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Detection and Sentiment Analysis Based on Mental Disorders Aspects Using Bidirectional Gated Recurrent Unit and Semantic Similarity

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Abstract: Mental disorders significantly impact daily life and are among the leading causes of suicide. Despite numerous studies on detecting mental disorders on social media, the focus has primarily been on identifying the presence or absence of indications in posts, with most studies concentrating solely on one specific mental disorder, particularly depression. There is a lack of comprehensive analysis of the detection results. Therefore, this study analyzes mental disorders in more detail by applying detection and sentiment analysis based on five aspects, namely ADHD (attention-deficit hyperactivity disorder), anxiety, bipolar, depression, and PTSD (post-traumatic stress disorder). The detection process utilizes bidirectional encoder representations from transformers (BERT) embedding and the bidirectional gated recurrent unit (BiGRU) model. Subsequently, aspect categorization employs semantic similarity, which assesses the resemblance between terms generated from hidden topic extraction via non-negative matrix factorization (NMF) and keywords linked to the five mental disorder aspects, extracted using a combination of term extraction methods. Additionally, sentiment classification leverages BERT embedding and the BiGRU model. The proposed method successfully identifies mental disorders, categorizes aspects, and classifies sentiment accurately. Optimal performance is achieved in mental disorders detection (0.9009) using BERT embedding + BiGRU, aspect categorization (0.8507) employing semantic similarity + BiGRU, and sentiment classification (0.8717) through BERT embedding + BiGRU. The analysis results unveil that texts related to mental disorders often convey negative sentiments, with the depression aspect exhibiting higher percentages of negative sentiment compared to other mental disorder aspects.

Keywords: Mental disorder detection, Aspect-based sentiment analysis, BERT, BiGRU, Semantic similarity.

1. Introduction

Mental disorders represent some of the most pervasive and severe public health challenges on a global scale [1]. These conditions can exert a profound impact on an individual's daily life and stand as a predominant contributor to suicide [2]. It is of utmost importance to identify individuals displaying early signs of mental health issues, as this recognition can carry substantial consequences and, in certain instances, even be instrumental in saving lives [3].

Real-time information on social media is abundant, dynamically evolving, and relatively straightforward to gather. These platforms have emerged as an alternative place for individuals grappling with mental disorders to express their emotions [4]. Seeking professional assistance can be a daunting prospect for many dealing with mental health challenges. Nevertheless, social media offers a more approachable avenue for individuals with such disorders to share their experiences and connect with others who can empathize with their predicament. Consequently, data derived from social media can be harnessed to acquire profound insights into individual behaviour, mental health conditions, and their progression [5].

Numerous studies have addressed the issue of detecting mental disorders through the analysis of data obtained from social media, notably textual data [6]. A wide array of social media platforms, including Twitter, Facebook, and Reddit, have been considered in research aimed at predicting mental health disorders. Predominantly, the research has centred on comprehending depression [7–9]. On the other hand, several studies have also been undertaken to gain insights into various other mental health disorders, including anxiety disorders, schizophrenia, and post-traumatic stress disorder (PTSD) [10–12].

Furthermore, most research uses conventional machine learning approaches to perform quantitative analysis or develop classification models [13]. However, applying conventional machine learning models in mental disorder detection systems has drawbacks. In some cases, the conventional machine learning model often struggles to capture the semantic significance of text distributed on social media [14]. Consequently, a sophisticated model is needed to accurately classify textual data related to mental health problems. Several studies have utilized more sophisticated deep learning methods by developing various models of convolutional neural networks (CNN), recurrent neural networks (RNN), and so on [15–17].

In natural language processing (NLP), a central challenge, in general, is capturing both the semantic and syntactic meanings of words within extensive textual corpora, a task often referred to as preserving long-range dependencies [18]. As a result, to tackle the processing of lengthy text data and facilitate text classification, researchers have turned to variants of RNN models, particularly long-short term memory (LSTM) and gated recurrent unit (GRU) [19–21]. In-depth, GRU stands out for its efficiency due to its streamlined architecture with fewer parameters than LSTM [22]. However, in practical applications, the GRU network predominantly focuses on the preceding context, neglecting the subsequent context. Consequently, GRU can only manage sequences from start to finish, leading to a loss of valuable information. The bidirectional GRU (BiGRU) model has been introduced to address this limitation. This model operates in both directions, processing data comprehensively and providing complete contextual information [23].

Although studies are abundant in detecting mental disorders within online posts, much of the research has concentrated on identifying suspected cases of positive and negative class mental disorders, mainly focusing on depression. The analyses conducted have been limited to determining whether social media posts contain indications of mental disorders. For example, consider text one: "*I felt trapped in the darkness of my thoughts and lost my enthusiasm for life; feelings of depression hit me non-stop*", and text two: "*Today I tried a new breakfast recipe*". From these texts, the research has identified which one indicates mental health issues. Moreover, the research focus has been restricted to text representation and the performance comparison of classification models. The final results primarily evaluate how well the classification model can recognize mental disorders, with only a few studies attempting a comprehensive analysis and endeavouring to gain insights from detection results [24].

For instance, research [25] discusses detecting mental disorders in Spanish Twitter text data using a linguistic approach. In addition to detection, this study also seeks to gain insight from detection results through sentiment analysis. However, the study only analyzed one type of mental disorder, namely depression. In particular, linguistic expression patterns can serve as indicators for assessing an individual's mental health condition [26]. Individuals experiencing mental disorders often convey negative sentiments. The link between sentiment and mental disorders text can be explored through sentiment analysis of mental disorders.

Nevertheless, sentiment analysis only provides a general explanation of sentiments related to mental disorders [27]. For example, given the mental disorder text: "*Recently, I started a new medication that has significantly alleviated my PTSD. Unfortunately, the constant pressure at work has been causing a surge in my anxiety levels*". Multiple aspects can be present in a given text, each with different sentiments: positive sentiment on the PTSD aspect and negative sentiment on the anxiety aspect. Consequently, a method for providing a more detailed explanation of sentiments based on specific aspects is required. Aspect-based sentiment analysis (ABSA) is one such method. ABSA is a method that can be used to extract aspects of text and related sentiments [28].

This study proposes the detection and analysis of sentiment based on aspects of mental disorders in Reddit's social media text posts. Three stages are carried out: detection of mental disorders, aspect categorization, and sentiment classification. In the first stage, binary classification is carried out to determine whether the social media data analyzed contains indications of mental disorders or not using bidirectional encoder representations from transformers (BERT) embedding and the BiGRU classification model. This paper employs three comparative methods in detecting mental disorders: BERT embedding + GRU, BERT embedding + bidirectional LSTM (BiLSTM), and BERT embedding + BiGRU.

Texts with indications of mental disorders will be further processed to categorize mental disorders. The five aspects of mental disorders analyzed were

ADHD, anxiety, bipolar, depression, and PTSD. The aspect categorization process utilizes the semantic similarity method. Semantic similarity is a measurement method that quantifies the distance between each document or term based on its semantic meaning [29]. Previous research on ABSA was applied in analyzing review texts and documents in various domains, including hotel reviews [30], restaurant reviews [31], and financial news [32], using semantic similarity, and it has a good performance in categorizing aspects.

In this study, semantic similarity is employed to discern document aspects by evaluating the similarity between the term list, which stems from the hidden topics derived through non-negative matrix factorization (NMF), and the keywords associated with mental disorders' aspects. These keywords are extracted through a combination of keyword extraction methods, including term frequency-inverse document frequency (TFIDF), yet another keyword extraction (YAKE), and BERT from both Wikipedia and the dataset.

It is worth noting that semantic similarity, when applied to an imbalanced glossary of terms, can introduce challenges in the form of elevated false positives and false negatives. Semantic similarity and deep learning models can be combined to bolster accuracy and mitigate the occurrence of inaccurate categorizations [32]. This paper employs semantic similarity, BiGRU, and a combination of both as comparative methods in aspect categorization.

The final stage of this study involves evaluating the sentiment of texts associated with mental disorders. Text that has been categorized into five aspects is first labeled by the annotator to determine its initial sentiment. BERT embedding and the BiGRU model will also be applied to conduct sentiment classification for the five aspects of mental disorders. Additionally, three comparative methods are applied in sentiment classification: BERT embedding + GRU, BERT embedding + BiLSTM, and BERT embedding + BiGRU.

Key contributions of this study include: (a) Introducing a detection and aspect-based sentiment analysis approach for a comprehensive analysis and an endeavor to gain insights from detection results. (b) Analyzing five distinct aspects of mental disorders, namely ADHD, anxiety, bipolar, depression, and PTSD, allows for a more in-depth understanding of various mental disorder conditions. (c) Utilizing BERT embedding to represent mental disorders' textual data while maintaining contextual and semantic relevance, combined with the proposed BiGRU model, effectively maximizes classifier performance. (d) Employing a combination of semantic similarity and the BiGRU model in aspect categorization to address challenges related to imbalanced glossaries and improve accuracy by leveraging the strengths of both semantic similarity and deep learning models.

The remainder of this paper is structured as follows: The second section discusses several pertinent theories. Following that, the third section outlines the research method. The fourth section presents the experimental results and discussion. Finally, the fifth section encapsulates the study's conclusions.

2. Related theories

This section discusses a range of theories pertaining to the research.

2.1 Pre-processing

In text mining, various commonly employed techniques are applied for effective pre-processing. These techniques include case folding, filtering, tokenization, stopword removal, and lemmatization.

2.2 Keyword extraction

Keyword extraction is implemented to identify essential terms within documents pertaining to predefined aspects. In this study, keyword extraction was performed by combining several term extraction methods, such as TFIDF, YAKE, and BERT.

TFIDF [33] is a statistical method for weighting words that consider the frequency of a word within a document. Eq. (1) computes the TFIDF weight by combining term frequency (TF) and inverse document frequency (IDF). In this equation, $tf_{a,b}$ denotes the frequency of word a in document b. N_D represents the total number of documents, and df_a is the number of documents containing the word a.

$$TFIDF_{ab} = tf_{a,b} \times \log \frac{N_D}{df_a} \quad (1)$$

YAKE [34] is another statistical method for term extraction that employs five-word features: term relatedness ($t_{related}$), term position ($t_{position}$), term casing (t_{case}), normalized term frequency (tf_{norm}), and term occurrence in sentences ($t_{sentence}$). YAKE computes a term score by considering these five features through Eq. (2).

$$YAKE(w) = \frac{t_{related} \times t_{position}}{t_{case} + \frac{tf_{norm}}{t_{related}} + \frac{t_{sentence}}{t_{related}}} \quad (2)$$

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BERT [35] considers the semantics of words within the context of a sentence, utilizing the entire sentence as input. It transforms input data into token, segment, and position embedding. The combination of TFIDF, YAKE, and BERT is intended to generate aspect keywords with statistical significance and semantic relevance [36].

$$Borda(t_l) = max\left(\sum_{l=0}^{n}\left(TFIDF_{t_l}, YAKE_{t_l}, BERT_{t_l}\right)\right) \quad (3)$$

Borda ranking is applied to combine the results from the three term extraction methods. Borda ranking is an aggregation-based ranking method utilized to calculate the rank of a list of candidate terms. It calculates term rankings based on their highest position, utilizing Eq. (3) to derive the ranking from the top term (t_l) position among the term extraction outputs of TFIDF, YAKE, and BERT, where n represents the maximum index number of candidate terms. The index l represents the sequential order of candidate terms, starting from 0.

2.3 Text representation

Word embedding is one of the most prevalent among widely adopted text representation methods [37]. In this study, text representation was accomplished using the BERT embedding method. BERT embedding can discern contextual relationships among words within a given text, unlike context-free word embedding methods such as word2vec and global vectors (GloVe) [38]. Consequently, incorporating BERT embedding enhances text processing accuracy, elevating text modelling and analysis quality.

2.4 Bidirectional GRU

GRU is one type of RNN architecture. The GRU architecture is almost the same as the LSTM, which was developed to overcome the vanishing and exploding gradient problems in RNNs. RNN networks are plagued by vanishing and exploding gradient problems, which limit their ability to learn long sequences. GRU is similar in performance to LSTM in most tasks [39]. However, the performance of GRU is significantly faster than LSTM's due to the simplicity of computation [40].

The GRU network has two main gates: the update gate and the reset gate. The update gate combines the forget gate and the input gate, which controls how much the hidden state will be updated. On the other hand, the reset gate controls how much information from the previous hidden state will be carried over to the new hidden state. Simultaneously, the update and reset gates control how information is updated to a particular state. Using the update gate and reset gate, the GRU network can solve the problem of vanishing and exploding gradients [41].

BiGRU is a deep learning architecture that combines two GRU networks that are in opposite directions; namely, one GRU network processes data from beginning to end (forward), and one GRU network processes data from end to beginning (backwards). Therefore, BiGRU can predict the following sequence better. The BiGRU can be implemented with the following functions:

$$\overrightarrow{h}_t = GRU_{fwd}\left(x_t, \overrightarrow{h}_{t_{t-1}}\right) \quad (4)$$

$$\overleftarrow{h}_t = GRU_{bwd}\left(x_t, \overleftarrow{h}_{t_{t+1}}\right) \quad (5)$$

$$h_t = W^T\overrightarrow{h}_t + W^V\overleftarrow{h}_t \quad (6)$$

$$o_t = (W^o h_t) \quad (7)$$

$$y_t = \sigma(W^t + b_t) \quad (8)$$

where x_t represents the input at timestep t, $\overrightarrow{h}_t$ signifies the forward GRU's hidden state at timestep t, and $\overleftarrow{h}_t$ denotes the backward GRU's hidden state at timestep t. W^T and W^V correspond to the weight matrices associated with the forward hidden state $\overrightarrow{h}_t$ and the backward hidden state $\overleftarrow{h}_t$ in the BiGRU, respectively. W^o represents the weight connecting the hidden and output layers. Ultimately, the output of the BiGRU is directed to the classifier for classification using Eq. (8), where σ represents a logistic sigmoid function. At the same time, W^t and b_t symbolize the weight matrix and bias in the output layer [42].

2.5 NMF

This study uses NMF [43] to extract hidden topics from the dataset. NMF is classified as a non-probabilistic, decompositional algorithm belonging to the family of linear algebraic methods. Compared to other methods for extracting hidden topics, NMF

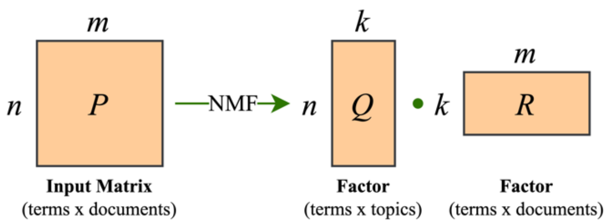

Figure. 1 Intuition of NMF

yields superior results because the algorithm depends on TFIDF weighting instead of raw word frequencies [44]. Also, NMF is effective when applied to social media data [45].

NMF operates on TFIDF-transformed data by breaking down a matrix into two lower-ranking matrices. As depicted in Fig. 1, NMF breaks down its input, represented as a term-document matrix (P), into the product of a matrix capturing terms and topics (Q) and a matrix representing topics and documents (R). Iteratively, the values of Q and R are changed, with the former containing the basis vectors and the latter containing the corresponding weights.

2.5 Semantic similarity

Semantic similarity is an assessment method that assigns a distance to each document or term according to its semantic significance [29]. There are two kinds of similarity calculations: those that use resources like a thesaurus and those that use the distribution of words in a corpus [46].

$$Sim(p,q) = \frac{\sum_{i=1}^{v} p_i q_i}{\sqrt{\sum_{i=1}^{v} {p_i}^2}\sqrt{\sum_{i=1}^{v} {q_i}^2}} \quad (9)$$

Eq. (9) calculates the similarity distance between word vector p and word vector q. $\sum_{i=1}^{n} p_i q_i$ indicates the number of iterations in the summation of v word vectors. The similarity distance has a value between 0 and 1. The similarity distance value is close to 1, which defines the meaning between the two adjacent words. Conversely, if the value of the similarity distance is close to 0, this indicates a significant difference in meaning between the two words.

2.6 Evaluation

In this study, the performance of the proposed method is evaluated to assess its effectiveness. This evaluation involves four key variables: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). Various evaluation metrics, including accuracy (Ac), precision (Pr), recall (Re), and the F1 score ($F1$), can be computed using these variables. These metrics provide insights into how well the model performs and are commonly used to assess the proposed method's effectiveness in analyzing mental disorders from social media content [47]. The Eq. (10), Eq. (11), Eq. (12), and Eq. (13) can be used to calculate these metrics.

$$Ac = \frac{TP+TN}{(TP+FN)+(FP+TN)} \quad (10)$$

$$Pr = \frac{TP}{TP+FP} \quad (11)$$

$$Re = \frac{TP}{TP+FN} \quad (12)$$

$$F1 = \frac{2TP}{2TP+FN+FP} \quad (13)$$

3. Research method

This study encompasses several processes. The initial step is text pre-processing, which is crucial for preparing textual data by eliminating noise and irrelevant elements. Aspect keyword extraction compiles a comprehensive list of essential keywords for the aspect categorization phase. The subsequent phase includes detecting mental disorders, utilizing BERT embedding and the BiGRU classification model. Aspect categorization employs semantic similarity to assess the resemblance between hidden topics extracted via NMF and keywords linked to mental disorder aspects. Following this, sentiment classification uses BERT embedding and the BiGRU method to discern and evaluate sentiment effectively. Finally, an evaluation process is conducted to measure the performance and validate the proposed method's effectiveness.

3.1 Dataset

The dataset utilized in this study was obtained from a Reddit dataset created by research [48]. This dataset comprises a collection of English Reddit posts acquired through crawling the Reddit API. It consists of 16,703 text posts, including both title text data and content data, which are combined for analysis. Each Reddit post in the dataset has been categorized into six classes: ADHD, anxiety, bipolar, depression, PTSD, and none.

The label assigned to each Reddit post is based on the topic of the subreddit to which they belong. Posts from subreddits dedicated to specific mental

Table 1. Count of mental disorder categories

Category	# Data
adhd	3,031
anxiety	2,584
bipolar	2,345
depression	3,534
ptsd	2,121
none	2,534

Table 2. Pre-processing results

Before	After
my mother has complex ptsd. she was emotionally abused by her ex husband	'mother', 'complex', 'ptsd', 'emotionally', 'abuse', 'husband'

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disorders, such as ADHD, anxiety, bipolar disorder, depression, and PTSD, are labelled according to the corresponding mental disorder. Additionally, posts from various general-topic subreddits, such as politics, science, music, travel, India, English, datasets, and mathematics, are grouped into a single category labelled as “none”, representing Reddit posts unrelated to mental disorders.

This study will re-labelled the dataset used to verify the label assigned to the related data. Nine annotators carried out labelling. Three differen annotators will label each Reddit data. After the labelling, a vote will be taken for each data to decide on the correct label. For data to be usable, each must receive the same label approval from at least two annotators. If it does not meet these conditions, the data will be ignored. Ultimately, 16,149 Reddit posts were retained for analysis after the re-labelling process. Table 1 shows the data distribution within the Reddit dataset used in this study.

3.2 Text pre-processing

The pre-processing stage in this study comprises two distinct components: pre-processing the analyzed Reddit text and pre-processing the Wikipedia text utilized for aspect keyword extraction. The Natural Language Toolkit (NLTK) library is used to carry out these tasks. An example of the text pre-processing results is presented in Table 2.

The Reddit dataset employed in this study has already undergone initial pre-processing steps, i.e., removing user mentions and hyperlinks and converting all text to lowercase. However, additional pre-processing steps are performed, encompassing filtering, tokenization, stopword removal, and lemmatization. For Wikipedia text, pre-processing steps are applied to ensure that the results derived from the aspect keyword extraction process comprise essential keywords representing mental disorders' aspects, which include case folding, filtering, tokenization, stopword removal, and lemmatization.

3.3 Aspect keyword extraction

This study applies aspect keyword extraction to acquire an extensive list of aspect keywords. This stage amalgamates statistical and semantic-based term extraction methods, encompassing TFIDF, YAKE, and BERT. The result of this aspect keyword extraction process is a list of keywords that delineate the five mental disorder aspects: ADHD, anxiety, bipolar, depression, and PTSD.

The aspect keyword extraction is conducted on documents from Wikipedia, specifically those related to each of the five mental disorder aspects, as well as on the Reddit dataset utilized in this study. Wikipedia documents are chosen to reduce the necessity for manual initialization of aspect keywords. Table 3 provides links to the pertinent Wikipedia documents used in the aspect keyword extraction process. The steps of the aspect keyword extraction process are elucidated as follows:

1) Initiate the process by utilizing the pre-processed text as input.
2) Proceed to execute term extraction, employing the TFIDF, YAKE, and BERT methods.
3) Implement borda ranking to combine the results from the three term extraction methods, utilizing Eq. (3).

3.4 Mental disorder detection

During the mental disorder detection stage, binary classification is performed to ascertain the presence or absence of indications of mental disorders within the identified data. Binary classification categorizes data into two distinct

Table 3. Wikipedia links of aspect keywords

Aspect	Wikipedia Links
adhd	https://en.wikipedia.org/wiki/Attention_deficit_hyperactivity_disorder
anxiety	https://en.wikipedia.org/wiki/Anxiety_disorder
bipolar	https://en.wikipedia.org/wiki/Bipolar_disorder
depression	https://en.wikipedia.org/wiki/Depression_(mood) https://en.wikipedia.org/wiki/Major_depressive_disorder
ptsd	https://en.wikipedia.org/wiki/Post-traumatic_stress_disorder

Table 4. Approach for mental disorder detection

Approach	Description
MD1	The approach employs BERT embedding and the GRU model to detect mental disorders.
MD2	The approach utilizes BERT embedding and the BiLSTM model to detect mental disorders.
MD3	The approach combines BERT embedding and the BiGRU model to detect mental disorders.

Table 5. Result of mental disorder detection

Term List	Prediction
'mother', 'complex', 'ptsd', 'emotionally', 'abuse', 'husband'	mental disorder
'amazing', 'beach', 'beautiful', 'sunset'	none

Table 6. Approach for aspect categorization

Approach	Description
AC1	Semantic similarity is employed to categorize the term list resulting from hidden topic extraction into the five predetermined aspects. It calculates the similarity of the term list to the aspect keywords.
AC2	Construct a trained model using BERT embedding and Bi-GRU for the classification of data into each aspect.
AC3	Aspect determination combines semantic similarity and the Bi-GRU model, utilizing the average aspect similarity score as a threshold.

classes: positive and negative. In this particular context, the positive class encompasses Reddit data that exhibits indications of mental disorders, specifically anxiety, ADHD, bipolar, depression, and PTSD, and is denoted as a “mental disorder”. Conversely, the negative class encompasses data that lacks any indications of mental disorders or is designated as “none”. Table 5 presents examples of the results from the mental disorder detection process.

The detection of mental disorders is accomplished through three distinct experiments aimed at identifying optimal performance in mental disorder detection, referred to as MD1, MD2, and MD3. The following are descriptions of these mental disorder detection experiments:

3.4.1. Mental disorder detection (MD) 1

MD1 employs the GRU model for binary classification. The textual data is transformed into vector values using the BERT embedding method. The resulting vector features of words are then used in constructing the GRU classification model.

3.4.2. Mental disorder detection (MD) 2

MD2 undergoes a similar process to MD1, with the difference being the deep learning model used. MD2 utilizes the BiLSTM model to detect mental disorders.

3.4.3. Mental disorder detection (MD) 3

MD3 utilizes the BiGRU model for binary classification. The textual data is converted into numerical vectors through the BERT embedding method, with the resulting vector features of words employed in constructing the BiGRU classification model.

3.5 Aspect categorization

Aspect categorization follows the mental disorder detection stage. The texts identified as related to mental disorders in the preceding stage are subsequently subjected to further processing, where they are categorized into five aspects of mental disorders: ADHD, anxiety, bipolar disorder, depression, and PTSD.

The aspect categorization process In this study Is carried out in three different experiments to determine the best aspect categorization performance, denoted as AC1, AC2, and AC3. These aspect categorization experiments are described as follows:

3.5.1. Aspect categorization (AC) 1

AC1 is conducted through semantic similarity calculations, as shown in Fig. 2. Semantic similarity measures the likeness between hidden topic data and the list of aspect keywords, facilitating data categorisation into the five predetermined aspects of mental disorders. These hidden topics are derived from extracting those within previously identified documents about mental disorders.

NMF is utilized to generate the hidden topic data, with the steps for hidden topic extraction elucidated in Fig. 3. The result of the hidden topic extraction using NMF is presented as a list of terms. Table 7 provides a sample of the results obtained from each mental disorder document’s hidden topic extraction process.

```
Start
    1. Take the list of aspect keywords and the
       results from the previous stage;
    2. Extraction of hidden topics from text analyzed
       with NMF;
    3. Compute the semantic similarity between
       hidden topics and aspect keywords by
       employing Eq. (9);
    4. Determine the aspect of the hidden topic with
       the highest similarity value of all aspects.
End
```

Figure. 2 Hidden topic extraction pseudocode

```
Start
    1. Take the results from the previous stage;
    2. Generate a term-document matrix using
       TFIDF;
    3. Conduct hidden topic extraction with Python
       NMF;
    4. Store the hidden topic data (important words
       or frequently occurring words in the corpus) as
       a list of terms.
End
```

Figure. 3 Pseudocode of AC2

Table 7. NMF hidden topic results

Text	Hidden Topic
Text 1	['ptsd', 'complex']
Text 2	['depression', 'focus', 'fear', 'doubt', 'regret', 'worry', 'uncertainty', 'lack', 'passion']
Text i	Hidden topic (i)

Table 8. Result of semantic similarity (AC1)

Hidden Topic: ['ptsd', 'complex']. **Aspect Prediction:** ptsd				
Aspect 1	Aspect 2	Aspect 3	Aspect 4	Aspect 5
adhd	*anxiety*	*bipolar*	*depression*	*ptsd*
0.5376	0.3865	0.4897	0.5296	0.5724
Hidden Topic: ['depression', 'focus', 'fear', 'doubt', 'regret', 'worry', 'uncertainty', 'lack', 'passion']. **Aspect Prediction:** depression				
Aspect 1	Aspect 2	Aspect 3	Aspect 4	Aspect 5
adhd	*anxiety*	*bipolar*	*depression*	*ptsd*
0.5740	0.6001	0.5126	0.6868	0.6280

Start
1. Take the results from the previous stage;
2. Use BERT embedding to expand each word into a vector value;
3. Classifying aspects with the Bi-GRU model, using Eq. (4) to Eq. (8).

End

Figure. 4 Pseudocode of AC2

Following the acquisition of hidden topics for each document, these results are subjected to semantic similarity calculations. This similarity calculation yields values within the range of 0 to 1. A similarity value approaching 0 signifies dissimilarity among the data concerning aspects, while a value nearing 1 indicates data congruence with the aspect. Consequently, the aspect with the highest similarity value is employed to determine the relevant data aspect. An example of the AC1 result is presented in Table 8. The green highlights denote the predicted aspect. In term list 1, the predicted aspect is “PTSD”, whereas in term list 2, the predicted aspect is “depression”.

3.5.2. Aspect categorization (AC) 2

AC2 involves utilizing a BiGRU model, as shown in Fig. 4. The texts previously identified concerning mental disorders are transformed into vector values through BERT embedding. Subsequently, the word vector features acquired from the text representation outcomes are harnessed in constructing the BiGRU classification model to categorize mental disorder

Table 9. Result of Bi-GRU (AC2)

Term List	Aspect Prediction
'mother', 'complex', 'ptsd', 'emotionally', 'abuse', 'husband'	ptsd

Start
1. Retrieve the result from AC1;
2. Determine the average similarity value for each aspect;
3. Compare the average aspect similarity value with the similarity value for each hidden topic;
4. If the similarity value of the hidden topic is above the average aspect similarity value, then the aspect does not change;
5. If the similarity value of the hidden topic is below the average aspect similarity value, then use the AC2 model to determine the aspect.

End

Figure. 5 Pseudocode of AC3

aspects. Table 9 furnishes an example of the AC2 results.

3.5.3. Aspect categorization (AC) 3

AC3 employs a blend of semantic similarity and the BiGRU model in its execution, with the process outlined in Fig. 5. The average value of aspect similarity serves as a threshold to identify errors in aspect categorization from AC1. In instances where the data’s similarity value falls below the average aspect similarity value, the model constructed in AC2 is utilized to ascertain the aspect of the data.

3.6 Sentiment classification

In this study, the sentiment classification process mirrors the detection of mental disorders using a deep learning method. After categorizing the text into five aspects of mental disorders, the annotator assigns labels to ascertain the text’s initial sentiment. Following this, the deep learning model is employed to classify the sentiment as positive or negative for the five aspects of mental disorders.

Three experiments will be conducted, i.e., SC1, SC2, and SC3, to determine the best performance in classifying sentiment. The description of each sentiment classification experiment is outlined as follows:

3.6.1. Sentiment classification (SC) 1

SC1 utilizes the GRU model for sentiment classification. The textual data is converted into vector values using the BERT embedding method, with the resulting vector features of words employed in constructing the GRU classification model.

Table 10. Approach for sentiment classification

Approach	Description
SC1	The approach utilizes BERT embedding and the GRU model for sentiment classification.
SC2	The approach employs BERT embedding and the BiLSTM model for sentiment classification.
SC3	The approach combines BERT embedding and the BiGRU model for sentiment classification.

Table 11. Result of sentiment classification

Term List	MD3	AC3	Sentiment
'mother', 'complex', 'ptsd', 'emotionally', 'abuse', 'husband'	mental disorder	ptsd	Negative

3.6.2. Sentiment classification (SC) 2

SC2 undergoes a similar process to SC1, with the difference lying in the deep learning model used. SC2 employs the BiLSTM model to classify sentiment.

3.1.1. Sentiment classification (SC) 3

SC3 employs the BiGRU model for sentiment classification. The textual data is transformed into numerical vectors through the BERT embedding method. The resulting vector features of words are used in constructing the BiGRU classification model.

3.7 Evaluation

The performance of mental disorder detection, aspect categorization, and sentiment classification was assessed through a comparative analysis of multiple results. The evaluation metrics employed include accuracy, precision, recall, and F1 score to assess each performance.

4. Result and analysis

This section explains the results of mental disorder detection, aspect categorization, and sentiment classification.

4.1 Mental disorder detection approach

The detection of mental disorders is conducted to determine whether the identified data contains indications of mental disorders or not. The Reddit dataset is divided into 80% for training data in modelling and 20% for testing. Mental disorder detection was carried out using MD1, MD2, and MD3 to determine the most effective approach, as described in Table 4.

The performance of mental disorder detection is evaluated using various metrics, including accuracy, precision, recall, and F1 score. The evaluation results for mental disorder detection are summarized in Table 12.

Table 12. Mental disorder detection performance

Mental Disorder Detection Performance			
Evaluation Metrics	**Approach**		
	MD1	MD2	MD3
Accuracy	0.8929	0.8997	0.9009
Precision	0.8858	0.8952	0.8942
Recall	0.8929	0.8997	0.9009
F1 score	0.8876	0.8968	0.8922

Table 13. The frequency distribution of the dataset and the detection results

Class	Dataset	Detection Results
mental disorder	13,615	14,367
none	2,534	1,782
Total	**16,149**	**16,149**

As shown in Table 12, MD3 performs better in detecting mental disorders than MD1 and MD2. MD3 employs a combination of BERT embedding and BiGRU, harnessing the contextual understanding of the text provided by BERT embedding and the bidirectional information processing capability of BiGRU. This combination yields good results, with an accuracy of 0.9009, precision of 0.8942, recall of 0.9009, and an F1 score of 0.8922.

Table 14. Aspect categorization performance

Approach	Data Test	Accuracy	F1 Score
AC1	13,423	0.7911	0.7882
AC2	2,685	0.8060	0.8059
AC3	13,423	0.8507	0.8493

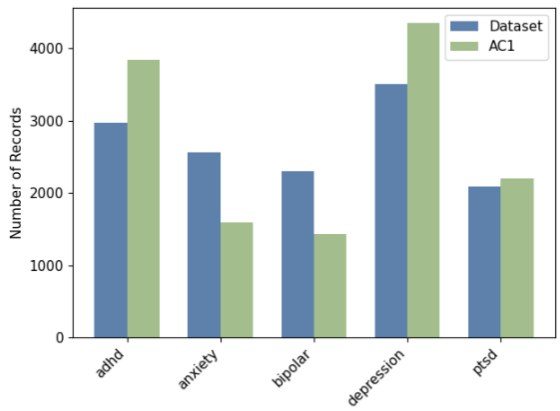

Figure. 6 AC1 frequency distribution

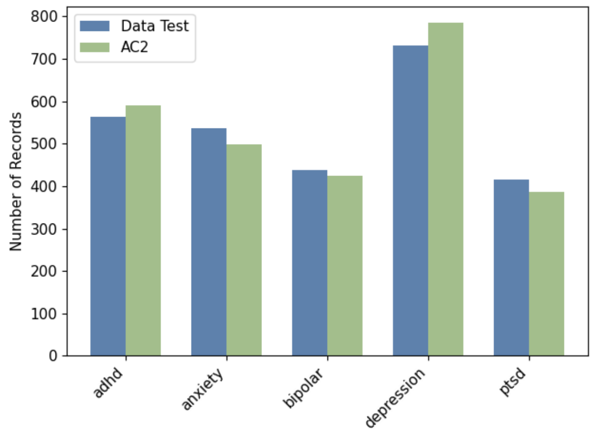

Figure. 7 AC2 frequency distribution

With the previously trained MD3 model for mental disorder detection, researchers analyze the predicted results and compare them with the ground truth from the dataset. Table 13 provides insights into the distribution of "mental disorder" and "none" classes. As per the ground truth of the dataset, the "none" class contains 2,534 data, while the "mental disorder" class contains 13,615 data. Compared with the mental disorder detection results, the "none" class contains 1,782 data, and the "mental disorder" class contains 14,367 data.

The correct prediction results for Reddit texts with indications of mental disorders or those labelled as "mental disorder" were 13,423, while the correct prediction results for Reddit texts that did not show indications of mental disorders or those labelled as "none" were 1,590. The percentage of incorrectly predicted data for the "none" class is approximately 37.25%, whereas the percentage of incorrectly predicted data for the "mental disorder" class is approximately 1.41%.

4.2 Aspect categorization approach

After the mental disorder detection stage, aspect categorization is conducted to determine the aspects of correctly predicted Reddit texts with indications of mental disorders. In this study, aspect categorization was performed using AC1, AC2, and AC3 to determine which approach yielded the best results, as outlined in Table 6.

AC1 utilized 13,423 data, representing the entire dataset of correctly predicted Reddit texts with indications of mental disorders. In contrast, the AC2 approach employed 2,685 data, equivalent to 20% of the dataset, while the remaining 80% served as training data for modelling. The performance of each approach was evaluated using metrics including accuracy and F1 score, as shown in Table 14.

Table 15. The frequency distribution of the dataset and AC1

Aspect	**Dataset**	**AC1**
adhd	2,972	3,845
anxiety	2,559	1,590
bipolar	2,301	1,435
depression	3,502	4,345
ptsd	2,089	2,208
Total	**13,423**	**13,423**

Table 16. The frequency distribution of data test and AC2

Aspect	**Data Test**	**AC2**
adhd	564	590
anxiety	537	499
bipolar	437	425
depression	732	784
ptsd	415	387
Total	**2,685**	**2,685**

Table 17. Average aspect similarity score

Aspect	**Average Similarity Score**
adhd	0.5465
anxiety	0.4784
bipolar	0.4670
depression	0.5497
ptsd	0.5476

According to Table 14, the performance of the AC1 approach is nearly comparable to that of the AC2 approach, with AC1 achieving an accuracy performance of up to 0.7911 and AC2 achieving an accuracy performance of up to 0.8060. AC2 outperforms AC1 by a margin of 1.49%. Fig. 6 and Fig. 7 illustrate that AC2 performs better than AC1 in determining the aspects of "adhd", "anxiety", and "bipolar". AC1 results in significant misclassification in these aspects, as indicated in Table 15.

As demonstrated in Table 16, all test data can be more accurately categorized into the five aspects using the AC2 approach, although some false positives and false negatives still exist. AC1 generated 13,423 data, and AC3 calculated the average aspect similarity score to determine the threshold value, as shown in Table 17. If the similarity score of the data falls below a specific threshold, the aspect is determined using the model from AC2; otherwise, the aspect from AC1 remains unchanged. Fig. 8 illustrates that AC3 outperforms AC1 and AC2, successfully reducing false positives and false negatives.

As presented in Table 18, the frequency distribution of each aspect in AC3 surpasses that of AC1 and AC2. As per the data in Table 14, there is a notable enhancement in AC3, with an accuracy increase of 4.47% compared to AC2.

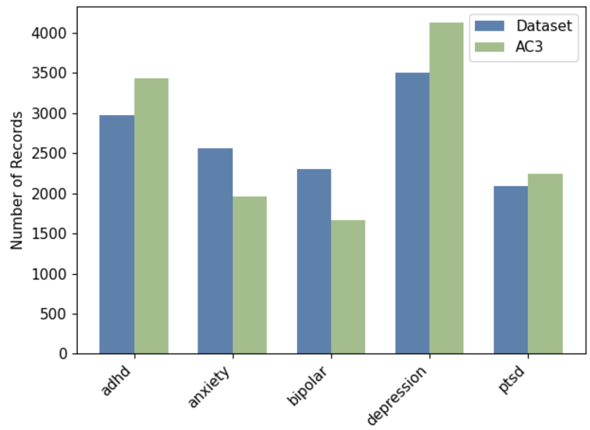

Figure. 8 AC3 frequency distribution

Table 18. The frequency distribution of the dataset and AC3

Aspect	Dataset	AC3
adhd	2,972	3,429
anxiety	2,559	1,958
bipolar	2,301	1,668
depression	3,502	4,124
ptsd	2,089	2,244
Total	**13,423**	**13,423**

4.3 Sentiment classification approach

Sentiment classification for texts correctly categorized into the five mental disorder aspects is performed after aspect categorization. The sentiment classification stage utilizes 11,419 data, constituting all correctly categorized AC3 results across the five mental disorder aspects. This data is split into 80% for the training set and 20% for the testing set.

Three approaches, namely SC1, SC2, and SC3, are employed to determine the optimal sentiment classification performance, as described in Table 10. The performance of sentiment classification is assessed using the same metrics as in the previous stage, which include accuracy, precision, recall, and F1 score. The results of the sentiment classification performance evaluation are presented in Table 19. Based on Table 19, it is evident that SC3 exhibits the best performance in sentiment classification. SC3 utilizes a combination of BERT embedding and BiGRU methods. This amalgamation yields good results, with an accuracy of 0.8717, precision of 0.8272, recall of 0.8717, and an F1 score of 0.8446.

The sentiment of each aspect from the AC3 results is analyzed using the previously trained SC3 model for sentiment classification and compared with the ground truth from the dataset. Table 20 provides

Table 19. Sentiment classification performance

Sentiment Analysis Performance			
Evaluation Metrics	**Approach**		
	SC1	SC2	SC3
Accuracy	0.8586	0.8673	0.8717
Precision	0.8137	0.8203	0.8272
Recall	0.8586	0.8673	0.8717
F1 score	0.8336	0.8398	0.8446

Table 20. Results of sentiment evaluation on aspects

Aspect	Sentiment	Dataset (in Percent)	Sentiment Results (in Percent)
adhd	positive	2.29	0.91
	negative	22.09	23.48
anxiety	positive	1.77	0.56
	negative	14.79	16.00
bipolar	positive	1.20	0.52
	negative	13.07	13.75
depression	positive	3.21	1.56
	negative	25.26	26.90
ptsd	positive	1.24	0.53
	negative	15.08	15.79
Total Percentage		100	100

insights into the distribution of sentiment in mental disorder texts. According to the ground truth of the dataset, positive sentiment contains 1,109 data, while negative sentiment contains 10,310 data. Compared with the sentiment classification results, positive sentiment contains 466 data, and negative sentiment contains 10,953 data.

The “bipolar” aspect exhibits the slightest difference between the ground truth and sentiment classification results for positive and negative

Upon closer examination, each aspect manifests both positive and negative sentiments, although the proportion of positive sentiment for each aspect is relatively low. Negative sentiment, on the other hand, exhibits a higher percentage for each aspect, with the “depression” aspect displaying a particularly elevated proportion of negative sentiment compared to other mental disorder aspects. This observation suggests that texts related to mental disorders frequently convey negative sentiments.

5. Conclusion

The results of this study underscore the efficacy of the proposed method in accurately detecting mental disorders, categorizing aspects, and classifying sentiments within social media texts, specifically on the five mental disorder aspects. Evaluation of three mental disorder detection approaches (MD1, MD2, and MD3) indicated that the proposed combination of BERT embedding and the

BiGRU model (MD3) outperformed the others. This combination effectively integrates the contextual understanding of text from BERT embedding with the bidirectional information processing capabilities of BiGRU, achieving an accuracy of 0.9009 in detecting mental disorders. In aspect categorization, the evaluation of three approaches (AC1, AC2, and AC3) revealed that the proposed combination of semantic similarity and BiGRU (AC3) achieved the highest accuracy at 0.8507. The integrated use of semantic similarity and deep learning models demonstrated superior performance compared to individual applications. This integration successfully enhanced accuracy and reduced errors in the categorization process. Regarding sentiment classification, the study assessed three approaches (SC1, SC2, and SC3), with SC3 utilizing a combination of BERT embedding and BiGRU, resulting in the best performance and an accuracy of 0.8717.

The sentiment analysis results for each aspect show that the "bipolar" aspect has a minimal difference, with a difference of only 0.68% in both positive and negative sentiments. In contrast, the most significant difference is found in the "depression" aspect, precisely positive sentiment, with a 1.65% difference. Moreover, texts related to mental disorders often conveyed negative sentiments, with the "depression" aspect standing out as the predominant conveyer of negative sentiments.

However, this study still has imperfections that need to be addressed. Future work can address data imbalance using under or oversampling techniques, enhance the term list for each aspect, and improve semantic similarity capabilities in categorization. Finally, the insights gained into sentiment patterns within texts related to mental disorders may offer valuable information for future research and interventions in the field of mental health.

Notations

$TFIDF_{ab}$	TFIDF weight for word a in document b
$tf_{a,b}$	Frequency of word a in document b
N_D	Total number of documents
df_a	Number of documents containing the word a
$YAKE(w)$	YAKE score for the term w
$t_{related}$	Term relatedness
$t_{position}$	Term position
t_{case}	Term casing
tf_{norm}	Normalized term frequency
$t_{sentence}$	Term occurrence in sentences
$Borda(t_l)$	The borda rank of the term t_l
$TFIDF_{t_l}$	TFIDF term extraction output
$YAKE_{t_l}$	YAKE term extraction output
$BERT_{t_l}$	BERT term extraction output
n	Maximum index number of candidate terms
l	Sequential order of candidate terms
x_t	BiGRU input at timestep t
$\vec{h}_t$	Forward GRU's hidden state at timestep t
$\overleftarrow{h}_t$	Backward GRU's hidden state at timestep t
h_t	The hidden state at timestep t
W^T	Weight matrices for the forward hidden state $\vec{h}_t$
W^V	Weight matrices for the backward hidden state $\overleftarrow{h}_t$
o_t	The output gate of the BiGRU at time t
W^o	Weight connecting the hidden and output layers
y_t	BiGRU output at timestep t
σ	Logistic sigmoid function
W^t	Weight matrix in the output layer
b_t	Bias in the output layer
$Sim(p,q)$	Similarity distance between word vector p and word vector q
p_i	ith component of the word vector p
q_i	ith component of the word vector q
v	Dimensions of the word vectors p and q

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, Abi Nizar Sutranggono and Riyanarto Sarno; *Methodology*, Abi Nizar Sutranggono; *Software*, Abi Nizar Sutranggono; *Validation*, Riyanarto Sarno and Abi Nizar Sutranggono; *Formal analysis*, Riyanarto Sarno and Abi Nizar Sutranggono; *Data curation*, Abi Nizar Sutranggono; *Writing—original draft preparation*, Abi Nizar Sutranggono; *Writing—review and editing*, Abi Nizar Sutranggono; *Visualization*, Abi Nizar Sutranggono; *Supervision*, Riyanarto Sarno.

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