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Artificial Intelligence for EEG Analysis: A Comprehensive Review of Deep Learning Techniques

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HIGHLIGHTS

- Presents a structured review of deep learning techniques for EEG analysis, covering preprocessing, feature extraction, and classification.
- Evaluates and contrasts traditional machine learning and deep neural networks in terms of performance, efficiency, and clinical utility.
- Identifies key limitations—such as cross-subject variability and interpretability—and outlines future directions including explainable and multimodal AI.

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ABSTRACT

This review systematically outlines the progression and implementation of artificial intelligence (AI) techniques, with a focus on deep learning (DL), for the analysis of electroencephalogram (EEG) signals. We cover the whole EEG processing pipeline from signal acquisition and preprocessing to feature extraction and classification. The survey begins with traditional machine learning techniques such as Common Spatial Patterns (CSP) and Support Vector Machines (SVMs), then transitions to more recent DL architectures—including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and their hybrid configurations—that have significantly expanded the analytical capabilities of neurophysiological systems. These methods have been widely applied in fields ranging from clinical diagnostics and brain-computer interaction to affective computing and cognitive assessment. Rather than relying on a singular methodology, research efforts emphasize tailored strategies to overcome persistent obstacles like signal denoising and the selection of meaningful features. We discuss applications in a broad array of areas like clinical diagnosis, brain-computer interfaces, emotion recognition, and cognitive tests. We compare performance metrics across methods and note existing limitations like interpretability issues and computational complexity. Finally, we mention future directions and trends, including multimodal integration and explainable AI. This review provides researchers and practitioners with a comprehensive overview of state-of-the-art AI techniques for EEG analysis and indicates some promising avenues for future advances in this rapidly evolving field.

I. INTRODUCTION

Over the past few years, interest in AI among healthcare stakeholders has dramatically shifted our methods to analyze healthcare data and make decisions. Instead of being restricted to help with simple tasks, AI can significantly help with more complex areas that generally require clinical reasoning. These areas are defined by their methods to decision-making approaches, which often serve a central function to determine complex and subtle patterns [1].

The application of these approaches has enhanced data analysis from both raw-data processing and pattern-recognition perspectives, thereby supporting diagnostic decision-making. A notable example is medical imaging, where continuous advances in computer vision techniques are integrated into clinical workflows. These technologies assist in clinical assessment and extend decision-making capabilities by detecting subtle features often overlooked by human observers. Their adoption has been accelerated by healthcare practitioners who acknowledge their value in managing complex visual information. Moreover, deep learning algorithms have demonstrated the capacity to process large-scale imaging datasets with efficiency and reliability that manual methods cannot consistently achieve. This transformation holds significant potential for streamlining diagnostic processes and improving patient outcomes [2].

Along with imaging methods, scientists are employing artificial intelligence to decipher brain's electrophysiological signals. The variable and complex nature of EEG recordings makes their analysis very challenging. This often demands setup of a modeling architecture that's especially suitable with data that's both time-dependent and noise-prone [3].

EEG is a non-invasive method that records the brain's electrical activity. It has high temporal resolution and can provide useful insights into different brain functions [4]. Over the last decades, EEG analysis has evolved from manual visual examination by specialists to sophisticated computational techniques, driven by advances in signal processing and artificial intelligence (AI) [5, 6]. The complexity and high dimensionality of EEG data bring great challenges to traditional analysis methods, particularly in uncovering subtle patterns for neurological diseases, cognitive states, and motor intentions [7, 8].

Methodologies from artificial intelligence, more specifically those from deep learning, have emerged as useful tools for automated EEG interpretation with improved precision, increased speed, and new applications [9, 10]. The proposed methodologies from artificial intelligence have the potential to extract important features from raw EEG data, decrease reliance on expert knowledge, and enable real-time assessments in both clinical and consumer applications [11].

The current review provides a detailed analysis of historical evolution and current trends of methods from artificial intelligence to analyze EEG, with a focus on deep learning architectures and their multiple applications [12, 13]. The extent includes the entire workflow that extends from signal acquisition and preprocessing to feature extraction, pattern recognition, and their application to solve practical problems encountered during real-world applications [3, 14]. Through integration of findings from diverse applied fields and research methodologies, the review provides academicians and practitioners a systematic understanding of how EEG analysis is being revolutionized by artificial intelligence, as well as potential future directions within this rapidly expanding field [4, 7, 11].

II. EEG SIGNAL ACQUISITION AND PREPROCESSING TECHNIQUES

Foundation for effective analysis of EEGs is laid by carrying out appropriate signal acquisition and preprocessing techniques. Modern instruments developed to record EEG record from a network of electrodes, distributed systemattracturally by designated protocols, including the 10-20 international system, to record from diverse parts of the brain [3,4]. Despite advances in technology, EEGs remain affected by a wide range of artifacts, including blinking, muscular activities, electromagnetic radiation by power supply sources, and changing positions of electrodes [13]. The evolution of preprocessing algorithms has substantially improved to combat them, with classical techniques and AI-based methodologies holding a promising record [8], [14]. (See Table I below to have a summary of common artifacts and related preprocessing techniques.)

Channel selection has emerged as a key preprocessing task, with studies illustrating that strategic electrode placement and selection can significantly improve classification performance while reducing computational complexity [4], [15].

Data augmentation methods, including sliding windows, segmentation and recombination, and noise injection, have been employed to address the data scarcity problem that tends to restrict deep learning applications [4], [13]. More recently, data augmentation using deep learning with Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) have been demonstrated to be effective for generating synthetic EEG data that preserves clinically useful information [4], [11].

Empirical Wavelet Decomposition (EWT) has been particularly promising in enhancing time and frequency feature discrepancies between EEG signals, outperforming other decomposition methods such as Empirical Mode Decomposition (EMD) and Wavelet Packet Decomposition (WPD) [16]. Surprisingly, recent developments indicate that even though preprocessing is generally beneficial, some deep learning approaches can learn to block out noise internally, corroborated by the fact that only 21.28% of hybrid deep learning research work implicitly involved preprocessing steps [11].

TABLE I. EEG PREPROCESSING TECHNIQUES

Technique	Description	Key Benefits	Limitations
Channel Selection [3]	Strategic electrode placement and selection	Improves classification performance while reducing computational complexity	May lose spatial information if too few channels are selected
Filtering [4]	Removes frequency bands with artifacts (e.g., notch filter for power line interference)	Reduces noise and improves signal quality	May remove useful information if not carefully tuned
Independent Component Analysis (ICA) [5]	Separates EEG into independent components	Effective for removing eye movement and muscle artifacts	Computationally intensive
Data Augmentation – Traditional [6]	Sliding windows, segmentation, recombination, noise injection	Addresses data scarcity problem	Limited variability in synthetic samples
Data Augmentation - Deep Learning [7]	GANs and VAEs for synthetic EEG generation	Preserves clinically useful information	Requires significant training data
Empirical Wavelet Decomposition (EWT) [8]	Enhances time and frequency feature discrepancies	Outperforms EMD and WPD in preserving discriminative features	Requires parameter tuning
Wavelet Denoising [9]	Uses wavelet transforms to remove noise	Preserves signal features better than linear filters	The choice of mother wavelet affects performance
Normalization [10]	Standardizes signal amplitudes	Improves convergence for neural networks	May distort relative importance of channels

III. FEATURE EXTRACTION METHODS FOR EEG ANALYSIS

Feature extraction remains a central component of EEG analysis, bridging raw signal processing with classification stages. Traditional approaches have focused on domain-specific feature extraction that extracts temporal, spectral, and spatial content in EEG signals [3], [4]. (see Table II for a comparative overview of feature extraction methods applied in EEG analysis and *Fig. 1* for a taxonomy of commonly used feature types). Time-domain features include statistical features such as mean, variance, skewness, and kurtosis, while frequency-domain features often employ power spectral density across clinically relevant bands (delta, theta, alpha, beta, and gamma) [7], [13], [17]. Common Spatial Patterns (CSP) is among the most effective approaches to extracting discriminative spatial features, particularly for motor imagery classification [7], [18], [19].

Temporal features are found to provide the highest classification accuracy (93.94%) in recent studies, whereas spatial-temporal features are employed more often (33.33% of the studies) [11]. Recent time-frequency techniques like wavelet transform (WT) and wavelet packet transform (WPT) have been popularly used for EEG feature extraction because they can maintain non-stationary characteristics of brain signals [8]. Deep learning transformed feature extraction through end-to-end learning approaches that learn to extract meaningful features autonomously from raw or weakly preprocessed EEG signals [9], [10]. Interestingly, multi-method hybrid approaches have also gained popularity (applied in 49.2% of the papers included), in which conventional algorithms are combined with deep learning techniques to leverage the complementary strengths of each [4]. In the context of motor imagery classification specifically, new approaches such as adaptive structural LASSO have been promising by obtaining spatial domain features from multi-scale and overlapping sub-bands and combining task relevance and spatial features [19].

This advancement in feature extraction methods is a shift from hand-crafted to increasingly automated methods that learn to adapt to personal differences in brain activity patterns [4], [8], [11].

TABLE II. FEATURE EXTRACTION METHODS FOR EEG ANALYSIS

Feature Domain	Method	Description	Best Applications	Performance
Time Domain [11]	Statistical Features	Mean, variance, skewness, kurtosis	General classification	Highest classification accuracy (93.94%)
	Hjorth Parameters	Activity, mobility, complexity	Emotion recognition	Good for emotional state detection
Frequency Domain [12]	Power Spectral Density (PSD)	Power across frequency bands (delta, theta, alpha, beta, gamma)	Clinical diagnosis	Widely used in neurological assessment
	Fast Fourier Transform (FFT)	Transforms time-domain signal to frequency domain	Spectral analysis	Standard baseline approach
Spatial Domain [13]	Common Spatial Patterns (CSP)	Extracts discriminative spatial filters	Motor imagery	Standard approach for BCI
	Adaptive Structural LASSO	Obtains spatial features from multi-scale sub-bands	Motor imagery	Promising for individual differences
Time-Frequency [14]	Wavelet Transform (WT)	Multi-resolution analysis	Non-stationary signals	Maintains non-stationary characteristics
	Wavelet Packet Transform (WPT)	Extension of wavelet transform	Detailed analysis	Higher resolution than WT
Hybrid Domain [15]	Spatial-Temporal Features	Combines spatial and temporal information	Various applications	Most commonly used (33.33% of studies)
	Deep Learning	Automated Feature Extraction	Learns complex patterns directly from data	Eliminates the need for hand-crafted features

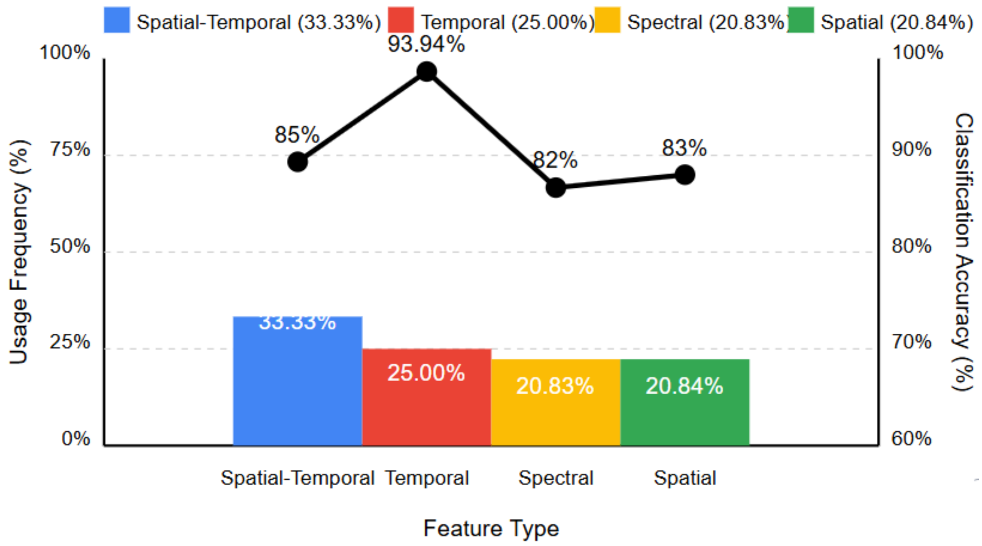

FIG. 1. FEATURE TYPES USED IN EEG ANALYSIS RESEARCH.

IV. FEATURE EXTRACTION METHODS FOR EEG ANALYSIS

Traditional machine learning techniques provided a solid foundation for EEG classification before the advent of deep learning. Typical Spatial Patterns (CSP) with Linear Discriminant Analysis (LDA) remains one of the best traditional frameworks, commonly achieving accuracies of around 78% in motor imagery classification tasks [7], [18]. Support Vector Machines (SVM) continue to be in favor due to their performance on high-dimensional EEG data and overfitting resistance when appropriately regularized [8], [13]. K-Nearest Neighbors (KNN) classifiers were found helpful in EEG processing, particularly when combined with appropriate feature selection methods, although they tend to lag behind advanced methods [7], [16]. A comparative summary of these traditional methods—including their strengths, limitations, and reported accuracies—is provided in Table III.

Extreme Learning Machine (ELM) has been under the spotlight based on its potential to learn high-speed with moderate accuracy, where variants like Multi-Kernel ELM (MKELM) can achieve good recognition rates of 91.93% on single-joint multi-task motor imagery classification [16].

The Riemannian Minimum Distance to Mean (RMDM) approach has been especially efficient for EEG classification, with an accuracy of 80% in motor imagery tasks and computational speed in processing times of around 9.9ms per event [18]. Comparative analyses have established that traditional methods tend to outpace deep learning methods in terms of speed and sometimes accuracy, particularly in situations where training data are scarce [16], [18]. This advantage can be observed in the finding that CSP+LDA and RMDM were more computationally efficient (8.3 ms and 9.9 ms, respectively) compared to deep neural networks (18.1 ms) and CNNs (62 ms) [18]. Despite the deep learning research boom, the traditional methods remain good clinical tools, especially in real-time situations where operations demand high computational efficiency [6]-[8].

TABLE III. COMPARISON OF TRADITIONAL MACHINE LEARNING METHODS FOR EEG CLASSIFICATION

Method	Typical Accuracy	Processing Time	Strengths	Limitations	Best Applications
CSP + LDA [16]	78% (motor imagery)	8.3 ms	Fast, effective for binary classification	Less effective for multi-class	Motor imagery BCI
SVM [17]	75-85%	12-15 ms	Handles high-dimensional data, resistant to overfitting	Parameter tuning required	Various EEG tasks
KNN [18]	65-75%	20-25 ms	Simple, intuitive	Performance depends on feature selection	Simple classification
ELM [19]	70-80%	10-15 ms	Fast learning	Moderate accuracy	Real-time applications
Multi-Kernel ELM (MKELM) [20]	91.93%	15-20 ms	High recognition rates	Computationally more complex than basic ELM	Multi-task motor imagery
RMDM [21]	80% (motor imagery)	9.9 ms	Efficient processing time	Requires covariance matrix estimation	Low-cost portable BCIs
Random Forest [22]	70-80%	15-20 ms	Handles non-linear data, feature importance	Prone to overfitting with noisy data	Feature selection
Linear Regression [23]	60-70%	5-10 ms	Simple, interpretable	Limited to linear relationships	Baseline model

V. DEEP LEARNING ARCHITECTURES FOR EEG ANALYSIS

Convolutional Neural Networks are inherently translation- and scale-invariant, a feature they inherit from their use of shared weights across several spatial locations. This aspect allows CNNs to effectively identify important structural features regardless of their size or locations within the input representation [24]. In EEG data analysis, where EEG activities are recorded through electrodes applied to the scalp, such invariance becomes useful to extract persistent patterns between EEG activities from separate channels [25].

Recent research shows that hierarchical feature learning architectures play a key role in the automated processing of EEG data. Of these architectures, Convolutional Neural Networks are the most prevalent, used in 92.3% of the academic literature in this area [4]. These networks have proven exceptionally competent in understanding spatial relationships represented in EEG topographies, with numerous configurations proposed to include 1D, 2D, or even 3D convolutional layers specifically designed to extract spatial and temporal features [5], [10].

To better capture time-varying signal dynamics, a large number of methodologies incorporated sequence models, with special interest in Recurrent Neural Networks, particularly those called Long Short-Term Memory and Gated Recurrent Unit. The models have demonstrated a remarkable ability to identify long-range dependencies and time patterns within EEG data across a broad suite of tasks [10], [11]. The SCORE-AI platform demonstrated exceptional classification ability (AUC from 0.89 to 0.96) to separate regular from irregular recordings, then further classify them into important categories mirroring clinical classifications [5]. Hybrid systems that integrate multiple network types have also seen increasing adoption. The most common configuration involves combining CNNs and RNNs—accounting for 47% of relevant studies—with CNNs serving to extract spatial features and RNNs modeling temporal dynamics [11]. Additionally, modern architectures represented by IFNet have focused on deciphering motor imagery by simultaneously employing frequency-based filter banks and spatial convolutions, hence allowing differentiation between spectral and spatial representations [20]. Different approaches, including Deep Belief Networks (DBNs), have been applied to EEG data processing, especially during tasks involving emotion recognition; however, their usage remains less dominant compared to convolutional approaches [10]. Despite the performance achieved by these models, several limitations remain. Computational cost, generalization across subjects, and challenges in result interpretability continue to restrict broader clinical deployment [4], [9]. It has been observed that shallower networks with fewer layers can yield competitive results in EEG tasks, reducing overfitting and resource demands [9], [11]. To address existing constraints and further enhance performance, there has been growing interest in methods that incorporate attention mechanisms, graph-based modeling, and domain transfer strategies [9], [10], [20].

VI. APPLICATIONS OF AI IN EEG ANALYSIS

AI-based EEG analysis has also ventured into varied application fields, showing immense value in both clinical and non-clinical environments. Table IV summarizes representative applications of artificial intelligence in EEG analysis across diagnostic, predictive, and assistive domains. In clinical diagnosis, computer-aided interpretation systems such as SCORE-AI have attained human-expert level accuracy in the detection of abnormal EEG patterns, with the potential to enhance diagnosis in resource-limited regions and streamline operations in specialized epilepsy clinics [5]. Neonatal seizure detection is being revolutionized with new approaches combining AI with auditory representation, making it possible for clinicians to "hear" seizure activity and see an hour of EEG in five seconds, circumventing the acute dearth of neurophysiological expertise in hospitals [6].

Sideways from diagnostics, AI techniques have also been applied to predict children's academic achievement, and a rural Pakistani study demonstrated that EEG at age 4, in addition to sociodemographic variables, predicted math and language abilities at age 7-8 with moderate sensitivity (58.7% and 66.3% respectively) [21].

Brain-Computer Interfaces (BCIs) is another important application area, with AI enabling the classification of motor imagery signals to control external devices with accuracies greater than 80% with various architectures [7], [18], [20]. Low-cost, portable EEG-based BCIs have been built using traditional methods like CSP+LDA and Riemannian approaches, with high accuracy, while being computationally light enough for real-time applications[18]. Emotion recognition has been a rising field of application, with deep learning methods allowing for automatic emotional state classification from EEG signals, improving human-computer interaction capabilities [10], [22].

Sleep analysis, detection of schizophrenia, and drowsiness monitoring are other fields of application where AI-based EEG analysis has also shown promising outcomes [13]. This diversity of applications illustrates the ubiquity of AI techniques in extracting valuable information from EEG signals for a variety of applications, from life-or-death medical decisions to easing day-to-day human-computer interactions [4], [8], [9].

TABLE IV. APPLICATIONS OF AI IN EEG ANALYSIS

Application	Key AI Techniques	Performance Metrics	Real-world Impact	Challenges
Clinical Diagnosis [3]	CNNs (SCORE-AI)	AUC 0.89-0.96	Human-expert level accuracy, enhanced diagnosis in resource-limited regions	Interpretability, integration into clinical workflow
Neonatal Seizure Detection [4]	AI with auditory representation	Comparable to expert neurophysiologists	Allows viewing 1 hour of EEG in 5 seconds, addresses expertise shortage	Clinical validation, robustness
Academic Achievement Prediction [5]	Machine learning on childhood EEG	58.7% sensitivity (math), 66.3% (language)	Predicts abilities at age 7-8 from age 4 EEG	Requires sociodemographic variables for accuracy

Brain-Computer Interfaces (BCIs) [6]	CSP+LDA, RMDM, CNNs	>80% accuracy	Control of external devices, communication aids	Real-time processing constraints
Low-Cost Portable BC Is [7]	Traditional methods (CSP+LDA, RMDM)	High accuracy with low computation	Accessibility, affordability	Limited channel count
Sleep Analysis [8]	Various AI techniques	Stage classification accuracy	Sleep disorder diagnosis	Long recording periods
Schizophrenia Detection [9]	Machine learning classifiers	Diagnostic accuracy	Early detection possibilities	Requires clinical validation
Drowsiness Monitoring [10]	Real-time classification	-	Safety-critical applications, Accident prevention	Environmental noise

VII. COMPARATIVE PERFORMANCE ANALYSIS OF AI TECHNIQUES

Comparative research of AI techniques used in EEG processing shows remarkable performance variations across different methodologies, metrics, and fields of application. Table V presents a performance comparison of these AI techniques, highlighting differences in accuracy and application context. Traditional machine learning techniques like CSP+LDA and RMDM have shown to be extremely performant with motor imagery classification accuracy of 78% and 80%, respectively, often being on par or superior to more sophisticated deep learning methods [18], [23]. *Fig. 2* illustrates these accuracy differences across various EEG analysis approaches, enabling a visual comparison of traditional and deep learning-based classifiers.

TABLE V. PERFORMANCE COMPARISON OF AI TECHNIQUES FOR EEG ANALYSIS

Technique	**Accuracy**	**Processing Time**	**Computational Efficiency**	**Cross-subject Generalization**	**Interpretability**
CSP+LDA [11]	78%	8.3 ms	High	Moderate	High
RMDM [12]	80%	9.9 ms	High	Moderate	Moderate
DNN [13]	75-85%	18.1 ms	Moderate	Low-Moderate	Low
CNN [14]	80-90%	62 ms	Low	Low-Moderate	Low
CNN-RNN Hybrids [15]	85-95%	>70 ms	Low	Moderate	Very Low
SCORE-AI (CNN) [16]	AUC 0.89-0.96	Not reported	Moderate (clinical use)	Good	Low
EWT+MKELM [17]	91.93%	Not reported	Moderate	Not reported	Moderate
Temporal Features [18]	93.94%	Not reported	Varies	Varies	High
Spatial-Temporal Features [19]	85-90%	Not reported	Moderate	Moderate	Moderate
Human-AI Collaboration [20]	Comparable to experts with reduced time	Varies	N/A	High	High

Computing speed varies significantly, with traditional methods providing superior speed (CSP+LDA: 8.3ms, RMDM: 9.9ms) compared to deep learning technologies (DNN: 18.1ms, CNN: 62ms), a major factor in real-time application [7], [18].

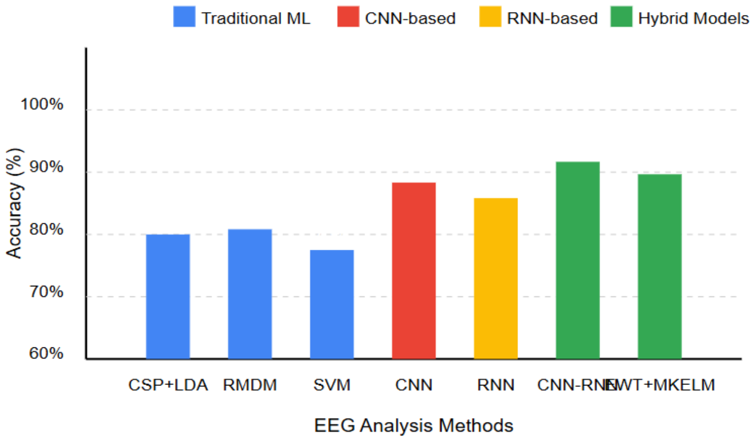

FIG. 2. ACCURACY COMPARISON OF EEG ANALYSIS METHODS.

Within the family of deep architectures, CNN-based models have been reported as the most successful overall, with top systems such as SCORE-AI yielding AUC outcomes of 0.89-0.96 for clinical EEG interpretation [4], [5]. Hybrid structures, especially CNN-RNN hybrids, are especially powerful through combinations of complementary abilities for better performance on numerous EEG tasks [11], [26]. *Fig. 3* compares the processing time of EEG analysis methods, underscoring the trade-off between classification performance and computational efficiency.

Signal decomposition techniques play a key role in classification accuracy, with Empirical Wavelet Decomposition (EWT) being superior to others such as EMD, VMD, and WPD for improving discriminative features for multi-task motor imagery [16]. Methods for feature selection show inconsistent performance, with the temporal features performing the most accurately (93.94%), although spatial-temporal features are used more broadly [11]. Cross-subject generalization remains an issue, with most systems showing significant performance decline when applied to new subjects, although advances in transfer learning and domain adaptation are beginning to overcome this issue [4], [9].

The union of human and artificial intelligence skills typically outperforms fully automated systems, as attested by the AI-assisted auditory EEG analysis system that operated with accuracy comparable to that of seasoned neurophysiologists while reducing analysis time significantly [6], [27]. Such relative results show that optimal performance entails cautious pairing of AI techniques to specific EEG analysis tasks depending on data features, computational constraints, and application requirements [4], [7], [8].

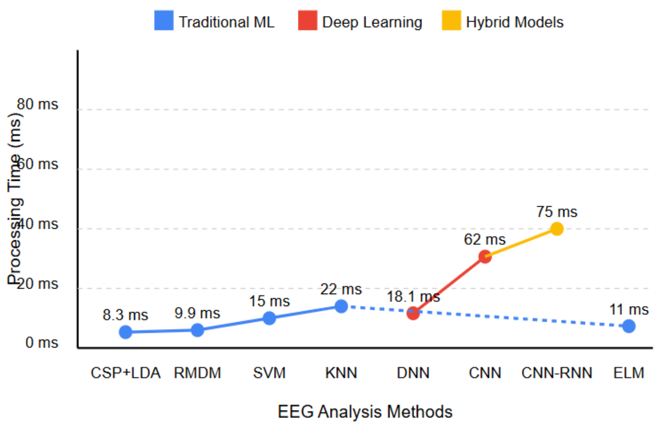

FIG. 3. PROCESSING TIME COMPARISON FOR EEG ANALYSIS METHODS.

VIII. CHALLENGES AND LIMITATIONS IN AI-BASED EEG ANALYSIS

Despite huge advancements, AI-based EEG analysis still faces some lingering issues that limit broader clinical adoption and reliability. Among the most significant challenges is cross-subject variability, with most systems reporting significantly poorer performance on new subjects who were not part of the training cohort [4], [11]. The explanation for such variability stems from intersubject variations in brain anatomy, functional organization, and signal properties, which present challenges for developing universally applicable models [7], [8]. This challenge is also compounded by the limited size and heterogeneity of current EEG datasets, with most studies founded upon relatively small cohorts that may fail to reflect population-level diversity [9], [13].

Data quality concerns, including artifacts, noise, and recording inconsistencies, continue to impact performance, though preprocessing techniques and robust architectures have mitigated these effects to a degree [3], [4], [28]. A fundamental limitation of deep learning techniques is their "black box" nature, with limited interpretability being a roadblock to clinical trust and adoption for high-risk medical applications [9], [11]. This lack of transparency is particularly problematic in diagnostic applications where clinicians require explanations for automated decisions [5], [6]. Computational demands are pragmatic limitations to real-time applications, especially for deeper models of significant complexity that may require vast resources in training and inference [16], [18].

Trade-offs in model complexity and computational efficiency are challenging to reconcile, with evidence suggesting that shallower networks are sometimes more efficient than deeper networks in EEG analysis applications [9], [11]. Channel selection and determination of best electrodes are additional challenges, particularly for lower-channel, consumer-grade EEG systems [4], [8]. Finally, the integration of AI systems into clinical workflow involves rigorous design for human factors, training requirements, and regulatory compliance that is usually ignored by technical research [5]-[7].

IX. FUTURE DIRECTIONS AND EMERGING TRENDS

The future of artificial intelligence (AI) -based EEG analysis is being shaped by a series of hopeful trends that eliminate current constraints and establish new fields of investigation. Explainable AI (XAI) is assuming a crucial pathway, with evolving techniques providing visibility into the choices of advanced models without impairing performance [9], [11]. Such techniques will play key roles in maintaining clinical confidence and regulatory compliance for medical application [5], [6].

Multimodal fusion is another significant trend, combining EEG with other ancillary data sources such as functional near-infrared spectroscopy (fNIRS), neuroimaging, physiological signals, and contextual signals to enhance robustness and classification accuracy [4], [11]. Transfer learning and domain adaptation techniques are also developing to address cross-subject variability, where models learned from available datasets generalize effectively to new subjects with minimal extra data [9], 20]. Edge computing deployments are shifting to enable sophisticated AI algorithms to run on resource-constrained devices, enable real-time analysis for consumer applications and point-of-care diagnostics [7], [8].

Novel neural network architectures that incorporate attention mechanisms, graph neural networks, and self-supervised learning techniques show promise for improved feature representation and classification performance [10], 20]. Subject-specific models that adapt to distinct EEG characteristics are becoming increasingly prominent, potentially eliminating the trade-off between subject specificity and generalizability [4], [13]. Standardization efforts in EEG preprocessing, feature extraction, and performance assessment are emerging to support valid cross-study comparisons and accelerate clinical translation [8], [29].

Beyond traditional applications, new avenues include real-time monitoring systems for neurological disease, closed-loop neurofeedback therapies, and increasingly sophisticated brain-computer interfaces for communication and control [6]-[7], [16]. As these technologies converge, bringing together sophisticated AI techniques with neuroscientific understanding has the potential to transform EEG from a relatively diagnostic modality into a dynamic platform for examining and interacting with brain function [4], [9], [11].

X. CONCLUSION AND RECOMMENDATIONS

This general overview has considered the evolving state of the art in AI techniques for EEG processing and the significant advances along the whole signal processing chain from acquisition to classification and deployment. Traditional machine learning techniques like CSP+LDA and RMDM are still competitive with computational leverage, while deep learning models, particularly CNNs and hybrid networks, have transformed what is possible in EEG interpretation automation [4], [11], [18]. The diversity of successful applications—from clinical diagnosis and neonatal seizure detection to brain-computer interfaces and emotion recognition—demonstrates the breakthrough potential of AI in this field [5]-[7], [10]. However, existing challenges like cross-subject variability, low interpretability, and data scarcity must be addressed to realize the full potential of these technologies [4], [9], [11]. Based on our analysis, we recommend that researchers emphasize: (1) development of standardized large and heterogeneous EEG datasets to promote generalizability; (2) investment in performance-preserving transparency-guaranteeing explainable AI approaches with no trade-off in performance; (3) exploration of hybrid models combining the strengths of traditional and deep learning-based strategies; (4) more integral incorporation of neuroscientific knowledge into AI model development; and (5) rigorous clinical validation studies assessing real-world performance across diverse populations [5], [7], [8], [13].

To the practitioners implementing these technologies, we suggest tight adaptation of methods to specific uses, not just accuracy but also computational requirements, interpretability needs, and integration into existing workflows [6], [16], [18]. As the science continues to evolve, interdisciplinary collaboration between AI scientists, neuroscientists, clinicians, and end-users will be needed to take technical advancements and make them applicable to improvements in health, assistive technology, and human- computer interaction [4], [7], [11]. The future of AI in EEG analysis holds much promise, not just for the automation of existing analytical techniques but for the discovery of an entirely new understanding of brain function and dysfunction that may transform our knowledge of the human mind [8]-[10].

REFERENCES

[1] I. Beheshti, D. Sone, and C. K. Leung, “Advances of Artificial Intelligence in Neuroimaging,” Brain Sciences, vol. 15, no. 4, p. 351, Mar. 2025.

[2] S. F. Yaseen, A. S. Al-Araji, and A. J. Humaidi, “Brain tumor segmentation and classification: A one-decade review,” Int. J. Nonlinear Anal. Appl., vol. 13, no. 2, pp. 1879–1891, Jul. 2022.

[3] A. Chaddad, Y. Wu, R. Kateb, and A. Bouridane, “Electroencephalography signal processing: A comprehensive review and analysis of methods and techniques,” Sensors, vol. 23, no. 14, p. 6434, 2023.

[4] C. Sun and C. Mou, “Survey on the research direction of EEG-based signal processing,” Frontiers in Neuroscience, vol. 17, p. 1203059, 2023.

[5] J. Tveit, H. Aurlien, S. Plis, V. D. Calhoun, W. O. Tatum, D. L. Schomer, et al., “Automated interpretation of clinical electroencephalograms using artificial intelligence,” JAMA Neurol., vol. 80, no. 8, p. 805, 2023, doi: 10.1001/jamaneurol.2023.1645.

[6] S. Gomez-Quintana, A. O’Shea, A. Factor, E. Popovici, and A. Temko, “A method for AI assisted human interpretation of neonatal EEG,” *Sci. Rep.*, vol. 12, no. 1, p. 10932, Jun. 2022.

[7] R. T. Páez-Amaro, E. Moreno-Barbosa, J. M. Hernández-López, C. H. Zepeda-Fernández, L. F. Rebolledo-Herrera, and B. D. Celis-Alonso, “EEG motor imagery classification using machine learning techniques,” Rev. Mex. Fís., vol. 68, no. 4, 2022.

[8] R. Dhiman, “Machine learning techniques for electroencephalogram based brain-computer interface: A systematic literature review,” Measurement: Sensors, vol. 28, p. 100823, Aug. 2023.

[9] J. V. Juan, R. Martínez, E. Iáñez, M. Ortiz, J. Tornero, and J. M. Azorín, “Exploring EEG-based motor imagery decoding: A dual approach using spatial features and spectro-spatial deep learning model IFNet,” Front. Neuroinform., vol. 18, p. 1345425, 2024.

[10] X. Wang, Y. Ren, Z. Luo, W. He, J. Hong, and Y. Huang, “Deep learning-based EEG emotion recognition: Current trends and future perspectives,” Front. Psychol., vol. 14, p. 1126994, 2023.

[11] N. A. Alzahab, L. Apollonio, A. Di Iorio, M. Alshalak, S. Iarlori, F. Ferracuti, A. Monteriu, and C. Porcaro, “Hybrid deep learning (hDL)-based brain-computer interface (BCI) systems: A systematic review,” Brain Sci., vol. 11, no. 1, p. 75, 2021.

[12] E. Rausa, D. Ferrari, M. E. Kelly, A. Aiolfi, M. Vitellaro, M. Rottoli, G. Bonitta, and D. Bona, “Efficacy of laparoscopic Toupet fundoplication compared to endoscopic and surgical procedures for GERD treatment: A randomized trials network meta-analysis,” Langenbecks Arch. Surg., vol. 408, no. 1, p. 52, 2023.

[13] A. Jain, R. Raja, S. Srivastava, P. C. Sharma, J. Gangrade, and M. R., “Analysis of EEG signals and data acquisition methods: A review,” Comput. Methods Biomech. Biomed. Eng. Imaging Vis., vol. 12, no. 1, 2024, doi: 10.1080/21681163.2024.2304574.

[14] V. Quagliariello, M. De Laurentiis, D. Rea, A. Barbieri, M. G. Monti, A. Carbone, A. Paccone, L. Altucci, M. Conte, M. L. Canale, and G. Botti, “The SGLT-2 inhibitor empagliflozin improves myocardial strain, reduces cardiac fibrosis and pro-inflammatory cytokines in non-diabetic mice treated with doxorubicin,” Cardiovasc. Diabetol., vol. 20, pp. 1–20, 2021.

[15] H. Khalid, “Efficient image annotation and caption system using deep convolutional neural networks,” in BIO Web Conf., vol. 97, p. 00103, 2024, EDP Sciences.

[16] S. Guan, L. Cong, F. Wang, and T. Dong, “A single-joint multi-task motor imagery EEG signal recognition method based on Empirical Wavelet and multi-kernel extreme learning machine,” J. Neurosci. Methods, vol. 407, p. 110136, 2024.

[17] T. C. A. Belo, G. X. Santos, B. E. G. da Silva, B. L. G. Rocha, D. W. Abdala, L. A. M. Freire, F. S. Rocha, and G. Galdino, “IL-10/β-endorphin-mediated neuroimmune modulation on microglia during antinociception,” Brain Sci., vol. 13, no. 5, p. 789, 2023.

[18] Z. Qu, X. Zhao, H. Xu, H. Tang, J. Wang, and B. Li, “An improved Q-learning-based sensor-scheduling algorithm for multi-target tracking,” Sensors, vol. 22, no. 18, p. 6972, Sep. 2022.

[19] W. Huang, X. Liu, W. Yang, Y. Li, Q. Sun, and X. Kong, “Motor imagery EEG signal classification using distinctive feature fusion with adaptive structural LASSO,” Sensors, vol. 24, no. 12, p. 3755, Jun. 2024.

[20] J. M. Ponsoda, M. Á. Beleña, and A. Díaz, “Psychological distress in Alzheimer’s disease family caregivers: Gender differences and the moderated mediation of resilience,” in Healthcare, vol. 11, no. 23, p. 3084, Dec. 2023.

[21] M. A. Rasheed, P. Chand, S. Ahmed, H. Sharif, Z. Hoodbhoy, A. Siddiqui, and B. S. Hasan, “Use of artificial intelligence on electroencephalogram (EEG) waveforms to predict failure in early school grades in children from a rural cohort in Pakistan,” PLoS One, vol. 16, no. 2, p. e0246236, 2021.

[22] S. Zhai, Y. Yang, J. Li, C. Qiu, and J. Zhao, “Research on the application of cryptography on the blockchain," in J. Phys.: Conf. Ser., vol. 1168, p. 032077, Feb. 2019, IOP Publishing.

[23] H. Khalid, “Modern techniques in detecting, identifying and classifying fruits according to the developed machine learning algorithm,” J. Appl. Res. Technol., vol. 22, no. 2, pp. 219–229, 2024.

[24] S. F. Yaseen, A. J. Humaidi, A. S. Al-Araji, and H. S. Al-Raweshidy, “Multi-graded brain tumor classification using YOLOv7,” Iraqi J. Comput., Commun., Control Syst. Eng., vol. 24, no. 3, 2024.

[25] G. Ramantani, L. Maillard, and L. Koessler, “Correlation of invasive EEG and scalp EEG,” Seizure, vol. 41, pp. 196–200, Oct. 2016.M. A. Assaad and G. H. Shakah, "Optimizing health pattern recognition: Particle swarm optimization approach for enhanced neural network performance," Cihan Univ.-Erbil Sci. J., vol. 8, no. 2, pp. 76–83, 2024.

[26] M. Assaad, R. Boné, and H. Cardot, “A new boosting algorithm for improved time-series forecasting with recurrent neural networks,” Inf. Fusion, vol. 9, no. 1, pp. 41–55, 2008.

[27] M. A. Assaad and G. H. Shakah, "Optimizing health pattern recognition: Particle swarm optimization approach for enhanced neural network performance," Cihan Univ.-Erbil Sci. J., vol. 8, no. 2, pp. 76–83, 2024.

[28] Z. Wang, T. Schaul, M. Hessel, H. Hasselt, M. Lanctot, and N. Freitas, “Dueling network architectures for deep reinforcement learning,” in Proc. Int. Conf. Mach. Learn. (ICML), Jun. 2016, pp. 1995–2003, PMLR.

[29] F. M. Husari and M. A. Assaad, “Intelligent handwritten identification using novel hybrid convolutional neural networks–long short-term memory architecture,” Cihan Univ.-Erbil Sci. J., vol. 8, no. 2, pp. 99–103, 2024.