# Beyond Today's MRI: Machine Learning and AI Pioneering Tomorrow's Imaging Landscape


## ABSTRACT

**Aims:** To survey the application of artificial intelligence and machine learning in magnetic resonance imaging.
**Objectives:** To discuss the fundamental knowledge behind the concepts of magnetic resonance imaging, artificial intelligence, and machine learning. The interconnectivity between utilizing AI models and different MRI images to achieve perfect evaluation was also examined.
**Discussion:** Various MRI images were discussed, including magnetic resonance angiography, anatomical MRI, diffusion MRI, and functional MRI. Supervised and unsupervised machine learning are the types of ML that have found wide applications in MRI. For supervised machine learning, the various methods under this are k-space methods, image restoration methods, cross-domain methods, direct mapping, and unrolled optimization. Nonetheless, recurrent neural networks (RNNs) and convolutional neural networks (CNNs) were the two noticeable AI models often employed during medical imaging.
**Conclusions:** In conclusion, artificial intelligence as a subset of machine learning has found wide medical applications to MRI.The emerging technology of AI in MRI has profound future applications in medical field.



*Keywords: Machine Learning, Magnetic Resonance Imaging, Cancer, Artificial Intelligence, Diagnosis tests*


## 1. INTRODUCTION

Medical imaging is fundamental in disease treatment and diagnosis, delivering complex optical visions into the human body. Magnetic resonance imaging (MRI) has experienced tremendous improvement in application among the already existing imaging methods because it captures high-resolution images that exhibit extraordinary contrast between soft tissues. The existence of magnetic resonance imaging has flowed due to its intensified recognition and technological improvements of its clinical value. These images, obtained from numerous anatomical domains and under different protocols, provide essential information regarding their usefulness, anatomical structures, and potential irregularities. Furthermore, MR image interpretation needs to be improved. Manual analysis conducted by radiologists can be a function of labor-intensive expertise and susceptible to inter-observer changes.

Additionally, the capacity improvement of images for each patient emphasizes the significance of precise analysis and efficiency to strengthen decision-making by clinical personnel [1]. Magnetic Resonance Imaging (MRI) is generally accepted in medical diagnosis and has an orientation standard in comprehensive applications. MRIs are beneficial imaging tests that can assist in detecting cancer. They can generate detailed tumor growth images due to its ability to see soft tissue. They help detect cancer of different types. They’re good at seeing tumor growth in tissues and organs, suggesting their inability to detect bone or blood cancers [2].

Extensive studies have unequivocally demonstrated that MRI scans boast an impressive 77% accuracy in distinguishing between benign (non-cancerous) and malignant (cancerous) tumors. This exceptional precision has led to the unanimous selection of MRI as the gold standard for soft-tissue tumor evaluation and imaging.

MRI has been an imaging tool for the human body since 1977 [1]. However, it was used for commercial benefits in 1980 for the general public until it was commonly adopted in diagnosing cancer and for body interior examination. MRI has earned recognition as a dependable medical imaging tool using powerful magnetic fields and radio waves to form understandable images of internal organs. In contrast to other medically related imaging examinations, MRI does not use ionizing radiation, making it harmless for patients. An MRI machine produces remarkably comprehensive images, allowing physicians to observe body tissues and organs excellently. It is principally beneficial in detecting and monitoring cancer and other factors affecting the organs, soft tissues, and bones. MRI scanners are proficient in tumor visualization and identifying precise locations within the body, thanks to a contrast dye injected via IV to aid the appearance of abnormal tissues. The contrast dye in the abnormal tissues reacts adversely to the process compared to the healthy tissues once the patient is in the MRI scanner, producing a flawless difference between normal and abnormal tissues in the subsequent images. The MRI scan perfectly captures detailed pictures of these structures and thus emphasizes these anxiety areas and enables doctors to make an excellent diagnosis [3].

The potential of advanced MRI imaging allows doctors to discover the tumor's presence and perfectly evaluate its size, location, and possible factors on neighboring tissues. This compelling evidence formulates the foundation of an efficient cancer treatment plan, ranking MRI as an essential instrument in the preliminary diagnosis of cancer [4]. MRI scans are vital in observing disease progress in patients with cancer. The images allow transformations in tumor size, which is against the perfect monitoring of cancer treatment order. After the subsequent preliminary scan and a few weeks of treatment, one can adopt an extra MRI scan for the evaluation of the radiation effectiveness on the tumor's size. By comparing MRI images obtained before the treatment and after, doctors can ascertain whether there is a developed, contracted, or stagnant tumor. This crucial evaluation helps decide whether the patient should continue the current treatment or consider other therapeutic options [2]. MRI is also vital in sensing the recurrence of cancer after treatment or the reoccurrence of cancer after a deceiving period of retardation. The grouping of cancer reappearance at the beginning as early as possible is vibrant in assuring quick intervention and increasing the patient's prognosis. MRI's comprehensive imaging proficiencies make it an excellent instrument for this task [5]..

Appointments are naturally given to patients for consistent MRI scans for post-treatment at approved periods by their healthcare squad. Taking a scan at an interval ranging between 3 to 6 months may be essential during the first couple of years and then less recurrently as time goes on. MRI scans can aid the detection of delicate transformations in the body's tissues and organs, which may denote the return of cancer. Matching the present and post-treatment images together allows physicians to categorize any new developments at their preliminary stage and begin instant intervention. MRI technology has transformed the cancer treatment landscape, its monitoring and detection [4].

An MRI scanner is made up of a long tube with a large, strong magnet. The patient lies on a table and moves into the tube, surrounded by a strong magnetic field in the MRI scanner. The machine uses a strong magnetic force and radiofrequency waves to combine signals from the hydrogen atoms nuclei in the body. A computer converts the signals into white and black pictures, taking several images during the test. The best way to view some types of tumors is using an MRI with contrast dye, such as spinal cord and brain tumors. Contrast is a dye inserted into the body via a vein to obtain clear MRI images. Once engrossed by the body, the contrast hurries up the speed at which tissues in the body respond to the MRI radio and magnetic waves. These stronger signals give pictures that are clear enough to view. MRI scans are usually executed on an outpatient basis [6]. Putting the patient in an enclosed and small space may be a problem, making it necessary for the patient to take medicine to relax while being placed in the scanner. In some situations, seeking guidance from the technologist or a counselor before conducting the test can be beneficial. At times, MRI imaging utilizes a contrast dye material. The patient may be required to swallow the contrast or have an intravenous (IV) catheter placed in an arm vein to inject the contrast into the bloodstream. Gadolinium is the contrast material usually adopted for an MRI examination.
However, artificial intelligence (AI) as a tool adopted in classifying magnetic resonance images has emerged as a promising resolution. AI can handle vast numbers of images accurately, thereby strengthening clinicians' ability to characterize, quickly detect, and constantly monitor diseases. Leveraging convolutional neural networks and machine learning techniques, the growth of automatic medical image grouping models has exhibited their effectiveness compared to conventional methods. These models outshine in astute, subtle designs and appear within MR images, facilitating precise prognoses and diagnoses for many conditions [4].

The Fourth Industrial Revolution adopts Artificial intelligence and machine learning as critical technologies. AI and machine learning involve (1) deep learning, natural language processing concepts, and machine learning methods; (2) knowledge and reasoning representation; and (3) the fundamental principle of rule-based expert systems modeling. AI is a multidisciplinary area of computer science that emphasizes creating machines that are competent in executing tasks that typically require human intelligence. AI systems development intends to simulate human reasoning functions, such as problem-solving, learning, language understanding, and perception. The concepts of AI include a wide range of applications and technologies that reflect its various and developing nature. AI is of two types: strong AI (General AI) and weak AI (Narrow AI). The former is trained and designed to perform specific tasks. It performs excellently for a particular function but lacks human intelligence and broad cognitive abilities [7].

Examples of AI applications include image recognition systems, virtual personal assistants, speech recognition software, recommendation systems, and autonomous vehicles. The latter has the potential to learn, understand and use knowledge over a broad range of tasks which are identical when compared with human intelligence. Strong AI achievement is a long-term objective making it a substantial area for future research. AI systems have the learning potential from experiences and data. Machine learning algorithms allow systems to increase their efficiency on a specific task as time progresses without being explicitly programmed. Logical reasoning can solve problems and help make decisions. They weigh different factors, process information and arrive at conclusions depending on learned patterns or predefined rules [8]. AI is designed to solve complex problems via breaking them down into components which involves patterns identification, data analysis and solutions generation.

AI systems based on Natural Language Processing (NLP) can interpret, understand, and generate languages that mimic human thinking. NLP allows communication between machines and humans, facilitating effective interactions between the duo via text or speech. AI systems can interpret and use sensory input to respond to the environment. A subset of AI called "computer vision" allows machines to understand and analyze visual information like videos and images. AI systems show adaptability by adjusting their behavior depending on new information or changing circumstances. This attribute allows AI to deal with dynamic and evolving situations. When adequately implemented, AI serves as a security automation engine and gives freedom of time and employee resources via the automation of repetitive tasks [9]. AI can also minimize human error by removing humans from a process or task. Figure 1 presents the interconnectivity between utilizing AI models for different MRI images to achieve perfect evaluation.

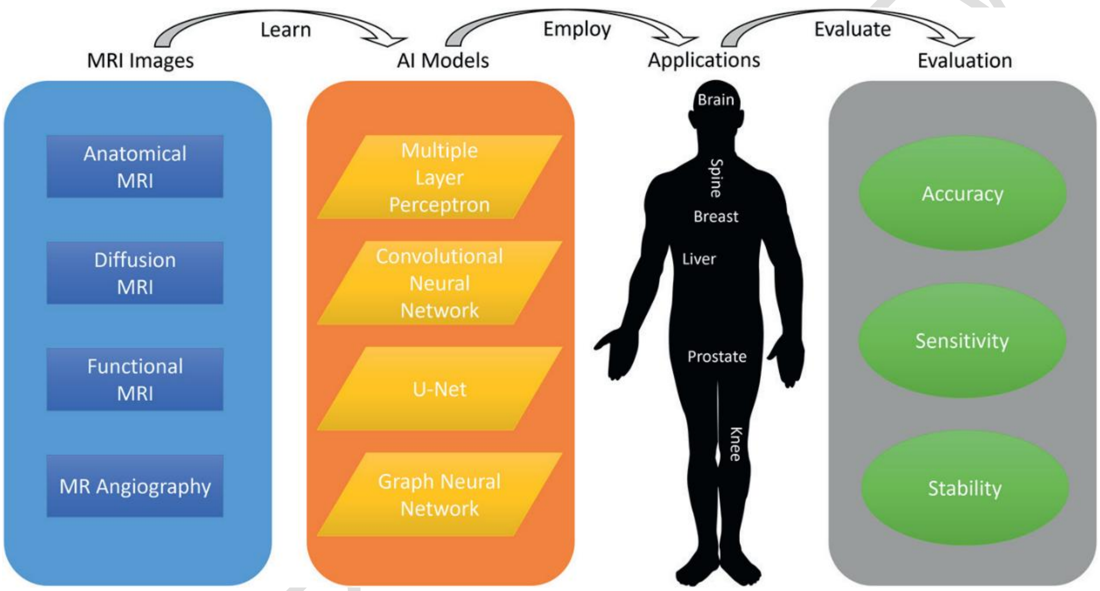


Figure 1: Interconnectivity between utilizing AI models for different MRI images in order to achieve perfect evaluation

## 2.0 MRI IMAGES

MRI possesses several image types, and each has its distinctive purpose. T1-weighted images offer exceptional functional features, while T2-weighted images are proficient in discovering defects like lesions and edema. Proton density (PD)-weighted images emphasize diffusion-weighted images (DWI) depicting water molecule movement and proton concentration. Magnetic resonance angiography (MRA) visualizes blood vessels, functional MRI (fMRI) maps brain activity, and magnetic resonance spectroscopy (MRS) assesses tissue chemistry. These images have extensive clinical applications, from spinal conditions to musculoskeletal assessments, from neuroimaging for brain and cardiovascular evaluations. MRI's functions include superb soft tissue contrast, the absence of ionizing radiation, and multi-planar imaging proficiency. However, there may be high sensitivity to be imbalanced for definite metal implants, motion artifacts, and at some periods, appears to waste patients' time. Additionally, MRI is still an irreplaceable tool that offers comprehensive views into the internal structures and functions present in the human body, thus modeling current healthcare activities [6].

## 2.1 ANATOMICAL MRI

The visualization of anatomical structures present in the human body is one of the elementary purposes of magnetic resonance imaging (MRI) regarding medical diagnosis. Many refer to Anatomical MRI as structural MRI because it is the basis of clinical imaging. It offers comprehensive, high-resolution images of different body components and presents significant insights into the integrity and morphology of organs and tissues. Sequences of anatomical MRI, such as T2-weighted and T1-weighted images, help display various tissues based on their inherent physical characteristics. T1-weighted images provide outstanding differences between fat-rich and water issues, enabling them to be perfect in visualizing anatomical boundaries and structures. On the contrary, the pictures of T2-weighted present differences in water content, which shows irregularities like inflammation, lesions, or edema effectively [9].

These MRI sequences are applicable in identifying numerous medical conditions. In neuroimaging, they facilitate the detection of brain malfunctions like vascular malformations, degenerative diseases, and tumors such as multiple sclerosis. Anatomical MRI facilitates the identification of joint disorders in musculoskeletal imaging and soft tissue injuries and assesses tendons and ligament integrity. Additionally, abdominal imaging aids in examining organs like kidneys, liver, and gastrointestinal tract and thus allows for detecting cysts, tumors, or structural anomalies [10].

## 2.2 FUNCTIONAL MRI

Functional magnetic resonance imaging (fMRI) is a newly detected MRI technology application that provides real-time visions into the human brain's working abilities, contrary to traditional MRI, which primarily captures structural information. The fMRI stresses the brain's vibrant activity by measuring changes in blood flow and oxygenation levels. The concept of neurovascular coupling stands for the fMRI heart. When a particular part of the brain is active, it needs an improvement in glucose and oxygen supply. To meet this requirement, dilation of the blood vessels in the activated area occurs with subsequent blood flow surges, causing the oxygenated hemoglobin levels to increase. This transformation in blood oxygenation can be visualized and noticed by fMRI [6].

Functional MRI is a non-invasive instrument that has changed our knowledge about brain function. It has many uses in both research settings and clinical areas. It allows clinicians and researchers to note how various brain regions react to stimuli, specific tasks, or cognitive processes. Functional localization is one of the most predominant uses of fMRI [8]. This methodology helps to know the brain's critical parts responsible for particular functions like motor control, language handling, and memory formation. For example, by instructing a subject to execute language-related assignments during an fMRI scan, researchers can locate the regions of the brain linked with language and speech functions.

In cognitive neuroscience specialization, fMRI is influential in studying complex mental processes such as emotion regulation, decision-making, and working memory. By examining brain activation patterns, researchers gain views of the neural substructures of these cognitive applications, which creates the way out for discoveries in fields like psychiatry and psychology. The clinical functions of fMRI are correspondingly deep, with applications in presurgical planning, especially in cases with brain tumors or lesions. fMRI aids surgeons in clearly identifying the functional parts of the brain, ensuring that the critical parts are conserved during surgery to reduce postoperative discrepancies [11].

## 2.3 DIFFUSION MRI

Diffusion Magnetic Resonance Imaging, also called diffusion MRI or dMRI, is defined as a distinct MRI method that provides an exceptional look into the tissue properties and microscopic structures within the human body. Contrary to traditional anatomical MRI, diffusion MRI emphasizes water molecule movement within tissues and thus provides critical knowledge regarding tissue microarchitecture and cellular structures. At its principal, diffusion MRI exploits the inherent water molecules' Brownian motion. Water molecules are not stable in biological tissues. Instead, they show random motion influenced by difficulties like fibers, cell membranes, and other cellular structures. This random movement, called "diffusion," can be evaluated and measured with diffusion MRI.

The apparent diffusion coefficient (ADC) is one of the main procedures of diffusion MRI. It describes the direction of water molecules and the rate of tissue diffusion. If the value of ADC is high, it symbolizes the existence of unrestricted diffusion, for example, in areas having cystic or fluid structures. Equally, low ADC values indicate diffusion restriction, which results from pathologies or dense cellular structures that obstruct the movement of water molecules. Diffusion MRI is mainly functional in neuroimaging, allowing white matter tract mapping in the brain. This methodology thoroughly examines brain connectivity via the tracking of water molecule diffusion along the nerve fibers, helping to quickly identify irregularities like white matter lesions that are predominant in conditions such as multiple sclerosis [12].

## 2.4 MAGNETIC RESONANCE ANGIOGRAPHY (MRA)

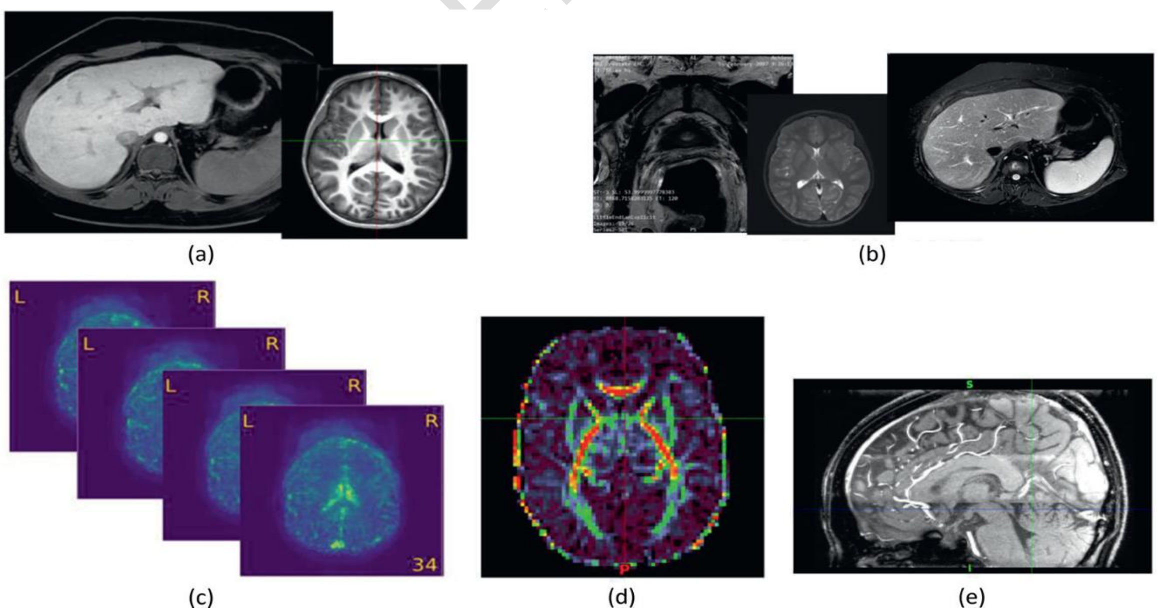


Figure 2: MRI images of different forms

## 3.0 APPLICATION OF MACHINE LEARNING IN HANDLING MRI

Generally, the formulation of machine learning cases is feasible unsupervised or supervised. Supervised learning utilizes existing data for mapping learning between data sets, while unsupervised learning gathers structures without labeled outputs within the sample. Presently, many functions in MRI reconstruction adopt supervised learning, while the unsupervised methods are still subject to discussion for future research. Many techniques for machine learning MRI reconstruction have evolved (based on both unsupervised and supervised methods) with the involvement of techniques that operate in image-space, work in different regions, active in k-space, unrolled optimization techniques, and learn the direct mapping ranging from k-space to image-space [13].

### 3.0.1 SUPERVISED MACHINE LEARNING

The machine learning algorithm learns a function in supervised learning that relates the input to an output from a data set used in training, comprising paired output and input images. The different methods categorized here include direct mapping, image restoration, cross-domain, k-space, and unrolled optimization. Image restoration methodologies work in the image domain alone [14]. These methods operate strictly to general image challenges in non-medical areas, including image processing. Due to this, they can benefit directly from and add to the existing stream of knowledge in the literature on CNN-based image enhancement, which includes super-resolution and de-noising. The first uses of machine learning in MRI reconstruction were due to image restoration methods [9]. A popular system in these techniques is the convolutional encoder-decoder architecture and skip connections tagged as “U-Net.”

Machine learning networks have been trained using k-space methods to execute k-space enhancement in a supervised way, just like GRAPPA [8]. Many methods utilize large training databases without explicit coil-sensitivity information, while others learn the connection between coil elements from minute samples of reference data. A few studies have revealed the prospect of directly knowing the transformation between the uncorrupted images and the under-sampled k-space data. These end-to-end reconstructions can curb errors from field inhomogeneity, phase distortions, eddy current effects, and re-gridding [15].

The cross-domain techniques are hybrid techniques that work in both the frequency and image domains. They depend on the idea that CNN’s operating on images and k-space show diverse properties, which implies that their combination can outperform them individually. Classically, frequency domain subnetworks try to evaluate the missing k-space samples while the image domain subnetworks eliminate the residual artifacts. Some cross-domain methods use a single k-space completion step, after which an image restoration approach follows [10].

Optimization methods that adopted step-wise optimization algorithms in compressed sensing MRI motivated them are called unrolled optimization methods. The technique involves unrolling the algorithm steps to an end-to-end neural network which then maps out the measured k-space to the corresponding reconstructed image [9]. This then allows the handling of regularized parameters, update rates, image changes and sparsity-promoting functions as either explicitly or implicitly fitted or trainable to a training data set using backpropagation. For instance, in the real-world application of enhancing MRI images to better diagnose neurological conditions, these unrolled optimization methods significantly reduce the time required for image reconstruction without compromising image quality. In response to classic optimization, three functions are accorded. The first involves learning parameters can be perfectly modified to image attributes than the hand-engineered types.

The second one involves the elimination of the manual tuning necessity, which is not a minor means. Finally, reconstruction is quicker because such learned step-wise patterns are trained to produce results with minor iterations [4].

### 3.0.2 UNSUPERVISED MACHINE LEARNING

In unsupervised learning, the machine learning algorithm locates patterns in the data without existing data or user guidance, resulting in profound applications in MRI reconstruction. Studies have shown the unavailability of excellent unsupervised learning methods in presenting images of good quality, like those obtained from supervised learning methods. Despite this, unsupervised learning techniques are substitutes when the existing collected datasets are unavailable and impossible to obtain [16]. Unsupervised learning has been used in image restoration methods training to eradicate noise from MRI images by using noisy training data alone. Examples of these are regularization by artifact-removal (RARE) and Noise2Noise. Additionally, Deep Resolve had applied unsupervised learning in training a 3D convolutional filter cascade purposely for super-resolution.

Nonetheless, algorithms that use image sparsity similar to compressive sensing have also found broad applications as unsupervised approaches. These cause learning sparsifying changes and image reconstruction concurrently for image patches, also called blind compressed sensing [12]. Nevertheless, Deep Basis Pursuit (DBP) has also found wide applications by utilizing recognized noise statistics for each data set. This unrolled optimization remains unstable between auto-encoder CNN layers and data consistency constraints with the foundation of pursuit de-noising. Cross-validation has equally adopted actual data consistency.

## 3.1 ARTIFICIAL INTELLIGENCE APPLICATION IN MRI

Artificial neural networks belong to a machine learning algorithm category that uses a series of cascaded layers (each layer comprises a series of neurons or connected nodes), connecting the inputs with the outputs. Each layer accepts inputs, executes a task, returns, and forwards an output to the successive layer. These layers possess two vital properties. The first is that most of these layers execute non-linear operations (usually a non-linearity followed by a linear transformation), representing extremely complex functions when combined. The second property is that the layers possess trainable parameters, i.e., parameters that are neither fixed nor designed but optimized in the training process. During the training process, the parameters are step-wisely adjusted via an optimization algorithm to reduce a loss function for a given training data set. As it learns, the network converges the connection of inputs with the outputs [17].

Artificial Intelligence (AI) became a transformative medical imaging tool. Many imaging modalities, including magnetic resonance imaging (MRI), have been revolutionized in their utilization and interpretation. AI models, usually driven by deep learning methods, have displayed outstanding capabilities in extracting meaningful information from medical images. This helps in the diagnosis of disease, assessment of prognosis, and planning of treatment.

At the core of the influence of AI on medical imaging are the applications of neural networks, precisely Convolutional Neural Networks (CNNs). CNNs have shown highly efficient contributions in features from images and learning of complex patterns, which makes them well-suited for assignments like segmentation, classification of images, and detection of objects. These models are similar to the ordered organization of neurons in the human brain, which allows them to identify complex facts within medical images [18]. Two major AI models usually adopted in medical imaging include:

• **Convolutional neural networks (CNNs)**: These have become the primary tools in medical imaging deep learning. They comprise multiple convolutional layers and merging operations that analytically remove ordered attributes from images. CNNs perform excellently in the execution of tasks such as image classification, in which they differentiate between abnormal and normal revelations within medical images. Variants of CNNs, such as ResNet50, VGG16, and Inception, have been fine-tuned and implemented for some particular medical imaging uses.

• **Recurrent neural networks (RNNs):** CNNs control image-related works while RNNs are dedicated to sequential data, making them precious for tasks about temporal information. RNNs mainly process time-series data in medical imaging, such as dynamic contrast-enhanced MRI (DCE-MRI) or functional MRI (fMRI). They can observe image sequence changes within a short period, which thus aids in the evaluation of conditions like tumor or epilepsy response to treatment.

The application of AI models regarding medical imaging is more than image classification. They are helpful in tasks such as segmenting images, in which they recognize and plan particular structures or regions of importance within an image. For example, in MRI, AI can segment blood vessels, tumors, or organs, allowing volumetric assessments and precise measurements. Nonetheless, AI models help in image registration and arrangement of images from different modalities or time points, essential for monitoring disease progression or treatment response. They also add to generative models such as Generative Adversarial Networks (GANs), which generate synthetic medical images for augmenting datasets and training, a mostly applicable capability in conditions where data is limited [14].

In applying AI models to analyze MRI images, a rich embroidery of architectures has been developed so that each can address specific challenges and tasks. The U-Net architecture and its complicated decoding or encoding pathways position itself as a commitment for semantic segmentation tasks, especially in medical image segmentation. Its potential to capture fine-grained attributes and conserve spatial information has made it essential in outlining anatomical structures [19]. However, the Multiple Layer Perceptron (MLP) is competent in dealing with structured data obtained from MRI images. MLPs are multipurpose and thus can leverage dense layers to test information and make predictions, applying them to different regression and classification tasks. However, graph neural networks (GNNs) have expanded the potential of MRI analysis via complex relationship modeling within medical data. GNNs shine in tasks requesting a better understanding of intricate connections like mapping neural pathways or identifying brain regions with functional significance. These architectures' flexibility additionally underlines the AI model's dynamism in MRI image analysis, providing for the diverse needs of medical professionals and researchers [20-24].

## 4.0 CONCLUSION

This technical review paper has examined the fundamental knowledge behind the concepts of magnetic resonance imaging, artificial intelligence, and machine learning. The paper also examined the interconnectivity between utilizing AI models and different MRI images to achieve perfect evaluation. Various MRI images discussed were anatomical MRI, magnetic resonance angiography, and diffusion MRI functional MRI. The forms of ML that have found extensive uses in MRI are unsupervised and supervised machine learning. For supervised machine learning, the various methods under this are image restoration methods, k-space methods, direct mapping, cross-domain methods, and unrolled optimization. Nonetheless, the two prominent AI models frequently employed in medical imaging are recurrent neural networks (RNNs) and convolutional neural networks (CNNs). In conclusion, artificial intelligence as a subset ofmachine learning has found wide medical applications to MRI.

## REFERENCES


1. Fang AM, Shumaker LA, Martin KD. Multi-institutional analysis of clinical and imaging risk factors for detecting clinically significant prostate cancer in men with PI-RADS 3 lesions. Cancer. 2022; 128(18):3287-3296. doi:10.1002/cncr.34355

2. Kim DY, Sun JS, Kim EY, Park KJ, You S. Diagnostic accuracy and safety of ctguided percutaneous lung biopsy with a coaxial cutting needle for the diagnosis of lung cancer in patients with UIP pattern. Scientific Reports. 2022; 12(1).

3. Marmolejo DH, Wong MYZ, Bajalica-Lagercrantz S, Tischkowitz M, Balmaña J. extended ERN-GENTURIS Thematic Group 3. Overview of hereditary breast and ovarian cancer (HBOC) guidelines across Europe. Eur J Med Genet. 2021; 64(12): 104350. doi:10.1016/j.ejmg.2021.104350

4. Marmolejo DH, Wong MYZ, Bajalica-Lagercrantz S, Tischkowitz M, Balmaña J. extended ERN-GENTURIS Thematic Group 3. Overview of hereditary breast and ovarian cancer (HBOC) guidelines across Europe. Eur J Med Genet. 2021; 64(12):104350. doi:10.1016/j.ejmg.2021.104350

5. Patel HD, Koehne EL, Shea SM. Systematic versus targeted magnetic resonance imaging/ultrasound fusion prostate biopsy among men with visible lesions. J Urol. 2022; 207(1):108-117. doi:10.1097/JU.0000000000002120

6. Rahman WT, Gerard S, Grundlehner P. Outcomes of High-Risk Breast MRI Screening in Women Without Prior History of Breast Cancer: Effectiveness Data from a Tertiary Care Center. J Breast Imaging. 2024; 6(1):53–63. doi: https://doi.org/10.1093/jbi/wbad092

7. Haji-Valizadeh H, Shen D, Avery RJ, Serhal AM, Schiffers FA, Katsaggelos AK. Rapid reconstruction of four-dimensional MR angiography of the thoracic aorta using a convolutional neural network. Radiology: Cardiothoracic Imaging. 2020;2:e190205.

8. Eo T, Jun Y, Kim T, Jang J, Lee H-J, Hwang D. KIKI-net: cross-domain convolutional neural networks for reconstructing undersampled magnetic resonance images. MagnReson Med 2018;80:2188–201.

9. Jethi AK, Murugesan B, Ram K, Sivaprakasam M. Dual-Encoder-UnetFor Fast Mri Reconstruction. 2020 IEEE 17th International Symposium on Biomedical Imaging Workshops (ISBI Workshops)2020. p. 1–4.

10. Liu J, Sun Y, Eldeniz C, Gan W, An H, Kamilov US. RARE: Image reconstruction using deep priors learned without groundtruth. IEEE J Sel Top Signal Process 2020;14:1088–99.

11. Sim AJ, Kaza E, Singer L, Rosenberg SA. A Review of the Role of MRI in Diagnosis and Treatment of Early Stage Lung Cancer, Clinical & Translational Radiation Oncology. 2020. doi:https://doi.org/10.1016/j.ctro.2020.06.002

12. Lehman CD, Lee JM, DeMartini WB, Hippe DS, Rendi MH, Kalish G, Porter P, Gralow J, Partridge SC. Screening MRI in Women with a Personal History of Breast Cancer. JNCI J Natl Cancer Inst. 2016; 108(3): 1-8.

13. Callender T, Emberton M, Morris S, Pharoah PDP, Pashayan N. Benefit, Harm, and Cost-effectiveness Associated With Magnetic Resonance Imaging Before Biopsy in Age-based and Risk-stratified Screening for Prostate Cancer. JAMA Network Open, 2021; 4(3):e2037657. doi:10.1001/jamanetworkopen.2020.37657.

14. Petralia G, Zugni F, Summers PE, Colombo A, Pricolo P, Grazioli L, Colagrande S, Giovagnoni A, Padhani AR. Whole‑ body magnetic resonance imaging (WB‑ MRI) for cancer screening: recommendations for use. La radiologia medica. 2021. 126:1434–1450 https://doi.org/10.1007/s11547-021-01392-2

15. Zhang CY. Effectiveness of early cancer detection method: magnetic resonance imaging and X-ray technique. Proceedings of the International Conference on Modern Medicine and Global Health. 2023. DOI: 10.54254/2753-8818/6/20230279

16. Lubinski J, Kotsopoulos J, Moller P, Pal T, Eisen A. MRI Surveillance and Breast Cancer Mortality in Women With BRCA1 and BRCA2 Sequence Variations. JAMA Oncol. 2024. doi:10.1001/jamaoncol.2023.6944

17. Patel HD, Remmers S, Ellis JL, Li EV, Roobol MJ, Fang AM, Davik P, Rais-Bahrami S, Murphy AB, Ross AE, Gupta GN. Comparison of magnetic resonance imaging–based risk calculators to predict prostate cancer risk. JAMA Network Open. 2024; 7(3):e241516. doi:10.1001/jamanetworkopen.2024.1516

18. Knoll F, Murrell T, Sriram A, Yakubova N, Zbontar J, Rabbat M, et al. Advancing machine learning for MR image reconstruction with an open competition: Overview of the 2019 fastMRI challenge. MagnReson Med 2023;84:3054–70.

19. Hauptmann A, Arridge S, Lucka F, Muthurangu V, Steeden JA. Real-time cardiovascular MR with spatio-temporal artifact suppression using deep learning–proof of concept in congenital heart disease. MagnReson Med 2024;81: 1143–56.

20. Knoll F, Zbontar J, Sriram A, Muckley MJ, Bruno M, Defazio A. fastMRI: A publicly available raw k-space and DICOM dataset of knee images for accelerated MR image reconstruction using machine learning. radiology: Artificial intelligence. 2023; 2:e190007.

21. Khanna VV, Chadaga K, Sampathila N, Prabhu S, Chadaga R, Umakanth S. Diagnosing COVID-19 using artificial intelligence: A comprehensive review. Netw. Model. Anal. Health Inform. Bioinform. 2022, 11, 25.

22. Zhuo Z, Zhang J, Duan Y, Qu L, Feng C, Huang X, Cheng D, Xu X, Sun T, Li Z.. Automated Classification of Intramedullary Spinal Cord Tumors and Inflammatory Demyelinating Lesions Using Deep Learning. Radiol. Artif. Intell. 2022, 4, e210292

23. Rocca MA, Anzalone N, Storelli L, Del Poggio A, Cacciaguerra L, Manfredi AA, Meani A, Filippi M. Deep learning on conventional magnetic resonance imaging improves the diagnosis of multiple sclerosis mimics. Investig. Radiol. 2021, 56, 252–260.

24. Liu S, Zheng H, Feng Y, Li W. Prostate cancer diagnosis using deep learning with 3D multiparametric MRI. In Medical Imaging 2017: Computer-Aided Diagnosis; SPIE: Orlando, FL, USA, 2017; Volume 10134, pp. 581–584.