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Artificial Intelligence Perspective on MRI-Driven Computer-Aided Diagnosis and Prognosis of the Brain: A Systematic Review

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Abstract. Recently, the involvement of Artificial Intelligence (AI) has empowered CAD in the diagnosis of brain illnesses. Due to the escalating incidence of brain diseases, there has been a low awareness among the population, and thus, the need for AI emerges to fulfill the requirements in this domain. Artificial intelligence (AI), encompassing various subfields of computer science, is essential for analyzing medical data and extracting datasets, which augment human intelligence. Specifically, in the brain investigation domain, several productive measures have been taken and executed remarkably in the disciplines of diagnosis, framing, and outcomes. In this study, we outline different artificial intelligence techniques used in diagnosing the brain sphere. Eventually, we will notice that AI has made it possible to revamp medical images in neuroscience applications. This study directs the current revolutionary trends as well as considers future diagnostic research that is based on Computer-Aided Diagnose and Computer-Aided Prognosis for the explicit detection of patients with brain disorders.

Keywords: Artificial Intelligence (AI), Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Machine Learning (ML), Computer-Aided Diagnostics (CAD).

1 Introduction

During the past decades, hospitals and health care centre systems have produced an extensive volume of unstructured information, including Medical Imaging data, from the monitoring system. The inspection of this input remarkably commutes the perspective that is practiced by pharmaceutical specialists and professionals for recognizing, interpreting, and treating the images of brain data input [1]. Moreover, developing the imaging datasets and processing

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algorithms contributed to progressively lucrative and robust analysis. Globally used techniques such as CT scan, and MRI, Positron Emission Tomography have transformed the aspect that transformed the way neural mechanisms are studied by empowering medical professionals to undertake advanced assessments of brain anatomy and to conclude the cause of abnormalities [2], [3]. Artificial intelligence legalized computer-aided diagnostics (CAD) to transform healthcare and medical practice, especially by leveraging medical imaging. This may include ultrasound and magnetic resonance imaging (MRI), which is widely used in medical healthcare. Artificial intelligence (AI) has encroached the medical area, with significant applications in radiology. Ever since the outbreak of COVID-19, which has infected millions of people globally, directing major live loss to over 800,000 deaths as per the record pre-test prospect, helps in minimizing the risk of multimorbidity patients and proposes a solution for estimating the risk. Therefore, we can estimate the importance of these methods, which have become a vital part of investigating and ameliorating the medical care system in every possible aspect of life .

Nevertheless, although the conventional method of evaluating medical datasets and brain imaging is very time-consuming, concerns about inaccuracy in the analysis are less relevant. For example, we can clearly see the divergence in the daily diagnostic error rate in radiology, exceeding 3%–5%. Recently, deep learning has played a major role in providing detailed solutions for detecting abnormalities in cancer, brain tumours, lung disorders, esophageal abnormalities, and ulcers across multiple imaging modalities of medical images [3].

Consequently, the application of Artificial Intelligence (AI) technology has become a specialized sector within neuroimaging, combined with computational medical approaches over the past decennium, as evidenced by the surge in evidence-based research articles. Within these, Machine Learning (ML) strategies have become well-known and extensively applied in the management of brain disorders. Machine Learning (ML) forms a subset within the broader field of Artificial Intelligence (AI) that are optimized for diagnostic purposes and future predictions or unspecified conditions with available data. Over the years, many solutions have been developed, and most are still used for diagnosing and analyzing brain data related to patient diseases [4].

Recently, another branch of AI, namely Deep Learning (DL), has transformed and expanded neural computing tasks as shown in Figure 1. The diagram highlights a hierarchical relationship: DL ⊆ ML ⊆ AI. This figure effectively illustrates the progression from general AI to specialized DL, which is particularly important in areas like medical imaging and computer-aided diagnosis. Deep Learning algorithms mark a significant shift in computer perception, outperforming various techniques on key image analysis benchmarks.

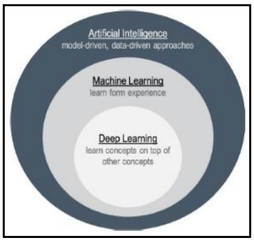

Fig. 1. Pie Chart Showing relations between deep learning, artificial intelligence, and machine learning

2 Overview

By incorporating machine learning, Computer-Aided Diagnostic (CAD) techniques allow a complementary sequel connecting the radiologist and the computer system, which provides coherent and swift diagnosis of the patient's circumstances [5]. This blending technique of data by CAD systems has demonstrated a useful edge, and they grant an amalgamation of statistics pertaining to the Encephalon and its matter from MRI in conjunction with various other modalities. All these multimodal fusions rectify the standard of brain image disorders by minimizing the repetition and volatility, thus contributing to the upgradation of medical diagnosis as compared to single modality. With the help of this article, we will find out the steps of the CAD system for MRI-based assessment of brain disorders [6]. Hence, the use of classification at different stages of technique for brain issues will be accentuated with their supremacy and flaws. Furthermore, we will compare the foundation of multimodal fusion upon the rise used. There is no denying the fact that magnetic resonance imaging (MRI), with the development and advancement, has been used for a long time to annihilate all the possible outcomes of brain disorders. This technology comes up with an all-inclusive interpretation of anatomy together with brain possible issues, having spatial resolution and tissue contrast [7].

Brain tumour treatment has always relied on efficient diagnosis and treatment based on the different features of the tumour, such as the kind of tumour, orientation, size, and its progression stage. MRI technique is adopted to estimate the mass of photon presence within the tissues, and their fundamental property, which spins and is based on magnetic movement. We can easily apprehend the initial human body structure that produces a brilliant quality of image [8], [9],[10]. Figure 2 shows the images of a brain tumour and a normal brain through the MRI technique.

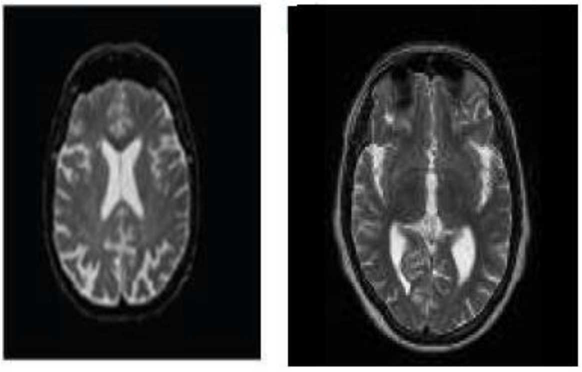

Fig. 2. Normal Image (Left) and Tumour MRI Image (Right)

Although the efficiency of structural MRI is limited, its results have several issues that have arisen. This MRI technique has evolved from slice-based to volumetric modality, significantly enhancing the level of analyzable detail and improving neuro-radiologist satisfaction. Further, SNR and resolution have acquired a higher standard [15].

The fusion of multimodal techniques accelerates the diagnosis and prognosis of merged images, combining both complementary and redundant data sets from MRI and Modalities like CT scans, SPECT, and PET. Each modality fulfils a unique role in radiology, with differing diagnostic objectives.

Correspondingly, enhanced features of fusion images for visual insight, and thus the derived fused images are better optimized for visual perception, and the graphic rectification and scrutiny function gives further compact and effective outcome for the given dataset. Besides, single merging of images is more powerful and accurate than having tons of multiple sources of images, which will reduce your memory size and costs.

3 Basic Methodology

Figure 3 depicts the general framework for brain disease diagnosis and segmentation. For the processing of brain images, MRI techniques are often used. We will consider the acquisition of images. The very first consideration of images of MRI scans for any patient may be either colour, grayscale, or image intensity, with the exposure of the default dimension of 220×220 [11]. At any point of converting the colour image, the grayscale image is represented using a primary matrix, where each entry corresponds to a numerical value ranging from 0 to 255, where pixel coefficient of 0 and 255 correspond to black and white, respectively [12]. Therefore, brain disorder diagnosis methods are broadly divided into edge detection and image segmentation techniques. Pre-processing stage: In this stage, the removal of noise takes place. Thus, it is done by using median filters, linear or nonlinear filters, whereas text removal is done by some linguistic operations.

Conversion from RGB to grey is also possible with this technique. However, the likelihood of noise is very minimal in advanced MRI images that observe a brain issue. The primary cause of this effect is simply the Thermal Effect. Image Conditioning involves simplifying the image while preserving the original data information. The aim is to reduce potential conflicts and unwanted distortion for further analysis. Image Certification involves registering the image by proposing two or more images and aligning them spatially. This process allows for simultaneous imaging of medical scans using various techniques such as MRI and CT, acquired at different times or from multiple patients. [13], [14].

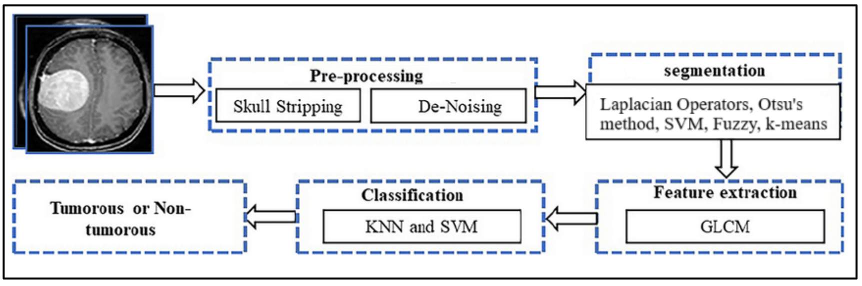

Fig 3. Step-by-step flowchart of the general framework

Furthermore, during surgery, deformations occur that make it difficult to relate super-resolution images to the intra-operative scans of the patient at reduced resolution. This can be solved with the help of image registration, which assists the surgeon in merging and working with two sets of images. Image segmentation: This step enables effective analysis of the image, as it influences the validity of previous and subsequent steps. Nevertheless, various approaches have been introduced to address this issue. Segmentation techniques are typically divided into the following categories:

1. Edge-Based Segmentation: This method detects boundaries between regions by identifying sharp intensity changes (edges) in an image. Techniques such as Sobel, Canny, Prewitt, and Laplacian operators are commonly used.
2. Threshold-Based Segmentation: It relies on dividing the image based on intensity values. E.g., Otsu's method.
3. Domain-Based Segmentation: Instead of focusing on edges, it groups pixels based on similarity in intensity, texture, or statistical properties. Methods include region growing, region splitting and merging, and watershed transformation.
4. Supervised Segmentation: It uses machine learning or deep learning models trained on labelled datasets. The system learns to classify pixels/regions into predefined categories (e.g., tumour vs. normal tissue). E.g., Convolutional Neural Networks (CNNs), Support Vector Machines (SVM), etc.
5. Unsupervised Segmentation: Here, no labelled data is required. Instead, clustering or statistical techniques are used to automatically discover patterns in the image. Common methods such as Fuzzy C-means, K-means clustering come under this.

4 Imaging Technique

Imaging techniques are methods used to capture the internal structural architecture and functionality of objects, most importantly the human anatomy, without invasive procedures. In medicine, these techniques are critical for diagnosis, treatment planning, and monitoring of diseases. Broadly, they can be divided into several categories. Here are the major imaging modalities and techniques that are clinically and research-wise most relevant:

1. X-ray Imaging: It uses ionizing radiation to visualize bones and dense tissues.
2. Computed Tomography (CT): It's an advanced form of X-ray that provides cross-sectional images using rotating beams.
3. Magnetic Resonance Imaging (MRI): It employs intense magnetic and radio frequency waves instead of radiation.
4. Ultrasound Imaging: It leverages high-frequency waves to produce real-time images.
5. Nuclear Medicine Imaging (PET & SPECT): It uses radioactive tracers to study physiological processes at the cellular level.

We know that MRI is a widely recognized medical imaging method. We will see the description of different imaging modalities for explaining the image verification and projection into other imaging modalities. Radiography uses rays such as an X-ray beam for investigating the imaging tissue. Magnetic Resonance Imaging or MRI scans are recognized as an accessible and non-invasive imaging method for imaging that makes an important tool for generating thorough information about the scan disorder image. As we investigated, we didn't find any reverse effect of the magnetic field; this can thus be used for narrow diagnosis of several issues in brain disorders of patients, leading to effective and prior diagnosis of any problem. However, if any patient has implanted devices such as any metallic element or any transplant, they should limit their use of MRI scanning. This MR imaging technique and equipment have a comparatively high cost, but the limitation of its diagnosis only relies on the lack of knowledge of physicians or radiology specialists for diagnosing the images and investigating the information about issues.

Analysis of intracranial soft tissue can be divided into three domains: local, global, and zonal. This range of local characteristics ranges from millimetres to some centimetres and has space, which is easily visible in MRI images of the brain. An attribute to be mentioned as peculiarity is unexpected and does not have any existence in the location of the predicted brain composition through the original shape and mass.
Investigation and analysis of zonal oddity requires recognition of systematic shape, and the intensity differences of brain internal structure and the fluctuation of signal intensity between neighbouring brain regions and tissue, colour imbalance, which holds the directional flow and helps in identifying the clashes between them. And the global standards help in identifying the characteristics of local and zonal analysis if they are expressive enough.
Here's a visual version of the MRI tissue brightness shading from dark to bright, as shown in Figure 4 along with the table as depicted in Table 1.

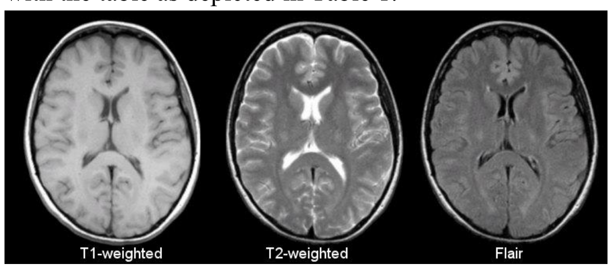

Fig. 4. Various MRI imaging techniques, T2-weighted, T1-weighted, FLAIR scan image.

Table 1- MRI Tissue Brightness

MRI Technique	CSF	White Matter	Gray Matter	Lesions
T1-weighted (T1)	░ Dark	▓ Bright	▒ Gray	–
T2-weighted (T2)	▓ Bright	░ Darker	▒ Gray	▓ Bright (if lesion contains fluid)
FLAIR	░ Dark	▒ Intermediate	▒ Gray	▓ Bright

Legend:- ░ = Dark, ▒ = Intermediate/Gray, ▓ = Bright

5 MRI Processing Techniques

The two-dimensional vision of brain tissue is generated by MRIs, which is then represented by a single horizontal axial representation of cross-sectional view that has two successive images, which are separated alongside vertical forms that range from 0.2 and 6.0 mm. The image data set ranges from 170 to 1500 images, depending upon the vertical formation, and determines the brain imaging and the number of imaging devices used.

5.1. MRI Data Preprocessing and Quantitative Analysis

The antiquity initiated the undone scans with the help of hardware for imaging, that is first used must first be separated before diagnosing algorithms for processing the MRI imaging. The axis of multiple correlation finds the orientation in the 2D portion that is perpendicular to the axis, leading to a clear vision of brain composition that enables the matching of the structural representation of brain tissues. The attenuation of image tissues is done with the help of an MRI device, considering the distance from the source of the beam. Whereas the low-grade images whose algorithm can be assigned in a group of grayscale and thus include the hierarchical and transform-based categories, and include supplementary rectification such as filtering, modifying, and conditioning of the task.

5.2. MRI Scan Techniques

For various imaging and investigating brain tissues, esoteric MRI techniques were developed for patient health care. Figure 3, shown above, gives the widely implemented MRI-based approaches, including T1-image, T2-image, and FLAIR sequences. In radio frequency, the technique that is used is pulse switching and substitution in the magnetic field, which helps in allowing for estimation of both frequency and phase alteration in the given area of interest. Short T1-relaxation time gives a bright T1-image, accordingly with elongated T2 relaxation time gives a bright T2-image, and a FLAIR image is like a T2-weighted image, and lastly, the cerebrospinal fluid (CSF) particles were restrained. All the space that gives a dark appearance is simply because of low signal.

Diffusion tensor imaging technique generates the standards of every voxel manipulation from several numbers of diffusion calculations and from several other representations of diffusion sensing descent, unlike the conventional method of MRI. In the DTI technique, the calculation of local diffusion specification is the average of the voxel if counted by water molecule displacement. Hence, the concluded form of voxel space or any 3D or multi-slicing of tissues of any organs. In DT-MRI techniques, eigenvalues are produced for the diffusion, and their orientation can thus help in finding the estimated direction of movement of fluid.

5.3. Dimensional Perspectives: Slice-Based Analysis and 3D Reconstruction

Medical imaging analysis can be categorized into two-dimensional (2D) analysis and three-dimensional (3D) reconstruction, each offering distinct capabilities. 2D analysis evaluates individual image slices independently, enabling feature extraction such as intensity, texture, and shape. It is computationally efficient and easier to implement but lacks inter-slice spatial information, which can result in incomplete characterization of anatomical structures or lesions.

In contrast, 3D reconstruction integrates sequential slices into a volumetric model, preserving spatial relationships and enabling comprehensive assessment of anatomical morphology. This approach supports volumetric measurements, accurate visualization, and advanced analyses, making it particularly useful in applications such as lesion quantification, surgical planning, and AI-driven computer-aided diagnosis. However, it demands higher computational resources and careful preprocessing to mitigate artifacts or misalignment.

While 2D analysis remains suitable for rapid evaluation, 3D reconstruction provides a holistic and anatomically accurate representation (Figure 5). Consequently, contemporary neuroimaging studies increasingly leverage 3D volumetric analysis to enhance diagnostic precision and improve the evaluation of advanced computational models.

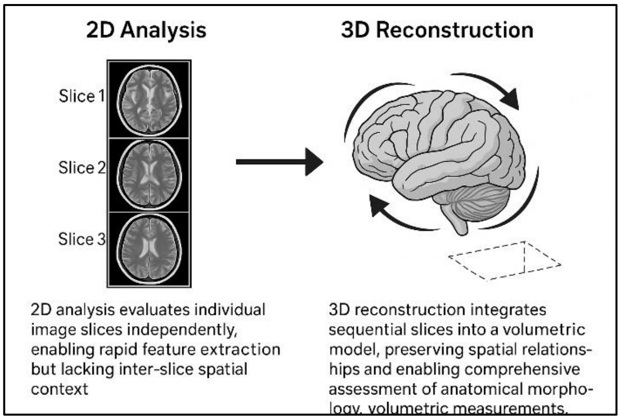

Fig 5. Illustration of labelled slices and a 3D brain model.

6 Computational Intelligence for Detecting Brain Pathologies

AI is primarily designed to develop software solutions or machine-controlled data sets that are possible for computer-based devices to work upon. This enables the medical help to investigate the images and analyze the brain disorder prior and effectively for making the work and diagnosis easy.

This also optimizes the previous result and makes an advancement in improving efficiency with the passage of time through a proper algorithm and optimization. Machine learning methods are generally indexed into these categories: supervised learning and unsupervised learning. When the solution to a specific problem is available beforehand, the learning process is referred to as supervised learning. Machine learning can permit the computer to transform data explicitly programmed, has been extensively applied to medical imaging. However, DL can be termed as a technique associated with ML, which gives a major family of AI (Figure 6).

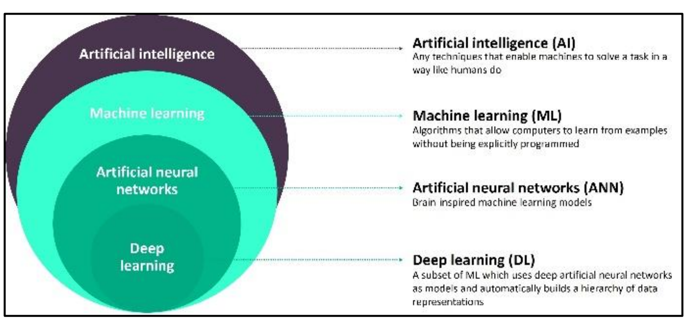

Fig. 6. This shows that DL is a specialized field within ML techniques

The major limitation in developing and evaluating computer-based models is their heavy reliance on extensive datasets, meticulously annotated ground truths, and high-performance hardware architectures to handle the substantial computational demands of these algorithms.

7 Future Perspectives

A machine learning–driven decision support system for medical professionals should ensure high diagnostic accuracy, maintain accountability of information, and provide traceable reasoning that links from image interpretation to diagnostic conclusion. Recent advances in user-centred design, human–computer interaction, interactive data visualization, and neural computing present potential solutions that minimize the cognitive burden on physicians, integrate effectively with existing medical image analysis workflows, and generate additional insights to aid diagnostic decision-making. The development of a user-oriented machine learning configuration should be grounded in the radiologist's expertise, emphasizing the core principles of intelligent support systems, including algorithm training and validation, as well as the clinical endorsement or dismissal of diagnostic outcomes. Heuristic assessment of the model's feature prioritization and misclassification patterns can be implemented using Adaptive Learning Frameworks. Interpreting the decision heuristics of a model can be facilitated by employing hierarchical and stacked ensembles instead of standard deep learning frameworks. Apart from computational demands, software development complexities, and limited availability of annotated datasets, we contend that developing such a machine learning framework as an intelligent clinical decision support system is achievable.

8 Strengths and Limitations

This review provides a comprehensive overview of the role of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) in MRI-based diagnosis of brain disorders. Its strengths lie in the systematic coverage of classical and modern diagnostic approaches, the inclusion of multimodal imaging perspectives, and the use of illustrative figures that aid in understanding complex methodologies. Furthermore, the paper highlights emerging trends and future directions, offering valuable insights for researchers and clinicians.

However, some limitations should be acknowledged. The paper does not present new experimental datasets or model evaluations, which may restrict its originality as a research contribution. While figures are included, their clinical significance could be further elaborated. Additionally, the conclusion remains generalized, and issues such as computational challenges, dataset availability, and integration of AI systems into clinical workflows require deeper critical analysis. Addressing these limitations in future work would enhance the impact and applicability of the study.

9 Conclusion

Recent advances in machine perception, intelligent systems, and robotic imaging have been accelerated by abundant datasets, the engineering of advanced algorithms, and high-throughput computing resources. Consequently, the effectiveness of artificial intelligence schemes in interpreting unstructured image data is advancing, and in some cases surpassing, human-level performance within constrained domains such as scene classification or object recognition. These emerging trends create the potential to implement and combine modern approaches for the largely underexplored domain of interpreting brain abnormalities from

MRI scans. Interpreting MRI datasets of the neural tissue introduces a distinct cluster of complications that must be overcome to develop decision support systems seamlessly integrated into the diagnostic routines of radiologists and healthcare practitioners. The system is designed to support and improve cognitive decision processes, rather than to replace clinicians with machines. The system must align with the clinician's decision-making pathway without significantly increasing workload or procedural difficulty.

These user-oriented design requirements complement the implementation difficulties inherent to MRI analysis, which include detecting scattered characteristics, denoising image data signals under varying frequency conditions, verifying features at different spatial resolutions, encoding inter-feature relationships in three dimensions, and developing specialized hardware and machine learning architectures to meet the high-performance computing needs for multi-modal MRI datasets.

Declaration

All authors listed have contributed substantially to this work and have approved the final manuscript for publication.

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