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Machine Learning Based Prediction and Recommendation System for Anxiety and Depression: A Comprehensive Survey and Analysis

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Abstract

People often express their emotional and mental state through social media platform. This review synthesizes the key findings from recent studies, reporting diverse approaches to the use of machine learning, natural language processing, and multimodal analysis of physiological and behavioral data. By leveraging diverse data types, including text, images, and videos, provide valuable insights into users' mental well-being. Predicating anxiety and depression based on social media content allows for early identification of mental health issues before they become severe. Earlier research was based on findings that social media can serve as a rich source of information for understanding users' emotional conditions. Additionally, discusses the need for automated systems that can detect depression across different age groups, utilizing sentiment analysis and facial expressions. The review paper provides a deep view of the current techniques and provide it's limitative along with the research challenges in the field of mental health issues diagnosis by using ML algorithms.

Introduction

Certainly, mental health state disorders presently represent one of the most enormous and fastest-growing public health challenges throughout the world, affecting tens of millions of people. Traditional methods are limited by subjective interpretations and may not capture the full spectrum of an individual's experience. Traditional approaches are also very laborious and susceptible to personal biases. Recent technological advancements, especially regarding AI and machine learning, have opened new ways toward more objective and quick identification of a mental health disorder. This review outlines recent progress in predicting mental health using technology and suggests the detection of early identification of various mental health conditions through machine learning, natural language processing & multimodal data analysis. These technologies use data from social media posts & physiological signals to neuroimaging detection and classification of variety of disorders, including depression, anxiety and suicidal ideation. Recent integrations of AI approaches and multimodal fusion techniques, hold great promise for both enhancement in the accuracy and scalability of mental health screening tools. It is therefore obvious that such developments offer a deeper understanding of the conditions but also invite new cultural adaptability and accessibility. Yet, even with these advances, a number of open issues still need to be taken into consideration, such as data confidentiality, diverse datasets, and clinical integration. This review aims to synthesize the key messages of such studies,

discussing both the potential impact of digital technologies on mental health care and those critical obstacles that must be overcome if its full benefit is to be realized in real- world settings.
The various methods for identifying anxiety and depression that have been created by various researchers are mentioned in Section II. Various challenges addressed are presented in Section
III. Section IV focuses on the proposed framework for detection of anxiety and depression.

Literature Review

The different techniques for detection of anxiety & depression have been developed by different researchers as follows:
Arfan Ahmed, Sarah Aziz, et al. [1] represents depression and anxiety are prevalent global mental health issues, with significant economic burdens and impact on individuals' health. Social media platforms provide a rich source of data that can be leveraged to develop predictive models for identifying mental health disorders based on user-generated content. Various AI, ML, and DL models including Ada-Boost, RF, CNN, LSTM and XGboost used to analyze data from different social sites. The predictive models used training data sets to learn patterns from social media content, with a focus on developing accurate models for mental health disorder detection. It is a need to focus on the level of predictive power required to justify the risks and consequences of false- negatives & false-positives in predictive models for mental health disorder detection.
Riya Aggarwal, Anjali Goyal [2] gives the significance of supervised learning in training machine learning algorithms using labelled datasets for effective data classification and prediction. The proposed system used four key ML algorithms as DT, NB, RF and Logistic Regression. Decision Tree is described as a method for processing output in a clear and interpretable manner, suitable for knowledge discovery despite potential accuracy limitations. The paper may not fully capture the complexities of relationship between youths online gaming and mental health issues like anxiety and depression.
Manju lata joshi, Nehal kanoongo [3] highlight the importance of automated systems to detect depression across different age groups and the need for effective identification methods. This paper uses various sources like sentiment analysis of Twitter tweets, facial expressions, and chatbots for detecting depression. Techniques such as NB, SVM and LSTM are used for emotion recognition from text and image processing. RF and Gradient Boosting Classifier is also used for classification tasks. Principal Component Analysis (PCA) extracts facial attributes for emotion detection. Haar-cascade algorithms detect facial expressions in images. Textual sentiment analysis is a non-invasive technique, it may not capture the full spectrum of an individual's mental health status.
Vandana, Nikhil Marriwala, et al. [4] emphasizes the importance of early detection of depression to provide timely treatment and support to individuals. This paper integrates CNN and LSTM algorithms to create a hybrid structure for depression detection. Textual CNN and audio CNN models are developed alongside a hybrid LSTM & Bi-LSTM model for enhanced accuracy. The model leverages audio features like Mel spectrograms and text responses to predict depression with high accuracy and minimal loss. The DAIC-WOZ database, which includes audio, video, and text responses from patients, serves as the primary dataset for the automatic depression detection system. The hybrid model combines audio and text features, the integration process may not fully capture the complexities of human emotions and behaviors associated with depression. This could lead to oversimplified interpretations of the data
P Lakshmi Priya, R Vijaya Prakash [5] majority of adults today use social networking sites like Facebook, Instagram, and Twitter to share updates about their lives. Social networking sites like Twitter have become platforms where users share updates about their lives, including their feelings and emotions. Authors have compared different methods for detecting depression, such as using tweets & texts over a period to predict scores on depression screening instruments. NLP techniques are employed to analyze the text data from social media platforms. It proposes a machine learning model that can learn to answer depression questionnaires and make population-level predictions, thus addressing the scarcity of rich datasets.
Khan Md Hasib, et al. [6] explored various ML techniques for detecting depression, including SVM, RF, Decision Trees, Ensemble methods, K-Nearest Neighbor, and Artificial Neural Networks. Different ML classifiers were utilized to distinguish between depressed, non-depressed individuals based on online behavior and language patterns. The Internet of Medical Things (IoMT) based early-stage stress detector measures temperature, movement rate, perspiration rate, and cortisol levels while under stress. The study employs a structured framework based on four research questions (RQs) to guide the analysis of various depression detection techniques. It emphasizes the role of social networks (SNs) in providing valuable

data for understanding users' mental states, thus contributing to the field of mental health analytics. It is a lack of standardized evaluation metrics across studies, which makes it difficult to compare results effectively.

Silje Steinsbekk, Jacqueline Nesi, et al. [7] Emphasizes social interaction as a key factor in understanding the rising rates of depression during adolescence. Sensitivity analyses examined specific behaviors that were documented by the use of social media in a self-oriented and other-oriented manner. The study examined within-person effects by presenting standardized estimates of RICLP Models. The authors concentrated on the specific symptoms of depression, social and generalized anxiety, potentially limiting broader understanding of mental health problems associated with social media use. This paper lacks in capturing specific social media behaviors.

Henry Onyeaka, et al. [8], aims to explore social media usage trends, health-related behaviors & association between social media use and healthy lifestyle behaviors in individuals with depression and anxiety. It explore impact of social media on behaviors such as physical activity, sedentary activity, strength training, fruit & vegetable intake in this population. Cross- sectional data from the HINTS survey was utilized to analyze the relationship amongst social media use & individuals health with depression and anxiety. Multivariable Logistic regression evaluated odds of social media utilization. The study focused on individuals with depression & anxiety, limiting generalizability of the findings to other mental illnesses like schizophrenia and bipolar disorder.

Akbobek Abilkaiyrkyzy, et al. [9], leverage natural language processing to develop a chatbot that can assist in diagnosing and managing mental health conditions, particularly depression, using the DSM framework for validation. The BERT sequence classification model is fine-tuned using the E- DAIC dataset to categorize user intents. The chatbot is developed using the Rasa framework, which allows for effective dialogue management and natural language understanding. To improve the model's training process and ensuring better convergence and performance during the fine-tuning stage, a linear warm-up scheduler and AdamW is used. Rahayu Ahmad, Syahida Hassan, et al. [10], emphasizes the detrimental effects of Instagram on mental well-being, such as anxiety, depression, and negative body image. The Social Comparison theory is introduced to explain that individuals compare themselves to others on platforms like Instagram, leading to both positive and negative effects on self-esteem and well-being. The authors point out that frequent use of Instagram can create more opportunities for social comparison, which may lead to anxiety and negative emotions.

Nazzere Oryngozha, Pakizar Shamoi, et al. [11], focuses on use of NLP and ML algorithms to automatically detect stress in Reddit posts. Authors have shown the effectiveness of models like BLSTM with attention mechanism, KC-Net, and SVM- based approaches in stress detection. Emotion detection and sentiment analysis using BERT models and LSTM have been successful in identifying stress markers in social media texts. Classification algorithms SVM, LR, NB & LSTM are used to estimate stress presence in text data. The study reliance on Reddit data may limit the generalizability of findings to broader academic communities The dataset size used in the research could impact the scalability and robustness of the depression and stress detection model

Subigya Nepal, et al. [12], highlights the potential of smartphones as a rich source of data for understanding individuals mental states. The authors used Logistic Regression, ElasticNet and Random Forest (RF) algorithms for classification and regression tasks, showing strong performance in predicting depression and PHQ-8 scores. The Visual Question Answering model was employed to contextualize image analysis and provide insights into users' interactions and environments. The study focused solely on clinically depressed individuals, lacking healthy controls, which could have enhanced the prediction model's accuracy and comprehensiveness.

Kaiden Hein, C.Morrison et al. [13], authors highlighting use of digital footprints and methodologies to analyze online behaviours for identifying mental health indicators. User-Avatar-Bond Questionnaire & Depression, Anxiety, & Stress Scale (DASS-21) in assessing mental health symptoms. The study employed a range of measures to evaluate symptoms of depression, anxiety & stress for providing insights into participants' mental well-being. The study utilized machine learning techniques to analyze the data and predict anxiety risk based on age, gaming experience, and user-avatar bond dimensions. Lack of exploration of potential variations in the User-Avatar Bond across different game genres, limiting generalizability of the results.

David Gimeno-Gómez, Ana-Maria Bucur, et al. [14], focuses on depression detection from non-verbal cues in videos. Authors used various techniques for extracting & encoding non-verbal

cues, such as audio-visual embeddings, landmarks, and gaze patterns, are detailed, highlighting the model's comprehensive approach. The datasets used for studying non-verbal behavior in depression, including D-Vlog, DAIC-WOZ, and E-DAIC, are described, showcasing the diversity and complexity of the data sources. The model primarily focuses on non-verbal cues, which may not fully capture the entire range of depression indicators. This limitation could lead to missed diagnoses in cases where verbal communication is crucial.

Sarah Myruski, Jennifer De Rutte, et al. [15] focusing on preferences for social-emotional communication through digital media, the study seeks to uncover the intricate relationships between digital media use, attention bias & anxiety symptoms. The SCARED self-report version was used to measure the symptoms of anxiety. The SCARED assessment captured various symptoms of anxiety subtypes in youth, providing a comprehensive evaluation of anxiety severity. Attention bias (AB) was measured using reaction time metrics and event-related potentials (ERPs) during a dot probe task to assess cognitive and emotional processes related to threat perception. The measure of digital media use captured general, retrospective preferences rather than assessing the actual content of adolescents' social interactions, whether face-to-face (FTF) or online. This limitation may affect the accuracy of the findings regarding the impact of DMU on anxiety.

Joseph Aina, O. Akinniyi, et al [16], objective is to develop advanced system for early prediction & diagnosis of mental disorders, leveraging facial expressions as indicators of emotional states. An ensemble model was created by fusing three learning architectures: an in-house CNN (MDNet), a pre- trained ResNet50, and a Vision Transformer, enhancing model predictive capabilities. The research demonstrated the effectiveness of combining YOLOv8 with DL models to create a mental disorder detection system. The facial emotion datasets used in the study, particularly the FER 2013 dataset, suffer from class imbalance. This indicates that some emotional classes are underrepresented, potentially resulting in biased model performance.

Noor Faris Ali, et al, [17], design and develop modern deep learning models for depression detection using electroencephalography (EEG). They use EEG biomarkers, particularly in the theta and beta frequency bands, have been identified as crucial for distinguishing between depressed and healthy individuals, with theta band activity linked to emotional processing. The dataset comprises EEG recordings from MDD patients and healthy controls, with rigorous quality checks to ensure data integrity. The CNN-LSTM model is trained to detect complex patterns in EEG data, aiming to minimize the number of parameters while preserving performance. The limitation highlights the need for robust validation methods to ensure the model's reliability in real- world scenarios

A. Basyouni, et al [18], feature engineering is divided into feature extraction, focusing on context-related features, and feature selection, which employs genetic algorithms to identify the most relevant features for classification. The framework utilizes several ML classifiers, containing Random Forest, K- Nearest Neighbors, Gradient Boosting Decision Trees (GBDT), & XGBoost, to classify posts as indicative of suicidal ideation or not. The study emphasizes potential of social media as a resource for detecting suicidal ideation, leveraging anonymous user-generated content to identify at-risk individuals. The framework employs a genetic algorithm for feature selection, there is still a risk of including redundant or irrelevant features in the analysis. These superfluous elements can mislead the learning algorithm, potentially reducing the overall effectiveness of the classification process

N. K. Iyortsuun, S. H. Kim, et al [19], Additive Cross-Modal Attention Network model encodes audio and text features into embeddings, utilizing BiLSTM as the backbone for both modalities. The study utilizes DAIC-WOZ dataset for training and evaluation, demonstrating the model's efficacy in both classification & regression tasks. Model focuses on most relevant parts of dataset, improving detection of depression symptoms. One of the significant limitation noted is the imbalance in the dataset, where the number of depressed samples may be lower than non-depressed samples. This can affect the model's performance and accuracy.

Based on heterogeneous dataset, Tongtong Li, et al [20] proposes a novel framework utilizing self-supervised contrastive learning to automatically diagnose MDD. Data was collected using a 3.0T MRI scanner, and the study was ethically approved, ensuring informed consent was obtained from all participants. Data augmentation techniques included image cropping, color distortion, and Gaussian blur to enhance the robustness of the model. The author describe various neuroimaging technologies, such as sMRI, fMRI, and DTI, allow for a more comprehensive understanding of brain structure & function, which can enhance diagnostic accuracy for MDD. A limitation in expressing the DMN and cerebellum- related

regions symbolically, despite their potential as biomarkers for depression diagnosis.

Zhongyi Jiang, Ying Zhou, et al [21] utilized various ML models, including KNN, Random Forest & Logistic Regression, were employed to classify depression based on eye movement variance entropy, capturing complex relationships in the data. Eye-tracking and machine learning methods offer significant advantages over traditional clinical assessments, providing objective measurements and reducing biases associated with self-reported data. The eye tracking algorithms used in the study faced challenges in accurately capturing pupil positions, leading to empty values in the data. This limitation could impact the reliability of the eye movement data collected. Suzan Elmajali, Irfan Ahmad [22], main focuses to classify Arabic tweets into nine depression symptoms using multi-class classification techniques, marking the first effort in this area for Arabic text. AraBERT and MARBERT models are built on the BERT architecture, designed specifically for Arabic, with extensive training on Arabic tokens to improve context understanding. The authors applied various machine learning models, including Support Vector Machine, K-Nearest Neighbors, Decision Tree, Random Forest, AdaBoost, & Stochastic Gradient Descent. The study faced challenges in detecting depression symptoms over time due to the unavailability of datasets that contain historical tweets from specific users, both depressed and non-depressed. This limitation restricts the ability to analyze the progression of symptoms and the context of tweets.

Sahar Ajmal, Muhammad Shoaib, et al [23], emphasizes role of social media, particularly Reddit, in identifying individuals at risk for depression through the analysis of their posts, leveraging Rhetorical Structure Theory (RST) to discern linguistic patterns indicative of mental health issues. The proposed methodology, RSTFusionX, aims to enhance depression detection by analyzing the rhetorical structures and sentiment of social media posts. RSTFusionX utilizes an ensemble of three differernt ML algorithms for classification tasks. The paper highlights that the lack of identification of rhetorical relationships related to depression.

Dabin Park, Geonju Lee, et al, [24], utilize data from the online community Everytime to assess the probability of meeting DSM-5 diagnostic criteria for depressive disorders. Word2Vec model numerically represents words based on their contextual relationships, using methods like CBOW and Skip-gram. KoBERT model specifically designed for Korean text, demonstrating performance in natural language. The interdisciplinary approach leverages advanced natural language processing techniques, bridging traditional psychiatric research with modern data analysis methods. The paper acknowledges a limitation in that more datasets and diverse experiments are required to obtain more generalizable results. This suggests that the findings may not be applicable across different contexts or populations without further validation.

M. A. Abbas, Kashif Munir, et al, [25] mainly focus on Arab- centered research, utilizing Twitter data to detect depression through supervised learning algorithms with models like Random Forest and Naive Bayes. The BERT-RF model address gaps by extracting contextualized embeddings and probabilistic features from textual data. Various machine learning models, including Random Forest, Multilayer Perceptron, and K-Neighbors Classifier, are employed to classify social media posts as depressed or not depressed based on extracted features. The Random Forest Classifier utilizes multiple decision trees to improve prediction accuracy, while the Multilayer Perceptron model employs a feed-forward neural network structure for classification tasks. Logistic Regression and Long Short-Term Memory networks are explored, for tasks involving sequential data like social media posts.

Table 1 summarizes different techniques used in detection of anxiety and depression

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Table 1: Summary of the different techniques used in detection of anxiety and depression.

Techniques	Ref	Contribution	Feature used	Dataset	limitations
CNN	[1] [4]	A deep learning-based hybrid model for depression detection is proposed.	COVAREP, Model Spectrograms, Pitch Tone, Rhythm	DAIC-WoZ database	Conventional therapies are time- consuming and often ineffective.
LSTM, Bi- LSTM	[1] [3] [4] [11]	The multi-faceted approach proposed enhances the	Emotional, temporal, and linguistic styles	Reddit.	Estimates based solely on Reddit social network.

	[17] [19]	understanding of the utilization of various inputs for emotion detection.			
Naive Bayes	[2] [3] [6] [11] [13]	Introduces avatar-mediated clinical assessment for anxiety evaluation.	User-Avatar Bond (UAB) dimensions: identification, immersion, compensation.	User-Avatar Bond (UAB)	Need for cautious interpretation due to small high-anxiety sample.
Random Forest	[2] [7] [12] [18][21] [22] [25]	MoodCapture asse sses depression using smartphone images.	Head Pose, Eye Gaze, 2D and 3D Landmarks	PHQ-8 depression survey. self-reported data.	Limited dataset size and diversity.
SVM	[3] [6] [11] [13] [22] [23]	Integrating Rhetorical Structure Theory with ensemble machine learning models, an accuracy of 97.1% is achieved in classifying posts.	Features include n-grams and TF-IDF for text classification.	Arabic tweets and Reddit.	It only analyzes long Reddit posts.
LR, NLP	[5] [8] [9] [11] [12] [13] [18] [25]	Combines natural language processing with machine learning for analysis.	Features include sentiment, topic, and behavioral analysis.	Twitter	Limited character count on platforms like Twitter hampers analysis. Insufficient scientific evidence on social media's health impact.

Challenges

Depression and anxiety detection face several challenges, including

- Datasets often lack sufficient size and diversity, particularly in high-anxiety samples.
- Text-based data from platforms like Twitter and Reddit faces platform-specific limitations.
- Integrating diverse modalities like audio, visual, and text-based features poses challenges in alignment, data quality, and cautious interpretation of complex interactions.
- Emotional and behavioral cues from social media may not fully capture the nuances of mental health.
- Lack of standardized frameworks for assessing mental health through social media.
- Avatar-mediated assessments face challenges in analyzing user engagement and understanding their psychological impact.
- Effective detection requires diverse datasets, but variability in quality and challenges in standardization and interpretation hinder their integration.

Proposed Framework

The proposed framework for detection of anxiety and depression as shown in Fig. 1.

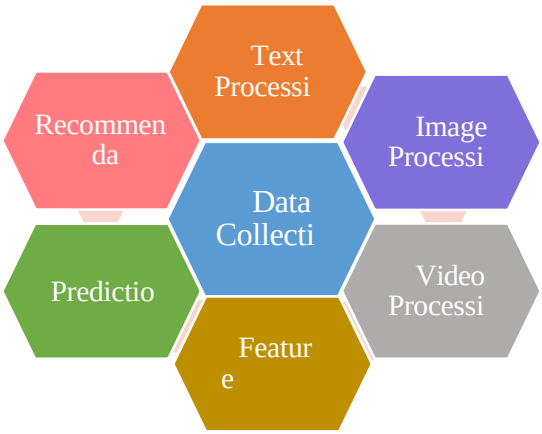

Fig. 1. Proposed System Framework

The Fig. 1 shows a multi-modal system for analyzing and recommending content to users based on their preferences. It begins with an input dataset that encompasses images, videos, and text. The system then undergoes a series of pre-processing stages. For videos and images, frames are extracted, resized, and converted to

grayscale. Textual data is tokenized, stop words and stemming are applied, along with topic modeling, sentiment analysis, and word usage/count are performed. In next step landmark detection and feature extraction are applied to the pre-processed data. The extracted features are then fed into a LSTM network for training. Once trained, model is used for prediction. Finally, the system will provide recommendations to the user based on results of the testing dataset. The models performance will be validated using standard evaluation metrics precision, recall, F1-score, & accuracy. This approach is designed to facilitate early intervention in mental health, helping to prevent the escalation of conditions.

Conclusion

This review discusses the advancements in mental health diagnostics enabled by innovations in AI, ML, NLP & multimodal data analysis, which will lead to transformative changes. The different techniques reviewed herein indicate that AI-driven approaches inject objectivity, scalability, and cultural adaptability into mental health screening by incorporating diverse sources of data emanating from social media, physiological signals, and neuroimaging. Transformer models, EEG-based analysis, and multimodal fusion may support promising pathways to the early and more precise diagnosis of mental health conditions such as depression, anxiety & suicidal ideation. Yet, challenges of translating these technological advances into clinical practice are considerable. These include, but are not limited to, data privacy issues, large and diverse datasets, and integration of these technologies into real clinical workflows. These very technologies hold the power to revolutionize the future of mental health toward more accessible, proactive, and personalized interventions. However, addressing such challenges will be important to ensure that AI-driven mental health tools are effective, ethical, and taken up widely into clinical practice. The proposed framework includes multiple steps, including text, image, and video preprocessing, feature extraction, and training of data for prediction of anxiety and depression. Once predictions are made, the system provide personalized recommendations to users based on their predicted anxiety and depression levels, aiming to facilitate early detection and intervention. As research is bound to evolve further, there is a strong indication that digital technologies will play the quintessential role in early detection and management of mental health disorders and will transform mental health delivery and outcomes globally.

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