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Depression Analysis Using Facial Recognition, Speech and Questionnaires

Daksh Patel, Omkar Bhor, Het Patel, Deepak Shingade

Ms. Ekta Choudhari

ABSTRACT

Depression has long been a source of worry in our culture, and it has remained a hot issue for scholars all around the world. Depression is a common cause of mental illness that has been associated with an increased risk of dying early. Furthermore, it is a leading cause of suicide ideation and significantly impairs everyday functioning. Despite the vast amount of research on understanding individual moods, including depression, anxiety, and stress-related activity, Predicting emotions using these activity records collected by ubiquitous computing devices such as cellphones remains an unsolved task. In this project, we have proposed a system for detecting suicidal thoughts and analysing depression, for predicting suicidal acts based on the level of depression.

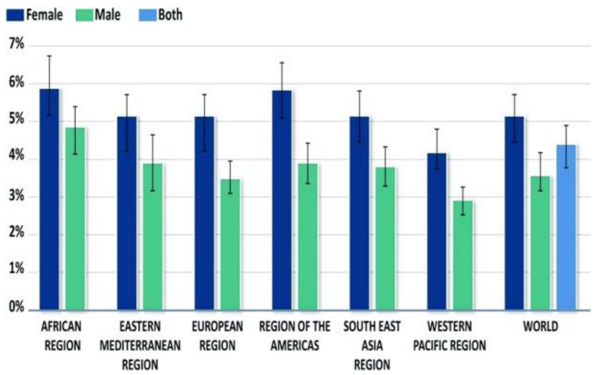
Keywords: Depression, Stress, Anxiety, Risk.

INTRODUCTION

Depression is a serious public health issue because of its frequency and, as a result, the misery, dysfunction, morbidity, and economic cost it causes. [1]. It's a serious enfeebling disorder that might have an effect on folks of all ages which might lead to low mood, feelings of guilt, insomnia, and cause problems like hurting chronic back pain, and bilateral medicine symptoms and might be fatal typically if left untreated. According to the World Health Organization (WHO), roughly 350 million human-being square units are suffering from depression nowadays [2]. United Nations agency ranks depression mutually of the foremost devastating diseases within the world [3]. Additionally, the two-third fraction of depressed folks does not look for applicable treatments, that cause major consequences. Medical science relies on asking the patients questions about their situations, which doesn't diagnose depression in a very precise way [4]. According to the Global Burden of Disease Study, if the current pace of change in mortality and disease patterns continues, depression would account for 5.7 percent of all disorders by 2022, and it will be the second greatest cause of disability globally, behind heart disease. With the ever-increasing threat of depression, there is a pressing need to create automatic approaches for detecting the existence and severity of depression and thereby preventing new occurrences from occurring. Therefore, the motivation of this paper, is to explore the whole different sources of information, like Facial Detection, Speech/Audio, and real-time data is collected from Questionnaires.

MOTIVATION:

The difficulty of detecting depression is one of the most pressing issues in psychology today. Depression is the world's fourth-leading disease and will be in the second in 2021 according to the statistics of the World Health Organization. Over 350 million people worldwide suffer from depression, which is about 5% of the total population. Close to 800 000 people die due to suicide every year and it is statistically the second leading cause of death among people 15–29 years old.

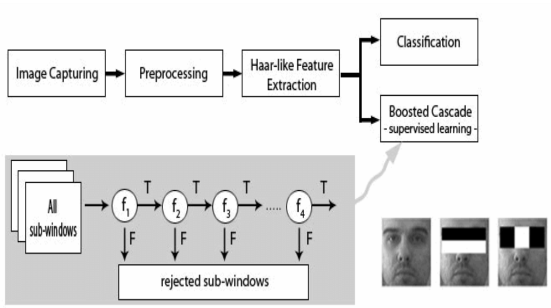


RELATED WORK

1. Automated Facial Expression Analysis of Neuropsychiatric Disorders Using Video.

Computers can automatically offer quantitative assessments of face expressions via automated facial expression analysis (AFEA). A number of things have contributed to the difficulty of AFEA. First, facial expressions vary across individuals due to the differences in the facial appearance, degree of facial plasticity, frequency of facial expressions, and morphology. Second, quantifying the strength of facial emotions is challenging, especially when they are mild. Many AFEA techniques have lately been developed to overcome such issues. Depending on the data utilized, these techniques can be classified as image-based, video-based, or 3D surface-based. We've outlined several common image- and video-based facial expression analysis methods below.

1.1 Image-Based Methods: By extracting attributes from individual photographs, image-based techniques involve classifiers to identify facial emotions. Geometric elements, texture traits, and their combinations are frequently used. Geometric aspects, such as the placements of the eyes and mouth, and the distance between two brows, reflect the spatial information of facial emotions. The geometric features used by Tian et al. are grouped into permanent and transient. Lips, eyes, brows, cheeks, and furrows are examples of permanent characteristics that have developed through time. Facial lines and furrows that are not present at rest but appear with facial emotions are among the transitory characteristics. The texture features include image intensity, image difference, edge, and wavelets. To determine subtle facial emotions, both major component features and image differences must be precisely aligned, which is not always attainable in real-world applications. Extracted characteristics are loaded into facial expression classifiers to detect facial expressions, Examples of facial expression classifiers are the Nearest Neighbor classifier, Neural Networks, SVM, Bayesian Networks, and AdaBoost classifier.



1.2 Video-Based Methods: It is claimed that temporal information can improve the accuracy of facial expression recognition by using static images. However, Only a few video-based approaches that leverage the temporal information of face expressions have been created. The work of each facial expression is divided into three segments: the beginning, the apex, and the ending. A set of principles determines the temporal model of facial expressions. Ad hoc principles like this can't be applied to complicated circumstances.

How to maintain precise tracking throughout the video sequence is a crucial aspect of video-based approaches. Although it has been shown that a complex deformable model may enhance face tracking accuracy, which in turn improves facial expression analysis accuracy, there are no comprehensive experiments showing which deformable model is superior to the others. In summary, video-based methods can capture subtle changes and temporal trends of facial expression, which cannot be achieved by static image-based methods.

2. Using Questionnaires, a Machine Learning-based Depression and Anxiety Thoughts Detection System.

Depression studies came much earlier and were a major focus than that of the Internet. Detecting depression from documents, in particular, has become an increasingly important research area, with interesting methods and results reported for Facebook, Twitter, and various other forum posts. Based upon the questionnaire survey throughout the world, many widely-accepted ways and criteria have been developed. The questions either provide many answers with varying ratings or ask users to rate the severity of their problems. The severity of depression is determined using a total score scale.

Richardson's previous research looked at the performance characteristics and validity of the Patient Health Questionnaire - 9 Items (PHQ-9) as a depression screening tool for adolescents. Our system uses a questionnaire similar to PHQ-9 that is, an enhanced version of its which covers all aspects or factors and symptoms leading to depression. Inspired by the use of deep learning in detecting emotion, presented an approach to analyzing emotion as well depression state of the person based on deep learning. On visual data, they employed a 50-layer Deep residual Network, and on audio, they used a Convolution Neural Network (CNN).

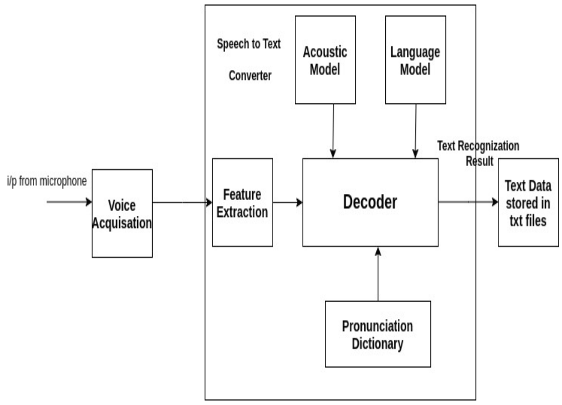
3. Human Clinical Depression Detection Using Sentiment Analysis.

Existing systems use mostly text data rather than voice data to accomplish sentiment analysis in each case scenario. This is capable of detecting the speaker's tone, but it has the problem of not being very useful in the detection of depression. This is because, in the case of depression, the amount of words said by the patient is critical, as is his tone, which can only be determined by his voice.

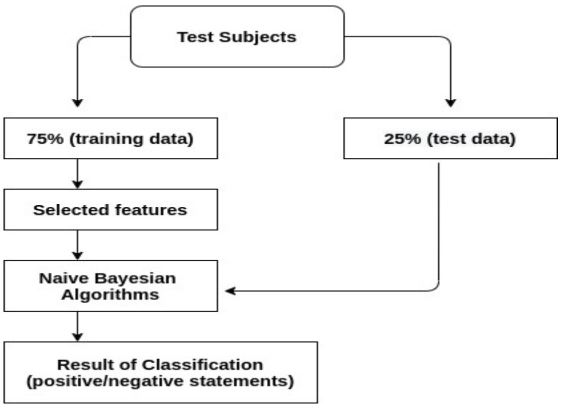
1. IN NATURALISTIC AUDIO, AUTOMATIC SENTIMENT DETECTION: Audio data is analyzed for sentiment using a number of realistic audio sources, such as YouTube. A second corpus named UT-Opinion was employed because Naturalistic Audio was used, which is audio that has not been converted into text for analysis. The approach utilized in this study is Key Word Spotting (KWS), It enhances accuracy by just looking for Key Words when processing audio The problem with this approach is that it uses realistic audio, which might result in a lot of unwanted noises, Multiple speakers can speak at the same time, and because the quantity of audio databases available for opinion mining is limited, creating a new audio corpus becomes a requirement.

A. AUDIO TO TEXT CONVERSION: With the assistance of the Google Speech API, this module turns audio input into text transcripts. Here, the features are extracted from the audio. That is, all extraneous sounds are eliminated, and just the essential (all) words are retrieved as characteristics. An acoustic model, a language model, and a pronunciation dictionary are used to decipher these sounds. These elements assist the decoder in determining aspects like language, slang, audio strength, and so on. These words are then saved as text files to be analyzed later. This is illustrated in Fig.1.

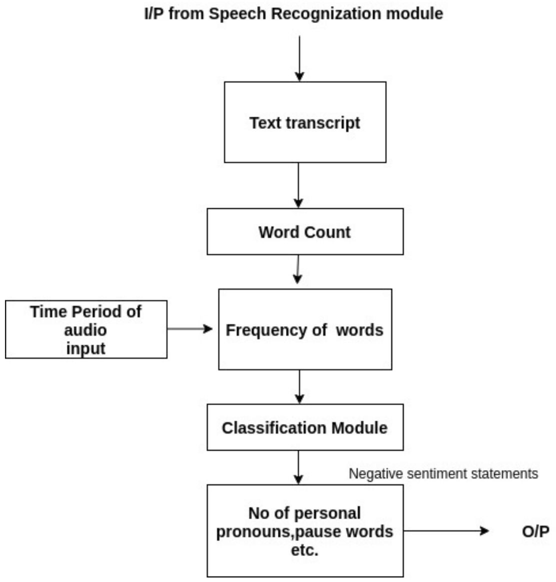
Fig. 1 Audio to the text conversion module



B. CLASSIFICATION OF TEXT USING NAÏVE BAYESIAN ALGORITHM: Using a naive Bayesian approach, this module classifies the text snippets as positive or negative. The test subjects are divided into training and test data at a ratio of 0.75:0.25, preferable. The model is trained by extracting pronouns, emotional words, and other essential properties. The test data is classified based on these results.



C. INTEGRATION WITH FREQUENCY FROM AUDIO INPUT: Furthermore, using the text transcript from the first module, the frequency of the words is determined. The number of words in this transcript are counted, as well as the time frame. These parameters help in deciding the average speed at which the patient speaks. This speed is a significant component in assessing the patient's anxiety level.



LIBRARIES: -

NumPy

- In Python, we have lists that serve the purpose of arrays, but they are slow to process.
- NumPy aims to make array objects 50 times faster than regular Python lists.
- NumPy arrays, unlike lists, are kept in a single continuous location in memory, allowing operations to access and manipulate them quickly. In computer science, this is referred to as the locality of reference..

Pandas

- Pandas is a widely used open-source Python tool for data science, data analysis, and machine learning.
- It's based on NumPy and allows you to work with multi-dimensional arrays.
- Pandas is interoperable with a broad range of other Python data science modules, being one of the most extensively used data-wrangling tools.

OpenCV

- OpenCV is a comprehensive open-source library for computer vision, machine learning, and image processing.
- OpenCV can process images and videos to identify objects, faces, or even the handwriting of a human.
- OpenCV is a cross-platform library using which we can develop real-time computer vision applications.

CV2

- OpenCV has a function to read video, which is cv2.
- OpenCV has a function to read video, which is cv2.VideoCapture().
- We may use the function parameter pass 0 to access our camera.

FUTURE WORK:

The model used in the project will be trained as it will be used more in the future. The more it gets trained, the better results we may obtain, so as to be more accurate. Also, we combine all three modules to get a better result.

CONCLUSION:

We proposed a system to detect depression from speech and Facial expressions and Questionnaires. The system effectively differentiates whether a person is depressed or not based on certain factors.

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