electrophysiological techniques, has produced impressive outcomes. They demand specialized operators, are expensive, and take time. They may delay the performance of scans and put patients in danger of delayed treatment due to inadequate resources [9]. The advantages of EEG over CT, MRI, and MEG are speed, cost, and portability. Furthermore, whereas EEG has a poorer spatial resolution, it has a high temporal resolution [10, 11]. In addition, EEG data has high inter-subject variability, which diminishes its utility. Physiological differences between individuals are the cause of this issue [12]. It is also challenging to distinguish between activities in closely related locations because numerous nearby channels can pick up exceptionally high electrical activity [13]. But now, more advanced technologies, such as machine learning, are available for estimating EEG data from a single source. Lai *et al.* [14] applied Long-Short-Term-Memory (LSTM) for the automatic feature extraction, and to classify mTBI, a "Support Vector Machine (SVM)" was used, where SVM achieved 100.00% accuracy. Also, Lai *et al.* [15] applied a Convolutional Neural Network (CNN) for automatic feature extraction, and an SVM was utilized for the classification of mTBI, where the SVM got 99.76% accuracy. Dhillon *et al.* [5], the EEG output from a single channel is used in this study to describe a mobile, real-time data gathering and automated processing system based on the Raspberry Pi that efficiently grades the different stages of sleep and leverages machine learning to detect TBI. Where average power and alpha: theta ratio are extracted and given into the XGBoost classifier. "Real-time EEG epochs" were divided by CNN and XGBoost into four pre-established categories: sham waking, sham sleeping, mTBI wake, and mTBI sleep. XGBoost achieved 98.00% accuracy due to its scalability, which enables parallel and distributed computation while speeding up training and model exploration, whereas CNN only achieved 80.00%. Vishwanath *et al.* [16] examine a variety of machine learning techniques, namely K-Neighbors Neighbor (KNN), Random Forest (RF), XGBoost, Neural Network (NN), Decision Tree (DT), and SVM, where the average power of EEG, and alpha: theta ratio, two features are extracted as a feature for mTBI detection. Here, KNN, RF, XGBoost, NN, DT, and SVM attained an accuracy of 87.00%, 86.00%, 86.48%, 84.85%, 82.90%, and 86.15%. In another study, Vishwanath *et al.* [17] investigated several machine learning methods, KNN, RF, DT, SVM, CNN, and NN where the average power of EEG is extracted as a feature for mTBI investigation. Here KNN, RF, DT, SVM, CNN, and NN attained respective accuracy of 74.30%, 75.60%, 71.00%, 75.60%, 92.03%, and 73.80%. Thanjavur *et al.* [18] utilized RNN only once, although it achieved encouraging results of 88.90% classification accuracy. Where LSTM-based Conc-Net is applied for automatic feature extraction, ConcNet 1 accurately identified 11 segment pairs, achieving a Consistency score of 91.70%.

Researchers have consistently shown that people with mTBI have trouble with their working memory (WM). The oscillatory strength of frontal-medial theta (FMT, 4-8Hz) over the Frontal-Medial Cortex (FMC) or Supplementary Motor Area (SMA) and the medial-Sensory Motor Cortex (mSMC) is systematically associated with efficient WM performance. Working Memory (WM) is a short-term information storage and manipulation capacity [19]. The oscillatory strength of FMT increases over the FMC or SMA by WM activities [20, 21, 22]. The FMT has been associated with behavioral WM effectiveness [23] and individual WM capability [24]. This study emphasizes the importance of suitable electrodes for FMT-based mTBI verification. The format of the research article is as follows: (a) The methodology, (b) the mTBI EEG-dataset collection and the workstation and software details, (c) the preprocessing of the mTBI EEG-data, (d) Multi-level Discrete Wavelet Transformation (MDWT) of FCz and Cz signals for separation of FMT rhythms, (e) the importance of statistical features measurements, (f) results, (g) discussion, and (h) the conclusion.

2. Materials and Methods

The proposed "Intelligence System (IS)" for studying mTBI using frontal-medial theta (FMT, 4-8Hz) EEG rhythm is depicted in Figure 1. In subsections 2.1-2.4, the proposed methodology (The Model) is described step-by-step. The critical steps of the essential parts of the proposed approach: (2.1) obtaining the mTBI EEG-dataset and its analysis, (2.2) preprocessing of the EEG-dataset, (2.3) Multi-level Discrete Wavelet Transformation (MDWT) of EEG signals of FCz and Cz electrodes for the separation of its FMT rhythm, (2.4). For the FMT of FCz and Cz electrodes, eight statistical features are derived. Finally, four machine learning classifiers, namely "Bagging Classifier," "XGB Classifier," "Decision Trees (DT) Classifier," and "Random Forest (RF) Classifier," are ensembled together and applied with different split ratios to classify the calculated 1768 features [712 features of healthy subjects + 1056 features of mTBI patients] for the FMT of FCz and Cz electrodes, respectively.

2.1. Data Set & System and Software

James F Cavanagh is the dataset's author, and the disclosed information is available in this section [25]. The "Human Research Protections Office" at the "University of New Mexico Health Sciences Center (UNMHSC)" approved the research, and each subject gave signed consent. All individuals were English natives and ranged in age from 18 to 55. None of the patients had any severe underlying medical or psychological conditions, and none currently or in the past used drugs. They weren't taking any medications that impacted their ability to think at the study's time, except selective serotonin reuptake inhibitors (SSRIs). SSRIs were taken by three control subjects and four subjects with mild traumatic brain injury (mTBI). Patients with subacute mTBI were admitted to the "UNMHSC's Neurosurgery and Emergency Medicine Departments" two weeks after their accident. Patients with subacute TBI had Glasgow Coma Scale (GCS) scores between 13 and 15 and had lost consciousness during the first 30 minutes following the injury. Three assessment sessions were held with both subacute mTBI and control clients. The first session covered the first three to fourteen days after the injury. Session 2 was about 1.5 to 3 months after Session 1, and Session 3 was about 3 to 5 months after that. This research only discusses the first session (pre-treatment session) of the patients with chronic TBI chosen from a comparable diagnostic trial. All chronic patients had lost consciousness within 24 hours. Multiple TBIs were confirmed by many (15 to 23) chronic clients. The EEGs are recorded for 25 to 30 minutes, according to the severity of the patients. Due to the varying severity of the most recent TBI (17-mild TBI and 6-moderate TBI), we categorized these chronic clients as having "chronic mild and moderate TBI (chronic mm-TBI)." Table 1 contains more specific information about the participant's group, and Table 2 provides information about mTBI clients.

The workstation Dell G15-5515-AMD-Ryzen-7 is used for designing the Intelligence System (IS) for mTBI investigation via FMT-EEG rhythm. It has RAM-16GB, VRAM-6GB. Its processor speed is 3.2GHz, and its memory clock speed is 3200MHz. The following software and libraries are used for performing the presented research: Python, Jupyter Notebook, SK-Learn (Scikit-Learn) Python, Spyder IDE, MNE-Python, and Anaconda Packages.

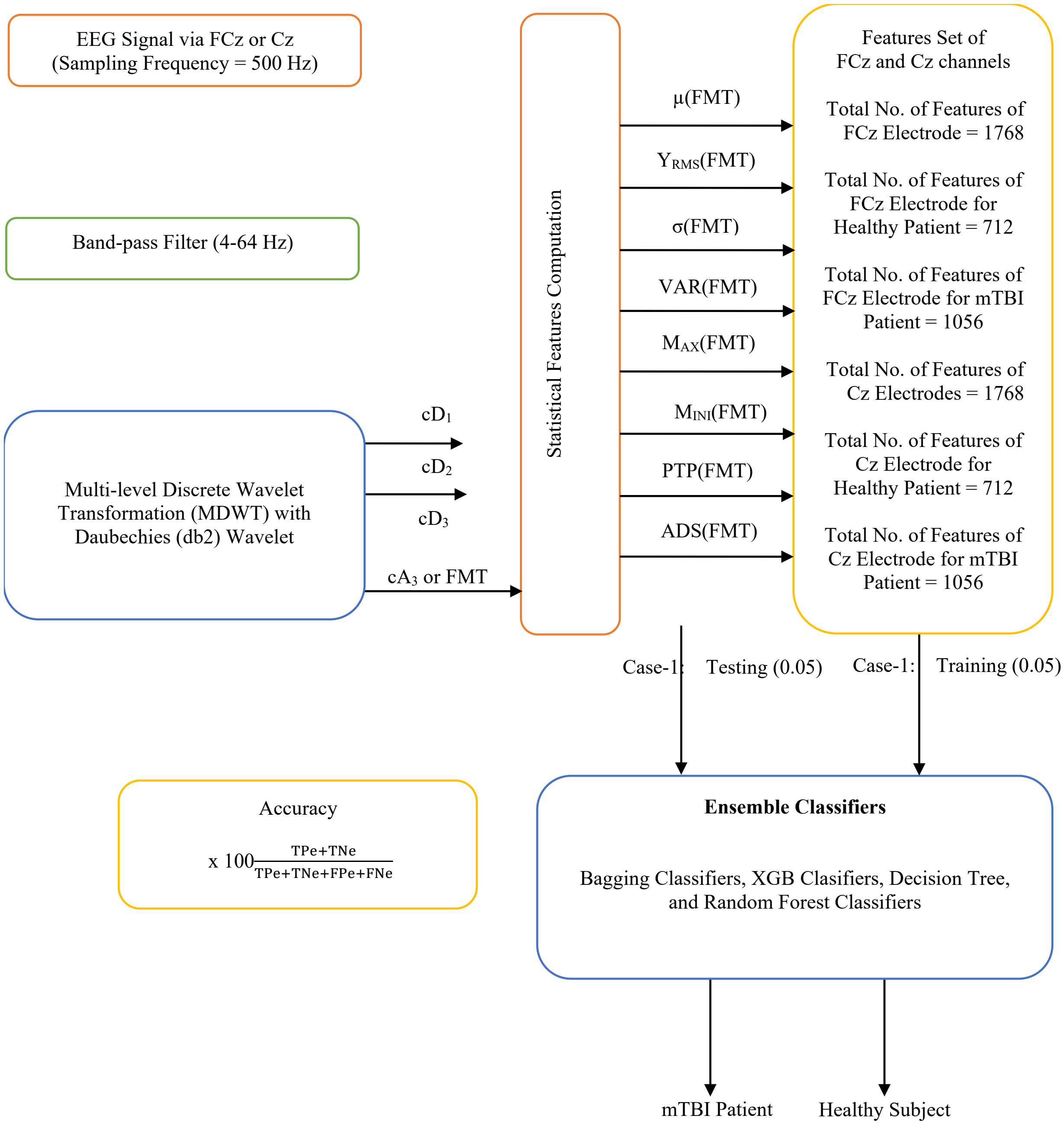

Figure 1. The FMT-based Intelligence System (IS) for verifying the mTBI

2.2. EEG Dataset Preprocessing

Researchers have consistently shown that people with "mild Traumatic Brain Injury (mTBI)" have trouble with their working memory (WM).

The oscillatory strength of frontal-medial theta (FMT, 4-8Hz) over the Supplementary Motor Area (SMA) or frontal-medial cortex (FMC) and the medial-sensory motor cortex (mSMC) is systematically associated with efficient WM performance. Figure 2 shows the placement of FCz and Cz electrodes in SMA/FMC and mSMC, respectively, in the brain architecture's 10-20 electrode system. The sampling frequency of the recorded EEG of FCz and Cz channels was 250Hz. It was resampled into 128.001Hz to satisfy the Nyquist-Criteria for the band-pass filter (4-64Hz) and to reduce the computational cost of the proposed Intelligence System (IS). Then, we needed to perform only a 3-stage Multi-level Discrete Wavelet Transformation

(MDWT) to extract the Frontal-Medial Theta (FMT) of the FCz and Cz electrodes.

Table 1. Specific information about the participants

Study Group	Values
Total Clients	91 (52 Males, 39 Females) [34 Control Clients (17 Males, 17 Females), 57 mTBI Clients (34 Males, 23 Females)]
Total mTBI Clients	57 [34 Subacute mTBI Clients (21 Males, 13 Females), 23 Chronic mm-TBI Clients (13 Males, 10 Females)]
Age of Control Clients	The average age of all control clients: 30.23. The average age of all male control clients: 30.05. The average age of all female control clients: 30.41.
Age of mTBI Clients	The average age of all mTBI clients: 29.74. The average age of all male mTBI clients: 28.62. The average age of all female mTBI clients: 30.86.

Table 2. Information of mTBI clients

Study Group	Values
GCS (13-15)	13 (2), 14 (1), 15 (38), Not Applicable (16)
Time since injury	mTBI Clients [10 (5) days], Chronic mm-TBI Clients [2 (3) years]
Loss of Consciousness in Minutes	4.5 (13.25)
Loss of Memory	Yes (27), No (23), Not Applicable (7)
Motor Vehicle	52%
Accident/Fall	17%
Sport	15%
Assault	15%

Nyquist-Criteria for EEG signal: Sampling Frequency > 2 F_{Max}, where 2 F_{Max} is the Nyquist rate, and F_{Max} is the upper frequency of the band-pass filter. In the proposed work, FMax is 64Hz. That's why we are setting the sampling frequency at 128.001Hz, which is slickly greater than the Nyquist rate (2 F_{Max} = 2 x 64 = 128Hz). The Nyquist frequency is 128.001/2Hz.

Delta rhythm 0-4Hz (associated with deep sleep) and high-frequency noise over 64Hz are removed

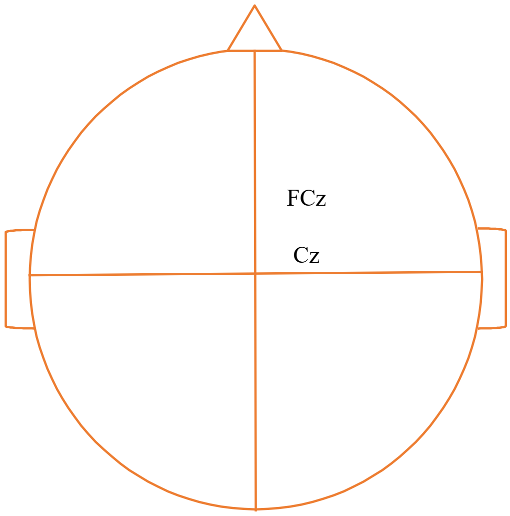

Figure 2. The placement of FCz and Cz electrodes in SMA/FMC and mSMC, respectively, to investigate mTBI

using a band-pass filter (4-64Hz). The line frequency of 60Hz is eliminated via a 60Hz notch-filter.

The non-filtered and filtered raw data of mTBI patients are shown in Figures 3 & 4, where the sampling rate is 128.001Hz. The unwanted variation in the EEG signal of FCz and Cz electrodes is settled in Figure 4 compared to Figure 3. The FMT recorded by FCz and Cz is associated with the degree of WM deficits, visible in Figure 3 at around 2 sec. The positive effect of a 4-64Hz band-pass and 60Hz notch filter is visual in Figure 4, and the 4-64Hz band-pass and 60Hz notch filter response for the Cz and FCz channels are shown in Figure 5 & Figure 6, respectively.

2.3. Multi-Level Discrete Wavelet Transformation (MDWT)

The EEG Rhythms are categorized through the 3-level Multi-level Discrete Wavelet Transformation (MDWT), as shown in Figure 7. The Daubechies wavelet of order 2 (db2) aids in analyzing the mental state of mild traumatic brain injury (mTBI) patients since it is particularly adept at detecting changes in EEG [26]. Therefore, MDWT is carried out with db2-wavelet. Mallat's Structure of MDWT [27], commonly referred to as the Fast Wavelet Transform, is depicted in Figure 7. The MDWT uses a downsampling rate of

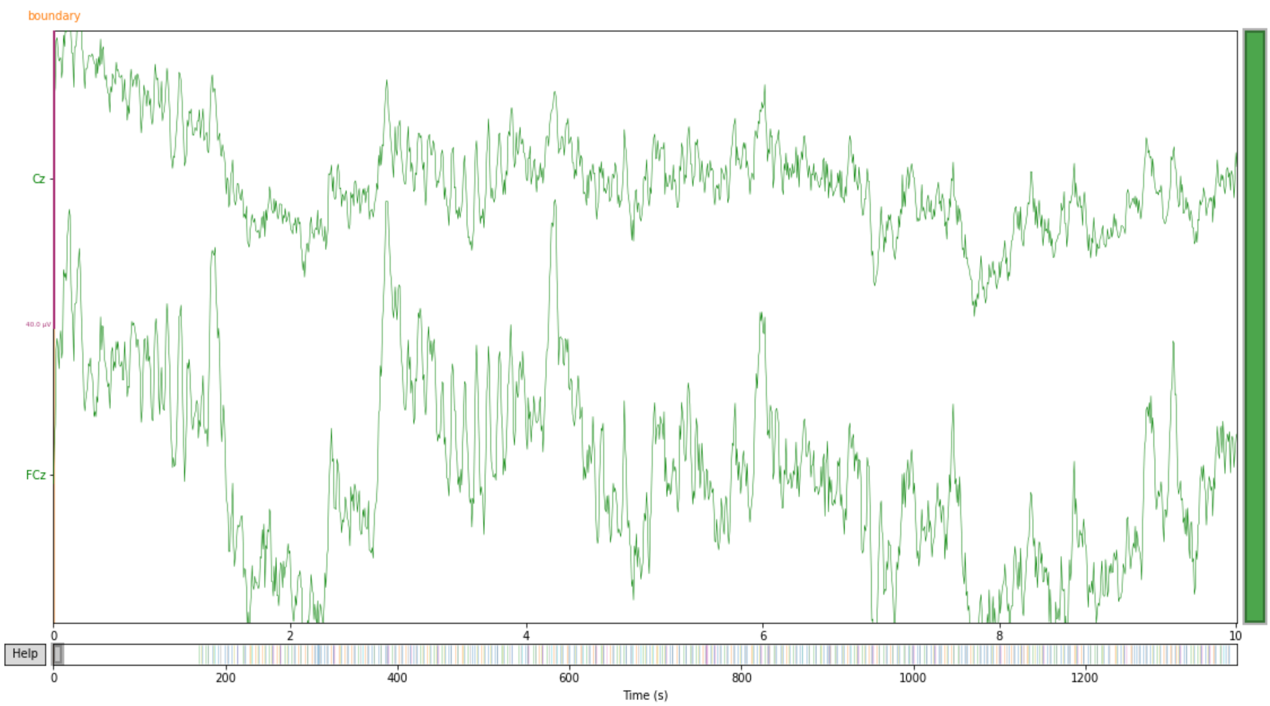

Figure 3. Non-filtered raw data of mTBI

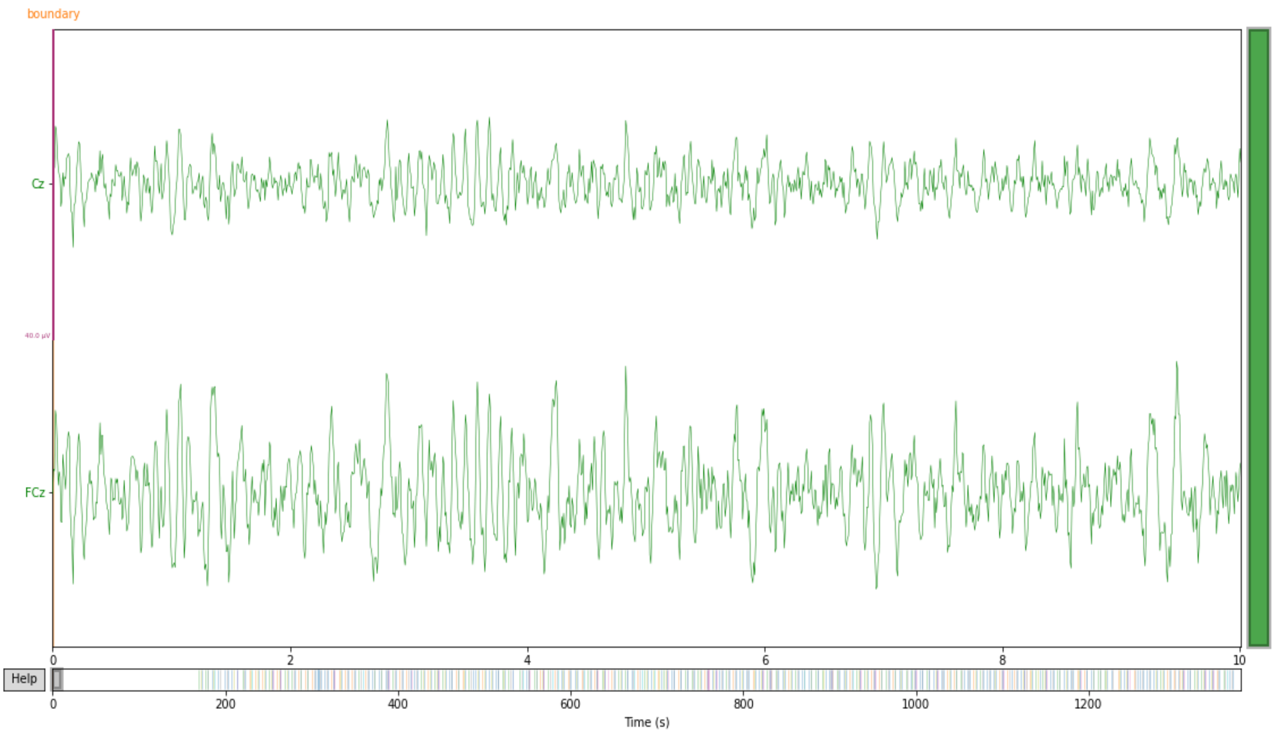

Figure 4. Filtered raw data of mTBI

2 and employs sequential time-frequency highpass and lowpass filtering. The highpass filter [a(n)] and lowpass filter [b(n)], respectively, represent the discrete "mother" wavelet and its mirror image. "Detailed (cD1)" and "approximations (cA1)," respectively, are the names of the first highpass and lowpass filter outputs. The cA1 is destroyed identically when the required number of decomposition levels has been reached.

The wavelet function is defined by Equation 1&2, at time *t* [28] wherein t = 0, 1.......Z-1, Z = Signal Length,

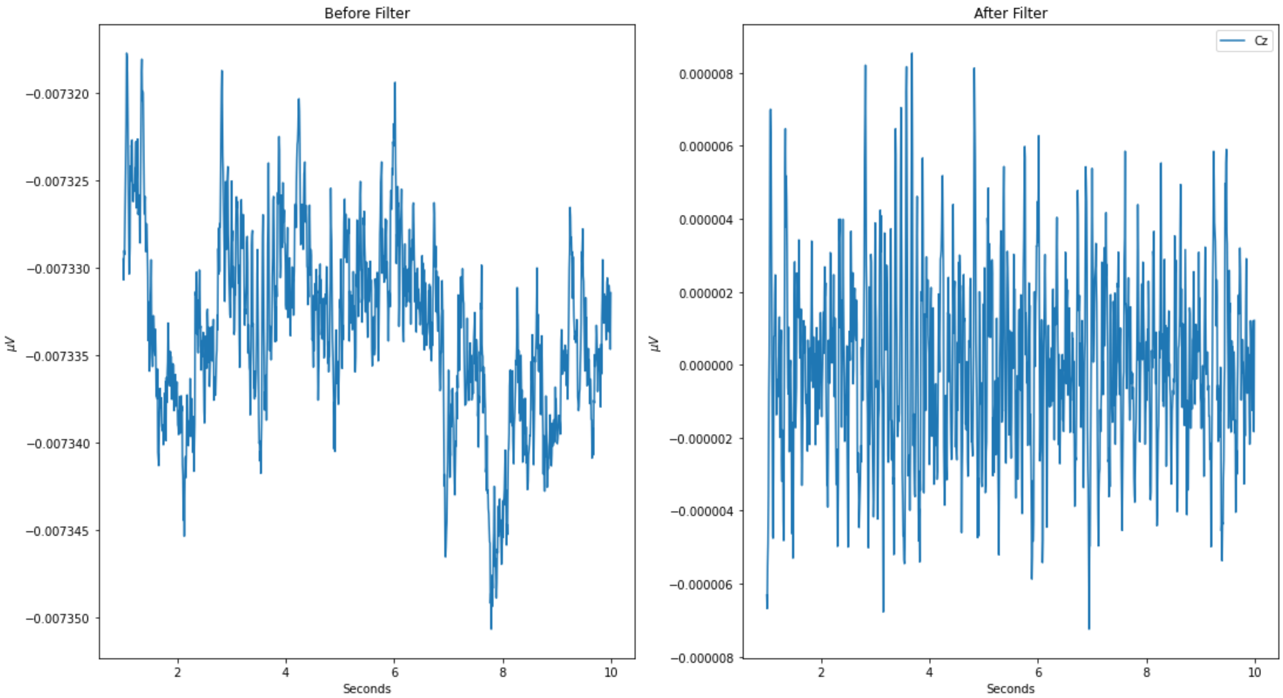

Figure 5. The 4-64Hz band-pass and 60Hz notch filter response for the Cz electrode of mTBI

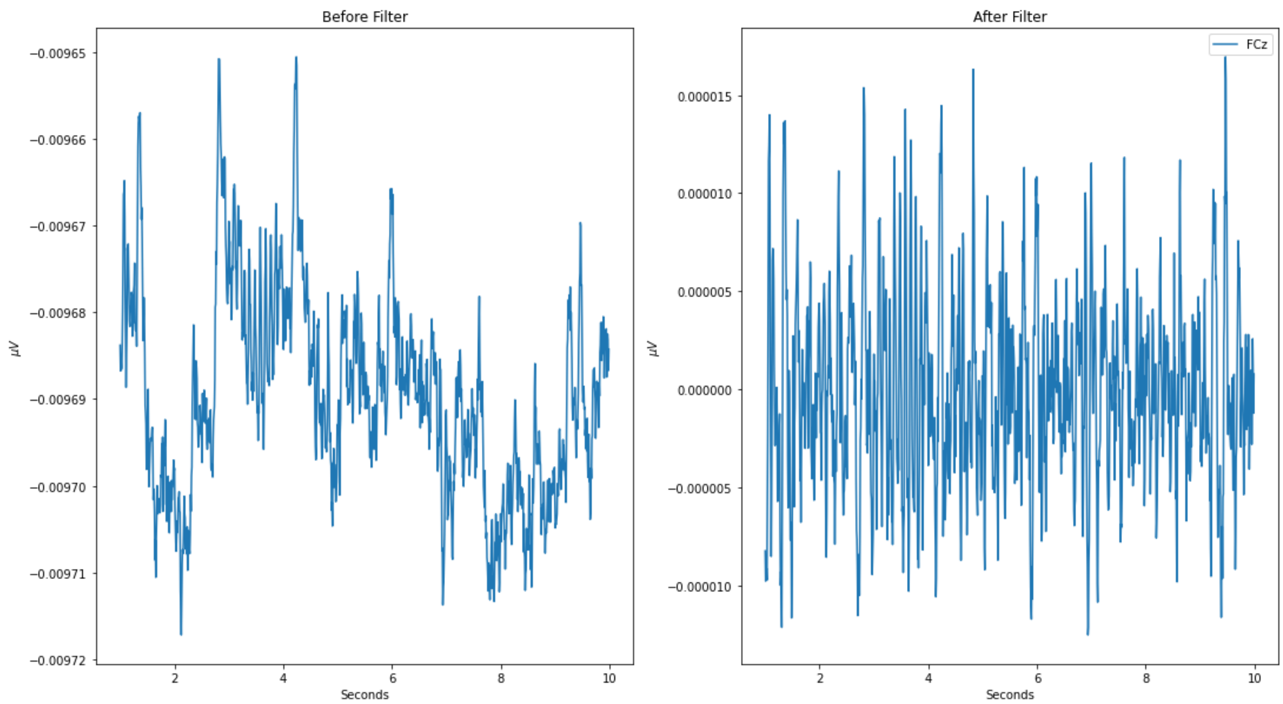

Figure 6. The 4-64Hz band-pass and 60Hz notch filter response for the FCz electrode of mTBI

p = 0, 1,…..2^q – 1, q = 0, 1,……Q – 1, Q = $\log_2(t)$, and set j_0 = 2 & k_0 = 1.

$$\int_{-\infty}^{\infty} \psi(t)dt = 0 \tag{1}$$

$$\Psi_{q,p}(t) = j_0^{-q/2}\, \psi\, (j_0^q t - p\, k_0) \tag{2}$$

Equations 3 & 4 represent the wavelet and scaling functions required to calculate the detailed coefficients (cD) and approximation coefficients (cA).

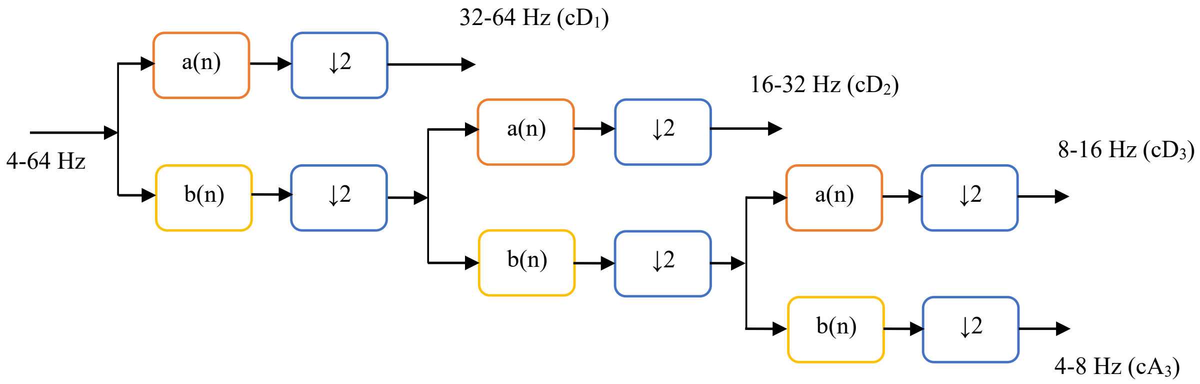

Figure 7. The MDWT Mallat's Structure uses a db2 wavelet (128.001Hz sampling rate)

$$\varpi q,p\ (t)\ =\ 2q/2\ a\ (2q\ t\ -\ p) \tag{3}$$

$$\phi q,p\ (t)\ =\ 2q/2\ b\ (2q\ t\ -\ p) \tag{4}$$

The ith-level calculations of detailed coefficients cDi and approximation coefficients cAi are shown in Equations 5 and 6, respectively.

$$cDi\ =\ \frac{1}{\sqrt{Z}}\sum_{t} f(t)\ \varpi q,p\ (t) \tag{5}$$

$$cAi\ =\ \frac{1}{\sqrt{Z}}\sum_{t} f(t)\ \phi q,p\ (t) \tag{6}$$

Table 3 provides the Daubechies (db2) wavelet coefficients of the 3-level MDWT for the EEG, and Table 4 presents the filter coefficients.

Table 3. The Daubechies (db2) wavelet coefficients of an EEG signal after 3-level MDWT

EEG sub-band	Frequency Interval (Hz)	Decomposition Level	Bandwidth (Hz)
θ	4-8 Hz	cA_3	4 Hz
α	8-16 Hz	cD_3	8 Hz
β	16-32 Hz	cD_2	16 Hz
γ	32-64 Hz	cD_1	32 Hz

Table 4. The wavelet filter coefficient for an EEG signal's Daubechies (db2) decomposition

Tap	Lowpass filter coefficient	Highpass filter coefficient
0	-0.1294095	-0.4829629
1	0.2241439	0.8365163
2	0.8365163	-0.2241439
3	0.4829629	-0.1294095

2.4. Significance of Statistical Features

The Frontal-Medial Theta (FMT) is one of the most crucial factors in mild Traumatic Brain Injury (mTBI) verification. Statistical features are critical for verifying mTBI because they can distinguish between spikes and variations in the EEG of individuals with mTBI and individuals in good health [29, 30]. Eight statistical features are determined for the FMT of both the FCz and Cz electrodes, including mean, variance, root mean squared, standard deviation, minima, maxima, peak to peak, and absolute difference of signals. A total of 1768 features [712 features of healthy subjects + 1056 features of mTBI patients] were calculated for the FMT-FCz and FMT-Cz. To classify mTBI, all the statistical characteristics examined positively affected the classifier's accuracy.

Features Set of FCz Channel:

Total No. of Features of FCz for Healthy Persons = No. of Electrodes × [(No. of Persons × No. of Sessions) + (No. of Persons × No. of Sessions) + (No. of Persons × No. of Sessions)] × No. of Features

$= 1 \times [(25 \times 3) + (5 \times 2) + (4 \times 1)] \times 8 = 1 \times 89 \times 8 = 712.$

Total No. of Features of FCz for mTBI Patients = No. of Electrodes × [(No. of Patients × No. of Sessions) + (No. of Patients × No. of Sessions) + (No. of Patients × No. of Sessions)] × No. of Features

$= 1 \times [(31 \times 3) + (13 \times 2) + (13 \times 1)] \times 8 = 1 \times 132 \times 8 = 1056.$

Features Set of Cz Channel:

Total No. of Features of Cz for Healthy Persons = No. of Electrodes × [(No. of Persons × No. of Sessions) + (No. of Persons × No. of Sessions) + (No. of Persons × No. of Sessions)] × No. of Features:

$= 1 \times [(25 \times 3) + (5 \times 2) + (4 \times 1)] \times 8 = 1 \times 89 \times 8 = 712.$

Total No. of Features of Cz for mTBI Patients = No. of Electrodes × [(No. of Patients × No. of Sessions) + (No. of Patients × No. of Sessions) + (No. of Patients × No. of Sessions)] × No. of Features:

$= 1 \times [(31 \times 3) + (13 \times 2) + (13 \times 1)] \times 8 = 1 \times 132 \times 8 = 1056.$

The computational expression of the statistical features is illustrated in Table 5.

The heatmap of eight statistical features of the FMT-FCz and FMT-Cz are shown in Figures 8 and 9, respectively.

Table 5. The Eight Statistical Features are expressed computationally

Different Features	Notation	Algebraic Explanation
Mean	μ	$\mu = \frac{1}{E}\sum_{e=1}^{E} z[e]$
Standard Deviation	σ	$\sigma = \sqrt{\frac{1}{E}\sum_{e=1}^{E} \lvert z[e]-\mu \rvert^2}$
Variance	$VAR = \sigma^2$	$VAR = \frac{1}{E}\sum_{e=1}^{E} \lvert z[e]-\mu \rvert^2$
Root Mean Squared	Y_{RMS}	$Y_{RMS} = \sqrt{\frac{1}{E}\sum_{e=1}^{E} \lvert z[e] \rvert^2}$
Maxima	M_{AX}	$M_{AX} = \max[z(e)]$
Minima	M_{INI}	$M_{INI} = \min[z(e)]$
Absolute Difference of Signals (Average Curve Length)	ADS	$ADS = \frac{1}{E}\sum_{e=2}^{E} \lvert z[e]-z[e-1] \rvert$
Peak to Peak	PTP	$PTP = M_{AX} - M_{INI}$ $PTP = \max[z(e)] - \min[z(e)]$

Figure 8. The heatmap of the FMT-FCz for its eight statistical features

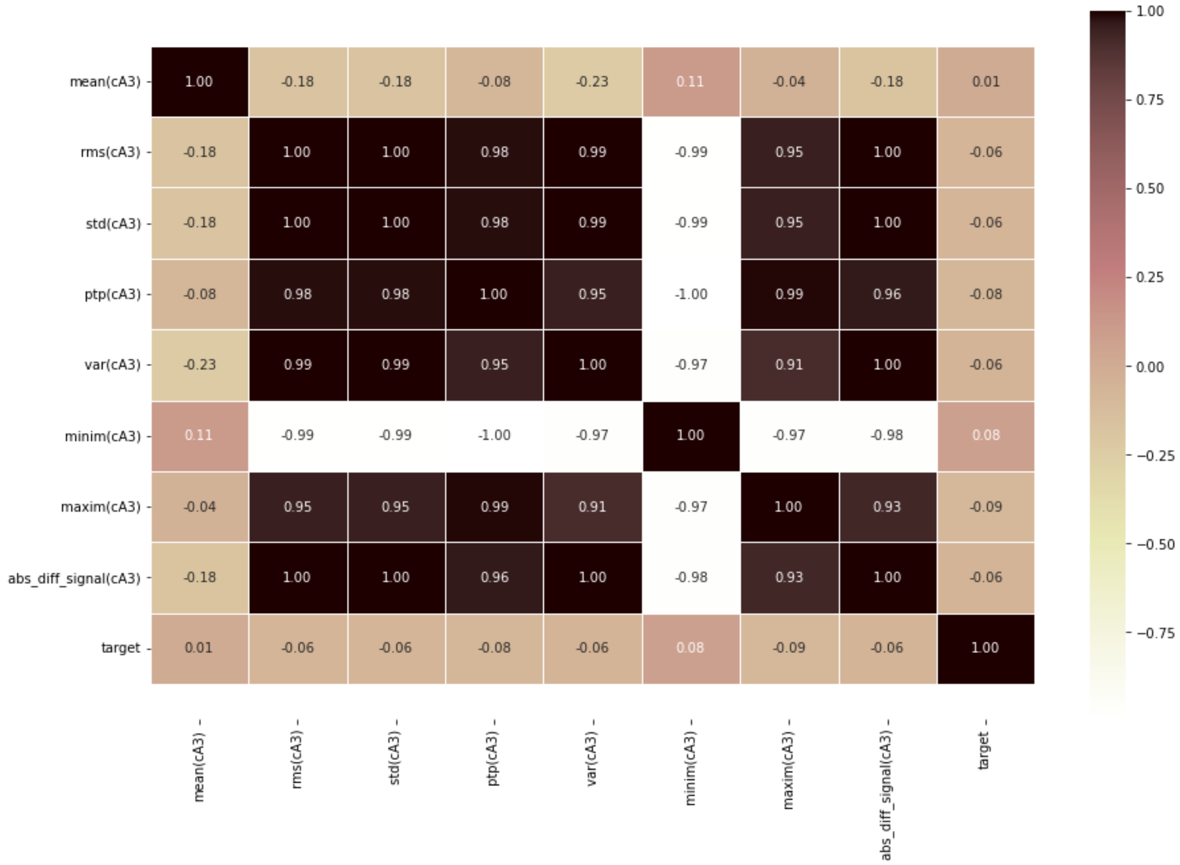

Figure 9. The heatmap of the FMT-Cz for its eight statistical features

3. Results

The research proved (a) The Frontal Medial Theta (FMT) strength of FCz and Cz electrodes is approximately the same, and both the electrodes are equally crucial for the investigation of mild Traumatic Brain Injury (mTBI), (b) The Random-Forest Classifier achieved 75.00% accuracy with the 5% split for both FCz and Cz electrodes, (c) The Random-Forest Classifier achieved 65.2174% accuracy with the 10% split for both FCz and Cz electrodes, (d) The Bagging Classifier achieved 83.3333% accuracy with the 5% split for the FCz electrode.

The performance of the FMT of FCz and Cz with different classifiers and splits is shown in Table 6.

4. Discussion

The EEG features of the examination formed the basis for comparing and discussing the work done by researchers to diagnose mild Traumatic Brain Injury (mTBI). The performed research extracts the frontal medial theta (FMT) of FCz and Cz channels by applying Multi-level Discrete Wavelet Transformation (MDWT). Then, eight statistical features were computed from FMT-FCz and FMT-Cz. To verify mTBI, the FMT is one of the most critical aspects. The oscillatory strength of frontal-medial theta (FMT, 4-8Hz) over the Supplementary Motor Area (SMA) or Frontal-Medial Cortex (FMC) and the medial-sensory motor cortex (mSMC) is systematically associated with efficient Working Memory (WM) performance. The oscillatory strength of the FMT-FCz and FMT-Cz are the same, and both have an identical influence on machine learning classifiers. Table 7 highlights the current research and earlier studies on mTBI.

Table 6. The performance of the Classifiers with FMT of FCz and Cz channels with various splits (5% and 10%)

Split ratio	Electrodes and their features	Ensemble Classifiers	Accuracy (%)	Precision (%)	Recall (%)
0.05	FCz and their eight statistical features of FMT	**Bagging Classifier**	**83.3333**	**80.00**	**80.00**
		XGB Classifier	66.6667	60.00	60.00
		Decision Trees	50.0000	40.00	40.00
		Random Forest	**75.0000**	**40.00**	**100.00**
	Cz and their eight statistical features of FMT	Bagging Classifier	66.6667	20.00	100.00
		XGB Classifier	50.0000	20.00	33.33
		Decision Trees	75.0000	60.00	75.00
		Random Forest	**75.0000**	**60.00**	**75.00**
0.10	FCz and their eight statistical features of FMT	Bagging Classifier	60.8696	30.00	60.00
		XGB Classifier	60.8696	30.00	60.00
		Decision Trees	52.1739	50.00	45.45
		Random Forest	**65.2174**	**30.00**	**75.00**
	Cz and their eight statistical features of FMT	Bagging Classifier	56.5217	30.00	50.00
		XGB Classifier	47.8261	30.00	37.50
		Decision Trees	52.1739	40.00	44.44
		Random Forest	**65.2174**	**40.00**	**66.67**

Our research surpasses Lewine *et al.* [6] and Vishwanath *et al.* [17]. We established that in EEG analysis, the "Multi-level Discrete Wavelet Transformation (MDWT)" remains superior to the "Discrete Fourier Transform" and the "Fast Fourier Transform." Additionally, the FMT-FCz and FMT-Cz are crucial in verifying mTBI compared to the other features used to verify mTBI, as shown in Table 6. Dhillon *et al.* [5], average power and alpha: theta ratio, two features are extracted via single-channel EEG, classified by CNN and XGBoost, where XGBoost achieved 98.00% accuracy due to its scalability, whereas CNN only reached 80.00%. Lai *et al.* [14] LSTM for the automatic feature extraction and SVM used to classify mTBI, where SVM achieved 100.00% accuracy. Also, Lai *et al.* [15] applied CNN for automated feature extraction, and SVM was used to classify mTBI, where the SVM got 99.76% accuracy.

5. Conclusion

The oscillatory strength of the Frontal Medial Theta (FMT, 4-8Hz) over the "Supplementary Motor Area (SMA)" or "Frontal Medial Cortex (FMC)," and medial-sensory motor cortex (mSMC) has been systematically associated with efficient working memory (WM) performance. The FCz and Cz electrodes are placed into the FMC/SMA and mSMC to take EEG because the FMT rhythm (extracted via MDWT) is crucial for verifying mTBI. The strength of the FMT-FCz and FMT-Cz electrodes is approximately the same, and both are equally crucial to investigating mild Traumatic Brain Injury. The primary benefit of the developed Intelligence System (IS) is that the implantation of electrodes into the FMC/SMA and mSMC directly verifies the mTBI.

Table 7. An overview of current and prior work on mTBI.

Research	Feature Extraction Method	Features	Classifiers Accuracy (%)
Present Research	Multi-level Discrete Wavelet Transformation (MDWT)	Eight statistical features of the FMT-FCz & FMT-Cz: mean, variance, root mean squared, standard deviation, minima, maxima, peak to peak, and absolute difference of signals	Bagging Classifier: 83.33% for FCz (5% split), RF: 75.00% for FCz & Cz (5% split)
Dhillon *et al.* [5]	Weltch's method with Hamming window	Average power and alpha: theta ratio	CNN: 80.00%, XGBoost: 98.00%
Lewine *et al.* [6]	Fast Fourier Transform, Cross-Spectral Analysis	Global-Relative-Theta (GRT) power, Global-Relative-Alpha (GRA) power, Global-High-Beta (GHB) absolute power, Global-Phase-Shift (GPS) magnitude in beta, and Interhemispheric-Coherence (IC) in the beta band	KNN: 59.00%, RF: 62.00%
Lai *et al.* [14]	Long-short-term-memory (LSTM)	Automatic features	SVM: 100%
Lai *et al.* [15]	Convolutional-Neural-Network (CNN)	Automatic features	SVM: 99.76%
Vishwanath *et al.* [17]	Discrete Fourier Transform, Decibel Normalization	The average power of EEG	KNN: 74.30%, RF: 75.60%

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