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Depression Detection and Analysis

Shweta Oak
Student, Sardar Patel Institute of Technology
Bhavans Campus, Andheri West
Mumbai 400058

Abstract

350 million people suffer from one of the most common mental disorders, depression. Depression can be of varied intensities. A prolonged phase of depression can lead to serious mental health issues. It greatly affects the productivity of a person and at worst may lead to self harm and suicide. A few of the symptoms are anxiety, feeling of loneliness, considering oneself not worthy enough, mood swings, eating disorders among a variety of others. Each person shows a different set of symptoms. During a phase of Depression, a person does not feel comfortable to talk to others about his/her problems to anyone. The paper focuses on an application which will take inputs as speech or text, identify the best response or recommendation. This system determines if the person suffers from depression and the root problem, or cause of depression is aimed to be identified. As the system gets trained by inputs given by the user, it starts customizing recommendations and responses that address the root cause.

Introduction

Depression is a common mental disorder, which can happen to anyone, at any age. The problem lies with the fact that it is still not identified and treated in many cases, leading to severely affecting the mental and physical health of a person. The biggest obstacle to treating depression may be a person's inability to recognize the problem or reluctance to seek treatment. It is generally characterized by the loss of interest, feelings of guilt or low self-worth, disturbed sleep or appetite, feelings of tiredness, poor concentration (Markus et al. 2012), social withdrawal and slowed speech.

It has been observed that many people feel uncomfortable to speak about the problems they face which leads to depression. Untreated depression leads to self harm or in extreme cases suicide. It adversely affects the physical health of a patient, such as increased aches and pain, insomnia or oversleeping and weight problems. According to the Harvard Mental Health Letter, Heart disease is linked to Depression. Recurrence of cardiovascular problems is linked more closely to depression than to smoking, diabetes, high blood pressure, or high cholesterol. If untreated, depression raises the risk of dying after a heart attack.

Employers lose an estimated $44 Billion every year due to workers with clinical depression, 81% of the productive time lost are explained by reduced performance while at work, because depressed people still go for work, but there is a marked reduction in performance while of they are there (Stewart et al. 2003)

Fortunately, studies have shown that depression can be treated. One of the methods of treatment is Psychotherapy, (Picardil and Gaetano 2014) also known as talk therapy by which practitioners treat patients without the use of medicines, by talking to them (Hadjipavlou, Hernandez and Ogrodniczuk 2015). This method of treatment is very closely related to this project.

Related Work

The diagnosis is done primarily by the self reporting of patients or the clinician's analysis of the severity of the symptoms. Recently, there has been research to use Artificial Intelligence for detection of depression from speech and text or telephonic conversations. The ongoing project of USC Institute for creative technologies, SimSei seeks to enable clinical decision support tools and interactive virtual agent-based health care delivery systems that identifies psychological distress from multimodal signals (DeVault et al 2014). Automated classification of psychological disorders is done by observing differences in the way a person communicates (Ma et al. 2016). Depression can be detected from vocal expression using Partial Least square Algorithm (Meng et al. 2013).

Increasingly, social media is being used for analyzing behavioral traits for health care like information about diseases based on Twitter posts (Paul and Dredze, 2011). Text from social media platforms like Twitter is analyzed to do a sentiment analysis (Wang et al. 2013) detect depression traits in users (Hasan, Rundensteiner and Agu 2014). Instead of considering the behavioral aspect, data from social media is also taken up as a text classification problem to identify depression (Nadeem et al. 20)

This project uses data of text and speech to detect and analyze the cause of depression.

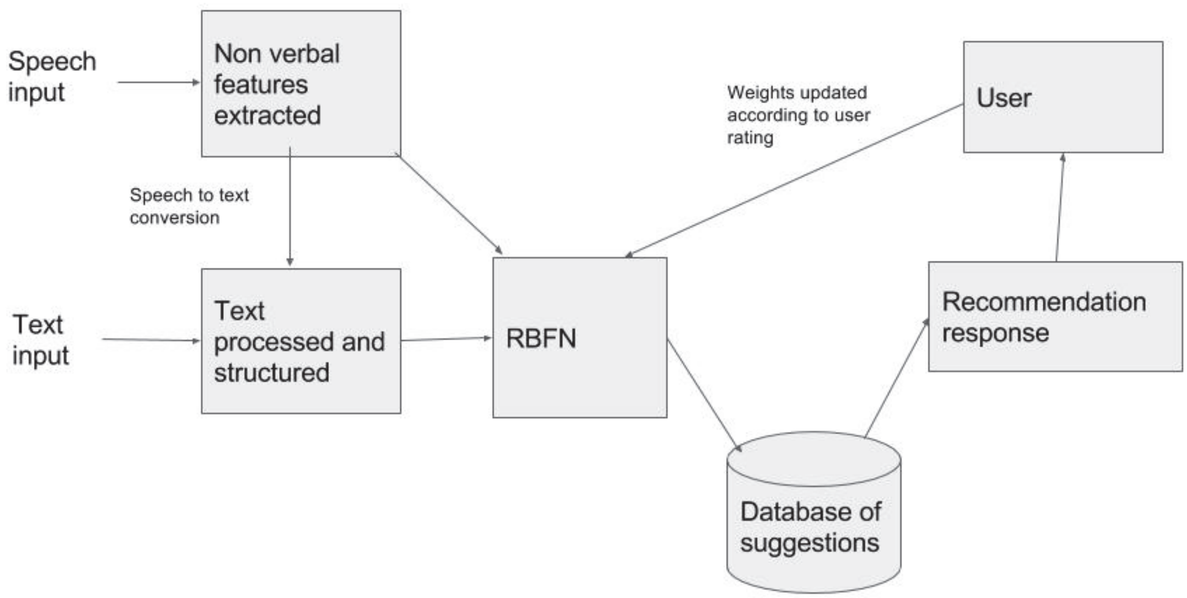

Figure 1: A diagram illustrating the working of the model.

Methodology

Design Goals

This project is about creating a chatbot which gives human like responses to the text entered by the user. These responses are customized to a user and contain article or music suggestions which help to analyze and address the reason depression in the user. The user can rate the articles on how helpful they found it. This rating would be used by the application for further article or music recommendations.

The goal of this project is (1) that the users should feel comfortable sharing their problems on the application (2) to reach out to those facing depression, but are unable to afford medical services or are reluctant to seek treatment. Depression goes untreated in many cases, which can result in suicides. This application gives the user a place where they can share any problems they face and receive help or a source of motivation, which can prove to be very helpful for some cases. Although this application is designed for depressed patients, it can be used by anyone as a medium to share problems and receive motivation in difficult times.

Data

The data from different people is necessary to identify if the application works differently for different people. On sending out flyers, 53 people volunteered to try the application in the age range 20-45 years. Out of the 53 volunteers, 28 claimed to be depressed and 8 claimed to have been depressed in the past. They were informed about the project, about the anonymity of their data and any queries about the application were cleared. They were asked to fill in a questionnaire. This Questionnaire had questions focusing on if they had faced problems like bullying, abuse, financial problems, loss of a person they were close to, illness. These answers were recorded and the user continued to use the application. The volunteers were asked to use the application for a week. They were asked to share their problems with the application, by means of typing it or speaking. Although, the questionnaire gives a rough idea about what the user has been through, more relevant and accurate information is found via the text and speech. Each user's data was anonymously stored. Each user has an ID. Corresponding to this ID, the responses of the questionnaire, the text input to the application, the audio file of speech input, suggestion given by the application and the rating given by the user for the suggestion was noted. The average of the ratings decide how well the model works for an individual.

Analysis of Speech

It has been seen that speech provides a very valuable insight for detection of depression. People in depression generally talk slowly, take long pauses, etc. These non-verbal features along with the interpretation of speech, depression signs in a person can be detected. Differences in verbal behavior like speaker-switch duration and change in vocal fundamental frequency (Cohn et al. 2009), slow speech, delays in delivery, and long silent pauses was found common among depressed patients.

The speech input is processed to extract features like pitch, change in speed of talking, loudness, pauses taken by the user. For doing this, the feature extraction capability of the the open source library pyAudioAnalysis is used. Then, The values of pitch, long pause duration, are sent as an input parameter to the RBFN, which is discussed later.

Once the nonverbal features are found, we can use a speech recognizer for converting the audio file into text. The Google Speech API for speech recognition, is used to convert speech to text. Another open source tools like CMU Sphinx can also be used. Once converted to text it is processed as explained in Analysis of Text section.

Analysis of Text

The model for analysis of text is trained on a corpus of movie dialogues provided by Cornell University. This module focuses on getting text input from the user and extract keywords for further processing and give a response to get more insight about the user's state. The text input is the message typed by the user or the user's speech input converted to text. This text is in natural language and is unstructured. The aim here is to structure this input data, so keywords extracted from it can be stored for the application to give suggestions. The following example will make the working clearer. The following text is entered:

> I feel lost and disconnected these days. Everything always goes wrong with me. It feels like I never have enough.

The above text would be abstracted into a structure which encapsulates what the user is trying to say:
feel: lost,disconnected
surroundings:
lack: enough
happy:

The above structure just enumerates a few of the categories that keywords describing the feeling or state are classified into. A record of the categories with their synonyms is kept. These words act as trigger words. The words linking to these trigger words are stored in the categories. The keywords and relationships between words can be found using models like the the skip-gram model (Mikolov et al. 2013) or Universal Stanford Dependencies (Marneffe et al. 2014). For instance, in the example, ''lack'' has the synonyms ''not have'', ''never have'', ''never had'' The model tries to get data about the blank categories. To the above example, it might send a response ''How do your surroundings affect you?'' or ''What makes you happy?''. The structure obtained here is then sent for further processing for depression analysis.

Depression analysis: finding the root cause

It is often difficult, to point out the real cause of depression. In some cases, there exists no such cause, however, the patient feels depressed and has a lack of interest in doing anything. This module aims at trying to find the cause of depression, or tries to find the kind of material to read or listen to, which keeps the user motivated.

Each user's data is processed in a different instance. A Radial Bias Function Network is used for estimating the root cause as it would finds the similarity between the current state and the new keywords. There are several possible reasons behind depression, however, for this project, only three major causes of depression were considered, Financial, Abuse and Deficiency. The previously used trigger words fall under these three categories. For each user, these values are initialized to the same value. The plot for different users domain of depression may look different, as they depend on their text messages or speech input.

When a new keyword from the input is placed into the structure, the weight for the category under which the corresponding trigger word lies is updated. For instance, if the above example text is followed by

> I don't have any qualities.

the keyword here is ''qualities'', it falls under the trigger word ''lack''. A keyword added to ''lack'' would update the weight for ''Deficiency''. So, the state moves towards Deficiency. When the user uses the application to talk about his/her problems over time, the state would predominantly be in one of these categories.

Recommendations

The recommendations given to a user are a part of responses generated by the application. The details of music suggestions, quotations and articles is stored in a database on a server. These are classified under categories that the text, in the previous module was structured in. For instance, under the category of ''lack'', there would be articles on how one must be content, Each one has his/her own merits. This database has a section with routines and tasks. It has been found that completing a task or routine can be helpful overcoming depression.

The user is given an option of rating the suggestion on a scale of 5. Where 5 translates to very helpful and 1 to not helpful at all. This rating decides the weight updation for finding the root cause.

Over time, the article or music recommendations are directed towards the aspect that the user is depressed about.

Conclusion

The measure of how well the project works was taken as the similarity in results of the RBFN and the questionnaire. If majority of the answers in the questionnaire in a domain were marked ''yes'' and the RBFN model too gave a higher value for that category, then the case was taken as positives. Any conflict resulted in a negative case.

For the speech model, 20 out of 28 volunteers who were depressed gave positive results that is 71.4% accuracy. For volunteers who were not depressed, 19 out of 25 cases gave positive results. For the text model, 18 out of 28 volunteers who were depressed gave positive results and 21 out of 25 positive cases for volunteers who were not depressed.

Although it is observed that the speech model works quite well as compared to the text model owing to the non verbal features, the volunteers' feedback was that it was easier to text than to speak about their problems, knowing that their data was not being compromised.

Future Scope

This project was to create a proof of concept for the creation of an application that could cater to each person facing depression.Keeping the volunteer's feedback in mind, efforts will be made to improve the text model and make the speech model computationally efficient.

The project is aimed at being accessible to everyone. This project aims at motivating people and indirectly preventing people from taking drastic steps such as suicide. The data transmission will be secure and not be released. This also aims at identifying people who are undergoing domestic abuse or any other kind of problem that people are not comfortable sharing. The application would provide steps to follow and actions to take to seek help to them.

A feature that is in being developed in this project is to provide regular status reports of the user's mental health to the Doctor, whose details would be provided by the user.

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