Machine Learning Approaches for Detection of Mental Disorders

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ABSTRACT - Mental disorders, such as depression, are very common and have been shown to have an effect on an individual's physical health. Recently, artificial intelligence (AI) approaches have been developed to help mental health professionals, such as therapists and psychologists, make decisions based on historical data from patients. As one of the most recent generations of AI technologies, machine learning (ML) has demonstrated superior success in a wide range of real-world applications ranging from computer vision to healthcare. The aim of this study is to conduct a review of existing literature on the use of ML algorithms in mental health outcome research. To be more specific, we will first provide a brief overview of current ML techniques. Then, we do a literature review on ML applications of mental health outcomes. We categorise these related papers into four categories based on the application scenarios: clinical data diagnosis and prognosis, genetics and genomics data analysis for understanding mental health disorders, voice and visual expression data analysis for disease detection, and social media data prediction of risk of mental illness. Finally, we address the complexities of using ML algorithms to enhance our understanding of mental health problems and propose some potential avenues for their use in improving mental health diagnosis and care.

Keywords: Mental disorders, Machine learning, Clinical decision support system, Classification

I. INTRODUCTION

A mental disorder is a form of health condition that alters a person's mind, feelings, or actions (or all three), and has been shown to have an effect on physical health [1, 2]. Depression, schizophrenia, attention deficit hyperactivity disorder (ADHD), and autism spectrum disorder (ASD), among other mental health concerns, are extremely common today, with an estimated 450 million people worldwide suffering from such issues1. In addition to adults, children and teenagers under the age of 18 are at risk of developing mental health problems. Furthermore, mental health disorders have become one of the most severe and widespread public health issues. Depression, for example, is a leading cause of impairment and can raise the risk of suicidal ideation and suicide attempts.

Early identification of mental health issues is critical for greater understanding of mental health conditions and providing better patient care. Unlike other chronic illnesses, which are diagnosed using laboratory tests and measures, mental disorders are usually diagnosed based on an individual's self-report to specific questionnaires designed to identify specific patterns of emotions or social interactions3. Since data on an individual's mental health status is becoming more readily available, artificial intelligence (AI) and machine learning (ML) technologies are being used to enhance our understanding of mental health problems and to assist mental health professionals in making better clinical decisions [6]. Deep learning (DL), one of the most recent developments in AI and ML, transforms data across layers of nonlinear computational processing units, providing a new framework for effectively learning from complex data [7]. In recent years, deep learning algorithms have outperformed in a variety of data-rich application scenarios, like healthcare [8].

ML aims at developing computational algorithms or statistical models that can automatically infer hidden patterns from data12,13. In recent years, there has been an increase in the number of ML models created to evaluate healthcare data4. Traditional ML approaches, on the other hand, necessitate a significant amount of feature engineering for optimal performance—a phase that is required for most application scenarios to achieve good performance and is typically resource- and time-consuming.

DL approaches, the newest wave of ML and AI technologies, aim to create an end-to-end framework that maps the input raw features directly into the outputs through a multi-layer network structure capable of capturing hidden patterns within the data. In this segment, we will look at several common deep learning model architectures, such as the deep feedforward neural network (DFNN), the recurrent neural network (RNN), the convolutional neural network (CNN), and the autoencoder.

II. RELATED WORK

The artificial neural network (ANN) is suggested with the aim of mimicking how the human brain functions, with the basic component being an artificial neuron. An artificial neuron is a mathematically defined nonlinear transformation unit that takes the weighted total of all inputs and feeds the result to an activation function such as sigmoid, rectifier (i.e., rectified linear unit [ReLU]), or hyperbolic tangent. An ANN is made up of a number of artificial neurons with varying communication architectures. The feedforward neural network (FNN) is the most basic ANN architecture, stacking neurons layer by layer in a feedforward fashion, with neurons across adjacent layers completely linked to each other. The first layer of the FNN is the input layer, which receives one dimension of the data vector from each node. The final layer is the output layer, which outputs the probabilities that a subject belongs to various groups (in classification). The secret layers are those that exist between the input and output layers. A DFNN usually has several hidden layers. As a result, and edge in the DFNN has a weight parameter that must be optimised by minimising some training loss calculated on a particular training dataset (usually through backpropagation). Following the learning of the optimum set of parameters, the DFNN can be used to predict the target value (e.g., class) of any testing data vectors. As a result, a DFNN can be viewed as an end-to-end process that layer by layer transforms a specific raw data vector to its target. DFNN has outperformed conventional ML models in many data mining activities and has been applied to the study of clinical and genetic data to predict mental health conditions. The implementations of these approaches will be discussed further in the Results section.

RNNs were created to analyse sequential data including natural language, voice, and video. When given an input sequence, the RNN processes it one element at a time by feeding it to a recurrent neuron. To encode the historical information along the chain, each recurrent neuron receives the input element at the corresponding time point and the neuron's output at the previous time stamp, as well as the neuron's output at the next time stamp.

III. PROPOSED ARCHITECTURE

Machine learning algorithms may be used to classify the presence or absence of a specific anxiety condition, predict risk levels, or predict treatment response levels. Figure 1 depicts the classification mechanism. Data can be gathered from a variety of sources, including demographic information, health records, medical history, various measuring scales, and so on. The data can yield a large number of features, and essential features can be chosen using an effective feature selection algorithm. These features include the classifier's training and testing data sets. The final step is to pick and tune a good classifier based on performance metrics using the training data collection.

Data from questionnaires, interviews, demographic data, medical health records, treatment history, and anxiety rating scales can be used to train machine learning algorithms. There are several scales available for clinical and health practitioners to use. Many tests, including functional magnetic resonance imaging (fMRI), electroencephalogram (EEG), electrocardiogram (ECG), and others, are used in the clinical setting to diagnose anxiety disorders. In addition to these types of data, researchers have recently begun to use data collected by wearable and non-wearable sensors without input from patients. The above-mentioned tests, as well as raw sensor data collected from wearable and non-wearable sensors, necessitate pre-processing and feature extraction methods.

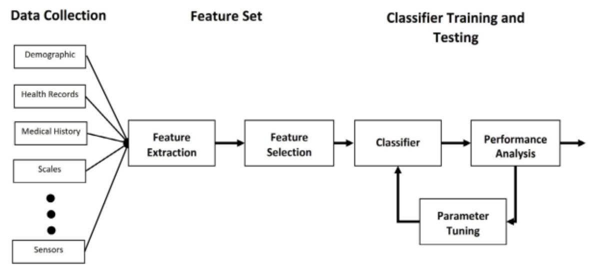

Figure 1. Proposed Architecture

IV. RESULTS AND OBSERVATION

Machine learning algorithms are increasingly being used in the diagnosis, treatment response, and prediction of anxiety disorders. Machine learning algorithms can be roughly divided into three groups, which are as follows. Table 1 compares the success of certain classifiers for various forms of anxiety disorders. The majority of the researchers used SVM and random forest classifiers to detect various forms of anxiety disorders. However, there is still room for progress in classification accuracy. Hierarchical classification can be used to classify a wide range of anxiety disorders. A binary classifier can be used at the first level for patients with anxiety disorders and healthy people. Different forms of anxiety disorders may be categorised at the second level.

Table 1. Performance of ML algorithms

Name of Disorders	ML Algorithm	Performance
MD	RF	92.1%
	SVM	94.6%
	NN	94.3%
	BN	95.7%
	DT	98.8%
	CNN	96.1%

V. CONCLUSION

Recent years have witnessed the increasing use of ML algorithms in healthcare and medicine. In this study, we reviewed existing studies on ML applications to study mental health outcomes. All the results available in the literature reviewed in this work illustrate the applicability and promise of ML in improving the diagnosis and treatment of patients with mental health conditions. Also, this review highlights multiple existing challenges in making ML algorithms clinically actionable for routine care, as well as promising future directions in this field.

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