AI Detection Social Media Users Depression Polarity Score And Diagnose Using Auto Creative Therapy

R.Bharathi [1],R.K.Harish Gowtham [2], B.Deepa[3],D.Muthukumar [3],R.Nandhini [5],T.Vanitha[6]

[1,2]Assistant Professor,Department of Computer Science And Engineering,Cheran College Of Engineering,Anna University,Karur,Tamilnadu,India.
[3,4,5,6] U.G.Student,Department of Computer Science And Engineering,Cheran College Of Engineering,Anna University,Karur,Tamilnadu,India.
[1]bharathimkce@gmail.com,[2]kalarangharish@gmail.com,[3]deepabecse21@gmail.com,
[4]muthukumardurai@gmail.com,[5]rruban272@gmail.com,[6]vaniviji01@gmail.com

Abstract

Depression is regarded as the leading cause of worldwide disability and a leading cause of suicide. Clinical psychologists often diagnose sad persons via face-to-face interviews based on clinical depression criteria. Patients, on the other hand, often do not seek medical help in the early stages of depression. People are increasingly adopting social media to communicate their feelings these days. Sentiment Analysis (SA) is a computer tool for examining the polarity of emotions and ideas represented in a text. In the text, sentiment might be represented indirectly or openly. Several research on mental depression have shown that tweets written by people suffering from severe depressive illness may be used to diagnose depression. The potential for sentiment analysis to diagnose depression by analysing social media postings has sparked increased interest in this subject. We want to forecast sad individuals and quantify their depression severity using social media (Twitter) data in this study, which will assist in sounding an alert. A lexicon-enhanced LSTM model is proposed. The model initially leverages the sentiment lexicon as additional information before training a word sentiment classifier, and then extracts sentiment embeddings for all words, even those not in the lexicon. Word representation may be improved by combining the sentiment embedding and its word embedding. These characteristics are the outcome of a mix of feature extraction algorithms that use sentiment lexicons and textual contents to offer outstanding results in terms of depression identification.

Keywords: Sentimentanalysis,lexiconLSTM,social media tweet, depression Api phase

1.INTRODUCTION

Depression is a mental illness characterised by a continuous sense of melancholy and lack of interest, as seen in fig. 1.1. It affects how you feel, think, and act, and may lead to a range of mental and physical difficulties. It's also known as major depressive disorder or clinical depression. You may find it difficult to carry out day-to-day tasks, and you may believe that life isn't worth living.

Figure 1.1. Depression

1.1.1. Depression may be dangerous to one's health, particularly if it is recurring and of moderate or severe degree. It may make the individual suffer a lot and make them perform badly at job, school, and at home. Suicide is a possibility when depression is severe. Every year, more than 700,000 individuals commit suicide. In young people aged 15 to 29, suicide is the fourth highest cause of mortality[1]-[5]

1.1.2. Social Media

Social media is an online communication platform. Users may hold discussions, exchange information, and produce online content on social networking networks. Blogs, microblogs, wikis, social networking sites, photo-sharing sites, instant messaging, video-sharing sites, podcasts, widgets, virtual worlds, and other types of social media exist.

1.2. Problem Identified

People nowadays utilise social media sites such as Facebook, Twitter, Weibo, and WhatsApp extensively. These social media platforms have evolved into a platform for users to discuss their thoughts, feelings, and emotions with their family, friends, and other connected individuals. The users' everyday activities and mental states are reflected in their social media posting and sharing habits. One of the most significant distinctions between today's teens and young adults and previous generations is that they spend much less time in person socialising with their friends and far more time connecting online, mostly via social media.[6]-[10]

1.3. Sentiment Analysis

The method of assessing whether a piece of text is good, negative, or neutral is known as sentiment analysis. To give weighted sentiment ratings to entities, topics, themes, and categories inside a sentence or phrase, a sentiment analysis system for text analysis combines natural language processing (NLP) with machine learning methods. Sentiment analysis aids data analysts in major organisations in gauging public sentiment, doing detailed market research, monitoring brand and product reputation, and comprehending customer experiences. We attempt to identify positive, negative, and neutral sentiment levels from depression-related posts and comments made on social media sites in this study. Social media platforms like Facebook and Twitter are becoming more effective for aiding needy individuals who need extra attention or care in terms of mental health. Using deep learning, we attempt to formalise depression-related posts and comments into a succinct vocabulary database and determine the sentiment levels from each instance.

2. RELATED WORK

• Sentiment Analysis is a sophisticated text analysis tool that uses machine learning and deep learning algorithms to automatically mine unstructured data (social media, emails, customer care problems, and more) for opinion and emotion.

• Deep learning is a kind of machine learning that use numerous algorithms in a sequential sequence to solve complicated problems. It enables you to process large volumes of data correctly and with little human intervention.

CRM automation is widely utilised in direct marketing. It's a good idea to estimate the worth of potential direct marketing activities based on the customer's lifetime value.

2.1 Deep Learning use cases

Deep learning startups have had success using it to huge data for knowledge discovery, application, and prediction. Deep learning, in other words, may be a strong engine for providing actionable outcomes. • The power of deep learning may also be demonstrated in how it's applied to social media technologies. Consider Pinterest, which has a visual search feature that allows you to zoom in on a certain item in a "Pin" (or pinned picture) and find visually comparable things, colours, patterns, and more. Using a heavily annotated data set of billions of Pins collected by Pinterest users, the company's technical team employed deep learning to train its system how to detect picture attributes. The characteristics may then be utilised to choose the best matches by computing a similarity score between any two photos.

2.2 Natural language processing

Natural language processing is another hot issue, about which I published an essay. It may be found here. Negative sampling, word embedding, constituency parsing, sentiment analysis, information retrieval, spoken language comprehension, machine translation, contextual entity linking, writing style identification, and other applications are among the most common.

2.3 Customer relationship management

- It's often utilised in direct marketing to automate CRM. It's a good idea to multiply the value of potential direct marketing efforts by the customer lifetime value. Systematic recommendations
- Deep learning has been utilised in recommendation systems to extract significant characteristics for suggestions. It has been used to learn user preferences from a variety of areas..

3. PROPOSED SYSTEM

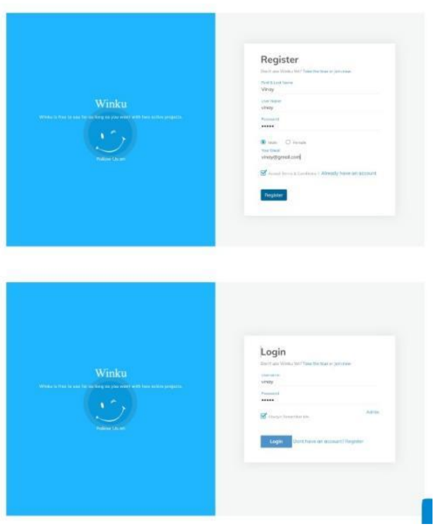
Propose a lexicon-enhanced LSTM model (LE-LSTM) that integrates sentimentlexicon into LSTM to capture additional word sentiment information. First, we pre-train a word sentiment classifier using sentiment lexicon as extrainformation. Then any word, even those not in the sentiment lexicon, may obtain its sentiment embedding. We concatenate the word embedding and its sentimentembedding as the input of the LSTM illustrated in fig 3.1 during the primary training phase and fine-tune the wordsentiment classifier network.

FIG 3.1 Lexicon Integration into LSTM Model

We initially apply a linear transformation on the lexical characteristics collected from datasets in order to retain the original sentiment distribution and have compatible dimensions for subsequent calculations. Later, the altered lexical characteristics are applied to the attention vector learnt in the baseline. Finally, all of the data is combined to provide the final projection.

Getting inspired is one of the most effective strategies to dig deep and conquer your obstacles. This module creates motivational phrases based on the osn user's depression level and motivates him automatically.

4. RESULTS AND DISCUSSION



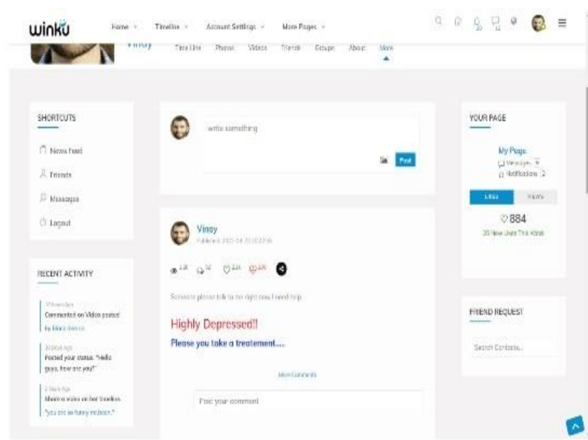


FIG NO 4.1 Register And Login FIG NO 4.2 Alert Notification

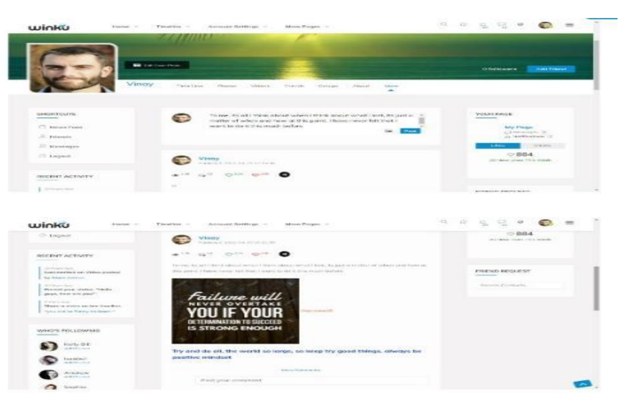


FIG NO 4.3 Motivational Quotes

It trains a shallow long short-term memory network to predict sad users and their depression intensities using the lexicon improved feature, as illustrated in fig 4. 1.Alert the most communicative osn user from their friends list (see fig 4) about their sadness level. 2.Automotivational loader automatically creates motivating quotations for the osn user and motivates him, as seen in fig 4.3.

5. **CONCLUSION**

For many sorts of positions, detecting and classifying depression levels is crucial. We provided a system for categorising depression levels using LE-LSTM algorithms in this study. We can acquire the sentiment embedding of each word by utilising the sentiment lexicon to train a word sentiment classifier. Concatenating the word embedding with its sentiment embedding as the LSTM input may improve sentiment analysis performance. The algorithms are intended to examine tweets for emotion recognition and the detection of suicide ideation among social media users.

6/ Future scope

Users of social networks may contact with their interested friends and share their thoughts, images, and videos that express their emotions, feelings, and sentiments. This opens up the possibility of analysing social network data for user emotions and sentiments in order to learn more about their moods and attitudes while using these online tools. The assessment takes a time-sensitive approach, rewarding early detections and penalising late detections. The potential for using language indicators in the research and diagnosis of depression is immense. Even without the use of complicated models, depression may be recognised in text quite rapidly. Visual analysis alone may reveal the difference between random Tweets and Tweets with depressed features simply by collecting, cleaning, and analysing accessible data. It is impossible to overestimate the value of language analysis in the field of mental health. You may get a good picture of a person's mental condition by analysing his or her speech. Even the most basic study of social media may provide us unparalleled access to people's thoughts and emotions, leading to much improved mental health knowledge and treatment. The results provide a new technique to identify and aid those suffering from depression.

7.References

[1]G. Xu, Y. Meng, X. Qiu, Z. Yu, and X. Wu, ``Sentiment analysis of comment texts based on BiLSTM,'' *IEEE Access*, vol. 7, pp. 51522_51532, 2019.

[2] Y. Li and H. B. Dong, ``Text emotion analysis based on CNN and BiLSTMnetwork feature fusion,'' Comput. Appl, vol. 38, no. 11, pp. 29-34, 2018.

[3] A.Yadav and D. K.Vishwakarma, ``Sentiment analysis using deep learningarchitectures: A review,'' Artif. Intell. Rev., vol. 53, no. 6, pp. 4335-4385,Aug. 2020, doi: 10.1007/s10462-019-09794-5.

[4] W. Meng, Y. Wei, P. Liu, Z. Zhu, and H. Yin, ``Aspect based sentimentanalysis with feature enhanced attention CNN-BiLSTM,'' IEEE Access,vol. 7, pp. 167240-167249, 2019.

[5] F. Hao, G. Pang, Y. Wu, Z. Pi, L. Xia, and G. Min, "Providingappropriate social support to prevention of depression for highly anxioussufferers," IEEE Trans. Comput. Social Syst., vol. 6, no. 5, pp. 879–887, Oct. 2019.

[6] G. Shen et al., "Depression detection via harvesting social media:A multimodal dictionary learning solution," in Proc. 27th Int. Joint Conf.Artif. Intell., Aug. 2017, pp. 3838–3844.

[7] T. Shen et al., "Cross-domain depression detection via harvestingsocial media," in Proc. 27th Int. Joint Conf. Artif. Intell., Jul. 2018,pp. 1611–1617.

[8] R. Xu and Q. Zhang, "Understanding online health groups for depression:Social network and linguistic perspectives," J. Med. Internet Res.,vol. 18, no. 3, p. e63, Mar. 2016.

[9] F. Sadeque, D. Xu, and S. Bethard, "Measuring the latency of depressiondetection in social media," in Proc. 11th ACM Int. Conf. Web SearchData Mining, Feb. 2018, pp. 495–503.

[10]M. Trotzek, S. Koitka, and C. M. Friedrich, "Utilizing neural networksand linguistic metadata for early detection of depression indicationsin text sequences," IEEE Trans. Knowl. Data Eng., vol. 32, no. 3,pp. 588–601, Mar. 2020.