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Depression Disorder Detection Using Facial Expression and Text Mining on Recorded Social Media Videos

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Abstract: *Suicide is one of the most serious public health problems in modern culture. Thoughts of suicide, also known as suicidal thoughts, refer to people's suicidal plans. It can be used as a suicide risk measure. India is one of the top countries in the world with an annual suicide rate. Social networks have been developed as a first way to measure its users to connect with their interested friends and to rate their captions, photos, and videos that express their feelings, feelings and emotions. Enlarge and intensify the version that takes the form of facial images such as inserts and symbols. On the basis of what it predicts the patient's reputation whether or not he or she has not been diagnosed due to depression. We can train the translation using pictures and we will use it to predict. Image caption can be completed after predicting to get a higher visibility of the report. We will also use the text mining process (NLP) to predict the melancholy use of symbols provided with human assistance. Finally we are able to make the final choice primarily based on the two strategies above. Generate a detailed dashboard of user status and design webpage for an advanced program. We will use CNN's algorithm to accelerate the detection of depressed characters and how to know about high-quality responses to mental health problems. We propose a system learning approach as an effective and measurable method. We are writing the implementation of the proposed approach. We evaluated the effectiveness of our proposed approach to the use of a set of different aspects of mental language. We demonstrate that our proposed approach can significantly improve the accuracy and pricing of class errors.*

Keywords: Suicide rate, Emotions, Convolutional Neural Network.

I. INTRODUCTION

In the Indian way, suicide is a big problem. Suicide kills over lakh people (100,000) in our country each year. The suicide rate has risen from 7.9 to 10.3 per 100,000 over the past two decades. There are a variety of suicide rates in the world. Kerala, Karnataka, Andhra Pradesh, and Tamil Nadu are among the southern regions with the highest suicide rates.

For the past two decades, this trend has continued. High suicide rates in the southern states may be explained by higher education, a stronger reporting system, lower external violence, a higher socioeconomic status, and higher ambitions. The number of suicides in India has risen to 230,314 in 2016. Suicide was the leading cause of death in both 15-29 and 15-39 age groups. Every year, about 800,000 people commit suicide worldwide, of which 135,000 (17%) are Indian citizens, accounting for 17.5% of the world's population. "Suspended" suicide (53.6%), "poisoning" (25.8%), "drowning" (5.2%), and "immersion" (3.8%) were the most common forms of suicide throughout the year, according to the report.

According to a new study by the World Health Organization (WHO), India had the highest suicide rate in the Southeast Asian region in 2016. For the past three years, India's official statistics, showing the number and causes of suicide in the country. , have not yet been identified, disrupting suicide prevention strategies and efforts to enforce WHO recommendations in the region. The study used data from the 2016 WHO Global Health Estimates to present suicide rates nationally and regionally. India is a region of Southeast Asia and a region of the Lower Middle-Income countries in terms of region and revenue. The suicide rate in India (16.5) was higher than in the surrounding regions (13.4) and in the group of immigrants (16.5) (11.4).

1.1 Problem Statement

Designing a system that involves the removal of facial features, as well as the detection of pressure based on facial expressions using the Convolutional Neural Network (CNN) algorithm and separating positive and negative emotions and receiving pressure based on the normal limit value.

II. Literature Review

There is a growing body of research on stress factors [9 - 12]. Choudhury et al. [13] suggest that depression is a true measure of personal and social well-being. A large number of people suffer the negative effects of depression, but only a small percentage receive appropriate care each year. They also looked at the possibility of using social media to identify and evaluate any signs of severe depression in humans. They rated ethical credits associated with social interactions, emotions, dialect and semantic forms, self-explanatory system descriptions, and stress-relieving drug notes in their web-based writing.

Choudhury et al. [14] saw online communication as a promising public health tool, focusing on the use of Twitter to build predictable models on the effect of childbirth on the behavior and behavior of young mothers. They used a Twitter post to track 376 maternal changes in relation to communication, emotions, and information. [15] It has been found that Twitter is increasingly being investigated as a tool for diagnosing psychological problems. Depression and social ills are examples of poor mental health for many people It was discovered during their research that it is possible to determine the level of anxiety among people who want to commit suicide. Using both human codes and machine learning algorithm, we were able to find similar tweets. Organized computer class Several studies have shown that the optimal use of user-generated content (UGC) will help determine people's psychological well-being. Aldarwish and Ahmad [17], for example, have found that the use of Social Network Sites (SNS) is increasing these days, especially among younger generations.

Clients may share their wishes and feelings on social media because they are available. Using emotions, psycholinguistic processes, and drug titles extracted from posts produced by people from these groups, Nguyen et al. [20] used machine learning and mathematical methods to distinguish online messages between stress and control groups. Park et al. [21] look at people's attitudes and behaviors about web-based social networking sites to see if they are depressed. They organized slightly built one-person meetings with 14 active Twitter users, half of whom were depressed and the other was absent. Alternatively, they look at a number of ways to address potential communication strategies that may better suit depressed users and include information to help depressed users deal with their problems through web-based social networking sites [22].

Holleran [9] found the first evidence that depression has a significant impact on the global epidemic of Facebook. Wang et al. [19] and Shen et al. [25] looked at various stress-related factors and developed a multimodal stress model to identify depressed users.

While some of the research mentioned above looked at emotional processes, transient processes, and language style to diagnose depression, current literature has the following errors:

SVM, KNN, Decision Tree, and Ensemble have all been used independently in a few studies. There are no known studies that have investigated differences in strategic outcomes using both methods in the same database. Not many studies have used the above machine learning strategies to detect depression using Facebook data. To correct the above errors, we are trying to diagnose depression from Facebook comments on this page; we also increase access to stress measures based on social media by explaining the various aspects of Facebook user comments. We used machine learning methods to find depressed people using certain tests.

III. Methodology

In this project, Faces are filmed using a camera. This acquired face is processed and emotions are classified as positive or negative emotions. The obtained image is processed to identify the surface of the subject using the Convolutional Neural Network (CNN) algorithm.

The title of the subject is captured using the camera module. This acquired face is processed and emotions are classified as positive or negative emotions. The obtained image is processed to identify the surface of the subject using the Convolutional Neural Network (CNN) algorithm.

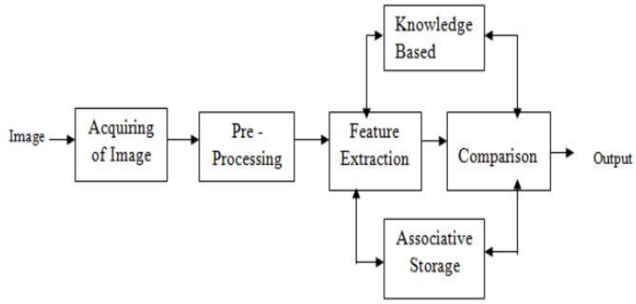

Figure: Methodology

3.1 Flowchart

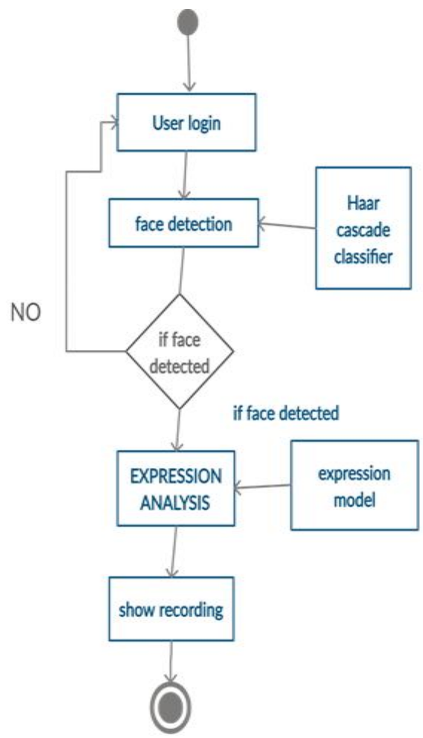

Figure: Flow of the system

IV. Conclusion

The prediction was successful compared to predicting test data from the same database used to train variants. However, the predictor remains poor in finding a statement associated with contempt. This may be due to a combination of lack of training and test images that clearly show contempt, poor labeling of previous data training, and internal difficulties in identifying contempt. The class divider also fails to predict the sensitivity of the test data to not only one of the seven key expressions, as they are not trained in other expressions. Future work should include improving the strength of class dividers by adding more training images from different data sets, investigating more accurate detection methods that still maintain mathematical performance, and considering classification of friendly and complex expressions.

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