Auxiliary Diagnosis of Depression Based on Multi-modal Data: A Survey

I. Introduction

Depression is one of the most common mental disorders [1]–[3], affecting more than 300 million people worldwide [4]. Depression is characterized by persistent grief, losing interest in things that are usually enjoyed, and the inability to participate in daily activities [5]. It will also make patients feel poorly and lose their living ability [6]. Worse still, patients with severe symptoms have thoughts of self-harm or suicide [7]–[9]. It is estimated that close to 70% of depressed patients have had suicidal thoughts, and over 50% have self-harmed [10]. In short, the dangers of depression are staggering.

To alleviate the damage caused by depression, a timely and effective diagnosis is essential. However, there are three main challenges in the clinical diagnosis of depression: (1) Lack of valid and accurate objective indicators. Compared with other physiological diseases, there are no objective and specific biochemical examination indexes, physiological data or medical images to diagnose and quantify depression. And clinicians can only make judgments based on the diagnostic criteria and their own working experience, as well as the clinical manifestations of patients [11], which may lead to biased diagnostic results due to some patients' uncooperative treatment and deliberate concealment of their true state. (2) Serious shortage of medical resources. At present, there is a serious shortage of medical professionals and medical resources for the diagnosis and treatment of depression. In particular, in low- and middle-income countries, up to 75% of patients do not receive timely diagnosis and treatment. In addition, face-to-face psychiatric consultations are time-consuming and inefficient, further exacerbating the shortage of resources for psychiatric treatment [12], [13]. (3) Deficiencies in social awareness. The low level of awareness of depression and the unconscious resistance or avoidance of mental illnesses can cause early depression to be underestimated or neglected, thus missing the best time for treatment, and may lead to the aggravation of the disease and increase the difficulty and complexity of treatment [14]–[17].

To address the difficulty of clinical diagnosis of depression, in recent years, researchers have proposed massive machine learning approaches. With the help of machine learning, researchers extract effective features from depression patient data automatically, and then tap the intrinsic connection between depression clinical symptoms and patients' physiological signals, which has become an important direction for auxiliary diagnosis of depression (ADD) [18]. The following advantages exist for machine learning-based ADD: (1) High efficiency: through the analysis of physiological signals of depression patients to establish objective diagnostic indicators, the efficiency of clinical diagnosis can be greatly improved

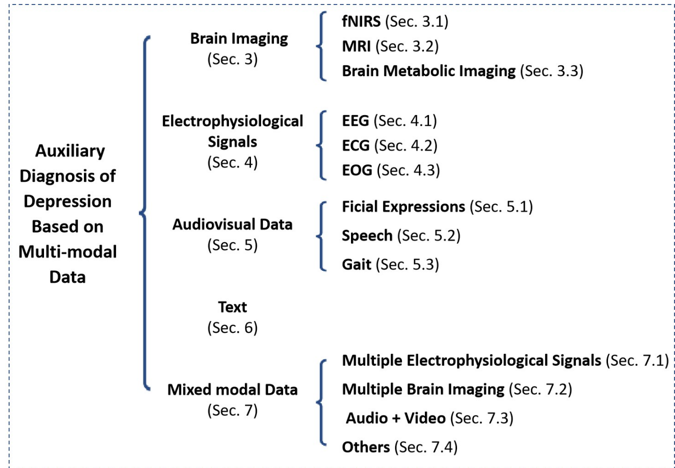

Fig. 1. The taxonomy of ancillary diagnosis of depression from the perspective of various categories of data.

by computer technology. (2) Low interference: the machine learning method is used for automatically ADD, which eliminates the need for deliberate observation by clinicians and reduces the difficulty in depression diagnosis and treatment due to patient non-cooperation. Despite the rapid evolution in this field, there is still no systematic study to review and discuss existing progress. To fill this gap, a systematic analysis is carried out recent ancillary diagnosis of depression (ADD) studies about the application of machine learning on various categories of data, and the research process and methods of machine learning in ADD are summarized, and finally, the research directions and challenges in the future are presented. As shown in Fig 1, we focus on the progress of the methods and potential research directions in five data contexts: *brain imaging* [19]–[23], *electrophysiological signals* [24]–[28], *Audiovisual data* [29]–[31], *text* [32]–[34], and *mixed-modal data* [35]. These commonly used representation forms of physiological signals are illustrated in Fig 2 and some rough descriptions of them are as follows:

(1) *Brain imaging:* Brain imaging refers to the usually non-invasive or minimally invasive techniques that enable imaging the structure or function of the brain [36]. This is achieved by scanning the subjects brain with various precision instruments. Its main data representations are: Functional Nearinfrared Spectroscopy (fNIRS), nuclebar Magnetic Resonance Imaging (MRI), etc. Studies have shown that, to some extent, brain imaging can identify different types of depression depending on the part of the brain affected [37].

(2) *Electrophysiological signals:* Electrophysiological signals are caused by changes in the membrane potential of individual cells [38], which are usually recorded by metal

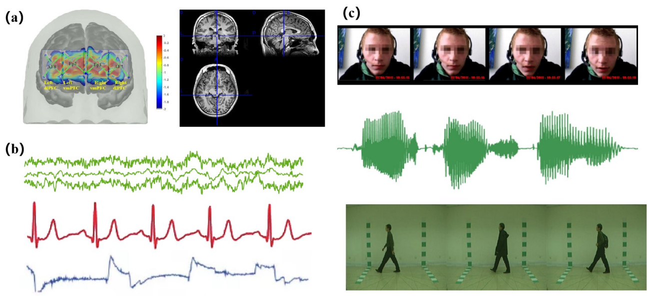

Fig. 2. Common types of physiological signals: subgraphs $a-c$ represent brain imaging,electrophysiological signals, and audiovisual data, respectively. These categories in turn have different representations: fNIRS, MRI, EEG, ECG, EOG, facial expression, speech, and gait.

electrodes placed on the body surface. The common electrophysiological signals that are of clinical interest are electroencephalography (EEG, tracing brain tissue activities), electrocardiography (ECG, recordings of the cardiac movement), and electrooculogram (EOG, examining the behavior of eyes). They have been used extensively to ADD because of their non-invasive detection and ease of use.

(3) *Audiovisual data:* Audiovisual data, whose forms mainly include facial expressions, speech, and gait, are captured by video and audio recording devices. Audiovisual data based ADD is the first recognition method proposed by researchers and the most widely used method, which has the advantage of low acquisition cost but can achieve better recognition results.

(4) *Text:* Text is the most direct vehicle for people to express their thoughts and emotions. Especially on social media platforms, people are more inclined to express their true feelings. Therefore, many researchers have examined the differences in textual expression between people with depression and normal ones in the context of social media platforms from a textual perspective [39].

(5) *Mixed-modal data:* In addition to the use of single physiological or behavioural data to assist in the diagnosis of depression, there have been many studies that have sought to employ multi-modal data for diagnosis [40]–[42]. Multi-modal data have more features than unimodal data, which can give a more complete picture of the symptomatology of depressed patients.

In this paper, we review the current state of research on machine learning in ADD regarding the five types mentioned above of data, with a focus on the progress of the use of machine learning techniques in different data contexts and potential research directions. The main contributions of this study are threefold.

(1) To the best of our knowledge, this is the first comprehensive survey about ADD on different modalities of data, which will provide researchers and clinical psychologists a better understanding of the use of machine learning for ADD.

(2) We provide an in-depth review of advanced ADD studies, summarize and compare the performance of of different methods in each data modality.

(3) We summarize and analyze the advantages and disadvantages of different data types for ADD and give insights on promising research directions in this field.

The rest of this survey will be organized as follows: Section 2 presents a summary of standard approaches to diagnosing clinical depression and abnormal changes in the physiology and behavior of depressed patients and introduces widely-used questionnaires, datasets, and metrics. Section 3-7 provides an in-depth analysis of machine learning-based approaches to depression diagnosis from the perspective of different data types. Section 8 provides insights into promising research directions. We conclude the survey in Section 9.

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