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A Short Review on Diagnosing and Predicting Mental Disorders with Machine Learning

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Abstract

Mental disorders like schizophrenia, anxiety, and depression impact millions worldwide, requiring early detection and accurate diagnosis. This paper reviews the use of machine learning (ML) in mental health, analyzing data from social media, neuroimaging, EEG, and surveys. ML models achieve high accuracy in detecting schizophrenia, anxiety, and depression, offering scalable and personalized solutions. Challenges include data privacy, diversity, and model interpretability, but advances in explainable AI and multimodal integration address these issues. This study highlights ML's potential to revolutionize mental health care through innovative and accessible technologies.

Keywords: Mental Disorders; Anxiety; schizophrenia; Machine Learning.

Introduction

Mental disorders are among the leading causes of disability worldwide, significantly impacting individuals, families, and communities. Conditions such as schizophrenia, depression, and stress-related disorders are prevalent and can lead to severe personal and societal consequences if left undiagnosed or untreated. According to the World Health Organization (WHO), depression alone affects over 280 million people globally, while schizophrenia impacts approximately 24 million individuals. Stress, a more common condition, often serves as a precursor to more severe mental health challenges if not effectively managed. Despite advancements in psychiatry and psychology, diagnosing these conditions remains complex due to their multifaceted and subjective nature [1]. The exploration of diverse methods and tools in related fields provides valuable insights into how innovative approaches can enhance the understanding and treatment of mental health disorders. For instance, [2] highlights the critical role of analyzing communication patterns, an approach that could inform strategies for mitigating misinformation about mental health. Similarly, [3] sheds light on the cognitive differences across age groups, which is crucial for addressing age-related mental health challenges. Studies like the review of Electromyography in Rehabilitation [4] demonstrate the utility of technology in monitoring and improving neurocognitive and physical functions, a principle that aligns with the goals of mental health rehabilitation. While researchers in [5] focus on neuro-oncology, it indirectly emphasizes the importance of understanding complex neurological processes, which are also key in mental health research. Also, the value of innovative assessment tools for evaluating cognitive and emotional states, offering potential applications for mental health diagnostics and interventions [6]. Traditional methods of diagnosing mental disorders rely heavily on clinical interviews, patient self-reports, and clinician observations. While these methods have proven effective, they are often limited by subjectivity, variability in clinician expertise, and the lack of standardized diagnostic tools. This underscores the need for innovative, data-driven approaches to enhance mental disorder diagnosis's accuracy, efficiency, and scalability. Understanding and diagnosing mental disorders is critical for early intervention, improving treatment outcomes, and reducing societal burdens. Early diagnosis can prevent the progression of conditions and enable personalized treatment strategies. However, the complexity of mental disorders and the stigma associated with seeking mental health care present significant barriers to timely diagnosis and treatment. Leveraging modern technological advancements could revolutionize this field by offering more precise and accessible diagnostic tools [7].

Artificial intelligence (AI) is the simulation of human intelligence in machines capable of performing tasks that typically require human cognitive abilities. Machine Learning (ML), a subset of AI, involves training algorithms to learn patterns from data and make predictions or decisions without explicit programming. ML encompasses various techniques, including neural networks, decision trees, and k-nearest neighbors (KNN), which have shown significant promise in analyzing complex datasets across various domains. The rise of AI and ML has been driven by advancements in computational power, the availability of large datasets, and the development of sophisticated algorithms. These technologies have been successfully applied in fields such as image recognition, natural language processing, and predictive analytics. In recent years, the application of ML to healthcare, particularly in mental health, has gained traction due to its potential to analyze large volumes of data and uncover hidden patterns that traditional methods might overlook [8]. Machine learning offers a transformative approach to diagnosing mental disorders by analyzing diverse datasets, including clinical records, imaging data, and behavioral patterns. By integrating ML techniques into mental health care, practitioners can enhance diagnostic accuracy, reduce biases, and provide personalized treatment recommendations. Moreover, these methods enable the analysis of multi-modal data, combining physiological, behavioral, and textual inputs to offer a holistic understanding of an individual’s mental health.

ML Applications in Mental Health

Machine learning (ML) can potentially transform mental health care by providing advanced tools for detection, diagnosis, prognosis, and treatment. In the realm of detection and diagnosis, ML algorithms can process diverse data types, such as clinical notes, brain imaging, genetic information, and patient-reported outcomes, to uncover subtle patterns that may indicate mental disorders like schizophrenia, depression, or stress-related conditions. For instance, neural networks can identify biomarkers in imaging data that may elude human observation, while natural language processing techniques can analyze textual data to detect linguistic patterns associated with depression or anxiety [9]. This data-driven approach helps reduce diagnostic errors, enhances objectivity, and provides standardized insights, overcoming some limitations of traditional methods. In prognosis and treatment, ML can predict disease progression and evaluate the likely outcomes of various therapeutic interventions. Decision trees and ensemble learning methods, for example, can identify the factors most likely to influence recovery or relapses, enabling clinicians to personalize treatment strategies. By incorporating wearable devices and sensors, ML systems can also monitor patient behavior and physiological states in real time, ensuring adherence to treatment plans and enabling timely adjustments. Additionally, predictive analytics can aid in tailoring interventions by considering an individual's unique profile, such as genetic predispositions or environmental stressors, ensuring treatments are not only effective but also minimally invasive. Moreover, ML enables a holistic understanding of mental health by integrating multi-modal data, such as combining behavioral patterns, physiological measurements, and genetic information [10]. This integration can improve the accuracy of diagnosis, offer deeper insights into disease mechanisms, and predict responses to treatments with higher precision. However, these advancements must be accompanied by rigorous attention to data quality, ethical considerations, and model interpretability to ensure equitable and responsible application in mental health care. By addressing these challenges, ML can play a pivotal role in enhancing mental health diagnostics and therapies, ultimately improving patient outcomes and reducing societal burdens.

Schizophrenia

Schizophrenia is a chronic and severe mental disorder that disrupts thought processes, perception, emotional responsiveness, and social interactions. Affecting about 1% of the global population, it poses significant challenges due to its long-term impact on individuals and society. Symptoms such as hallucinations, delusions, disorganized speech, and impaired cognition make early and accurate diagnosis critical for effective treatment. However, the lack of definitive biomarkers and reliance on subjective assessments complicates the diagnostic process. Recent advancements in machine learning (ML) have demonstrated promise in addressing these challenges [11,12] by leveraging diverse data sources like social media, neuroimaging, and EEG signals to enhance diagnostic accuracy and understand the underlying mechanisms of schizophrenia.

In the study of Schizophrenia Detection Using Machine Learning Approach from Social Media Content, researchers used linguistic features from Reddit posts to identify schizophrenia-related patterns. Supervised learning classified posts with 96% accuracy, revealing markers like increased use of third-person plural pronouns and negative emotion words. This approach demonstrates the potential of social media as a tool for early detection and outreach to at-risk individuals [13]. Similarly, the paper Machine Learning of Schizophrenia Detection with Structural and Functional Neuroimaging employed multimodal imaging (fMRI and sMRI) to combine structural and functional brain data effectively [14]. Using the M3 approach, the model achieved an accuracy of 83.49% while identifying discriminative brain regions. Notably, excluding global signal regression improved model performance, emphasizing the importance of preserving neuronal information. EEG-based approaches also hold significant promise, as shown in the study Development of a Machine Learning-Based Algorithm to Accurately Detect Schizophrenia Based on One-Minute EEG Recordings. Using Random Forest classifiers and a granular division of EEG spectra, the researchers achieved a balanced accuracy of 96.77%, providing a fast and non-invasive diagnostic method. Further advancing EEG analysis, the study Fusion of Multivariate EEG Signals for Schizophrenia Detection Using CNN and Machine Learning Techniques combined CNNs and logistic regression to analyze multichannel EEG signals. By selecting three key channels (T4, T3, and Cz), the approach achieved accuracies of 90% for subject-based testing and 98% for non-subject-based testing, demonstrating a resource-efficient method for real-time diagnosis with wearable devices [15].

Another study investigated the application of machine learning techniques to classify schizophrenia proneness levels based on behavioral and demographic features, including age, fatigue, slowing, pain, hygiene, and movement. Using a dataset of 1,000 samples categorized into five levels of proneness they evaluated the performance of Logistic Regression, Support Vector Machine (SVM), Gradient Boosting, and Decision Tree classifiers. Among the models, Logistic Regression achieved the highest accuracy of 94.2%, demonstrating its effectiveness in capturing feature relationships and its suitability for datasets with linear or near-linear patterns [16].
These studies illustrate the versatility of ML in diagnosing schizophrenia, from analyzing linguistic markers to leveraging neuroimaging and EEG data. Social media analysis offers large-scale accessibility, while neuroimaging and EEG provide clinically relevant insights. Together, they highlight the potential of ML to revolutionize schizophrenia diagnostics, though challenges like data standardization, generalizability, and ethical considerations remain to be addressed.

Anxiety

Anxiety is a pervasive mental health condition characterized by excessive fear, worry, and behavioral disturbances that can significantly impact daily life and overall well-being. Affecting individuals across all age groups, it is particularly prevalent among older adults and university students, where it can hinder social interactions and academic performance. Anxiety often coexists with other mental health disorders, making its early detection and management essential for preventing severe outcomes. Despite its prevalence, traditional diagnostic methods for anxiety, such as self-reported questionnaires and clinician evaluations, are subjective and time-consuming. Machine learning (ML) offers a transformative approach to anxiety detection by analyzing physiological, behavioral, and survey data, providing faster, more objective, and scalable solutions for monitoring and diagnosing anxiety [17].

A wide range of ML applications has been explored for anxiety detection, leveraging diverse data sources and algorithms. One notable study, Machine Learning-Based Anxiety Detection in Older Adults Using Wristband Sensors and Context Feature, demonstrated the potential of wearable sensors for long-term anxiety monitoring in older adults [18]. By analyzing electrodermal activity (EDA) and blood volume pulse (BVP) signals, combined with context-based features, the study achieved up to 6.41% higher accuracy than models using only physiological data. This approach highlights the feasibility of using low-cost consumer devices for real-time anxiety detection, offering a scalable solution for older populations. Another significant contribution [19] is the paper Detection and Classification of Anxiety in University Students Through the Application of Machine Learning, which targeted anxiety among Indian university students. Using data collected through Likert-scale-based questionnaires, the study employed various ML algorithms, including Naïve Bayes, decision trees, random forests, and support vector machines (SVMs). Random forests demonstrated the highest accuracy (78.9%), showcasing the potential of ML for quantifying anxiety levels and identifying its effects among young adults. This research underscores the importance of tailored interventions to address anxiety in educational settings. EEG-based anxiety detection has also emerged as a promising field [20]. The study A Comprehensive Exploration of Machine Learning Techniques for EEG-Based Anxiety Detection examined the impact of feature extraction and labeling methods on model performance. By employing the discrete wavelet transform (DWT) and power spectral density (PSD) for feature extraction and labeling data with the Hamilton Anxiety Rating Scale (HAM-A), the random forest classifier achieved the highest accuracy of 87.5%. This work highlights the importance of selecting optimal features and classifiers for anxiety detection using non-invasive EEG signals. Lastly [17], the study Predicting Mental Health Outcomes: A Machine Learning Approach to Depression, Anxiety, and Stress explored ML models to classify anxiety and related disorders using responses from the Depression Anxiety Stress Scales (DASS). Among the models, SVM demonstrated the highest overall performance, achieving an impressive 99% accuracy across datasets. The study emphasizes the potential of questionnaire-based data combined with ML for accurately predicting anxiety severity, enabling early and effective intervention strategies.

These studies collectively highlight the versatility and effectiveness of ML in detecting and diagnosing anxiety. By utilizing diverse data sources, from physiological signals to self-reported surveys, and leveraging advanced ML techniques, researchers have paved the way for objective, scalable, and real-time anxiety monitoring and management systems. However, challenges such as data privacy, generalizability, and ethical considerations must be addressed to ensure widespread adoption in clinical and non-clinical settings.

Depression

Depression is a leading mental health disorder that significantly impacts individuals' emotional, physical, and social well-being. It affects over 280 million people globally and is a primary contributor to suicide, which claims approximately 800,000 lives annually. Depression manifests as persistent feelings of sadness, loss of interest, fatigue, and cognitive impairments, often accompanied by physical symptoms such as changes in sleep and appetite. Despite its prevalence, many cases remain undiagnosed and untreated due to social stigma, lack of awareness, or limited access to mental health care. Early detection and intervention are crucial to preventing severe outcomes and improving quality of life. Machine learning (ML) has emerged as a transformative tool for depression detection by leveraging diverse datasets, such as social media texts, behavioral patterns, and demographic information, enabling timely, scalable, and accurate diagnostics.

Machine learning has been applied in various innovative ways to detect and predict depression, particularly through social media analysis and structured datasets. In the study Depression Detection from Social Network Data Using Machine Learning Techniques, researchers analyzed Facebook data to detect signs of depression [21]. Psycholinguistic features were extracted from user-generated content, and various ML techniques were evaluated for classification. Decision Tree (DT) models achieved the highest accuracy, demonstrating the efficacy of psycholinguistic analysis in detecting depression. This study highlights the potential of analyzing users' online behavior to uncover mental health insights and reach underserved populations. Another study [22] explored depression detection on multiple social media platforms, including Twitter, Facebook, Reddit, and electronic diaries. The researchers focused on text preprocessing and feature extraction methods to train ML models, including ensemble approaches. Their findings demonstrated that the proposed methodology could effectively detect depression even when training datasets lacked explicit depression-related keywords. This robustness across diverse social media platforms and data sources underscores the scalability and adaptability of ML approaches for identifying depression. Child and adolescent depression is another critical area addressed in the study Detection of Child Depression Using Machine Learning Methods. Utilizing the Young Minds Matter (YMM) dataset, the researchers identified key predictors of depression, such as irritable mood, diminished interest, and concentration problems. The study employed Boruta for feature selection and tested several ML models, including Random Forest (RF), XGBoost (XGB), and Decision Tree (DT). RF outperformed other algorithms, achieving a 95% accuracy rate and 99% precision. The research not only identified significant features contributing to child depression but also highlighted the role of family activities and socioeconomic factors, providing actionable insights for early intervention [23].

These studies collectively demonstrate the versatility of ML in detecting depression across different populations and data types. Social media-based approaches enable large-scale and accessible screening, while structured datasets like YMM offer valuable insights into demographic and psychosocial factors. By integrating innovative algorithms and diverse data sources, ML has the potential to revolutionize depression detection, offering early diagnosis and personalized treatment strategies. However, challenges such as data privacy, model interpretability, and ensuring ethical applications must be addressed to realize their full potential in clinical and non-clinical settings.

Challenges and Future Works

Current Challenges

While machine learning (ML) has shown tremendous potential in the detection and diagnosis of mental disorders, several challenges remain that hinder its full-scale implementation in clinical and non-clinical settings:

- Data Quality and Availability: High-quality, representative, and diverse datasets are critical for training robust ML models. However, most datasets in mental health research are limited by small sample sizes, lack of diversity, and inherent biases. This limitation impacts the generalizability of ML models to broader populations, especially underrepresented groups.

- Model Interpretability: Many ML models, particularly deep learning algorithms, function as black boxes, making it difficult for clinicians to understand the rationale behind predictions. The lack of transparency limits trust and adoption in clinical practice, where explainability is crucial.

- Integration into Healthcare Systems: Incorporating ML models into existing healthcare workflows is challenging due to compatibility issues with electronic health record (EHR) systems, resistance to technological change, and the need for training healthcare professionals to use ML tools effectively.

- Multimodal Data Fusion: While ML models can analyze diverse data types (e.g., imaging, textual, and physiological data), effectively integrating multimodal data remains a technical challenge. Issues such as missing data, alignment of different modalities, and computational complexity must be addressed.

Future Directions

- Developing Larger and More Diverse Datasets: Collaborative efforts across institutions and regions are needed to create large, diverse, and standardized datasets. Open-access repositories can facilitate research and improve the generalizability of ML models.

- Explainable AI (XAI): Developing interpretable models or post-hoc explainability techniques will enhance trust and usability in clinical settings. Transparent ML systems can provide actionable insights, helping clinicians understand and validate predictions.

- Real-World Testing and Deployment: To bridge the gap between research and practice, ML models must undergo extensive testing in real-world clinical environments. This involves collaborating with healthcare providers, integrating models into EHR systems, and ensuring usability in diverse clinical contexts.

- Multimodal Learning: Advances in multimodal ML will enable the integration of diverse data types, such as EEG, imaging, and text, providing a holistic understanding of mental health disorders. Techniques like cross-modal attention and shared representation learning can address current limitations.

By addressing these challenges and focusing on future advancements, ML can revolutionize mental health care, enabling early detection, accurate diagnosis, and personalized treatment for millions of individuals worldwide.

Conclusion

This paper reviewed the significant contributions of machine learning (ML) to the detection, diagnosis, and treatment of mental disorders such as schizophrenia, anxiety, and depression. Various studies demonstrated that ML techniques effectively analyzed diverse data sources, including social media texts, neuroimaging, physiological signals, and structured surveys, to identify subtle patterns and markers associated with these conditions. For schizophrenia, methods like EEG-based detection and social media analysis achieved remarkable accuracy, while multimodal neuroimaging approaches highlighted the potential for uncovering neural mechanisms. In the case of anxiety, wearable sensors and EEG signals proved useful for real-time monitoring and classification, especially in older adults and students. Similarly, ML models addressed depression detection through psycholinguistic analysis of social media data and structured datasets for child and adolescent populations, achieving high precision and reliability. Despite these advancements, several challenges persisted, such as data privacy concerns, the lack of diverse datasets, and the limited interpretability of ML models. Researchers emphasized the importance of explainable AI, multimodal data integration, and privacy-preserving ML techniques to overcome these barriers. Moreover, real-world validation and the development of regulatory frameworks were highlighted as essential steps for ensuring the safety and effectiveness of ML tools in mental health care.

Conflict of Interest

The authors imply no conflict of interest.

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