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Academic Bulletin of Mental Health

Review Article

Challenges and Future Research Directions in Automated Detection of Mental Illness Using Machine Learning

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Received: 02 August 2024

Accepted: 20 August 2024

Published: 21 September 2024

DOI
10.25259/ABMH_19_2024

Quick Response Code

ABSTRACT

The financial burden and prevalence of mental health disorders have enhanced globally, especially after the pandemic. Mental illness patients, especially children, find it hard to cope with educational, personal, and societal growth. Most of the children cannot access the treatment. Artificial intelligence (AI) models are exploited to identify the characteristics of mental illness. In this review, the focus is mainly on cognitive and developmental disorders. These disorders are attention-deficit/hyperactivity disorder (ADHD), Posttraumatic stress disorder, Tourette syndrome, obsessive-compulsive disorder, anxiety, schizophrenia, and autism spectrum disorder (ASD). Future research directions and current challenges in developmental and mental disorders are discussed.In this study, recent advancements like explainability, uncertainty, hardware implementation, and deep learning strategies are also described.

Keywords: Mental disorder, Deep learning, Machine learning, Children, Physiological signals

INTRODUCTION

Mental disorder is experienced by approximately 14% of adolescents and children across the globe.[1] Between the ages of 10 and 14, there are 80 million, and between 15 and 19 years, 86 million teenagers experience it.[2] Childhood mental illness is considered a major health burden globally.[3] One teenager every 11 minutes commits suicide every year.[2] The fifth prime cause of mortality is identified as suicide by young girls and boys. The majority of teenage boys and girls feeling depressed or have no interest in doing some substantial work belong to low- and middle-income countries.[4] While Spain, Japan, and Ethiopia are the least affected, the highest share is between the Asian and African continents.[2]

Mental disorders in children can have an adversative effect on academic outcomes, social functioning, and family functioning, and in adulthood, it can lead to more serious consequences. Before the age of 14 years, about 50% of adult mental illness occurs.[5] It is of utmost importance to detect children with mental disorders at an early stage so that they can be treated properly. There are very few children with mental disorders who receive proper treatment on time. The most widely exposed and common mental and developmental disorders among children are anxiety, depression, obsessive-compulsive disorder, schizophrenia, dyslexia, attention-deficit/hyperactivity disorder (ADHD), Tourette syndrome, and autism spectrum disorder (ASD).

In this study, the challenges faced by the researchers and prospects of research for automated diagnosis of mental health disorders among children applying deep learning (DL) and machine learning (ML) models are presented. The rest of this paper is organized as—Section 2 discusses the challenges, Section 3 presents the future research direction; and Section 4 concludes the study.

CHALLENGES

In this section, the challenges faced by the researchers for computer-aided diagnosis of mental illness among children are presented.

The availability of public dataset

There are a few publicly available mental illness diagnosis datasets. For ADHD and ASD, there are only two electroencephalogram (EEG) datasets and for depression and schizophrenia, the available public dataset is one. The highest accuracy for ADHD and ASD detection is above 99%.[6] The researchers usually applied smaller datasets with fewer subjects. Data imbalance is another major issue in ML. The learning and mental disorders among children are normally comorbid.[7] For instance, a child with ADHD is comorbid with depression and ASD. There are very few studies targeting the comorbid conditions, and hence it opens new avenues for exploring comorbid conditions utilizing physiological signals.

Multimodal datasets and data fusion

Multiple modalities such as EEG with electrocardiogram (ECG) or other similar modalities are not explored fully by different studies. Although some studies applied EEG with ECG, the limitation is that ECG modality was not utilized for DL- or ML-oriented decision-making but used some statistical tools. The models did not exploit the signal analysis for multimodal fusion. For the identification of mental disorders among children, the necessity is the cleaned EEG records. Obtaining such EEG signals are troublesome and are sporadic due to various noises in the case of a child.[8] The modal performance is degraded because of noisy EEG signals. Also, crucial information may be lost due to high noise in EEG signals. Attaining multimodal signals, including polysomnography (PSG), electromyogram (EMG), photoplethysmography (PPG), and ECG with EEG, can aid in studying variations in physiology during various learning and mental disorders.

Lack of trust in deep learning and machine learning models

There is a trust issue with existing automated decision support systems for its stakeholders, clinicians, and experts. These models fail to generate trust after devising technologically advanced decision-making, feature engineering, and signal analysis. A few real-time automated expert systems are installed in research institutes and hospitals. There is a lack of explainability and interpretability of such intelligent systems to elucidate their predictions. Hence, the decisions made by the artificial intelligence (AI) systems must be interpreted by clinicians to build trust in such automated intelligent systems.

Lack of standardization

Due to restricted dataset usage, the experiments of decision support systems or signal processing were carried out on random validation techniques. The DL or ML model must perform with accuracy and efficiency to diagnose mental illnesses like brain disorders that can impact the future of the child. Overfitting and bias are the bottlenecks in making the AI models efficient, whereas training such models are rather simple. Hence, such models can prove their efficacy if such bottlenecks are tackled properly.

Paradigm shift

Nonlinear and nonstationary are the features of EEG signals.Noise-free environment is a prerequisite to attaining EEG signals. The attainment of EEG signals from children is more problematic because of eye movement, motion artifacts, frequent movement, and low amplitude. Moreover, EEG signals deal with brain regions and multichannels to demonstrate the efficacy of the model.Most of the EEG signals come with noise in the case of children. Hence, there is a need to explore other similar signals. Mental illness can be diagnosed by analyzing heart rate variability (HRV) signals.

The acquisition from wearable devices is a simpler technique to achieve. PPG signals' acquisition is easy because of the attainment methods from wearable watches and sensors.[9]

FUTURE RESEARCH DIRECTIONS

Availability of physiological datasets

It is high time to devise an efficient mental disorder detection system as mental illness among children is rising alarmingly and also enhancing the financial burden due to it. The restrictions of the datasets need to be lifted and make them publicly available for research. The data attainment process and decorum should be made public so that scientists around the globe can follow the same to generate more data.

Physiological signals and their fusion

The central nervous system in the human body is shaped in such a manner that alterations in one body part replicate in another. To study the variation in organs, brain–eyes interaction, brain–heart–eyes–muscle communication, and brain–heart interaction is crucial. EEG signals are hard to analyze because they are noise-prone. A paradigm shift is desired as the studies may focus on other physiological signals like Saturation of Peripheral Oxygen (SPO2)/HRV/

ECG/PPG.[10] The study revealed that the deviations in ECG may result from the alternations in the brain.The acquisition of PPG signals does not require multiple electrodes and special arrangements.HRV signals can be derived from PPG signals that help diagnose mental illness and other heart-related illnesses. Different physiological signals can be fused as well as features like nonlinear frequency and linear features may pave the way for designing more accurate mental health disorder detection intelligent systems.

Mental disorder and information fusion

Health-related problems among children pose serious concerns. Moreover, mental illness is usually comorbid with other physical or mental health issues. Information fusion helps detect mental disorders accurately in computer-aided systems. Information fusion combines modalities of different kinds like questionnaires, imaging, and signals to devise more accurate models that can aid in the detection of people with mental illness. A broader aspect of the features may be studied that may trigger the disorders, including biological, psychological, and behavioral aspects.[11] Modality fusion may mitigate the trust issue among clinicians. The fusing of physiological signals obtained from various parts of the children can aid experts and clinicians in making accurate decisions in mental disorder detection.[12]

Fusion of models

Smaller data size affects the performance of the system. Medium neural networks or traditional ML models showcased superior performance on cleaned and smaller data sizes. The performance of the model has a reciprocal effect from the prospect of size.[13] DL models can excerpt representative features, thus making them perform better on complex and huge data. DL models require lots of time for the predictions and training. A single DL or ML model is not suitable in real-time scenarios for the dynamic nature of data. For the diagnosis of mental disorders, a fusible and robust computer-aided model can be handy. In such cases, the fusion of different types of models can be very operative. To extract features from physiological signals, transfer learning models that are lightweight in nature can also be convenient. The best performing ML models can be devised by fusing features extracted from numerous lightweight models and fed to different ML classification techniques.

Uncertainty

The majority of the AI models were developed with preprocessed and conditioned signals. The performance of such models is altered in the presence of noise. The alternation may negatively affect the performance of the system because of uncertainty. The uncertainty occurs due to noise, class overlap, and mismatch in the testing and training data. Epistemic uncertainty arises from inadequate knowledge. The model can be untrustworthy due to uncertainty. Uncertainty quantification (UQ) can be utilized in ML and DL models for quantifying, characterizing, locating, and handling uncertainty. A few state-of-the-art UQ models like imprecise probability, Dempster–Shafer theory, and rough classification can be applied, and to ensure trust in the models, Monte Carlo simulation can be applied.[14] To reduce the noise within the data tuning of parameters can be explored to tackle the issue of uncertainty. Uncertainty impacts the child patients of ADHD as there is a few publicly available datasets of all modalities except magnetic resonance imaging (MRI) and a lack of emphasis on applying data from wearable devices.[15] Various noises in MRI modalities and factors like tiredness lead to uncertainty for the correct diagnosis of ASD.[16]

Generalized mental health diagnosis system

For intelligent mental health detection and monitoring systems, there is a need for decision-makers, experts, patients, staff, data, and clinicians. Cloud-centric or edge-centric frameworks may be devised with upgradation, limpidness, and security. There is a requirement that local healthcare models should be interconnected, upgradable, efficient, and swift and may be integrated with a national or regional unit with monitoring facilities. The national system may be then connected to the global healthcare model with patient history, data storage, data upgradation, and following international standards of periodic monitoring for mental health issues.

Hardware resources

The present models rely on complex nonlinear functions for decision-making. In some scenarios, decision-making at a faster pace is difficult. Edge implementation comes to the rescue in such situations. The edge implementation can be achieved by implementing a field programmable gate array (FPGA), application-specific integrated circuit (ASIC), or graphical processing unit (GPU).[17] GPU is effective in floating-point operations but less efficient in performance in comparison to FPGA or ASIC. FPGA is more preferable to ASIC and GPU due to its faster performance and upgradability. There is a limitation of FPGA for nonlinear operations that need to be overcome by converting it to piecewise linear approximation.

Interpretable and explainable AI models

Most of the existing models do not explain how it achieved the outcome, prediction accuracy, and so on. It makes the stakeholders understand and trust the performance of the model. Hence, the demand for interpretable and explainable AI models comes into the picture. Local predictions are explained by SHapley Additive exPlanation (SHAP) and Locally Interpretable Model Agnostic Explanations (LIME) values. Heatmap, that is, class activation map (CAM), is extensively applied for convolutional neural network (CNN)-based explainable models. Grad-CAM, Eigen-CAM, Grad-CAM++, U-CAM, Score-CAM, SMOOTHGRAD, and more are various CAM types deployed for the purpose.[18]

CONCLUSION

Different persons at different stages struggle with mental disorders around the globe. There is an increase in death rates and suicide among children due to mental illness despite advancements in the medical field. Researchers deploy numerous techniques to classify and diagnose mental illness among adolescents and children. Such diagnoses are possible due to the utilization of physiological signals.

The EEG signals are extensively used in such scenarios. The decisions based on EEG signals are hard to accept due to significant noise, complex collection settings, and low amplitude. The paradigm shift from EEG to ECG/SPO2, PPG, and the fusing of these signals can open new avenues for the researchers as there is a connection between the behavior of various organs and numerous mental health issues.

Fewer electrodes, higher amplitudes, and economical in nature make the ECG, SPO2, and PPG signal acquisition more effective and simpler compared to EEG signals. ML models applied SVM classification techniques extensively in mental illness cases. Automatic extraction of features from the physiological signals by the DL models makes them more reliable and usable. As the DL models need a good amount of data to demonstrate their full potential, they are not explored fully in the case of mental illness detection as the available datasets are limited. Limited standardized protocols, the availability of public datasets, and the lack of fusibility of features or sensors are some of the key challenges in this hot research topic. Different clinical settings impact the performance of such computer-based AI models.

The reliable and effective computer-aided mental health diagnosis model is possible with the use of huge and complete datasets, signal fusion, the proper utilization of hardware, explainability, and the quantification of uncertainty.

Ethical approval

Institutional Review Board approval is not required.

Declaration of patient consent

Patient's consent not required as there are no patients in this study.

Financial support and sponsorship

Nil.

Conflicts of interest

There are no conflicts of interest.

Use of artificial intelligence (AI)-assisted technology for manuscript preparation

The authors confirm that there was no use of AI-assisted technology for assisting in the writing of the manuscript and no images were manipulated using AI.

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How to cite this article: Hussain S. Challenges and Future Research Directions in Automated Detection of Mental Illness Using Machine Learning. Acad Bull Ment Health. 2024;2:56-60. doi: 10.25259/ABMH_19_2024