International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 05 Issue: 05 | May - 2021 ISSN: 2582-3930

Depression Detection On Social Media Data Using Naive Bayes, CNN And Flask

Sumit Pandilwar[1], Rahul Shinde[2], Utkarsh Shinde[3], Priyanka Misal[4], Prof. Sabanaz Peerzade[5]

[1234]*B.E. Student, Dept of Computer Engineering, Sinhgad College of Engineering, Vadgaon, Pune-411041, Maharashtra, India*

[5]*Assistant Professor, Dept of Computer Engineering, Sinhgad College of Engineering, Vadgaon, Pune-411041, Maharashtra, India*

---***---

Abstract - India is among the top countries among in the world to have annual suicide rate. Social networks have been developed as a first-rate factor for its users to communicate with their interested buddies and proportion their captions, photos, and videos reflecting their moods, emotions and sentiments. To increase and put in force a version which takes a facial expression images as an enter and symptoms. Based on that it predicts the repute of that patient whether he/she has been detected or now not detected for depressed. We can train version using photographs & will use it for prediction. Image captioning can be accomplished after prediction for higher visualization of report. We will also use text mining (NLP) technique to predict melancholy the usage of signs furnished with the aid of person. At final we can make final choice primarily based on above two techniques. To generate detailed dashboard of user disease status and to design webapp for above system. We will use CNN algorithm for speed up detection of depressed character instances and approach to become aware of high-quality answers of mental health troubles. We suggest system learning method as an efficient and scalable technique.

***Key Words*:** Suicide rate, Emotions, Convolutional Neural Network.

1.INTRODUCTION

In the Indian sense, suicide is a serious problem. Suicide claims the lives of over one lakh (one hundred thousand) people in our country each year. The suicide rate has risen from 7.9 to 10.3 per 100,000 in the last two decades. Within the world, there is a wide range of suicide rates. Kerala, Karnataka, Andhra Pradesh, and Tamil Nadu are among the southern states with the highest suicide rates.

Over the past two decades, this variable trend has remained consistent. Higher suicide rates in the southern states may be explained by higher literacy, a stronger reporting system, lower external violence, higher socioeconomic status, and higher aspirations. The number of suicides in India rose to 230,314 in 2016. Suicide was the leading cause of death in both the 15-29- and 15-39-year age groups. Every year, approximately 800,000 people die by suicide around the world, with 135,000 (17%) of these being citizens of India, which accounts for 17.5 percent of the global population. Suicide by "hanging" (53.6%), "eating poison" (25.8%), "drowning" (5.2%), and "self-immolation" (3.8%) were the most common methods of suicide throughout the year, according to the report.

According to a new World Health Organization (WHO) survey, India had the highest suicide rate in the South-East Asian region in 2016. For the past three years, India's own official statistics, which map the number and causes of suicides in the country, have been unavailable, hampering suicide prevention strategies and efforts to enforce WHO recommendations in this region. The study used data from the WHO Global Health Estimates for 2016 to present suicide rates for countries and regions. India belongs to the South-East Asia region and the Lower Middle-Income category of countries when ranked by region and income. India's suicide rate (16.5) was higher than its geographic region's (13.4) and income group's (16.5) rates (11.4).

1.1 Problem Definition

To design system which involves extraction of facial features, and detection of stress using emotions expressed through face using the Convolutional Neural Network (CNN) algorithm and classify positive and negative emotions and detects the stress based on usual threshold value.

2. LITERATURE SURVEY

There is a growing body of research on the characteristics of depression [9–12]. Choudhury et al. [13] suggest that depression is a true measure of one's own and society's well-being. Many people suffer from the negative effects of depression, but only a small percentage receives adequate care each year. They also looked into the possibility of using social media to detect and assess any signs of serious depression in people. They quantified behavioral credits associated with social interaction, feeling, dialect and semantic types, meaning of the self-system, and notes of antidepressant drugs via their web-based social networking postings.

Choudhury et al. [14] saw online networking as a promising tool for public health, focusing on the use of Twitter to construct predictive models about the effect of childbirth on new mothers' behavior and disposition. They used Twitter posts to track 376 mothers' postpartum changes in terms of social interaction, feelings, and information. [15] Found that Twitter is increasingly being investigated as a tool for detecting psychological issues. Depression and sociality are examples of poor mental health in the general population It was discovered during their investigation that it is It's possible to determine the extent of anxiety among suicidal people. Using both human coders and a machine learning algorithm, we were able to find similar tweets. Computer classifier that has been programmed Many studies have shown that properly using user-created content (UGC) will aid in determining people's psychological well-being. Aldarwish and Ahmad [17], for example, found that the use of Social Network Sites (SNS) is increasing these days, particularly among the younger generations.

Clients may share their desires and feelings on social media sites because they are available. Using mood, psycholinguistic processes, and drug subjects omitted from the posts generated by individuals from these groups, Nguyen et al. [20] used machine learning and statistical techniques to distinguish online messages between depression and control groups. Park et al. [21] looked at people's attitudes and behaviors toward online web-based social networking to see whether they were discouraged or not. They arranged semi-structured one-on-one meetings with 14 active Twitter users, half of whom were discouraged and the other half were not. Aside from that, they looked at a few strategy implications for potential social networks that could better suit users with depression and include information to help discouraged users deal with their problems through online web-based social networking [22].

Holleran [9] discovered preliminary evidence that depression is a major contributor to the overall global burden of diseases by Facebook mining. Wang et al. [19] and Shen et al. [24] looked at a variety of depression-related characteristics and developed a multimodal depressive model to identify depressed users.

While some of the above-mentioned research has looked at emotional processes, temporal processes, and linguistic style to diagnose depression, the current literature has the following flaws:

SVM, KNN, Decision Tree, and Ensemble have all been used independently in a few studies. There are no well-known studies that have investigated the differences in technique-based results using both methods on the same dataset. There has been no substantial study that has used the above-mentioned machine learning techniques to detect depression using Facebook data. To fix the above flaws, we attempt to diagnose depression from Facebook comments in this paper; we also broaden the reach of social media-based depression measures by explaining the various characteristics of Facebook user comments. We used machine learning methods to detect individuals suffering from depression using certain tests.

3. METHODOLOGY

In this project, Face is captured using the camera. This detected face is processed, and the emotions are classified as either positive or negative emotions. The detected image is processed to identify the face of the subject using Convolutional Neural Network (CNN) algorithm.

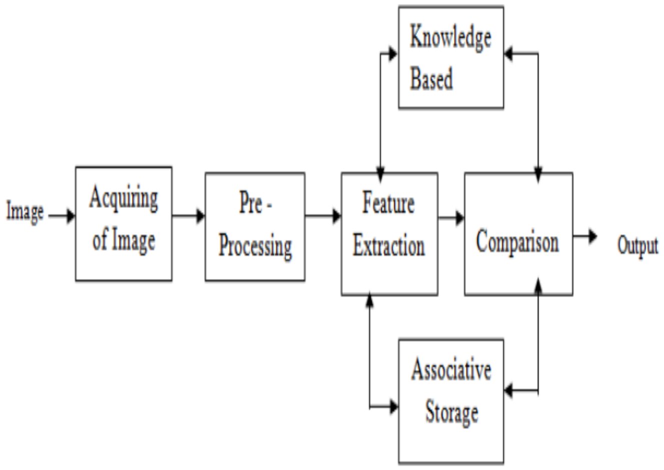

Fig-1: Methodology

Face of the subject is captured using the camera module. This detected face is processed, and the emotions are classified as either positive or negative emotions. The detected image is processed to identify the face of the subject using Convolutional Neural Network (CNN) algorithm.

3.1 Flowchart

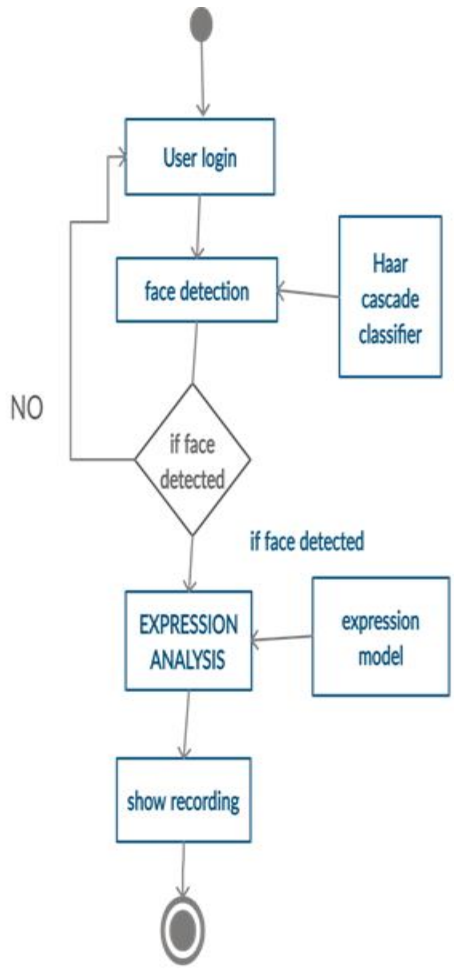

Fig-2: Flow of the system

4. CONCLUSIONS

The predictor is relatively successful at predicting test data from the same dataset used to train the classifiers. However, the predictor is consistently poor at detecting the expression associated with contempt. This is likely due to a combination of lacking training and test images that clearly exhibit contempt, poor pre-training labelling of data, and the intrinsic difficulty at identifying contempt. The classifier is also not successful at predicting emotions for test data that have expressions that do not clearly belong exclusively to one of the seven basic expressions, as it has not been trained for other expressions. Future work should entail improving the robustness of the classifiers by adding more training images from different datasets, investigating more accurate detection methods that still maintain computational efficiency, and considering the classification of more nuanced and sophisticated expressions.

5. REFERENCES

[1] Scott J. Social network analysis. Thousand Oaks: Sage; 2017.

[2] Serrat O. Social network analysis. In: Knowledge solutions. Singapore: Springer; 2017. p. 39–43.

[3] Mikal J, Hurst S, Conway M. Investigating patient attitudes towards the use of social media data to augment depression diagnosis and treatment: a qualitative study. In: Proceedings of the fourth workshop on computational linguistics and clinical psychology—from linguistic signal to clinical reality. 2017.

[4] Conway M, O'Connor D. Social media, big data, and mental health: current advances and ethical implications. Curr Opin Psychol. 2016; 9:77–82.

[5] Ofek N, et al. Sentiment analysis in transcribed utterances. In: Pacific-Asia conference on knowledge discovery and data mining. 2015. Cham: Springer.

[6] Yang Y, et al. User interest and social influence based emotion prediction for individuals. In: Proceedings of the 21st ACM international conference on Multimedia. 2013. New York: ACM.

[7] Tausczik YR, Pennebaker JW. The psychological meaning of words: LIWC and computerized text analysis methods. J Lang Soc Psychol. 2010;29(1):24–54.

[8] Pennebaker JW, Francis ME, Booth RJ. Linguistic inquiry and word count: LIWC 2001, vol. 71. Mahway: Lawrence Erlbaum Associates; 2001. p. 2001.

[9] Holleran SE. The early detection of depression from social networking sites. Tucson: The University of Arizona; 2010.

[10] Greenberg LS. Emotion-focused therapy of depression. Per Centered Exp Psychother. 2017;16(1):106–17.

[11] Haberler G. Prosperity and depression: a theoretical analysis of cyclical movements. London: Routledge; 2017.

[12] Guntuku SC, et al. Detecting depression and mental illness on social media: an integrative review. Curr Opin Behav Sci. 2017;18:43–9.

[13] De Choudhury M, et al. Predicting depression via social Media. In: ICWSM, vol. 13. 2013. p. 1–10.

[14] De Choudhury M, Counts S, Horvitz E. Predicting postpartum changes in emotion and behavior via social media. In: Proceedings of the SIGCHI conference on human factors in computing systems. New York: ACM; 2013.

[15] O'Dea B, et al. Detecting suicidality on Twitter. Internet Interv. 2015;2(2):183–8. Signs Symptoms Behaviour Not going out any longer Not completing things at work Not doing regular charming exercises Unfit to focus Feelings Overwhelmed Blameworthy Irritate Disappointed Unlucky Worried Thoughts He is winner It's my pleasure Nothing good ever happens to me He was unlucky Life is not the bed of roses He would not be able to work without me Physical Tired Illness Headaches Depression problem Misfortune Islam *et al. Health Inf Sci Syst (2018).*

[16] Zhang L, et al. Using linguistic features to estimate suicide probability of Chinese microblog users. In: International conference on human centered computing. Berlin: Springer; 2014.

[17] Aldarwish MM, Ahmad HF. Predicting depression levels using social media posts. In: 2017 IEEE 13th international Symposium on Autonomous decentralized system (ISADS). 2017.

[18] Zhou J, et al. Measuring emotion bifurcation points for individuals in social media. In: 2016 49th Hawaii international conference on system sciences (HICSS). 2016. Koloa: IEEE.

[19] Wang X, et al. A depression detection model based on sentiment analysis in micro-blog social network. In: Trends and applications in knowledge discovery and data mining (PAKDD). 2013.

[20] Nguyen T, et al. Affective and content analysis of online depression communities. IEEE Trans Affect Comput. 2014;5(3):217–26.

[21] Park M, McDonald DW, Cha M. Perception differences between the depressed and non-depressed users in Twitter. In: ICWSM, vol. 9. 2013. p. 217–226.

[22] Wee J, et al. The influence of depression and personality on social networking. Comput Hum Behav. 2017;74:45–52.

[23]. Bachrach Y, et al. Personality and patterns of Facebook usage. In: Proceedings of the 4th annual ACM web science conference. 2012. New York: ACM.

[24] Shen G, et al. Depression detection via harvesting social media: A multimodal dictionary learning solution. In: Proceeding of the twenty-sixth international joint conference on artificial intelligence (IJCAI-17). 2017. p. 3838–3844.