A Decision Support System for predicting socially depressed users using Bidirectional Encoders Representations from Transformers (BERT)

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Abstract: Depression is one of the leading causes of suicides in society. The youth of the 21st century are inclined towards social media for all their needs and expressions. Close friends can easily predict if someone is happy, sad, or depressed from a user's daily social media activity like status uploads/shares/reposts/check-ins, etc. This activity can be analyzed in order to understand the pattern of mental health. Such data is easily available and if suspected, it can be reported to a Psychiatrist and Psychologist to prevent socially active depressed patients from taking any wrong decisions regarding their life thus providing a Decision Support System (DSS). Various natural language processing techniques have been used in order to detect depression but there is a need for a unified architecture that is based on contextual data and is bidirectional in nature. This can be achieved by using example be achieved by using the Google research project (BERT) Bidirectional Encoder Representations from Transformers.

Keywords: — Social Media Analysis, Depression Detection, Natural Language Processing, Embedding System, BERT.

1. INTRODUCTION

The current social media tools are known to keep us engaged by keeping the screen on our fingertips at all times. The dependence on these platforms has grown to a point where an individual feels the inherent need to be sharing every thought and feeling they have with their social followers for a sense of validation. However, when an individual witnesses their peers doing better, it can lead to low self-esteem and self-judgment can produce anxiety, anger, and depression.

Fig.1. A lonely Snapchat Users Story

People share their positive and negative experiences on social media. Users also tend to upload/share information which can lead to the path of hacking, cyberbullying, scams and frauds. Dependence on these platforms has grown to the point where one feels that there is a natural need to share all their thoughts and feelings with their social followers in a sense of reassurance. However, when a person proves that his peers are doing better, it also breeds envy that leads to feelings of inferiority.

While depression and other mental illnesses can lead to people avoiding social gatherings and often isolate themself from their close friends/relatives, it has been found that social media is widely used by such affected people to communicate with others, share experiences, and support each other all this digitally. It is also seen that many users show symptoms of loneliness, depression, anxiety, depression, etc. try finding their peace of mind by sharing their thoughts over the internet. Using a machine-readable method, this research paper focuses on ways to distinguish the first symptoms of depression from the text in its earlier stages. A complete analysis of the various machine learning algorithms is studied in detail and describes past and present work in relation to text classification; we can build a useful foundation for this work by using techniques that consider past and present information of the data and compute the sentiment in a bidirectional format.

Early detection is critical for rapid intervention. By noting and distinguishing these thoughts and behaviors

in their premature stage, enough time to implement safety measures can be taken. A deep bidirectional transformer is the proposed new training objective. BERT [8] (Bidirectional Encoder Representations from Transformers) is the new method of training language models. BERT (Bidirectional Encoder Representations from Transformers) is the first deeply bidirectional, unsupervised language representation, pre-trained using only a clear text corpus. It is supported by a way of automatic text classification, in the development environment of the web of things. BERT has proven to outperform the Machine Learning methods in accuracy as it undertakes state-of-the-art advances for eleven NLP tasks [3]. This method can persuasively improve and predict Depression concerning text data with sequence features and obvious local features.
The rest of the paper is organized as follows. The proposed algorithm using BERT is explained in section 2. Experimental results with respect to the same are presented in section 3. Concluding remarks and future scope are given in section 4.

2. LITERATURE REVIEW

Marcel Trotzek et al.[1] in their research work have implemented a deep learning CNN-based model along with different word embedding techniques like GloVE, FastText, and Word2Vec for detection of depression from social media analysis.

Wenting Li et al.[2] explore an automatic text classification method using the BERT model and feature fusion. The outputs of the traditional deep learning algorithms like CNN and BiLSTM are merged together to make full use of the local features. Such a hybrid approach outperforms the state-of-art methods of accuracy.

Songsong Liu et al.[3] analyzes the Bayes network along with in combination with the BERT model. Classification of text is carried out using Bayes Network whereas the BERT model classifies the text into specific categories. This combination reduces the error rates and therefore finds an improvement in the accuracy levels of text classification.

Manish Munikaret al. [4] have explored the sentiment classification problems. They have used a promising BERT Model for solving fine-grained sentiment classification. The effect of Transfer learning in natural language processing is also seen in this research.

3. PROPOSED SYSTEMS

3.1 Need for Transformers Bi-directional

Using a simple text corpus, BERT is the primary bidirectional, unsupervised language representation.

BERT’s primary innovation is utilizing the Transformer for bidirectional training, an attention-based modeling technique that is widely preferred. This replaces the previous efforts of unidirectional movement combined right-to-left and left-to-right training. What Makes BERT Different is that unlike the previous models, BERT is the first bidirectional model which is deep. This pre-trained model which uses a raw text corpus is built upon recent contributions including OpenAI GPT (Generative Pre-Training), ELMo, Semi-Supervised Sequence Learning ULMFit [1]. This is important because pre-trained descriptions can either be context-free or contextual. Contextual descriptions can further be unidirectional or bidirectional.

Context-free models like GloVe or word2vec formulate one-word embedding descriptions for every word within the dictionary. Let’s take the word “capital” for example. Capital would have an equivalent context-free description in “capital amount” and “Capital of India.” Contextual models instead formulate a description of every word that is based on the opposite words within the sentence. For example, within the sentence “The total flow of capital amount has to be revised,” a unidirectional contextual model would represent “capital” supported “The total flow of capital” but not “amount.” However, BERT represents “capital” using both its previous and next context — “The total flow ... amount” — ranging from the very bottom of a deep neural network, making it primarily bidirectional.

A unidirectional language model does not have a deeper sense of language context and flows as compared to bi-direction models as per the findings from the analysis of literature. As per the work presented, the novel technique namely Masked LM (MLM) allows bidirectional training. Initially, this was impossible to achieve with a single directional movement. The target being predicting the initial word of a masked word based on its context only. The next step followed is Next sentence prediction (NSP) which will be understood in detail in further information.

3.2 BERT Architecture

BERT is that the first deep multi-layer bidirectional Transformer encoder. There are two models introduced within this work. It generally comes in 2 flavors namely:

BERT base: 12 layers (transformer blocks), 12 attention heads, and 110 million parameters.

BERT Large: 24 layers, 16 attention heads and, 340 million parameters.

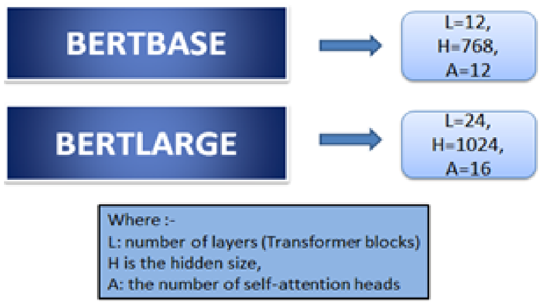

Fig.2.Types of BERT.

Composed of two parts, Transformer is an attention-based architecture for NLP. It comprises the Encoding component and the Decoding component. BERT being a multi-layered bidirectional Transformer encoder a series of tokens is passed as an input to the transformer through an In BERT experiments, the number of blocks N was chosen to be 12 and 24.

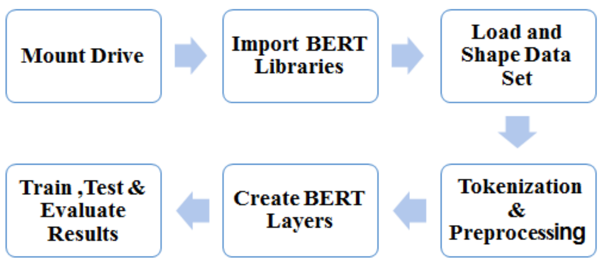

Fig.4.Steps involved in the proposed algorithm.

Pre-training in BERT

The pre-training required for BERT is carried out in 2 steps namely:

Step 1: MLM: Masked Language Model.

Masking is done randomly, and 15% of all WordPiece tokens in each input sequence are masked. Only the masked tokens are predicted rather than predicting the entire input sequence.

Input: I am feeling sad.

Procedure:

Pre-Training Step 1: MLM: Masked Language Model

- 80% of the time: Replacement was done with [MASK]. --> I am feeling [MASK].
- 10% of the time: Word Replaced randomly --> I am feeling apple.
- 10% of the time: Kept same --> I am feeling sad

Step 2: NSP: Next Sentence Prediction.

During the training process, the model receives a set of sentence pairs. The system learns to predict of the sentences are related to each other or not. That is whether the problem of depression is observed over a period of time for a particular user.

Pre-Training Step 2: NSP: Next Sentence Prediction

Input = [CLS*] the girl went to the* [MASK] [SEP] *she bought a basket of* [MASK] [SEP]

- Label = IsNext

Input = [CLS] *the girl went to the* [MASK] [SEP] *penguin don't* [MASK] *as they are flight ##less birds* [SEP]

- Label = NotNext

Fine Tuning in BERT

Fine-tuning the BERT model for specific tasks can result in state-of-the-art performances. The final hidden representation for each token is fed to a classification layer and the Softmax function is used to calculate label probabilities.

3.3 BERT Algorithm for Depression Detection

1. Collect input data
   Input Corpus to be fed to the system should comprise textual information collected from the Social Media Account of the user.
2. Tokenization
   Tokenize the given sentences for which [CLS] special classifier token is added at the beginning and [SEP] at end of the tweet. (Considering data collected from the Twitter account).
3. Pre-Training Process
   MLM (Masked Language Model): Only the masked tokens are predicted rather than predicting the entire input sequence.
4. Fine-Tuning Process
   The fine-tuning for Depression Detection using BERT can simply be done by adding a

classification layer on the Transformer Output for the [CLS] token.

4. EXPERIMENT AND RESULTS

The research work and implementation of BERT-based approaches for detecting depression are as follows. Here the algorithm is applied to a set of comments that helps us detect whether the user's comment is depressed or not.

```
[ ] pred_sentences = [
      "I am verry depressed of the work",
      "I get to spend New Year's home again alone and lonely.",
      "He is a great man with good behaviour",
      "Learning to pretend to have a good time had become a natural skill.
    ]
```

```
[('I am verry depressed of the work',
  array([-5.7912216e+00, -3.0588764e-03], dtype=float32),
  'Depression'),
 ("I get to spend New Year's home again alone and lonely.",
  array([-5.7624536e+00, -3.1483627e-03], dtype=float32),
  'Depression'),
 ('He is a great man with good behaviour',
  array([-0.06757547, -2.7281084 ], dtype=float32),
  'No depression'),
 ('Learning to pretend to have a good time had become a natural skill.
  array([-3.5576475 , -0.02891993], dtype=float32),
  'Depression')]
```

Fig.5. Figures show the execution of the BERT algorithm to predict depressed and not depressed comments in the data set

Evaluation	Result
AUC	0.93938315
Accuracy	0.9395161
Precision	0.9375
Recall	0.9448819
F1	0.9411765
TP	240.0
TN	226.0
FP	16.0
FN	14.0

Fig.6. Figures show evaluation results of BERT.

The true job of applied machine learning is to explore the space of possible models and discover what a good model score looks like relative to the baseline on the specific dataset. Statistically, this paper **compares** the **accuracy** between the two Models namely Word2Vec with CNN and BERT-Base and has the resultant Analysis.

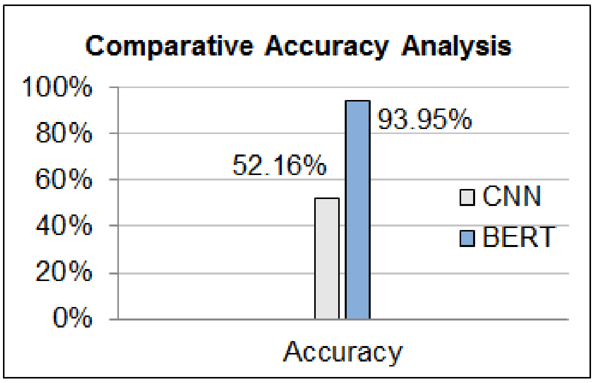

Fig.7.Accuracy comparison of CNN and BERT.

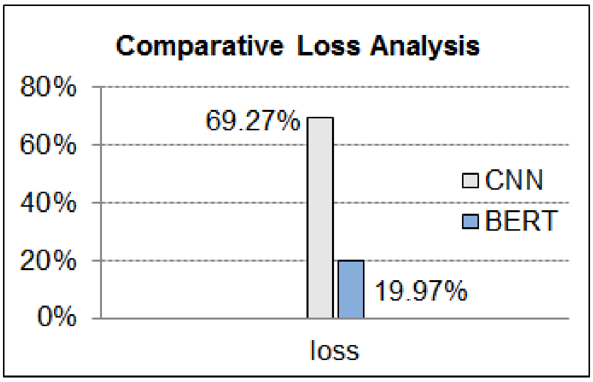

Fig.7.Loss comparison of CNN and BERT.

5. CONCLUSION & FUTURE WORK

In this implementation, the approach for early detection of depression from social media analysis is carried out using the BERT model. It has been observed that accuracy of 52.1 % with a loss of 69% is seen using Word2Vec along with CNN Model and accuracy of 93% and loss of 19% is observed with the BERT Model. Better results are observed using the BERT Model. The advantage of this process is that the Transformer encoder does not know which words will be asked to predict or replace random names, so it is imperative to keep the representation of the content being distributed to all input tokens. from findings aims at using BERT as a word processing model along with Next sentence prediction which will help us monitor the user's behavior over a period of time This will help doctors understand the behavior of depressed patients easily by observing user's activity on social media over the period of time.

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