SSN_MLRG3 @LT-EDI-ACL2022-Depression Detection System from Social Media Text using Transformer Models

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Abstract

Depression is a common mental illness that involves sadness and lack of interest in all day-to-day activities.The task is to classify the social media text as signs of depression into three labels namely "not depressed", "moderately depressed", and "severely depressed". We have built a system using Deep Learning Model "Transformers". Transformers provides thousands of pretrained models to perform tasks on different modalities such as text, vision, and audio. The multi-class classification model used in our system is based on the ALBERT model(Lan et al., 2019). In the shared task ACL 2022, Our team SSN_MLRG3 obtained a Macro F1 score of 0.473.

1 Introduction

Social media is developed as a great point for its users to communicate with their friends, relatives and share their opinions, photos, and videos reflecting their feelings and sentiments. This creates an opportunity to analyze social media data for user's feelings and sentiments to investigate their moods and attitudes when they are communicating through the Social Media Apps. Depression is the common issue of today's youngsters and suicide due to depression is growing day by day. People often communicate their moods through tweets or messages but people around them fail to understand the underlying truth behind the words. Katikalapudi et al. (2012) conducted depression survey among 216 undergraduate students with real time Internet data. Feuston and Piper (2018) analyzed instagram posts, pictures, captions and concluded that mental health and illness are interrelated through the application of the coded gaze.

The task 4 in Second Workshop On Language Technology For Equality, Diversity, Inclusion (LT-EDI-2022) Sampath et al. (2022) was conducted to detect the signs of depression from social media text in English language. We tried to classify each message as "not depressed", "moderately depressed", and "severely depressed". The training set provided by the organizers contains 8,891 social media messages. The given dataset is used to train our model.

2 Related Works

In last five years, the use of social media has increased drastically and the data available too, has increased. Hence, numerous studies on emotion analysis and depression analysis have been carried out in recent times. Most of them revolve around machine learning and deep learning techniques.

Liu and Lapata (2019) showcased how Bidirectional Encoder Representations from Transformers (BERT)(Devlin et al., 2018) models can be used for text summarization. They proposed a general framework for extractive and abstractive models. This helped us to understand the BERT encoder-decoder architecture.

O'dea et al. (2015) carried out work on detecting suicidality on Twitter using Support Vector Machine (SVM) and Logistic Regression with cross-validation methods. SVM-TF-IDF filter algorithm showed best results with combined dataset accuracy of 76%. It stated that more searches on suicide related terms can improve the accuracy of the model.

Tripathi et al. (2019) built an emotion recognition system using speech features and transcriptions. Different Deep Neural Network (DNN) architectures were used among which Text-MFCC(mel frequency cepstral coefficients) gave an accuracy of 76.1%.

Shah et al. (2020) used deep learning based models for analyzing the depression state. They tried different combinations of metadata features and word embedding techniques with Bidirectional Long Short Term Memory (BiLSTM). Among different features, Word2VecEmbed+Meta features performed well with a F1 score of 81%.

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We have worked in contextual emotion and sentiment analysis with various machine learning and Gaussian process models in (Angel Deborah et al., 2019), (Angel Deborah et al., 2021), (Rajalakshmi et al., 2018), (Rajendram et al., 2017b), (S et al., 2022) and (Rajendram et al., 2017a) which form the base for dealing with emotions and kindle our interest in depression detection.

3 Methodology and Data

The task is to discover the mood of the user from the social media posts and it is always difficult to extract the emotions from the text. A post can have different combination of emotions. The architecture diagram for the depression classification is shown in Figure 1. The training dataset is preprocessed to remove the unwanted information and is given to ALBERT model to learn the features. Test data is given to the built model to classify the text into 3 states of depression.

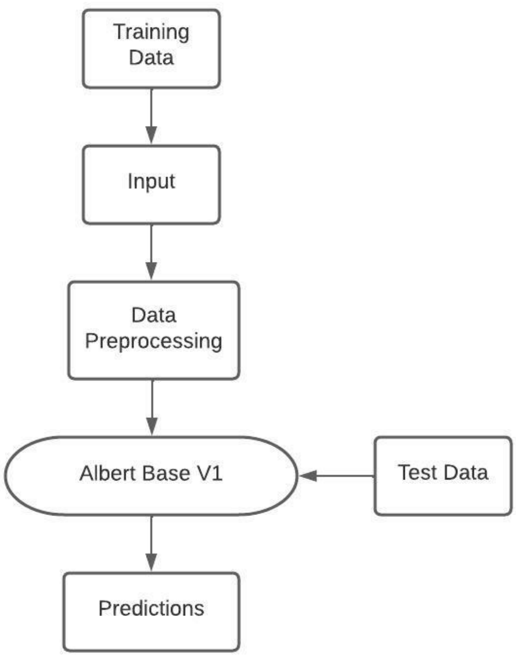

Figure 1: Architecture of Proposed System

3.1 Acquiring Datasets

The dataset given by the organizers (Sampath et al., 2022) contains social media posts in English Language. All the dataset files are in tsv format. The dataset is based on multi-class classification. Each post is annotated by three labels namely moderate, severe and not depression. The distribution of the dataset is shown in Table 1.

Label	Train	Dev	Test
Not depression	1,971	1,830	
Moderate	6,019	2,306	
Severe	901	360	
Total	8,891	4,496	3,245

Table 1: Data Distribution for Depression Analysis

3.2 Data Preprocessing

Data preprocessing is vital for the success of deep learning solution. The given dataset has unwanted characters which is a classic signature of any collection of social media posts. In order to bring the posts into textual form, we performed normalization. The dataset is cleaned and processed using functions from NLTK toolkit.

During preprocessing, we removed stopwords, URLs, special characters, symbols, annotated emojis, and emoticons. We expanded contractions and lemmatized the text. The accented characters, extra whitespaces are reduced.The long words are reduced and uppercase are converted to lowercase.

3.3 Model Description

We classified the social media posts with the help of the below transformer model.

3.3.1 ALBERT base v1 - Transformer Model

A Lite BERT (ALBERT) architecture has significantly fewer parameters as compared to traditional BERT architecture.ALBERT incorporates two-parameter reduction techniques which are factorised embedding parameterisation and cross-layer parameter sharing in order to deal with the obstacles in scaling pre-trained models in NLP. The first step in learning is a factorized embedding parameterization. The large vocabulary embedding matrix are decomposed into two small matrices.Then, size of the hidden layers are separated from the size of vocabulary embedding.This separation makes it simpler to grow the hidden size without significantly increasing the parameter size of the vocabulary embeddings. Cross-layer parameter sharing is the second technique.This technique is used to prevent the growth of the parameters with the growth in the depth of the network. ALBERT configurations have fewer parameters compared to

BERT-large but achieve significantly better performance. ALBERT model used here has 12 encoder segment, 768 hidden state size and embedding size. We have trained the model for 3 epochs.The train batch size is 8 and the learning rate is 4e-5.

The Evaluation metrics of development dataset using ALBERT is shown in table 2.

Parameters	Score
Accuracy	0.56
Macro F1-score	0.38
Macro Recall	0.38
Macro Precision	0.38
Weighted F1-score	0.56
Weighted Recall	0.56
Weighted Precision	0.56

Table 2: Evaluation metrics of ALBERT Base

3.3.2 Random Forest

Random forest classifiers fall under ensemble-based learning methods.A random forest algorithm consists of various decision trees.It establishes the outcome based on the predictions of the decision trees.Random forest reduces overfitting of dataset and increases precision.

The Evaluation metrics of development dataset using Random forest is shown in table. 3.

Parameters	Score
Accuracy	0.50
Macro F1-score	0.32
Macro Recall	0.34
Macro Precision	0.33
Weighted F1-score	0.47
Weighted Recall	0.50
Weighted Precision	0.49

Table 3: Evaluation metrics of Random Forest

4 Result

We have used evaluation metrics as accuracy, macro F1-score, macro recall, macro precision, weighted F1-score, weighted recall and weighted precision. The performance is shown in Table 4.

We obtained 20^{th} rank with an accuracy of 57% while the top ranked team obtained 66% as accuracy. Due to the resource constraints we trained

Parameters	Score
Accuracy	0.573
Macro F1-score	**0.473**
Macro Recall	0.516
Macro Precision	0.458
Weighted F1-score	0.585
Weighted Recall	0.573
Weighted Precision	0.605

Table 4: Result for ALBERT Base

our model with fewer epochs. The accuracy of the system may improve with hyperparameter optimisation.

4.1 Error Analysis

The confusion matrix for the results obtained with the ALBERT model is shown in figure 2.

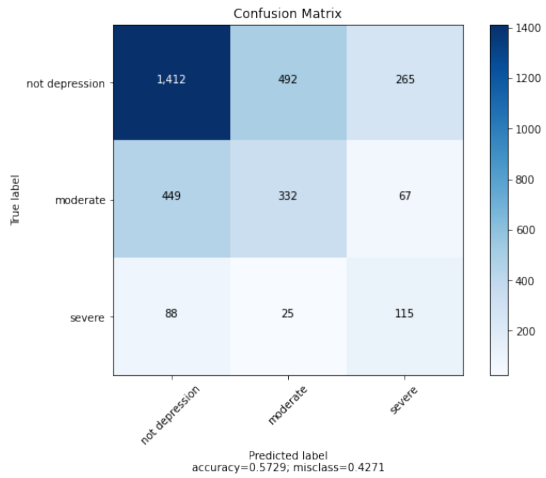

Figure 2: Confusion matrix for results with ALBERT

5 Conclusion

We have built ALBERT base Model for the task to detecting signs of depression from social media posts. All the models are preprocessed with NLTK, which we think is an important factor for building a good model. The emotion of a social media posts depends on individual's perception and cannot be judged by simple conventional models. This is one of the reason for the reduced accuracy. Understanding one's feelings and mood is too delicate for models to detect them accurately. Imbalanced data distribution among the output class labels can be another reason for less accuracy. The training data has high number of moderately depressed posts followed by not depressed and severely depressed.

We intend to investigate further by using different transformer models and methods to augment the data.

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