Exploring the Link Between Social Media Engagement and Mental Wellness

Shiva teja Nakka
CSE AI&ML
SR UNVIERSITY
WARANGAL,INDIA
nsteja17@gmail.com

Prannetha sakulabatkthula
CSE AI&ML SR UNVIERSITY
WARNGAL,INDIA
prannetha2003@gmail.com

Abstract-In recent years, social media platforms in our daily lives has raised concerns about their potential impact on mental health, specifically regarding depression. Understanding the intricate dynamics and challenges that have emerged in this context is crucial for both mental health professionals and individuals seeking to maintain their well-being in the digital age. Further research is necessary to untangle the nuanced interplay between social media and depression in a rapidly evolving technological landscape.

There are many factors that are affecting the mental health of once Notably, over the past two decades, there has been a noticeable increase in adolescent depression and suicidal tendencies, coinciding with the widespread adoption of social media, particularly among adolescents. This scoping review aims to investigate the intricate relationship between adolescents' use of social media, with a focus on social networking sites and their experiences of depression and suicidal thoughts or behaviors. It is recommended that future research in this field adopts longitudinal study designs, incorporates objective and timely measures of social media engagement, delves deeper into the underlying mechanisms connecting social media use and depression or suicidal tendencies, and includes investigations with clinical populations. These steps can help enhance clinical practices and provide a more comprehensive understanding of the relationship between social media and mental health.

Keywords—Social media, depression, suicidal tendencies, clincal population, mental health

I. INTRODUCTION

In recent times, the connection between mental health and social media has gained significant attention. Platforms like Facebook, Instagram, and Twitter have drastically changed how we interact and share information, offering both advantages in terms of connection and community, but also sparking concerns about their effects on mental well-being.

The World Health Organization (WHO) has brought attention to concerning suicide rates, particularly among young adults aged 15-29, with over 700,000 deaths annually and a rising number of attempted suicides. Similarly, the US Centers for Disease Control and Prevention (CDC) have noted an unsettling increase in suicide rates.

Over the past decade, there has been notable growth in computational research focusing on mental health using non-clinical data, including data sourced from social media. These studies have become prominent due to their relevance in today's culture.

This study seeks to explore various factors such as ADHD, PTSD, and anxiety and their impact on mental health within the context of social media. The carefully crafted images of life often portrayed on social media can lead to harmful comparisons and feelings of inadequacy, commonly referred to as the "social comparison theory."

Mental health issues present significant public health challenges, characterized by symptoms such as loss of interest, changes in appetite, low mood, or heightened anxiety. Researchers have extensively investigated the use of social media text to identify and understand these conditions.

Moreover, concerns about privacy and data security arising from the sharing of personal information on social media platforms have added to the stress and anxiety experienced by users.

In conclusion, the relationship between mental health and social media is intricate and undeniable. While these platforms offer support and resources for mental well-being, they also pose risks to individual welfare. It is crucial for individuals, communities, and organizations to recognize and address these impacts, fostering positive online environments and promoting digital well-being as social media continues to evolve.

II. BACKGROUND

In this study, various factors, such as ADHD, PTSD, and anxiety, will be explored as parameters impacting mental health within the realm of social media
The curated, often idealized portrayals of people's lives on social media platforms can foster detrimental comparisons and evoke feelings of inadequacy, commonly referred to as the "social comparison theory"
Mental health issues present a substantial public healthcare challenge, often characterized by distinct symptoms like loss of interest, appetite, depressed moods, or excessive anxiety. Researchers have extensively delved into the use of social media texts to identify and detect these conditions.

GitHub - sergioburdisso/pyss3: A[26]

The practice of sharing personal information on social media platforms has raised valid concerns regarding privacy and data security, contributing to stress and anxiety among users In summary, the intricate relationship between mental health and social media is undeniable. While social media platforms can offer valuable support and resources for mental health, they also pose risks to individual well-being. As the use of social media continues to evolve, it becomes imperative for individuals, communities, and organizations to remain cognizant of its impact on mental health and to work collaboratively in promoting positive online environments and digital well-being [10]

A. *Equations*

We created user embeddings using a method similar to the one introduced by Amir et al. (2016). This method aims to capture the relationships between users and the content they produce, such as words in their posts. In essence, we optimized the likelihood of sentences given their authors. To formalize, let U denote the set of users, Cj represent a set of posts authored by user uj from U, and S be a post composed of words from a vocabulary V. Our objective was to estimate the parameters of a user vector uj to maximize the conditional probability:

$$P(\mathcal{C}_j|u_j) \propto \sum_{S\in\mathcal{C}_j} \sum_{w_i\in S} \log P(w_i|\mathbf{u}_j)$$

Eq1:vector parameter equation

Estimating these quantities directly, for instance using a log-linear model, would necessitate computing a normalizing constant across a potentially extensive range of words, which is computationally intensive. Since our primary interest lies in the user vectors uj rather than the precise probabilities themselves, we can approximate the term P(wi | uj) by minimizing the following Hinge-loss objective:

$$\mathcal{L}(w_i, u_j) = \sum_{\tilde{w}_k\in\mathcal{V}} \max(0, 1 - \mathbf{w}_i \cdot \mathbf{u}_j + \tilde{\mathbf{w}}_k \cdot \mathbf{u}_j)$$

Eq 2:minimaziation equation of vector parameters

In this context, the term "word ˜wk" refers to a negative sample, meaning a word that does not appear in the post being analyzed (authored by user uj). These negative samples, along with their associated embeddings, w˜k, are used in the learning process. By training the model to distinguish between observed positive examples and these pseudo-negative examples, it adjusts the probability distribution towards more plausible observations (as described by Smith and Eisner, 2005).

Both words and users are represented by d-dimensional vectors in this approach: word vectors, wi ∈ R^d, are assumed to have been pre-trained using a neural language model, while user vectors uj ∈ R^d are the parameters to be learned. This method is referred to as "user vec." It's worth noting that, with some operational distinctions, this model aligns closely with the pv-bow variant of Paragraph2vec, particularly when users are considered analogous to paragraphs. The primary differences lie in the fact that: (i) user2vec predicts all the words in a post, whereas pv-dbow moves a window along the paragraph and predicts one word per step; and (ii) user2vec operates under the assumption that the word embedding... [the rest of the sentence seems to be cut off] In contrast to traditional methods, we approach mental health analysis differently. Instead of just classifying data, we use a model that can generate responses. This model handles multiple mental health analysis tasks at once, like spotting issues and explaining why it made certain decisions.

Each task has its own set of training pairs, containing a post and a question, along with the model's response and an explanation in natural language. All these pairs are combined into one big training set. The model learns from this data to improve its accuracy and the quality of its explanations.

$$\max_{\phi} \sum_{(q,r)\in\mathcal{D}} \sum_{j=1}^{|r|} log(P_{\phi}(r_j|q, r_{<j}))$$

Eq 3:maximaziation of the parameters

B. *Data set and preprocessing*

The process of turning raw data into useful insights begins with data preparation. It includes several crucial activities meant to improve the data's quality and organization so that machine learning or analysis can use it more effectively.

In data preprocessing, handling long and cumbersome attribute names is an essential step. Working with these names can be difficult, and they could confuse while doing analyses. The dataset is made easier to use and traverse by renaming or abbreviating attribute names to make them simpler. Subsequent analytic activities become more clear and efficient as a result of this simplification since analysts and data scientists can now easily find and refer to pertinent attributes without being hampered by long names.

Moreover, reducing the number of columns or selecting features is a calculated method of simplifying the dataset. In addition to adding noise and complexity, not all qualities may contribute equally to the analysis or modeling work at hand. It is possible to remove extraneous columns and concentrate attention on the most significant and educational elements by carefully assessing and choosing the ones that remain. By lowering overfitting and redundancy, this dimensionality reduction not only makes the dataset simpler but also enhances computing effectiveness and model performance.

Managing missing values is a crucial component of data preparation. Due to a variety of issues, including human error, malfunctioning sensors, and restrictions on data collection, real-world datasets frequently contain inaccurate or inconsistent information. The validity and integrity of subsequent analyses in the industry may be jeopardized if missing values are not addressed.

The process of turning raw data into useful insights begins with data preparation. It includes several crucial activities meant to improve the data's quality and organization so that machine learning or analysis can use it more effectively.

In data preprocessing, handling long and cumbersome attribute names is an essential step. Working with these names can be difficult, and they could confuse while doing analyses. The dataset is made easier to use and traverse by renaming or abbreviating attribute names to make them simpler. Subsequent analytic activities become more clear and efficient as a result of this simplification, since analysts and data scientists can now easily find and refer to pertinent attributes without being hampered by long names.

III. ARICHITECTURE

The process of extracting features from Facebook posts for mental health research typically involves several steps. Initially, researchers collect and clean text data from these posts to remove any irrelevant information and ensure consistency. Then, they use word embedding techniques to represent words as compact vectors, capturing their meanings and relationships. These embeddings help extract features relevant to mental health, such as sentiment analysis or linguistic style analysis. Finally, these features are analysed using machine learning models or statistical methods to uncover patterns and insights into individuals' mental well-being, contributing to our understanding of psychological factors in the digital age.

There are various stages involved in gathering features from Facebook posts for studies on mental health. First, the researchers gather and clean up the textual data from these posts, making sure that all of the information is consistent and that nothing unnecessary is left in. Then, using advanced word embedding techniques, they efficiently capture the relationships and meanings of words by condensing them into vectors. These vectors are useful models for sentiment analysis and linguistic style analysis, which extract aspects related to mental health. Through analyzing the subtle emotional overtones and language patterns present in these messages, researchers are able to acquire a more profound understanding of people's mental states.

The collected features are then thoroughly analyzed using state-of-the-art approaches such as statistical analysis or machine learning algorithms. These analytical techniques reveal latent patterns.

Tables and figures

Table 1 User profile feature extraction for mental health state

Category	Sub-category	Feature	Type	Research articles
Demographic	Users' Meta-data	Age	User	[36, 39, 53, 60]
		Gender	User	[36, 36, 39, 53, 60]
		Education	User	[39, 53]
		Occupation	User	[39, 53]
	Users' Network	Follower	User	[61]
		Ego-network	User	[62]
Spatio-temporal	Temporal	Timeline	User	[7, 36, 39]
	Spatial	Location	User	–
Behavioural	Posting Behavior	Gen. Behaviour	User	[39]
		Ruminative	User	[11]
		Posting Time	User	[59, 63]

An interesting study introduce bridge , a big data based feature extraction approach from social media data which contains both user-profile features and social networking features. • The community specific information of the user comprises of the information about followers, and favorites. We associated these features with the user's social networking and thus, are discussed in Social Features.

Sets	Accuracy	Sensitivity	specificity
Set 1	99.16	98.23	99.42
Set 2	99.25	97.19	99.56
Set 3	99.19	98.37	99.42
Set 4	99.19	98.70	99.54

Table 2: Performance of the proposed model in different testing set.

100 users of Barnsley region was detected as depressive, where it was 24.1% (4,672 out of 19,386) in pre-pandemic phase, which indicates an average elevation of 6.9% depressive tweets in Barnsley region. There is a significant rise (36.54%) in total number of tweets, which indicates more activity in social media than pre-pandemic phase.

The highest percentage of depressive post that was posted by 100 random Twitter user of Bradford region detected by the proposed model before the COVID-19 pandemic was in November-19 (19.39%) and the lowest depressive posts were noticed in Jan-20 (18.30%). The sudden rise of depressive post was noticed in February-20 (23.26%), when COVID-19 cases started to rise. However, comparatively lower number of new cases was found out in this region. It also shows lower impact of COVID-19 in depressive post percentage. In total, 4,534 out of 23,880 (18.98%) tweets by 100 users were classified as depressive during pre-COVID stage, where it increased to 6,979 out of 32,918 (21.20%) during selected four months of COVID-19 phase. It shows a rise of 11.69% average detection of depressive tweet in Bradford. An elevation of 37.84% tweets was noticed during COVID-19 that shows an increment of social media activity in this region.

In Huddersfield, the highest percentage of depressive post detected during COVID-19 pandemic was in May-20 (30.74%), where the lowest percentage was in February (21.83%). As COVID-19 cases increased, the percentage of depressive post also increased in this region. In the pre pandemic situation, the highest percentage of depressive post was in October-19 (28.99%). A total of 5,269 out of 19,898 tweets (26.48%) were detected as depressive in this region during COVID-19, where it was 24.6% (3,468 out of 14,063) in four pre-pandemic months. It shows an elevation of 7.6% average depressive tweets and 41.49% greater total tweets by the same set of Twitter user in Huddersfield during COVID-19 pandemic.

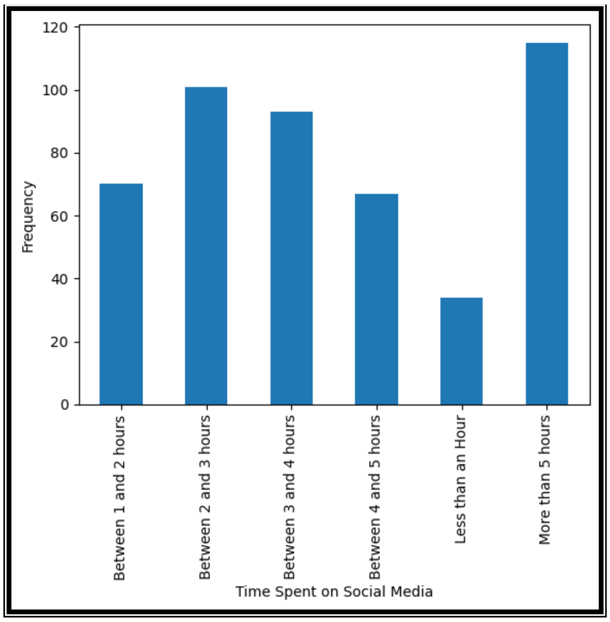

Fig 1:This is the graph between time spent and the frequency of the people

The link between social media usage and mental health is a topic of great importance in today's conversations. With social media now a central aspect of many people's lives worldwide, it's crucial to grasp how excessive use affects mental well-being. Research indicates that spending too much time on social media is associated with negative mental health outcomes like increased feelings of loneliness, depression, anxiety, and a decrease in self-esteem. This connection highlights the need for deeper exploration into how social media impacts mental health, especially considering issues like comparing oneself to others, exposure to idealized lifestyles, and cyberbullying. Age also plays a role, with adolescents and young adults, who are heavy social media users, being particularly vulnerable, especially during crucial stages of identity formation. While acknowledging

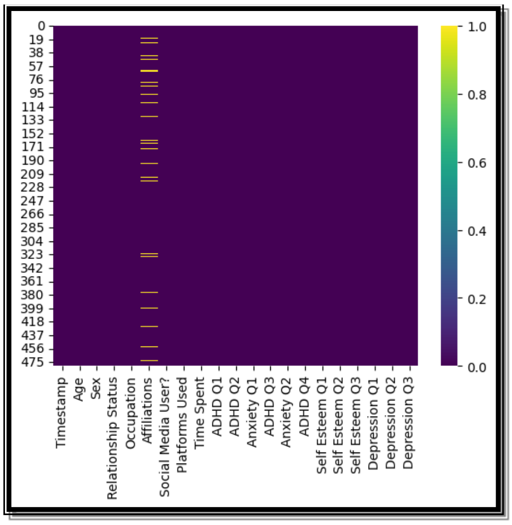

Fig2:this figure shows about the frequency of the affiliation and time stamp.

Understanding mental health involves considering a range of factors, such as age, gender, relationship status, occupation, social connections, digital habits, and symptoms of conditions like ADHD and anxiety. Age affects individuals differently, with each life stage bringing its own set of challenges. Gender influences societal expectations and biological factors that impact mental well-being. Relationships, whether positive or strained, play a significant role in shaping mental health. Job-related stress and satisfaction levels affect well-being, as do social affiliations, which can offer support or lead to feelings of isolation. Additionally, how people engage with digital technologies, particularly social media, can influence their mental health, particularly if usage becomes excessive. Recognizing the interplay of these factors helps tailor interventions to meet the specific needs of individuals, fostering mental well-being across diverse communities.

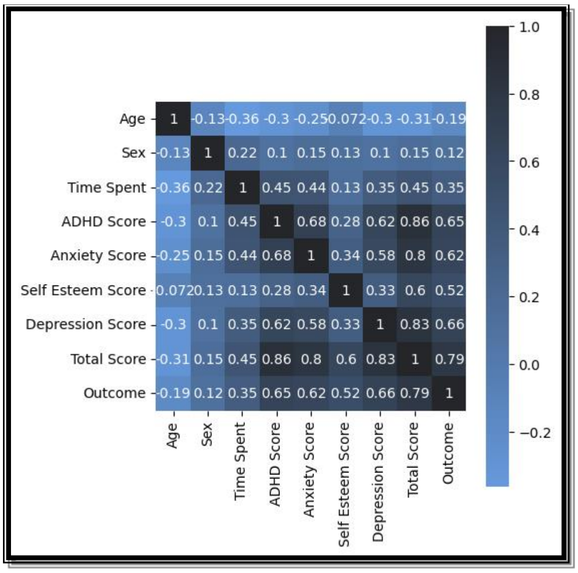

Fig3 :heat map of the attributes and their matrix box

Heatmaps are vital visual aids that present data in a color-coded format, facilitating easy interpretation and identification of patterns and relationships within datasets. They offer a quick overview of data distribution, aiding in the efficient identification of clusters, outliers, and areas of interest, particularly in large datasets with multiple variables. Notably, heatmaps excel in highlighting correlations between variables through color differentiation, providing insights into underlying relationships within the data. They also enable visualization of data across multiple dimensions simultaneously, aiding in the comprehensive understanding of complex datasets. In fields such as mental well-being research, heatmaps play a crucial role in analyzing factors affecting psychological states, offering valuable insights for interventions and support systems. Overall, heatmaps serve as powerful tools for data exploration, analysis, and communication, facilitating informed decision-making processes in various domains.

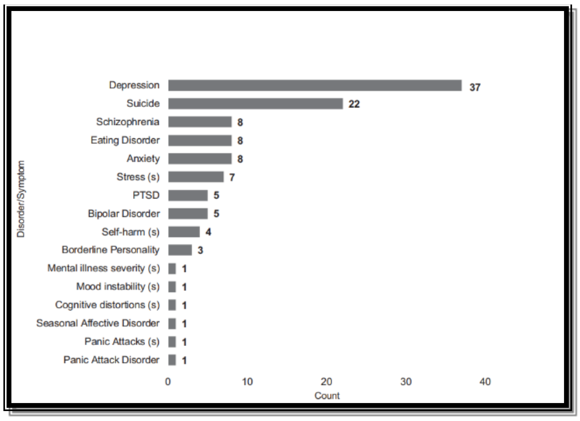

Fig 4: Publication counts by disorder and symptomatology. In this graph, we display the counts of publications that study specific disorders and symptomatology

To visualize publication counts by disorder and symptomatology, you'll first need to collect relevant data categorizing publications by the disorders and symptoms they address. Once you've organized the data, count the number of publications associated with each category. Then, choose a suitable graph type such as a bar graph or histogram to represent the counts effectively. Use graphing software like Excel or Python with libraries such as Matplotlib to create the graph. Ensure clear labeling of axes and add necessary titles for clarity. Customizing the appearance can enhance visual appeal.

Result

We've chosen Naive Bayes over logistic regression for our project because it's simpler and easier to interpret. Even though logistic regression achieved an impressive 93.8% accuracy, it tends to overfit on datasets with many dimensions. This means it can become too complex, making predictions based on individual features that might not generalize well to new data.

Naive Bayes, on the other hand, is better suited for handling high-dimensional datasets. Its simplicity comes from assuming that features are independent of each other, allowing it to model complex relationships efficiently without overfitting. By treating each feature separately, Naive Bayes reduces the risk of overfitting and performs well even with limited training data.

Moreover, Naive Bayes is attractive because it's easy to understand. Its straightforward probabilistic framework makes it clear how each feature contributes to the final classification decision. This transparency is especially valuable in fields like healthcare or finance, where being able to explain decisions is crucial.

In summary, while logistic regression may have high accuracy, its tendency to overfit on complex datasets is a concern. Naive Bayes offers simplicity, reliability, and interpretability, making it our preferred choice for the project.

Conclusion *:*

Understanding the intricate relationship between social media and mental health involves navigating a complex landscape of both positive and negative influences on individuals' well-being. Given the project's focus on unraveling these connections amidst the myriad influencing factors, the decision to utilize Naive Bayes over logistic regression was made. This choice reflects the need to manage the complexity and multi-layered nature of the data, ensuring prevention of overfitting and enabling a broader scope for analysis and comprehension.

Moving forward, the realm of research exploring the dynamics between social media use and mental health presents promising avenues for advancement. As technological advancements persist and studies in this domain evolve, there are numerous opportunities for enhancement and expansion.

One promising avenue for future inquiry involves the collection of larger, more diverse datasets. Incorporating data from a variety of sources, including academic research, mental health institutions, social media platforms, and user-generated content, holds potential to bolster the accuracy and reliability of predictive models. Expanding the dataset offers the chance to develop a more holistic understanding of the intricate factors influencing individuals' mental well-being in the digital era, accounting for emerging trends and evolving online behaviors.

Additionally, leveraging natural language processing (NLP) techniques can significantly enhance our capacity to analyze and interpret textual data sourced from social media platforms. NLP tools can aid in discerning sentiment, emotions, and nuances in user-generated content, thereby providing deeper insights into the ramifications of online interactions on mental health.

Acknowledgment *(Heading 5)*

The preferred spelling of the word “acknowledgment” in America is without an “e” after the “g”. Avoid the stilted expression “one of us (R. B. G.) thanks ...”. Instead, try “R. B. G. thanks...”. Put sponsor acknowledgments in the unnumbered footnote on the first page.

References

[1]Ghanadian, H., Nejadgholi, I., & Osman, H. A. (2023). ChatGPT for Suicide Risk Assessment on Social Media: Quantitative Evaluation of Model Performance, Potentials and Limitations. *arXiv preprint arXiv:2306.09390*.

[2] Harrigian, K., Aguirre, C., & Dredze, M. (2020). On the state of social media data for mental health research. *arXiv preprint arXiv:2011.05233*.

[3] Song, H., Shin, J., Lee, H., & Park, J. C. (2023). A Simple and Flexible Modeling for Mental

Disorder Detection by Learning from Clinical Questionnaires. *arXiv preprint arXiv:2306.02955*.

[4] Wu, B., Cheng, W. H., Zhang, Y., Huang, Q., Li, J., & Mei, T. (2017). Sequential prediction of social media popularity with deep temporal context networks. *arXiv preprint arXiv:1712.04443*.

[5] Bucur, A. M., Cosma, A., Rosso, P., & Dinu, L. P. (2023, March). It's Just a Matter of Time: Detecting Depression with Time-Enriched Multimodal Transformers. In *European Conference on Information Retrieval* (pp. 200-215). Cham: Springer Nature Switzerland.

[6] Medruț, F. P. (2021). The Impact of Social Media Use on Adolescent Mental Health–Depression and Anxiety: A Review. *Social Work Review/Revista de Asistenta Sociala*, (2).

[7] Santarossa, S., & Woodruff, S. J. (2017). # SocialMedia: Exploring the relationship of social networking sites on body image, self-esteem, and eating disorders. *Social Media+ Society*, *3*(2), 2056305117704407.

[8] Cingel, D. P., Carter, M. C., & Krause, H. V. (2022). Social media and self-esteem. *Current Opinion in Psychology*, *45*, 101304.

[9] Rui, J. R., & Stefanone, M. A. (2013). Strategic image management online: Self-presentation, self-esteem and social network perspectives. *Information, Communication & Society*, *16*(8), 1286-1305.

[10] The Effects of Instagram's Visual Culture on Users' Body Image and Mental Health

[11] Gkotsis, G., Oellrich, A., Velupillai, S., Liakata, M., Hubbard, T. J., Dobson, R. J., & Dutta, R. (2017). Characterisation of mental health conditions in social media using Informed Deep Learning. *Scientific reports*, *7*(1), 45141.

[12] McGorry, P. D., Purcell, R., Hickie, I. B., & Jorm, A. F. (2007). Investing in youth mental health is a best buy. *Medical Journal of Australia*, *187*(S7), S5-S7.

[13] Georgakopoulou, A. (2011). Computer-mediated communication. *Pragmatics in practice*, *9*, 93.

[14] Nesi, J. (2020). The impact of social media on youth mental health: challenges and opportunities. *North Carolina medical journal*, *81*(2), 116-121.

[15] Hou, Y., Xiong, D., Jiang, T., Song, L., & Wang, Q. (2019). Social media addiction: Its impact, mediation, and intervention. *Cyberpsychology*, *13*(1).

[16] Nesi, J. (2020). The impact of social media on youth mental health: challenges and opportunities. *North Carolina medical journal*, *81*(2), 116-121.

[17] Strickland, A. (2014). Exploring the effects of social media use on the mental health of young adults.

[18] Hou, Y., Xiong, D., Jiang, T., Song, L., & Wang, Q. (2019). Social media addiction: Its impact, mediation, and intervention. *Cyberpsychology*, *13*(1).

[19] Nesi, J. (2020). The impact of social media on youth mental health: challenges and opportunities. *North Carolina medical journal*, *81*(2), 116-121.

[20] Vidal, C., Lhaksampa, T., Miller, L., & Platt, R. (2020). Social media use and depression in adolescents: a scoping review. *International Review of Psychiatry*, *32*(3), 235-253.

[21] the University of Maryland Reddit Suicidality Dataset(UMD) (Zirikly et al., 2019; Shing et al., 2018)

[22] (Guntuku et al., 2017; Wongkoblap et al., 2017; Chancellor and De Choudhury, 2020

[23] Abdel-Baki, A., Lal, S., Charron, D.-C., Stip, E., & Kara, N. (2017). Etc

[24] Institute of Computing Technology, Chinese Academy of Sciences, China 2University of Chinese Academy of Sciences, China 3Academia Sinica, Taiwan 4University of Surrey, UK 5Microsoft Research, China.[24]

[25] [DataReportal – Global Digital Insights](#)

[GitHub - cime-enriched-multimodal-depression-detection](#)

To benchmark our method, we use in our experiments multiRedditDep [51] and the Twitter multimodal depression dataset from Gui et al. [20]7 . Reddit and Twitter are two of the most popular social media platforms where users choose to disclose their mental health

problems.[25]

[26]. GitHub - sergioburdisso/pyss3: A[26]
[27]

[27] M. H. Al Banna, T. Ghosh, K. A. Taher, M. S. Kaiser, and M. Mahmud, ''A monitoring system for patients of autism spectrum disorder using artificial intelligence,'' in Proc. Int. Conf. Brain Informat. Cham, Switzerland: Springer, 2020, pp. 251–262.

[28] M. S. Kaiser, K. T. Lwin, M. Mahmud, D. Hajializadeh, T. Chaipimonplin, A. Sarhan, and M. A. Hossain, ''Advances in crowd analysis for urban applications through urban event detection,'' IEEE Trans. Intell. Transp. Syst., vol. 19, no. 10, pp. 3092–3112, Oct. 2018.

[29] M. Mahmud and M. S. Kaiser, ''Machine learning in fighting pandemics: A COVID-19 case study,'' in COVID-19: Prediction, Decision-Making, and its Impacts (Lecture Notes on Data Engineering and Communications Technologies), K. Santosh and A. Joshi, Eds. Singapore: Springer, 2021, pp. 77–81.

[30] N. Dey, V. Rajinikanth, S. Fong, M. Kaiser, and M. Mahmud, ''Social group-optimization assisted Kapur's entropy and morphological segmentation for automated detection of COVID-19 infection from computed tomography images,'' Cogn. Comput., vol. 12, no. 5, pp. 1011–1023, 2020.