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Depression Detection Using Sentiment Analysis Of Social Media Posts

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Abstract—Depression has become a major cause of concern worldwide. According to the World Health Organization (WHO), more than 264 million people of all ages suffer from depression worldwide. Almost 75% of these remain untreated, with almost 1 million people taking their lives each year. This makes depression one of the leading causes of suicide esp. amongst adolescents. The WHO reports that anxiety disorders are the most common mental disorders worldwide with specific phobia, major depres- sive disorder and social phobia being the most common anxiety disorders. Social media platforms are becoming an integral part of people's life. They reflect the user's personal life. People like to share happiness, joy, and sadness on social media. These platforms are used by researchers to identify the causes of depression and detect it. Detecting early depression can be a huge step to address this mental illness. Our model addresses this issue by deploying a hybrid machine learning model using XGBoost and Naive Bayes, which would help in detecting individuals with symptoms of clinical depres- sion. The model will be developed for twitter data and would flag tweets which are found to be depressive. The project is expected to give an accuracy of 90% and a very good F1-Score. Thus, this project would help us employ emotional AI in twitter which would in turn lead to lower suicide rates and improved mental health.

Index Terms—Depression, Mental Health, Social Networking Sites, Twitter, Machine Learning, Emotional AI.

I. INTRODUCTION

Depression is the leading cause of disability worldwide. Almost 75% of people with mental disorders remain untreated in developing countries with almost 1 million people taking their lives each year. In addition, according to the World Health Organization (WHO), 1 in 13 globally suffers from anxiety. Depression is different from usual mood fluctuations and short-lived emotional responses to challenges in everyday life. Especially when long-lasting and with moderate or severe intensity, depression may become a serious health condition. It can cause the affected person to suffer greatly and function poorly at work, at school and in the family. At its worst, depression can lead to suicide.

Although there are known, effective treatments for mental disorders, between 76% to 85% of people in low- and middle-income countries receive no treatment for their mental disorder. Barriers to effective care include a lack of resources, lack of trained health-care providers and social stigma associated with mental disorders. Another barrier to effective care is inaccurate assessment. In countries of all income levels, people who are depressed are often not correctly diagnosed, and others who do not have the disorder are too often misdiagnosed and prescribed antidepressants.

Depending on the number and severity of symptoms, a depressive episode can be categorized as mild, moderate or severe. A key distinction is also made between depression in people who have or do not have a history of manic episodes. Both types of depression can be chronic (i.e., over an extended period) with relapses, especially if they go untreated.

- **Recurrent depressive disorder** : This disorder involves repeated depressive episodes. During these episodes, the person experiences depressed mood, loss of interest and enjoyment, and reduced energy leading to diminished ac- tivity for at least two weeks. Many people with depression also suffer from anxiety symptoms, disturbed sleep and appetite, and may have feelings of guilt or low self-worth, poor concentration and even symptoms that cannot be explained by a medical diagnosis.
- **Bipolar affective disorder** : this type of depression typically consists of both manic and depressive episodes separated by periods of normal mood. Manic episodes involve elevated or irritable mood, over-activity, pressure of speech, inflated self-esteem & decreased need for sleep.

II. LITERATURE SURVEY

Using machine learning models based on messages on a social platform. In particular, a convolutional neural network based on different word embeddings is evaluated and compared This is a field where immense research is taking place. Over the last few years, social media has been used to examine mental health by many researchers. In “Proceedings of the Fifth Workshop on Computational Linguistics and Clinical Psychology: From Keyboard to Clinic” [1] the authors considered that social media platforms can reflect the users’ personal life on many levels. Their primary objective was to detect depression using the most effective deep neural architecture from two of the most popular deep learning approaches in the field of natural language processing: Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs).

According to the report, “Exploring opportunities to support mental health care using social media: A survey of social media users with mental illness” [2], young people are more open to talk about their mental health issues over the social platforms. Over the years there had been a significant improvement in the field of Machine Learning (ML) in order to solve real problems or for introduction of automated system.

In “Predicting future mental illness from social media: A big-data approach” [3], the author predicted future mental illness based on the posts from an individual’s post on Reddit, by gathering the posts from clinical sub - reddits and then classifying them to the corresponding mental illness. After gathering the posts, clustering was applied on those posts to find the markers of mental illnesses present in their everyday spoken language.

In “Depression detection using Emotional Artificial Intelligence” [4], Natural Language Processing was applied on Twitter feeds for conducting emotion analysis focusing on depression. Individual tweets were classified as neutral or negative, based on a curated word-list to detect depression tendencies. In the process of class prediction, support vector machine and Naive-Bayes classifier have been used. The results showed that Naive Bayes gave a better accuracy and F1-Score than SVM.

In “X-A-BiLSTM: a Deep Learning Approach for Depression Detection in Imbalanced Data” [5] the authors proposed a deep learning model (X-A-BiLSTM) for depression detection in imbalanced social media data. This approach focused on solving the problem caused by data imbalance in the real world. The X-A-BiLSTM model consisted of two essential components: the first XGBoost component, which permitted acquiring balanced data by means of an end-to-end scalable tree boosting system, and the second component, BiLSTM with the attention mechanism, which achieved good classification performance. Results demonstrate that this approach significantly outperforms the previous state-of-the- art models on the RSDD dataset.

In “Utilizing Neural Networks and Linguistic Metadata for Early Detection of Depression Indications in Text Sequences”

[6] the authors addressed the early detection of depression to a classification based on user-level linguistic metadata. Furthermore, the currently popular ERDE score as metric for early detection systems is examined in detail and its drawbacks in the context of shared tasks are illustrated. Finally, a new word embedding was trained on a large corpus of the same domain as the described task and is evaluated as well.

In “Detection of Mood Disorder Using Modulation Spectrum of Facial Action Unit Profiles” [7] the authors constructed a database of facial expressions responding to emotional stimuli from the patients with BD, UD and healthy controls. To detect mood disorder, the subject’s facial expressions in CHIMEI database were applied to generate the AU profiles. The MS characterizing the fluctuation of AU profile sequence over a video segment was then used for mood disorder detection. From the comparison results of mood disorder detection, we can find that the proposed ANN-based method achieved the best performance.

In “Depression Detection by Analyzing Social Media Posts of User” [8] it has been demonstrated that depression can lead an individual to severe mental illness, even to the path of suicide and how a machine learning approach can detect depression of social media users. Micro-blogging social networking sites such as: twitter and Facebook provide users to express their day-to-day thoughts and activities which reflect users’ behavioral attributes and personality traits. This paper proposed a model that takes a username and analyzes the social media posts of the user to determine the levels of vulnerability to depression. Correlating with this result the authors evaluated the accuracy of this model to be 74% and a precision of 100%.

In “Facebook Social Media for Depression Detection in the Thai Community” [9] the author provides a tool by which depression could be easily and early detected. This would help people to be aware of their emotional states and seek help from professional services. This research employs Natural Language Processing (NLP) techniques to develop a depression detection algorithm for the Thai language on Facebook where people use it as a tool for sharing opinions, feelings, and life events. Results from 35 Facebook users indicated that Facebook behaviors could predict depression level.

In “Twitter Analysis for Depression on Social Networks based on Sentiment and Stress” [10] the author says that Detecting words that express negativity in a social media message is one step towards detecting depressive moods. To understand if a Twitter user could exhibit depression over a period of time, we applied techniques in stages to discover words that are negative in expression. The authors applied a multistep approach which allowed us to identify potential users and then discover the words that expressed negativity by these users. Results showed that the sentiment of these words can be obtained and scored efficiently as the computation on these datasets were narrowed to only these selected users. They also obtained the stress scores which correlated well with negative sentiment expressed in the content.

In “A novel Co-training based approach for the classification of mental illnesses using Social media posts” [11] the authors performed several experiments to classify the posts and their associated comments related to four mental issues such as Anxiety, ADHD, Depression and Bipolar. They also mined date from the Reddit platform where community related posts are published. The Authors used an API to extract posts and associated comments and performed experiments by using SVM, NB, and RF classifiers. The experimental results indicate that SVM, NB, and RF outperformed with Co-training technique as compared to their individual use in terms of Precision, Recall, and F-measure.

In “Realizing a Stacking Generalization Model to Improve the Prediction Accuracy of Major Depressive Disorder in Adults”

[12] the authors developed a stacking generalization model for improving the accuracy in predicting MDD. In the first step, they have implemented a KNN Imputation preprocessing technique for handling the missing values in the data. Then in the next step, the authors have used Random Forest-Based Backward Elimination, which is a wrapper-based feature selection method for reducing the feature dimension, which would reduce the feature interactions and helps in increasing the prediction accuracy. The initial number of features was 22, and then RF-BE has reduced to 12 features with which further process. The stacking generalization is made by combining three low learners MLP, SVM, and RF and then averaging them into a Meta level learner (MLP). The classifiers are also implemented individually to compare the results. The accuracy of individual classifiers MLP, SVM, RF is 96.38%, 95.06%, and 96.90%, respectively. The accuracy of the stacking generalization model is 98.16%.

In “A Machine Learning based Depression Analysis and Suicidal Ideation Detection System using Questionnaires and Twitter” [13] the authors analyzed social media posts (especially twitter), conducted questionnaire and asked students and parents to give their opinion and also scrapped blogs on internet. According to the research, major factors of depression among the age group of 15-29 which they found during the course of the project are parental pressure, love, failures, bullying, body shaming, inferiority complex, exam pressure, peer pressure, physical and sexual abuse etc. Depression being a recurrent type of illness, repeated episode of the same are common. Finally, little is known about

the prevention and identification of the disorder at an early stage. Among future directions, the authors researched to understand how social media behavior analysis can help in leading to development of methods for analyzing depression at scale.

III. BACKGROUND

A. Naive Bayes Classifier

Naive Bayes methods are a set of supervised learning algorithms based on applying Bayes' theorem with the "naive" assumption of conditional independence between every pair of features given the value of the class variable.

It is a classification technique based on Bayes' Theorem with an assumption of independence among predictors. In simple terms, a Naive Bayes classifier assumes that the presence of a particular feature in a class is unrelated to the presence of any other feature.

In spite of their apparently over-simplified assumptions, Naive Bayes classifiers have worked quite well in many real-world situations, famously document classification and spam filtering. They require a small amount of training data to estimate the necessary parameters.

Naive Bayes learners and classifiers can be extremely fast compared to more sophisticated methods. The decoupling of the class conditional feature distributions means that each distribution can be independently estimated as a one dimensional distribution. This in turn helps to alleviate problems stemming from the curse of dimensionality.

B. XG Boost

XGBoost is an optimized Gradient Boosting Machine Learning library. It is originally written in C++, but has API in several other languages. The core XGBoost algorithm is parallelizable i.e. it does parallelization within a single tree. XGBoost is usually used with a tree as the base learner, that decision tree is composed of the series of binary questions and the final predictions happens at the leaf. XGBoost is itself an ensemble method. The trees are constructed iteratively until a stopping criterion is met.

XGBoost uses CART(Classification and Regression Trees) Decision trees. CART is the trees that contain real-valued score in each leaf, regardless of whether they are used for classification or regression. Real-valued scores can then be converted to categories for classification, if necessary.

XGBoost is a more regularized form of Gradient Boosting. XGBoost uses advanced regularization which improves model generalization capabilities.

XGBoost delivers high performance as compared to Gradient Boosting. Its training is very fast and can be parallelized across clusters.

C. Figures and Tables

The literature survey conducted earlier provides a solid ground for further project work to be carried out. Since the data is highly imbalanced, the F1-score will serve as our primary metric and accuracy is the secondary metric. The comparison of various models explored already have been summarized in the table below along with the F1-Score comparison chart.

Model	Accuracy	Recall	Precision	F1-Score
Multinomial Naïve Bayes	0.830	0.831	0.836	0.833
Support Vector Machine	0.790	0.793	0.804	0.797
Random Forest	0.846	0.889	0.846	0.889
CNN	-	0.450	0.590	0.510
LSTM	-	0.390	0.500	0.440
Multi-Layer Perceptron	0.628	1.000	0.800	0.890
X-A-BiLSTM	-	0.530	0.690	0.600

Fig. 1. Comparison of different models

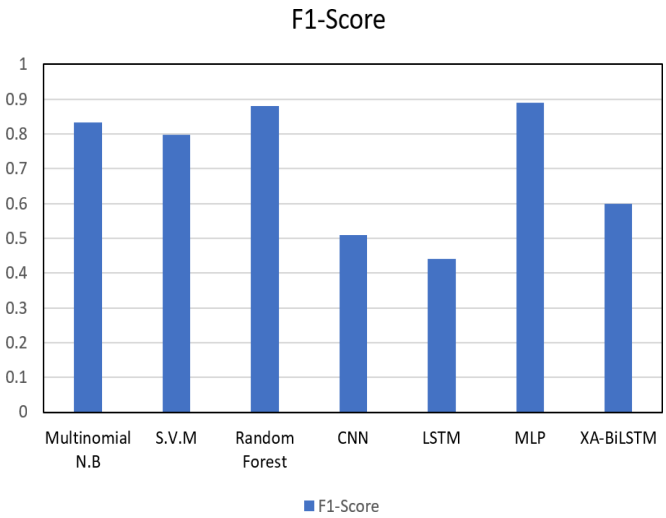

Fig. 2. F1-Score Comparison

D. Drawbacks of Previous Models

- Deep Learning models like Multi Layer Perceptron (MLP) give better results for large datasets but social media datasets for depression detection are generally small and thus deep learning models lead to wastage of time and effort.
- The datasets are highly imbalanced which makes Ma- chine Learning models very inefficient as they become biased.
- None of the algorithms provides exceptional accuracy along with high F1-Score which makes them susceptible to erroneous results.

IV. PROPOSED METHODOLOGY

A. Proposed Solution

The algorithms described above are state of the art algorithms which work very well with balanced datasets. But we are dealing with highly imbalanced datasets and thus, our algorithm must have the ability to remove this imbalance and avoid any bias.
Our model will be developed as a combination of XGBoost and Naive Bayes. This hybrid model would be able to extract most relevant information using the power of both algorithms. The XGBoost layer will act as a filter which would remove imbalance in the data and the Naie Bayes layer would final make predictions on the refined data.
Our model is expected to surpass accuracy and F1-scores of all the previous models.

B. Mathematical Modelling and Equations

Our algorithm will be implemented as a combination of two algorithms - XGBoost and Naive Bayes. Thus, the mathematics of the proposed system is based on these algorithms.

Let our dataset be comprised of the following sets of features: -

1. The set of independent features, X = F1, F2, F3, …….
2. The dependent feature, y.

The data is first passed through the XGBoost layer. The objective function for XGBoost is shown below: -

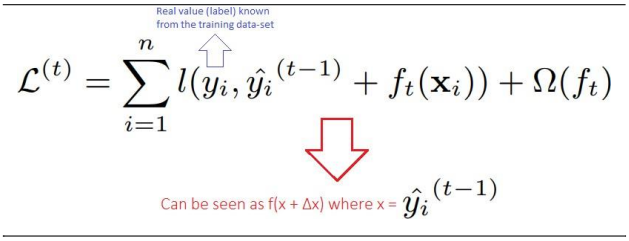

Fig. 3. XG Boost Objective Function

The objective function above comprises of the loss function as well as the regularization function. Our motive is to minimize the above function. This is done internally using the Taylor approximation technique. And finally, we will have our prediction.
Let the probability of prediction for XGBoost be P(xg). This will be used further to calculate final result

At the Naïve Bayes layer, Bayes Theorem is used for prediction. The standard Bayes Theorem is represented by the formula below: -

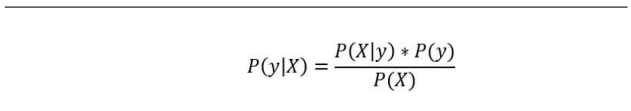

Fig. 4. Bayes Theorem

Here,
P(y / X) is the posterior probability of class (y, target) given predictor (X, features).
P(y) is the prior probability of class.
P(X y) is the likelihood which is the probability of predictor given class.
P(X) is the prior probability of predictor.
In Na¨ıve Bayes we make the na¨ıve assumption that all the features are independent hence we'll have: -

$$P(X|y) = P(x_1|y) * P(x_2|y) * ... * P(x_n|y)$$

Fig. 5. Independence of Features

$$P(y|X) \propto P(X|y) * P(y)$$

-or-

$$P(y|X) \propto P(y) * \prod_{i=1}^{n} P(x_i|y)$$

Fig. 6. Proportionality Relation

The goal of Naive Bayes is to choose the class y with the maximum probability. Thus, our final optimization function will be: -

$$y = argmax_y[P(y) * \prod_{i=1}^{n} P(x_i|y)]$$

Fig. 7. Optimization Function

Let the Na¨ıve Bayes probability of prediction be P(nb).

Finally, we will take weighted average of the probabilities of prediction of both the algorithms and set a threshold value. If the final probability will surpass the threshold only then the tweet will be classified as depressive.
Final Probability = (k1∗P (xg)+k2∗P (nb))/(k1+k2) (1)

v. CONCLUSION

Depression has been a menace facing our society for a long time and is one of the major causes suicides in millenials. It is thus the need of the hour to make use of technology to prevent this mental health issue. Our model will play a significant role in achieving this goal.

The model will use the best of XGBoost and Naive Bayes algorithms to eradicate data imbalance and produce accurate results with minimum bias. Hence, the model will go a long way in preventing depression especially in young adults.

REFERENCES

[1]A. H. B. P. O. M. H. . I. Orabi, "Deep Learning for Depression Detection of Twitter Users.," Proceedings of the Fifth Workshop on Computational Linguistics and Clinical Psychology: From Keyboard to Clinic. doi: 10.18653/v1/w18-0609, 2018.

[2]J. A. Naslund, K. A. Aschbrenner, G. J. McHugo, J. Un ützer, L. A. Marsch, and S. J. Bartels, "Exploring opportunities to support mental health care using social media: A survey of social media users with mental illness," Early Interv. Psychiatry, 2019.

[3]R. Thorstad and P. Wolff, "Predicting future mental illness from social media: A big-data approach," Behav. Res. Methods, 2019.

[4] Mandar Deshpande and Vignesh Rao, " Depression detection using Emotional Artificial Intelligence., " 2017.

[5] Cong, Z. Feng, F. Li, Y. Xiang, G. Rao and C. Tao, "X-A- BiLSTM: a Deep Learning Approach for Depression Detection in Im- balanced Data," 2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Madrid, Spain, 2018, pp. 1624-1627, doi: 10.1109/BIBM.2018.8621230.

[6] Trotzek, Marcel Koitka, Sven Friedrich, Christoph. (2018). "Utilizing Neural Networks and Linguistic Metadata for Early Detection of Depres- sion Indications in Text Sequences". IEEE Transactions on Knowledge and Data Engineering. 32. 588-601. 10.1109/TKDE.2018.2885515.

[7]T. Yang, C. Wu, M. Su and C. Chang, "Detection of mood disorder using modulation spectrum of facial action unit profiles," 2016 International Conference on Orange Technologies (ICOT), Melbourne, VIC, 2016, pp. 5-8, doi: 10.1109/ICOT.2016.8278966.

[8]N. A. Asad, M. A. Mahmud Pranto, S. Afreen and M. M. Islam, "Depression Detection by Analyzing Social Media Posts of User," 2019 IEEE International Conference on Signal Processing, Information, Com- munication Systems (SPICSCON), Dhaka, Bangladesh, 2019, pp. 13-17, doi: 10.1109/SPICSCON48833.2019.9065101.

[9]K. Katchapakirin, K. Wongpatikaseree, P. Yomaboot and Y. Kaewpi- takkun, "Facebook Social Media for Depression Detection in the Thai Community," 2018 15th International Joint Conference on Computer Science and Software Engineering (JCSSE), Nakhonpathom, 2018, pp. 1-6, doi: 10.1109/JCSSE.2018.8457362.

[10]X. Tao, R. Dharmalingam, J. Zhang, X. Zhou, L. Li and R. Gururajan, "Twitter Analysis for Depression on Social Networks based on Sentiment and Stress," 2019 6th International Conference on Behavioral, Economic and Socio-Cultural Computing (BESC), Beijing, China, 2019, pp. 1-4, doi: 10.1109/BESC48373.2019.8963550.

[11]S. Tariq et al., "A Novel Co-Training-Based Approach for the Classifi- cation of Mental Illnesses Using Social Media Posts," in IEEE Access, vol. 7, pp. 166165-166172, 2019, doi: 10.1109/ACCESS.2019.2953087.

[12]N. Mahendran, P. M. Durai Raj Vincent, K. Srinivasan, V. Sharma and D. K. Jayakody, "Realizing a Stacking Generalization Model to Improve the Prediction Accuracy of Major Depressive Disorder in Adults," in IEEE Access, vol. 8, pp. 49509-49522, 2020, doi: 10.1109/AC- CESS.2020.2977887.

[13]S. Jain, S. P. Narayan, R. K. Dewang, U. Bhartiya, N. Meena and V. Kumar, "A Machine Learning based Depression Analysis and Suicidal Ideation Detection System using Questionnaires and Twitter," 2019 IEEE Students Conference on Engineering and Systems (SCES), Allahabad, India, 2019, pp. 1-6, doi: 10.1109/SCES46477.2019.8977211.

[14] https://github.com/halolimat/Social-media-Depression-Detector/blob/master/depression lexicon.json

[15] https://towardsdatascience.com/xgboost-mathematics-explained- 58262530904a

[16] https://towardsdatascience.com/a-mathematical-explanation-of-naive-bayes-in-5-minutes-44adebcdb5f8

[17] https://www.kaggle.com/kazanova/sentiment140[18]https://medium.com/topic/machine-learning