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AUTOMATIC MICROSLEEP DETECTION BASED ON KNN CLASSIFIER UTILIZING SELECTED AND EFFECTIVE EEG CHANNELS

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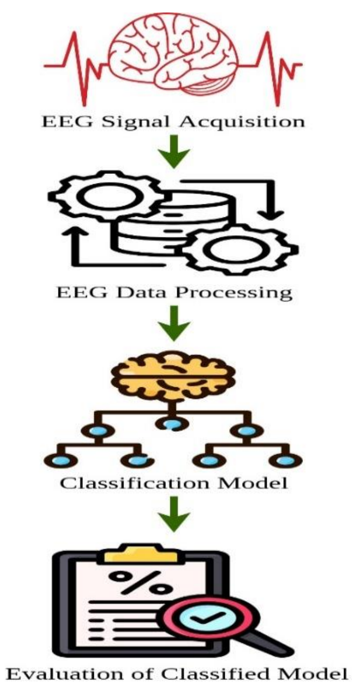
Graphical abstract



Abstract

Annually, the global economy suffers significant financial losses due to decreased productivity of work, accidents, and crashes in traffic resulting from microsleep. To reduce the adverse impacts of microsleep, it is necessary to have a discreet, dependable, and socially acceptable method of detecting microsleep episodes consistently throughout the day, every single day. Regrettably, the current solutions fail to match these specified criteria. Moreover, by utilizing sophisticated features and employing machine learning techniques, it is possible to process electroencephalogram (EEG) information in a highly efficient manner, enabling the rapid and successful detection of microsleep. The selection of an optimum channel and the use of a competent classification algorithm are crucial for effective microsleep detection. One unique channel selecting strategy has been introduced in the current study to evaluate the classifying accuracy of microsleep detection based on EEG. This strategy is based on correlation coefficients and utilizes the K-Nearest Neighbor (KNN) method. Furthermore, the Fast Fourier Transform (FFT) was employed for extracting the feature, so validating the endurance of the proposed technique. In order to enhance the speed of the microsleep detecting system, the study was performed using 3 distinct time windows: 0.5s, 0.75s, and 1s. The study revealed that the suggested approach achieved a classification accuracy of 98.28% within a time window of 0.5 seconds to detect microsleep using EEG signal. The exceptional effectiveness of the given system can be efficiently utilized in detecting microsleep using EEG signal.

Keywords: Microsleep detection, electroencephalogram signal, channel selection, correlation coefficient, k-nearest neighbor

Abstrak

Setiap tahun, ekonomi global mengalami kerugian kewangan yang ketara disebabkan oleh penurunan produktiviti kerja, kemalangan di tempat kerja dan kemalangan trafik akibat terlelap seketika ketika memandu atau dipanggil microsleep. Jadi, untuk mengurangkan kejadian microsleep ini, adalah perlu untuk mempunyai kaedah yang berkesan, boleh dipercayai dan diterima oleh masyarakat untuk mengesan kehadiran microsleep terutamanya semasa memandu ke tempat kerja atau pulang dari tempat kerja. Malangnya, teknik penyelesaian semasa masih gagal untuk mengelak microsleep daripada berlaku. Oleh kerana microsleep berkaitan dengan isyarat yang dihasilkan oleh otak manusia, penggunaan teknik electroencephalogram (EEG) untuk merekodkan isyarat yang dihasilkan oleh otak manusia semasa memandu dan menganalisa isyarat tersebut secara pembelajaran algorithma komputer atau pembelajaran mesin, adalah teknik yang pantas dan efektif di dalam pengesanan microsleep. Ciri-ciri isyarat unik dari analisa yang dijalankan kepada isyarat otak yang direkodkan oleh EEG dan pembelajaran mesin digunakan di dalam pengelasan isyarat tersebut oleh kaedah K-Nearest Neighbor (kNN) untuk mengenalpasti ciri-cirit isyarat yang berkaitan dengan microsleep. Disamping itu, teknik Fast Fourier Transform (FFT) digunakan untuk memastikan ciri-ciri isyarat yang tepat dihantar kepada kNN untuk pengelasan isyarat yang berkaitan dengan microsleep. Untuk meningkatkan kelajuan sistem pengesanan microsleep, kajian menggunakan tempoh masa tetingkap yang berbeza iaitu 0.5 saat, 0.75 saat dan 1 saat telah dijalankan kepada ciri-ciri isyarat yang dianalisa. Kajian ini mendapati bahawa teknik yang telah digunakan mencapai ketepatan klasifikasi atau pengelasan isyarat berkaitan microsleep sebanyak 98.28% untuk masa tetingkap 0.5 saat. Keberkesanan sistem yang digunakan adalah amat baik dan cekap dalam mengesan kehadiran microsleep semasa memandu.

Kata kunci: Pengesanan microsleep, isyarat electroencephalogram (EEG), *ciri-ciri isayarat,* pengelasan isayarat, k-nearest neighbor, masa tetingkap

1.0 INTRODUCTION

Microsleep arises from a variety of circumstances, including insufficient sleep and medical conditions such as narcolepsy and sleep apnea. However, it most generally occurs when a person experience sleep deprivation or engages in monotonous activity is depicted in Figure 1. Microsleep is a significant concern when individuals engage in activities such as driving, functioning large-scale machines, and additional safety-critical tasks that can involve repetitive and dull motions. The NSC (National Safety Council) states that a driver's consciousness, swiftness of response, hazardous awareness, and capacity to sustain concentration are compromised when they experience periods of microsleep. Over 100,000 incidents of car wrecks involving a drowsy driver have been reported by the police annually, resulting in 1,550 deaths and around 71,000 injuries [1].

According to the same report, driving for more than 20 hours without sufficient sleep would be comparable to operating a vehicle with a 0.08% blood-alcohol accumulation, that is legally permissible in the United States. The occurrence of microsleeps leading to fatalities has resulted in cascading consequences in previous instances, resulting in over 200 deaths and more than 400 injuries in a single catastrophe [2]. Such occurrences serve as a reminder of the significance of implementing modern technologies that could prevent them.

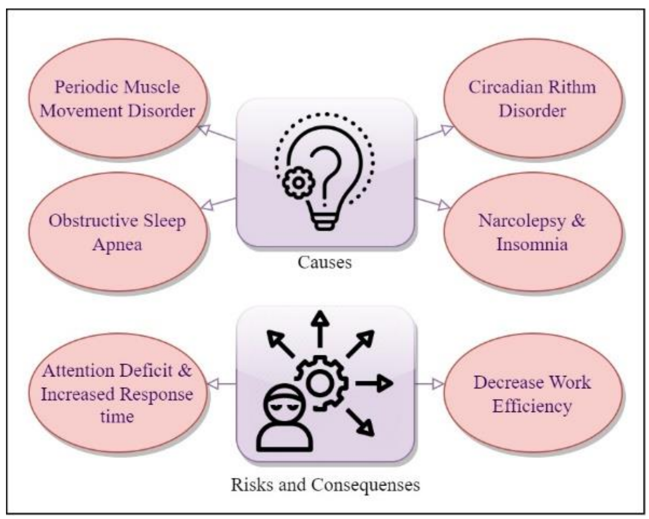


Figure 1 Causes, risks, and consequences associated with microsleep [3]

Multiple physiological signals, including electroencephalogram (EEG), electrocardiogram (ECG), electrooculogram (EOG), and photoplethysmogram, have been explored for the purpose of assessing microsleep, drowsiness, and fatigue. Nevertheless, EEG has emerged as the predominant and reliable indicator for measuring microsleep, drowsiness, and fatigue [4 – 7]. EEG is a noninvasive method that can be easily obtained with a small number of electrodes. The changes in spectral behavior of the EEG signal clearly indicate the impact of sleepiness [8]. Microsleep detection can involve the use of sensors technology based on computer vision, measuring head motility, observing facial expressions, or monitoring the duration of eye blinks. Utilizing biological indicators such as EEG, EMG, ECG, EOG, etc. for exploitation poses challenges, despite their capacity to accurately represent human states [8]. After obtaining these signals, they are subjected to quantitative machine learning and deep learning techniques for classification purposes. These classifying techniques must possess a high level of precision, as any mistake on their part could result in disastrous consequences. Examining brain signals is crucial as they serve as indicators of neuronal activity throughout a microsleep phase [10]. Microsleep is characterized by a distinct reduction in the aggregate frequency of signals generated by the EEG [11].

In order to analyze the EEG signal, distinct features can be obtained in the domains of time, frequency, and nonlinearity. Time-domain feature encompass statistical metrics such as mean, standard deviation, root mean square, skewness, and kurtosis, as well as Hjorth parameters including activities, mobilities, and complexities [12], frequency-domain feature including power spectrum analysis, median frequency, and wavelet transform. The often-employed nonlinear features are entropies, the largest Lyapunov exponent, and the Hurst exponent [13]. Spectral power fluctuations in EEG frequency bands are frequently used in literature to assess the transition of psychological states from wakefulness to sleepy [14 - 15]. Nevertheless, there are conflicting perspectives regarding the alterations in spectral patterns across various brain regions caused by conventional methods used for identifying drowsiness [8]. It is essential to annotate EEG microsleeps in order to assess them accurately. Failing to do so can lead to misleading findings. The process of manually scanning and interpreting by extensively skilled professionals is both time-consuming and costly [16]. At the present time, subjective assessments such as the Karolinska Sleepiness Scale (KSS) and the Psychomotor Vigilance Task (PVT), which rely on participants' subjective experiences, are predominantly employed to evaluate microsleep occurrences, stages of fatigue, and levels of drowsiness [17 – 19]. The applicability of these methods for quantifying microsleep episodes in EEG is modest. However, right now, these techniques have primarily been employed to measure the duration of microsleeps. Although multi-channel EEG recordings offer an in-depth assessment of EEG activities, particular channels may contain noises and redundant data. Consequently, it is necessary to choose an appropriate method for selecting channels in order to minimize the reckoning burden. Due to these challenges, robust microsleep detection has emerged as an essential component in the present day.

The main points that this article brings forth are:

1. This study chose three distinct time intervals (0.5, 0.75 and 1s) to avoid computational complexities for identifying microsleep.
2. This study investigated the technique of channel selection in order to decrease computational expenses.
3. This study was conducted an analysis and provided a report on the most optimal parameter values that result in the highest performance of the microsleep detection model.

1.1 Understanding Microsleep

This section contains a concise summary of the foundational knowledge regarding the incidence and detection process of microsleep, as well as an explanation of the challenges associated with developing an optimal solution for detecting microsleep that is widely accepted in society.

1.1.1 Microsleep Incidence

Microsleep refers to a brief period of sleep or dizziness that can range from a fraction of a second to 15 seconds. Throughout a microsleep, the individual who is undergoing it is unable to respond to any random sensory stimuli. Individuals who encounter such incidents may inadvertently fall asleep. It manifests as abrupt transitions between waking and sleep phases, and is marked by sagging eyelids, wagging of the head, and sluggish, sporadic eyelid closures. Microsleep is a phrase used in Electroencephalography to describe a change in the frequency of EEG waves [3]. Specifically, it refers to the replacement of the 8-13 Hz alpha wave background pattern with 4-7 Hz theta wave oscillations is illustrated in Figure 2.

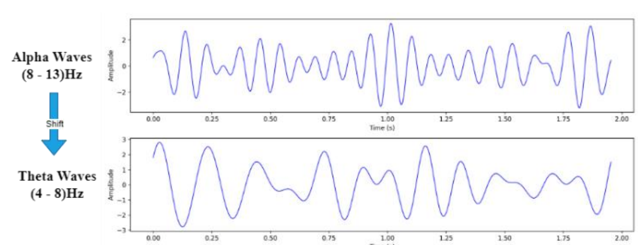


Figure 2 Changeover from alpha to theta wave regime

The Orexin structure functions as a complex interconnected system responsible for maintaining wakefulness that spans the entire neurological system, as depicted in Figure 3. It enhances the function of neurons in the middle cerebral cortex, cerebrum, and visual cortex. The neuronal activity that occurs in the brain is expressed by waves in the brain, specifically the fast Beta (β) and Alpha (α) bands that occur when the brain is awake and conscious, and the slow Theta (θ) bands that occur when the brain involuntarily experiences sleepiness. In addition, research conducted on animals [20] has demonstrated that orexin neurons are responsible for the regulation of size of the pupil, eyelids positioning, and perhaps convergence and proper eye posture through the function of motoneurons of various muscle fibers. As a consequence of this, the awake state is further demonstrated by the activity and movements contained within the eyes. Furthermore, multiple investigations [21] have demonstrated that, it is through the stimulation of the autonomic nervous system (ANS) through links to the ventrolateral medulla (VLM) and spinal cord that orexin is able to modulate alertness in the ANS. This stimulation ultimately leads to the suppression of sleep. The alterations in commiserative activity are subsequently manifested by modifications in face musculature and perspiration secretory organ function.

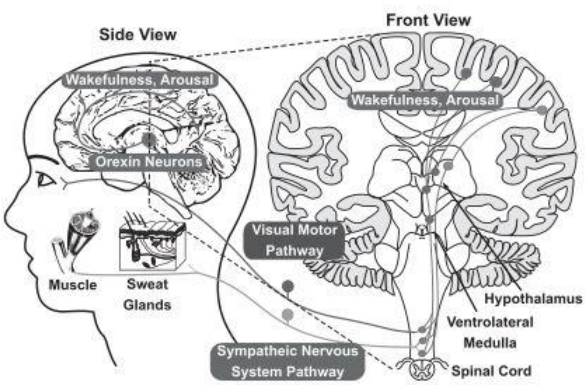


Figure 3 Neuronal mechanism of consciousness [22]

1.1.2 Detection of Microsleep

Microsleeps refers to a brief period of unconsciousness and plays a crucial role in switching from being awake to falling asleep. The duration of a microsleep occurrence can range from a few seconds to 30 seconds, and individuals are capable of awakening following such an episode. Microsleep is evident by both behavioral indicators, such as eyes which gradually drift, prolonged eye-lid closures, and head shrugs [23], as well as electrical changes in EEG, characterized by a transition from fast α and β bands to slower θ manners [24]. These symptoms are associated with the suppression of the Orexin function. Microsleep poses a significant risk for tasks that demand continuous vigilance, as individuals experiencing microsleep episodes are typically oblivious to them and maintain a false perception of wakefulness throughout [25]. This is a common occurrence among individuals with Excessive Daytime Sleepiness (EDS).

Traditionally, the requirement of integrating many sensors on the head of the user in order to record various biomarkers for precisely detecting microsleep poses difficulties in developing a device that can be worn and is accepted in society [22]. To address this problem, the study employed 8-channel EEG equipment, which is frequently used by researchers. The comprehensive specification of this device is elaborated upon in the Data Acquisition section.

1.2 Related Works

A variety of strategies have been utilized in the mechanism of channels selection, such as the wrapper methodology, filtering method, hybrid strategy, embedding method, and human-based strategy [26]. Furthermore, methods for selecting channels can be categorized into filter and wrapper methods. Generally, filter techniques rely on particular requirements such as the fisher criteria or mutual information [27]. Wrapper methods are frequently used to select channels when combined with a specific classifier, such as a decision tree and evolutionary algorithm [28]. A new method was established for selecting EEG channels called Granger causality (GC), where all the GC computations are performed in the time domain [29]. A method for selecting EEG channels using the bispectrum technique proposed in [30]. Nevertheless, the impact of the various ranges of frequencies of the filter on the calculation of the bispectrum is overlooked. Another method was investigated by Liu *et al*., in [31], that utilizes Fisher's criterion to automatically choose the most suitable subject-specific distribution of channels. In essence, current methods for channel selection are either inefficient or shortage a neurophysiological foundation.

Pham *et al.,* [32] developed WAKE, a hardware apparatus worn behind the ears that can effectively distinguish genuine EEG signal from other types (EMG, EOG, EDA) and achieve precise classification with high accuracy. Along with that, the combination of features has been employed to identify fatigue based on EEG activity, changes in pupil size, and movements of the eye and eyelid [33]. Reservoir computing, employing echo state systems, has also been employed to attain outstanding results [34]. Kweon *et al*., [35] proposed an alternative methodology utilizing DSN, U-Net, and tSNE to address the issue of data imbalance. Jabbar *et al*., [36] aimed to develop CNN models with reduced computational complexity suitable for deployment on resource-constrained embedded devices, such as smartphones and automobile dashboards. A mobile application capable of accurately detecting microsleep using standard techniques has also been introduced [37]. Furthermore, there have been applications of combined Haar cascade and CNNs techniques in image processing [38]. Malafeev *et al*., [39] achieved high accuracy in distinguishing microsleep episodes from alertness by utilizing EEG and EOG data. They employed a CNN-LSTM model that was trained on data obtained from seventy-six individuals. EEG-based interfaces between brains and computers have also been utilized in conjunction with humanoids and robots for diverse objectives [11].

Conversely, the effectiveness of multiple linear and nonlinear single classification models, such as Decision Tree (DT), Support Vector Machine (SVM), Neural Network, Hidden Markov Model (HMM), and Fisher Discriminant Analysis, has been evaluated in predicting driver weariness using EEG signals [40]. Tuncer *et al.*, [41] employed a generic KNN classifier to categorize the retrieved characteristics based on EEG readings gathered while the person was awake and sleepy. Although, channel selection using KNN classification is a relatively recent notion in the identification of microsleep in humans using EEG signal.

2.0 METHODOLOGY

This study utilized its own dataset, which was collected by considering a variety of ages and genders to enhance the reliability and validity of the results we obtained. The specifics of data collection processes, device specifications, and experimental protocols are addressed in sections 2.1, 2.2, and 2.3.

2.1 Participants and Experimental Protocol

A total of ten individuals, including undergraduate students, postgraduate students, and faculty members, ranging in age from 22 to 55 years old, and without any previous medical conditions, were selected to participate in the EEG signal collection sessions. The individuals who participated were selected exclusively from the Pekan Campus of Universiti Malaysia Pahang Al-Sultan Abdullah. They were instructed to abstain from consuming any form of medication or substances, such as alcohol or coffee, both prior to and during the period of experimentation. The participants lack any medical history of psychiatric, neurological, or physical ailments and possess either normal or correct visions. Prior to enrolling in the trial, the subjects were given informed permission. The research investigation received ethical approval from the IIUM Research Ethics Committee (IREC 2023-239). The experiment took place in the Applied Electronics and Computer Engineering Laboratory and Signal Processing Laboratory at the Faculty of Electrical and Electronics Engineering Technology, Universiti Malaysia Pahang Al-Sultan Abdullah. These labs provided a disturbance-free environment for the individuals who participate in the experiment and maintain concentration during the sessions. The experimental conditions were carefully controlled to maintain a tranquil setting devoid of any auditory disturbances, while also maintaining a comfortable ambient temperature, in order to promote relaxation among the participants. The participant was instructed to adopt a comfortable posture and remain still, refraining from any physical movement or eye blinking so order to minimize the occurrence of noise or undesired signals during the experiment [42].

2.2 Data Acquisition

The EEG data was acquired by using an eight-channel wearable EEG headset equipment called the Unicorn Hybrid Black, shown in Figure 4. Several researchers have previously utilized this equipment in their research projects [43 – 44]. The device undergoes sampling at a resolution of 24 bits and a rate of 250 Hz per channel. The data has been assessed and obtained through the licensed Unicorn Suite software, specifically version 1.18.0.2085. Figure 5 is a representation of the user interface that is included in the Unicorn Suite program.

Figure 4 Eight-channels wearable EEG headset Unicorn Hybrid Black device

A personal computer was connected to the Unicorn Hybrid Black device through the use of the Bluetooth interface that had been integrated inside the device. Eight channeled EEG signals were captured at the following electrode positions: Fz, C3, Cz, C4, Pz, PO7, OZ, and PO8. These positions correspond to the channels CH1, CH2, CH3, CH4, CH5, CH6, CH7, and CH8. Figure 6 presents a visual representation of the channel placements. An individual experiences instances of microsleep, which have been recorded and illustrated in Figure 7.

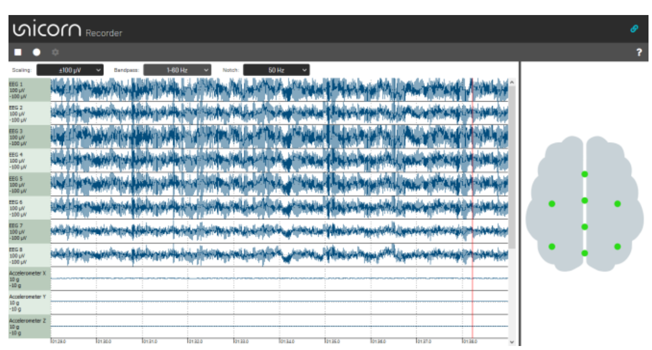


Figure 5 User interface of Unicorn Suite software while recording participants' data

All of this work was carried out using a laptop that was equipped with a central processing unit (CPU) of Intel(R) Core(TM) i3-6006U, 12 gigabytes of random access memory (RAM), and the Windows 10 operating system.

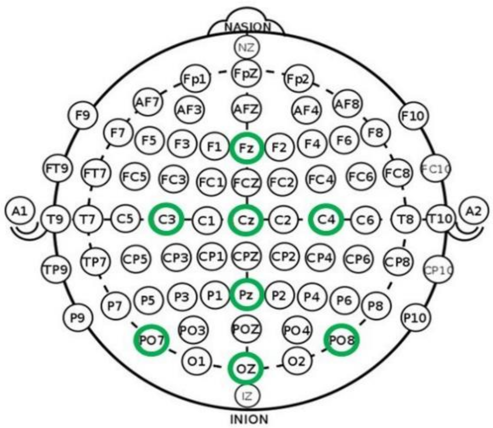


Figure 6 Location of the eight electrodes Unicorn Hybrid Black (marked in green): Fz, C3, Cz, C4, Pz, PO7, OZ, and PO8, according to the international 10–20 system

2.3 Data Preparation

This experiment was carried out for a total of around four hours with ten participants (twenty to twenty-five minutes for each), and the participants were asked to enter the KSS (Karolinska Sleepiness Scale) number that corresponds to the microsleep condition and the level of somnolence that they experienced. The validation set is comprised of only two classes, which are denoted by the numbers 0 (Wakefulness) and 1 (Microsleep). This is because the primary objective of this experiment is to identify EEG measurements that correlate to microsleeps. In accordance with this, this study is required to categorize them as either wakefulness or microsleep. The KSS value of '0' relates to a value that is less than 7, while the KSS value of '1' refers to a value that is more than or equal to 7. Because each participant is accountable for meticulously entering their value into the KSS scale, investigators are unable to make certain that all of the participants will have entered the appropriate KSS value. One subject can submit a KSS number that is greater than or equal to seven for a specific level of sleepiness, while another subject can enter a KSS value that is less than six for the same level of sleepiness.

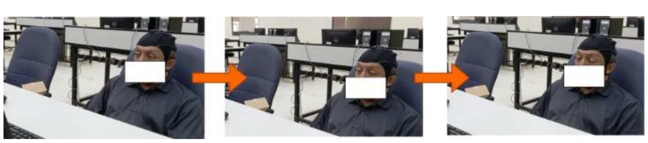


Figure 7 Microsleep occurrences captured during data recording

In order to catch the beginning of the sleep cycle during the data preprocessing time, the study captured the frequency change from 8-13 Hz (alpha band) to 4-7 Hz (theta band). This change reflects the beginning of the sleep cycle. This study conducts experiments with shift part as microsleeps in order to identify the change in the EEG signals that take place throughout this transition (from alpha to theta). This is because microsleep is characterized by frequency range that falls between 4 and 7 Hz.

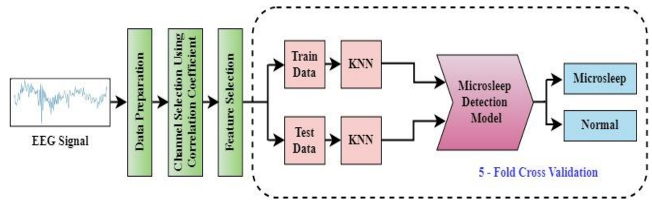


Figure 8 Comprehensive framework of the present investigation

Moreover, Figure 8 illustrates the complete sequence of steps that comprise this study. This work aspires toward improving the accuracy of the classification of binary-class EEG data that includes microsleep and wake conditions. In order to reduce the operational spending, three separate time frames have been chosen. This investigation has employed three distinct time frame intervals, namely 0.5 seconds, 0.75 seconds, and 1 second. To determine the minimum duration depicted in Figure 9. The study utilized a novel channel selection technique called correlation coefficient analysis. Once the most meaningful channel has been chosen, extraction of features process should be applied to the EEG data. The current study has retrieved the feature using Fast Fourier Transform (FFT). With the intention to mitigate the issue of overfitting, this work has implemented a five-fold cross-validation strategy. In the first iteration, the datasets have been divided into two parts: 20% of the feature vectors are used for testing, while the remaining 80% are used for training. In a similar manner, an additional 80% of the feature vectors are utilized for the training, while the remaining 20% have been assigned to the test in the upcoming iteration. This process is iterated until the test encompasses all functionalities. The K-Nearest Neighbor (KNN) classification model has been employed to categorize the extracted features. The training model has been affirmed through rigorous testing sessions, while several metrics have been employed to assess its success. Afterwards, a range of measures was used to assess the effectiveness of the classification model.

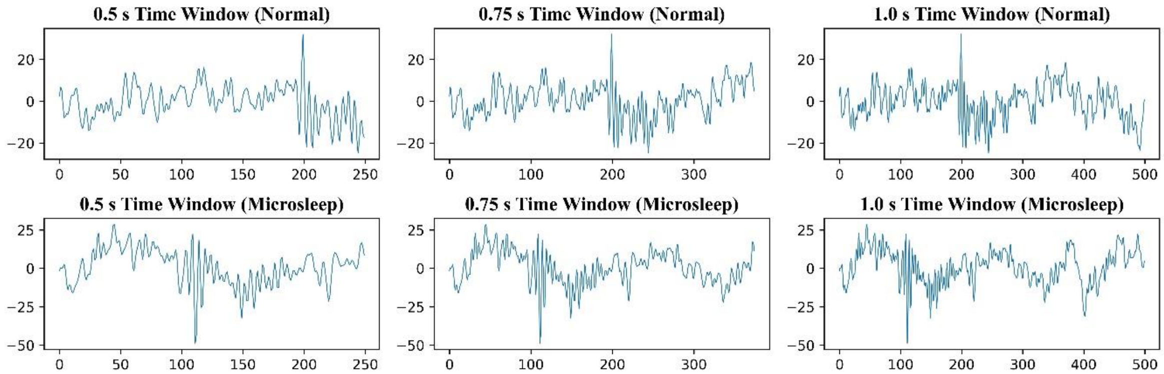


Figure 9 Time-varying depiction of participants' normal and microsleep data

2.4 Correlation Coefficient

The detection of brain activations related to tasks is best accomplished using correlation-based methods [45]. The intention of this step is to reduce the number of EEG channels by excluding the channels which have minimal correlation with each other during trial. It is assumed that the channels related to microsleep conditions carry distinct information which remains the same in all trials. When comparing various channels, it is possible that other channels may have minimal similar features. The correlation coefficient is employed to ascertain similarity, relying on this premise. Hence, our whole focus lies in the resemblance between any two channels, disregarding their directional impact. Prior to anything else, normalization needs to be accomplished. The EEG signal obtained from different individuals exhibit temporal variations in their amplitudes. Normalization is an effective strategy for minimizing this unpredictability. For the purpose of normalizing the mean of all the data to zero and the standard deviation (STD) to one, the Z-score normalization is that which is utilized [28]. The Z-score has been determined by taking Equation (1) into consideration.

$$Z_{xv} = S_{xv} - mean_x \quad (1)$$

Where S_{xy} represents the y^{th} sample value of the y^{th} channel, $mean_x$ defines mean value of the y^{th} channel, and σ_x indicates STD of the y^{th} channel. Furthermore, the correlation coefficients are quantified. Pearson's correlation analysis is utilized in our approach throughout the process. Pearson's correlation coefficient is a statistical measure that quantifies the degree of linear association between any number of random variables [46]. The equation (2) provides an acronym for Pearson's correlation coefficient.

$$\varphi(A,B) = \frac{1}{N_{trial} - 1} \sum_{i=1}^{N_{trial}} \left(\frac{X_i - \bar{\mathrm{A}}}{\sigma_B}\right)\left(\frac{X_i - \bar{\mathrm{B}}}{\sigma_B}\right) \quad (2)$$

Where, A and B be two variables that are observable, Ntrial represents the observations number, while $\bar{\mathrm{A}}$ and $\bar{\mathrm{B}}$ indicate the respective mean of two variables. The σ_A and σ_B are the symbols that represent the STD of two variables. Within the context of our situation, the value of (A, B) range from 0 to 1, indicating a connection that is of low to high strength. Measurement of the correlation coefficients are carried out among every pair of EEG channel. During each trial, a correlation measurement is conducted, resulting in the formation of a correlation matrix R of dimensions N × N. The mean value for each row can be derived from this matrix. The row i with the greatest mean correlation can be determined. This analysis indicates a strong correlation between channel-i and other channels, emphasizing that channel-i holds considerable importance. By applying this criterion, this study categorized $N_{selected}$ channels into a unified channels class that exhibit a high degree of correlation. After conducting N_{trial} trials, a total of $N_{trial} \times N_{selected\ channel}$ channels were recorded. The $N_{selected\ channel}$ channels are chosen based on their highest frequency of appearance, considering that most channels are repeated. Consequently, the data dimensionality decreased from $N_{trial} \times N_{channel} \times N_{sample}$ to $N_{trial} \times N_{selected\ channel} \times N_{sample}$. It will make the process of feature extraction more efficient while also reducing the amount of time it takes. The following is an expression of the flowchart of the algorithm that has been proposed, is illustrated in Figure 10.

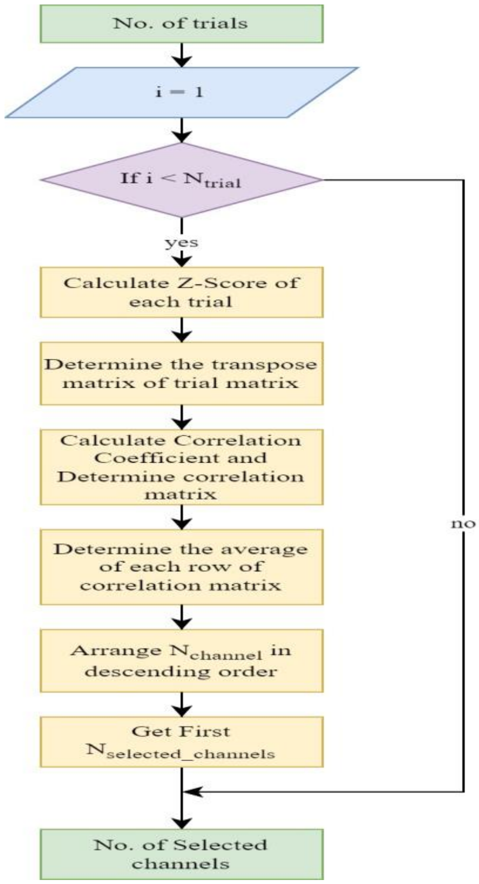


Figure 10 Flowchart of the suggested method for selecting the channel

2.5 Fast Fourier Transform (FFT)

For the present study, the feature has been extracted in terms of Fast Fourier Transform (FFT). Applications of the FFT can be found in a variety of domains, including digital signal processing, the resolution of partial differential equations, and the development of algorithms to multiply integers in huge numbers. The FFT is a technique that computes discrete Fourier transforms (DFT) in a quick and effective manner. Because the Fourier transform is employed for demonstrating the domain of frequencies because numerous signals in a transmission system are continuous in the time domains [47]. Figure 11 shows the variation of time and frequency domain signals.

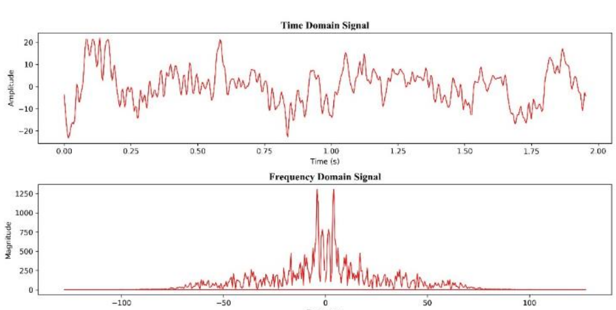


Figure 11 EEG time and frequency domain signals

FFT is a highly efficient technique for handling and evaluating data, such as EEG signals, that are in the shape of a sine wave. Previous research has demonstrated its effectiveness in real-time applications due to its greater performance compared to other approaches. Nevertheless, it is not appropriate for analyzing brief EEG signal. The FFT is mathematically expressed in Equation (3).

$$S(f) = \int s(t)e^{-j2\pi ft}dt \tag{3}$$

The complex changes that are carried out by DFT can be simplified with the help of FFT. To provide a point of comparison, the complexity of the transformation is N2 when utilizing DFT. Moreover, by utilizing the FFT approach and achieving shorter transformation times, the level of complexities of the process of transformations are significantly reduced to (N) log (N).

2.6 K - Nearest Neighbor (KNN)

The K-Nearest Neighbor (KNN) algorithm is a classification approach that assigns objects to classes on the basis of the training data that is nearest to the item in question. KNN demonstrates superior performance in classification problems by adjusting the positions of nearest neighbors considering sampling data [48]. The information is then supplied with a measurement of interspace to be integrated into a mathematical computation. Euclidean distance is employed for the computation in this categorization. The training that has the smallest interspace are referred to as neighbors and subsequently arranged in order from the nearest distance to the longest distance. Each neighbor is distinct from one another or similar individuals. The object being classed corresponds to the same neighbors with the highest number amongst k neighbors [49]. When attempting to determine the neighbor, it employs distance metrics such as the Euclidean distance, as specified in Equation (4).

$$D(a,b) = \sum_{k=1}^{N} \sqrt{(a_k - b_k)^2} \tag{4}$$

The variable D (a, b) represents the distance between facilities a and b, where a_k - b_k denotes the two coordinates a and b of variable k (k = 1,3,5,… n). So as to prevent misinterpretation, it is necessary for the value of k to be an odd number, but the number of training data should be even. This value is essential for facilitating the attainment of categorization outcomes based on the number of nearest neighbors. Since a class has the highest number of neighbors, the test data will be assigned the result of that class [50].

2.7 Performance Evaluation

The following metrics are used for evaluating the classification outcomes and the performance of the classifier: classification accuracy (CA), sensitivity, specificity, precision, recall, F1 score, MCC, and AUC, which are expressed in the following Equations (5-11):

$$CA = \frac{TP + TN}{TP + FN + TN + FP} \times 100\% \quad (5)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (6)$$

$$Specificity = \frac{TN}{TN + FP} \quad (7)$$

$$Precision = \frac{TP}{TP + FP} \quad (8)$$

The precision refers to the classifier's capacity to accurately identify positive samples as positive and negative samples as negative within the entire dataset.

$$Recall = \frac{TP}{TP + FN} \quad (9)$$

The recall value is a measure that shows the proportion of positive samples that are correctly identified.

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (10)$$

The F1 score can be described as the weighted average of precision and recall, with the best values at 1 and the worst values at 0.

The Matthews correlation coefficient (MCC) is a statistic that can be utilized in machine learning to assess the accuracy of binary classifications [51]. The MCC represents the correlation coefficient, which ranges from -1 to +1.

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (11)$$

Where TP, TN, FP, and FN depict the semantics of true positive, true negative, false positive, and false negative, respectively.

3.0 RESULT AND DISCUSSION

3.1 Performances in Distinct Time Windows

In the beginning, the study evaluated the classification model's performances by analyzing the trials of all subjects together. To evaluate their performance, we utilized three distinct time periods (0.5s, 0.75s, and 1s) for the selection process. In section 6.2, the outcome of the channel selection procedure is explained. Figure 12 demonstrates that the three time periods attained accuracy rates of 98.28%, 98.13%, and 98.00% respectively. For the purpose of optimizing the classification accuracy and minimizing the duration of each trial, this investigation has selected a time window of 0.5 seconds. This smaller time window makes the framework speedier by lowering the sample numbers in every trial. Therefore, the remaining analysis of this current investigation has been constrained to a time frame of 0.5 seconds.

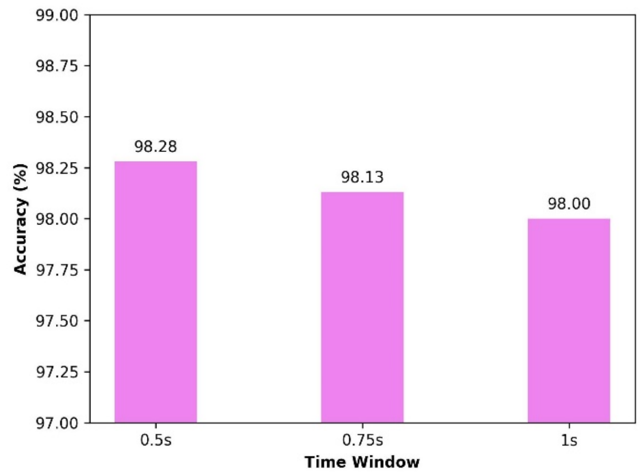


Figure 12 Classification accuracy in three different time windows

The collective trials of all subjects were utilized to assess the performances of the classifier. This research employed two distinct states, namely normal and microsleep. During the labelling process, the states of normal and microsleep have been represented by the numbers 1 and 2, respectively. The classifier's effectiveness has been evaluated employing the k-fold cross-validation strategy. The value of k in the k-fold cross-validation procedure has been predetermined as 5 for the present study. The confusion matrix of the KNN classification model is displayed in Figure 13, which provides an illustration of the misclassification details.

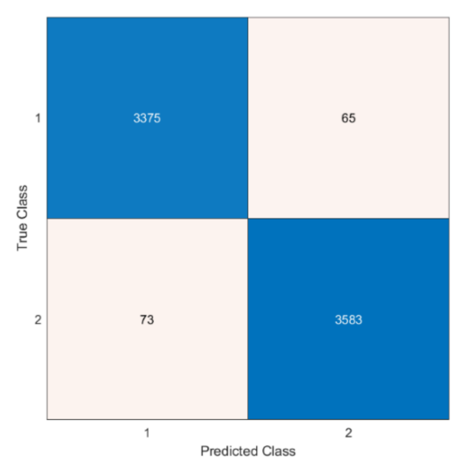


Figure 13 Confusion matrix of KNN classifier

Alongside determining the degree of accuracy that the classifier possessed in terms of classification, this study also investigated its efficacy by employing a variety of effectiveness metrics. This study utilizes many performance assessment metrics, such as sensitivity, specificity, precision, F1-score, MCC, kappa, and AUC. Figure 14 depicts the performances metrics of the KNN classification model, which are measured using several evaluations of performance indications. The sensitivity, specificity, precision, F1-score, MCC, and Cohen's Kappa have values of 0.9994, 0.9995, 0.9995, 0.9995, 0.999, and 0.999 correspondingly. Schematic representation of the receiver operating characteristic (ROC) of the KNN classification model is depicted in Figure 15. The reason behind the improved accuracy of a classifier can be deduced by analyzing the true positive rate against false positive rate curve for each class on the ROC curve.

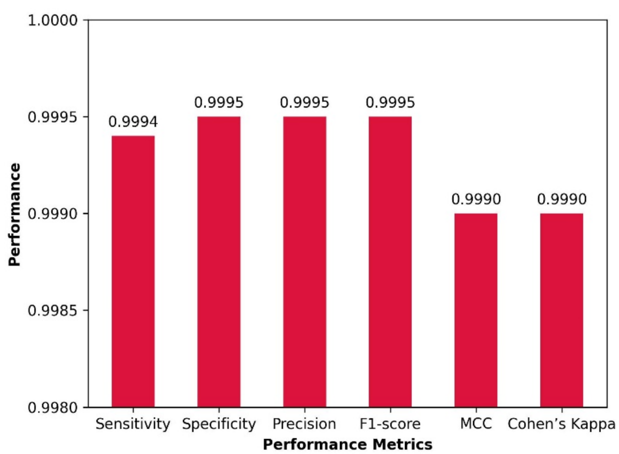


Figure 14 Performance of the KNN classifier with different metrics

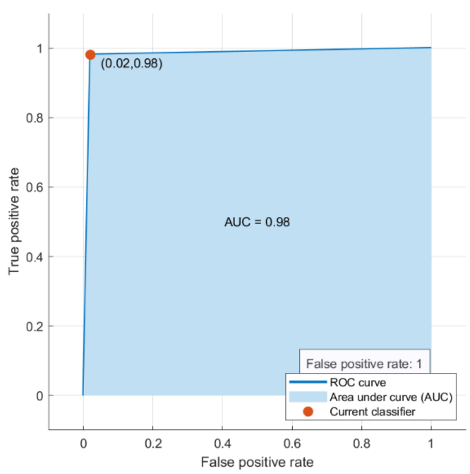


Figure 15 Receiver operating curve (ROC) of KNN classifier

3.2 Channel Selecting Algorithm Performances

This experiment utilized a total of 8 EEG electrodes to produce the EEG datasets. Electrode selection is crucial for minimizing the computational load, as not all electrodes transmit the needed information. The electrodes are organized based on their significance. Therefore, the Oz electrode provides the most substantial information compared to the others. Upon prioritizing the electrodes, this study computed the accuracy of the KNN algorithm. Table 1 presents the categorization accuracy obtained using different arrangements of electrodes. The Oz electrode, chosen based on the correlation coefficient, has obtained an accuracy rate of 95.37%. The attained precision utilizing a solitary electrode is quite promising.

Table 1 Accuracy in classifying the selected electrode

Selected electrodes number	Name of electrodes	Accuracy (%)
1	OZ	95.37
2	OZ, PO8	96.15
3	OZ, PO8, PO7	98.22
4	OZ, PO8, PO7, Pz	98.22
5	OZ, PO8, PO7, Pz, C3	98.25
6	OZ, PO8, PO7, Pz, C3, Cz	98.28
7	OZ, PO8, PO7, Pz, C3, Cz, C4	98.27
8	OZ, PO8, PO7, Pz, C3, Cz, C4, Fz	98.28

However, the objective of this research was to provide a structure to identify microsleep by utilizing EEG readings. While EEG signals can be reliably utilized for detecting microsleep, this approach has several limitations, such as increased processing expense and the potential for classifiers to overfit. To overcome these challenges and obtain high classification accuracy, a combination of the channel selecting procedure, feature extracting techniques, and classification model should be utilized optimally. In addition, reducing the duration of each trial would enhance the system's speed. Hence, this study presents a new technique for EEG channel selection to detect microsleep. The K-nearest neighbors (KNN) classifier, when applied to the dataset, yielded a classification accuracy of 98.2%. This high accuracy was achieved using only three specifically chosen channels within a time window of 0.5 seconds. The three prominent channels were selected based on their correlation coefficient. To the best of the authors' knowledge, this may be the first research investigation which presents correlation coefficient as selection of channels technique for microsleep identification based on EEG signal with the greatest accuracy in a compact time frame. The strategy that has been designed has the capacity to provide a novel method for monitoring an individual's microsleep or wake state using an EEG signal.

The following are the technical benefits of the current investigation:

1) The proposed system attained the utmost accuracy, specifically 98.28%, within a time window of 0.5 seconds. The system's speed is enhanced by decreasing the number of samples in each trial within this limited time frame.

2) The KNN method can be effectively utilized to identify microsleep using EEG data, because of its effectiveness and resilience.

3) Nevertheless, in terms of speed during testing, this method demonstrated comparable performance to other classification algorithms. The test duration is not only short, but it is also independent of the training sample. In addition, the solution given here is also helpful for portable devices.

4) The suggested channel selecting approach identifies mostly associated channel through correlation analysis. The suggested channel selecting procedure has demonstrated exceptional accuracy using only 3 electrodes, which can significantly enhance the efficacy of the microsleep detection technique utilizing EEG.

While the suggested method has the potential to effectively detect microsleep, it also has certain limitations. Regrettably, the study's usefulness is impeded by the restricted number of subjects and dataset size. Further inquiries should be undertaken to ascertain the efficacy of the proposed technique on a substantial sample size. Although the EEG exhibits very susceptible characteristics to artifacts, no artifact reduction technique was implemented in this study. Consequently, the presence of noisy EEG signals may lead to a reduction in accuracy. Various methods for removing artifacts can be used to address this problem, which requires further investigation. This study will assess the effectiveness of the method by considering multiple bands of frequencies and selections of time frame automatically. These factors have the capabilities to substantially reduce the computational complexities of the suggested approach. This study will further investigate this multi-parameter optimization difficulty in our future study.

4.0 CONCLUSION

The correlation coefficient method, combined with FFT feature extraction and KNN classification, shows promise in enhancing microsleep detection accuracy using EEG signals. Through a trial separation of time intervals (0.5s, 0.75s, and 1s), this technique achieved remarkable accuracy of 98.28% using just three electrodes within a 0.5-second window. This suggests that the proposed approach is effective in evaluating wakefulness and detecting microsleep episodes efficiently. By leveraging physiological measurements like EEG, this methodology offers a reliable and computationally efficient means of assessing alertness levels in various contexts, from driving safety to workplace productivity monitoring.

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Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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