



Fusion of Topic Modeling and RoBERTa for Detecting Signs of Depression from Social Media

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Abstract

Depression, or Major Depressive Disorder, is a serious and common medical condition that affects people worldwide. It negatively affects the person's feelings, thoughts, and actions. Depression causes a loss of interest in activities he enjoyed in the past. It can lead to physical and emotional problems that hamper the daily activities at work and home. In recent years, much research has been done to identify Depression through various modalities of image, speech, and text through artificial intelligence. Social media is an important medium where many discussions and mentions happen about Depression. The current study proposes a novel approach to understand how the depressed and non-depressed communicate differently with the help of Topic Modeling with latent-Dirichlet allocation (LDA) and also detect depression with the help of Robustly Optimized BERT Pretraining Approach (RoBERTa). The current study achieved an accuracy of 66.4% for the depression detection model, which outperformed the previous approaches with similar methodology. The current study is helpful for self-diagnosis of signs of Depression at very early stages.

Keywords: Clinical Depression; Artificial Intelligence; Machine Learning; Natural Language Processing; Mathematical Fusion; Bidirectional Encoder Representations from Transformers; Social media; Twitter; Reddit; Latent Dirichlet allocation; Fusion Based; Topic Modeling

1. Introduction

According to the article mentioned in [1], depression is one of the leading causes of global disability worldwide. Depression in adults is estimated at one in 15 adults which is about (6.7%) in any year. One in six people (16.6%) experience depression at a certain point of time in their life. Depression can happen anytime, but it is majorly observed during the late teens to mid-20s. Women are more likely to experience depression than men, and one-third of women experience major depressive disorder in their lifetime. Depression can also be related to hereditary if first-degree relatives have depression. Symptoms of depression can be severe and can include symptoms like feeling sad, change in appetite, troubled sleeping, increased fatigue, difficulty thinking, concentrating, or making decisions, suicidal thoughts, etc.,

Social media has simplified communication and information exchange, reaching geographical distances due to the rapid expansion of the Internet. Additionally, individuals can express their sentiments regarding posts, news, and discussions on social platforms using text and videos. This phenomenon has attracted the attention of researchers interested in analyzing the emotional expressions found in user comments. For example, the study [2] introduced a Twitter dataset for speech act classification, incorporating an attention mechanism to consider intra-modal and inter-modal information. AudiBERT, designed to capture the multimodal aspects of the human voice, was suggested for depression screening by [3]. Furthermore, the study in [4] proposed a social-contagion-based framework utilizing meta-learning for the early detection of depression.

The current study proposes a novel approach to detecting signs of depression through social media data with topic modeling techniques and AI methods. Data preprocessing is performed with the help of Natural Language Processing techniques for feature extraction. Topics are identified and segregated into clusters, and the model is trained with the help of LDA (Latent Dirichlet allocation). Depression detection has three classes, namely severely depressed, moderately depressed, and non-depressed, which are labeled from the Twitter dataset. The depression detection model is trained with the help of RoBERTa. The paper is divided into the following sections: Related Work describes the latest research on the LDA and Topic modeling for Depression. Data Analysis explains the dataset, data preprocessing steps, LDA algorithm and RoBERTa. The proposed Methodology describes the architecture and model algorithm. Finally, Results and Discussions conclude the experimental results.

2. Related Work

Using topic modeling in identifying topics within documents has gained widespread acceptance in various applications, including text mining [5] and recommendation systems [6]. Recently, it has been used in the application of depression and neuroticism [7]. In this study, the authors illustrate that considering automatically derived topics enhances the predictive performance in assessments. The application of topic modeling has shown promising outcomes in detecting mental health issues. Authors in [20] showcased models like Latent Dirichlet Allocation (LDA) [21], which can reveal meaningful latent structures within depression-related language obtained from Twitter. A study [22] showed the potential of using social media content, such as Twitter posts, for binary classification of depression and Post-Traumatic Stress Disorder (PTSD). Furthermore, [23] demonstrated the viability of utilizing Twitter content for topic extraction. At the same time [24] emphasized the capabilities of topic modeling and LDA in uncovering hidden structures associated with user behavior in social media.

Social media users often share their feelings and situations with one another, and the discussions on internet forums can play a role in identifying individuals at risk [25, 26]. The experiments focus on assessing the impact of both shared and specific topic modeling. Specific topic modeling involves extracting topics from a dataset associated with a single mental health issue. In contrast, shared topic modeling is applied to combined corpora, where specific datasets are combined into a unified corpus. The data utilized are sourced from the recurring eRisk shared task, which broadly evaluates the risk for different mental health issues based on the social media text. To identify depression, diverse data collection methods have been used, including clinical interviews [27], behavior analysis, monitoring facial and speech modulations, and physical exams with Depression scales [28], as well as the analysis of videos and audio [29]. With the continuous growth of social media users, social media data has emerged as a significant source for mental health detection. This concept led to the development of the widely used E-Risk@CLEF-2017 pilot task dataset [30], which was gathered from Reddit. Apart from this dataset, several others, such as the DAIC corpus [31], AVEC [32], and more, have emerged, all designed to identify depression from social media data. Despite the existence of a few benchmark datasets for depression detection, an increasing number of researchers opt to collect data from social media and create their datasets.

Research on detecting depression through text analysis has been explored using user-generated data. The CLEF eRisk challenge focuses on predicting depression severity from online data, including responses to questionnaires [8] and written content on social media [9]. Similarly, CLPsych has organized tasks related to PTSD and anxiety detection from user-generated texts [10]. Text-based methods for early depression detection on the eRisk dataset have exhibited promising results [11], [12]. Various text feature sets have been examined, ranging from features like n-grams, Bag of Words, etc., In the study [13], the author developed a dataset derived from Reddit posts, wherein users were categorized into two groups: those experiencing depression and a control group. Their analysis used the Linguistic Inquiry and Word Count Tool (LIWC) [14], among other methods. Authors in [15] also leveraged Reddit as a data source, and in conjunction with other datasets, they investigated how training data influenced the quality of an SVM-based model for identifying depression. Reddit, in particular, offers a wealth of textual data, making it a prime focus for analyzing posts to measure the extent of depression. Furthermore, many studies have concentrated solely on detecting the presence of depression rather than assessing its severity.

Authors in [16] employed various text encoding approaches, including the LIWC dictionary, Latent Dirichlet Allocation (LDA) topics, and N-grams, to examine the linguistic patterns in posts with signs of depression. Study [17] analyzed tweets related to depression and anxiety, utilizing Multinomial Naive Bayes and the Support Vector Regression (SVR) Algorithm as classifiers. Authors in [18]

introduced the SenseMood system, designed to detect depression in tweets through visual and textual features, using the Convolutional Neural Network (CNN) and the BERT language model. Study [19] proposed an innovative summarization-boosted deep framework for depression detection named DepressionNet.

Current research introduces an innovative method for depression detection. The study mentioned aims to explore the effectiveness of Latent Dirichlet Allocation (LDA) in segregating topics related to various mental health issues by extracting them from relevant data. This approach proves effective for identifying depression at its early stages.

2. Data Analysis

A. Dataset

In the study, we have used the competition dataset which has English posts from Reddit, each annotated with labels indicating whether they exhibit no signs of depression, moderate depression, or severe depression [33]. Specifically, the first label denotes instances where no depression symptoms were identified, while the other two labels indicate posts showing moderate or severe depression symptoms.

B. Data Processing

The dataset was partitioned into train, dev, and test segments. To assess the quality of the collections used for the solution, we initially examined their diversity by eliminating duplicate records with identical posts. Common practice suggests making the train set larger than the dev or test set, especially in machine learning or deep learning methods where the number and variety of training samples directly influence the model's quality. Consequently, we opted to utilize part of the dev set for training, reserving 1,000 examples for verification while maintaining a class distribution close to the original one. This decision resulted in a train set for our experiments comprising 6,006 unique examples. The entire dataset preparation process is illustrated in Figure 1.

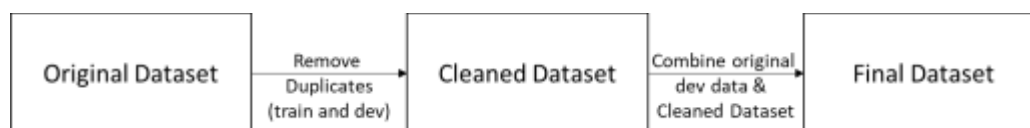


Figure 1: Data Processing

C. Latent Dirichlet Allocation (LDA)

LDA, introduced in [21] is a model employed for unsupervised dimensionality reduction in datasets, commonly applied to textual corpora. It operates as a generative model, assuming that text is generated from a discrete distribution of words referred to as a "topic." These topics collectively constitute a document with a probabilistic distribution of topics. This enables the representation of a document using only K topics instead of V words. It's important to note that, as a document is essentially a collection of words, LDA does not consider the order of these words but focuses on their frequency. They define the generative model for each document of N words, $w = \langle w_1; w_2; \dots; w_N \rangle$, in a corpus D with K topics as below in Algorithm 1.

Algorithm 1: Generative Process of LDA

1	Choose $N \sim \text{Poisson}(\xi)$.
2	Choose $\theta \sim \text{Dir}(\alpha)$, where θ is a K -vector Dirichlet random variable defining the topic mixture, and $\text{Dir}(\alpha)$ is a Dirichlet distribution parameterized by the K -vector α .
3	For each of the N words w_n : <ol style="list-style-type: none"> (a) Choose topic z_n from $\text{Multinomial}(\theta)$. (b) Choose a word w_n from $p(w_n z_n, \beta)$, a multinomial probability conditioned on the topic z_n and the $K \times V$ matrix β where $\beta_{ij} = p(w^j = 1 z^i = 1)$.

The probability of generating a particular document is as in equation (1). The product of all document probabilities leads to corpus probability.

$$p(w|\alpha, \beta) = \int_{\theta} p(\theta|\alpha) \prod_{n=1}^N \sum_{z_n} p(z_n|\theta) p(W_n|z_n, \beta) d\theta \quad (1)$$

As the observed variable in this context is the text corpus, and the desired output is the "latent" topics that generated it, an inference algorithm must be used for approximation. Gibbs Sampling is a frequently used method for this purpose, utilizing a Markov-chain Monte Carlo technique where each distribution dimension is alternately sampled while keeping all others fixed. Gibbs Sampling aims to deduce the topics for a document, which are represented by the "latent" parameter z .

$$p(z_i = k|z_{-i}, w) \propto \frac{n_{k,-i}^{(t)} + \beta_t}{\sum_{t=1}^V n_{k,-i}^{(t)} + \beta_t} \cdot \frac{n_{m,-i}^{(k)} + \alpha_k}{[\sum_{k=1}^K n_{m,-i}^{(k)} + \alpha_k]^{-1}} \quad (2)$$

In equation (2), m represents the index of the current document, n is the index of the current word within that document, t is the index of that word in the vocabulary, and "-i" denotes the exclusion of item i from a set. The sampling process involves iterating over each document and then each word within the document. During this iteration, the assignment of a topic to that word is updated by re-sampling from $p(z_i|z_{-i}, w)$ as per Equation 2. Subsequently, this assignment is used to modify the relevant counts of words assigned to topics and topics assigned to the document. This iterative process continues until convergence is achieved, resulting in the final distribution of topics for each document and words for each topic being produced as output.

D. Robustly Optimized BERT Approach

RoBERTa (short for "Robustly Optimized BERT Approach") [34] is a variant of the BERT (Bidirectional Encoder Representations from Transformers) model, which was developed by researchers at Facebook AI. Like BERT, RoBERTa is a transformer-based language model that uses self-attention to process input sequences and generate contextualized representations of words in a sentence. One key difference between RoBERTa and BERT is that RoBERTa was trained on a much larger dataset and using a more effective training procedure. In particular, RoBERTa was trained on a dataset of 160GB of text, which is more than 10 times larger than the dataset used to train BERT. Additionally, RoBERTa uses a dynamic masking technique during training that helps the model learn more robust and generalizable representations of words.

RoBERTa has been shown to outperform BERT and other state-of-the-art models on various natural language processing tasks, including language translation, text classification, and question answering. It has also been used as a base model for many other successful NLP models and has become a popular choice for research and industry applications. In the current study, we have downloaded the model from Hugging Face Hub. RoBERTa pre-trained model was used to train with our dataset for detecting depression from Reddit posts.

3. Proposed Methodology

This research uses the dataset [33] and introduces Latent Dirichlet Allocation (LDA) for topic modeling and Robustly Optimized BERT Approach (RoBERTa) for classifying depression. The training dataset has 6006 posts with moderately depressed, severely depressed and non-depressed as the classes and test data has 3245 posts. The framework for topic modeling and depression detection from Reddit posts is illustrated in Figure 2.

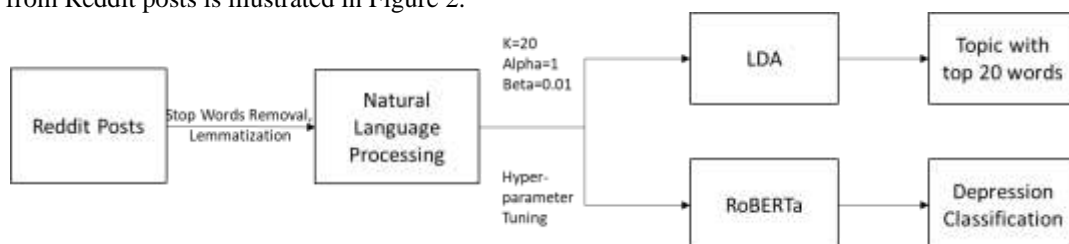


Figure 2: Topic Model and Depression Detection Framework

A. LDA

We used LDA with the following parameters: number of topics (k) = 7, document-topic Dirichlet hyperparameter (α) = 1, and topic-word Dirichlet hyperparameter (β) = 0.01, aligning with the experimental setup in [20]. In our experiments, we reproduced this methodology using a different LDA implementation and the vocabulary derived from combined, preprocessed datasets. An initial comparison of the top 20 words in the resulting topics revealed a robust correlation with the study in [20]. Specifically, 25% of the top words were common in both listings. Furthermore, 7 topics shared five or more top words with topics. Notably, seven topics exhibited significant similarity, with over half the top 20 words shared between both models, as illustrated in Table 1.

Table 1: LDA topics along with their clinician's label for the topic

Clinical Label	Top 20 words
LIFESTYLE	'games', 'music', 'sports', 'video', 'care', 'pet', 'dog', 'party', 'event', 'fb', 'facebook', 'instagram', 'twitter', 'sing', 'play station', 'ps', 'book', 'tysm', 'hope'
MENTAL SYMPTOMS	'lonely', 'guilt', 'worthless', 'helpless', 'hopeless', 'overreacting', 'empty', 'suicidal', 'feel bad', 'low mood', 'anxiety', 'worry', 'harm', 'disturbed', 'agitated', 'irritable', 'suicidal thoughts', 'suicide', 'end life', 'no mood'
CAUSES	'abuse', 'assault', 'sexual assault', 'harassment', 'torture', 'rape', 'trauma', 'accident', 'death', 'substance abuse', 'drugs', 'alcohol', 'break up', 'ditched', 'divorce', 'gambling', 'flashbacks', 'war', 'attack', 'suffer'
SWEAR WORDS & CURSING	'shit', 'bull', 'bull shit', 'jesus', 'dafuq', 'holy shit', 'oh god', 'damn', 'trash', 'goddamn', 'hell', 'what the hell', 'Jesus Christ'
PHYSICAL SYMPTOMS	'pain', 'headache', 'migraine', 'body pain', 'back pain', 'nightmare', 'insomnia', 'no sleep', 'constipation', 'ache', 'fatigue', 'low energy', 'laze', 'lathargic', 'soreness', 'aching', 'vision', 'weight loss', 'weight gain', 'digestive problem'
TREATMENT	'therapy', 'counselling', 'doctor', 'therapist', 'shrink', 'antidepressants', 'pills', 'meds', 'medicines', 'supplements', 'essential oils', 'psychotherapy', 'behavioral therapy', 'cognitive', 'counselor', 'psychologist', 'psychiatrist', 'hospital', 'clinic', 'celexa'
COPING	'exercise', 'gym', 'work out', 'fitness', 'yoga', 'healthy', 'diet', 'meditation', 'support group', 'motivation', 'hobby', 'family', 'parents', 'goals', 'wife', 'husband', 'sunshine', 'support', 'pamper', 'get help'

B. RoBERTa

The RoBERTa model follows the same architecture as the BERT model, essentially serving as a reimplementations of BERT with slight modifications to key hyperparameters and minor adjustments

to embeddings. The general pre-training and fine-tuning procedures for BERT are illustrated in Figure 3, where, except for the output layers, identical architectures are used in both pre-training and fine-tuning. The pre-trained model parameters are shared across various downstream tasks, and during fine-tuning, all parameters undergo adjustment.

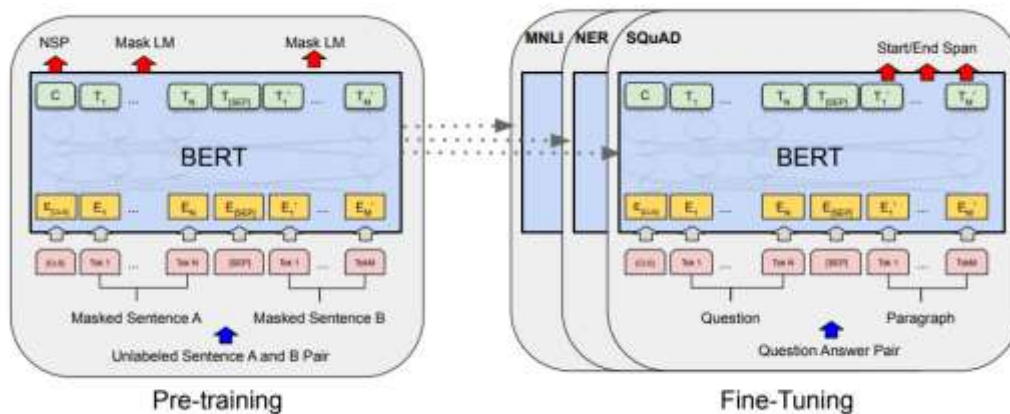


Figure 3: Visualization of Feature Map

In contrast, RoBERTa deviates from BERT by not utilizing the next-sentence pretraining objective. Instead, RoBERTa is trained with larger mini-batches and learning rates. Additionally, it adopts a distinct pretraining scheme and replaces the byte-level BPE tokenizer with a character-level BPE vocabulary. Model architecture for fine tuning RoBERTa is shown in Figure 4.

Parameter	Value
Optimizer	AdamW
Learning rate	5e-6
Batch size	16
Dropout	0.1
Weight decay (L2)	0.1
Epochs	10
Validation after no. steps	100
Max sequence length	300

Figure 4: Hyperparameters for Fine Tuning Model

4. Results and Discussions

In the "human-intuition" aspect of topic modeling, we executed each model on the datasets. For every topic in the resulting topic, we identified the 20 words with the highest weights, commonly regarded as the words most indicative of that topic. These posteriors represented the topic-word distributions averaged over samples obtained from 500 iterations of sampling, with the initial 100 iterations excluded as burn-in.

Frequency count for each 7 topics and its corresponding highest frequency count word is shown in Figure 5. For depression classification, we used an additional pre-training approach wherein the model weights were initialized using the weights of the RoBERTa large model. This choice was influenced by the improved results obtained during the fine-tuning of this specific model in the initial step. The resulting model was stored for the depression classification on the test dataset. We used the Simple Transformers library for conducting experiments, including the fine-tuning and pre-training of the RoBERTa model. The fine-tuning process for each model was iterated five times using the train and dev sets. All experiments were executed on a Google Colab.

LIFESTYLE	WordCount	MENTAL SYMPTOMS	WordCount	CAUSES	WordCount	COPING	WordCount
party	294	depression	295	trauma	288	wife	298
event	153	hate	272	attack	264	healthy	244
art	148	mental	271	suffer	236	support group	244
hope	137	hurt	266	alcohol	193	gym	238
dog	129	depressed	188	rape	177	husband	191
music	124	sad	132	war	151	diet	181
book	97	suicide	124	death	103	exercise	133
pet	92	know	63	assault	64	family	124
video	87	anxiety	57	abuse	58	motivation	103
care	31	stress	21	divorce	55	support	36

PHYSICAL SYMPTOMS	WordCount	TREATMENT	WordCount	SWEAR WORDS & CURSING	WordCount
fatigue	294	drug	273	bullshit	285
cough	237	doctor	216	shit	245
vision	211	lexapro	202	damn	222
tired	162	psychologist	192	crap	218
cold	162	psychiatrist	186	trash	165
flu	102	therapy	145	hell	135
pain	92	medication	129	goddamn	98
ache	70	hospital	102	feel shit	65
insomnia	70	therapist	47		
vomit	58	cognitive	35		

Figure 5: Frequency Count for Topic Words

Metrics used are accuracy, macro-averaged precision, macro-averaged recall, and macro-averaged F1-score across all classes. The macro-averaged F1-score served as the primary measure for assessing the model. Among the fine-tuned transformer-based language models, the RoBERTa large model outperformed others, achieving the highest accuracy (0.664) and F1-score (0.605) and it performed best for the non-depressed class. Confusion Matrix is shown in Figure 6.

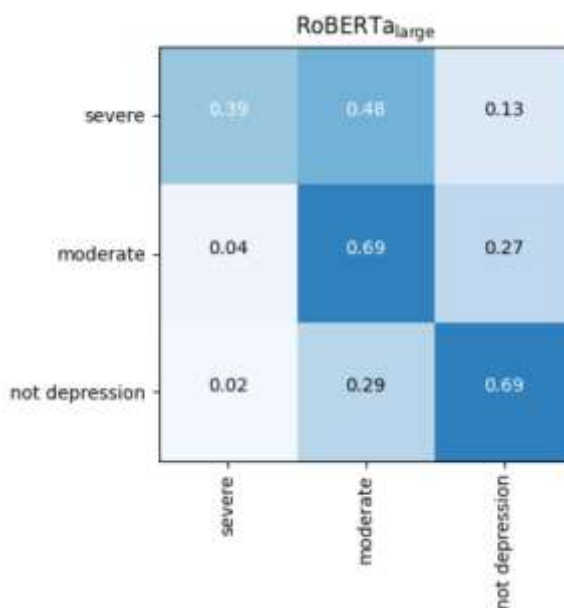


Figure 6: Confusion Matrix for RoBERTa

5. Conclusion

In this paper, we introduced a solution for Topic Modeling and detecting signs of depression from Social Media Text. Utilizing topic modeling proves advantageous in extracting mental health-related information from extensive datasets of naturally occurring text. Topic Modeling is effective when using advanced versions of topic modeling beyond conventional LDA or integrating these techniques with additional features within a supervised learning framework. The most effective approach involved finetuning the previously fine-tuned RoBERTa model. This model can potentially find applications in future tasks related to depression detection. RoBERTa model achieved an accuracy of 66.4% and it performed well for non-depressed class. As part of future work, we aim to integrate topic modeling approaches into larger feature sets that have demonstrated efficacy in related work. We also

plan to tap into untapped data in social media, such as timestamps, friend lists, and geotags, which were not utilized in our current topic modeling.

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