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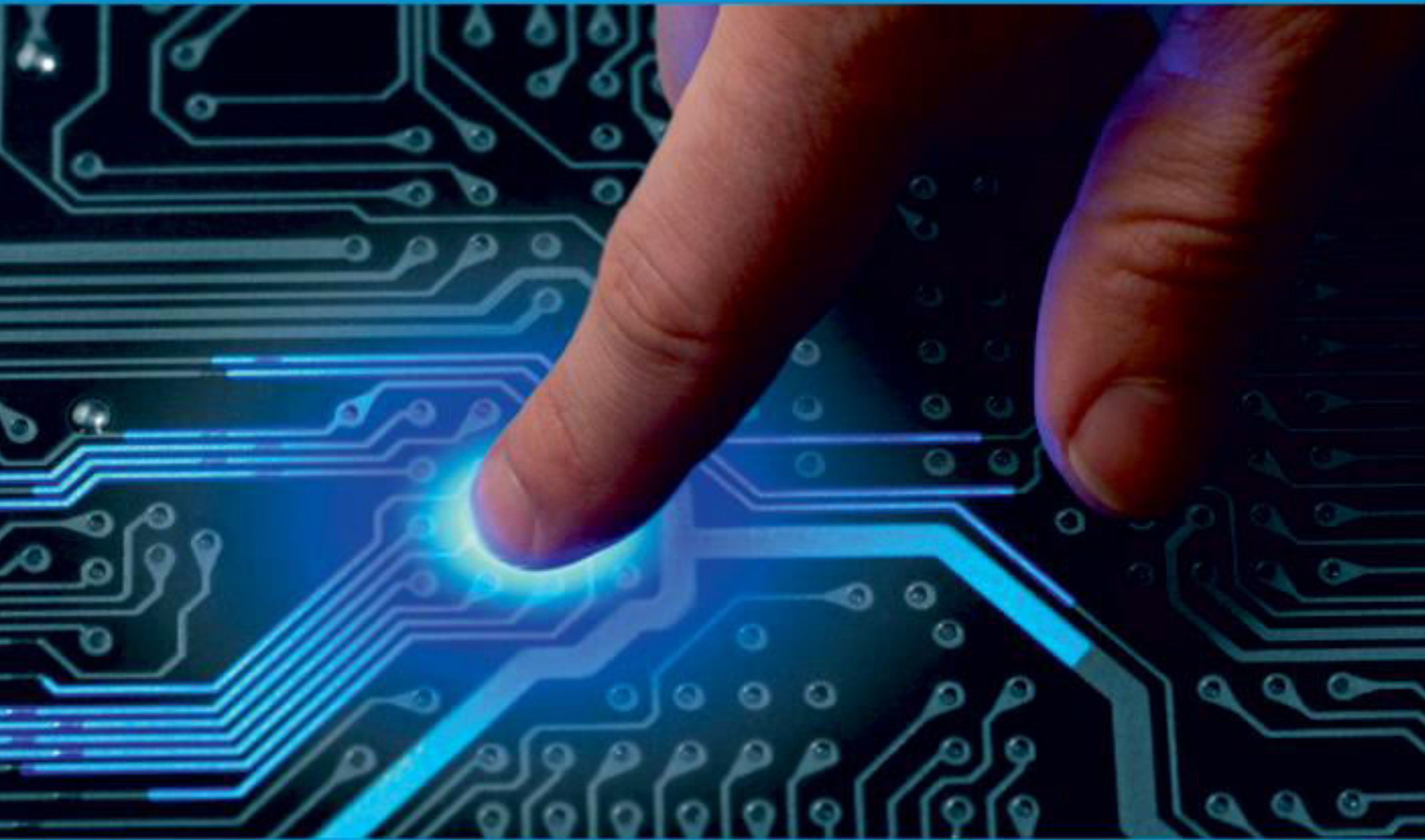

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Early Emotional and Deep Learning-based Depression Detection in Social Media

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ABSTRACT: Depression is a psychological disorder related to a combination of genetic, biological, environmental and psychological factors. One of the causes of suicide and a common comorbidity with disabilities, depression poses a threat to public health. Many people who deal with depression turn to social media as a resource or a safe space to discuss their struggles. Finding people who may be suffering from depression in these online communities has been the subject of some research. A hurdle to practical use, nonetheless, remains the insufficient efficacy. Therefore, we provide a strategy for early social media depression identification using a convolutional neural network, context-independent word embeddings, and the Early and Late Fusion methods. Taking into account the significance of the underlying emotions conveyed by the emoticons, these methods are tested experimentally. With a precision of comparable or better performance compared to numerous baselines, the findings demonstrate that the suggested technique might identify users who may be suffering from depression. Better results were also achieved by the semantic mapping of emoticons, which led to an increase in recall and a decrease in accuracy. Our semantic mapping of emoticons improved recall by percent and accuracy the percent compared to the baseline word embedding method. When taking into account both the fusion-based methods and individual embeddings, this study enhanced the state-of-the-art in terms of overall efficacy. Important suggestive evidence of the issue and a useful tool for early identification may be found in the emotions exhibited by depressed persons and encoded via emoticons. A number of variables, including heredity, biology, the environment, and mental health, interact to cause depression. Some of the symptoms that people with this disease may experience include fatigue, changes in appetite, worry, trouble concentrating, difficulty making a choice, and low self-esteem, guilt, and despair. The prevalence of depression has been steadily increasing over the years, despite improvements in screening for the disorder and its treatment. As a matter of fact, depression ranks first among all global health issues and disabilities. Recent estimates by the World Health Organisation (WHO) put the global prevalence at around 300 million cases. Between 2005 and 2015, there was an 18.4% rise in the number of cases. Among the over 800,000 people who take their own lives each year, severe depressive disorder is a leading cause. This illness is really serious, and we need to find ways to make it easier to diagnose and slow its spread. Thus, using data created on social media is a viable alternative that complements the original strategy. People were now able to express themselves fully and openly with the rise of social media sites like Reddit, Facebook, and Twitter. Social media posts not only convey meaning in an overt way, but they also reveal a lot about the people who wrote them in an indirect way. According to users might also discover symptoms that suggest the beginning of depression on social media.

KEYWORDS: Twitter, Social media, World Health Organisation, Depresion, Media, prevalence

I. INTRODUCTION

A number of variables, including heredity, biology, the environment, and mental health, interact to cause depression. Anxiety, changes in appetite, decreased focus, hesitation, feelings of worthlessness, remorse, or despair are some of the symptoms that people with this illness often experience. The prevalence of depression has been steadily increasing over the years, despite improvements in screening for the disorder and its treatment. Actually, illness and disability caused by depression are the most common on a global scale. The globe Health Organisation (WHO) has recently estimated that over 300 million individuals throughout the globe are affected by it. The data also revealed that the number of instances increased by 18.4 percent from 2005 to 2015. There are almost 800,000 suicides every year, and depression is a leading cause of these fatalities. It emphasises how serious this illness is and how important it is to find ways to better diagnose it and slow its course. Less than half of the world's depressed people get the help they need, despite the

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abundance of treatment options. There are a lot of causes for untreated conditions, such as wrong or faulty diagnoses and evaluations. A pertinent difficulty that arises from this circumstance is the need to enhance the process of recognising depression. Therefore, using data from social media is a great complimentary option. People were now able to express themselves fully and openly with the rise of social media sites like Reddit, Facebook, and Twitter. Not only can social media posts convey meaning in an overt sense, but they also include information about their writers that is less obvious. Therefore, as mentioned in , social media also allows us to discover symptoms that define the onset of depression in people.

Because people with depression often conceal their symptoms, making a professional diagnosis difficult, it is possible to find clues about their mental health in the information they share on social media. This makes these platforms a potential resource for identifying depressed individuals. Therefore, it's a good idea to look at how people use language on social media. In particular, preventative actions may be implemented more effectively with early social media detection. When faced with the challenge of large-scale data analysis, one may use either expert-led direct evaluation methods or automated methods, such machine learning, to complete the work .Natural language processing (NLP), object identification in photos and videos, and voice recognition are only a few examples of the challenging pattern-oriented issues that machine learning has accomplished remarkable success in solving. The challenge of obtaining discriminative elements from social media messages means that conventional classification algorithms may fail when it comes to depression diagnosis. The use of cutting-edge methods like Deep Learning (DL) has emerged as a new option. DL has shown to be surprisingly effective in several domains, including as medical diagnosis, picture synthesis , and autonomous vehicle driving. Furthermore, DL has shown encouraging outcomes in the early diagnosis of depression although it is still in its early stages. Because lives are at stake, early identification is crucial for depression therapy because it enables preventative actions to be performed to lessen or minimise difficulties. Regardless, a lot of suggestions only think about a fix in the here and now, disregarding the problem of time. The time component, however, must be taken into account, as detection upon the subject's clear demonstration of the condition can be too late, leading to treatment delays or a significant decline in quality of life. The problem of social media depression identification has been studied and worked on in many ways over the years. The majority of these methods depend on textual representations that have been extracted using deep learning. Unfortunately, the efficacy of the offered methodologies falls short of what is needed for implementation in real-world scenarios. Data fusion solutions, which seek to include the best features of each system by capitalising on complementary data perspectives (models), provide a viable alternative to these methods. But research on depression identification is few, and even less has evaluated the efficacy of using several representation models simultaneously.

Hence, our study suggests a way to use DL and Early and Late Fusion techniques to identify signs of depression in social media at an early stage. Experimental evaluations employing various word embeddings as feature representations show that it improves the process of detecting people who may be sad. To summarise, this work's main contributions are as follows We suggest a new method that investigates early and late fusion to aid in the early detection of social media users' depression.We carry out comprehensive experiments and show that the suggested method performs better than the baselines in different scenarios. We show that emoticons, which stand in for users' emotions, have a significant impact on detection performance.

In light of the need of identifying and monitoring mental health concerns at an early stage, the possibility of depression detection from user-generated material on social media platforms has attracted considerable interest. In this research, we provide a thorough method for detecting sadness in user tweets using ML approaches. The research included the following methods: feature extraction, data preprocessing, and model training using logistic regression, Bernoulli Naive Bayes, random forests, The dataset used in the study was 632,000 tweets. In order to measure how well the models work, we use evaluation criteria including F1 score, recall, accuracy, and precision. The model outperforms all others in diagnosing depression from tweets, with an accuracy ratio of 0.981 and a mean accuracy of 0.97 (over 10 cross-validation folds), according to the data. Using social media data for mental health analysis, this study shows that machine learning and sophisticated transformer-based models work well. This study adds to the expanding area of user-generated content analysis for mental health by providing important insights on the possibility of early depression diagnosis and monitoring using internet platforms. Depressive disorder is a common mental illness that affects a large portion of the global population. A major decrease in general health and quality of life is associated with this disorder, which is defined by depressive symptoms, lack of interest, and reduced functioning. Effective management and treatment of depression need prompt identification and action. Severe deficits in personal, social, and vocational

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functioning may result from untreated depression . The rise of social media has made it possible to research depression and other mental health issues on a massive scale, something that has never been possible before. The microblogging service Twitter in particular has become an invaluable resource for studying people's mental processes. Because Twitter users are so forthcoming with their thoughts, feelings, and experiences, it is feasible to study and detect symptoms of depression in their public posts.

With the use of machine learning algorithms, massive amounts of textual data may be automatically analysed and valuable insights can be extracted . Specifically, computer models that may identify signs of depression in user-generated information, like tweets, have been developed using natural language processing (NLP) methods . These models give a great opportunity to supplement current diagnostic methods and enable a large-scale screening for depression that is efficient, scalable, and affordable This project aims to examine the viability of applying machine learning algorithms to identify sadness from user tweets. An accurate and reliable prediction model that can identify Twitter users at risk of depression is our goal in analysing a dataset consisting of tweets. People in need of mental health help may benefit from this study since it can lead to the creation of new digital health solutions that help with early intervention.

The development of specialised datasets for depression identification is often hindered by time and financial limitations. In order to close the gap, the research suggests modifying an existing dataset that was made for sentiment analysis so that it can be used for depression identification. This will be done utilising cost-effective and realistically-aligned proprietary algorithms. Furthermore, there is a dearth of in-depth comparisons between transformer models and conventional machine learning for depression identification in the current literature. To fill this need, this research compares and contrasts the efficacy of several deep learning models in detecting depressed content. These models include logistic regression, Naive Bayes, but also random forests. With an emphasis on the use of machine learning techniques, this study provides a survey of relevant work in the area of depression identification using social media data. Information gathering, preprocessing, and feature engineering procedures were all part of our study's methodology, which we detail below. We also go over how to choose the right machine learning algorithms for categorisation and what attributes to employ to describe tweet text. We conclude by presenting the experimental findings, discussing possible applications and future prospects for this study, and evaluating the performance of the models tested.

Feature selection was carried out as part of the preprocessing procedure in order to detect and eliminate characteristics that were either unnecessary or duplicated. The characteristics 'ids,' 'date,' 'flag,' and 'user' were removed from the dataset since they were not found to be significant to the aim of depression identification from tweets in this research. The existence of missing values was evaluated to guarantee the dataset's quality and integrity. Thankfully, the twitter data did not include any missing numbers. Because of this, we were able to skip imputation and remove incomplete instances before moving on to the preprocessing stages. Text Preparation: We used a suite of cleaning techniques to get the tweets' text ready For the sake of uniformity and to prevent repetition due to differences in capitalisation, we changed all of the text to lowercase. Because they don't add anything to the tweets' semantic meaning and potentially inject noise into the analysis, we eliminated any URLs or hyperlinks that were there.

We removed user mentions from the tweets since they often do not convey much sentiment information and may be seen as background noise in the analysis. Take Out Non-Letters: Since they don't add anything to the emotion or useful analysis, we got rid of any non-alphabetic letters like numerals or special characters. Eliminating Stop Words: Stop words like "and," "the," and "is" usually do not convey much emotion information. Therefore, in order to make the study more precise and less noisy, we extracted them from the tweet text. To simplify the terms, we used stemming and lemmatisation to get at their simplest forms. Words may be stemmed to their basic form or lemmatised to their base form according to their dictionary meaning (like "better" to "good"). By using these methods, the text may be standardised and the dataset's dimensionality can be decreased. The normalisation and noise removal performed by these cleaning processes prepared the twitter data for feature extraction and machine learning.

The methodology used to evaluate the performance of the models for depression detection from user tweets is outlined here. The evaluation employed common classification metrics, including accuracy, precision, recall, F1 score, and confusion matrix diagram.

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Accuracy measures the proportion of correctly classified instances out of the total instances. It is a fundamental metric that provides an overall assessment of the model's performance. In depression detection, it indicates the model's ability to correctly identify both depressive and non-depressive tweets, offering a clear picture of its general effectiveness.

The F1 score is the harmonic mean of precision and recall, both of which measure the proportion of prediction against actual instances. It provides a balanced measure that considers both false positives and false negatives. In depression detection, the F1 score helps strike a balance between minimizing both types of errors. A high F1 score indicates a model that effectively identifies depressive tweets while maintaining a low rate of misclassification.

Precision measures the proportion of true positive predictions out of all positive predictions made by the model. In the context of depression detection, precision signifies the model's ability to correctly identify tweets as depressive without making many false positive predictions. This is crucial, as misclassifying non-depressive tweets as depressive could have negative consequences.

Recall, also known as sensitivity or true positive rate, measures the proportion of true positive predictions out of all actual positive instances. In depression detection, recall indicates how well the model captures all the depressive tweets present in the dataset. It is particularly important because missing depressive tweets (false negatives) can be as problematic as false positives.

The confusion matrix diagram provides a detailed breakdown of the model's predictions, including true positives, true negatives, false positives, and false negatives. It offers insights into the distribution of correct and incorrect predictions, helping researchers understand where the model excels and where it may need improvement. Visualizing the confusion matrix can also aid in identifying specific areas of concern and fine tuning the model accordingly. To ensure an unbiased evaluation of the models, the dataset of 632,000 rows was split into two subsets: a training set and an evaluation set. The splitting ratio chosen was 80% for training and 20% for evaluation. This means that approximately 80% of the dataset, which corresponds to 505,600 rows, was allocated for training the models. The remaining 20%, amounting to 126,400 rows, was reserved for evaluating the models' performance. To ensure robustness and reliable performance assessment, all machine learning models employed in this study underwent a rigorous cross-validation process with 10 splits using 100,000 entries for traditional ML models and 50,000 entries for the transformer models. Each split involved dividing the dataset into 80% for training and 20% for validation. This approach allowed us to mitigate the potential impact of data partitioning on model performance and effectively evaluate the models' generalizability. Furthermore, to provide a comprehensive summary of the model performance, we calculated the mean and standard deviation of the performance metrics across the 10 splits. The mean values provided an estimate of the models' average performance, while the standard deviation indicated the degree of variation in their performance across the splits. These statistics offered insights into the stability and reliability of the model's predictions. Feature Engineering

Using label encoding, we prepared the target variable for machine learning methods. We used numerical values to encode the labels that indicated depression and non-depression. For example, tweets that indicated sadness were given the number 1 while tweets that indicated no depression were given the value 0. We were able to encode the target variable in a manner that was suited for training and assessment by using label encoding. There are a variety of formats that machine learning models accept as input data. Transforming the textual twitter data into numerical representations suited for certain models was achieved in this work using the TF-IDF (Term Frequency-Inverse Document Frequency) vectorisation approach. As a numerical vector, TF-IDF represents each tweet and takes into account the relevance of terms in the tweet and in the overall dataset. Scaling the term frequency (TF) of each word in a tweet by its inverse document frequency (IDF) throughout the dataset is what it does. Many models, including SVM and To determine which natural language processing models were most successful at correctly identifying depressive mood in Twitter tweets, we compared them using the methodology in Figure 5. We evaluated each model's classification accuracy and compared the results it produced. The depression dataset is created by merging the Sentiment140 dataset with a word cloud associated with depression. Following this, the dataset is subjected to further preparation such as lemmatisation and stop word removal. The next step in getting the data ready for the ML algorithms to utilise is to finish up some feature engineering. As far as the transformer models are concerned, the only feature engineering that is done on the data prior to training and assessment is label encoding. Label encoding and vectorisation are prerequisites to training and assessment for classic ML algorithms like logistic regression, Naive Bayes, and random forests.

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II. CONCLUSION

The pros of social media

While virtual interaction on social media doesn't have the same psychological benefits as face-to-face contact, there are still many positive ways in which it can help you stay connected and support your wellbeing.

Social media enables you to:

- Communicate and stay up to date with family and friends around the world.
- Find new friends and communities; network with other people who share similar interests or ambitions.
- Join or promote worthwhile causes; raise awareness on important issues.
- Seek or offer emotional support during tough times.
- Find vital social and professional connections (such as online therapy) if you live in a remote area, for example, or have limited independence, social anxiety, or are part of a marginalized group.
- Find an outlet for your creativity and self-expression.
- Discover (with care) sources of valuable information and learning.

The cons of social media

- Since it's a relatively new technology, there's little research to establish the long-term consequences, good or bad, of social media use. However, multiple studies have found a strong link between heavy social media and an increased risk for depression, anxiety, loneliness, self-harm, and even suicidal thoughts.
- Social media may promote negative experiences such as:
- **Inadequacy about your life or appearance**. Even if you know that images you're viewing on social media are manipulated, they can still make you feel insecure about how you look or what's going on in your own life. Similarly, we're all aware that other people tend to share just the highlights of their lives, rarely the low points that everyone experiences. But that doesn't lessen those feelings of envy and dissatisfaction when you're scrolling through a friend's airbrushed photos of their tropical beach holiday or reading about their exciting new promotion at work. **Fear of missing out (FOMO) and social media addiction**. While FOMO has been around far longer than social media, sites such as Facebook and Instagram seem to exacerbate feelings that others are having more fun or living better lives than you are. The idea that you're missing out on certain things can impact your self-esteem, trigger anxiety, and fuel even greater social media use, much like an addiction. FOMO can compel you to pick up your phone every few minutes to check for updates, or compulsively respond to each and every alert even if that means taking risks while you're driving, missing out on sleep at night, or prioritizing social media interaction over real world relationships. **Isolation**. A study at the University of Pennsylvania found that high usage of Facebook, Snapchat, and Instagram increases rather decreases feelings of loneliness. Conversely, the study found that reducing social media usage can actually make you feel less lonely and isolated and improve your overall wellbeing. **Depression and anxiety**. Human beings need face-to-face contact to be mentally healthy. Nothing reduces stress and boosts your mood faster or more effectively than eye-to-eye contact with someone who cares about you. The more you prioritize social media interaction over in-person relationships, the more you're at risk for developing or exacerbating mood disorders such as anxiety and depression. **Cyberbullying.** About 10 percent of teens report being bullied on social media and many other users are subjected to offensive comments. Social media platforms such as Twitter can be hotspots for spreading hurtful rumors, lies, and abuse that can leave lasting emotional scars. **Self-absorption.** Sharing endless selfies and all your innermost thoughts on social media can create an unhealthy self-centeredness and distance you from real-life connections.

REFERENCES

1. Marcus M, Yasamy MT, Ommeren M, Chisholm D, Saxena S (2012) Depression: a global public health concern. WHO Mental Health Gap Action Program (mhGAP).
2. Cassano, P.1., Fava, M. "Depression and public health: an overview." J Psychosom Res 2002 Oct;53(4):849-57.
3. Coryell, W.1., Endicott, J., Winokur, G., Akiskal, H., Solomon, D., Leon, A., Mueller, T,. Shea T. "Characteristics and significance of untreated major depressive disorder." Am J Psychiatry. 1995 Aug;152(8):1124-9.
4. Smith K. M., Renshaw, P. F., & Bilello, J. (2013). "The diagnosis of depression: current and emerging methods", Comprehensive psychiatry, 2013, 54(1); 1-6.

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5. Costello, J. Erkanli, A., Angold, A. “Is there an epidemic of child or adolescent depression?” J Child Psychol Psychiatry, 2006, 47 (12); 1263–1271.
6. Lewinsohn, P.M., Rohde, P., Seeley,J.R. Major depressive disorder in older adolescents: prevalence, risk factors, and clinical implications, Clin Psychol Rev, 1998, 18 (7);765– 794.
7. Zahn-Waxler, C., Klimes-Dougan, B., & Slattery, M.J. “Internalizing problems of childhood and adolescence: Prospects, pitfalls, and progress in understanding the development of anxiety and depression.” Development and Psychopathology, 2000, 12(3), 443-466.
8. Wehner, M. R., Chren, M. M., Shive, M. L., Resneck, J. S., Pagoto, S., Seidenberg, A. B., & Linos, E. (2014). Twitter: an opportunity for public health campaigns. The Lancet, 384(9938), 131-132.
9. Velardi, P., Stilo, G., Tozzi, A. E., & Gesualdo, F. (2014). Twitter mining for fine-grained syndromic surveillance. Artificial intelligence in medicine.
10. Pagoto, S., Schneider, K. L., Evans, M., Waring, M. E., Appelhans, B., Busch, A. M., & Ziedonis, M. (2014). Tweeting it off: characteristics of adults who tweet about a weight loss attempt. Journal of the American Medical Informatics Association, amiajnl-2014.
11. De Choudhury, M., Gamon, M., Counts, S., & Horvitz, E. "Predicting depression via social media." AAAI Conference on Weblogs and Social Media. 2013.
12. Neuman, Y., Cohen, Y., Assaf, D., & Kedma, G. "Proactive screening for depression through metaphorical and automatic text analysis." Artificial intelligence in medicine 56.1 (2012): 19-25.
13. Papageorgiou, C. & Wells, A. Nature, functions, and beliefs about depressive rumination. In C. Papageorgiou &A. Wells (Eds.), Depressive Rumination: Nature, Theory and Treatment (pp. 3-20). West Sussex: John Wiley & Sons, 2004.
14. Ghafoor et al. “An Intelligent approach to discover common symptoms among depressed patients”, Springer, August 2014.
15. Parvez Ahmad et al. “Techniques of Data Mining in Healthcare: A review”, International Journal of Computer Applications, 2015.

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