

# Al-assisted Diagnosing, Monitoring, and Treatment of Mental Disorders: A Survey

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Globally, 1 in 7 people has some kind of mental or substance use disorder that affects their thinking, feelings, and behaviour in everyday life. People with mental health disorders can continue their normal lives with proper treatment and support. Mental well-being is vital for physical health. The use of AI in mental health areas has grown exponentially in the last decade. However, mental disorders are still complex to diagnose due to similar and common symptoms for numerous mental illnesses, with a minute difference. Intelligent systems can help us identify mental diseases precisely, which is a critical step in diagnosing. Using these systems efficiently can improve the treatment and rapid recovery of patients. We survey different artificial intelligence systems used in mental healthcare, such as mobile applications, machine learning and deep learning

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methods, and multimodal systems and draw comparisons from recent developments and related challenges. Also, we discuss types of mental disorders and how these different techniques can support the therapist in diagnosing, monitoring, and treating patients with mental disorders.

# $\label{eq:ccs} CCS \ Concepts: \bullet \ Computing \ methodologies \rightarrow Natural \ language \ processing; \ Machine \ learning; \ Artificial \ intelligence.$

Additional Key Words and Phrases: Mental Health; Artificial Intelligence; Large language models; Machine Learning; Natural Language Processing.

#### **1 INTRODUCTION**

Millions of people worldwide are affected by mental disorders that influence their thinking, feeling, or behaviour. Mental health is an essential prerequisite for physical and general health. People with mental disorders often require appropriate treatment and support to lead a normal life [1]. Mental healthiness is a condition of wellbeing in which an individual recognises his or her abilities, can cope with the everyday tensions of life, works productively, and can contribute to his or her community. Mental health affects the lives of people with a mental disorder, their professions, and the community's productivity. Mental health and resilience are essential to our biological health, human connections, education, work, and achieving our potential [2]. The COVID-19 pandemic has significantly impacted people's mental health, in particular groups such as health and other front-line workers, students, people living alone, and those with preexisting mental health conditions. Moreover, services for mental, neurological, and substance use disorders have been significantly disrupted.

Mental disorders represent disturbances to mental health, often characterised by troubling thoughts, emotions, behaviour, and relationships with others. Mental disorders are considered complex to diagnose due to the similarity of symptoms. Regular health inspections of people with severe mental disorders can deter premature death [3]. The difficulty of experts in diagnosing is usually caused by the similarity of symptoms in mental disorders, such as schizophrenia and bipolar disorder. 1 in 4 people will experience a mental health problem at some point, and 1 in 6 adults have a mental health problem. 1-in-10 children aged between 5 and 16 years has a mental health problem, and many continue to have mental health problems into adulthood. One billion individuals have a mental disorder, and anyone can be impacted. In particular, depression is a leading cause of disability worldwide and significantly contributes to the general global disease burden. Globally, it is calculated that 5% of adults suffer from depression. Half of all such disorders start by the age of 14 years, but most are undetected and untreated [4]. The lost productivity coming from depression and anxiety, two of the most specific mental disorders, costs the international economy US 1 trillion \$ each year. Governments spend 2% of their national health funding on mental health. This has changed little in current years; despite an increase in development assistance for mental health, it has never exceeded 1% of outcome assistance for health [5].

In Europe, 165 million people are affected annually by a disorder or mental disorder. Only a quarter of patients with mental disorders receive treatment, and only 10% have appropriate treatment. Mental disorders have become, in recent years, the leading cause of disability, and it is a significant cause of morbidity in societies. In the particular case of Portugal, SPPSM reports that more than one-fifth of Portuguese suffer from a psychiatric disorder (22.9%) and that Portugal is the second country with the highest prevalence of psychiatric disorders, depression and anxiety, can be treated by talking with therapies, medication, or a combination of both. Generalist health workers can be trained to analyse and treat mental health conditions. For every US\$ 1 supported in scaled-up treatment for depression and anxiety, there is a recovery of US\$ 5. For every US\$ 1 supported in evidence-based treatment for drug addiction, there is a recovery of up to US\$ 7 in decreased crime and criminal justice costs [7].

Personalised psychiatry also plays a vital role in predicting mental disorders and improving diagnosis and optimised treatment. The use of intelligent systems is expected to grow in the medical field, and it will continue

to pose abundant opportunities for solutions that can help save patients' lives. As it does for many industries, AI systems can support mental health specialists in their jobs. Algorithms can explore data much faster than humans, propose possible treatments, monitor a patient's progress, and alert human professionals to concerns [8]. Healthcare organisations have a large quantity of information available, and a significant portion is unstructured and clinically applicable. Researchers are testing how intelligent systems can help screen, diagnose, and treat mental disorders. To focus this review on recently published literature, We reviewed 97 studies published 2013–2022(Figure 3) from different literature databases like Google Scholar, Web of Science (WoS), Scopus, IEEE Xplore, PubMed, and Science Direct of AI and mental health that used expert systems, novel monitoring systems (e.g., smartphone, video), the app for early detection, networking site, and social media platforms to predict, classify, or subgroup mental health disorders, including depression, bipolar, autism spectrum disorder, panic disorder, schizophrenia or other psychiatric disorder.

This survey about diagnosing mental disorders and monitoring mental health is organised as follows: The first section provides the introduction of the problem statement, as well as the objectives and goal of this survey. The second section describes related background mental healthcare, factoid and non-factoid questions and the latest research. The third section describes intelligent systems, a brief history of AI in mental health, and the use of AI in mental health to diagnose and monitor patients with mental disorders. In this session, we will also discuss the different machine learning and Deep Learning methods, mobile applications for mental health, and mental health datasets. Finally, we will address AI as assisted decision-making for professionals. The fourth session discusses the approaches used in different works, performance metrics, best classifiers, and a brief summary of mental health challenges and limitations. Finally, The conclusions are in the fifth section.

#### 2 BACKGROUND AND RELATED WORK

Mental, physical, and social health are vital aspects of any individual's life and are completely interconnected and interdependent to the point that we cannot consider health without mental health. The more we understand this correlation, the clearer it becomes that mental health is central to the well-being of individuals, societies, and countries.

#### 2.1 Types of Mental Health Issues and Disorders

The World Health Organization (WHO) [3] conceptualises mental health as a "state of well-being in which the individual realises his or her abilities, can manage with the usual stresses of life, can work constructively and fruitfully, and can contribute to their community". According to [8], mental health is the ability of individuals and all of us to feel, think, and operate in ways that improve our ability to enjoy life and deal with our challenges. It is an optimistic sense of emotional and spiritual well-being that appreciates the significance of culture, equity, social justice, interconnections, and personal dignity. Mental disorders result from a complex interaction of genetic, biological, personality and environmental factors with the brain as the final common pathway for controlling behaviour, cognition, mood, and anxiety. Most mental disorders can be broadly classified as psychoses or neuroses. Psychoses (e.g., schizophrenia and bipolar disorder) are severe mental illnesses distinguished by acute symptoms such as delusions, hallucinations, and the inability to objectively evaluate reality. Neuroses are less severe and more treatable illnesses, such as depression, anxiety and paranoia, as well as obsessive-compulsive disorder and post-traumatic stress disorder [9].



Fig. 1. Number/million with a mental disorder by type, European Region 2019.

Mental disorders or illnesses are characterised by altered thinking, mood, or behaviour or are associated with significant distress and impaired functioning. The symptoms of mental disorders vary from mild to severe, depending on the type of mental disorder, the individual, the family, and the socioeconomic environment. Mental disorders take many forms, including mood disorders, schizophrenia, anxiety disorders, personality disorders, eating disorders, and addictions such as substance dependence and gambling. According to World Mental Health Day 2019 [10], based on global data for all ages genders, the most common mental disorders include depression 5.45%, anxiety disorders 3.34%, schizophrenia 1.78%, other mental disorders 1.01%, bipolar disorder 0.99%, conduct disorder 0.56%, intellectual disability 0.51%, autism spectrum 0.5%, eating disorders 0.34% and attention deficit hyperactivity disorder 0.12%, as illustrated in Fig. 1.

Among the major diseases, this survey addresses mental disorders such as depressive disorders, panic disorders, bipolar disorders, schizophrenia, anxiety disorders and autism spectrum disorders, and some proposed solutions using artificial intelligence systems.

# Depressive Disorders

Depressive disorders are a primary care disease and are one of the most common categories of psychiatric disorders [11]. The WHO [12] declares depression is a common mental disorder and one of the leading reasons for disability worldwide. Globally, a calculated 264 million people are affected by depression. Depression is a common and severe medical disorder that negatively affects how one feels, thinks, and acts [13]. Because of wrong perceptions, nearly 60% of people with depression do not seek medical help. Many sense that the stigma of a mental health disorder is unsuitable in society and may hinder personal and professional life. Depression causes sadness, and a loss of interest in activities once enjoyed. The standard features of all depressive disorders are sadness, emptiness, or irritable mood, attended by somatic and cognitive changes that affect the individual's capacity to function [14].

#### **Bipolar Disorder**

The American Psychiatric Association's Diagnostic and Statistical Manual of Mental Disorders (DSM-5) [15] describes bipolar disorders as a class of brain disorders that cause severe fluctuation in a person's mood, energy, and capacity to function. Bipolar disorder occurs in up to 2.5% of the population [16]. People with bipolar disorder experience great excitement, over-activity, deception, euphoria (mania) and other times of feeling sad and hopeless

(e.g., depression). Bipolar disorder is characterised by at smallest one manic/hypo-manic or crossbred episode (mania and depression) with or without a history of influential depression [8].

During the period of mood disorder, three or more of the subsequent symptoms have prevailed and have been present to a considerable degree [16]:

- Inflated self-esteem or grandiosity.
- Reduced need for sleep (e.g., feels rested after only 3 hours).
- More conversational than usual or pressured to keep talking.
- Flight of ideas or subjective knowledge that thoughts are racing.
- Distractibility (i.e., attention is too easily drawn to unimportant or irrelevant external stimuli).
- Addition in goal-directed activity (socially, at work or school, or sexually) or psychomotor agitation.
- Exaggerated involvement in pleasurable activities with a high possibility for painful consequences (e.g., engaging in unrestrained buying sprees, sexual improprieties, or foolish business investments).

#### Autism Spectrum Disorder (ASD)

ASD is a neurodevelopmental condition denoted by deficits in social communication and the presence of restricted interests and repetitive behaviours [17]; other features are atypical patterns of activities and conduct, such as difficulty with the change from one activity to another, a focus on details and unusual reactions to sensations [18]. Autism is an illness that usually starts in infancy, at the latest, in the first three years of life. Parents often become concerned because their child is not using words to communicate, even though he or she recites passages from videotapes or says the alphabet. Autism is a heterogeneous condition; no two children or adults with autism have the same profile, but difficulties fall into core domains that are reliably measured and usually consistent across time, even though specific behaviours may change with development [19, 20].

People with autism are usually subject to stigma, intolerance, and human rights violations. Care for people with autism needs to be accompanied by actions at community and societal levels for greater accessibility, inclusivity, and support.

#### **Panic Disorder**

Panic disorder is a typical mental disorder that affects up to 5% of people at some point in life. It is often disabling, especially when complicated by agoraphobia, and is associated with substantial functional morbidity and reduced quality of life [21]. According to [22], panic disorder is an anxiety disorder characterised by unexpected and repeated episodes of severe fear accompanied by physical symptoms that may include chest pain, heart palpitations, shortness of breath, dizziness, or abdominal distress. The typical features of panic disorders [23] are:

Palpitations	Unsteady	Chest pain or discomfort
Sweating	Trembling or shaking	Nausea or abdominal distress
Shortness of breath	Feelings of choking	Feeling dizzy
Feeling of smothering	g lightheaded or faint	pounding or accelerated heart rate

#### Schizophrenia

Schizophrenia is a specific reaction to severe anxiety, having its origin in childhood and experienced similarly and reinforced in a later time of life, and it generally affects a motivational use of progressive impairment of the abstract attitude [24]. Schizophrenia is a syndrome: a group of signs and symptoms of unknown aetiology, defined mainly by observed signs of psychosis. Schizophrenia shows paranoid delusions and auditory hallucinations late in adolescence or earlier adulthood in its most common form. These manifestations of the disease have changed little over the past century. Schizophrenia is conceptualised as a psychotic disorder, and this change requires psychotic pathology in the diagnosis [25]. Delusions, hallucinations, and disorganised speech are core "positive symptoms" diagnosed with high reliability and might reasonably be considered necessary for a reliable

diagnosis of schizophrenia. People with schizophrenia have 2-3 times more potential to die earlier than the general population [26].

Schizophrenia is a psychiatric disease with a complex and multi-factorial aetiology resulting from the cumulative effect of several risk factors. Among them, genetic factors reflect the weight of hereditary factors in the genesis of schizophrenia, in which susceptibility to various spectrum diseases is inherited. According to WHO [27], schizophrenia is a psychosis, a type of mental disorder characterised by distorted thinking, perception, feelings, language, sense of self, and behaviour. Typical experiences include hallucination: hearing, seeing, or feeling things not there.

Other everyday experiences include:

- Delusion: selected false beliefs or suspicions not shared by others in the person's culture and firmly held even when there is proof of the opposite.
- Abnormal behaviour: disorganised behaviour such as wandering, mumbling, or laughing to self, strange appearance, self-neglect, or unkempt.
- Disorganised speech: incoherent or irrelevant speech;

• Disturbances of emotions: marked apathy or disconnect between reported emotion and what is observed, such as a facial expression or body language.

#### 2.2 Related work

There is some research on specific types of AI-assisted diagnosis [28–30], monitoring [28, 30, 31], predict [32], and treatment [28, 29, 33] applications for mental disorders. In [28], the author explores applications in the prevention, supplementary diagnosis, treatment and rehabilitation of mental illness; the survey also discusses the advantages, shortcomings and opportunities of AI applications in mental disorders to provide references for research related to mental health applications based on AI technology. In [32], the author explores AI and mental health that use electronic health records, brain imaging data, novel monitoring systems, and social media platforms to predict, classify, or subgroup mental health diseases. In [31], the author gives a survey on mental health monitoring systems (MHMS) using sensor data and machine learning.

Reference	Application Scope	Topic Focus
Xishuang et al. [28]	Prevention, diagnosis, treatment of mental illness.	Natural language processing, deep learning techniques and Applications
Graham et al. [32]	Predict and classify mental illness.	Electronic health records (EHRs), mood rating scales, brain imaging data, novel monitoring systems, and social media platforms
Garcia-Ceja et al. [31]	Patient monitoring	Sensor data and machine learning.
Gravenhorst et al [34]	Support therapy and monitoring the current state and development of their mental disorders.	Mobile phones
David D. Luxton [33]	Activities in psychological practice and research.	Human–computer, augmented reality applicationsinterface
Su et al [29]	Diagnosis and prognosis	Applications of DL algorithms in mental health outcome research.
Vidhi and Vrushti [30]	Diagnosis and monitoring	Systems for mental health monitoring
This survey	All the above applications and other prevention, diagnosis, monitoring, treatmentof mental illness applications.	Deep learning, machine learning techniques, natural language processing, mobile applications(mhealth), multimodal systems, applications,performance results, and ethical considerations.

Table 2. Summary of Related Survey on Application of Artificial Intelligence in Mental Health Context

This survey is different from existing ones because its scope is not limited to any specific type of application or algorithms but also to prevent, diagnose, monitor, and treat mental illness, as summarised in Table 2 that is not limited to one mental disease. The scope of application of this research includes the diagnosis, monitoring and prevention of various mental problems. The research provides a comprehensive summary and comparison of types of mental disorders and the role of intelligent systems in the automatic diagnosis and monitoring of mental disorders. Machine learning classifiers usually fall into two primary categories: supervised learning and unsupervised learning. We also present several studies that used DL in their approaches. Finally, the research presents a brief discussion and future challenges of intelligent systems in aiding the diagnosis and monitoring of patients with mental problems.

2.2.1 Review Method. A critical literature review was performed in this study to define a wide variety of methods of machine learning, natural language processing, deep learning, and multimodal systems to help diagnose, monitor and treat patients with mental disorders and their markers in recent years until 2022 (2013-2022) as shown in Fig 3. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) [35] method was used to discover and identify relevant articles. Selected articles were identified using the electronic literature search method of Google Scholar, Web of Science (WoS), Scopus, IEEE Xplore, PubMed, and Science Direct using the query term combination of the search keywords. Keyword searches for suitable articles include: "Mental Health", "Artificial Intelligence", "Machine Learning", "classification methods", "elassification problem", "arrest methods", "diagnostic methods", "treatment methods", "Large Language Models", "mental health dataset", "Transformers", and "Natural Language Processing" in the field of detection, diagnosis, treatment and monitoring of mental illnesses.

The search results were filtered to filter the articles that did not capture such discourse. The screening of articles was based on titles, abstracts, and search keywords. The total number of reports collected at the end of the search was 271. After eliminating duplicate articles, the original number was reduced to 198. Based on the title and abstract review, we identified 153 records as eligible and excluded 45 records. The 153 selected articles were read and scanned to eliminate results that did not correlate with the research topic, resulting in 99 articles that we considered relevant to our study.

Ineligible articles were articles that performed text recognition from handwritten datasets, those whose datasets were not in English, articles written before 2013, articles unrelated to mental problems, and articles that did not allow downloads. Criteria of Inclusion: articles in the English language, mobile applications, articles that used ML methods, DL methods, NLP methods, and a combination of learning methods and articles that do not fulfil any inclusion criterion.

Finally, a total of 99 articles met our eligibility criteria. Most of the reviewed articles were published between 2015 and 2022. To summarise these articles, we grouped them into four categories according to the types of data analysed, including studies of the background of mental health, deep and machine learning algorithms, mobile applications, and studies of mental health datasets. Figure 2 presents a flowchart of the article selection process from the initial search stage to the final number of articles selected.

## 3 ARTIFICIAL INTELLIGENT SYSTEMS FOR MENTAL HEALTH

Intelligent systems (IS) provide a standardised methodological approach to solve critical and relatively complex problems and obtain consistent and reliable results over time [36]. The definition of intelligent systems is a complex problem and is subject to a great deal of debate. Independently from the definition, there is not much doubt that AI is an essential basis for building intelligent systems [37].

According to Russel and Norvig [38], AI consists of two main directions. One is humanistic AI (HAI), which studies machines that think and act like humans. The other is Rationalistic AI (RAI), which examines machines that can be built on the understanding of intelligent human behaviour [39]. An intelligent system is a system that



Fig. 2. **PRISMA flow diagram: application of artificial intelligence in a mental health context.** In total, 99 studies, in terms of mental health background, deep and machine learning algorithms, mobile applications, and mental health datasets, which met our eligibility criteria, were included in this review.

emulates some aspects of intelligence exhibited by nature. These include learning, adaptability, robustness across problem domains, improving efficiency (over time and/or space), information compression (data to knowledge), and extrapolated reasoning. Doucet et al. [40] declare that an intelligent system refers to different software tools that enable decision-makers to draw on experts' knowledge and decision processes in producing decisions. The

first use of AI in the psychological field was the creation of the ELIZA computer program in 1966 [41], a humancomputer interface was designed to imitate the empathetic communication style of Carl Rogers psychotherapist [33, 42]. ELIZA used language syntax to provide formulated responses based on a programmed model and only mimicked conversation. Shortly after, PARRY was created by psychiatrist Kenneth M. Colby [33]. The computer program simulated a patient suffering from paranoid schizophrenia and held conversations, like ELIZA, with its users. PARRY became so realistic that expert psychiatrists had difficulty differentiating PARRY from real-life patients. PARRY has been the closest AI system to pass the Turing Test.

The mathematician Alan Turing proposed the Turing Test (TT) to replace the question: "Can a machine think?". Turing's views have been widely discussed, attacked, and defended over and over [43]. At one extreme, Turing's paper has been considered to represent the "beginning" of AI, and the TT has been considered its ultimate goal [42]. The Turing Test is among the many disputed cases in artificial intelligence, philosophy of mind, and cognitive science.

In addition to these more mediatic milestones, the use of AI in mental health remained inexpressive for several decades. On the one hand, AI, in particular machine learning, was not sufficiently developed; on the other hand, the possibility of accessing and computationally processing medical data on a large scale only became possible in the last two decades. It is only more recently, approximately since 2014, that we have started to see some more concrete research work using AI in mental health [32].

Table 3. Types of mental disorders and role of the Intelligent Systems.

Summarising the critical comparisons between the primary contributions of the approaches and review of recently published literature, we included only studies published from 2013 to 2021, corresponding to the upsurge in AI systems publications about mental health.

Authors	Disorder Type Y	lear	Keywords used	Methodology	Primary contribution
Jayshree Lavhare [44]	Stress disorder 2	2021	On-line social net- working site, Mental disorders detection, Feature extracted, & Social network mental disorder classifying.	On-line societal net- work and a random forest classification	Machine learning framework for detecting the Social Net- work Mental Disorder Detec- tion (SNMDD)
Abel and Greis [45]	Bipolar Disor- 2 der	2019	Bipolar disorder, mental disorders, and health lit- eracy	BraPolar: App for Re- mote Monitoring of People with Bipolar Disorder	Detecting fluctuations in mood and behaviour. Indi- cate early mood changes before the disease reaches extreme functional conse- quences
Desti Fitriati [46]	Bipolar Disor- 2 ders	2019	Mental disorders, Bipolar disorder, Early detection of Bipolar disorder, Back- propagation	Backpropagation Algorithm, Website and Android App	Conduct an early detection study of bipolar disorder by using screening question- naire data.
Aditya Thota [47]	Stress Disorder 2	2018	Stress prediction, Health- care, Machine Learning	Machine Learning Techniques: Boosting, Bagging and Decision Trees	Using ML methods to de- velop a model to predict the risk of stress experienced and if treatment is required by an individual.
Shahidul Khan et al. [48]	Schizophrenia 2	2018	Data mining; Mental dis- ease; Bangladesh; Health Data; Classification algo- rithm.	Machine Learning Techniques: Random Forest, SVM and K-Neighbor	This model will help the psy- chiatrist to understand the at- tributes related to mental dis- order patients.
Priyanka Dhaka [49]	Anxiety, Mood, 2 Psychotic, & Personality Disorder	2016	Mental health, disorders, MongoDB, extracting	Genetic Algorithm	Help us to better understand what treatment works for which kind of patient.
Philip and Thomas [50]	Alzheimer dis- 2 ease and De- mentia	2015	Patient Monitoring, Mental Disorders, Sensor Technologies, Big Data Analytics, Psychometric Scales	Multimodal Systems	Multimodal Systems where patients can be diagnosed, treated and monitored.
Sri Mulyana [51]	Schizophrenia 2 and Mood Disorders	2013	Text processing, Natural Language Processing (NLP), Mental disorders, Symptoms, Medical record	Natural Language Pro- cessing (NLP)	Shareasoning computer sys- tem to help to diagnose the types of mental disorders and their management.
Stefan et al. [52]	Panic Disorder 2	2013	Mobile communication, Smartphones, Mental dis- orders, Psychology	Mobile Application for People with Panic Dis- order	Treatment for people with panic disorder with and with- out agoraphobia.

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Using artificial intelligence tools, researchers aim to diagnose (or predict) and monitor mental conditions before reaching the severe stages of mental disorders.



# Artificial Intelligence and Mental Health

Fig. 3. Statistics on the number of AI and mental health literature in recent years.

#### 3.1 Machine Learning Methods

Machine learning is a branch of AI and computer science that concentrates on using data and algorithms that emulate the process of human learning. How do we identify patterns and induce/abstract knowledge from the environment (data) and make decisions accordingly? Machine learning aims to provide artificial systems with the ability to learn with minimal human intervention and thus adapt quickly to new situations and data. Machine learning classifiers usually fall into two primary categories [53]: *supervised learning* and *unsupervised learning*.

*Supervised learning*, also known as supervised machine learning, is described by its use of tagged datasets to train algorithms that classify data or predict effects accurately. Some methods used in supervised learning include linear regression, random forest, logistic regression, support vector machine, neural networks, naive Bayes and others.

*Unsupervised learning*, also known as unsupervised machine learning, applies learning algorithms to induce knowledge from unlabelled data, thus in an autonomous fashion. Typically, these algorithms find hidden patterns in data collections without human intervention. In this category, we can highlight the *k-means clustering*, methods of *probabilistic clustering*, and association rules, among others [54, 55].

In the remainder of this section, we further detail some of these algorithms still relevant in different areas of AI and its applications, including naturally the area of *mental health*.

*3.1.1 Support Vector Machine.* Most known simply as SVM, this supervised learning algorithm seeks the hyperplane that best separates the data points from different classes. Data is usually represented by n-dimensional

points, also called n-dimensional vectors. The data points (vectors) nearest to the potential boundaries are key vectors that help to define the hyperplane during training. A Support Vector Machine is a statistical model applied for scenarios requiring classification or regression. SVM is quite efficient and makes decisions efficiently, even in the case of a large dataset. Among all learning algorithms observed in AI for mental health, SVM is the most popular one. In this survey, it was the algorithm used in [48, 56–61].

*3.1.2 Decision Tree.* The decision tree is a supervised learning method for classification and regression problems. That has a tree-like structure in a leaf node corresponding to a class or a decision node containing a test on some attribute. Each test result has an edge for a sub-tree, and each sub-tree has the same structure as the tree. In a decision tree, there are two kinds of nodes: decision nodes and Leaf nodes. The latter contains the outcome (the class or value) for a combination of attribute values defined by the path of decision nodes. Decision trees can produce coherent rules without requiring any complex computations. In this survey, decision trees ranked third in the most used learning methods. It was found in four articles addressing mental health issues [56, 57, 62, 63].

*3.1.3 Random Forest.* Random forest is a supervised machine learning method known as the ensemble classification method; it deals with two types of problems: classification and Regression. The random forest algorithm combines the output of multiple decision trees to generate the final output or for making decisions. By sampling the subsets of the training data, the tree bagging method fits a decision for each tree and aggregates their result. In this survey, random forest ranked second in the most used learning methods. It was found in five articles addressing mental health [56–59, 63].

3.1.4 *K Nearest Neighbour.* The K Nearest Neighbour (K-NN) is one of the most commonly used non-parametric algorithms. It is one of the most straightforward machine learning algorithms based on supervised learning and can be used for classification and predictive regression problems. K-NN is mainly used for Classification problems, but it can also be used for Regression. K-NN captures all the information of the training data. It assumes the similarity between the new case/data (to be predicted) and available cases (previously observed/learned), assigning the new case into the category most like the available categories on some proximity measure. It is easy to execute and does not make any additional assumptions, but it gets significantly slower with the expansion in the number of independent variables. In this survey, we have observed this technique in three works [48, 56, 63].

3.1.5 Naive Bayes. Naive Bayes (NB) is an easy but powerful algorithm derived from the Bayes theorem proposed by Thomas Bayes (1701 - 1761) that is mainly used for building predictive models — used in situations where probabilistic dependencies between datasets are expected, something like  $D \Rightarrow C$  meaning that the observation of data configuration in D is likely to produce the outcome/classification in C. For example, D might represent a set of all possible mental diseases' symptoms and C the set of possible diagnostics. In this setting, the Bayes Rule states that:

$$\mathbb{P}(C|D) = \frac{\mathbb{P}(C) \cdot \mathbb{P}(D|C)}{\mathbb{P}(D)}$$

where:

- $\mathbb{P}(C|D)$  is the posterior probability;
- $\mathbb{P}(D|C)$  is the likelihood of observing data *D* when class *C* is certain;
- $\mathbb{P}(C)$  and  $\mathbb{P}(D)$  are the prior or marginal probabilities; the normalisation of that evidence under any circumstance.

In the example formulated above,  $\mathbb{P}(C|D)$  represents the distribution of the diagnosis taking into account the observed symptoms (*D*). While  $\mathbb{P}(D|C)$  is the distribution of data (symptoms) observed for a given disease ( $c \in C$ ).  $\mathbb{P}(C)$  is the distribution of diseases. In learning based on Bayes' formula, one tries to maximise the disease (class)

that best fits the observed data (evidence) through the formula:

$$\underset{c \in C}{\operatorname{argmax}} \ \frac{\mathbb{P}(c) \cdot \mathbb{P}(D|c)}{\mathbb{P}(D)}$$

which is equivalent:

$$\underset{c \in C}{\operatorname{argmax}} \ \mathbb{P}(c) \cdot \mathbb{P}(D|c)$$

The *Bayes Rule* and *Naive Bayes* are the foundation of many other machine learning algorithms [64] and are widely used on countless problems. In this survey, we have observed using Naive Bayes in three works related to mental diseases [57, 59, 62].

*3.1.6 Ensemble.* Ensemble methods are statistical and computational learning techniques based on human social learning, which involves pursuing input from multiple sources before making any crucial decision. Ensemble methods merge several models to reduce variance and enhance predictions. The ensemble has the particularity of being the studied algorithm with the best classifier in all the cases compared with other techniques used. The popular ensemble methods are bagging and boosting. Even though it is not the most used technique, as can be seen in Figure 4, it was used by the following authors [48, 60, 63, 65, 66].

#### 3.2 Deep Learning Methods

Deep Learning (DL) is the most recent generation of learning algorithms based on neural networks. Architectures containing multiple layers of artificial neurons are carefully engineered to achieve performance breakthroughs in the existing problems. Deep learning discovers complex structures in large datasets by using the back-propagation algorithm [46], which indicates how a machine should modify its inner parameters to compute the representation per layer from the representation in the previous layer [67].

*3.2.1 Deep Neural Networks.* Deep neural networks is a field of DL, inspired by the structure and functioning of the brain for the construction and training of Artificial Neural Networks (ANN). The evolution of intelligent systems, especially AI technologies, has greatly improved the capabilities of clinical expert systems. Recent advancements in Neural Networks, in particular the emergence of modern *Deep Learning* architectures based on *CNNs*<sup>1</sup>, *RNNs*<sup>2</sup>, and *Transformers*, opened new avenues of possibilities in many sub-fields of AI, including *Natural Language Processing* (NLP) and *Intelligent Image Processing* (IIP), both being fundamental for the challenges of mental health diagnosis and monitoring. CNN architectures and Transformer models can be integrated to improve the model's ability to understand and interpret the nuanced language patterns associated with psychological assessment and intervention. In the context of COVID-19 for early patient recognition, Irfan et al. [68], using a hybrid deep neural network, obtained a classification accuracy of 99% on test set data. Almalki et al. [69], the authors used AI techniques such as deep learning (DL) to detect suspected Coronavirus patients non-intrusively. In this survey, we have observed methods based on DL in the works of Espinola et AI. [57] and Fitriati et AI. [46].

*3.2.2 Transformers.* Transformers have significantly succeeded in many AI fields, such as NLP and computer vision. These fields have demonstrated their effectiveness on fundamental tasks such as classification, detection, segmentation, and multimodal data stream. The transformer is the first transduction model that relies entirely on self-attention to compute models of its input and output without using sequence-aligned RNNs or CNNs[70]. To automatically estimate the level of several symptoms associated with depression at [71], the authors explore the potential of a BERT-based classifier for early detection of self-harm and depression. To identify individuals

<sup>&</sup>lt;sup>1</sup>Convolutional Neural Network.

<sup>&</sup>lt;sup>2</sup>Recurrent Neural Network.

predisposed to depression based on linguistic and cognitive characteristics in [72], the authors use transformerbased language models such as RoBERTa and self-attention and obtain an accuracy of 96.86

*3.2.3 Large Language Models.* (LLMs) are sophisticated AI systems created to interpret and generate human language. These models use DL techniques based on ANN, which are abstract mathematical models of brains. They use extensive text datasets to learn patterns, semantics, and grammar. The LLMs such as Flan-T5 [73], LLaMa [74], Mistral [75], and MentalLLaMa [76] are emerging as potent tools increasingly capable of performing human-level tasks across various research domains, including medicine, education, and finance. Due to their adaptability and general-purpose design, LLMs excel at processing and generating text across various topics, providing reassurance about their versatility in different fields. In the context of mental health, using a comprehensive assessment of several LLMs such as Alpaca, Alpaca-LoRA, FLAN-T5, GPT-3.5, and GPT-4, the authors[77] applied various mental health prediction tasks via online text data.

# 3.3 Mobile Applications for Mental Health

Recently, there has been a proliferation in the use of software applications for medical and health-related purposes. Such applications can be organised according to their functionality. In particular, many mobile applications use cognitive behavioural therapy (CBT), mindfulness training, mood monitoring, and cognitive skills training to treat depressive symptoms [78]. Such applications are gaining momentum as it has been shown that by enabling users to self-monitor their mood (by periodically reporting their thoughts, behaviours, and actions), their emotional self-awareness could be increased, which resulted in the reduction of the symptoms [79]. However, the evidence of efficiency in mental health applications is mixed. Indeed, the study of 22 mobile mental health applications presented in [80] found that they were only effective in users who had self-reported mild-to-moderate depression but had no significant impact on patients with major depression, bipolar or anxiety disorders.

Earle E Bain et al. [81] developed a *Novel Artificial Intelligence Platform on Mobile Devices* resulted in more successful medication adherence for patients with schizophrenia over 24 weeks, it was 89.7% (standard deviation 24.92), and for subjects receiving nicotinic receptor agonists who were monitored using the AI platform than modified directly observed therapy 71% (standard deviation 24.92). In [52] Stegemann et al. developed a GET.ON PAPP, a mobile application for panic disorder that integrates an internet-based treatment into daily life. The program can be used by people with panic disorder with and without agoraphobia. In [82], Festersen et al. developed a re:Mind; a mobile application designed to treat bipolar disorder patients. Re:Mind can be used by both patients and medical personnel. In re:Mind, patients can proactively enter personal health-related data, display it, manage their medicaments and prescriptions, and communicate with their physicians. The impact of mobile technology on health can be far-reaching and cost-effective: digital content can be accessed, stored, manipulated, and transmitted at an affordable price, in real-time, from anywhere, anytime.

## 3.4 Mental Health Datasets

The authors in [83] propose a virtual assistant (VA) as a first contact point for depressed or discouraged users. The VA should be able to provide motivational and affirming responses and offer users a safe environment in which to share their thoughts and anonymously ask for help and advice. To address these different aspects, they created a large-scale dataset, MotiVAte, consisting of dyadic conversations between the depressed user and the VA (conveying hope and motivation). The proposed dataset is evaluated using state-of-the-art generative models. Empirical results based on automatic and human evaluation are presented. According to the authors, this is the first application of natural language generation in the mental health domain.

Depression is a common mental illness that must be detected and treated early to avoid serious consequences. There are many methods and modalities for detecting depression that include a physical examination of the person. However, diagnosing mental health based on social media data is more effective because it avoids these physical examinations. In addition, people can express their emotions well on social media, so it is desirable to diagnose their mental health based on data from social media. Although many systems detect a person's mental illness by analysing their social media data, determining the degree of depression is also essential for further treatment. All existing systems are designed to detect depression based on texts in social networks. Although depression detection is more important, depression-level detection is equally important. The study in [84] developed a baseline dataset that identifies the degree of depression as "non-depressed", "moderately depressed", and "severely depressed" based on posts in social media. The dataset can also be augmented by considering images and text to provide more accurate detection.

The research community has observed a significant increase in identifying mental health problems and their causes through social media analysis. Authors in [85] present a new dataset for causal analysis of mental health problems in social media posts (CAMS), a dataset of 5051 instances to categorise direct causes of mental disorders based on users' mentions in their posts. Their contribution to causal analysis is twofold: causal interpretation and causal categorisation. An annotation scheme for this causal analysis task is presented. The effectiveness of their scheme is demonstrated on two different datasets: (i) by examining and annotating 3155 Reddit posts and (ii) by re-annotating the public SDCNL dataset of 1896 instances for interpret-able causal analysis and then combining these data to form the CAMS dataset and make this resource publicly available with the associated source code: https://github.com/drmuskangarg/CAMS.

The Distress Analysis Interview Corpus (DAIC) [86] contains clinical interviews to support the diagnosis of mental disorders such as anxiety, depression, and post-traumatic stress disorder. Interviews are conducted by humans, agents, and autonomous agents, and participants include both sufferers and non-sufferers. The data collected included audio and video recordings, numerous questionnaire responses, and verbal and nonverbal characteristics. The corpus was used to develop an automated interview agent and research the automatic detection of mental health problems.

ETAD corpus [87] is the first Chinese dataset on depression. It contains the audio responses of 162 volunteers to three emotion-related questions. The text transcripts were extracted from the audio, manually corrected, and inserted into the EATD corpus. Given the lack of public multimedia data on depression, the EATD corpus provides valuable data for psychologists and computational researchers studying depression.

The TILES-2018 dataset (Tracking Individual performance with Sensors, the Year 2018) [88] comes from a prospective longitudinal study with an intensive multimodal assessment of workers and their environment to understand the dynamic relationships between individual differences, work, and well-being and the contexts in which they appear. The aim is to support the development and validation of sensor-based methods for assessing workers' well-being and work performance over time. The data was collected in partnership with Keck Hospital at the University of Southern California to directly follow 212 workers who volunteered to participate in the study over ten weeks, both on and off the job. Biobehavioral data was continuously and passively collected throughout the study using wearable devices (bracelets, smart underwear, audio clip recorders, Bluetooth badges, and personal smartphones). These data streams were combined with environmental and behavioural data from Internet of Things (IoT) devices and applications that recorded personal smartphone usage. To link sensor data to interesting constructs, participants also completed an initial series of online and daily surveys aimed at identifying individual difference variables (e.g., personality, intelligence, socioeconomic status), states, and psychological traits (e.g., positive and negative affect, anxiety, stress, fatigue, psychological flexibility), psychological capital), health and well-being (e.g., sleep, physical activity, cardiovascular exercise, smoking and alcohol consumption, health-related quality of life, and life satisfaction), and work behaviour (e.g., performance, organisational, civic behaviour, counterproductive work behaviour, work engagement, perceived support, and stressors).

The MAIKI [89] is a real-world longitudinal dataset that was collected as part of the Mobile Artificial Intelligence Interaction-Centered Daily Living Therapy Assistant for Depression (MAIKI) project [90], which collected different active and passive data modalities, e.g., telephone data, GPS data or different questionnaires, from 48 patients over three months. The study procedures were approved by the ethics committee of the Friedrich-Alexander University of Erlangen-Nuremberg (385\_20B). During the study period, there were days when data were not collected from some participants. This was because some individuals did not complete a diary for each day. A brief comparison of datasets discussed above is given in 4.

Instances	Data-type	Source	Year	Reference
4000	dialogue	multiple	2021	[83]
20,008	text	reddit	2022	[84]
5051	text	reddit	2022	[85]
24,348	multimodal	interviews	2014	[86]
162	audio & text	counselling	2022	[87]
212	sensors & multimodal	wearable devices	2018	[88]
48	sensors & multimodal	mobile phones	2022	[89]
	Instances           4000           20,008           5051           24,348           162           212           48	InstancesData-type4000dialogue20,008text5051text24,348multimodal162audio & text212sensors & multimodal48sensors & multimodal	InstancesData-typeSource4000dialoguemultiple20,008textreddit5051textreddit24,348multimodalinterviews162audio & textcounselling212sensors & multimodalwearable devices48sensors & multimodalmobile phones	InstancesData-typeSourceYear4000dialoguemultiple202120,008textreddit20225051textreddit202224,348multimodalinterviews2014162audio & textcounselling2022212sensors & multimodalwearable devices201848sensors & multimodalmobile phones2022

Table 4. Overview of dataset presented in this study (SM = Social Media)

#### 3.5 Assisted Decision Making For Professionals

*3.5.1 Factoid and non-factoid questions.* Issues related to mental health are usually complex and very subjective for each individual. People going through the same experiences deal uniquely and individually. Usually, in psychiatry, patients deal with questions that can help them understand their situation and thus determine their condition. These questions can be separated into two main categories: factoid and non-factoid questions. Factoid questions have specific answers that can be looked up and have a basis for determining a correct answer. For example, the factoid questions comprise a significant fraction of all user queries submitted to search engines [91]. The question "What is the capital of Portugal?" is a factoid question as there is only one capital of Portugal, Lisbon. The related questions to mental health are not direct, so they often involve other processes. Non-factoid questions requiring complex answers, like descriptions, opinions, or explanations, which are primarily passage-level texts [92]. An example of a non-factoid question may be: "how do you feel about your new cell phone?".

Mental health questions are open-ended and do not have one exact answer. For instance, if a person asks him or herself, "Why do I have post-traumatic stress disorder (PTSD)?" the answers will vary among those with PTSD. One may experience PTSD due to domestic violence or rape, while another may have PTSD from seeing a friend die in combat in the army. Diagnosis of mental disorders is difficult to pinpoint one root cause, and many symptoms overlap in different disorders, making it hard to diagnose mental disorders. Doctors, nurses, psychiatrists, etc., must trust their patients to give the correct symptoms to indicate what is wrong. The symptoms signs are even harder to pinpoint, especially if someone is not looking for the signs. These reasons make it difficult for artificial intelligence systems to give feedback, let alone humans [42, 93].

3.5.2 Diagnostic and prediction tools. Diagnosis is an essential initial step in the treatment of mental disorders. One defiance for clinicians in making diagnoses is that patient exchanges only offer a snapshot of an individual's mental state, yet mood conditions are dynamic and fluctuate over time. Currently, psychiatric examination of patients includes observation of their mental state and subjective self-report questionnaires. These approaches are subjective, difficult to repeat, and time-consuming [94]. The therapist can be aided in his/her diagnosis by AI systems that simulate practitioners' reasoning capacities. As such, the artificial diagnosis can confirm the intuition of the health professional or alert him/her to a possible difference. The artificial system can act as advice for a second colleague.

Students at Columbia University and the New York State Psychiatric Institute have developed a machinelearning system capable of predicting if a person at risk of developing psychosis caused by schizophrenia will develop the condition with 90 per cent accuracy by analysing his or her speech, which can exhibit telltale signs of the condition. Also, IBM researchers developed a machine learning speech classifier with 79% accuracy in predicting psychosis onset in those with clinically high-risk [95, 96]. In addition to helping with diagnosis, such tools may support monitoring patients' progress. Table 5 shows the literature review about automatic mental diagnosis solutions.

	Table 5. Comparison of various automatic mental diagnosis solutions.	
Author	Automatic Diagnosis tool	Accuracy
Chen et al. [56]	The authors used different Machine Learning Methods (Support Vector Machine, Logistic Regression, Decision Tree, K Nearest Neighbor, and Random Forest) to the Automatic Diagnosis of Attention Deficit Hyperactivity Disorder (ADHD).	73%
Jaiswal et al. [58]	The authors showed how computer vision can detect ADHD and Autism Spectrum Disorders based on video analysis of a person's behaviour.	96%
Dharun et al. [63]	The authors used ML algorithms to detect stress in working employees and found features contributing to mental stress.	75.13%
Husain et al. [97]	The authors adopt a random forest approach to identifying hidden patterns and relationships that can be used for predicting generalised anxiety disorder.	90%
Agnes et al. [98]	The authors used a smartphone-based sensor system and developed an early warning system to find the changes in the states of bipolar disorder patients.	97%

3.5.3 Monitoring. To support the therapist in his/her diagnosis of patients, monitoring systems have been developed that identify specific verbal and non-verbal descriptors which can manifest mental disorders. In mental health, monitoring mood and mental health outside the clinical setting is the written record that patients keep throughout the treatment process, such as a diary. All but the most extreme psychiatric care takes position in an outpatient setting, so additional monitoring in the community would offer significant benefits. Early detection and prevention of relapse can considerably impact outcomes [94].

AI can be integrated with other technologies, such as sensors and mobile applications, to continuously monitor patients, clinicians/therapists, or researchers to view changes and symptom trajectories over time. Another characteristic of monitoring is medication adherence, which is an issue in all chronic health issues and may exceptionally be so in mental health disorders; the calculations of non-adherence to antipsychotic prescriptions meander from 20% to 89% for patients with schizophrenia or bipolar condition [94, 99], medication being an essential part of the treatment of these patients. Table 6 synthesises the literature review about automatic mental monitoring solutions.

Table 6.	A brief	comparison	of automati	ic monitoring	solutions	for mental	disorders.

Author	Monitoring tool
Valenza et al. [100]	Monitored through the smartphone and a sensorized t-shirt, the authors developed bipolar an m-Health application for remote monitoring of patients with BD, detecting fluctuations in mood and behaviour.
Upkar Varshney [101]	An IT-enabled framework to support mental health monitoring. This includes comprehensive monitoring of patients for symptoms, behaviour, and medication compliance.
Ha et al. [102]	To monitor electroencephalography, hemoencephalography, and heart rate variability (HRV) for accurate mental health monitoring, the authors proposed a multimodal mental management system in the shape of the wearable headband and earplugs.
Muhammad et al. [103]	Using the IoT Long Range technology, the authors propose a system design for the tracking and monitoring of mental disorder patients.
Philip Moore et al. [50]	The authors implemented multi-modal systems where patients can be diagnosed, treated, and monitored. The systems incorporate triage and treatment capabilities in both hospital settings while monitoring the community.

#### 4 DISCUSSION

In this session, we identify the algorithms used by different studies and their performance. SVM, DL, RF, and Ensemble method are among the most used algorithms. In the performance comparison, the ensemble algorithms performed best in all the implemented studies. This is due to the amount of data used in the different studies. The datasets presented balancing problems in their studies due to data limitations. As an assisted decision-making aid for professionals in diagnosis, SVM, RF and DT were the most implemented for monitoring and treatment; in the different studies, they used a combination of sensors, ML algorithms and mobile devices. We compared several machine learning techniques and which algorithms performed best, as shown in Fig 4.

A wide variety of mental health conditions have been researched, but the limited availability of open-source datasets restricts many. Frequently studied mental conditions include Stress disorder: [44, 47, 63, 86], Bipolar disorder: [45, 46, 82, 98–100], Schizophrenia: [48, 51, 59, 81, 94, 95, 104], Anxiety disorder: [49, 60, 80, 86, 97, 104], Depression: [61, 66, 71, 72, 80, 84, 86, 87, 89, 104]

New intelligent systems that, through visual perception, correctly interpret the patient's emotional states and can interact with him verbally are crucial for the new *automatic therapies*. With NLP, IIP, Machine Learning, and all their associated areas, we have a plethora of tools to start with predictive modelling of these diseases through the treatment of large volumes of already existing data, in addition to the more specific ones that will prove to be relevant in the future. There are a significant number of data science problems in this field that need to be addressed. Even more, each specific clinical context will require special attention regarding data analysis. Nowadays, these areas already provide several important algorithms that can identify patterns and trends, predicting target classifications through supervised and unsupervised learning. Many such algorithms have been extensively used to diagnose or detect the prevalence of mental disorders.

Author	Problems Addressed	Techniques used	Metrics	Best classifier
Astari et al. [46]	Bipolar Disorder	Backpropagation algorithm	-	Backpropagation algo- rithm
Chen et al. [56]	ADHD	Support Vector Machine, Logis- tic Regression, Decision Tree, K Nearest Neighbor, and Random Forest.	Accuracy, AUC score	Random Forest
Dhaka [49] and Jo- hari	Anxiety disorder, Mood Disorder, Psychotic Disorder, Personality Disorder	Genetic algorithm	Accuracy, Pre- cision	Genetic algorithm
Dooshima et al. [62]	General	Naïve Bayes, Dtree	Accuracy, Pre- cision	Decision Tree
Espinola et al. [57]	Major Depressive	MLP, NB, SVM, dtree, RF, Bayes Net, Regression	Accuracy, Kappa, Sen- sibility and Specificity	SVM
Jayshree and Kulkarni [58]	SNMDD	SVM and Random Forest.	Precision, Re- call, F1-Score and Accuracy	Random Forest
Kamal et al. [59]	Schizophrenia, Autism and PTSD	Random Forest, XGboost, NB, SVM	Precision, Re- call, F1-score	XGboost
Khan et al. [48]	General	Random forest, SVM, K-nearest neighbor	Recall, Preci- sion	Random forest
Makhija et al. [65]	General	Sentence embedding, Ensembling kstar, MLP	Accuracy	Ensemble
Ming-Yi and Chih- Ying [60]	Anxiety	Ensemble and SVM	Precision and Recall	Ensemble
Parameswaran et al. [61]	Depression	Viola Jones face detection algo- rithm, Gabor filter, SVM	Accuracy, Sensitivity Specificity, Pre- cision F1-score, False positive rate	SVM
Silvana et al. [104]	Schizophrenia Para- noid, Phobia, Depres- sion, Anxiety, OCD and Anti-Social.	Mamdani fuzzy inference	Accuracy	Mamdani fuzzy infer- ence
Tasnim et al. [66]	Depression	Network, Gradient Boosting Tree	Accuracy, Precision- Recall	Deep Neural Network
Thota and Dranu [63]	General	Logistic Regression, K-NN, De- cision Tree, Random Forest, Bagging, Boosting	Accuracy, False Positive Rate, Precision, AUC Score	Boosting

 Table 7. Comparative analysis of machine learning and best classifier algorithms.

For performance assessment of models and systems, authors use various metrics to perform a comparative analysis of different algorithms in terms of several parameters like *accuracy*, *recall*, *precision*, *F1-score*, *specificity*, etc. All these metrics are calculated based on the confusion matrix. Some algorithms may perform more useful with improving accuracy and precision, while others may perform better in decreasing errors. Table 7 shows a comparative performance analysis of the different works we have observed for diagnosing and monitoring mental disorders. It focuses on the authors' techniques and the algorithms with the best classifier.



Fig. 4. A comparative analysis of the techniques most used by the authors in their different works and the techniques that had a higher performance based on various metrics. The x-axis represents the number of articles in our review.

AI can be highly beneficial when predicting mental health issues, creating personalised treatment strategies, and ensuring compliance[105]. However, it also brings typical challenges requiring cooperation between AI researchers and healthcare employees. It's an emerging field that includes other dimensions of various modalities; hence, there are fusion and hybrid models, etc., and no one solution is applicable in all scenarios.

#### 4.1 Challenges and limitations

The complexity of using intelligent systems for areas such as mental health mainly focuses on subjective questions present in treating patients with mental problems. This subjectivity often becomes so complex for the surrounding elements (e.g., patient and psychiatrist). As previously discussed, factoid questions and non-factoid questions, intelligent systems, when involved in a diagnostic patient with a mental disorder, will have to deal with non-factoid questions [42, 91], many of which are the basis for the study of sciences such as philosophy and psychology science. However, intelligent systems are generally more accurate than humans and may support enhanced decision-making [106]; just as with a human practitioner, AI systems are exposed to mistakes in judgement and incorrect risk inspection [107]. In the case of diagnosis, many other factors (besides the question-and-answer process) should be considered as part of this process. For example, most systems we study do not deal with subjective issues at the level of voice tone, sign language, and other aspects of the patient's physical condition.

Another field of this study that should be considered is the cases of technologies related to patient monitoring. The first aspect focuses on using electronic equipment to monitor patients with mental problems. On the one

hand, it helps the psychiatrist monitor the patient's processes in real time. Still, on the other hand, this equipment can increase the index of addiction to the use of electronic equipment by patients.

Using intelligent systems to offer diagnostic and monitoring treatment services brings new complexities related to legal and ethical issues in psychological practice. These issues need to be carefully addressed to ensure that the benefits are maximised without causing harm. For instance, systems accessible over the internet, like current avatar systems, can offer services across different legal jurisdictions[33]. Legal and ethical considerations include obtaining informed consent, ensuring safety and transparency, addressing algorithmic bias and rights, and safeguarding data privacy. Legal concerns also encompass evaluating safety and effectiveness, addressing liability, and providing data protection and privacy. Intelligent systems have the potential to significantly enhance the delivery of healthcare services and support various public health interventions. However, ethical principles and human rights must remain central to these systems' design, implementation, and use.

#### 5 CONCLUSION

An intelligent system is increasingly a part of digital medicine and will contribute to mental health research and practice. Many techniques like NLP, multimodal systems, machine learning, and AI algorithms have significantly contributed to building models/solutions to diagnose and monitor societal mental disorders. This survey observed that no particular techniques are suitable in all situations, and several other factors can contribute to the technique's performance. Different techniques show high accuracy and precision with fewer error rates according to different circumstances. So, we must choose a specific technique or classifier for each domain of interest without getting stuck on one particular technique. Although none of the techniques can necessarily solve all problems, whether for diagnosis, monitoring, or treatment, with interactive studies, applied methods, and results that obtained the best classifications, we can consider that ML algorithms such as Support Vector Machine, Deep Learning, Random Forest, Decision Tree, and essential Ensemble algorithms such as Bagging and Boosting have shown the potential to be applied for diverse mental health-related issues.

The practice of mental health for the care of patients and the help of psychiatrists for diagnosis and monitoring can be improved with the advancement of intelligent systems. This is by collaborating with diverse professionals such as data scientists, computer engineers, and health professionals. The aim should be to focus on the assistive part of AI instead of replacing the professionals with intelligent systems. The future of intelligent systems in mental healthcare is promising. The data source for training intelligent systems for mental disorders could become more consistent if we add data from multiple sources. So far, most of the data has been obtained from interview questionnaires. As part of future work, we propose the construction of a hybrid system to detect the majority and severity of mental disorders in people through body language and multimodal data. The detention and mental health process deals with multiple data sources. This system can be used by mental health professionals for therapeutic intervention.

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