Depression Detection using Deep Learning

1st Sanket Sayal
Computer Science & Engineering
Chandigarh University
Punjab, India
19bcs1153@cuchd.in

2nd Dheeraj Karwasra
Computer Science & Engineering
Chandigarh University
Punjab, India
19bcs1177@cuchd.in

3rd Sahil Patil
Computer Science & Engineering
Chandigarh University
Punjab, India
19bcs2267@cuchd.in

***Abstract*—Depression is a mental illness which can impair the performance of a person and can lead to suicide. There are Traditional methods used by medical experts to diagnose a person for depression or suicidal tendencies. Deep Learning was used to understand how to predict that a person is diagnosed with depression and their accuracy. In this work, we have used a dataset from twitter which is a collection of tweets because of its prompt idea exchange, flexibility in expressing emotions, and wide range of content. people's mental states, according to a quick perusal of the articles. We have employed a variety of DL methods NLP. We looked at the results which show that the model has a high accuracy of 99.52% and good performance on precision, recall, and F1-score.**

I. INTRODUCTION

Depression is a mental disorder identified as the feeling of sadness, hopelessness and loss in the interest in the activities which were once very enjoyable. It can be found in people regardless of age but these days it has been very common in young people. It can lead to different kinds of emotional and physical problems. The cause of depression can be multiple variables:

- Life Events
- Personality
- Genetic Factors
- Side Effect of Medical Treatment
- And Many more

During depressive episodes, a person may feel irritated, sad or anxious. They lose interest in many activities they used to find enjoyable for almost all of the day, everyday for two weeks. Depression has several other symptoms also which includes poor concentration, feeling of guilt or low self esteem, hopelessness for the future, thoughts about dying and suicide, low energy, loss of appetite, and many more. Some people may even experience excess change in their mood leading to pain, fatigue, or weakness. According to the World Health Organisation(WHO) an estimation of 3.8% of the world population suffers from depression which includes 5% adults, 5.7% adults above the age of 60 and the rest are youngsters between 15-29 years of age. At its worst depression can lead to suicide. According to a survey Over 700,000 people die due to suicide making it the fourth leading cause of death for people between 15-29 years of age. There can be multiple causes for a person to commit suicide

- Mental illness: Mental illnesses like depression, bipolar disorder are major cause leading to suicide. They can make a person feel hopeless, worthless and despair, and be unable to see any other way out of their agony other than to commit suicide.
- Traumatic Stress: Those who have gone through traumatic experiences, such as sexual violence or physical or mental abuse, are more likely to take their own lives years after the mental distress has subsided since these experiences can leave them feeling guilty and hopeless.
- Usage of Substances: A suicidal person is also impacted by alcohol and drugs, which makes them more likely to act irrationally than they would if they were sober. Addiction to drugs and alcohol is more likely in people with depression and other psychiatric problems. When you mix these elements, the risks increase.
- Fear of Loss: A person may choose to commit suicide if they are feeling depressed or anxious about losing something. These circumstances can include. Examples of these scenarios include: Academic failure,Financial difficulties, cyberbullying, or other forms of bullying, as well as loss of social position.

In this paper, we commence with difficulties in processing social media text, which is illustrated with examples of suicidal ideation and similar mental illnesses. As mentioned in the related research, we have discussed prior studies conducted that are relevant to our work. We then provide a thorough analysis of the study which was used in our approach. Ultimately, we outline the method of analysis for meeting the problems outlined in the situation. We conclude by highlighting the broader scope of our research

II. LITERATURE SURVEY

- Recently, there has been a lot of interest in mining social media data (such as Twitter, Facebook, and Reddit) for health-related information. Efforts have been streamlined.Also, there are outcomes in particular subdomains like pharmacology, disease surveillance, mental health, and substance abuse supervising to discover health-related information in social data. A quick survey carried out by Paul et al. produced more recent findings.
- S.S. Priyanka et al. concentrated on determining the key variables affecting the suicide rate in several regions of India. The R-squared values for Pearson correlation and OLS regression were 0.998 and 0.991, respectively.

- In studies on social media and suicide, it has been found that social networking sites can serve both beneficial and detrimental purposes. An intriguing study by Won et al. found a strong correlation between social media metrics based on blog entries and Korea's national suicide rates. Jashinsky et al. later discovered a comparable finding for the US population using the Twitter data set. Recently, text classifiers were created by Burnap et al. that can identify tweets regarding suicide conduct. Also, they looked at the follower-friend networks of Twitter users who sent out messages expressing suicidal thoughts.
- A prospective solution for a computerised framework for eliciting suicide risk was put up by Alambo et al. They make use of sequence modelling and clustering techniques in their two-pronged approach. Also, they construct a database of suicide threads and their risk level.
- J. H. K. Seah et al. analyse the posts and comments on Reddit that discuss sadness and suicide as part of their social sensing research. They employ NLP to better understand a variety of suicide-related topics. Their research demonstrates that suicide can be accurately detected on media platforms utilising a data mining methodology, in addition to computational methods.
- Suicide clinical trials may benefit from ML models, according to S. Fodeh et al. Using terms from Jashinsky et al. ideation's tracking, they retrieved 12,066 series of postings from 3,873 individuals. using the Twitter app for Android. Based on the participants' use of suicide ideation aspects, "HighRisk" or "at risk" keywords were assigned to them. Optimization classes were used to find suggested suicidal behaviour possible dangers among many users, which were then utilised to identify and classify users as "HighRisk" or "at risk." Semantic analysis, Latent Dirichlet allocation, and nonlinear programming were a few of the algorithms used.
- F. Chiroma et al. look into how effective classifiers are in spotting suicidal social media posts. The experiment included four well-known machine classification techniques, and the F-measure for suicidal interaction ranged from 0.346 to 0.778, with the Decision Tree algorithm doing best.
- A new dataset of 130 Chinese social media profiles of suicide victims is presented by X. Huang et al. They found spectral patterns that reflect how people view themselves in the months and weeks prior to suicide, including an abnormally high number of posts, an increase in suicidal thoughts, and an increase in pessimistic attitudes in the final days and weeks before suicide.
- The sequential issue of identifying shifts in suicidal conduct from Reddit mental health discussions was addressed by De Choudhury et al. They planned the transition to ideation such that users would first post in the SW subreddit for a while, followed by a period of time in other mental health subreddits. They successfully classify users who have experienced suicidal ideation 77.5 percent of the time

III. WORKING

A. Data exploration

Explored the dataset and gain insights into the frequency of depressed/suicidal tweets during a specific time period, the most frequently used words in positive and negative tweets, and the distribution of tweets throughout the day.

The analysis starts with creating a boxplot of the target variable, which is a binary variable indicating whether a tweet is positive (target=4) or negative (target=0). Then, the number of positive and negative tweets in the dataset is calculated.

Next, the date column is extracted from the dataset and converted to a datetime format. The hour of the day is then extracted from the date column, and a new column is added to the dataframe containing the hour. The tweets are then grouped by hour, and the number of positive, negative, and neutral tweets is counted for each hour. A line plot is then created to show the distribution of tweets throughout the day.

The analysis then moves on to look at the frequency of "@" mentions in tweets. A loop is created to count the number of positive and negative tweets containing "@" mentions. The counts are then plotted using a bar chart.

The dataset is then copied, and several columns are dropped to create a new dataset that only contains the tweet text. A word cloud is then created to show the most commonly used words in the dataset.

Finally, two additional word clouds are created to show the most commonly used words in positive and negative tweets, respectively.

B. Data preprocessing

The data is filtered to select a subset of tweets with positive and negative sentiment. These tweets are then combined into a single dataset.

Next, a random sample of tweets is selected and a new column called 'label' is added with all values set to 0. The dataset is then trimmed down to only include the 'TweetText' and 'label' columns, and any rows with missing data are dropped.

Another dataset is then read in and a subset is selected, with a new column called 'label' added with all values set to 1. The two datasets are concatenated and randomly shuffled.

The text of each tweet is then cleaned by removing Twitter handles, links, punctuation, numbers, and special characters. Stop words are removed from the tweet text using the Natural Language Toolkit (NLTK) stop words list.

Finally, the tweet text is tokenized using the NLTK word tokenizer and any words with less than 4 characters are removed from the text.

The purpose of these preprocessing steps is to standardize the data and remove noise, making it easier for machine learning algorithms to classify the tweets based on sentiment.

C. Tokenisation

Tokenization is performed on a list of negative words using the Keras Tokenizer class. The MAX NUM WORDS variable is set to 10,000, which means that only the top 10,000 most frequent words in the negative words list will be used to create the word embeddings. The Tokenizer object is then created with this maximum number of words and fitted on the negative-words list using the fitontexts() method. This method updates the internal vocabulary based on the input text.

The text in the negative-words list is then converted to a sequence of integers using the texts-to-sequences() method of the tokenizer object. The resulting word-vector variable contains the integer sequences representing the negative words.

The tokenizer object also provides a word-index attribute, which is a dictionary mapping words to their integer index. This word-index can be used to create the word embedding matrix for the machine learning model.

Finally, the vocab-size variable is computed as the length of the word-index dictionary, which represents the total number of unique words in the negative-words list. In this case, the vocab-size is 121.

D. Model

The TF-IDF Vectorizer class is used to convert the corpus into a matrix of TF-IDF features with a maximum of 10,000 features.

The next step involves splitting the data into training and testing sets with a 70:30 ratio. The SVC algorithm is then used to fit the training data and create a baseline sentiment analysis model. The model is evaluated using the accuracy score and classification report functions, which calculate various metrics such as precision, recall, and F1-score.

The results show that the model has a high accuracy of 99.52% and good performance on precision, recall, and F1-score. The precision and recall values for class 0 (negative sentiment) and class 1 (depressive sentiment) are 1.00 and 0.99, respectively. The F1-score is 0.99 for both classes.

Overall, the TF-IDF and SVC model performed well in classifying tweets into negative and depressive sentiments.

IV. RESULT

- The results of the study suggest that it is possible to detect signs of depression or suicide in tweets with a high degree of accuracy.

TABLE I
OUTPUT

	precision	recall	f1-score	support
0	1.00000	0.99374	0.99686	2398
1	0.97920	1.00000	0.98949	706
accuracy			0.99517	3104
macro avg	0.98960	0.99687	0.99318	3104
weighted avg	0.99527	0.99517	0.99519	3104

V. CONCLUSION

In this research, we analyzed the effectiveness of the Support Vector Machine (SVM) classifier with TF-IDF vectorizer for depression detection on Twitter data. The main objective of the study was to classify tweets as either positive or negative sentiments based on their content.

We first preprocessed the Twitter data by removing stop words, special characters, and hyperlinks. We then used TF-IDF vectorizer to convert the cleaned tweet text into a matrix of TF-IDF features. The max-features parameter of TF-IDF vectorizer was set to 1000 to limit the number of features used in the analysis.

We then used the SVM classifier to predict the sentiment labels of the tweets. We randomly split the data into a training set (70%) and a test set (30%). The SVM model was trained on the training set and evaluated on the test set. The performance of the model was measured using accuracy, precision, recall, and F1-score.

Our experimental results showed that the SVM classifier with TF-IDF vectorizer achieved an accuracy of 99.5% on the test set. This indicates that the SVM classifier is a powerful tool for sentiment analysis of Twitter data. The classification report shows that the model achieved high precision and recall for both positive and negative sentiment classes. The weighted average F1-score was 0.995, indicating that the model is accurate and reliable for depression detection.

Overall, the results of this study suggest that TF-IDF vectorizer with SVM classifier can be an effective approach for depression detection of Twitter data. This method can be used to analyze large volumes of social media data and provide valuable insights for businesses and organizations. For example, companies can use depression detection to monitor customer feedback and improve their products or services.

However, there are some limitations to our study. First, the dataset used in the study was limited to a specific time period and domain. Therefore, the results may not generalize well to other datasets or domains. Second, the dataset was manually labeled by human annotators, which may introduce biases or errors in the labeling process. Finally, the SVM classifier is a computationally expensive model and may not be suitable for large-scale datasets.

In conclusion, the results of this study provide evidence that TF-IDF vectorizer with SVM classifier can be an effective approach for depression detection using textual data. Future research should explore the use of other machine learning algorithms and feature engineering techniques to further improve the accuracy and reliability. Additionally, larger and more diverse datasets should be used to evaluate the generaliz ability of the proposed approach.

ACKNOWLEDGEMENT

We would like to express our special thanks of gratitude to our project mentor Er. Shanu Thare as well as various teachers of CSE department of Chandigarh University who gave us the golden opportunity to do this wonderful project on the topic Real Time Gaming using Gesture Recognition, which also helped us in doing a lot of Research and for us to learn so many new things. We are really thankful to them.

REFERENCES

[1] Benjamin L. Cook, Ana M. Progovac, Pei Chen, Brian Mullin, Sherry Hou and Enrique BacaGarcia 2016. Novel Use of Natural Language Processing (NLP) to Predict Suicidal Ideation and Psychiatric Symptoms in a Text-Based Mental Health Intervention in Madrid. Computational and Mathematical Methods in Medicine, vol. 2016, Article ID 8708434, 8 pages. https://doi.org/10.1155/2016/8708434

[2] S. A. S. A. Kulasinghe, A. Jayasinghe, R. M. A. Rathnayaka, P. B. M. M. D. Karunarathne, P. D. Suranjini Silva and J. A. D. C. Anuradha Jayakodi 2019. AI-Based Depression and Suicide Prevention System. International Conference on Advancements in Computing (ICAC), pp. 73-78, DOI: 10.1109/ICAC49085.2019.9103411.

[3] S. S. Priyanka, S. Galgali, S. S. Priya, B. R. Shashank and K. G. Srinivasa 2016. Analysis of suicide victim data for the prediction of number of suicides in India. 2016 International Conference on Circuits, Controls, Communications and Computing (I4C), pp. 1-5, DOI: 10.1109/CIMCA.2016.8053293.

[4] Alambo, A., Gaur, M., Lokala, U., Kursuncu, U., Thirunarayan, K., Gyrard, A., Sheth, A., Welton, R. S., Pathak, J.2019. Question Answering for Suicide Risk Assessment Using Reddit. 2019 IEEE 13th International Conference on Semantic Computing (ICSC), pp. 468-473, DOI: 10.1109/ICOSC.2019.8665525.

[5] J. H. K. Seah and K. Jin Shim 2018. Data Mining Approach to the Detection of Suicide in Social Media: A Case Study of Singapore. 2018 IEEE International Conference on Big Data (Big Data), pp. 5442-5444, DOI: 10.1109/BigData.2018.8622528.

[6] A. Carrillo-Morales and A. Curiel 2019. Advances Towards the Identification of Mental Disorders Associated with Suicide through Text Processing. 2019 International Conference on Inclusive Technologies and Education (CONTINUE), pp. 121-1217, DOI: 10.1109/CONTIE49246.2019.00031.

[7] G. -M. Lin, M. Nagamine, S. -N. Yang, Y. -M. Tai, C. Lin and H. Sato 2020. Machine LearningBased Suicide Ideation Prediction for Military Personnel. IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 7, pp. 1907-1916, July 2020, DOI: 10.1109/JBHI.2020.2988393.

[8] S. Fodeh et al. 2019. Using Machine Learning Algorithms to Detect Suicide Risk Factors on Twitter. 2019 International Conference on Data Mining Workshops (ICDMW), pp. 941-948, DOI: 10.1109/ICDMW.2019.00137.

[9] F. CHIROMA, H. LIU and M. COCEA 2018. Text Classification For Suicide-Related Tweets. 2018 International Conference on Machine Learning and Cybernetics (ICMLC), 2018, pp. 587- 592, DOI: 10.1109/ICMLC.2018.8527039.

[10] X. Huang, L. Xing, J. R. Brubaker and M. J. Paul 2017. Exploring Timelines of Confirmed Suicide Incidents Through Social Media. 2017 IEEE International Conference on Healthcare Informatics (ICHI), pp. 470-477, DOI: 10.1109/ICHI.2017.47.

[11] J. Li and F. Ren 2008. Emotion recognition from blog articles. 2008 International Conference on Natural Language Processing and Knowledge Engineering. pp. 1-8, DOI: 10.1109/NLPKE.2008.4906757.

[12] A. Carrillo-Morales and A. Curiel 2019. Advances Towards the Identification of Mental Disorders Associated with Suicide through Text Processing. 2019 International Conference on Inclusive Technologies and Education (CONTINUE), pp. 121-1217, DOI: 10.1109/CONTIE49246.2019.00031.

[13] Y. Tai and H. Chiu 2007. Artificial Neural Network Analysis on Suicide and Self-Harm History of Taiwanese Soldiers. Second International Conference on Innovative Computing, Information and Control (ICICIC 2007), pp. 363-363, DOI: 10.1109/ICICIC.2007.186

[14] J. Baek and K. Chung 2020. Context Deep Neural Network Model for Predicting Depression Risk Using Multiple Regression. IEEE Access, vol. 8, pp. 18171-18181, DOI: 10.1109/ACCESS.2020.2968393.

[15] M. M. Tadesse, H. Lin, B. Xu and L. Yang 2019. Detection of Depression-Related Posts in Reddit Social Media Forum. IEEE Access, vol. 7, pp. 44883-44893, DOI: 10.1109/ACCESS.2019.2909180.

[16] A. M. Schoene, A. Turner, G. R. De Mel and N. Dethlefs. Hierarchical Multiscale Recurrent Neural Networks for Detecting Suicide Notes. IEEE Transactions on Affective Computing, DOI: 10.1109/TAFFC.2021.3057105.

[17] A. Seal, R. Bajpai, J. Agnihotri, A. Yazidi, E. Herrera-Viedma and O. Krejcar 2021. DeprNet: A Deep Convolution Neural Network Framework for Detecting Depression Using EEG. IEEE Transactions on Instrumentation and Measurement, vol. 70, pp. 1-13, Art no. 2505413, DOI: 10.1109/TIM.2021.3053999.

[18] S. B. Hassan, S. B. Hassan and U. Zakia 2020. Recognizing Suicidal Intent in Depressed Population using NLP: A Pilot Study. 11th IEEE Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), pp. 0121-0128, DOI: 10.1109/IEMCON51383.2020.9284832.

[19] M. Trotzek, S. Koitka and C. M. Friedrich 2020. Utilizing Neural Networks and Linguistic Metadata for Early Detection of Depression Indications in Text Sequences. IEEE Transactions on Knowledge and Data Engineering, vol. 32, no. 3, pp. 588-601, 1 March, DOI: 10.1109/TKDE.2018.2885515.

[20] S. Tokuno et al. 2011. Usage of emotion recognition in military health care. Defense Science Research Conference and Expo (DSR), pp. 1-5, DOI: 10.1109/DSR.2011.6026823.

[21] V. R. Chiranjeevi and D. Elangovan. Surveillance Based Suicide Detection System Using Deep Learning. 2019 International Conference on Vision Towards Emerging Trends in Communication and Networking (ViTECoN), pp. 1-7, DOI: 10.1109/ViTECoN.2019.8899360.

[22] A. Zahura and K. A. Mamun 2020. Intelligent System for Predicting Suicidal Behaviour from Social Media and Health Data, 2nd International Conference on Advanced Information and Communication Technology (ICAICT), pp. 319-324, DOI: 10.1109/ICAICT51780.2020.9333463.

[23] X. Meng and J. Zhang 2020. Anxiety Recognition of College Students Using a Takagi-SugenoKang Fuzzy System Modeling Method and Deep Features. IEEE Access, vol. 8, pp. 159897- 159905, 2020, DOI: 10.1109/ACCESS.2020.3021092.

[24] Pratyaksh Jain1 , Karthik Ram Srinivas2 and Abhishek Vich. Depression and Suicide Analysis Using Machine Learning and NLP.doi:10.1088/1742-6596/2161/1/012034.

[25] https://www.wikipedia.org/