

Depression Detection from Social Media Data using CNN and Linguistic Metadata Features

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Abstract— Depression is a major cause of disability and a major contributor to the worldwide burden of mental diseases. Research shows that women are more prone than men to be depressed. More than 700,000 people kill themselves each year. Suicide ranks as the fourth leading cause of death for individuals aged 15 to 29 years. In this research, we employ several Machine Learning algorithms derived from messages and postings on social media networks to facilitate the early detection of melancholy. WORD2VEC, GLOVE, the Machine Learning algorithm LOGISTIC REGRESSION, and the neural network algorithm CONVOLUTIONAL NEURAL NETWORK (CNN) are trained and compared to classification-based user-level linguistic input.

Index Terms— Depression, Word2vec, Glove, Logistic Regression, Convolutional neural network, Linguistic Metadata.

I. INTRODUCTION

The World Health Organization (WHO) states that more than 300 million individuals, or around 4.4% of the world's population, are sad. Women are more likely to be depressed (5.1 percent) than males (3.6 percent), and the percentage of depression changes from place to place. It may happen to anyone, no matter how old they are or what stage of life they are in. The most recent statistics from the 2016 National Survey on Drug Use and Health in the United States suggest that 12.8% of youths aged 12 to 17 and 6.7% of adults had a severe depressive episode in 2016. (MDE). It is hard to figure out what depression is because numerous varieties of it have been defined and evolved over time, and the word "being depressed" is now used in everyday English.

Depression is marked by a change in mood, which is followed by symptoms like a negative view of oneself, a desire to run away or hide, changes in vegetative functions, and a lower level of activity in general.

People who are depressed may have symptoms that make it hard for them to handle everyday things. These symptoms are substantially distinct from the mood swings that most people have. In the most severe cases, depression might result in suicide. They also claim that fear of bias may have had a little effect on their research because a lot of people want to keep their mental health care private. Even while depression and other mental disorders can make people want to be alone and stay away from others, studies have shown that people who are affected are using social media more and more to connect with others, tell their stories, and help others.

These results suggest that peer-to-peer social media networks may assist individuals with mental illnesses by mitigating stigma, facilitating access to professional care, and providing direct online support. This all highlights how crucial it is to learn more about how to help people who are depressed on social media and the internet in general. As a result, our study focuses on using machine learning algorithms to find signs of depression in written texts as soon as possible.

This research aims to predict early-stage depression using machine learning and neural network models (WORD2VEC, GLOVE) based on social media posts. A classification employing user-level verbal input is contrasted with a convolutional neural network based on distinct criteria.

word embeddings. Also, the current popular ERDE score as a metric for early detection systems is looked at in depth, along with its drawbacks when it comes to shared tasks. A considerably altered measure is compared to the original score. Finally, a new word embedding was trained and evaluated on a huge set of words that were in the same field as the original job.

II. LITERATURE SURVEY

"Employing Neural Networks and Linguistic Metadata for the Early Detection of Depression Indicators in Text Sequences A close look at the present ERDE metric has showed that one of the most important things to do in this area in the future is to come up with a new metric for early detection jobs like eRisk. In relation to the models discussed in this study, further experimentation is required to identify more effective methods for directly incorporating metadata elements into the neural network. However, using groups of more than two models and adjusting the resulting probability looks like a good idea. It has not yet been tested to see what happens when you combine the word embeddings of two models in one neural network. Another potential enhancement may involve utilizing contemporary language modeling techniques such as BERT as input for the network, and subsequently comparing a self-trained model employing this methodology to the fastText word embeddings referenced in this study [1].

"Fine-tuning a universal language model for classifying text" Authors have put up ULM Fit, a highly effective and sample-efficient transfer learning technique suitable for any NLP work. We have also put forward a number of new fine-tuning methods that work together to stop catastrophic forgetting and make learning strong over a wide range of jobs.

On six example text categorization problems, our strategy worked much better than the best transfer learning techniques and the state of the art. We anticipate that our findings will stimulate advancements in transfer learning for NLP [2].

"A sensitivity analysis of convolutional neural networks for sentence classification" In this instance, the author employed a neural network model for text classification. The author suggested a Convolutional Neural Network model for classifying sentences. The author determined that CNNs are utilized to investigate the impact of each component of the architecture on performance [3].

"Adding subword information to word vectors" The author suggested that NLP may be used to map words from a lexicon to a vector that can be used to make predictions about words. Word vector algorithms, such as Word2Vec and Glove, as well as many others used in NLP, change text into vector representations [4].

III. METHODS / PROJECT PLANNING

When we build a project, we need to follow a set of steps. We can't just go from one module to the next because it would hurt our project in the end.

The major goal of our project was to determine the fastest way to diagnose depression early on and which hybrid algorithm works best. To begin, we need to learn about neural network models and word embedding methods and how they work. We suggest using Python programming to build this project since it has a lot of built-in modules and functions that make it easy for the developer to implement.

Figure 1 below shows the architectural diagram, which is another way of saying the project plan for the depression detection model.

Step 1: Make or get a dataset

You can either make your own dataset or get one from the internet that is already there. A dataset is a compilation of data that has been put together or grouped. It must have the primary features that are needed to train the model. One of the datasets that is already on the internet is CLEF 2017. This dataset is made up of postings from the well-known social media site Reddit. You can see that this dataset has certain important parts, such as userid, social media post, the date the post was made on Reddit, and so on.

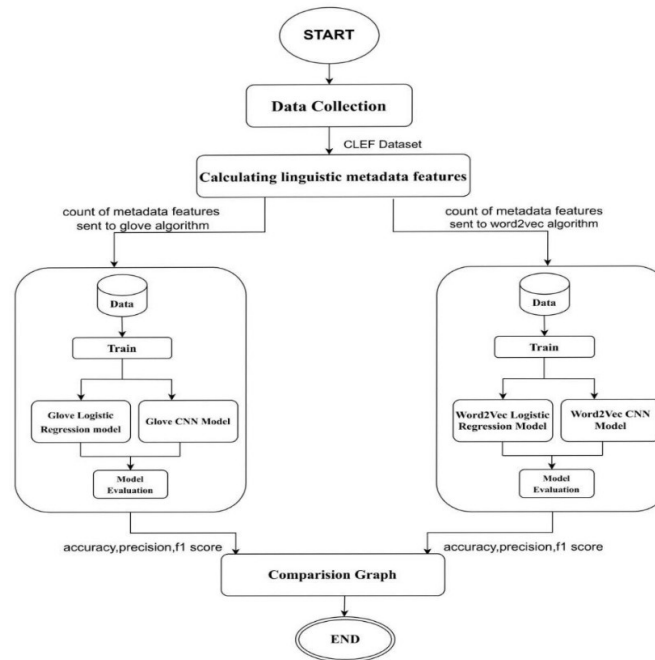


Fig. 1 Architecture Diagram for Depression Detection

Step 2: Figure out the linguistic metadata features

There are 14 primary parts to the Linguistic metadata features. These characteristics significantly contribute to the identification of depression in an individual. These attributes include "I" count in title and text, possessive pronouns, past-tense verbs, text length, title length, personal pronouns, anxiety, depression, therapist, diagnosis, antidepressants, and four readability ratings.

This stage is similar to a feature extraction method that pulls out the most important parts of the text so that the model can quickly tell if the person is depressed or not.

Step 3: Model for Glove Logistic Regression

After computing the linguistic metadata features, the result is passed to the Glove algorithm, which changes the text into the right vector shapes. Then, the Logistic Regression Algorithm is used to classify the data. Because it is made up of two algorithms, it is a hybrid algorithm.

Step 4: The Glove CNN model

The Glove approach takes the output of linguistic metadata characteristics as input and uses a co-occurrence matrix to turn the text into the right vector forms. Then, CNN is utilized for text classification. So, it is a hybrid algorithm because it uses both CNN and Glove.

Step 5: Word2Vec Logistic Regression Computed Word2Vec is a word embedding algorithm that gives words linguistic features. It changes the text into a vector representation, then we use logistic regression to classify the text.

Step 6: Word2Vec CNN Count of Metadata The Word2Vec takes features as input and turns English text into vector forms. Then, a neural network model called CNN is used to sort the text.

Step 7: Graph for Comparison

This comparison graph will let us compare all the hybrid algorithms. To compare those hybrid models, we employ metrics like accuracy, f1 score, precision, and recall. Figure 2 in the findings section shows how different models compare to each other.

IV. RESULTS AND DISCUSSION

The numbers below illustrate what our initiative accomplished. We talked about the modules that need to be done in the section above. We need to figure out the metrics for each hybrid model. We have created four hybrid models: GloVe-CNN (Fig. 2.1), GloVe-Logistic Regression (Fig. 2.1), Word2Vec-CNN (Fig. 2.2), and Word2Vec-Logistic Regression (Fig. 2.2).



Fig. 2 Metrics calculation for GloVe-CNN and GloVe-LR models

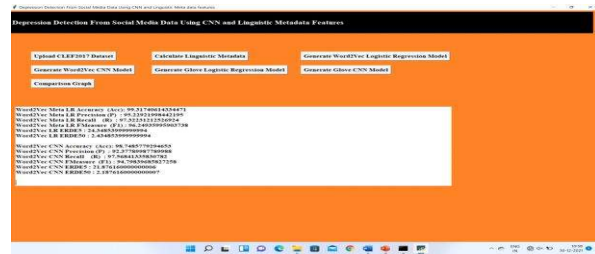


Fig. 3 Metrics calculation for Word2Vec-CNN and Word2Vec-LR models

The result of our endeavor is a comparison graph. We need to figure out which hybrid model works best for finding out if someone is depressed. The figure below, Fig. 2.3, shows the comparison of models using a comparison graph.

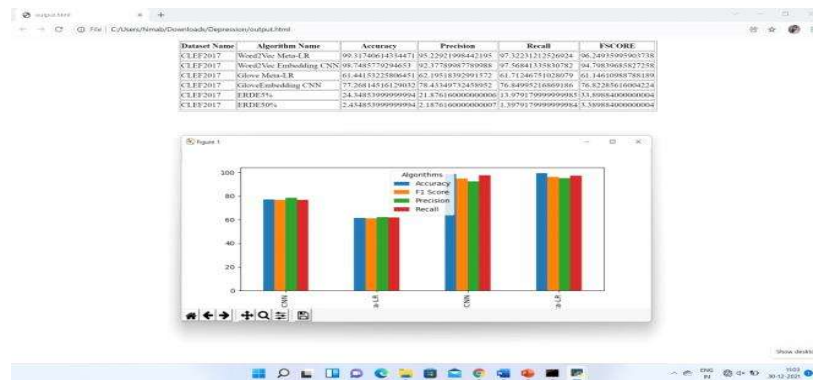


Fig. 4 Comparison graph

V. CONCLUSION

This study examined the commonly employed ERDE metric for early detection jobs in greater detail, revealing that ERDE5, specifically, is not an effective measure for the specified shared duty. This score only changes when a small number of positive samples are predicted correctly. So, the best results are often achieved by minimizing false positives. For shared workloads that require reading information in chunks, a more understandable variant of this signal, ERDE percent, has been suggested. For the experiments in this publication, exemplary scores derived from this metric were compared to ERDE scores. The examination of the generated word vectors indicated that the model has acquired certain domain-related attributes and can address general syntactic issues in the English language, as demonstrated by the standard word analogies test. In both challenges, the five provided predictions earned the highest F1 and ERDE50 scores. The CNN without metadata performed the best in the new anorexia challenge. The new ERDE % statistic was tested using the same working notes. This showed how the original ERDE5 metric helps systems that can properly guess test users with only a few documents, no matter how well they do overall.

FUTURE ENHANCEMENT

We use a comparison graph that shows accuracy, precision, recall, and f1score to test all of the algorithms in this project. We will choose the best algorithm for finding depression that works best of all the options. It also seems like employing ensembles of more than two models and adjusting the resulting probabilities could be a method to make this model better. It has not yet been tested to put the word embeddings from two models into one neural network. Another possible improvement is to use new language modeling techniques as input for the network, like the BERT algorithm, and then compare a self-trained model that uses this method to the FastText word embeddings used in this study. This might be very helpful for faster execution and more accurate numbers, which would make the model work better.

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