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Psychiatric disorders: diagnosis and treatment using Artificial Intelligence techniques

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ABSTRACT

The surge in artificial intelligence (AI) applications within psychiatric research and diagnosis has witnessed significant growth in recent years. This study investigates the use of AI to facilitate early medical condition diagnosis and enhance our understanding of disease progression, particularly in the realm of psychiatric disorders. The primary objective is to explore and employ various AI algorithms for the identification of biomarkers associated with psychiatric conditions. Data and methods involve the application of diverse algorithms for classifying psychiatric disorders, with a meticulous comparison of their accuracy. Additionally, a model is developed based on these algorithms, aiming to optimize diagnostic precision. Results indicate a notable 70% accuracy in the dataset, highlighting the efficacy of deep learning approaches in handling extensive data sets. The findings underscore the potential of deep learning in clinical datasets and its application in the future detection of mental health issues. Despite the commendable performance of deep learning, criticisms persist regarding its accountability during development and assessment phases. While AI has made significant strides in detecting psychiatric diseases, this study identifies areas for improvement in AI-based applications. Notably, the current model's limited generalizability due to its analysis of homogeneous datasets prompts the consideration of future approaches, including migration learning, multi-view learning, and ensemble learning, to handle diverse and extensive psychiatric disease data sets.

Keywords: Artificial intelligence, Diagnosis, Machine learning, Management, Mental illness, Psychiatric disorders.

1. Introduction

Psychiatric disorders constitute a significant global health challenge, contributing substantially to the burden of disease, as indicated by the Global Burden of Disease Study of 1990 and 2010 (Walker et al., 2015). Mental and substance use disorders rank as the leading cause of the fourth most significant disease load in disability-adjusted life years (DALYs). The impact of psychiatric disorders extends beyond the individual, affecting societal structures through increased medical leave, early retirement, and treatment rates (Wittchen et al., 2011). Approximately a quarter of the global population experiences mental illness each year, with rates of mental disorders, including major depressive disorder (MDD), bipolar disorder (BD), schizophrenia (SCZ), anxiety disorders (ANX), and post-traumatic stress disorder (PTSD), reported at 22.1% (Charlson et al., 2019). These disorders not only compromise the affected individuals' quality of life but also pose a substantial burden on society. Despite the prevalence of psychiatric disorders, less than a third of patients receive medical treatment (Wittchen and Jacobi, 2005), and suicide rates associated with mental disorders surpass those of AIDS, most cancers, and violence (Goldsmith et al., 2002). Mental disorders contribute to about one-third of all disabilities globally, underscoring their significant personal and societal impact (Collins et al., 2011). Current diagnostic approaches, such as the Diagnostic and Statistical Manual of Mental Disorders (DSM) and the International Classification of Diseases (ICD), rely on presenting signs and symptoms, lacking alignment with observations from genetic factors and clinical neuroscience (Insel et al., 2010; Cuthbert and Insel, 2013;). Despite advancements in psychiatric research, no clinically identified biomarkers for mental disorders exist using genetics, blood plasma, or brain imaging (Stephan et al., 2016). The advent of artificial intelligence (AI) offers a promising avenue for transforming psychiatric research and diagnosis.

While psychiatric disorders have long been identified based on subjective experiences, recent years have witnessed a surge in AI applications for these disorders (Fig. 1) (Gao et al., 2017; Jan et al., 2017; Dwyer et al., 2018; Esteva et al., 2019). Despite these advancements, there is a noticeable gap in systematic reviews demonstrating the comprehensive utilization of AI techniques for psychiatric research and diagnosis. This research aims to address this gap by exploring various AI techniques for diagnosing psychiatric disorders, comparing the accuracy of different algorithms, and proposing a model based on these techniques. The study will delve into the application of AI in the diagnosis process, focusing on essential techniques such as magnetic resonance imaging (MRI), electroencephalography (EEG), and kinesics diagnosis. The subsequent sections will discuss these techniques and their AI-based applications, providing insights into the challenges faced by current diagnostic methods and the potential opportunities presented by AI in revolutionizing the field of psychiatry.

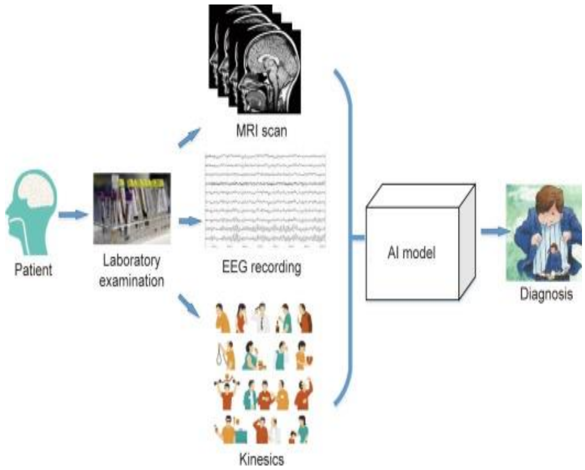

Fig. 1. Important AI techniques in diagnosing psychiatric disorders

2. Materials and Methods

Search strategy.

To comprehensively investigate the accuracy of different algorithms in diagnosing psychiatric disorders, a comparative methodology was adopted. This approach was deemed suitable for addressing the research question effectively. Additionally, a thorough review of the existing literature was conducted to enhance the understanding of AI-based algorithms' integration in the precise diagnosis of various psychiatric disorders. For data collection, a systematic search strategy was implemented using reputable databases such as Google Scholar, Medline, Springer, Elsevier, and PubMed. The keywords utilized for the search included Artificial intelligence, Psychiatric disorders, Neuroimaging, Imaging techniques, Machine learning, AI-based algorithms, Diagnostic procedure, Mental health, Mental illness, Technology, Deep learning, and Neural network models. Hand-searching was also performed to identify specific sources referenced in the included research. Moreover, consultation with experts in the field contributed to identifying pertinent scholarly materials.

Inclusion and exclusion criteria

The inclusion criteria encompassed original research studies and peer-reviewed scholarly papers in English that addressed the research subject. To maintain a focus on recent developments, only papers published after 2017 were considered, reflecting the surge in AI-related publications concerning mental disorders during this period. The literature under consideration predominantly delved into mental disorders and AI-based techniques for accurate diagnosis, encompassing both descriptive and evaluative studies. Conversely, studies in languages other than English and those failing to meet the stipulated inclusion criteria were excluded. Publications discussing future AI applications, or the development of unverified algorithms or frameworks were also excluded. Furthermore, research related to neurocognitive problems, despite their association with mental health, was omitted to warrant a dedicated study for this domain. The final dataset for analysis comprises 39 original research studies and 9 peer-reviewed scholarly papers on AI and mental health, ensuring a comprehensive exploration of the subject matter.

Steps of selection and exclusion of articles "literature review"

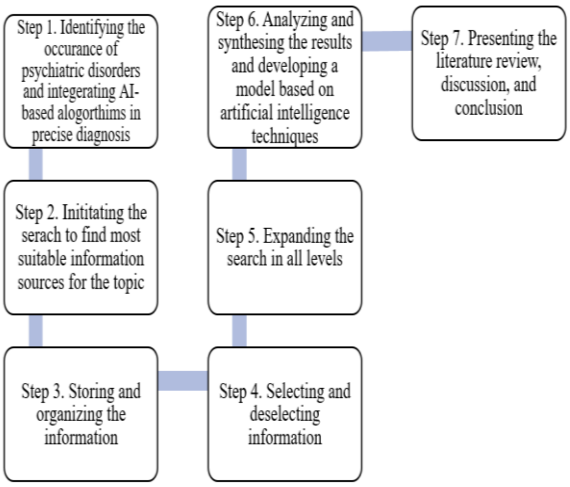

Fig. 2. Seven steps to a comprehensive literature review.

In following these steps, Database searching was the first step (Scopus, PubMed, BioMed Central, Popline, Science direct, and Google scholar) for original research studies on the subject. The related websites were also searched for peer-reviewed publications, scientific papers, and technical reports. The second step included the removal of articles that did not apply to the subject and redundant articles. After reading their abstracts, the publications left were tested for eligibility in the third step. In the fourth step, hand-searching was done to obtain more relevant articles from the reference list of publications left after the second stage. Finally, the completely screened/hand-searched publications omitted not important publications for the research. In the final Step, peer-reviewed publications and original research studies left were used for the study, including technical publications that meet the unique inclusion requirements (Fig. 3).

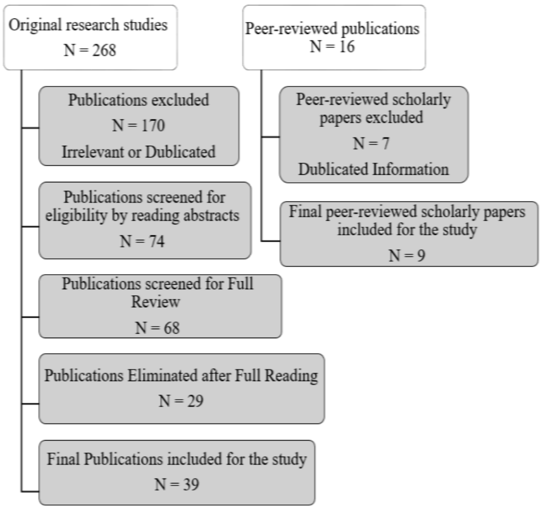

Fig. 3. Flow Diagram demonstrating inclusion and exclusion of original research studies and Peer-reviewed publications used for this study.

3. Results

Artificial intelligence algorithms

The significance of performing research in the mental health clinical settings is generally perceived, like the requirement for assessment-based consideration beyond clinical exploration. In clinical and cognitive practices and centers, the viability of directing broad reviews of clinical investigation is challenging. Hence, any procedure that diminishes the weight of strictly based evaluation can further develop results through estimation based clinical independent direction. A patient's health estimation depends on the traditional test hypothesis. A patient's impedance level is assessed by an all-out score, requiring similar things directed to all respondents. The advantage of AI-based clinical choice emotionally supportive networks is that they can manage undeniable degrees of intricacy in information and help professionals remove essential data and settle on ideal choices. These frameworks can assist professionals with working vulnerability and speed with increasing navigation. The utilization of AI-empowered clinical choice emotionally supportive networks can decrease staff time requests and help with diminishing boundaries of restricted expert capability, specifically regions. Concerning the AI calculations, this is commonly portrayed as "straightforwardness" or "opening the black box" to uncover to clients the inward systems that drive PC forecast.

While transparency is a commendable objective, it very well might be unattainable for specific sorts of calculations. The communications as a rule between enormous quantities of factors at which point expectations are made are so complicated as to challenge simple perception by non-expert clients – think about financial figures as one model. Profound learning neural organization draws near, and other AI frameworks are more complex in which expectations result from many secret hubs and layers. Such frameworks are intrinsically dark: while their conduct can be noticed and assessed, the exact components through which choices are made are mysterious even to their architects. Hence, they can't be made utterly upfront to clients.

People are vulnerable to committing errors because of intellectual mistakes and weariness. AI innovation can upgrade abilities and diminish human blunders in clinical decision making in all medical care fields. With discourse identification and regular language handling creation,

AI-empowered augmented human simulation symbols could improve master frameworks by giving a human-like verbal exchange interface. These frameworks could get to the corpus of master information regarding mental and clinical issues and be taken care of from patient clinical records and testing results. Artificial intelligence (AI)- built an application that has been quickly produced for mental examination and finding. They proposed an artificial intelligence framework to screen wretchedness to foresee Beck Depression Inventory-II scores from vocal and visual articulations. Moreover, separated multi-type dim white matter highlights are dependent on multimodal neuroimaging. They utilized a multicore learning classifier to distribute loads to the elements of every component. Nonetheless, as far as we can know, no precise survey defines the utilization of these AI-based applications for mental exploration and analysis. Subsequently, we will briefly and generally involve AI-based applications for mental issues and exhibit how to apply artificial intelligence innovation to examine mental health biomarkers.

Bayesian model

In artificial intelligence, the naïve Bayes categorizes an overall term for a characterization calculation. The guileless Bayesian strategy is an order technique dependent on Bayes' algorithm and trademark condition-independent theory. The model should enclose both paired and polytomous effects. There are two fundamentals (and broadly utilized), the three-boundary strategic model for paired results and the polytomous reaction model presented by Birnbaum (1968). These models are given by:

$$pij\,(1) = P\,(yij = 1|\theta, \omega j) = cj + (1 - cj)\, logit - 1(tij), \text{and (}$$

$$pij(r) = P\,(yij = r|\theta, \omega j\,, d) = (gr - tij) - (gr - 1 - tij), (2$$

Here pij(r) denotes the probability that examinee i = 1 receives score r = 1, Rj on item j = 1, J (e.g., pij(1) is the probability of a correct binary item), cj is the lower asymptote ("guessing" parameter) for binary item j , ωj is the set of item j's parameters, gr is the latent cutoff for the Polytomous items such that observed score yij = r if latent score sij = tij + Єij satisfies gr−1 < sij ≤ gr (the set of cutoffs is denoted g), Єij is a standard unit Gaussian random variable, is the average cumulative density function, logit(x) = log(x/(1-x)), and tij (described below) is the latent linear predictor of score. We use the Birnbaum model for the twofold things as it (a) incorporates less complex two-boundary and Rasch models as exceptional cases and (b) represents the likelihood that uncouth examinees tij = −∞ may answer a parallel thing accurately because of possibility. As we fuse in our projects, the chance of "switching off" the additional elements of the Birnbaum model and the information can illuminate the degree of intricacy of the model required, using a broader construction appears to be justified. The Same Jima model for polytomous things has a decent instinctive clarification as an idle genuine score model for examinee-thing mix ij. When examinee I is defied with thing j, she reacts with idle capability revolved around her actual score tij with arbitrary mistake Єij. Noticed score yij = r happens when the dormant score is inside an expected (idle) range [gr−1, gr]. The ability of our approach to model extra dependence due to test lets, first described in BW&W, is by extending linear score predictor tij from its standard form:

$$tij = aj\,(\theta i - bj), \quad (3)$$

where aj, bj, and θi have their standard interpretations as item slope, item difficulty, and examinee proficiency to

$$tij = aj\,(\theta i - \gamma\text{id (j)}), \quad (4)$$

with γid (j), the test let effect (interaction) of item j to person i, which is nested in Gtest let d (j). The extra dependence of items within the same test let (by a given examinee) is modelled in this manner as both would share the effect γid(j) in their score predictor. By definition, γid (j) = 0 for all independent items, test let size one. We suppose the following general testing setup thoroughly explains our model using these kernels as a base.

Suppose I examinees each take an examination composed of J items where J = Jb + Jp, with Jb the number of binary items in the test and Jp the number of polytomous items. Furthermore, let Jb denote the binary things and Jp the collection of polytomous items. We further suppose that each of the J items is nested within K test lets, that is, d (j) ∈ {1..., K}, where kd (j) and Kd (j) denote the number of items and set of items nested within test let d (j). Bayesian models have been used frequently in the latest research to diagnose psychiatric disorders. For example, the Strüngmann Forum on Computational Psychiatry proposed using Bayesian inference to connect primary reasons (genetics and sociocultural factors), underlying proposed conceptual frameworks, and symptoms. Grove et al (2018). also investigated the association between visual integration and general comprehension using a Bayesian model comparison approach. The results showed that a Bayesian model could compare the disease cataloguing systems and have standard psychopathological information from diagnostic groups.

Logistic regression

Logistic models (or logit models) are commonly used in statistics, and LR is a key AI technique. LR models are frequently used in recent studies to identify psychiatric diseases. Hagen et al., for example, used an LR technique to examine the relationships between psychological discomfort and two cognitive screening instruments. The findings showed that achievement evaluation might help lessen the adverse effects of psychological strain on cognitive screening. We utilized descriptive statistics to evaluate the outcomes. We distinguished all correlations among LR and AI strategies and determined numerous examinations inside a similar proposal due to executing different AI calculations, creating models for more than one result, models dependent on various indicator sets (e.g., once with and once without research Centre estimations), or making models for quite some time independently. Although the inquiry string stood standard LR from punished techniques, we consider LR instead of machining learning. A few articles stood out LR from conventional measurable calculations, such as discriminant investigation, strategic relapse, and summed up assessing conditions.

We looked at the LR and AI models utilizing the distinction. The data arranged AI calculations into five general points: single grouping trees, arbitrary backwoods, false neural organizations, support vector machines, and different analyses. We broke down contrasts for all examinations and separation for the hazard of predisposition. We played out a meta-relapse of the distinction between logit changes utilizing an arbitrary impact model to consider the bunching of articles' correlations and weighted by the square base of the approval test size. Logit was used to dodge the limited nature. We observed a few contrasts between AI and Logistic regression. In machine learning literature, alignment regular indicates to changing non-probabilistic model results in probabilities. The adjustment identifies with assessing the firm quality of probabilistic appraisals. Altering the model results into conceivable outcomes is essential for the model turn of events. Besides, the AI writing has focused on the utility of models. For instance, the choice tree, SVM, and Bayesian models assess the choice bend investigation. Furthermore, Barker et al. (2018) used multivariable LR models to predict 30-day psychiatric readmission. Their observations are a significant predictor of psychiatric readmission, and they have offered a better technique to predict readmission. Classification and regression tree technique produces a stratification risk model to regulate mental comorbidities' odds ratio (OR). Between participants with and without borderline personality disorder, the OR of psychiatric comorbidities was estimated using the LR approach. In practice, the precision of the LR models is so high that they are commonly applied in clinical practice.

Decision tree

A decision tree is a figure that looks like a flowchart and depicts the many consequences of a set of decisions, such as chance event consequences and efficacy. Decision trees are one of the most broadly involved calculations for regulated order learning. A choice tree is an expectation model in computerized reasoning that addresses planning between object ascribes and values. Most current decision tree learning calculations utilize an actual-based empirical outcome. Eq. characterizes data gain (D, X) (1). A decision tree is a flowchart figure that shows the different results from a progression of choices, including coincidental occasion results and utility. Choice trees are one of the most generally and comprehensively involved calculations for managed characterization learning. In AI, a choice tree is a visionary model addressing planning between object properties and element values. Most of the current decision tree learning calculations hold factual, empirical consequences. Data gain, gain (D, X), is characterized by Eq. (1).

$$\text{gain}(D, X) = \text{info}(D) - \sum x \, |Dx| / |D| \, \text{info}(Dx) \quad (1)$$

where D is a set of training instances, X is an attribute, x is its value, Dx is a subset of D consisting of the instances with X=x, and inf0 (D) is defined as shown in Eq. (2).

$$\text{Info}(D) = -\sum_{i=1}^{m} pi \ \log 2 \ (pi) \quad (2)$$

where the percentage of instances and m estimates pi is the number of classes. Next, we detail two commonly used decision tree applications for psychiatric disorders.

Carpenter et al. (2016) tried whether individual Preschool Age Psychiatric Assessment (PAPA) things can foresee if a child is probably going to have summed up the outcomes uneasiness issue (GAD) or fear of abandonment utilizing the choice tree technique (SAD) (Carpenter et al., 2016). They utilized a choice tree to distinguish kids, nearly creating nervousness issues. Their discoveries uncovered that the decision tree might precisely foresee GAD and SAD in up to 96 per cent of cases. Sattler et al. utilized a choice tree to examine the SCAS and SCAS-P over the top habitual problem sub dimensions of the Spence Children's Anxiety Scale (SCAS) (Sánchez & Soriano-Mas, n.d.). They created two normalized appraisal calculations to analyze youngsters and families over the top habitual problem in a clinical and standardized test. The detections exposed the calculations brought down the quantity of SCAS-P things needed to make a passionate, enthusiastic issue conclusion by 67–83 per cent without losing the personality of the complete subscale scores.

Support vector machines.

The SVM is a modern supervised learning approach, with the maximum margin hyperplane as its decision border for solving learning patterns. The following description: Begin with an n-point testing form (xi, yi), (xn, yn), where yi € -1,1 denotes the class labels. A p-dimensional real vector is each xi. The purpose is to locate the hyperplane with the most significant margin that splits the cluster of points xi for which yi=1 from the group of points for which yi= -1. Fisher linear discriminant examination and group investigation. This segment will portray support vector relapse, perhaps the most famous expansions of the help vector method and refer to different augmentations. The thoughts basic help vector relapse is like those inside the arrangement conspire. From an intuitive perspective, the information is planned into an element space, and afterwards, a hyperplane is fitted to the scheduled report. According to a numerical viewpoint, the help vector relapse work is inferred inside the RKHS setting. For this situation, the misfortune work included is known as the ε-unfeeling misfortune work, which is characterized as L(Yi,f(xi)) = (|f (xi)−yi|−ε)+, ε ≥ 0. This misfortune work overlooks size mistakes, not exactly ε (see Fig. 6). A conversation of the relationship of the ε-insensitive work loss and the ones utilized in robust statistics. The way into this specialization lies in the development of the choice capacity in three stages: In the primary stage, an SVM is prepared, and the help vectors are gotten; in the subsequent step, new information focuses are created by changing these help vectors under specific gatherings of changes, revolutions, and interpretations. The ultimate choice hyperplane is inherent in the third stage via preparing an SVM with the new spaces. SVM execution is basically like the best non SVM technique. For example, we should foresee subcellular protein positions from prokaryotic groupings in the protein subcellular area forecast.

There are three potential area classifications: cytoplasmic, periplasmic, and extracellular. According to an unadulterated characterization perspective, the issue diminishes to ordering 20-layered vectors into three (exceptionally unequal) classes. Forecast exactness for SVMs (with a Gaussian piece) adds up to 91.4%, while neural organizations and a first-request Markov chain have 81% and 89.1%, separately. SVM models are frequently employed in the diagnosis of mental diseases. Peng et al., for example, used a multi-kernel SVM-based model to discover potential users who could suffer from depression by extracting three social approaches to represent users' conditions (user microblog text, user profile, and user behavior's). Al-Shargie et al. (2018) proposed a discriminant analysis approach based on a multiclass SVM. According to the findings, the method could identify different stress levels for EEG with an average classification accuracy of 94.79 percent.

Deep learning

For a long time, traditional machine learning approaches like the Bayesian model and SVM have been widely used in psychiatric and neuroscience research. A popular machine learning research direction, deep learning now surpasses the models as mentioned above' AI by a significant margin. Deep learning is a collection of algorithms on a multi-layer neural network that use various machine learning methods to address issues like these.

$$\Delta\omega\ (t+1) = \Delta\omega\ (t) + n\partial C/\partial\omega \quad (3)$$

Where Δw(t) represents the weight of time t, η represents the learning rate, and C represents the cost function. The activation function and the kind of learning (supervised learning, unsupervised learning, and enhanced learning) influence the choice of this function. Two widely utilized deep learning applications for psychiatric condition diagnosis are discussed here. Khan et al. suggested a computational technique (integrated mental-disorder Genome score, or images) to assess whole genome/exome sequencing data on human genomes by employing DNNs on the TensorFlow framework. This application generates prioritized gene scores for psychiatric conditions using a deep learning architecture. When extensive supervised learning is provided, the results show that this product's property outperforms competing techniques. In addition, Heinsfeld et al. (2018) used deep learning methods to find individuals with autism diagnoses using a large brain imaging dataset (Heinsfeld et al., 2018).

The results showed that the dataset had a 70 per cent accuracy rate and that deep learning approaches can identify massive datasets better than previous methods. Additionally, the findings demonstrated the potential of deep learning for clinical datasets and showed the potential of AI in detecting mental diseases in the future. Despite demonstrating incredibly advanced performance in various domains and highly advanced performance in multiple disciplines, deep learning. Deep understanding, for example, has been referred to as a "black box." Techniques like LR, on the other hand, are essential and obvious. As a result, current efforts in the open to interpretation DNNs are shown here. The detections exposed that 70% precision was accomplished in the dataset and that profound learning techniques can group massive datasets better than different strategies. Moreover, the outcomes showed the guarantee of deep learning for clinical datasets and delineated the future use of AI to recognize mental issues. Although profoundly progressed execution has been exhibited in a few fields, deep learning has been under close worry for its absence of straightforwardness during the learning and testing processes. For instance, deep learning has been alluded to as a "black box." In the examination, methods such as LR are straightforward and straightforward. Consequently, the ongoing undertakings in interpretable DNNs are presented here. For instance, as far as convolutional neural network (CNN) perception. In deprived, an artificial intelligence model ought to gain from information, rules, and experiences and be interpretable, for the most part pertinent, and valuable.

The most common way of diagnosing mental issues is depicted as follows: first, macromolecular varieties, like protein articulation, are analyzed by EEG; second, changes in mind underlying framework, explicit neural circuits, and cerebrum work are investigated by MRI; lastly, kinesics information is utilized to perceive conduct changes when patients have clinical aggregate switches. The outcome of these modifications at the primary, practical, and conduct levels, specifically, can support diagnosing mental infections and treating them. On the other pointer, psychiatric diseases have many clinical signs. Diagnosing mental diseases is one of medicine's more labor-intensive activities and fits squarely within machine learning. Patients cannot always

be diagnosed quickly and adequately by the conventional medical system. Continuous advancements in clinical examination technology and artificial intelligence (AI) can significantly cut expenses and provide real-time assisted diagnosis findings. AI can assist clinicians in providing more accurate and efficient diagnostics, resulting in a higher level of clinical diagnosis for neuropsychiatric illnesses. The most common use of AI in this area is DNNs to diagnose conditions. DNNs may reliably predict the risk of disease or aberrant lesions through a deep learning model based on relevant illness data. Although deep learning's analytic performance for identifying psychiatric disorders is improved in the literature, there are specific issues: firstly, more computer configuration is required. Secondly, more data is needed (experimental performance improves only with more data). Third, more time is used for experiments. These issues should be researched and debated more in the future. In the artificial intelligence has made significant progress in detecting psychiatric diseases, there are still numerous areas where AI-based applications might be improved.

First, because present study is focused on traditional surface learning methods, sharing, and using information among high-dimensional characteristics is challenging. As a result, deep learning is an area of research that will be pursued in the future. Second, unsupervised learning must be used to explain unlabeled mental disease imaging information automatically. Finally, the existing AI-based model's generalizability is insufficient since it can only analyze homogeneous datasets. As a result, in the not-too-distant future, relocation learning ensemble learning, and multi-view learning, will be utilized to handle large amounts of psychiatric disease data.

Discussion:

As on the chapter will discuss the findings as presented above. The analysis of the theoretical model will be discussed. The analysis aims to discuss the advantages of the AI model in the precise diagnosis of psychiatric disorders and address the efficacy of AI models if they were theoretically applied in psychiatric care. Additionally, some recommendations will be presented. Over the last decade, the usage of artificial intelligence approaches has attracted interest in the fields of brain imaging and computational neurosciences. Machine learning (ML) techniques are now well-known and widely employed for handling brain-related issues, and they are one of these approaches. ML has shown the most potential for clinical tasks include quantitative and qualitative characterization investigations of normal and diseased components (Akkus et al., 2017). In this respect, ML approaches have been extensively utilized to detect psychiatric disorders utilizing brain data analysis. In addition, methods for segmenting and detecting brain structures and diseased tissues are being researched extensively (Balafar et al., 2010).

For diagnosis, accurate detection and localization of diseased tissue and neighboring healthy tissues are critical. Nonetheless, it's worth emphasizing that ML approaches typically require several steps to complete a task due to the complexity and volume of brain data. Image pre-processing, image segmentation and sorting, and data pre-processing, for example, are frequently required as first steps to improve algorithm efficiency (Gudigar et al., 2020). Deep Learning (DL), a subset of AI, has revolutionized a range of neurosurgical jobs in recent years (Valliani et al., 2019). DL algorithms have risen to prominence in computer vision, surpassing other techniques on a few high-profile image analysis assessments.

Unlike typical machine learning models, DL automatically learns meaningful interpretations and features from raw data, eliminating the need to manually compute and pick potentially relevant variables. Such algorithms began to be efficiently employed for learning from 3D and 2D images typical of the medical domain thanks to important advancements in computing power, including the usage of a Graphics Processing Unit (GPU) (Gudigar et al., 2020).

This paper primarily aims to provide an insight into current data on AI techniques that support brain care. We briefly outlined essential AI concepts and applications and the main techniques and knowledge bases employed in neuroscience. First, we summarized the key clinical uses of AI in the brain, such as classification and predictive methods. Second, we offered a complete explanation of recent classification methods based on brain connectivity. Finally, we discuss how AI might transform brain care in the near and long term, identifying open issues and promising directions for future research, considering the latest advancements and the fast-expanding potential of the field. In recent years, many academics in the neuroscience discipline have become increasingly interested in AI algorithms. To optimize neurosurgical treatments, machine learning has been applied to uncover approaches to improve diagnostic and peri-operative decision-making quality and precision. In this research, recent applications and AI based models and algorithms have been presented to discuss their accuracy in the precise diagnosis of psychiatric disorders. When it comes to diagnosis, neural models are commonly used.

Even though artificial learning frameworks have been shown to produce outstanding outcomes, they have a few disadvantages that must be considered. One of the most challenging issues to overcome is the vast volume of data to avoid overfitting and increase performance. Acquiring them, meanwhile, may not be simple. Several works address this problem by developing appropriate frameworks that can yield outstanding results even with small quantities of data (Basaia et al., 2019), training from partial data (Ghazi et al., 2019), and employing semi-supervised and unsupervised techniques.

These algorithms are still a dark box in terms of the foundations on which the predictions are created from the input data. As a result, "precision" will be a critical component in the advancement of new algorithms, and numerous research projects will be conducted in this area. An intriguing alternative to this goal is the brain connection representation of the human brain. Such information enables us to describe the brain using mathematical models, allowing us to investigate hidden disease changes outside of visible items in traditional imaging. For the diagnosis and interclass classification of numerous neurodegenerative illnesses, good efficiency has been achieved using classical ML and DL models. The adoption of innovative graph-based DL techniques, such as graph neural networks, can provide an important view in this regard. Although AI's capability in brain care is exciting, it's important to recognize some obstacles to see actual improvements in real-world systems. Some of the primary challenges are data quality, data inconsistency and instability, and huge size and variety limitations in support of new investigations. To achieve this goal, researchers developed and developed public libraries and leaderboards to make materials readily accessible and to submit new discoveries, implicitly dealing with medical-related difficulties such as verification and legal challenges. Additionally, efforts are made to foster collaboration between AI researchers and nanotech consumers (as clinicians and medical experts). Web tools geared at collaborative learning paradigms, which enable research hospitals and institutions to interact and generate more robust AI algorithms and collect annotated data, play a critical role in this context.

Conclusion

This research offered a broad analysis of the current studies on AI approaches that directly help brain care. Artificial intelligence approaches are slowly but steadily delivering effective theoretical options to a significant number of real-world therapeutic problems involving the brain. It has considerably expanded our knowledge of complicated brain mechanisms in recent years, mainly to the gathering of relevant data and the creation of increasingly powerful algorithms. As discussed in previous chapters, these algorithms help precisely predict different psychiatric disorders, which in turn help to manage the consequences of these disorders. The initiatives of academics are resulting in the development of advanced, efficient, and easily understandable algorithms, which could lead to the more significant usage of "intelligent" devices in therapeutic settings of brain care.

The theoretically constructed Artificial intelligence model has the potential to provide abilities that could strengthen the foundation for brain specialists or neurologists to make appropriate medical decisions. The next phase in the AI model is to make the essential data accessible and able to respond to the AI's input. This means that adopting the AI model's diagnostic and forecasting functions could temporarily benefit the psychiatric care sector. Because these aspects have characteristics that are very compatible with existing practice in the psychiatric care sector, they are a good match. The attributes could achieve high precision in the delivered output in the long term. As time passes, the AI performance will likely increase to the point where it will be able to outperform a human's capacity to execute a similar activity. Additionally, while the AI model's diagnosis function is theoretically viable, there is a limited possibility that the feature will be able to achieve greater efficiency.

Because of the current framework of the PA work process, the diagnosis feature's effectiveness would be severely limited. In conclusion, while AI has made significant progress in detecting psychiatric diseases, there are still numerous areas where AI-based applications might be improved. First, because current research is focused on traditional shallow learning methods, sharing, and using information among high-dimensional characteristics is problematic. As a result, deep learning is an area of research that will be pursued in the future. Second, unsupervised learning must be used to accomplish automatic annotation for unlabeled mental disease imaging data. Finally, the existing AI-based model's generalizability is insufficient since it can only analyze homogeneous datasets. As a result, in the not-too-distant future, migration learning, multi-view learning, and ensemble learning will be utilized to handle large amounts of psychiatric disease data. The future of artificial intelligence in mental health care seems bright. We must play a more productive role in enlightening the overview of AI into clinical care as scholars and practitioners interested in enhancing mental health care by transferring our medical knowledge and collaborating with information and analytical scientists and other professionals to help reshape mental health practice and enhance the quality of care.

Conflict of interest: All authors declare no conflicts of interest.
the patients.

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