EEG-Based Eye State Recognition via Multi-Domain Feature Engineering and Ensemble Learning

Melanie Qiu, Yiting Wei[1], and Nima TaheriNejad

Institute of Computer Engineering, Heidelberg University,
Im Neuenheimer Feld 368, Heidelberg, Germany
yiting.wei@uni-heidelberg.de

Abstract. Eye state recognition aims to determine whether a person's eyes are open or closed. Although it is a simple binary classification task, it plays an important role in wearable sensing and human–computer interaction, as eye state provides valuable cues for fatigue monitoring, attention assessment, safety-critical systems, and adaptive user interfaces. In this work, we study electroencephalography (EEG)-based eye state recognition using the UCI EEG Eye State dataset. Instead of relying on deep learning models, we propose a transparent machine learning pipeline based on explicit signal preprocessing and hand-crafted feature engineering. The workflow includes band-pass filtering, non-overlapping one-second window segmentation with majority-vote labeling, multi-domain feature extraction, feature standardization, and supervised classification. Under a unified experimental protocol, several conventional classifiers are systematically trained and compared, with hyperparameters optimized using randomized search and cross-validation. Experimental results show that XGBoost achieves the best overall performance on the held-out test set, reaching a macro-F1 score of 0.873, a balanced accuracy of 0.871, a Matthews correlation coefficient (MCC) of 0.749, and an area under the receiver operating characteristic curve (ROC-AUC) of 0.832. Overall, the results demonstrate that combining carefully designed feature engineering with ensemble learning can provide reliable EEG-based eye state recognition while remaining computationally efficient and easy to interpret.

Keywords: electroencephalography · eye state recognition · wearable sensing · feature engineering · ensemble learning

1 Introduction

Eye state recognition (open vs. closed) is a simple binary classification problem; nevertheless, it provides informative cues regarding an individual's level of attention and fatigue [8]. In many real-world scenarios, prolonged eye closure or frequent blinking is commonly associated with reduced alertness, which is

[1] Corresponding Author: Yiting Wei

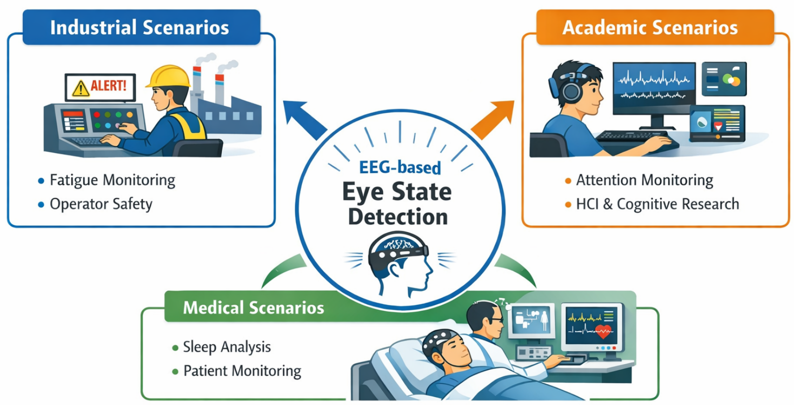

Fig. 1. Different senarios for EEG-based eye state detection.

particularly relevant for fatigue monitoring in safety-critical applications, such as industrial operation or human supervision tasks, as illustrated in Fig. 1. Beyond safety-related contexts, eye state information is also valuable for human–computer interaction (HCI), where user interfaces can adapt to the user's cognitive state, for example by reducing interaction complexity, adjusting feedback, or recommending rest breaks [17].

In practical systems, eye state is commonly detected using vision-based approaches, such as red–green–blue (RGB) cameras or infrared sensors [19]. These methods have demonstrated strong performance in controlled laboratory environments, where factors such as lighting conditions, camera placement, and user posture can be carefully regulated. However, their reliability often degrades in unconstrained real-world settings, as performance can be adversely affected by variations in illumination, head movements, partial occlusions, or suboptimal camera positioning [10]. In addition to these technical limitations, continuous camera-based monitoring may raise privacy concerns, particularly in long-term or sensitive applications, which motivates the exploration of alternative sensing modalities that do not rely on continuous video streams.

Electroencephalography EEG is intrinsically related to the eye open or closed state at the level of physiological mechanisms[1]. Eye closure induces pronounced changes in cortical neural activity, most notably characterized by an increase in occipital alpha rhythms and broader alterations in overall EEG dynamics[7]. These changes reflect cortical excitability modulation driven by reduced visual input and can be reliably captured in EEG signals. Compared to approaches based on external visual observation, EEG directly characterizes the neurophysiological processes associated with eye state, enabling the detection of eye state changes even when they are not visually apparent[20]. Despite these advantages, EEG-based classification remains challenging. EEG signals are noisy, susceptible to artifacts (e.g., muscle activity and movement), and can vary across time and individuals[6]. These factors make robust preprocessing and informative signal representations critical for stable classification performance.

This paper proposes an EEG-based eye state recognition approach grounded in interpretable multi-domain feature engineering. Aimed at addressing the challenges of EEG signal modeling under small-sample and high-noise conditions, as well as the strong reliance of existing methods on complex and poorly interpretable models, we construct a transparent, systematic, and easily reproducible end-to-end recognition pipeline. The core contributions of this work can be summarized as follows: (1) We design an interpretable multi-domain EEG feature representation for window-level eye state recognition. (2) We construct a comprehensive EEG eye state recognition pipeline that enables systematic modeling from raw EEG signals to final classification decisions. (3) Through empirical analysis, we demonstrate that combining feature engineering with ensemble learning yields stable and competitive performance for this task.

The structure of this paper is organized as follows. Section 2 reviews related work on EEG-based eye state recognition. Section 3 describes the dataset. Section 4 presents the proposed method. Section 5 reports results and discussion. Finally, Section 6 concludes the paper and outlines limitations and future work.

2 Related Work

EEG-based eye state recognition has been studied for more than a decade and is commonly used as a benchmark task for evaluating different classification pipelines. Early work by Rösler and Suendermann [14] demonstrated that eye state information can be inferred from EEG signals using supervised learning techniques. Subsequent studies explored alternative learning settings and experimental designs. For example, Wang et al. [18] investigated time-series–oriented learning strategies to better account for the sequential nature of EEG data. Rösler et al. [13] further examined practical aspects of EEG-based eye state recognition by comparing different EEG devices and analyzing how hardware characteristics affect signal quality and downstream classification performance.

From a modeling perspective, a wide range of learning paradigms have been applied to this task. Several studies reported that relatively lightweight baseline models can already achieve competitive performance under appropriate experimental conditions [15]. Other work emphasized the importance of experimental design choices, such as data partitioning strategies and training protocols, which can substantially influence reported performance on this dataset [16, 2]. More recent research has extended toward stronger combination-based learning strategies and modern model structures, often reporting improved robustness under specific settings [4, 9]. In parallel, deep learning approaches have also been explored for EEG eye state detection, reflecting continued interest in end-to-end modeling for this problem [11].

Despite these advances, EEG-based eye state recognition remains challenging in practical scenarios. EEG signals are inherently noisy and sensitive to artifacts, and substantial variability can arise across time, recording conditions, and subjects. Moreover, differences in experimental protocols—such as the definition of prediction units, data splitting strategies, and evaluation metrics—can lead to inconsistent conclusions across studies. These challenges highlight the need for systematic and reproducible experimental pipelines, as well as balanced evaluation practices that fairly assess performance on both eye state classes.

3 Dataset

All experiments in this study are conducted using the UCI EEG Eye State dataset [12], which is publicly available through the UCI Machine Learning Repository. The dataset was originally collected by Rösler and consists of EEG recordings acquired using an Emotiv EEG Neuroheadset. The headset provides 14 EEG channels, and the signals are sampled at 128 Hz.

In total, the dataset contains 14,980 EEG samples arranged as a continuous multivariate time series. Each sample is annotated with a binary eye state label, where 0 denotes eyes open and 1 denotes eyes closed, as shown in Fig. 2. According to the dataset documentation, eye state labels were obtained through camera-based observation during data acquisition and subsequently assigned to the EEG samples. All samples are chronologically ordered, and no missing values are reported. Therefore, eye state labels are available at the sampling-point level, which enables window-level labeling through aggregation after segmentation.

The recording corresponds to a single continuous EEG session with a duration of approximately 117 seconds. However, the public dataset description does not provide detailed information about the experimental protocol, such as the number of subjects involved, demographic characteristics (e.g., age or gender), specific task instructions, or recording conditions.

4 Proposed Method

We propose a transparent EEG-based eye state recognition pipeline based on explicit preprocessing and multi-domain feature engineering. Continuous EEG signals are segmented into 1-second windows with majority-vote labeling, and a structured 154-dimensional feature vector is extracted per window. An overview of the complete pipeline is shown in Fig. 3.

4.1 Problem Definition

We formulate EEG-based eye state recognition as a binary classification problem. Let $\mathbf{X} \in \mathbb{R}^{T \times C}$ denote a continuous EEG recording, where T is the number

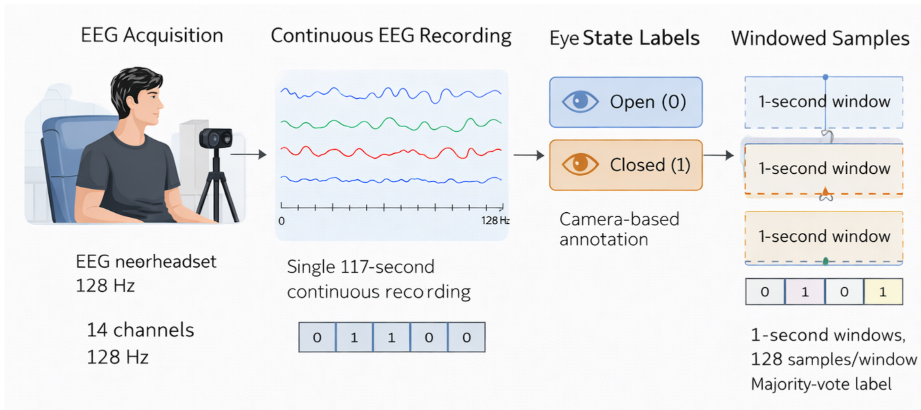

Fig. 2. Data collection process of the UCI EEG Eye State dataset.

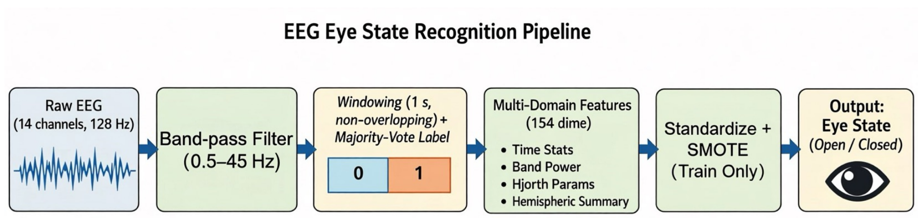

Fig. 3. Overview of the proposed EEG eye state recognition pipeline.

of time steps and $C = 14$ is the number of EEG channels. Each time step corresponds to one EEG sampling point acquired at a sampling rate of 128 Hz.

The continuous EEG signal is segmented into a sequence of fixed-length time windows. The i-th window is denoted as $\mathbf{W}_i \in \mathbb{R}^{L\times C}$, where L is the window length in sampling points. Each window is associated with a binary eye state label $y_i \in \{0, 1\}$, where 0 indicates eyes open and 1 indicates eyes closed.

Given a training set composed of window–label pairs

$$\{(\mathbf{W}_i, y_i)\}_{i=1}^{N}. \tag{1}$$

the objective is to learn a classification function $f(\cdot)$ that can accurately predict the eye state of unseen EEG windows.

4.2 Signal Preprocessing

Raw EEG signals often contain low-frequency drift and high-frequency noise. To suppress these components, a 4th-order Butterworth band-pass filter with cut-off frequencies of 0.5 Hz and 45 Hz is applied to each channel. The lower cut-off removes slow baseline fluctuations, while the upper cut-off reduces high-frequency noise. Filtering is performed prior to window segmentation so that feature extraction operates on a cleaner and more stable signal representation.

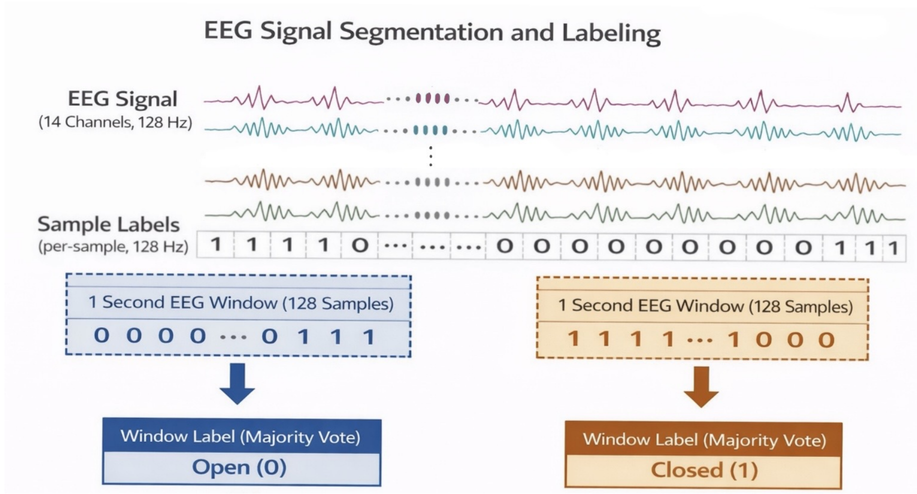

Fig. 4. EEG signal segmentation and labeling method.

4.3 Window Segmentation and Label Assignment

After preprocessing, the continuous EEG signal is segmented into fixed-length, non-overlapping windows of 1 second. Given the sampling rate of 128 Hz, each window contains 128 sampling points across 14 EEG channels.

The choice of a 1-second window represents a commonly adopted compromise in EEG analysis. Such a duration is sufficiently long to capture informative temporal and spectral characteristics of EEG rhythms, while remaining short enough to preserve temporal resolution and reduce label ambiguity. Similar window lengths have been widely used in prior EEG-based eye state recognition studies [14, 18, 15].

Non-overlapping windows are intentionally employed to reduce temporal dependence between adjacent windows. Using overlapping segments would substantially increase the number of training samples, but at the cost of introducing highly correlated instances, which can lead to overly optimistic performance estimates. By adopting non-overlapping windows, the evaluation protocol prioritizes conservative and more realistic performance assessment.

In the UCI EEG Eye State dataset, eye state annotations are provided at the sampling-point level, meaning that each EEG sample is associated with an eye state label. As a result, each 1-second window contains 128 sample-level labels. To obtain a single label per window, majority voting is applied over the corresponding sample-level labels. The window is assigned to the eye state that occurs most frequently among its constituent sampling points.

4.4 Feature Extraction

A multi-domain feature representation is extracted for each EEG window to characterize the signal from complementary perspectives. The feature design combines time-domain statistics, frequency-domain information, signal dynamics, and coarse spatial descriptors. In total, 154 features are computed per window, as shown in Table 1.

Time-domain features For each channel, the mean and standard deviation are computed to summarize the amplitude level and variability of the EEG signal within the window. This results in 28 features across all channels.

Frequency-domain features Spectral information is captured using band power features computed from the power spectral density estimated via Welch's method. Five standard EEG frequency bands are considered: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (30–45 Hz). For each channel, the band power within each frequency range is calculated, yielding a total of 70 features.

Complexity and dynamics features To capture signal dynamics beyond amplitude and spectral content, Hjorth parameters are extracted for each channel[5]. Specifically, activity, mobility, and complexity are computed, describing signal variance, normalized slope, and waveform complexity, respectively. These parameters provide a compact characterization of EEG temporal dynamics and have been widely used in EEG analysis. With 14 channels, this results in 42 features.

Hemispheric summary features To incorporate lightweight cross-channel spatial information, hemispheric summary features are introduced. The 14 EEG channels are grouped into left- and right-hemisphere sets based on their electrode locations. For each window, summary statistics are computed separately for the two hemispheres.

Specifically, the maximum signal amplitude across right-hemisphere channels and the minimum signal amplitude across left-hemisphere channels are extracted. These descriptors provide a coarse representation of hemispheric asymmetry while avoiding high-dimensional spatial modeling. The resulting 14 features complement the channel-wise feature set and contribute to the final 154-dimensional representation.

4.5 Model Training and Evaluation Protocol

Model training is performed using a unified pipeline that integrates feature normalization, imbalance handling, and supervised classification. Feature standardization is first applied using StandardScaler, which rescales each feature to zero

Table 1. Overview of extracted EEG features per window.

Feature category	Included features	Number
Time-domain statistics	Mean, standard deviation (per channel)	28
Frequency-domain features	Band power (delta, theta, alpha, beta, gamma)	70
Signal dynamics	Hjorth activity, mobility, complexity	42
Hemispheric summaries	Left/right hemisphere max–min descriptors	14
Total	–	154

mean and unit variance. This step ensures that features with different numerical ranges contribute comparably during learning and is particularly important for distance-based and gradient-based classifiers.

To mitigate class imbalance in the training data, Synthetic Minority Oversampling Technique (SMOTE) is employed. SMOTE generates synthetic samples for the minority class by interpolating between neighboring minority instances in feature space, thereby reducing bias toward the majority class during classifier learning[3]. Both StandardScaler and SMOTE are implemented within the cross-validation pipeline and are fitted exclusively on the training folds of each split, preventing information leakage.

All model hyperparameters are optimized using cross-validation on the training set. Once the best-performing configuration is identified, the final model is retrained on the full training set and evaluated on a held-out test set that is not used during model selection.

5 Results and Discussion

This section reports the classification performance of the proposed EEG eye state recognition pipeline and discusses the observed patterns.

5.1 Overall Performance

As shown in Table 2, the results demonstrate that boosted ensemble models consistently outperform simpler baselines on the proposed feature representation. Among all evaluated classifiers, XGBoost achieves the strongest overall performance, suggesting that its ability to model nonlinear feature interactions and perform implicit feature selection is particularly well suited to the heterogeneous, multi-domain EEG feature set.

Quantitatively, XGBoost improves balanced accuracy from 0.83 (gradient boosting machine (GBM)) to 0.87 and increases MCC from 0.67 to 0.75, indicating not only higher classification accuracy but also substantially stronger agreement beyond chance. These results support the hypothesis that boosted ensembles are better able to exploit nonlinear interactions among complementary EEG feature groups. In contrast, k-nearest neighbors (kNN) and support vector machine (SVM) exhibit weaker performance. This can be attributed to the relatively high feature dimensionality compared to the limited number of window-level samples, which exacerbates the curse of dimensionality and increases sensitivity to noise. Similarly, multilayer perceptron (MLP) performance is constrained by the small dataset size, limiting its ability to learn stable representations without overfitting. These limitations are particularly pronounced in the present setting, where non-overlapping window segmentation intentionally reduces sample redundancy while also restricting the effective training set size. The relatively small number of window-level samples is therefore an important factor influencing result variability. While the use of non-overlapping 1-second windows provides a conservative and realistic evaluation protocol, it also increases variance in test-set performance estimates. For this reason, balanced evaluation metrics such as macro-F1 and MCC are emphasized over raw accuracy, as they more reliably reflect performance under class imbalance and limited data conditions.

From a practical perspective, these results indicate that feature engineering combined with ensemble learning can provide reliable EEG-based eye state recognition under constrained data regimes. The proposed approach is computationally efficient, transparent, and suitable as a strong baseline for future studies. Nevertheless, the limited dataset size and the lack of subject-level metadata restrict conclusions regarding subject-independent generalization, motivating further investigation on larger and more diverse datasets.

5.2 Baseline Comparison

Table 2 compares all conventional classifiers evaluated in this work. Overall, the results reveal a clear performance hierarchy across model families. Boosted ensemble methods achieve the strongest and most stable performance on the extracted feature representation. Single-tree models and weak-learner ensembles perform competitively but with reduced robustness. Specifically, Gradient Boosting attains competitive results but remains consistently inferior to XGBoost across all metrics. Decision Trees and AdaBoost perform moderately well, yet exhibit reduced stability compared to the stronger ensemble models.

In contrast, kNN, MLP, and SVM show weaker performance under the current feature design and the limited number of window-level samples. This suggests that, in small-sample and noisy EEG settings, these baselines struggle to capture relevant feature interactions as effectively as boosted ensemble approaches.

5.3 Comparison with Existing Work

To contextualize the results, Table 3 summarizes representative studies on the UCI EEG Eye State dataset. Different works often adopt distinct preprocessing procedures, segmentation strategies (e.g., overlapping versus non-overlapping windows), and evaluation protocols. As a result, the reported numbers are not directly comparable in a strict sense, but they nevertheless provide a useful reference range for typical performance levels.

Table 2. Comparison of conventional classifiers on the test set.

Model	BACC	F1	MCC	ROC-AUC
GBM	0.825175	0.828571	0.669342	0.769231
DT	0.779720	0.782214	0.591312	0.741259
AdaBoost	0.734266	0.733333	0.513610	0.706294
kNN	0.615385	0.531250	0.347677	0.590909
SVM	0.576923	0.466667	0.277350	0.419580
MLP	0.569930	0.499051	0.186989	0.489510
XGBoost	**0.870629**	**0.873016**	**0.749159**	**0.832168**

Table 3. Comparison with representative prior studies on the UCI EEG Eye State dataset.

Reference (Year)	Method	Reported Accuracy
Sabanci and Koklu (2015) [15]	kNN, MLP baselines	84.05% (kNN)
Bharati et al. (2018) [2]	Classical machine learning (ML) (kNN, decision tree (DT), SVM, Logistic)	83.65%
Dritsas et al. (2024) [4]	Ensemble macro-F1, MCC, balanced accuracy, and ML with imbalance handling	84.0%
This work	Feature engineering + XGBoost	**87.06% (Balanced ACC)**

In addition, it should be noted that this work adopts balanced accuracy as the primary evaluation metric. By assigning equal importance to both classes, balanced accuracy provides a more stringent and conservative assessment than standard accuracy under class-imbalanced conditions. Consequently, compared to prior studies that primarily report standard accuracy, the results presented in this work offer a more cautious and methodologically rigorous evaluation of performance.

5.4 Interpretation and Practical Considerations

The results show that EEG-based eye state recognition can be effective when the signal is processed in a structured and interpretable manner. The adopted multi-domain feature engineering strategy enables the signal to be characterized from complementary perspectives. Time-domain features capture overall amplitude levels and variability within each window, while frequency-domain band power features reflect changes in EEG rhythms associated with eye closure, particularly in lower frequency ranges. Hjorth parameters further describe signal dynamics and capture temporal behaviors that are not evident from simple statistical measures. In addition, hemispheric summary features provide a lightweight means of incorporating cross-channel information and may reflect coarse spatial differences between electrode groups.

Among all evaluated models, XGBoost achieves the best overall performance, also outperforms the exsiting methods. This is consistent with its ability to model nonlinear feature relationships while maintaining regularization. Compared to simpler baselines such as kNN or SVM, XGBoost more effectively integrates information from different feature domains. At the same time, the approach remains computationally efficient, as the classifier operates on a compact feature vector rather than raw EEG signals. Overall, the proposed pipeline offers a favorable balance between performance, interpretability, and practical feasibility.

6 Conclusion

This work presented a transparent and interpretable machine learning pipeline for EEG-based eye state recognition using the UCI EEG Eye State dataset. The proposed approach integrates explicit signal preprocessing, non-overlapping one-second window segmentation with majority-vote labeling, and multi-domain feature engineering to characterize EEG signals from complementary perspectives. A compact 154-dimensional feature representation was constructed by combining time-domain statistics, frequency-band power features, Hjorth parameters, and hemispheric summary descriptors. Under a unified training and evaluation protocol, multiple conventional classifiers were systematically benchmarked. Among them, XGBoost achieved the best overall performance on the held-out test set, demonstrating strong balanced accuracy, macro-F1, MCC, and ROC-AUC. These results indicate that combining carefully designed feature engineering with ensemble learning can provide reliable EEG eye state recognition while maintaining computational efficiency and interpretability, making the proposed pipeline a strong and practical baseline.

Despite these encouraging results, several limitations should be acknowledged. The use of non-overlapping windows results in a relatively small number of window-level samples, which may increase variability in performance estimates. Moreover, the lack of subject-level metadata in the public dataset restricts conclusions regarding subject-independent generalization. Future work will therefore focus on more robust artifact handling, subject-independent evaluation protocols, and the exploration of overlapping or multi-scale windowing strategies to better capture transitions between eye states and improve generalization across users.

Acknowledgment This work has been partially funded by Hector Stiftung.

References

1. Barry, R.J., Clarke, A.R., Johnstone, S.J., Magee, C.A., Rushby, J.A.: Eeg differences between eyes-closed and eyes-open resting conditions. Clinical neurophysiology **118**(12), 2765–2773 (2007)
2. Bharati, S., Podder, P., Raihan-Al-Masud, M.: Eeg eye state prediction and classification in order to investigate human cognitive state. In: 2018 International Conference on Advancement in Electrical and Electronic Engineering (ICAEEE). pp. 1–4. IEEE (2018). https://doi.org/10.1109/ICAEEE.2018.8643015
3. Chawla, N.V., Bowyer, K.W., Hall, L.O., Kegelmeyer, W.P.: Smote: Synthetic minority over-sampling technique. Journal of Artificial Intelligence Research **16**, 321–357 (2002). https://doi.org/10.1613/jair.953
4. Dritsas, E., Trigka, M., Fidas, C.: Eye state classification using ensemble machine learning models and smote on eeg data. In: 2024 9th South-East Europe Design Automation, Computer Engineering, Computer Networks and Social Media Conference (SEEDA-CECNSM). pp. 1–6. IEEE (2024). https://doi.org/10.1109/SEEDA-CECNSM63478.2024.00038
5. Hjorth, B.: Eeg analysis based on time domain properties. Electroencephalography and Clinical Neurophysiology **29**(3), 306–310 (1970). https://doi.org/10.1016/0013-4694(70)90143-4
6. Islam, M.K., Rastegarnia, A., Sanei, S.: Signal artifacts and techniques for artifacts and noise removal. In: Signal Processing Techniques for Computational Health Informatics, pp. 23–79. Springer (2020)
7. Jiang, Y., Guo, Z., Jiao, R., He, H., Jiang, N., He, J.: Abnormal resting-state eeg neural oscillations and functional connectivity in mild cognitive impairment. Frontiers in Aging Neuroscience **17**, 1640966 (2025)
8. Marshall, S.P.: Identifying cognitive state from eye metrics. Aviation, space, and environmental medicine **78**(5), B165–B175 (2007)
9. Nilashi, M., Abumalloh, R.A., Ahmadi, H., Samad, S., Alghamdi, A., Alrizq, M., Alyami, S., Nayer, F.K.: Electroencephalography (eeg) eye state classification using learning vector quantization and bagged trees. Heliyon **9**(4), e15258 (2023). https://doi.org/10.1016/j.heliyon.2023.e15258
10. Palermo, F., Casciano, L., Demagh, L., Teliti, A., Antonello, N., Gervasoni, G., Shalby, H.H.Y., Paracchini, M.B., Mentasti, S., Quan, H., et al.: Advancements in context recognition for edge devices and smart eyewear: Sensors and applications. IEEE Access (2025)
11. Peya, Z.J., Joly, N.A., Hasan, M.M.: A comparative study of eeg signal based eye state detection using deep learning. In: 2023 IEEE 9th International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE) (2023). https://doi.org/10.1109/WIECON-ECE60392.2023.10456522
12. Repository, U.M.L.: Eeg eye state dataset. `https://archive.ics.uci.edu/ml/datasets/EEG+Eye+State`, accessed: 2026-01-25
13. Rösler, O., Bader, L., Forster, J., Hayashi, Y., Heßler, S., Suendermann-Oeft, D.: Comparison of eeg devices for eye state classification. In: Proceedings of the International Conference on Applied Informatics for Health and Life Sciences (AIHLS). Kusadasi, Turkey (Oct 2014), `http://www.suendermann-oeft.de/su/pdf/aihls2014.pdf`
14. Rösler, O., Suendermann, D.: A first step towards eye state prediction using eeg. In: Proceedings of the International Conference on Applied Informatics for Health and Life Sciences (AIHLS). Istanbul, Turkey (Sep 2013), `https://suendermann.com/su/pdf/aihls2013.pdf`

15. Sabancı, K., Koklu, M.: 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 **3**(4), 127–130 (2015). https://doi.org/10.18201/ijisae.75836
16. Sahu, M., Nagwani, N.K., Verma, S., Shirke, S.: An incremental feature reordering (ifr) algorithm to classify eye state identification using eeg. In: Information Systems Design and Intelligent Applications, Advances in Intelligent Systems and Computing, vol. 339, pp. 803–811. Springer, New Delhi, India (2015). https://doi.org/10.1007/978-81-322-2250-7_80
17. Singh, H., Singh, J.: Real-time eye blink and wink detection for object selection in hci systems. Journal on Multimodal User Interfaces **12**(1), 55–65 (2018)
18. Wang, T., Guan, S.U., Man, K.L., Ting, T.O.: Eeg eye state identification using incremental attribute learning with time-series classification. Mathematical Problems in Engineering **2014**, 1–9 (2014). https://doi.org/10.1155/2014/365101
19. Zhang, X., Hu, M., Zhang, Y., Zhai, G., Zhang, X.P.: Recent progress of optical imaging approaches for noncontact physiological signal measurement: A review. Advanced Intelligent Systems **5**(9), 2200345 (2023)
20. Zhu, L., Lv, J.: Review of studies on user research based on eeg and eye tracking. Applied Sciences **13**(11), 6502 (2023)