Indian Journal of Natural Sciences *www.tnsroindia.org.in ©IJONS*

Vol.15 / Issue 84 / Jun / 2024 *International Bimonthly (Print) – Open Access* *ISSN: 0976 – 0997*

RESEARCH ARTICLE

A Comprehensive Review on Artificial Intelligence based Depression Detection through Social Media Data Analysis

T.Tamil Elakya[1]* and K.Manikandan[2]

[1]Research Scholar, Department of Computer Science, PSG College of Arts and Science, Coimbatore - 641014, Tamil Nadu, India.
[2]Associate Professor, Department of Computer Science, PSG College of Arts and Science, Coimbatore - 641014, Tamil Nadu, India.

Received: 22 Jan 2024 Revised: 09 Feb 2024 Accepted: 11 May 2024

***Address for Correspondence**
T.Tamil Elakya
Research Scholar,
Department of Computer Science,
PSG College of Arts and Science,
Coimbatore - 641014, Tamil Nadu, India.
Email: tamilelakya360phd@gmail.com

ABSTRACT

Depression is a range of psychological conditions that affect attitude, feelings, and overall well-being, and is influenced by various factors. Common symptoms include negative emotions, loss of interest, and persistent sadness. Maintaining a high quality of life is important for managing mental health issues. Social media plays a significant role in allowing individuals to express their emotions and share life events. As mental health challenges continue to increase, there is growing interest in using social network data for early detection of depression. Recent years have seen progress in using Artificial Intelligence (AI) to identify depression on online platforms. This manuscript surveys AI frameworks, such as Machine Learning (ML) and Deep Learning (DL) algorithms, utilized in studies of depression detection from 2020 to 2023. The paper not only presents advancements but also examines the limitations and challenges of these algorithms, such as data heterogeneity, noise, and the subjective nature of mental health expressions online. It aims to identify research gaps and suggest future directions for improving methodologies on online platforms. This exploration contributes to the ongoing discussion about mental health and AI, with implications for researchers, practitioners, and policymakers.

Keywords: Depression detection, Social media, AI, Machine learning, Deep learning

INTRODUCTION

Depression is a widespread psychological issue affecting over 300 million individuals globally, with increased internet and social media use linked to higher rates of anxiety, depression, and suicide [1]. Women are twice as likely to experience depression as men. During the last centuries, 15.08% of young people aged 12-17 have experienced a minimum of a single catastrophic depression incident, with 10.6% dealing with acute depressive symptoms. Over 60% of young people with acute symptoms do not receive any therapy, and merely 27.2% receive regular therapy. Less than one in three young people with severe depression receive regular care, even when the number of visits is counted [2].

Types of Depression

Depression is categorized by symptoms such as unhappiness, lack of motivation, regret, poor dignity, inability to eat or sleep, fatigue, and failure to focus. It can lead to worsening conditions such as joint inflammation, asthma, cardiovascular disease, diabetes, and obesity. Depression may considerably affect an individual’s willingness to participate in everyday tasks, and can even lead to thoughts of suicide [3]. It can be divided into two groups based on the intensity of the symptoms: mild and temporary occurrences, and acute and chronic episodes of depression.

Two primary categories of depression include

- Major depressive disorder is an acute depression categorized by enduring melancholy, desperation, and unimportance [4]. A minimum of 5 depression signs should occur during a two-week period to be recognized. This condition is classified into unusual, hybrid, melancholy, psychotic, and catatonia by the American Psychiatric Association.
- Persistent Depressive Disorder (PDD): PDD, also called dysthymia, is a less acute yet constant category of depression. To be diagnosed, symptoms must be present for at least two years. It can have a greater impact on a person's life than major depression due to its longer duration [5]. Individuals with PDD often experience sadness, decreased productivity, low self-confidence, and a loss of motivation in daily tasks.

Social and Cultural Factors Influencing Depressive Disorders in India

Mental health diseases are widespread in India, affecting a significant portion of the population. The frequency of psychiatric illnesses in India ranges from 9.5 to 370 per 1000 individuals, reflecting the variety of mental health conditions prevalent in the nation [6]. Common mental health illnesses in India include depression, anxiety, bipolar syndrome, schizophrenia, and drug use conditions [7]. Several societal and cultural factors impact depression in India, including stigma surrounding mental illness, gender inequality, poverty, rapid urbanization, family dynamics, and cultural beliefs. These factors contribute to discrimination, isolation, fear, and limited access to quality care, and hinder open discussions about mental health. Addressing these issues is crucial to providing efficient interventions and support networks for the population's mental health needs.

Social Media Use and Depression

Social media usage is a highly popular online activity worldwide and it continues to grow. In 2017, over 2.73 billion people used social media, and this number is projected to reach6 billion by 2027 (see Figure 1). According to Figure 2, Facebook, the leading social networking platform, has over three billion monthly active users and was the first to reach 1 billion registered accounts. It is part of Meta Platforms, which also maintains WhatsApp, Facebook Messenger, and Instagram, with a combined total of over 1 billion monthly users. In the 2ndquarter of 2023, Facebook stated over 3.8 billion monthly active users. Social networking sites, existing in various languages, enable users to connect across borders. In 2024, these sites are expected to reach 5.17 billion users, with continued growth expected due to increased mobile device usage and access to underserved markets. Figure 3 shows that 53.8% of internet users globally are men, with 29.8% being aged 20-39, and 31% being aged 20-29, with users over 60 years making up only 9% of web activity in January 2023. According to Figure 4, in January 2023, Facebook's largest user base is aged 25-34, with 43% female. Instagram has 30.8% 18-24 users, with 17% male. Twitter has 62.9% male and 37.1% female. YouTube has 54% male users, while TikTok has 54% female users. Figure 5 shows that individuals with higher depression symptoms use social media more frequently [9], with 29% of those using it at least 58 times per week experiencing high depression symptoms, and only 16% experiencing low depression symptoms, compared to 36% of those using it 8 times or fewer. Additionally, it revealed that 32% of social media users follow therapists and mental health professionals, 25% follow individuals with similar mental health conditions, and 20% follow mental health advocates and brands. Frequent social media use is associated with negative moods and may contribute to higher rates of depression, leading to social isolation, reduced enjoyment in activities, and increased anxiety [10]. Multitasking can exacerbate feelings of shame, worthlessness, and jealousy. Comparing oneself online can trigger inadequate emotions, fueling a cycle of jealousy [11]. Studies suggest envy may be a cause of depression, not just a result of social media use. Negative experiences on social media can increase the risk of developing depression [12].

Social Networks as a Data Source for Depression Detection

Social networks are useful for detecting depression by analyzing the content and patterns of posts [13]. Key aspects include expressive content, sentiment analysis, behavioral patterns, temporal analysis, social collaboration dynamics, multimodal data analysis, and real-time monitoring. Users often share personal experiences and emotions on social media, allowing for the identification of linguistic cues associated with depression. Natural Language Processing (NLP) techniques can assess sentiment, while changes in online behavior can signal emotional distress. Temporal analysis offers insights into the progression of depressive symptoms, while multimodal data analysis provides a comprehensive understanding of an individual's digital footprint and emotional expressions.

Significance of Depression Detection

Detecting depression from social media involves analyzing language, behavior, and social interactions to identify potential signs of depression [14]. This information can be used to provide early intervention and support for those struggling with depression, leading to more effective treatment, reduced stigma, and improved resource allocation. In the workplace, early detection can safeguard employee well-being and improve productivity, ultimately transforming lives and promoting empathy [15].

General Methodology for Depression Detection

The detection process involves data pre-processing, feature extraction, feature selection, and classification to detect depression levels [16], as illustrated in Figure 6. This section describes each phase in detail.

- **Pre-processing:** It is a crucial process in analyzing online information, ensuring that the data is clean and suitable for analysis [17]. Key steps include identifying relevant platforms, collecting data using APIs or web scraping tools, cleaning the text by removing irrelevant characters and symbols, breaking down the text into individual words, eliminating common words, reducing words to their base form, handling missing values, removing duplicates, converting emojis and emoticons, normalizing numerical features, converting categorical variables, removing irrelevant data points, handling timestamps and time zones, and addressing class imbalances.
- **Feature extraction:** It involves extracting relevant features that capture linguistic, behavioral, and contextual patterns associated with depressive symptoms [18]. Depression detection on social networking can be achieved using various feature extraction techniques. These include Bag-of-Words (BoW), TF-IDF (Term Frequency-Inverse Document Frequency), word embedding, N-grams, sentiment analysis, user features, content length, hashtag and mention counts, temporal features, user metadata, named entity recognition, network analysis, image and video features, topic modeling, and emotion analysis features. These methods help identify important words, user behavior, content complexity, and temporal patterns in social media behavior. They also consider user metadata, named entity recognition, network analysis, image and video features, topic modeling, and emotion analysis features. These techniques help in identifying important words, identifying latent topics, and analyzing emotional content in social media data.

- **Feature selection:** It is a technique used to choose the most significant features by removing redundant ones [19]. Common feature selection techniques include SelectKBest, Particle Swarm Optimization (PSO), maximum Relevance Minimum Redundancy (mRMR), Boruta, and ReliefF.
- **Classification:** Social media data is often used to detect depression by using classification algorithms, which include both ML and DL models to differentiate between people with and without depressive symptoms [20].The most widely used ML-based classification algorithms [21-23] are Naïve Bayes (NB), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), Gradient Boosting DT (GBDT), Extreme Gradient Boosting (XGBoost),Logistic Regression (LR), and Support Vector Regression (SVR).DL is a category of ML that allows machines to understand the domain through a pyramid of concepts. This allows for complex ideas to be learned by building them from simpler ones. Neural Networks (NNs) such as Artificial NN (ANN), Deep NN (DNN), CNN, and Recurrent NN (RNN) are used as classifiers in detecting depressive disorders [24-26].

This review explores the use of AI in detecting depression through user-generated content on social media. It surveys ML and DL algorithms used for depression detection, highlighting advancements and examining limitations. Additionally, it aims to identify research gaps and suggest future directions to improvedepression detection methodologies on online platforms.

SURVEY ON DEPRESSION DETECTION FROM SOCIAL MEDIA USING ARTIFICIAL INTELLIGENCE MODELS

Recent studies on detecting depression from online data is primarily split into ML and DL models. This review covers the use of these models in systems developed to identify depression from online information, organized by year of publication.

ML-Based Depression Detection

Online platforms are often utilized to identify depression owing to the large quantity of user-created text data and societal behavior. Many studies have used outdated MLalgorithms, along with feature engineering techniques to classify and identify depression in online users. This section provides a review of some of these studies. de Jesús Titla-Tlatelpa et al. [27] developed a profile-based sentiment-aware technique using SVM and RF classifiers to detect depression in social media. This technique focuses on classifying user profiles (e.g., males or females) and analyzing the opinions conveyed in their posts using a novel text representation, which learns their polarity (e.g., +ve or -ve). Aguilera et al. [28] used a One-Class Categorizer (OCC) for detecting depression in online networks. They also introduced a new measure for determining the relevance of texts for a given task, using lexicons demarcated by standard knowledge-based techniques. Chiong et al. [29] explored the use of ML classifiers and online data to identify depression in users' posts, even without explicit keywords such as 'depression' or 'diagnosis'. Zhou et al. [30] conducted a study on the detection of community depression dynamics in Australia caused by the COVID-19 epidemic using user-created information on Twitter. First, sentiment, subject, and domain-explicit traits were retrieved. Then, the TF-IDF was developed to accurately identify depression in tweets. Pool-Cen et al. [31] developed a simple classification algorithm to differentiate between tweets associated with depression in English and Spanish.Safa et al. [32] developed an automated method for analyzing tweets and predicting depression signs using N-gram, LIWC lexicons, automated picture labeling, BoW, correlation-based attribute selection, and multiple supervised classifiers. Ghosal & Jain [33] introduced a method for detecting depression on online platforms. The Reddit text data was first pre-processed and normalized. Then, TF-IDF and fast Text embedding were applied to obtain attributes, which were later passed to the XGBoost classifier to identify depressive content. Table 1 evaluates the ML algorithms used in the above-discussed studies for depression detection.

DL-Based Depression Detection

Recent studies have shown that DL is more accurate and reliable than traditional ML methods to identify depression in online users. DL's ability to learn complex patterns from large datasets has led to superior performance in depression detection. This section will review recent studies on DL-based approaches for detecting depression from online information. Ding et al. [34] collected Sina Weibo data of college students, utilized DNN for extracting attributes, and adopted a Deep Integrated SVM (DISVM) classifier to detect depression. Wu et al. [35] developed a new method called D3-HDS (DL-based Depression Detection for Heterogeneous Data Sources) using the RNN to calculate the post representations for each individual, which were then integrated into the content-based, social, and living atmosphere attributes to estimate the individual's depression using DNN. Shrestha et al. [36] developed an unsupervised technique using RNN to identify miserable users. They analyzed the users' comments and their networking behavior in the forum. First, user embedding was computed from their post sequence using RNN and then combined with networking behavior. Then, unsupervised anomaly detection was used to classify users as depressed or not. Chiu et al. [37] developed a multimodal depression detection system for Instagram, focusing on the timing of posts. A depression lexicon was generated to gather information on users with miserable tendencies. A 2-phaserecognition strategy was also developed to identify miserable users based on the time interval between their posts.Ren et al. [38] developed a new sentiment-based attention network model for improved depression identification, combining semantic and sentiment understanding networks to extract +ve and -ve emotional data. Lara et al. [39] developed Deep Bag-of-Sub-Emotions (DeepBoSE) to detect depression in online using a differentiable BoW. This model enhances standard BoF that may not be easily combined with the DL structures.

Cha et al. [40] developed the DL prediction system to identify high-risk groups for depression using social media data. They classified depression posts in multiple languages and created a depression vocabulary for all languages. Ansari et al. [41] introduced a hybrid ensemble learning approach for automated depression detection, which involves pre-processing social media posts, extracting sentiment features, using an attention-based LSTM for temporal characteristics, and a linear classifier for final prediction, combining outputs in an ensemble classifier. Amanat et al. [42] developed a text prediction model utilizing One-Hot encoding, Principal Component Analysis (PCA), and LSTM with RNN to detect depression early. Yang et al. [43] developed the KC-Net model utilizing Gated Recurrent Units (GRU) and a knowledge-aware mentalization module to detect depression on online platforms. Nijhawan et al. [44] conducted a study to identify depression in individuals depending on online posts and comments. They utilized large-scale datasets, and Bidirectional Encoder Representations from Transformers (BERT). Additionally, they used Latent Dirichlet Allocation (LDA) to identify word and phrase patterns within documents. Rizwan et al. [45] developed deep-transfer learning language models to classify depression from tweets using a labeled dataset. They assessed the efficiency of different transformer-based models and fine-tuned them for three intensity classes:'severe','moderate', and'mild'. Zhou et al. [46] created a Time-aware Attention Multimodal Fusion Network (TAMFN) to detect depression in video content using non-verbal cues like acoustics and visuals. The TAMFN model includes a Temporal Convolutional Network (GTCN), Intermodal Feature Extraction (IFE), and a Time-aware Attention Multimodal Fusion (TAMF) module. The GTCN extracts local and global time-based features, IFE captures similarity features, and the TAMF guides feature fusion.

The fused features were then fed to the fully connected layer to detect depression. Zogan et al. [47] developed the Multi-Aspect Depression Detection with Hierarchical Attention Network (MDHAN) to automatically identify miserable users on online platforms. The model uses attention strategies at the tweet and word levels to calculate the importance of all tweets and words, obtaining semantic sequence characteristics for reasonable outcomes. Kour and Gupta [48] developed a hybrid DLframework to detect depression from user tweets utilizing a feature-rich CNN and Bidirectional LSTM (BiLSTM). The model categorizes depressive and non-depressive tweets, analyzing semantic context. Nadeem et al. [49] developed a method using Natural Language Processing (NLP) and DL techniques to detect depression from text data. They manually annotated a tweet dataset, creating binary and ternary labels. This DL-based hybrid SSCL classification framework utilized GloVe for feature extraction, LSTM-CNN for capturing tweet sequence and semantics, GRUs with self-attention for capturing contextual and hidden features, and a fully connected layer for identifying depression. Li et al. [50] developed a Multimodal Hierarchical Attention (MHA) framework to detect depression on online platforms, processing multiple data types simultaneously and using an attention mechanism to identify depression-related information. A distribution normalization method improved performance by aligning data distribution. Table 2 evaluates the DL algorithms used in the above-discussed studies to identify depression on social networks. The reviewed studies show different methods for using ML and DL algorithms to detect depression in social media users. Each algorithm has strengths and weaknesses, highlighting the complexity of detecting depression. Evaluation metrics like Acc, P, R, and F1 offer awareness of algorithm effectiveness. Figure 7-10 illustrates the importance of selecting the most suitable algorithm based on specific context and data characteristics. It can be inferred that [49] achieves the highest Acc and F1, [48] has the maximum P, and [38] has the highest R compared to other DL algorithms. However, a robust ensemble DL algorithm that incorporates multi-source data is necessary to improve depression detection accuracy as the field evolves.

CONCLUSION

This article discusses recent studies on using AI to identify depression from online text. Additionally, it highlights the importance of advanced AI techniques in depression detection. The study found that DL with attention strategies is more effective than traditional ML for detecting depression. Future advancements could include multimodal analysis, temporal analysis, and privacy-preserving methods. These techniques could enable real-time monitoring and proactive interventions, while also addressing privacy concerns and promoting user acceptance.

REFERENCES

1. J.M. Twenge, "Increases in Depression, Self-Harm, and Suicide among US Adolescents after 2012 and Links to Technology Use: Possible Mechanisms," *Psychiatric Research and Clinical Practice*, vol. 2, no. 1, pp. 19-25, Sep. 2020.
2. *The State of Mental Health in America*. (n.d.). Mental Health America. https://www.mhanational.org/issues/state-mental-health-america
3. M.D. Manzar, A. Albougami, N. Usman, and M.A. Mamun, "Suicide among Adolescents and Youths during the COVID-19 Pandemic Lockdowns: A Press Media Reports-Based Exploratory Study," *Journal of Child and Adolescent Psychiatric Nursing*, vol. 34, no. 2, pp. 139-146, May 2021.
4. L. Gutiérrez-Rojas, A. Porras-Segovia, H. Dunne, N. Andrade-González, and J.A. Cervilla, "Prevalence and Correlates of Major Depressive Disorder: A Systematic Review,"*Brazilian Journal of Psychiatry*, vol. 42, pp. 657-672, Aug. 2020.
5. E. Schramm, D.N. Klein, M. Elsaesser, T.A. Furukawa, and K. Domschke, "Review of Dysthymia and Persistent Depressive Disorder: History, Correlates, and Clinical Implications," *The Lancet Psychiatry*, vol. 7, no. 9, pp. 801-812, Sep. 2020.
6. R. Sagar, R. Dandona, G. Gururaj, R.S. Dhaliwal, A. Singh, A. Ferrari, ... and L. Dandona, "The Burden of Mental Disorders across the States of India: The Global Burden of Disease Study 1990–2017," *The Lancet Psychiatry*, vol. 7, no. 2, pp. 148-161, Feb. 2020.
7. V.R. Meghrajani, M. Marathe, R. Sharma, A. Potdukhe, M.B. Wanjari, A.B. Taksande, ... and M. Wanjari, "A Comprehensive Analysis of Mental Health Problems in India and The Role of Mental Asylums," *Cureus*, vol. 15, no. 7, pp. 1-11, Jul. 2023.
8. M.G. Hunt, R. Marx, C. Lipson, and J. Young, "No More FOMO: Limiting Social Media Decreases Loneliness and Depression," *Journal of Social and Clinical Psychology*, vol. 37, no. 10, pp. 751-768, Dec. 2018.
9. L.Y. Lin, J.E. Sidani, A. Shensa, A. Radovic, E. Miller, J.B. Colditz, ... and B.A. Primack, "Association between Social Media Use and Depression among US Young Adults," *Depression and Anxiety*, vol. 33, no. 4, pp. 323-331, Apr. 2016.
10. Z.E. Seidler, M.J. Wilson, S.M. Rice, D. Kealy, J.L. Oliffe, and J.S. Ogrodniczuk, "Virtual Connection, Real Support? A Study of Loneliness, Time on Social Media and Psychological Distress among Men," *International Journal of Social Psychiatry*, vol. 68, no. 2, pp. 288-293, Mar. 2022.
11. J. Goodwin, L. Behan, and N. O'Brien, "Teachers' Views and Experiences of Student Mental Health and Well-Being Programmes: A Systematic Review," *Journal of Child & Adolescent Mental Health*, vol. 33, no. 1-3, pp. 55-74, Sep. 2021.

12. A.Hartanto, F.Y. Quek, G.Y. Tng, and J.C. Yong, "Does Social Media Use Increase Depressive Symptoms? A Reverse Causation Perspective," *Frontiers in Psychiatry*, vol. 12, p. 641934, Mar. 2021.
13. F.T. Giuntini, M.T. Cazzolato, M.D.J.D. dos Reis, A.T. Campbell, A.J. Traina, and J. Ueyama, "A Review on Recognizing Depression in Social Networks: Challenges and Opportunities," *Journal of Ambient Intelligence and Humanized Computing*, vol. 11, pp. 4713-4729, Nov. 2020.
14. K.C. Bathina, M. Ten Thij, L. Lorenzo-Luaces, L.A. Rutter, and J. Bollen, "Individuals with Depression Express more Distorted Thinking on Social Media," *Nature Human Behaviour*, vol. 5, no. 4, pp. 458-466, Apr. 2021.
15. L.E. Søvold, J.A. Naslund, A.A. Kousoulis, S. Saxena, M.W. Qoronfleh, C. Grobler, and L. Münter, "Prioritizing the Mental Health and Well-Being of Healthcare Workers: An Urgent Global Public Health Priority," *Frontiers in Public Health*, vol. 9, p. 679397, May 2021.
16. S. Aleem, N.U. Huda, R. Amin, S. Khalid, S.S. Alshamrani, and A. Alshehri, "Machine Learning Algorithms for Depression: Diagnosis, Insights, and Research Directions,"*Electronics*, vol. 11, no. 7, p. 1111, Mar. 2022.
17. M.O. Hegazi, Y. Al-Dossari, A. Al-Yahy, A. Al-Sumari, and A. Hilal, "Preprocessing Arabic Text on Social Media," *Heliyon*, vol. 7, no. 2, pp. 1-15, Feb. 2021.
18. S. Guohou, Z. Lina, and Z. Dongsong, "What Reveals about Depression Level? The Role of Multimodal Features at the Level of Interview Questions," *Information & Management*, vol. 57, no. 7, p. 103349, Nov. 2020.
19. Z. Dai, H. Zhou, Q. Ba, Y. Zhou, L. Wang, and G. Li, "Improving Depression Prediction Using a Novel Feature Selection Algorithm Coupled with Context-Aware Analysis,"*Journal of Affective Disorders*, vol. 295, pp. 1040-1048, Dec. 2021.
20. N.V. Babu and E.G.M. Kanaga, "Sentiment Analysis in Social Media Data for Depression Detection Using Artificial Intelligence: A Review," *SN Computer Science*, vol. 3, pp. 1-20, Jan. 2022.
21. D. Liu, X.L. Feng, F. Ahmed, M. Shahid, and J. Guo, "Detecting and Measuring Depression on Social Media Using a Machine Learning Approach: Systematic Review," *JMIR Mental Health*, vol. 9, no. 3, p. e27244, Mar. 2022.
22. A. Ahmed, S. Aziz, C.T. Toro, M. Alzubaidi, S. Irshaidat, H.A. Serhan, ... andM. Househ, "Machine Learning Models to Detect Anxiety and Depression through Social Media: A Scoping Review," *Computer Methods and Programs in Biomedicine Update*, vol. 2, p. 100066, Sep. 2022.
23. J. Mothe, F. Ramiandrisoa, and M.Z. Ullah, "Comparison of Machine Learning Models for Early Depression Detection from Users' Posts," In: *Early Detection of Mental Health Disorders by Social Media Monitoring: The First Five Years of the eRisk Project*, Cham: Springer International Publishing,pp. 111-139, Sep. 2022.
24. M.Z. Uddin, K.K. Dysthe, A. Følstad, and P.B. Brandtzaeg, "Deep Learning for Prediction of Depressive Symptoms in a Large Textual Dataset," *Neural Computing and Applications*, vol. 34, no. 1, pp. 721-744, Jan. 2022.
25. S. Ghosh and T. Anwar, "Depression Intensity Estimation via Social Media: A Deep Learning Approach," *IEEE Transactions on Computational Social Systems*, vol. 8, no. 6, pp. 1465-1474, Jun. 2021.
26. J. Kim, J. Lee, E. Park, and J. Han, "A Deep Learning Model for Detecting Mental Illness from User Content on Social Media," *Scientific Reports*, vol. 10, no. 1, p. 11846, Jul. 2020.
27. J. de Jesús Titla-Tlatelpa, R.M. Ortega-Mendoza, M. Montes-y-Gómez, and L. Villaseñor-Pineda, "A Profile-Based Sentiment-Aware Approach for Depression Detection in Social Media," *EPJ Data Science*, vol. 10, no. 1, p. 54, Dec. 2021.
28. J. Aguilera, D.I.H. Farías, R.M. Ortega-Mendoza, and M. Montes-y-Gómez, "Depression and Anorexia Detection in Social Media as a One-Class Classification Problem," *Applied Intelligence*, vol. 51, pp. 6088-6103, Aug. 2021.
29. R. Chiong, G.S. Budhi, S. Dhakal, and F. Chiong, "A Textual-Based Featuring Approach for Depression Detection Using Machine Learning Classifiers and Social Media Texts,"*Computers in Biology and Medicine*, vol. 135, p. 104499, Aug. 2021.
30. J. Zhou, H. Zogan, S. Yang, S. Jameel, G. Xu, and F. Chen, "Detecting Community Depression Dynamics due to Covid-19 Pandemic in Australia," *IEEE Transactions on Computational Social Systems*, vol. 8, no. 4, pp. 982-991, Jan. 2021.

31. J. Pool-Cen, H. Carlos-Martínez, G. Hernández-Chan, and O. Sánchez-Siordia, "Detection of Depression-Related Tweets in Mexico Using Crosslingual Schemes and Knowledge Distillation,"*Healthcare*, vol. 11, no. 7, p. 1057, Apr. 2023.
32. R. Safa, P. Bayat, and L. Moghtader, "Automatic Detection of Depression Symptoms in Twitter Using Multimodal Analysis," *The Journal of Supercomputing*, vol. 78, no. 4, pp. 4709-4744, Mar. 2022.
33. S. Ghosal and A. Jain, "Depression and Suicide Risk Detection on Social Media Using fastText Embedding and XGBoost Classifier," *Procedia Computer Science*, vol. 218, pp. 1631-1639, Jan. 2023.
34. Y. Ding, X. Chen, Q. Fu, and S. Zhong, "A Depression Recognition Method for College Students Using Deep Integrated Support Vector Algorithm," *IEEE Access*, vol. 8, pp. 75616-75629, Apr. 2020.
35. M.Y. Wu, C.Y. Shen, E.T. Wang, and A.L. Chen, "A Deep Architecture for Depression Detection Using Posting, Behavior, and Living Environment Data," *Journal of Intelligent Information Systems*, vol. 54, pp. 225-244, Apr. 2020.
36. A.Shrestha, E. Serra, and F. Spezzano, "Multi-Modal Social and Psycho-Linguistic Embedding via Recurrent Neural Networks to Identify Depressed Users in Online Forums," *Network Modeling Analysis in Health Informatics and Bioinformatics*, vol. 9, pp. 1-11, Dec. 2020.
37. C.Y. Chiu, H.Y. Lane, J.L. Koh, and A.L. Chen, "Multimodal Depression Detection on InstagramConsidering Time Interval of Posts," *Journal of Intelligent Information Systems*, vol. 56, 25-47, Feb. 2021.
38. L. Ren, H. Lin, B. Xu, S. Zhang, L. Yang, and S. Sun, "Depression Detection on Reddit with an Emotion-Based Attention Network: Algorithm Development and Validation," *JMIR Medical Informatics*, vol. 9, no. 7, p. e28754, Jul. 2021.
39. J.S. Lara, M.E. Aragón, F.A. González, and M. Montes-y-Gómez, "Deep Bag-of-Sub-Emotions for Depression Detection in Social Media," In" *Proceedings of 24th International Conference on Text, Speech, and Dialogue*, Springer International Publishing, pp. 60-72, Sep. 2021.
40. J. Cha, S. Kim, and E. Park, "A Lexicon-Based Approach to Examine Depression Detection in Social Media: The Case of Twitter and University Community," *Humanities and Social Sciences Communications*, vol. 9, no. 1, pp. 1-10, Sep. 2022.
41. L. Ansari, S. Ji, Q. Chen, and E. Cambria, "Ensemble Hybrid Learning Methods for Automated Depression Detection," *IEEE Transactions on Computational Social Systems*, vol. 10, no. 1, pp. 211-219, Mar. 2022.
42. A. Amanat, M. Rizwan, A.R. Javed, M. Abdelhaq, R. Alsaqour, S. Pandya, and M. Uddin, "Deep Learning for Depression Detection from Textual Data,"*Electronics*, vol. 11, no. 5, p. 676, Feb. 2022.
43. K. Yang, T. Zhang, and S. Ananiadou, "A Mental State Knowledge–Aware and Contrastive Network for Early Stress and Depression Detection on Social Media," *Information Processing & Management*, vol. 59, no. 4, p. 102961, Jul. 2022.
44. T. Nijhawan, G. Attigeri, and T. Ananthakrishna, "Stress Detection Using Natural Language Processing and Machine Learning over Social Interactions," *Journal of Big Data*, vol. 9, no. 1, pp. 1-24, Dec. 2022.
45. M. Rizwan, M.F. Mushtaq, U. Akram, A. Mehmood, I. Ashraf, and B. Sahelices, "Depression Classification from Tweets Using Small Deep Transfer Learning Language Models,"*IEEE Access*, vol. 10, pp. 129176-129189, Nov. 2022.
46. L. Zhou, Z. Liu, Z. Shangguan, X. Yuan, Y. Li, and B. Hu, "TAMFN: Time-Aware Attention Multimodal Fusion Network for Depression Detection," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, pp. 669-679, Nov. 2022.
47. H. Zogan, I. Razzak, X. Wang, S. Jameel, and G. Xu, "Explainable Depression Detection with Multi-Aspect Features Using a Hybrid Deep Learning Model on Social Media,"*World Wide Web*, vol. 25, no. 1, pp. 281-304, Jan. 2022.
48. H. Kour and M.K. Gupta, "An Hybrid Deep Learning Approach for Depression Prediction from User Tweets Using Feature-Rich CNN and Bi-Directional LSTM," *Multimedia Tools and Applications*, vol. 81, no. 17, pp. 23649-23685, Jul. 2022.
49. A. Nadeem, M. Naveed, M. Islam Satti, H. Afzal, T. Ahmad, and K.I. Kim, "Depression Detection Based on Hybrid Deep Learning SSCL Framework Using Self-Attention Mechanism: An Application to Social Networking Data," *Sensors*, vol. 22, no. 24, p. 9775, Dec. 2022.

50. Z. Li, Z. An, W. Cheng, J. Zhou, F. Zheng, and B. Hu, "MHA: A Multimodal Hierarchical Attention Model for Depression Detection in Social Media," *Health Information Science and Systems*, vol. 11, no. 1, p. 6, Jan. 2023.

Table 1. Comparison of ML-Based Depression Detection Models

Ref. No.	Algorithms	Benefits	Limitations	Data Source	Evaluation Metrics
[27]	SVM and RF	Gender-based classification was highly effective than age-based ones.	The results were impacted by the size and time variation in users' message records.	Reddit and Twitter	**F1:** *Gender-based classifier:* Reddit = 0.71; Twitter = 0.89 *Age-based classifier:* Reddit = 0.68; Twitter = 0.88
[28]	OCC with k-strongest strengths scheme	A competitive method for detecting psychologicalillnesses from online data.	There are often few positive examples (depressed individuals), which creates an imbalanced dataset and makes it difficult for the model to accurately identify positive cases.	Depression and Anorexia collections from eRisk forum	Average F1 = 0.557
[29]	LR, linear kernel SVM, Multi-Layer Perceptron (MLP), DT, RF, adaptive boosting, bagging predictors, and GB	The efficiency was enhanced when utilizing less rigidly structured corpora, particularly while detecting depression in data from various sources.	The training of the classifiers was restricted to using labeled datasets, and the accuracy was decreased in a dataset with a significant imbalance.	Twitter, Victoria's diary, Reddit, and Facebook	**Twitter:** Acc = 99.8%; **Victoria's diary:** Acc = 1.61%; **Reddit:** Acc = 40.54%; **Facebook:** Acc = 16.3%
[30]	TF-IDF features, LR, linear discriminant analysis, and Gaussian NB (GNB)	It can efficiently identify community depression dynamics at the nation level.	There was no analysis done on how depression changed over period and in different locations.	Twitter	**LR:** Acc = 0.903; P = 0.908; R = 0.899; F1 = 0.902 **Linear discriminant analysis:** Acc = 0.904; P = 0.912; R = 0.899; F1 = 0.903 **GNB:** Acc = 0.879; P = 0.891; R = 0.874;

					F1 = 0.878
[31]	Knowledge distillation, IVIS-based dimensionality reduction, LR, SVM, and Quadratic Discriminant Analysis (QDA)	Improved performance even without labeled data.	High computational cost due to two stages: building embedded space for sentences in different languages and using dimensionality reduction algorithms.	Twitter data in English and Spanish languages	**LR:** Acc = 0.95; P = 0.96; R = 0.94; F1 = 0.95 **SVM:** Acc = 0.95; P = 0.96; R = 0.93; F1 = 0.95 **QDA:** Acc = 0.95; P = 0.96; R = 0.93; F1 = 0.94
[32]	SVM, LR, DT, GB, RF, Ridge categorizer, AdaBoost, CatBoost, and MLP	The performance was acceptable.	It did not take into account every significant attribute in the user profile.	Twitter	**LR:** Acc = 0.75; P = 0.74; R = 0.75; F1 = 0.75 **GB:** Acc = 0.91; P = 0.97; R = 0.84; F1 = 0.89 **Ridge categorizer:** Acc = 0.77; P = 0.77; R = 0.75; F1 = 0.76 **CatBoost:** Acc = 0.91; P = 0.99; R = 0.82; F1 = 0.89 **MLP:** Acc = 0.70; P = 0.69; R = 0.72; F1 = 0.7
[33]	fastText embedding and XGBoost	High accuracy of classifying lengthy Reddit posts.	It needs various negative emotions and anxiety-based features.	Reddit	P = 0.71; R = 0.71; F1 = 0.71; Acc = 71.05%

***Note: P=Precision; R=Recall; F1=F1 score; Acc=Accuracy**

Table 2. Comparative Analysis of DL-Based Depression Detection Systems

Ref. No.	Algorithms	Benefits	Limitations	Data Source	Evaluation Metrics
[34]	DISVM	It decreased the execution period and increased detection efficacy.	The accuracy relies on the selection of features, which was subjective in this case.	Sina Weibo	**Precision:** Training = 0.881; Testing = 0.8615
[35]	D3-HDS using RNN and DNN	By concurrently considering all content-based, behavioral, and demographic features, it can achieve better performance.	Additional features such as demographic and psychological characteristics are needed to enhance the efficiency of detection.	Real dataset include Facebook records and the CES-D screening test results	P = 83.3%; R = 71.4%; F1 = 76.9%
[36]	RNN	Improved detection by fusing network and psycho-linguistic features.	The performance depends on the choice of model parameters.	ReachOut.com platform	F1 = 0.64; P = 0.64 R = 0.64
[37]	AlexNet, BiLSTM, RF and AdaBoost	It improved detection performance.	Collecting more data features took a long time.	Instagram	P = 0.895; R = 0.782; F1 = 0.835
[38]	BiLSTM & dynamic fusion mechanism	Improved detection by incorporating emotional semantic information.	Multitask learning was essential for detecting depression based on symptom levels.	Reddit	Acc = 91.3%; P = 91.91%; R = 96.15%; F1 = 93.98%
[39]	DeepBoSE	The performance was satisfactory.	The deep representation learning capability was ineffective.	eRisk17 and eRisk18	**eRisk2017:** F1 = 0.6415; Acc = 0.91; P = 0.6296; R = 0.6538 **eRisk2018:** F1 = 0.6545; Acc = 0.93; P = 0.6279; R = 0.6835
[40]	1D-CNN, BiLSTM, and BERT	It achieved a satisfactory F1 score.	The accuracy between different domain communities was low due to the absence of demographic data.	Twitter data in Koeran, English, and Japanese languages	**Acc:** 1D-CNN = 0.5831; BiLSTM = 0.5638; BERT = 0.7252
[41]	LR and attention-based LSTM with linear classifier	Using sentiment lexicon features results in enhanced performance.	It should be included additional features like POS tags to	CLPsych, Reddit, and eRisk	**CLPsych:** P = 0.655; R = 0.65; F1 = 0.6509;

			handle imbalanced datasets.		Acc = 0.65 **Reddit:** P = 0.8115; R = 0.7512; F1 = 0.7701; Acc = 0.751 **eRisk:** P = 0.8005 R = 0.7455; F1 = 0.7655; Acc = 0.755
[42]	One-hot encoding, PCA, LSTM and RNN	It achieved maximum accuracy.	It didn't consider user's behavior and psycho-linguistic features.	Tweets-Scraped dataset from Kaggle	P = 0.98; R = 0.99; F1 = 0.98; Acc = 99%
[43]	KC-Net using GRU	It can maximize performance by fully utilizing label information to capture class-specific features.	It did not taken into account other information like demographic and behavior features of users.	Depression_Mixed, Dreaddit, and SAD	**Depression_Mixed:** P = 95.5%; R = 95.3%; F1 = 95.4% **Dreaddit:** P = 84.1%; R = 83.3%; F1 = 83.5% **SAD:** P = 75.6%; R = 77.6%; F1 = 77%
[44]	LDA and BERT	It achieved the highest accuracy.	It did not take into account the mental health factors, making it difficult to handle bipolar emotions.	Twitter	Acc = 94%
[45]	Electra small generator, Electra small discriminator, XtremeDistil-L6, and Albert base V2	It achieved a high F1 score in a relatively short training time per epoch.	The model was trained using short tweets, so it may not be effective at predicting the intensity of depression in longer pieces of text.	Twitter	**Acc:** Electra smallgenerator = 92%; Electra small discriminator = 92%; XtremeDistil-L6 = 92%; Albert base V2 = 92%
[46]	TAMFN	By combining multiple features, it was able to achieve a high recall rate.	Accurate detection was difficult to get because of the varying distribution of test and training data	D-Vlog dataset from YouTube	P = 66.02%;R = 66.5%; F1 = 65.82%

			caused by the complexity and noise of non-verbal variables.		
[47]	MDHAN	Computationally effective for identifying depressed users.	It didn't consider a mix of short and long user-generated content.	Twitter	Acc = 0.89; P = 0.902; R = 0.892; F1 = 0.893
[48]	Feature-rich CNN and BiLSTM	The best detection performance was achieved.	Various mixtures of NN layers and activations should be explored to increase the model's accuracy.	Twitter	Acc = 94.28%; P = 96.99%; R = 92.66%; F1 = 94.8%
[49]	Hybrid SSCL	Detection performance was improved.	The tweet did not accurately convey the context and subject, making it difficult for classification of multiple classes.	Twitter dataset from Kaggle	**Binary data:** Acc = 97%; F1 = 97.4% **Ternary data:** Acc = 82.9%; F1 = 82.9%
[50]	MHA	This improves data distribution and detection efficiency.	The user's data does not show signs of depression, making it challenging for the model to make accurate predictions.	Sina Weibo	Acc = 92.84%; F1 = 92.78%

***Note: P=Precision; R=Recall; F1=F1 score; Acc=Accuracy**

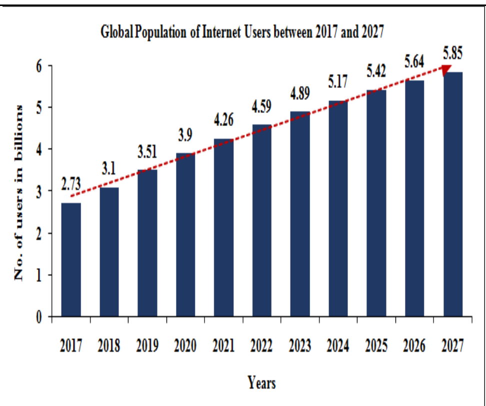

Figure 1. No. of Internet Users Worldwide between 2017 and 2027(Source: Statista 2024)

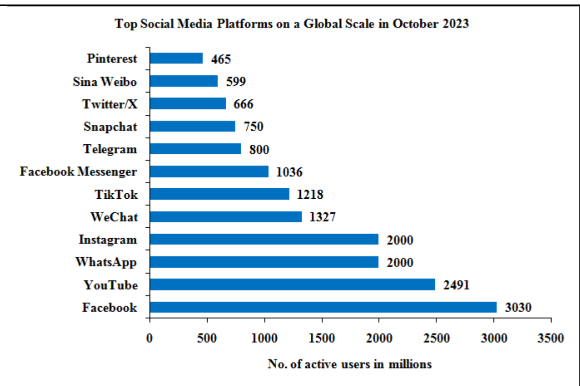

Figure 2. Social Media Platforms Sorted by No. of Users Worldwide in 2023 (Source: Statista 2024)

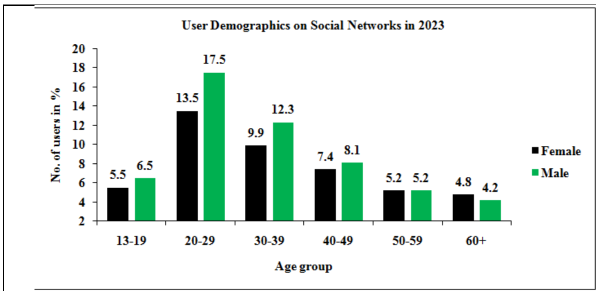

Figure 3. User Demographicson Social Networks in 2023 (Source: datareportal.com June 2023)

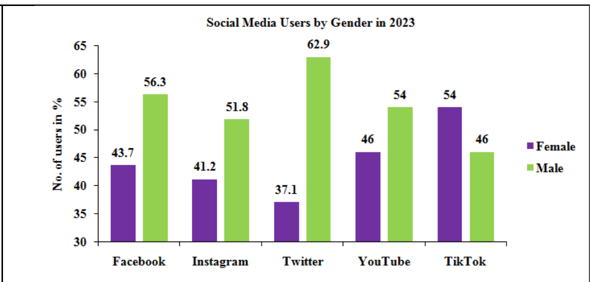

Figure 4. Social Media Users by Gender in 2023 (Source: Social media statistics and trends in 2024 by Antara Agarwal)

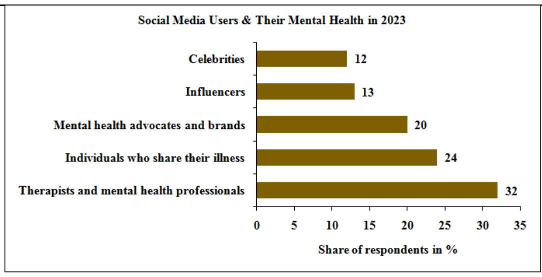

Figure 5. Social Media Users & Mental Health in 2023 (Source: StyleCaster; Mental.; The Mental Health Coalition; 2023; 2255 respondents; 25-44 years; active social media users)

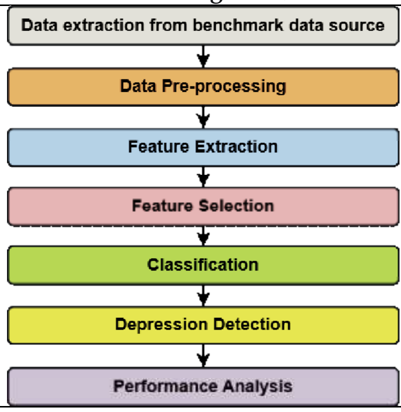

Figure 6. General Methodology in Depression Detection

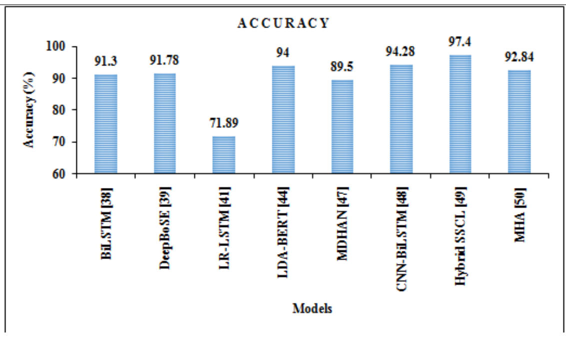

Figure 7. Comparison of Accuracy for Different Depression Detection Models

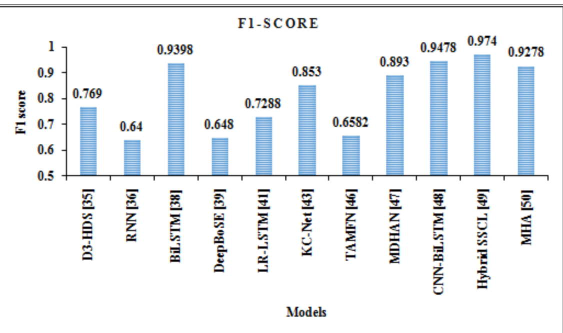

Figure 8. Comparison of F1 Score for Different Depression Detection Models

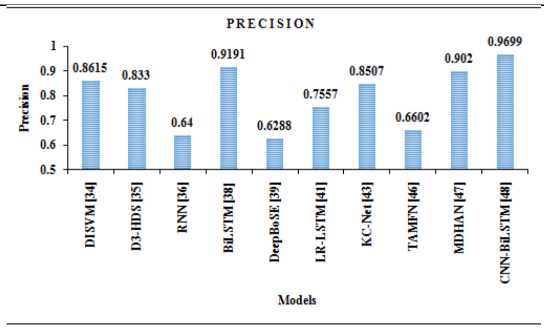

Figure 9. Comparison of Precision for Different Depression Detection Models

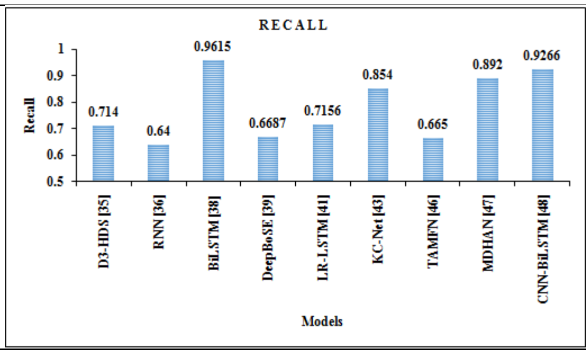

Figure 10. Comparison of Recall for Different Depression Detection Models