

Nightmare Disorder Assistant Tool

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Abstract- *Nightmare Disorder is a sleep condition characterized by recurrent distressing dreams that lead to abrupt awakenings, emotional distress, and impaired sleep quality. It is strongly associated with psychiatric conditions such as post-traumatic stress disorder (PTSD), anxiety, and depression. Traditional diagnostic approaches rely heavily on subjective measures including patient self-reports, sleep diaries, and clinician interpretation, which often lack consistency and scalability. This paper proposes an automated EEG-based framework for detecting nightmare episodes using deep learning techniques. The system leverages spectrogram-based feature extraction to transform EEG signals into time-frequency representations, enabling effective use of Convolutional Neural Networks (CNNs) for pattern recognition. The model is trained on REM sleep EEG data, including perturbed samples designed to simulate abnormal neural activity associated with nightmares. It also incorporates a severity analysis module that evaluates the intensity of detected episodes based on spectral deviations. A web-based dashboard built using React.js and Next.js provides an interactive interface for users to upload EEG segments and visualize results. FastAPI is used as the backend framework to integrate the trained model and handle inference requests efficiently. Experimental results demonstrate classification accuracy ranging from 89% to 94.6%, indicating strong performance in distinguishing between normal and abnormal REM patterns. The system provides an objective, scalable, and interpretable solution for nightmare detection, contributing toward AI-driven advancements in sleep disorder diagnostics.*

Index Terms- EEG, Sleep Disorder, REM Sleep, Nightmare Disorder, Deep Learning.

I. INTRODUCTION

Sleep is a fundamental physiological process that plays a critical role in maintaining cognitive function, emotional stability, and overall health. Disruptions in sleep patterns can significantly impact daily functioning, leading to fatigue, impaired concentration, and long-term neurological and psychological complications [11]. Among various sleep disorders, Nightmare Disorder is particularly significant due to its strong association with emotional distress and trauma-related conditions. It is characterized by recurrent disturbing dreams that often result in abrupt

awakenings and difficulty returning to sleep, thereby affecting sleep quality and mental well-being.

Nightmares most commonly occur during Rapid Eye Movement (REM) sleep, a stage associated with heightened brain activity and vivid dreaming. During REM sleep, the brain exhibits patterns of neural activation similar to wakefulness, particularly in regions associated with emotion processing such as the amygdala and limbic system. In individuals experiencing frequent nightmares, these patterns are often dysregulated, leading to exaggerated emotional responses and fear-related dream content. Over time, repeated disturbances can contribute to chronic sleep fragmentation, increased anxiety, and even the development or worsening of psychiatric conditions such as post-traumatic stress disorder (PTSD) and depression.

Currently, the diagnosis of Nightmare Disorder primarily relies on subjective clinical methods. These include patient self-reports, structured clinical interviews, and sleep diaries maintained over extended periods. While these approaches provide valuable insights into a patient's experiences, they are inherently limited by recall bias, inconsistency, and lack of objectivity. Patients may not accurately remember dream content or frequency, and clinicians often depend on qualitative descriptions rather than measurable physiological data [12]. This makes it difficult to achieve consistent and reliable diagnosis, particularly in early or mild cases.

Polysomnography (PSG), which includes EEG monitoring, is considered a more objective method for studying sleep disorders. EEG captures electrical activity in the brain and provides insights into different sleep stages, including REM and non-REM phases [13][14]. In clinical settings, EEG recordings are manually analyzed by experts to identify abnormalities in brain wave patterns. However, this process is highly

time-consuming, requires specialized expertise, and is not scalable for large populations. Additionally, traditional EEG analysis often focuses on sleep stage classification rather than identifying specific pathological events such as nightmares.

Recent advancements in signal processing techniques have introduced methods such as spectral analysis, wavelet transforms, and time-frequency decomposition for analyzing EEG signals. These approaches enable the extraction of features from different frequency bands, including delta, theta, alpha, and beta waves. Studies have shown that abnormalities in these frequency bands, particularly increased theta activity during REM sleep, are associated with nightmare occurrences [15][16]. However, these traditional approaches rely heavily on handcrafted feature extraction, which may fail to capture complex and non-linear patterns present in EEG data.

With the rise of artificial intelligence, machine learning techniques have been increasingly applied to EEG analysis. Classical machine learning models such as Support Vector Machines (SVMs) and Random Forests have been used for sleep stage classification and anomaly detection [17]. While these methods offer improvements over manual analysis, they still depend on manually engineered features and struggle to generalize across diverse datasets. Furthermore, most of these approaches are designed for broad classification tasks and do not specifically address nightmare detection or emotional abnormalities within sleep stages.

Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated significant success in processing complex data representations [20]. By transforming EEG signals into spectrograms, it becomes possible to treat them as images and leverage CNNs for automatic feature extraction. This approach allows models to learn hierarchical patterns directly from data, eliminating the need for manual feature engineering [18][19]. Despite these advancements, most existing deep learning applications in EEG focus on sleep stage classification, seizure detection, or general neurological disorders, with limited research dedicated to nightmare-specific detection.

Another critical gap in current systems is the lack of integration between analysis and usability. Most research models remain confined to experimental settings and are not deployed as accessible tools for real-world use. There is a lack of interactive systems that allow users or clinicians to upload EEG data, receive predictions, and visualize results in an interpretable manner. Additionally, existing systems rarely incorporate severity analysis, which is crucial for understanding the intensity and clinical relevance of detected abnormalities.

In response to these limitations, this paper proposes a comprehensive deep learning-based framework for automated nightmare detection using EEG signals. The system integrates spectrogram-based feature extraction, CNN-based classification, and severity analysis within a user-friendly dashboard interface. By combining objective signal analysis with modern AI techniques and practical deployment through a web-based platform, the proposed approach aims to bridge the gap between research and real-world application, providing a scalable and interpretable solution for nightmare disorder diagnosis.

II. MOTIVATION FOR THE PAPER

The motivation for this research arises from the limitations of existing diagnostic methods for Nightmare Disorder. Current approaches rely heavily on subjective assessments, which can lead to inconsistencies, delayed diagnosis, and lack of scalability. With increasing awareness of mental health and sleep-related disorders, there is a growing need for objective, data-driven diagnostic tools.

Initial research into EEG-based sleep analysis revealed that while significant progress has been made in sleep stage classification, limited work focuses specifically on detecting nightmare episodes. Most existing systems classify sleep into REM and non-REM stages without identifying abnormalities within these stages.

Further investigation into neuroscience literature showed that nightmares are associated with distinct neural patterns, particularly in REM sleep. Variations in theta and beta frequency bands, along with irregular spectral activity, indicate abnormal emotional processing during dreams.

Additionally, advances in deep learning have demonstrated that CNNs can automatically learn complex patterns from spectrogram representations of EEG signals. However, existing research primarily focuses on general classification tasks rather than disorder-specific detection.

This motivated the development of a system that:

- Detects nightmare episodes using EEG signals
- Uses spectrogram-based deep learning
- Provides severity analysis
- Offers interpretability through visualization
- Includes a real-world dashboard for usability

The goal is to bridge the gap between subjective diagnosis and objective, scalable, AI-driven sleep disorder analysis.

III. LITERATURE SURVEY

[1] Towards a Dream Decoder: A Study Identifying Dream Emotions during REM Sleep with Machine Learning and EEG – M. Packiyathan, M. Molinas, and L. A. Moctezuma (2023).

This study explores the classification of emotional states during REM sleep using EEG signals and supervised learning techniques. The authors extract temporal and frequency-domain features to identify patterns corresponding to different emotional states in dreams. The results demonstrate that EEG signals contain meaningful indicators of emotional processing during REM sleep. However, the approach relies heavily on handcrafted feature extraction and does not utilize deep representation learning. Additionally, the study focuses on general emotional classification rather than specifically identifying nightmare episodes or evaluating severity levels.

[2] A Deep Learning Method Approach for Sleep Stage Classification with EEG Spectrogram – C. Li, Y. Qi, X. Ding, J. Zhao, T. Sang, and M. Lee (2022).

This work proposes a CNN-based framework that utilizes spectrogram representations of EEG signals for automatic sleep stage classification. By converting EEG data into time-frequency images, the model effectively captures spectral patterns associated with different sleep stages. The study demonstrates

improved accuracy compared to traditional methods. However, the system focuses primarily on sleep staging and does not address pathological conditions such as nightmares or abnormal dream activity.

[3] Classification of Sleep Stage with Biosignal Images Using Convolutional Neural Networks – H. Kim, J. Lee, and S. Lee (2022).

This research converts EEG and EOG signals into time-frequency domain representations and applies CNNs for classification into sleep stages. The study highlights the effectiveness of image-based deep learning models in analyzing biosignals. Despite its success in sleep stage classification, it lacks specialization in detecting abnormal dream patterns or nightmare-related neural activity.

[4] Deep Convolutional Neural Networks for Interpretable Analysis of EEG Sleep Stage Scoring – A. Vilamala, K. H. Madsen, and L. K. Hansen (2017).

This study introduces interpretable CNN models for EEG sleep stage classification using multitaper spectral analysis. The model generates visually interpretable representations, improving transparency in predictions. However, the work focuses on general sleep stage scoring and does not address emotional or nightmare-related analysis.

[5] Analysis and Classification of Sleep Stage Using Deep Learning Network from Single-Channel EEG Signal – Y. Zhang, Y. Wang, and J. Wang (2017).

The authors propose a deep learning approach using single-channel EEG signals and time-frequency transformations for sleep stage classification. The system demonstrates that even limited EEG data can achieve reliable classification. However, it does not explore abnormal sleep events such as nightmares or emotional disturbances.

[6] Automatic Sleep Stage Scoring with Single-Channel EEG Using Convolutional Neural Networks – O. Tsinalis, P. M. Matthews, Y. Guo, and S. Zafeiriou (2016).

This study employs CNNs for automatic sleep stage classification using single-channel EEG data. It

demonstrates the ability of deep learning models to learn task-specific features without prior domain knowledge. However, the focus remains on general sleep stage classification rather than nightmare detection.

[7] REM Sleep Theta Changes in Frequent Nightmare Recallers – L.-P. Marquis, T. Paquette, C. Blanchette-Carrière, G. Dumel, and T. Nielsen (2017).

This research identifies significant increases in slow-theta activity during REM sleep in individuals with frequent nightmares. The findings highlight the role of theta band activity in emotional memory processing and fear-related responses. This provides a strong neurological basis for using spectral analysis in nightmare detection.

[8] Sleep Spindle and Psychopathology Characteristics of Frequent Nightmare Recallers – C. Picard-Deland, T. Paquette, L. Pigeon, and T. Nielsen (2018).

This study examines sleep spindle patterns in individuals experiencing frequent nightmares and identifies correlations with anxiety and depression. The findings suggest that abnormalities in NREM sleep also contribute to nightmare-related pathology.

[9] The Spectral Fingerprint of Sleep Problems in Post-Traumatic Stress Disorder – M. D. de Boer, M. J. Nijdam, and R. A. Jongedijk (2020).

This work analyzes EEG spectral patterns in individuals with PTSD and identifies distinct abnormalities across REM and NREM stages. The findings support the use of EEG-based spectral analysis for detecting trauma-related sleep disturbances.

[10] Deep Learning for Electroencephalogram (EEG) Classification Tasks – A. Craik, Y. He, and J. L. Contreras-Vidal (2019)

This review highlights the effectiveness of CNNs in learning hierarchical representations from EEG spectrograms. It emphasizes the advantages of deep learning over traditional feature-based methods, supporting the use of CNNs in this research.

III. LITERATURE FINDINGS

The literature survey highlights a clear transition from traditional EEG analysis methods toward deep learning-based approaches. Early studies primarily relied on handcrafted features and statistical analysis, which limited their ability to capture complex neural patterns. A key observation is that most existing research focuses on sleep stage classification rather than detecting abnormalities within those stages. Nightmare-specific detection remains largely unexplored, indicating a significant research gap.

Another important finding is the effectiveness of spectrogram-based representations in capturing time-frequency characteristics of EEG signals. Studies consistently demonstrate that CNNs perform well when applied to spectrogram images, enabling automatic feature extraction. The survey also reveals that neural activity associated with nightmares is closely linked to specific frequency bands, particularly theta waves during REM sleep. These findings reinforce the importance of frequency-aware analysis in detecting abnormal dream activity.

However, there is a lack of systems that integrate detection, severity analysis, and user interaction within a single framework. Existing tools often lack interpretability and practical usability.

These insights directly inform the proposed system, which combines spectrogram-based CNN classification, severity analysis, and an interactive dashboard for real-world application.

IV. METHODOLOGY

The methodology of this research is structured as a multi-stage pipeline that integrates signal processing and deep learning techniques to ensure accurate and reliable detection of nightmare episodes. Each stage is designed to progressively refine the raw EEG data into meaningful representations that can be effectively analysed by the classification model.

The process begins with EEG data acquisition, where neural signals are collected from sleep studies, particularly focusing on REM sleep stages. These signals are typically recorded using multiple

electrodes placed on the scalp and sampled at high frequencies to capture detailed brain activity. Due to the limited availability of datasets containing labelled nightmare episodes, this study utilizes perturbed REM samples to simulate abnormal neural patterns associated with nightmares. These perturbations are designed to introduce variations in frequency and amplitude that resemble irregular brain activity observed during distressing dreams.

Once the data is collected, preprocessing is performed to enhance signal quality and remove unwanted noise. EEG signals are highly susceptible to artifacts caused by eye movements, muscle activity, and external electrical interference. To address this, bandpass filtering is applied to retain only the relevant frequency range, typically between 0.5 Hz and 50 Hz. Artifact removal techniques such as Independent Component Analysis are then used to isolate and eliminate noise components. The cleaned signals are further normalized to ensure consistent scaling across all samples, which is essential for stable model training. Finally, the continuous EEG recordings are segmented into smaller time windows, allowing the model to analyze localized patterns within the signal.

Feature extraction is carried out using Short-Time Fourier Transform (STFT), which converts the one-dimensional EEG signals into two-dimensional spectrograms. This transformation provides a time-frequency representation of the data, capturing how the spectral content evolves over time. The resulting spectrograms highlight variations in key EEG frequency bands such as delta, theta, alpha, and beta waves. These variations are crucial for identifying abnormalities associated with nightmare episodes, as disruptions in these frequency patterns often indicate irregular neural activity during REM sleep.

The classification stage employs a Convolutional Neural Network designed to process spectrogram images and distinguish between normal REM sleep and nightmare episodes. The network consists of multiple convolutional layers that extract hierarchical features from the input data, followed by pooling layers that reduce dimensionality while preserving important information. Fully connected layers are then used to perform the final classification, producing probability scores for each class.

The model is trained using labeled data and optimized through techniques such as dropout and batch normalization to improve generalization and prevent overfitting. Additionally, model training is optimized using Adam optimizer and categorical cross-entropy loss. Data augmentation techniques such as noise injection and temporal shifting are applied to improve generalization. Hyperparameters including learning rate, batch size, and convolutional layers are tuned to achieve optimal performance. Evaluation metrics such as accuracy, precision, recall, and F1-score are used to assess model effectiveness.

In addition to classification, the methodology includes a severity analysis component that quantifies the intensity of detected nightmare episodes. This is achieved by measuring deviations in spectral features relative to baseline REM patterns. Based on the magnitude of these deviations, episodes are categorized into mild, moderate, or severe levels. This additional layer of analysis enhances the clinical usefulness of the system by providing more detailed insights into the condition.

To further improve interpretability, the system incorporates visualization techniques using Gradient-weighted Class Activation Mapping (Grad-CAM). This method generates heatmaps that highlight regions of the spectrogram contributing most significantly to the model's predictions. By identifying the frequency bands and time intervals associated with nightmare detection, these visualizations provide valuable insights into the underlying neural mechanisms and increase trust in the system's outputs.

V. ARCHITECTURE

The overall system architecture is designed as a modular framework that integrates multiple components into a cohesive pipeline. This modular design ensures flexibility, allowing individual components to be modified or upgraded without affecting the entire system. The architecture begins with the data input module, which handles the acquisition and storage of EEG signals. This module ensures that data is organized and accessible for subsequent processing stages.

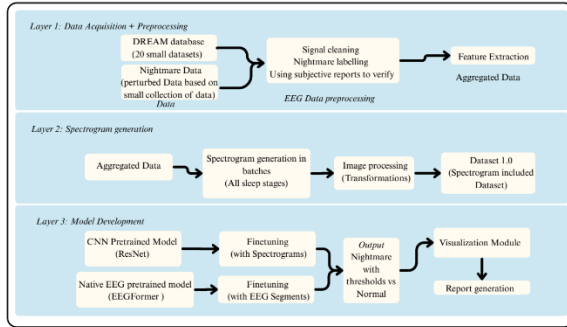


Figure 1.1: System Architecture diagram

The preprocessing module is responsible for cleaning and preparing the raw EEG data. It performs filtering, artifact removal, normalization, and segmentation, ensuring that the input to the feature extraction stage is of high quality. The feature extraction module then transforms the preprocessed signals into spectrogram representations, effectively converting time-series data into image-like formats suitable for deep learning models.

The classification module forms the core of the system, where the CNN processes the spectrograms and generates predictions. This module is designed to be robust and efficient, capable of handling large volumes of data while maintaining high accuracy. Following classification, the severity analysis module evaluates the intensity of detected episodes by analyzing spectral deviations. This module provides an additional layer of information that enhances the system's diagnostic capabilities.

The visualization module plays a crucial role in making the system interpretable. By generating heatmaps and highlighting important regions in the spectrograms, it allows users to understand how the model arrives at its decisions. Finally, the output interface presents the results in a clear and user-friendly manner, including the classification outcome, severity level, and visual explanations. This comprehensive architecture ensures that the system is not only accurate but also practical for real-world applications.

The system architecture is extended to include a full-stack application for real-world usability.

- Frontend: Built using React.js and Next.js for interactive UI

- Backend: FastAPI for handling model inference
- Model Integration: CNN model deployed via API
- User Flow:
 1. User uploads EEG segment
 2. Backend processes input
 3. Model predicts (Nightmare / Normal)
 4. Results displayed with visualization

V. RESULTS AND ANALYSIS

The performance of the proposed system was evaluated using experimental datasets containing both normal REM sleep samples and perturbed nightmare-like samples. The dataset was divided into training, validation, and testing subsets to ensure unbiased evaluation. Standard performance metrics such as accuracy, precision, recall, and F1-score were used to assess the effectiveness of the model.

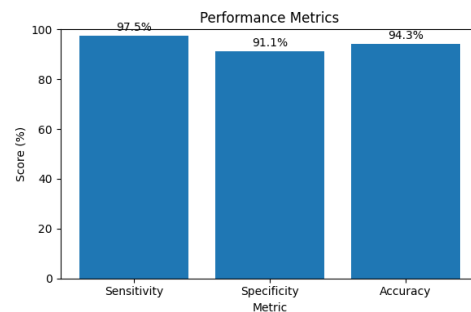


Figure 1.2: Performance Metrics

The results demonstrate that the system achieves high classification accuracy, ranging from 89% to 94.6%, indicating strong capability in distinguishing between normal and abnormal REM patterns. The model also exhibits a low false-negative rate, which is particularly important in clinical contexts where missed detections could lead to underdiagnosis. Precision values remain consistently high, suggesting that the model produces minimal false positives.

Further analysis of the model's behaviour reveals that the CNN effectively learns discriminative features from the spectrograms. The confusion matrix indicates clear separation between classes, with only a small number of misclassifications. Visualization through Grad-CAM shows that the model focuses on specific frequency bands, particularly those associated with REM sleep activity, such as theta and beta waves. These findings align with existing knowledge of

neural activity during dreaming, providing additional validation for the model.

The dashboard implemented provides real-time prediction results and visualization of EEG spectrograms. Users can:

- Upload EEG segments
- View classification results
- Analyze spectrogram patterns
- Understand model decisions

The integration of visualization enhances interpretability and usability, making the system suitable for practical applications.

Despite these promising results, certain limitations must be acknowledged. The use of perturbed samples instead of real nightmare data may not fully capture the complexity of actual nightmare episodes. Additionally, the dataset size and diversity may limit the model's generalizability. These factors highlight the need for further research using real-world datasets and more comprehensive data collection methods.

VI. CONCLUSION

This study presents a comprehensive approach to the automated detection of Nightmare Disorder using EEG signals and deep learning techniques. By integrating spectrogram-based feature extraction with CNN classification, the proposed system provides an objective and efficient alternative to traditional diagnostic methods. The inclusion of severity analysis and interpretability features further enhances its clinical relevance.

The high accuracy and robust performance of the model demonstrate its potential as a diagnostic support tool in sleep medicine. However, future work is necessary to validate the system using real-world data and to improve its generalization capabilities. Expanding the model to incorporate additional physiological signals and more advanced architectures could further enhance its effectiveness.

Overall, this research contributes to the growing field of AI-driven healthcare by addressing a critical gap in sleep disorder diagnostics. It lays the groundwork for future developments in automated, scalable, and

interpretable systems for analyzing complex neurological conditions.

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REFERENCES

- [1] M. Packiyathan, M. Molinas, and L. A. Moctezuma, "Towards a Dream Decoder: A Study Identifying Dream Emotions during REM Sleep with Machine Learning and EEG," Specialization Project, Norwegian University of Science and Technology, Dec. 2023.
- [2] C. Li, Y. Qi, X. Ding, J. Zhao, T. Sang, and M. Lee, "A Deep Learning Method Approach for Sleep Stage Classification with EEG Spectrogram," *International Journal of Environmental Research and Public Health*, vol. 19, no. 9, 2022.
- [3] H. Kim, J. Lee, and S. Lee, "Classification of Sleep Stage with Biosignal Images Using Convolutional Neural Networks," 2022.
- [4] A. Vilamala, K. H. Madsen, and L. K. Hansen, "Deep Convolutional Neural Networks for Interpretable Analysis of EEG Sleep Stage Scoring," 2017.
- [5] Y. Zhang, Y. Wang, and J. Wang, "Analysis and Classification of Sleep Stage Using Deep Learning Network from Single-Channel EEG Signal," 2017.
- [6] O. Tsinalis, P. M. Matthews, Y. Guo, and S. Zafeiriou, "Automatic Sleep Stage Scoring with Single-Channel EEG Using Convolutional Neural Networks," 2016.
- [7] L.-P. Marquis, T. Paquette, C. Blanchette-Carrière, G. Dumel, and T. Nielsen, "REM Sleep Theta Changes in Frequent Nightmare Recalls," 2017.

- [8] C. Picard-Deland, T. Paquette, L. Pigeon, and T. Nielsen, "Sleep Spindle and Psychopathology Characteristics of Frequent Nightmare Recallers," *Sleep Medicine*, 2018.
- [9] M. D. de Boer, M. J. Nijdam, and R. A. Jongedijk, "The Spectral Fingerprint of Sleep Problems in Post-Traumatic Stress Disorder," *Journal of Sleep Research*, 2020.
- [10] A. Craik, Y. He, and J. L. Contreras-Vidal, "Deep Learning for Electroencephalogram (EEG) Classification Tasks," *Journal of Neural Engineering*, 2019.
- [11] Horváth K., Simor P., Sándor P., Vida R., Lihi R., Sulyok Z., Bódizs R.: Spectral sleep EEG features of nightmare sufferers: evidence for a NREM disorder? *Ducog III., Learning and Perception (2011) Supplement – Sleep and Chronobiology Research Group*," 2015.
- [13] K. Ramar et al., "Sleep is essential to health: an American Academy of Sleep Medicine position statement," 2021. Available: <https://doi.org/10.5664/jcsm.9476>
- [14] T. Morgenthaler et al., "Position Paper for the Treatment of Nightmare Disorder in Adults: An American Academy of Sleep Medicine Position Paper," 2018. Available: <https://doi.org/10.5664/jcsm.7178>
- [15] . L. Markun and A. Sampat, "Clinician-Focused Overview and Developments in Polysomnography," 2020. Available: <https://doi.org/10.1007/s40675-020-00197-5.pdf>
- [16] . R. Berry et al., "Rules for Scoring Respiratory Events in Sleep: Update of the 2007 AASM Manual for the Scoring of Sleep and Associated Events," 2012. Available: <https://www.ncbi.nlm.nih.gov/pmc/articles/3434592>
- [17] Y. Wang, S. Ye, Z. Xu, Y. Chu, J. Zhang, and W. Yu, "Research on Sleep Staging Based on Support Vector Machine and Extreme Gradient Boosting Algorithm," 2024. Available: <https://dovepress.com/research-on-sleep-staging-based-on-support-vector-machine-and-extreme-gradient-boosting-peer-reviewed-fulltext-article-NSS>
- [18] B. Mandhouj, M. Cherni, and M. Sayadi, "An automated classification of EEG signals based on spectrogram and CNN for epilepsy diagnosis," 2021. Available: <https://doi.org/10.1007/s10470-021-01805-2>
- [19] X. He, "Deep Learning Architectures for EEG: From CNN to Transformers," *Transactions on Computer Science and Intelligent Systems Research*, n.d. Available: <http://tcsisr.org/index.php/ojs/article/view/37>
- [20] L. Alzubaidi et al., "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions," 2021. Available: <https://doi.org/10.1186/s40537-021-00444-8>