INSIGHTS OF ARTIFICIAL INTELLIGENCE IN PSYCHOLOGY WITH EVIDANCE OF ARTIFICIAL INTELLIGENCE ALGORITHMS

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Abstract

The use of brain-computer interfaces, often known as BCIs, to connect the active regions of living brains to actuators in real time has shown some encouraging results. The development of artificial intelligence (AI), which may significantly improve ways of analysing and interpreting brain activity, has provided a considerable boost to research on brain-computer interfaces (BCIs). Over the past decade, a large number of additional BCI applications that make use of AI have come into existence. These "smart" BCIs, which include motor and sensory BCIs, have demonstrated exceptional therapeutic effectiveness, increased the athletic potential of common people, improved the quality of life for paralysed patients, and sped up the development of robotics and neurophysiological discoveries. The extensive training times, real-time input, and monitoring that are required with BCIs continue to be problematic, despite the fact that technological breakthroughs have been made. This article presents a comprehensive study of the current situation of artificial intelligence (AI) in the context of brain-computer interfaces (BCIs). It does so by presenting recent breakthroughs, difficulties, and potential future paths for BCI applications.

Keywords: Artificial intelligence, Psychology, Algorithms, Patients

Introduction

There is no doubting artificial intelligence's (AI) significant impact on contemporary culture. Artificial intelligence (AI) has established itself as a helpful tool in a wide variety of industries, from manufacturing to finance to the classroom, as processing power advances, new ideas and techniques appear, and data volumes increase exponentially. Although there is no universally accepted definition of AI, it is generally accepted that the ability to mimic human intellect in machines is what the discipline is all about. The creative fusion of computer science, algorithms, machine learning, and data science allows AI to solve problems as well as or better than humans. [1]

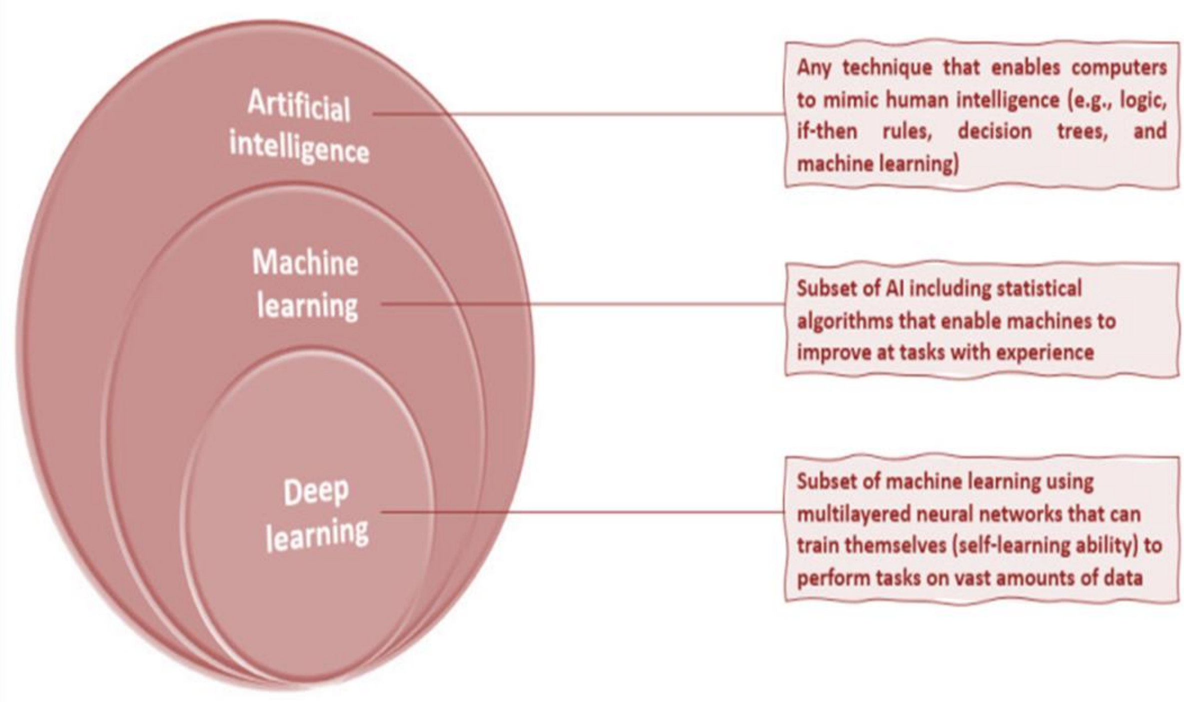

Fig: 1 Relationship between AI, MI, DI

To go into more detail, artificial intelligence (AI) refers to any system that is capable of sensing, reasoning, engaging in activity, and learning. These abilities allow the system to perform a variety of tasks that are typically associated with humans, such as digital image recognition, speech recognition, motion tracking, and planning and organising. On the other hand, machine learning (ML) is a subfield of artificial intelligence that applies statistical approaches to offer computers the ability to learn and improve over time. ML was first developed in the 1980s. Specifically, machine learning encompasses the AI tools that may adjust their models in order to obtain better predictions, which, in turn, leads to improved overall performance on the task that is being performed.[2] It is true that machine learning techniques can be applied to datasets of any size; but, when it comes to training a model, having a larger amount of data is almost always preferable. Using these characteristics as inputs into computational models that might shed insight on the data by, for example, clustering similar observations into clusters or forecasting specific events is the fundamental concept behind machine learning (ML). Deep learning (DL) is a subfield of machine learning in which algorithms self-train through a "self-learning" capability gained through a chain of important features retrieved from input data. This power allows the algorithms to learn without being explicitly programmed. Deep neural networks, also known as DNNs, are able to master data representations on their own and are capable of learning exceedingly complicated nonlinear mathematical functions. When talking about neural networks, the "depth" of the network is determined by the number of layers (or "neurons") that are present between the initial input and the culmination of the process. The method, which gets its start with the input features being fed into the first layer of neurons and then spreading towards the output layer, was designed after being inspired by the information processing principles of biological neurons.[3] The relationship between artificial intelligence, machine learning, and deep learning is illustrated graphically in Figure 1.

Different types of AI

Two unique types of artificial intelligence can be distinguished from one another based on the features and capabilities that they offer. The earliest sort of artificial intelligence (AI) is known as narrow AI or weak AI, and it is designed to carry out one particular task. This might refer to everything from facial recognition to using Siri on the internet to self-driving cars. In truth, many of the currently available systems that boast the utilisation of "AI" are probably only utilising a limited type of AI that was created to do a single, constrained task. This is because AI was originally supposed to execute multiple tasks simultaneously. Some people are concerned that, despite the fact that AI appears to have positive effects on human existence, it nevertheless offers a risk since, in the event of a malfunction, it may cause disruptions in the electric grid or even cause nuclear power plants to be destroyed. The development of powerful AI, commonly referred to as artificial general intelligence (AGI), is the ultimate objective of a significant number of researchers[4]. The concept of artificial general intelligence (AGI) refers to the hypothetical intelligence of a machine that is capable of comprehending or learning any intelligent work that human beings are capable of, and which may thus assist people in addressing any problem that they are faced with. Narrow artificial intelligence may be superior than humans at certain tasks, such as doing arithmetic or playing chess, but its influence will be restricted. On the other hand, AGI has the potential to excel in every cognitive endeavour, including those that are currently dominated by humans. Strong artificial intelligence represents a departure from the traditional definition of artificial intelligence for those who subscribe to the view that AI can be programmed to mimic the human mind in every way, from its ability to learn and adapt to new situations to its capacity to form perceptions, beliefs, and other cognitive abilities. For example, strong AI can learn and adapt to new situations.[5]

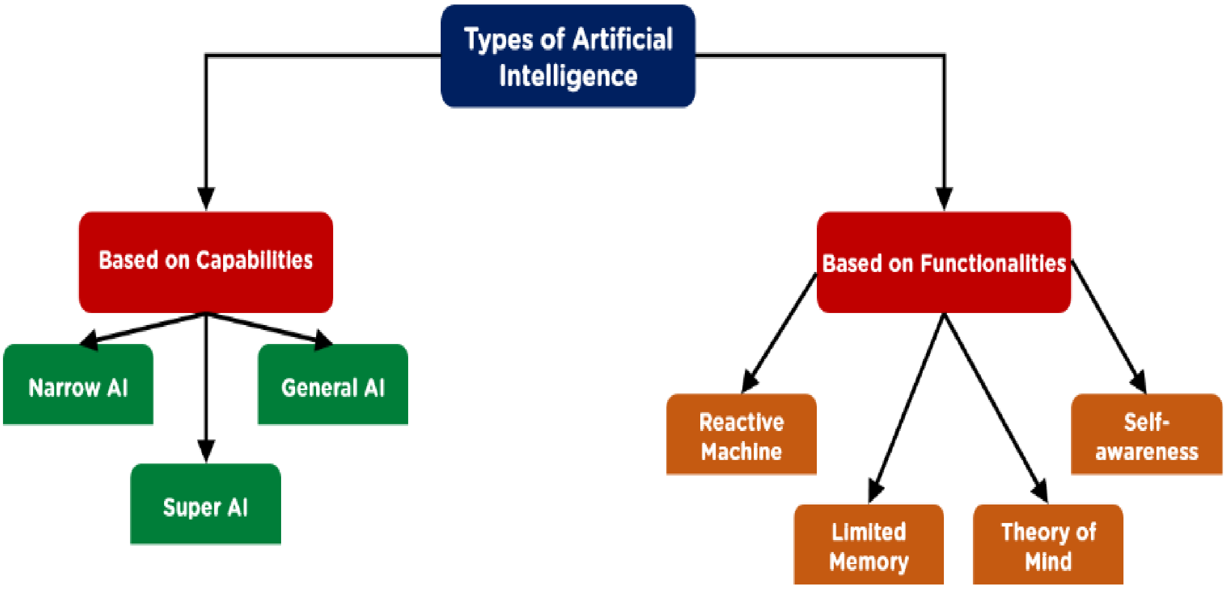

Fig: 2 Types of Artificial Intelligence

Research Gap on between AI & PSYCOLOGY

At the present time, the healthcare systems in both India and the United Arab Emirates have a lot of room for development and improvement. Because of this, we need to get better at utilising the various tools provided by ICT in the healthcare industry. Because of ICT-enabled primary healthcare, the quality of healthcare received by people living in rural, urban, and peri-urban areas of the United Arab Emirates and India would improve.[6] In addition, it enables access to a plethora of digital materials, which may be utilised by both patients and medical professionals. The goal of this study is to offer a distributed memory architecture (DMA) that is both modular and scalable, and that makes use of recent developments in information and communication technology. E-learning platforms, telehealth, telemedicine, health informatics, and e-commerce will all benefit from DMA that is designed using the most cutting-edge information and communication technologies that are available today.

Problem Description

The design and deployment of a platform that will allow for the real-time recording of data by smart devices is a key component of the National Health Information Architecture. This platform will facilitate the exchange of health information data (NHIA). The guiding principles of the NHIA are, to a significant part, congruent with the PAHO Strategy and plan of action on eHealth (Scott,).[7] The National Health Information Authority (NHIA), the Pan American Health Organization (PAHO), and the strategy and plan of action on eHealth all share four essential goals that will contribute to the general goal of making medical treatment more reasonably priced.

- **Health Informatics**: It achieves its purpose by bringing together data coming from a variety of healthcare sources. Second, it attempts to centralise healthcare data by bringing together electronic health records and accompanying services for integrating and analysing healthcare data. This will allow for the data to be centralised and easier to access.

- **Tele health and Telemedicine**: Patients who are unable to leave their homes due to a sickness or accident are now able to more readily contact (either in person or online) with health care providers who are stationed in distant locations. (The Institute of Medicine in the U.S.
- **E-Learning**: It promotes the utilisation of information and communication technology resources for the purpose of enhancing the education and training of people who are responsible for providing healthcare services. E-learning has made it possible for people working in healthcare to further their education at their own speed and without leaving the convenience of their own homes or places of business. The classes can be viewed as many times as the learner deems necessary and repeated whenever it is most convenient for them. The mass dissemination of knowledge and the individualization of political agency are both greatly facilitated by the Internet.[8]
- **Electronic commerce**: Contains information regarding the business side of the healthcare industry. One example of this kind of application is the utilisation of hospital information systems for the administration of patient-related services (cost of the treatment, administrative information etc).

ARTIFICIAL INTELLIGENCE IS IMPROVED MENTAL HEALTH THERAPY

According to the findings, those who report higher levels of psychological well-being had a lower risk of dying prematurely as a consequence of improvements in their physical health, positive health practises, and optimism. Researchers have recently started focusing their attention on the concept of psychological well-being, with the goal of developing theories and frameworks that can assist individuals in achieving greater levels of sustained happiness.[9]

The use of artificial intelligence (AI) in the field of medicine is becoming increasingly widespread, and as a result, researchers have begun applying the technology to develop such structures. In this inquiry, the model was developed by the application of deep learning, which is a subfield of machine learning. The examination of data by deep learning typically involves the use of intricate computational frameworks that are nested within one another. An individual's psychological age, or the age they believe they are based on their emotions, behaviours, and outlook on life, as well as their likelihood of experiencing future negative outcomes, can be predicted using data obtained from a psychological questionnaire. Psychological age can also be thought of as an individual's self-perception of their actual age. In order to arrive at these estimations, the researchers utilised data collected across both waves of the Midlife in the United States (MIDUS) study. For MIDUS1, these waves were collected in 1995 and 1996; for MIDUS2, they were collected in 2004 and 2006. Included in these data are profiles of well-being based on the Ryff scale, which is a common instrument for gauging how people feel about various aspects of their lives, such as their capacity for personal development, their sense of control over their surroundings, their sense of belonging to a community, their sense of meaning in life, and their ability to accept themselves. Researchers investigated the MIDUS data set to determine whether aspects of the study were associated with positive results.[10] They came up with a list of 32 characteristics that were essential in teaching the AI to determine a person's psychological age and how happy they are. After that, these projections were put to use in order to produce "self-organizing maps" (SOMs) for each individual. The maps displayed areas connected with "mountains" and "pits" related to high and low well-being levels based on the individual's initial estimate of their own well-being and tendency for depression. The individual's initial estimate of their own well-being and tendency for depression was used to create the maps. These ups and downs can be used as a guide for cognitive behavioural therapy as well as other interventions for mental health, helping to map out an individualised strategy for improved mental health that can be observed in real time. There is also the possibility of utilising this tool on its own as a client-facing application for self-help purposes. Using the self-organizing maps, the most depressing psychological configurations were also determined, and an algorithm was devised to aid people in moving out of these states. Dr. Nancy Etcoff, co-author of the study and director of the Program in Aesthetics and Well-being at the Massachusetts General Hospital, made the following statement in a press release: "The deep learning model demonstrates that one's baseline well-being is not the determining factor of future well-being." This statement disproves the hedonic treadmill theory, which asserts that people are destined to quickly return to a relatively stable level of happiness despite major positive or negative events or life In this paper, we provide a dynamic model of human psychology that allows for the maximisation of future happiness. In addition, we bring attention to patterns of happiness as they vary with age.[11]

Technology Advancement

The field of artificial intelligence (AI) and data science has experienced a significant amount of progress over the previous decade. Although there has been a consistent stream of excitement around artificial intelligence for a variety of applications for the past several decades, the current spike of interest is unlike any excitement that has come before it. The convergence of these three factors has led to a rapid advancement in artificial intelligence tools and technologies, including those used in the medical field.[12] These factors are the rise in computing power, the expansion of data libraries, and the proliferation of experts in the field of artificial intelligence. As a direct consequence of this development, a momentous change is on the horizon for both the current state of the art in artificial intelligence technology and the far-reaching social impact it has. Deep learning (DL), which has fundamentally altered how we think about AI technology in the present day, is responsible for a significant number of the most recent breakthroughs in artificial intelligence (AI). Previous methods of machine learning would have had a difficult time displaying the correlations that are now made available by DL. Deep learning is dependent to a large extent on artificial neural networks; however, in contrast to classic neural networks, which typically had just three to five layers of connections, DL networks typically comprise more than ten of these layers. This is comparable to running a simulation of millions of manufactured neurons. Watson, developed by IBM, and Deep Mind, developed by Google, are only two of the numerous market leaders in this field. These companies have proven that their artificial intelligence systems are superior to those of humans at certain tasks and activities, such as playing chess and Go.[13] IBM Watson and Google Deep Mind are currently finding applications in a wide variety of industries, and healthcare is one of those fields. IBM Watson is currently being used for research in a variety of fields, including the treatment of diabetes, advanced cancer care and modelling, and the discovery of drugs;

nevertheless, it has not yet demonstrated its therapeutic value to patients. Deep Mind is conducting research into a variety of fields related to medicine, including medical imaging-based diagnostics, patient deterioration prediction, and mobile medical assistants, to name just a few. The expansion of a wide variety of technologies that are based on data and computers has been exponential. Moore's rule, which is likely the most well-known example of this type of example, illustrates the significant rise in processing speed found in current computer chips. Several applications that are geared toward consumers have seen tremendous expansion as a result of the fact that they offer valuable services at low cost. As a result of mapping the human genome and digitising medical data, a similar pattern of expansion may occur in the fields of healthcare and life sciences as a result of mapping the human genome. The cost of genetic sequencing and profiling is expected to decrease, and electronic health records and other comparable tools will serve as a platform for data collection. At first look, these regions may appear to be unimportant; yet, in the long run, exponential expansion will become the primary driving force. As a species, we have a propensity to underestimate the impact that newly developed technology will have on our lives in the far future, whereas we have a tendency to overestimate the influence that newly developed technologies will have on our lives in the near future (say, within the next decade).[14].

Artificial Intelligence Algorithms for Diagnostic Analysis of Medical Images

Recent advancements in the field of deep learning technology have aroused great interest in the application of artificial intelligence (AI) in the medical industry. In particular, convolutional neural networks, a sort of deep learning technology also referred to as "computer vision," have gained a great deal of attention due to the possibility that they may be applied in the diagnostic analysis of a wide variety of different types of medical images. It is essential that AI algorithms go through stringent clinical validation prior to its deployment in clinical practise through well-conducted research. This is necessary to guarantee patient benefit and safety while minimising any dangers that might be unintentionally introduced. In the context of this investigation, the term "validation" does not relate to the process of algorithm tweaking as it does in the field of machine learning; rather, it means confirmation, just as it does in the medical field.[15] Clinical validation of AI technology may aim for a number of different aims, including diagnostic performance, influence on patient outcome, societal efficacy taking into consideration cost-benefit and cost-effectiveness analyses, and more. External validation that is well-designed is necessary for high-dimensional AI algorithms that employ deep learning to analyse medical imagery in order to demonstrate their therapeutic usefulness. It is advised that big datasets be used for the purpose of external validation because this will allow for a more realistic representation of the manifestation spectrum, which is defined as "all relevant variances in patient demographics and illness states." These datasets may be gathered from patients who have recently been recruited, or they may be collected at institutions other than those that contributed training data. During the validation process, it is absolutely necessary to use data from a large number of distinct external institutions if one wishes to confirm that the algorithm can generalise across the anticipated diversity present in various healthcare systems. Producing and annotating this volume of medical image data is particularly challenging and resource intensive.[16] However, it is necessary for the training of complex mathematical and statistical AI models, such as deep learning algorithms, which interpret medical pictures. These models are used to automate diagnostic processes. For this reason, those working on such AI algorithms may resort to using whatever data are at hand (what is technically known as convenience case-control data), despite the fact that such data may be subject to selection biases and artificial disease prevalence and may not accurately portray real-world clinical settings. This is because of the fact that such data may not accurately portray real-world clinical settings. Due to the strong dependence of an AI algorithm's performance on its training data, there is a significant chance that AI algorithms will underperform when they are put to their intended use in the real world, and there is also a chance that an algorithm developed at one institution will produce inaccurate results when it is used on data collected at another institution.[17].

Effectiveness of Internet- and mobile-based psychological interventions

Researchers have, for a considerable amount of time, proceeded under the fair presumption that certain treatments will be more effective than others in the treatment of a range of disorders. Research conducted in clinical settings has shown that psychotherapy is useful for the majority of people, but not all. In point of fact, according to some estimates, up to forty percent of patients either do not exhibit any recovery or only show a partial reaction to psychiatric therapy. As Grimley Evans pointed out in the middle of the 1990s, patients want healthcare practitioners to perform better than that.[18] While administrators and academics may be delighted that therapies succeed on average, patients want practitioners to perform better than that. If we want to achieve progress in the field of psychotherapy, we need to shift our focus from researching the efficacy of treatment for a large population to figuring out which therapeutic approaches work best for individual patients. Only then will we be able to make significant strides forward. A symptom-reduction approach, for instance, has been shown to be more beneficial for patients who struggle with externalising difficulties, whereas an insight-based therapy is typically more effective for patients who struggle with internalising problems. Not all psychotherapies will be equally effective across individuals; for instance, a symptom-reduction approach has been proven to be more beneficial for patients who struggle with externalising difficulties.[19] The key question that was raised by Gordon Paul over half a century ago is still as relevant now as it was then. The question asks, "Which treatment, administered by whom, is most beneficial for this particular person with that exact illness and under those circumstances?"

Unfortuitously, previous tech-supported psychological therapies for ED self-management have consisted of generically supplied, static processes that fail to account for individuals' specific requirements and growth during the course of treatment. These methods have been used for decades. Even for evidence-based psychotherapies that are delivered face to face, it is not advisable to slavishly adhere to more or less manualized treatment procedures or to offer predetermined responses to patient behaviours[20]. This is the case even when such practises are possible. As a consequence of this, a number of authors support the idea of a model that endorses the use of therapies that are not completely governed by manual procedures. This adjustment in viewpoint may be made easier by ecological momentary interventions (EMIs), which are supported by artificial intelligence.

Alterations to the therapeutic process that are made on the fly or in the near future based on input from the patient obtained from ecological and instantaneous assessments are known as interim modifications (EMIs) (EMAs). These interventions can be used to monitor and encourage active involvement in tasks. Additionally, they can be used to supplement existing psychological therapies provided by a therapist, such as in the case of internet treatments (for example, by sending a notification on the mobile phone that encourages patients to do the tasks;). This has the potential to be an extremely valuable way for boosting the efficacy as well as the adherence of therapies that can be applied by the patient themselves thanks to advancements in technology.[21]

AI & PSYCOLOGY PRACTICE

EMIs have the potential to become an essential component of the psychological treatment of the future since they can provide patients with therapeutic guidance or instructions as soon as problems arise in their lives. It has been said that this is an ideal paradigm to adopt in the next generation of psychological treatments for EDs because it reduces the amount of patient suffering, boosts treatment effectiveness, and reduces the amount of money spent on therapy.[22]

It is common knowledge that not everyone reacts in the same way to psychological treatments, particularly those that are assisted by technology. Even though the typical rigidity of EMIs represents a significant improvement over episodic face-to-face interventions and even self-applied psychotherapy, it is also common knowledge that not everyone responds in the same way to psychological treatments. And this is why, for quite some time now, researchers have been attempting to determine what it is in certain individuals that causes them to respond favourably to a treatment while other individuals do not. Artificial intelligence can be of assistance in this regard by analysing large amounts of complex data and supplying the therapist with the relevant information for effective management of an individual's problem in real-time or very close to it. This can be done in either of these two time frames: real-time or very close to it.[23]

John McCarthy was the first person to use the term "artificial intelligence" (AI) to refer to the ability of machines to mimic human intelligence by carrying out activities such as reasoning, learning, interacting, making decisions, adapting to new situations, and processing sensory input. AI was originally intended to describe the capacity of machines to perform tasks such as reasoning, learning, interacting, making decisions, and adapting to new situations. A good illustration of technology that can expertly manage human-machine contact are conversational chatbots, for instance. Therefore, in situations when there are not enough human physicians to go around, chatbots can step in to help those who are in need of mental health care. In recent years, there has been a shift in the meaning of the term "artificial intelligence," with the term now commonly referring to agents or calculators of historical records that may develop prediction models. This change came about as a result of recent developments in the field of artificial intelligence. The development of artificial intelligence (AI) has made it possible for computers to learn on their own through the use of self-learning algorithms and to get better as they gain more experience, which has led to improved precision in many processes. In the field of psychology, for example, artificial intelligence has been used in post-treatment evaluations to determine which factors better predicted a positive outcome.[24] However, the utilisation of AI to enhance psychological therapies in real time or in a setting that is nearly identical to real time is not as widespread. In the context of self-applied psychiatric therapy that makes use of technology, AI can be extremely beneficial since it can be used to investigate the efficacy of various EMIs and then adjust interventions to the specific needs of individual patients. This makes AI particularly useful. This project aims to give a complete evaluation of the research on the usefulness of utilising AI to improve psychotherapy outcomes in real-time or near-real-time situations. The findings of this study will be presented in the form of a report. Over the course of the last few decades, a significant amount of study has been conducted on the neurobiology of mental diseases. Despite significant advancements in research, there is widespread discontentment with the rate of overall development in recognising and treating psychiatric diseases. This is despite the fact that there have been significant advances in research.[25] The current approaches for diagnosing psychiatric disorders rely mainly on physician-patient questionnaires, which are well-known for their notorious unreliability in providing an accurate assessment of symptoms. The incorporation of artificial intelligence (AI) into electronic medical databases and health records, on the other hand, makes it possible to overcome these challenges. The use of computational tools and algorithms to the research of mental disease as well as its treatment, prevention, and diagnosis is what is meant by the term "artificial intelligence" (AI) in the field of psychiatry. What exactly this means for the discipline of psychiatry is still a confusing and unsolvable problem, but a rising number of medical fields have begun incorporating AI into their day-to-day operations. This chapter provides a concise summary of what is currently known about the role that AI plays in the field of medicine. Topics covered include its application to the diagnosis, prediction, and treatment of psychiatric illnesses, as well as its limitations and potential hazards. This systematic review and meta-analysis will contribute to the previous research by examining, synthesising, and addressing the available evidence on Internet- and mobile-based preventative interventions for mental diseases. The findings of this analysis will extend further than those of other systematic studies of the same nature because they will be applicable to a greater variety of mental illnesses. Therefore, the proposed systematic review and meta-analysis will provide clinical practitioners, researchers, and decision-makers in public health policy with a comprehensive overview and synthesis of the entire field of Internet- and mobile-based mental disease prevention interventions.[26]

With the help of the following characteristics, the findings of this review and the ways in which they can be applied can be put into context. The purpose of this review is to give a complete overview of mental disorders by including studies with a wide variety of research designs, populations of interest, therapeutic approaches, control conditions, and outcome measures. The inherent diversity in clinical, methodological, and statistical approaches will limit the amount of quantitative pooling of studies that can be done, despite the fact that this will provide an in-depth summary of the ways in which Internet and mobile-based interventions are being used to reduce the prevalence of mental health problems. When solely taking into account research that has been published in English or German, it is possible that the language bias will cause an overestimation of the effects. This is due to the fact that statistically significant results are more likely to be published in the English language. Because only the most significant discoveries are released, the findings could be misleading as a result. In an effort to integrate previously unpublished and lesser-known studies, we intend to initiate communication with the lead investigators of the relevant studies and study procedures. Historically, preventative efforts for mental disorders have been hampered by challenges such as limited resources available through health care systems and the difficulty of providing an intervention on a wide scale.[27] Through the use of internet delivery, it is possible to get around this restriction. Because the extent to which an intervention is effective is critical data for making decisions about the introduction of new health care practises, it plays such an essential role in shaping public health policy. Internet and mobile-based treatments face a significant challenge in the form of attrition. As a result, we will keep a record of and talk about the attrition rates associated with the various treatments and interventions. The review that is being proposed would go further than merely providing a summary of the data that is already available; rather, it would offer a qualitative appraisal of the treatments that have been tried in the past and are currently being tried. By doing so, we are able to fill in the blanks in the existing body of literature, describe the fundamental components of efficient preventative programmes, and identify research domains that have not yet been investigated. As a result of the fact that there will be many planned Internet- and mobile-based prevention intervention studies on mental disorders but no matching systematic review, the proposed review is not only desperately required but will also greatly add to the existing body of knowledge. Our findings will be of use to researchers in identifying potential new paths of inquiry, as well as to public health policy makers in evaluating the effectiveness of preventative measures for mental health.[28]

Stroke

Imaging with a CT scan is essential during the acute phase of a stroke. Prior to performing stroke thrombolysis and endovascular thrombectomy, there is a substantial lack of knowledge that is now available and considerable delays in the interpretation of emergency CT images. It is common practise for emergency radiologists to be swamped with normal CT scans before they become aware of anything that is out of the ordinary. When cerebral haemorrhage or early symptoms of infarct are identified, neuronal death typically occurs before therapeutic interventions may be undertaken.[29] A patient who has such a delay almost always winds up being chronically incapacitated as a result. After an acute stroke, every 15 minutes that is saved in order to achieve a Large Vessel Occlusion (LVO) recanalization results in a better prognosis for the patient's ability to recover from the handicap caused by the stroke.

The identification of infarcts and haemorrhages, the detection of large vessel occlusions, the grading of Alberta Stroke Program Early CT Scores (ASPECTS), and prognostication are all potential therapy approaches for strokes that could benefit from the application of artificial intelligence. In the evaluation of the severity of acute ischemic stroke, the ASPECTS severity grading score has been widely adopted for use with non-contrast CT scans. A trained artificial intelligence (AI) Machine Learning (ML) model had a specificity of 91.8% and a sensitivity of 66.2% when it came to judging ASPECT scores on CT scans of acute stroke patients. These figures are presented in percentages. Another artificial intelligence model had a specificity of 96% in a patient cohort of 223 people when it came to detecting an early symptom of stroke called hyperdense vascular sign in Middle Cerebral Artery (MCA). The model had a mean algorithm run time of 1 minute and 30 seconds.[30] At the moment, non-contrast CT head scans are utilised in conjunction with an artificial intelligence system to recognise stroke patterns of LVOs in acute stroke. This results in an automatic alarm being sent to a team of people who specialise in treating strokes. An alarm is sent to the doctor working in the emergency department, as well as the neurologist and the neuro-interventional radiologist, using an app on their mobile phones. The amount of time it took to start emergency care for stroke victims was reduced by 52 minutes on average thanks to the AI system. In situations of acute stroke, the interpretation of data obtained from CT perfusion imaging takes a lot of time and calls for the knowledge and expertise of an expert in order to decide whether or not brain tissue may be spared. RAPID (IschemaView, Menlo Park, CA) gives information on brain tissue that can be rescued with prompt intervention by automatically computing the ischemia core and hypo-perfused tissue volumes from CT scans. This information can be utilised to improve patient outcomes. Within a few short minutes, the results are available to the attending physician. The programme has been subjected to extensive testing and validation, which demonstrates that it is reliable and accurate.

In order to identify strokes and separate infarct tissue into an ischemic core and a salvageable penumbra, perfusion-weighted magnetic resonance imaging, also known as PWI, is utilised. Huang et al. identified recoverable brain tissue with a ROC-AUC of 88% after 30 minutes, 94% after 60 minutes, and 97% after permanent MCA closure by using PWI-derived cerebral blood flow (CBF) and apparent diffusion coefficient (ADC) datasets.[31] These results were obtained by using PWI. After the traditional window period for thrombolysis had passed, a research version of the artificial intelligence application RAPID (Stanford University and iSchemaView) was used in order to locate hypo-perfused but salvageable parts of the brain. This application was developed by Stanford University (4.5 h). The imaging was done with CT perfusion imaging and perfusion-diffusion MRI, and the image processing was done with the research version of RAPID. There were 225 people who took part in the study; 113 of them were given the drug alteplase, and the other 112 were given a placebo. (adjusted risk ratio, 1.44; 95% confidence interval [CI], 1.01 to 2.06; P = 0.04) The primary outcome was experienced by forty patients in the alteplase group (35.4% of the total), and by thirty-three patients in the placebo group (29.5% of the total). This ground-breaking research, which was made possible by cutting-edge artificial intelligence software, has the potential to broaden the application of intravenous thrombolysis in patients for whom endovascular treatment is not a viable option.

Multiple sclerosis

Multiple sclerosis has traditionally been classified based on clinical symptoms rather than the underlying illness causes. This is because clinical symptoms are easier to see and measure (MS). The four phenotypes of multiple sclerosis are known as relapsing-remitting MS (RRMS), CIS, PPMS, and SPMS (SPMS). The current classification is derived from disease activity and the evolution of disability, although it is not possible to make accurate predictions regarding recurrence rate or proven disability advancement using this method. Clinicians have had a tough time beginning treatment and determining when to quit since there are gaps in the classification system.[32] An unsupervised machine learning system was used to analyse the MRI scans of MS patients who had already been diagnosed with the disease (an AI technique). This has made it possible to identify MS subtypes that were unknown up to this point. Using the algorithm known as Subtype and Staging Inference, researchers have identified subtypes of disease that exhibit distinctive patterns of temporal progression (SuStaIn). Different clinical classifications of multiple sclerosis have been recognised more recently, including lesion-led MS, normal-appearing white-matter-led MS, and cortex-led MS. Patients who have the lesion-led subtype are thought to have the highest relapse rate and the greatest potential for proven disability progression, at least according to one hypothesis. Some clinical trials also report encouraging results with the lesion-based MS subtype. These groundbreaking findings were validated by analysing data from a separate group of 3068 patients.[33]

Epilepsy

In the field of epilepsy, there has been a significant increase in the usage of ML approaches for the analysis of MRI data. A machine learning algorithm was able to classify histologic subtypes with 98% accuracy using a dataset that included 41 patients with focal cortical dysplasias (FCDs) and matched controls. After an average of 4 years of follow-up, the ML approach had a success rate of 92 and 82% in lateralizing the lesion for type I and type II FCDs, respectively. Additionally, the ML approach had a success rate of 92 and 82% in predicting Engel I seizure independence after an average of 4 years of follow-up.[34] 16 An additional artificial intelligence (AI) algorithm called an artificial neural network demonstrated a sensitivity of 73.7% and a specificity of 90.0% in detecting single FCDs when it was applied to an MRI dataset consisting of 61 patients with type II FCDs and 120 controls from three different epilepsy centres. The dataset was obtained from magnetic resonance imaging (MRI).

A Support Vector Machine (SVM) algorithm, a type of artificial intelligence, was able to accurately differentiate between patients with active epilepsy, those in remission (seizure-free for 12 months while not on medications), and controls by examining MRI imaging characteristics (fractional anisotropy, mean diffusivity, radial diffusivity, and axial diffusivity in diffusion tensor imaging data) from 20 paediatric patients and 29 controls. This was accomplished by examining In the process of preparing for epilepsy surgery, refractory temporal lobe epilepsies have also been lateralized with the help of machine learning algorithms.[35]

Dementia and neurodegenerative diseases

It has been established that artificial intelligence can improve the diagnostic accuracy of a variety of neurodegenerative illnesses, including dementia. Using ML approaches, researchers were able to attain an accuracy of over 84 percent when automatically differentiating between AD and VD. MRI scans have been used to generate nuanced neuroimaging signals that have been particularly developed for the aim of diagnosing Alzheimer's disease. An artificial intelligence algorithm was trained using data from the Alzheimer's Disease Neuroimaging Initiative (ADNI; n = 417), and it was then validated using data from three separate cohorts: the Australian Imaging, Biomarker and Lifestyle Flagship Study of Aging (AIBL; n = 382), the Framingham Heart Study (n = 102), and the National Alzheimer's Coordinating Center (NACC; n = 582). The AI algorithm's predictions of high-risk cerebral areas were highly compatible with the post mortem histology findings. In terms of the diagnostic accuracy forecasts they were able to make, a group of practising neurologists from around the world (n = 11) was unable to outperform the AI systems.[36]

Currently, Parkinson's disease (PD) is diagnosed mostly by observing the patient's clinical symptoms. Because of its prohibitively expensive price, the positron emitted topography method of detecting the dopamine transporter cannot be utilised in a clinical setting. Using neuromelanin sensitive magnetic resonance imaging, or NMS-MRI, abnormalities in the substantia nigra pars compacta (SNc) have been found in patients with Parkinson's disease (PD). An artificial intelligence programme called Convolutional Neural Network has been able to identify Parkinson's disease (PD) with a high testing accuracy of 80% by using the neuromelanin signal in MRI imaging data. The algorithm detects the most discriminative regions on the neuromelanin contrast images and is able to differentiate between Parkinson's disease (PD) and atypical parkinsonian syndromes with an accuracy of 85.7% during testing.[37]

Electrophysiology

Seizures

Electrodes for electroencephalography (EEG) make it possible to record signals in a number of different frequency bands that do not overlap with one another. This opens the door to the examination of a wide variety of disorders and health conditions. When it came to the identification of seizures, an artificial intelligence algorithm that relied on scalp EEG achieved a sensitivity of 93% and a specificity of 94%. In addition, the use of intracranial electrode recordings in conjunction with a machine learning (ML) system that is able to detect seizures while they are occurring in real time is potentially a possibility[38]. It can be difficult to localise the epileptogenic zone in the brain during a seizure because the electrical activity that characterises the seizure quickly and concurrently spreads across large cortical regions. Intracranial electroencephalogram (EEG) data from six patients undergoing resection surgery was utilised by Dian et al. in order to train a deep learning system that is able to locate the epileptogenic zone. The algorithm was able to identify seizures and pinpoint the most effective locations for resection by analysing oscillations at both high and low frequencies that were present in the recordings. People who are prone to having seizures can also have artificial intelligence help them predict when they will have an ictus. The outcomes of a new artificial intelligence (deep learning) algorithm that used long-term scalp EEG data to predict epileptic seizures in individual patients were as follows: an accuracy rate of 99.6%, a sensitivity of 99.72%, a specificity of 99.60%, a false alarm rate of 0.004% per hour, and a prediction time of 1 hour before the seizure onset. These outcomes were achieved by the algorithm using long-term scalp EEG data.[39-41]

Coma

Using AI algorithms, a diagnosis of coma was obtained as well as a prediction of its prognosis. Supervised learning algorithms have shown that up to 15% of people who were clinically declared to be permanently unconscious after suffering an acute brain injury have observable brain activity in response to vocal commands. This was discovered in people who were clinically declared to be permanently unconscious (AI). Another artificial intelligence system has been developed that is capable of predicting functional prognosis at six months using EEG data in comatose individuals 12 hours after cardiac arrest (deep-learning artificial neural network). At 6 months, it predicted a good functional outcome with 48% precision and 0% false-positive rate, whereas it predicted a horrible functional outcome with 58% precision and 5% false-positive rate.[42]

Retinal and fundus scans

A machine learning algorithm was trained on 14,341 photos taken from a retrospective dataset, and then it was tested on 1,505 photographs to see whether or not it could detect papilledema. The method has a sensitivity of 96.4% (95% CI, 93.9 to 98.3) and a specificity of 84.7% (95% CI, 82.3 to 87.1) when it is evaluated on an external dataset. Its AUC for diagnosing papilledema is 0.96 (95% CI, 0.95 to 0.97) and it has a 95% confidence interval (CI) ranging from 0.95 to 0.97. An additional artificial intelligence (AI) method for diagnosing diabetic retinopathy (DR) was validated by third-party researchers with the help of a prospective dataset that was built over the course of half a year. This system was trained using 30,000 photos that were tagged by experts and taken from three different retrospective datasets (DiaRetDB1, Kaggle (Eye-PACS), and Australian Tele-eye care DR). 17 people out of a total sample size of 193 individuals who were examined as part of primary care were found to have diabetic retinopathy of a severity that called for additional testing. We were able to attain a specificity of 92% (95% confidence interval [CI], 87%-96%), which was higher than the reference level of ophthalmologist evaluation.[43]

Limitations

In sharp contrast to the more generalizable learning that distinguishes humans, artificial intelligence systems thrive at acquiring specific subfields of expertise. To offer just one illustration, an algorithm that has been trained to recognise papilledema in fundus images will do very poorly when it is asked to recognise optic atrophy. This is just one example. The ability of a trained physician, given appropriate resources, to make predictions that are competitive with those of AI provides a reasonable benchmark by which to measure the effectiveness of such systems.[44] Metrics for artificial intelligence systems that appear to be impossible to achieve could very well be. Results from isolated in-silico experiments with extraordinary performance measures frequently stand in stark contrast to the mayhem that occurs in actual clinical practise. Does the utilisation of the AI tool result in improved outcomes for patients? The question that needs to be answered is whether or not it will continue to be a new invention or whether it will merely become a showy instrument. It is possible that these questions can be answered by conducting prospective randomised controlled trials in clinical settings and comparing the outcomes obtained by AI with those obtained by clinicians. Applications of artificial intelligence are extremely dependent on the accuracy of vast volumes of training data, which may be biassed due to the biases of those who are training the system.[45]

The more advanced an AI tool is, the less you will be able to comprehend about how it operates on the inside. The "Black Box" problem emerges in the field of artificial intelligence when people are unable to fully describe how their tools arrive to their final projections. Metrics regarding the health of the patient should be considered separately from performance indicators. A wrong diagnosis of an illness can have catastrophic consequences, but the incorrect classification of a healthy individual might lead to a waste of healthcare resources by provoking investigations that aren't necessary. The ramifications of AI from a legal and ethical standpoint, as well as the question of how to hold technology accountable for errors it causes, are both at the forefront of current debates. When putting these AI strategies into practise on a large scale, it is essential to proceed with extreme caution. The Food and Drug Administration (FDA) has established stringent guidelines for the clinical application of artificial intelligence technologies.[46]

AI applications approved by FDA

There are three different forms of FDA approvals for AI/ML-based medical technology: the de novo method, the premarket approval, and the 510(k) clearance. De novo classification is utilised in situations in which there is no legally marketed counterpart of a novel piece of medical equipment, yet the device is both safe and effective when subjected to general restrictions. The Food and Drug Administration (FDA) does a risk-based examination of a device in order to determine whether or not it should be approved and authorised for commercialization before doing so. Before being made available to the general public for usage, algorithms that have a significant potential to have a negative impact on human health are put through a more rigorous line of questioning from both the scientific community and regulatory agencies.[47] Before the FDA will provide its approval, the agency needs to be persuaded that there is sufficient proof of both the device's safety and its effectiveness. If the application is accepted, the applicant will be able to start selling the product. The 510(k) approval is granted by the FDA to an algorithm once it has been demonstrated to be at least as safe and effective as another algorithm that has been similarly licenced. The applicant will need to provide substantial proof of equivalence in order to receive this clearance. The algorithm that is now being reviewed for clearance cannot be legally sold unless it can be demonstrated that it is "substantially equivalent" to the other algorithm.

Following a 510(k) premarket notification in 2017, the Food and Drug Administration (FDA) gave the go-ahead for EnsoSleep, an artificial intelligence app developed by EnsoData, Inc., to diagnose sleep disorders (approval number K162627). The obtained physiological data are analysed by the software, and an automated scoring system for sleep study outcomes including sleep staging, arousal detection, leg movement, and sleep disordered breathing event scoring are generated (including obstructive apneas).[48]

Through the de novo regulatory procedure, the FDA has given its blessing to the IDx (IDx LLC.) test for the detection of diabetic retinopathy (FDA approval number, DEN180001). IDx is a neural network that was developed specifically to analyse retinal images that were taken by the Topcon NW400. The retinal images that were captured by the attending physician are saved on a cloud server, which is where IDx is hosted. Depending on the quality of the photographs, the software provides the physician with either of the following outcomes: There are two scenarios that could take place here: (1) "more severe diabetic retinopathy discovered; consult an eye care professional" or (2) "negative for more severe diabetic retinopathy; rescreen in one year"

In 2018, the Food and Drug Administration granted approval for the use of ContaCT (Viz.AI) for the de novo diagnosis of stroke based on CT scan (FDA approval number, DEN170073). The device performs an analysis on the brain CT angiography pictures that were collected in the emergency room. It then notifies the neurovascular expert of the risk of an obstruction in a major artery.[49] A sneak peek of the photographs is currently available on a mobile app. The 510(k) premarket notification process gave iSchemaView, Inc.'s Rapid LVO the green light to go to market in the year 2020. (FDA approval number, K200941). Results from the Rapid LVO test can be obtained in less than three minutes by using a vessel tracker in conjunction with assessment of brain regions with reduced blood vessel density on CT images. This method has a sensitivity of 97% and a specificity of 96% for identifying suspected ischemic lesions in the brain. As soon as the possibility of an LVO is raised, the stroke team is notified as soon as possible. Strokes brought on by LVOs are treatable with emergency endovascular procedures.

The Food and Drug Administration has awarded its approval to the utilisation of Icobrain (icometrix NV) for the purpose of automatically labelling, visualising, and volumetrically quantifying segmentable brain regions derived from MRI data. This approval was the consequence of submitting a 510(k) premarket notification to the relevant authorities. In order to contour (segment) brain tumours on MRI images for use in radiation therapy treatment planning, VBrain (Vysioneer Inc.), which is expected to be approved for use in 2021, uses an artificial intelligence technique known as deep neural networks.[50]

Future applications

General artificial intelligence (as envisioned by AI pioneers in the 1950s), in which robots might feel, reason, and think like people, is likely to remain a science fantasy idea for the foreseeable future. This would mean that robots could feel, reason, and think like people. In spite of the fact that applications of artificial intelligence (AI) present a new set of tools to supplement traditional clinical approaches for triage, diagnosis, treatment decisions, and prognosis, it is anticipated that clinicians and clinical methods will continue to be essential in the future. There is a possibility that artificial intelligence might be used to classify seizures, such as distinguishing epileptic from nonepileptic seizures or classifying the phenotypic manifestations of complex hereditary epilepsies. This would be a useful application of AI. Novel algorithms may be able to discover early signals of disease in large population-based datasets. This would allow for rapid and reliable evaluation of whole genome or exome sequencing data. The syndromic diagnosis of rare genetic illnesses, the syndromic diagnosis of neurocutaneous conditions, and the pathological identification of conditions based on biopsy specimens are all potential applications for AI algorithms. It may be possible for future AI capabilities to assist with predicting how the human body would respond to different treatments.

AI has the potential to completely upend the way drug discovery is approached by bringing together patient-driven data from a wide variety of sources, such as academic articles, patents, clinical trials, and patient records. There is presently no known cure for amyotrophic lateral sclerosis (ALS), but researchers are exploring the possibility of using artificial intelligence (AI) as a potential therapy option. BenevolentBio, a London-based startup business, has developed an artificial intelligence engine that has found over one hundred existing compounds that show promise as treatments for amyotrophic lateral sclerosis (ALS). Researchers from the Sheffield Institute of Translational Neuroscience in the UK picked five of these substances to explore using cells extracted from patients. These cells were obtained from the patients themselves. According to research that was presented at the International Symposium on ALS/MND in December 2017 in Boston, Massachusetts, four of these chemicals showed promise, and one of them was demonstrated to postpone neurological symptoms in rats. The symposium was held in conjunction with the American Association for the Study of ALS and Motor Neuron Disease.

Conclusion

Within the scope of this examination, a survey of the available research on artificial intelligence techniques that have the potential to be employed to assist in brain care was offered. The application of various approaches of artificial intelligence is allowing for the discovery of gradually more effective theoretical answers to an increasing number of practical clinical challenges connected to the brain. To be more specific, the accumulation of relevant data and the development of increasingly potent algorithms have led to a tremendous increase in our understanding of the complex mechanisms that are found in the brain over the course of the past several years. The efforts of the researchers are leading to the development of algorithms that are both more complicated and more easily interpretable. This could, in the long run, result in a larger use of "intelligent" gadgets in genuine clinical settings.

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