Journal of Innovative Computing and Emerging Technologies

A Comparative Study of Sentiment Analysis for Mental Health Related Posts at Reddit & Twitter Using Machine Learning and Pre-Trained Models

Laiba Suhail[1], Sohail Masood[1], Ammar Haider*[2]

Received: 01 April,2024; Accepted: 10 Jun, 2024; Published: 1 Oct, 2024

Abstract: The enormous increase in social media platforms and their usage among people have caused a massive surge in online posting. It has been observed that people find it easy to express themselves in a virtual environment rather than in a real environment. There have been multiple social media platforms where people tend to go to write their feelings out, out of which Twitter and Reddit are among the most used ones when it comes to be expressive about mental health. Therefore, pertinent questions about the efficiency of either of the platforms for the detection of anxiety disorders and depression have arisen, i.e., how much social media is effective in identifying different anxiety disorders and depression, plus the relevance of anxiety to depression. The main purpose of this research work is to come up with a comparative study of pre-trained models for automatic detection of mental health issues. The finding and analysis have been focused on two distinct datasets: the Reddit dataset comprising Anxiety disorders related posts that were manually scraped using Python Library PRAW, and the Twitter dataset with depression-related posts downloaded from an online repository Kaggle. Further, the study has been focused on finding the linguistic similarities between depression and anxiety disorder while highlighting the proposed model functioning with cross platform analysis. This study's findings are expected to provide better insights with social media insights focused on improving mental health-related discussion. In the future, it is suggested to apply deep learning models with large datasets.

Keywords: Mental Health, Anxiety, Reddit, Machine learning, Social Media, Twitter

1- Introduction

Mental health is a vital component of human beings around. Based on the findings and report of WHO, World Health Organization, different types of mental illnesses and disabilities have the ratio of 1:4 i.e. it is affecting approximately one out of four people around the globe. This study is focused on two significant mental health related issues that are generally discussed over the social media sites like Twitter and Reddit. In order to better know and understand the nuances of these mental health issues require a diverse approach with analysis of data from multiple sources.

[1] *Department of Computer Science Superior University, Gold Campus Lahore, Pakistan, su92-msdsw-f22019@superior.edu.pk, sohailmasood@superior.edu.pk.*
[2] *School of System and Technology, Department of Computer Science, University of Management and Technology, Lahore, Pakistan, ammar.haider@umt.edu.pk.*
**Corresponding Author ammar.haider@umt.edu.pk*

Genetic [1] and neurochemical variables contribute to the susceptibility of individuals to specific mental health disorders.

Table 1: Anxiety Disorders with Symptoms and Prevalence rate

Disorder	Symptoms	Prevalence Rate
Generalized Anxiety Disorder	Trembling Twitching Excessive worry about everyday tasks Headache	2.70%
Panic Disorder	Fear Of Loss Trembling Feeling the risk of danger	4.7% US adults
Agoraphobia	Excessive Fear & avoidance of places or situation causing panic attacks	1.30%
Social Anxiety	Fear of social environments fear of insults in public avoiding gathering dating Meeting new people	5.10%
Separation Anxiety	excessive worry about separation difficulty in sleeping	5%-25%
Health Anxiety	Restlessness Fatigue constantly seeking health information	5.70%
Selective Mutism	A person's Inability to speak in certain situations Clingy shy	0.47%-0.76%
Other Phobias	fearing specific objects, places	3%-15%

Note: *The data is taken from www.who.int . Data for prevalence rate for GAD is from www.nimh.nih.gov, data for prevalence rate for panic disorder is from www.nimh.nih.gov, data for prevalence rate for Agoraphobia is from www.ncbi.nlm.nih.gov data for prevalence rate for Social Anxiety is from my.clevelandclinic.org, data for prevalence rate of separation anxiety is from https://www.ncbi.nlm.nih.gov/books/NBK560793/ , data for prevalence rate for Health Anxiety is from bmcpublichealth.biomedcentral.com Data for prevalence rate for selective mutism is from www.ncbi.nlm.nih.gov and the data for prevalence rate for other phobias is from www.ncbi.nlm.nih.gov. [6, 7, 8, 9, 10, 11, 12, 13]*

Mental health disorders [2] can have a profound effect on multiple facets of life, such as interpersonal connections, employment, and day-to-day activities, frequently resulting in emotional suffering and functional limitations. Anxiety disorders can also increase the highly ever increasing risk of developing depression, substance use disorders, and suicidal thoughts or behaviors [5]. A number of researchers have examined content generated by users on social media to observe the emotional state or mental health of individuals, A recent study gathered Twitter tweets from the users claimed to be suffering from depression. The collected postings were examined using the Linguistic Inquiry as well as the Word Count (LIWC) to examine their linguistic and affective qualities [3]. The study employed sophisticated psychometric tools to assess the degree of postpartum depression before and after childbirth. Furthermore, Boettcher [4] employed image data to identify depression among users on social network platforms the research conducted will be useful for raising the awareness about mental health conditions using Twitter and Reddit data as well as provide the comparison between the most used platform that people use to express such emotions. The observations will be helpful in detecting and developing the methods for detecting the presence of detailed anxiety disorders.

2-Literature Review

Loukas Ilias, Spiros Mouzakitis , and the author Dimitris Askounis proposed and come up with a research based on deep neural networks specifically Bert for the early mental issues detection. The author further expands the research since the transformer-based models have strides thus these models struggle to capture the broad knowledge spectrum. Therefore a novel approach integrating the non-linguistic data into Bert was introduced. [14].

Researchers show the utilization of linguistic data gathered from social sites for the reason to detect the depression among individuals. The framework combined machine learning and the data driven approaches to locate as well as identify the signs of depression in social networking sites users specifically Facebook. They analysed the data of 4350 users that was accessed with CESD, further identified the differentiating characteristics between healthy as well as the depressed users. [15].

Since the go to place for many people where they express themselves with personal experiences are social media sites, Guangyao Shen, , Jia Jia, , Wenwu Zhu, Fuli Feng, , Cunjun Zhang, , Tianrui Hu, , Tat-Seng Chua, and Liqiang Nie researched for prompt and appropriate depression detection. A labelled Twitter dataset was compiled and six feature groups relevant to depression was extracted. Several baselines by 3% to 10% were outperformed. [16].

The authors Alina Trifan, Rui Antunes, Sergio Matos, and Jose Luis explains the influence and examination of psycholinguistic patterns on a machine learning methods used to categorise the sad individuals by the social media posts analysis. The research focuses on employing the psycholinguistic characteristics in rule based estimator while assessing the influence on classification task. Initially the dataset was split into equal sized portions, further Multinomial Naïve Bayes as well as the Linear SVM (Support Vector Machine) with Stochastic gradient Descent and Passive Aggressive classifiers were tested [17].

The study aims to classify psychiatric diseases using social media posts language. The dataset was originally taken by reddit from the users having eight different kind of disorders. Zhengping Jiang, the author Jonathan Zomick, as well as Sarah Ita Levitan, and Julia Hirschberg analyses the language features to differentiate between diagnostic categories building the robust classification models with contextualized word representations. Therefore the study focuses on contextual representation techniques comparing them with logistic regression baseline trained on LIWC features [18].

The research tends to discuss how NLP models uncover the mental health signs from social media language. Integrating such models in diagnostic and therapeutic processes aid in identifying the mental disorders including depression. The authors Ayah Zirikly and Mark Dredze further tends to explain the proposal as employing PHQ-9 categories to enhance the depression model based on social media sites [19].

The authors used three different kind of machine learning techniques including BERT, AutoML for feature creation and classifier selection. However it could be seen that the model, utlising the knowledge graph and text was a bit less effective, it showed results with 4.9% drop in Macro F1 and 1.9% in terms of recall [20].

A language model with the technique of double domain adaptation was employed that was first tailored to language of and then further to mental health discourse. Further, by guiding the model's masking process with lexical resource, the focus on mental health was enhanced. [21].

Researchers Amrul Faruq, Merinda Lestandy, Adhi Nugraha, and Abdurrahim explored that in the realm of social media, people openly share their experiences at Reddit. Therefore the study aimed to predict mental states by categorizing the posts in depressive and non-depressive categories with machine learning and word embedding. It was observed that the BILSTM-BIGRU model incorporating Fastext embedding efficiently identifies the disorder symptoms with sequential data analysis [22].

The research aims to increase the efficiency of existing models for diagnosing the mental illness like depression by incorporating additional factors like time into the analytical model. The model, using the predictive techniques analyses social media posts to identify depressive sentiments achieving an accuracy score of 80% [23].

This research aids in identifying psychiatric conditions with BoSE representation outperforming recommended baselines in emotions analysis. Further, adding dynamic sub emotion analysis (A-BoSE) , the research claims to enhance the detection of relevant symptoms. By using two different datasets, this study focuses on the effectiveness of these methods to capture emotional nuance [24].

The study claims that current studies for sadness and detection of mental disorder from social forums relies on machine learning classifies and feature extraction techniques. Therefore to improve the performance, Loukas Ilias, Siros Mouzakitis, and Dimitris Askounis proposed a novel approach integrating non-linguistic data into the transformer based models including BERT and Mental-BERT. The methodology employs multimodal adaptation gate to create a combined embedding for inputs [25].

The research proposed by Jini Jojo Stephen, and Prabu P aimed to classify depression in Twitter users by the tweets analysis. A correlation was established between the tweets content and depression levels. However it was observed that personal verification ensured accuracy. Additionally, Sentiment analysis indicated the severity of depression while the study highlights the potential of using online activity to assess mental health [26].

The research explores how the significant spike in depression can be seen yet the unawareness of many individuals around. The study is focused to detect depression from Twitter dataset using two distinct classifiers i.e; Naïve Bayes as well as NBTree. The results show the model performance is equally well in categorising the depressive as well as the non-depressive data. Further it could be seen that the NBTree gives an accuracy of almost 97.31% while Naïve Bayes and at the other hand showed an accuracy of 97.31% on the 3000 tweets dataset and 92.34% on 1000 entries dataset.[27].

This systematic review analysed the machine learning as well as the NLP as known as natural language processing techniques in the mental health research, in order to asses clinical applications and methodology. The authors further follows the PRISMA criteria registered with PROSPERO. The results were seen to be organized through qualitative perspective. Population studies were grouped and combined into three different categories, it included medical databases, emergency rooms patients as well as the social media users. The Natural Language processing techniques tend to provide useful information from the unexplored data that are specifically the habits of daily life that are inaccessible to healthcare professionals. [28].

Many researches have been presented on natural language processing for detecting depression signs however most of the current methods lack high-level emotional semantic understanding. The authors Lu Ren, Hongfei Lin, Bo Xu, Shaowu Zhang, Liang Yang, Shichang Sun introduced emotions based attention network, with semantic and emotion understanding modules. It could be seen that the semantic module captured contextual information while the emotion module captured positive and negative emotions data with dynamic fusion. The testing on Reddit data showed the model achieving 91.30% accuracy, 91.91% precision, 96.15 recall and 93.98% F-measure [29].

Individuals affected from depression usually seek support in online forums expressing suicidal thoughts. Existing models struggle to extract sentiment data from vast number of user posts. Tehrefore to overcome this, the research proposed Multi-Gated Leaky ReLU CNN (MGL-CNN). It is a hierarchical model for depression detection in forums. Further, a single gated LeakyReLU CNN (SGL-CNN) was also introduced as an alternative method. The model surpassed previous models on Reddit with self-reported diagnosis for the depression as well as datasets of early detection of depression based on online postings [30].

Online activities specifically on social media reflects emotional distress including the explicit expressions of suicidal thoughts. Therefore the research introduced KAREN, a system designed using machine learning and rule-based classification to detect emotionally distressed people in Chinese language blogs. The experiments show that KAREN outperforms the existing methods in classification performance and the professionals seem to rate it better for identifying bloggers online with mental health issues [31].

The author Muhammad Asad Abbas, Kashif Munir, Ali Raza, Nagwan Abdel Samee, Mona M. Jamjoom, and Zahid Ullah presents a research utilizing machine learning to analyse over 20,000 categorised tweets and developed BERT-RF feature engineering technique. The methods combines contextualized embedding and probabilistic features to identify depression indicators. This approach outperforms the traditional methods achieving 99% accuracy with logistic regression. Validation trials further confirm the efficacy of the method, offering significant contribution to computational linguistics as well as mental health analytics [32].

3- Proposed Method

Our proposed method comprises of the following stages.

To gather comprehensive data for this study, the social media websites & platforms Reddit and Twitter was chosen. The data from Reddit was scraped using a Python library known as PRAW while Twitter dataset was downloaded from Kaggle.

3.1- Data Preprocessing

It includes the elimination of noise or any kind of inconsistencies that can adversely affect the model implementation phase. We started with handling the missing values through imputation or exclusion, and errors were corrected. Removal of stop words, punctuation was also done.

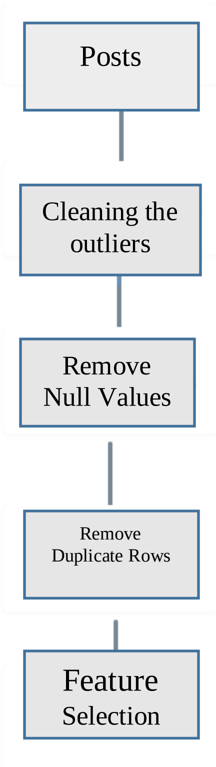

Figure 3: Twitter Data Cleaning

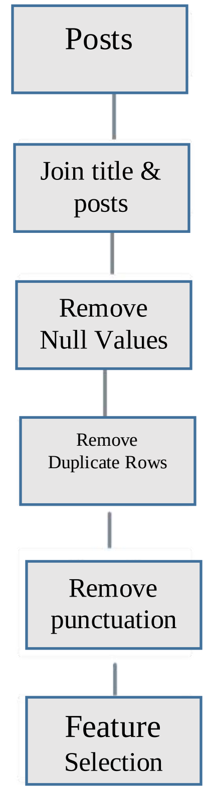

Figure 4: Reddit Data cleaning

3.2- Data Analysis

The preprocessed data was further used for analysis including the approach to extract useful information. Initially, exploratory data analysis (EDA) was conducted, using descriptive statistics and visualizations to summarize and identify patterns within the data.

Figure 6: Word Cloud for Reddit data

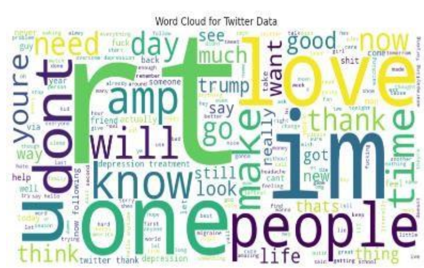

Figure 7: Word Cloud for Twitter

3.3-TF-IDF Analysis:

We first calculated the frequency of the most occurring words in our datasets. We found our diversity in the occurrence of words in both datasets. We further applied TD-IDF and z-score standardization on the top 20 words. Further it helped us to determine which terms were central to discussions.

$$TF - I(t,z,D) = TF(t,z) \times IDF(t,D) \tag{1}$$

3.4- Sentiment Analysis

We created different binary classifications including /anxiety, /PTSD (Post-traumatic Stress Disorder), /health anxiety, /OCD (Obsessive Compulsive Disorder), /obsessive compulsive disorder, /loneliness, /phobia, /agoraphobia, and some others as well. Then we had a model that is known as GRU. After the training the accuracy was calculated and the model was tested.

$$Y = (Dens(GRU(Embedding(Z)))) \quad (2)$$

We used VADER NLTK sentiment analysis tools as well, in order to classify text data as positive or negative. We also trained catboost classifier model, and similarly we also trained xgboost and lightgbm models as well. Another method we used was pre-trained-BERT, it helped in fine tuning the binary sentiment classification. We first loaded the BERT Tokenizer and model. Then defined a function to predict the sentiments. RCNN was implemented with the convolutional layer and LSTM layer. We performed sentiment analysis using logistic regression where first the data was converted into TF-IDF features, then generated the labels using textblob, and finally split the data into training and testing with 80:20 ratio.

$$Y = \sigma(x_{tf-idf} \cdot w + b) \quad (3)$$

Further we used XLNet model and tokenizer during the research for sentiment analysis. It defines the function to predict sentiments from the given text using encoding, the text further passed through the model and interpreted the result in either 0 or 1, 1 represented the positive while 0 for the negative. Further the results were saved in a new file.

$$Sentiment = \begin{cases} 1 \\ 0 \end{cases} if\ logits[1] > logits[0] \quad (4)$$

We implemented decision trees classifier, and loaded the data first then, converted into TFIDF features. We also assigned sentiment labels using textblob, further divided the data into testing and training datasets and then the decision tree model was fully trained to predict the sentiments of our data,

Decision Tree Model:

$$Z = \left| decision\, tr(Ytf - idf) \right| \quad (5)$$

We also applied Naive Bayes to get better efficiency for the research. The process was initialized by vectorising the text data into numerical features. That was further followed by dividing the data into training and testing. The multinomial Naïve Bayes was trained and evaluated to reflect the predictive performance. Therefore the predictions were generated for entire dataset.

$$P\,(C_k \mid d) = \frac{P(C_K)\prod_{i=1}^{n} P(t_i \mid C_K)}{P(d)} \quad (6)$$

4- Results

4.1- Reddit & Twitter Dataset results:

Catboost with 72%, AACN with 70%, and XLNet with 70% accuracy surpassed and exceeded the results of other models if we talk about accuracy while DistilBert and catboost outperformed other models in terms of precision with 0.54 and 0.98 score. For Twitter Catboost, and Gradient Boosting outperformed other models when it came to performance accuracy with an accuracy score of 85.9%, and 84%.

4.2- Words Frequency Analysis:

Table 3: Reddit words Frequency

Reddit Words	Frequency
I	194422
to	96019
and	93846
be	82723
the	70536
a	61218
my	59146
it	52461
of	46877
have	40631
that	37782
me	36866
t	35858
in	32709
you	28672
for	27424
but	26523
m	26146
this	25785
so	22658

Table 4: Twitter words Frequency

Twitter Words	Frequency
the	5972
i	5577
to	5038
a	4303
you	4144
rt	3838
and	3355
is	2847
of	2686
for	2483
in	2384
my	2023
it	1861
me	1798
on	1756
this	1591
that	1581
with	1302
im	1296
so	1261

We have demonstrated and presented the results of all the experiments taken out during the research that was conducted on two different datasets i.e.; Twitter & Reddit.

Table 5: Results for Reddit Dataset

Model	Accuracy	Precision	Recall	F1-Score
Vader NLTK	0.496	0.5237	0.3977	0.4521
TextBlob	0.495	0.5233	0.3977	0.4519
SVM	0.49	0.51	0.522	0.51
Naïve bayes	0.48	0.48	0.51	0.496
Logistic Regression	0.497	0.51	0.55	0.53
Decision Tree	0.505	0.52	0.53	0.52
Catboost	0.72	0.66	0.63	0.65
Gradient Boosting	0.49	0.51	0.49	0.50
XGboost	0.47	0	0	0
Lightgbm	0.49	0.51	0.50	0.51
FastText	0.490	0.5137	0.48	0.49
GRU	0.49	0.51	0.47	0.49
RCNN	0.50	0.521	0.61	0.56
XLNet	0.70	0.521	0.986	0.68
BERT	0.4928	0.530	0.260	0.34
DistilBERT	0.48	0.54	0.036	0.067
Attention Augmented Convolutional Network	0.70	0.21	0.29	0.24
Tensorflow	0.49	0.51	0.55	0.53
Gensim	0.49	0.5	0.39	0.45
Spacy	0.50	0.52	0.58	0.55

Table 6: Results for Twitter Dataset

Model	Accuracy	Precision	Recall	F1-Score
Vader NLTK	0.41	0.21	0.65	0.32
TextBlob	0.59	0.21	0.34	0.26
Naïve bayes	0.50	0.50	0.21	0.30
Logistic Regression	0.82	0.82	0.22	0.35
SVM	0.50	0.21	0.5	0.30
Decision Tree	0.51	0.22	0.50	0.30
Catboost	0.85	0.61	0.90	0.73
XGboost	0.44	0.21	0.60	0.31
Gradient Boosting	0.84	0.66	0.59	0.62
Lightgbm	0.48	0.22	0.58	0.31
FastText	0.59	0.21	0.34	0.26
GRU	0.49	0.212	0.50	0.29
RCNN	0.47	0.20	0.50	0.29
XLNet	0.78	0.16	0.01	0.02
BERT	0.78	0	0	0
DistilBERT	0.788	1.0	0	0
Attention Augmented Convolutional Network	0.81	0.71	0.26	0.39
Tensorflow	0.49	0.21	0.49	0.29
Gensim	0.77	0.44	0.15	0.23
Spacy	0.59	0.21	0.34	0.26

From the above tables we can see, after the models implementation, the Twitter dataset with better evaluation metrics with maximum accuracy score of 85% with catboost, and Gradient boosting with 84%, best recall score 0.90 with catboost and F1-score value as 0.73 with catboost. However at Reddit dataset, we could see most of the models were not producing desirable results, AACN with 70% accuracy, while catboost with 72% accuracy has shown to be providing maximum accuracy. However maximum recall with score of 0.98 has been provided with XLNet.

5- Conclusion

This study demonstrated the effectiveness of using a diverse set of models for sentiment analysis on mental health discussions across Reddit and Twitter. Transformer-based models like BERT showed superior performance due to their contextual understanding, while traditional models provided valuable benchmarks. The findings marks, and underscore the importance of model selection with a strong foundation that is truly based on the specific characteristics of the text data, with attention mechanisms and sequential models offering significant advantages for complex and lengthy social media content. The difference of posts length have shown to be effective on models performance. Models performed well at Twitter dataset while struggled to show better results at Reddit dataset.

This research has shown effectiveness of different models for sentiment analysis discussions. Pre-trained models showed better results at Twitter as compared to Reddit dataset. Some transformer based models like AACN, DistilBERT, and XLNET showed superior performance with accuracy score of 81%, 78%, and again 78% at Twitter dataset, however simultaneously at Reddit dataset, we experience the maximum of 72% accuracy with catboost model.and then with AACN having 70% score. Overall, the models found out to be performing well at the twitter dataset, with better measure of handling imbalanced classes. Therefore the results suggests that traditional machine learning models like logistic regression work well at concise data whereas more models like XLNet are needed to work with the complex platforms like Reddit. In conclusion this analysis not only highlights the strengths and weaknesses of certain models, but also put emphasis on platform specific approaches in understanding and interpreting the social media data. With the understanding of specific challenges of each social media platform researchers can develop better sentiment analysis tools having better insights of general public sentiments. Therefore this approach will likely to contribute in providing better understanding of how people express their emotions and mental state across different platforms

6- REFERENCES

1. Bracher-Smith, M., Crawford, K., & Escott-Price, V. (2020). Machine learning for genetic prediction of psychiatric disorders: a systematic review. *Molecular Psychiatry*, *26*(1), 70–79. https://doi.org/10.1038/s41380-020-0825-2
2. Gautam, S., Jain, A., Chaudhary, J., Gautam, M., Gaur, M., & Grover, S. (2024). Concept of mental health and mental well-being, it's determinants and coping strategies. *Indian Journal of Psychiatry*, *66*(Suppl 2), S231–S244. https://doi.org/10.4103/indianjpsychiatry.indianjpsychiatry_707_23
3. Kim, J., Lee, J., Park, E., & Han, J. (2020b). A deep learning model for detecting mental illness from user content on social media. *Scientific Reports*, *10*(1). https://doi.org/10.1038/s41598-020-68764-y
4. Boettcher, N. (2021). Studies of Depression and Anxiety Using Reddit as a Data Source: Scoping Review. *JMIR Mental Health*, *8*(11), e29487. https://doi.org/10.2196/29487
5. *Anxiety disorders*. (2023b, September 27). https://www.who.int/news-room/factsheets/detail/anxiety-disorders
6. *Anxiety disorders*. (2023, September 27). https://www.who.int/news-room/factsheets/detail/anxiety-disorders
7. *Generalized Anxiety Disorder*. (n.d.). National Institute of Mental Health (NIMH). https://www.nimh.nih.gov/health/statistics/generalized-anxiety-disorder
8. *Panic Disorder*. (n.d.). National Institute of Mental Health (NIMH). https://www.nimh.nih.gov/health/statistics/panic-disorder
9. Balaram, K., & Marwaha, R. (2023, February 13). *Agoraphobia*. StatPearls - NCBI Bookshelf. https://www.ncbi.nlm.nih.gov/books/NBK554387/
10. Professional, C. C. M. (n.d.). *Social Anxiety Disorder (Social Phobia)*. Cleveland Clinic. https://my.clevelandclinic.org/health/diseases/22709-social-anxiety
11. Feriante, J., Torrico, T. J., & Bernstein, B. (2023, February 26). *Separation Anxiety Disorder*. StatPearls - NCBI Bookshelf. https://www.ncbi.nlm.nih.gov/books/NBK560793/
12. Hannah, K., Marie, K., Olaf, H., Stephan, B., Andreas, D., Michael, L. W., Till, B., & Peter, D. (2023b, November 13). *The global economic burden of health anxiety/hypochondriasis- a systematic review*. BMC Public Health. https://doi.org/10.1186/s12889-023-17159-5

13. Wong P. (2010). Selective mutism: a review of etiology, comorbidities, and treatment. *Psychiatry (Edgmont (Pa. : Township))*, *7*(3), 23–31.
14. Ilias, L., Mouzakitis, S., & Askounis, D. (2024, April). Calibration of TransformerBased Models for Identifying Stress and Depression in Social Media. *IEEE Transactions on Computational Social Systems*, *11*(2), 1979–1990. https://doi.org/10.1109/tcss.2023.3283009
15. Hussain, J., Satti, F. A., Afzal, M., Khan, W. A., Bilal, H. S. M., Ansaar, M. Z., Ahmad, H. F., Hur, T., Bang, J., Kim, J. I., Park, G. H., Seung, H., & Lee, S. (2019, August 12). Exploring the dominant features of social media for depression detection. *Journal of Information Science*, *46*(6), 739–759. https://doi.org/10.1177/0165551519860469
16. *Depression detection via harvesting social media | Proceedings of the 26th International Joint Conference on Artificial Intelligence*. (n.d.). Guide Proceedings. https://doi.org/10.5555/3172077.3172425
17. Trifan, A., Antunes, R., Matos, S., & Oliveira, J. L. (2020). Understanding Depression from Psycholinguistic Patterns in Social Media Texts. *Lecture Notes in Computer Science*, 402–409. https://doi.org/10.1007/978-3-030-45442-5_50
18. Jiang, Z., Levitan, S. I., Zomick, J., & Hirschberg, J. (2020, January 1). *Detection of Mental Health from Reddit via Deep Contextualized Representations*. https://doi.org/10.18653/v1/2020.louhi-1.16
19. Zirikly, A., & Dredze, M. (2022). Explaining Models of Mental Health via Clinically Grounded Auxiliary Tasks. *Proceedings of the Eighth Workshop on Computational Linguistics and Clinical Psychology*. https://doi.org/10.18653/v1/2022.clpsych-1.3
20. Tavchioski, I., Koloski, B., Škrlj, B., & Pollak, S. (2022). E8-IJS@LT-EDI-ACL2022 - BERT, AutoML and Knowledge-graph backed Detection of Depression. *Proceedings of the Second Workshop on Language Technology for Equality, Diversity and Inclusion*. https://doi.org/10.18653/v1/2022.ltedi-1.36
21. Aragon, M., Lopez Monroy, A. P., Gonzalez, L., Losada, D. E., & Montes, M. (2023). DisorBERT: A Double Domain Adaptation Model for Detecting Signs of Mental Disorders in Social Media. *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. https://doi.org/10.18653/v1/2023.acl-long.853
22. Merinda Lestandy, Amrul Faruq, Adhi Nugraha, & Abdurrahim. (2024, April 28). Analyzing Reddit Data: Hybrid Model for Depression Sentiment using FastText Embedding. *Jurnal RESTI (Rekayasa Sistem Dan Teknologi Informasi)*, *8*(2), 288–297. https://doi.org/10.29207/resti.v8i2.5641
23. Kumar Singh, K. (2023, January 31). Study of Early Risks of Depression by Analysing Social Media Posts. *IIMS Journal of Management Science*, *14*(1), 9–25. https://doi.org/10.1177/0976030x221112529
24. Aragón, M. E., López-Monroy, A. P., González-Gurrola, L. C., & Montes-y-Gómez, M. (2023, January 1). Detecting Mental Disorders in Social Media Through Emotional Patterns - The Case of Anorexia and Depression. *IEEE Transactions on Affective Computing*, *14*(1), 211–222. https://doi.org/10.1109/taffc.2021.3075638
25. Ilias, L., Mouzakitis, S., & Askounis, D. (2024, April). Calibration of Transformer-Based Models for Identifying Stress and Depression in Social Media. *IEEE Transactions on*

Computational Social Systems, *11*(2), 1979–1990. https://doi.org/10.1109/tcss.2023.3283009

26. Stephen, J. J., & P., P. (2019, August 1). Detecting the magnitude of depression in Twitter users using sentiment analysis. *International Journal of Electrical and Computer Engineering (IJECE)*, *9*(4), 3247. https://doi.org/10.11591/ijece.v9i4.pp3247-3255

27. Govindasamy, K. A., & Palanichamy, N. (2021, May 6). Depression Detection Using Machine Learning Techniques on Twitter Data. *2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS)*. https://doi.org/10.1109/iciccs51141.2021.9432203

28. Le Glaz, A., Haralambous, Y., Kim-Dufor, D. H., Lenca, P., Billot, R., Ryan, T. C., Marsh, J., DeVylder, J., Walter, M., Berrouiguet, S., & Lemey, C. (2021, May 4). Machine Learning and Natural Language Processing in Mental Health: Systematic Review. *Journal of Medical Internet Research*, *23*(5), e15708. https://doi.org/10.2196/15708

29. Ren, L., Lin, H., Xu, B., Zhang, S., Yang, L., & Sun, S. (2021, July 16). Depression Detection on Reddit With an Emotion-Based Attention Network: Algorithm Development and Validation. *JMIR Medical Informatics*, *9*(7), e28754. https://doi.org/10.2196/28754

30. Rao, G., Zhang, Y., Zhang, L., Cong, Q., & Feng, Z. (2020). MGL-CNN: A Hierarchical Posts Representations Model for Identifying Depressed Individuals in Online Forums. *IEEE Access*, *8*, 32395–32403. https://doi.org/10.1109/access.2020.2973737

31. Chau, M., Li, T. M. H., Wong, P. W. C., Xu, J. J., Yip, P. S. F., & Chen, H. (2020). Finding People with Emotional Distress in Online Social Media: A Design Combining Machine Learning and Rule-Based Classification. *MIS Quarterly*, *44*(2), 933–955. https://doi.org/10.25300/misq/2020/14110

32. Abbas, M. A., Munir, K., Raza, A., Samee, N. A., Jamjoom, M. M., & Ullah, Z. (2024). Novel Transformer Based Contextualized Embedding and Probabilistic Features for Depression Detection From Social Media. *IEEE Access*, *12*, 54087–54100. https://doi.org/10.1109/access.2024.3387695