Findings of the Shared Task on Detecting Signs of Depression from Social Media

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Abstract

Social media is considered as a platform where users express themselves. The rise of social media as one of humanity's most important public communication platforms presents a potential prospect for early identification and management of mental illness. Depression is one such illness that can lead to a variety of emotional and physical problems. It is necessary to measure the level of depression from the social media text to treat them and to avoid the negative consequences. Detecting levels of depression is a challenging task since it involves the mindset of the people which can change periodically. The aim of the DepSign-LT-EDI@ACL-2022 shared task is to classify the social media text into three levels of depression namely "Not Depressed", "Moderately Depressed", and "Severely Depressed". This overview presents a description on the task, the data set, methodologies used and an analysis on the results of the submissions. The models that were submitted as a part of the shared task had used a variety of technologies from traditional machine learning algorithms to deep learning models. It could be observed from the result that the transformer based models have outperformed the other models. Among the 31 teams who had submitted their results for the shared task, the best macro F1-score of 0.583 was obtained using transformer based model.

1 Introduction

According to the World Health Organization (WHO) (Organization et al., 2017), depression is a common disorder across the world that has an impact on the affected person's mood and feelings. This mental health disorder affects a large part of society every year with varying symptoms like lack of interest, insomnia, thought of death etc. The symptoms may vary according to the intensity of disorder. If the intensity is too extreme and left untreated, it may lead to serious consequences (Luddington et al., 2009). Thus, early prediction of depression is inevitable. On the other hand, in this digital era, social media applications have become a great platform to look over one's mood and feelings (Katikalapudi et al., 2012). Thus, social media data can be used to detect depression.

Erisk@CLEF (Losada et al., 2017) served as a root for this task, which aims to detect depression from the social media data. In addition to this, many custom data sets (Al Hanai et al., 2018; Morales and Levitan, 2016), arose that aims to detect mental illness from various social media platforms like Twitter (Reece et al., 2017; Tsugawa et al., 2015; Deshpande and Rao, 2017; Lin et al., 2020), Facebook (Eichstaedt et al., 2018), Reddit (Wolohan et al., 2018; Tadesse et al., 2019), etc. Among these social media platforms, Reddit possesses more textual data and thus, postings from Reddit were analysed to detect the level of depression. Also, many research works were based only on the detection of the presence of depression rather than detecting the level of depression. Thus, this shared task aims to detect the level of depression from Reddit postings.

2 Task description

DepSign-LT-EDI@ACL-2022[1] aims to detect the signs of depression of a person from their social media postings wherein people share their feelings and emotions. Given social media postings in English, the system should detect the signs of depression into three levels of depression namely "Not Depressed", "Moderately Depressed" and "Severely Depressed".

3 Data description

For detecting the level of depression from social media data, postings from Reddit were scraped and labeled into three class labels namely "Not De-

[1] https://competitions.codalab.org/competitions/36410

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pressed", "Moderately Depressed", and "Severely Depressed". The guidelines and details of annotation are explained in (Kayalvizhi and Thenmozhi, 2022). The data set is a "Tab Separated Valued" data that has been distributed in three splits namely train set, evaluation set and test data. The details of data distribution are shown in Table 1. The sample instances are shown in Table 2.

DepSign-LT-EDI @ACL-2022	Train	Dev	Test	Total instances
Not depressed	1,971	1,830	848	**4,649**
Moderate	6,019	2,306	2,169	**10,494**
Severe	901	360	228	**1,489**
Total instances	**8,891**	**4,496**	**3,245**	**16,632**

Table 1: Data set distribution

4 Methodology

The number of teams that participated in the shared task was 31 by which we received a total of 68 submissions. The details of methodologies used by the submissions are explained in this section.

- **OPI (Rafał and Michał, 2022):** The three runs submitted used RoBERTa based models for classification. The first run used a fine-tuned Transformer architecture based on RoBERTa large on a data set which was prepared by an arrangement and augmentation of the provided data set. Second run used a fine-tuned pretrained RoBERTa large on a parsed Reddit Mental Health data set[2] which was then fine-tuned on the previously prepared training set. Third run was an ensemble (mean) of predictions from the previous two models.

- **NYCU_TWD (Wei-Yao et al., 2022):** Three runs were submitted which included machine learning based methods, pretrained language models, and pretrained language models with supervised contrastive learning. VAD score was adopted into ML based models and pretrained language models with contrastive learning to make the system better learn the representation of given sentences. Power weighted sum technique was employed to ensemble these models.

- **ARGUABLY:** The first run used an ensembled approach of combining XLNET, BERT and RoBERTa by which the contextual and semantic lingual knowledge of a particular sentence was better understood. The second run was implemented using a fine tuned RoBERTa model.

- **BERT 4EVER (Xiaotian et al., 2022):** Two models based on prompt-learning were constructed using different adjectives and three other models were constructed based on sentiment embedding. While training K-fold stacking and back-translation data set were also used. The first four models were combined for the first run, first two and the fourth model were combined for the second run and the first two and the last two models were combined for the third run. The t5-base was leveraged as the base model and different adjectives were used to indicate different degrees of depression. BERT model with sentiment embedding and adversarial training was used to improve the recognition ability of the model.

- **KADO (Morteza et al., 2022):** One run was submitted which used a BERT based Hybrid Transformer model for the purpose of classification.

- **UMUTeam (José Antonio and Rafael, 2022):** The model combined the linguistic features, sentence embeddings from FastText and two distilled embeddings from ROBERTA and BERT. The first run was implemented using a neural network. The other two runs used ensembled approaches of which the mode of predictions was used by run 2 and average probabilities was used by run 3.

- **DeepBlues (Nawshad et al., 2022):** The first submission used a Depression Specific BERT pre-trained model called MBERT which was fine-tuned over the provided data set. The second run fine tuned the Mental BERT model using Relevant Excerpts that were extracted from the data set and the third model submitted used a Depressive Sentence Proportion based Method.

- **Titowak:** Similar data instances from other data sets like Sentiment140, Suicide Detection were added to the existing data set using

[2]https://zenodo.org/record/3941387#.YfcI9_lKiUl

PID	Text Data	Class label
train_pid_1	My life gets worse every year : That's what it feels like anyway....	moderate
train_pid_2	Words can't describe how bad I feel right now : I just want to fall asleep forever.	severe
train_pid_3	Is anybody else hoping the Coronavirus shuts everybody down?	not depressed

Table 2: Sample instances of data set

Doc2Vec and then the training was done using pre-trained language models like BERT and RoBERTa and the predictions obtained were submitted.

- **E8@IJS (Ilija et al., 2022):** Three submissions were done of which the first one was based on the RoBERTa model, the second using Automated Machine Learning (AutoBOT model) and the third run using a combination of textual features and knowledge-graph.

- **SSN (Adarsh and Betina, 2022):** The first run used a simple Embedding layer followed by 2 dense layers. The second run used a RNN with 2 Bidirectional LSTM layers followed by 2 Dense layers and the third run used a transfer Learning model using BERT, the output of which was passed to a Dense layer for classification.

- **Ablimet:** Balancing of the data set was done using RandomOverSampler. Then Roberta-base was used as a pretrained language model and used 2 linear fully connected layers for the process of classification.

- **Viswaas:** The submissions were various ensembled models using different transformer models. The weights to each model were obtained using XGBoost and Bayesian Optimization methods.

- **sclab@cnu:** The three submissions done were based on the transformer models namely RoBERTa, BERT and an ensembled model which was constructed by combining both the above models.

- **ai901@cnu:** The first run submitted used a transformer based approach namely RoBerta. The other two runs were based on Machine Learning algorithms namely Support Vector Machine and Logistic Regression.

- **Beast:** Three models were submitted in which the first model was trained on Pretrained BERTWEET, second and third model was trained on ROBERTA and ROBERTA with commonsense knowledge respectively.

- **Unibuc_NLP:** The model submitted had implemented the classification using a Convolutional Neural Network together with GloVe embedding scheme.

- **BFCAI:** Different Machine Learning algorithms were used for different submissions which had used TF/IDF vector space models.

- **MUCS (Asha et al., 2022):** The first run had used a transformer based BERT model and the next two runs had used Ensemble of different Machine Learning models for the purpose of classification.

- **DepressionOne (Suman and Radhika, 2022):** Two runs were submitted in which the first run was built on pretrained transformers and the other run uses oversampling and under sampling techniques together with a SVM classifier.

- **SSN_MLRG3 (Sarika et al., 2022)** A transformer model was submitted. The data set was initially processed by removing unwanted symbols and characters. Then, the model was trained on a Transformer based ALBERT model.

- **nikss:** The submission was done based on a transformer based approach.

- **UAGD:** A keras neural network model was submitted with two hidden layers of 64 neurons each was used, with dropout of 0.01. They had also used SGD optimizer with a learning rate of 0.03.

- **scubeMSEC (Sivamanikandan et al., 2022):** Three transformer based models namely DistilBERT, ALBERT and RoBERTa were used

S.No.	Team name	Features extraction	Classifier	Additional data set used (if any)
1	NYCU_TWD (Wei-Yao et al., 2022), Vishwaas, ai901@cnu , MUCS (Asha et al., 2022), DepressionOne (Suman and Radhika, 2022), KUCST (Manex and Amann, 2022), kecsaiyans, KEC_Deepsign_ACL2022	Word embeddings	Machine learning classifiers	-
2	IISERB (Tanmay, 2022)	Cbow, Doc2Vec	Machine learning classifiers	Erisk-CLEF
3	BFCAI, IISERB (Tanmay, 2022)	Tf-Idf	Machine learning classifiers	-
4	E8@IJS (Ilija et al., 2022)	-	AUTOBOT	-
5	UAGD	-	Keras Neural Network	-
6	Unibuc_NLP	Glove	CNN	-
7	GA	Custom word embeddings	CNN	-
8	SSN (Adarsh and Betina, 2022)	-	Transfer Learning	-
9	SSN, niksss	-	Recurrent neural networks	-
10	niksss, kecsaiyans, KEC_Deepsign_ACL2022	-	Long Short Term Memory	-
11	UMUTeam (José Antonio and Rafael, 2022)	Linguistic features, sentence embeddings	Transformers	-
12	E8@IJS (Ilija et al., 2022)	Combination of textual (sentence-transformers, distilbert, lsa) features and knowledge-graph	Transformers	-
13	OPI (Rafał and Michał, 2022)	-	Transformers	Reddit Mental Health data set
14	ARGUABLY, BERT 4EVER (Xiaotian et al., 2022), KADO (Morteza et al., 2022), SSN, Ablimet, Vishwaas , sclab@cnu, ai901@cnu , Beast, MUCS (Asha et al., 2022), DepressionOne (Suman and Radhika, 2022), SSN_MLRG3 (Sarika et al., 2022), niksss, ScuBEMSEC (Sivamanikandan et al., 2022), SSN_MLRG1 (Karun et al., 2022), RACAI	-	Transformers	-
15	Titowak	-	Transformers	Sentiment140, Suicide Detection
16	DeepBlues (Nawshad et al., 2022), FilipN (Filip and György, 2022)	-	Domain specific transformers	-

Table 3: Summary of methodologies

S.No.	Team Name	Accuracy	Weighted F1-score	Weighted Recall	Weighted Precision	Macro Recall	Macro Precision	Macro F1-score	Rank (based on Macro F1 score)
1	OPI	0.658	0.629	0.623	0.639	0.565	0.512	**0.583**	1
2	NYCU_TWD	0.633	0.612	0.612	0.624	0.539	0.490	0.552	2
3	ARGUABLY	0.625	0.569	0.550	0.627	0.569	0.479	0.547	3
4	BERT 4EVER	0.625	0.632	0.625	0.644	0.581	0.522	0.543	4
5	KADO	0.618	0.622	0.633	0.615	0.474	0.498	0.542	5
6	UMUTeam	0.625	0.644	0.651	0.641	0.543	0.537	0.538	6
7	DeepBlues	0.651	0.606	0.602	0.615	0.473	0.492	0.537	7
8	Titowak	**0.671**	0.614	0.602	0.640	0.571	0.515	0.536	8
9	E8@IJS	0.602	0.538	0.586	0.499	0.348	0.256	0.533	9
10	SSN	0.636	0.628	0.618	0.648	0.570	0.526	0.531	10
11	Ablimet	0.623	0.586	0.584	0.588	0.460	0.447	0.530	11
12	Vishwaas	0.609	0.562	0.546	0.588	0.473	0.432	0.524	12
13	sclab@cnu	0.642	0.545	0.524	0.607	0.557	0.455	0.503	13
14	ai901@cnu	0.612	0.642	0.633	0.658	0.573	0.539	0.496	14
15	Beast	0.550	0.666	0.658	0.685	**0.591**	**0.586**	0.495	15
16	Unibuc_NLP	0.569	0.613	0.671	0.595	0.384	0.395	0.486	16
17	BFCAI	0.633	0.630	0.642	0.624	0.495	0.517	0.484	17
18	MUCS	0.612	0.527	0.511	0.617	0.519	0.461	0.479	18
19	DepressionOne	0.602	0.638	0.636	0.641	0.533	0.528	0.478	19
20	SSN_MLRG3	0.573	0.576	0.585	0.572	0.403	0.436	0.473	20
21	niksss	0.524	0.585	0.573	0.605	0.516	0.458	0.467	21
22	UAGD	0.577	**0.658**	**0.671**	**0.653**	0.515	0.571	0.464	22
23	scubeMSEC	0.511	0.632	0.625	0.643	0.557	0.525	0.457	23
24	kecsaiyans	0.584	0.633	0.625	0.646	0.572	0.530	0.453	24
25	KUCST	0.546	0.610	0.612	0.612	0.497	0.475	0.443	25
26	IISERB	0.530	0.586	0.577	0.606	0.469	0.470	0.438	26
27	SSN_MLRG1	0.585	0.585	0.569	0.617	0.541	0.469	0.412	27
28	KEC_Deepsign_ACL2022	0.569	0.619	0.609	0.636	0.542	0.513	0.398	28
29	RACAI	**0.671**	0.550	0.530	0.585	0.481	0.427	0.372	29
30	GA	0.513	0.574	0.569	0.580	0.399	0.398	0.364	30
31	FilipN	0.586	0.527	0.513	0.554	0.373	0.365	0.291	31

Table 4: Team Wise results

to classify the social media posts into different levels of depression.

- **kecsaiyans:** To detect signs of depression from social media text, a machine learning model with logistic regression was submitted.

- **KUCST (Manex and Amann, 2022) :** Two model were submitted which were based on Logistic Regression of which the first model considered information about words, POS-tags and readability measures and the second model included the ratio of first/third person and the ratio of singular/plural words.

- **IISERB (Tanmay, 2022):** The first run submitted used an entropy based feature weighting scheme which used the Bag of Words model and Support Vector Machine classifier. The second run used Term Frequency and Inverse Document Frequency (TF-IDF) based feature weighting scheme instead of the entropy based model. The third run used a paragraph embedding based feature weighting scheme (Doc2Vec) followed by CBOW and Skipgram model and random forest classifier. The anxiety data sets released as part of CLEF eRisk 2021 shared task were used to build the paragraph embeddings in addition to the given training data [3].

- **SSN_MLRG1 (Karun et al., 2022) :** Three runs were submitted of which the first run used a fine-tuned version of Distilbert, trained for 4 epochs with a learning rate 1e-4. W&B Sweep was run on BERT, ALBERT, ROBERTA and DISTILBERT with various parameters and the model with the least evaluation loss and best accuracy was chosen as the second run. And a basic random forest classifier to test how well a default model adapts to the given data set was submitted as the third run.

- **KEC_Deepsign_ACL2022:** Three runs were submitted of which the first run was a voting based ensemble method among machine learning models like Naive Bayes, Random forest,

[3] https://erisk.irlab.org/2021/index.html

Decision tree, Ada boost method. Second run used Bidirectional LSTM and the third run used a simple LSTM with dropout.

- **RACAI:** The system used the XLM-ROBERTA model with an intermediate layer before the classification head. The system employed a new layer configuration inspired by the biological process of lateral inhibition.

- **GA:** The model with custom word embeddings trained on one-dimensional Convolutional Neural Network was submitted.

- **FilipN (Filip and György, 2022):** Three runs that used Mental BERT were submitted with different assemblies for longer text. First run used the head and tail of the tokens, the second run used the head and tail tokens with more training steps, and the third run used only the tail tokens with less training steps.

5 Evaluation

The evaluation was done using all the performance metrics of sklearn. The submitted runs were ranked using macro F1 score, since the data set is unbalanced. The rank list of the teams were tabulated in Table 4.

From the table, it is clear that the system designed by the OPI team (RoBERTa large with additional data set) achieved a best macro F1-score of 0.583. The best accuracy score of 0.671 was achieved by two teams namely Titowak (RoBERTa with additional data set) and RACAI (XLM-RoBERTa). The best macro precision and recall scores of 0.591 and 0.586 were attained by team Beast. Regarding the weighted scores of F1, precision and recall, the system designed by team UAGD (Keras Neural Network) performed better than the other systems.

6 Analysis and discussion

Out of the 31 teams that participated, 27 teams used deep learning models to detect the level of depression. The methodologies of the teams are summarized in Table 3. Among the deep learning models, 25 teams used pre-trained transformers models like RoBERTa, XLM-RoBERTa, BERT, XLNET, DistilBERT, AlBERT and T5. Other than pre-trained transformers models, deep learning models such as convolutional neural network, RNN, LSTM and bi-directional LSTM were also used. In addition to deep learning models, machine learning models were also implemented. In the machine learning models, feature extraction was done using word embeddings, TF-IDF, doc2vec, bag of words, fastText and glove. The machine learning classifiers like XG-Boost, SVM, linear regression, SGD etc. were used for training the models. Additional data sets namely Anxiety data set of e-risk@clef-2021, Reddit mental health data set, sentiment140 and suicide detection data sets were used along with the provided data set for training. Some systems were trained on balanced data set, after balancing the data set using random over sampler(Lemaître et al., 2017).

7 Conclusion

Depression is a common mental illness that has an impact on a person's mood and feelings which may lead to serious consequences if not noticed and treated at an early stage. Thus, detecting depression at an early stage is a very predominant need. In this shared task DepSign-LT-EDI@ACL-2022, the Reddit postings were used to detect levels of depression using three labels namely "Not Depressed", "Moderately Depressed", and "Severely Depressed". A total of 31 teams submitted their results and most of the systems were built using transformers and its variants. The systems were evaluated using macro-averaged F1-score. The best performing system of Team OPI has used an ensemble method of RoBERTa and attained an F1 score of 0.583.

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