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Depression Tendency Processing Based on LSTM Technique for Text Emotion Recognition

Minhao Gao*

SWJTU-Leeds Joint School, Southwest Jiaotong University, Chengdu, China

*Corresponding author: sc22m2g@leeds.ac.uk

Abstract. Depression is a common mental disorder that can lead to suicide in specific severe cases. A large number of suicides occur each year due to a lack of timely observational attention and treatment worldwide. This paper indicates that social media posts should be monitored for implicit depression and categorized immediately to reduce the risk of suicide and improve public mental health. In the data preprocessing, the NLTK library is used to slice the labeled social media text collected from Kaggle. Words not relevant to sentiment analysis are deleted. Words from sentiment lexicon can represent the positive and negative and filter the noise. The original data was randomly divided into training set(70%) and prediction set(30%). In the machine learning stage(for classification results and evaluation), a bidirectional LSTM mode(used to solve the problem of gradient explosion or disappearance from the preamble text.)l is used. The accuracy, precision, recall and F1-score are 72.85%, 73.88%, 72.37%, 73.12%. They can be components of confusion matrix to evaluate the model. It is difficult for CNN algorithm to capture good n-gram feature results. The quality of the model can be improved by using higher quality and larger numbers of datasets and noise handling, perfecting a better sentiment lexicon and adjusting model parameters, to prevent overfitting. Finally, the most suicidal users(top 3.6% high score) in the text to prevent the tragedy of suicide can be found and more attention to public mental health and safety should be paid.

Keywords: LSTM; gradient explosion gradient disappearance; confusion matrix; Depression tendency identification.

1. Introduction

According to the 2023 report of the United Nations World Health Organization (WHO) [1], depression is a very common mental disorder, which has affected 5% of adults worldwide and deeply affected people's lives. Depression not only profoundly affects the quality of life of individuals, but even severe patients may have suicidal thoughts and even lead to serious consequences such as suicide. Every year, tens of thousands of tragic suicides are caused by depression that has no immediate diagnosis or effective treatment.

In the highly developed digital media era, many users express their thoughts and emotions on various social media platforms. At the same time, many web users reveal depression when they send posts. This situation is more common [2], and there have even been many tragic incidents of severe depression in individuals leading to suicide. Therefore, the analysis of user posts for early detection of depression tendency and early intervention to reduce suicide or other serious consequences not only saves countless families but also has a positive effect on the society. Based on Baune, B. T., & Christensen, M. C.'s study[3], depression has many physical and psychological symptoms such as persistent sadness, loss of interest, changes in appetite, insomnia or excessive sleep, fatigue, feelings of worthlessness, lack of concentration, and thoughts of self-harm. These symptoms can also have other negative effects on daily work productivity and social relationships, which can lead to worsening conditions and an increased risk of suicide. Conventional treatments for depression include medication, psychotherapy and combination therapy. Medication means the use of anti-depressants in order to regulate the chemicals in the brain and thus relieve the symptoms of depression. Psychotherapy (e.g. CBT) is the use of professional knowledge by psychologists to help patients change negative thinking and behavior patterns so that patients can spontaneously reduce depressive symptoms. Comprehensive treatment is to combine the previous two treatment methods together, in order to better treatment effect. However, for most members of society, the stigma of mental health problems, the lack of medical resources and the neglect of self-psychological problems are important factors that lead to their lack of immediate access to effective treatment.

Deep learning has advanced development for text processing and sentiment analysis, and its application fields cover many aspects. Deep learning is of great significance for the analysis of suicide tendency caused by depression [4]. It can accurately extract and process suspicious depression and suicide information in the face of massive social information on various platforms, and classify users for further intervention. According to Nathan, N.A. and Nathan, K.I.[5] in Suicide, Stigma, and Utilizing Social Media Platforms to Gauge Public Perceptions. Frontiers in Psychiatry. Using questionnaires, most people think depression suicide can be prevented. Deep learning algorithms can realize the monitoring and intervention of depression through the following steps: The first is data collection, and the authoritative data sets that have been used by multiple people are searched online to ensure the diversity and representative of the data. Then there is data preprocessing, which cleans and labels the collected data, including removing noise, labeling sentiment categories and splitting into training and testing sets. Next comes model training, where deep learning models such as bidirectional LSTM are used to train the preprocessed data to learn the sentiment features in the text. This is followed by risk assessment, which evaluates the depression risk of users based on the sentiment analysis results, and identifies high-risk users based on the depression risk scores obtained from the obtained feature functions. Finally, intervention measures, timely intervention for high-risk users, including pushing comfort content, providing psychological counseling resources, and even triggering an alarm mechanism when the situation is serious.

Therefore, this paper aims to analyze the emotions of users based on their posts on social media. Tadesse, M. M., Lin, H., Xu, B., & Yang, L.[6] used LSTM algorithm in their research to find out possible potential suicidal behaviors and intervene their users. Dissuade them from despising their lives and prevent tragedies. Finally, such technical means can improve the level of public mental health.

2. Research methods

2.1. Data preprocessing

In the data collection phase, this paper searches for social media posts by depressed people from kaggle. Each post is labeled with a depressed or non-depressed label and converted into a csv file. Since the direct processing of large sections of natural language text needs high requirements for the model, the text information in csv files cannot be dealt directly. The model needs multiple sliced text input information to get high accuracy results, so author chooses to use NLTK (library) to slice the text. On the premise of preserving the maximum original meaning of the text, the coherence of the text is maintained and the meaningless words that have no effect on the meaning of the text are reduced. This measure can optimize the running efficiency of the model and reduce the running cost of the program.

Words or phrases that can reflect the user's emotion should be retained in the text to the greatest extent [7]. The processed words are stored in the third column of the table. According to [7], the sentiment lexicon [8] is of great referential significance for the parameter selection of text sentiment analysis, and the words in the sentiment lexicon can be selected from the extracted words. The words in the sentiment dictionary are divided into two categories: positive and negative, and are set respectively. Only the words contained in the sentiment dictionary are retained in the sliced text. The words that do not appear in the sentiment dictionary, such as abbreviations and emojis, are deleted.

Noise filtering is a key step of data preprocessing, in order to reduce the impact of noise on sentiment analysis. This article will clean the data of stop words, punctuation, and white space that is not related to the content. After the data preprocessing is completed, 70% of the text is randomly selected as the training set and 30% is assigned to the test set. This not only ensures that there is enough training order in the model, but also that adequate test set is ensured for evaluating the performance of the model. In addition, the cross-validation method is used to ensure the quality of data and the accuracy of sentiment analysis. It lays a solid foundation for subsequent model training and prediction, and finally improves the model's ability to detect and analyze depression in texts. Fig.1 is a summary of the above:

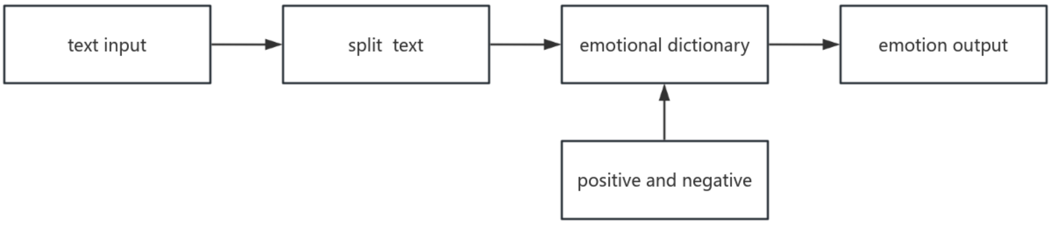

Fig.1 Data preprocessing diagram

2.2. Depression analysis with basic machine learning

Li Shan [9] recommended the use of LSTM (Long Short-Term memory network) model for text analysis in the depression text screening algorithm. The LSTM algorithm (which belongs to the RNN recurrent network) extracts the parts of each text that appear in the sentiment lexicon, sets up a matrix, and then performs supervised learning and sets up coefficients(positive adds, negative deletes). The algorithm can use gate control technology to make it able to obtain the dependence between data in a long time span, so as to solve the problem of gradient disappearance and gradient explosion in processing long data.

This model can calculate the score of each post, while the single data is too long, so the proportion of processing the first part of the text in the classical RNN algorithm is too low [10] (because RNN weights are shared, the weight of the preorder input decreases with the change of time). This is similar to how human memory forgets early information in the text, which eventually leads to the disappearance of the gradient and the model will not continue to learn. Therefore, the model needs to use the mechanism of cell state and gate control in the LSTM algorithm to delete the preorder data that has weak influence on sentiment analysis, and screen and retain the data useful for long-term memory to effectively retain the dependencies in the long time span.

Therefore, it is necessary to use the LSTM algorithm to screen and save the long-term memory, and the specific implementation is as follows: The LSTM network retains and transmits information through the cell state in order to effectively capture long-term dependencies. Among them, the forget gate determines which information needs to be scraped due to weak dependence through the sigmoid function. The input gate determines which new information to add to the cell state, and after updating the cell state, the output gate calculates through the sigmoid and tanh functions to determine which information to use as the output of the LSTM. Through the above gate control method, it can ensure that the model retains and emphasizes the preorder information of long texts in sentiment analysis, and indirectly optimizes the performance and rationality of the model.

2.3. Classify the depressed texts after analysis and give encouragement to the depressed people

When the prediction program is given a score for each data, the higher the score, the more likely the text is to be depressed. According to existing studies [11], 3.6% of the population suffers from depression, so 3.6% of the data with the highest score are extracted and marked as depression patients, and warm tips are sent to them and their speech emotions are monitored to avoid suicide developed from severe depression. According to research [12], social comfort for depressed people can reduce the occurrence of many suicides, and social contact will have a positive effect on mentally unhealthy people. Therefore, it is necessary to strengthen the communication with their family and friends, which has a positive effect on them. This measure will significantly improve psychosocial well-being and reduce suicide rates in society.

2.4. The confusion function evaluates the classification results

The confusion function has an intuitive display for evaluating deep learning models [13], and can be used to evaluate the comprehensive performance of the model in distinguishing between depressed and non-depressed texts. Among them, accuracy, precision, recall and f1 score measure the performance indicators of the model in four dimensions. It is of great help to optimize the model by predicting and calculating the confusion function and visualizing it. For example, adjusting the learning rate and the number of recurrences can greatly improve the performance of the model. Setting the appropriate number of hidden layers can give the maximum saving of computing power resources under the premise of ensuring performance. In addition, data preprocessing and feature selection can be improved through confusion functions to directly improve model performance.

3. Research results

3.1. Results of preprocessing

First and foremost, the sentiment dictionary [7] of HowNet is selected to divide words into positive and negative words and store them respectively for subsequent extraction operations.

First the authors of this article use Pandas library to read raw input file and store it in DataFrame. Next step is to keep the text column from the original data and rename it to Text_Tokens NLTK (used).

Spaces, emojis, etc. are removed, because they are not useful for text sentiment analysis. The words that appear in the sentiment lexicon in the faceted Text_Tokens are then stored in the columns of class 1 and class 0 as positive and negative, respectively. The table after processing is as follows:

Table 1. Preprocessing result preview

Text_Token	class	1	0
Too much F...	suicide	Keep real	Trying alone
I can’t wait...	suicide	Care love	Alone ill
My friend is...	Non-suicide	Jealous mind	Mind action
I feel kind...	suicide	Cite kind	Ill
I’ve been wanting...	suicide	Accept be	Change un

Finally, the table is divided by python functions, and 70% is used as the training set and 30% is used as the test set. And the two tables are stored as training and test data CSV files respectively for subsequent model training and performance evaluation.

3.2. Classification results

In this paper, the training set file is input, and the target column is label mapped. "Suicide" is mapped to 1 and "non-suicide" is mapped to 0."TfidfVectorizer"(library) is used to extract text features and convert the data into PyTorch "Tensor" to create a data loader "DataLoader". This paper then uses the bidirectional LSTM model, through the input feature dimension, hidden layer dimension and output layer dimension. The initialization weights part initializes the LSTM layer and the fully connected layer with Xavier normal (W: weights of the LSTM layer, weight N: normal distribution, nin: number of input features, nout: number of output features):

$$W \sim N\left(0, \sqrt{\frac{2}{n_{in} + n_{out}}}\right) \tag{1}$$

And zero-initialize the bias:

$$b = 0 \tag{2}$$

In the forward propagation part, in order to adapt to the input format of LSTM, a dimension is firstly added to the data and input as follows:

$$x' = \text{unsqueeze}(\text{x}, \text{dim} = 1) \tag{3}$$

Then get the hidden layer output from LSTM layer (hlstm):

$$h_{lstm} = LSTM(x') \tag{4}$$

To avoid overfitting, this essay chooses to use Dropout strategy:

$$h_{dropout} = Dropout(h_{lstm}) \tag{5}$$

Finally, the output of the last time state of the LSTM is taken through the fully connected layer:

$$y_{fc} = W_{fc} \cdot h_{dropout}[:; -1, :] + b_{fc} \tag{6}$$

The connected result uses the Sigmoid activation function to limit it to [0,1]:

$$\text{y} = \sigma(\text{y}_{\text{fc}}) = \frac{1}{1 + \text{e}^{-\text{z}}} \tag{7}$$

Because this item is binary, the output dimension is set to 1. As shown in Table 2:

Table 2. Data output result

Text_Token	Class	Train	Score
Too much P..	1	1	0.9951825
I can’t wait...	1	1	0.9875703
My friend...	0	0	0.0055687
I feel kin...	1	0	0.4661762

3.3. Confusion function results

According to the classification results of the prediction model, the four evaluation indicators are as follows:

Accuracy: 72.85%

Precision: 73.88%

Recall: 72.37%

F1-score： 73.12%

According to the above indicators, the accuracy of the model is good. However, because the expression of depression can be hidden and very obscure, there may be a small part of the data can not be accurately identified. The number of words in the sample is not consistent, which leads to the uneven sample and makes the prediction result inaccurate. Even because depression can be hidden, the prediction is not accurate, and the posts collected on social media are not standardized, which makes the data noise too large to affect the evaluation indicators. The key parameters in the algorithm of the used bidirectional LSTM can be further tuned. Here are the proposed improvements based on the evaluation results of the confusion function results:

1. Use higher quality datasets, reduce data noise and ensure that the labels are consistent with the actual results to prevent parameter sizes from being affected. Using a larger dataset results in a better fit to the model. Research by Emily Lin and Jian Sun [14] (Deep Learning-Based Depression Detection from Social Media: Comparative Evaluation of ML and Transformer Techniques) points to further increases in the learning rate with larger training sets (160 gigabits of memory) and longer training times (smaller learning rates).

2. For text preprocessing, it is necessary to find out the noise data that affect the accuracy and deal with it. The irregular language expressions are deleted when they appear in a small amount, and are set as new emotional words when they appear in a large number and saved in the sentiment lexicon.

3. For the model can adjust the parameters, and combined with other algorithms. It is of significance to improve the complexity of the model, improve the fit of the prediction model, and prevent the training model from overfitting.

In conclusion, the F1-score of 73.12% has a good detection result for depression emotion detection, and there is still some room for improvement. The results can be optimized by selecting better data sets, refining data preprocessing and model upgrading, and finally obtaining high-quality prediction results. The result of the confusion function is shown in Fig.2:

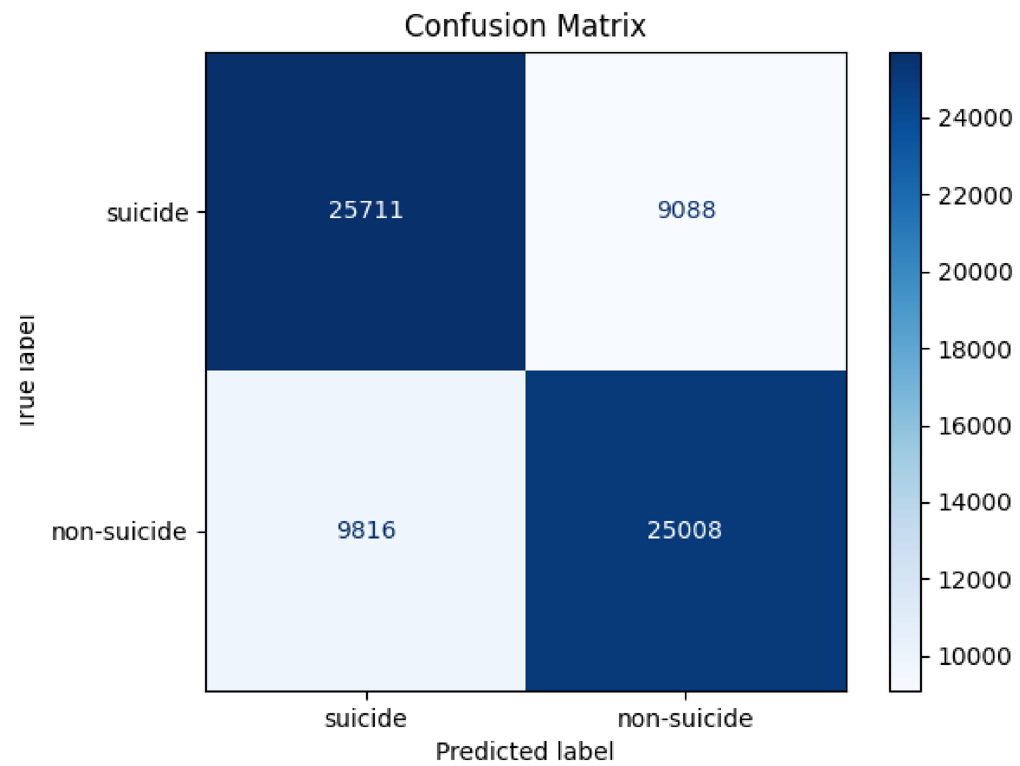

Fig.2 Display of the resulting confusion matrix

4. Conclusion

The phenomenon of suicide caused by depression has a huge impact on the world. In order to avoid missed diagnosis and early intervention, this paper uses deep learning to slice social media texts after removing unintentional words using the NLTK library. And the data is divided into 70% and 30% training and test sets. The training process uses LSTM (Long Short-Term Memory) method, which introduces the cell state by using the control gate mechanism in order to solve the problem of gradient explosion and gradient disappearance. The accuracy, precision, recall and F1-score of the final model are 72.85%, 73.88%, 72.37% and 73.12%, respectively.

Although the model has a high accuracy with a small amount of data, there are still some parts that need to be improved. The first step is to use a higher quality and larger data set as input to the model predictions. At the same time, it is possible to use other analytical processing for other languages besides English. Next step, the sentiment lexicon needs to go through more stringent labeling and screening standards by professionals to ensure higher quality and reliability of the data.

For model accuracy improvement, more and more accurate(by multiple regression) models such as BERT and Transformer can be used. In order to better analyze the depression of media users, text and video, pictures and audio data types can be comprehensively analyzed. This method can significantly improve the prediction accuracy, and at the same time read the user's historical imprint to analyze the emotional changes and analyze the corresponding depression analysis for different users.

At the same time, sentiment analysis still needs the cooperation of multiple disciplines, such as psychology and psychiatry, which can provide more scientific evaluation methods and application scenarios. It also works with mental health agencies and social media platforms to immediately prevent suicide among depressed users and improve public mental health. Finally, with the efforts of all parties, there will be a better solution to the world-class problem of depression in the future. Although the use of social media to monitor suicide in depression is only partially beneficial to public mental health, many other ways to solve this public mental health problem are believed to be proposed in the near future.

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