SIS@LT-EDI: Detecting Signs of Depression from Social Media Text Using Ensemble Techniques

Sulaksha B K, Shruti Krishnaveni S, Ivana Steeve, B.Monica Jenefer
Meenakshi Sundararajan Engineering College, Chennai
bksulaksha@gmail.com, ivanasteeve@gmail.com,
shrutiks33@gmail.com,monicamaheswaran@gmail.com

Abstract

Various biological, genetic, psychological or social factors that feature a target oriented life with chronic stress and frequent traumatic experiences, lead to pessimism and apathy. According to WHO, about 280 million of the population have depression. The massive scale of depression should be dealt with as a disease rather than a 'phase' that is neglected by the majority. However, not a lot of people are aware of depression and its impact. Depression is a serious issue that should be treated in the right way. Many people dealing with depression do not realize that they have it due to the lack of awareness. This paper aims to address this issue with a tool built on the blocks of machine learning. This model analyzes the public social media texts and detects the signs of depression as three labels namely "not depressed", "moderately depressed", and "severely depressed" with high accuracy. The ensembled model uses three learners namely Multi-Layered Perceptron, Support Vector Machine and Multinomial Naive Bayes Classifier. The distinctive feature in this model is that it uses Artificial Neural Networks, Classifiers, Regression and Voting Classifiers to compute the final result or output.

Index Terms- Ensemble Modeling, Neural Networks, Naive Bayes Classifier, Multilayer Perceptron(MLP), Support Vector Machine.

1 Introduction

Depression is a chronic feeling of emptiness, sadness, or inability to feel pleasure that may appear to happen for no clear reason, according to 'Medical News Today'. It is distinct from grief and other emotions. It is considered to be a common mental disorder. A sense of melancholy pervades through a single word or text and to detect this the project is assigned to analyze the text with its highest accuracy rate of depression. As described in the World Health Organization's Comprehensive Mental Health Action Plan 2013-2020 [1], depression alone affects more than 300 million people worldwide and is one of the largest single causes of disability worldwide, particularly for women. Depression currently accounts for 4.3 percent of the global burden of disease, and it is expected to be the leading cause of disease burden in high-income countries by 2030 (Halfin, 2007). It is important to note that each individual's experience with depression is unique, and the causes can vary from person to person. Some of the common factors leading to Depression is said to be competitive lifestyle, need to meet high expectations and low self-esteem. People are much concerned about getting a good qualification, better career paths, social dignity etc., The spawn of internet and communication technologies, distinctly the online social networks have modernized how people interact and communicate with each other digitally. People tend to express more on Social Media compared to real life interactions and communications.It is also important to note that measuring the severity of the disorder is also a difficult task that could only be done by a highly trained professional with the use of different techniques such as text descriptions and clinical interviews, as well as their judgments (Husseini Orabi et al., 2018). This project depicts a deep architecture for explicitly predicting and classifying depression levels as 'Not Depressed', 'Moderately Depressed', or 'Severely Depressed' from their Social Media texts. Strong Learners such as Support Vector Machine (SVM), Multilayer Perceptron (MLP), Deep Neural Networks and Naive Bayes are used for classifying texts. This Project uses data from social media networks to explore various methods of early detection of Major depressive disorder (MDD) based on machine learning techniqies. A thorough analysis of the dataset to characterize the subjects' behavior based on different aspects of their writings (Halfin, 2007). The main contributions of the project can be summarized as follows: Depression is a chronic feeling

[1] https://www.who.int/health-topics/depressiontab=tab$_1$

LT-EDI 2023 – Third Workshop on Language Technology for Equality, Diversity and Inclusion, pages 131–137, Varna, Bulgaria, Sep 7, 2023.
https://doi.org/10.26615/978-954-452-084-7_019

of emptiness, sadness, or inability to feel pleasure that may appear to happen for no clear reason, according to 'Medical News Today'. It is distinct from grief and other emotions. It is considered to be a common mental disorder. A sense of melancholy pervades through a single word or text and to detect this the project is assigned to analyze the text with its highest accuracy rate of depression. As described in the World Health Organization's Comprehensive Mental Health Action Plan 2013-2020 (**?**), depression alone affects more than 300 million people worldwide and is one of the largest single causes of disability worldwide, particularly for women. Depression currently accounts for 4.3 percent of the global burden of disease, and it is expected to be the leading cause of disease burden in high-income countries by 2030 (Halfin, 2007). It is important to note that each individual's experience with depression is unique, and the causes can vary from person to person. Some of the common factors leading to Depression is said to be competitive lifestyle, need to meet high expectations and low self-esteem. People are much concerned about getting a good qualification, better career paths, social dignity etc., The spawn of internet and communication technologies, distinctly the online social networks have modernized how people interact and communicate with each other digitally. People tend to express more on Social Media compared to real life interactions and communications. This project depicts a deep architecture for explicitly predicting and classifying depression levels as 'Not Depressed', 'Moderately Depressed', or 'Severely Depressed' from their Social Media texts. Strong Learners such as Support Vector Machine (SVM), Multilayer Perceptron (MLP), Deep Neural Networks and Naive Bayes are used for classifying texts. This Project uses data from social media networks to explore various methods of early detection of Major depressive disorder (MDD) based on machine learning technqiues. This paper is writtern in the format (Sampath et al.) A thorough analysis of the dataset to characterize the subjects' behavior based on different aspects of their writings (Halfin, 2007). The main contributions of the project can be summarized as follows:

• The model provides the combined outcome computed by various Learners.

• A Voting Classifier is used to get the majority outcome of the text.

• Our ensemble method achieved competitive performance in the shared task in detecting signs of depression from social media text with 72 percent f1-score accuracy. Each sample is composed of three columns: PID, Text, and Label. The below figure contains an image of the Training Dataset.

618	train_pid_	Feeling numb. : Okay this is my first post, apologies if it's	severe
619	train_pid_	my mom is terribly sad and its making me anxious : Im	not depression
620	train_pid_	1/1/20. Iâ€™m really really hurting today. : The holidays w	not depression
621	train_pid_	I'm tired of being a nobody. : God, I just want to fucking	moderate
622	train_pid_	Love This Song. Itâ€™s Been Helping Me When I Feel My W	not depression
623	train_pid_	Does anyone feel MORE depressed after they go out/leave	moderate
624	train_pid_	I know I'm a good person but I've come to the realization t	not depression
625	train_pid_	Getting more depressed as time goes by and its scary : Hov	not depression
626	train_pid_	Do people just fake being excited? : Recently there was	moderate
627	train_pid_	I'm so lonely and nobody's favorite : Last night (New Year's	not depression
628	train_pid_	Why is it that talking to people about depression is so	not depression

Figure 1: Samples from the Training Dataset.

2 Existing works

There have been many projects that have dealt with finding a tool to detect depression in social media. Most of them included the implementation of machine learning techniques such as support vector machines and naive bayes. The overall accuracy obtained from those works is 70 percent. This paper aims to increase the accuracy level of detecting depression and in a way that it doesn't affect the user's privacy. Halfin's study (Halfin, 2007) demonstrated that the early detection, intervention, and appropriate treatment can promote easing and reduce the emotional and financial burdens of depression, and (Picardi et al., 2016) observed significant improvements in depressive symptoms among subjects who had undergone early screening or diagnosis of depression. (Rost et al., 2004) found that early intervention for depression can improve employee productivity and reduce major problems and complications. The prediction of Major Depressive Disorder (MDD) at early stages is proved to improve the health and maintain peace of a subject. The Detection of MDD is so far has been predicted by one method or one weak learner.

3 Proposed Method

By extending the work done previously, this Machine Learning Model is based on Support Vector Machine(SVM), Multinomial Naive Bayes and Multi layer Perceptron(MLP). By combining the above algorithms, the result thus obtained will have higher accuracy as it is built on not one, but 3 highly effective ML models. The final prediction of the text is classified or computed using an ensembling technique called Bagging (Bootstrap Aggregating) and a Voting Classifier. A Voting Classifier is a

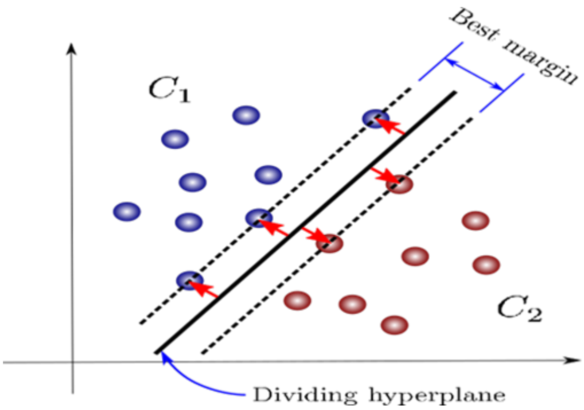

Figure 2: Illustration of Support Vector Machine.

machine learning estimator that trains various base models and predicts an outcome on the basis of aggregating and considering the majority output regarding the findings of each base estimator(Ganaie et al., 2022).

Brief explanation about the algorithms used in the final model:

Support Vector Machine (SVM): The SVM algorithm is implemented through the 'SVC' class. SVMs (Malviya et al., 2021) are powerful classifiers that aim to find an optimal hyperplane to separate different classes in the data. In this code, SVM with a linear kernel ('kernel='linear'') is used, which takes a linear decision boundary between classes. The Figure 2 is an illustration of Support Vector Machine and how it classifies different data points using regression function. Support Vector Machine (SVM) is a type of algorithm in supervised machine learning domain most used for undertaking classifications tasks(Malviya et al., 2021). While SVM algorithms can be employed for regression analysis tasks, but in practice they are most used for classification applications, such as classifying binary data into two distinct classes(Gupta et al., 2021).

Multilayer Perceptron (MLP): The MLP algorithm is implemented through the 'MLPClassifier' class . It's a type of neural network that consists of multiple layers of nodes. It uses a process called backpropagation to navigate through complex data. The Figure 3 is an illustration of Multilayer Perceptron and how it classifies different data points using multiple hidden layers. In this code, an MLP classifier with a single hidden layer containing 100 neurons is used. Multilayer Perceptron is used because it uses generalized delta learning rules and easily gets trained in less number of iterations(Aggarwal and Singh, 2015). A minimal Multilayer Perceptron has 3 layers including one hidden layer, one input layer and one output layer. The increase in the number of hidden layers corresponds to more accurate results.

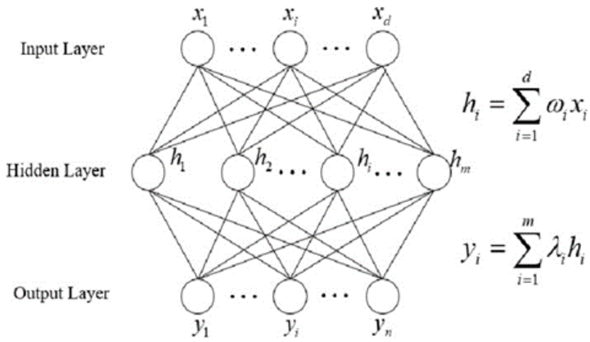

Figure 3: Illustration of Multilayer Perceptron.

If it has more than 1 hidden layer, it is called a deep ANN. An MLP is a typical example of a feedforward artificial neural network.

Multinomial Naive Bayes (NB): Bayesian algorithms predict the class depending on the probability of belonging to that class [2]. It calculates a set of probabilities from the frequency count and the combinations of values in a given data set. This algorithm is based on Bayes' theorem, assuming that all variables are independent. Bayes' theorem follows the following formula(**?**) .

$$P(A) = P((B)(A))/(B)(1)$$

Naive Bayes algorithms assume features are independent of each other, and hence no correlation between the features tend to implement through the 'MultinomialNB' class are probabilistic classifier based on Bayes' theorem. In the code, the MultinomialNB classifier is used, which is optimal for discrete features such as word frequencies or TF-IDF values commonly encountered in text classification tasks. Including NB as a weak learner in the ensemble can improve accuracy by taking advantage of its ability to handle text data and make independent assumptions. Multinomial Naive Bayes Classifier is used to classify data that is not dependent on a time period or a scale. These algorithms are combined in the ensemble approach to leverage the strengths of each individual algorithm and create a more robust and accurate model. Hence, by combining multiple algorithms the model is gives a prediction with high accuracy. Multinomial Naïve

[2]https://towardsdatascience.com/naive-bayes-classifier-explained-50f9723571ed

Bayes Classifier is a supervised learning method that uses probability and is focused on text classification cases. This method follows the principle of multinomial distribution in conditional probability. Although using multinomial distributions, this algorithm can be applied to text cases by converting to a nominal form that can be computed with an integer value. The probability calculation is described in the below equation(Farisi et al., 2019).

$$P(c|d) \propto \ P(c)\Pi P(t|c)](2)$$

Where P(t) is the conditional probability of the word in the text that belongs to class c and P(c) is the prior probability.(Farisi et al., 2019)

Ensemble Learning: Ensemble learning is a machine learning archetype or theory where multiple learners are trained or applied to datasets to solve the same problem by extracting multiple predictions then combined into one composite prediction(Ganaie et al., 2022). Deep learning architectures are showing better performance compared to the shallow or traditional models. Deep ensemble learning models combine the advantages of both the deep learning models as well as the ensemble learning such that the final model has better generalization performance. It is a process that uses a set of models, each of them obtained by applying a learning process to a given problem. This set of models (ensemble) is integrated in some way to obtain the final prediction. Ensemble learning is a technique that combines multiple individual models (weak learners) to make predictions.(Kotsiantis and Pintelas, 2007) The model use the Voting Classifier and Bagging Classifier.The ensemble combines the predictions of the various learners to obtain the final prediction. In the first version of the code, a VotingClassifier is used with three weak learners: Multilayer Perceptron(MLP), Support Vector Machine (SVM), and Multinomial Naive Bayes. In the another model , a BaggingClassifier is used, where the ensembling model combines Multilayer Perceptron (MLP), Support Vector Machine (SVM) and Random Forest(rf). Though both models tend to compute outcomes with promising accuracy, the first model provides the highest accuracy. To prove that average voting in an ensemble is better than individual model, Marquis de Condorcet proposed a theorem wherein he proved that if the probability of each voter being correct is above 0.5 and the voters are independent, then addition of more voters increases the probability of majority vote

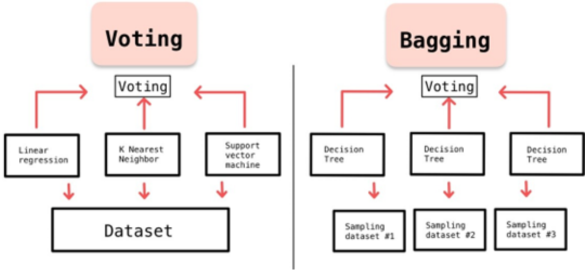

Figure 4: Illustration of ensembling techniques.

being correct until it approaches 1 (Condorcet, 1785) (Ganaie et al., 2022; Kotsiantis and Pintelas, 2007). Although Marquis de Condorcet proposed this theorem in the field of political science and had no idea of the field of Machine learning, but it is the similar mechanism that leads to better performance of the ensemble models. Assumptions of Marquis de Condorcet theorem also holds true for ensembles (Ganaie et al., 2022; Kotsiantis and Pintelas, 2007),(Hansen and Salamon, 1990). The reasons for the success of ensemble learning include: statistical, computational and representation learning, bias–variance decomposition and strength-correlation(Ganaie et al., 2022; Kotsiantis and Pintelas, 2007; Breiman, 2001).

4 Working of the model

The code is implemented more than once in order to obtain the optimal result, a total of 4 compilations were implemented.

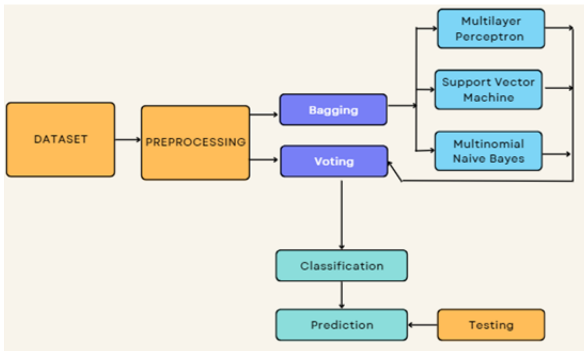

Figure 5: Working of model

Version 1: The classification report provides an evaluation of the model's performance in each class. The ensemble method - Voting Classifier is used here, which compares the prediction of multiple weak learners to make the final prediction. While using the voting ensemble technique, the predictions for the "not depression" and "severe" classes have been classified in terms of the precision , recall and F1-score. The accuracy if this model is 58 percent. This accuracy score is not appreciable for this type of text classification. So this problem needs to be addressed in the next run. The overall accuracy for detecting severe depression is 98 percent using this classifier. But the other classes remain moderately accurate. This is not the goal of this paper, hence certain changes are made to make it more accurate. The Classification Report while using the Voting Classifier is depicted below stating the model's accuracy.

	Precision	Recall	F1-Score	Support
Moderate	0.61	0.72	0.66	275
Not Depressed	0.37	0.37	0.37	135
Severe	0.98	0.46	0.63	89
Average			0.58	499
Macro Avg	0.65	0.52	0.55	499
Weighted Avg	0.61	0.58	0.58	499

Table 1: The Classification Report while using the Voting Classifier

Version 2: In the updated version of the code, Bagging Classifier is implemented instead of a voting classifier. In bagging, multiple weak learners are trained on different subsets of training data and their predictions are aggregated to make the final prediction. One of the weak learners used here is Multinomial Naive Bayes, a variant of Naive Bayes instead of the random forest classifier. It's used as it provides better accuracy while handling text classification, and provides ensemble diversity. That is, adding the MNB(Multinomial Naive Bayes) alongside MLP and SVM,provides diversity to the ensemble which improves the overall accuracy. In this run, the overall accuracy obtained is 72 percent, hence the accuracy is improved compared to the previous model and this is also greater than the accuracy obtained in the existing methods. To make sure this is the maximum accuracy, the same model is run twice. It is observed that the maximum and highest accuracy of detecting depression in texts is 72 percent. The Classification Report while using Bagging Classifier is depicted below stating the model's accuracy.

	Precision	Recall	F1-Score	Support
Moderate	0.72	1.00	0.84	358
Not Depressed	0.00	0.00	0.00	138
Severe	0.00	0.00	0.00	3
Average			0.72	499
Macro Avg	0.24	0.33	0.28	499
Weighted Avg	0.51	0.72	0.60	499

Table 2: The Classification Report while using the Bagging Classifier

5 Data

The dataset used in the paper is of public data, ensuring that the user's privacy is not invaded at any cost. But the public data might contain depressive texts in a disingenuous meaning too. This might make it hard to separate the genuine texts from them, hence public data needs to be further filtered. The dataset contains 7202 texts for training, 3,246 texts for development, and 500 texts for testing, while each sample is composed of three columns: PID(Person Identity), Text, and Label. The Test Dataset contains only PID and text for which the label is predicted using the model.

6 Implementation

The model can be implemented in any Python environment as long as it supports the necessary modules and libraries used in the code. Such machine learning frameworks are Jupyter Notebook, Python IDLE or Google Colab. This model is implemented in Google Colab. Libraries and modules like Pandas, Vectorizer, neural network, svm(Support Vector Machine), naive bayes are used for the implementation.

7 Result Analysis

As discussed previously, the updated version of the model provides the prediction with the highest accuracy of 72 percent(F1 score). This final version of the model is implemented by using the weak learners SVM, Naive Bayes, MLP, Ensemble Learning(Bagging Classifier). The model correctly predicted and classified the texts into labels namely ‘Not Depressed’, ‘Moderately Depressed’, or ‘Severely Depressed’. Since preprocessing can eliminate unneeded words and make the word more structured in the created model so that it is more efficient and performance will increase. Factors like sarcastic texts, threatening, fabricated content etc.., seem to affect the accuracy and consistency of the model. Though this is a model with high accuracy to detect depression, it can be improved to give better results. The predicted results computer by the model are given in Table 3 for reference.

Pid	Predicted label
test id 1	moderate
test id 2	moderate
test id 3	not depression
test id 4	severe
test id 5	moderate
test id 6	not depression

Table 3: Predicted Result

8 Conclusion

In this era it is important to keep lead and awareness on the depression rate, some phases or events make us more vulnerable to depression. There are various factors that could trigger emotional influx, and to detect all these, different algorithms with the highest accuracy have been opted. Based on the results of testing and analysis, it can be concluded as follows: The system that was built successfully classified texts into labels namely ‘Not Depressed’, ‘Moderately Depressed’, or ‘Severely Depressed’. with the most optimal result is F1-Score average of 72 percent using preprocessing based on the classification process. The optimal classification principle is to improve the model performance with standardized classification and management with the dependence of word occurrence. This change improved the performance of the dataset classification model. The ensemble technique algorithm is a fast, easy-to-implement, almost modern text classification algorithm. Proposed method and algorithm offers many possibilities for text classification. The main findings of this study is the importance of using ensemble techniques in the early detection of MDD to prevent any occurrences of tragic incidents, the comparison of the Voting Classifier and Bagging Classifier to predict the depression condition, and the improvement of state-of-the-art algorithms. It does have its own demerits that are to be figured out, yet it still provides us by attaining the goal of detecting the depression levels.

9 Future Enhancement

Though this model is better compared to the existing methods, it has its own shortcomings that need to be improved. It can be enhanced in several ways to improve its performance and functionality. Firstly, applying hyperparameter tuning to the individual classifiers used in the ensemble can optimize their parameters for better accuracy. Techniques like grid search or random search can be employed to find the best combination of hyperparameters. Next, considering a diverse range of classifiers or combining more models into the ensemble learning can enhance its predictive capabilities. To address imbalanced and inconsistent data, techniques like oversampling, undersampling, or generating synthetic samples can be used to balance the class distribution. Furthermore, performing thorough error analysis to identify common misclassifications or patterns where the model struggles can improve the overall performance.

References

Ashutosh Aggarwal and Karamjeet Singh. 2015. Handwritten gurmukhi character recognition. In *2015 international conference on computer, communication and control (IC4)*, pages 1–5. IEEE.

Leo Breiman. 2001. Random forests. *Machine learning*, 45:5–32.

Arif Abdurrahman Farisi, Yuliant Sibaroni, and Said Al Faraby. 2019. Sentiment analysis on hotel reviews using multinomial naïve bayes classifier. In *Journal of Physics: Conference Series*, volume 1192, page 012024. IOP Publishing.

M.A. Ganaie, Minghui Hu, A.K. Malik, M. Tanveer, and P.N. Suganthan. 2022. Ensemble deep learning: A review. *Engineering Applications of Artificial Intelligence*, 115:105151.

Brij Mohan Gupta, Surinder M Dhawan, and Ghouse Modin N Mamdapur. 2021. Support vector machine (svm) research in india: A scientometric evaluation of india’s publications output during 2002-19. *The Journal of Indian Library Association*, 57(3):12–25.

Aron Halfin. 2007. Depression: the benefits of early and appropriate treatment. *American Journal of Managed Care*, 13(4):S92.

Lars Kai Hansen and Peter Salamon. 1990. Neural network ensembles. *IEEE transactions on pattern analysis and machine intelligence*, 12(10):993–1001.

Ahmed Husseini Orabi, Prasadith Buddhitha, Mahmoud Husseini Orabi, and Diana Inkpen. 2018. Deep learning for depression detection of Twitter users. In *Proceedings of the Fifth Workshop on Computational Linguistics and Clinical Psychology: From Keyboard to Clinic*, pages 88–97, New Orleans, LA. Association for Computational Linguistics.

SB Kotsiantis and PE Pintelas. 2007. Combining bagging and boosting. *International Journal of Mathematical and Computational Sciences*, 1(8):372–381.

Keshu Malviya, Bholanath Roy, and SK Saritha. 2021. A transformers approach to detect depression in social media. In *2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS)*, pages 718–723. IEEE.

A Picardi, I Lega, L Tarsitani, M Caredda, G Matteucci, MP Zerella, R Miglio, A Gigantesco, M Cerbo, A Gaddini, et al. 2016. A randomised controlled trial of the effectiveness of a program for early detection and treatment of depression in primary care. *Journal of affective disorders*, 198:96–101.

Kathryn Rost, Jeffrey L Smith, and Miriam Dickinson. 2004. The effect of improving primary care depression management on employee absenteeism and productivity a randomized trial. *Medical care*, 42(12):1202.

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.