Viti i XVI-të i Botimit, Nr.1
Qershor 2024

QASJET E INTELIGJENCËS ARTIFICIALE DHE SHKENCËS KOMPJUTERIKE PËR KLASIFIKIMIN E SINJALIT EEG: ALGORITMET DHE APLIKIMET

Aurela Qamili *, Jozef Kola **

** Albanian University, Fakulteti i Shkencave të Aplikuara dhe Ekonomike,*

Departamenti i Inxhinierive

Abstrakt

Aplikimi i inteligjencës artificiale (AI) në shkencën mjekësore, veçanërisht përmes analizës së të dhënave të elektroencefalografisë (EEG), përfaqëson një hap të rëndësishëm drejt kuptimit dhe interpretimit të kompleksitetit të aktivitetit të trurit të njeriut. Përdorimi i të dhënave EEG përfshin fusha të ndryshme, duke përfshirë, por pa u kufizuar në, neurologjinë, psikiatrinë dhe ndërfaqet tru-kompjuter (BCI), duke ofruar një vështrim jo-invaziv në aktivitetet elektrike të trurit me implikime për diagnostikimin, ndërhyrjet terapeutike, dhe zhvillimin e teknologjive ndihmëse. Me avamcimin e teknikave të sofistikuara të machine-learning (ML) dhe deep-learning (DL), potenciali për të deshifruar dhe klasifikuar këto sinjale është rritur në mënyrë eksponenciale, duke premtuar përparime në shkencën mjekësore, neuropsikologji dhe më gjerë.

Ky punim eksploron në mënyrë sistematike aplikimin e metodologjive të machine-learning të aplikuara në klasifikimin e sinjalit EEG, duke shqyrtuar si algoritmet tradicionale ML ashtu edhe modelet e avancuara DL. Studimi ynë përpilon dhe vlerëson algoritme të ndryshme, duke përfshirë Makinat Vektoriale Mbështetëse (SVM), Rrjetet Neurale Konvolucionale (CNN) dhe Rrjetat Neurale Recurrent (RNN), ndër të tjera, për efikasitetin e tyre në klasifikimin e saktë të sinjaleve EEG në një mori aplikimesh duke filluar nga konfiskimet, zbulimi deri në analizën e gjendjes mendore. Ne thellojmë nuancat teknike të këtyre algoritmeve, duke theksuar pikat e forta, kufizimet dhe grupet specifike të të dhënave EEG që ato janë aplikuar. Ky artikull rishikues shërben si një burim për studiuesit dhe praktikuesit në fushat e neuroshkencës, inteligjencës artificiale dhe më gjerë, duke ofruar njohuri mbi marrëdhënien e ndërlikuar midis aktivitetit të trurit dhe machine-learning.

Fjalë çelës: *Inteligjenca Artificiale, EEG, marrja e të dhënave, algoritmet e klasifikimit, trendet në zhvillim.*

MACHINE LEARNING APPROACHES FOR EEG SIGNAL CLASSIFICATION: ALGORITHMS AND APPLICATIONS

Abstract

The fusion of artificial intelligence (AI) with medical science, particularly through the analysis of Electroencephalography (EEG) data, represents a significant leap toward understanding and interpreting the complexities of human brain activity. The utility of EEG data spans various domains, including, but not limited to, neurology, psychiatry, and brain-computer interfaces (BCI), offering a non-invasive peek into the electrical activities of the brain with implications for diagnostics, therapeutic interventions, and the development of assistive technologies. With the advent of sophisticated machine learning (ML) and deep learning (DL) techniques, the potential to decode and classify these signals has grown exponentially, promising breakthroughs in medical science, neuropsychology, and beyond.

This review systematically explores the breadth of machine learning methodologies applied to EEG signal classification, scrutinizing both traditional ML algorithms and advanced DL models. Our study compiles and assesses various algorithms, including Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN), among others, for their efficacy in accurately classifying EEG signals for a multitude of applications ranging from seizure detection to mental state analysis. We delve into the technical nuances of these algorithms, highlighting their strengths, limitations, and the specific EEG datasets they have been applied. This review article is poised to serve as an invaluable resource for researchers and practitioners in the fields of neuroscience, artificial intelligence, and beyond, offering insights into the intricate relation between brain activity and machine learning.

Keywords: *Artificial Intelligence, EEG, data acquisition, classification algorithms, emerging trends.*

1. Introduction

Electroencephalography, or EEG, is a technique used to analyze electrical signals in the brain. It involves monitoring voltage variations produced by ionic currents in the brain's neurons. An EEG signal is created by continually collecting EEG impulses with scalp electrodes. The main applications of EEG are in the diagnosis and treatment of a variety of brain conditions, including epilepsy, tremors, concussions, strokes, and sleep problems. Additionally, its use in conjunction with machine learning is growing in areas such as research on sleep disorders and the detection of epileptic seizures. EEG signals are useful for researching brain activity and can even be utilized in video games to manipulate objects using brainwaves [1]. By decoding neural activity, EEG classification enables diagnosis and monitoring of neurological disorders, empowers individuals with motor disabilities through brain-controlled devices, enhances our understanding of cognitive processes and emotional states, enables brain-machine interaction, aids in mental health assessment and treatment, facilitates drug development research, and drives innovation in healthcare technologies. Its versatility and applicability make EEG signal classification a cornerstone in unlocking the mysteries of the brain and improving human well-being [2].

Machine learning significantly enhances EEG data analysis by employing algorithms to decipher brain activity, facilitating the detection of conditions like epilepsy, and analyzing sleep stages. Techniques such as Support Vector Machines, neural networks, and wavelet transforms extract crucial information, improving EEG pattern classification accuracy. This advancement enables early diagnosis, continuous monitoring, and preemptive treatment, marking a shift towards personalized healthcare. Leveraging vast EEG data, machine learning offers precise diagnostic outcomes, embodying a transformation in managing neurological disorders with previously unattainable insights [1][3].

The purpose of this review is to present a thorough examination of the significance of classifying EEG signals in various fields. We intend to highlight its role in neuroscience, brain-computer interfaces, cognitive psychology, robotics, mental health monitoring, biomedical research, and pharmaceutical development. By analyzing innovative classification methods, obstacles faced, and upcoming trends we aim to offer insights for researchers and professionals. This review strives to underscore the significance of EEG signal classification in advancing knowledge and promoting advancements to encourage collaborative endeavors and drive progress within the industry.

2. CLASSIFICATION ALGORITHMS AND APPLICATIONS

Classification algorithms in machine learning are techniques that allow computers to categorize or classify data into predefined classes or groups. These algorithms analyze input data and use patterns to determine the category it belongs to. Common examples include decision trees, support vector machines, neural networks, and k-nearest neighbors. Classification is widely used in applications such as spam detection, image recognition, and medical diagnosis, where the objective is to accurately assign each input to one of several categories based on its characteristics. This section covers several types of classification techniques used in analyzing EEG signals. This includes Support Vector Machines, Convolutional Neural Networks, and Recurrent Neural Networks. The section delves into how these methods are used for diagnosing conditions by creating interfaces between the brain and computers and studying cognitive functions. It also looks at the benefits, obstacles, and practical applications of these algorithms, in different fields.

2.1. Support Vector Machines (SVM)

The foundation of support vector machines (SVMs) is the advancement of computational learning theory. Their precision and capacity to manage several predictors increased attention in biomedical applications. By projecting the predictors onto a new, higher-dimensional space where they may be separated linearly, SVMs extend the separation to data that cannot be separated linearly [4]. SVMs are commonly used in EEG classification because they excel at managing data and recognizing nonlinear connections allowing for tasks, like identifying seizures, understanding emotions, and classifying cognitive states. Their principles rely on maximizing the margin between different classes while minimizing classification errors, making them robust and effective for various EEG analysis tasks [5][6]. Fig 1 shows the steps involved in using SVM for EEG data classification, from initial data handling to the output of classified results, and Fig 2 shows how the SVM algorithm works.

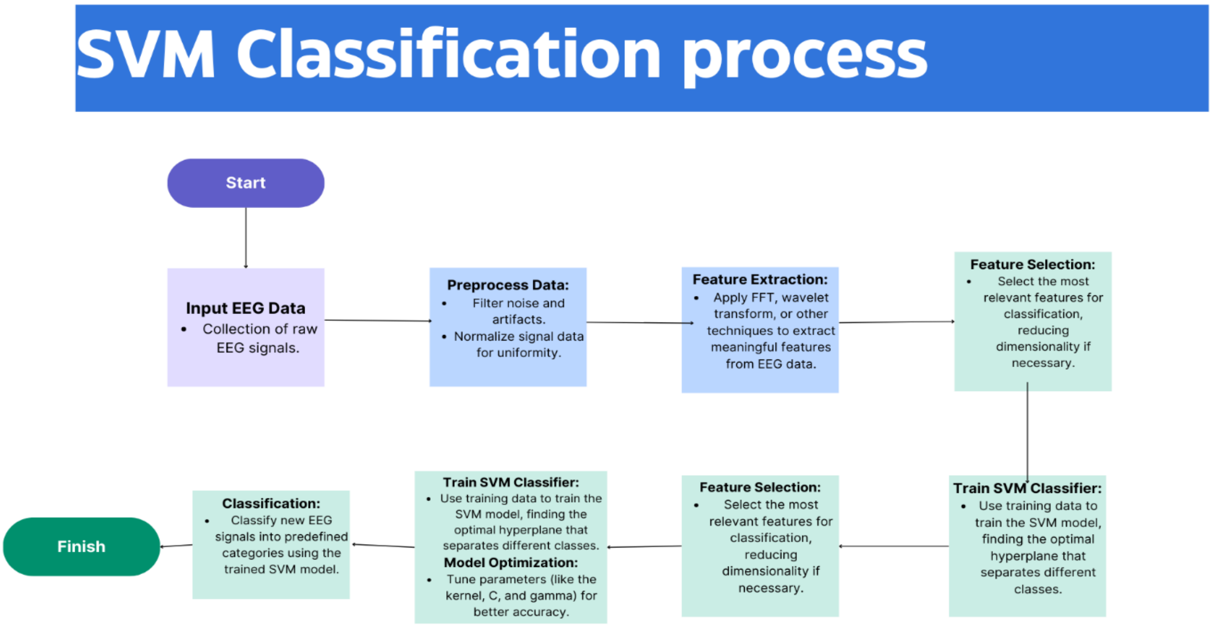

Figura 1. Flowchart of the SVM Classification process

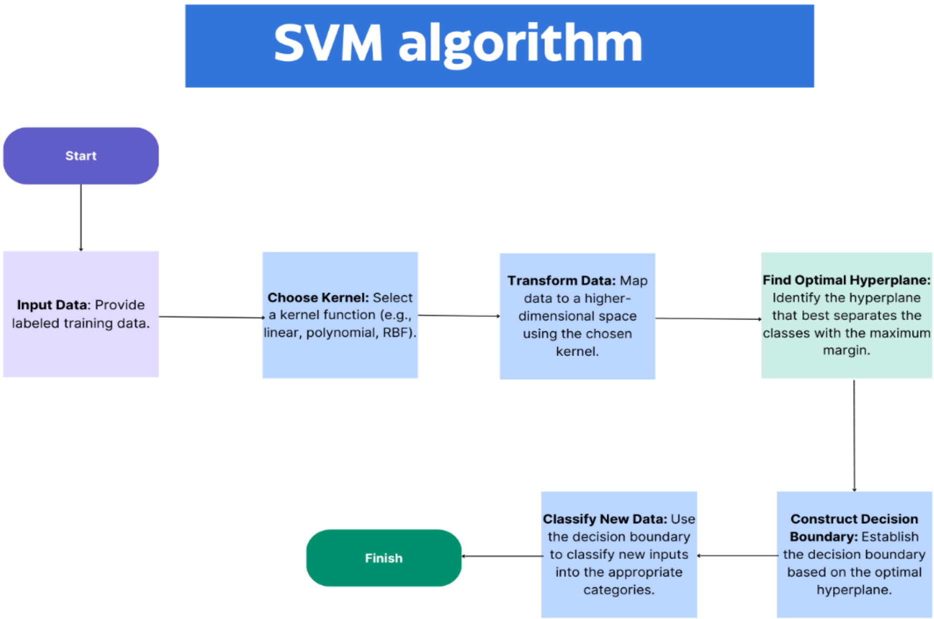

Figura 2. How the SVM algorithm works

SVM selection depends on the specific task performed. Table 1 shows different applications and optimization techniques used for SVM while performing EEG analysis.

Table 1. Applications and optimization techniques used for SVM.

Variant	**Optimization**	**Task**	**Reference**
Kernel Selection	- Linear, Polynomial, RBF kernels	EEG feature classification	[7][8]
Hyperparameter Tuning	- Grid search, Randomized search	EEG-based emotion recognition	[9]
Class Imbalance Handling	- Class-weighted SVM, Resampling methods	Seizure detection	[10]
Multi-class Classification	- One-versus-Rest (OvR) SVM, One-versus-One (OvO) SVM	Cognitive state classification	[11][12]
Incremental Learning	- Online SVM	Real-time EEG analysis	[13]
Ensemble Methods	- Bagging, Boosting	EEG-based motor imagery decoding	[14][15]
Feature Selection and Dimensionality Reduction	- Recursive Feature Elimination, PCA	EEG-based mental workload assessment	[16]
Domain-Specific Adaptations	- Task-specific feature engineering, Regularization	EEG-based cognitive load estimation	[17][18]

2.2. *Convolutional Neural Networks (CNN)*

Convolutional Neural Networks (CNNs) are a class of deep learning models specifically designed for analyzing grid-like data, such as images or sequences. In the context of EEG data analysis, CNNs are adapted to take advantage of the spatial and temporal relationships present in EEG signals. The architecture of a CNN typically consists of multiple layers explained in Table 2.

Table 2. Layers found in a Convolutional Neural Network (CNN) architecture used for EEG data analysis.

Layer Type	**Description**
Input Layer	Represents the raw EEG data input, typically in the form of a time-series matrix or tensor.
Convolutional Layers	Perform feature extraction by convolving learned filters across the input data to capture spatial features and patterns.
Pooling Layers	Downsample the feature maps obtained from the convolutional layers, reducing spatial dimensions while preserving key features.
Fully Connected Layers	Perform high-level feature representation and classification, mapping extracted features to output classes.

Different training strategies are used based on the specific application. Table 3 shows the used techniques in various aspects of EEG analysis.

Table 3. Training strategies for Convolutional Neural Networks (CNNs) in EEG data analysis.

Training Strategy	EEG Application	Reference
Data Preprocessing	Motor imagery classification	[19]
Architecture Design	Seizure detection	[20]
Regularization Techniques	Emotion recognition	[21]
Optimization Algorithms	Cognitive workload estimation	[22]
Validation and Testing	Sleep stage classification	[23]

Convolutional neural networks, or CNNs, have several benefits regarding EEG categorization. This is mostly because of their capacity to extract pertinent features from unprocessed EEG data automatically. CNNs can identify patterns at various temporal and spatial scales by obtaining hierarchical representations of EEG signals, which improves classification accuracy. Furthermore, they are more robust to minor changes in signal alignment because of their translation invariance property, which enables them to detect EEG patterns independent of their exact temporal placement. But to guarantee that CNN-based EEG classification models are effective, issues including overfitting, data scarcity, and computational complexity need to be resolved. To attain dependable and comprehensible classification outcomes, mitigating these issues necessitates careful consideration of data augmentation, regularization strategies, and model complexity management.

2.3. *Recurrent Neural Networks (RNN)*

Recurrent Neural Networks (RNNs) are designed to effectively model sequential data, making them well-suited for analyzing time-series EEG signals [24]. LSTM and GRU networks, two popular variants of RNNs, address the vanishing gradient problem by introducing gating mechanisms that regulate the flow of information through the network [25]. LSTM networks maintain long-term dependencies in EEG sequences by incorporating memory cells with forget gates, input gates, and output gates [24], while GRU networks simplify this architecture by combining the forget and input gates into a single update gate [25]. Both LSTM and GRU networks have demonstrated success in EEG classification tasks [26], offering advantages such as capturing temporal dynamics, managing variable-length sequences, and mitigating gradient vanishing issues. However, optimizing these networks requires careful consideration of hyperparameters, training strategies, and model architecture design to ensure effective learning and generalization of EEG data.

2.3.1. *Sequential modeling of EEG time-series data*

Sequential modeling of EEG time-series data with Recurrent Neural Networks (RNNs) is a powerful approach that leverages the temporal dependencies inherent in EEG signals. RNNs are well-suited for this task as they can capture sequential patterns and dynamics over time, allowing for the analysis of EEG data in its entirety [27]. By processing EEG data sequentially, RNNs can learn to identify complex temporal relationships, such as the propagation of neural activity during different cognitive tasks or the emergence of characteristic patterns preceding epileptic seizures. This sequential modeling capability enables RNNs to provide insights into the dynamic nature of brain activity and its correlation with various cognitive processes and neurological conditions [28]. However, training RNNs on EEG data presents challenges such as vanishing gradients, long-range dependencies, and model interpretability issues. Addressing these challenges requires careful consideration of network architectures, optimization techniques, and regularization strategies to ensure robust and reliable performance in analyzing EEG time-series data.

2.4. *Random Forests and Decision Trees*

Random Forests and Decision Trees are widely employed in EEG analysis for tasks ranging from classifying cognitive states to artifact detection and removal. These ensemble learning techniques offer straightforward interpretation and effective classification capabilities, making them valuable tools for deciphering EEG data [29]. Decision Trees provide insights into feature importance, aiding in understanding neural mechanisms and biomarkers associated with cognitive processes or neurological disorders [30]. Moreover, Random Forests enhance classification robustness by aggregating multiple decision trees, mitigating overfitting, and improving generalization. Their applications extend to personalized healthcare, where they assist in diagnosis, prognosis, and treatment planning based on individual EEG patterns. In brain-computer interface systems, these techniques decode mental commands from EEG signals, enabling direct communication between the brain and external devices.

Table 4 outlines interpretability and scalability considerations for Random Forests and Decision Trees.

Table 4. Interpretability and scalability considerations for Random Forests and Decision Trees in EEG.

Consideration	Random Forests	Decision Trees
Interpretability	- Lower interpretability compared to individual decision trees due to their ensemble nature. - The final decision is based on the aggregation of multiple trees, making it challenging to interpret the overall model logic. - Feature importance analysis can be performed to understand the contribution of distinctive features to classification decisions.	- Each tree represents a sequence of simple decision rules based on feature thresholds. - The decision-making process is transparent and easy to understand. - This transparency allows for a straightforward interpretation of the model's logic and feature importance.
Scalability	-Excellent scalability in handling large datasets and high-dimensional feature spaces. -The parallel construction enables efficient training on distributed computing architectures. -Suitable for large-scale EEG analysis tasks.	- Scalability limitations, especially with large datasets or high-dimensional feature spaces. - The recursive partitioning process can become computationally intensive, leading to slower training times and memory constraints for large datasets.

2.5. *K-Nearest Neighbors (KNN) and Other Similarity-Based Methods*

KNN classifies EEG patterns based on the majority vote of their closest neighbors in the feature space. It is non-parametric and does not require explicit model training, which makes it appropriate for a range of EEG classification tasks. Its performance is, however, very dependent on the number of neighbors (k) chosen and the distance metric chosen [31].

Besides KNN, other similarity-based methods, such as Locally Weighted Learning (LWL) and Dynamic Time Warping (DTW), are utilized for EEG pattern recognition. LWL assigns weights to neighboring samples based on their distance from the query point, while DTW measures the similarity between time-series EEG data by aligning and stretching their temporal sequences. These methods offer flexibility and robustness in capturing complex patterns in EEG signals but may require parameter tuning and computational resources [32].

3. *Challenges in EEG Classification*

Due to the complexity and diversity of EEG data, there are several challenges in EEG categorization, which call for creative solutions [33]. Classification algorithms have considerable hurdles due to the high-dimensional and noisy nature of EEG data, as well as intra- and inter-subject variability [34]. Furthermore, non-stationary properties are frequently observed in EEG signals, necessitating the use of techniques that can capture temporal dynamics and changes across time. In addition, classification performance may be distorted by class imbalance, which occurs when some classes are underrepresented in the dataset and call for specific handling methods [35]. Furthermore, in clinical contexts where the reasoning behind classification judgments needs to be apparent and comprehensible, the interpretability of classification models is critical to EEG analysis [36]. To overcome these obstacles, reliable classification algorithms that can manage noisy, dynamic, high-dimensional EEG data while maintaining interpretability and generalizability across a range of EEG applications must be developed. Table 5 shows the most usual challenges in EEG data classification.

Table 5. Challenges in EEG classification and practical solutions

Challenges	**Possible Solutions**
High-dimensional and noisy EEG data	Feature selection and extraction techniques, dimensionality reduction methods (e.g., PCA), noise removal algorithms
Inter-subject and intra-subject variability	Domain adaptation techniques, transfer learning approaches, data augmentation methods
Non-stationary characteristics of EEG signals	Adaptive learning algorithms, time-frequency analysis methods (e.g., wavelet transform), online learning approaches
Class imbalance in EEG datasets	Resampling techniques (e.g., oversampling, under-sampling), class-weighted loss functions, ensemble learning methods
Lack of interpretability of classification models	Transparent model architectures (e.g., decision trees), feature importance analysis, model-agnostic interpretability methods

4. *Evalutaion metrics and methodologies*

When evaluating the efficacy and performance of classification models in EEG analysis, evaluation metrics and procedures are essential. EEG signals are intricate and multidimensional, so it is essential to precisely assess how well classification algorithms function to guarantee consistent and understandable outcomes [37]. Researchers and practitioners can advance the area of EEG-based categorization and enable informed decision-making by gaining useful insights into the strengths and limitations of their models using suitable assessment metrics and procedures [38]. In this context, assessing the performance of classification algorithms rigorously and enhancing their usefulness in practical applications requires a grasp of the wide range of evaluation metrics and approaches that are accessible. Table 6 provides an overview of key evaluation metrics and methodologies for assessing the performance of classification models in EEG analysis.

Table 6. Key evaluation metrics and methodologies for assessing the performance of classification models.

Category	Metrics and Methodologies	
Performance Metrics for Accuracy	- Accuracy - Precision - Recall (Sensitivity) - Specificity	- F1 Score - ROC Curve - AUC (Area Under the ROC Curve)

Cross-Validation Strategies	- k-Fold Cross-Validation - Leave-One-Out Cross-Validation - Stratified Cross-Validation	- Repeated Cross-Validation - Shuffle Split Cross-Validation
Model Selection Techniques	- Grid Search - Random Search - Bayesian Optimization	- Cross-Validation Grid Search - Ensemble Methods for Model Selection

5. *Conclusion*

In conclusion, the collective efforts undertaken have provided a comprehensive exploration of EEG signal processing and classification, highlighting key methodologies, challenges, and advancements in the field. Through the examination of various signal processing techniques, and classification algorithms such as machine learning and deep learning approaches, significant insights have been gained into the intricate nature of EEG data analysis.

This study provides an extensive overview of evaluation metrics and methodologies for assessing classification models in EEG analysis. Through the exploration of performance metrics for accuracy, cross-validation strategies, and model selection techniques, we have identified critical tools and approaches essential for rigorously evaluating classification models' performance in EEG-based classification tasks.

Leveraging these insights and approaches will be essential to promoting additional innovation and easing the translation of research findings into significant real-world applications as EEG signal processing and categorization research continues to advance.

References

[1]. Hosseini, M. P., Hosseini, A., & Ahi, K. (2021). A Review on Machine Learning for EEG Signal Processing in Bioengineering. *IEEE Reviews in Biomedical Engineering*, *14*, 204–218. https://doi.org/10.1109/rbme.2020.2969915

[2]. Khosla, A., Khandnor, P., & Chand, T. (2020, April). A comparative analysis of signal processing and classification methods for different applications based on EEG signals. *Biocybernetics and Biomedical Engineering*, *40*(2), 649–690. https://doi.org/10.1016/j.bbe.2020.02.002

[3]. Rasheed, K., Qayyum, A., Qadir, J., Sivathamboo, S., Kwan, P., Kuhlmann, L., O'Brien, T., & Razi, A. (2021). Machine Learning for Predicting Epileptic Seizures Using EEG Signals: A Review. *IEEE Reviews in Biomedical Engineering*, *14*, 139–155. https://doi.org/10.1109/rbme.2020.3008792

[4]. Subasi, A., & Ismail Gursoy, M. (2010, December). EEG signal classification using PCA, ICA, LDA and support vector machines. *Expert Systems With Applications*, *37*(12), 8659–8666. https://doi.org/10.1016/j.eswa.2010.06.065

[5]. Pooja, Pahuja, S., & Veer, K. (2021, May 4). Recent Approaches on Classification and Feature Extraction of EEG Signal: A Review. *Robotica*, *40*(1), 77–101. https://doi.org/10.1017/s0263574721000382

[6]. Kumar, P. N., & Kareemullah, H. (2014, February). EEG signal with feature extraction using SVM and ICA classifiers. *International Conference on Information Communication and Embedded Systems (ICICES2014)*. https://doi.org/10.1109/icices.2014.7034090

[7]. Gupta, R., Alam, M. A., & Agarwal, P. (2020, August 1). Modified Support Vector Machine for Detecting Stress Level Using EEG Signals. *Computational Intelligence and Neuroscience*, *2020*, 1–14. https://doi.org/10.1155/2020/8860841

[8]. WANG, L., JOHNSON, D., & LIN, Y. (2021, May 31). Using EEG to detect driving fatigue based on common spatial pattern and support vector machine. *Turkish Journal of Electrical Engineering and Computer Sciences*, *29*(3), 1429–1444. https://doi.org/10.3906/elk-2008-83

[9]. Rahman, A. A., Faisal, F., Nishat, M. M., Siraji, M. I., Khalid, L. I., Khan, M. R. H., & Reza, M. T. (2021, December 8). Detection of Epileptic Seizure from EEG Signal Data by Employing Machine Learning Algorithms with Hyperparameter Optimization. *2021 4th International Conference on Bio-Engineering for Smart Technologies (BioSMART)*. https://doi.org/10.1109/biosmart54244.2021.9677770

[10]. Masum, M., Shahriar, H., & Haddad, H. M. (2020, July). Epileptic Seizure Detection for Imbalanced Datasets Using an Integrated Machine Learning Approach. *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. https://doi.org/10.1109/embc44109.2020.9175632

[11]. Jeon, J., & Cai, H. (2022, August). Multi-class classification of construction hazards via cognitive states assessment using wearable EEG. *Advanced Engineering Informatics*, *53*, 101646. https://doi.org/10.1016/j.aei.2022.101646

[12]. Sharma, N., Kolekar, M. H., & Jha, K. (2021, January). EEG based dementia diagnosis using multi-class support vector machine with motor speed cognitive test. *Biomedical Signal Processing and Control*, *63*, 102102. https://doi.org/10.1016/j.bspc.2020.102102

[13]. Thanigaivelu, P. S., Sridhar, S. S., & Sulthana, S. F. (2023, February 27). OISVM: Optimal Incremental Support Vector Machine-based EEG Classification for Brain-computer Interface Model. *Cognitive Computation*, *15*(3), 888–903. https://doi.org/10.1007/s12559-023-10120-z

[14]. Echtioui, A., Zouch, W., Ghorbel, M., Mhiri, C., & Hamam, H. (2021, June 28). A Novel Ensemble Learning Approach for Classification of EEG Motor Imagery Signals. *2021 International Wireless Communications and Mobile Computing (IWCMC)*. https://doi.org/10.1109/iwcmc51323.2021.9498833

[15]. Miah, M. O., Muhammod, R., Mamun, K. A. A., Farid, D. M., Kumar, S., Sharma, A., & Dehzangi, A. (2021, December). CluSem: Accurate clustering-based ensemble method to predict motor imagery tasks from multi-channel EEG data. *Journal of Neuroscience Methods*, *364*, 109373. https://doi.org/10.1016/j.jneumeth.2021.109373

[16]. Zhang, Y., Guo, H., Zhou, Y., Xu, C., & Liao, Y. (2023, January). Recognising drivers' mental fatigue based on EEG multi-dimensional feature selection and fusion. *Biomedical Signal Processing and Control*, *79*, 104237. https://doi.org/10.1016/j.bspc.2022.104237

[17]. Zhou, Y., Wang, P., Gong, P., Wei, F., Wen, X., Wu, X., & Zhang, D. (2023). Cross-Subject Cognitive Workload Recognition Based on EEG and Deep Domain Adaptation. *IEEE Transactions on Instrumentation and Measurement*, *72*, 1–12. https://doi.org/10.1109/tim.2023.3276515

[18]. Li, X., Zhang, Y., Tiwari, P., Song, D., Hu, B., Yang, M., Zhao, Z., Kumar, N., & Marttinen, P.

(2022, November 21). EEG Based Emotion Recognition: A Tutorial and Review. *ACM Computing Surveys*, *55*(4), 1–57. https://doi.org/10.1145/3524499

[19]. Mattioli, F., Porcaro, C., & Baldassarre, G. (2021, December 1). A 1D CNN for high accuracy classification and transfer learning in motor imagery EEG-based brain-computer interface. *Journal of Neural Engineering*, *18*(6), 066053. https://doi.org/10.1088/1741-2552/ac4430

[20]. O'Shea, A., Lightbody, G., Boylan, G., & Temko, A. (2020, March). Neonatal seizure detection from raw multi-channel EEG using a fully convolutional architecture. *Neural Networks*, *123*, 12–25. https://doi.org/10.1016/j.neunet.2019.11.023

[21]. Samavat, A., Khalili, E., Ayati, B., & Ayati, M. (2022). Deep Learning Model With Adaptive Regularization for EEG-Based Emotion Recognition Using Temporal and Frequency Features. *IEEE Access*, *10*, 24520–24527. https://doi.org/10.1109/access.2022.3155647

[22]. Das Chakladar, D., Dey, S., Roy, P. P., & Dogra, D. P. (2020, July). EEG-based mental workload estimation using deep BLSTM-LSTM network and evolutionary algorithm. *Biomedical Signal Processing and Control*, *60*, 101989. https://doi.org/10.1016/j.bspc.2020.101989

[23]. Yang, B., Zhu, X., Liu, Y., & Liu, H. (2021, July). A single-channel EEG based automatic sleep stage classification method leveraging deep one-dimensional convolutional neural network and hidden Markov model. *Biomedical Signal Processing and Control*, *68*, 102581. https://doi.org/10.1016/j.bspc.2021.102581

[24]. Zeng, W., Guo, Z., Shen, Y., Bashir, A. K., Yu, K., Al-Otaibi, Y. D., & Gao, X. (2021, January 6). Data-driven management for fuzzy sewage treatment processes using hybrid neural computing. *Neural Computing and Applications*, *35*(33), 23781–23794. https://doi.org/10.1007/s00521-020-05655-3

[25]. Cossu, A., Carta, A., Lomonaco, V., & Bacciu, D. (2021, November). Continual learning for recurrent neural networks: An empirical evaluation. *Neural Networks*, *143*, 607–627. https://doi.org/10.1016/j.neunet.2021.07.021

[26]. Du, Y., & Liu, J. (2022, June 1). IENet: a robust convolutional neural network for EEG based brain-computer interfaces. *Journal of Neural Engineering*, *19*(3), 036031. https://doi.org/10.1088/1741-2552/ac7257

[27]. Sikka, A., Jamalabadi, H., Krylova, M., Alizadeh, S., van der Meer, J. N., Danyeli, L., Deliano, M., Vicheva, P., Hahn, T., Koenig, T., Bathula, D. R., & Walter, M. (2020, February 24). Investigating the temporal dynamics of electroencephalogram (EEG) microstates using recurrent neural networks. *Human Brain Mapping*, *41*(9), 2334–2346. https://doi.org/10.1002/hbm.24949

[28]. Hashemnia, S., Grasse, L., Soni, S., & Tata, M. S. (2021, July 8). Human EEG and Recurrent Neural Networks Exhibit Common Temporal Dynamics During Speech Recognition. *Frontiers in Systems Neuroscience*, *15*. https://doi.org/10.3389/fnsys.2021.617605

[29]. Antoniou, E., Bozios, P., Christou, V., Tzimourta, K. D., Kalafatakis, K., G. Tsipouras, M., Giannakeas, N., & Tzallas, A. T. (2021, March 27). EEG-Based Eye Movement Recognition Using Brain–Computer Interface and Random Forests. *Sensors*, *21*(7), 2339. https://doi.org/10.3390/s21072339

[30]. Bastos, N. S., Marques, B. P., Adamatti, D. F., & Billa, C. Z. (2020, July 9). Analyzing EEG Signals Using Decision Trees: A Study of Modulation of Amplitude. *Computational Intelligence and Neuroscience*, *2020*, 1–11. https://doi.org/10.1155/2020/3598416

[31]. Sha'abani, M. N. A. H., Fuad, N., Jamal, N., & Ismail, M. F. (2020). kNN and SVM Classification for EEG: A Review. *Lecture Notes in Electrical Engineering*, 555–565. https://doi.org/10.1007/978-981-15-2317-5_47

[32]. Fatlawi, H. K., & Kiss, A. (2022, November 11). Similarity-Based Adaptive Window for Improving Classification of Epileptic Seizures with Imbalance EEG Data Stream. *Entropy*, *24*(11), 1641. https://doi.org/10.3390/e24111641

[33]. Kappenman, E. S., Farrens, J. L., Zhang, W., Stewart, A. X., & Luck, S. J. (2021, January). ERP CORE: An open resource for human event-related potential research. *NeuroImage*, *225*, 117465. https://doi.org/10.1016/j.neuroimage.2020.117465

[34]. Chaddad, A., Wu, Y., Kateb, R., & Bouridane, A. (2023, July 16). Electroencephalography Signal Processing: A Comprehensive Review and Analysis of Methods and Techniques. *Sensors*, *23*(14), 6434. https://doi.org/10.3390/s23146434

[35]. Bates, S., Hastie, T., & Tibshirani, R. (2023, May 15). Cross-Validation: What Does It Estimate and How Well Does It Do It? *Journal of the American Statistical Association*, 1–12. https://doi.org/10.1080/01621459.2023.2197686

[36]. Alpaydin, E. (2020, March 24). *Introduction to Machine Learning, fourth edition*. MIT Press. http://books.google.ie/books?id=uZnSDwAAQBAJ&printsec=frontcover&dq=Introduction+to+Machine+Learning,+fourth+edition&hl=&cd=1&source=gbs_api

[37]. Boonyakitanont, P., Lek-uthai, A., Chomtho, K., & Songsiri, J. (2020, March). A review of feature extraction and performance evaluation in epileptic seizure detection using EEG. *Biomedical Signal Processing and Control*, *57*, 101702. https://doi.org/10.1016/j.bspc.2019.101702

[38]. Vivaldi, N., Caiola, M., Solarana, K., & Ye, M. (2021, November). Evaluating Performance of EEG Data-Driven Machine Learning for Traumatic Brain Injury Classification. *IEEE Transactions on Biomedical Engineering*, *68*(11), 3205–3216. https://doi.org/10.1109/tbme.2021.3062502