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AI-Driven Neuro-Monitoring: Advancing Schizophrenia Detection and Management Through Deep Learning and EEG Analysis

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Abstract: Schizophrenia is a complex neuropsychiatric disorder characterized by disruptions in brain connectivity and cognitive functioning. Continuous monitoring of neural activity is essential, as it allows for the detection of subtle changes in brain connectivity patterns, which could provide early warnings of cognitive decline or symptom exacerbation, ultimately facilitating timely therapeutic interventions. This paper proposes a novel approach for detecting schizophrenia-related abnormalities using deep learning (DL) techniques applied to electroencephalogram (EEG) data. Using an openly available EEG dataset on schizophrenia, the focus is on preprocessed event-related potentials (ERPs) from key electrode sites and applied transfer entropy (TE) analysis to quantify the directional flow of information between brain regions. TE matrices were generated to capture neural connectivity patterns, which were then used as input for a hybrid DL model, combining convolutional neural networks (CNNs) and Bidirectional Long Short-Term Memory (BiLSTM) networks. The model achieved a performant accuracy of 99.94% in classifying schizophrenia-related abnormalities, demonstrating its potential for real-time mental health monitoring. The generated TE matrices revealed significant differences in connectivity between the two groups, particularly in frontal and central brain regions, which are critical for cognitive processing. These findings were further validated by correlating the results with EEG data obtained from the Muse 2 headband, emphasizing the potential for portable, non-invasive monitoring of schizophrenia in real-world settings. The final model, integrated into the NeuroPredict platform, offers a scalable solution for continuous mental health monitoring. By incorporating EEG data, heart rate, sleep patterns, and environmental metrics, NeuroPredict facilitates early detection and personalized interventions for schizophrenia patients.

Keywords: schizophrenia; EEG; deep learning; CNN-BiLSTM; transfer entropy; mental health monitoring

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1. Introduction

Widely regarded as one of the most debilitating health disorders impacting humanity, schizophrenia remains a multifaceted condition that continues to evade full comprehension. Despite ongoing research, the disorder's intricate nature and varied manifestations continue to challenge precise characterization. Schizophrenia is considered a chronic, very severe, neuropsychiatric condition characterized by psychosis and significant functional impairment. Patients with schizophrenia often exhibit persistent delusions, continuous hallucinations, disorganized thought and speech processes, and erratic behavior, resulting in an abnormal view of the surrounding environment. According to the World Health Organization (WHO), as of 2022, approximately 24 million individuals globally are affected by this disorder [1]. Epidemiological data show that the incidence of schizophrenia ranges from 8 to 60 per 100,000 people per year [2], which varies depending on factors such as geographic region, socioeconomic status, and genetic predisposition. This wide range highlights the complexity of identifying consistent risk patterns and the need for further research into the underlying causes and distribution of the disorder.

Individuals with schizophrenia face a significantly elevated risk of premature mortality compared to the general population, largely driven by comorbid conditions, such as cardiovascular disease (CVD) [3]. This heightened vulnerability to CVD and other physical health issues is compounded by the fact that people with schizophrenia are often less likely to receive adequate access to physical health services [4]. Furthermore, their physical health is frequently under-investigated and insufficiently monitored, leaving many health problems untreated or unnoticed [5]. This gap in healthcare contributes to worsening health outcomes and a further decline in life expectancy for this population [6].

The intersection of poor physical health management and the chronic psychiatric symptoms of schizophrenia adds an additional layer of complexity to the overall healthcare burden. Effective diagnosis and continuous monitoring of both mental and physical health are essential in improving outcomes for individuals with schizophrenia. The integration of tools, like the electroencephalogram (EEG), which has been shown to distinguish between individuals with schizophrenia and healthy controls (HCs) with high accuracy, may help streamline the diagnostic process for mental health conditions [7]. This could also allow for a more holistic approach to care, ensuring that both psychiatric and physical health are more effectively addressed. Given the lower cost and ease of EEG implementation compared to other neuroimaging techniques, it offers a practical solution for enhancing early detection and comprehensive care in this high-risk population, ultimately alleviating pressure on healthcare systems while improving patient outcomes [8].

The EEG has proven to be a valuable tool for distinguishing between individuals with schizophrenia and HCs by analyzing electrical brain activity via scalp recordings, yielding highly accurate diagnostic results. Compared to other neuroimaging techniques, such as functional magnetic resonance imaging (fMRI) and magnetoencephalography (MEG), the EEG offers several advantages, including lower cost and reduced need for specialized training for its implementation [9]. These features make the EEG a practical and accessible option for the study and diagnosis of schizophrenia.

Given the chronic nature of schizophrenia and the high risk of comorbid physical conditions, there is a growing need for innovative approaches to patient care that go beyond traditional in-person medical visits. A remote monitoring system could play a pivotal role in the continuous management of both mental and physical health in individuals with schizophrenia. Remote monitoring tools could allow healthcare professionals to track key physiological and behavioral indicators in real time, enabling early intervention when symptoms of psychosis worsen or when signs of physical health deterioration, such as cardiovascular issues, arise [10]. In recent years, continuous monitoring has become crucial in improving healthcare outcomes, particularly for managing complex conditions, such as schizophrenia. By collecting real-time granular data, this approach enables more informed and timely decisions, enhancing the precision and personalization of interventions. However, it also introduces challenges related to data storage, coding efficiency, and energy management. IoT-based systems generate vast amounts of data from devices, like wearable EEGs, raising concerns about digital storage. Local storage offers control but lacks scalability and incurs high costs, while cloud storage provides scalability but requires stringent security to protect sensitive health information [11]. Additionally, the continuous operation of IoT systems demands significant energy resources. Advances in low-power computing and efficient data transmission have reduced energy consumption [12], but scaling these systems increases energy demands, necessitating a balance between real-time transmission and batch processing to conserve power [13]. While IoT-based continuous monitoring offers significant benefits for healthcare, particularly in the real-time management of mental health conditions, such as schizophrenia, these systems require careful planning to address challenges related to data storage, energy efficiency, and scalability. Future research should focus on optimizing storage solutions and advancing energy-efficient technologies to ensure these systems are sustainable and scalable across broader healthcare applications.

Moreover, integrating a remote monitoring system could significantly improve mental health management for people with schizophrenia [14]. Since access to mental health services can be limited due to geographic, financial, or logistical barriers, especially in low-resource settings, remote monitoring could ensure consistent oversight of patients, even in rural or underserved areas. Tools such as wearable devices, mobile apps, and telemedicine platforms could be used to monitor patients' mental states, medication adherence, sleep patterns, and stress levels. These data could then be shared with healthcare providers in real time, allowing for personalized and adaptive treatment plans. Continuous mental health monitoring would enable the early detection of symptom relapse or medication side effects, ensuring prompt adjustments to treatment regimens [15].

Incorporating such a system would not only enhance the quality of care for individuals with schizophrenia but also alleviate some of the burdens on healthcare professionals and family caregivers [16]. By automating certain aspects of monitoring, remote systems would enable healthcare providers to focus their efforts on the most critical interventions while still maintaining a high level of oversight. Furthermore, they empower patients by giving them an active role in managing their condition, promoting greater autonomy, and potentially improving long-term outcomes. When combined with diagnostic tools, like the EEG, remote monitoring would provide a comprehensive, cost-effective solution for the holistic care of schizophrenia patients, addressing both their psychiatric needs and physical health concerns [17].

E-health technologies, including mobile devices and telepsychiatry, play a critical role in schizophrenia management by improving continuity of care, supporting medication adherence, and enabling remote monitoring and virtual consultations [18,19]. These tools enhance patient outcomes by providing accessible care and boosting patient engagement. Treisman et al. (2016) emphasized the potential of digital technologies to promote independent living and medication adherence through reminders and virtual check-ins [18]. Wearable devices, equipped with sensors and connected to telemedicine platforms, provide real-time data, such as EEG readings and physiological signals [20]. AI algorithms analyze these datasets to detect early signs of schizophrenia, enabling proactive interventions that reduce episode severity. Henson et al. (2021) also highlight the use of smartphone-based sensors for continuous monitoring, identifying behavioral changes that may signal impending relapses [21].

In recent years, Artificial Intelligence (AI) has seen remarkable growth, unlocking transformative potential across multiple sectors, including healthcare. AI's integration into mental healthcare has notably improved diagnostic accuracy, early detection, and treatment of mental health conditions. This integration has been particularly impactful through AI-powered chatbots and virtual therapists, offering stigma-free, personalized interventions based on real-time data analysis [22,23].

One of AI's key contributions to mental health is personalized treatment. Addressing challenges related to data privacy, accessibility, and ethical concerns is essential for successful integration into mainstream mental healthcare. As AI advances, it holds the potential to revolutionize schizophrenia care with more effective and individualized treatment strategies. AI algorithms can analyze patient data from diverse sources, such as electronic health records (EHRs) and wearable devices, to recommend tailored interventions. While these data sources are valuable, the challenge of obtaining sufficient and high-quality data for analysis must be addressed. Collecting adequate data for AI models involves ensuring that data streams from various sources are reliable, comprehensive, and representative of the diverse patient population. For instance, wearable devices and telepsychiatry provide continuous monitoring and generate significant amounts of real-time data, but they must be carefully integrated into healthcare workflows to avoid gaps in coverage or biases in the data collected. The combination of AI with telepsychiatry and wearable technologies further supports mental healthcare by improving access to treatment and enhancing the personalization of care [24]. AI algorithms detect early signs of mental health conditions, and wearable devices continuously monitor mental well-being through sensors that track physiological data, such as sleep patterns and physical activity. Ensuring sufficient data from these devices requires active participation from patients and continued advancements in sensor technology, which can help capture more precise and relevant information. Furthermore, immersive technologies, like virtual reality (VR) and augmented reality (AR), are increasingly being integrated into therapeutic approaches, offering innovative solutions across various medical and psychological conditions [22,25]. For example, during the post-COVID-19 era, VR telemedicine has shown positive results in improving treatment outcomes for patients with post-traumatic stress disorder (PTSD), especially when combined with cognitive behavioral therapy [26]. A meta-analysis assessed the performance of wearable AI in detecting anxiety, demonstrating promising accuracy and specificity in the early detection of anxiety disorders using wearable devices [27]. In addition to improving treatment outcomes, VR environments can be designed to display visual settings that reduce physiological stress, supporting faster recovery times. For instance, research has demonstrated that calming virtual environments, such as those simulating nature views, can significantly reduce stress in patients, potentially accelerating recovery times [28]. This concept is further supported by Ulrich's research, which demonstrated that natural views could enhance patient recovery post-surgery, providing further rationale for using VR to create stress-relieving environments in clinical settings [29]. By combining AI, VR, and wearable technologies, mental healthcare can benefit from a holistic, integrated approach that supports both psychological and physiological recovery. These tools provide the ability to monitor patients in real time, offer personalized therapeutic interventions, and reduce stress through calming visual environments. However, the successful deployment of these digitalized technologies will require overcoming challenges such as data privacy, infrastructure limitations, and patient compliance. Ensuring that these barriers are addressed will be essential for the wider adoption and success of AI and VR in healthcare. These applications of VR and AR provide a more supportive and immersive environment for patients, facilitating both psychological and physiological recovery. Whether used to augment cognitive therapies or to create stress-reducing settings, these digitalized technologies offer new opportunities for improving patient care and treatment outcomes across a wide range of medical conditions.

Building on this, the integration of passive sensing data with AI models enables continuous, unobtrusive monitoring of schizophrenia patients, enhancing the ability to detect subtle behavioral changes that may precede a psychotic relapse. However, ensuring that sufficient data are obtained from passive sensing remains a key challenge. Data collection relies on the continuous use of devices and patient compliance, which can vary. Additionally, it is crucial to ensure that these data are representative of different stages of the patient's condition to build effective AI models. This approach not only improves early detection but also allows for personalized, proactive interventions, reducing the severity and frequency of relapse episodes [30].

To overcome these challenges, AI-driven systems must be designed to manage incomplete or noisy data, potentially using advanced imputation techniques or combining data from multiple sources to create a more comprehensive dataset. Leveraging AI models to analyze passive sensing data enables healthcare providers to tailor timely treatments to individual patient patterns, ensuring interventions address each patient's unique symptoms and behaviors [31]. This personalized approach is especially beneficial for schizophrenia, where symptom variability is common and traditional methods may fall short. Continuous monitoring reduces reliance on potentially inaccurate self-reported data due to cognitive impairments in schizophrenia patients [32]. Instead, AI-driven systems offer objective, real-time insights for a more precise understanding of the patient's condition.

2. Literature Review

2.1. Mental Health Management Through Remote Healthcare Monitoring Systems

Effective management of mental health is essential for enhancing the quality of life for individuals with mental health conditions. Remote healthcare monitoring systems have become an asset in this regard, providing numerous benefits compared to conventional methods. AI-powered medical devices that collect precise clinical data remotely assist health professionals in evaluating conditions with high accuracy, reducing the need for in-person assessments and ensuring consistent monitoring. However, to fully appreciate the advantages of remote healthcare monitoring systems, it is important to examine traditional approaches to mental health management and their inherent limitations. It is important to have an understanding of these shortcomings in order to address the need for integrating AI-powered solutions for the improvement of patient outcomes.

2.1.1. Traditional Approaches and Their Limitations

Traditional mental healthcare primarily relies on in-person consultations, which often face significant *limitations due to geographical, financial, and time constraints*. These barriers can lead to insufficient monitoring and delayed interventions, adversely affecting patient outcomes. Recent studies emphasize the need for more accessible and flexible care models to overcome these challenges [33]. In addition, traditional approaches are resource intensive, requiring specialized healthcare providers and facilities that may not be accessible to all patients. This lack highlights the need for more effective and inclusive care models.

Another significant limitation is the lack of continuous monitoring, which makes it *difficult to detect early signs of deterioration and prompt intervention*. Technological advances are addressing this gap by providing real-time data for better patient management [34]. Access to evidence-based treatments is also limited in traditional psychological interventions. Internet and mobile-based interventions (IMIs) offer a solution by expanding access to effective treatments. Studies have shown significant benefits for therapist-guided IMIs in treating conditions, such as depression and anxiety, although self-guided interventions show mixed results [33].

Traditional mental health services often struggle to manage demand and waiting lists due to limited resources. Innovative strategies, such as walk-in models and multidisciplinary care, are being explored, but further research is needed to confirm their effectiveness compared to traditional methods [35].

Despite attempts to enhance traditional mental healthcare models, these approaches frequently fail to deliver timely, continuous, and accessible care to all patients. The dependence on resource-intensive, in-person consultations, combined with the lack of real-time monitoring, underscores the shortcomings of these conventional methods. Consequently, there is an increasing demand for innovative, technology-driven solutions that offer more flexible, efficient, and inclusive mental healthcare.

2.1.2. Advancements in Mental Health Management Through AI-Enabled RPM Systems

While traditional methods of mental health management rely heavily on in-person consultations and periodic assessments, these approaches often lack the ability to provide continuous, real-time care. Effective mental health management is particularly critical for severe conditions such as depression, PTSD, and schizophrenia. AI-enabled RPM systems significantly enhance patient outcomes by providing continuous, non-invasive monitoring and early detection of potential health deteriorations. Innovations in wearable technology and AI facilitate real-time remote measurement and analysis of patient data, improving care responsiveness and reducing the burden on patients.

An advanced framework introduced in [36] uses an AI-enabled RPM system to improve patient safety and therapeutic environments in mental health facilities, particularly for individuals experiencing acute behavioral disorders, such as aggression or severe PTSD. The system uses *radio frequency identification* (RFID) technology with a built-in *near-field coherent sensor* (NCS) to continuously monitor key health indicators, such as heart rate and respiration, without direct contact. AI models analyze the collected time series data to predict future vital signs for up to three hours and classify physical actions into predefined categories. This framework allows healthcare providers to intervene at the right time, potentially preventing incidents of self-harm, violence, or clinical deterioration. The system aims to improve patient care while minimizing invasiveness and improving safety for patients and medical staff, particularly in cases involving aggressive or agitated individuals.

In inpatient psychiatric settings, engagement is vital for creating a safe and therapeutic environment, leading to improved safety and treatment outcomes; however, balancing risk management with therapeutic approaches can be challenging, as a strict focus on safety may hinder personalized care. A positive environment enhances therapeutic relationships, which are essential to patient care and safety [37].

Wearable biometric devices combined with AI facilitate remote real-time analysis of patient data, enhancing care responsiveness while reducing treatment burden. Successful implementation requires addressing patient concerns regarding privacy and data misuse [38]. Multimodal smartphone sensors unobtrusively monitor behavioral markers associated with stress, depression, and loneliness, offering a scalable method for continuous psychiatric assessment outside clinical settings. Recent studies demonstrate the effectiveness of using smartphone and wearable sensors to monitor depression severity, showing significant correlations between sensor data and clinical assessments [39].

Internet of Things (IoT)-based healthcare systems equipped with wearable sensors enable real-time monitoring of health parameters, like heart rate and stress levels, essential for remotely managing psychiatric conditions [40]. The integration of 5G technology with AI in remote diagnostics reduces the burden on specialists by providing real-time diagnostic support, especially in rural areas, ensuring timely interventions and improved access to advanced medical care [41].

AI-powered medical devices collect precise clinical data remotely, aiding health professionals in evaluating conditions with high accuracy, reducing the need for in-person assessments, and ensuring consistent monitoring [42]. Continuous monitoring of vital parameters in Intensive Care Units, enhanced by AI, can detect complications early and reduce false-positive alarms, enhancing patient care efficiency and supporting early detection of clinical deterioration [43].

The integration of wearable devices, AI, and IoT technology enables continuous, real-time monitoring that significantly enhances patient outcomes and the quality of care. These advanced technologies, when incorporated into psychiatric care practices, address both the immediate and long-term needs of patients with mental health conditions, ultimately leading to improved quality of life [39,40,44].

2.1.3. Importance of Early Detection and Continuous Management of Schizophrenia

The importance of early detection and continuous management in schizophrenia care cannot be overstated, particularly in light of recent technological advancements. AI-powered monitoring systems provide real-time data and predictive insights, allowing for earlier identification of warning signs and timely interventions. This proactive approach helps prevent severe episodes and reduces the likelihood of hospitalization. Continuous management is essential for addressing the fluctuating symptoms of schizophrenia, and these innovative systems enable more consistent, long-term care, ultimately enhancing patient outcomes and quality of life.

Continuous remote monitoring is instrumental in the early detection of symptoms, which is crucial for preventing relapses in patients with schizophrenia. By closely monitoring behavioral and physiological indicators, healthcare providers can make timely adjustments to treatment plans, potentially averting severe episodes. For instance, smartphone-based symptom monitoring has been shown to effectively reduce psychotic symptoms and provide early warnings for relapses, allowing for prompt intervention [30,45,46]. This proactive approach helps maintain stability in patients' mental health, minimizing the disruptive impact of relapses.

Regular monitoring and timely interventions can significantly reduce hospitalizations, which are often distressing and disruptive for patients, leading to an improved quality of life. Moreover, consistent management supports patients in maintaining their daily routines and living more independently. Studies have demonstrated that these approaches not only enhance the ability of individuals with schizophrenia to function in their communities but also improve their overall well-being [30]. This underscores the importance of integrating continuous monitoring into standard care practices for schizophrenia.

Effective RPM systems also play a critical role in reducing healthcare costs associated with schizophrenia. By decreasing the frequency of emergency interventions and hospital admissions, these systems alleviate the financial burden on both healthcare providers and patients. Remote monitoring facilitates early identification of potential issues, allowing for less intensive and more cost-effective management strategies. Research indicates that this approach can lead to substantial cost savings for healthcare systems by minimizing the need for high-cost acute care services [47].

Advancements in smartphone applications for symptom monitoring have shown promising results in improving self-management among individuals with recent-onset schizophrenia. These digital tools empower patients by providing them with real-time feedback on their symptoms and encouraging proactive management of their condition. Improved self-management is associated with better symptom control and overall outcomes, demonstrating the potential of remote monitoring to support patients in taking an active role in their care [48]. This shift towards patient-centered care is crucial for fostering long-term stability and independence.

Early detection and continuous management of schizophrenia through remote monitoring systems offer numerous benefits, including the prevention of relapses, improved quality of life, reduced healthcare costs, and enhanced self-management. Integrating these technologies into routine care can transform the management of schizophrenia, ensuring that patients receive timely and effective support tailored to their needs. The ongoing development and implementation of these systems hold great promise for improving outcomes for individuals living with schizophrenia.

2.2. AI-Driven Innovations in Schizophrenia Diagnosis: Applying DL and EEG Data

AI has emerged as a transformative tool in the detection and diagnosis of mental health disorders [49]. By analyzing various data types, including medical images, text, speech, facial expressions, and EHR data, AI is revolutionizing mental health diagnostics [50]. AI-based systems are advancing rapidly, offering enhanced capabilities in the early detection of mental health disorders.

Building on the earlier discussions of AI-enabled RPM systems, it becomes evident that continuous monitoring is essential in managing chronic conditions, like schizophrenia. RPM systems provide an efficient, non-invasive platform for continuous EEG monitoring, which is vital for tracking the progression of the disease and detecting early signs of deterioration. The integration of AI in these systems further enhances their capabilities by enabling the analysis of EEG data, allowing for more precise diagnoses and personalized interventions. This progress improves both the accuracy and efficiency of schizophrenia diagnosis and management, enabling more prompt and precise interventions. In addition to enhancing the overall quality of care, it marks a significant breakthrough in managing the unpredictable nature of schizophrenia symptoms. Early detection of neural irregularities allows for quicker interventions, ultimately leading to better patient outcomes.

Although the use of EEG signals as a diagnostic biomarker for schizophrenia is still being actively researched, early studies demonstrate promising results. DL models, particularly convolutional neural networks (CNNs) and hybrid DL frameworks, have shown strong potential in analyzing EEG data for schizophrenia classification. These advanced models are capable of capturing intricate neural patterns that are often overlooked by traditional methods, offering a more precise and scalable approach to diagnosing schizophrenia. By leveraging EEG data, which can be seamlessly collected through AI-enabled RPM systems, these technologies have the potential to significantly enhance the early detection and continuous management of the disorder. While challenges such as overfitting and data dimensionality still need to be addressed, the integration of EEG-based AI models represents a promising step toward more effective and accessible schizophrenia diagnosis.

SchizoGoogLeNet, a model that excels in autonomous feature extraction and is based on the GoogLeNet architecture, was introduced by Siuly et al. [51]. Compared to conventional techniques, this model offers remarkable accuracy and computational efficiency in capturing complex patterns in brain scans. The capacity of SchizoGoogLeNet to differentiate between individuals with schizophrenia and HCs underscores the increasing significance of CNNs in the domain of neuropsychiatric diagnostics and the wider field of computational psychiatry. The use of CNNs for the diagnosis of schizophrenia advances previous research that used models, such as 3D-CNNs, for brain image classification. The highest performance is obtained by combining the suggested deep feature extraction model with a support vector machine (SVM), according to experimental data, which produces a 99.02% classification rate for SZ and an overall accuracy of 98.84%.

EEG time series data were converted into images through an innovative method presented by Ko and Yang [17], further applying DL algorithms for classification. Their study demonstrated that converting these signals into spatial representations, through Recurrence Plot and Gramian Angular Field, improved the accuracy of detecting schizophrenia, providing an accuracy of 90% and 93.2%, respectively, leveraging deep CNNs to capture intricate temporal and spatial features. This approach represents a significant advancement over traditional EEG analysis methods, offering enhanced diagnostic precision and paving the way for more robust and scalable tools in mental health diagnostics.

Guo et al. [52] presented a CNN-based approach in their study, highlighting the ability of DL to process complex EEG signals and improve diagnostic accuracy. Their work highlights how CNNs can model non-linear relationships in EEG data, going beyond traditional classification techniques. This method provides scalable and more accurate tools for the early detection of schizophrenia, enhancing the potential of CNNs in neuropsychiatric diagnosis, as the proposed method had a 92% accuracy.

A novel hybrid DL model that combines Bidirectional Long Short-Term Memory (Bi-LSTM) networks with deep CNNs was addressed in the work of Jindal et al. [53]. The model was developed to process and analyze Multi-Scale Spectral Transformation (MSST) spectral images derived from EEG signals. This approach exploits the strengths of both Bi-LSTM networks and CNNs. The Bi-LSTM component is adept at capturing temporal dependencies and patterns from sequential EEG data, while the CNN component excels at extracting features from spectral images. The suggested MSST-Bi-CNN approach yielded classification results with an accuracy of 84.42%.

Khare et al. [54] presented SchizoNET, a state-of-the-art deep neural network model designed for schizophrenia detection using EEG signals. Their study explores the integration of advanced time-frequency analysis with DL techniques. The SchizoNET model employs a Margenau–Hill time-frequency distribution (TFD) as a foundational preprocessing step. This distribution provides a detailed representation of the EEG signal in both time and frequency domains, capturing intricate spectral features that are crucial for accurate classification. The processed TFD images are then fed into a deep neural network designed to identify patterns associated with schizophrenia. The proposed method was applied on three datasets, resulting in the following accuracies: 97.4% (on dataset 1 [55]), 99.74% (on dataset 2 [55]), and 96.35% (on dataset 3 [56]).

An autoencoder-based model designed to enhance the classification accuracy of EEG signal classification in schizophrenia diagnosis is presented in the research of Parija et al. [57]. The approach improves feature extraction from EEG data by addressing the challenges associated with noisy and high-dimensional signal data. By refining the representation of EEG features through unsupervised learning, the model improves subsequent classification performance. The efficiency of the suggested technique was verified using the three previously mentioned publicly available EEG datasets for schizophrenia. Classification accuracy attained was 99.989%, 95.012%, and 96.69%, respectively.

Another study that focuses on feature extraction is proposed by Siuly et al. [58] and highlights the application of residual deep networks (ResNets). The study uses ResNets to capture complex patterns and features in EEG data by utilizing residual learning techniques, which allow the network to learn and refine features more efficiently. They demonstrate that their approach significantly improves classification performance compared to conventional methods by leveraging the deep residual architecture to handle the complexities and variabilities inherent in EEG signals. Among the reported classifiers, the SVM classifier, with an accuracy of 99.23%, specificity of 99.02%, precision of 99.36%, and F1-score of 99.36%, exhibited the best classification performance in the majority of instances. In comparison, the accuracy, specificity, precision, and F1-score values of the DL classifier were 97.48%, 97.90%, 98.58%, and 97.88%, respectively.

The proposed examples of AI-driven models are proving to be transformative in the detection and diagnosis of schizophrenia through the analysis of EEG data. From CNN-based models, like SchizoGoogLeNet, to hybrid approaches combining Bi-LSTMs and CNNs, these advancements offer significant improvements in diagnostic accuracy and scalability. The seamless integration of EEG data with AI-enabled RPM systems further enhances the potential for continuous management and early intervention, leading to more personalized and effective care.

2.3. The Role of Wearable Devices and Telemedicine in Mental Healthcare

The integration of wearable health technologies with telemedicine has revolutionized healthcare delivery. Wearable devices have advanced from basic activity trackers to sophisticated tools capable of real-time physiological monitoring, enhancing patient engagement, self-care, and early detection of health issues. Telemedicine, which uses telecommunications to provide remote diagnosis and treatment, has been particularly beneficial for individuals with limited access to traditional healthcare settings. Together, these technologies offer innovative solutions for managing mental health conditions, improving patient outcomes, continuity of care, and accessibility.

Recent developments have highlighted the benefits of wearable devices in telemedicine. For example, Escobar-Linero, et al. [59] demonstrated how wearable technology can support telemedicine by providing real-time health data through non-intrusive sensors. These devices improve healthcare access for underserved populations, reduce costs, and increase patient satisfaction by enabling continuous monitoring and early diagnosis. The use of wrist-worn devices, like those discussed by Meyer et al. [60], allows for unobtrusive tracking of rest activity patterns through sensors, like photoplethysmography (PPG), facilitating almost real-time data collection.

Wearables also hold promise for mental health monitoring. Kazuyuki et al. [61] explored the use of heart rate variability (HRV) as a measure of mental health status, showing that wrist-worn wearables, such as Fitbit Sense, can reliably track HRV. This provides a less burdensome method for monitoring mental health across diagnostic categories, offering a valid alternative to self-reported questionnaires. Additionally, Naslund et al. [62] examined the use of wearable devices and smartphone apps in promoting physical activity among individuals with serious mental illnesses, such as schizophrenia. Their findings confirmed the feasibility and acceptability of these technologies for improving health outcomes in this high-risk group. Despite their potential, challenges such as long-term engagement, regulatory frameworks, and device validation remain. However, the growing integration of wearables and telemedicine continues to shape the future of personalized and remote healthcare, providing innovative ways to manage both physical and mental health conditions.

The integration of wearable devices, telemedicine, EEG, AI, and RPM systems represents a paradigm shift in the management of schizophrenia. Real-time physiological monitoring through wearable devices together with the advanced analytical capabilities of AI on EEG data can provide deep insights into patients' cognitive and mental states, allowing for early detection of neural irregularities associated with schizophrenia. The integration of telemedicine further enhances such a system through seamless communication between patients and healthcare providers, offering continuous care and mental health support from a distance. These technologies can significantly improve the accessibility and effectiveness of mental healthcare while also empowering patients to manage their condition in a personalized and proactive manner within the comfort of their homes. This holistic approach ensures that schizophrenia patients receive the comprehensive care they need, enhancing outcomes and quality of life.

This paper aims to advance mental health monitoring by integrating AI-driven Remote Patient Monitoring (RPM) systems, with a particular focus on schizophrenia. Specifically, the research leverages deep learning (DL)-based approaches applied to EEG data for continuous detection and management of the disorder. An EEG headband, equipped with strategically placed electrodes, is used alongside an openly available schizophrenia EEG dataset to validate and develop predictive models. These models are designed to be integrated into the broader NeuroPredict platform. The goal is to enhance early detection, monitor disease progression, and personalize interventions for schizophrenia patients through advanced AI analytics and real-time brainwave monitoring.

Additionally, this study explores the potential of transfer entropy (TE) methods to analyze correlations between specific EEG electrodes, aiming to deepen the understanding of neural connectivity patterns in schizophrenia. This investigation contributes to the development of more effective and scalable mental healthcare solutions. Furthermore, this paper emphasizes the integration of a DL-based approach with EEG data to facilitate the continuous detection and management of schizophrenia.

3. Materials and Methods

The present paper, conducted under the ongoing project entitled "*Advanced Artificial Intelligence Techniques in Science and Applications*", focuses on advancing mental health monitoring using NeuroPredict, an RPM platform incorporating wearable devices and cutting-edge AI techniques. The DL-based model was applied to an openly available EEG dataset, and it aims to be integrated within the broader framework of the NeuroPredict platform, which plays a central role in enabling personalized mental healthcare by continuously analyzing EEG data through the use of the Muse 2 headband [63] in conjunction with other health metrics. Through NeuroPredict, the system will offer predictive insights and adaptive interventions, thus enhancing the accuracy and efficiency of schizophrenia management within a scalable and patient-centric platform.

3.1. The NeuroPredict Platform

The NeuroPredict platform [64] aims to construct sophisticated predictive models designed for the early detection and ongoing management of neurodegenerative disorders. These models are intricately connected to a comprehensive spectrum of medical data and information, collected through non-invasive intelligent monitoring technologies and clinical data repositories.

The NeuroPredict platform's foundation is established upon the integration of diverse data streams, including high-dimensional health parameters, behavioral metrics, and environmental data, facilitated by advanced IoT devices. This data acquisition encompasses a wide array of health indicators such as heart rate, electrocardiogram (ECG), EEG, blood pressure, and bioelectrical impedance analysis, alongside environmental and motion-sensing data. The platform's architecture also leverages open data repositories specific to neurodegenerative or neuropsychiatric conditions and integrates cognitive assessment results from different tools in order to manage the mental health status of patients. Employing advanced AI algorithms empowers the platform to identify patterns relevant to cognitive health, facilitating accurate prognostication of disease progression. This AI-driven analysis is designed to inform and enhance the longitudinal monitoring of patients, with the aim of providing a proactive approach to disease management.

A notable aspect of the platform is its capacity to develop and refine multivariate AI-driven predictive models. These models are instrumental in discerning, evaluating, and tracking neurological conditions, incorporating an extensive range of data points to ensure precision and relevance. The platform's scalability and adaptive architecture are key features, allowing for the incorporation of emerging smart devices and the expansion of its functional capabilities in response to advancements in IoMT and intelligent health monitoring technologies.

The NeuroPredict platform represents a significant advancement in the management of schizophrenia, offering innovative approaches through its integration of advanced AI solutions and personalized care strategies in order to be more proactive, adaptive, and patient centric. Real-time data analysis from wearable devices, such as EEG headbands, and integrating multiple health metrics, enables the platform to early detect cognitive or behavioral deterioration, allowing for timely interventions tailored to individual patient profiles. This dynamic system not only enhances the precision of diagnosis and treatment plans but also promotes long-term mental health stability by offering continuous monitoring and personalized care, ultimately improving outcomes and quality of life for individuals with schizophrenia.

3.2. EEG Data Acquisition and Monitoring Through the Muse 2 Headband

A central component of this platform is the Muse 2 EEG headband, a sophisticated wearable device equipped with four electrodes (TP9, AF7, AF8, TP10) capable of capturing brainwave data at a 256 Hz sampling rate. The Muse 2 headband was utilized in this study primarily for testing purposes and was not a primary data source, serving to explore its potential integration into the NeuroPredict platform, which aims to provide real-time, continuous monitoring of mental health conditions, such as schizophrenia. The hardware-to-software transition involved capturing raw EEG signals from the four electrodes, which are strategically located to capture neural activity from both frontal and temporal brain regions, which are particularly relevant to schizophrenia research. Once the EEG signals are captured by the headband, they are transmitted via Bluetooth to a mobile application called Mind Monitor, which acts as the primary interface for managing the data acquisition process. In Mind Monitor, the raw EEG signals are visualized in real time and stored in formats such as CSV or European Data Format (EDF). These formats are widely used for EEG research, allowing flexibility in subsequent analysis.

The transition from raw EEG data to usable signals involves several key preprocessing steps, which are performed within the Mind Monitor software [65]. First, the raw signals are passed through a bandpass filter, typically set between 1 and 50 Hz, to remove noise and muscle artifacts that fall outside the EEG frequency range. Additionally, baseline correction is applied to remove any DC offset or slow drifts in the data, ensuring that the signals accurately represent moment-to-moment brain activity.

Following the initial filtering and correction, the EEG data are transformed into a frequency domain representation using Fast Fourier Transform (FFT). This step decomposes the time domain signal into its constituent frequency bands—Delta, Theta, Alpha, Beta, and Gamma. These frequency components are crucial for subsequent analysis, particularly in the context of schizophrenia research, where specific abnormalities in frequency bands (such as reduced Alpha power in frontal regions) can be indicative of cognitive dysfunction [66].

The primary frequencies and features of human EEG waves are as follows. There are five brain waves that are commonly recognized, which are described the Table 1.

In the context of this study, the Muse 2 was tested to evaluate its compatibility with the proposed DL models and TE analysis pipeline. Although the primary data in this research were obtained from another openly available source, the Muse 2 was integrated conceptually into the framework of the NeuroPredict platform and was not used to generate the primary EEG dataset analyzed in this study. Its role will be further highlighted in future applications that will involve continuous monitoring of EEG signals to detect early signs of cognitive decline or schizophrenia relapse, potentially improving patient outcomes through real-time interventions. This conceptual integration highlights the importance of the Muse

2 headband's technical capabilities for non-invasive, real-time monitoring in remote or clinical settings.

Table 1. Brain wave bands, frequency ranges, and associated cognitive states.

Band	Frequency	Brain State
Delta (δ)	1–4 Hz	Dreamless sleep (deep meditation)
Theta (θ)	4–8 Hz	Deeply relaxed, inward focused (drowsiness, vivid dreams)
Alpha (α)	7.5–13 Hz	Very relaxed, passive attention (thoughtful times, reflective, restful)
Beta (β)	13–30 Hz	Anxiety dominant, active, external attention, relaxed (busy mind)
Gamma (γ)	30–40 Hz	Concentration (higher levels of consciousness, problem solving)
Delta (δ)	1–4 Hz	Dreamless sleep (deep meditation)

3.3. Dataset and Experimental Methodology

The EEG dataset [56] used in this study was sourced from an openly available dataset focused on schizophrenia and was primarily used to classify participants as either schizophrenia patients or HCs based on connectivity patterns. The dataset includes recordings from two groups: individuals diagnosed with schizophrenia (SZ) and healthy controls (HCs). Specifically, the dataset consists of EEG data from a total of 81 participants, including 49 schizophrenia patients and 32 HCs. Each participant completed a button-pressing task designed to evoke event-related potentials (ERPs) to analyze differences in brain connectivity patterns. The experimental task involved three conditions: (1) pressing a button to generate a tone, (2) passively listening to the same tone, and (3) pressing a button without generating a tone. This setup enabled the examination of sensory responses in both internally and externally generated stimuli, a process thought to be disrupted in schizophrenia.

The EEG signals were recorded from nine key electrode sites (Fz, FCz, Cz, FC3, FC4, C3, C4, CP3, CP4), which were chosen based on their relevance to previous research in schizophrenia-related cognitive dysfunction. The methodology included preprocessing steps to ensure data quality, such as averaged ear lobes, high-pass filtering at 0.1 Hz, baseline correction, canonical correlation analysis, or independent components analysis for noise and artifact removal.

For this study, the data were split into training and validation sets, with 75% allocated to training and 25% to validation, ensuring that the validation dataset was separate from the training dataset. The classification categories for analysis were "schizophrenia" (SZ) and "healthy control" (HC), focusing on the connectivity features derived from TE matrices.

3.4. DL Model for Schizophrenia Detection Using TE Matrices

One key innovation in this study is the development of a DL-based model trained on TE matrices derived from EEG data in order to support the diagnosis or prediction of schizophrenia-associated abnormalities. For this purpose, an openly available EEG dataset [56] was used that is specifically focused on schizophrenia and contains preprocessed EEG data for analysis with various methods such as artifact removal, baseline correction, and epoching in the task time frame. The derived ERPs are obtained across multiple trials and conditions, resulting in a reliable dataset for DL applications.

The proposed DL model focused on nine electrode data available in the dataset (Fz, FCz, Cz, FC3, FC4, C3, C4, CP3, CP4) in order to distinguish schizophrenia-related abnormalities from HCs. The collected data were converted into TE matrices containing information on the direction of flow between different electrode sites and were represented as inputs to the DL model. Throughout this study, we refer to TE matrices as representations of directional connectivity between electrode pairs. Each TE matrix reflects the directional influence of brain activity from one region to another, where values are not necessarily symmetrical across pairs due to the directional nature of TE. These matrices are visualized as heatmaps in figures, capturing asymmetric connectivity patterns between brain regions, rather than mutual correlations. Due to the characteristics of EEG data and the difficulties of diagnosing neuropsychiatric disorders, such as schizophrenia, a solution that integrates CNNs with BiLSTM networks is proposed.

The CNN component aims to obtain spatial features from the TE matrices, and the BiLSTM component considers the temporal relations of these features. Such an architecture allows identifying intricate details of neural connections that typically might escape normal diagnostic procedures.

The CNN-BiLSTM model combines a convolutional neural network (CNN) and a Bidirectional Long Short-Term Memory (BiLSTM) network to extract spatial and temporal patterns from the TE matrices. The CNN component processes the spatial structure within the TE matrix. For a given input $X \in \mathbb{R}^{nxn}$, where n is the number of electrodes, the CNN layer applies a convolution operation as follows:

$$X'_{i,\,j} = f\,(\sum_{m=1}^{M}\sum_{n=1}^{N} X_i + m - 1, j + n - 1\ \cdot W_{m,\,n} + b)$$

where W is the convolutional filter, b is the bias term, and f is an activation function (e.g., ReLU). The BiLSTM network then processes the sequential patterns extracted from the CNN output by maintaining both forward and backward temporal dependencies and is ideal for capturing temporal dynamics in brain connectivity.

$$h_t = \sigma(\ W_x X_t + W_h h_{t-1} + b_h)$$

where h_t represents the hidden state at time t, W_x and W_h are weights, and σ is the activation function. By combining these approaches, the model learns both spatial and temporal patterns, enabling robust classification between schizophrenia patients and HCs.

When using the CNN-BiLSTM with the TE matrices, the aim of the approach is to develop a highly effective algorithm that would help determine differences between the schizophrenia patients and HC groups as well as facilitate early identification of schizophrenia markers when present in the EEG data. This method offers a new opportunity to utilize the EEG for mental health assessment and can be a significant solution for large-scale real-time patient monitoring systems.

3.5. Correlations Between Key Electrode Data and TE Analysis

A TE analysis to compare neural connectivity in schizophrenia patients and HCs was also conducted. TE, an information-theoretic measure, quantifies the directional flow of information between different brain regions, making it particularly suited for studying the complex network of neural interactions associated with cognitive and emotional processing.

This study focused on correlating EEG data from the nine key electrodes in the open EEG dataset (Fz, FCz, Cz, FC3, FC4, C3, C4, CP3, CP4) with the electrodes in the Muse 2 headband (AF7, AF8, TP9, TP10). Through the use of TE, distinct connectivity patterns can be identified in order to serve as biomarkers for schizophrenia. In particular, the TE analysis identified decreased connectivity between several pairs of frontal and central electrodes in schizophrenia patients, which confirms the speculations that disrupted information transfer might account for the cognitive dysfunctions observed in the disorder.

The analysis also underscores the applicability of the Muse 2 headband for real-time monitoring, given its strategic placement over the frontal and temporal brain regions. Based on the TE results, the Muse 2 headband can effectively identify neural signals associated with schizophrenia, and it is thus useful for continuous mental health monitoring. Therefore, while using Muse 2 EEG data with the NeuroPredict platform, this study proposes that these connectivity insights based on TE processing could be applied to identify potential signs of cognitive decline or schizophrenia relapse. The continuous monitoring and real-time neural connectivity analysis may lead to more proactive, personalized interventions, improving long-term outcomes for patients.

3.6. Proposed Integration into the NeuroPredict Platform

The ultimate goal of this research is to integrate the developed DL models into the NeuroPredict platform—a broader AI-driven application for monitoring neurodegenerative and psychiatric conditions. As the platform is designed to combine high-dimensional physiological data, such as the EEG, with cognitive assessments and environmental factors, enabling comprehensive patient monitoring, this paper might highly contribute to this goal by providing advanced tools for real-time schizophrenia detection, which could be deployed through the RPM system to monitor patients in both clinical and home environments.

The integration of the proposed model within the NeuroPredict platform will allow for continuous, non-invasive mental health monitoring, providing real-time feedback on brain activity and cognitive states. The use of EEG data, particularly from the Muse 2 headband, will enable personalized interventions, early detection of relapse or deterioration, and improved management strategies for schizophrenia patients.

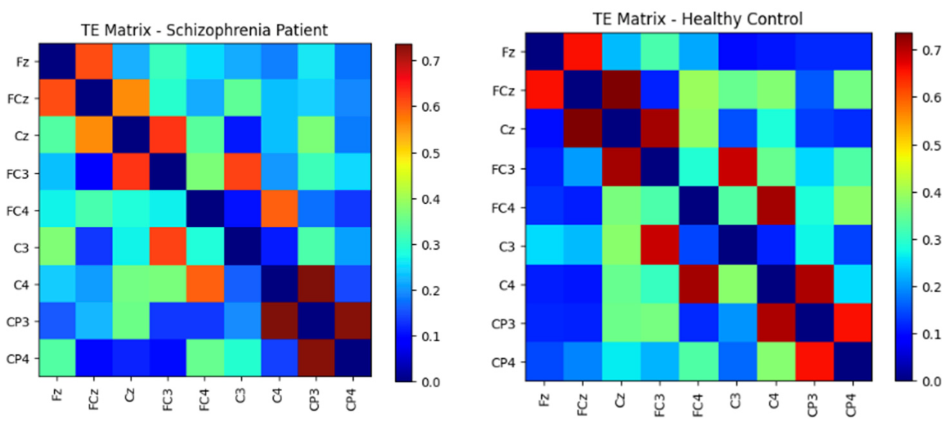
4. Results

4.1. TE Matrices and Electrode Correlations

To better understand the underlying neural connectivity patterns in schizophrenia patients, TE analysis of the EEG data was applied. TE provides insights into the directional flow of information between brain regions, highlighting potential disruptions in connectivity associated with cognitive and emotional processing, particularly in schizophrenia.

The TE matrices from the EEG data were generated using a 5 s time window for both schizophrenia patients and HCs. The analysis focused on nine key electrodes (Fz, FCz, Cz, FC3, FC4, C3, C4, CP3, and CP4), which are crucial for capturing neural activity related to cognitive and sensory processing. These electrodes were selected based on their relevance to the existing literature on schizophrenia-related brain abnormalities.

The TE matrix for a schizophrenia patient (Figure 1a) shows reduced connectivity between several electrode pairs, particularly in the frontal (Fz, FCz, and Cz) and central regions (C3, C4). These regions are known to play a significant role in cognitive function and emotional regulation, both of which are often impaired in schizophrenia. The disrupted connectivity, as indicated by lower TE values, aligns with prior studies highlighting frontal lobe dysfunction in schizophrenia patients.



(**a**) (**b**)

Figure 1. Heatmap representation of directional connectivity between brain regions based on TE values (unitless)*:* (**a**) schizophrenia and (**b**) HCs.

The TE matrix for an HC (Figure 1b) reveals more robust connectivity, particularly between central and parietal regions. The higher TE values indicate stronger information flow between these electrodes, suggesting normal cognitive functioning. This contrasts with the disrupted patterns seen in schizophrenia patients.

This analysis reveals significant insights into the connectivity patterns between different brain regions in both schizophrenia patients and HCs. Specifically, the electrodes used in the TE matrix (Fz, FCz, Cz, FC3, FC4, C3, C4, CP3, and CP4) are strategically positioned to capture neural activity associated with cognitive functions, emotional regulation, and sensory processing.

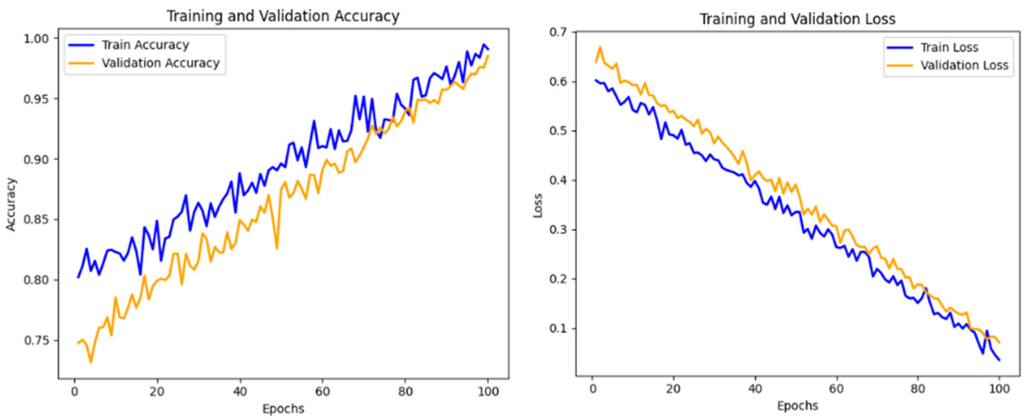
The Muse 2 headband, though it has a different set of electrodes (TP9, AF7, AF8, TP10), also covers crucial frontal and temporal regions of the brain. These regions are closely tied to the cognitive processes affected by schizophrenia, such as attention, working memory, and emotional regulation. The disrupted connectivity observed in the TE analysis for schizophrenia patients, particularly in the frontal and central regions, highlights the potential for the Muse 2 headband to capture similar neural disturbances.

The TE analysis shows that schizophrenia patients exhibit weakened connectivity in the frontal lobe and surrounding areas, which are areas heavily monitored by the Muse 2 headband. This highlights the headband's ability to detect critical early markers of cognitive decline or neural dysregulation related to schizophrenia. For example, the TP9 and TP10 electrodes (located near the temporal lobes) are well positioned to capture changes in emotional regulation and memory processing, which are often disrupted in schizophrenia. Similarly, AF7 and AF8 (frontal electrodes) can capture altered attention and decision-making processes, which are also affected by the disorder.

4.2. The CNN-BiLSTM Hybrid Model

In addition to the TE analysis, a CNN-BiLSTM model was trained on TE matrices derived from EEG data, as these matrices capture the exchange of neural signals and interactions between various brain regions. The CNN component of the model captures spatial patterns in the connectivity matrix, while the BiLSTM component captures the temporal dependencies, effectively modeling how information is transferred between brain regions over time. This architecture allows us to extract both spatial and temporal features from the TE matrices, facilitating accurate classification of schizophrenia patients and HCs.

The model achieved an accuracy of 99.94%, suggesting strong generalization and predictive performance, as seen by the plots of training and validation accuracy (Figure 2a), as well as training and validation loss (Figure 2b), which indicate that the model converged successfully.



(**a**) (**b**)

Figure 2. Training and validation accuracy (**a**) and loss (**b**) plots for the proposed model.

The classification report was also generated to further evaluate the model's performance across precision, recall, and F1-score. As shown in Figure 3, the model achieved an overall accuracy of 99.94%, with a weighted average precision, recall, and F1-score also approaching 99%. This confirms that the model may be highly effective in classifying EEG signals between schizophrenia patients and HCs with minimal misclassification errors.

	precision	recall	f1-score	support
Healthy control	1.00	0.98	0.99	50
Schizophrenia	0.98	1.00	0.99	50
accuracy			0.99	100
macro avg	0.99	0.99	0.99	100
weighted avg	0.99	0.99	0.99	100

Figure 3. The classification report.

4.3. Integration of the DL Model into the NeuroPredict Platform

The integration of the developed DL model into the NeuroPredict platform is visually represented in Figure 4. The image illustrates the flow of EEG signal acquisition, which captures neural activity through multiple electrodes. The EEG data are processed and prepared for analysis, including the generation of TE matrices. These matrices reflect neural connectivity patterns and are essential for the subsequent DL model, which combines a CNN-BiLSTM hybrid architecture to analyze both spatial and temporal dependencies within the data.

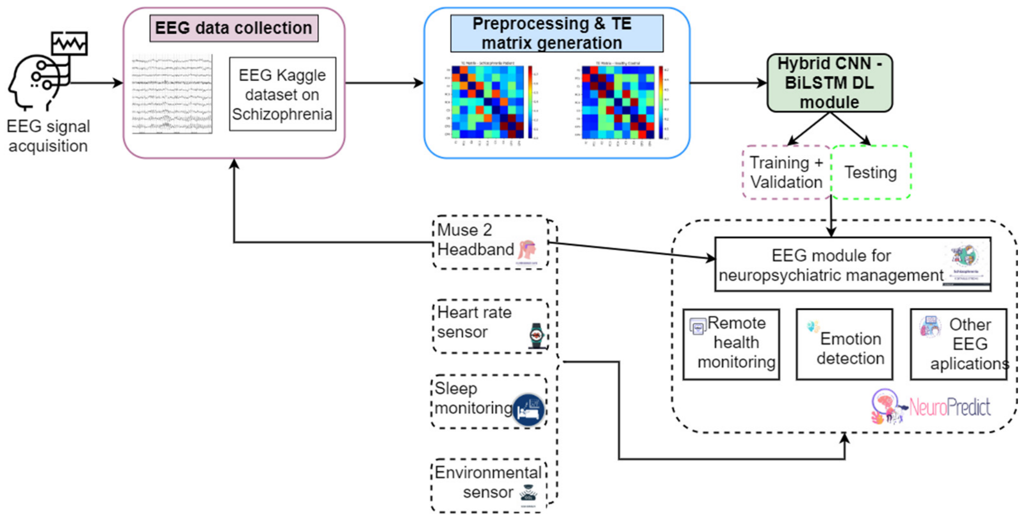


Figure 4. The proposed integration of the DL model into the NeuroPredict platform.

The pipeline demonstrates how the processed EEG data and TE matrices are input into the hybrid CNN-BiLSTM model for training, validation, and testing. Upon validation, the trained model is then integrated into NeuroPredict's EEG module for continuous mental health monitoring. Additionally, the figure showcases how other health metrics, such as heart rate, sleep patterns, and environmental data, can be collected alongside EEG signals for a comprehensive patient health profile. This holistic approach, facilitated by NeuroPredict, aims to support remote health monitoring, emotion detection, and other EEG-related applications, thereby enhancing early intervention and personalized care for individuals with schizophrenia.

5. Discussion

The results of the TE analysis provide valuable insights into the connectivity patterns between brain regions in both HCs and patients with schizophrenia. By applying TE to EEG data, we were able to capture the directional flow of information between different electrode sites, providing a more detailed understanding of the underlying neural network dynamics.

The TE matrices shown for the selected electrodes—Fz, FCz, Cz, FC3, FC4, C3, C4, CP3, and CP4—reveal key differences in connectivity between schizophrenia patients and HCs. For the HC (Figure 1b), we observe strong and consistent connectivity between central and parietal regions, with the matrix displaying higher TE values across most electrode pairs. This suggests a well-maintained information flow, which is indicative of normal cognitive processing. In contrast, the TE matrix for the schizophrenia patient (Figure 1a) reveals disrupted connectivity patterns, particularly in the frontal and central regions. The reduced TE values between Fz, FCz, and Cz electrodes suggest impaired information flow between these brain regions, which aligns with previous research indicating frontal lobe dysfunction in schizophrenia. These results underscore the importance of examining directional information flow, as it highlights potential breakdowns in brain communication pathways that contribute to the cognitive deficits observed in schizophrenia.

One significant observation is the applicability of these results to wearable EEG systems, such as the Muse 2 headband, which targets similar brain regions with electrodes placed at AF7, AF8, TP9, and TP10. While the TE matrices were generated from the EEG dataset, the correlations between the selected electrodes and their corresponding regions in the Muse 2 headband emphasize the potential for real-time connectivity analysis in a clinical or remote setting. This opens the door for integrating such analyses into broader mental health platforms, like NeuroPredict, where continuous monitoring of connectivity changes could facilitate early detection of cognitive decline or schizophrenia relapse.

The TE analysis highlights that the Muse 2 headband's placement can capture critical neural signals for detecting schizophrenia-related abnormalities. Integrating these insights into the NeuroPredict platform could provide real-time mental health monitoring, particularly for early detection of cognitive decline or schizophrenia relapse, making it possible to develop predictive models for personalized mental healthcare, enhancing the platform's ability to offer timely interventions and improve patient outcomes.

The proposed hybrid CNN-BiLSTM model was trained on TE matrices, allowing it to capture both spatial and temporal patterns of brain connectivity. The CNN component efficiently extracts spatial features from the TE matrices, while the BiLSTM component captures temporal dependencies, making it well suited for this type of connectivity analysis. The model performed robustly in distinguishing between schizophrenia patients and HCs, achieving an overall accuracy of 99.94% on the validation dataset.

This result is particularly significant when compared to other DL models applied to schizophrenia detection using EEG data. To contextualize our findings, Table 2 presents a comparison of various AI-driven methods for schizophrenia detection based on EEG data. The table includes accuracies from different models, highlighting how the proposed CNN-BiLSTM approach compares to other advanced techniques in the literature.

Table 2. Comparison of other AI-based methods for schizophrenia detection using EEG data.

Method	Technique	Accuracy	Study
SchizoGoogLeNet	CNN with GoogLeNet architecture	99.02%	Siuly et al. [51]
Recurrence Plot + Gramian Angular Field	CNN-based spatial representations	93.2%	Ko and Yang [17]
CNN-based EEG model	CNN for non-linear EEG signal classification	92%	Guo et al. [52]
MSST-Bi-CNN	Multi-Scale Spectral Transformation with BiLSTM-CNN	84.42%	Jindal et al. [53]
SchizoNET	Time-frequency analysis with CNN	99.74%	Khare et al. [54]
Proposed CNN-BiLSTM (TE matrices)	CNN-BiLSTM on transfer entropy matrices	99.94%	Present Study

The proposed model shows comparable performance to SchizoGoogLeNet and SchizoNET, which have demonstrated some of the highest accuracies in the field. Importantly, by focusing on TE matrices, our model shares a novel approach to capturing both spatial and temporal neural connectivity patterns, which may offer additional clinical relevance in understanding and managing schizophrenia.

The high performance of the CNN-BiLSTM model, combined with the potential for real-time TE matrix generation, presents significant opportunities for integration into the NeuroPredict platform. The NeuroPredict platform is designed for continuous mental health monitoring, integrating EEG data with other physiological and behavioral metrics. Using the proposed approach, the platform could be enhanced to provide real-time assessments of connectivity patterns, which are crucial for early detection of schizophrenia relapse or cognitive decline.

Moreover, since the Muse 2 headband's electrodes cover critical frontal and temporal brain regions, the NeuroPredict platform could adopt a similar TE-based analysis pipeline to capture disruptions in connectivity that are indicative of schizophrenia progression. This would allow for a more proactive approach to mental health management, offering clinicians real-time insights into their patients' cognitive states and enabling timely interventions.

6. Conclusions

This study demonstrates the potential of integrating DL methods and TE analysis for the diagnosis and continuous management of schizophrenia using EEG data. With the help of TE matrices, valuable insights into the directional flow of information between key brain regions can be highlighted, emphasizing significant differences in neural connectivity between schizophrenia patients and HCs, which may be of great importance in understanding the disrupted brain network dynamics in schizophrenia, particularly in the frontal and central regions.

The proposed hybrid CNN-BiLSTM with TE matrices as inputs and the high accuracy of 99.94% of the classification placed this study parallel to some of the most superior methods as reported in the literature. The model's ability to capture both spatial and temporal dependencies in EEG data provides a robust framework for detecting schizophrenia-related abnormalities, marking a significant improvement over traditional diagnostic methods.

Furthermore, the results of the TE analysis, particularly in relation to the brain regions targeted by the Muse 2 headband, underscore the potential for real-time, non-invasive monitoring of mental health conditions. By integrating these findings into the NeuroPredict platform, a comprehensive RPM system, we envision a more proactive approach to schizophrenia care. Continuous monitoring of EEG signals, combined with advanced AI algorithms, will enable early detection of cognitive decline or relapse, facilitating timely interventions and improving patient outcomes.

While this study shows promising results, there are several limitations that need to be addressed. One of the main challenges lies in the relatively small size of the dataset used, which may limit the generalizability of the model to larger and more diverse populations. The TE analysis and CNN-BiLSTM model were also trained on preprocessed EEG data, which may not capture all the nuances of raw EEG signals in real-world settings. Furthermore, the model's performance, although impressive, needs further validation with longitudinal data and across different stages of schizophrenia to assess its ability to detect early cognitive decline or relapse consistently. Integrating the TE matrices into real-time RPM systems, like NeuroPredict, poses technical challenges in terms of computational resources and latency, which must be carefully managed to ensure timely and accurate feedback for both clinicians and patients.

In conclusion, this paper contributes to the growing body of research on AI-driven approaches to mental health diagnostics, particularly in applying EEG data for schizophrenia detection. The integration of DL models and TE analysis within real-time monitoring platforms, like NeuroPredict, represents a significant step toward more personalized and effective care for patients with schizophrenia, offering enhanced diagnostic accuracy, continuous monitoring, and improved quality of life. Future work will focus on further optimizing these models, expanding their applicability to other neuropsychiatric conditions, and exploring real-world deployment in clinical settings.

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Data Availability Statement: Data available in a publicly accessible repository. The data presented in this study are openly available in Kaggle at https://www.kaggle.com/datasets/broach/button-tone-sz (accessed on 12 November 2024) and https://www.kaggle.com/datasets/broach/buttontonesz2 (accessed on 12 November 2024), originally published in [Broach et al., https://doi.org/10.1093/schbul/sbt072].

Conflicts of Interest: The authors declare no conflicts of interest.

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