Asian Journal of Computer Science and Technology
ISSN: 2249-0701 (P) Vol.11 No.1, 2022, pp.17-20
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DOI: https://doi.org/10.51983/ajcst-2022.11.1.3209

Sentiment Analysis in Social Media for Depression Identification Using BiLSTM

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(Received 10 January 2022; Accepted 3 February 2022; Available online 10 February 2022)

***Abstract* - Social networks have evolved into an excellent platform for users to engage with their interested friends and share their thoughts, photographs, and videos that show their emotions, feelings, and sentiments. This opens up the possibility of analyzing social network data for user feelings and sentiments in order to examine their moods and attitudes when talking through these online platforms. Although the diagnosis of depression using social network data has gained popularity around the world, there are other dimensions that have yet to be discovered. In this study, aim to perform a depression analysis on social media data collected from an online public source. The proposed is to explore the impact of Rule based Vader Analyzer and a BiLSTM. The results are calculated and shown using the performance metrics such as recall, precision and accuracy.**
***Keywords:* Depression, Machine Learning, Mental Health, Sentiment Analysis, Social Media**

I. INTRODUCTION

The growth of internet and communication technologies, particularly online social networks, has revitalized how individuals engage and communicate electronically with one another. Apps like Facebook, Twitter, and Instagram not only host written and multimedia information, but also allow users to communicate their feelings, emotions, and sentiments about a topic, subject, or issue online. On the one hand, this is great for users of social networking sites to openly and freely contribute and respond to any topic online; on the other hand, it creates opportunities for people working in the health sector to gain insight into what might be happening at the mental state of someone who reacted to a topic in a specific manner. In order to provide such insight, machine learning techniques could potentially offer some unique features that can assist in examining the unique patterns hidden in online communication and processing them to reveal the mental state (such as ‘happy’, “sadness,’ ‘anger,’ ‘anxiety,’ depression) among social network users.

In this study, we look at several linguistic clues that can help us detect emotion-related events: the position of the cause event and the experience in relation to the emotion keyword: good emotion (e.g. ‘happy’, ‘love’, ‘nice’), negative emotion (e.g. ‘worthless’, ‘loser’, ‘hurt’, ‘ugly’, ‘nasty’), sadness (e.g. ‘worry’, ‘crying’, ‘grief’, ‘sad’) A temporal process that includes present focus (e.g. ‘today’, ‘is’, ‘now’, past focus (e.g. ‘ago’, ‘did’, ‘spoke’, and future focus (e.g. ‘shall’, ‘may’, ‘will’, soon’). Linguistic words like articles (e.g. ‘a’, ‘an’, ‘the’), prepositions (e.g. ‘for’, ‘the’, ‘of’, ‘to’, ‘with’, ‘above’), auxiliary verbs (e.g. ‘do’, ‘have’, ‘am’, ‘will’), conjunctions (e.g. ‘and’, ‘but’, ‘whereas’), personal pronoun (e.g. ‘I’, ‘them’, ‘her’, ‘him’), impersonal pronouns (e.g. ‘it’, ‘it’s’, ‘those’), verbs (e.g. ‘go’, ‘good’) and negation (e.g. ‘deny’, ‘dishonest’, ‘no’, ‘not’, ‘never’).

Early detection and expert intervention are the most effective treatments for mental illnesses such as depression. Delayed diagnosis and therefore delayed treatment can often lead to severe case of the illness. This leads to suicide thoughts, and they come to the conclusion that ending it all is a much better option than seeking help, etc.

In this study, we aim to analyze social media data to detect any factors that may reflect the depression of relevant social media’s users, so the proposed is to explore the impact of Rule based Vader Analyzer and a BiLSTM.

II. RELATED WORK

Mandark Deshpande and Vignesh Rao [5] used NLP to evaluate depression-related emotion on Twitter. Furthermore, tweets are classified as good or negative based on a list of terms that indicate how much the user is prone to depression. They created a dataset from 10,000 tweets obtained via the Twitter API and used the Nave Bayes classifier to predict sadness with 83 percent accuracy.

M. Hemanthkumar and A. Latha [9] employed Nave Bayes and SVM algorithms to detect depression in user tweets. The dataset utilised consisted of 43000 tweets obtained from the Kaggle website. The dataset was divided between training and testing sets in a 70 by 30 ratio. They utilised the Bag of Words approach to count the frequency of each word in the dataset to generate features. The model is trained using Nave Bayes and SVM using the features given by the Bag of Words model.

Salma Almouzini, Maher Khemakhem & Asem Alageel [1] utilised Random Forest, Naïve Bayes, Liblinear for detection of depression. They scraped tweets using Twitter4j, a scrapper programme. For depressed tweets, they conducted a search for users who said in their tweets that they have suffered or are suffering from depression, resulting in 35 depressed tweets and 62 non-depressed tweets.

Chempaka Seri Abdul Razak and Muhammad Ameer Zulkarnain [12] proposed Vader Sentiment Analysis and two machine learning algorithms, Nave Bayes and CNN, to detect melancholy Twitter users. They introduced Tweep, a system development that uses Machine Learning to estimate a user's depression degree based on the user's tweet.

III. PROPOSED METHODOLOGY

The proposed approach in this work is VADER with Bi LSTM. The first stage is data collection, followed by pre-processing and feature selection as prerequisites for BiLSTM model training.

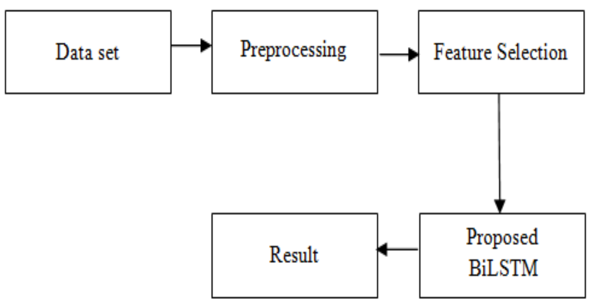

Fig. 1 Methodology

A. Preprocessing

Pre-processing procedures are used to exclude the undesired from a group of datasets. some preprocessing approaches are,

1. *Text Case Change*: Each tweet's words are all altered to lowercase.

2. *Slang Substitution:* Slang plays an important part in depression identification and can also improve model efficiency by substituting complete forms of abbreviations such as xD, LOL, and so on.

3. *Hyperlink Removal:* Hyperlinks are the noisy data in tweets so removing them makes the model more efficient.

4. *Digits Removal:* Numerals have no meaning, they must be filtered out.

5. *Spelling Checking:* Tweets frequently contain spelling errors, which can be remedied in two ways: shortening and correction.

6. *Lemmatization:* It is a phenomenon in which words are mapped into their lemma-like root words based on their meaning. Essentially, it is superior to the stemming process because stemming directly eliminates the suffix (final portion of the word) of the original word, resulting in a shift in meaning. For example, using lemmatization, the term better can be replaced by good.

7. *Removal of Stop Words:* Stop words are those words that are the mostly utilized terms having no meaning that can be ignored since their presence can damage the model efficiency in adverse manner. For example, "are", "I", "is", and so on.

8. *Word Cloud Analysis:* Word cloud analysis of pre-processed tweets in datasets was performed for data visualization purposes.

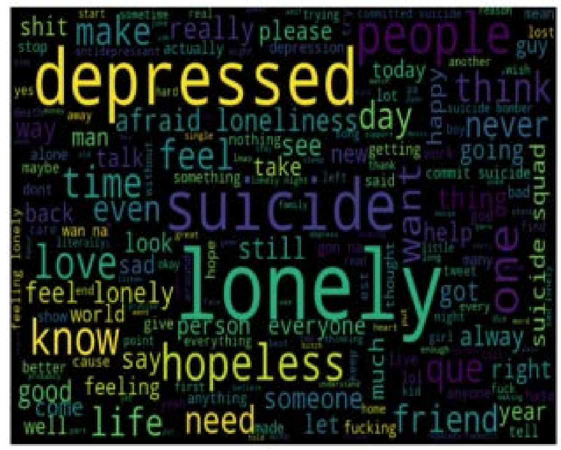

Fig. 2 Depressive Tweets

B. Sentiment Extractions

Sentiment extraction is the process of extracting the polarity of a tweet in order to determine its overall emotion. The VADER (Hutto & Gilbert, 2014) Valence Aware Dictionary and Sentiment Reasoner was utilised for a full sentiment analysis of Tweets. It is a rule-based and lexicon-analyzing tool designed specifically for emotions expressed in social media for general sentiment analysis that is specifically suited to sentiment in microblog-like contexts [6]. It takes into consideration not only the emotion classification but also the corresponding sentiment intensity scores. VADER requires no preparation data and is built from a human-curated, valence-based, generalizable conclusion language that is sufficiently fast to be used with streaming data. While VADER cannot detect depression in text, it does give a foundation for interpreting the data's overall emotion.

C. Word2Vec

When given a text corpus as input, the word2vec tool returns word vectors as output. The framework of Word2Vec is relatively easy. This tool can be used to offer a systematic execution of the continuous bag-of-words and skip-gram frameworks that are used to determine words as vector It is a feed-forward neural network including only one hidden layer. Because they are likely to capture the semantic and syntactic definition of a word, trained word embeddings are one of the most powerful ways of representing text. It creates a lexicon from the training text data before grasping a vector representation of words. The completed word vector file can be used as a feature in many machine learning and NLP applications.

D. Classification

The classification procedure began at the bottom of the model. Embedded features were supplied into a layer of Bidirectional Long Short Term Memory (BiLSTM) [12] with an output dimension of 600. BiLSTM was utilised in this case because it included knowledge about the past and future at any time step, which helped the model predict more accurately. The BiLSTM layer output was then fed into hidden layer 1 with an output dimension of 300. Metadata Normalization With an output dimension of 10, features were sent into hidden layer 2. In hidden layers 1 and 2, the activation function Rectified linear unit (ReLU) was used. The vectors returned by these two hidden layers were then concatenated. As a result, the concatenation layer's output dimension was 310. To avoid overfitting, a dropout of 0.2 was implemented. Finally, hidden layer 3 was created, with an output dimension of 1 and a sigmoid activation function because we were undertaking binary classification. All of the secret layers were completely connected.

We established these characteristics by watching the outcome of a limited amount of test data. We kept the measurements that gave us the best results. Our model was built using the Keras API. On batches of size 32, we utilised the Adam optimizer [14], and the learning rate was 0.001. The other hyper parameter settings remained unchanged. We left them as default settings.

Our training period was divided into two stages. First, we created a dataset of 4656 posts evenly distributed into two categories: depressive posts and non-depressive posts. We used Reddit's sadness subreddit to collect depressive posts. We used the text adventures portal for non-depressive posts. We personally inspected posts that were more appropriate for our task, assigned them a class (i.e. depressive or non depressive), and then trained the model. The dataset did not include class information for the users' posts. As a result, after training the model, we categorised each train data post because not all of a user's posts are of the same class. Then, in the second phase, we used this categorised data to train our model once more.

We employed the risk window idea [3] to forecast a user's state. A danger flag is triggered if the model predicts that a post is depressing. The person is classified as depressed if the model continuously generates the identical (depressive) prediction for the consecutive n posts (the size of the risk window is represented by n), or if a person has less than n posts and the model continuously predicts the identical (depressive) prediction for all of that person's posts. If a non-depressive post appears in the middle of the user's prediction process, the risk flag is raised. If the algorithm fails to forecast n consecutive depressive episodes, the user is eventually penalized.

IV. RESULTS ANALYSIS

Various measurement criteria are presented here to assess how well our model performed and how quickly sad users are anticipated to be depressed. In addition, a result comparison of several aspects is provided to determine which performed the best.

Accuracy refers to the percentage of accurately predicted data points among all accessible data points. It motivates us to quantify how frequently the algorithm correctly groups the data point.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision is defined as the percentage of true positives (significant occurrences) among all retrieved instances.

$$Precision = \frac{TP}{TP + FP}$$

Recall or sensitivity is the proportion of true positive occurrences among all applicable occurrences, i.e., True positive and false negative.

TABLE I PERFORMANCE OF PROPOSED CLASSIFIER

Methods	Accuracy	Precision	Recall
RF	0.81	0.78	0.79
SVM	0.80	0.81	0.78
LSTM	0.82	0.80	0.81
Proposed BiLSTM	0.84	0.83	0.82

Table I displays a graph depicting the model's accuracy on training and validation data over time. In compared to existing models, our model performs marginally better in all performance parameters.

V. CONCLUSION

This work proposes a model for detecting depressed tweets using sentiment analysis, and based on the results and performance measures, we can conclude that BiLSTM did exceptionally well in depression identification, as shown in Table I. In terms of accuracy and precision, the BiLSTM model came out on top. Many pre-processing activities are carried out, such as dataset preparation, filtering, feature extraction, and so on. This study can also assist specialists in gathering preliminary data for analysing depressed people. This research can be expanded in the future by looking at how a user's social network and interactions affect his depressive mood and finding a more reliable approach to quantify the impact of elements.

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