A SYSTEM TO PREDICT MENTAL DEPRESSION USING NATURAL LANGUAGE PROCESSING

Ashwini Arun Durbude[1], Dr. Avinash J. Agrawal[2]

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Abstract

People have the ability to manage and control their emotions. They frequently are aware of their feelings. Consider what may happen if someone is unable to identify their emotions. There is a chance that it is problem connected to mental illness, this may be the case. The first step is early symptom detection. The method to predict levels of depression and emotions is presented in this paper. Firstly, the analysis of a DAIC-WOZ dataset involves using several Deep Learning models with three modalities—text, audio, and video features—are combined to predict patient depression. This method of fusion regulates the amount of contribution from each modality. The candidate can evaluate their own mental health at the pre-diagnosis stage. To do this, text and voice data are combined to create a system that can estimate the severity of depression. Chats are the textual data as inputs. Voice recognition is performed on audio data, and the audio is then transformed to text representation. By classifying the emotions into several emotional levels—such as angry, sad, etc.—the emotions are recognized. The user learns about their degree of depression, which helps to some extent with the diagnosing portion of treatment.

Keywords: Deep Learning Models, Depression prediction, Geriatric Depression Scale, Natural Language Processing, Patient Health Questionnaire

[1,2]Shri Ramdeobaba College of Engineering and Management, Nagpur, India

Email: [1]durbudeaa@rknec.edu, [2]agrawalaj@rknec.edu

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1. Introduction

The current situation in terms of society demands for a feasible, self-sufficient, and easy-to-use method to identify depression. As lifestyle changes, a greater percentage of the population is exhibiting depressive tendencies as a result of more difficult environments. One can only endeavour to treat it if they can find it in the first place. Clinical interviews with the individuals need to be conducted in order to generate the three modalities that will be used as input in our model's testing. It has been discovered via significant research in this area that despairing individuals showcases an extensive number of complex symptoms that might involve an observation more effectively by combining the three potential approaches. A variation in intellectual behaviour can cause a variety of physiological changes. Depression might have a major detrimental impact on the capacity of an individual and it may result in self-harm as well. Depression in youth is precursor to catastrophic neurological disorders and mood issues pertaining to later life. Depression has a significant negative influence on one's ability to perform at job, school, and in the family, could potentially ensue self-harm. Adolescent depression is associated with serious mental disease and mood problems.

There are many mental disorders causing impairment and incapacity, with depression being the most common. Therefore, depression causes a huge burden of disease. In adults, depression affects around 5% of people globally and 20% of people with milder types (such as partial symptoms, moderate depression, and probable depression). The middle-aged group is the most vulnerable among adults. Meanwhile, there were and has been an 18% increase in depression cases globally between 2005 and 2015. However, prompt professional support may usually help somatic issues like gastrointestinal issues and sleeping disturbances as well as mental symptoms like lack of self-confidence and ruminating.

Clinical diagnoses of depression comprises of physical signs which includes anorexia, sleep issues, aches, and psychological traits such a depressed mood, melancholy, and waning interests. In order to perform deep cognition for various types of data, most researchers are currently focused on studying behaviour information such as audio, video, and text data. By taking into account textual content, audio recording, and visual information a multi-modal fusion paradigm for depression is developed. Identification based on deep neural networks. Assessment of the scores for the level of severity a state of depression is done by using the Patient Health Questionnaire with 9 questions (PHQ-9).

When there is a chance that someone is dealing with a problem connected to mental illness, people could be reluctant to see a psychiatrist because of shame. With the use of a user-interactive platform, this gap may be closed. To do this, text, audio, and visual data are combined to create a chatbot that can estimate the severity of depression. Chats use the textual data as inputs. Chats use the textual data as inputs. Voice recognition is performed on audio data, and the audio is transformed to text representation. The user learns about their degree of anxiety and sadness, which helps to some extent with the diagnosing portion of treatment. Users' words and writing are responded to by chatbot. Because interacting with a chatbot is analogous to speaking with a human, users find them to be incredibly enticing. Chatbots are helpful in medical diagnosis because they can simplify the pre-diagnostic phase and aid in the evaluation of depression.

The majority of techniques for detection utilise survey materials, in particular the Hamilton Depression Rating Scale (HDRS) and the Beck Depression Inventory (BDI), and the Physical Health Questionnaire Depression Scale (PHQ) [Table 1]. These questions are all utilised in the screening process. The patient's answer is involved, which is unreliable because they can potentially fake it. Here are some specifics of such evaluations:

PHQ-9: Patient Health Questionnaire This is a questionnaire which contains nine questions regarding how frequently people experience symptoms like depression, boredom, exhaustion, and sleep difficulties. The severity of depression is calculated by adding the scores from each scaled question.

The Geriatric Depression Scale (GDS) is a questionnaire designed particularly for senior citizens. It offers questions on 15 depressive symptoms, including mood, energy level, and memory. The severity of depression is calculated by assigning a score to each symptom and then summing the scores.

Total Score	Depression Severity
1 to 4	Minimal
5 to 9	Mild
10 to 14	Moderate
15 to 19	Moderately Severe
20 to 27	Severe

Table 1. PHQ-9 Score Chart

Artificial intelligence (AI) Deep learning, machine learning (ML), and natural language processing (NLP) are examples of technologies also natural language understanding (NLU), are used to build chatbot. It can determine a question's purpose to offer a precise response and offer alternatives to confirm or fix the problem. Every chatbot developer strives to create the most human-like chatbot possible, and these elements will enable the chatbot to be more human-like. To accomplish this, the chatbot must comprehend language, context, tone, etc. Sentiment analysis is a technology that can improve this since it automatically extracts the topic and feeling from text or voice input.

2. Literature Review

The area of Natural Language Processing in Psychology has been the subject of several studies and investigations. Since there are no simple diagnostic procedures for depression, doctors must frequently evaluate patients to identify whether they are suffering from clinical or chronic depression.

The Physical Health Questionnaire, which comprises items to assess for depressive symptoms, is used by the majority of medical professionals. The study in [1] states that PHQ-8 was evaluated as a depression indicator in a sizable epidemiological population-based research with the goals of comparing depression according to the PHQ with 8 questions diagnostic criteria to a cut-point of less than 10.The study came to the conclusion that the PHQ-8 is a helpful tool for measuring depression in population-based studies, and that present depression may be defined using either its diagnostic algorithm or at a point of greater than or equal to 10.

There is significant behavioral evidence that depressive symptoms may be detected through speech and facial expression [3]. In patients receiving therapy for depression, the automated measurement of facial movements and vocal prosody with the clinical diagnosis of severe depression is evaluated. Face and voice emotion is analyzed using active appearance modeling (AAM), pitch extraction and manual FACS coding. Manual FACS had an accuracy of 88% and AAM had an accuracy of 79% for diagnosing depression. Vocal prosody accuracy was 79%. According to this exploratory investigation, nonverbal emotional information correlates with diagnosis and has a substantial potential to further research.

In study [4], investigation of capabilities to detect signs of psychiatric problems using automated audio and visual nonverbal behavior characteristics of psychological disorders such as mental disorder, anxiety, and symptoms of PTSD is done. A great deal of non-verbal characteristics that can be effortlessly evaluated from auditory and visual information is suggested. The evaluation on Distress Assessment Interview Corpus dataset shows correlation of the method described in paper that is automatic behavior descriptors with the derived general distress measure.

The study in paper [5] analyses numerous ML and AI-based studies that have been conducted in the past to identify depression. This study investigates how one's emotions and depression may be accurately detected using facial expressions, photos and messages on social media sites. The various ML techniques used for predicting emotions from text processing include Naive-Bayes, Logistic Regression, Long Term Short Memory (LSTM), Support Vector Machines (SVM), Radial Neural Networks (RNN), Artificial Neural Networks (ANN) are used for feature extraction and classification.

Rather than approaching classifier construction as a behavioural challenge, paper [6] treats it as a text-classification problem. The capacity to continually identify and pursue the diagnosis of certain tweets is established. The bag of words method, which analyses word frequencies, is used to assess depression. A 2.5 M tweet collection was used to produce an 81% classification accuracy rate and precision score of 0.86 is achieved.

Paper [7] describes a Chatbot created as a component of a framework for managing stress that intends to assist professionals in controlling their working stress. In order to quantify people's stress using a Sense of Coherence (SOC) model and subsequently to give assistance based on the determined SOC value, the framework uses chatbots and robots to converse with people. The LINE chatbot platform was used to construct a smart phone-based chatbot for experiments, making it simple for users of Apple or Android devices to access the chatbot. As a component of stress management system, it is created utilising the helper theory to construct a help-receiver peer assistance approach in a chatbot to support healthcare professionals.

According to the study [8], depressive disorders in children can be identified as early as two years of age using analysis of speech and categorization. According to the study article provided in [10], interactive virtual agent-based healthcare delivery systems are required in order to diagnose sadness. With the help of a chat application, the user may discuss difficulties, and the chatbot responds with human-like comments in accordance with the questions presented. This research analyses audio and text input to find sadness. Speech is converted into text before processing in order to extract nonverbal properties. For voice recognition, speech is converted to text using the Google voice API. The Radial Basis Network Function (RBNF), that makes use of database search and suggests responses, receives the data after that. When revising weights, the ratings in RBFN are taken into consideration.

In papers [11, 12], the DAIC-WOZ dataset is described. It provides information on data gathering methods, modalities, and a thorough interview corpus with HCI. A content-based ensemble technique (CBEM) to improve depression identification accuracy is described in Paper [13]. The suggested model separated the EEG or EMs dataset into subgroups according to the experimental situation. Using two sets of data, free viewing eye movement as well as resting-state EEG, the approach's validity is established, with a total of 36, 34 participants in each. CBEM yields accuracy values of 82.5% and 92.65% for these two datasets, respectively.

In addition to identifying a person's level of depression, the system [14] also offers treatments to lessen that level of depression. The goal of project is create a cognitive behavioural system, often known as Therapy Chat bot that can meet a user's informational and health demands. The focus of this project is using technology to combat depression in humans. In addition, the system meets the user's informational demands by assisting with name, location, and item searches as well as weather and other informational needs. Python is used as the study's foundation language since it can be connected with Android and used as a messaging platform to reach a wider audience.

The approach suggested in [15] uses ML algorithms to find effective solutions for mental-health issues and diagnose depressive disorders amongst social networking users, notably face book users. Phases which include data collection, data cleaning, and data normalisation, extraction of features, depression classification, and detection outcomes are all part of the paradigm for Face book analysis of information for mental illness analysis. The set of data is put according to Linguistic Inquiry Word Count (LIWC). In this study, 7146 comments were analyzed to identify the significant time. It was found that 54.77% depressive indicative users communicate from mid of night till midday. And 45.22% from midday till mid of night. Furthermore, the results point out that Decision Tree (DT) provides higher accuracy in several experiments than any other methods used by machine learning to identify depression.

To determine if a person is sad or not, machine learning classifiers are used in the study [16] using the twitter dataset. With accuracy of 74.42%, deep learning models including LSTM, CNN, logistic regression, and random forest are employed. It is separated into two halves. Sentiment analysis is used in the first step to examine a user's Twitter postings. Machine learning classifiers and a few optimized ensembles are utilized in the second stage to enhance the results of the first stage's planned work. The outcome includes the weighted mean of each second-stage alternative.

EMOTHAW is a revolutionary database for the identification of emotional feelings from handwriting and art, was introduced in Paper [18]. The Depression-Anxiety-Stress measures questionnaire measures were used to examine the emotional states of 129 persons in the database, including depression, anxiety, and stress. Drawings of houses, circles, and clocks, as well as the copying of one sentence in cursive writing, are a few of the jobs that may be recorded with a digitizing tablet. Random forest analysis is used to identify characteristics linked to a specific emotional state. In the beginning, videos are recorded and converted into frames. Emotions are classed based on the regions of the mouth. The Viola-Jones approach is used to locate facial area. The method proposed is evaluated using 810 frames from video that feature neutral facial emotions, such as a child's grin and scream, and are utilized to recognize face emotion. This model's depression accuracy is 72.8%. Stress and anxiety are both detected with accuracy of 55.5% and 59.7%, respectively. However, each state has a unique collection of pertinent in-air and on-paper qualities and activities that define it.

3. Proposed Work

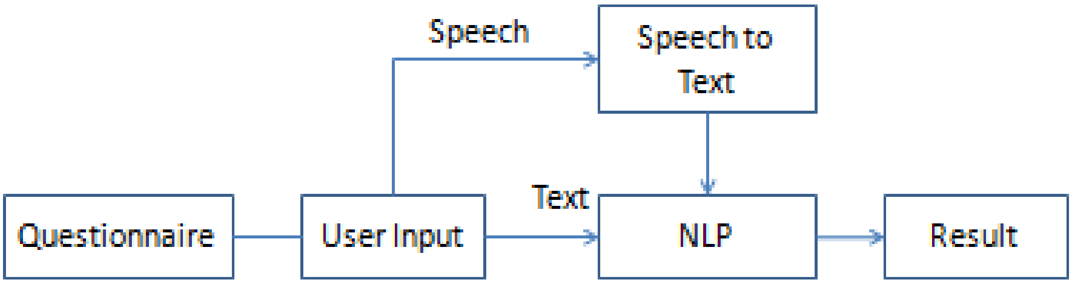

Fig 1. Flow of the system built using Audio and Text inputs

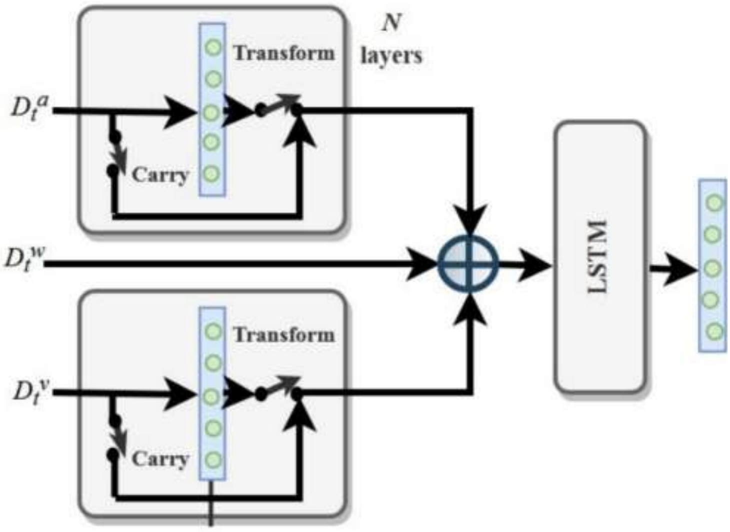

Fig 2. LSTM with gating mechanism

The system initially extracts features before applying a gating on the features. Making use of timestamps, audio, visual, and textual features are combined for feature extraction. To understand the meaning of words in a sentence, analysis is done both at the word and sentence levels. There is noise present in the characteristics of different modalities, and different modalities have varied effects on the outcome. Gating is then used to govern how much information is modified and sent to the following levels. The vectors from all of the modalities are concatenated for each step, and they are then sent to the LSTM having gating mechanism. The standard DAIC-WOZ dataset is used for the processing of data in Phase 1. The proposed system is divided in 2 different phases. Phase 1 is study of DAIC-WOZ dataset processing and extracting features using different Deep Learning modules. Phase 2 is building of a web application to detect depression using text and audio features with the help of PHQ9 and GDS questionnaire.

Phase 1- Dataset Processing (DAIC Dataset):

The dataset is collected by the University of South California. This dataset contains video, audio and text features. It is used to study the dataset and give a model to identify if person is depressed or not on the basis of modalities defined in the dataset. The processing is done on data of 30 subjects having text, audio and video modalities.

Phase 2 – Web Application:

This phase contains a web application built using web3 technology. A front-end hosted using a local server. PHP is used as a backend technology to store the data related to text and processing it in describing mood of the user.

- **Module 1 – Questionnaire-based assessment**

The user logs into the system and responds to the PHQ-9 questionnaire's questions. The score is totaled, and the degree of depression is defined using the score range in Table 1.

- **Module 2 – Speech to text conversion**

The audio is taken as an input where speech is converted to text. For this purpose Geriatric Depression Scale is used as questions. The answers are stored for further processing the result. A set of words is defined for each of the following classes (emotions); as Happy, Excite, Sad and Nervous. For conversion purpose, Google provides an API called the Google Cloud Speech-to-Text API that can be used to transcribe audio into text.

4. Methodology

The main objective is to create a model that can offer a visual user interface for analysis. As a result, the inputs are divided into two categories: Textual input, such as responses to inquiries posed to a user from the platform from which the audio is separated.

a) Text Analysis: The pipeline for text-based personality identification is organized as follows:
- o Data retrieval from text
- o Individualized natural language processing (NLP)
- o Absence of punctuation
- o Reducing the tokens value
- o Deletion of designated stop-words
- o Part-of-speech tags are applied to the remaining tokens
- o Token lemmatization using part-of-speech markers for improved accuracy
- o To limit the form of the input vectors, pad the character sequences of each page
- o 300-dimension Word2Vec embedding that can be trained
- o Utilizing trained model, make predictions

b) Audio Analysis: This is how the voice emotion recognition pipeline is created:
- o Voice capture
- o Discrete audio signal processing
- o Audio to text convert using Google API

5. Result and Analysis

In Phase 1, the results are calculated by taking a weighted mean of the two classes, i.e. class 0 is not depressed and class 1 is depressed. The data is provided in the ratio 7:3. The database, the Distress Analysis Interview Corpus i.e. DAIC consists of medical interviews which are designed to support the diagnostic assessment of psychological disorders. They were gathered for an aspect of a wider project for development of an artificial intelligence (AI) robot that can conduct interviews and spot verbal and nonverbal signs of mental illness. In addition to detailed questionnaire responses, audio and video recordings were also made.

CNN Model - A CNN model with six layers is constructed, the first four of which had Max Pooling layers and convolution layers for the text, audio, and video modalities. The activation function of ReLU is used to create additional layer flattening and connectivity. The last layer made use of sigmoid activation. The results from the audio and visual modalities were still insufficient. The dataset is not well-classified by it.

BiLSTM model - Although the model performs well than CNN it is not able to learn much from the data.

LSTM (Sentence) - The results indicate that model works better than BiLSTM for all modalities combined. It is because gating only amplifies the most important features and others are discarded.

LSTM - gating (word) - The result for word-level LSTM is better than LSTM at sentence level but not as good as expected. The reason might be that on a word level, the model does not get the meaning of the conversation as much as it does on a sentence level.

LSTM - gating (sentence) - The result for sentence-level LSTM is best as compared to the other models. All modalities combined as well as considering two modalities at a time also give the better results. It might be because gating highlights only important features and at sentence level the context of sentences is understood by the model.

Model	Modality	Precision	Recall	F1 - Score
CNN	Audio	0.07	0.27	0.11
	Image/Video	0.07	0.27	0.11
LSTM (Sentence)	Text, Audio, Image/Video	0.61	0.21	0.312
LSTM - Gating (Sentence)	Text, Audio	0.68	0.7	0.69
	Text, Image/Video	0.66	0.68	0.67
	Text, Image/Video, Audio	0.63	0.61	0.62
LSTM - Gating (Word)	Text, Audio, Image/Video	0.60	0.42	0.49
BiLSTM (Word)	Text, Audio, Image/Video	0.68	0.17	0.272

Table 2. Performance Measures

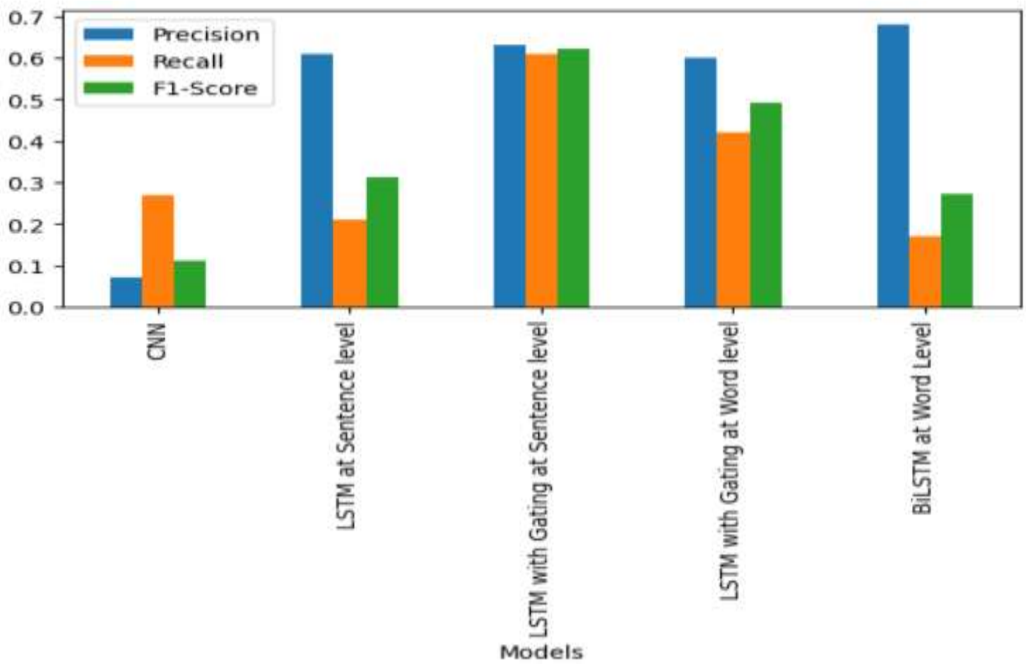

Fig 3. Bar graph depicting individual model's performance

6. Conclusion & Future Scope

A framework for evaluating a person's level of depression using linguistic, audio visual features is presented. It has been concluded in two parts as a result. A model for determining the chance that the subject is depressed based on labeling from audio, video, and textual modalities has been released for Phase 1. For the project, sentence-level architecture with a gating mechanism is set up. Models indicate that, when compared to the other techniques, sentence-level looks to do the best. A higher level of feature retrieval could be feasible in the future. To better understand the symptoms, several auditory metrics may be studied, such as reaction time, the frequency of pauses, speech modulation, and quiet rate.

For further work the image modality can be built. However, it also has a future scope in recording the electrophysiological signals from one's body. It can be emulated just like in an interview a person's body posture can be observed thus helping to diagnose better. While most seriously depressed patients refrain from talking much during the screening exam, some people tend to whine a lot even when they just have mild depression. Hence, it is still challenging to assess depression in early stages. These questionnaires can be helpful in detecting depression, but they should not be used as a substitute for a clinical diagnosis.

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