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Depressonify: BERT a deep learning approach of detection of depression

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Abstract

INTRODUCTION: Depression is one of the leading psychological problems in the modern tech era where every single person has a social media account that has wide space for the creation of depressed feelings. Since depression can escalate to the point of suicidal thoughts or behavior spotting it early can be vitally important. Traditionally, psychologists rely on patient interviews and questionnaires to gauge the severity of depression.
OBJECTIVES: The objective of this paper is earlier depression detection as well as treatment can greatly improve the probability of living a healthy and full life free of depression.
METHODS: This paper introduces the utilization of BERT, a novel deep-learning, transformers approach that can detect levels of depression using textual data as input.
RESULTS: The main result obtained in this paper is the extensive dataset consists of a total of 20,000 samples, which are categorized into 5 classes and further divided into training, testing, and validation sets, with respective sizes of 16,000, 2,000, and 2,000. This paper has achieved a remarkable result with a training accuracy of 95.5% and validation accuracy of 92.2% with just 5 epochs.
CONCLUSION: These are the conclusions of this paper, Deep learning has a lot of potential for use in mental health applications, as seen by the study's outstanding results, which included training accuracy of 95.5%. But the path towards comprehensive and morally sound AI-based mental health support continues into the future.

Keywords: Bidirectional Encoder Representations from Transformers, Deep learning, Transformers, Depression Detection

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1. Introduction

A significant portion of the world's population is affected by depression, a serious mental health condition. This crippling disorder shows itself as a wide range of painful symptoms, including extreme melancholy, a pervading sense of hopelessness, a loss of interest in once-loved pursuits, and disruptions in sleep and eating cycles. Most alarmingly, depression frequently carries the potential to trigger thoughts and dangerous behaviours. The ability to improve the quality of life for persons with the illness makes early diagnosis of depression and subsequent therapeutic intervention of the utmost im- portance. However, the early stages of this condition can be quite difficult to diagnose because of their extraordinary elusiveness. Patient interviews and random questionnaires are commonly used in conventional approaches for diagnosing depression; how- ever, they are time-consuming and rely on human interpretation [1-3].

The succeeding research introduces a painstakingly designed BERT-based model specifically created for the job of depression detection [4]. This model has been carefully trained using an extensive corpus of text and related data, which has been appropriately tagged with depression levels. After that, the model is rigorously tested against a separate test dataset. The model's astounding accuracy in identifying depression is demonstrated by the actual results. The proposed BERT-based model has a lot of potential to develop into a cutting-edge tool for the identification of depression [5-6]. Its potential uses include screening persons in primary care settings, educational institutions, and businesses, among other environments [7]. The paradigm also shows potential for aiding the creation of novel measures designed for the ongoing assessment of depression symptomatology and therapy outcomes.

2. Literature Survey

It is crucial to establish a solid theoretical foundation for our research in the body of literature before moving forward with early depression identification using deep learning techniques and BERT-based models. Now with the help of table1 lets understand how the literature Gap of the current works on the domain.

Table 1. This Table illustrates the gap of the work on the Domain

Ref.	Year	Type of Approach	Data type	Advantages	Limitations	Model corresponding solution
[1]	2023	ML & Dl	Text	The comparative analysis had given a brief overview of different methods in the Domain.	The accuracy and f1 score of the GMT method have less values compared to BERT	The BERT has set a bench mark for the detection of depression in terms of F1 score and accuracy.
[2]	2023	DL	Text	It is more efficient in con- text of small dataset availability.	Their model can only read the data from left context of word makes it difficult to deploy in real time.	BERT is bidirectional which im- plies that it can read data in both left and right con- text of word.
[3]	2023	ML	Text	Due to less complexity the model consumes less computational power.	The BETO model cannot handle complex data which results inefficiency to deployment in real time.	The BERT is capable of complex analysis thus it can easily detect even for complex text speaker in real time.
[4].	2023	DL	audio and video	Can handle Large and complex graphs effectively	The interpretation of GCNs is comparatively difficult and it cannot handle non graphic data	The BERT is de- signed to handle even Graph data and it computationally and interpretation friendly
[5]	2022	DL	audio and text	For under- standing long- term dependencies in data, LSTMs are ideally suited.	Multimodal LSTM is both computation- ally expensive and also it is difficult to interpret	The BERT is comparatively low cost on computation terms and it is easy to interpret.
[6].	2022	DL	audio and video	This may lower the quantity of training data needed for each task.	The procedure is both computationally costly as well as hard to ana- lyse multi-task using DAIC.	The BERT is comparatively low cost on computation terms, and it is easy to interpret.

Summary of the table:
The table provides a thoughtful analysis of each article, outlining both of its advantages and disadvantages. This sparked a protracted debate about how to overcome the limitations of the current study. This study highlights areas for improvement and proposes novel techniques by carefully assessing the body of existing literature. The

value and significance of the studies are significantly increased by using this comparison analysis, which highlights trends, strengths, and weaknesses and offers innovative solutions for constraints.

3. Methodology

Dataset Description: The data required to compute the project is self-picked textual data from various online websites like reddit Quora subreddit posts etc. A total of 20,000 thousand textual samples are self-picked from the sources mentioned above, which is further divided into training, testing and validation as 16000, 2000, 2000 respectively. All these 20,000 samples are labeled into 6 classes as Neutral, happy, joy, depressed, sadness, Disappointment, in the division of class happy of 5326 sample neutral of 4666 samples, dis- appointment of 2159 samples, sadness of 1937 samples, joy of 1304 samples, depression of 572 samples. The below graph 1 represents the same as pie chart.

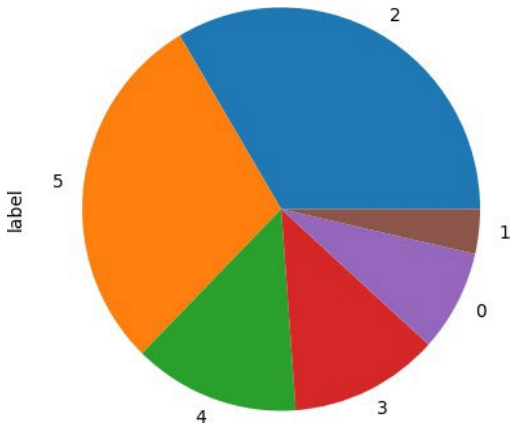

Figure 1. shows the representation of class wise data distribution in training.

Table 2. Samples of the dataset

No	Text	Class
1	I didn't feel humiliated	Depressed
2	I can go from felling hopeless to damned…	Depressed
3	I am grabbing a minute to post I feel greedy wron	Sadness
4	I am never feeling nostalgic about the fireplace …	Joy

Data Preprocessing: The results we achieve by the project is highly proportional to the how well the data is cleaned and pre-processed. So, let's look on the preprocessing of data in this project. Primarily the data collected from the different sources is labeled and shuffled and adjusted to the 6 labels discussed above, then it moved to textual cleaning, where removing of punctuations, white spaces, numbers, URL's, extra white spaces, special characters and stop word. And after performing all the cleaning the data is divided to training, testing and validation. By doing this the paper was able to achieve the results mentioned in results and analysis section.

BERT the proposed methodology: The English Wikipedia (2,500 million words) and the Book Corpus (800 million words) were used to pretrain the BERT basic model for two tasks. In the job of modelling masked language, 15% of the words were hidden, and the objective was to anticipate them. The second pre-training activity is the next sentence prediction, where the objective is to determine which of two sentences will come after the other. A vector representation of 768 dimensions and 14 stacked encoder blocks with 12 self-attention heads make up the model [8-9]. There are 110 million parameters in total [10]. We used the bert base cased model and tokenizer (an algorithm for breaking down text into a series of tokens) from the Hugging Face framework [11].

BERT goes through a dual-objective training programme that combines next sentence prediction (NSP) and masked language modelling (MLM). In MLM, a subset of tokens in a sequence are hidden, and the model is tasked with predicting the hidden tokens [12- 13]. On the other hand, NSP asks the model to determine if the second sentence comes after the first in the sequence by giving it with two sentences.

MLM & NSP objectives:

L_MLM = -log (P (mskd_token | cntxt) (1)

L_NSP = -log (P (is_nxt | cntxt_1, cntxt_2)) (2)

BERT's training includes both MLM and NSP objectives to help it become more adept at understanding the subtleties of word and sentence context [14]. As a result, BERT is excellent at understanding word and phrase meanings in the context of the surrounding material.

4. Results and Analysis

Using Google Colab, the foundational works, and the reference code provided by the original authors, the aforementioned structures were duplicated. The results were then analyzed after combining the aforementioned dataset with its own. The experiment is performed using a Google Colab laptop (pro edition), which features an Intel i10 7th generation 8-core CPU operating at 5.30 GHz and 16 GB of RAM.

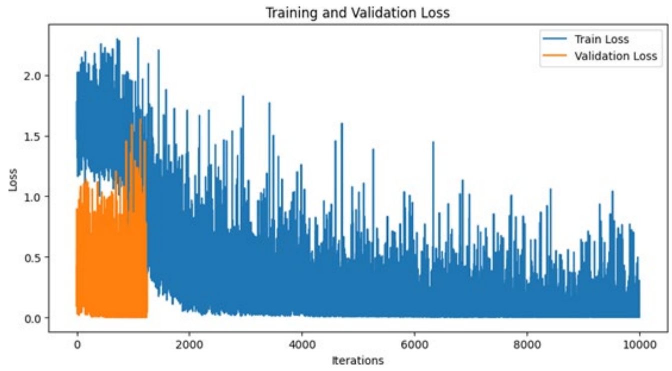

Figure 2. The above graph shows the training loss and validation loss with loss

The below figure 2 & 3 shows the effectiveness of the BERT in terms of detecting the depression.

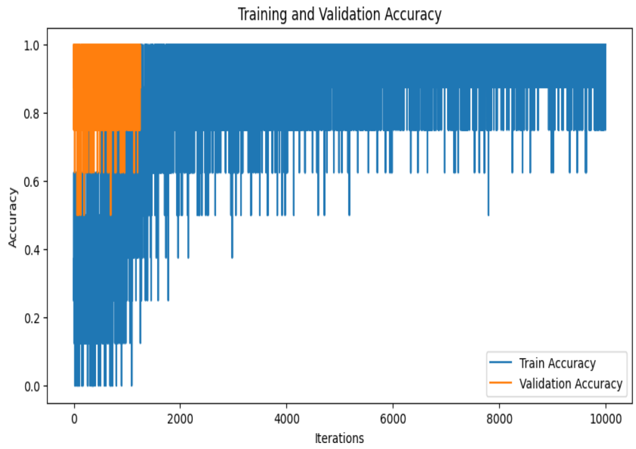

Figure 3. This graph resembles the training and validation accuracies attained

Accuracy in Training and Validation: The study offers a validation accuracy of 92.2% and a training accuracy of 95.5%. These metrics show how effectively the BERT-based model performed throughout the research's training and validation phases.

High Training Accuracy: An incredibly high training accuracy of 95.5% indicates that the model has become quite adept at fitting the training data. The danger of overfitting must be taken into account, in which case the model may have memorized the training data rather than generalizing to fresh, untested data.

Validation Accuracy: The model works well on data that it hasn't encountered before during training, as evidenced by the validation accuracy of 92.2%. This indicates that the model may be used in the actual world to identify depression using textual data.

5. Conclusion and Future scope

In summary, this study offers a substantial advancement in the field of depression identification employing cutting-edge NLP methods, particularly BERT-based deep learning models. The urgent need for efficient early detection is highlighted by the severe issue of depression in the contemporary technological era, which is made worse by the pervasive influence of social media. Deep learning has a lot of potential for use in mental health applications, as seen by the study's outstanding results, which included training accuracy of 95.5% and validation accuracy of 92.2% with only 5 epochs. But the path towards comprehensive and morally sound AI-based mental health support continues into the future.

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