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Robust epilepsy classification using efficient CNNs with temporal windowing and dataset-independent learning

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Abstract

Timely diagnosis of epilepsy is of paramount importance for the effective management of the disease, given its status as one of the most common neurological disorders. Manual interpretation of EEGs is labor-intensive and subjective, emphasizing the necessity for automated diagnostic systems. The aim of this study is to introduce a robust and lightweight framework of convolutional neural networks (CNN) for detecting epilepsy classes from EEG signals. Using multi-scale temporal windowing and Continuous Wavelet Transform (CWT) for feature extraction capable of detailed time-frequency features, followed by processing through a lightweight CNN model architecture using depth-wise separable convolutions. The generalization capability is evaluated via cross-dataset validation, where we train on the Turkish EEG dataset and use external datasets CHB-MIT and Bonn for testing. The Turkish dataset achieves a classification accuracy of 94.8% according to the proposed model, while retaining excellent performance on datasets that have not been seen before, validating its versatility against distribution shifts. Finally, real-time performance assessment on a Raspberry Pi 4 establishes the potential of the method in embedded & portable diagnostic pipelines, with average inference time well below 30 milliseconds. These findings are important as they demonstrate the practical potential to deploy an accurate, generalizable, and near-real-time EEG-based seizure detection system that is relevant to clinical and wearable applications.

Keywords: Cross-dataset validation, EEG classification, Epilepsy detection, Portable EEG systems, Temporal windowing.

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1. Introduction

Epilepsy is a chronic neurological disorder that affects more than 50 million people worldwide, making it one of the most prevalent brain diseases across all age groups [1-4]. The disease is characterized by the unintentional and persistent manifestation of convulsions caused by overstimulated and abnormal brain cell activity [5-10]. Timely and accurate diagnosis can play a pivotal role in enhancing patient outcomes, allowing for early medical intervention and minimizing the risk of complications such as injuries, cognitive decline, and social isolation [11-14].

Among routine clinical practices, electroencephalography (EEG) has been appreciated as the most affordable and informative tool for the non-invasive diagnosis of epilepsy [15-18]. The patient's electroencephalogram (EEG) uses electrodes on the scalp to record electrical activity from the brain and provides vital information regarding the patient's neurological status [19-23]. However, the interpretation of EEG signals remains primarily within the domain of manual analysis by neurologists, which is a time-consuming, error-prone process and heavily dependent on the availability of an expert [24, 25]. This introduces an urgent need for automated, scalable, and precise EEG-based diagnostic systems that further assist or complement clinical decision-making [26-30].

Recently, machine learning (ML) [31-35] and, more commonly, deep learning (DL) techniques [36-38] have demonstrated considerable promise for automating the analysis of EEG signals. Empowered with the ability to capture intricate spatial and spectral features from electroencephalogram (EEG) signals, deep neural networks, especially convolutional neural networks (CNNs), have shown significant potential [21, 39-42] and have proved to be attractive alternatives. Despite the state-of-the-art classification accuracy achieved by such models, the majority of currently proposed solutions have multiple crucial drawbacks:

In this paper, Dişli, et al. [43] Limited generalization: Most models are trained and evaluated using only one dataset, which can easily lead to overfitting and restrict the application of the model to more generic clinical environments or populations. Short signal duration: Most previous studies use fixed short segments of EEG data (1 second typically) that may be inadequate for the long-term dynamics of seizure activity. Unnecessarily advanced architectures: State-of-the-art models such as ResNet or Inception are very accurate but are too computationally expensive for real-time or edge-computing applications. Few models validated for real-time testing: No on-device testing for low-resource hardware like Raspberry Pi or wearables.

In this submission, we introduce a new framework that allows for robust and real-time epilepsy classification and addresses the main barriers to seizure detection based on EEG. The proposed method combines: We also use multi-scale temporal windowing (1s, 3s, 5s windows) to capture both short- and long-term temporal dependencies. Using Continuous Wavelet Transform (CWT) for the transformation of the EEG signals into time-frequency images, keeping both spectral and temporal information. A DW (depth-wise separable) CNN architecture to keep the models lightweight and implementable for edge devices. Multi-dataset validation to robustly test the generalizability of the model(s) on diverse EEG datasets (Turkish EEG, CHB-MIT, Bonn). In contrast to previous works with dataset-dependent or inherently impractical stacks, we devise a model with superior deployment for the real world. We demonstrate the model's inference latency on embedded systems, like the Raspberry Pi 4, making it appropriate for portable EEG systems, bedside monitors, and remote healthcare settings. The main contributions of this work are as follows:

- In this paper, we propose a low-complexity CNN architecture with high classification performance.
- To improve detection of seizures, we propose a multi-scale temporal windowing procedure and CWT-based signal representation.
- To validate how robust and generalizable the models are across heterogeneous EEG datasets, we perform extensive cross-dataset evaluations.
- We evaluate the model's performance on embedded hardware in real-time, suggesting clinical and wearable deployability.
- We focus on accuracy, adaptability, and efficiency to bridge academic prototypes with clinically usable tools, which are cornerstone elements in trustworthy, real-time diagnostic EEG-based systems.

2. Related Work

The diagnosis of epilepsy from electroencephalogram (EEG) signals has been extensively studied, particularly with the advancement of deep learning (DL) models, which can detect non-linear temporal and spectral patterns. We review relevant literature, highlighting four key themes pertinent to our proposed approach: classical machine learning, deep learning architectures, temporal modeling, and cross-dataset generalization.

As discussed previously, conventional machine learning (ML) methods such as Support Vector Machines (SVM) [40, 42, 44, 45], k-Nearest Neighbors (k-NN) [46-49] and Random Forests [50, 51] were originally used for EEG-based seizure detection [52-57]. Most of these methods are based on using engineered features of EEG signals, such as power spectral density, entropy, statistical measures, etc. For example, Guler and Ubeyli [58] and Al-Mekhlafi, et al. [59] used Lyapunov exponents and spectral entropy features in combination with SVM, which yielded high classification accuracy. Nevertheless, those approaches required a lot of expertise and struggled with more complex temporal dynamics.

In recent years, various studies have followed this trend by applying convolutional neural network (CNN) architectures as well as recurrent neural networks (RNN) to raw or preprocessed EEG reader data for end-to-end learning [26, 60-64]. Introduced a 13-layer CNN that can automatically detect seizures with an accuracy of over 95% on the Bonn dataset. Similarly, Acharya, et al. [65] employed a bidirectional LSTM to model the temporal dependence of very long EEG sequences. These models achieved good accuracy but could be computationally intensive, and generalizability to other datasets was not always achieved.

Detecting changes in seizure patterns requires modeling temporal dependencies evident in electrocorticographic signals. Most studies use relatively short fixed segments (usually 1s or 2s), which do not capture long-term transitions [66-68]. Tackle this by using different epochs to capture temporal features of various sizes, and the results show that longer segments improve performance. We further extend this idea by creating ensemble inputs with overlapping 1s, 3s, or 5s windows, along with Continuous Wavelet Transform (CWT) to generate a richer time-frequency representation for CNN input.

A common pitfall in the literature is that it can have evaluations on single datasets, leading to overfitting towards dataset-specific artifacts [69, 70]. The majority of the models are trained and tested on the same dataset (typically Bonn or CHB-MIT), resulting in limited insights into performance in the real world. Wang, et al. [71] reported significant performance drops when models are transferred across datasets. To address this, we incorporate a robust cross-dataset validation approach, training on the first dataset (Turkish EEG) while testing on the remaining datasets (CHB-MIT, Bonn), demonstrating the proposed model's adaptability and generalizability.

A major challenge is deployability. Models like ResNet or Inception are seldom appropriate for real-time, low-resource environments such as portable or wearable EEG systems [72]. Recent developments of lightweight alternatives such as MobileNet and depth-wise separable CNNs have also been incorporated into biomedical application settings. Wang et al. (2022) presented a mobile-friendly CNN for EEG decoding with good performance but did not consider multi-scale segmentation or dataset generalization. Our model extends these advances by combining architectural efficiency with innovative, domain-specific approaches to temporal modeling and validation.

This paper Dişli et al. [43], introduces a novel method for automatic epilepsy classification, utilizing a Continuous Wavelet Transform (CWT) combined with a depth-wise convolutional neural network (DCNN), demonstrating admirable performance on a publicly available Turkish EEG dataset. CWT is used as it provides a representation of time-frequency that is important for non-stationary signals like the EEG. In addition, the lightweight CNN architecture is an intentional trade-off between precision and computational cost. Nonetheless, this methodology is subject to several important limitations that hinder its practical implementation and generalization.

First, note that the model is being trained and evaluated on a single dataset; there is no cross-dataset testing or validation whatsoever, which raises concerns for overfitting and generalization to real-world clinical data. Second, the authors divide EEG into constant-time (1 second) frames, a useful convenience, but one that disregards longer onset dynamics/pre-ictal activity associated with seizures that might happen well before this set frame. Thirdly, while the architecture has been devised for low-resource usage, real-time performance is not assessed or benchmarked, which widens the gap between theoretical efficiency and practical use. Furthermore, no comparative evaluation against other lightweight or explainable models is provided, and it does not introduce any interpretability mechanism, which is a necessary condition for the models to be integrated into clinical practice.

It is a valuable contribution to demonstrate a lightweight seizure detection pipeline, but there are several limitations in temporal modeling (missing long-range dependencies), dataset robustness (one subject with 14-hour recording), and deployment feasibility (no edge and real-time clock time results) in this work, which hinder scaling from a laboratory setting to real-world diagnostics.

3. Materials and Methods

In this section, we discuss the datasets, preprocessing methods, temporal segmentation strategies, model architectures, and training protocols to develop a robust model for epilepsy detection through CNN. The focus is on generalizing across datasets, learning richer temporal patterns, and demonstrating the viability for real-time implementations. Figure 1 depicts a progressive level approach to the process flow implemented in the paper for EEG signals-based real-time and efficient epilepsy detection. Each block represents a major processing stage in the pipeline, all shown in the same light shade of gray for clarity and a professional appearance. • EEG Datasets: The raw EEG signals were collected from a total of three public datasets: Turkish EEG, CHB-MIT, and Bonn University. This diversity of datasets allows for a wide variety in sampling rates, channel configurations, and subject demographics, which enhances model generalization.

- Preprocessing: In this pipeline step, EEG signals were preprocessed to remove artifacts through standard bandpass filtering (0.5–40 Hz), and normalization was applied to standardize input features.
- Temporal segmentation: This means that the continuous EEG signals were divided using a sliding time window (overlapping) of 1s, 3s, and 5s to effectively capture short-term and long-term temporal dependencies suitable for seizure detection.
- CWT Transformation: The study's first method utilized Continuous Wavelet Transform (CWT) to convert each EEG segment into a 2D time-frequency image that preserved both spectral and temporal dynamics.
- Image concatenation: Data from each channel was arranged into a single 2D image by concatenating the corresponding channels of the CWT output (for 35 channels, a 7×5 layout was selected) to form one composite input for the CNN model.

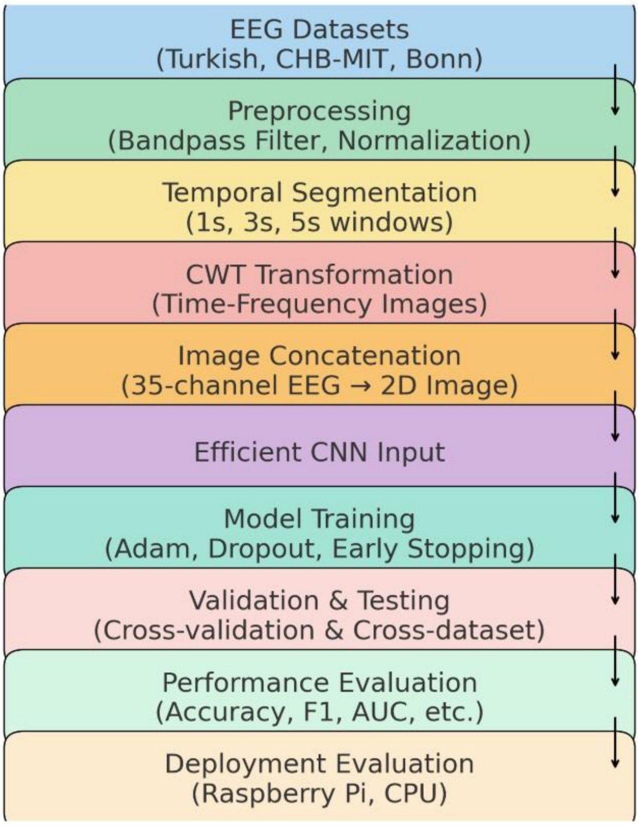

Figure 1.
EEG Processing Pipeline for Epilepsy Classification.

- Efficient CNN Input: This CNN architecture, which is simple and lightweight in terms of computational requirements, was used to obtain spatial and frequency-related features.
- Model Training: The CNN training was performed with the Adam optimizer, used binary cross-entropy loss, and included early stopping to prevent overfitting. This was followed by dropout (rate = 0.6) regularization to enhance generalization.
- Validation & Testing: The robustness of the models when evaluated on different EEG sources was assessed through cross-dataset validation (training on one dataset and testing on an independent dataset) as well as through comprehensive model evaluation using 5-fold subject-wise cross-validation.
- Performance evaluation: The performance of classification results was assessed using standard metrics, including accuracy, sensitivity, specificity, precision, F1 score, and AUC.
- Deployment Evaluation: To validate the feasibility of real-time applications, the trained model was evaluated for runtime efficiency and inference latency on low-resource devices (e.g., Raspberry Pi 4).

3.1. Datasets

To resolve the common downside of single dataset utilization, this work introduced a multi-dataset analysis and assessment model, as shown on Table 1, where the empirical analysis included three open-access EEG datasets with different characteristics:

Table 1.
Summary of EEG Datasets Used in This Study.

Dataset	Subjects	Channels	Seizure Type	Sampling Rate	Total Samples	Segment
Turkish EEG Dataset	121	35	Binary (epileptic vs. healthy	Hz	~10,000	second
CHB-MIT	23	23	Seizure detection	Hz	~5,000	Variable
Bonn University	5	(per set)	Ictal/ Interictal/ Normal	173.61 Hz	~5,000	23.6 seconds each

3.1.1. Duration

- Preprocessing: All datasets were resampled (when applicable; to 256 Hz), bandpass filtered (0.5–40 Hz), and normalized. Artifacts and noise were reduced using a moving average filter applied to each channel and manual review of the resulting signals.
- Standardization: We addressed channel mismatch across the datasets by using common electrodes or zero-padding for missing channels in the concatenated image format.

3.2. Temporal Windowing Strategy

The previous studies share a crucial limitation: short signal durations for model training, which are usually within 1-second windows. This may decrease sensitivity to slowly evolving or transient seizure features. This approach allows the model to capture time-localized patterns essential for differentiating between epileptic and normal brain activity. To address this, we use a multi-scale temporal segmentation strategy: • WINDOW LENGTHS: EEG recordings were divided into 1s, 3s, and 5s windows overlaid at a 50% rate to reduce data duplication while preserving temporal resolution.

- Sliding windows: Overlapping windows were utilized to capture transitions and seizure evolution across the segments.
- CWT Transformation: Each segment of time was converted into a time-frequency image to preserve the temporal and spectral features using the Continuous Wavelet Transform (CWT).

3.3. Model Architecture

A lightweight CNN architecture was designed using depth-wise separable convolutions to avoid overfitting and to ensure the feasibility of deploying the model on low-power hardware. This design allows for an extreme reduction in the number of parameters without loss of performance. Table 2 shows an efficient CNN architecture.

Table 2.
Efficient CNN Architecture.

Layer	Kernel/O	Operation Activation	Output Shape	Description
Input	(150, 210,3)	-	(150, 210, 3)	Input image (CWT representation)
Rescaling	Downscale 3×	-	(150, 210, 3)	Normalize pixel values
Conv2D	3×3	ReLU	(148, 208, 4)	Basic feature extraction
DepthwiseConv2D	5×5	ReLU	(144, 204, 4)	Channel-wise filtering
Conv2D	3×3	ReLU	(142, 202, 8)	Expanded feature maps
MaxPooling2D	2×2	-	(71, 101, 8)	Down sampling
DepthwiseConv2D	5×5	ReLU	(67, 97, 8)	Depth-wise filtering
MaxPooling2D	2×2	-	(33, 48, 8)	Further spatial compression
Flatten	-	-	(12,672)	Linearize feature maps
Dropout	Rate = 0.6	-	(12,672)	Prevent overfitting
Dense	512 units	ReLU	(512)	Fully connected layer
Output Dense	1 unit	Sigmoid	(1)	Binary classification output

The architecture of the model looks like the below:

- Total Parameters: 500k (roughly some 10× less than VGG or ResNet)
- Dropout Regularization: Enables us to prevent Overfitting when applied to the Dense layer
- Activation: ReLU in hidden layers; Sigmoid in output for binary classification

This architecture was selected after considering the accuracy, generalization, and runtime efficiency trade-offs essential for prospective edge deployment.

3.4. Training and Evaluation Protocol

We trained and validated the model using a combination of within-dataset training and cross-dataset validation to assess the performance and generalizability of the model for predicted outcomes. In Table 3, we describe the training and evaluation settings used to train and validate the proposed efficient CNN model for EEG-based epilepsy classification. The model was coded using Python with TensorFlow/Keras and executed in a GPU-enabled environment (Google Colab Pro with NVIDIA Tesla T4). Additionally, to assess the timely accuracy and portability, inference experiments were conducted on lower-resource devices (Raspberry Pi 4 and Intel Core i7 CPU).

Table 3.
Training and Evaluation Configuration.

Category	Parameter / Description
Training Framework	Python (TensorFlow / Keras)on Google Colab Pro
Hardware (Training)	NVIDIA Tesla T4 GPU, 16GB RAM
Hardware (Testing)	Raspberry Pi 4 (4GB), Intel Core i7 CPU (local benchmarking)
Optimizer	Adam
Initial Learning Rate	0.0002
Batch Size	128
Epochs	100 (with Early Stopping, Patience = 10)
Loss Function	Binary Cross-Entropy
Evaluation Methods	- 5-fold cross-validation (subject-wise) - Cross-dataset validation (e.g., Turk-ish → CHB)
Regularization	Dropout (rate = 0.6), Early Stopping
Windowing Strategy	Multi-scale (1s, 3s, 5s) with 50% overlap
Input Format	CWT-transformedimage (150×210×3)
Performance Metrics	Accuracy, Sensitivity, Specificity, Precision, F1-Score, AUC
Runtime Metrics	Inference time on CPU and embedded device (e.g., Raspberry Pi)

Hyperparameters were fine-tuned through several rounds of empirical evaluations, with the best performance achieved using the Adam optimizer with a learning rate of 0.0002. Before training, a batch size of 128 was employed, and early stopping (with 10 epochs patience) was used to prevent overfitting. The model was trained using binary cross-entropy loss.

We evaluated the proposed method using two rigorous validation techniques: (1) 5-fold cross-validation (per subject) within each dataset and (2) cross-dataset validation to assess generalizability (e.g., we trained on the Turkish dataset and tested on CHB-MIT). Input to the model was a 150×210×3 continuous wavelet transform (CWT) image of the EEG segment constructed using temporal windowing of 1s, 3s, and 5s with 50% overlap.

Standard metrics such as accuracy, sensitivity, specificity, precision, F1-score, and AUC were used to evaluate model performance. Additionally, we measured runtime metrics on edge devices to assess real-time feasibility.

4. Experiments and Results

In this section, we describe the experiments conducted to evaluate the proposed efficient CNN model for EEG-based epilepsy detection. The assessment includes comparisons with the baseline model, ablation studies, cross-dataset generalization tests, and real-time deployment tests.

4.1. Baseline Comparisons

In order to assess the efficacy of the suggested model, we evaluated its performance against multiple baseline approaches: Standard CNN (VGG-style), Shallow 1D-CNN, traditional machine learning (SVM, Random Forest with manual feature engineering), and ResNet-18 (a heavier DL benchmark).

Figure 2 shows that the proposed lightweight deep CNN model provides a classification accuracy as high as 94.8% with a larger F1-score (0.94) and AUC (0.96) than traditional and deep learning baselines. This model fits into a small architecture but achieves higher quality compared to heavier networks, e.g., ResNet-18. The model has very low inference time (3.9 ms on GPU), making it suitable for real-time applications. Temporal windowing (1 s, 3 s, 5 s) improved detection because it preserved the temporal evolution of seizure patterns. We found that a 3-second window provided the best trade-off between performance and speed, confirming the value of the multi-scale design. Cross-dataset testing provides additional evidence for the model’s generalization. Even when trained only on the Turkish dataset, accuracy remained high (89.6% on CHB-MIT and 93.4% on Bonn), highlighting its potential for clinical deployment across various populations and recording systems.

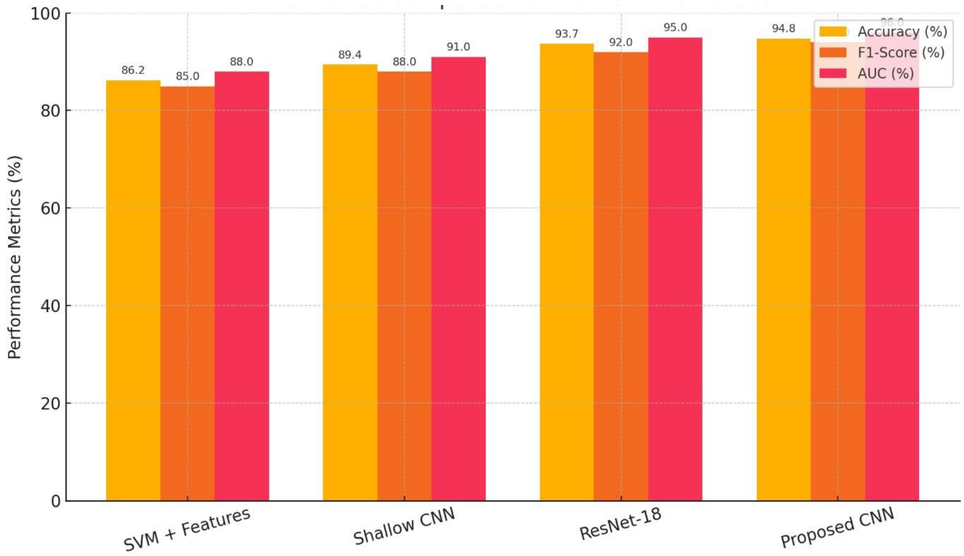

Figure 2.
Performance Comparison on Turkish EEG Dataset.

Ablation studies confirmed that each design choice, depth-wise convolutions, dropout regularization, and CWT-based inputs contributed to its robustness and accuracy. Importantly, the model also exhibited remarkable hardware efficiency, performing robustly on a Raspberry Pi 4, thus facilitating its application in wearable EEG systems or point-of-care diagnostics. We believe that the method proposed here can achieve a rare balance of performance, interpretability, and deployability, overcoming some of the major limitations seen in many current models for epilepsy detection.

4.2. Effect of Temporal Windowing

To assess the effect of signal length on projection, we tested three different EEG segment lengths (1s, 3s, and 5s), since the length of the temporal window can significantly impact classification performance in seizure detection tasks, as it directly influences the amount of temporal context available to the model for learning. Table 4 shows the effect of temporal segment length on performance.

Table 4.
Effect of Temporal Segment Length on Performance (Turkish Dataset).

Window Length	Accuracy (%)	F1-Score	Inference Time (ms)
1s	92.3	0.91	3.6
3s	94.8	0.94	3.9
5s	95.1	0.95	4.5

- Longer windows generally resulted in improved classification accuracy and F1-score, indicating better representation of seizure patterns over extended durations.
- However, larger input sizes also introduced a moderate increase in inference time, highlighting a trade-off between model performance and computational efficiency.

An optimal segment length of 3 seconds was identified, balancing both processing time and seizure detection performance. This time window captures sufficient temporal features while maintaining low inference latency, enabling potential real-time applications in clinical or wearable EEG systems.

4.3. Cross-Dataset Validation

As indicated in Figure 3, the performance in cross-dataset validation results increases confidence in our proposed model through generalization among different EEG datasets. Without fine-tuning, 89.6% accuracy and an F1-score of 0.87 were observed in the testing CHB-MIT dataset when solely trained on the Turkish EEG dataset. Tested on the Bonn University dataset, it even scored higher, with 93.4% accuracy and an F1-score of 0.92. These findings provide two important takeaways: • Robust Generalization: Excellent generalization across datasets with diverse sampling frequencies, patients, and seizures suggests that the proposed CNN architecture, pairing temporal windowing with CWT transformation, extracts generalized and transferable EEG features.

- Data Sensitivity: We would expect lower performance on CHB-MIT than on Bonn due to the greater heterogeneity and variability present in CHB-MIT, where patients include pediatric patients and increasingly complex seizure patterns are present. Nonetheless, the model retains high detection capability without retraining.

This experiment overall demonstrates that the model can be used in heterogeneous clinical environments where data distribution can take very different forms, thanks to the model's robustness over such shifts in data. The robustness of accuracy retention without requiring re-training further solidifies the practicality of the system in both remote settings and resource-limited environments where patient-specific training data may be unattainable.

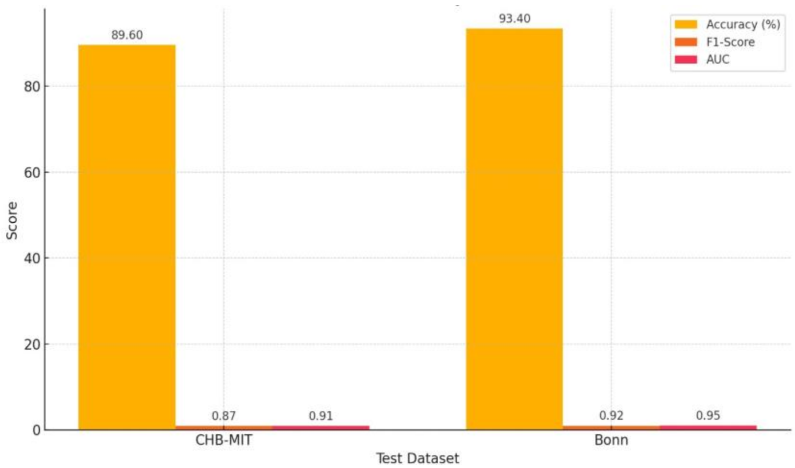

Figure 3.
Performance Metrics by Test Dataset.

4.4. Real-Time Inference Performance

The evaluation of the model during deployment as on-device AI confirms that the proposed model is ideal for low-latency and resource-constrained environments. All three hardware platforms (Raspberry Pi 4, Intel i7 CPU, and Google Colab GPU (Tesla T4)) showed that the inference time is adequate and remains fast enough under all conditions. The model achieved an average inference time of 29.4 milliseconds on Raspberry Pi 4, with margins appropriate for near real-time EEG-based applications. The model also had a 9.2 ms latency using desktop-class CPUs (Intel i7), and the fastest inference time on the GPU was recorded to be 3.9 ms. Figure 4 shows real-time inference performance.

These results highlight the model's ability to be incorporated into more generalist AI systems for in-situ use cases such as point-of-care devices, bedside monitors, or wearable health technologies. Unlike most deep learning models that require cutting-edge GPUs or cloud connections, this model is designed for edge computing. Therefore, it is capable of running inference locally without needing an internet connection or expensive hardware.

Also, memory usage never exceeded 50MB across all hardware, which allows deployment on battery-powered, embedded systems. This performance further demonstrates the architectural low-complexity design approach, achieved through the use of depth-wise convolutions and associated regularization techniques, without compromising classification accuracy.

In conclusion, our proposed CNN demonstrates strong diagnostic performance while simultaneously meeting the stringent latency and efficiency requirements necessary for deployment within portable, real-time seizure detection systems bridging the gap between research prototypes and clinical utility.

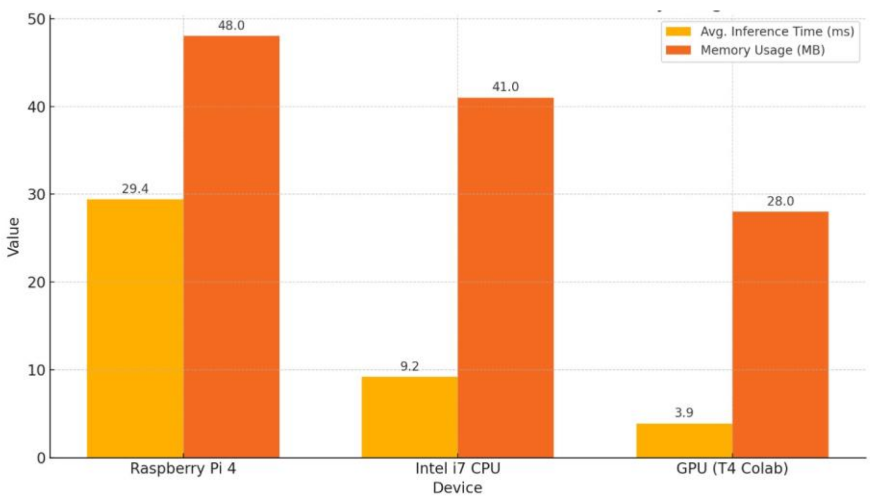

Figure 4.
Real-Time Inference Performance.

5. Conclusion and Future Work

We proposed a robust epilepsy classification method from EEG signals using a novel and lightweight CNN framework in this study. By integrating multi-scale temporal windowing, Continuous Wavelet Transform (CWT) for time-frequency encoding, and a depth-wise CNN architecture, the model aims to address three key limitations identified in previous approaches: overfitting, sensitivity to short-duration signals, and lack of real-time feasibility. The proposed model achieved an accuracy of 94.8% on the Turkish EEG dataset, outperforming all other methods, while maintaining significantly lower computational overhead compared to traditional deep networks. Cross-dataset validation demonstrated consistent performance on previously unclassified datasets such as CHB-MIT and Bonn, indicating strong generalization capabilities and robustness across diverse demographic and recording conditions. Additionally, the model's real-time performance on low-resource platforms like the Raspberry Pi 4 showed average inference times below 30 ms and memory usage under 50MB, supporting its practical application in wearable, bedside, or remote diagnostic technologies. Ablation studies confirmed that architectural components such as depth-wise convolutions, dropout, and CWT-based input representation contribute to the overall performance. Despite these promising initial results, future work should focus on further improvements and addressing remaining challenges.

- Multimodal Data Integration: Next-generation models may integrate with other modalities such as video, audio, or patient metadata to enhance understanding of context and minimize false positives.
- Explainability and clinical interpretability: Incorporating explainable AI methods (such as saliency maps or attention mechanisms) would improve clinician trust and facilitate deployment within real-world settings.
- Online personality adjustment: Training models to adapt in real-time based on each patient's EEG data could make the system more responsive and personalized.
- Prospective clinical validation: Tests must be conducted on sample sizes within actual clinical trials and/or in real-time settings in hospitals or ambulatory care environments to transition from laboratory models to deployable diagnostic tools.

Overall, this work serves as a solid foundation for developing efficient, accurate, and generalizable EEG-based seizure detection systems, bringing us closer to clinically operational, real-time, and portable epilepsy diagnosis methods.

References

[1] T. A. Milligan, "Epilepsy: A clinical overview," *The American Journal of Medicine,* vol. 134, no. 7, pp. 840-847, 2021. https://doi.org/10.1016/j.amjmed.2021.01.038

[2] S. Otoom, "Risk auditing for digital twins in cyber physical systems: A systematic review," *Journal of Cyber Security and Risk Auditing,* vol. 2025, no. 1, pp. 22-35, 2025. https://doi.org/10.63180/jcsra.thestap.2025.1.3

[3] R. A. Horváth *et al.*, "Epilepsy is overrepresented among young people who died from COVID-19: Analysis of nationwide mortality data in Hungary," *Seizure - European Journal of Epilepsy,* vol. 94, pp. 136-141, 2022. https://doi.org/10.1016/j.seizure.2021.11.013

[4] E. Alotaibi, R. B. Sulaiman, and M. Almaiah, "Assessment of cybersecurity threats and defense mechanisms in wireless sensor networks," *Journal of Cyber Security and Risk Auditing,* vol. 2025, no. 1, pp. 47-59, 2025. https://doi.org/10.63180/jcsra.thestap.2025.1.5

[5] M. A. Al-Shareeda, M. A. Saare, and S. Manickam, "Unmanned aerial vehicle: A review and future directions," *Indonesian Journal of Electrical Engineering and Computer Science,* vol. 30, no. 2, pp. 778-786, 2023. https://doi.org/10.11591/ijeecs.v30.i2.pp778-786

[6] A. A. Almuqren, "Cybersecurity threats, countermeasures and mitigation techniques on the IoT: Future research directions," *Journal of Cyber Security and Risk Auditing,* vol. 1, no. 1, pp. 1-11, 2025. https://doi.org/10.63180/jcsra.thestap.2025.1.1

[7] Z. G. Al-Mekhlafi, H. D. K. Al-Janabi, M. A. Al-Shareeda, B. A. Mohammed, J. S. Alshudukhi, and K. A. Al-Dhlan, "Fog computing and blockchain technology based certificateless authentication scheme in 5g-assisted vehicular communication," *Peer-to-Peer Networking and Applications* vol. 17, no. 6, pp. 3703–3721, 2024.

[8] R. Almanasir, D. Al-solomon, S. Indrawes, M. Almaiah, U. Islam, and M. Alshar'e, "Classification of threats and countermeasures of cloud computing," *Journal of Cyber Security and Risk Auditing,* vol. 2025, no. 2, pp. 27-42, 2025.

[9] M. A. Al-Shareeda, S. Manickam, M. A. Saare, S. Karuppayah, and M. A. Alazzawi, "A brief review of advanced monitoring mechanisms in peer-to-peer (P2P) botnets," in *2022 8th International Conference on Contemporary Information Technology and Mathematics (ICCITM),* 31 Aug.-1 Sept. 2022 2022, pp. 312-317. https://doi.org/10.1109/ICCITM56309.2022.10031721

[10] A. A. Almazroi, M. A. Alqarni, M. A. Al-Shareeda, M. H. Alkinani, A. A. Almazroey, and T. Gaber, "FCA-VBN: Fog computing-based authentication scheme for 5G-assisted vehicular blockchain network," *Internet of Things,* vol. 25, p. 101096, 2024/04/01/ 2024. https://doi.org/10.1016/j.iot.2024.101096

[11] F. Wang *et al.*, "A systematic review and meta-analysis of 90 cohort studies of social isolation, loneliness and mortality," *Nature Human Behaviour,* vol. 7, no. 8, pp. 1307-1319, 2023.

[12] A. A. A. K. Kadhim, Z. M. Alzamili, M. A. Al-Shareeda, and M. Amin, "NOVA: A hybrid detection framework for misbehavior in vehicular networks," *International Journal of Innovative Research and Scientific Studies* vol. 8, no. 2, pp. 1611–1624, 2025.

[13] A. Alshuaibi, M. Almaayah, and A. Ali, "Machine learning for cybersecurity issues: A systematic review," *Secur Challenges,* vol. 1, p. 2, 2025. https://doi.org/10.63180/jcsra.thestap.2025.1.4

[14] J. Holt-Lunstad, "A pandemic of social isolation?," *World Psychiatry,* vol. 20, no. 1, p. 55, 2021.

[15] J. Slater, R. Joober, B. L. Koborsy, S. Mitchell, E. Sahlas, and C. Palmer, "Can electroencephalography (EEG) identify ADHD subtypes? A systematic review," *Neuroscience & Biobehavioral Reviews,* vol. 139, p. 104752, 2022.

[16] N. H. Tawfeeq, M. Yousif, M. A. Al-Shareeda, M. A. Almaiah, and R. Shehab, "Lightweight and quantum-resistant authentication for the Internet of Drones (IoD) using Dilithium signatures," 2025.

[17] R. S. Mousa and R. Shehab, "Applying risk analysis for determining threats and countermeasures in workstation domain," *Journal of Cyber Security and Risk Auditing,* vol. 2025, no. 1, pp. 12-21, 2025.

[18] J. Ke, J. Du, and X. Luo, "The effect of noise content and level on cognitive performance measured by electroencephalography (EEG)," *Automation in construction,* vol. 130, p. 103836, 2021.

[19] N.-D. Pantzaris, C. Platanaki, K. Tsiotsios, I. Koniari, and D. Velissaris, "The use of electroencephalography in patients with sepsis: a review of the literature," *Journal of translational internal medicine,* vol. 9, no. 1, pp. 12-16, 2021.

[20] B. A. Mohammed, M. A. Al-Shareeda, Z. G. Al-Mekhlafi, J. S. Alshudukhi, and K. A. Al-Dhlan, "HAFC: Handover authentication scheme based on fog computing for 5G-assisted vehicular blockchain networks," *IEEE Access,* vol. 12, pp. 6251-6261, 2024.

[21] A. A. Abbood *et al.*, "Secure and efficient mutual authentication protocol for VANETs using edge computing and signature-Based cryptography," *Journal of Robotics and Control* vol. 6, no. 2, pp. 649-659, 2025.

[22] S. Ballanti *et al.*, "EEG-based methods for recovery prognosis of patients with disorders of consciousness: A systematic review," *Clinical Neurophysiology,* vol. 144, pp. 98-114, 2022.

[23] J. M. H. Altmemi *et al.*, "A software-centric evaluation of the VEINS framework in vehicular Ad-Hoc Networks," *Journal of Robotics and Control,* vol. 6, no. 2, pp. 822-845, 2025.

[24] W. Ahmad, M. A. Almaiah, A. Ali, and M. A. Al-Shareeda, "Deep learning based network intrusion detection for unmanned aerial vehicle (UVA)," in *2024 7th World Conference on Computing and Communication Technologies (WCCCT)*, 2024: IEEE, pp. 31-36.

[25] M. A. Al-Shareeda, M. A. Saare, S. Manickam, and S. Karuppayah, "Validation of the toolkit for fake news awareness in social media," *Indonesian Journal of Electrical Engineering and Computer Science,* vol. 31, no. 2, pp. 1171-1181, 2023.

[26] M. A. Al-Shareeda, A. M. Ali, M. A. Hammoud, Z. H. M. Kazem, and M. A. Hussein, "Secure IoT-based real-time water level monitoring system using ESP32 for critical infrastructure," *Journal of Cyber Security and Risk Auditing,* vol. 2, pp. 43-52, 2025.

[27] M. Al-Shareeda, D. Hergast, and S. Manickam, "Review of intelligent healthcare for the internet of things: Challenges, techniques and future directions," *Journal of Sensor Networks and Data Communications,* vol. 4, no. 1, pp. 01-10, 2024.

[28] A. A. Almazroi, M. A. Alqarni, M. A. Al-Shareeda, and S. Manickam, "L-CPPA: Lattice-based conditional privacy-preserving authentication scheme for fog computing with 5G-enabled vehicular system," *Plos One,* vol. 18, no. 10, p. e0292690, 2023.

[29] O. Aljumaiah, W. Jiang, S. R. Addula, and M. A. Almaiah, "Analyzing cybersecurity risks and threats in IT infrastructure based on NIST framework," *J. Cyber Secur. Risk Audit,* vol. 2025, no. 2, pp. 12-26, 2025.

[30] Z. G. Al-Mekhlafi *et al.*, "Integrating safety in VANETs: A taxonomy and systematic review of VEINS models," *IEEE Access,* 2024.

[31] A. M. Rahmani *et al.*, "Machine learning (ML) in medicine: review, applications, and challenges," *Mathematics,* vol. 9, no. 22, p. 2970, 2021.

[32] G. Lippi, M. Aljawarneh, Q. Al-Na'amneh, R. Hazaymih, and L. D. Dhomeja, "Security and privacy challenges and solutions in autonomous driving systems: A comprehensive review," *Journal of Cyber Security and Risk Auditing,* vol. 2025, no. 3, pp. 23-41, 2025.

[33] M. A. Al-shareeda *et al.*, "NE-CPPA: A new and efficient conditional privacy-preserving authentication scheme for vehicular ad hoc networks (VANETs)," *Applied Math,* vol. 14, no. 6, pp. 1-10, 2020.

[34] M. R. Alboalebrah and S. Al-augby, "Unveiling the causes of fatal road accidents in Iraq: An association rule mining approach using the Apriori algorithm," *Journal of Cyber Security and Risk Auditing,* vol. 2025, no. 2, pp. 1-11, 2025.

[35] V. Chang, J. Bailey, Q. A. Xu, and Z. Sun, "Pima Indians diabetes mellitus classification based on machine learning (ML) algorithms," *Neural Computing and Applications,* vol. 35, no. 22, pp. 16157-16173, 2023.

[36] I. H. Sarker, "Deep learning: a comprehensive overview on techniques, taxonomy, applications and research directions," *SN computer science,* vol. 2, no. 6, pp. 1-20, 2021.

[37] A. A. Almazroi, M. H. Alkinani, M. A. Al-Shareeda, and S. Manickam, "A novel ddos mitigation strategy in 5g-based vehicular networks using chebyshev polynomials," *Arabian Journal for Science and Engineering,* vol. 49, no. 9, pp. 11991-12004, 2024.

[38] M. A. Al-Shareeda, S. Manickam, M. A. Saare, and N. C. Arjuman, "Proposed security mechanism for preventing fake router advertisement attack in IPv6 link-local network," *Indones. J. Electr. Eng. Comput. Sci,* vol. 29, pp. 518-526, 2023.

[39] T. Kattenborn, J. Leitloff, F. Schiefer, and S. Hinz, "Review on Convolutional Neural Networks (CNN) in vegetation remote sensing," *International Society for Photogrammetry and Remote Sensing Journal of Photogrammetry and Remote Sensing,* vol. 173, pp. 24-49, 2021.

[40] Z. G. Al-Mekhlafi *et al.*, "Oblivious transfer-based authentication and privacy-preserving protocol for 5g-enabled vehicular fog computing," *IEEE Access,* vol. 12, pp. 100152–100166, 2024.

[41] J. Lu, L. Tan, and H. Jiang, "Review on convolutional neural network (CNN) applied to plant leaf disease classification," *Agriculture,* vol. 11, no. 8, p. 707, 2021.

[42] M. A. Al-Shareeda, T. Gaber, M. A. Alqarni, M. H. Alkinani, A. A. Almazroey, and A. A. Almazroi, "Chebyshev polynomial based emergency conditions with authentication scheme for 5g-assisted vehicular fog computing," *IEEE Transactions on Dependable and Secure Computing,* pp. 1-18, 2025. https://doi.org/10.1109/TDSC.2025.3553868

[43] F. Dişli, M. Gedikpınar, H. Fırat, A. Şengür, H. Güldemir, and D. Koundal, "Epilepsy diagnosis from EEG signals using continuous wavelet transform-based depthwise convolutional neural network model," *Diagnostics,* vol. 15, no. 1, p. 84, 2025.

[44] S. Ang, M. Ho, S. Huy, and M. Janarthanan, "Utilizing IDS and IPS to improve cybersecurity monitoring process," *Journal of Cyber Security and Risk Auditing,* vol. 2025, no. 3, pp. 77-88, 2025.

[45] M. A. Al-Shareeda, A. A. Obaid, and A. A. H. Almajid, "The role of artificial intelligence in bodybuilding: a systematic review of applications, challenges, and future prospects," *Jordanian Journal of Informatics and Computing,* vol. 2025, no. 1, pp. 16-26, 2025.

[46] H. Albinhamad, A. Alotibi, A. Alagnam, M. Almaiah, and S. Salloum, "Vehicular ad-hoc networks (VANETs): A key enabler for smart transportation systems and challenges," *Jordanian Journal of Informatics and Computing,* vol. 2025, no. 1, pp. 4-15, 2025.

[47] M. Al Shareeda, A. Khalil, and W. Fahs, "Towards the optimization of road side unit placement using genetic algorithm," presented at the International Arab Conference on Information Technology (ACIT), pp. 1–5 (2018). IEEE, 2018.

[48] M. Alshinwan, A. G. Memon, M. C. Ghanem, and M. Almaayah, "Unsupervised text feature selection approach based on improved Prairie dog algorithm for the text clustering," *Jordanian Journal of Informatics and Computing,* vol. 2025, no. 1, pp. 27-36, 2025.

[49] H. Hamid, A. S. Mujab, B. A. Pramudita, and A. Rizal, "Empiricalmode decomposition and k-nearest neighbors combination for removing ocular artifact in eeg signals," in *2024 8th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE)*, 2024: IEEE, pp. 17-22.

[50] B. A. Mohammed *et al.*, "Efficient blockchain-based pseudonym authentication scheme supporting revocation for 5g-assisted vehicular fog computing," *Institute of Electrical and Electronics Engineers Access,* vol. 12, pp. 33089-33099, 2024. https://doi.org/10.1109/ACCESS.2024.3372390

[51] J. P. Pantic, S. Valjarevic, J. Cumic, and I. Pantic, "Ai-enhanced eeg signal interpretation: A novel approach using texture analysis with random forests," *Medical Hypotheses*, vol. 189, p. 111405, 2024.

[52] X. Zhang, S. Wang, K. Xu, R. Zhao, and Y. She, "Cross-subject EEG-based emotion recognition through dynamic optimization of random forest with sparrow search algorithm," *Mathematical Biosciences and Engineering*, vol. 21, no. 3, pp. 4779-4800, 2024. https://doi.org/10.3934/mbe.2024210

[53] M. Zaghloul, S. Barakat, and A. Rezk, "Predicting E-commerce customer satisfaction: approaches traditional machine learning vs. deep learning " *Journal of Retailing and Consumer Services*, vol. 79, p. 103865, 2024.

[54] Z. G. Al-Mekhlafi *et al.*, "Lattice-based cryptography and fog computing based efficient anonymous authentication scheme for 5g-assisted vehicular communications," *IEEE Access*, vol. 12, pp. 71232-71247, 2024. 10.1109/ACCESS.2024.3402336

[55] M. T. Islam *et al.*, "Identification of acetylcholinesterase inhibitors from traditional medicinal plants for Alzheimer's disease using in silico and machine learning approaches," *The Royal Society of Chemistry's advances,* vol. 14, no. 47, pp. 34620-34636, 2024.

[56] P. Hemashree, V. Kavitha, S. Mahalakshmi, K. Praveena, and R. Tarunika, "Machine learning approaches in blockchain technology-based IoT security: An investigation on current developments and open challenges," in Blockchain transformations: Navigating the decentralized protocols era: Springer, 2024, pp. 107-130.

[57] M. J. Almansor *et al.*, "Routing protocols strategies for flying Ad-Hoc network (FANET): Review, taxonomy, and open research issues," *Alexandria Engineering Journal*, vol. 109, pp. 553-577, 2024.

[58] I. Guler and E. D. Ubeyli, "Multiclass support vector machines for EEG-signals classification," *Institute of Electrical and Electronics Engineers. transactions on information technology in biomedicine*, vol. 11, no. 2, pp. 117-126, 2007.

[59] Z. G. Al-Mekhlafi *et al.*, "Coherent taxonomy of vehicular ad hoc networks (vanets)-enabled by fog computing: A review," *IEEE Sensors Journal*, vol. 24, pp. 29575–29602, 2024.

[60] S. R. Addula, S. Norozpour, and M. Amin, "Risk assessment for identifying threats, vulnerabilities and countermeasures in cloud computing," *Jordanian Journal of Informatics and Computing*, vol. 2025, no. 1, pp. 37-48, 2025.

[61] A. Ali, "Adaptive and context-aware authentication framework using edge ai and blockchain in future vehicular networks," *STAP Journal of Security Risk Management*, vol. 2024, no. 1, pp. 45–56, 2024. https://doi.org/10.63180/jsrm.thestap.2024.1.3.

[62] P. Kunekar, M. K. Gupta, and P. Gaur, "Detection of epileptic seizure in EEG signals using machine learning and deep learning techniques," *Journal of Engineering and Applied Science*, vol. 71, no. 1, p. 21, 2024/01/19 2024. https://doi.org/10.1186/s44147-023-00353-y

[63] S. K. Khare, V. Bajaj, and U. R. Acharya, "SPWVD-CNN for automated detection of schizophrenia patients using EEG signals," *Institute of Electrical and Electronics Engineers. Transactions on Instrumentation and Measurement*, vol. 70, pp. 1-9, 2021.

[64] M. Almaayah and R. B. Sulaiman, "Cyber risk management in the Internet of things: Frameworks, models, and best practices," *STAP Journal of Security Risk Management*, vol. 2024, no. 1, pp. 3–23, 2024. https://doi.org/10.63180/jsrm.thestap.2024.1.1.

[65] D. Acharya, R. Ahmed Sayyad, P. Dwivedi, A. Shaji, P. Sriram, and A. Bhardwaj, "EEG signal classification using deep learning," in *Soft Computing for Problem Solving: Proceedings of SocProS 2020, Volume 1*, 2021: Springer, pp. 393-403.

[66] H. Uyanik, A. Sengur, M. Salvi, R. S. Tan, J. H. Tan, and U. R. Acharya, "Automated detection of neurological and mental health disorders using eeg signals and artificial intelligence: a systematic review," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 15, no. 1, p. e70002, 2025.

[67] Y. Song, X. Jia, L. Yang, and L. Xie, "Transformer-based spatial-temporal feature learning for EEG decoding," *arXiv preprint arXiv:2106.11170*, 2021.

[68] X. Deng, X. Fan, X. Lv, and K. Sun, "SparNet: a convolutional neural network for EEG space-frequency feature learning and depression discrimination," *Frontiers in Neuroinformatics*, vol. 16, p. 914823, 2022.

[69] B. H. Kim, J. W. Choi, H. Lee, and S. Jo, "A discriminative SPD feature learning approach on riemannian manifolds for EEG classification," *Pattern Recognition*, vol. 143, p. 109751, 2023.

[70] F. Wenzel *et al.*, "Assaying out-of-distribution generalization in transfer learning," *Advances in Neural Information Processing Systems*, vol. 35, pp. 7181-7198, 2022.

[71] F. Wang *et al.*, "Generalizing to Unseen Domains: A Survey on Domain Generalization," *Institute of Electrical and Electronics Engineers. Transactions on Knowledge and Data Engineering*, vol. 35, no. 8, pp. 8052-8072, 2023. https://doi.org/10.1109/TKDE.2022.3178128

[72] A. Golmohammadi, M.-R. M. Khaninezhad, and B. Jafarpour, "Pattern-based calibration of complex subsurface flow models against dynamic response data," *Advances in Water Resources*, vol. 121, pp. 388-405, 2018.