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# Addressing Imbalanced EEG Data for Improved Microsleep Detection: An ADASYN, FFT and LDA-Based Approach

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**ABSTRACT**

Microsleep, brief lapses in consciousness lasting less than 15 seconds, are often accompanied by feelings of fatigue and are detectable through a deceleration in electroencephalogram (EEG) signal frequencies. Accurate identification of microsleep is critical for assessing driver alertness and preventing accidents. This paper introduces a novel approach to detecting driver microsleep by leveraging EEG signals and advanced machine learning techniques. The methodology begins with preprocessing raw EEG data to improve quality and balance, utilizing the ADASYN algorithm to address dataset imbalances. After preprocessing, features are extracted using Fast Fourier Transform (FFT), which provides a comprehensive frequency domain analysis of the EEG signals. For classification, Linear Discriminant Analysis (LDA) is employed to effectively distinguish between microsleep events and normal wakefulness based on the extracted features. The proposed framework was rigorously validated using a well-established publicly available EEG dataset, which included recordings from 76 healthy individuals. The validation results revealed a high testing accuracy of 92.71% in detecting microsleep episodes, demonstrating the effectiveness of the proposed approach. These results underscore the potential of combining EEG signal analysis with machine learning models for practical applications in monitoring driver alertness. The framework could significantly enhance driver safety by providing an effective tool for detecting microsleep and thereby reducing the risk of accidents caused by drowsy driving. This research highlights the promising application of advanced signal processing and machine learning techniques in the field of driver alertness monitoring.

## 1. Introduction

Microsleeps are brief (≲15 seconds) involuntary lapses in consciousness, during which a person momentarily falls asleep and temporarily ceases to function [1]. Microsleeps are characterized by hanging eyelids, behavioural signs of ocular closure, and a complete lack of visuomotor responsiveness [1-2]. These episodes differ significantly from other fatigue-related states, such as the unresponsiveness associated with exhaustion and the drowsiness linked to somnolence [3-5]. Research indicates that even individuals in good physical health and without sleep deprivation can experience multiple episodes of microsleep [1, 4]. Additionally, a strong correlation has been observed between the duration of microsleeps and the increased likelihood of accidents [6]. During activities requiring sustained attention, such as driving, microsleeps can have fatal consequences. However, with the

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development of accurate and non-invasive methods to predict these events, their occurrence can be significantly reduced.

Microsleep can be triggered by various factors, including insufficient sleep, medical conditions such as narcolepsy or sleep-apnea, and often occurs during monotonous tasks or in sleep-deprived individuals (see Figure 1).

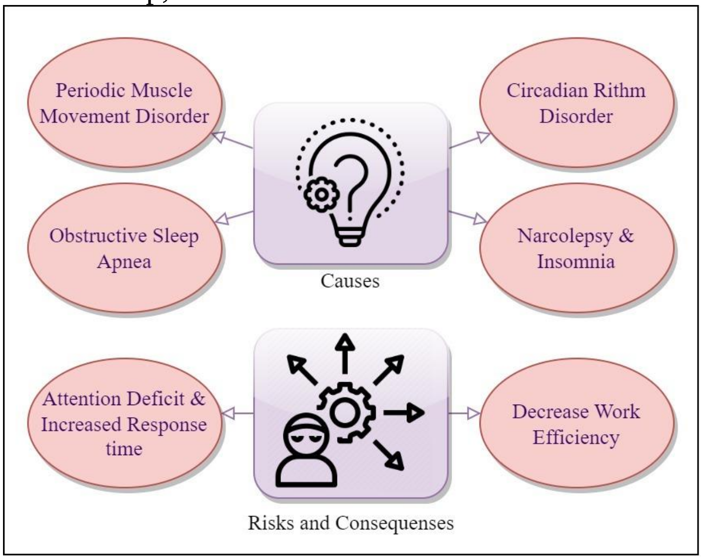


**Figure 1.** Causes, risks and consequences associated with microsleep [10]

Furthermore, it seems more likely that microsleep is caused by mental and physical fatigue, disturbances in the circadian cycle, and monotony due to repetitive work [7]. Nevertheless, such errors can occur even in individuals who are not sleep-deprived but are engaged in repetitive tasks without showing signs of exhaustion [8]. Those involved in such incidents often seem unaware of how long their post-crash adrenaline masked their fatigue or the brevity of their loss of consciousness or concentration. This presents significant safety concerns, particularly for those in high-risk professions such as driving, flying, navigating, maritime transportation, and process control, where sustained visuomotor capabilities are essential. Therefore, implementing effective surveillance to detect impending microsleeps can prevent catastrophic accidents and save lives. Microsleep is a troubling phenomenon that happens suddenly and involuntarily [9].

Machine learning is being increasingly used in various research studies to detect micro-surges in EEG data. Recent technological advancements, which enable the extraction, analysis, and interpretation of data from unstructured sources, offer a comprehensive solution. Machine learning can prioritize the development of systems that improve the accuracy of microsleep prediction [11-12]. The selection of features plays a critical role in the operational effectiveness of model. Personalized features are often derived from data using specialized techniques based on expert knowledge, which can limit the way characteristics and signals within the data are represented. Additionally, machine learning models use a training process to extract meaningful patterns from datasets to achieve specific objectives. Results from earlier research on the detection of microsleeps were noteworthy. However, none of this research used unbalanced EEG data to identify microsleep, and this is still a major concerning issue, which needs to be solved.

To solve this, the contributions of this proposed research study are summarized as follows:

- This study proposes a unique ADASYN technique to mitigate the dataset imbalanced issues to precisely detects the microsleep states.
- The effectiveness of the suggested framework is thoroughly assessed quantitatively to provide a clear understanding of its importance and to

demonstrate that the suggested investigation performs better than cutting-edge techniques for microsleep detection.

This paper is structured as follows for the remainder of it. The required literature regarding prior, comparable works is included in Section II. The materials and methods of the study are thoroughly described in Section III, along with the data description, preprocessing, feature extraction, classification model, and model evaluation metrics. Section IV enumerates and analyzes all the findings produced. Conclusion is depicted in Section V.

## 2. Literature review

In order to do this, it is vital to understand the characteristics and subtleties of EEG information associated with brain function in different situations [13]. Further investigation is required to determine whether EEG can be used to detect the occurrence of microsleeps. An EEG is a diagnostic tool that detects and records the electrical activity of the brain of a person, offering valuable information about how it works. This simple test illustrates the gradual evolution of the brain [14]. Investigators and doctors commonly employ EEG to investigate brain activity and identify neurological conditions. EEG is an essential element of modern research in various fields. This medical methodology may be employed to ascertain a person's cerebral demise, the extent of strokes or head injuries, epileptic activities, sleep disorders, and various other ailments. The utilization of this tool can be advantageous in linguistic and clinical investigations pertaining to diseases such as aphasia, and also in additional study endeavors exploring mental processes such as remembering or concentration [15–16].

To assign scores, experts need personally evaluate the different stages of sleep over a long period of time. Automated recognizing sleep stages is preferred for diagnosing and treating sleep-related problems. A reaction lapse refers to the inability of an individual to react to an ongoing action. Blackouts can manifest in various diverse forms, contingent upon the fundamental mental activities. While certain faults may lead to incorrect results, others can create obstacles in delivering a timely resolution. Complete sensory-motor breakdowns can occur due to certain mistakes. Attention lapses arise when an event occurs, a temporary interruption which prevents an individual from responding to the main work while not causing them to lose consciousness [17]. Under certain situations, a person may unintentionally engage in an additional activity, such as walking, observing, or operating a vehicle. Microsleep refers to a situation when there is an involuntary decrease in focus that is linked to sleep. During a short duration, the individual enters a state of light drowsiness. Microsleeps are characterized by observable behaviours like partially closing the eyes, nodding the head, and displaying insufficient facial emotions. Nevertheless, a duration of inactivity beyond thirty seconds is indicated as sleep [18-19].

Various classifiers and a mix of attributes are being employed to attain the current standard for tracking microsleep states. This standard indicates the highest level of effectiveness in recognizing microsleep stages using unpruned data. Despite numerous studies on the subject, no approach has yet demonstrated sufficient effectiveness to be implemented in real-world situations [20]. The fractal dimension of the EEG to identify behavioural microsleep episodes (MSEs) is used in [21]. These episodes were detected by specialists using facial recording and lapses in a tracking task. There was a limited association with automatic identification and expert rating. Davidson et al. [22] employed a long short-term memory (LSTM) recurring neural network, achieving a sensitivity of 48% and a specificity of 93%. In contrast, Peiris et al. [23] utilized linear discriminant analysis, resulting in a sensitivity of 73.5% and a specificity of 25.5%. Both studies utilized intriguing methodologies; however, they could not achieve satisfactory results. The detection process relied on execution of tasks, which rendered them unsuitable as benchmarks for our investigation. Golz et al. [24] utilized EEG data collected in a driving simulator to classify (identify and forecast) MSE using support vector machines and improved learning vector quantization. The evaluation of mean square errors was conducted by experts who visually examined video footage, lane departure time series, and the electrooculogram (EOG). The input data consisted of features that were obtained from spectral power and achieved accuracy levels greater than 80%. Different research conducted an online identification of MSEs [25], utilizing a means comparison test to identify variations in relative alpha power. The detection method achieved a sensitivity of 85% and a specificity of 80%achieved a sensitivity of 85% and a specificity of 80%.

However, a different approach using DSN, U-Net, and tSNE was put up by Kweon et al. [26] to deal with the problem of data imbalances. Shoorangiz et al. [27] conducted research on predicting microsleeps using EEG. He employed Linear Discriminant Analysis (LDA) to forecast microsleeps based on early EEG readings.

Prior studies yielded notable findings in detecting microsleeps. But none of these studies utilized imbalanced EEG data to detect microsleep. The objective of this work is to propose a framework that can autonomously detect microsleep in a clinical environment from an imbalanced EEG condition.

## 3. Materials and methods

Figure 2 illustrates the detailed structure of this present investigation, depicting the successive processing processes carried out on the EEG signal for the purpose of detecting microsleep episodes. The process begins with raw EEG data and progresses through several stages: data preprocessing using the ADASYN method, feature extraction via Fast Fourier Transformation, classification using a Linear Discriminant Analysis model, and finally, result and performance evaluation. This pipeline represents a typical approach in neuroscience and machine learning for analyzing brain activity data and deriving meaningful insights from it.

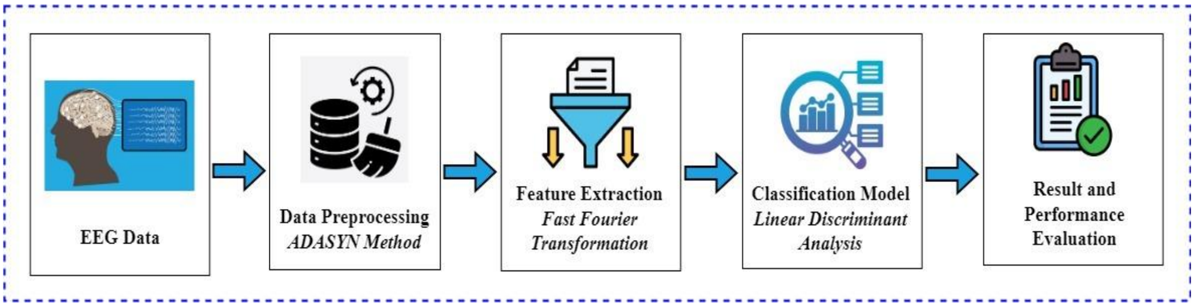


**Figure 2.** Comprehensive design of the current study

### *3.1 Data description*

For our investigations, we utilized an online EEG dataset that included 76 people, with 50 being men and 26 being women [28]. The MWT comprises four trials that occur throughout a day, with two trials occurring before lunch and two trials occurring after lunch. There is a mandatory minimal rest of 2 hours between each trial. Two EEG channels have been addressed in these recordings. One of the EEG channels, O1-M2, corresponds to the mastoid electrodes on the other side, whereas the remaining EEG channel, O2-M1, corresponds to the mastoid electrodes on the other side. These EEG signals were captured with a 200 Hz sampling rate. Each sample has these designated EEG channels, which are then further divided into four stages: wake, MSE, MSEc, and ED states. The third MWT experiment, as anticipated, was selected to coincide with the well-documented period of decreased alertness that typically occurs after lunch. It was expected that the majority of MSEs would take place throughout this trial.

RemLogic (Embla Systems LLC) devices were used to record the data. The sampling and storage rates were set at 200 Hz. Additionally, the data was filtered using specific hardware filters: a high-pass filter with a cut-off frequency of 0.3 Hz, a low-pass filter with a cut-off frequency of 70 Hz, and a notch filter with a center frequency of 50 Hz. The data was transmitted in the European Data Format (EDF) for subsequent analysis. The investigation was carried out in accordance with the Declaration of Helsinki, Swiss Law, and the ethical permission of the local ethics commission (KEK-Nr. 308/15). The data was incorporated based on a broad consent that patients signed with the institution.

### *3.2 Data Pre-processing*

The study utilized the pre-processed version of the data for this investigation. However, the dataset exhibits asymmetry, which leads to a machine learning classifier displaying a leaning favouring the majority class. Consequently, the classifier struggles to accurately classify instances belonging to the minority class due to the disparity [29]. In datasets with unequal class distribution, examples belonging to the minority class are frequently misclassified as instances of the dominant class. This poses a significant challenge in situations when accurately recognizing instances of the minority class is essential, such as in fraud detection or medical diagnostics. To address this problem and enhance the resilience of the model, this study implemented the Adaptive synthetic (ADASYN) sampling technique to equalize the data. This method effectively reduces the influence of imbalanced classes, resulting in better model performance, particularly for algorithms that are affected by uneven class distributions [30].

*ADASYN Technique*

A method pertaining to adaptive synthetic sampling is the ADASYN technique [31]. The main concept is to weigh various minority class samples based on how difficult it is for them to understand [32]. Compared with minority instances that are simpler to learn, these minority instances will produce more thorough data. By achieving a roughly consistent effect, the sample rate can lessen the issue of data imbalances. This ADASYN strategy helps classifiers in two distinct manners: first, it reduces errors caused by class imbalances, and second, it focuses artificially generated information on samples that are difficult to learn [33]. When using the oversampling strategy in a multiple-class situation, all the sampled minority classes will be closer to 1 until the unbalanced rate approaches 1. Figure 3 provides a clear demonstration of the functionality of ADASYN.

The training dataset $D$, whereas $x_i$ is a component in the n-dimensional feature set $X$, contains m samples $\{x_i, y_i\}$, $I = 1,..., m$ and the class identification label for $x_i$ is $Y = \{0,1,...\}$. There are two interpretations for $m_s$ and $m_l$, the quantity of instances belonging to the minority class and the quantity of instances belonging to the majority class. Consequently, $m_s \leq m_l$ and $m_s + m_l = m$.

The ADASYN technique has the following steps:

- Step 1: This formula determines the extent of class disparity:

$$d = m_s / m_l \,,\; d \in [0, 1] \tag{1}$$

- Step 2: When $d < d_{th}$, the subsequent algorithmic processes are to be performed. Initially, the quantity of synthetic data instances required for the minority class is determined using the following calculation:

$$G = (m_l - m_s) \times \beta,\; \beta \in [0, 1] \tag{2}$$

Where the parameter $\beta$ is used to provide the required balance threshold upon generating the synthetic data, a value of $\beta = 1$ indicates that a completely balanced dataset is achieved following the generalizing procedure.

- Step 3: Subsequently, according to Euclidean distances in the space of n dimensions, it is discovered that every instance $x_i$ of the minority class has K-nearest neighbours. The formula for the specified percentage $r_i$ is as below:

$$r_i = \Delta_i / K \,,\; i = 1, \ldots, m_s \tag{3}$$

Hence, $\Delta i$ is the total amount of instances in the K-nearest neighbours of $x_i$ which comprise a predominant class. Consequently, $r_i \in [0 , 1]$.

- Step 4: Following that, the $r_i$ from Equation (3) gets normalized as follows:

$$\hat{r}_i = \frac{r_i}{\sum_{i=1}^{m_s} r_i} \qquad (4)$$

Thus $\hat{r}_i$ represents a distribution of density, indicating that $\sum_i \hat{r}_i = 1$.

- Step 5: After that, the following formula is used to determine how many synthetic data instances must be created for each minority instance:

$$g_i = \hat{r}_i \times G \qquad (5)$$

The value of $G$ is the total number of synthetic data samples required to be produced specifically for the minority class, as described in Equation (2).

- Step 6: Eventually, $g_i$ synthetic samples are generated for every minority class data example $x_i$, following a loop that iterates from 1 to $g_i$.

A minority sample $x_{zi}$ is chosen at random from the K-nearest neighbours of $x_i$; To produce the synthetic data instances $s_j$, the subsequent equation is used, where $\lambda$ is a randomized number, $\lambda \in [0, 1]$.

$$s_j = x_i + (x_{zi} - x_i) \times \lambda \qquad (6)$$

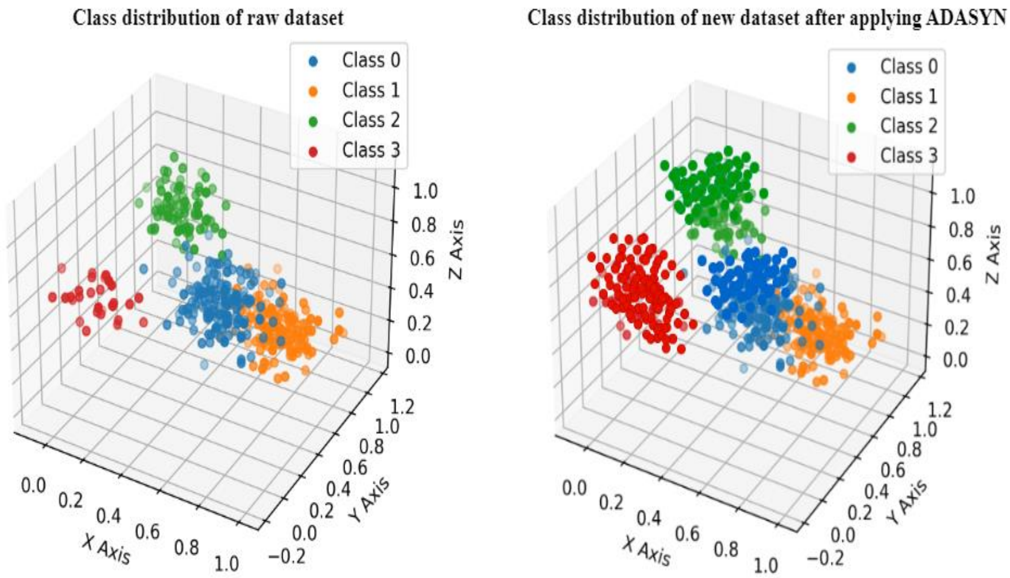


**Figure 3.** Working mechanism of ADASYN

*3.3 Feature Extraction*

The present experiment utilizes Fast Fourier Transformation as the characteristic extraction approach.

*Fast Fourier Transformation*

Fast Fourier Transformation (FFT) is utilized in various fields such as digital signal processing, solving partial differential equations, and creating algorithms for large-scale integer multiplication. Figure 4 illustrates the fluctuations of data in both the time and frequency domains.

The FFT is a method for efficiently and rapidly computing discrete Fourier transforms. The Fourier transform (FT) is utilized to illustrate the frequency domain due to the persistent nature of multiple signals within a transmission system in the time domain [34]. A thorough description and appropriate analysis of EEG signals in the frequency domain can be obtained from the traditional FT analysis [35]. An FFT-based technique is used to transform an EEG sample into a matrix in order to extract such insightful data from EEG in a numerically effective manner. The following steps outline the steps involved:

- Step 1: Calculate the Fourier coefficients of an input signal $x(t)$ within the frequency spectrum $[0, 2\pi]$ utilizing FF method. The computation of the FT is precisely specified as:

$$F_r = \sum_{u=0}^{M-1} x_n e^{-i2\pi r\frac{u}{M}} \qquad (7)$$

Where $F_r$ represents the FT coefficients and $M$ represents the length of the input signal.

- Step 2: Determine the magnitudes of the variables as $A_r = |F_r|$.
- Step 3: In order to match the order of the sample indications, convert $A_k$ into the $m \times n$ matrix form. The matrix $X$ is represented as follows:

$$X = \begin{bmatrix} A_1 & A_2 & \cdots & A_n \\ A_{n+1} & A_{n+2} & \cdots & A_{n+n} \\ \vdots & \vdots & \ddots & \vdots \\ A_{(m-1)n+1} & A_{(m-1)n+2} & \cdots & A_{(m-1)n+n} \end{bmatrix}, \quad (8)$$

$$r = m \times n$$

Where $m$ represents the number of rows in the matrix and $n$ represents the number of columns in the matrix.

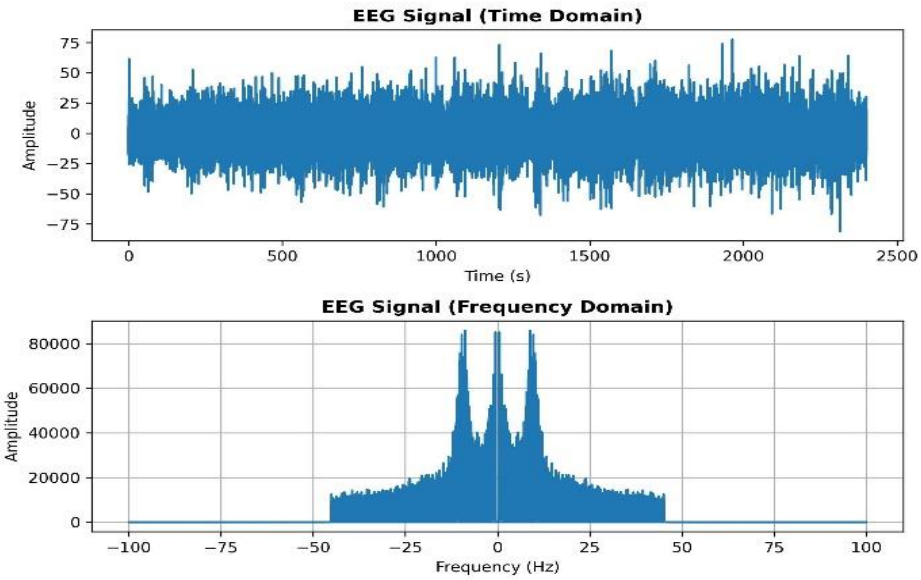


**Figure 4.** EEG time and frequency domain signal

*3.4 Classification Model LDA*

To enhance the precision of the Linear Discriminant Analysis (LDA) classifier, it is recommended to decrease the dimension of the feature vector by retaining the relevant information and deleting any redundant information. The vector that is obtained as a result is referred to as the decreased feature vector. A total of two primary approaches of reducing dimensionality.

Feature Selection: This approach selects the optimal subset from the initial feature vector based on a set of criteria that differentiate subsets from one another. While the minimization of misclassification probability is the ideal criterion for classification, simplified criteria based on class separability are typically selected [36]. In such a strategy, LDA is implemented.

LDA examines signals in order to extract the most salient characteristics. The primary objective of LDA feature extraction is to enhance the signal's content of data by reducing the dimensionality of the feature vector composed of the regions. The recovered characteristics exhibit greater informational content and distinctiveness, while also possessing a lesser amount of distortion and repetition in comparison to the initial data.

LDA is a supervised approach since it calculates the linear discriminant features by increasing the gap across classes and reducing the gap within classes [37]. The LDA projection might be represented by a unified matrix, as shown in Equation (9).

$$Y = K * W \quad (9)$$

where $Y$ and $X$ stand for the original characteristics and data, correspondingly. The matrix $W$ is generated by taking the first $k$ eigenvector of $S_w^{-1} S_b$ and projecting them onto a $d \times k$ matrix. where $S_w$ represents the scatter matrix within the class and $S_b$ represents the scatter matrix between the classes.

$$S_w = \frac{1}{N}\sum_{l=1}^{L}\sum_{i=1}^{N_l}(x_i^l - \mu_l)^T(x_i^l - \mu_l) \quad (10)$$

$$S_b = \frac{1}{N}\sum_{l=1}^{L} N_l(\mu_l - \mu)^T(\mu_l - \mu) \quad (11)$$

## 4. Results and discussion

This section provides an explanation of the thorough experimental analysis. There are four different kinds of unbalanced EEG scenarios in the EEG dataset. In Figure 5, the classification errors determined by the initial imbalanced data set is represented by $\beta$ = 0, and the completely balanced data set produced using the ADASYN approach is represented by $\beta$ = 1. Figure 5 illustrates how the ADASYN can lessen the bias added to the initial unbalanced data sets to enhance ability to classify. Additionally, it illustrates the trend for reduced errors when ADASYN raises the equilibrium level.

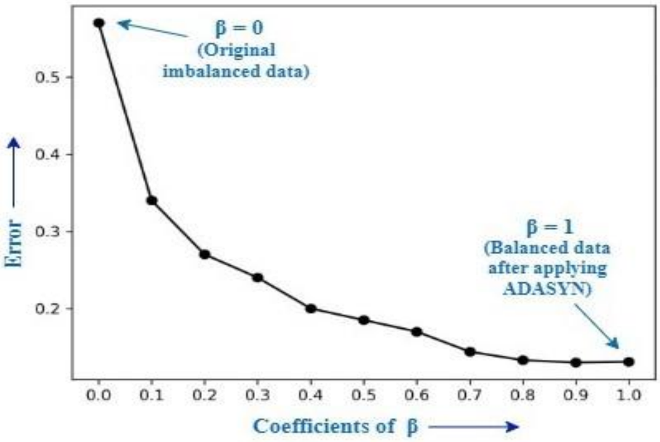


**Figure 5.** ADASYN technique for imbalanced learning

To evaluate the quality of categorization, many metrics are used to examine the outcomes of classification and the performance of the classifier. The metrics encompassed in this set are classification accuracy, precision, recall, F1-score, and Cohen's Kappa.

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \times 100\% \quad (12)$$

Precision is the ability of a classifier to correctly classify positive samples as positive and negative samples as negative over the whole dataset.

$$Precision = \frac{TP}{TP + FP} \times 100\% \quad (13)$$

Recall is a metric that quantifies the percentage of positive samples that are accurately recognized.

$$Recall = \frac{TP}{TP+FN} \times 100\% \quad (14)$$

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

The F1-score is a metric that quantifies the balance between precision and recall by calculating their weighted average. The optimal F1-score is 1, indicating perfect performance, while a score of 0 represents the lowest possible performance.

$$F1 = \frac{2 \times Precision \times Recall}{Precision+Recall} \times 100\% \quad (15)$$

Cohen's Kappa is a statistical metric employed to evaluate the level of cooperation or dependability between raters when dealing with category items. Cohen’s kappa statistic quantifies the level of agreement among two raters, taking into account the agreement that would be predicted by chance alone. Table 1 displays the degree of assessment according to Cohen's Kappa.

**Table 1:** Evaluation Criterion of Cohen's Kappa

| Value of Cohen's Kappa | Level of Agreement |
|---|---|
| ≤ 0 | No agreement |
| 0.01 – 0.20 | None to slight |
| 0.21 – 0.40 | Fair |
| 0.41 – 0.60 | Moderate |
| 0.61 – 0.80 | Substantial |
| 0.81 – 1.00 | Almost perfect agreement |

A randomized process was used to divide the whole dataset into training and testing sets. In this work, the framework was trained using 70% of the dataset, and the remaining dataset was utilized to test the validity of the framework. Figure 6 depicts the relationship between the accuracy of the test and training data as a function of the number of periods.

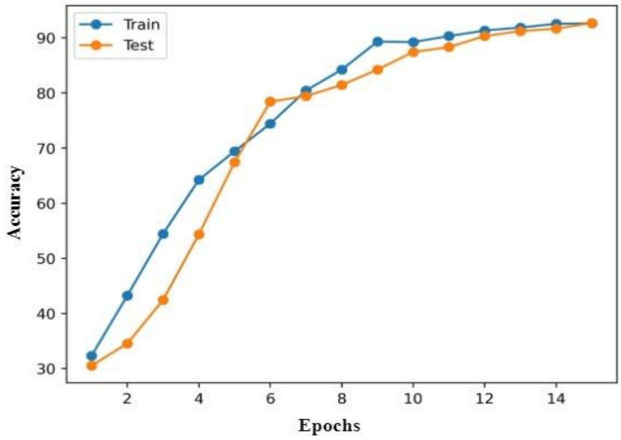


**Figure 6.** Proposed framework performance in terms of train and test data

To identify microsleep, this study utilized the Adaptive synthetic sampling approach to adjust the data and reduce the effects of class instabilities. Following that, the FFT was utilized as a tool for extracting features. The classification model LDA has been evaluated and its outcome and performance metrics, including accuracy, precision, recall, F1-score, and Cohen's Kappa score, have been determined. These metrics are presented in Table 2.

**Table 2:** Performance of the proposed study

| Metrics | Performance |
|---|---|
| Accuracy | 92.71% |
| Precision | 92.32% |
| Recall | 92.05% |
| F1-Score | 92.18% |
| Cohen's Kappa | 90.26% |

Table 2 illustrates the evaluation results of our suggested methodology. In the experimental analysis, we have attained a peak testing accuracy of 92.71%. The alternative performance evaluation criteria, namely precision, recall, F1-score, and Cohen's Kappa score, have values of 92.32%, 92.05%, 92.18%, and 90.26%, accordingly.

Figure 7 displays the confusion matrix of the proposed model, with each row representing the actual class and each column representing the predicted class. The diagonal elements show the correct classification rates for each class, which are notably high: 0.91 for wake, 0.94 for MSE, 0.92 for MSEc, and 0.92 for ED. The off-diagonal elements represent misclassifications. For instance, wake (Class 1) is most often misclassified as MSE (Class 2) at a rate of 0.05. MSE is occasionally misclassified as wake or ED at a rate of 0.02 and 0.03 respectively. MSEc (Class 3) has some misclassifications as MSE at 0.06. ED (Class 4) is sometimes misclassified as wake or MSE at rates of 0.03 and 0.05.

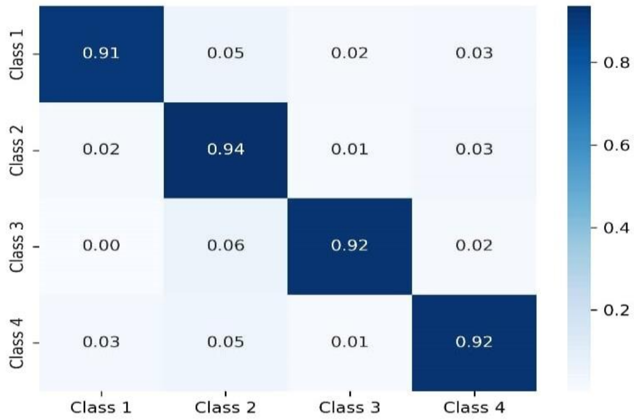


**Figure 7.** Normalized confusion matrix of proposed study

However, the objective of the research is to provide an outline for identifying microsleep by utilizing imbalanced EEG signals. While EEG signals have been used successfully for detecting microsleep phases, there are some limitations associated with this approach. These include the increased processing requirements, the need for plenty of electrodes, and the potential issue of excessive fitting in classifiers. To address these challenges and attain high accuracy in classification, it is crucial to utilize feature extraction methods and a classifier as part of the data pretreatment approach. The method that was suggested achieved a classification accuracy of 88.80%. The system that has been created has the capacity to provide a novel method for monitoring microsleep or wake states using an EEG signal.

The classification performance of the proposed method is compared to past research on microsleep detection. A multitude of well-conducted studies have also been carried out to identify microsleep episodes using EEG data, as outlined in Table 3. The results show that the suggested framework outperforms previous state-of-the-art methods in terms of classification efficiency for microsleep detection.

**Table 3:** Performance comparison of related microsleep studies

| **Reference** | **Features** | **Classification Algorithm** | **Accuracy** |
|---|---|---|---|
| [38] | EN | SVM | 86% |
| [39] | MVAR | KPCA-SVM | 81.64% |
| [40] | FD | FLDA | 79.20% |
| [41] | AR | BNN | 88.2% |
| [42] | FD and EN | SVM | 67.00% |
| [43] | FD | NN | 88.20% |
| [44] | FD | FLDA | 75.90% |
| [45] | TD and FD | NN | 87.40% |
| *Our Proposed Approach* | *FFT* | *LDA* | *92.71%* |

Upon a closer look of Table 3, it is evident that the proposed technique had markedly superior performance in detecting driver microsleep. Although our technique demonstrated outstanding performance, this study encountered difficulties during the analysis. EEG signals exhibit inter-subject variability and intra-subject variability between trials. In addition, the EEG signals exhibit high levels of instability, non-linearity, and non-stationarity.

Therefore, it is difficult to create a driver microsleep identification method that is efficient for all individuals. Furthermore, the investigation involved the use of various EEG headgear, each with an individual set of electrodes. Consequently, obtaining datasets of similar nature is highly challenging. There are uncertainties regarding the quantity and type of electrodes that can effectively capture high-quality data for detecting driver microsleep. Furthermore, the ability of this study to accurately recognize patterns is inadequate for usage in real-time applications.

## 5. Conclusions

This study introduces an innovative approach for detecting driver microsleep using EEG signals and machine learning techniques. By addressing data imbalance with ADASYN sampling and employing FFT for feature extraction and LDA for classification, the method achieves a high accuracy of 92.71%, surpassing previous approaches. The results demonstrate the potential of this framework to significantly improve road safety by accurately identifying microsleep episodes. In terms of real-world applicability, this approach could be integrated into driver monitoring systems within vehicles, particularly in urban areas where traffic density and complexity increase the risk of accidents. Implementing such a system in public transportation networks, commercial fleets, and autonomous vehicles could contribute to reducing fatigue-related incidents. Moreover, urban planners and policymakers could consider this technology when designing smart cities, incorporating it into infrastructure to enhance overall traffic safety.

However, challenges such as EEG signal variability and real-time application remain. Future research should focus on refining the method to account for individual differences in EEG patterns, ensuring robust performance across diverse populations. Additionally, exploring the integration of this system with other in-vehicle sensors could improve detection accuracy and response times. Policymakers should consider the development of regulations that mandate the use of advanced driver-assistance systems incorporating microsleep detection to mitigate risks associated with driver fatigue.

Overall, this work makes a valuable contribution to the field of microsleep detection and opens new avenues for preventing fatigue-related accidents. By addressing these challenges and expanding the framework's implementation, future advancements could have a profound impact on road safety and urban planning.

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