International Journal of Scientific Research in Computer Science, Engineering and Information Technology

ISSN : 2456-3307 OPEN ACCESS

Available Online at : www.ijsrcseit.com

doi : https://doi.org/10.32628/CSEIT2390510

Detecting Depression on Social Media : A Comprehensive Review on AI in Mental Health

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ARTICLE INFO

Article History:

Accepted: 05 Sep 2023

Published: 16 Sep 2023

Publication Issue

Volume 9, Issue 5

September-October-2023

Page Number

103-117

ABSTRACT

Social media platforms are vast reservoirs of human sentiment and behaviour, making them ripe for depression detection. This literature review delves into approaches for this detection using data analysis, deep learning, natural language processing (NLP), and machine learning (ML). We discuss data types used and explore deep learning techniques like CNN, RNN, and DNN, applied across platforms such as Facebook, Twitter, and Reddit. The review also highlights NLP's role and ML algorithms, notably SVM, Naive Bayes, K-Nearest Neighbour, Random Forest, and Decision Trees. We analyse depression causes, its link with social media, and variations across age and gender. This comprehensive study guides researchers and practitioners in technology-driven mental health solutions.

Keywords : Depression Detection, Social Media Analysis, Deep Learning Techniques, Natural Language Processing, Machine Learning Algorithms, Data Analysis, Mental Health, Age and Gender Variability

I. INTRODUCTION

Social media offers insights into human sentiments and a tool for mental health monitoring. As depression concerns rise, its detection becomes crucial. This paper explores depression detection using data analysis, deep learning techniques (CNN, RNN, DNN), and NLP. We delve into ML, highlighting SVM, Naive Bayes, K-Nearest Neighbour, Random Forest, and Decision Trees. We also examine depression causes, social media's influence, and variations across age and gender.

This review aims to bolster future innovations in tech-driven mental health solutions.

1.1 DATA ANALYSIS:

Data analysis is the process of cleaning, transforming and modeling of raw data to discover useful information and make an analysis using various techniques. To mention some of the techniques used include filtering, processing, categorizing, condensing and contextualizing the data.

Data analysis is like a spotlight on information. It shows future trends using past data. For example, businesses predict popular products by looking at past sales. It also helps find patterns. This could be when a website is busiest or how customers behave over time. These patterns guide decisions.

Digging into data also shows hidden links. This might be how shopping habits relate to music tastes or the link between weather and flu outbreaks. Understanding these relationships helps in many areas, from business to daily life. Overall, data analysis gives us foresight and a deeper understanding in various fields.

Data analysis has clear goals-:

- One main aim is prediction. In banking, it predicts if a transaction might be fraudulent. In weather forecasting, it predicts rain on specific days. In healthcare, it's used to determine if a tumour is benign or malignant.
- Another goal is to detect patterns. Weather data can show us the top 10 coldest days in a year. Website analysis highlight the most visited pages on a site. And by analysing search data, we can see which celebrity was most searched in a given year.
- The third goal is finding relationships. Search engines like Bing and Google use it to find similar news articles. In healthcare, similar patient records can be identified. E-commerce sites use it to recommend related products. And analysts might look for links between news items and stock prices.

1.2 DEEP LEARNING:

Deep learning is a subset of machine learning that utilises neural networks to copy the human brain functioning. "Deep" refers to multiple layers in a neural network. In contrast, shallow neural networks have a maximum of two layers between input and output [1]. Deep learning has many applications. These include computer vision, phonetic recognition, and voice search. It's used in conversational speech recognition and coding features in speech and images. It helps in classifying semantic utterances and understanding natural language. Hand-writing recognition, audio processing, and information retrieval also benefit from it. Even robotics and new drug discoveries rely on deep learning analysis of molecules as reported recently by [2]. It requires large dataset and high computation power to be used efficiently.

1.3 NATURAL LANGUAGE PROCESSING (NLP):

Natural Language Processing (NLP) is a subset of artificial intelligence focused on human-computer language interaction. It helps machines understand and interpret human language [3]. NLP can play a significant role in retrieving data from social media and for detecting or predicting depression. We will see in the next sections that the data is sorted by countries such as Russia, Spain, Thailand, Bangladesh, and Arab nations. Each country has unique depression patterns. This approach shows cultural variations in depression expression. It also emphasizes early detection methods. NLP can play a significant role in retrieving data from social media and for detecting or predicting depression in the following ways:

- **Text Analysis:** NLP scans social media content for depressive keywords and patterns.

- **Sentiment Analysis:** The technology gauges user sentiment, identifying negative tones or despair.
- **Temporal Analysis:** Post frequency and timing can highlight erratic sleep or inactivity.
- **Linguistic Patterns:** NLP detects language nuances, like increased self-reference, hinting at depression.
- **Topic Modeling:** Techniques like LDA flag posts around sadness or hopelessness.
- **Interaction Analysis:** Evaluating user interactions can reveal negative exchanges or peer concerns.
- **Data Aggregation:** NLP combines various data points, offering a comprehensive view of a user's mental state.

1.4 MACHINE LEARNING (ML):

The process of teaching a system to make accurate predictions using data is called as machine learning [4]–[6]. Machine learning shows the working of an algorithm which learns more accurate in its predictions [7].The basic approaches that involves in the machine learning are supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning [8].

- **Supervised Learning**: It involves labeled data to train models and make predictions.
- **Unsupervised Learning**: This method uses unlabeled data to find patterns and structures.
- **Semi-Supervised Learning**: It combines labeled and unlabeled data for training, bridging the gap between supervised and unsupervised learning.
- **Reinforcement Learning**: It focuses on decision-making by training agents through interaction with an environment to maximize rewards.

1.5 SENTIMENT ANALYSIS OF SOCIAL MEDIA:

Sentiment Analysis classifies text as positive, negative, or neutral. It aims to gauge public interest to aid business growth, focusing on polarity and emotions like happiness or anger. Using Natural Language Processing algorithms, it mines word context to gauge brand sentiment and predict market product demand [8]. Two techniques used for sentiment analysis include:

- Rule-based Sentiment Analysis: Uses rules and polarity-labeled words to discern text sentiment, often needing enhancements for sarcasm, negations, or dependent clauses.
- Machine Learning-based Analysis: Trains models to determine polarity considering word order, using sentiment-labeled datasets.

1.6 DEPRESSION:

Globally, depression is a prevalent mental health issue affecting countless individuals across all demographics. Manifesting as constant sadness, hopelessness, and lost interest in previously cherished activities, it's not just a mental burden but also a physical threat. The World Health Organization labels it a top disability cause worldwide. Due to its multifaceted nature, research delves deep into understanding its triggers, trajectories, and treatment avenues.

1.6.1 DEPRESSION BECAUSE OF SOCIAL MEDIA:

The ascent of social media in the modern era raises mental health concerns. Numerous studies indicate that heavy use correlates with increased depression, anxiety, and loneliness. While these platforms connect individuals, they simultaneously become breeding grounds for comparison, cyberbullying, and the spread of impractical standards. The constant flow of 'perfect life' portrayals heightens feelings of worthlessness and detachment. The adverse effects don't stop there; extended usage can disrupt sleep and increase screen exposure, amplifying mental health woes.

This relationship between depression and social media is underscored by a detrimental 'feedback loop'. Users, seeking refuge or diversion, often find content reinforcing their desolation, perpetuating their depressive moods.

1.6.2 DIFFERENCES IN AGE AND GENDER ON SOCIAL MEDIA:

The interplay between social media and depression exhibits variations across ages and genders. Particularly susceptible are adolescents and young adults, still forming their self-concepts. The need for approval and identity formation at this stage makes them prime targets for the negatives of online comparison and the quest for validation.

For example, teenage girls, under societal beauty pressures, might find curated 'perfect body' content distressing. On the other hand, young men may struggle with adhering to portrayed 'masculinity' standards.

Older individuals, although fewer on these platforms, face their challenges. Often, their mental strain arises from feelings of disconnect or being left behind in the rapid digital evolution.

The gender perspective adds complexity. Women, given their higher online presence, endure more virtual harassment, intensifying their depressive triggers. In contrast, men might internalize struggles, stemming from societal masculinity norms, complicating early identification and intervention.

II. METHODOLOGIES

2.1 DATA ANALYSIS:

As discussed earlier, data analysis predicts trends, spots patterns, and finds relationships in diverse fields. Similarly with the rise of social media, researchers collect data from these social media platforms to spot signs of depression in users. Our aim is to categorize this data by country. This list includes countries like Russia, Spain, Thailand, Bangladesh, and Arab nations. Each country has unique patterns related to depression. This approach helps understand how different cultures view and express depression and how various methodologies were used to detect depression at an earlier stage.

Language can show our thoughts, and psychiatrists use it to check mental health. Nowadays, computers help study social media posts of people feeling down. There are a few ways to do this. One way is to look for phrases like “I was diagnosed with depression” on Twitter. Another is using online surveys. People fill them out, and if they show signs of depression, their social media is checked. Another method looks at users in specific online groups, like certain Reddit communities as mentioned in [9]. In a similar way, we’ll employ various algorithms to achieve the same goal.

2.1.1 TYPES OF DATA:

2.1.1.1 QUALITATIVE DATA ANALYSIS:

Qualitative data analysis delves into non-numerical data to understand patterns, themes, and meanings. This form of analysis is instrumental when aiming to grasp underlying motivations, reasons, or opinions. Often used in social sciences, it provides depth and context to phenomena.

Qualitative data analysis is intricate. Descriptions of its practical aspects can oversimplify the process. There isn't a singular approach to handling this data; it's often best learned through practice. Despite its challenges, the research literature doesn't extensively address it. Many researchers face issues that question the reliability of their findings. Moreover, there's a notable absence of guidelines for analysing vast amounts of qualitative interview data [10], [11].

2.1.1.2 QUANTITATIVE DATA ANALYSIS

Quantitative data analysis evaluates numerical data using statistical methods. It allows for measurable, objective outcomes. Common in scientific research, this approach is useful for generalizing results across larger populations and drawing precise conclusions.

Qualitative data analysis is frequently linked with text analysis. This association has caused some hesitation among researchers. They are deterred from integrating such data into quantitative models. The primary challenge lies in the difficulty of transforming qualitative data into a quantitative format [12].According to [13], a mixed-method network analysis can be used to manage and transform secondary data. This approach harnesses the depth of qualitative analysis to guide the creation and examination of quantitative data in social network structures or relationships.

2.2 DEEP LEARNING:

We studied DL's objective to emulate the human brain's structure for optimal problem-solving. The study employed three prominent DL algorithms: DNN, CNN, and RNN, implemented using the Python-based Keras library. The researchers converted tweets into integer vectors, with each word represented by its dictionary number, maintaining word sequence. Rather than using TF-IDF, which was ineffective for their dataset, they established word embeddings from scratch for Arabic tweets via a one-hot bag-of-word encoding. The dataset was split into 20% testing and 80% training, employing a five-fold cross-validation. Their model consisted of four layers: Input, Embedding, Flatten, and Dense layers [3].

2.2.1 TECHNIQUES:

2.2.1.1 CNN:

CNNs, inspired by human and animal brain neurons, offer three key benefits: parameter sharing, sparse interactions, and equivalent representations. Instead of using fully connected networks, CNNs leverage local connections and shared weights, capitalizing on the two-dimensional input data structure. This reduces parameters, making the network quicker and simpler to train. Essentially, these cells focus on specific parts of a scene, acting as local filters that detect spatial correlations in the data [14].

2.2.1.2 RNN:

RNN leverages sequential data, essential in applications where data sequence patterns provide valuable insights. An RNN, a DL network with internal loops, predicts the next value using prior information. These networks effectively identify data sequences, retain key features, and forecast future data [15].

2.2.1.3 DNN:

The DNN determines the appropriate mathematical operations to convert input into output, whether linear or non-linear. The network processes layers to compute the likelihood of each outcome. Each such operation constitutes a layer, with complex DNNs having multiple layers, leading to the term "deep" networks. The aim is for the network to break down images into features, recognize consistent trends, and classify new images based on similarities autonomously [16].

2.3 NLP:

We have already discussed about the various analysis we can do using NLP, applied to social media data which aids in depression detection. Through specialized techniques mentioned below, relevant information is extracted to identify signs of depression in users.

2.3.1 NORMALIZATION

Standardizes text. It can involve lowercasing words, removing numbers and punctuation, changing text numbers to numerals, and expanding abbreviations.

2.3.2 STOP WORD REMOVAL

Stop Word Removal gets rid of frequently used words like "and", "the", and "is", which often don't add value in NLP tasks.

2.3.3 STEMMING

Stemming identifies words with similar meanings, reduces redundancy, and obtains the base form by removing suffixes.[17], [18] For example, "running" becomes "run". However, stemming might not always produce actual words, like "flies" to "fli".

2.3.4 TOKENIZATION

Tokenization is a fundamental step in natural language processing. Essentially, it involves breaking down text into smaller pieces, called tokens. These tokens are sequences of characters grouped together. When you take a piece of text, be it a sentence or a document, and run it through a tokenization process, you're converting that text into these individual tokens. Each token stands as a countable unit. These units or tokens play a crucial role in many NLP tasks, as they can be employed as features or attributes in algorithms and models, aiding in tasks like text classification, sentiment analysis, and more [18]–[20].

2.4 MACHINE LEARNING:

We'll explore five leading classification algorithms: SVM, KNN, RF, NB, and J48 [3]. Below, we offer a theoretical overview for each classifier.

2.4.1 SVM:

SVM, introduced by Vapnik, aims to divide data into two classes using an optimal hyperplane, thereby grouping similar items [21].

2.4.2 NAIVE BAYES

The NB algorithm classifies data using Bayes' theorem, assuming no inter-feature relationships [22]. It's simple yet effective, especially with large datasets. The method determines similarity by measuring distances between documents [23].

2.4.3 K NEAREST NEIGHBOUR:

Based on proximity, data close to each other are deemed similar and distant ones dissimilar. KNN is a lazy learning algorithm relying on statistics. However, selecting the optimal value of K is a limitation of KNN [24].

2.4.4 RANDOM FOREST:

RF boasts high flexibility and accuracy, excelling particularly with large datasets. However, its complexity results in longer implementation times. The algorithm uses numerous trees for comparison [25] and outperforms SVM in terms of accuracy, especially when handling large datasets [26].

2.4.5 DECISION TREES J48:

This algorithm segments data into subsets using specific attributes. In the decision tree model, each node signifies an input variable (x) and its split point. The DT is quick to learn, versatile in addressing various problems, and requires no data preparation [27], [28].

2.5 DEPRESSION:

2.5.1 DEPRESSION DETECTION ON VARIOUS PLATFORMS:

2.5.1.1 TWITTER:

Boasting 326 million users and 90 million daily tweets, Twitter provides invaluable data for understanding social dynamics and emotions [29].

Prominent Studies on Twitter and Mental Health:

- **De Choudhury** [30]:
  - **Focus**: Linguistic patterns in tweets hinting at depression.
  - **Method**: They utilized specific linguistic features to train a model. The classifier was designed to sift through a vast number of tweets and detect those indicative of depression.
  - **Significance**: This marked a shift towards automated depression detection, paving the way for early interventions based on digital footprints.

- **Coppersmith** [31]:
  - **Focus**: Explicit mentions of depression.
  - **Method**: The researchers zeroed in on tweets with straightforward declarations like "I was just diagnosed with depression."
  - **Significance**: By targeting overt mentions, they ensured higher accuracy in detecting genuinely depressed individuals.

- **Preotiuc-Pietroi** [32]:
  - **Focus**: Broader textual patterns related to PTSD.
  - **Method**: A combination of techniques was used, including Latent Dirichlet Allocation (LDA), Linguistic Inquiry and Word Count (LIWC), and frequent 1-3 grams.
  - **Findings**: Users proclaiming PTSD were notably older and exhibited a heightened sense of conscientiousness when compared to those with depression.
  - **Significance**: The study illuminated the overlap between language predictive of depression, PTSD, and personality traits. It suggested that certain personality types might be more inclined to share their mental health status on social media.

- **Resnik** [33]:
  - **Focus**: Identifying topics related to depression.
  - **Method**: Leveraging the LDA model, the team aimed to unearth latent structures and topics that could be indicative of depressive sentiments.
  - **Significance**: Their work validated the LDA model as a potent tool for zeroing in on relevant topics, making automated depression detection more nuanced and accurate.

- **Tsugawa's Study** [34]:
  - **Focus**: Analyzing tweets from a Japanese demographic.
  - **Method**: A concentration on topic modeling to discern depressive or suicidal tendencies in users.
  - **Findings**: Topic modeling, even in a culturally distinct dataset, proved invaluable in recognizing depressive sentiments.

- **Benton** [35]:
  - **Focus**: The potential of multi-task learning models.
  - **Method**: The study utilized feed-forward networks and multi-task models, focusing on predicting multiple conditions simultaneously or individually.
  - **Significance**: The experiments demonstrated that multi-task learning could effectively function in the domain of mental health, especially when target data might be limited.

- **Reece** [36]:
  - **Focus**: Early detection of depression onset.

- **Findings**: It was observed that Twitter data could hint at the initial stages of depression several months before a clinical diagnosis.
- **Significance**: This opens avenues for preventive measures and early interventions, offering a more proactive approach to mental health care.

Twitter, more than a social platform, emerges as a crucial tool in mental health research. By integrating machine learning, linguistic analysis, and algorithms, it allows for predictive analysis and early intervention in mental health. As the digital age progresses, platforms like Twitter will remain central to combining technology and mental health care.

2.5.1.2 FACEBOOK:

Holding a staggering user base of 2.2 billion, Facebook isn't merely a social platform—it's an expansive reservoir of data ripe for exploration [29].

Prominent Studies on Facebook and Mental Health:

- **Moreno** [37]:
  - **Focus**: Analysing status updates of Facebook users.
  - **Method**: The study delved into 200 user statuses. The aim was to spot self-revelations of mental distress, particularly through expressions like "I feel hopeless."
  - **Significance**: Such research paves the way for real-time depression detection, potentially signalling individuals in need of help.

- **Schwartz** [38]:
  - **Focus**: The nature and intensity of depression.
  - **Method**: Schwartz didn't perceive depression as merely present or absent. He approached it as a spectrum.
  - **Findings**: The study shed light on the seasonality of depression, emphasizing its fluctuating nature. There was a notable uptick in depressive sentiments during the colder, winter months.
  - **Significance**: This insight into the seasonality of depression challenges traditional, static views of the condition. By acknowledging its dynamic nature, researchers and clinicians can better address and anticipate depressive bouts.

- **Eichstaedt, J.C.** [39]:
  - **Focus**: Predicting depression through electronic medical records.
  - **Method**: Eichstaedt sought to understand if online records could signal upcoming depressive episodes within a six-month timeframe. The study achieved an AUC performance of 0.72.
  - **Findings**: Eichstaedt's research tapped into Facebook statuses of patients from a particular emergency department. These statuses, when aligned with their medical records, showed linguistic markers of depression. Notably, they included heightened perceptual processes, mentions of sadness, disparities, and an overall surge in negative emotions.
  - **Significance**: The merger of online behaviour with electronic medical records can be transformative. Not only does it validate the predictive power of social media in mental health diagnostics, but it also emphasizes the value of linguistic cues. Words, phrases, and the overall tone can become instrumental in early detection, potentially averting crisis situations.

Facebook's enormous user engagement transforms it into an indispensable tool for researchers. Beyond its social connectivity, it serves as a mirror reflecting global mental health patterns. Individual status updates, often considered mundane or routine, carry weight.

They can act as distress signals, highlighting potential mental health concerns. As technology intertwines more deeply with our daily lives, platforms like Facebook will increasingly become integral to health diagnostics. Their data, when interpreted accurately, can drive early interventions, fostering a proactive approach to mental health. This crossroad of technology and health stands as a testament to the evolving landscape of diagnostics and care.

2.5.1.3 REDDIT:

Reddit, a renowned online forum, is characterized by its structure of diverse communities, known as "subreddits." It stands out due to its commitment to user anonymity. This particular feature has made it a favored platform for discussing taboo or stigmatized subjects.

Prominent Studies on Reddit and Mental Health:

- **Choudhury** [30]:
  - **Focus**: Behavioural shifts in Reddit users.
  - **Method**: The research centered on users initially discussing general mental health topics and then transitioning to suicidal ideation.
  - **Findings**: Specific indicators forecasted this shift: increased self-focus, a deteriorating linguistic style, diminished social interaction, and heightened feelings of hopelessness or anxiety.

- **Bagroy** [40]:
  - **Focus**: Mental health trends among university students.
  - **Method**: This study inspected posts from college students across 100+ universities.
  - **Findings**: An upward trend in depression-linked posts was observed throughout the academic year. This uptick was especially pronounced at institutions following a quarter-based academic calendar.

- **Maupom** [41]:
  - **Focus**: Utilization of topic extraction and neural networks.
  - **Method**: The system revolved around an algorithm extracting 30 latent topics, paired with rudimentary neural networks.
  - **Findings**: The effectiveness of the Multi-layer Perceptron (MLP) was restricted by the limited user data.

Recent Developments and Collaborative Initiatives:

Recently, the value of collective tasks suited for varied contexts has surged within the broad research community. One such initiative, the CLEF eRISK or the Conference and Labs of Evaluation Forum for Early Risk Prediction, is a notable example. This forum propels interdisciplinary collaboration, anchoring the development of standardized measures for assessing early risk detection tools across diverse fields, including health and safety.

Specifically, CLEF eRISK 2018 spotlighted the early identification of depression and anorexia markers. Their primary data source? Reddit textual content. To derive actionable insights from this rich dataset, participants employed a gamut of machine learning approaches and honed feature engineering strategies [42]–[44].

Reddit, given its unique structure and emphasis on anonymity, emerges as an instrumental resource for mental health researchers. The platform's capacity to host candid conversations on sensitive subjects provides unprecedented insights into user psyche and behaviour. As studies like those of Choudhury, Bagroy, and Maupom demonstrate, there's immense potential in harnessing this data for early detection and intervention. Collaborative forums like CLEF eRISK further amplify the platform's relevance, indicating a promising trajectory for Reddit-based mental health research in the years to come.

2.5.2 DEPRESSION DETECTION IN VARIOUS COUNTRIES:

When it comes to understanding and predicting depression based on social media activities, various countries have employed different methodologies, revealing unique findings.

In **Thailand**, the primary medium of analysis was Facebook. The findings reveal that one's activity and messages on the platform can be predictive of depression. However, this research was hampered by a smaller sample size, a direct result of Facebook's restrictive data collection policy. Another limitation was the potential for translation errors, given the necessity of translating Thai language features into English for analysis. This translation could inadvertently leave out crucial sentiment-related words, leading to potential inaccuracies [45].

Contrastingly, **China** approached the problem by analysing the natural language used on social media. They identified that the specific choice of words and phrases can serve as markers to differentiate those vulnerable or at risk. Notably, this study highlights the importance of cultural nuances. Such subtleties can heavily influence the effectiveness of these markers, which means any automatic computer program aiming to assist in assessing risk needs to account for these cultural differences to remain accurate [46].

The **Arabic nations** employed a more technologically intricate method by proposing a deep learning model for emotion classification on tweets. Several preparatory steps were used, including normalization and stemming, and an emphasis was placed on translating frequently used emojis into their actual meanings. For feature selection, word embeddings, specifically the Aravec pre-trained model with Continuous Bag of Words (CBOW), were deemed the most efficient. Interestingly, Bi-directional Long Short-Term Memory (BiLSTM) was the classification method of choice, primarily because it provided a more comprehensive understanding of context and enhanced information flow. It's noteworthy that this method also faced limitations, particularly due to the Keras library's inability to support specific functions [47].

Bangladesh shared a similar approach to the Arabic nations. They employed the same deep learning model and faced analogous challenges, particularly concerning the limitations of the Keras library [48].

Lastly, **Spain** sought to understand emotion recognition in their native language texts. They experimented with two different machine learning strategies and delved deep into the efficacy of various emotion lexicons. One significant finding was that language-specific resources could drastically enhance emotion recognition systems. It was discovered that merely translating lexicons from one language to another was insufficient due to inherent cultural differences in word usage. This revelation emphasizes the need for dedicated research in creating emotion lexicons for languages beyond English [49].

In conclusion, while each country and culture presents its unique challenges and intricacies, advancements in AI techniques are providing promising pathways for depression detection across the globe. However, it's crucial to consider the cultural and linguistic nuances of each region to ensure the accuracy and effectiveness of these methods.

2.5.3 DEPRESSION DIFFERENCES IN AGE AND GENDER ON SOCIAL MEDIA:

Reading some researchers, our study aimed to replicate prior research on the relationship between age and depression in a mixed-age group of unipolar major depression patients referred to a mood disorders unit. It was found that certain diagnoses and clinical features, including melancholia [50], psychosis, psychomotor agitation[51], retardation, non-interactiveness, hypochondriasis [52], and severe guilt, were more prevalent in older patients. Hypersomnia was less common, and clinician-rated depression severity increased with age. These effects seemed to be age-related rather than linked to depressive recurrence, except for hypochondriasis, which was more frequent in patients with a later onset of depression [53].

The study confirmed differences in the severity of subjectively and clinician-rated depression measures. Older patients had lower subjective depression scores but higher objective scores, with the gap widening with age, possibly due to variations in scale items or older individuals accepting depressive symptoms as normal. The findings underscored the importance for clinicians to not rely solely on spontaneous depression complaints.

Moreover, the research highlighted gender-related differences in the effects of age on depression phenomenology. Older women were more likely to experience motor agitation, severe guilt, psychomotor changes, and more severe psychological depression symptoms [54]. This gender effect became apparent when age and gender were considered together. While elderly men and women were not significantly different cross-sectionally, their lifetime patterns of depressive phenomenology might diverge around age 60, influenced by factors like increased depression acceptance in older women.

In summary, older age was associated with melancholic and psychotic depression, certain clinical features, and diagnostic differences in unipolar depression. Phenomenological distinctions, such as increased hypochondriasis, guilt, and decreased appetite, were observed with age, while older individuals tended to underreport symptom severity. Age at onset had limited influence on phenomenology, and gender differences in depression severity were more pronounced in older age groups, particularly among women [55].

III. CONCLUSION

Depression detection on social media represents a progressive stride in modern health solutions. The literature reaffirms the efficacy of combined data analysis, deep learning, NLP, and machine learning techniques to tackle this challenge. Social media platforms, replete with human sentiments, provide rich datasets. Their unique characteristics have driven varied technological approaches.

Deep learning, through CNN, RNN, and DNN, demonstrates compelling capability in discerning intricate patterns in content, both textual and visual. On platforms like Facebook, laden with multimedia, these models excel. NLP emerges powerfully on text-intensive platforms like Twitter and Reddit. Through NLP, linguistic nuances and user sentiments are captured meticulously, enriching detection outcomes.
Machine learning algorithms, including SVM, Naive Bayes, K-Nearest Neighbour, Random Forest, and Decision Trees, have exhibited consistent utility. Less complex than deep learning, they offer interpretability and reliability, invaluable in scenarios where clarity surpasses complexity.

Social media's connection with depression is dual-edged. On one side, platforms can amplify stress or facilitate cyberbullying. Conversely, they're an unmatched data source for early intervention. As platforms intertwine with daily life, they wield potential both as potential triggers and detection tools.

Demographics, notably age and gender, critically influence depression's detectability. Teenagers might openly express their mental states, whereas other age brackets might be reserved. Gender-driven expression differences, shaped by societal norms, necessitate adaptive detection models. Addressing these demographic variations guarantees comprehensive detection.

Ethics emerges as a crucial facet. The promise of tech-driven mental health solutions should never overshadow concerns like user privacy, data security, or consent. Automated detection systems, while groundbreaking, cannot replace human empathy in mental health care.

This review encapsulates the promising fusion of technology and mental health. Deep learning, NLP, and ML's convergence promises precise detection and timely intervention. With ethically grounded and adaptive methodologies, the digital age can witness a revolution in mental health care.

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Cite this article as :

Tamanna Dhaker, Aarju Kumar, Dr. Abirami G "Detecting Depression on Social Media: A Comprehensive Review on AI in Mental Health", International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT), ISSN : 2456-3307, Volume 9, Issue 5, pp.103-117, September-October-2023. Available at doi : https://doi.org/10.32628/CSEIT2390510

Journal URL : https://ijsrcseit.com/CSEIT2390510