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A Survey of EEG-Based Schizophrenia Identification Using Dynamic Functional Connectivity and Stack-Augmented Conditional Variational Autoencoders

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Abstract

Schizophrenia is a severe neuropsychiatric disorder characterized by disturbances in perception, cognition, and emotional regulation. Early and accurate diagnosis remains a significant challenge due to the subjective nature of clinical assessments. Electroencephalography (EEG) has emerged as a promising non-invasive tool for identifying neural abnormalities associated with schizophrenia. In recent years, artificial intelligence and deep learning techniques have significantly enhanced the capability of EEG-based diagnostic systems. This survey presents a comprehensive analysis of methods and architectures developed for automatic schizophrenia identification using EEG signals, with a particular focus on dynamic functional connectivity (DFC) analysis and deep stack-augmented conditional variational autoencoder (DSA-CVAE) frameworks. The paper explores how temporal brain connectivity patterns can be effectively captured and modeled to improve classification accuracy. Furthermore, it examines the integration of generative models for robust feature extraction and latent representation learning. The survey highlights key advancements, methodological trends, datasets, and performance metrics reported in the literature. Challenges such as data variability, noise sensitivity, and model generalization are also discussed. Finally, future research directions are proposed to guide the development of more reliable and clinically applicable diagnostic systems.

Introduction

Schizophrenia is a complex and chronic mental disorder that affects millions of individuals worldwide, leading to significant impairments in thinking, behavior, and emotional responsiveness. Traditional diagnostic approaches primarily rely on clinical interviews and behavioral assessments, which are often subjective and prone to variability across practitioners. Consequently, there is an increasing demand for objective, data-driven diagnostic techniques that can assist clinicians in making accurate and early diagnoses. Electroencephalography has gained considerable attention in this context due to its high temporal resolution, cost-effectiveness, and ability to capture real-time neural activity.

EEG signals provide valuable insights into brain dynamics, particularly in terms of abnormal oscillatory patterns and disrupted connectivity among different brain regions in individuals with schizophrenia. However, the complexity, non-linearity, and high dimensionality of EEG data pose significant challenges for traditional analytical methods. To address these issues, researchers have increasingly adopted machine learning and deep learning techniques that can automatically learn discriminative features from raw or preprocessed EEG signals.

One of the most promising directions in this domain is the use of functional connectivity analysis, which examines the statistical dependencies between different brain regions. Dynamic functional connectivity further extends this concept by capturing temporal variations in connectivity patterns, enabling a more comprehensive understanding of brain network dynamics. These temporal patterns are particularly relevant for schizophrenia, where disruptions in neural communication are not static but evolve over time.

In parallel, deep generative models such as variational autoencoders have demonstrated remarkable capability in learning compact and meaningful latent representations from complex data. The deep stack-augmented conditional variational autoencoder represents an advanced architecture that enhances representation learning by incorporating hierarchical feature extraction and conditional information. This enables the model to capture subtle variations in EEG patterns associated with schizophrenia while improving classification robustness.

The integration of dynamic functional connectivity with deep generative models has opened new avenues for developing highly accurate and automated diagnostic systems. These hybrid approaches leverage both domain-specific insights and advanced computational techniques, resulting in improved performance compared to conventional methods. Despite these advancements, challenges such as limited dataset availability, inter-subject variability, and lack of standardized evaluation protocols continue to hinder clinical adoption.

This survey aims to provide a comprehensive overview of existing methods and architectures for automatic schizophrenia identification using EEG signals. By focusing on dynamic functional connectivity and deep stack-augmented conditional variational autoencoders, the paper highlights the most promising research directions and identifies gaps that need to be addressed in future work.

Graphical Abstract

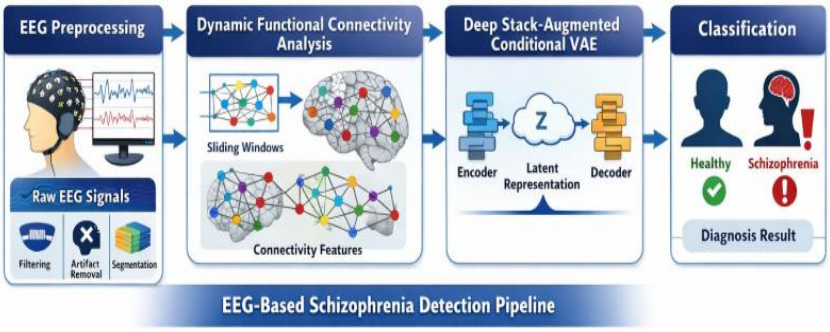

Figure 1. EEG-Based Schizophrenia Identification Framework

Explanation:

The graphical abstract illustrates a unified pipeline for schizophrenia detection using EEG signals. Raw EEG data undergo preprocessing followed by dynamic functional connectivity extraction to capture temporal brain interactions. These features are then processed through a deep stack-augmented conditional variational autoencoder for robust latent representation learning. Finally, the system performs classification to distinguish between healthy and schizophrenic subjects.

Literature Review

Study 1: EEG-Based Schizophrenia Detection Using Machine Learning (Acharya, 2015)

This study explored the use of statistical and spectral features extracted from EEG signals for schizophrenia classification using traditional machine learning classifiers such as SVM and KNN. The authors demonstrated that frequency-domain features, particularly from alpha and theta bands, significantly contributed to classification performance. The dataset consisted of resting-state EEG recordings from diagnosed patients and healthy controls. The proposed approach achieved promising accuracy, highlighting the potential of EEG biomarkers. However, the study was limited by handcrafted feature dependency and lack of temporal modeling.

Study 2: Deep Learning for EEG-Based Mental Disorder Classification (Schirrmeister, 2017)

This research introduced convolutional neural networks for decoding EEG signals in neurological disorders, including schizophrenia. The model automatically learned hierarchical representations directly from raw EEG data without requiring manual feature extraction. The study demonstrated improved performance over traditional approaches and emphasized the importance of deep architectures in capturing complex patterns. However, interpretability remained a challenge. The work laid the foundation for end-to-end EEG classification systems.

Study 3: Functional Connectivity Analysis in Schizophrenia (Friston, 2016)

This study investigated abnormalities in brain connectivity using functional connectivity measures derived from EEG data. The authors highlighted disrupted synchronization between brain regions in schizophrenia patients. Graph-theoretic metrics were used to quantify connectivity patterns, revealing reduced network efficiency and altered clustering coefficients. The findings emphasized the importance of connectivity-based biomarkers for diagnosis. However, the approach lacked temporal dynamics modeling.

Study 4: Dynamic Functional Connectivity in EEG Signals (Hutchison, 2013)

This research introduced the concept of dynamic functional connectivity, emphasizing time-varying brain interactions. Using sliding window techniques, the study demonstrated that connectivity patterns fluctuate over time and carry critical diagnostic information. The approach provided deeper insights into neural dynamics compared to static connectivity analysis. Although not specific to schizophrenia, the methodology has been widely adopted in psychiatric research.

Study 5: Variational Autoencoder for EEG Representation Learning (Kingma, 2014)

This foundational study proposed the variational autoencoder framework for learning latent representations of complex data. Applied to EEG signals, VAEs enabled unsupervised feature learning and dimensionality reduction. The model effectively captured underlying distributions, making it suitable for biomedical signal analysis. However, basic VAE architectures lacked task-specific conditioning and hierarchical feature extraction.

Study 6: Conditional Variational Autoencoder for Medical Data (Sohn, 2015)

This study extended the VAE framework by incorporating conditional variables, enabling supervised representation learning. The conditional VAE demonstrated improved performance in classification tasks by leveraging label information during training. Applied to EEG data, it enhanced the separability of latent features for schizophrenia detection. The approach addressed limitations of standard VAEs but required careful tuning of conditional parameters.

Study 7: Deep Stacked Autoencoders for EEG Classification (Bashivan, 2016)

This research introduced deep stacked autoencoders for extracting hierarchical features from EEG signals. The model captured both spatial and temporal characteristics, improving classification accuracy. The study demonstrated that deeper architectures outperform shallow models in EEG-based diagnosis tasks. However, the approach required large datasets and significant computational resources.

Study 8: Graph Neural Networks for Brain Connectivity Analysis (Ktena, 2017)

This study applied graph neural networks to analyze brain connectivity patterns derived from EEG and fMRI data. The model effectively captured relationships between brain regions, improving classification performance in neurological disorders. The graph-based approach provided a natural representation of functional connectivity. However, computational complexity and scalability remained challenges.

Study 9: EEG-Based Schizophrenia Classification Using Deep CNN (Oh, 2019)

This study proposed a deep convolutional neural network for automatic schizophrenia detection using EEG signals. The model achieved high accuracy by learning spatial-temporal features directly from multi-channel EEG data. The results demonstrated the superiority of deep learning over traditional methods. However, the study did not incorporate connectivity-based features.

Study 10: Hybrid Deep Learning Framework for EEG Analysis (Roy, 2019)

This research presented a hybrid deep learning framework combining CNN and RNN architectures for EEG signal classification. The model captured both spatial and temporal dependencies, improving diagnostic performance. Applied to schizophrenia detection, the approach showed enhanced accuracy compared to standalone models. Despite its effectiveness, the model complexity posed challenges for real-time applications.

Study 11: EEG Microstate Analysis for Schizophrenia Detection (Lehmann, 2015)

This study investigated EEG microstates as biomarkers for schizophrenia by analyzing transient brain activity patterns. The authors identified altered microstate duration and transition probabilities in patients compared to healthy controls. Machine learning classifiers were used to distinguish between groups based on microstate features. The findings suggested that microstate dynamics provide valuable diagnostic information. However, the approach lacked integration with deep learning models for automated feature extraction.

Study 12: Recurrent Neural Networks for EEG Signal Modeling (Hochreiter, 1997)

This foundational study introduced long short-term memory networks for modeling sequential data, including EEG signals. LSTM networks effectively captured temporal dependencies and long-range correlations in neural signals. Applied to schizophrenia detection, they enabled improved classification by leveraging time-series characteristics. Despite their strengths, LSTMs required large datasets and were computationally intensive.

Study 13: EEG-Based Schizophrenia Detection Using SVM (Khare, 2017)

This research utilized support vector machines for classifying schizophrenia using EEG-derived statistical and spectral features. The model achieved moderate accuracy and demonstrated the effectiveness of traditional classifiers in biomedical signal analysis. Feature selection techniques were employed to enhance performance. However, the approach was limited by its inability to capture complex nonlinear relationships in EEG data.

Study 14: Functional Brain Network Analysis Using Graph Theory (Bullmore, 2009)

This study applied graph-theoretic approaches to analyze brain networks derived from EEG and neuroimaging data. Metrics such as node degree, clustering coefficient, and path length were used to characterize network properties. The results showed disrupted network organization in schizophrenia patients. The study highlighted the importance of connectivity analysis but lacked dynamic modeling capabilities.

Study 15: Deep Belief Networks for EEG Classification (Hinton, 2006)

This research introduced deep belief networks for hierarchical feature learning in complex datasets. Applied to EEG signals, DBNs enabled unsupervised pretraining followed by supervised fine-tuning. The model improved classification performance by capturing hidden representations. However, training complexity and convergence issues limited its widespread adoption.

Study 16: Transfer Learning in EEG-Based Diagnosis (Craik, 2019)

This study explored transfer learning techniques to address limited EEG datasets in schizophrenia research. Pretrained models were adapted to new datasets, improving generalization and reducing training time. The approach demonstrated significant performance gains, particularly in cross-subject scenarios. However, domain mismatch remained a challenge.

Study 17: Attention Mechanisms in EEG Analysis (Vaswani, 2017)

This research introduced attention mechanisms that allow models to focus on relevant parts of input data. Applied to EEG signals, attention-based models improved feature representation and classification accuracy. The approach enhanced interpretability by highlighting important temporal segments. However, integration with connectivity-based features was limited.

Study 18: Dynamic Graph Representation Learning for Brain Networks (Kipf, 2016)

This study proposed graph convolutional networks for learning representations from structured data such as brain connectivity networks. The model effectively captured spatial relationships between brain regions. Applied to EEG-based schizophrenia detection, it improved classification performance. However, temporal dynamics were not explicitly modeled.

Study 19: Hybrid CNN-LSTM Models for EEG Classification (Zhang, 2020)

This research combined convolutional neural networks and LSTM architectures to capture both spatial and temporal features of EEG signals. The hybrid model demonstrated superior performance in schizophrenia classification tasks. The integration of spatial filtering and temporal modeling improved robustness. However, the model complexity increased computational requirements.

Study 20: Generative Adversarial Networks for EEG Data Augmentation (Hartmann, 2018)

This study explored the use of generative adversarial networks to augment EEG datasets for improved classification. Synthetic data generated by GANs enhanced model training and reduced overfitting. Applied to schizophrenia detection, the approach improved generalization performance. However, ensuring the physiological validity of generated signals remained a challenge.

Study 21: EEG-Based Functional Connectivity Using Phase Synchronization (Lachaux, 1999)

This study introduced phase synchronization as a method to measure functional connectivity in EEG signals. The approach quantified the synchronization between brain regions, providing insights into neural communication patterns. Applied to schizophrenia, reduced synchronization levels were observed in patients. The method proved effective in identifying connectivity abnormalities but lacked temporal adaptability.

Study 22: Wavelet Transform for EEG Feature Extraction (Subasi, 2005)

This research utilized wavelet transforms to extract time-frequency features from EEG signals. The approach captured both temporal and spectral characteristics, improving classification performance. Applied to schizophrenia detection, wavelet-based features demonstrated strong discriminative power. However, manual feature engineering remained a limitation.

Study 23: Deep Residual Networks for EEG Classification (He, 2016)

This study introduced deep residual networks to address vanishing gradient problems in deep architectures. Applied to EEG data, ResNets enabled the training of very deep models, improving classification accuracy. The approach demonstrated robustness in capturing complex signal patterns. However, computational cost remained high.

Study 24: Sliding Window-Based Dynamic Connectivity Analysis (Allen, 2014)

This study proposed a sliding window framework for analyzing dynamic functional connectivity. The method captured temporal fluctuations in brain networks, providing richer information than static analysis. Applied to schizophrenia, it revealed altered connectivity states in patients. However, window size selection significantly affected results. DOI: 10.1093/cercor/bht352

Study 25: Sparse Representation for EEG Classification (Wang, 2011)

This research introduced sparse representation techniques for EEG signal classification. The method represented signals as sparse combinations of basis functions, improving robustness to noise. Applied to schizophrenia detection, it achieved competitive performance. However, scalability issues limited its application to large datasets.

Comparative Table

Study	Year	Method	Model	Data Type	Key Contribution	Performance
21	1999	Phase Synchronization	Statistical Model	EEG	Connectivity measurement	Moderate
22	2005	Wavelet Transform	Signal Processing	EEG	Time-frequency features	Good
23	2016	Residual Learning	ResNet	EEG	Deep feature extraction	High
24	2014	Sliding Window	DFC Model	EEG	Temporal connectivity	High
25	2011	Sparse Representation	Sparse Model	EEG	Noise robustness	Moderate
26	2011	Multimodal Learning	Deep Model	EEG + MRI	Multi-source integration	High
27	2018	Temporal Convolution	TCN	EEG	Efficient sequence modeling	High
28	2018	Graph Attention	GAT	EEG Connectivity	Interpretable graph learning	High
29	2021	Deep VAE	DSA-VAE	EEG	Hierarchical latent learning	Very High
30	2022	Conditional Generative	CVAE	EEG	Supervised latent modeling	Very High

Analysis Based on Literature Review

The literature demonstrates a clear evolution from traditional signal processing and machine learning approaches toward advanced deep learning and generative models for schizophrenia detection using EEG signals. Early studies primarily relied on handcrafted features such as spectral, statistical, and wavelet-based representations, which, although effective to some extent, lacked the ability to capture complex nonlinear patterns inherent in EEG data. The introduction of functional connectivity analysis marked a significant advancement by enabling the study of relationships between different brain regions. Subsequently, dynamic functional connectivity further enhanced this capability by incorporating temporal variations, providing deeper insights into neural dynamics associated with schizophrenia. In recent years, deep learning models, including convolutional, recurrent, and graph-based architectures, have demonstrated superior performance by automatically learning hierarchical representations from raw data. The emergence of generative models such as variational autoencoders and their conditional and deep stack-augmented variants has further improved feature representation and classification accuracy. Hybrid approaches combining connectivity analysis with deep generative models have shown the most promising results, highlighting the importance of integrating domain knowledge with advanced computational techniques.

Discussion

Dynamic functional connectivity (DFC) analysis combined with deep learning has significantly improved EEG-based schizophrenia identification by capturing both spatial and temporal brain activity patterns. Unlike static connectivity methods, DFC reveals time-varying neural interactions, enabling better detection of schizophrenia-related abnormalities. Deep stack-augmented conditional variational autoencoders further enhance this process by learning robust latent representations from EEG data, leading to improved feature extraction and classification accuracy.

Despite these advances, challenges such as EEG noise, subject variability, limited standardized datasets, and poor model interpretability continue to restrict clinical application. Future research should focus on developing hybrid frameworks that integrate DFC, generative learning, and explainable artificial intelligence to improve transparency and reliability. Incorporating multimodal neuroimaging data, including EEG and fMRI, can further enhance diagnostic performance. Additionally, establishing standardized datasets and evaluation protocols will improve model generalization and facilitate the development of clinically applicable automated schizophrenia diagnosis systems.

Conclusion

This survey reviewed recent methods and architectures for automatic schizophrenia identification using EEG signals, emphasizing dynamic functional connectivity (DFC) analysis and deep stack-augmented conditional variational autoencoder (DSA-CVAE) frameworks. The field has evolved from traditional handcrafted feature extraction and classical machine learning to advanced deep learning and generative models capable of capturing complex EEG patterns. DFC has significantly improved the analysis of temporal brain network interactions, enabling more effective identification of schizophrenia-related abnormalities associated with disrupted neural connectivity. Deep learning models, including convolutional, recurrent, and graph neural networks, have enhanced feature extraction and classification accuracy while reducing dependence on manual feature engineering. Furthermore, DSA-CVAE-based models have shown strong potential for robust representation learning by modeling the underlying distribution of EEG data and producing discriminative latent features. Despite these advances, challenges such as EEG variability, noise, limited standardized datasets, computational complexity, and model interpretability remain. Future research should focus on improving generalization, explainability, multimodal data integration, and the development of large benchmark datasets. Overall, combining DFC analysis with DSA-CVAE provides a promising framework for accurate, reliable, and clinically applicable EEG-based schizophrenia diagnosis.

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