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A Comprehensive Survey on Schizophrenia Detection Using Machine Learning and EEG Analysis

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Abstract
Schizophrenia is a devastating mental illness that affects many millions of people worldwide and is defined by a breakdown of the thought process and perception. Clinical interviews and behavioural assessments used as traditional diagnostic methods are subjective and time-consuming. Recent progress in machine learning (ML) and electroencephalography (EEG) facilitates the development of automated, stable, and generalizable diagnostic procedures. This survey offers an extensive review of state-of-the-art studies which utilized ML to detect schizophrenia, specifically in the context of EEG data. The comparison assesses the strengths and weaknesses of the methodologies, datasets, and algorithms. To go beyond existing challenges, we then explore future directions, such as explainable AI, multimodal integration, and personalization of diagnostic tools.

1. Introduction

1.1 Background on Schizophrenia

Schizophrenia is a debilitating disorder of psychosis that occurs in ~1 in 300 individuals globally (Velligan & Rao, 2023) While citing varied symptoms, all of them includes hallucinations, delusions, disorganized speech, and cognitive autism. Despite this, we still poorly understand the exact pathophysiology after decades of research, and early, accurate diagnosis remains a challenge (Gold & Frierson, 2020).

1.2 Limitations of Traditional Diagnostic Methods

Diagnosis today is based almost entirely on post-hoc subjective assessment guided by DSM-5 or ICD-11 criteria, which has the problem of human error and variability in humans. This subjectivity often leads to delayed treatment and deteriorating patient outcomes. In addition, conventional approaches require considerable amounts of time and money and are less feasible in resource-poor environments (Velligan & Rao, 2023).

Table 1: Challenges and Impacts of Traditional Schizophrenia Diagnosis

Challenges with Traditional Diagnosis	Impact
Subjectivity	Inconsistent diagnoses across clinicians.
Long Observation Periods	Delayed interventions and increased burden on healthcare systems.
High Costs	Limited access in low-resource regions.

1.3 Rise of Machine Learning and EEG-Based Approaches

Machine learning (ML) has emerged as a transformative tool in healthcare, particularly in psychiatry. It enables the detection of complex patterns in high-dimensional data, such as EEG recordings. EEG, a non-invasive technique that measures brain electrical activity, is highly sensitive to the disruptions in neural connectivity and oscillations observed in schizophrenia patients (Shen et al., 2023). These disruptions, reflected in frequency bands like alpha, beta, and theta, serve as biomarkers that can be leveraged by ML models for automated detection.

Advantages of EEG in Schizophrenia Diagnosis

Non-invasive and cost-effective.

Provides temporal resolution for brain activity.

Sensitive to neural connectivity disruptions.

1.4 Objectives of This Survey

This paper aims to:

1. Review ML techniques applied to schizophrenia detection using EEG.
2. Compare preprocessing, feature extraction, and classification methods.
3. Highlight gaps in the current literature and propose future research directions.

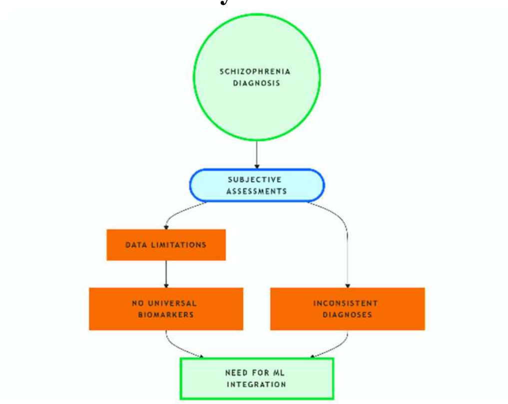
2. Challenges in Schizophrenia Diagnosis

2.1 Complexity of the Disorder

Schizophrenia comprises a spectrum of symptoms, making the search for ubiquitous biomarkers difficult. Notably, the cognitive, emotional, and behavioral dimensions influenced vary across individuals (Soria et al., 2023).

2.2 EEG Data Challenges

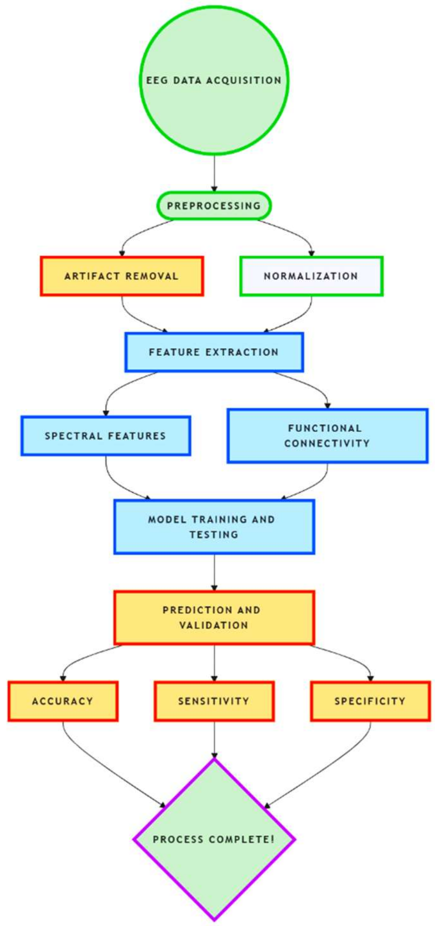
- **Signal Noise:** EEG signals are often contaminated with artifacts from muscle movement or eye blinks.
- **Data Scarcity:** Public datasets for schizophrenia EEG are limited in size and diversity.
- **Variability:** Differences in EEG recording protocols across institutions make generalization difficult.



Flowchart 1: Challenges in Schizophrenia Detection

3. Machine Learning Framework for Schizophrenia Detection

3.1 General Workflow



Flowchart 2: ML-Based Schizophrenia Detection Workflow

3.2 Algorithms and Techniques

Algorithm	Strengths	Weaknesses
SVM	Robust for small datasets.	Struggles with high-dimensional data.
CNN	Automatically extracts spatial features.	High computational cost.
3D CNN	Captures spatiotemporal EEG dynamics.	Requires large datasets.
Random Forest	Handles imbalanced data well.	Limited interpretability.
Hybrid Models	Combines strengths of multiple techniques.	Complexity in implementation.

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4. Comparative Analysis of Studies

Study	Algorithm	Dataset	Accuracy (%)	Key Findings
Shen et al. (2023)	3D CNN	Public EEG Dataset	95.8	High accuracy using dynamic functional connectivity.

Kumar et al. (2023)	CNN	Custom Dataset	96.2	Effective feature extraction from EEG descriptors.
Sobahi et al. (2022)	Signal-to-Image	Kaggle SZ Data	93.7	Image-based approach yielded competitive results.

Expanded Future Directions and Conclusion

Future Directions

1. Multimodal Integration

The complex pathology of schizophrenia also highlights the need for a multifactorial approach to diagnostics145. Fusing EEG with other modalities, including functional MRI (fMRI), diffusion tensor imaging (DTI), and genomic data, can enhance diagnostic power. The temporal resolution of EEG is high, while that of fMRI is very low, hence EEG can accurately detect temporal sequential activity while fMRI can localize it. By combing these modalities, we may identify complementary biomarkers. Likewise, addition of behavioral data (e.g. cognitive task performance) and patient-reported symptoms can inform behavioral analysis.

Modality	Strengths	Weaknesses
EEG	Non-invasive, high temporal resolution.	Low spatial resolution, noise-prone.
fMRI	High spatial resolution.	Expensive, less temporally precise.
Genetic Data	Identifies risk predisposition.	Requires advanced bioinformatics.
Behavioral Metrics	Adds real-world context.	Subject to patient variability.

2. Explainable AI (XAI) for Clinical Acceptance

ML systems should be interpretable to foster trust among clinicians. XAI sheds light on reasons of decisions made by a model, thus making it transparent. SHAP (Shapley Additive Explanations), LIME (Local Interpretable Model-agnostic Explanations) are useful techniques that can be used to identify important features contributing to the predictions. For instance: XAI to identify distinct EEG frequency bands or channel activations associated with schizophrenia diagnosis, so that clinicians could cross-reference these with known biomarkers.

1. Applying Explainable AI in research of Schizophrenia
2. Model Visualisation: EEG features of significance can be shown using Heatmaps for the attention layers in neural networks.
3. Feature Importance Analysis: Find out which EEG channels and frequency ranges are important for prediction.
4. Joining with Clinical Expertise: Ensure models are interpretable to allow clinicians to check findings against diagnostic standards.

3. Real-Time Monitoring via Wearable EEG Devices

Schizophrenia Real-Time Monitoring in Wearable EEG Devices These devices, augmented with lightweight ML models, track patients' neural activity over time, harvesting data that flag early warning signs of a psychotic breakdown.

Future research should focus on optimizing algorithms for low-power wearable systems and ensuring reliable performance in noisy environments.

Key Areas for Development	Challenges
Lightweight Algorithms	Balancing accuracy and computational efficiency.
Artifact-Resilient Systems	Ensuring robust performance in real-world conditions.
Longitudinal Data Analysis	Extracting trends from continuous data streams.

4. Dataset Standardization and Collaboration

The field would benefit greatly from larger, standardized datasets. Current publicly available datasets, such as TUH EEG or Kaggle SZ, are limited in scope. Establishing global collaborations between hospitals, research institutions, and private organizations can result in more diverse datasets that improve model generalizability.

Proposed Steps for Dataset Standardization

1. Define common EEG recording protocols (e.g., electrode placements, sampling rates).
2. Create a centralized repository for schizophrenia-related EEG data.
3. Encourage anonymized patient data sharing while adhering to ethical guidelines.

5. Personalized and Adaptive Models

Individual variability in brain structure and function necessitates personalization. Adaptive ML models that evolve based on patient-specific data can improve diagnostic and treatment outcomes. This may include transfer learning techniques where pre-trained models are fine-tuned for specific individuals.

Potential Applications

- Patient-Specific Biomarker Identification: Tailor EEG feature extraction to individual brain activity patterns.
- Dynamic Models: Incorporate real-time data updates to refine predictions continuously

Conclusion

Machine learning and EEG analysis have shown immense potential in transforming schizophrenia diagnosis. They address critical limitations of traditional diagnostic methods, offering objective, scalable, and real-time solutions. However, challenges such as data scarcity, interpretability, and variability across studies must be overcome for clinical adoption. Future research should focus on multimodal integration, explainable AI, and wearable systems to enable early, accurate, and accessible diagnostics. By addressing these areas, we move closer to achieving precision psychiatry for schizophrenia, significantly improving patient outcomes and reducing the global burden of this debilitating disorder.

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