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Exploring Machine Learning Techniques for Schizophrenia Diagnosis: A Comprehensive Review

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***Abstract:* -** Background:
Schizophrenia is a prevalent neuropsychiatric disorder affecting a significant portion of the global population, with an increasing prevalence in the United States. This rise has led to more diagnoses, highlighting the need for efficient detection methods. Recently, machine learning has shown promise in detecting schizophrenia, enabling quicker and more accurate diagnoses.
Objectives:
This review aims to examine all physiological signals used in schizophrenia detection, inform researchers about available public datasets, and compare the advantages and disadvantages of these physiological signals.
Method:
A comprehensive search was conducted using databases such as Scopus, Web of Science, and the National Institutes of Health (NIH), focusing on studies published between 2020 and 2024. Keywords included "schizophrenia," "EEG," "MRI," and "machine learning." A comparative analysis synthesized the findings.
Findings:
The primary finding of this review is that Electroencephalogram (EEG) signals have been identified as the most effective choice for schizophrenia detection following a thorough comparative analysis. Additionally, it has been observed that detection accuracy is significantly influenced by the mental state or task during signal capture. Another notable outcome is that Support Vector Machines (SVM) yield superior results when used in conjunction with EEG signals. The limited size of available datasets has hindered the use of Deep Convolutional Neural Networks (CNN).
Significance:
This review offers a detailed comparison of various physiological signals used for schizophrenia detection, presenting a novel perspective. It serves as a valuable resource for novice researchers, guiding their decision-making process. The comprehensive presentation of publicly available datasets will benefit all researchers in the field. Identifying research gaps and providing future research directions are significant contributions of this paper.

Keywords: Schizophrenia, Machine Learning, EEG, MRI, Data Modalities.

1. Introduction

Schizophrenia, a complex psychiatric disorder, presents a spectrum of cognitive, behavioural, and emotional disturbances, typically emerging in young adulthood. Core symptoms include delusions, hallucinations, disorganized thinking, abnormal behaviours, and social withdrawal. These symptoms often lead to significant impairments in daily functioning and quality of life for affected individuals[1].

Underlying the manifestation of schizophrenia are structural and functional alterations in the brain. These alterations are influenced by a combination of genetic, environmental, and yet-to-be-determined factors. Genetic

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predisposition is evident, with a substantial concordance rate of 46% among monozygotic twins and a 40% risk of developing schizophrenia when both parents are affected. These findings underscore the significant genetic component in the ethology of schizophrenia, contributing to our understanding of its multifactorial nature and the complex interplay of genetic and environmental influences in its development[2]. Understanding the genetic underpinnings of schizophrenia is critical for elucidating its pathophysiology, informing early detection and intervention strategies, and advancing personalized treatment approaches. As such, further research is warranted to explore the intricate genetic mechanisms involved in schizophrenia susceptibility and to develop targeted interventions that address its heterogeneous etiology and symptomatology.

Schizophrenia, affecting about 1% of the population, occurs equally among males and females, with onset typically in late teens or early adulthood[3]. Men usually experience symptoms between 17 and 20, while women are diagnosed in their twenties. Onset before age 12 or in late adulthood is rare, and older adults exhibit slightly higher prevalence[4].

Schizophrenia presents a spectrum of dysfunctions outlined in the DSM-5 diagnostic criteria, requiring the presence of at least two of the following symptoms for six months [5]

- Delusions: Fixed false beliefs.
- Auditory hallucinations: Perceiving non-existent sounds.
- Catatonic symptoms: Marked motor abnormalities.
- Negative symptoms: Reduced emotional expression and motivation.
- Disorganized speech: Impaired communication.

Many current reviews do not comprehensively cover all physiological signals utilized in schizophrenia detection, often focusing on a single type of signal, such as EEG or MRI. This approach provides an incomplete picture. Additionally, there is a lack of emphasis on publicly available datasets, which are crucial for facilitating ongoing research and development in this domain. Moreover, many reviews do not adequately address the integration of multiple signal types, a vital aspect that could significantly enhance the accuracy and reliability of machine learning models in schizophrenia detection.

The proposed review aims to address these limitations by providing a comprehensive examination of all physiological signals used in schizophrenia detection. Researchers will be informed about available public datasets, thus facilitating their research endeavors. By comparing the advantages and disadvantages of various physiological signals, a more holistic understanding of their respective contributions to machine learning-based detection methods will be offered.

In addressing these limitations, several critical problems will be tackled. A unified framework that integrates multiple signal types will be provided, enhancing the diagnostic accuracy of machine learning models. A detailed list of publicly available datasets will be compiled, serving as a valuable resource for researchers. Furthermore, by identifying research gaps and outlining potential future research directions, the development of more effective and standardized approaches will be guided, ultimately contributing to better diagnosis and management of schizophrenia.

In recent years, the application of artificial intelligence (AI) has revolutionized various domains, offering innovative solutions to complex challenges. These include enhancing student engagement[6], facilitating virtual reality exposure therapy, text classification[7], bolstering cyber security, and detecting and managing neurological diseases[8]. Moreover, AI has contributed significantly to elderly care, biological data mining, combating pandemics, and optimizing healthcare service delivery[9]. By leveraging AI analytics, disease preventive measures can be significantly enhanced, thereby improving overall quality of life. AI algorithms, particularly Machine Learning (ML) and Deep Learning (DL) techniques, have demonstrated exceptional capabilities in accurately diagnosing diseases. The unprecedented advancements witnessed in recent years are primarily attributed to the remarkable ability of AI methods to analyze complex medical data, often characterized by high-dimensionality, with unparalleled accuracy and efficiency[10]. This progress has been facilitated by the availability of faster GPUs and the abundance of diverse and comprehensive medical datasets, allowing for more robust and insightful analyses.

The motivation for the current study is rooted in two significant developments:

- Recent advancements in massive parallel processing have facilitated the widespread adoption of Machine Learning (ML) and Deep Learning (DL) methods for analyzing complex medical data. A decade ago, such endeavors posed significant challenges due to limited computing capabilities. However, with the advent of high-performance computing devices, twhthe application of ML and DL techniques has surpassed human-level performance in certain cases.

- High-power computing devices have played a crucial role in deciphering brain activities and their interconnections through various biomarkers. This has led to the emergence of numerous tools and techniques for classifying and predicting Schizophrenia (SZ) disease. These advancements have greatly enhanced our understanding of SZ and opened new avenues for diagnosis and treatment.

2. Review Methodology

2.1 LITERATURE REVIEW

A comprehensive search was conducted using standard databases, including Scopus, Web of Science, and the National Institutes of Health (NIH). Studies published between 2020 and 2024 were included to ensure the most recent research was considered. The search employed keywords such as "schizophrenia," "EEG," "MRI," and "machine learning" to identify relevant studies. Following the search, the identified studies were systematically reviewed and filtered to ensure relevance and quality. A detailed comparative analysis was then conducted to synthesize the findings, allowing for a thorough evaluation of the various physiological signals used in schizophrenia detection. The comparative analysis focused on assessing the strengths and weaknesses of each signal type and their respective contributions to machine learning-based detection methods.

In the pursuit of detecting schizophrenia, a multitude of methodologies have emerged, propelled by advancements in machine learning techniques and the utilization of various physiological modalities. These approaches can be broadly categorized into three distinct categories.

1. Detection using Electroencephalogram (EEG) Signals: which delve into the electrical activity of the brain to identify patterns indicative of schizophrenia.
2. Detection using Magnetic Resonance Imaging (MRI) Signals: which scrutinize structural and functional brain abnormalities associated with the disorder.
3. Detection using Alternative Signals or Social Media Content: This category explores novel approaches that leverage alternative signals or social media content in conjunction with machine learning algorithms.

Through meticulous review and synthesis of literature from each domain, this paper navigates through a structured framework. Each approach is meticulously examined, beginning with an exploration of the datasets utilized, followed by an elucidation of the employed methods. Subsequently, the findings gleaned from these studies are presented, shedding light on the efficacy and limitations of each approach. Furthermore, the paper delves into the identified limitations and proposes avenues for future research, thereby charting a course towards enhanced diagnostic accuracy and clinical utility. This sequential approach serves as a comprehensive roadmap for the systematic review of literature, facilitating a nuanced understanding of the current landscape and avenues for advancement in schizophrenia detection methodologies.

2.2 DETECTION USING ELECTROENCEPHALOGRAM (EEG) SIGNALS

EEG (Electroencephalography) emerges as a valuable tool for detecting schizophrenia, enabling non-invasive analysis of brain activity and offering crucial insights into the disorder. Numerous studies have leveraged EEG to construct pattern recognition frameworks aimed at accurately diagnosing schizophrenia. These frameworks typically involve pre-processing EEG signals using methods like Fast-Independent Component Analysis , bandpass filtering, and Empirical Mode Decomposition (EMD) [11]. Furthermore, machine learning algorithms have been deployed to classify and distinguish between individuals with schizophrenia and healthy controls using EEG data. Advanced features extracted from EEG signals have been incorporated into classification models, resulting in commendable accuracy rates[12]. In summary, EEG represents a valuable and efficient modality for schizophrenia detection, offering potential benefits for clinicians in terms of diagnosis.

This study investigates the potential of machine learning for Schizophrenia diagnosis using electroencephalogram (EEG) recordings. While acknowledging the dataset's heterogeneity in illness duration, treatment variations, and potential impact on EEG signals, the research proposes an XG Boost-based machine learning method for EEG analysis. This method achieves high accuracy (AUC: 0.94) in classifying Schizophrenia patients, suggesting its potential as a complementary tool for clinical diagnosis[13]. However, limitations include the lack of detailed dataset information and potential generalizability issues due to sample heterogeneity.

The research utilizes an EEG dataset comprising signals from both schizophrenic patients and healthy control subjects, encompassing a total of 81 participants, with 49 individuals diagnosed with schizophrenia and 32 healthy controls. A novel method termed "SchizoGoogLeNet" is introduced, leveraging the GoogleNet model to automatically discern schizophrenia through EEG signals. This approach surpasses traditional methods by employing deep learning techniques to unveil crucial latent features within EEG signals, enhancing accuracy in schizophrenia identification. By combining the deep features extracted by SchizoGoogLeNet with a support vector machine, the study achieves an impressive correct classification rate of 99.02% for schizophrenia. Although the investigation exclusively focuses on two groups—individuals with schizophrenia and healthy controls—the authors express a future inclination towards incorporating additional cohorts in subsequent research endeavors. Despite the study's limitation in sample size, consisting of only 81 participants, the findings provide promising insights into the potential efficacy of deep learning models in psychiatric diagnostics[14]. In this study, the researchers leveraged three distinct public datasets containing EEG signals from individuals diagnosed with schizophrenia (SZ) and healthy controls (HC) to develop the SchizoNET model. Dataset 1 encompassed EEG signals from adolescents, comprising 45 SZ subjects and 39 HC subjects, while Dataset 2 included EEG signals from adults, with an equal distribution of 14 SZ and 14 HC subjects. Dataset 3, also comprising EEG signals from adults, consisted of 49 SZ subjects and 32 HC subjects. Introducing SchizoNET, a novel model utilizing EEG signals for schizophrenia detection, the paper addresses the inherent challenges associated with EEG signal analysis. Notably, this research pioneers the utilization of these three publicly available EEG datasets for automated schizophrenia detection, marking a significant advancement in the field. Demonstrating robustness, efficacy, and accuracy, SchizoNET outperforms existing techniques, potentially facilitating neurologists in schizophrenia diagnosis. However, it's important to acknowledge common limitations inherent in such studies, including dataset size and diversity, which may impact the model's generalizability to diverse populations. Additionally, overfitting remains a concern when employing deep learning models, potentially affecting performance on unseen data[15].

In this investigation[16], data from a cohort consisting of 54 individuals with schizophrenia and 54 healthy controls were utilized to scrutinize their brain activity. Emphasis was placed on event-related potentials (ERPs), particularly the P300 and mismatch negativity (MMN) components, which are intricately linked to cognitive functions. The analysis involved three categories of features derived from ERP signals: peak-related features, peak-to-peak related features, and signal-related features. This paper introduces the utilization of Multiple Kernel Learning (MKL) classifiers for schizophrenia diagnosis through brain signal analysis, a novel approach not previously explored. Demonstrating the efficacy of MKL, the study illustrates its capability to effectively differentiate between schizophrenia patients and healthy individuals using ERP measures. Furthermore, it highlights the utility of the Boruta feature selection method in enhancing classification accuracy and reducing computational complexity. Despite these advancements, it's important to note the potential limitation of the study's sample size, which may hinder generalizability to the broader population of individuals with schizophrenia. Additionally, while the research centres on specific ERP components, such as P300 and MMN, schizophrenia being a multifaceted disorder, reliance on a limited set of features could overlook other pertinent information crucial for comprehensive understanding and diagnosis[16].

This study utilizes publicly available EEG datasets to detect schizophrenia, focusing on a dataset with recordings from 14 healthy individuals and 14 patients with schizophrenia. These recordings, taken with closed eyes at a sampling frequency of 250 Hz, span 12 to 15 minutes and cover 19 scalp channels. Introducing an automated diagnostic method, the paper avoids manual feature extraction, simplifying the process. By employing the Short-time Fourier Transform to convert EEG data into 2D spectrogram images, a novel approach is proposed. Training a VGG-16 Convolutional Neural Network, the study achieves high classification accuracies of 95% and 97% on separate datasets, surpassing existing methods. Furthermore, insights into the relationship between EEG frequency components and schizophrenia are provided, emphasizing the importance of mid-level frequency components. However, limitations arise from the reliance on publicly available datasets, which may vary in size, diversity, and quality. Moreover, the method's practical applicability in clinical settings remains untested, and computational demands associated with deep learning models like VGG-16 may pose challenges in resource-constrained environments[17]. This research utilizes EEG signals to detect schizophrenia by comparing data from diagnosed individuals and a control group. Employing phase space reconstruction, complex brain dynamics are visualized for analysis. Graphical features extracted from this reconstruction train a machine learning model to recognize schizophrenia patterns, potentially enhancing detection accuracy. However, limitations include potential oversight of subtle patterns and constraints due to dataset size and diversity, emphasizing the need for validation with larger, diverse datasets to ensure robust and generalizable findings[18].

The paper presents[19] an innovative approach utilizing EEG (electroencephalogram) signals to develop an automated system for schizophrenia detection. EEG signals, which capture brainwave patterns from the scalp, serve as the foundation for this system. Introducing a novel technique inspired by the Collatz conjecture, the paper transforms EEG data into distinctive patterns facilitating differentiation between healthy individuals and those with schizophrenia. Machine learning algorithms are then employed to classify these transformed EEG patterns, trained to identify schizophrenia-associated patterns, thereby enabling the automated detection system to diagnose the condition accurately. By leveraging the Collatz pattern, this study pioneers a method to decipher brainwave data, significantly enhancing schizophrenia diagnosis[19]. The resulting tool holds significant promise for rapid and precise diagnosis, benefiting both healthcare providers and patients. Additionally, the paper underscores the potential for system enhancement through the inclusion of more diverse datasets, thereby improving its diagnostic accuracy and efficacy.

The researchers accessed EEG data from an online repository, comprising recordings from 43 individuals with schizophrenia and 39 healthy controls, recorded using 16 scalp electrodes. Signal processing techniques were applied to eliminate noise, followed by feature extraction such as mean, median, standard deviation, energy, and kurtosis from various brainwave bands. Introducing the Dual Tree Complex Wavelet Transform, the study decomposed EEG signals into brainwave bands, a pivotal step for feature extraction. Notably, the proposed method exhibited high accuracy in classifying schizophrenic and healthy individuals, with select channels achieving 100% test accuracy. This presents potential for unsupervised schizophrenia detection and real-time monitoring, particularly beneficial for individuals in remote areas or with limited access to healthcare. However, the study's limitations include a relatively small sample size and lack of diversity in participant characteristics, underscoring the need for expanded research incorporating larger and more diverse datasets to enhance the robustness and generalizability of findings. Moreover, future investigations could explore alternative machine learning algorithms or deep learning techniques to potentially improve schizophrenia detection accuracy[20].

In this study, EEG recordings from a cohort of 70 individuals, comprising 35 participants diagnosed with schizophrenia and 35 healthy controls, were utilized to investigate patterns of brain activity. Employing the Smoothed Pseudo Wigner Ville Distribution (SPWVD), the researchers transformed the EEG recordings into temporal images to visualize changes over time. Subsequently, these images underwent analysis using the Vision Transformer (ViT) model to interpret the observed temporal dynamics. Validation of the proposed method was conducted through 5-fold cross-validation, examining schizophrenia detection under blinded and known health condition scenarios[21]. The study introduces an innovative approach, translating EEG data into visually interpretable images and employing advanced computational techniques for analysis. Results demonstrate high accuracy in schizophrenia identification, particularly notable when the individual's health condition is known. While suggesting potential broader applications beyond schizophrenia detection, such as in other brain-related conditions, the study is limited by its relatively small sample size and exclusive focus on schizophrenia. Further research is warranted to validate and generalize the findings across diverse populations and clinical settings. Additionally, real-world implementation may encounter challenges, considering the uncertainties inherent in clinical diagnosis scenarios[21].

The study conducted by the researchers involved collecting EEG signals from two distinct groups: 14 healthy individuals and 14 patients diagnosed with schizophrenia. These EEG signals, which reflect brain activity, serve as valuable resources for investigating brain-related disorders. Employing a convolutional neural network (CNN), consisting of eleven layers, the researchers analyzed the brainwave signals. The CNN autonomously identifies features in the signals during the convolution stage and highlights significant ones during the max-pooling stage. Utilizing these features, the fully connected layer of the CNN distinguishes between signals from healthy individuals and those with schizophrenia. This novel approach represents a pioneering method utilizing a deep learning model with eleven layers to automatically detect crucial patterns in brain signals. The study demonstrates the program's ability to accurately identify schizophrenia, showcasing its potential for early diagnosis. However, the success rate diminishes when the program encounters new subjects, suggesting limitations in real-life applications. To address this, the paper advocates for expanding the study's participant pool to enhance generalizability and diversity. Furthermore, it proposes refining the program to improve its ability to identify schizophrenia in new subjects, thereby enhancing its utility in real-world settings[22].

2.3 DETECTION USING MAGNETIC RESONANCE IMAGING (MRI) SIGNALS

Magnetic resonance imaging (MRI) plays a significant role in aiding the diagnosis of Schizophrenia by offering valuable insights into brain structure and function. Studies have demonstrated its utility in detecting structural abnormalities associated with the disorder[23]. Deep learning algorithms, when applied to structural neuroimaging data obtained from MRI scans, have shown promise in improving classification and diagnostic accuracy for Schizophrenia[24]. Additionally, resting-state functional network connectivity (rsFNC) analysis of MRI data can be employed to identify characteristic functional brain patterns often observed in Schizophrenia patients. Expanding on these applications, MRI can also contribute to the development of multimodal predictive biomarkers. By analysing gray matter volume and functional activation patterns, particularly in the frontotemporal cortex, researchers can explore brain-based markers that may offer improved prediction of Schizophrenia risk. These findings collectively highlight the significant potential of MRI as a valuable tool for Schizophrenia detection. By enabling the visualization and analysis of both structural and functional brain abnormalities, MRI has the potential to refine diagnostic accuracy and contribute to the development of more effective treatment strategies.

This study[25] utilizes the publicly available COBRE dataset, focusing on subcortical structures such as the amygdala, caudate, pallidum, putamen, and thalamus, comprising structural magnetic resonance (MR) images of individuals diagnosed with schizophrenia and healthy controls. It aims to analyze textural characteristics within specific brain regions using Gray-Level Co-occurrence Matrix (GLCM) features extracted from MR images to differentiate between individuals with schizophrenia and healthy controls. The findings indicate superior performance in classifying schizophrenia using GLCM features from predetermined left hemisphere brain regions. Notably, the Linear Discriminant Analysis (LDA) algorithm achieves remarkable classification metrics, including a 100% Area Under the Curve (AUC), 94.4% accuracy, 92.31% sensitivity, 100% specificity, and an F1 score of 91.9%. This research underscores the significance of textural characteristics within specific brain regions as critical indicators for schizophrenia identification, advocating for focused analysis over examining the entire brain volume[25].

The paper delves into the utilization of magnetic resonance imaging (MRI) brain images for detecting signs of schizophrenia, employing a convolutional neural network (CNN) to analyze these images. It provides an overview of various advanced techniques for identifying schizophrenia, including brain scans and brainwave tests to discern patterns indicative of the illness. Introducing a novel approach, the paper proposes using eye movements and specialized inkblot tests to aid in schizophrenia diagnosis, potentially facilitating easier identification by healthcare professionals. However, it underscores that while eye movement analysis holds promise, it still necessitates specialist supervision and cannot entirely replace a clinician's expertise. Moreover, the paper highlights limitations in studies utilizing muscle and heartbeat signals for schizophrenia detection, citing weaker correlations with the condition. Future research directions include assessing the efficacy of these methods using real-time MRI images from clinical settings and developing models capable of integrating diverse factors such as lifestyle and environment for enhanced schizophrenia detection[26].

In this research[27], structural Magnetic Resonance Imaging (sMRI) scans from 146 subjects were analyzed for schizophrenia detection. The dataset included images from individuals with schizophrenia and healthy controls for comparison. Preprocessing steps were applied to prepare the MRI scans for analysis, including conversion to grayscale and flattening. Five machine learning classifiers were evaluated, including Support Vector Machine, Logistic Regression, Decision Tree, k-Nearest Neighbor, and Random Forest. Validation was conducted using hold-out and stratified 10-fold cross-validation methods. Results indicated high accuracy of the Support Vector Machine classifier in stratified 10-fold cross-validation, while the k-Nearest Neighbor classifier performed better in simpler validation methods. However, the study's sample size of 146 subjects raises concerns regarding generalizability, and the performance of the models on new data remains uncertain. Future research should focus on larger datasets and real-world validation to confirm the models' effectiveness in varied populations and clinical scenarios[27].

In this study[28], brain MRI images from 40 patients, half with schizophrenia and half healthy controls, were analyzed to develop an automatic identification framework for schizophrenia. The researchers extracted complex patterns (deep features) using the VGG16 method and manually defined handcrafted features from these images. Employing the mayfly algorithm, they selected the most informative features. These features were then utilized to train a computer program to differentiate between healthy and schizophrenia-afflicted MRI images, achieving an accuracy exceeding 95%. Notably, combining deep and handcrafted features yielded the highest accuracy, followed by using solely deep features (accuracy > 91%) and solely handcrafted features (accuracy > 85%). However, the study's limitation lies in its small sample size of 40 patients, potentially limiting representativeness and generalizability. Furthermore, the results' reproducibility may vary depending on the specific hardware setup. The paper suggests the framework's application in clinical settings for schizophrenia diagnosis and advocates for further research to enhance diagnostic processes by integrating this framework with other tools[28].

In this study[29], a clinical dataset from Open-NEURO was utilized to analyze brain images of schizophrenia patients and healthy controls, focusing on functional magnetic resonance imaging (fMRI) data to elucidate cognitive, emotional, and behavioral limitations in schizophrenia. Introducing a modified VGG16 deep learning model for schizophrenia diagnosis, the study compared its performance with various deep learning architectures. Achieving an impressive 99.5% accuracy rate in schizophrenia detection holds promise for early diagnosis and disease management. Additionally, correlation analysis on fMRI data time series feature extractions and Receiver Operating Characteristic (ROC) curve analysis provided insights into brain image processing and diagnostic model performance. Nonetheless, the study's limitations include a lack of discussion on model generalizability to other datasets and fMRI data acquisition variations, as well as its performance across different disease stages and diverse populations. Further validation in real-world clinical settings is necessary to confirm the model's effectiveness beyond research environments, with recommendations for future refinement and testing on diverse datasets to enhance diagnostic capabilities and disease management strategies[29].

The study utilized magnetic resonance imaging (MRI) images to identify structural brain changes associated with schizophrenia diagnosis, drawing data from open-source benchmark databases including MCICShare, COBRE, and fBRINPhase-II. Preprocessing steps were applied to align images to a standard template and minimize errors. Introducing a lightweight 3D convolutional neural network (CNN), the paper proposes an efficient approach for analyzing MRI images in schizophrenia diagnosis, leveraging both spatial and spectral features. Employing an ensemble bagging classifier mitigates overfitting risks, enhancing model accuracy. Rigorous testing on multiple benchmark datasets demonstrates the model's reliability and superior performance over existing techniques, showcasing its potential as a clinical diagnostic tool. While specific limitations of the model are not discussed, challenges regarding generalization to new data and reliance on high-quality MRI images are acknowledged. Recommendations include further research to streamline model complexity without compromising performance and exploring integration with other brain imaging modalities to enhance schizophrenia diagnosis[30].

The study employed T1-weighted MRI scans to investigate the brain structure of individuals diagnosed with schizophrenia and healthy controls, sourced from three publicly available datasets. Following standard processing protocols, the researchers extracted the 3D whole-brain structure for comprehensive analysis. Leveraging a deep learning model tailored for this purpose, they meticulously developed and optimized it to effectively differentiate between schizophrenia patients and healthy individuals using 3D structural MRI data. Through regional analysis, key areas such as subcortical regions and ventricles emerged as pivotal in predicting schizophrenia. The deep learning model exhibited remarkable accuracy, with an area under the ROC curve of 0.987, underscoring its proficiency in classification. Notably, the study corroborated the association between structural alterations in subcortical brain regions and schizophrenia. However, limitations exist, including potential implications of the modest MRI scan dataset on real-world applicability and the absence of comparative assessments with alternative diagnostic methodologies[31]. The paper advocates for enhancements, including diversifying the training dataset with additional MRI scans and exploring the model's capacity to discern schizophrenia from other psychiatric conditions.

The study utilized MRI images from 32 individuals diagnosed with schizophrenia and 18 healthy controls to investigate and classify the disorder. Examining parameters such as grey matter, white matter, and voxel-based morphometry, novel features including Hausdorff dimension and Euclidean distance were extracted and proved significant in the classification process. Introducing a simplified approach to schizophrenia classification using MRI images, the paper underscores the potential for early diagnosis and treatment. Notably, the Hausdorff dimension emerged as a pivotal feature, supported by a student’s t-test with high significance. Demonstrating robust classification performance with 100% sensitivity, 88.9% specificity, and 94.4% accuracy, despite a limited dataset, the study acknowledges its small sample size, emphasizing the need for larger cohorts for improved generalization. Furthermore, the reliance solely on MRI images prompts consideration for incorporating additional clinical data or biomarkers to enhance diagnostic accuracy. The paper advocates for expanded sample sizes encompassing diverse demographics and disease stages to bolster the reliability and applicability of future findings[32].The study leveraged brain MRI data to investigate structural alterations in schizophrenia patients, focusing on diminished hippocampal and thalamic volumes. Employing a deep learning approach, researchers integrated brain images with genetic data to enhance schizophrenia identification. Extracting features from MRI scans using a pre-trained deep neural network, they captured brain structure nuances. Concurrently, they analyzed single nucleotide polymorphisms (SNPs) using layer-wise relevance propagation on a pre-trained 1-D convolutional network to pinpoint schizophrenia-linked SNPs. Merging MRI and SNP features, a tree-based classifier discerned schizophrenia, yielding a 5.3% accuracy improvement over prior methods. Validated on a clinical dataset, this integrated approach showcased efficacy in schizophrenia classification. While the study's dataset size remains unspecified, its implications for generalization across diverse populations warrant consideration. Suggestions for future research entail refining classification accuracy via larger, more varied datasets and evaluating model robustness across diverse cohorts and datasets to ensure broad reliability and applicability[33].

The study utilized structural magnetic resonance imaging (MRI) scans sourced from the OpenNeuro database to discern cerebral disparities between individuals with and without schizophrenia. Employing the ResNet-50 deep learning network, researchers extracted salient features from MRI scans and employed the ensemble deep random vector functional link (edRVFL) network for schizophrenia classification. Voxel-based morphometry (VBM) facilitated understanding brain alterations across individuals. The deep learning model exhibited a robust performance, accurately identifying schizophrenia from MRI images with a success rate of 96.5%. White matter analysis revealed 1363 significantly distinct spots in schizophrenia patients, with T-value and Z-value metrics of 6.90 and 6.21, respectively, underscoring the observed disparities. Despite leveraging a limited dataset of 99 MRI images, the study's implications for broader schizophrenia cases may be constrained. Future endeavors aim to expand the dataset's breadth and incorporate functional MRI (fMRI) data to augment the model's diagnostic capability in clinical settings[34].

2.4 DETECTION USING ALTERNATIVE SIGNALS OR SOCIAL MEDIA CONTENT

In the realm of Schizophrenia detection, researchers are extending beyond conventional neuroimaging methods like EEG and MRI, exploring alternative data reservoirs aided by machine learning. This quest involves scrutinizing social media content, including posts and tweets, to unveil language patterns that may signify the disorder. Eye tracking, a technique monitoring eye movements, emerges as another avenue of inquiry, with studies revealing distinctive eye-tracking patterns in Schizophrenia patients during specific tasks. By integrating these patterns with machine learning algorithms, scholars strive to craft diagnostic tools for Schizophrenia. Moreover, there is a burgeoning interest in amalgamating these non-traditional data sources with established methods, potentially amplifying diagnostic efficacy through a multimodal approach. Nevertheless, leveraging social media data raises ethical quandaries concerning privacy and susceptibility to misdiagnosis, underlining the imperative of upholding ethical principles and implementing robust data anonymization protocols in such investigations.

The study gathered social media posts from Reddit, focusing on discussions related to schizophrenia and various unrelated topics to form a control group. Linguistic features and content topics were extracted from these posts to aid in the machine learning process for detecting signs of schizophrenia. Employing supervised machine learning techniques, the researchers successfully differentiated schizophrenic posts from the control group with a 96% success rate. Linguistic markers such as third-person plural pronouns and negative emotion words were identified as important in distinguishing schizophrenic posts. Additionally, unsupervised clustering of linguistic features revealed patterns in language use among schizophrenia-related posts. However, the study's reliance on data solely from one social media platform and its assumption regarding the poster's actual condition raise questions about generalizability[35]. Future research could explore posts from diverse social media platforms and languages to validate the findings and assess the robustness of the machine learning approach.

This paper utilizes Twitter tweets as data sources, focusing on expressions related to schizophrenia discourse. Introducing a machine learning approach, it employs a Deep Neural Network (DNN) to automatically detect patterns indicative of schizophrenia discourse, enabling the use of various supervised machine learning algorithms for prediction without extensive feature engineering expertise. The study suggests the DNN's potential for early detection of schizophrenia and its adaptability to diverse algorithms, highlighting its role in mental health monitoring. However, limitations include potential misclassification due to language nuances and privacy concerns associated with analyzing personal social media data[36]. Future research avenues involve improving the model's contextual understanding of tweets and exploring optimal supervised machine learning algorithms for enhanced accuracy across diverse demographic datasets.

In this study, various brain measurements[37], encompassing the size of distinct brain regions, cortical thickness, and surface smoothness, were utilized to discern individuals with schizophrenia from those without the disorder. Additionally, the researchers investigated the correlation between these brain metrics and individuals' subjective well-being and social functioning. Employing Ensemble methods in machine learning, they amalgamated diverse techniques to enhance the accuracy of schizophrenia identification. The study revealed significant associations between specific brain features and quality of life indicators among individuals with schizophrenia, underscoring the potential of incorporating varied brain measurements and employing combined machine learning approaches to enhance schizophrenia identification. However, potential limitations include the exclusion of certain brain metrics and the specificity of findings to the studied population, warranting further exploration across diverse cohorts and brain measurement modalities to enrich our understanding of schizophrenia[37].

In this study, eye-tracking data was gathered from 44 participants, comprising 22 individuals diagnosed with schizophrenia and 22 healthy controls. Employing a free-view image test with Rorschach inkblots and an eye tracker, the researchers recorded participants' gaze patterns and eye movements. The dataset encompassed various eye-movement features, including heat maps, gaze plots, and spectral analyses. Using machine learning techniques such as neural networks and Hidden Markov models, they analyzed these eye-tracking data to discern patterns indicative of schizophrenia. The study identified heat maps combined with convolutional networks as the most effective method, achieving a 78.8% accuracy rate in identifying schizophrenia[38]. However, the study's limited sample size and imperfect accuracy underscore the need for further research to validate its findings across diverse populations and clinical settings. The paper suggests expanding the study cohort and exploring the practicality and longitudinal efficacy of eye-tracking tests in clinical settings to enhance schizophrenia diagnosis and treatment monitoring.

This study explores the potential of machine learning for Schizophrenia diagnosis by analyzing a combination of neuroimaging data, voice and language patterns, mobile phone data, and serum biomarker concentrations in a sample of 217 Schizophrenia patients and 90 healthy controls. Five machine learning models were developed using logistic regression, deep neural networks, decision trees, support vector machines, and k-nearest neighbors for binary classification. The deep neural network achieved slightly higher sensitivity and specificity, highlighting its potential for improved accuracy. The study emphasizes the importance of combining multiple biomarkers, but acknowledges limitations including a small sample size and lack of demographic details, potentially affecting generalizability. Future research should address these limitations and explore the impact of confounding factors for more robust Schizophrenia diagnosis[39].

The table 1 provides a comparative summary of established neuroimaging methods (EEG, MRI) alongside novel approaches integrating social media content or eye tracking signals. It also recognizes the potential of multimodal strategies that amalgamate these data sources to augment diagnostic precision.

3. Overview

3.1 DATASETS

The utilization of standard datasets in research holds significant importance, facilitating easy comparison of results across different approaches and enabling reproducibility of findings by other researchers. Moreover, the availability of standard datasets allows reviewers to effectively assess the impact of claimed results. In this paper, our primary objective is to provide comprehensive insights into the sources and standard datasets utilized for schizophrenia detection. Specifically, we focus on publicly available datasets, ensuring accessibility and transparency in our analysis. We present detailed descriptions of two standard datasets pertaining to EEG signals and two standard datasets related to MRI signals, aiming to enhance the understanding and utilization of these valuable resources within the research community.

Table 1. Comparative Overview of Neuroimaging Techniques and Emerging Approaches for Schizophrenia Detection

Category	Data Source	Machine Learning Approach	Potential Advantages	Limitations
EEG Signals	Electroencephalogram (EEG)	- Feature extraction (e.g., Fast-ICA, bandpass filtering)	- Non-invasive	- Requires expertise
		- Classification algorithms (e.g., SVM)	- High accuracy rates	- Limited generalizability
		- Deep learning models (e.g., CNN, VGG-16)	- Improved feature extraction	- Computational demands
		- Event-related potentials (ERPs)	- Focus on specific cognitive functions	- Limited dataset size
		- Collatz pattern technique	- Novel data transformation	- Requires validation
		- Dual Tree Complex Wavelet Transform	- Potential for unsupervised detection	- Small sample size
		- Smoothed Pseudo Wigner Ville Distribution (SPWVD) & Vision Transformer (ViT)	- Visually interpretable data	- Limited generalizability
MRI Signals	Structural Magnetic Resonance Imaging (sMRI)	- Gray-Level Co-occurrence Matrix (GLCM) features	- Analysis of specific brain regions	- Requires predefined regions
		- Convolutional Neural Networks (CNNs)	- Automated feature extraction	- Limited generalizability
		- Deep learning with handcrafted features	- Improved accuracy	- Small sample size
		- Functional Magnetic Resonance Imaging (fMRI)	- Analysis of brain activity	- Requires specialized equipment

		- 3D CNNs with ensemble classifiers	- Efficient and reliable	- Relies on high-quality MRI
		- Voxel-based morphometry (VBM)	- Analysis of brain structure	- Limited dataset size
		- Deep Learning from Imaging Genetics	- Combines MRI and genetic data	- Dataset size limitations
		- Deep learning with Voxel-based morphometry	- Identifies white matter abnormalities	- Limited dataset size
Alternative Signals	Social Media Content	- Machine learning analysis of language patterns	- Non-invasive, potentially scalable	- Privacy concerns, misdiagnosis risk
	Eye Tracking Signals	- Eye movement analysis	- Objective measure	- Requires controlled testing environment
	Multimodal Approach	- Combines various data sources (e.g., EEG, Social Media)	- Potentially improves accuracy	- Increased complexity, data redundancy

3.2 EEG DATASETS

3.2.1 DATASET -1

The dataset comprises electroencephalogram (EEG) recordings obtained from a total of 28 participants, including 14 patients diagnosed with paranoid schizophrenia and 14 healthy controls. EEG data acquisition was conducted at a sampling frequency of 250 Hz, ensuring high temporal resolution. The recordings were captured using a standard 10-20 electrode montage, featuring 19 channels strategically positioned across various brain regions. Specifically, electrodes were placed over the frontal (Fp1, Fp2, F7, F3, Fz, F4, F8), central (C3, Cz, C4), temporal (T3, T4, T5, T6), parietal (P3, Pz, P4), and occipital lobes (O1, O2). Additionally, a reference electrode was meticulously positioned between electrodes Fz and Cz to ensure accurate signal interpretation. This dataset provides comprehensive EEG recordings, facilitating in-depth analyses of neural activity patterns in individuals with paranoid schizophrenia compared to healthy controls across various brain regions[40].

3.2.2 DATASET 2:

In this study, a dataset was collected to investigate corollary discharge deficits in individuals with schizophrenia compared to control subjects. The dataset includes EEG recordings obtained from participants who performed a simple button pressing task. During the task, participants were instructed to engage in one of three actions: (1) press a button to immediately generate a tone, (2) passively listen to the same tone, or (3) press a button without generating a tone. Analysis of the EEG data revealed that control subjects exhibited suppression of the N100 component, a negative deflection in EEG brain wave occurring 100 milliseconds after the onset of a sound, when pressing a button to generate a tone compared to passive playback. However, patients with schizophrenia did not demonstrate this suppression. To replicate and expand upon these findings, the current dataset incorporates EEG data from a larger sample size, comprising recordings from 22 control subjects and 36 patients with schizophrenia, in addition to data from 10 control subjects and 13 patients obtained from a previous study. This dataset presents an opportunity for further exploration of the neural mechanisms underlying corollary discharge deficits in schizophrenia, potentially providing insights into biomarkers and therapeutic targets for the disorder[41].

3.3 MRI DATASET

3.3.1 DATASET 1

The Center for Biomedical Research Excellence (COBRE) has provided a dataset comprising raw anatomical and functional magnetic resonance (MR) data from a total of 72 patients diagnosed with Schizophrenia and 75 healthy control subjects. The age range for both groups falls between 18 to 65 years. Prior to inclusion, all subjects underwent thorough screening to ensure eligibility criteria were met, excluding individuals with a history of neurological disorders, mental retardation, severe head trauma resulting in loss of consciousness exceeding five minutes, and substance abuse or dependence within the past 12 months. Diagnostic assessments were conducted using the Structured Clinical Interview for DSM Disorders (SCID), ensuring consistency and reliability in the determination of psychiatric diagnoses. This dataset offers a valuable resource for researchers aiming to investigate structural and functional brain differences associated with schizophrenia, while maintaining stringent standards for subject selection and diagnostic characterization[42].

3.3.2 DATASET 2

The Consortium for Neuropsychiatric Phenomics has released a comprehensive dataset containing neuroimaging data alongside phenotypic information for a total of 272 participants. This diverse subject population comprises healthy controls (130 subjects) and individuals diagnosed with adult ADHD (43 subjects), bipolar disorder (49 subjects), and schizophrenia (50 subjects). The primary objective of the study is to investigate brain function and anatomy associated with these prevalent neuropsychiatric syndromes, with a specific focus on memory and response inhibition. To achieve this goal, the study employs a wide array of assessment tools, including questionnaires, neurocognitive tasks, neuropsychological assessments, and multiple neuroimaging modalities. Detailed information regarding the complete assessment for each participant can be accessed in the provided data descriptor. With 155 men and 117 women, ranging in age from 21 to 50 years (mean: 33.23; median: 31.0), the dataset encompasses individuals with diverse demographic characteristics. Additionally, all participants have completed at least 8 years of formal education and primarily speak either English or Spanish. Recruitment efforts involved community advertisement and outreach to local clinics and online platforms. Notably, the consortium applied stringent exclusion criteria, ensuring that patients with diagnoses spanning multiple patient groups were not included in the dataset. This dataset represents a valuable resource for the academic community, offering insights into the intricate relationship between brain function, behavior, and neuropsychiatric disorders[43].

Table 2 curates details of four publicly available standard datasets (two EEG, two MRI) commonly utilized for schizophrenia detection research. It summarizes participant demographics, data types, and unique characteristics of each dataset, facilitating informed selection for future studies. This comprehensive review systematically analyzed 25 research papers to investigate the landscape of schizophrenia detection, focusing on the utilization of four standard datasets. The examination encompassed a wide array of machine learning methodologies applied to EEG and MRI signals, as well as innovative techniques leveraging non-traditional data sources like social media content and eye tracking. The following sections discuss the key findings, emerging trends, and future directions identified in this exploration.

Table 2: Standard Datasets for Schizophrenia Detection: A Summary

Category	Dataset Name	Description	Participants (Schizophrenia/Control)	Age Range
EEG Signals	EEG in Schizophrenia (RepOD)	Recordings from patients with paranoid schizophrenia and healthy controls.	14/14	18-65
	Corollary Discharge Deficits in Schizophrenia (Kaggle)	EEG data from a button-pressing task to investigate corollary discharge deficits.	36/22	N/A
MRI Signals	COBRE Schizophrenia Dataset (NITRC)	Raw anatomical and functional MRI data.	72/75	18-65
	Neuroimaging Consortium Dataset (F1000Research)	Includes MRI data alongside phenotypic information for diverse neuropsychiatric	50/130	21-50

		conditions (including Schizophrenia).		

3.4 DISCUSSION

KEY FINDINGS AND INSIGHTS:

i. **Machine Learning for Schizophrenia Detection:** Across the reviewed studies, machine learning algorithms showcased remarkable potential in scrutinizing neuroimaging data, including EEG and MRI scans, to discern between individuals with schizophrenia and healthy counterparts. Notably, classification algorithms such as Support Vector Machines (SVMs) and deep learning models like Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs) demonstrated promising results. These findings underscore the efficacy of machine learning in identifying subtle patterns in brain activity associated with schizophrenia.

ii. **Standardization and Generalizability:** The presence of standardized datasets, such as the EEG in Schizophrenia and COBRE Schizophrenia Dataset, is paramount for promoting consistency across studies and facilitating the reproducibility of research outcomes. However, concerns regarding sample size limitations and potential biases in certain datasets have been noted. Addressing these issues necessitates the development of larger and more diverse datasets to enhance the generalizability and robustness of machine learning models for schizophrenia detection.

iii. **Emerging Data Sources:** The exploration of alternative data sources, including social media language patterns and eye tracking data, marks an exciting frontier in schizophrenia research. Although still in its infancy, these novel approaches offer non-invasive and scalable means for detecting schizophrenia. Particularly compelling is the potential synergy between traditional neuroimaging techniques and these emerging data sources, which may lead to more comprehensive and accurate diagnostic tools. Overall, this review highlights the evolving landscape of schizophrenia detection, emphasizing the pivotal role of machine learning and the promising avenues presented by alternative data sources. Moving forward, continued efforts to standardize datasets, expand sample sizes, and integrate diverse data modalities hold immense potential for advancing our understanding and diagnostic capabilities in the field of schizophrenia research.

3.5. FUTURE DIRECTIONS AND OPEN QUESTIONS

1. **Integration of Multimodal Data:** The future of schizophrenia detection lies in the integration of multimodal data sources, including EEG, MRI, social media content, and eye tracking data. By combining information from different modalities, researchers can gain a more comprehensive understanding of the disorder's underlying mechanisms. This integrative approach may lead to improved diagnostic accuracy and provide insights into the complex interactions between brain function, behavior, and social factors in schizophrenia.

2. **Explainable AI and Interpretability:** While deep learning models have shown promising results in schizophrenia detection, their complex nature often hinders interpretability. Addressing this challenge requires the development of explainable AI frameworks that provide insights into how these models arrive at their decisions. By enhancing transparency and interpretability, researchers can build trust in machine learning-based diagnostic tools and facilitate their translation into clinical practice.

3. **Clinical Utility and Personalized Medicine:** Transitioning from research findings to clinical applications is essential for improving patient outcomes in schizophrenia. Future studies should focus on assessing the clinical utility of machine learning models in real-world diagnostic settings. By evaluating the feasibility and effectiveness of integrating these models into clinical workflows, researchers can determine their practical value for healthcare providers and patients. Additionally, exploring personalized medicine approaches that tailor interventions based on individual patient characteristics holds promise for optimizing treatment strategies and improving long-term outcomes in schizophrenia management.

.3.6. LIMITATIONS AND CHALLENGES

1. **Data Privacy and Ethical Considerations:** The utilization of personal data, particularly from sources like social media, presents significant ethical considerations and privacy challenges. To uphold ethical standards,

researchers must implement stringent data privacy safeguards and obtain informed consent from participants. Additionally, ensuring the anonymization of sensitive information is crucial to protect individuals' privacy rights while still enabling valuable research insights.

2. **Addressing Heterogeneity of Schizophrenia:** Schizophrenia is characterized by a diverse array of symptoms and clinical presentations, making it a highly heterogeneous disorder. Future research endeavors must address this heterogeneity by implementing robust subgroup analyses and exploring the potential of machine learning models to identify distinct subtypes of schizophrenia. By acknowledging and accommodating the variability within the disorder, researchers can develop more tailored and effective diagnostic and treatment approaches.

4. Conclusion

The features of non-invasiveness, portability, low cost, and dry electrodes identified in this review lead to the conclusion that EEG signals are the most preferred physiological signal for the detection of schizophrenia. Social cognitive tasks and the oddball paradigm are the most commonly employed neurocognitive tasks when capturing these signals.

The selection of mental state activity is identified as the most critical step. Without proper selection of mental activity, the system's input will be flawed, leading to inaccurate outputs and system failure. This is the central finding of this research, emphasizing the necessity of selecting the appropriate mental activity for accurate signal capture.

Support Vector Machine (SVM) classifiers have demonstrated remarkable results when used with EEG signals due to their effectiveness in high-dimensional spaces, robustness to overfitting, optimal margin classification, and efficacy with non-linear data.

This review highlights the critical role of physiological signals in schizophrenia detection and the potential of machine learning to enhance diagnostic accuracy. By conducting a comprehensive search of studies published between 2020 and 2024, the review systematically examines the use of various physiological signals, such as EEG and MRI, in the context of schizophrenia detection. The findings reveal significant gaps in standardized methodologies and a limited understanding of integrating multiple signal types.

A comprehensive list of publicly available datasets has been compiled, providing a valuable resource for future research. These datasets lay the foundation for further exploration and validation of machine learning algorithms in schizophrenia detection. The comparative analysis conducted in this review underscores the need for standardized protocols and the development of novel machine learning techniques to improve detection accuracy.

In conclusion, this review provides a unique and comprehensive synthesis of current research on physiological signals used in schizophrenia detection and identifies key public datasets. It emphasizes the importance of addressing research gaps and outlines potential future research directions. The insights gained from this review can guide researchers in developing more effective and standardized approaches, ultimately contributing to better diagnosis and management of schizophrenia.

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