Eye State Classification Using Ensemble Machine Learning Models and SMOTE on EEG Data

Maria Trigka*, Elias Dritsas*, and Phivos Mylonas†
*Industrial Systems Institute, Athena Research and Innovation Center, Patras 26504, Greece
{trikga,dritsas}@isi.gr
†Department of Informatics and Computer Engineering, University of West Attica, Egaleo 12243, Greece
{mylonasf}@uniwa.gr

***Abstract*—Electroencephalography (EEG) data presents complex and high-dimensional signals, offering great potential for applications in various fields such as neurofeedback, clinical diagnostics, cognitive neuroscience, human-computer interaction (HCI), and beyond. Analyzing EEG signals requires expertise not only from neuroscience, but also from signal processing, machine learning (ML), and statistics to extract meaningful information from brain activity recordings. Specifically, the combination of EEG and ML can provide an advantage in addressing challenging classification tasks in these fields. The present study focuses on the classification of eye state (open or closed) using Ensemble ML models such as Random Forest (RF), Gradient Boosting (GB), AdaBoost, XGBoost, and LightGBM on EEG data. We apply the Synthetic Minority Over-sampling Technique (SMOTE) to address the class imbalance and conduct a comparative analysis of the models' performance with and without SMOTE using 10-fold cross-validation across several metrics namely, Accuracy, Precision, Recall, F1-score, and the Area Under the Curve (AUC). The experimental results highlight the importance of addressing the class imbalance in EEG data to improve model performance.**

***Index Terms*—eye-state, classification, machine learning, brain-computer interface**

I. Introduction

EEG has become an essential tool in neuroscience and cognitive science, offering a non-invasive means to monitor electrical activity within the brain. The intricate patterns of EEG signals provide valuable insights into various neural processes and states, making it a crucial component in the study of human cognition and behaviour. One particularly promising application of EEG analysis is the classification of eye states, such as distinguishing between open and closed eyes [1], [2].

Accurate classification of eye states has significant implications for fields ranging from clinical diagnostics and neurology (diagnosis of epilepsy, sleep disorders, and brain injuries), cognitive neuroscience (studying brain function during tasks and activities) to HCI (for communication and control) and the development of advanced brain-computer interfaces (BCIs). Understanding EEG fundamentals is crucial for interpreting brain activity patterns and extracting meaningful insights from EEG recordings in research, clinical, and practical applications [3], [4].

Traditional methods for detecting eye states predominantly rely on electrooculography (EOG) or visual observation. While these approaches can be effective, they are often limited by susceptibility to noise and the need for direct visual input, which may not be feasible in all scenarios. In contrast, EEG provides a richer dataset that can capture the underlying brain activity associated with different eye states, offering a potential pathway to more robust and versatile classification methods [5]–[7].

In recent years, ML has revolutionized the approach to EEG signal analysis and eye state classification. ML models and methods, including supervised, unsupervised, and reinforcement learning techniques, offer powerful tools for feature extraction, pattern recognition, and classification. These techniques can effectively handle the complex, high-dimensional nature of EEG data, enabling the development of models that can accurately distinguish between different eye states [8], [9].

This research work explores the effectiveness of ensemble ML models in classifying EEG signals, focusing also on the impact of SMOTE [10] on handling class imbalance. The primary contributions of this paper are:

- Evaluating the performance of five ensemble ML models on EEG data.
- Assessing the impact of SMOTE on model performance.
- Providing a detailed comparative analysis of the models with respect to multiple performance metrics.

The remaining paper is structured as follows. Section II outlines similar works with the subject under investigation. Moreover, Section III describes the used dataset, the main steps in the context of EEG signals preprocessing, the spatial EEG features correlation and, finally, the class-balancing method used for making the training data balanced. Next, in Section IV, the evaluation metrics and the ML models are noted. Besides, in Section V, we discuss the acquired research results. Finally, conclusions and future directions are outlined in Section VI.

II. Related Works

In this section, we provide related works for the eye-state classification with the contribution of ML techniques and models.

Firstly, [11] aims to enhance the classification performance of ear-EEG-based eye-state identification by utilizing deep convolutional neural networks (CNNs). Traditional ear-EEG methods, despite being more convenient than scalp-EEG, typically suffer from lower classification accuracy due to fewer electrodes and less information. The researchers proposed three CNN models for this task: EEGNet, deep ConvNet, and shallow ConvNet. Among these, the shallow ConvNet demonstrated the best performance, significantly surpassing the conventional linear discriminant analysis (LDA) algorithm. The study showed that the shallow ConvNet not only improved the classification accuracy of ear-EEG to levels comparable with scalp-EEG but also maintained high reliability in a pseudo-online simulation, indicating its potential for real-time applications.

Moreover, the purpose of the study [12] is to develop a CNN-based method for classifying nonstationary biomedical signals, specifically EEG signals, to identify eye states. The proposed models include a CNN architecture that utilizes the spectrogram of EEG signals as input, complemented by non-negative matrix factorization (NMF) features to enhance performance. The models were tested on an EEG eye state dataset, and the combination of CNN with NMF achieved an accuracy of 96.16%, outperforming other methods such as standalone CNN and NMF models.

Besides, [13] focuses on classifying eye states using EEG signals by employing and comparing different ML models. The study utilizes the EEG Eye State dataset from the UCI Machine Learning Repository, which includes continuous EEG measurements. The proposed models are k-nearest Neighbors (kNN) and Multilayer Perceptron (MLP) neural networks. The highest classification success rate for the kNN model was achieved with 3 nearest neighbours, yielding an accuracy of 84.05%. In contrast, the MLP model achieved its highest accuracy of 56.45% when the hidden layer had 7 neurons.

In [14], various ML techniques are compared for detecting eye states using EEG signals, including feature extraction methods and classification techniques. The proposed models involve feature extraction methods such as Discrete Fourier Transform (DFT), Discrete Wavelet Transform (DWT), and Independent Component Analysis (ICA), and classification techniques including Support Vector Machine (SVM) and LDA. The study shows that the combination of DFT with ICA yields the highest accuracies, with SVM achieving up to 100% accuracy for some subjects in identifying eyes-open states, and LDA achieving similar accuracy levels for eyes-closed states. Overall, the inclusion of ICA improves system performance, and both SVM and LDA classifiers provide robust results depending on the eye state.

Furthermore in [15] three ML models namely logistic regression, ElasticNet classifier, and SVM with different kernels were evaluated to classify eye states (open or closed). EEG data was gathered from individuals using an Emotiv EEG Neuroheadset and preprocessed for analysis. The results demonstrated that the SVM with a radial basis function (RBF) kernel was most effective, achieving an accuracy of 77%, compared to 57.2% for logistic regression and 57.8% for the ElasticNet classifier. The SVM showed robustness in handling complex EEG data, while logistic regression provided interpretability, and the ElasticNet classifier offered a balanced approach.

The authors in [16] seek to classify eye states (open or closed) using EEG data by leveraging deep learning architectures for improved accuracy and speed, suitable for real-time BCI applications. The proposed models include a multi-layered neural network (MLN) with ReLU and dropout, deep belief networks (DBNs) based on unsupervised learning, and dropout masks on deep neural networks. The results showed that the best-performing architecture was a three-layer neural network with ReLU activation, achieving an accuracy of 97.5% and a classification speed of at least 1000 samples per second, significantly faster than traditional classifiers like K* and (K*+RRF) which had accuracies of 97.3% and 97.4%, respectively, but much slower processing times.

Similarly, in [17] the authors proposed and implemented two specific models: DBN and Stacked Autoencoder (SAE). The study demonstrated that the SAE model, particularly the one designated as SAE 2, outperformed other models with an impressive accuracy of 98.9% and an error rate of 1.1%. This model's performance was superior to traditional methods, including the K* algorithm (97.3% accuracy) and ensemble classifiers combining K* and Regularized Random Forest (97.4% accuracy).

Finally, [18] compares various machine learning techniques for identifying eye states (open or closed) using EEG signals. The proposed models include feature extraction methods like DFT and DWT, combined with classification algorithms such as SVM and LDA. The study also employs ICA for pre-processing the data. The results show that the combination of these techniques achieves a high accuracy of eye state identification, with the best-performing model reaching an accuracy of 98.9%. This research highlights the potential of using deep learning architectures, specifically DBN and SAE, in improving the accuracy and efficiency of EEG-based eye state classification.

III. Dataset Description and Preprocessing Methods

A. Overview of the Dataset

This research work utilized the EEG eye state classification dataset from the UCI Machine Learning Repository [19]. The dataset contains 14 columns corresponding to EEG measurements from different electrodes and one column indicating the eye state related to various brainwave measurements (likely from EEG sensors). All data is from one continuous EEG measurement with the Emotiv EEG Neuroheadset [20]. The EEG signals were recorded over 117 seconds with a sampling frequency of 128 Hz. It contains 14,980 samples, each featuring 14 distinct EEG signal measurements, corresponding to specific 14 electrodes positioned on different brain areas (lobes) on the scalp according to the 10/20 standard EEG placement system:

- Frontal: AF3, F3, F7, AF4, F4 and F8
- Central: FC5 and FC6,
- Temporal: T7 and T8,
- Parietal: P7 and P8,

- Occipital: O1 and O2.

Also, the dataset includes one dependent variable indicating the eye's status. The eye state was detected via a camera during the EEG measurement and added manually to the file after analysing the video frames. A value of 0 represents an open eye (8,257 samples), while a value of 1 (6,723 samples) indicates a closed eye.

B. Pipeline of EEG Signals Processing

EEG signals analysis involves the processing and interpretation of electrical brain activity recorded from electrodes placed on the scalp [21]. Here's an overview of the steps involved and depicted in Figure 1.

Signal Acquisition [22]: EEG signals are recorded using the Emotiv EEG Neuroheadset, a wearable device that allows users to monitor brain activity and control devices using their thoughts. It's equipped with electrodes that detect electrical signals produced by the brain. Although the headset's software can interpret the user's mental state or intentions, here, the raw data were exploited for applying the following preprocessing techniques.

Preprocessing [23]: The obtained raw EEG signals often contain unwanted interference, namely, noise from various sources, including muscle activity, eye movements, and environmental factors. Therefore, the data was pre-processed offline with a Butterworth bandpass filter to retain frequencies between 0.5 and 64 Hz, and a notch filter at 50 Hz was applied to eliminate powerline noise. Then, after data re-referencing, the ICA method opted for artefacts' handling, identification and removal [24].

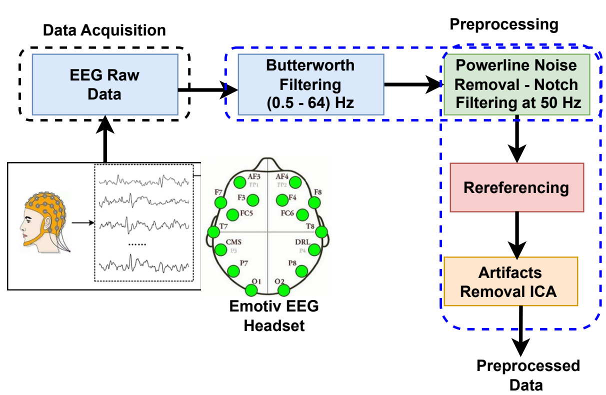

Fig. 1. Pipeline from acquisition to preprocessing.

C. Spatial EEG Features Analysis using Pearson Correlation

In this subsection, we focus on understanding the correlations among the spatial EEG features associated with different brain lobes using the Pearson correlation coefficient, which is represented as r. This coefficient is a measure of the linear correlation between two feature variables f and g. It is defined as the covariance of the two variables divided by the product of their standard deviations [25]. The Pearson correlation coefficient is given by the following equation:

$$r = \frac{\sum_{i=1}^{K}(f_i - \bar{f})(g_i - \bar{g})}{\sqrt{\sum_{i=1}^{K}(f_i - \bar{f})^2}\sqrt{\sum_{i=1}^{K}(g_i - \bar{g})^2}}, \quad (1)$$

where f_i, g_i are the individual sample points indexed with i, $\bar{f}, \bar{g}$ are the mean values of the f, g variables, respectively, and K is the number of sample points.

Following the results of Figure 2, we identified associations of different strengths among the 14 EEG spatial channels. Some indicative pairs are the following:

- F8 and FC6: With a correlation of around 0.921, there is a strong positive relationship, indicating that as F8 values increase, FC6 values also tend to increase.
- AF4 and F4: This pair shows a high positive correlation of approximately 0.869, suggesting that they often move together in the same direction.
- AF3 and AF4: A correlation of approximately 0.841 suggests a high positive relationship. Higher values in AF3 tend to be associated with higher values in AF4.
- AF4 and F3: A correlation of approximately 0.832 suggests a strong positive relationship. Higher values in AF4 tend to be associated with higher values in F3.
- Other pairs of channels with high positive correlations are again in the frontal area: (F3, AF3, 0.787), (F4, AF3, 0.787), (F7, AF3, 0.758).
- P7 and FC6, P7 and F8: The correlation of around -0.879 and -0.792 indicates a high but inverse relationship between the channels that stem from frontal and parietal brain areas. When the P7 value increases, FC6 and F8 tend to decrease. Negative correlations could indicate lateralized brain activity, where one hemisphere's activity increases while the other's decreases.
- AF3 and P7 have a moderate negative correlation of around -0.634 which might suggest that these regions (frontal and parietal) while they have a relationship, it is not as strong or high implying partial connectivity or that they share some but not all neural processing tasks.

The strong and high correlations can imply that these pairs of electrodes capture related or similar neural activities. In neuroscience, this can be indicative of functional connectivity or similar responses to stimuli across these regions. Also, the occipital channels O1 and O2 and the temporal channels T7 and T8 noted low to negligible correlations with the channels in the frontal area, except for the pairs (T8, F8), (T8, FC6), (T8, P8), where the moderate and high association was observed.

The low correlations with 'eye-state' indicate that eye state (open or closed) might not have a strong direct influence on the recorded EEG features, or the relationship is non-linear. This might be expected as eye state could be influenced by other factors or external variables not included in this dataset.

D. Eye state class balancing with SMOTE

SMOTE is a technique used to address class imbalance in the dataset by creating synthetic examples of the minority class

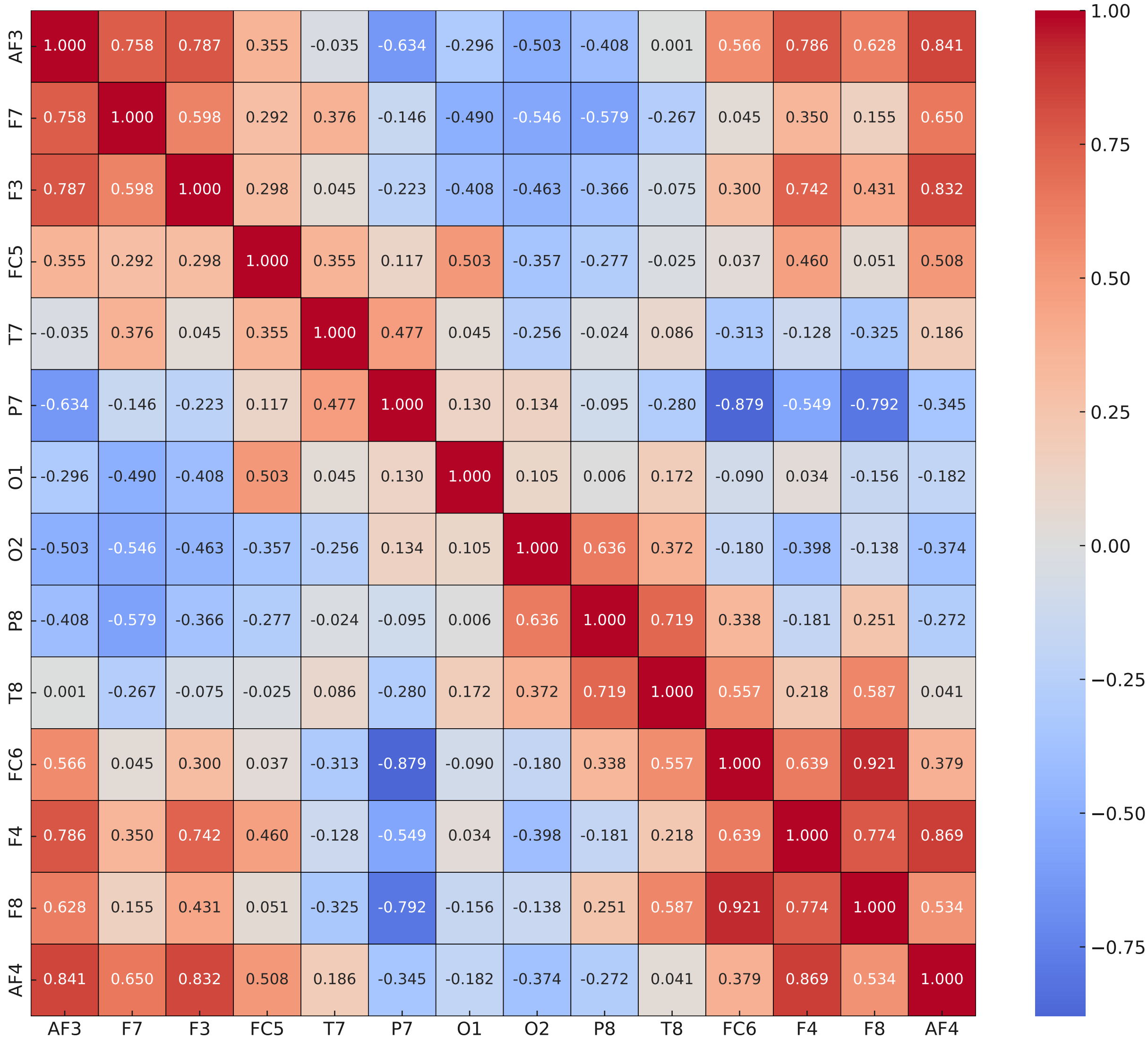

Fig. 2. Features Analysis using Pearson Correlation Coefficient.

(eyes closed). According to Alg.1, it works by selecting two or more similar instances of the minority class and generating new instances that lie along the line segments connecting these instances. This helped to create a more balanced dataset, which improved the performance of machine learning models.

IV. ML Models and Evaluation Metrics for Eye State Detection

The evaluation of our ML models was carried out with a widely known free software, namely WEKA [26], which contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. The experiments were performed on a computer system with the following specifications: Apple MacBook Pro 13.3", Retina Display (M2/ 16GB RAM/ 256GB SSD). As for the ML methodology, we selected ensemble ML models [27], such as

- Random Forest [28]: Utilizes multiple decision trees to improve classification accuracy.
- Gradient Boosting Machine [29]: Combines the predictions of several base estimators to reduce bias and variance.
- AdaBoost [30]: Enhances the performance of weak classifiers by focusing on misclassified instances.
- XGBoost [31]: An optimized version of gradient boosting that improves speed and performance.
- LightGBM [32]: A highly efficient gradient boosting framework that uses tree-based learning algorithms.

Also, for the specific dataset, the optimal hyperparameter tuning of the above-mentioned ML models is shown in Table I.

Algorithm 1 SMOTE

Input: Dataset D with minority class samples M, desired number of synthetic samples N

Set K to the number of nearest neighbours

for $m \in M$ **do**

Find the K nearest neighbors of m from the minority class samples;

Randomly select one of the K nearest neighbors, say n;

Generate a new sample by interpolating between m,n:

$$\text{new\_sample} = m + \text{random}(0,1) \times (n - m)$$

Add the new_sample to the dataset D;

end for

Repeat steps 2a-2d until N synthetic samples are generated;

Output: Augmented dataset D with N new synthetic samples;

In order to evaluate the selected ML models, we relied on metrics commonly used in the ML field [33], namely accuracy, precision, recall, f1-score, and AUC. Note that the final score in each metric is derived by averaging the scores from all folds. The definition of these metrics is based on the confusion matrix consisting of the elements true positive (Tp), true negative (Tn), false positive (Fp) and false-negative (Fn). Hence, the aforementioned metrics are defined as follows:

- $\text{Accuracy} = \frac{\text{Tn+Tp}}{\text{Tn+Fn+Tp+Fp}}$, proportion of correctly classified instances.
- $\text{Precision} = \frac{\text{Tp}}{\text{Tp+Fp}}$, proportion of true positive predictions among all positive predictions.
- $\text{Recall} = \frac{\text{Tp}}{\text{Tp+Fn}}$, proportion of true positive predictions among all actual positives.
- $\text{F1} - \text{score} = 2\frac{\text{Precision}\cdot\text{Recall}}{\text{Precision+Recall}}$, the harmonic mean of precision and recall.
- AUC: Area under the Receiver Operating Characteristic (ROC) curve. To assess the separability of a model, the AUC $\in$ [0,1] metric is used.

V. Results and Discussion

In the comparative analysis of the experimental results of the five ensemble ML models with and without the application of SMOTE (see Table II), it is evident that SMOTE significantly enhances the performance metrics across all models. Without SMOTE, the models showed varying degrees of effectiveness in classifying eye states from EEG data, with RF achieving the highest accuracy at 0.85 and AdaBoost recording the lowest at 0.81. The other models, GBM, XGBoost, and LightGBM, showed intermediate performance with accuracies of 0.83, 0.84, and 0.82 respectively. The precision, recall, f1-score, and AUC values also reflected a similar trend, indicating that while the models could perform reasonably well, there was still room for improvement, especially in handling the class imbalance inherent in the EEG dataset.

The application of SMOTE resulted in significant improvements across all performance metrics for each ML model.

TABLE I
Hyperparameter Tuning of Machine Learning Models

Model	Hyperparameters	Tuned Values
	Number of Trees	100
	Maximum Depth	10
RF	Minimum Samples Split	2
	Minimum Samples Leaf	2
	Bootstrap	True
	Number of Trees Learning Rate	100 0.1
GBM	Maximum Depth	5
	Minimum Samples Split	2
	Minimum Samples Leaf	2
	Number of Estimators	50
AdaBoost	Learning Rate	0.1
	Algorithm	SAMME.R
	Number of Trees Learning Rate	300 0.2
XGBoost	Maximum Depth	7
	Subsample	1.0
	Colsample_bytree	0.8
	Number of Trees	100
	Learning Rate	0.1
LightGBM	Maximum Depth	5
	Subsample	1.0
	Colsample_bytree	0.8

TABLE II
Results

Model	SMOTE	Accuracy	Precision	Recall	F1-Score	AUC
RF	No	0.85	0.8	0.75	0.77	0.88
RF	Yes	0.89	0.86	0.84	0.85	0.92
GBM	No	0.83	0.78	0.72	0.75	0.85
GBM	Yes	0.87	0.83	0.81	0.82	0.9
AdaBoost	No	0.81	0.76	0.7	0.73	0.82
AdaBoost	Yes	0.86	0.82	0.8	0.81	0.88
XGBoost	No	0.84	0.79	0.73	0.76	0.87
XGBoost	Yes	0.88	0.84	0.82	0.83	0.91
LightGBM	No	0.82	0.77	0.71	0.74	0.84
LightGBM	Yes	0.87	0.83	0.81	0.82	0.89

For instance, the accuracy of RF increased from 0.85 to 0.89, precision from 0.80 to 0.86, recall from 0.75 to 0.84, f1-score from 0.77 to 0.85, and AUC from 0.88 to 0.92. Similar trends were observed in the other models; GBM's accuracy improved to 0.87, XGBoost to 0.88, AdaBoost to 0.86, and LightGBM to 0.87. These enhancements underscore the effectiveness of SMOTE in mitigating the adverse effects of class imbalance, thus enabling the models to better learn the patterns associated with both open and closed-eye states in the EEG data. The increase in AUC values, in particular, highlights the improved discriminative ability of the models when SMOTE is applied.

Comparing the models' post-SMOTE application, RF emerged as the top performer with the highest scores across all metrics, reinforcing its robustness in handling high-dimensional EEG data. XGBoost and LightGBM, known for their efficiency and performance optimization, also demonstrated significant improvements, closely following RF in terms of overall performance. GBM and AdaBoost, while improved, were slightly less effective compared to the top three models but still showed considerable gains over their No-SMOTE counterparts.

This comparative analysis clearly illustrates that addressing class imbalance through SMOTE not only enhances the accuracy but also the reliability and robustness of ML models in EEG eye state classification tasks. Future studies could further explore the integration of other resampling techniques and advanced ML models to continue improving classification performance in various EEG-based applications.

VI. Conclusions

The present research work aimed to evaluate the performance of five ensemble ML models namely Random Forest, Gradient Boosting Machine, AdaBoost, XGBoost, and LightGBM on the eye-state classification of EEG signals. Among the evaluated models, Random Forest with SMOTE emerged as the leading model, demonstrating superior performance across all metrics (accuracy, precision, recall, f1-score and AUC with 0.89, 0.86, 0.84, 0.85, and 0.92, respectively). These findings underscore the importance of addressing class data imbalance and pave the way for more accurate and reliable EEG signal classification, ultimately contributing to better diagnostic and analytical tools in neuroscience. Future research could apply the spatial features correlation analysis per eye state, explore the generation/selection of new features (time-domain, frequency-domain or time-frequency-domain), integrate other advanced resampling techniques and apply these ML models to different EEG data for generalizing their high performance in eye state classification.

References

[1] A. Biasiucci, B. Franceschiello, and M. M. Murray, "Electroencephalography," *Current Biology*, vol. 29, no. 3, pp. R80–R85, 2019.

[2] W. O. Tatum IV, *Handbook of EEG interpretation*. Springer Publishing Company, 2021.

[3] K. Värbu, N. Muhammad, and Y. Muhammad, "Past, present, and future of eeg-based bci applications," *Sensors*, vol. 22, no. 9, p. 3331, 2022.

[4] R. Abiri, S. Borhani, E. W. Sellers, Y. Jiang, and X. Zhao, "A comprehensive review of eeg-based brain–computer interface paradigms," *Journal of neural engineering*, vol. 16, no. 1, p. 011001, 2019.

[5] A. Suiçmez, C. Tepe, and M. S. Odabas, "An overview of classification of electrooculography (eog) signals by machine learning methods," *Gazi University Journal of Science Part C: Design and Technology*, vol. 10, no. 2, pp. 330–338, 2022.

[6] A. Chrysanthakopoulou, E. Dritsas, M. Trigka, and P. Mylonas, "An eeg-based application for real-time mental state recognition in adaptive e-learning environment," in *2023 18th International Workshop on Semantic and Social Media Adaptation & Personalization (SMAP) 18th International Workshop on Semantic and Social Media Adaptation & Personalization (SMAP 2023)*. IEEE, 2023, pp. 1–6.

[7] M. Soufineyestani, D. Dowling, and A. Khan, "Electroencephalography (eeg) technology applications and available devices," *Applied Sciences*, vol. 10, no. 21, p. 7453, 2020.

[8] M. Trigka, E. Dritsas, and P. Mylonas, "Mental confusion prediction in e-learning contexts with eeg and machine learning," in *Novel & Intelligent Digital Systems Conferences*. Springer, 2023, pp. 195–200.

[9] S. Aggarwal and N. Chugh, "Review of machine learning techniques for eeg based brain computer interface," *Archives of Computational Methods in Engineering*, vol. 29, no. 5, pp. 3001–3020, 2022.

[10] V. Rattan, R. Mittal, J. Singh, and V. Malik, "Analyzing the application of smote on machine learning classifiers," in *2021 International Conference on Emerging Smart Computing and Informatics (ESCI)*. IEEE, 2021, pp. 692–695.

[11] C.-H. Han, G.-Y. Choi, and H.-J. Hwang, "Deep convolutional neural network based eye states classification using ear-eeg," *Expert Systems with Applications*, vol. 192, p. 116443, 2022.

[12] D. Gurve and S. Krishnan, "Deep learning of eeg time–frequency representations for identifying eye states," *Advances in Data Science and Adaptive Analysis*, vol. 10, no. 02, p. 1840006, 2018.

[13] M. Koklu and K. Sabancı, "The classification of eye state by using knn and mlp classification models according to the eeg signals," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 3, no. 4, pp. 127–130, 2015.

[14] F. Laport, P. M. Castro, A. Dapena, F. J. Vazquez-Araujo, and D. Iglesia, "Study of machine learning techniques for eeg eye state detection," in *Proceedings*, vol. 54, no. 1. MDPI, 2020, p. 53.

[15] N. Priyadharshini Jayadurga, M. Chandralekha, and K. Saleem, "An empirical study on comparison of machine learning algorithms for eye-state classification using eeg data," in *International Conference on Communication and Intelligent Systems*. Springer, 2023, pp. 113–122.

[16] T. K. Reddy and L. Behera, "Online eye state recognition from eeg data using deep architectures," in *2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. IEEE, 2016, pp. 000 712–000 717.

[17] S. Narejo, E. Pasero, and F. Kulsoom, "Eeg based eye state classification using deep belief network and stacked autoencoder." *International Journal of Electrical & Computer Engineering (2088-8708)*, vol. 6, no. 6, 2016.

[18] M. Nilashi, R. A. Abumalloh, H. Ahmadi, S. Samad, A. Alghamdi, M. Alrizq, S. Alyami, and F. K. Nayer, "Electroencephalography (eeg) eye state classification using learning vector quantization and bagged trees," *Heliyon*, vol. 9, no. 4, 2023.

[19] "Eeg," https://archive.ics.uci.edu/dataset/264/eeg+eye+state, (accessed on 12 June 2024).

[20] "Eeg headset," https://www.emotiv.com/products/epoc-x, (accessed on 12 June 2024).

[21] M. Trigka, E. Dritsas, and C. Fidas, "A survey on signal processing methods for eeg-based brain computer interface systems," in *Proceedings of the 26th Pan-Hellenic Conference on Informatics*, 2022, pp. 213–218.

[22] B. Li, T. Cheng, and Z. Guo, "A review of eeg acquisition, processing and application," in *Journal of Physics: Conference Series*, vol. 1907, no. 1. IOP Publishing, 2021, p. 012045.

[23] S.-P. Kim, "Preprocessing of eeg," *Computational EEG Analysis: Methods and Applications*, pp. 15–33, 2018.

[24] M. Trigka, G. Papadoulis, E. Dritsas, and C. Fidas, "Influences of cognitive styles on eeg-based activity: An empirical study on visual content comprehension," in *IFIP Conference on Human-Computer Interaction*. Springer, 2023, pp. 496–500.

[25] D. Risqiwati, A. D. Wibawa, E. S. Pane, W. R. Islamiyah, A. E. Tyas, and M. H. Purnomo, "Feature selection for eeg-based fatigue analysis using pearson correlation," in *2020 International Seminar on Intelligent Technology and Its Applications (ISITIA)*. IEEE, 2020, pp. 164–169.

[26] "Weka," https://www.weka.io/, (accessed on 12 June 2024).

[27] E. Dritsas, M. Trigka, and P. Mylonas, "Ensemble machine learning models for breast cancer identification," in *IFIP International Conference on Artificial Intelligence Applications and Innovations*. Springer, 2023, pp. 303–311.

[28] A. Parmar, R. Katariya, and V. Patel, "A review on random forest: An ensemble classifier," in *International conference on intelligent data communication technologies and internet of things (ICICI) 2018*. Springer, 2019, pp. 758–763.

[29] C. Bentéjac, A. Csörgő, and G. Martínez-Muñoz, "A comparative analysis of gradient boosting algorithms," *Artificial Intelligence Review*, vol. 54, pp. 1937–1967, 2021.

[30] B. Thilagavathi, K. Suthendran, and K. Srujanraju, "Evaluating the adaboost algorithm for biometric-based face recognition," in *Data Engineering and Communication Technology: Proceedings of ICDECT 2020*. Springer, 2021, pp. 669–678.

[31] J. Chen, F. Zhao, Y. Sun, and Y. Yin, "Improved xgboost model based on genetic algorithm," *International Journal of Computer Applications in Technology*, vol. 62, no. 3, pp. 240–245, 2020.

[32] G. Ke, Q. Meng, T. Finley, T. Wang, W. Chen, W. Ma, Q. Ye, and T.-Y. Liu, "Lightgbm: A highly efficient gradient boosting decision tree," *Advances in neural information processing systems*, vol. 30, 2017.

[33] G. Naidu, T. Zuva, and E. M. Sibanda, "A review of evaluation metrics in machine learning algorithms," in *Computer Science On-line Conference*. Springer, 2023, pp. 15–25.