Original Article

Insights Of Artificial Intelligence In Brain Disorder With Evidence Of Opportunity And Future Challenges

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Abstract

Artificial intelligence (AI), a well-known subject of computer science, has several therapeutic applications, including the analysis of intricate medical data and the extraction of significant correlations from datasets. For instance, in the field of brain care, a variety of unique approaches have shown promising outcomes and offer fresh directions for ongoing research on diagnosis, treatment planning, and outcome estimation. In this paper, we evaluate the many AI methods to brain care and talk about their most important clinical uses. A thorough literature search was conducted using the keywords "artificial intelligence" and "brain" throughout many of the most well-known scientific databases, including Pubmed, Scopus, and the Web of Science. Cross-referencing from primary articles allowed for the incorporation of more sources. A total of 2696 publications were discovered, and 155 of them contained some application of AI methods (diagnosis, surgical treatment, intra-operative assistance, and postoperative assessment). Artificial neural networks (ANNs) have gained popularity recently as effective analytical tools. Two of the mainstays of the machine learning canon, support vector machines and random forests, are still frequently used. To deal with a given problem, algorithms created specifically for that task are created. The brain's image data is among the most common. AI in neurology could improve medical professionals judgement. Before AI can be used effectively in the brain, however, there are still a number of obstacles that must be overcome.

Keywords: Artificial intelligence, Brain, Treatment, Neurodisease

Introduction

Despite increasing costs and demand, the healthcare industry is still confronted with a number of obstacles that prevent them from improving the quality and efficiency of the care they provide to patients. Internal inefficiencies, such as a delayed patient flow, can have a negative impact on outcomes and the quality of care provided as a whole, as well as on the level of satisfaction experienced by both patients and staff [1, 2]. The field of mental health is inherently more complicated than other fields of study that are equivalent to it. The demand for medical care is increasing, but there are not enough resources to meet it. As a result, the implementation of technical and digital solutions, such as artificial intelligence (AI), has become an option for addressing some of the issues. In addition to improved clinical results and patient safety, artificial intelligence offers the ability to save money, accelerate research, and evaluate populations [3]. "the capacity of healthcare systems to manage patients efficiently and with little delay as they go through phases of care" [4] is one description of patient flow. Another definition of patient flow is "the capacity of healthcare systems to manage patients effectively." Patient flow is the process of ensuring that quality and patient happiness are maintained throughout the entirety of the treatment. This process takes place throughout the entire process. As a result of this, there is a growing interest in the concept of utilising patient flow in order to improve care, "especially in connection to improvements in patient waiting times for emergency and elective care" [5,6]. In spite of the fact that a significant amount of time and energy has been invested in the implementation of AI in the environment in which patients interact, there is still room for development in the "back-end" operations and service supply. Despite the fact that research has been conducted on the potential applications of artificial intelligence in both mental health and patient flow, relatively few studies have particularly zeroed in on the idea that AI could be used to improve patient flow in inpatient mental health facilities. When properly implemented, information and communication technology, also known as ICT, has the potential to improve an organization's operational efficiency and give it a competitive advantage [7,8,9]. Organizations that have made the transition to digital operations recognise the importance of this aspect of their business. In this period of the Fourth Industrial Revolution (4IR), modern advanced digital technologies and equipment are used extensively across all industries for the purposes of innovation and value development [10]. This guideline is applicable to all different kinds of businesses, including the medical one. Hospitals and other care providers are aggressively implementing digital technologies such as artificial intelligence (AI), machine learning, smart sensors and robots, big data analytics, and the Internet of Things (IoT) to improve the quality of care they provide and the efficiency with which they provide it throughout the world, but especially in developed economies [11]. According to study that was conducted by a subsidiary of Hewlett-Packard Enterprise called Aruba [12] which is more than sixty percent of hospitals all over the world. The Internet of Things is now utilised at these establishments. Research into the manner in which cutting-edge digital devices are affecting service encounters in the healthcare industry [13,14] would be useful in light of the aforementioned circumstances.

Recent years have seen a proliferation of applications of technologies backed by artificial intelligence (AI) in healthcare facilities, with the goal of elevating the quality of care services and increasing the efficiency of medical resources [15,16]. Because of advancements in AI-based technology, the knowledge-heavy healthcare industry has a significant amount of space for innovation [17,18]. This is done so that artificial intelligence will eventually be able to encompass intelligent robotics, natural language processing, and machine learning. At the annual conference of the Radiological Society of North America (RSNA), which took place in Chicago in December 2018, a large number of image device startups and established manufacturers gave presentations about their artificial intelligence (AI) initiatives. These initiatives support accurate and reliable patient diagnosis as well as appropriate patient care based on data from clinical examinations [19]. These programmes were developed to assist precise and reliable patient diagnosis as well as appropriate patient care based on information gained from clinical examinations. Their purpose was to help patients receive better care.[20][21]

Researchers, medical professionals, technology and programme developers, as well as consumers in a variety of industries have all been aroused by the potential for game-changing advancements in the treatment of human diseases and the enhancement of public health [22,23,24,25]. According to research conducted by Accenture [26], the global healthcare industry will invest $6.6 billion annually in AI-related technology by the year 2021. According to the forecasts provided by Safavi and Kalis [27], by the year 2026, "AI applications might potentially offer up to $150 billion in annual savings for U.S. [28]

Because they are able to learn and diagnose from a massive volume of medical research and the treatment records of patients, AI-supported technologies play an important part in enhancing the decision-making process that physicians deploy for diagnosing and treating patients [29,30,31]. On page 449, the authors of the study by Shiraishi et al. [32]

made the observation that "AI-based diagnostic algorithms are used in the diagnosis of breast cancer, serving as a'second opinion' in supporting radiologists' picture interpretations." [33] Moreover, it has been suggested that artificial intelligence technology is able to make a more accurate diagnosis of skin cancer than a dermatologist [34]. When it is evaluated using knowledge that has been acquired from a substantial body of prior knowledge and data, the diagnosis can be treated more swiftly and efficiently as a result [35]. Moreover, sophisticated virtual avatars that are being used to conduct the necessary dialogues for diagnosing and treating people with mental diseases [36] are being used. These avatars look and act like humans.

Material & Methods

We search from different source like Scopus, Pubmed, Web of science etc, Our study Period for AI tool use in neuro disorder 2016-2022. Keywords: AI, Brain, Neuroprotective, AD, PD.

Role of AI in Healthcare

Miyashita and Brady [37] gave an example of released patients who were given a Wi-Fi-enabled bracelet that remotely monitors vital signs such as respiratory rate, oxygen levels, pulse, blood pressure, and body temperature in a set of hospitals that serve 500,000 people in southeast England. The bracelets were given to patients after they were discharged from the hospitals. The patients received the armbands prior to being discharged from the hospitals and allowed to go home. In this hypothetical situation, the use of artificial intelligence (AI) programmes that conduct data analysis on patient information in real time resulted in a considerable reduction in the number of patients who were readmitted to hospitals and who went to emergency rooms. As a direct consequence of this, 22% fewer time-consuming and financially burdensome house calls were required. There was a 96% rise in the number of patients who subsequently adhered to the suggested course of therapy. This compares to the industry norm of 50%, which is the standard for the field. Another example is the Grady Hospital in Atlanta, Georgia, which implemented an AI-enabled tool to identify patients who were "at risk" [38]. As a result, the hospital was able to reduce the number of patients who were readmitted to the facility by 31% over a period of two years. The Grady Hospital is one of the public hospitals in the area. As a direct consequence of this, the medical centre was able to reduce its expenses by $4 million.[39]

Some people may believe that doctors won't be necessary in the not-too-distant future because of the proliferation of artificial intelligence (AI) apps that assist or augment diagnostic, therapeutic, and surgical operations. This line of thinking may be supported by the expanding number of AI apps. However, before looking into the potential and obstacles that are related with the use of AI applications in the healthcare industry, it is essential to first conduct an analysis of the function that AI can play. This should be done before looking into the potential of AI applications. It is evident, based on the numerous examples of AI applications that have been put into practise in real-world settings, that AI has a tremendous and far-reaching potential with almost everything, ranging from the most fundamental improvements in operational processes to the most complex treatments of emergency patients [40]. This can be seen by looking at the numerous examples of AI applications that have been put into practise in real-world settings. [41]

The widespread adoption of AI and digital devices is accompanied by a number of noteworthy challenges, the most notable of which include concerns regarding privacy, cybersecurity, data integrity, data ownership, the issue of data-sharing by various organisational silos, concerns regarding medical ethics, risks associated with system failure, and accountability for medical errors [42,43]. Due to the very nature of healthcare services, ethical challenges are an extremely significant barrier. The use of artificial intelligence technology might have an effect on the preferences of patients, in addition to their right to privacy and their well-being [44]. The rules and ethical standards for healthcare services that use AI and its applications are now lagging behind the pace of innovation in AI by a significant margin [45]. In addition, technologies that are based on AI should incorporate human-centered principles and be flexible in their approach to problem-solving. In spite of this, AI-based solutions continue to be a contentious topic within the healthcare business. [46] This is mostly due to the fact that they are not yet easily available to all healthcare practitioners. The ongoing debate regarding these technologies includes this as one of the variables that contribute to the argument. [47] It is necessary to conduct an investigation into previously implemented examples of AI-based technologies and the applications of these technologies in order to understand the potential future applications of these technologies in terms of diagnoses, the quality of care services, and operational strategies. This is because it is only through such an investigation that it will be possible to comprehend the potential future applications of these technologies.

The purpose of this research is to gain an understanding of the effects that AI has on the care services and operational procedures that are carried out within the healthcare business by analysing a number of real-world scenarios in light of the context that was previously discussed. [48] We will be able to provide a set of ways for boosting the efficacy of illness prevention and patient care, as well as the efficacy of hospital operations, with the assistance of this research. In order to identify AI-based technologies and the applications they have in healthcare systems, we undertook an extensive review of the relevant literature as well as a wide range of real-world situations. This allowed us to identify AI-based technologies and the applications they have in healthcare systems. This research is important because it offers fresh perspectives on how technology-based service operations management ought to develop in the years to come. It is anticipated that those working in hospital administration, on medical staff, developing medical school curricula, education and training managers, human-machine roles and responsibilities specialists, privacy and cybersecurity analysts, and medical ethics specialists will find the conclusions of our research to be useful.[49][50]

An increasing n umber of papers have been published over the past few years discussing and evaluating the applications of AI in various aspects of depression and other fields of psychiatry, such as "clinical predictive analytics, neuropsychiatric diseases' treatment and healthcare, and biomedical applications," according to the findings of a bibliometric analysis that was conducted by Tran, McIntyre, and Latkin et al. [51]. This was found in the results of an analysis that was conducted by Tran, Yet, the results of their keyword and abstract analysis revealed that there was a paucity of published material in the body of medical research that addressed the privacy and confidentiality concerns raised by the application of AI with medical data. In this age of huge data, it is absolutely necessary to find a solution to this fundamental AI challenge. [52] Due to the sheer volume of knowledge, the nature of the field's rapid advancement, and the lack of consensus on best practises, this review will make an important contribution to the existing body of work on artificial intelligence (AI). [53] By conducting a literature review covering the preceding five years and determining the areas in which further investigation is required, the purpose of this report is to investigate the possibility that artificial intelligence (AI) could improve patient flow in inpatient mental health facilities. This article will provide a more in-depth discussion of the logistical, legal, and technical challenges that artificial intelligence faces.

When aberrant tissues come together in a cluster, this can lead to the formation of a tumor's structure. A tumour has the potential to damage a wide variety of organs and tissues throughout the body, including but not limited to the skin, muscles, and glands that produce fluids. These tumours can be broken down into two primary categories: those that are malignant and those that are benign, as seen in figure 1. Tumors that eventually develop into cancer are referred to as malignant. One such classification is one that does not have cancer and is otherwise healthy [8]. The treatment for each of these tumours needs to be approached in a different way. In light of this, it is absolutely necessary to first and foremost identify the sort before embarking on any preliminary actions.[54]

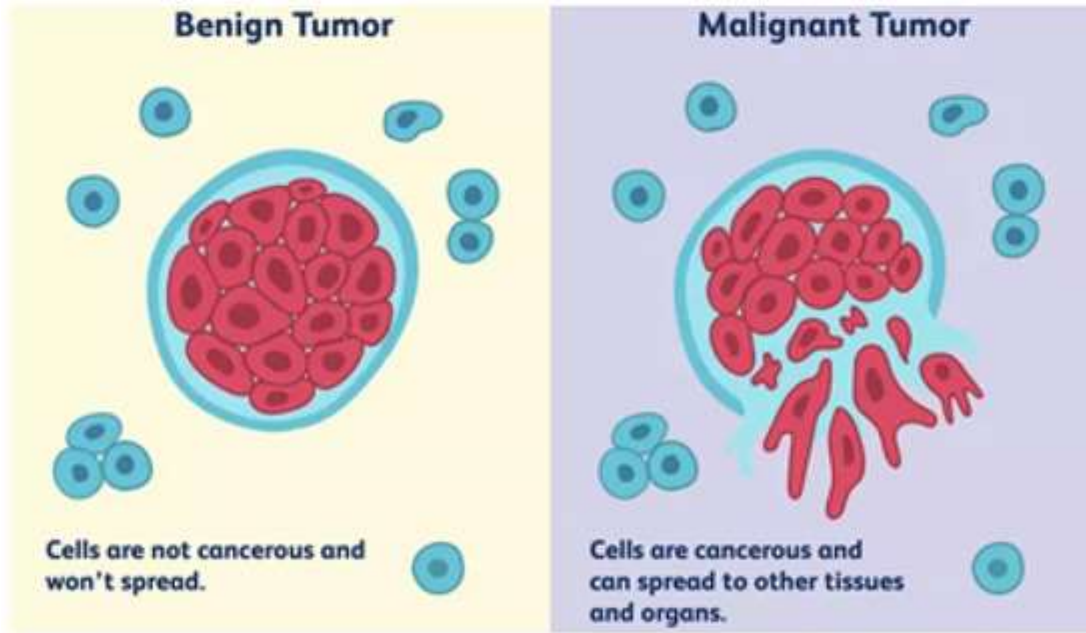

Fig 1: Types of tumor.

Malignant tumours are those that have the ability to spread, while benign tumours do not. They continue to expand in these locations. They do not put the cells that are adjacent in jeopardy. They do not provide any hazard. There is no possibility of recovery after having this kind of tumour removed; it is incurable. On the other hand, cancerous tumours can arise in any part of the body. As they continue to expand, businesses often relocate to different areas. These cells pose a threat because of their ability to generate cancer in the body. They do this by infecting the cells that are nearby, which is harmful. Thus, medical intervention is required for the management of these conditions. Immunotherapy and chemotherapy are the two main treatment modalities [55].

A tumour forms when the growth of cells in the brain is allowed to continue unchecked. Many different symptoms might be experienced in conjunction with the presence of these tumours. Tumors of the brain can originate in a variety of locations, including the cranial nerves, the meninges (membranes), the pineal secretory organs, and the pituitary secretors. [56] There is still a great deal of mystery surrounding the causes of brain tumours. Melanoma is a special type of brain tumour that originates from the cells of the skin and has the ability to metastasize, or spread, to other parts of the body. A recent study suggests that environmental variables may be to blame for developing brain cancer. [57] Air pollution is one among the primary factors that contributes. [58]. Individuals who are exposed to radiation on the job have an increased risk of developing brain tumours. Variations in people's genes are one of the factors that contribute to this phenomenon. There is a member of the patient's immediate family with a brain tumour in 5-10% of all cases of this ailment being diagnosed. After developing in the skin, lungs, or breast, malignant tumours can eventually migrate to other parts of the body, including the brain. By the year 2021, around 84,000 new cases of primary brain tumours will be identified. According to some estimations, this primary brain tumour can be broken down into 120 distinct subgroups. One third of all tumours are cancerous (malignant). Anybody, of any age, is capable of recognising a malignant growth. Each year, more than 28,000 children and adolescents in the United States are given a diagnosis of this life-threatening illness. Over 18,000 people have lost their lives as a result of primary brain tumours [59]. FIGURE 2 depicts a tumor's general appearance as well as its growth pattern while it is located on a mass of tissue.

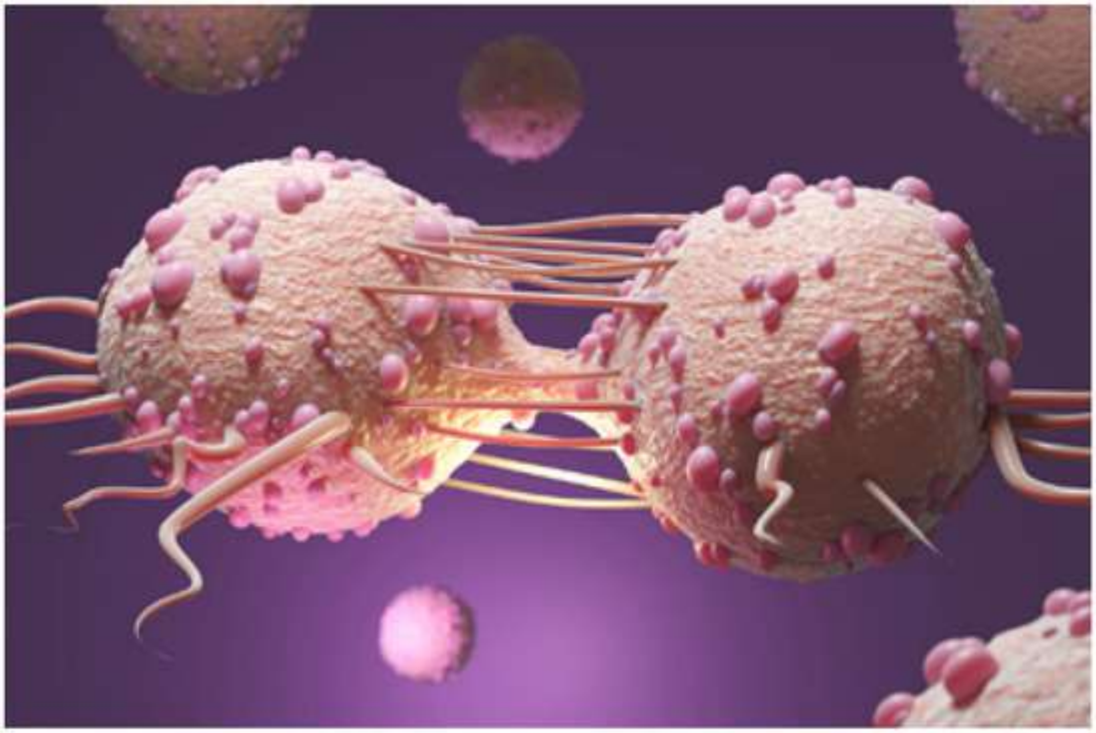

Figure 2: Shape of tumor.

The subfield of artificial intelligence known as computer vision focuses on teaching computers to "see" (CV). CV is able to assist computers in recognising particular visual cues [60]. These robots are able to process and understand digital multimedia files such as photographs and videos. Decisions are made based on the information that is received through the examination of photographs. CV consists of a camera, several different lighting effects, and other electronics that interpret the scene. With this Method, computers are being instructed to learn how to recognise objects contained within photos. Because computers are unchanging and can only render objective judgements, training a system like this involves a significant amount of prior knowledge. CVs are also often utilised in industries other than health, such as digital marketing, where they are an essential part of the hiring process. CV has a wide variety of possible applications, including but not limited to those listed here: traffic management, autonomous driving assistance, semiconductor unit inspection, medical visualisation, consumer research, and industrial robotics [61]. There has been a significant uptick in the utilisation of deep learning algorithms for CV work in the realm of medicine. CV includes a number of different types of operations, such as image categorization, object identification and tracking, and image retrieval based on the image's content. CV makes use of a wide variety of specialised approaches in order to teach computers how to analyse massive datasets. Following the completion of the programme, the digital photographs are sent. Data extracted from pictures is used to teach machines how to learn on their own. The items are then classified using the extracted features. The responsibilities of segmentation, detection, and classification are illustrated in Figure 3. In order to demonstrate the efficiency of the trained model, photos of both cats and dogs are shown for the model to analyse. With digital pictures, accurate object classification and detection can be achieved through the use of feature extraction.[62]

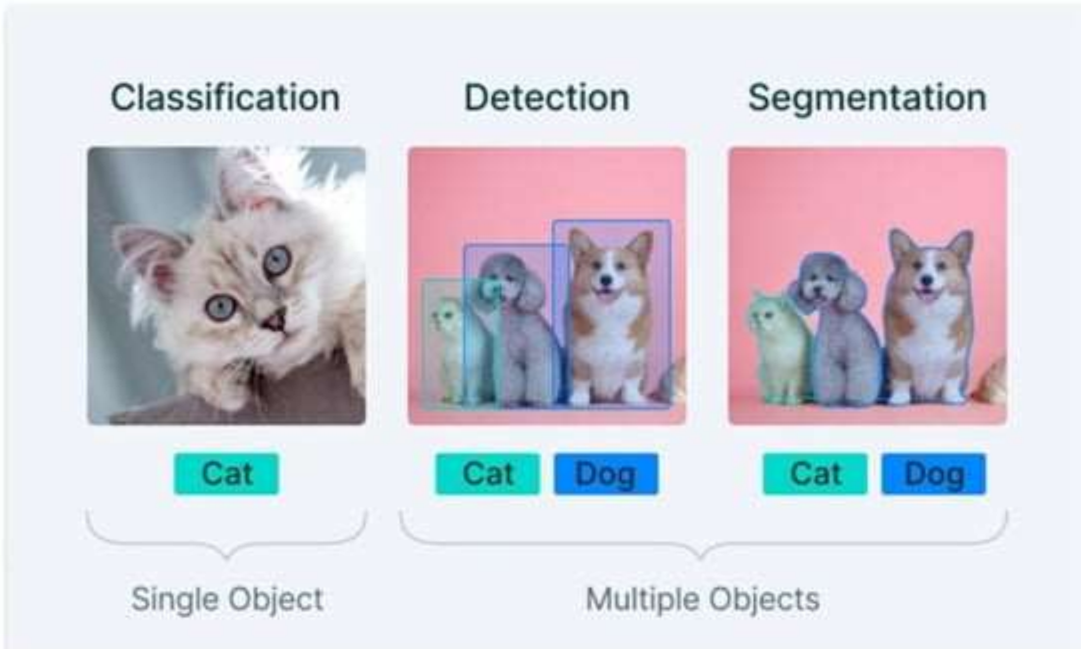

Figure 3: Tasks of computer vision.

The subfield of artificial intelligence (AI) that is known as "deep learning" (DL) is experiencing significant growth. Computational models can acquire new knowledge and develop their capabilities in this way, making them more like humans. Because it is built with multiple layers, you can abstract information while still easily retrieving it [8]. In the field of data science, deep learning plays an important part in many different fields, such as analytical modelling employing data. Because it makes the process of gleaning valuable insights from enormous datasets easier, it is an excellent tool for data scientists to have at their disposal. Deep learning is able to achieve higher outcomes because it compiles and examines information from a wide variety of sources [63]. The method of analysing data has also been simplified and made more efficient. Convolutional neural networks (also known as CNNs) are the primary tool that we use for pattern recognition [64]. It is possible to understand digital photos with the help of CNN. CNN disassembles photographs into their component elements and labels them in accordance with these dissections. The models that are used for object classification are then trained using these indicators. Figure 4 illustrates both machine learning (ML) and deep learning (DL), which are shown side by side in the figure. (DL). There are many obstacles that must be overcome in order to successfully implement ML approaches for the accurate diagnosis of brain cancer [15,16]. Methods of machine learning are applied in order to discover attributes [65].

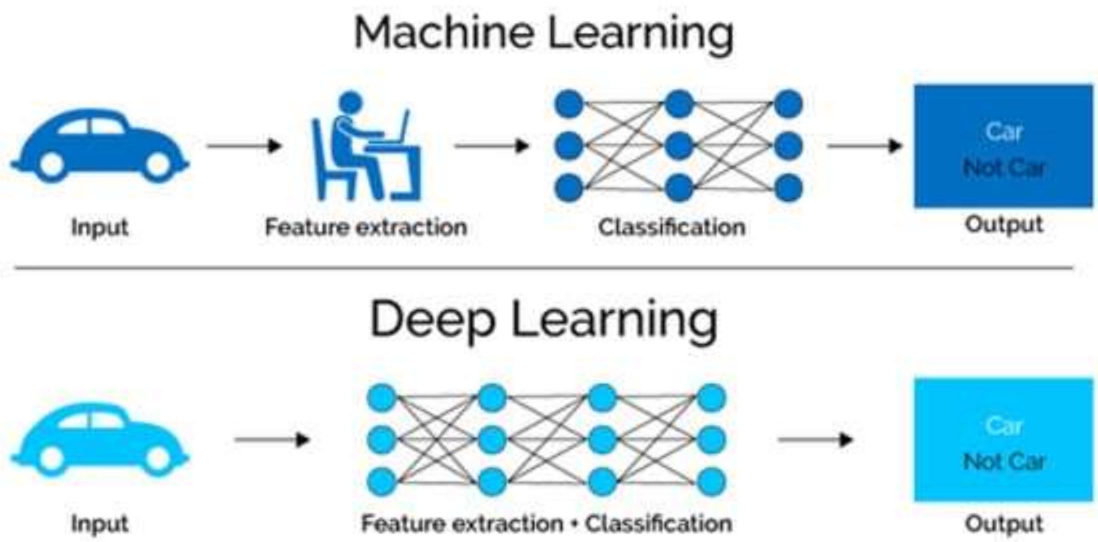

Figure 4: Working on deep-learning model.

Brain tumour MR images that share comparable properties or presences provide a hard task for manual sorting [66]. Computed tomography (CT) and magnetic resonance imaging (MRI) scans are two examples of imaging modalities that can swiftly discover abnormalities in the cell tissues of the brain [67]. The CT scan as well as the X-ray approach are both helpful in doing the evaluation [68]. After being discovered, MRI images are subsequently separated into distinct groups representing grey and white matter.

The most important thing that came out of this study was a convolutional neural network that was trained with the help of a deep learning framework and an SGD optimization technique. This network has the ability to recognise and classify different types of brain tumours. In contrast to the majority of the earlier research, which utilised a significantly smaller dataset for CNN implementation, the suggested method is tested using a publicly available dataset that contains three times as many examples (figshare, SARTAJ, and Br35H). While extracting features from MRI scan images, the method known as ResNet-50, which is based on transfer learning, is utilised. The SGD classifier combined with CNN was used to properly detect and categorise these photographs, resulting in accurate results. With the help of a deep convolutional neural network that was optimised by stochastic gradient descent, we were able to obtain a training accuracy of 99.82% and a testing accuracy of 99.5%. (SGD). Brain cells are responsible for the production of EVs that are referred to as brain-derived EVs (BDEVs).[69] It is common knowledge that they are able to pass through the BBB unnoticed and reach the bloodstream. Messenger RNAs, noncoding RNAs, proteins, and metabolites are some of the components that can be found in BDEVs [70]. These components can be used to infer the cell from whence the BDEV originated. Hence, by collecting BDEVs in the blood and analysing the molecules found inside of them (Fig. 5), it is possible to forecast illness and indirectly identify the state of the brain. Research into brain illnesses has been done by analysing EVs in the blood that are positive for the L1 neuronal cell adhesion molecule (L1CAM). The role of L1CAM as a BDEV is debatable due to the fact that a number of studies have demonstrated that it only has a limited selectivity for the brain and that it is expressed in cells other than brain cells. The identification of more specific biomarkers is required in order to perform an accurate diagnosis of brain diseases.

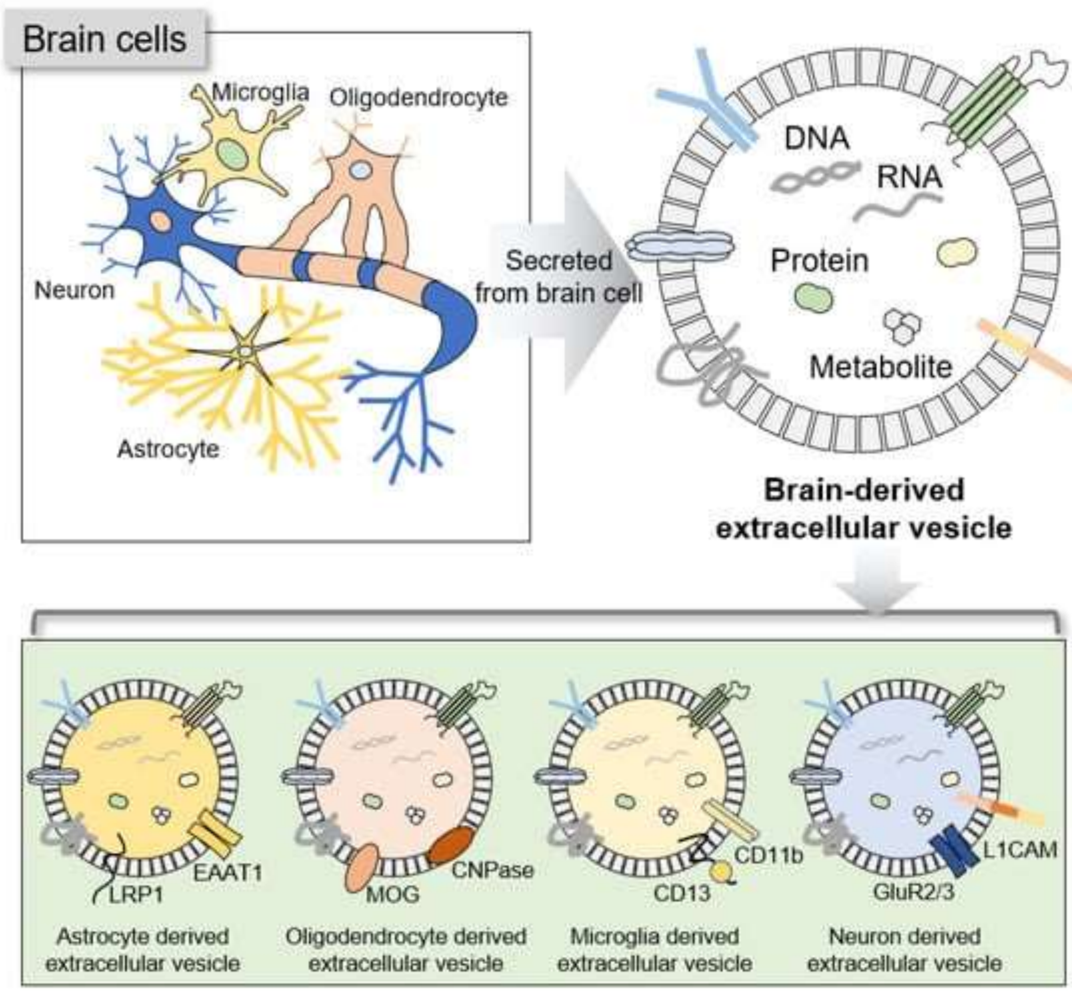

Figure 5: Vesicles released by brain cells Neurons, oligodendrocytes, astrocytes, and microglia are only few of the brain's many cell types; each of these, and others, secretes EVs that are uniquely suited to its function. These EVs transport many different substances, including genes, RNA, proteins, and metabolites. As EVs take on the traits of their parent cells, it is possible to separate EVs based on their individual brain cell of origin by utilising surface markers.

Proposed BDEV Biomarker Discovery Strategy

The following four parameters must be met in order for novel BDEV biomarkers for blood biopsy to be discovered: two known compounds are found in EVs, and first, they are expressed specifically in brain tissue. Four recognised biomarkers have been found in blood, three of which are present in EV membranes for BDEV enrichment via immune capture from EVs of varying origins (fig:6)

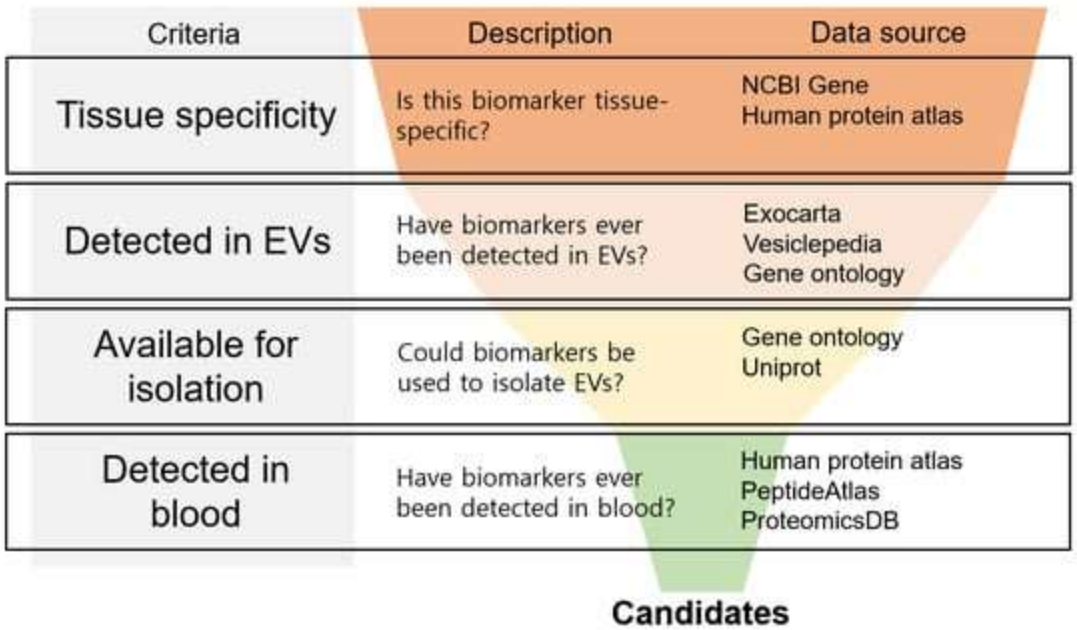

Figure 6: A plan for finding new BDEV markers. A detailed set of criteria for selecting promising new biomarker candidates for BDEV is presented. The marker, first, needs to be very selective for brain tissue. Second, there should be strong evidence that this marker may be found in or has been found in an EV. Finally, it is important that the biomarker can be isolated as a BDEV from a pool of EVs. It would have been wonderful if the biomarker had also been discovered in the blood.

One disadvantage of the BDEV biomarkers that are now in use is that they can be detected in different tissues. Therefore, it is vital to discover new biomarkers that are specific to the brain. Because the RNA expression of human tissues is catalogued in the NCBI and other databases, it is feasible to find genes that are solely expressed in the brain. One example of this would be Alzheimer's disease. The immunohistochemistry data provided by the Human Protein Atlas for each organ can also be utilised to validate the degree to which protein expression is present.

The capacity of a gene to express itself alone in the brain is insufficient for its application in a BDEV-based strategy if the gene is not loaded into an EV. Because of this, it is extremely important to select a biomarker that has either been observed in EVs or that is anticipated to be present in EVs. In response to the growing interest in electric cars, resources such as ExoCarta and Vesiclepedia have begun categorising EV cargoes [71]. In addition to annotating genes, the database known as Gene Ontology (GO) provides a description of the location in a cell where a gene product can be found [72]. As a direct consequence of this, knowledge on genes the products of which may be found in EVs is readily available. The investigation of EVs has progressed to the point where we now have a better knowledge of whether or not proteins are transported by EVs. Exosomes and membrane shedding (also known as microparticles) are two ways that can be used to load proteins onto EVs, which can then be secreted in a subsequent step [73]. Using these fundamental biological processes, we are able to determine whether or not EVs are stuffed with proteins derived from the endosomal system or the membrane. EV loading has been demonstrated to be made easier by certain protein patterns, according to a number of studies [74]. If we have a better understanding of the patterns that encourage EV loading, we will be able to make more accurate predictions regarding the biomarkers that will be loaded into the EVs. If the databases and information are used correctly, it will be possible to select a particular protein biomarker that has either been definitively established as EV cargo or that has been provisionally recognised as a candidate for EV cargo. EVs coming from a number of different organs can be found together in the blood; despite this, however, only BDEVs need to be raised in order to be utilised for neurological diagnoses.[75] Immunoprecipitation and many other antigenantibody affinity procedures are typically utilised in order to accomplish this enrichment. Because of this, any biomarker that is chosen for BDEV enrichment needs to be easily accessible to the antibody. As antibodies have a tough time penetrating the lipid membrane that encircles the EV, the BDEV biomarker ought to be present extracellularly in the same form as a membrane protein. According to the definition provided by the Gene Ontology (GO) term "cellular component," the vast majority of the proteins that are utilised now as cell- and tissue-specific EV biomarkers are membrane proteins and receptors. Fusing EVs has been looked into as a potential method for determining the RNA payload that is contained within them. This method can be utilised to separate non-coding RNAs (miRNAs, lncRNAs, and so on) that are known to have a tissue or cell-specific specialisation. It is possible to selectively capture targeted EVs by making use of the interaction between ligands and receptors in addition to the affinity between antigens and antibodies. As relevant technologies continue to progress, further options for BDEV biomarkers will become available.[76] [77]

It is possible to detect markers during the process of isolating the blood-borne disease exclusion virus (BDEV), but doing so is completely voluntary.

The aforementioned criteria can be utilised to locate possible biomarkers; however, it is still unknown whether or not the prospective biomarker is present in the EV or whether or not it is able to cross the BBB and enter the blood [78]. At the absolute least, the detection of the biomarker in the blood needs to be guaranteed in order to reduce the likelihood of these kinds of errors occurring. When used in conjunction with the PeptideAtlas database, the ExoCarta database provides information on the origin of EVs, including data on EVs collected from blood and cell cultures. Moreover, the Human Protein Atlas provides information on the relative abundance of proteins in the blood. When it comes to EVs, for example, using thesis or open proteomics data from a database can be used with ProteomeXchange to assess whether or not a biomarker has been discovered in the blood. This can be done using the platform. The use of databases to collect the absolute minimum of necessary data before beginning the inquiry might help minimise the detrimental consequences of trial and error. [79] Because different areas of the human brain are responsible for different functions and contain a variety of cell subtypes, the molecular and biological aspects of brain illnesses that occur in different sections of the brain are varied. Indications that are unique to each region of the brain are essential for making a correct diagnosis of a variety of brain conditions. Due to the fact that the early pathological indications of brain disorders are frequently the same and mixed [80], it might be difficult to precisely diagnose a specific brain disease when it is still in its early stages. Hence, utilising BDEVs for molecular-level diagnosis that is targeted at specific brain regions or cell types may make it possible to detect brain disorders at an earlier stage. Fig:7 Because of the development of analysis methods and the collection of data, researchers have been successful in locating expression biomarkers that are specific to particular cell types and brain areas. Both the Allen Brain Atlas and the Human Protein Atlas contain maps that show the results of in situ hybridization as well as information on RNA expression for various parts of the human brain. These maps may be found in both of these atlases. For example, single-cell analysis has been essential in assisting researchers in locating biomarkers that are specific to the many different types of brain cells [80]. It will be advantageous to identify a biomarker that can be used to distinguish the considerable levels of BDEVs secreted by the entire brain in order to carry out a more in-depth examination. This is because finding a biomarker that can be used will be beneficial. Even if the biomarkers are not specific to the brain, this will make it possible to double-capture additional biomarkers that are region- or cell-type-specific. Because it is known that cancer cells release more EVs than healthy cells, the appropriate diagnosis of cancer can be facilitated by analysing the subpopulation of ech BDEV biomarker. This is because it is known that cancer cells are more likely to divide than healthy cells. Instead, brand-new diagnostic methods that are region- or cell-type-specific might be established by the use of molecular monitoring of EVs released from the brain.

Conclusion

The future of healthcare may be significantly influenced by AI and precision medicine. AI has the potential to drastically change how these disorders are recognised, managed, predicted, and priced in the domains of neurology and neurosurgery. When will I have my next seizure? is a common concern for people with neurological disorders. Will this medication make me feel better after I use it? Do I really need surgery? Have I have depression? One day, advances in AI technology may increase the certainty of both the diagnosis and the management of every type of neurological condition. Nevertheless, this cannot be done without a large investment in financing for extensive study that makes use of information derived from actual clinical documentation that includes participant outcome assessments. By doing this, a priceless resource that will advance healthcare into the future will be created.

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