Hybrid Model for Analysis of Social Media Posts for Identification of Depression and Measuring Its Severity

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2023 International Conference on Data Science and Network Security (ICDSNS) | 979-8-3503-0159-5/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICDSNS58469.2023.10245441

***Abstract*—Amongst vast variety of mental health disorders one of the most common is Depression. Depression is characterized by feeling sad, empty-minded and complete lack of interest. The time period of depression ranges from a few hours up to even a fortnight or even more. Depression, in turn, also results into feeling low self-esteem, guilty, inability to concentrate, seeing no hope, sleep disorders and even thoughts of committing suicide. Thus, depression is one of the greatest challenges to the individual in particular and society at large in general. Depression has also made it to the list of high-priority conditions under by Mental Health Gap Action Programme of the World Health Organization. Use of social media has been an integral part of modern lifestyle. Vast majority of people from developing and developed countries have cheaper access to Internet and they prioritize engaging themselves in social media for sharing every minute detail of their personal life and express their feelings on multiple social media platforms. As a result of this, their posts on social media are nearly true reflections of their state of mind. In this research work, we proposed a hybrid model for sentiment analysis which aims at identifying depression along with its severity levels. The proposed model employs pre-trained language model and makes use of information available through day-to-day social media posts by various users. The proposed model was built around the principles of contrastive learning. The results showed significant improvement achieved by the proposed approach. Thus, it can be concluded that the hybrid ensemble approach does offer better and competitive performance over usage of single model.**

Keywords*—Mental health disorders, Depression, ML algorithms, Depression detection, Deep learning, Text Analysis, Affective Computing, Emotion AI Introduction

I. INTRODUCTION

Remarks, opinions, comments, critics and responses posted on global social media platforms often reflect human emotions such as happiness, disgust, frustration, fear, sadness and even depression. Therefore, such posts can be a potential source for analysis and detection of certain psychological conditions including depression. The human emotions have three components which represent the degree of pleasantness, intensity and of control as in [1]

The Valence-Arousal-Dominance (VAD) model as in [2] presents a quantitative metric for measuring six emotions- anger, disgust, surprise, joy, sadness and fear. Here, valence represents the degree of pleasantness, arousal represents the degree of intensity and dominance represents the degree of dominance.

Sentiment analysis aims at detecting polarity in human emotions. It can be formulated as a classic problem of classification as follows: Given a text, analyse its contents and determine if the text reflects a positive, negative or neutral opinion. Study of consumer trends, level of political support and emotion recognition are a few important use cases of such predictions. The emotion recognition is a typical use case of Affective Computing.

The affective computing is a trending inter-disciplinary field. According to the latest research-based forecast for the period from 2016 to 2026, estimates that the global affective computing market is estimated at over 12 billion USD for the year 2019 and is projected to grow at a CAGR of over 28% and reach a market size of over 72 billion by the year 2026.

In this research work, we proposed a hybrid model for sentiment analysis which aims at identifying depression along with its severity levels. The proposed model employs pre-trained language model and measures its performance against three other models. Here, pre-trained models produce sentence embedding and VADER generates VAD scores. We used 16632 posts from the dataset provided by (Kayalvizhi and Thenmozhi, 2022). We used 8891 posts for training and 4496 posts for testing.

The paper is organized as follows:

In section II, we discussed significant research contributions in the area of depression detection and analysis of social media posts.

Section III includes the proposed model, step-by-step procedure to implement the proposed model and summary of dataset.

Comparative performances in terms of Macro-F1 scores and accuracy, and discussion are included in Section IV.

Contributions made by this research, limitations and future scope are discussed in Section V.

II. RELATED WORK

As in [3], Hahn and Buechel peformed exploratory analysis of the features and studied their impact on detecting the depression.

Liu,Feng,Ahmed, Shahid and Guo as in [4] reviwed and summarised the findings of previous studies in which various machine learning algorithms were applied to posts from

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social media to detect depressive symptoms and to suggest directions for future research in this area.

Kanungo and Joshi as in [5] analysed various existing studies based on Artificial Intelligence (AI) and diverse Machine Learning (ML) techniques being used to detect depression

Aleem et. al.as in [6] reviewed different machine learning algorithms used to detect and diagnose depression. The ML-based depression detection algorithms were categorized into three classes, classification, deep learning, and ensemble.

Zhao and Feng as in [7] explored the diagnostic ability of three machine learning methods for evaluating the depression status of Chinese recruits, using the Chinese version of Beck Depression Inventory-II (BDI-II) as the standard.

Similarly, Pasalkar and Kalbande as in [8] identified the deep formation of the neural network among a few selected structures that successfully complemented natural language processing activities to analyze and predict depression.

Billah and Hasan as in [9] proposed a model to predict depressed or not depressed using machine learning from Bangla Facebook Status. The work was done with 50 Facebook users' data, among them 17 people had committed suicide. The work achieved satisfying accuracy as the first work in Bangla language.

Depressika as in [10] is Early Risk of Depression Detection with opinions is a web application which detects the early risk of depression from the social media posts created by the users with appropriate Recurrent Neural Networks [RNN].

Punithavathi et al. [11] investigated on different machine learning algorithms to process voice signals which in turn will be used for detecting depression levels.

Shaikh, Pratap , Bhusari and Shaikh as in [12] proposed a system wherein the historical data was collected from the videos which the users watched and the keywords they used for the search, and attempt to detect depression was made.

Studies have clearly shown that more than one machine learning algorithm such as Support Vector Machine, Random Forest, Logistic Regression, and Gradient Boosting are utilized successfully as a decision-making tool to identify depression based on individual clinical information. Moreover, it can be extended for the prediction of other critical illnesses such as cancer, diabetes, brain tumour etc.

III. Proposed Model

Fig. 1 shows the proposed model. The text web-scrapped from a popular social media platform will serve as input and if this text indicates absence, presence or limited presence of depression will be the final output.

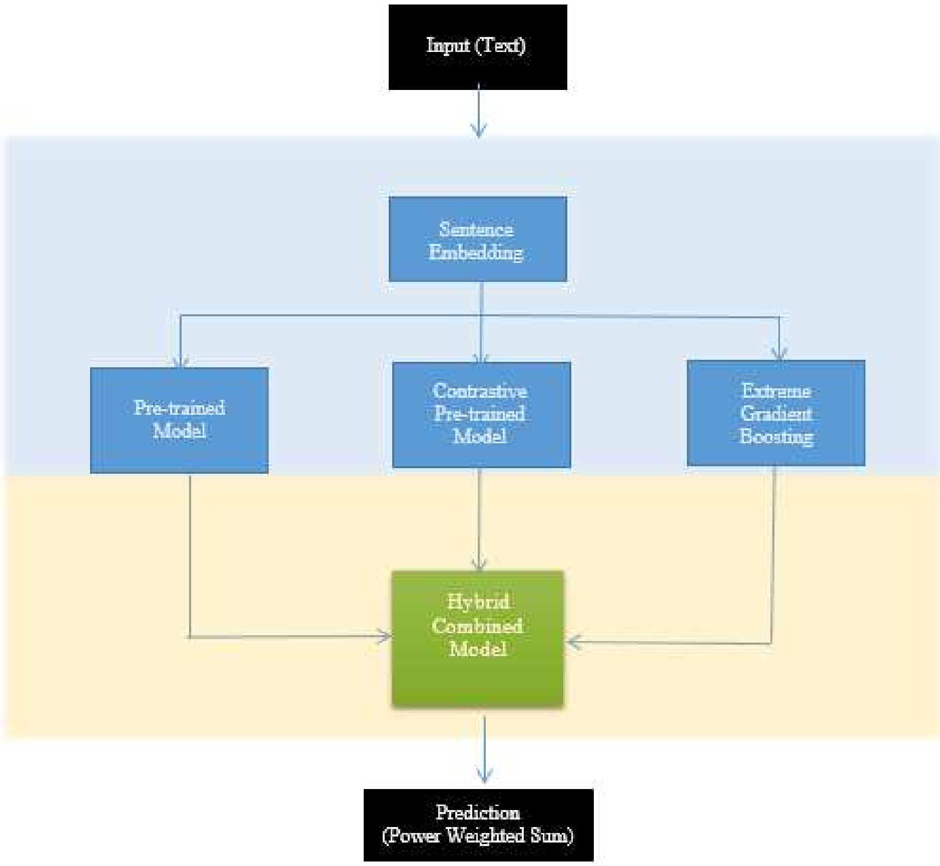

Fig. 1. The Proposed Model

A. *Step-by-step Procedure:*

1. Given the input, VAD scores are generated.
2. Sentence Transformers generate pre-trained sentence embeddings. Sentence embeddings are concatenated with sentiment feature embeddings. The probability of each category is predicted with the help of XGBoost and LGBM. The values of the hyper-parameters are optimized with the help of cross-entropy.

3. Sentence embeddings are generated with the help of pre-trained models: GPT-3 as in [13], RoBERTa as in [14] and ELMO as in [15]. These sentence embeddings are used by an MLP to predict the probability.

4. VAD scores are applied through a layer with the activation function GeLU. Sentence embeddings and VAD embeddings are combined and then used as input to an MLP for classification.

5. To improve the performance, the final predicted value is calculated as the power weighted sum as in [16], as follows:

$$P = w1 * (P1)\ N * + w2 * (P2)\ N + w3 * (P3)\ N \quad (1)$$

Here, N is the weight of the power whereas w1, w2 and w3 are weights of the model mentioned above in step 2, 3 and 4 respectively. In our work, we took N=4 whereas w1=1.00, w2=0.67 and w3=0.69.

The following measures have been used to understand performance of various models as in [17,18]:

- macro averaged F1-Score
- macro averaged Precision and
- macro averaged Recall.

B. Datatset

The dataset [19] contains 16632 posts in total. We used 8891 posts for training and 4496 posts for testing. We used the remaining posts for evaluation. Each record consists of three columns: PID, Text, and Label.

PID represents unique serial number assigned to each post within the training dataset.

Table I shows structure of three samples of different severity, taken randomly from the dataset:

TABLE. I. SAMPLE RECORDS FROM THE DATASET

PID	Text	Label
train_1	Is anyone else thinking that Indian IT companies will take strict actions against moonlighting?	No depression
train_2	I have stopped enjoying most of the things now-a-days. I don't know why but nothing appeals me anymore.	Moderate
train_3	Life is going nowhere. No hopes left. I feel I better be a dead person.	Severe

The dataset is stored in a tab-separated-value (.tsv) file. Table II reports summarized dataset.

Hyper-parameters of each model are mentioned in Table III, Table IV and Table V.

SMOTE (Synthetic Minority Oversampling Technique) is used here to deal with the problem of imbalanced classification.

TABLE. II. SUMMARY OF DATASET

Category	Severity			Total
	Severe	Moderate	No Depression	
Training	882	2125	5884	8891
Development	452	1889	2155	4496
Test	296	1445	1504	3245

C. Hyper-parameters

TABLE. III. HYPER-PARAMETERS OF MODEL-1

Method	Batch size	Seed	Warm-up
GPT-3	3	13	4
RoBERTa	6	49	8
ELMO	2	17	5

TABLE. IV. HYPER-PARAMETERS OF MODEL-2

Batch size	Seed	Epochs	Warm-up	LR	HD	Drop-out	Lambda_scl	Lambda_ce
8	17	20	5	4e-5	512	0.1	0.3	0.7

TABLE. V. HYPER-PARAMETERS OF MODEL-3

Method	max_depth	LR	n_estimators	num_leaves	gamma	sub_sample
XGBoost	6	0.1	100	NA	0.02	0.98
Light Gradient Boost	9	0.5	70	64	NA	NA

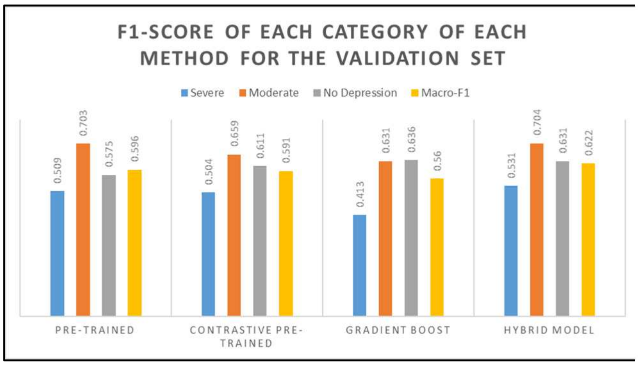

Fig. 2. Performance for the validation set

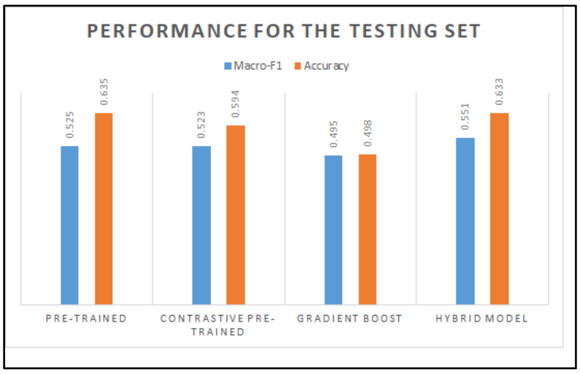

Fig. 3. Performance for the testing set

IV. RESULTS AND DISCUSSIONS

Fig. 2 represents F1-score of all the three models which used for comparison with the proposed model. F1-score of each category - Severe, Moderate and No Depression, is reported for the validation set. Further macro-F1 score is also used as the classes were imbalanced.

Fig. 3 represents performance of the models in terms of macro-f1 score and accuracy on testing set.

The F1 score of each category of each approach for the validation set, is reported in Table 6. It can be noted that each approach specializes in predicting severity of depression. As a result of this, the hybrid approach combines different models to improve accuracy and performance.

TABLE. VI. F1-SCORE OF EACH CATEGORY OF EACH METHOD FOR THE VALIDATION SET

Model	Category			Macro-F1
	Severe	Moderate	No Depression	
Hybrid	0.531	0.704	0.631	0.622
Pre-trained	0.509	0.703	0.575	0.595
Contrastive Pre-trained	0.504	0.659	0.611	0.597
Gradient	0.413	0.631	0.636	0.561

The Macro-F1 score and accuracy of each category of each approach for the testing set, is reported in Table 7. It is evident that the proposed approach offers highest accuracy among all the models under consideration.

TABLE. VII. MACRO-F1 AND ACCURACY FOR TEST SET

Model	Macro-F1
Pre-trained	0.525
Contrastive Pre-trained	0.523
Gradient Boost	0.495
Hybrid Model	0.551

V. CONCLUSION

In this paper, we introduced a hybrid approach which aims at analysing posts on social media platform and attempted to identify signs of the mental disorder of depression. We used three techniques: pre-trained, contrastive pre-trained and gradient boost. Moreover, these three techniques were combined to integrate exclusive strength of each method. The results showed significant improvement achieved by the proposed approach. Thus, it can be concluded that the hybrid ensemble approach does offer better and competitive performance over usage of single model.

Contribution of the research include:

- Proposing a hybrid models with traditional learning classifiers.
- Analysing the impact of concatenating sentence embedding with sentiment features.

Limitations of the study:

- The proposed model is dependent on the VAD scores.
- Only macro-F1, macro-Precision and macro-Recall are used for comparing performance of all models.
- Sentence embeddings are generated with the help of pre-trained models: GPT-3, RoBERTa and ELMO. Results may differ if other pre-trained models are employed.

Future scope of the study:

- The proposed model can be enhanced to analyze recorded conversations which take place between the subject and the care-giver or healthcare provider. Instead of posts, speech can be analyzed, annotated and used as the dataset.
- The hybrid model can be cross-trained and then can be employed to predict severity of other illnesses.

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