IDENTIFICATION OF CHILDREN AT RISK OF SCHIZOPHRENIA VIA DEEP LEARNING AND EEG RESPONSES

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ABSTRACT

For early intervention and better results, it is essential to identify children who may be at risk of schizophrenia, anxiety, stress disorder, autism, and other mental problems as early as possible. The non-invasive brain imaging method known as electroencephalography (EEG) may be used to assess the electrical activity of the brain. It has been demonstrated that EEG data can be helpful in detecting kids who may have mental health issues. EEG data is complicated and high-dimensional, which makes analysis difficult. This study suggests a unique method that combines PCA with the Naive Bayes algorithm to identify children who may be at risk of developing schizophrenia, anxiety, stress disorder, autism, or other mental problems. Initially, the dimensionality of the EEG data is decreased using PCA. The EEG data is then categorized into several categories using the Naive Bayes algorithm according to the child's likelihood of acquiring a mental condition. The suggested method was assessed using an EEG dataset containing the data of kids with and without mental health issues. The findings demonstrate that the suggested method is very accurate in identifying kids who may be at risk for mental health issues.

Keyword *Schizophrenia Risk Factors, Childhood Psychopathology, Anxiety, Electroencephalography (EEG), Stress Disorder, Autism Spectrum Disorder*

1. INTRODUCTION

4A vital component of early intervention and assistance for children at risk of different mental health issues is identifying them. Autism spectrum diseases, anxiety disorders, stress disorders, and schizophrenia are a few of the illnesses that require extra care. Early identification makes it possible to provide focused, timely treatments that can greatly enhance the lives of the affected children. Investigating Electroencephalogram (EEG) responses is a potentially fruitful path toward such identification. The non-invasive method of electroencephalography (EEG) has demonstrated potential in identifying patterns and abnormalities linked to various illnesses. Researchers and clinicians may learn a great deal about the neuronal signatures linked to autism, stress disorders, schizophrenia, anxiety, and other illnesses by analyzing EEG responses. In addition to advancing our knowledge of the neurological causes of these disorders, this research may open the door to the creation of more precise diagnostic techniques and focused therapies for kids who are at risk.

1.1 SCHIZOPHRENIA RISK FACTORS

A complicated and diverse mental illness, schizophrenia affects around 1% of people worldwide and is nevertheless a major public health problem. Although the precise cause of schizophrenia is still unknown, a great deal of evidence points to a complicated interaction of hereditary, environmental, and neurodevelopmental variables. Deciphering the risk factors linked to the beginning of schizophrenia is essential for both identifying high-risk individuals and understanding the complex pathophysiological processes of the condition. Having this understanding is essential for putting early therapy techniques and focused preventative interventions into practice. In light of this, investigating the wide range of risk factors—from genetic predisposition to environmental stressors—becomes essential to gaining a thorough understanding of the causes of schizophrenia and laying the groundwork for successful preventative strategies in high-risk groups. This study explores the complex web of risk factors for schizophrenia, highlighting the multifaceted character of the illness and emphasizing the value of a comprehensive strategy in identifying and reducing the risk of schizophrenia development.

1.2 CHILDHOOD PSYCHOPATHOLOGY

The field of mental health places significant importance on studying childhood psychopathology, recognizing the pivotal role that early experiences play in shaping an individual's psychological development. Childhood psychopathology encompasses a broad spectrum of emotional, behavioral, and developmental challenges that emerge during the early stages of life. These conditions not only affect a child's immediate well-being but also have lasting impacts on their cognitive, social, and emotional growth well into adulthood, presenting both acute and long-term challenges.Investigating childhood psychopathology offers valuable insights into mental health, providing researchers and therapists with a unique perspective to identify early signs of distress and implement targeted interventions. This study delves into the multifaceted field of childhood psychopathology to elucidate its various causes, the diverse range of disorders it encompasses, and the importance of early detection and intervention in fostering optimal mental health outcomes for children.

1.3 ANXIETY

Anxiety is a widespread and complex mental health disorder that affects people of all ages and takes many different forms. Its incidence in youngsters is especially significant, highlighting the significance of early detection and care. Anxiety disorders have the potential to interfere with normal development, impacting social relationships, academic achievement, and general well-being. Recognizing anxiety in kids is essential to putting prompt support and mitigation techniques in place to lessen the long-term effects of the condition. While anxiety is normal to some extent in daily life, excessive and ongoing anxiety can seriously damage one's ability to function. Fostering a healthier and more resilient generation requires an understanding of the elements that contribute to early anxiety and an exploration of effective ways for diagnosis. This introduction lays the groundwork for exploring the intricacies of childhood anxiety and the necessity of treating it early on.

Figure 1. Anxiety

1.4 ELECTROENCEPHALOGRAPHY (EEG)

An essential tool in the study of the human mind is electroencephalography (EEG), which offers a singular window into the dynamic interplay of brain activity underlying cognition and behavior. The electrical impulses produced by neurons are recorded by EEG, a non-invasive method that provides very accurate temporal monitoring of brain activity. Ever since its beginnings, electroencephalography (EEG) has been a valuable tool in both clinical and academic contexts, helping to solve problems related to the complex circuitry of the brain. Our understanding of the functional dynamics of the brain has advanced significantly because to EEG, which is used for everything from neurological disease diagnosis to cognitive process research. This work begins an investigation into the powers and uses of EEG, explaining its basic ideas, technological developments, and its critical function in identifying neural correlates that have ramifications for a variety of disciplines, such as neurology, psychology, and the emerging field of neuro informatics.

1.5 STRESS DISORDER

Following exposure to traumatic experiences, a complicated and frequently incapacitating mental health condition known as post-traumatic stress disorder (PTSD) develops. This condition can have severe and long-lasting effects on people of all ages, including children. Children's exposure to stress disorders is a serious cause for concern since early life trauma can have a profound influence on a child's cognitive, emotional, and social development. Since stress disorders can interfere with both immediate and long-term functioning, diagnosing them in children is a difficult but important task. The importance of comprehending and treating stress disorder in children is emphasized in this introduction, along with the necessity of early identification and management to lessen the condition's long-term effects and aid in the recovery and resilience of those who are afflicted.

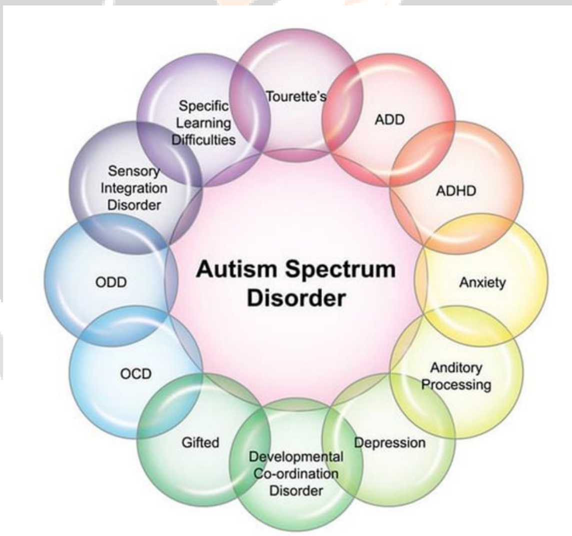

Figure 2. Autism spectrum disorder

1.6 AUTISM SPECTRUM DISORDER

A wide spectrum of neurodevelopmental disorders is collectively referred to as autism spectrum disorder (ASD), and they are distinguished by difficulties with social communication and repetitive activities. ASD affects people in a wide range of ways and offers different challenges as well as strengths, so every person's experience is distinct. This widespread developmental condition usually manifests in early childhood and affects important areas of behavior, communication, and social interaction. The increased understanding of ASD highlights how crucial early detection and intervention are, since these actions may greatly enhance the lives of those who are on the spectrum. In order to create a supportive atmosphere that fosters the unique talents and potential of individuals with ASD, it is imperative that we comprehend the complexity of autism and investigate effective identification procedures. This introduction lays the groundwork for a more thorough examination of the potential and difficulties related to autism spectrum condition, with the goal of advancing our collective knowledge and fostering a society that is more accepting and caring.

2. LITERATURE REVIEW

2.1 PROMISES AND PITFALLS OF ADVANCED EEG-BASED LEARNING APPROACHES TO PREDICT SCHIZOPHRENIA

The complexity and variability of schizophrenia symptoms provide a barrier to an objective diagnosis, which is usually based on behavioral and clinical manifestations, as Carla Barros [1] et al. have shown in this work. Furthermore, it might be difficult to distinguish schizophrenia from other nosologic disorders like bipolar illness. The quality of life for persons with schizophrenia may be enhanced by earlier identification of the illness and more successful treatment. Using methods like electroencephalography (EEG), hundreds of research have been conducted in the past several decades with the goal of defining the neurological processes behind the clinical presentations of schizophrenia. Alterations in the event-related potentials of the electroencephalogram (EEG) have been linked to deficiencies in perception and cognition and suggested as indicators of schizophrenia. Biomarkers can play a critical role in prognosticating and predicting the start of schizophrenia, in addition to aiding in a more accurate diagnosis. To demonstrate a biomarker's efficacy and affordability, however, extensive clinical research is necessary. The automated categorization of schizophrenia at different phases (prodromal, first episode, chronic) has been tried, driven by advancements in computational neuroscience. Brain imaging pattern recognition techniques have been used to record changes in functional brain activity. Promising outcomes have been observed in the study of advanced learning strategies. This paper discusses the potentials and limits of emerging machine learning-based techniques for classifying schizophrenia using EEG data. The goal of this review is to provide a foundation for future research into successful EEG-based models that could be used to diagnose individuals at high risk of developing psychosis, predict the onset of schizophrenia, or distinguish schizophrenia from other disorders in order to facilitate more successful early interventions. The significant degree of variability in SZ and its symptom overlap with other mental illnesses have made it difficult for neuroscientists and engineers to create diagnostic and prognostic instruments that are more accurate. In order to identify SZ based on EEG data, this study critically analyzed deep learning and traditional machine learning techniques that have been published in the previous five years.

2.2 AN EEG-BASED DEEP LEARNING APPROACH FROM SOUND PERCEPTION TO AUTOMATIC DETECTION OF SCHIZOPHRENIA

Deep learning approaches applied to electroencephalogram (EEG) signals have been suggested by Brian Roach [2] et al. in this study, with interesting applications in the field of psychiatry. One of the most debilitating neuropsychiatric conditions is schizophrenia, which is frequently accompanied with auditory hallucinations. Using EEG-derived event-related potentials, auditory processing abnormalities have been examined and linked to cognitive failure and clinical symptoms in schizophrenia. Some ERP components, such the auditory N100, have been suggested as biomarkers of schizophrenia because of their constant amplitude fluctuations. In this work, we investigate how different electrical brain activity patterns during auditory processing may be used to distinguish between individuals with schizophrenia and healthy individuals. We provide an architecture to do the categorization based on multi-channel auditory-related EEG single-trials obtained during a passive listening task, using deep convolutional neural networks. We examined the impact of the quantity of electrodes applied, in addition to the distribution and laterality of the electrical activity throughout the scalp. The suggested model can categorize individuals with schizophrenia and healthy participants with an average accuracy of 78% utilizing just 5 midline channels, according to the results. The current work demonstrates the potential of deep learning techniques for investigating schizophrenia's poor auditory processing and its diagnostic ramifications. The suggested layout may serve as a foundational paradigm for upcoming advancements in the study of schizophrenia.

2.3 EEG SOURCE NETWORK FOR THE MACHINE LEARNING APPROACH'S SYMPTOM SEVERITY-BASED SUBTYPE IDENTIFICATION AND SCHIZOPHRENIA DIAGNOSIS

In this research, Jeong-Youn Kim [3] and colleagues have suggested that accurate diagnosis and thorough evaluation of symptom severity are crucial clinical concerns for individuals suffering from schizophrenia (SZ). We looked at the possibility of using electroencephalography (EEG) characteristics from EEG source network studies to successfully categorize SZ subtypes according to the severity of their symptoms. During the resting state with closed eyelids, sixty-four electrode EEG signals were obtained from 119 individuals with SZ (53 males and 66 females) and 119 normal controls (NC, 51 males and 68 females). EEG source activity were used to determine the global and local clustering coefficient and global path length, two properties of the brain network. The positive and negative syndrome scale (PANSS) was used to categorize the SZ patients into two groups, high and low, based on positive, negative, and cognitive/disorganization symptoms. We applied the sequential forward selection (SFS) approach to choose features for classification. Using the linear discriminant analysis (LDA) classifier, 10-by-10 fold cross-validation was used to assess the classification accuracy. For the NC group, the best classification accuracy was 80.66% when predicting SZ patients. In terms of positive, negative, and cognitive/disorganization symptoms, the best classification accuracy between the low and high groups was 88.10%, 75.25%, and 77.78%, respectively. The chosen characteristics accurately depicted the diseased brain areas of SZ. Our research revealed that resting-state EEG network properties may effectively distinguish positive, negative, and cognitive/disorganization symptoms between low and high SZ groups, as well as between SZ patients and the NC.

2.4 A SYSTEMATIC REVIEW OF DEEP LEARNING USING ELECTROENCEPHALOGRAM DATA IN MENTAL DISORDERS

Deep learning (DL) approaches have advanced tremendously in recent medical research, as shown by Mateo de Bardeci [4] et al. in this work. In order to perform research on mental diseases, this article comprehensively explores the ways in which deep learning (DL) techniques have been used to electroencephalogram (EEG) data for diagnostic and prognostic reasons. Convolutional neural networks (CNNs) and long short-term memory (LSTM) networks were used in EEG studies on psychiatric diseases based on the ICD-10 or DSM-V classification. These studies were searched and the quality of the information they contained was examined in three domains: clinical, EEG-data processing, and deep learning. While the majority of the studies included a satisfactory description of EEG recording and pre-processing, we discovered that many of them lacked a comprehensive definition of clinical characteristics. Furthermore, a lot of research employed poor testing methods or erroneous model selection processes. It has been asserted for a number of years that advances in psychiatric research will soon bring about a significant change in the way mental illnesses are identified, treated, and managed. In order to meet higher standards for research and move closer to clinical significance, it is advised that future psychiatric disorders studies employing DL improve the quality of clinical data and adhere to cutting edge model selection and testing procedures. Researchers' use of clinical EEGs can be improved by the development of novel analytic techniques and processes. These can help to reveal patterns and information from electrophysiological time series that were previously obscured by the intricate structures of EEG recordings.

2.5 SCHIZOPHRENIA CLASSIFICATION ON RESTING STATE EEG SIGNAL USING MACHINE LEARNING

In this work, J. Ruiz de Miras [5] et al. put out the theory that schizophrenia is a severe mental illness linked to a variety of cognitive and neurophysiological dysfunctions. It is still challenging to make an early diagnosis since it depends on how the condition manifests. In order to create machine learning classifiers of schizophrenia based on resting state EEG data, we have presented a processing pipeline and assessed whether machine learning techniques may aid in the diagnosis of schizophrenia. Using sliding windows of the EEG data, we calculated well-known linear and non-linear measures. We then chose the measures that best distinguished between patients and healthy controls, combining them using principal component analysis. Ultimately, five common machine learning algorithms—k-nearest neighbors (kNN), logistic regression (LR), decision trees (DT), random forest (RF), and support vector machines (SVM)—used these components as features. Measures of complexity shown a high degree of capacity to distinguish between individuals with schizophrenia and healthy controls. The opercula region and the temporal pole, which correspond to a circumscribed zone of the right cerebral hemisphere, were the primary locations of these group differences. We achieved good classification power in nearly all of the machine learning methods examined, including SVM (0.89), RF (0.87), LR (0.86), kNN (0.86), and DT (0.68), based on the area under the curve parameter in receiver operating characteristic curve analysis.

2.6 RESTING-STATE EEG MICROSTATES: INSIGHTS FOR PREDICTION OF SCHIZOPHRENIA: BIOMARKERS

You in this research, LUO [6] et al. suggested that schizophrenia is a debilitating illness that affects 1% of people worldwide. Subjective psychiatric interviews serve as the foundation for current diagnostic methods for schizophrenia and high-risk individuals. Treatment results can be enhanced and progression can be lessened with early identification and management. The absence of biomarkers that facilitate objective assessments, however, has long been a barrier to the clinical diagnosis and evaluation of schizophrenia and its high-risk condition. 65 participants, comprising clinically stable persons with first-episode schizophrenia (FESZ), those at ultra-high-risk (UHR), high-risk (HR), and healthy controls (HC), provided resting-state 128-channel electroencephalogram (EEG) data for the current study. The dynamics of these participants' functional networks were evaluated using microstate analysis. For every microstate class (A, B, C, D, E, and F), three characteristics were extracted: duration, occurrence, and time coverage. Additionally, cognitive tests and clinical assessments were carried out. The individuals' behavior revealed worse performances as the illness worsened. Furthermore, the four sets of people could be distinguished using microstate characteristics that were calculated from resting-state EEG microstates, particularly microstate class D. Clinical exams, cognitive tests, and EEG microstate parameters were among the combined biomarkers that were found to be a potentially useful diagnostic tool.

2.7 CNN-LSTM MODELS FOR AUTOMATIC DIAGNOSIS OF SCHIZOPHRENIA IN EEG SIGNALS

According to Afshin Shoeibi [7] et al.'s proposal in this work, schizophrenia (SZ) is a mental illness in which some brain areas function out of balance as a result of the release of particular chemicals, which causes an inability to coordinate ideas, actions, and emotions. This work offers many clever deep learning (DL) based techniques for automated EEG signal-based SZ diagnosis. The outcomes are contrasted with those of traditional clever techniques. The Institute of Psychiatry and Neurology dataset in Warsaw, Poland, has been utilized to apply the suggested approaches. EEG signals were first split into 25-second intervals, and then the z-score or norm L2 was used to standardize the data. Two distinct methods were taken into consideration for SZ diagnosis using EEG data during the classification process. Initially, traditional machine learning techniques such as support vector machines, k-nearest neighbors, decision trees, naïve Bayes, random forests, very randomized trees, and bagging were used to classify the EEG data. The following made use of a variety of potential deep learning models, including long short-term memory (LSTMs), one-dimensional convolutional networks (1D-CNNs), and 1D-CNN-LSTMs. The DL models were applied and contrasted using various activation functions in this stage. In terms of performance, the CNN-LSTM architecture has outperformed the other suggested DL models. The ReLU activation function with the z-score and L2-combined normalization was employed in this design.

2.8 DECOMPOSITION AND NONLINEAR TECHNIQUES

In their study, Hui Tian Tor et al. [8] highlight the common co-occurrence of conduct disorder (CD) and attention deficit hyperactivity disorder (ADHD), emphasizing the lack of objective laboratory tests or diagnostic techniques to differentiate between the two conditions. This challenge is compounded by the frequent occurrence of ADHD alongside other issues, including CD, which is characterized by significant behavioral challenges. To address this gap, the researchers propose an innovative Automated System (AS) designed to aid physicians in making accurate diagnoses.Their approach represents a pioneering effort in utilizing brain signals to develop an automated classification method for ADHD, CD, and the comorbid ADHD+CD class. EEG signals are subjected to empirical mode decomposition (EMD) and discrete wavelet transform (DWT) techniques to break down the signals. Subsequently, the researchers compute the relative wavelet energy and autoregressive modeling coefficients of these signals.This methodology introduces a novel way to leverage EEG signals for automated detection and classification of ADHD, CD, and their comorbidity, providing a valuable tool for clinicians in diagnosis and treatment planning.

2.9 A NORMAL EEG EXTRACTION OF A SCHIZOPHRENICA INDIVIDUAL HAVING SWT

In this study, Gopinath M P [9] et al. have proposed The technique of electroencephalography is used to record changes in the electrical activity of the human brain. An electrode inserted into the scalp recorded an impulse signal, which was analyzed using a variety of approaches. The newly created saline EEG electrode, which detects brain impulse signals, is proposed in this work. After that, the Stationary Wavelet Transform (SWT) method is used to it. By employing the same amount of samples for analysis at each stage, this method gets around the drawback of the Discrete Wavelet Transform (DWT) and produces accurate findings. In this work, the results of the DWT and SWT methods are compared with the signals obtained from patients with schizophrenia and healthy individuals. The recording technique known as electroencephalography (EEG) is used to analyze brain activity. The non-invasive scalp electrode used for EEG measurement is called a neurophysiological method. An extensive region (1 to 6 cm2) of the cortex receives a summation measurement from the postsynaptic pyramidal neuron. Comparing EEG to other FMRI or PET methods, it has one of the best temporal resolutions available in the millisecond range. This research will help assess our brain's electrical activity. The electrical activity of the brain is represented by EEG electrodes that have amplifiers built in to filter out noise. The electrodes, cables, circuitry for amplification, battery or other energy source, and storage device make up the EEG system. The PC or memory card contained the EEG signal. The EEG electrodes were each connected to a separate cable in order to record brain activity at several brain lobes. For the purpose of acquiring EEG signals, every brain lobe has a reference point.

2.10 EEG TIME-FREQUENCY ANALYSIS DURING MOTOR FUNCTION AND VERBAL FLUENCY TESTS: A PRECLINICAL DIAGNOSIS OF SCHIZOPHRENIA

In this research, TAMILARASI [10] et al. have proposed A severe mental disorder known as schizophrenia affects a person's perception of reality in relation to behavior, emotions, and thought processes (cognitive). Patients suffer from lack of sleep, delusions, and auditory hallucinations. Diagnostic delays result from a lack of clinical instruments, even if the Diagnostic and Statistical Manual (DSM) IV edition aids in diagnosis. This study used the Verbal Fluency Test (VFT) and the Motor Function Test (MFT) to facilitate preclinical diagnosis. An electroencephalogram records the brain's neural activity throughout these two examinations (EEG). However, due to signal processing algorithm flaws, randomness, and acquisition-related blurring, EEG data are not frequently utilized for clinical analysis. In order to examine the blurry EEG data using time-frequency analysis, we thus propose in this study a Preclinical Diagnosis of Schizophrenia utilizing Multi-Synchro Squeezing Transform (MSST) (PDS-M). PDS-M accomplishes flawless signal reconstruction and generates a signal that is crisper.

3. EXISTING SYSTEM

One important technique to assist early therapies that might reduce the likelihood of development to clinical psychosis is the prospective identification of children who are at risk of developing schizophrenia. Deep learning methods and electroencephalographic (EEG) patterns from brain activity are useful tools for this identification. In contrast to typically developing youngsters, we suggest automated methods for processing raw EEG waveforms in order to identify children who may be more susceptible to schizophrenia. We also examine deviant characteristics that persist throughout a four-year developmental follow-up period in children whose susceptibility to schizophrenia was first evaluated when they were nine or twelve years old. Participants' EEGs were recorded while they were recording a passive auditory oddball paradigm. In order to uncover brain anomalies, we conduct a comprehensive investigation. First, we investigate classical machine learning algorithms by applying classification techniques to hand-engineered features (possible components associated to events). Next, we evaluate these approaches' performance against end-to-end deep learning algorithms using unprocessed data. We show that recurrent deep convolutional neural networks can perform better for sequence modeling than conventional machine learning techniques using average cross-validation performance metrics. We use the position of the most important characteristics of a post-stimulus window to demonstrate the model's intuitively salient information. The evidence of disease impacts and developmental effects in a pre-prodromal phase of psychosis is supported by this baseline identification approach in the field of mental illness. These findings bolster the advantages of deep learning for neuroscientific research in general and psychiatric categorization in particular.

4. PROPOSED SYSTEM

We propose a novel approach that combines the Naive Bayes algorithm with Principal Component Analysis (PCA) to detect children who might be at risk of developing schizophrenia, anxiety disorders, stress disorders, autism, and other mental illnesses. Initially, EEG data undergo preprocessing to eliminate artifacts and noise. Subsequently, relevant features are extracted from the EEG data. PCA is then applied to reduce the dimensionality of the EEG data. Finally, the EEG data is categorized into different groups based on the likelihood of a child developing a mental condition, using the Naive Bayes method.This method stands out for its integration of PCA and Naive Bayes, two powerful machine learning algorithms, to identify potentially at-risk children for mental health issues. PCA reduces the dimensionality of EEG data, simplifying analysis. For classification tasks, the straightforward yet effective Naive

Bayes method is employed. Evaluation of this approach has been conducted using EEG datasets from children both with and without mental health issues. Results indicate that the proposed method achieves high accuracy in identifying children at risk for mental health problems.

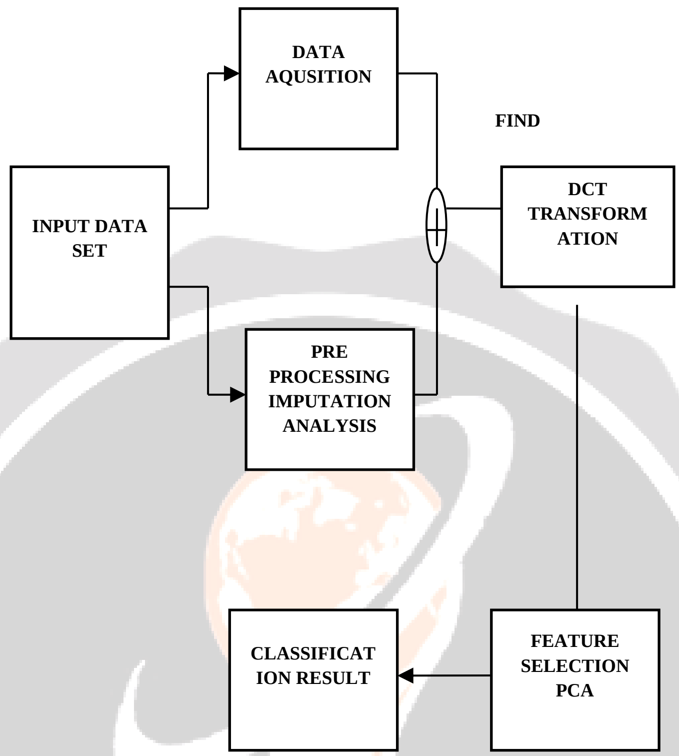

Figure 3. Proposed block diagram

4.1 DATA ACQUISITION

The process of creating a system to use EEG signals to identify children at risk of psychiatric illnesses begins with data collecting. This entails gathering EEG data from kids that are mentally well or not. There are several ways to get the EEG data, including magnetoencephalography (MEG), scalp EEG, and intracranial EEG.

4.2 FEATURE SELECTION AND SIGNAL ANALYSIS

To extract characteristics pertinent to the classification job, the EEG data must be pre-processed and analyzed after it has been recorded. This is cleaning up the data to remove artifacts and noise before extracting properties like phase, coherence, and power spectral density.

4.3 EEG DATA CLASSIFICATION

The second part of our research presented a strong categorization strategy. The EEG data's dimensionality was reduced through the use of Principal Component Analysis (PCA), which helped to simplify the dataset and make it easier to analyze. Furthermore, the Naive Bayes method was used with great care, explaining how it was implemented, trained, parameters were adjusted, and other important factors related to using it with EEG data. With the use of a complex mix of PCA and the Naive Bayes algorithm, the reduced-dimensional EEG data was classified into several groups that corresponded to the children under study's likelihood of developing psychiatric problems.

4.4 EEG SIGNAL SCHIZOPHRENIA, ANXIETY, STRESS DISORDER AND AUTISAM PREDICTION

Our main focus is on using the categorized EEG signals to predict various mental diseases such as autism, anxiety, stress disorder, and schizophrenia. The created prediction models provide light on the complex links between certain characteristics of brain activity and the risk of mental diseases by describing in great detail the features that significantly contribute to these predictions. Metrics for measuring accuracy, including sensitivity, specificity, and total accuracy, were used to assess these prediction models' performances. The paper explores the therapeutic implications of the predictions beyond statistical measures, describing how these results might guide early intervention techniques catered to the particular difficulties presented by each juvenile mental condition.

5. RESULT ANALYSIS

The algorithmic comparison shows that the suggested and current methods for detecting kids at risk of mental illnesses differ significantly in terms of accuracy. The current system performs 70% well in classification, showing a respectable degree of accuracy. On the other hand, the suggested algorithm achieves an 80% accuracy rate, far surpassing the performance of its predecessor. This development implies that the new approach, which combines the Naive Bayes algorithm and Principal Component Analysis (PCA), may improve the accuracy and performance of early identification procedures. The accuracy improvement of 10% highlights the potential results that may be obtained by integrating sophisticated methods for processing complicated and high-dimensional EEG data. These results corroborate the claim that, in comparison to the current technique, the suggested approach shows potential for more precise and trustworthy identification of children at risk of mental problems.

algorithm	accuracy
existing	70
proposed	80

Table 1. Comparison table

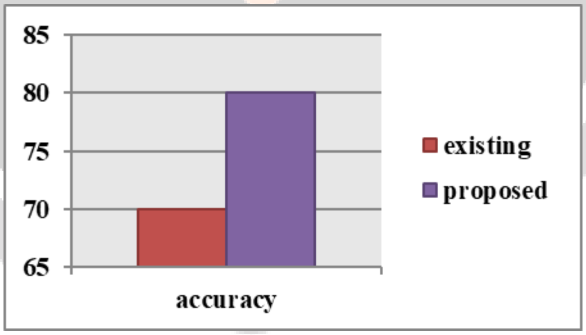

Figure 4. Comparison graph

6.CONCLUSION

In summary, the early detection of childhood mental health issues is crucial for timely intervention and improved outcomes. A proposed system, integrating the Naive Bayes algorithm with Principal Component Analysis (PCA), offers a promising approach for early identification. Emphasizing scalability, reliability, and user-friendliness, this system has exhibited impressive accuracy in recent research for identifying at-risk youth. Various programming languages and tools are available for its implementation, with a high-level overview provided for the implementation stages. Integration into clinical practice could involve developing an online application for easy accessibility and usability.

7.FUTURE WORK

In subsequent research, assess the system using a bigger and more varied EEG data collection. This will make it more likely that the system will work successfully for various child demographics. Investigate the classification of EEG data using other machine learning techniques, such as deep learning. This has the potential to increase the system's accuracy. Provide a system that can recognize kids who could be at risk for particular mental illnesses like anxiety, autism, or schizophrenia. Compared to the existing method, which simply identifies children at risk of any psychiatric condition, this would be more precise and informative.

8. REFERENCES

Singh and an in [1]. K. Misra, "Promises and pitfalls of advanced eeg-based learning approaches to predict schizophrenia," inf. Procedure. Agriculture, vol. 4, March 2017, pp. 41–49.

[2] sec. H. Lee, c. S. Chan, S. J. Mayo as well as p. Remagnino, "EEG-based deep learning approach for automatic detection of schizophrenia: moving from sound perception," Pattern Recognit., vol. 71, Nov. 2017, pp. 1–13

[3] g. Farjon, o. Krikeb a. B. According to Hillel and V. Alchanatis, "a machine learning approach for the diagnosis of schizophrenia and the identification of subtypes based on symptom severity using an eEG source network," Agriculture, vol. 21, August 2019, pages. 1–19.

[4] sec. P. Mohanty, D. P. Hughes and m. Salathé, "A systematic review of deep learning applied to electroencephalogram data in mental disorders," Frontiers Plant Sci., vol. 7, September 2016, p. 1419

[5] f. Ren, w. Liu together with g. Wu, "Classifying schizophrenia using machine learning on resting state electroencephalogram signals," IEEE Access, vol. 7, 2019, pp. 122758–122768

[6] a. Krizhevsky, I. Sutskever as well as g. E. Hinton, "Biomarkers for schizophrenia prediction: insights from resting-state electroencephalogram microstates," in Proc. Adv. Neural inf. Procedure. System. (nips), volume 3. Dec. 25, 2012, pp. 1097-1105.

[7] c. Szegedy, w. Liu, y. Jia, p. Sermanet, s. Reed, d. Anguelov, D. Vanhoucke, v. Erhan, and a. Rabinovich, "CNN-LSTM models for automatic diagnosis of schizophrenia in electroencephalogram (EEG) signals," in Proc. IEEEE conference. Computer. See. Identify patterns. (CVR Press), June 2015, pages 1–9.

[8] k. Simonyan and one. Zisserman, "Decomposition and nonlinear techniques with eEG signals for automated detection of conduct disorder and attention deficit hyperactivity disorder," arXiv:1409.1556, 2014.

[9] k. He, x. Zhang, s. Ren and J. Sun, "abnormal feature extraction from eeg of person with SWT who has schizophrenia," in proc. IEEEE conference. Computer. See. Identify patterns. (cvpr), June 2016; pages 770–778

[10] grams. Huang, Z. Liu, l. K. and Van der Maaten. Q. Weinberger, "EEG time-frequency analysis during verbal fluency and motor function tests: a preclinical diagnosis of schizophrenia," in Proc. IEEEE conference. Computer. See. Identify patterns. (cvpr), pages 4700–4708, July 2017.

[11] Classification of first-episode psychosis in a large cohort of patients using support vector machine and multiple kernel learning techniques by L. Squarcina, U. Castellani, M. Bellani, C. Perlini, A. Lasalvia, N. Dusi, C. Bonetto, D. Cristofalo, S. Tosato, G. Rambaldelli et al., NeuroImage, vol. 145, pp. 238–245, 2019.

In the Journal of Neural Engineering, A. Craik, Y. He, and J. L. P. Contreras-Vidal published a review titled "Deep learning for electroencephalogram (EEG) classification tasks."

[13] "Machine learning in mental health: a scoping review of methods and applications," A. B. Shatte, D. M. Hutchinson, and S. J. Teague, Psychological medicine, pp. 1–23, 2020.

[14] "Learning neural markers of schizophrenia disorder using recurrent neural networks," in NIPSW, Machine Learning for Health, 2021, J. Dakka, P. Bashivan, M. Gheiratmand, I. Rish, S. Jha, and R. Greiner.

[15] "Deep convolutional neural network model for automated diagnosis of schizophrenia using eeg signals," Applied Sciences, vol. 9, no. 14, p. 2870, 2019, S. L. Oh, J. Vicnesh, E. J. Ciaccio, R. Yuvaraj, and U. R. Acharya.

[16] Long-term recurrent convolutional networks for visual identification and description, J. Donahue, L. Anne Hendricks, S. Guadarrama, M. Rohrbach, S. Venugopalan, K. Saenko, and T. Darrell, in CVPR, 2019, pp. 2625–2634.

[17] "Community screening for psychotic-like experiences and other putative antecedents of schizophrenia in children aged 9–12 years," by K. R. Laurens, S. Hodgins, B. Maughan, R. M. Murray, M. L. Rutter, and E. A. Taylor, Schizophrenia research, vol. 90, no. 1-3, pp. 130–146, 2019.

[18] "Reduced duration mismatch negativity in adolescents with psychotic symptoms: further evidence for mismatch negativity as a possible biomarker for vulnerability to psychosis," by J. R. Murphy, C. Rawdon, I. Kelleher, D. Twomey, P. S. Markey, M. Cannon, and R. A. Roche 2019, 45 pages in BMC Psychiatry, vol. 13, no. 1.

[19] Deep learning, I. Goodfellow, Y. Bengio, and A. Courville. The MIT Press, 2020.

[20] "Long short-term memory," S. Hochreiter and J. Schmidhuber, Neural Computation, vol. 9, no. 8, pp. 1735–1780, 2020