Impact of EEG Signal Preprocessing Methods on Machine Learning Models for Affective Disorders

E. Jovicic*, A. Jovic*, M. Cifrek*
* University of Zagreb, Faculty of Electrical Engineering and Computing, Zagreb, Croatia
eda.jovicic@fer.hr

***Abstract*—Affective disorders belong to a group of psychiatric disorders that are diagnosed according to the criteria of standardized diagnostic manuals. The diagnostic protocol consists of assessing a patient's symptoms, but to date, there are no methods to objectively evaluate or measure them. Electroencephalography (EEG) is a non-invasive brain electrical activity measuring technique. Current research mainly focuses on the use of EEG data and feature extraction, machine learning (ML), and deep learning (DL) to classify affective disorders. In this paper, the focus is on measuring the impact of preprocessing EEG signals on ML models for affective disorders. The impact of the following preprocessing methods is evaluated: signal filtering, independent component analysis (ICA), and canonical correlation analysis (CCA). The methods are assessed on a dataset consisting of EEG signals from 70 subjects diagnosed with affective disorders and 35 healthy subjects. After preprocessing, 570 features are extracted for each subject and several ML models are used for classification. CCA provided the best results compared to the other methods, with the highest F1 score of 0.9756 achieved with the decision tree classifier. CCA should be considered as a beneficial preprocessing method to potentially improve classification results when building complex models for EEG data.**

***Keywords*—*electroencephalography, canonical correlation analysis, independent component analysis, preprocessing, affective disorders* Hokdoitujkl**

I. INTRODUCTION

Affective disorders belong to a group of psychiatric disorders characterized by problems in mood regulation [1]. They are diagnosed according to the criteria of standardized diagnostic manuals [1], [2]. The diagnostic protocol consists of assessing a patient's symptoms through interviews with the patient and using various psychometric tests such as Beck Depression Inventory (BDI) [3] and Hamilton Depression Rating Scale (HAM-D) [4]. Although tests and interviews provide valuable information about the patient's state, to date, there are no methods that objectively evaluate or measure a patient's symptoms of an affective disorder.

Electroencephalography (EEG) is a non-invasive brain electrical activity measuring technique. In the process of diagnosing affective disorders, the EEG is inspected visually in order to rule out brain damage or epileptogenic activity. However, EEGs contain more information that is not accessible by visual inspection of the signal but requires feature extraction with signal processing methods [5]. Current research mainly focuses on the use of EEG data and feature extraction, statistical analysis, machine learning (ML), and deep learning (DL) to classify affective disorders [6]–[8]. The main hypothesis is that EEG characteristics could serve as biomarkers of affective disorders, and identifying them could serve as a step towards understanding the underlying mechanisms of dysfunction [9].

During the recording of an EEG, various artifacts occur that must be removed in order to enable further analysis of the signal. The most common artifacts include eye movement, muscle and heart artifacts, line noise, and others caused by the recording equipment or by the subject's movement [10]. There are several common preprocessing steps used for EEG signals like filtering, re-referencing, segmenting signals into epochs, removing or interpolating bad channels, and artifact removal with various methods like independent component analysis (ICA) or canonical correlation analysis (CCA) [11]. Applying some of the steps is inevitable due to numerous artifacts that make EEGs not accurately represent signals from the brain. In this paper, the goal is to measure the impact of different preprocessing methods for EEG signals on ML models for affective disorders. Using the optimal preprocessing steps enables ML algorithms to work with a more accurate representation of EEG signals and more successfully discover patterns in data.

The impact of the following preprocessing methods is evaluated in this work: signal filtering, independent component analysis, and canonical correlation analysis. Filtering and ICA are chosen because they are the most commonly used methods [12], while CCA is chosen as a novel method, not commonly used, but potentially better than ICA at removing some types of artifacts. Research related to ICA focuses on finding optimal hyperparameters for using ICA [13], or combining ICA with other methods to create the best possible preprocessing pipeline [14]. Even though ICA is the most commonly used method, some papers report that CCA is better at removing specific types of artifacts. In Roy and Shukla [15], CCA proved to be better at removing motion artifacts. When removing eye blinks, CCA was more accurate and faster than ICA [16], as well as when the task was removing muscle artifacts [17], [18]. Most of these papers use simulated signals or a dataset created specifically for the purpose of experimenting with preprocessing methods. This paper researches chosen methods on a real-life dataset where the impact of each method is measured through metrics of ML models on a classifying task instead of signal-to-noise ratio (SNR). The motivation behind this research is to find the most effective preprocessing methods that would potentially improve the classification accuracy of affective disorders ML models that use EEG features.

The remainder of this paper is organized as follows. Section II gives an insight into the process of data acquisition and a detailed description of the dataset. Section III describes the applied methods, while Section IV displays the experimental setup used in research. Section V shows the classification results and compares the inspected preprocessing methods. Finally, all results are discussed and a conclusion is given in Section VI.

II. DATA ACQUISITION AND DESCRIPTION

The EEG dataset was obtained at the University Psychiatric Hospital Vrapce, Zagreb. The dataset contains EEG recordings of 105 subjects, of whom 70 are diagnosed with affective disorder according to ICD-10 [1] and 35 are healthy control subjects. The subjects are age and sex-matched in the ratio 2:1, meaning that for every healthy subject, there are two subjects with depression diagnoses of the same sex and similar or same age. For machine learning purposes, the dataset is divided into a training set (75 subjects) and a testing set (30 subjects), as shown in Table I.

TABLE I: Diagnosis and sex of subjects

Diagnosis	Training Set		Testing Set	
	Female	Male	Female	Male
Affective Disorder (F32)	6	9	1	0
Affective Disorder (F33)	22	13	8	11
Healthy	14	11	4	6

During the recording protocol, the subject was in a relaxed laying position to minimize artifacts created by subject movement. The recording protocol consisted of three parts: rest-state with eyes opened and closed (duration: 5-10 minutes), photo-stimulation with five different flash frequencies - 4 Hz, 8 Hz, 16 Hz, 24 Hz and 30 Hz (duration: 15 seconds for each frequency) and an induced state of hyperventilation (duration: 5 minutes). During the recording, a technician marked the onset of each event. For each subject, EEG was recorded using a 19-channel EEG amplifier with standard 10-20 electrode placement, as shown in Fig 1. The EEG electrodes included Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1 and O2, with Oz as the reference electrode. The sampling frequency was 256 Hz.

The dataset acquisition was carried out in accordance with the guidelines of the Declaration of Helsinki and approved by the ethics committee of the University of Zagreb, University Psychiatric Hospital Vrapce.

III. METHODS

A key step in EEG signal analysis is signal preprocessing. During the recording of EEG signals, it is not possible to avoid recording artifacts caused by line noise at 50 Hz and its harmonics, as well as the artifacts caused by movement of the subject, electrodes or wires, muscle artifacts, and eye movement artifacts. The goal during preprocessing is to use methods that will preserve the EEG signal whose amplitude is around 10 μV, while removing the artifacts that have an amplitude of a higher order of magnitude - a few mV. Three preprocessing steps will be explored in this paper: filtering, ICA, and CCA.

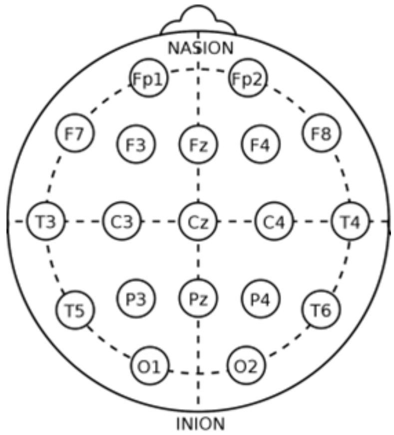

Fig. 1: 10-20 system of electrode placement with 19 electrodes [19]

A. Filtering

The raw EEG signal is first filtered with a passband finite impulse response (FIR) filter from 0.1 to 40 Hz implemented using the MATLAB function *filfilt()* with Hamming window and default filter order defined by EEGLAB. The low-frequency edge is chosen to eliminate the slow drifts in the signal while the high-frequency edge is chosen to remove the 50 Hz line noise and at the same time retain the frequency components of interest [20]. After filtering, the channels are re-referenced to the average value of all 19 channels.

B. Canonical correlation analysis

Canonical correlation analysis, CCA, is a way of measuring the linear relationship between two multidimensional variables. The method finds two bases, one for each variable, that are optimal with respect to correlations and, at the same time, finds the corresponding correlations [21]. For EEG signal preprocessing, CCA is used as a blind source separation method (BSS), where the goal is to force sources to be maximally autocorrelated and mutually uncorrelated [22].

Let the observed EEG signals be $\mathbf{X}(t) = [\mathbf{x_1}(t), \mathbf{x_2}(t), ..., \mathbf{x_M}(t)]^T, t = 1, 2, ..., N$ where N is the number of samples and M is the number of EEG electrodes. BSS is performed to recover sources $S(t) = [s_1(t), s_2(t), ..., s_M(t)]^T$ by observing $\mathbf{X}(t)$ as a mixture of a set of unknown source signals in a linear combination

$$\mathbf{X}(t) = \mathbf{A} \cdot S(t), \tag{1}$$

where $\mathbf{A}$ is the unknown mixing matrix. The unknown source signals $S(t)$ are derived by introducing the demixing matrix $\mathbf{W}$,

$$\tilde{S}(t) = \mathbf{W}\mathbf{X}(t), \tag{2}$$

where $\tilde{S}(t)$ approximates the unknown source signals in $S(t)$, and ideally, $\mathbf{W}$ is the inverse of the unknown mixing matrix $\mathbf{A}$. In practice, a temporal CCA analysis is used where the two variables are: observed EEG signals $\mathbf{X}(t)$, and a delayed version of the observed EEG signals $\mathbf{Y}(t)$ such that $\mathbf{Y}(t) = \mathbf{X}(t-1)$ [23]. Suppose two canonical variables, U and V, are linear combinations of the components in $\mathbf{X}$ and $\mathbf{Y}$,

$$\begin{aligned} U(t) &= \mathbf{w_x^T}\mathbf{X}(t), \\ V(t) &= \mathbf{w_y^T}\mathbf{Y}(t). \end{aligned} \tag{3}$$

CCA is used to find the matrices $\mathbf{w_x} = [w_{x_1}...w_{x_M}]$ and $\mathbf{w_y} = [w_{y_1}...w_{y_M}]$ that maximize the correlation ρ between U and V; the following problem has to be solved:

$$\max_{\mathbf{w_X},\mathbf{w_Y}} \rho(U,V) = \frac{\mathbf{w_x^T C_x y w_y}}{\sqrt{(\mathbf{w_x^T C_x x w_x})(\mathbf{w_y^T C_y y w_y})}}, \tag{4}$$

where $\mathbf{C_{xx}}$ and $\mathbf{C_{yy}}$ are the autocovariance matrices of $\mathbf{X}$ and $\mathbf{Y}$, and $\mathbf{C_{xy}} = \mathbf{C_{xy}^T}$ are the cross-covariance matrices of $\mathbf{X}$ and $\mathbf{Y}$. After some manipulations, the demixing matrices $\mathbf{w_x}$ and $\mathbf{w_y}$ can be calculated by solving the following eigen-value problem:

$$\begin{aligned} \mathbf{C_x x^{-1} C_x y C_y y^{-1} C_y x w_x} &= \rho^2 \mathbf{w_x}, \\ \mathbf{C_y y^{-1} C_y x C_x x^{-1} C_x y w_y} &= \rho^2 \mathbf{w_y}. \end{aligned} \tag{5}$$

After calculating the demixing matrix $\mathbf{W}$, the next step is getting the approximate source signals $\tilde{S}(t)$ sorted by the autocorrelation coefficient. To remove muscle activity, CCA uses the fact that the autocorrelation of muscle activity and other artifacts is weaker than that of brain activity [24].

C. Independent Component Analysis

Independent component analysis, ICA, is a method for automatically identifying the underlying factors in a given dataset. Moreover, it is essentially a method for extracting individual signals from a mixture of signals thus making it a good tool for removing artifacts from EEG signals as a BSS method [25]. The goal of using ICA for preprocessing EEG signals is to find individual components of the signal produced by specific brain regions. A critical problem is that the method must have an equal number of mixtures to the number of sources in the signal.

Let the EEG signal coming from one electrode be $x_i = [x_i^1, x_i^2, ..., x_i^N]^T$ where N represents the number of independent source signals. Each mixture x_i contains a contribution from each source signal $s_j = [s_j^1, s_j^2, ..., s_j^N]^T$. The relation between each source s_j and x_i can be defined with a weighting factor A_{ij} for each source. If $N = 2$ then the relative contribution of each source s_j to a mixture x_i is

$$x_i = (s_1 A_{1i}) + (s_2 A_{2i}) = \mathbf{s}A_{.i}. \tag{6}$$

If there are $M = 2$ electrodes, then each source has a different relative amplitude defined by A_{ij} at each electrode, so that each electrode records a different mixture x_i

$$(x_1, x_2) = (\mathbf{s}A_{.1})(\mathbf{s}A_{.2}) = \mathbf{s}(A_{.1}, A_{.2}) = \mathbf{s}A, \tag{7}$$

where each column of the mixing matrix A specifies the relative contributions of the source signals $\mathbf{s}$ to each mixture x_i. Matrix A defines a linear transformation on the signals $\mathbf{s}$ which can usually be reversed to get an estimate $\mathbf{u}$ of source signals $\mathbf{s}$ from signal mixtures $\mathbf{x}$

$$\mathbf{s} \approx \mathbf{u} = \mathbf{x}W, \tag{8}$$

where the separating matrix $W = A^{-1}$ is the inverse of A. The mixing matrix A is unknown, therefore it cannot be used to find the separating matrix W which maps a set of M mixtures $\mathbf{x}$ to a set of N source signals $\mathbf{u} \approx \mathbf{s}$. To find an estimation $\mathbf{u} = \mathbf{x}W$, so that the source signals $\mathbf{s}$ are mutually independent, the estimation of source signals $\mathbf{u}$ must also be mutually independent. This can be achieved by adjusting W to maximize the entropy of $\mathbf{U} = g(\mathbf{u}) = g(W\mathbf{x})$, where the function g is assumed to be the cumulative density function (CDF) of s.

To identify and remove independent components from EEG signals that are artifacts, a tool called *ICLabel* is used [26]. *ICLabel* is a classifier that computes independent component class probability across seven possible classes: brain, muscle, eye, heart, line noise, channel noise, and others. Independent components classified as anything but the brain above a certain threshold of probability can be removed to clean the dataset from artifacts.

IV. EXPERIMENTAL SETUP

For evaluating the preprocessing methods, the following pipeline is used:

1) Data acquisition
2) Preprocessing
3) Feature extraction
4) Classification with ML models

Three classification experiments are conducted, where the only difference is in the second step: preprocessing. In the first experiment, signals are only filtered and re-referenced. For the second experiment, the signals are filtered and re-referenced, and CCA is applied. After CCA, two canonical components are removed from the signal: the first component which represents eye movement, and the last component which represents muscle artifacts. For the third experiment, the signals are also filtered and re-referenced, and ICA is applied together with ICLabel. Independent components labeled as artifacts with certainty above 75% are removed from the EEG signals.

After preprocessing, for each of the five characteristic brain rhythms recognizable in EEGs (delta, theta, alpha, beta, and gamma), six features are extracted:

- absolute band power,

- relative band power,
- spectral centroids,
- relative wavelet energy,
- wavelet entropy,
- Katz fractal dimension.

Although there are many EEG features available in the literature [5], the features were chosen as the most promising ones in the research on EEG biomarkers for affective disorders and were already used in an earlier paper where a more detailed description of each feature is given [27]. Feature extraction was upgraded in comparison to [27] by adding Katz fractal dimension, a feature that measures the non-linear characteristics of the EEG signal [28]. All features are extracted using MATLAB. Features are extracted only from the first part of the recording protocol - the resting state, where the subject lies still with eyes open and closed. For each subject, six different feature types are extracted, for five characteristic brain rhythms, for all 19 EEG channels, totaling 570 unique features per subject.

After feature extraction, different machine learning models are evaluated in the Classification Learner application in MATLAB [29]. The input data are the features table and the output is two classes: depressed or healthy. The models are trained with a training dataset (75 subjects) using 10-fold cross-validation. After training, the models are further tested on the testing dataset (30 subjects) and evaluated using four metrics: accuracy (Acc), precision (Pr), recall (Re), and F1-score (F1) [30]. Eight machine learning models are compared: decision tree, linear discriminant (LD), logistic regression (LR), naive Bayes (NB), support vector machine (SVM), K-nearest neighbours (KNN), ensemble (RUSBoosted trees) and kernel SVM for three classification experiments.

V. RESULTS

First, EEG recordings of each subject were loaded into EEGLAB in MATLAB for the preprocessing steps. Fig. 2 shows 5 seconds of EEG signals from subject 4011 after each preprocessing step. Every EEG recording consists of 19 channels and a reference channel which are stacked to visualise artifacts better.

The depicted signal contains several common EEG artifacts: line noise, blinks at the 28^{th}, 30^{th}, and 32^{nd} seconds, and drifts. Figure 2a) shows a raw signal where no preprocessing methods have been used. Figure 2b) shows the EEG signal filtered with the FIR filter and re-referenced to the average reference. The scale of the signal has changed and the line noise at 50 Hz is successfully removed. Figure 2c) shows the effects of applying CCA and removing components containing artifacts on EEG signals. Figure 2d) shows the effects of applying ICA and removing components labeled by ICLabel. While ICA managed to remove blinks from the signal, the drift remained, while CCA was successful in removing both blinks and drift.

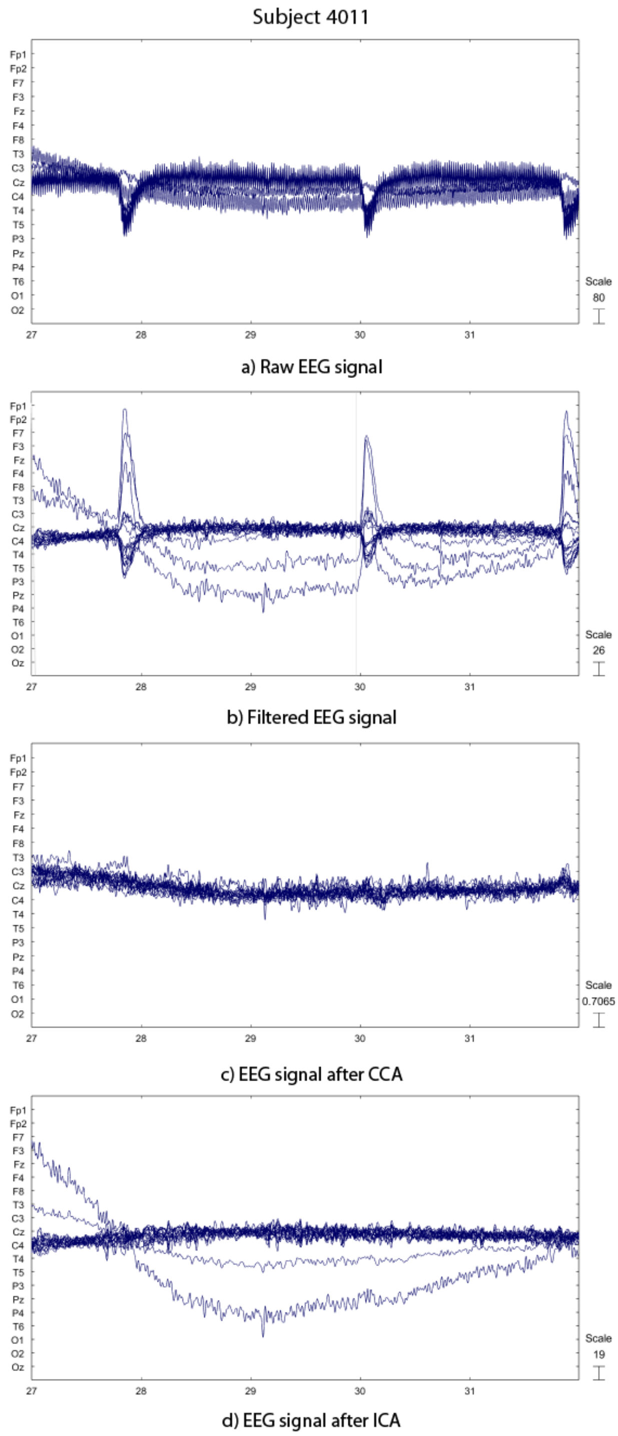

Fig. 2: A representative example for the effects of preprocessing methods on EEG signal – subject 4011

After preprocessing, signals are decomposed into five characteristic brain rhythms and features are extracted. Once all the features are extracted, machine learning models are trained with 10-fold cross-validation and tested with a testing set. Classification results on the testing dataset for classes depressed and healthy are shown in Table II. All 570 features are used for each subject. Overall, the decision tree and kernel SVM show the highest classification accuracy in the third experiment where CCA was used as a preprocessing method.

TABLE II: Classification results

Experiment	Model	Acc	Pr	Re	F1
1) Filter	Tree	0.5333	0.4500	0.7500	0.5625
	LD	0.5333	0.5000	0.7143	0.5882
	LR	0.6667	0.8000	0.7273	0.7619
	NB	0.7667	0.9500	0.7600	0.8444
	SVM	0.7333	0.7500	0.8333	0.7895
	KNN	0.7333	0.8500	0.7727	0.8095
	Ensemble	0.8000	0.9000	0.8182	0.8571
	Kernel SVM	0.6667	0.9500	0.6786	0.7917
2) ICA	Tree	0.7667	0.9000	0.7826	0.8372
	LD	0.4667	0.4500	0.6429	0.5294
	LR	0.7000	0.6000	0.9231	0.7273
	NB	0.7333	0.8500	0.7727	0.8095
	SVM	0.7000	0.8000	0.7619	0.7805
	KNN	0.7000	0.9000	0.7200	0.8000
	Ensemble	0.7667	0.9500	0.7600	0.8444
	Kernel SVM	0.7000	1.0000	0.6897	0.8163
3) CCA	**Tree**	**0.9667**	**1.0000**	**0.9524**	**0.9756**
	LD	0.6667	0.6000	0.8571	0.7059
	LR	0.6333	0.6000	0.8000	0.6857
	NB	0.8000	0.9500	0.7917	0.8636
	SVM	0.9000	0.9500	0.9048	0.9268
	KNN	0.9000	0.8500	1.0000	0.9189
	Ensemble	0.9333	0.9500	0.9500	0.9500
	Kernel SVM	**0.9667**	**1.0000**	**0.9524**	**0.9756**

Model accuracy is compared for all three experiments in Fig. 3 where all the models show a higher accuracy when CCA is used as a preprocessing method. When comparing ICA and filtering as preprocessing methods, both have similar results across all models except for the decision tree.

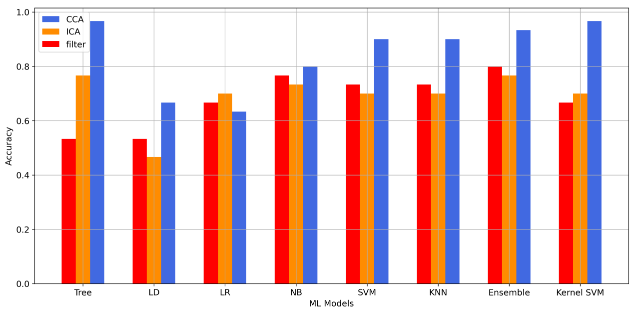

Fig. 3: Comparison of model accuracy for three experiments

VI. Conclusion

In conclusion, this study measured the impact of EEG signal preprocessing methods on machine learning models for classifying subjects diagnosed with affective disorders and healthy subjects. Three preprocessing methods are compared: filtering, canonical correlation analysis, and independent component analysis. To evaluate the listed preprocessing methods, three experiments are performed with the same pipeline: data acquisition, preprocessing, feature extraction, and classification with machine learning models. The only difference in each experiment was the preprocessing step. The goal of this study was not to find the best features or a subset of features and optimize hyperparameters of ML models because varying these steps would not allow interpreting the impact of preprocessing steps.

For the chosen EEG dataset, of the three chosen preprocessing methods, CCA had the best results with all ML models except with logistic regression. When visually comparing signals, it is noticeable that CCA successfully removed both artifacts caused by eye movement or blinks, as well as drifts and muscle artifacts. On the other hand, ICA showed similar results to filtering, even though better results were expected due to ICA using a pre-trained model ICLabel for classifying and removing artifacts from EEG signals. ICA could be further improved by using manual inspection and removal of components, which would be time-consuming when working with large datasets containing hundreds of recordings. On the other hand, no such model for labeling CCA components exists and could help further choose more precise components for removal.

When recording EEGs, the raw signal contains artifacts coming from various sources, from the subject itself and the environment. The obtained results show that preprocessing is a key step in preparing EEG recordings for future analysis. The main difference between all used preprocessing methods is the balance between keeping the target signal intact and, at the same time, removing all artifacts. Choosing different preprocessing steps can significantly vary the accuracy of predictions in ML models.

Acknowledgment

We thank University Psychiatric Hospital Vrapce, Zagreb for providing the dataset for this study.

References

[1] WHO, *The ICD-10 classification of mental and behavioural disorders: clinical descriptions and diagnostic guidelines*. World Health Organization, 1992, vol. 1.

[2] D. A. Regier, E. A. Kuhl, and D. J. Kupfer, "The DSM-5: Classification and criteria changes," *World psychiatry*, vol. 12, no. 2, pp. 92–98, 2013.

[3] A. Beck, R. Steer, and G. Brown, *BDI-II, Beck Depression Inventory: Manual*, ser. Gutman Reserve Test Collection. Psychological Corporation, 1996. [Online]. Available: https://books.google.hr/books?id=Ka1wAAAACAAJ

[4] A. M. Carneiro, F. Fernandes, and R. A. Moreno, "Hamilton depression rating scale and montgomery–asberg depression rating scale in depressed and bipolar I patients: psychometric properties in a Brazilian sample," *Health and quality of life outcomes*, vol. 13, no. 1, pp. 1–8, 2015.

[5] I. Stancin, M. Cifrek, and A. Jovic, "A Review of EEG Signal Features and Their Application in Driver Drowsiness Detection Systems," *Sensors*, vol. 21, no. 11, 2021. [Online]. Available: https://www.mdpi.com/1424-8220/21/11/3786

[6] F. S. de Aguiar Neto and J. L. G. Rosa, "Depression biomarkers using non-invasive EEG: A review," *Neuroscience Biobehavioral Reviews*, vol. 105, pp. 83–93, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0149763419303823

[7] Y. Liu, C. Pu, S. Xia, D. Deng, X. Wang, and M. Li, "Machine learning approaches for diagnosing depression using EEG: A review," *Translational Neuroscience*, vol. 13, no. 1, pp. 224–235, 2022.

[8] A. Safayari and H. Bolhasani, "Depression diagnosis by deep learning using EEG signals: A systematic review," *Medicine in Novel Technology and Devices*, vol. 12, p. 100102, 2021.

[9] T. Insel, B. Cuthbert, M. Garvey, R. Heinssen, D. S. Pine, K. Quinn, C. Sanislow, and P. Wang, "Research domain criteria (RDoC): toward a new classification framework for research on mental disorders," *American Journal of psychiatry*, vol. 167, no. 7, pp. 748–751, 2010.

[10] R. Ranjan, B. Chandra Sahana, and A. Kumar Bhandari, "Ocular artifact elimination from electroencephalography signals: A systematic review," *Biocybernetics and Biomedical Engineering*, vol. 41, no. 3, pp. 960–996, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0208521621000838

[11] Y. Zhou, S. Huang, Z. Xu, P. Wang, X. Wu, and D. Zhang, "Cognitive Workload Recognition Using EEG Signals and Machine Learning: A Review," *IEEE Transactions on Cognitive and Developmental Systems*, vol. 14, no. 3, pp. 799–818, 2022.

[12] X. Jiang, G.-B. Bian, and Z. Tian, "Removal of Artifacts from EEG Signals: A Review," *Sensors*, vol. 19, no. 5, 2019. [Online]. Available: https://www.mdpi.com/1424-8220/19/5/987

[13] H. A. Abbass, "Calibrating independent component analysis with Laplacian reference for real-time EEG artifact removal," in *Neural Information Processing: 21st International Conference, ICONIP 2014, Kuching, Malaysia, November 3-6, 2014. Proceedings, Part III 21*. Springer, 2014, pp. 68–75.

[14] M. Klug and K. Gramann, "Identifying key factors for improving ICA-based decomposition of EEG data in mobile and stationary experiments," *European Journal of Neuroscience*, vol. 54, pp. 8406 – 8420, 2020.

[15] V. Roy and S. Shukla, "Designing Efficient Blind Source Separation Methods for EEG Motion Artifact Removal Based on Statistical Evaluation," *Wireless Personal Communications*, pp. 1–17, 2019.

[16] M. H. Soomro, N. Badruddin, and M. Yusoff, "Comparison of blind source separation methods for removal of eye blink artifacts from EEG," *2014 5th International Conference on Intelligent and Advanced Systems (ICIAS)*, pp. 1–6, 2014.

[17] W. De Clercq, A. Vergult, B. Vanrumste, W. Van Paesschen, and S. Van Huffel, "Canonical Correlation Analysis Applied to Remove Muscle Artifacts From the Electroencephalogram," *IEEE Transactions on Biomedical Engineering*, vol. 53, no. 12, pp. 2583–2587, 2006.

[18] J. Gao, C. Zheng, and P. Wang, "Online Removal of Muscle Artifact from Electroencephalogram Signals Based on Canonical Correlation Analysis," *Clinical EEG and Neuroscience*, vol. 41, no. 1, pp. 53–59, 2010, pMID: 20307017. [Online]. Available: https://doi.org/10.1177/155005941004100111

[19] Wikimedia Commons, "Electrode locations of International 10-20 system for EEG (electroencephalography) recording," 2010, last accessed 28 January 2024. [Online]. Available: https://commons.wikimedia.org/wiki/File:21_electrodes_of_International_10-20_system_for_EEG.svg

[20] S. Sanei and J. A. Chambers, *EEG signal processing and machine learning*. John Wiley & Sons, 2021.

[21] M. Borga, "Canonical correlation: a tutorial," *On line tutorial http://people. imt. liu. se/magnus/cca*, vol. 4, no. 5, 2001.

[22] C.-T. Lin, C.-S. Huang, W.-Y. Yang, A. K. Singh, C.-H. Chuang, Y.-K. Wang *et al.*, "Real-time EEG signal enhancement using canonical correlation analysis and Gaussian mixture clustering," *Journal of healthcare engineering*, vol. 2018, 2018.

[23] O. Friman, M. Borga, P. Lundberg, and H. Knutsson, "Exploratory fMRI analysis by autocorrelation maximization," *NeuroImage*, vol. 16, no. 2, pp. 454–464, 2002.

[24] D. Safieddine, A. Kachenoura, L. Albera, G. Birot, A. Karfoul, A. Pasnicu, A. Biraben, F. Wendling, L. Senhadji, and I. Merlet, "Removal of muscle artifact from EEG data: comparison between stochastic (ICA and CCA) and deterministic (EMD and wavelet-based) approaches," *EURASIP Journal on Advances in Signal Processing*, vol. 2012, no. 1, pp. 1–15, 2012.

[25] J. V. Stone, "Independent component analysis: an introduction," *Trends in cognitive sciences*, vol. 6, no. 2, pp. 59–64, 2002.

[26] L. Pion-Tonachini, K. Kreutz-Delgado, and S. Makeig, "ICLabel: An automated electroencephalographic independent component classifier, dataset, and website," *NeuroImage*, vol. 198, pp. 181–197, 2019.

[27] I. Kinder, K. Friganovic, J. Vukojevic, D. Mulc, T. Slukan, D. Vidovic, P. Brecic, and M. Cifrek, "Comparison of machine learning methods in classification of affective disorders," in *2020 43rd International Convention on Information, Communication and Electronic Technology (MIPRO)*. IEEE, 2020, pp. 177–181.

[28] R. A. Movahed, G. P. Jahromi, S. Shahyad, and G. H. Meftahi, "A major depressive disorder classification framework based on EEG signals using statistical, spectral, wavelet, functional connectivity, and nonlinear analysis," *Journal of Neuroscience Methods*, vol. 358, p. 109209, 2021.

[29] G. Ciaburro, *MATLAB for machine learning*. Packt Publishing Ltd, 2017.

[30] D. V. Carvalho, E. M. Pereira, and J. S. Cardoso, "Machine Learning Interpretability: A Survey on Methods and Metrics," *Electronics*, vol. 8, no. 8, 2019. [Online]. Available: https://www.mdpi.com/2079-9292/8/8/832