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A comprehensive review of predictive analytics models for mental illness using machine learning algorithms

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ABSTRACT

Our emotional, psychological, and social well-being are all parts of our mental health, influencing our thoughts, emotions, and behaviors. Mental health also influences how we respond to stress, interact with others, and make good or bad decisions. There has been growing interest in the use of machine learning for the early detection of mental illness. This study reviews the machine learning models, algorithms, and applications for the early detection of mental disease, particularly emphasizing the data modalities. We further propose a comprehensive methodology for assessing mental health that synergistically combines social media monitoring, data analytics from wearable devices, verbal polls, and individualized support. We provide an overview of the field's current state, highlight the potential benefits and challenges of using machine learning in mental health care, and a new taxonomy of mental disorders issues based on five domains of data types. We review existing research on using machine learning to detect and treat mental illness and discuss the implications for future research. Finally, the value of this work lies in its potential to provide a fast and accurate method for predicting the mental health status of a person, which may assist in the diagnosis and treatment of mental illness.

Contents

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1. Introduction

Mental illness is a significant public health concern worldwide, affecting an estimated one in four people at some point in their lives. The World Health Organization (WHO) estimates that mental disorders account for 14% of the global burden of disease and injury. Mental illness, also known as a mental disease or psychiatric disorder, refers to a wide range of conditions that affect a person's mood, thoughts, and behavior. Mental illness can range in severity and may be temporary or long-term [1]. Mental illness can occur at any age and can be caused by a variety of factors, including genetics, environmental stressors, and life events [2,3]. It is more common in certain populations, such as people who have experienced trauma or abuse, people who are disadvantaged or marginalized, and people who have certain medical conditions [3]. Stressful situations such as the COVID-19 pandemic in recent times, have been reported by WHO to have a significant impact on increased stress and anxiety among the common population and might have a long-term effect. Also, it is reported in the literature that some specific populations were more vulnerable in the COVID-19 situation such as frontline healthcare workers, people who have lost their relatives, and individuals with pre-existing mental health conditions [4–6]. Mental illness can have a significant impact on a person's quality of life and may lead to disability, social isolation, and economic burden. It is also associated with an increased risk of other health problems, such as cardiovascular disease and substance abuse.

There are many effective treatments available for mental illness, including therapy, medication, and lifestyle changes. Early detection and treatment of mental illness can have significant benefits for individuals and society. Some potential advantages of early detection include improved quality of life, reduced risk of long-term disability, cost savings, improved outcomes, etc. Despite the potential benefits of early detection, it is challenging to identify mental illness in a timely manner. Because, mental illness is often complex, as it may involve multiple factors such as genetics, environment, and life experiences.

However, traditional methods for diagnosing and treating mental illness, such as interviews with healthcare providers, can be subjective and time-consuming. In recent years, machine learning has emerged as a promising tool for the detection and treatment of mental illness. Machine learning algorithms can analyze large amounts of data, such as electronic health records, brain scans, and genetic data, to identify patterns and predict the probability of certain mental health conditions. By automating certain tasks, machine learning can help healthcare providers diagnose and treat mental illness more efficiently and accurately [7]. The use of machine learning in mental health care is an active area of research and development, and there is growing evidence to support its effectiveness.

Recent review articles in the field of machine learning for mental health detection have focused on various aspects of the research landscape. Some reviews have examined articles based on specific mental health issues [8–10], while others have explored works in a specific data domain [11–14]. Additionally, certain reviews have investigated the efficacy of different machine-learning techniques in this context [14–17]. However, none of the existing review articles have explicitly addressed the question of which type of data provides more comprehensive information on mental health conditions and the potential gaps that arise when applying machine learning methods to specific types of data. Addressing this knowledge gap would be invaluable to guide future researchers in selecting robust methodologies for mental health research.

This paper aims to provide an overview of the current state of the field and highlight the potential benefits and challenges of using machine learning in mental health care. We review existing research on the use of machine learning in the detection and treatment of mental illness and discuss the implications for future research. The major *contribution* of our work is as follows:

- Review the machine learning models, algorithms, and applications for the early detection of mental disease.
- Propose a comprehensive methodology for assessing mental health that synergistically combines social media monitoring.
- Provide an overview of the field's current state and highlight the potential benefits and challenges of using machine learning.
- Provide a fast and accurate method for predicting the mental health status.

The rest of this study goes through the following organized. Section 2 deals with the empirical study of mental illness. This section adds a taxonomy of mental disease and machine learning. In Section 3, the method of the study is discussed including the selection procedure (PRISMA), and five different data types used in mental disease classification based on machine learning. The research direction and suggestions are drawn in Section 4. Lastly, Section 5 concludes the study.

2. Taxonomies of mental disorders and machine learning models

Mental disease (also called mental illness, mental disorder, mental health issues, etc.) refers to different mental conditions that affect a person's mood, behavior, and cognition. In simple words, if one's normal way of feeling and behaving gets changed negatively then we say he has mental illness [18]. There may be different reasons for mental illness and also there is diversity in symptoms. World Health Organization (WHO) has emphasized the detail of mental illness research, as it is becoming very common in today's world [19]. With the advancement in modern technologies, different techniques of diagnosing mental illness have evolved. The traditional way of detecting mental illness was through questionnaires and interviews. In the modern era, brain signals, social media posts, sensory data, and medical records are also

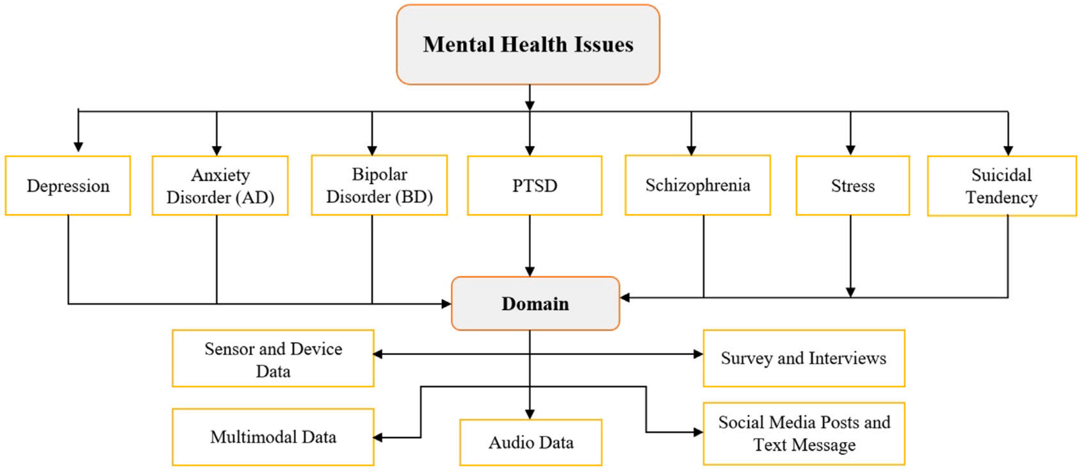

Fig. 1. Taxonomy of mental health issues.

being used in diagnosing mental health issues. Machine learning approaches are also becoming very popular among researchers as they can learn patterns from huge amounts of data and predict more correctly one's mental health condition [20]. In this section, we will first discuss the different types of mental diseases. Then we will explore different machine-learning approaches used in mental illness detection. Then we will discuss recent work on mental disease detection with machine learning from a methodological perspective.

2.1. Taxonomy of mental disease

According to the WHO, 1 in 8 people suffer from mental problems. Despite the availability of effective prevention and treatment systems for mental health problems, most people are anti-treatment. Also, many people do not even know they have mental problems. Different types of mental issues are seen in people. These include depression, anxiety disorder, bipolar disorder (BD), post-traumatic stress disorder (PTSD), and schizophrenia. The taxonomy of mental health issues is presented in Fig. 1 and discussed below. According to 2019 data from the Institute of Health Matrices and Evaluation, 280 million people worldwide suffer from depression. Furthermore, 23 million of them are children and minors. People suffering from depression have psychological symptoms such as not feeling well, wanting to die, suicidal tendencies, feeling worthless, feeling angry at themselves, feeling guilty, lack of focus, etc. Physical symptoms such as disturbances in sleep, weight changes, and differences in food habits are also noticeable [21]. Various social, work, and relationship factors can be responsible for depression. The incidence of depression varies by age, sex, and culture [22]. Recurrence of depression after treatment is observed in patients with depression [23].

Anxiety Disorder (AD) is one of the most common mental disorders and most people suffering from anxiety disorder do not seek any kind of treatment [24]. Anxiety disorder refers to the inability to control fear and abnormal behavior caused by it. There are different types of anxiety disorders. Patients suffering from generalized anxiety disorder suffer from excessive fear. Panic disorder, another kind of anxiety disorder, causes panic attacks that can be lethal. People suffering from social anxiety fear facing different social situations. Fearing excessively to lose someone to whom one is emotionally attached is characterized as a separation anxiety disorder.

Bipolar Disorder (BD) is another common mental disorder in which a patient experiences alternating depressive and manic symptoms. Sometimes, they experience a mixture of depressive and manic symptoms. Depressive symptoms are the same as the patients with depression suffer; again in a manic episode, they experience an increase in energy, less need for sleep and food, irritability, etc. Patients with bipolar disorder are at higher risk of committing suicide [25].

PTSD is caused by experiencing some traumatic situation that is emotionally disturbing to the person who experienced it. PTSD is very much conflicting with other mental disorders at the symptomatic level [26]. A patient suffering from PTSD often re-experiences the trauma by remembering the scene. Similar incidents happening in front of him always disturb him and often make him temporarily unstable.

According to the Institute of Health Matrices, every 1 in 300 people in the world can be diagnosed with Schizophrenia. People with schizophrenia may have 10–20 years less life expectancy than a non-schizophrenic person [27]. Schizophrenia refers to experiencing continuous delusion and hallucination. It disturbs one's cognition and behavior. Impairment in thinking is commonly seen in schizophrenic patients.

Stress is one of the common reasons that results in different mental health issues. Any change that creates physical, emotional, or psychological discomfort is called stress. Though stress is not a mental illness the stress level of a person is directly connected to his mental condition [28]. Therefore, researchers often work to analyze the stress level of a person and try to predict his probability of becoming mentally ill.

Another derived mental issue that is more common with depression and bipolar disorder is suicidal tendency [29]. People in the depressive episode while feeling worthless tend to self-harm. This tendency often leads to suicide. Researchers working in the domain of mental health problems often try to identify people with a risk of suicidal tendencies to prevent them from self-harming by interviewing or analyzing their thoughts expressed in a candid situation.

2.2. Machine learning approach

Machine learning (ML) is a subset of AI in which the main goal is to build a system that mimics human behavior and learns without explicit programming [30]. The overall process is that a set of data is used to train the system, and then the system learns to calibrate and enhance performance without further explicit programming automatically. Machine learning is mainly three types. They are — supervised ML, Unsupervised ML, and Reinforcement learning.

2.2.1. Supervised learning

Supervised learning is teaching like a human child. In supervised learning, the machine is taught by example with a labeled dataset. Two types of problems can be solved with supervised learning.

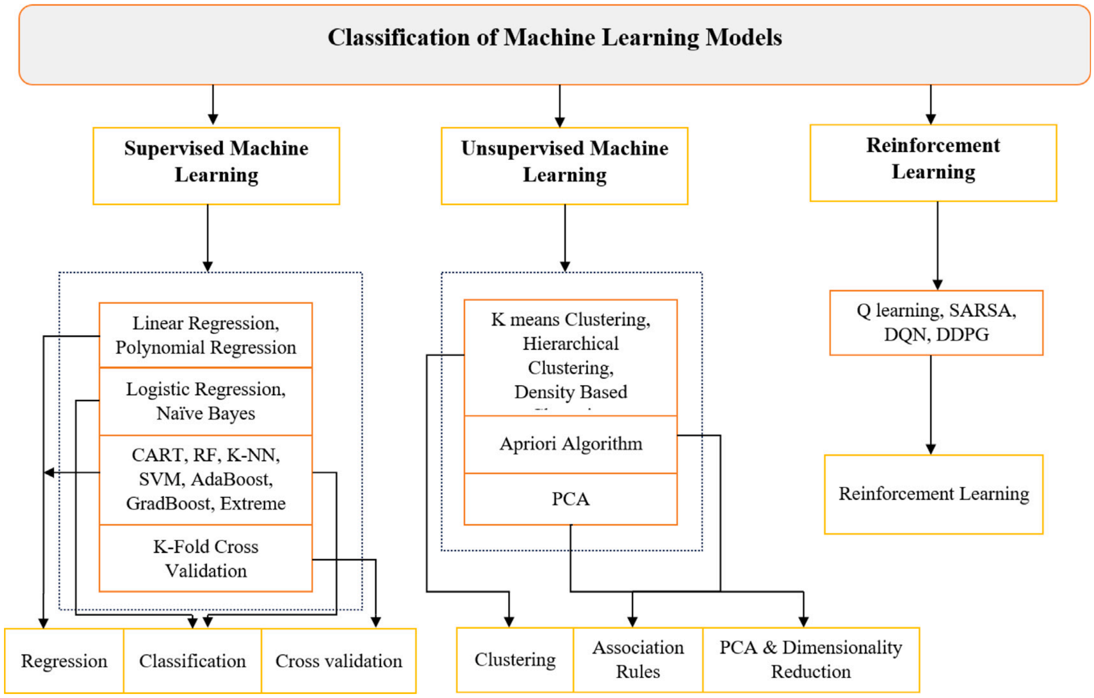

Fig. 2. Classification and applied fields of each model of ML.

- Regression: Numerical value is predicted through regression. This algorithm is used for future forecasting. In [31], the authors used the regression types model for predicting the risk of depression.
- Classification: Different classes are predicted through classification. For example, for classifying mental disorders affecting people. Many researchers applied classification methods to diagnose mental diseases [32,33] and so on.

2.2.2. Unsupervised learning

In the case of unsupervised learning, no predictions are made. In this case, there is no need to teach the machine with a labeled dataset. Unsupervised learning identifies different hidden similar groups inside machine data. Thus, through unsupervised learning, the machine discovers the various groups within the data. To solve the clustering problem, supervised models are needed [34]. The researchers used unsupervised models for different tasks about mental disorders like brain functional connectivity [35], Alzheimer [36–38].

2.2.3. Reinforcement learning

Reinforcement learning (RL) is mainly applied in self-driving cars, robots, various AI games, etc. Nowadays, some researchers use RL in the case of mental disease tasks [39,40]. The classification and applied areas of each type of machine learning model are shown in Fig. 2.

3. Machine learning-based mental disease prediction

To predict a very complex situation like mental disease in humans, machine learning models have been used for many years [41]. A diverse range of machine learning methods on different types of datasets has already been used for the accurate detection of mental diseases. Also, Deep Learning (DL), ML with artificial neural networks, has become popular in mental health studies specifically with text data. In this section, we have discussed machine learning-based approaches used in mental illness prediction in recent times in detail.

3.1. Study selection method

The process of study selection method is presented in Fig. 3. To identify the relevant studies, we have used four reputed databases:*Scopus, Google Scholar, IEEE Xplore*, and *Web of Science*. For searching relevant studies, we used the search string: "Mental Disease Prediction using Machine Learning". Then from the search result, we tried to identify the papers having one of the following keywords: Mental Disease using machine learning, Mental Illness using machine learning, Mental Disease using Deep learning, and Mental Illness using Deep learning. We searched the keywords in those papers' titles, abstracts, or keyword sections. We have limited our search to those papers written in the English language and published between the year 2018–2024. At the beginning of our selection process, we started with 780 papers. These articles included original, review, and survey articles. For our study, we decided to include those papers with original experimental results and having open access (or full text available).

To exclude the papers that do not meet our inclusion criteria We have used a four-step filtering process:

Step-1: Removing duplicate, review articles, and survey articles.
Step-2: Removing articles with no full text available.
Step-3: Removing articles having no experimental results.
Step-4: Removing articles without proper details of data sources.

After removing the duplicates and the review papers at the first step, we come up with 519 articles for screening. We looked for the open access criteria (full text available) and we found 132 papers among those articles fall into this criteria. We read the title, abstract, methodologies, and results. After our primary screening process, we selected 98 full texts of our interest which provide some original experimental output. Then we decided our eligibility criteria based on the type of data used and the availability of the data in the public domain. In some papers, the dataset is not publicly available but the details on the process of recreating the data are available. The data types we considered are discussed in the next subsection. Forty-nine among 98 articles passed our eligibility criteria. We also reviewed the reference lists of the 49 articles and from the list, we selected two more papers. Finally, we ended up with 51 papers in total.

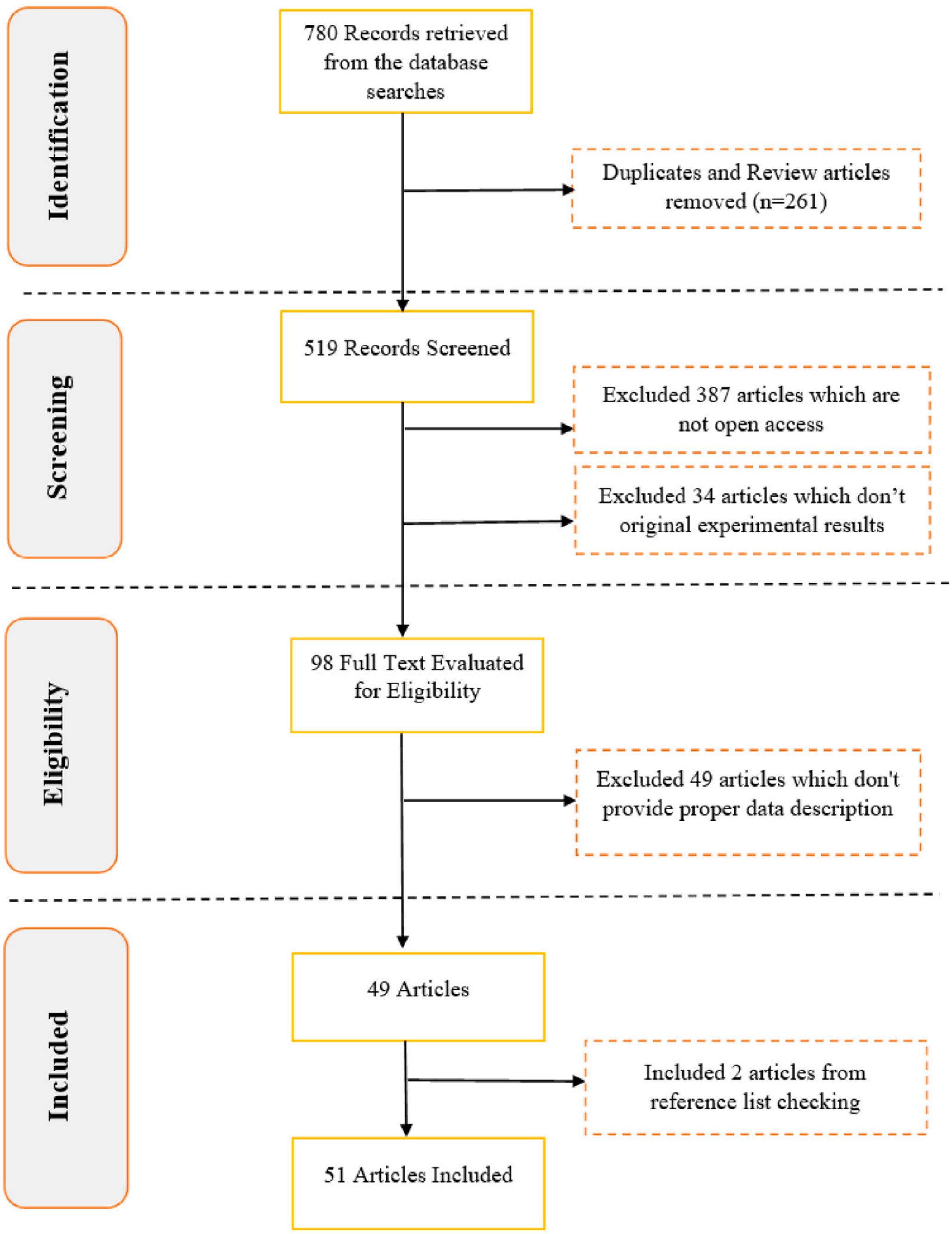

Fig. 3. Flowchart of the study selection method.

The publisher of the 51 papers we selected for inclusion is mentioned in Table 1. There are 8 papers from 2018, 6 papers from 2019, 6 papers from 2020, 7 papers from 2021, 5 papers from 2022, 12 papers from 2023, and 7 papers from 2024.

3.2. *Multiple heterogeneous datasets used for ML-based prediction of mental diseases*

Machine learning is a data-driven approach that has become very popular in detecting mental diseases in recent times. Many attempts have been made to identify one's mental condition based on different data types. We can broadly classify these different types of data used in mental disease classification into these five categories:

- Surveys and interviews
- Social media posts and text messages
- Audio data
- Sensor and device data
- multi-modal data

In this section, we have briefly discussed 51 notable works in these five above-mentioned categories for mental disease prediction published by reputed publishers from the year 2018 to the year 2024.

3.2.1. *Surveys and interviews*

Quantitative data collected from questionnaire responses and Verbal interviews with closed questions have been used for a long time to identify and classify mental disorders among people with mental illness symptoms [42]. Eleven works of Mental illness prediction using machine learning techniques based on surveys and interviews are included

Table 1
List of publishers.

Publisher	Count
Hindawi	1
ACM	10
MDPI	3
IEEE Xplore	7
Springer	8
EAI	1
Elsevier	10
ISCA	1
Nature Publishing Group	2
Public Library of Science San Francisco, CA USA	1
Arxiv	1
Wiley Online Library	2
JMIR Publications Inc., Toronto, Canada	2
SAGE Publications, Sage CA: Los Angeles, CA	1
Cambridge University Press	1

in Table 2. From the table, we can observe that with this type of data, one can identify different mental health issues like stress, depression, anxiety, and bipolar disorder. For classifying depression by analyzing the response to open-ended questions, language models like LSTM and GRU-BiLSTM are employed [43,44] where GRU-BiLSTM outperforms LSTM [44]. But in most cases, interviews and surveys contain close-ended questions. In that case, ML algorithms were found to perform well. M. Srividya et al. [45], found RF to achieve 90% accuracy in classifying different mental conditions. Reducing features using appropriate feature selection techniques can also help increase the accuracy of the classifiers [46]. Ensemble methods outperform single machine learning models [47]. The performance of machine learning algorithms greatly depends on the wise choice of questions. Also, the datasets are often large dimensional. However, survey and interview-based data are very suitable for classifying mental diseases with higher accuracy [48].

3.2.2. Social media posts and text messages

Social media has become very popular for expressing and communicating emotions. And so the information obtained from a person's social media can play an effective role in analyzing his mental state [55]. In Table 3, we list 11 literature on classifying human mental issues using social media information and text messages. In most of the literature, Natural Language Processing (NLP) techniques are used to understand emotions from social media posts and are used for detecting mental problems such as Post Traumatic Stress Disorder (PTSD), suicidal tendencies, stress, depression, etc. Transfer Learning (TL), using a pre-trained model for some new task, is recently becoming popular and in the case of social media data analysis, it can achieve high performance with a small dataset [56]. However, achieving higher accuracy in this approach is challenging. Because often social media posts and text-message data are noisy and may contain different forms of information such as jokes, sarcasm, and cultural nuances. Also, it is found that variability in language and lack of available training data limits the accuracy of the system with this type of data [57].

3.2.3. Audio data

Voice vibration and context of speech are indicative of the person's mental state [68]. Most recent studies have converted audio data to text data and then used NLP techniques to diagnose mental disorders. Some works have been shown to exploit the characteristics of audio data such as frequencies, time periods, etc., and achieve greater accuracy. In Table 4, we list 9 literature on classifying human mental issues using audio recordings of participants' unstructured interviews and predetermined speech. Audio data is mostly used to identify depression. Language is a considerable factor while analyzing audio data [69]. Although Deep Learning (DL) approaches are more well performing on audio data the accuracy is not so high.

3.2.4. Sensor and device data

In recent times, studies of data from different sensors and wearable devices like smart watches, smart glasses, etc. are bringing important insights. Smartphones are also being used to track behavioral data [78]. In the detection of mental disorders, these types of data help us to learn the association between physical or environmental responses and the mental condition of a person. Also, electroencephalogram (EEG) and Magnetic resonance imaging (MRI) data are being used for associating the activity of different parts of the brain with mental conditions. In Table 5, we list 12 literature on classifying human mental issues using sensor and device data. The diseases for which these sensor and device data are used are Depression, Stress, Bipolar Disorder (BD), and Generic Mental Health, for depression detection Deep Learning (DL) based approaches seem to achieve better accuracy on the EEG dataset [79]. Performance of Self Supervised Learning (SSL) for stress detection from wearable devices data is promising [80].

3.2.5. Multimodal data

Multimodal data is formed by combining data from different sources to identify mental health issues. Video can be thought of as an example of multimodal data, as it comprises audio and visual. Smartwatches are also used to acquire data from different sensors and combine them to form multimodal data. Multimodal data modeling has been proven to increase accuracy compared to unimodal data [91,92]. In Table 6, we list eight articles in the literature on the classification of mental health issues using multimodal data. Multimodal DL networks are mostly used to manipulate these types of data.

3.2.6. Benchmark datasets

In this subsection, we have listed several datasets that are used in several works in this domain. These publicly available datasets are listed in Table 7. This list will be helpful for future researchers in this domain.

4. Future research directions

In the previous section, we discussed a few prominent works in the field of the classification of mental disorders using machine learning. We categorized the work based on the different types of data that they used to build the model. We have observations for all of these categories. In this section, we go into more detail about our findings and suggest future research directions that address significant limitations, improve accuracy, and broaden the applicability of mental health detection models.

4.1. Gender consideration in mental health assessment

We found that the most common type of data used in the classification of mental diseases is a questionnaire. Evidence shows that there are differences in male and female personalities and mental health problems [114,115]. However, the studies we mentioned here did not consider the impact of gender differences on the detection of mental health. The creation of gender-specific questionnaires or their adaptation for use in future research should be given priority. The precision and applicability of mental health evaluations can be greatly enhanced by including gender factors in classification models. Additionally, investigating how gender affects the effectiveness of various machine learning algorithms and methodologies may aid in identifying the most effective methods for gender-specific mental health detection.

Table 2
Survey and Interviews' data-based works.

Source	Year	Disease	Age	Location	Approach	Performance	Limitations
[46]	2018	BD	–	China	Different ML models with feature selection	AUC score 0.913	Small dataset that have restricted the depth, breadth, and generalizability of the research findings.
[45]	2018	Multiple	18–26	India	Clustering based Classification	accuracy 90%.	Authors suggested applying a deep learning model to increase the accuracy and to use more classes on their utilized dataset which now contains only three classes including Mentally distressed, Neutral, and Happy.
[49]	2019	Depression	50+	UK	Ensemble techniques with feature ranking	Logloss 0.251	For specific age group. Focusing only on the top 50 features for XGB and LGB models may overlook crucial factors in predicting depression in older age.
[43]	2018	Depression	–	–	LSTM	f1 score 0.67	Low performance, Potential biases in training data, the small sample size of 142 individuals, and poor model calibration.
[44]	2022	Depression	–	China	GRU-BiLSTM	f1 score 0.85	The authors released this dataset based on 162 persons and applied ML to this. Their sample size and accuracy rate can be increased.
[50]	2020	AD	–	Israel	ML models.	accuracy 71.44%	Small dataset and the accuracy is low as well as the results are not validated with an external dataset.
[51]	2020	Generic Mental Health	9–15	Sweeden	ML models	AUC score 0.739	Challenging & low performing model and the model is not accurate enough for clinical usage
[52]	2019	AD	–	India	ML models.	Accuracy 82.6%	Profession-specific data, lacks justification for feature selection technique and proper discussion.
[47]	2023	Generic Mental Health	–	–	Different ML models	88.80% accuracy.	Use of Binary Classification limits the application in multi-class, complex mental health issues. Occupation-specific data lacks generalization.
[53]	2023	Multiple	–	–	Different ML models	89% accuracy.	The dataset from the Psikometrist web portal limits the generalizability of the findings. Additionally, the NEPAR algorithm used for feature selection may have biases, affecting the transparency and explainability of the AI models.
[54]	2024	Depression & Suicidal Tendency	19–25	Bangladesh	ML	91.45% accuracy with KNN.	Unestablished causal relationship.

4.2. Cultural context consideration in social media analysis

Social networking sites provide a wealth of data that can be used to identify mental health problems. However, current research usually ignores cultural variations between nations [116,117]. Every culture has different styles of writing and emotional expressions, which makes a conventional approach ineffective for correctly diagnosing mental health problems. Researchers can improve the sensitivity and specificity of mental health detection models, allowing for more precise evaluations in a variety of groups, by creating algorithms that take cultural variations into account. Examining methods such as adapting cross-cultural algorithms and culturally sensitive sentiment analysis can help advance our understanding of mental health indicators within certain cultural contexts. They also did not consider gender-wise differences [116]. Considering gender-specific social media data analysis will help us understand and identify hidden patterns between specific gender social media usage and their mental health. One's social media profile information such as age, geo-location, education, work, profile picture, etc. have a relationship with mental condition identification [118]. But this information was not considered. In future studies, cultural context, gender, and profile information should be considered when analyzing social networks for mental health analysis.

4.3. Enhancing audio data quality

Addressing issues with data quality and accessibility is crucial to ensure the dependability and usability of machine learning models for the detection of mental health. Studies using audio characteristics have frequently used poor-labeled data sets, which can reduce the efficiency of the models. To increase the precision of mental health classification using audio data analysis, future research should prioritize creating well-annotated audio datasets. Furthermore, investigating cutting-edge strategies such as active learning or transfer learning can help overcome the difficulties posed by the lack of labeled data in audio-based mental health research [119].

4.4. Researching towards affordable technology

The price of electroencephalogram (EEG) data is still a barrier to its widespread adoption among the general public, despite the fact that it has great analytical value for physicians. Future research should investigate less expensive options or technological developments that make EEG equipment more widely available. This could involve creating wearable EEG equipment or using mobile technology to gather pertinent physiological signs without being intrusive. Machine learning models can gain by including neurophysiological variables by improving the accessibility and affordability of EEG data collection, resulting in more precise mental health diagnoses.

4.5. Using multimodal data for a comprehensive analysis

While individual data sources, such as surveys or posts on social media, can offer insightful information, an integrated strategy incorporating multimodal data has the greatest potential for the early diagnosis

Table 3
Social media posts and text messages-based works.

Source	Year	Disease	Age	Location	Approach	Performance	Limitations
[58]	2018	Generic Mental Health	–	–	ML	False positive rate reduced	Weak interpretation of Reddit posts
[59]	2018	PTSD	–	–	DL	89% accuracy	Low accuracy, Depending on Twitter's data completely introduces bias and limits the mental health situation and representation of behavior.
[60]	2018	Depression	–	–	ML	93.06% accuracy	Understanding of temporal changes in emotion are difficult
[61]	2018	Suicidal Tendency	17–24	US	DL	70% accuracy	Selection bias from focusing on undergraduates limits generalizability. Potential recall bias persists despite mitigation. Reliance on third-party software for SMS data and DNN hinders feature extraction. High data collection costs suggest crowdsourcing as an alternative.
[62]	2019	Schizophrenia	–	US	Temporal based Classification model	Reduced false positive rate	Limited diversity, population bias exists and lacks generalization as the data consists only tweeter posts of english speaking people.
[63]	2021	Depression	–	–	ML	99.80% accuracy	Imbalanced dataset and model is limited to labeled datasets for training.
[64]	2021	Generic Mental Health	–	–	NLP	0.96% AUC	Self-diagnosed dataset, Limited subject diversity due to non-medical record datasets, Missing demographic info (gender, age).
[65]	2022	Depression	–	–	MDHAN	90% confidence	Explanation stability is challenging.
[66]	2023	Depression	–	India	ML	73.15% accuracy with SVM.	The authors achieved accuracy less than the existing work where they mentioned accuracy 82.6% of existing work. They need to fine-tune their models as well.
[67]	2023	Suicidal Tendancy	–	–	ML	96.33% accuracy with XGB.	Limited ML models were investigated.
[56]	2024	Depression	–	–	TL	97% accuracy.	Lacks comparison among different TL models.

Table 4
Audio-based works.

Source	Year	Disease	Age	Location	Approach	Performance	Limitations
[70]	2018	AD	17–18	–	NLP	90% accuracy	Weakly labeled small dataset.
[71]	2019	Depression	–	–	DL and ML	0.735 f1 score	Low performing and limited audio clips in the EMU dataset.
[72]	2020	Different Mental Health Issues	28–51	Canada	RNN	74.35% accuracy	The accuracy indicates room for improvement; handling imbalanced datasets remains a challenge; lack of offspring's audio samples and clinical narrative summaries could enhance predictive accuracy and mental mood predictions.
[73]	2021	Different Mental Health Issues	–	–	DL & NLP	96.51% accuracy	Proper comparative analysis not provided.
[74]	2022	Depression	–	–	BGRU	F1 score 0.92	Lacks generalizability because of less diversified data and also lack explorations and inclusion of other modality.
[69]	2023	Depression	–	Korea	DL	78.14% accuracy.	A small sample size, needing to recruit more participants; Audio samples recorded only in quiet environment, need testing in different and noisy conditions; And relying only on speech data, future research needs to integrate video and physiological signals for more robust and natural detection.
[75]	2023	Depression	–	China	DL	74.45% accuracy.	The study's Thai speech dataset may limit generalizability. Model comparisons are limited. Performance comparisons of deep learning are lacking and performance is low.
[76]	2023	Depression	–	–	DL	95.8% accuracy.	Investigating low-level acoustic features might give more insights.
[77]	2024	Depression	–	–	DL	90% accuracy.	While MFCCs are sensitive to individual speakers' characteristics, they are not designed to capture temporal dependencies or long-term context.

Table 5
Sensor and device data-based works.

Source	Year	Disease	Age	Location	Approach	Performance	Limitations
[81]	2019	Depression	–	–	One-dimensional CNN	0.70 f1 score	Low performing, limited model's generalizability and rely on only motor activity measurements.
[82]	2020	Different Mental Health Issues	–	Canada	Smartphone app to record environmental sound and behavioral data	Correlated with the severity of depression is r=−0.37; P<.001.	High withdrawal rate of app affects reliability.
[83]	2021	Depression	–	–	NeuralNet and AdaBoost.	90% accuracy	Lacks clear ground truth and limited feature interpretability.
[79]	2021	Depression	18–25	USA	DepHNN	99.10% accuracy	Small, imbalanced dataset and lacks generalization.
[84]	2021	Depression	–	–	Ensemble ML	89.60% accuracy	Randomly ensembles models. Lacks proper causality.
[85]	2022	Generic Mental Health	–	–	ML	95.36% accuracy.	Very small dataset and some models overfitted the results.
[86]	2023	Stress	–	–	CNN-LSTM	91.52% accuracy.	Large set of parameters is needed.
[87]	2023	Depression	16–56	–	ML and DL	97% accuracy with CNN.	Imbalanced data and individual variance might affect the detection process.
[80]	2023	Stress	–	–	SSL	RMSE 0.024	Limited generalizability.
[88]	2024	Depression	–	–	Non-linear ML	63% accuracy with SVM rbf.	Low and inconsistent performance for different subgroups.
[89]	2024	BD	–	–	DL	95.91% accuracy with 2D CNN.	Highly imbalanced Data and high sensitivity with low specificity.
[90]	2024	BD	15–35	–	SVM	63.1% accuracy.	Wide confidence interval, very low accuracy, and additional demographic data need to be considered.

Table 6
Multimodal data-based works.

Source	Year	Disease	Age	Location	Approach	Performance	Limitations
[68]	2019	Depression	–	–	Multilevel attention network	Reduced RMSE by 17.52%	Inductive biases available. Lacks generalizability, challenges in integrating data modalities, and specific features influencing depression prediction.
[93]	2020	Depression & Suicidal Behavior	–	–	Multimodal DL framework	No experimental result was provided.	Profile information might provide more insight.
[94]	2020	Different Mental States	–	Korea	Multi-modal DL model	89.5% accuracy	Quite a small sample of only 8 participants was used and might be validated only for specific geographical area.
[91]	2021	Stress	–	Netherlands	DL model	96.09% accuracy.	Accuracy depends on the number of modalities
[95]	2022	BD	–	–	Multimodal architecture	91.6% accuracy.	Small datasets and neglecting advanced neural network architectures like attention-based LSTMs may hinder performance improvements and limit real-world applicability.
[96]	2023	Depression	–	–	DL	88% accuracy.	Imbalanced Dataset and model might have sensitivity towards individual data.
[92]	2023	Depression	18+	India	ML	86% accuracy.	a small sample size, specific selection criteria, reliance on Pearson's correlation, and a costly 14-day smartphone data collection period.
[97]	2024	Generic Mental Health	–	–	DL	82% accuracy.	Only 73 subjects, yet low accuracy and the best feature (heart rate) found correlated to mental health need to be clinically validated.

of mental illness. According to our findings, combining data from several sources, such as social media profiles and spoken responses to specific questions, can provide a more complete picture of a person's mental health. The creation of a multimodal system that seamlessly integrates data from numerous sources while taking into account user demographics such as nationality, gender, and age is thus a future research path. This all-encompassing strategy may result in more accurate and personalized mental health assessments, giving researchers a more complex picture of people's well-being. The prediction potential of integrated models can also be increased by researching efficient fusion methods for multimodal data, such as deep learning architectures or attention mechanisms.

4.6. *Overview of a comprehensive integrated system for mental health assessment with personalized support*

Based on our discussion in the previous subsections, here, we propose a high-level overview of a comprehensive integrated system for mental health assessment that incorporates social media monitoring, wearable device data analysis, oral surveys, and personalized support.

Table 7
Benchmark datasets for mental health research.

Data type	Dataset name	Disease	Source
Survey and interviews	DAIC	Depression	[98]
	The Depression Dataset	Depression	[99]
	Mental Disorder Classification	Generic Mental Health	[100]
	Suicidal Behaviors Among Adolescents	Suicidal tendency	[101]
	Depression Anxiety Stress Scales Responses	Depression, Anxiety and Stress	[102]
Social media posts and text messages	Suicidality on Reddit	Suicidal Tendency	[103]
	Twitter Suicidal Data	Suicidal Tendency	[104]
	Sentiment140 dataset with 1.6 million tweets	Depression	[105]
	Human Stress Prediction	Stress	[106]
	Counsel Chat Data	Depression	[107]
Audio data	Depression Audio Dataset	Depression	[108]
	PAIR	Depression	[109]
Sensor and device data	Nurse Stress Prediction Wearable Sensors	Stress	[110]
	Biometrics for stress monitoring	Stress	[111]
Multimodal	HOPE	Generic Mental Health	[112]
	MEMO	Depression	[113]

The system aims to provide accurate predictions while offering specialized treatments and appropriate intervention for people at risk. The system takes gender, age, and nationality into account in the primary assessment, uses health monitoring data for the secondary assessment, and incorporates an oral survey with acoustic analysis. This system can either be a web application or a mobile application that, we assume, has the functionality to collect one's public data from social media and can be connected to one's wearable devices like a smartwatch to collect data. Fig. 4 illustrates the key components and interactions within the proposed integrated system for the assessment of mental health.

4.6.1. Primary assessment: monitoring social media and profile analysis

The integrated system starts the initial evaluation by keeping track of a person's public social media activity and examining their public profile data. To maintain cultural relevance and gender-specific mental health issues, it is crucial that the system takes into account the user's gender, age, and nationality. The user's social media interactions and public posts are analyzed using natural language processing algorithms. The algorithm can learn important information about a person's mental health by analyzing the sentiment, linguistic patterns, and substance of their online activity. This thorough initial evaluation offers a preliminary assessment of the person's mental health while taking into account demographic and cultural variables.

4.6.2. Secondary assessment: analysis of health monitoring data

The integrated system analyzes health monitoring data from wearable devices to improve the accuracy of mental health assessments. These gadgets record physiological information such as heart rate, sleep patterns, levels of activity, and stress markers. The system examines these data to find trends and abnormalities that might be related to mental health problems. When applying machine learning algorithms, demographic information about the person is taken into account to find links between physiological signals and mental health. This secondary evaluation acts as an additional source of data, giving a more thorough picture of the person's mental state and enhancing forecast accuracy.

4.6.3. Verbal response analysis for oral surveys

The integrated system asks the user to take an oral survey if the combined findings of the primary and secondary assessments show a higher probability of a mental health problem. The user responds verbally to the system's generated guided questions, which the system then speaks aloud. The user's responses are recorded, transcribed, and analyzed using automatic voice recognition techniques. To learn more about the respondent's mental state, the system takes into account both the substance of the responses and auditory cues such as tone and voice patterns. This oral survey offers a further layer of evaluation, allowing for a more thorough understanding of the subject's mental health.

4.6.4. Comprehensive mental health prediction and support

The integrated system incorporates all available data to forecast the person's mental health condition by merging the results of the primary assessment, the secondary assessment, and the oral survey. The system offers individualized suggestions and treatments based on the user's gender, age, and cultural background if it notices symptoms of depression, stress, or associated conditions. Additionally, the system automatically alerts volunteer organizations that specialize in supporting people with suicidal tendencies or notifies selected family members if the system anticipates a higher probability of suicidal tendencies, guaranteeing quick intervention and support. This all-encompassing strategy strives to increase public awareness of mental health issues, provide personalized care, and prevent possible crises.

4.6.5. Theoretical comparison of effectiveness among proposed system and existing tools for mental health assessment

It is theoretically possible to compare the effectiveness of the suggested integrated system with current mental health assessment tools by assessing several factors, including user experience, accessibility, efficiency, and accuracy. Though we have discussed many different research works for mental health assessment, the most commonly used tools for clinical assessment are interviews and surveys. In this section, we present a hypothetical comparison between our proposed method and existing tools using these standards:

- **Accuracy:** The existing methods of mental health assessment like interviews and surveys are subjective to individual interpretation. On the other hand, our proposed system is data-driven. It uses multimodal data and advanced machine-learning techniques for assessment. Hence, more accurate results can be achieved.
- **Efficiency:** The clinical assessments and traditional questionnaires are time-consuming. It takes multiple sessions to conclude. Also, it employs a blind method. On the other hand, our proposed method has a guided step-by-step assessment process. It takes less time and is more efficient.
- **Accessibility:** Traditional clinical mental health assessment tools are less accessible as there are resource restrictions and a lack of professionals, especially in remote areas. The proposed integrated solution would enable people to get assessed from the comfort of their own homes by being remotely accessible through online or mobile applications. Furthermore, wearable device integration makes mental health evaluation tools more accessible by enabling continuous monitoring.
- **User-experience:** In the traditional system, the questions are repetitive and tedious as well as it might create discomfort among the participants in front of a human interrogator. But, our proposed system will have interaction with the user only after primary assessment, and if needed. So, it will be more convenient for the users.
- **Long-term Monitoring:** In the traditional systems, assessments are done mostly at discrete times. In our proposed system, long-term monitoring is possible.

4.6.6. Privacy and ethical consideration for the proposed integrated system

In this proposed integrated system there are some ethical and privacy considerations that should be addressed. As the system needs to analyze a large amount of personal data, the system should secure the data from unauthorized access [120]. Though the system uses social

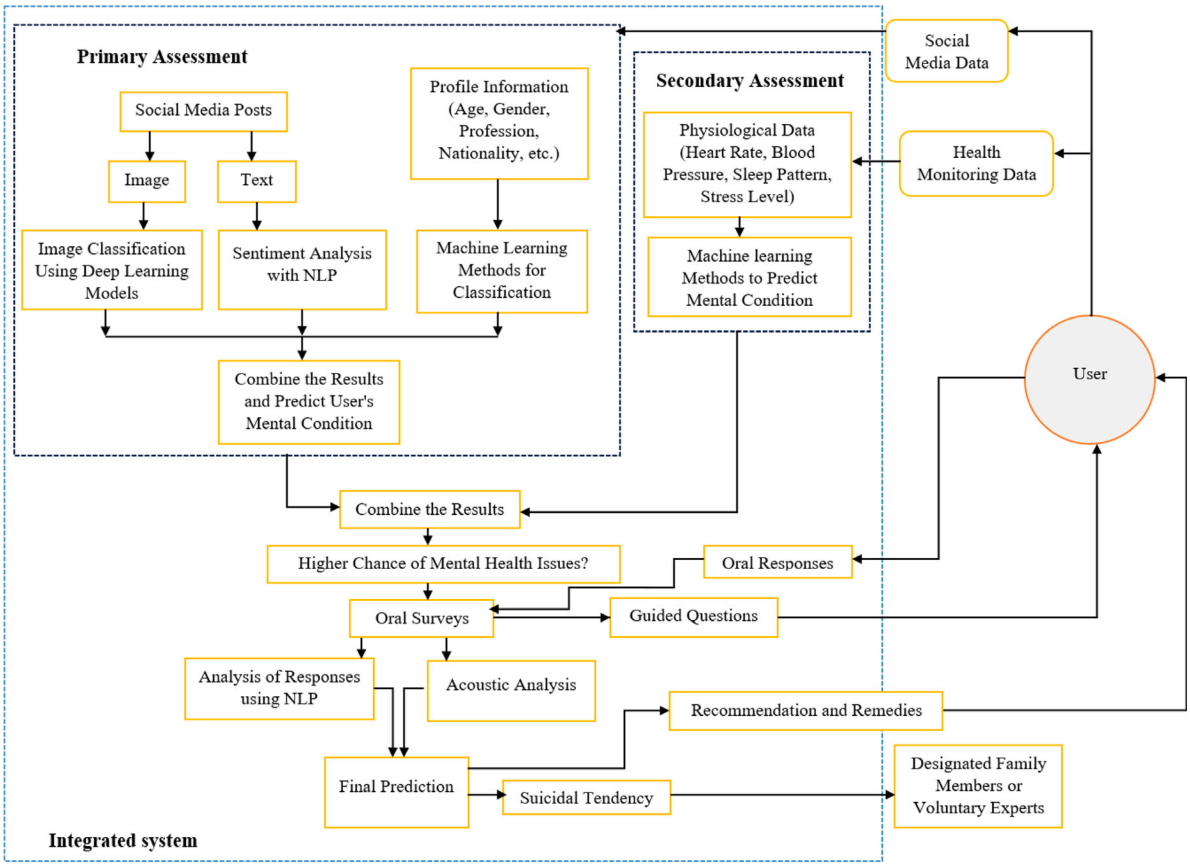

Fig. 4. Comprehensive Integrated System for Mental Health Assessment.

media profile data that is publicly available, user consent should be taken [121]. As the issue is a sensitive one, the output of the black-box model should be interpreted with Explainable AI (XAI) models [122, 123].

4.6.7. Limitations and challenges in implementing the proposed integrating system

The first challenge in implementing the system is data collection to train the model [8]. The social media data or interview responses are not readily available for people from different nationalities and ages. Again, the collected data must remain unbiased. It is important to achieve high accuracy [124]. Legal and regulatory challenges are the second largest challenge [8]. Adoption can be another challenge. Still, people are less serious about mental health. Also gaining user trust will take time.

5. Conclusion and future works

In this work, we have discussed different machine-learning approaches for the early detection of mental illness. In our study, We have included all the recent works that provide some original experimental results in this domain. We have compared the works based on the different methods and data types used. We also established a taxonomy of mental disorders issues and machine learning models based on five domains sensors and device data, survey and interviews, multimodal data, audio data, and social media posts and text messages. After analyzing all the works, we proposed a future direction for developing an integrated system that will include multiple domain data of an individual to provide a final prediction. We have also compared our proposed model with existing methods. We listed some benchmark datasets for mental health research which will be helpful for researchers. Finally, we discussed the challenges in implementing the integrated system. Our paper has some limitations which we want to state here:

- Even though every effort was taken to include all relevant research in this review, there is still a chance that any relevant research was missed in the process of conducting the systematic search as our keyword considerations are limited and we only searched into a few specific databases. Moreover, the search was limited to research written in only English language, which eliminated research written in other languages from consideration. There are many research conducted in China, Spain, Saudi Arabia, and India that are not written in the English language [125], hence are left out of this study.
- This review does not explore specific details such as identifying the optimal model based on discriminating relevant features. Furthermore, it does not mention which dataset performs better in a specific data domain. Comparative analysis among different related works is not done.
- We have not provided any experimental analysis for the system that we proposed for the early detection of mental illness.

In the future, we would like to consider more articles from different databases and also provide a comparative analysis among related works. We will gather sufficient data for our experiment and provide experimental analysis for our proposed integrated system in the future. However, this paper will provide a solid overview of recent works and a future direction for the new researchers in this field.

Declaration of competing interest

We do not have any conflict of interest.

Data availability

No data was used for the research described in the article.

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