Letter to Editor

ARTIFICIAL INTELLIGENCE IN AID EFFICIENT MENTAL HEALTHCARE IN CONTEXT OF STATE-OF-THE -ART SIR COWASJEE MENTAL HEALTH INSTITUTE AT HYDERABAD SINDH PAKISTAN

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ABSTRACT
Artificial intelligence (AI), often described, as the machine simulation of human intelligence, is a branch of computer science that solves problems automatically using computational algorithms. AI systems work by first consuming massive volumes of labeled training data, analyzing it for patterns, and finally using these patterns to make predictions. On the other hand mental health issues are increasing in human thus use AI in provision of mental health aid would be a novel approach.

Key Words: Artificial Intelligence, mental health, machine simulation

INTRODUCTION

Globally, over 70% of adults and younger population live with mental illness without receiving any treatment or approaching mental health care facility(1). There are a number of societal barriers and taboos in receiving mental health care as compared to physical health. Thus there is a huge difference in true prevalence and treated prevalence of mental health (ie treatment gap)(2). Among many reasons for this include stigma, discrimination, capacity & minimal investment in mental health. Historical lunatic asylums journey tertiary level mental facilities like Sir C.J. Institute of Psychiatry (CJIP) Hyderabad Sindh Pakistan, which was established as an asylum in 1865., could not had an impact until year 2000, with the publishing of World Health Report which estimated the Burden of Disease–Disability Weights. There was a shock for the world to Mental Health Disorders were included in top five diseases causing disabilities.

Artificial intelligence (AI), often described, as the machine simulation of human intelligence, is a branch of computer science that solves problems automatically using computational algorithms. AI systems work by first consuming massive volumes of labeled training data, analyzing it for patterns, and finally using these patterns to make predictions(3).

AI in mental healthcare has the great potential. It is used to identify behavioral traits of individuals with mental illness and to improve the management of mental healthcare interventions. In fact, mental healthcare is one of the domains in which telehealth and AI can be integrated seamlessly(4). Academics from the fields of psychology and computer science have collaborated to use artificial intelligence to gain a better understanding of mental illnesses in order to develop systems that can detect the disease using computational machines(5).

This letter briefly describes the use of four modalities namely audio, visual, text, and physiological signals in conjunction with AI-powered machine learning systems to spot signs of mental illness. We cite research studies that have demonstrated the efficacy of such solutions. Our focus in the letter shall be on the AI-based automated recognition of depression since according to WHO [5], depression is the most common type of disability worldwide, affecting more than 5% of the global adult population. It is also well-known that untreated depression may lead to suicide(6).

Human speech consists of linguistic and paralinguistic parts. It has been shown already that AI-based systems can leverage paralinguistic characteristics of speech to recognize human emotions, trustworthiness, and sincerity(7). There is an emphasis on investigating how speech can be used as a biomarker of diseases that affect speech production, such as depression.(8) The aim is to use the information contained in a paralinguistic speech to build and subsequently deploy AI-based systems to identify depression from everyday conversations. Key studies in this regard are the works from Alghowinem et al.(9) and Williamson et al.(10) who highlighted that computational speech analysis may yield biomarkers for depression. We refer the reader to the survey from Cummins et al.(11) for a detailed review of speech-based screening for depression and suicide risk.

Natural-language processing (NLP) is a sub-field of AI that is used to evaluate textual documents automatically to infer meanings. NLP deals with the linguistic aspects of human communication. It has received a lot of attention recently for its potential in mental healthcare(12). Bathina et al.(13) reported that individuals with depression express atypical and distorted language on social media. Jain et al.(14) demonstrated that NLP can be used to identify social media posts related to depression and suicidal intent, whereas, Rinaldi et al.(15) proposed a novel approach to interview transcripts of depressed individuals to provide psycholinguistic insights about the disease. These are encouraging signs that show that NLP holds great potential to support the mental healthcare of patients and may be integrated into the AI-based system for automated depression screening.

Facial expressions provide the most powerful, natural, and straightforward way to communicate emotion. Human beings perceive emotional feedback and reciprocate behavior based on recognizing others' facial expressions. However, it is well known that individuals' mental illnesses have atypical facial behavior that can provide cues to mental state. To this end, Girard et al. hypothesize automated systems can be trained to recognize traits of depression from the facial expressions of individuals.(16) In, we showed that cues of psychomotor retardation can be used to build domain-knowledge-based handcrafted features to screen for depression. Stratou et al.(17) reported that as the severity of depression increased, subjects in their experiment showed reduced facial activity in terms of facial muscle movement and head movement. They also had reduced eye gaze variations such that they appeared passive and disinterested. Based on their experiments, they also reported that individuals with depression demonstrated facial expressions of hostility, grief, and diminished signs of joy. These studies suggest that it is possible to screen for individuals with depression based on their facial appearance and movement, and that is the rationale for integrating visual modality for automated depression screening.

Amongst other modalities, multiple studies have shown that physiological signals such as heart rate, blood pressure, electrodermal activity, and electroencephalogram offer an alternate way to recognize stress, anxiety, and depression.(18) Similarly, body movement information can be used to gauge for psychomotor activities of patients with depression. It should be mentioned here that an automated system to recognize depression can also work by ingesting information from multiple modalities, learning from it, and making predictions of the patient's mental state. In fact, several studies, have shown that integrating multiple modalities can help improve the systems performance. Thus, there is ample evidence to investigate the use of AI-based automated systems for screening depression.

Now we shall discuss the experimental methodology for automated depression screening based on conversations that include a clinician and the patients with depression in a hypothetical clinical setup. The setup consists of hardware and software parts. The hardware part includes electronic sensors to acquire audio, visual, physiological and body movement data. The software part consists of algorithms that implement the AI-based system featuring engineering and machine learning parts.

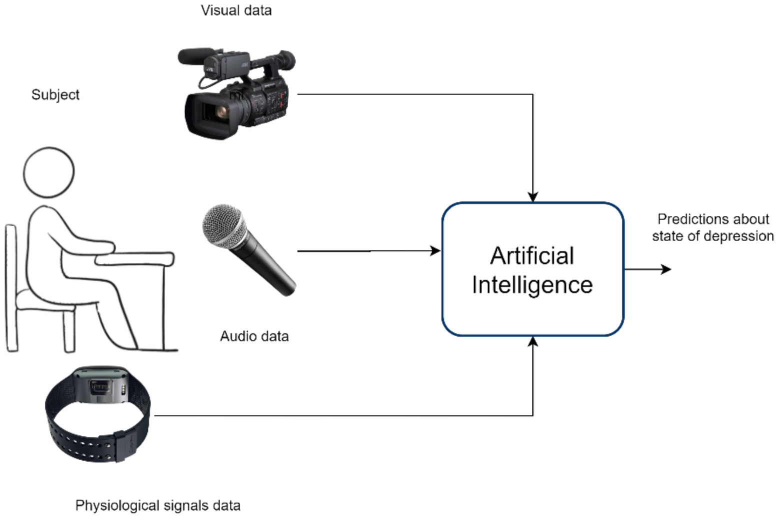

Figure 1: Conceptual setup for data collection where audio, visual, and physiological signals data is acquired from both, the subject and the clinician

Figure 1 illustrates the data collection setup for the task of automated depression screening. This hardware setup is placed in a hospital environment where patients typically meet the clinician to seek medical and/or therapeutic support. The communication between the two is required in the form of video recordings through a video camera and microphone facing the patient – these provide necessary data for audio and visual modalities. A suitable speech transcription tool can be used to generate transcripts for conversation between the clinician and patients. This modality can subsequently be used for NLP, as discussed earlier. Physiological signals such as temperature, blood pressure, heart rate, and electro-dermal activity are recorded through the Empatica E4 band. The efficacy of this module has already been demonstrated with tasks related to stress detection. In addition to physiological signals, the E4 band also records body movement data through the built-in IMU. Thus, the recording setup enables the recording of multimodal signals that can be leveraged for automated depression recognition.

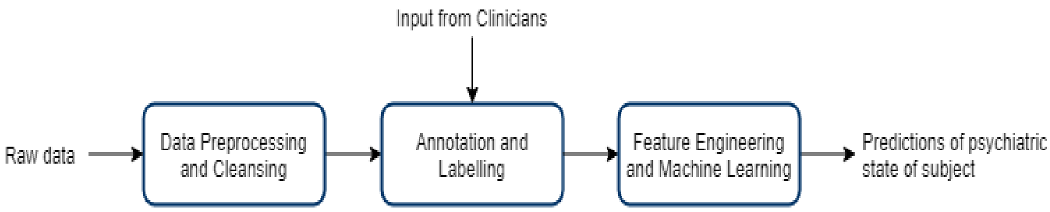

Figure 2: Conceptual framework for signal processing and machine learning pipeline

The conceptual process flow diagram for the signal processing and machine learning pipeline is illustrated in Figure 2. It starts with data preprocessing and cleansing which ensures that the acquired data is of sufficiently good quality for training AI-based systems. The data so far does not contain ground-truth labels regarding the psychiatric state of subjects, for example, whether the patient is healthy or has depression. Labels can also include depression severity, for example, in terms of the Patient Health Questionnaire-9 score.(19) At the annotation and labeling stage of this framework, labels will be assigned to each recording based on the input from clinicians. These labels are provided by the clinician after assessing the patient.

The Feature Engineering and Machine Learning pipeline consist of feature computation, feature selection, and classification based on cross-validation. At the feature computation stage, audio, visual, and physiological signals data is transformed into representations that are meaningful for the classifier. For example, prosody, voice quality, and spectral features are more meaningful for classifiers than raw audio waveforms. Similar transformations are also required for visual and physiological signals data.

At the machine learning stage, the dataset is divided into three parts, training, validation, and test. The sub-datasets are used to train the machine learning model, validate its performance for different hyperparameters, and finally test its performance on a previously unseen part of data. The choice of a machine learning algorithm depends on the type of labels. If the dataset has been labeled for binary classes of depressed and not-depressed, then a classifier will be used. On the other hand, if the dataset has been labeled for depression severity, then a regressor will be used. Once the machine learning model has been trained, it can be used to recognize the existence of depression as well as its severity in a real-world environment.

The World Health Report 2000 was alarming to developed world even. The stigma, discrimination, capacity & low investment in Low Middle Income Countries (LMICs) like Pakistan face great challenges specially in backdrop of pandemic effects of social psychology.(20) Wave of change of policies towards mental health, set in by the World Health Report, can be seen in form of transformation of CJIP Hyderabad into an autonomous multidisciplinary Mental Health facility. Still the technology has fill the gaps in our context specially "The 10/90 Gap"[35] and the treatment gap.(20)

The 10/90 discovers that between 2002-4, only 3.7% of research on psychiatry in leading journals was from the least developed countries, whereas they represent >80% of the world population. This means we are relyging on the western sociocultural context for our knowledge to address our own mental challenges. This Category fallacy (Kleinman, 1987): Applying a category that makes sense for a particular cultural group in another group, for whom this category may not make sense, creates treatment gap. So we need to adopt Leapfrog strategy to include Artificial Intelligence in planning and development of state-of-the-art Sir C.J Institute of Psychiatry & Behavioral Sciences Hyderabad for diagnosis, treatment , monitoring & evaluation and recovery.

To conclude, in this letter, we provided a brief overview of multiple modalities through which behavioral cues for mental illness can be recognized. We also discussed the steps of data collection, data annotation, feature engineering, and machine learning for the AI-based system for automated depression screening. We hope this letter encourages collaboration between psychologists, computer scientists, and engineers to begin research into automated depression screening systems in Pakistan.

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