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A New Method Design for Multi-modal Depression Auxiliary Diagnosis from Perspective of Psychology

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Abstract: Current depression diagnostic methods are subjective and single in nature. Therefore, an objective screening mechanism based on physiological and behavioral signals is needed. Through feature extraction and fusion of multi-modal data, we propose a design idea of combining the deep learning algorithm with classical psychological experiment technology, which enriches the idea of depression diagnosis and provides an objective basis for clinical diagnosis.

Keywords: Depression, multi-modal, auxiliary diagnosis, psychological self

1. Introduction

Depression is one of the most common mental disorders, which is characterized by significant and persistent depression and decreased activity. The current diagnosis of depression through the scale, such as: the Hamilton Depression Rating Scale (HAMD, Hamilton (1960)), Beck Depression Inventory (BDI) (Beck et al.,1996), Quick Self-Rating Depression Scale (QIDS) (Rush, Trivedi & Ibrahim, 2003), etc., as shown in Table 1.

Table 1. *Commonly Used Depression Rating Scales*

Scale	Clinician-led	Self-Report	Number of items	Minutes to complete
HAMD	√	×	17/21/24	20-30
BDI	×	√	21	5-10
QIDS	×	√	16	5-10
PHQ-9	×	√	9	<5

Recently, the research based on depression is dominated by biological and psychosocial factors. There are still many problems in the current theoretical research and practical application. First of all, most of the previous experimental studies on depression were carried out around psychiatry and neuroscience, ignoring the specific performance of depressed individuals in psychological self-related processing (Acarturk & Cetinkaya, 2018). Besides, it is rarely exploring the feasibility of using it as an objective detection indicator for depression diagnosis.

2. Research Objectives

Previous studies have focused on the occurrence and severity of neuropsychological impairment during the onset of depression (Coveñas & Werner, 2013). It is difficult for researchers to construct a typical attribute model of neuropsychological impairment in depressive individuals (Mucci & Giorgi, 2016). However, it is noteworthy that Northoff summarizes three characteristics of self-related processing abnormalities in depression: enhanced self-focusing, self-attribution of negative emotions, and enhancement of self-cognitive processing, as shown in Figure 1.

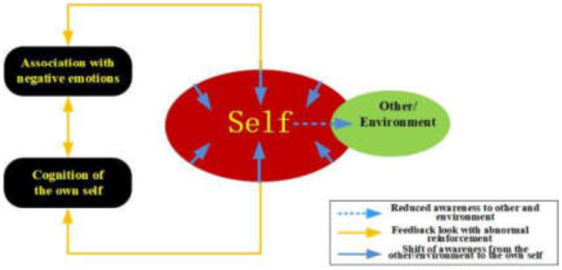

Figure 1. Changes in self, others and body in individuals with depression (Georg, 2007;2015;2016).

In addition to the above theoretical concepts, some empirical evidences also indicate that self-stimulation or self-related processing is related to cortical midline structures in the regions of abnormal brain involved in depression, including orbital medial prefrontal cortex (MOFC), ventromedial prefrontal cortex (VMPFC), etc., as shown in Figure 2.

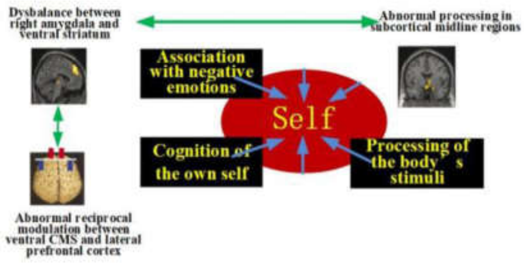

Figure 2. Self-psychopathology of depressive individuals.

Therefore, based on the self-learning theory of depression individuals and self-related processing abnormalities, the project proposes that depression individuals have abnormal self-processing effects. It holds that the special mode of self-related processing is a significant feature of depression individuals. In order to integrate the objective advantages of phonetic and acoustics and enrich the experience of psychological counseling, a dynamic hybrid model based on phonetics and acoustics information of depression, which integrates eye movement and head position are established. The establishment of a multi-modal recognition of depression diagnosis model based on deep learning under abnormal psychology process, to achieve a high degree of accuracy depression evaluation.

3. Research contents

Self is an important concept in psychology, philosophy, social cognitive neuroscience and other fields. Many studies have revealed that depressed individuals have cognitive bias relative to non-depressed individuals.

This research is to observe the specificity of self-related processing in depressed individuals, to construct a study of auxiliary diagnosis and recognition of depression by using deep learning to mine multi-modal features, to expand the experimental paradigm of classical self-reference processing focus on the principle of "limited goals, highlighting key points".

Among them, the first stage of research content is the theoretical study of self-related processing abnormalities (Friedman et al., 1968); the second stage of research content is the multi-modal information fusion modeling based on deep learning; and the third stage of research content is the application and validation of the multi-modal depression diagnosis and model recognition (Konstantina & Kourou et al., 2015).

4. Approach & Methodology

The technical route arrangement of this study is shown in Figure 3. It adopts technical methods such as data acquisition, feature extraction and fusion, modeling and application, evaluate and improve the model.

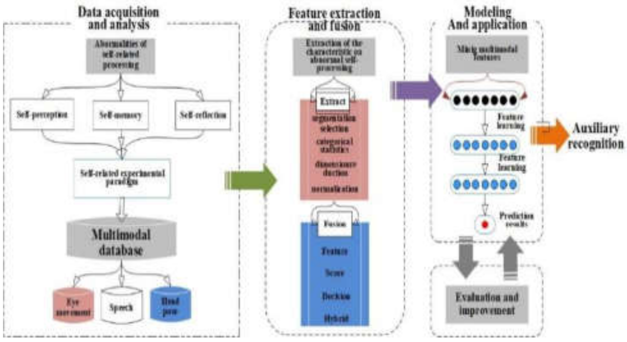

Figure 3. Technology roadmap.

4.1 Data Acquisition

Screening the subjects with unipolar depression into the experimental analysis, exclude the individuals with symptoms of mania-related self-exaggeration and other symptom individuals. The subjects' multi-modal behavior data were obtained through different stimulus tasks under self-related processing materials. Recording is done in a recording studio. As shown in Figure 5.

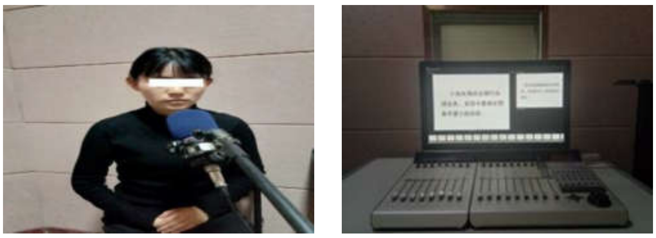

Figure 4. The subject sits in a professional recording studio.

4.2 Feature Extraction and Fusion

Considering the extraction of multi-modal features and the particularity of the subjects, extracting the multi-modal behavior features that reflects the abnormal self-processing of depressed individuals (Sahu et al., 2016). Among them, the analysis of acoustic feature mainly focuses on the feature of rhythm, frequency spectrum and sound quality, as well as eye appearance feature, head posture tracking trajectory as the input basis of the training of computer neural network model. The overall process is shown in Figure 6.

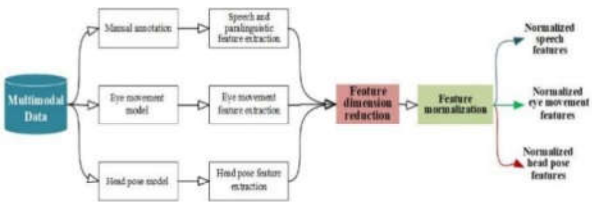

Figure 5. Feature extraction and fusion.

4.3 Modeling and Application

Based on the obtained multi-modal behavioral feature of depressed individuals that have been reduced in dimension, normalized and fused as the original feature input of the model, which is processed by multilayer nonlinearity, combined with the recognition task of multi-modal auxiliary diagnosis of depression under abnormal psychological self-processing, and the classifier is constructed by the feature representation of automatic learning to achieve the task of classification and recognition, as shown in Figure 6.

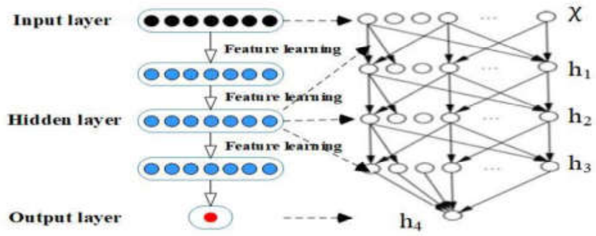

Figure 6. Modeling and application.

4.4 Model Evaluation and Improvement

Referring to the existing application strategies in the field of natural language processing, for the deep learning model established in the previous link, the project team will evaluate and improve this model. The process steps are roughly divided into check model, model initialization, model optimization and adjust model, as shown in Figure 7.

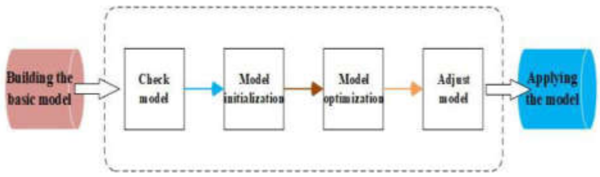

Figure 7. Model evaluation and improvement.

5. Challenge

Therefore, establish a multi-modal behavior database combining speech, eye movement, head posture and other multi-modal behaviors is one of the challenges facing this research.

Additionally, explore the perception, recognition mechanisms of multi-modal information from audiovisual and contextual to find the abnormal and unrelated factors of self-processing dependent on multi-modal behavior characteristics realize the study on classification and recognition of diagnosis depression will be another challenge of this research.

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