The Mavericks@LT-EDI: Detection of Signs of Depression from Social Media Text Quotes using Naive Bayes Approach

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Abstract

Social media platforms have revolutionized the landscape of communication, providing individuals with an outlet to express their thoughts, emotions, and experiences openly. This paper focuses on the development of a model to determine whether individuals exhibit signs of depression based on their social media texts. With the aim of optimizing performance and accuracy, a Naive Bayes approach was chosen for the detection task.The Naive Bayes algorithm, a probabilistic classifier, was applied to extract features and classify the texts. The model leveraged linguistic patterns, sentiment analysis, and other relevant features to capture indicators of depression within the texts. Preprocessing techniques, including tokenization, stemming, and stop-word removal, were employed to enhance the quality of the input data. The performance of the Naive Bayes model was evaluated using standard metrics such as accuracy, precision, recall, and F1-score.it acheived a macro- avergaed F1 score of 0.263.

1 Introduction

Depression, Brown and Harris [1989] a widespread and serious medical illness, poses a significant burden on individuals globally. The timely detection of depression signs plays a crucial role in providing appropriate interventions and improving treatment outcomes. Social media platforms have emerged as a valuable resource for identifying mental health issues, including depression. By analyzing social media text, researchers can gain valuable insights into an individual's emotional state and detect potential signs of depression.

This paper presents our solution for the Shared Task on Detecting Signs of Depression from Social Media Text. Our main objective is to classify the level of depression in English social media posts, categorizing them as 'not depressed,' 'moderately depressed,' or 'severely depressed.' We aim to contribute to the improvement of individuals' lives by effectively detecting and addressing depression through the analysis of social media text.

For this task, we utilize a carefully curated dataset specifically designed for the LT-EDI@RANLP Shared Task. This dataset is composed of social media posts in English, annotated with the corresponding depression levels. We describe the dataset in detail, including its composition, annotation process, and any necessary modifications made for the task. Additionally, we discuss the preprocessing steps employed to ensure the quality and suitability of the data for training our depression detection model.

In conclusion, our solution for the LT-EDI@RANLP Shared Task on Detecting Signs of Depression from Social Media Text demonstrates the potential of utilizing social media platforms to detect and address depression. By leveraging social media text, we aim to facilitate the timely identification of depression and contribute to improved intervention and treatment outcomes. In our study, we employed five distinct models - K-Nearest Neighbors (KNN), Naive Bayes, Random Forest, Decision Tree, and Support Vector Machine (SVM). The evaluation process encompassed various metrics, including accuracy, macro-averaged precision, macro-averaged recall, and macro-averaged F1-score across all classes. Notably, the macro-averaged F1-score emerged as the primary measure for assessing solutions. Among these models, our solution harnessed Naive Bayes, as it yielded a commendable F1-score, solidifying its effectiveness in addressing the problem at hand.

2 Related Works

The study by Reece and Danforth [2017] demonstrated the effectiveness of ML algorithms in analyzing Twitter data for depression detection. By

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incorporating lexical, syntactic, and social network features, the model achieved promising results, revealing strong correlations between linguistic patterns and depression.

Tsugawa et al. [2015]conducted a comprehensive study using ML techniques to detect depressive symptoms from social media data. Their classification model integrated linguistic,Varsini et al. [2022] sentiment, and behavioral features, showcasing the potential of ML in accurately identifying individuals with depression.

MacAvaney et al. [2018] focused on detecting depression and PTSD(Post-traumatic stress disorder) from Reddit posts using an ML approach. Their model incorporated linguistic, psycholinguistic, and social contextual features, achieving high accuracy in identifying individuals with depression.

Kim et al. [2020] developed a deep learning-based approach for depression detection from social media text. Their hierarchical attention network effectively captured textual information and demonstrated the power of deep learning in accurately detecting depression symptoms.

Coppersmith et al. [2018] conducted a large-scale study involving various social media platforms for depression detection. Their ML algorithms analyzed linguistic, sentiment, and contextual features, showcasing the scalability of depression detection from social media data.

Research was conducted by a large-scale study utilizing the BERT model on multiple social media platforms to detect depression. The machine learning algorithms analyzed linguistic, sentiment, and contextual features, demonstrating the BERT model's effectiveness and scalability in identifying depression from social media data Anantharaman et al. [2022].similary another variant of BERT ALBERT model was used for detecting the signs of depression Esackimuthu et al. [2022].
A chat bot was created using the Bayesian modeling and it was used to detect single emotion only.Employing multiple kernels may be used to predict several labels with higher performance Angel Deborah et al. [2021].

These notable works collectively emphasize the potential of ML models in detecting signs of depression from social media text. By incorporating diverse features and utilizing advanced techniques such as deep learning, researchers have achieved significant advancements in accurately identifying individuals with depression. These studies contribute to the growing understanding of the role of social media analysis in mental health monitoring and highlight the importance of continued research in this critical field.

3 Data Set

The dataset used in the competition for detecting signs of depression from social media text comprises English posts. Each post was annotated with one of three labels: ”not depression,” ”moderate,” or ”severe” . The ”not depression” label indicates posts without any signs of depression, while the other labels indicate varying levels of depression severity.

The dataset was divided into train, dev, and test sets. The test set, used for evaluating solutions, had undisclosed labels. The datset had a large number of duplicate records this was the reason for the lower efficiency.The data was biased containing a large number of moderately depressed samples.

It is worth noting that the dataset is unbalanced, with the ”severe” class being underrepresented.

we used a similar dataset as a reference that was created by Kayalvizhi, S and Thenmozhi, D Sampath et al..

In summary, the dataset used for detecting signs of depression from social media text exhibited class imbalance .The sample data is shown in Table 1

4 Experimental Results using various models

The data was examined on multiple models after the preparation processes, and the results are reported below.

4.1 Experimental Setup

1. Tokenization: The text data is split into individual words or tokens.
2. Vocabulary Building: A vocabulary is created by collecting all unique words from the corpus.
3. Counting: Each document is represented as a vector, where each element represents the frequency of a word from the vocabulary within that dataset.

4.2 Navie Bayes Algorithm

For training a model for detecting signs of depression using the Naive Bayes algorithm Peng et al. [2019].we Extracted numerical features using techniques like Bag-of-Words or count vectorization. we Split the dataset into training and testing sets

Table 1: Samples from the dataset

PID	Text	Label
train_pid_1550	New year : New year and it feels like I am already behind. Is this ever going to end?	Not Depressed
train_pid_5	Sat in the dark and cried myself going into the new year. Great start to 2020 :	Moderate
train_pid_617	Feeling numb. : Okay this is my first post, apologies if it's long or anything. I'm just venting about stuff so if it's boring or anything you don't have to read it, that's fine.	Severe

Table 2: Dataset Description

Dataset Information	
Labels	"not depression", "moderate", "severe"
Train set size	7201
Dev set size	3245
Test set size	499

and train the Naive Bayes model by estimating probability distributions. we then Evaluated the model's performance using metrics like accuracy, precision, recall, F1 score. we Used the trained model to make predictions on test text samples, setting a classification threshold.The accuracy was about 59.62

4.3 KNN

The k-Nearest Neighbors (kNN) algorithm is a non-parametric and instance-based learning method used for classification and regression tasks.It classifies data points based on the majority class among their k nearest neighbors in the feature space.We tried using the k-Nearest Neighbors (kNN) algorithm,Islam et al. [2018] we Determined the value of k, the number of neighbors to consider.we then trained the kNN model by storing feature vectors and labels.we then Evaluated the model using metrics like accuracy and F1 score.The accuracy was about 43.74.

4.4 Random Forest

we used random forest to train our model because of its use in robustness and to handle high dimensional data.Narayanrao and Kumari [2020] The Random Forest model is an ensemble learning method that combines multiple decision trees to make predictions.Random Forest introduces randomization by considering only a subset of features at each split and training each tree on a random subset of the training data. The predictions of individual trees are combined through voting or averaging to obtain the final prediction. Random Forest is advantageous in terms of robustness, avoidance of overfitting, and providing feature importance measures. It is trained using labeled data, evaluated using appropriate metrics,and the accuracy obtained was

4.5 Decision Tree

Decision Trees are supervised machine learning algorithms that construct tree-like structures to make predictions based on feature values. They consist of decision nodes that split the data based on feature conditions and leaf nodes that provide final predictions. Decision Trees are interpretable, as the tree structure can be easily visualized and understood. They handle missing values and are susceptible to overfitting, we then Evaluated the model using metrics like accuracy and F1 score.The accuracy was about

4.6 support vector machine

Support Vector Machines (SVM)is a supervised machine learning algorithm that aims to find an optimal hyperplane to separate classes by maximizing the margin between them.Tadesse et al. [2019] It can handle linearly separable data and nonlinearly separable data using the kernel trick. SVM focuses on support vectors, which are crucial data points near the decision boundary. It introduces a regularization parameter to balance the margin size and misclassifications. SVM can be used for multi-class classification and regression tasks. It is evaluated using metrics like accuracy and mean squared error and the accuracy obtained is

4.7 Metrics

The metrics used during the experiments are accuracy, macro-averaged precision, macro-averaged recall and macro-averaged F1-score across all the classes. The macro-averaged F1-score was the main measure when evaluating solutions.

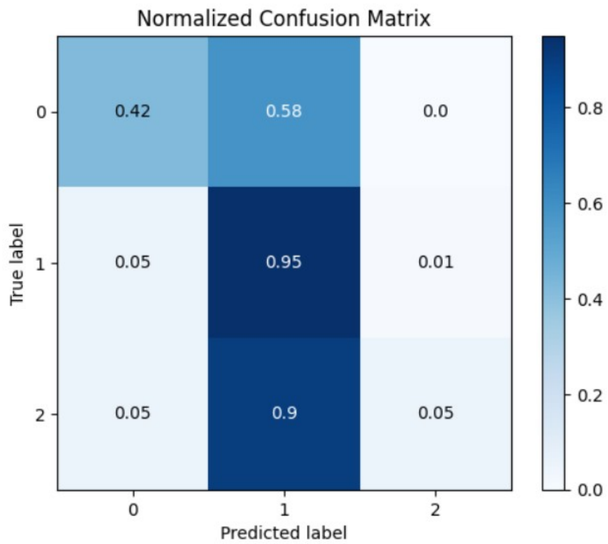

Figure 1: Navie Bayse

4.8 Model Evaluation

The results obtained different models are shown in the Table 3.

5 Our Solution

When comparing the results of several machine learning algorithms like random forest, support vector machine (SVM), k-nearest neighbors (KNN), decision tree, and naive Bayes algorithms, each has its strengths and weaknesses that make them suitable for different scenarios. Random forest is

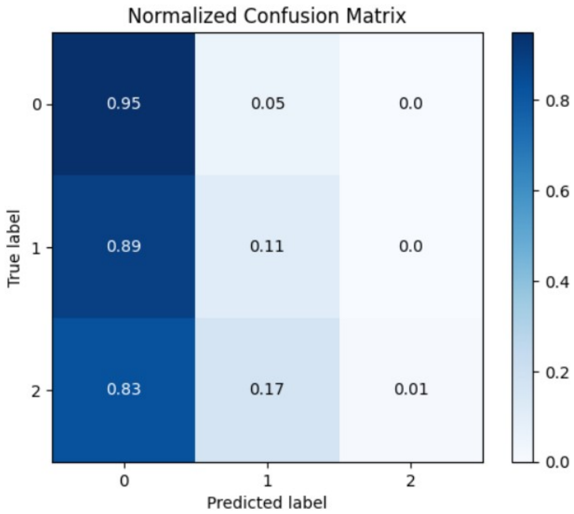

Figure 2: KNN

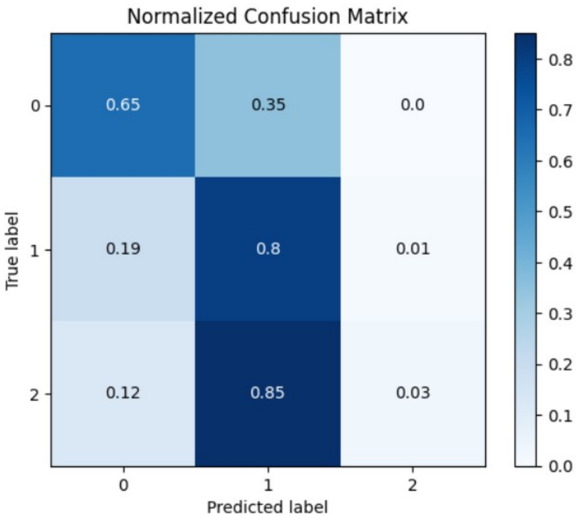

Figure 3: Random Forest

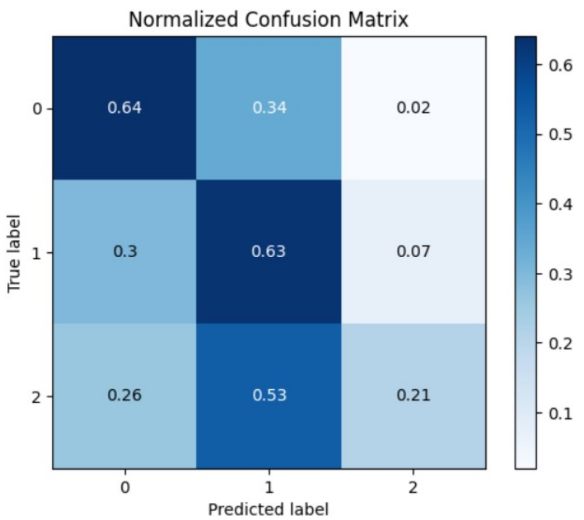

Figure 4: Decission Tree

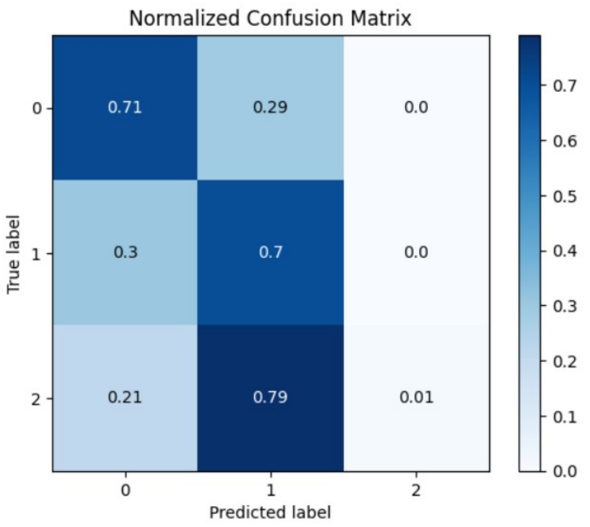

Figure 5: Support Vector Machine

Table 3: Comparison of Metrics

Model	Precision	Recall	F1 Score	Accuracy
Naive Bayes	0.66	0.47	0.47	65.82
KNN	0.68	0.36	0.26	43.73
Random Forest	0.60	0.49	0.48	63.28
Decision Tree	0.51	0.49	0.50	59.76
SVM	0.48	0.47	0.45	64.27

an ensemble method that effectively handles non-linearity and noisy data, making it useful for large datasets. However, it is less interpretable due to its ensemble nature.

SVM is a powerful algorithm that can handle non-linearity through kernel functions. However, it can be sensitive to noisy data and might not scale well with larger datasets.

KNN is an instance-based algorithm that is relatively interpretable but can struggle with high-dimensional data. It is also sensitive to noisy data and can be influenced by outliers.

Naive Bayes is a probabilistic algorithm that assumes feature independence, making it efficient and scalable for large datasets. It provides interpretable results but may not capture complex non-linear relationships well.

In the context of text processing, naive Bayes is often favored due to its computational efficiency, handling of high-dimensional data, interpretability, and ability to work with limited training data.

However, the choice of algorithm ultimately depends on the specific problem, dataset characteristics, and desired performance metrics. So we implemented all the above mentioned algorithms and we found that naïve bayes is good for this problem. The implementation results are given below

6 Future Work

As a future work, the efficiency of the model can be further enhanced by addressing two key aspects: removing duplicates from the given dataset and fine-tuning the model to achieve a balanced representation of the data. Currently, the dataset exhibits an underrepresented distribution, which can impact the model's performance. By implementing duplicate removal techniques and leveraging the robustness of models like RoBERTa, it is possible to optimize the model's efficiency and enhance its overall performance.

7 Conclusion

In conclusion, the application of the naive Bayes algorithm in detecting signs of depression from social media text LT-EDI@RANLPhas shown promising results. Naive Bayes offers several advantages in this context, making it a suitable choice for such tasks. The computational efficiency of naive Bayes enables the processing of large volumes of social media text data efficiently. Its ability to handle high-dimensional feature spaces, often encountered in text data, is advantageous when dealing with the diverse and extensive vocabulary found in social media posts.

References

Karun Anantharaman, S Angel, Rajalakshmi Sivanaiah, Saritha Madhavan, and Sakaya Milton Rajendram. Ssn_mlrg1@ lt-edi-acl2022: Multi-class classification using bert models for detecting depression signs from social media text. In *Proceedings of the Second Workshop on Language Technology for Equality, Diversity and Inclusion*, pages 296–300, 2022.

S Angel Deborah, TT Mirnalinee, and S Milton Rajendram. Emotion analysis on text using multiple kernel gaussian... *Neural Processing Letters*, 53: 1187–1203, 2021.

George W Brown and Tirril O Harris. Depression. *New York: Guilford*, 1989.

Glen Coppersmith, Ryan Leary, Patrick Crutchley, and Alex Fine. Natural language processing of social media as screening for suicide risk. *Biomedical informatics insights*, 10:1178222618792860, 2018.

Sarika Esackimuthu, Shruthi Hariprasad, Rajalakshmi Sivanaiah, S Angel, Sakaya Milton Rajendram, and TT Mirnalinee. Ssn_mlrg3@ lt-edi-acl2022-depression detection system from social media text using transformer models. In *Proceedings of the Second Workshop on Language Technology for Equality, Diversity and Inclusion*, pages 196–199, 2022.

Md Rafiqul Islam, Abu Raihan M Kamal, Naznin Sultana, Robiul Islam, Mohammad Ali Moni, et al. Detecting depression using k-nearest neighbors (knn) classification technique. In *2018 International Conference on Computer, Communication, Chemical, Material and Electronic Engineering (IC4ME2)*, pages 1–4. IEEE, 2018.

Jina Kim, Jieon Lee, Eunil Park, and Jinyoung Han. A deep learning model for detecting mental illness from user content on social media. *Scientific reports*, 10 (1):1–6, 2020.

Sean MacAvaney, Bart Desmet, Arman Cohan, Luca Soldaini, Andrew Yates, Ayah Zirikly, and Nazli Goharian. Rsdd-time: Temporal annotation of self-reported mental health diagnoses. *arXiv preprint arXiv:1806.07916*, 2018.

Purude Vaishali Narayanrao and P Lalitha Surya Kumari. Analysis of machine learning algorithms for predicting depression. In *2020 international conference on computer science, engineering and applications (iccsea)*, pages 1–4. IEEE, 2020.

Zhichao Peng, Qinghua Hu, and Jianwu Dang. Multi-kernel svm based depression recognition using social media data. *International Journal of Machine Learning and Cybernetics*, 10:43–57, 2019.

Andrew G. Reece and Christopher M. Danforth. Instagram photos reveal predictive markers of depression. *EPJ Data Science*, 6(1):15, 2017.

Kayalvizhi Sampath, Thenmozhi Durairaj, Bharathi Raja Chakravarthi, Jerin Mahibha C, Kogilavani Shanmugavadivel, and Pratik Anil booktitle = Rahood. Overview of the second shared task on detecting signs of depression from social media text.

Michael M Tadesse, Hongfei Lin, Bo Xu, and Liang Yang. Detection of depression-related posts in reddit social media forum. *IEEE Access*, 7:44883–44893, 2019.

Sho Tsugawa, Yusuke Kikuchi, Fumio Kishino, Kosuke Nakajima, Yuichi Itoh, and Hiroyuki Ohsaki. Recognizing depression from twitter activity. In *Proceedings of the 33rd annual ACM conference on human factors in computing systems*, pages 3187–3196, 2015.

S Varsini, Kirthanna Rajan, S Angel, Rajalakshmi Sivanaiah, Sakaya Milton Rajendram, and TT Mirnalinee. Varsini_and_kirthanna@ dravidianlangtech-acl2022-emotional analysis in tamil. In *Proceedings of the Second Workshop on Speech and Language Technologies for Dravidian Languages*, pages 165–169, 2022.