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Comparing Traditional MRI Techniques and Deep Learning Innovations in Advanced Imaging

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abstract

Magnetic Resonance Imaging (MRI) remains paramount in the diagnostic evaluation of various medical conditions. This research delves into a comparative study between conventional MRI methods and emerging deep learning techniques. Traditional MRI operates through sequences such as T1-weighted, T2-weighted, and FLAIR. The transformation of K-space data into an image traditionally utilizes Fourier transformations, followed by post-processing techniques like multi-planar reformatting. On the other hand, deep learning approaches have initiated innovations in the MRI landscape. Techniques such as data augmentation expand the dataset for better model generalization, while accelerated imaging through neural networks offers reduced scan durations. Image segmentation and anomaly detection, powered by deep learning, show promise in specificity for tasks like tumor differentiation. Moreover, deep learning has the potential to enhance image quality, providing clearer and higher-resolution visuals. A comparative analysis suggests that deep learning could offer faster scans and sharper images. However, its flexibility for task-specific functions stands in contrast to the general-purpose nature of traditional methods. Despite the potential of deep learning, challenges persist. The vast data requirements, the 'black box' nature inhibiting interpretability, and concerns over model generalization necessitate cautious optimism. The future may see a convergence of traditional and deep learning methods, leading to hybrid models that amalgamate the strengths of both realms. In conclusion, while traditional MRI techniques have anchored imaging for years, deep learning's innovative potential could redefine the MRI domain, ushering in an era of accelerated and precise diagnostics, subject to rigorous validation.

Keywords: Magnetic Resonance, Imaging (MRI), Deep learning, Image segmentation, Anomaly detection, Accelerated imaging

introduction

Magnetic Resonance Imaging (MRI) is a non-invasive imaging technique that utilizes the principles of nuclear magnetic resonance (NMR) to generate detailed images of the internal structures of the body. The basic principle behind MRI involves the interaction between atomic nuclei and external magnetic fields. When placed in a strong magnetic field, certain atomic nuclei, such as hydrogen, align themselves with the direction of the magnetic field. These aligned nuclei can then be manipulated using radiofrequency (RF) pulses, causing them to resonate. The resonance generates signals that are detected and processed to create images. Unlike X-rays or CT scans, MRI does not involve ionizing radiation, making it a safer option for many types of diagnostic imaging [1]–[3].

Magnetic resonance is the underlying phenomenon that makes MRI possible. When a nucleus with a magnetic moment, such as a hydrogen nucleus, is subjected to an external magnetic field, it aligns itself either with or against the direction of the field. When subjected to an RF pulse at a specific frequency known as the Larmor frequency, these nuclei are excited to a higher energy state. As they relax back to their lower energy state, they emit signals that can be detected and used to create images. The Larmor frequency is directly proportional to the strength of the magnetic field and the gyromagnetic ratio of the nucleus, allowing for precise control and manipulation of the resonance process.

The role of hydrogen atoms in MRI is particularly significant due to their abundance in the human body, primarily in the form of water and fat. Hydrogen nuclei have a high gyromagnetic ratio, making them highly responsive to magnetic fields and RF pulses. This results in strong signals that contribute to high-contrast images. The different environments in which hydrogen atoms are found within biological tissues lead to variations in the relaxation times, which can be exploited to distinguish between different types of tissues, thereby providing detailed images that are invaluable for diagnostic purposes [4].

The magnetic field and radiofrequency pulses are key elements in the MRI process. The magnetic field is generated by a superconducting magnet and is responsible for aligning the hydrogen nuclei. The strength of the magnetic field is measured in Tesla (T), and clinical MRI machines typically operate at field strengths between 1.5T and 3T. Radiofrequency coils are used to transmit RF pulses to the area being imaged and to receive the emitted signals. The RF pulses are tuned to the Larmor frequency of the hydrogen nuclei, causing them to flip and resonate. Gradient coils are also used to create slight variations in the magnetic field, allowing for spatial encoding of the signals, which is essential for image reconstruction.

An MRI machine comprises several key components: the magnet, gradient coils, RF coils, and a computer system. The magnet is usually a superconducting magnet cooled by liquid helium and is responsible for generating the strong, stable magnetic field required for imaging. Gradient coils are used to produce small, controlled variations in the magnetic field, enabling the spatial localization of signals. RF coils are used both to transmit the RF pulses and to receive the signals emitted by the resonating nuclei. Finally, the computer system controls the sequencing of RF pulses and gradient fields, acquires the emitted signals, and processes them to reconstruct the final images. The integration of these components allows for the high-resolution, high-contrast imaging that makes MRI a critical tool in modern medicine.

Magnetic Resonance Imaging (MRI) offers a variety of scan types, each with its unique advantages and applications. T1-weighted scans and T2-weighted scans are among the most commonly used sequences in clinical practice. In T1-weighted scans, the contrast is primarily determined by the longitudinal relaxation time (T1) of the tissue. These scans are useful for visualizing anatomical structures and are particularly effective in distinguishing between grey and white matter in the brain. Fat appears bright in T1-weighted images, while water and cerebrospinal fluid (CSF) appear dark. This type of scan is often used for detecting lesions, assessing musculoskeletal conditions, and evaluating the anatomy of organs [5]–[7].

T2-weighted scans, on the other hand, rely on the transverse relaxation time (T2) for generating image contrast. In these scans, water and fluids appear bright, making them particularly useful for detecting edema, inflammation, and certain types of tumors. T2-weighted images are commonly used in neuroimaging to identify pathological changes in the brain, such as those associated with multiple sclerosis or stroke. The high contrast between fluids and surrounding tissues in T2-weighted scans also makes them valuable for imaging the spinal cord and assessing joint abnormalities [8].

Functional MRI (fMRI) is a specialized type of MRI that measures and maps the brain's activity. Unlike standard MRI scans, which capture static images, fMRI captures rapid sequences of images to monitor changes in blood flow to different parts of the brain. This allows for the observation of neural activity, as areas with increased neural activity require more oxygen and thus experience increased blood flow. fMRI is widely used in neuroscience research to study brain function, and in clinical settings to map brain activity before surgical procedures involving critical regions like the motor cortex or language centers.

Diffusion Tensor Imaging (DTI) is another advanced MRI technique that focuses on the diffusion of water molecules in tissues. By measuring how water diffuses along white matter tracts in the brain, DTI provides insights into the integrity and orientation of these tracts. This is particularly useful for studying conditions that may affect white matter, such as traumatic brain injury, multiple sclerosis, and certain developmental disorders. DTI is also employed in neuroscience research to study brain connectivity and to map neural pathways, providing a more comprehensive understanding of brain structure and function.

Each of these MRI scan types serves specific diagnostic or research purposes and may be used in combination for a more complete understanding of a patient's condition. The choice of scan type depends on what anatomical or functional information is needed. T1 and T2-weighted scans offer detailed anatomical views with different contrast mechanisms, fMRI provides a dynamic view of brain activity, and DTI offers a unique look at white matter integrity and connectivity. These diverse capabilities make MRI an incredibly versatile tool in both clinical and research settings.

Magnetic Resonance Imaging (MRI) has a wide range of clinical applications, each tailored to provide critical information for diagnosing and treating various medical conditions. Neuroimaging is one of the most common applications of MRI, offering unparalleled detail of the brain and spinal cord. MRI is often the imaging modality of choice for evaluating neurological disorders such as multiple sclerosis, stroke, and brain tumors. It is also used to assess congenital anomalies, traumatic injuries, and degenerative diseases like Alzheimer's. Advanced techniques like functional MRI (fMRI) and Diffusion Tensor Imaging (DTI) further extend the utility of MRI in neuroimaging by allowing for the mapping of brain activity and neural pathways, respectively.

Musculoskeletal imaging is another significant application of MRI, providing detailed images of bones, joints, and soft tissues like muscles, tendons, and ligaments. MRI is particularly useful for detecting abnormalities in soft tissues, which are often not visible on X-rays [9]–[11]. Conditions such as torn ligaments, muscle strains, and herniated discs can be accurately diagnosed using MRI. T1 and T2-weighted images offer different contrast mechanisms that are useful for distinguishing between various types of tissues and identifying pathological changes. MRI is also used to guide treatment plans for orthopedic surgeries and to monitor the healing process [12].

In the realm of cardiovascular imaging, MRI offers a non-invasive method for assessing the structure and function of the heart and blood vessels. Cardiac MRI can provide detailed images of the heart's chambers, valves, and major vessels, making it invaluable for diagnosing conditions like congenital heart defects, coronary artery disease, and myocardial infarctions. It can also measure blood flow and cardiac output, providing functional information that is critical for treatment planning. Unlike other imaging modalities like angiography, cardiac MRI does not expose patients to ionizing radiation or require the use of potentially harmful contrast agents.

Oncological applications of MRI are extensive and continue to evolve with advancements in technology. MRI is used for tumor detection, characterization, and staging [13], [14]. It offers high-resolution, high-contrast images that are crucial for differentiating between benign and malignant tumors. Specialized MRI techniques, such as magnetic resonance spectroscopy (MRS) [15], [16], can even provide metabolic information about tumors, aiding in diagnosis and treatment planning. MRI is also used to guide biopsies and to monitor the effectiveness of treatments like chemotherapy and radiation therapy [17].

traditional mri techniques

In the realm of Magnetic Resonance Imaging (MRI), the process of generating images can be broadly categorized into three main stages: image acquisition, image reconstruction, and image post-processing. Image acquisition is the initial phase where raw data is collected based on specific MRI sequences. Traditional sequences include T1-weighted, T2-weighted, and Fluid-Attenuated Inversion Recovery (FLAIR) scans. Each of these sequences provides different contrast mechanisms that are useful for visualizing specific types of tissues or pathological conditions. For example, T1-weighted scans are often used for anatomical imaging and are particularly effective in distinguishing between grey and white matter in the brain. T2-weighted scans are useful for detecting fluid-filled areas and are commonly employed in the diagnosis of conditions like edema and tumors. FLAIR is particularly useful for eliminating the bright signal from cerebrospinal fluid, making it easier to detect lesions in the brain [18]–[20].

The second stage, image reconstruction, involves converting the raw data collected during the acquisition phase into interpretable images. This is typically achieved through the use of mathematical algorithms, most commonly Fourier transformations. In MRI, the raw data is often collected in a frequency-space domain known as k-space. Each point in k-space represents spatial frequency components of the image, and the central region of k-space contains information about the low-frequency components, which are crucial for the overall contrast of the image. Fourier transformations are used to convert this k-space data into the spatial domain, generating the image that will be interpreted by clinicians. The quality and resolution of the reconstructed image are highly dependent on the sampling density in k-space and the algorithms used for the Fourier transformations [21].

Image post-processing is the third stage and involves various techniques aimed at enhancing the quality and interpretability of the reconstructed images. Tools commonly used in this stage include multi-planar reformatting, intensity normalization, and manual segmentation. Multi-planar reformatting allows for the reconstruction of images in different anatomical planes from a single data set, providing multiple perspectives of the area of interest. Intensity normalization is used to standardize the brightness and contrast across different images or sequences, making it easier to compare them [22]. Manual segmentation involves the delineation of specific regions of interest within the image, often performed by a trained radiologist, to isolate particular structures or abnormalities for further analysis [23].

Each of these stages plays a crucial role in the overall MRI process, contributing to the generation of high-quality, clinically relevant images. Image acquisition sets the foundation by collecting raw data based on sequences tailored to the diagnostic needs. Image reconstruction transforms this data into a visual format through complex mathematical algorithms. Finally, image post-processing enhances the utility and interpretability of the images through various optimization techniques. Together, these stages ensure that MRI remains a versatile and invaluable tool in medical imaging, capable of providing detailed insights into a wide range of pathological conditions [24], [25].

deep learning approaches in mri

Deep learning approaches have increasingly been integrated into Magnetic Resonance Imaging (MRI) processes to address various challenges and improve the efficiency and accuracy of imaging. One such approach is data augmentation, which involves artificially expanding the available dataset to improve the generalization capabilities of deep learning models. In the context of MRI, data augmentation techniques may include operations like rotation, scaling, and flipping of images, as well as the addition of noise or other modifications. These augmented datasets provide a more comprehensive training environment for neural networks, enabling them to better understand the variability in medical images. This is particularly beneficial in scenarios where the available medical imaging data is limited or imbalanced, as it helps to prevent overfitting and improves the model's ability to generalize to new, unseen data.

Another significant application of deep learning in MRI is in the area of accelerated imaging. Traditional MRI scans can be time-consuming, which is not only inconvenient for patients but can also be problematic in cases where rapid imaging is essential, such as in acute stroke assessment. Deep learning models, particularly neural networks, have been employed to produce high-quality images from under-sampled k-space data, effectively reducing the time required for image acquisition. By training neural networks on large datasets of fully-sampled and under-sampled images, these models learn to reconstruct high-quality images from fewer data points. This accelerated imaging approach has the potential to significantly reduce scan times without compromising image quality, making MRI more accessible and less burdensome for both patients and healthcare systems [26].

Both data augmentation and accelerated imaging exemplify how deep learning techniques can enhance the capabilities of MRI. Data augmentation addresses the challenges associated with limited or imbalanced datasets, improving the robustness and generalizability of deep learning models in medical imaging applications. Accelerated imaging, on the other hand, tackles the issue of lengthy scan times, making the MRI process more efficient without sacrificing the quality of the images produced. These advancements not only have immediate clinical implications but also open the door for further innovations in the integration of artificial intelligence and medical imaging [27], [28].

Deep learning techniques have also been applied to other aspects of Magnetic Resonance Imaging (MRI), such as image segmentation, anomaly detection, and image enhancement and super-resolution. Image segmentation is a critical step in many medical imaging applications, as it involves isolating specific regions of interest within an image for further analysis or measurement. Traditional segmentation methods often require manual intervention and can be time-consuming. Deep learning architectures like U-Net have been developed to automate and enhance the segmentation process. U-Net is particularly well-suited for biomedical image segmentation due to its ability to learn from a relatively small number of labeled images and produce precise segmentations. Its architecture consists of a contracting path to capture context and a symmetric expanding path to enable precise localization, making it efficient for segmenting complex anatomical structures in MRI scans [29].

Anomaly detection is another area where deep learning has shown promise [30], [31]. Detecting abnormalities in medical images is a crucial task for diagnosis and treatment planning. Deep learning models can be trained on a large dataset comprising both normal and abnormal scans to identify anomalies effectively. These models can learn the intricate patterns and features that distinguish abnormal tissue structures from normal ones, thereby aiding in the early detection of conditions like tumors, lesions, or other pathological changes. The advantage of using deep learning for anomaly detection lies in its ability to automatically learn features without manual engineering, making it a more scalable and potentially more accurate approach compared to traditional methods [32].

Enhancement and super-resolution are additional applications of deep learning in MRI that focus on improving the quality of the images. Traditional MRI scans may suffer from various issues like noise, low contrast, or low resolution, which can hinder accurate diagnosis. Deep learning models can be trained to enhance the quality of these images by making them clearer and increasing their resolution. Techniques like Generative Adversarial Networks (GANs) have been used for super-resolution, where the network learns to generate high-resolution images from lower-resolution inputs [33], [34]. This not only improves the visual quality of the images but also may reveal details that were not apparent in the original scans, thereby aiding in more accurate diagnosis and treatment planning [35].

Each of these applications—image segmentation, anomaly detection, and enhancement and super-resolution—demonstrates the versatility and efficacy of deep learning techniques in MRI [36], [37]. These methods offer automated, accurate, and efficient solutions to challenges that have traditionally been addressed through more labor-intensive or less effective means. As deep learning algorithms continue to evolve and as more labeled data becomes available for training, it is likely that these techniques will play an increasingly significant role in the advancement of MRI technology and its clinical applications [38].

comparative analysis

In the context of Magnetic Resonance Imaging (MRI), deep learning offers distinct advantages in terms of speed and image quality when compared to traditional imaging methods. One of the most compelling benefits is the acceleration of image acquisition. Traditional MRI methods often have fixed scan times that are determined by the sequence parameters and the need to fully sample k-space for image reconstruction. Deep learning models, particularly neural networks trained for this purpose, can significantly reduce the time required for image acquisition by enabling the reconstruction of high-quality images from under-sampled k-space data. This acceleration is not merely a matter of convenience; it has clinical implications as well. Faster scans can be particularly beneficial in emergency situations, for patients who have difficulty remaining still for extended periods, or for throughput efficiency in busy clinical settings [39], [40].

Image quality is another domain where deep learning has shown promise. Traditional MRI methods rely on the complete sampling of k-space data to reconstruct images, and the quality of the resulting images is often constrained by factors such as signal-to-noise ratio and resolution. Deep learning algorithms can generate high-quality images from fewer data points, effectively overcoming some of these limitations. For example, neural networks trained on large datasets can learn to identify and preserve important features in the images while eliminating noise, thereby producing sharper and clearer images. In certain scenarios, the image quality achieved through deep learning techniques has the potential to surpass that of traditional methods. This enhanced image quality can be critical for accurate diagnosis and treatment planning, as it allows for better visualization of anatomical structures and pathological conditions [41].

Both speed and image quality are critical factors in the utility and effectiveness of MRI as a diagnostic tool. Deep learning offers tangible improvements in these areas, making it a valuable complement to traditional MRI techniques. By accelerating image acquisition, deep learning not only makes the MRI process more efficient but also broadens its applicability in time-sensitive clinical situations. Improved image quality, on the other hand, enhances the diagnostic capabilities of MRI, potentially leading to more accurate and timely medical interventions. As deep learning technology continues to evolve and as more research is conducted to validate its efficacy, it is likely to become an increasingly integral part of MRI procedures and healthcare more broadly [42], [43].

Deep learning techniques in Magnetic Resonance Imaging (MRI) offer a level of flexibility that is often not achievable with traditional imaging methods. Traditional MRI techniques are generally designed to be general-purpose, providing a broad range of imaging capabilities but often lacking the specificity required for certain diagnostic tasks. Deep learning models, on the other hand, can be trained for highly specialized tasks, such as differentiating between specific types of tumors or identifying subtle features associated with particular diseases. For instance, a neural network can be trained on a dataset comprising images of various kinds of brain tumors, enabling it to learn the unique characteristics of each type. This level of task-specific customization can be invaluable in clinical settings where precise diagnosis is critical for effective treatment planning. The flexibility of deep learning models allows for the development of specialized imaging protocols that can be tailored to the needs of individual patients or specific medical conditions.

While the advantages of deep learning in MRI are evident, it is crucial to consider the aspect of reliability, especially when comparing it to traditional methods. Traditional MRI techniques have undergone years, if not decades, of rigorous validation and have been widely accepted in clinical practice. They are supported by a large body of evidence that attests to their efficacy and reliability. Deep learning models, although promising, are relatively new in the field of medical imaging and have not yet been subjected to the same level of rigorous clinical validation. Before these models can be widely adopted for clinical use, they must undergo extensive testing to ensure their reliability, accuracy, and safety. This includes not just validation on diverse and representative datasets, but also real-world clinical trials to assess their performance in practical, patient-centered scenarios [44].

The flexibility offered by deep learning models in MRI presents exciting possibilities for more personalized and precise medical imaging. However, this must be balanced with a thorough understanding and validation of the reliability of these techniques. As the field moves forward, it will be essential to integrate deep learning models into existing clinical frameworks carefully, complementing rather than replacing traditional methods until sufficient validation is achieved [45], [46]. This cautious approach will ensure that the adoption of deep learning in MRI enhances, rather than compromises, the quality and reliability of medical imaging in clinical practice.

conclusion

Deep learning techniques in Magnetic Resonance Imaging (MRI) come with their own set of challenges and considerations, among which data requirements, interpretability, and generalization are particularly noteworthy. One of the most significant challenges is the data requirement for training deep learning models. These models often require vast amounts of labeled data to learn effectively. In the context of medical imaging, acquiring such large datasets can be difficult due to issues like patient privacy, data sharing restrictions, and the sheer effort required to curate and label the data accurately. The need for large datasets also raises questions about the feasibility of using deep learning models in specialized applications where only limited data may be available [47].

Interpretability is another critical concern when employing deep learning models in MRI. Neural networks, the cornerstone of many deep learning applications, are often considered 'black boxes' because, although they can make highly accurate predictions or classifications, the internal workings that lead to these decisions are not easily interpretable. This lack of transparency can be a significant drawback in clinical settings where understanding the rationale behind a diagnosis or treatment recommendation is crucial for patient care. Efforts are being made to develop techniques for making neural networks more interpretable, but this remains an active area of research and a point of caution for clinical adoption [48].

Generalization is a further challenge that impacts the reliability of deep learning models in MRI. A model trained on data from a specific MRI machine, or on images from a particular demographic group, may not perform well when exposed to data that differs from what it was trained on. This is a critical issue in medical imaging, where variations in imaging hardware and patient populations are common. For a deep learning model to be clinically useful, it must be able to generalize well across different machines, imaging protocols, and patient demographics. This requires careful design of the training data and may necessitate additional steps like data normalization or domain adaptation techniques.

Each of these challenges—data requirements, interpretability, and generalization—poses significant hurdles for the widespread adoption of deep learning in MRI. While these models offer the promise of improved speed, image quality, and diagnostic precision, their limitations must be carefully considered. Addressing these challenges will require concerted efforts from researchers, clinicians, and regulatory bodies to ensure that deep learning models are both effective and reliable tools in the realm of MRI and medical imaging at large.

The integration of traditional MRI techniques with emerging deep learning methods offers the potential for hybrid models that leverage the strengths of both approaches. Traditional MRI methods bring to the table years of clinical validation and a broad applicability across various medical conditions. These methods are robust and well-understood, providing a reliable foundation upon which to build. Deep learning, on the other hand, offers the advantages of speed, flexibility, and the potential for enhanced image quality. By combining these two approaches, it may be possible to develop hybrid models that offer the reliability of traditional MRI techniques while also benefiting from the speed and precision that deep learning algorithms can provide. Such hybrid models could be particularly useful in scenarios where rapid and highly accurate diagnostics are required, or where specialized imaging protocols are needed for particular medical conditions [49].

The potential for deep learning to revolutionize the MRI landscape is significant, but it comes with the caveat that further research and rigorous clinical validation are essential. The development of deep learning models for MRI is still a relatively new field, and while early results are promising, these models must be subjected to the same level of scrutiny as any other clinical diagnostic tool. This includes validation on diverse and representative datasets, as well as real-world clinical trials to assess their efficacy and reliability. Only through such rigorous testing can the medical community gain the confidence needed to adopt these new technologies widely [50], [51].

The challenges associated with the adoption of deep learning in MRI, such as data requirements, interpretability, and generalization, also need to be addressed in this context. Hybrid models that combine traditional MRI techniques with deep learning could offer a pathway to mitigate some of these challenges. For example, the reliability and interpretability of traditional methods could help offset the 'black box' nature of neural networks, while the data efficiency of traditional methods could complement the data-hungry nature of deep learning algorithms.

The ultimate goal of integrating deep learning into MRI is to improve patient care by offering quicker and more accurate diagnostics. Time is often of the essence in medical settings, and the ability to rapidly acquire high-quality images could have a direct impact on patient outcomes. Similarly, the enhanced image quality and diagnostic precision offered by deep learning could lead to more effective treatment plans, thereby improving the overall standard of care [52].

The potential benefits in terms of speed, image quality, and diagnostic accuracy are substantial, but they must be balanced against the challenges and limitations that this new technology presents [53], [54]. With careful research, rigorous validation, and thoughtful integration with existing methods, deep learning has the potential to significantly enhance the capabilities of MRI, offering tangible benefits for both clinicians and patients.

references

[1] X. Meng, A. B. Rosenkrantz, and N. Mendhiratta, “Relationship between prebiopsy multiparametric magnetic resonance imaging (MRI), biopsy indication, and MRI-ultrasound

fusion–targeted prostate biopsy outcomes," *Eur. Urol.*, 2016.

[2] J. A. Dowling *et al.*, "Automatic Substitute Computed Tomography Generation and Contouring for Magnetic Resonance Imaging (MRI)-Alone External Beam Radiation Therapy From Standard MRI Sequences," *International Journal of Radiation Oncology*Biology*Physics*, vol. 93, no. 5, pp. 1144–1153, Dec. 2015.

[3] H. Kalbkhani, M. G. Shayesteh, and B. Zali-Vargahan, "Robust algorithm for brain magnetic resonance image (MRI) classification based on GARCH variances series," *Biomed. Signal Process. Control*, vol. 8, no. 6, pp. 909–919, Nov. 2013.

[4] A. Aljarbouh and B. Caillaud, "On the regularization of chattering executions in real time simulation of hybrid systems," 2015, p. 49.

[5] R. Trampel, P.-L. Bazin, K. Pine, and N. Weiskopf, "In-vivo magnetic resonance imaging (MRI) of laminae in the human cortex," *Neuroimage*, vol. 197, pp. 707–715, Aug. 2019.

[6] R. D. Muchow, D. K. Resnick, M. P. Abdel, A. Munoz, and P. A. Anderson, "Magnetic resonance imaging (MRI) in the clearance of the cervical spine in blunt trauma: a meta-analysis," *J. Trauma*, vol. 64, no. 1, pp. 179–189, Jan. 2008.

[7] J. K. Logan *et al.*, "Current status of magnetic resonance imaging (MRI) and ultrasonography fusion software platforms for guidance of prostate biopsies," *BJU Int.*, vol. 114, no. 5, pp. 641–652, Nov. 2014.

[8] A. Aljarbouh, "Accelerated Simulation of Hybrid Systems: Method combining static analysis and run-time execution analysis.(Simulation Accélérée des Systèmes Hybrides: méthode combinant analyse statique et analyse à l'exécution)." University of Rennes 1, France, 2017.

[9] P. Caravan, "Protein-targeted gadolinium-based magnetic resonance imaging (MRI) contrast agents: design and mechanism of action," *Acc. Chem. Res.*, vol. 42, no. 7, pp. 851–862, Jul. 2009.

[10] M. J. Thali, K. Yen, W. Schweitzer, and P. Vock, "… , a new imaging horizon in forensic pathology: virtual autopsy by postmortem multislice computed tomography (MSCT) and magnetic resonance imaging (MRI) …," *Journal of forensic*, 2003.

[11] T. Stanescu, H.-S. Jans, N. Pervez, P. Stavrev, and B. G. Fallone, "A study on the magnetic resonance imaging (MRI)-based radiation treatment planning of intracranial lesions," *Phys. Med. Biol.*, vol. 53, no. 13, pp. 3579–3593, Jul. 2008.

[12] A. Aljarbouh, Y. Zeng, A. Duracz, B. Caillaud, and W. Taha, "Chattering-free simulation for hybrid dynamical systems semantics and prototype implementation," 2016, pp. 412–422.

[13] J. A. Dowling *et al.*, "An atlas-based electron density mapping method for magnetic resonance imaging (MRI)-alone treatment planning and adaptive MRI-based prostate radiation therapy," *Int. J. Radiat. Oncol. Biol. Phys.*,

vol. 83, no. 1, pp. e5-11, May 2012.
[14] C. Baldock *et al.*, "Experimental procedure for the manufacture and calibration of polyacrylamide gel (PAG) for magnetic resonance imaging (MRI) radiation dosimetry," *Phys. Med. Biol.*, vol. 43, no. 3, pp. 695–702, Mar. 1998.
[15] U. Blum *et al.*, "Magnetic resonance imaging (MRI) for detection of active sacroiliitis--a prospective study comparing conventional radiography, scintigraphy, and contrast enhanced MRI," *J. Rheumatol.*, vol. 23, no. 12, pp. 2107–2115, Dec. 1996.
[16] S. G. Rugg, R. J. Gregor, B. R. Mandelbaum, and L. Chiu, "In vivo moment arm calculations at the ankle using magnetic resonance imaging (MRI)," *J. Biomech.*, vol. 23, no. 5, pp. 495–501, 1990.
[17] A. Aljarbouh and B. Caillaud, "Robust simulation for hybrid systems: chattering path avoidance," *arXiv preprint arXiv:1512.07818*, 2015.
[18] J. Juranek, P. A. Filipek, G. R. Berenji, C. Modahl, K. Osann, and M. A. Spence, "Association between amygdala volume and anxiety level: magnetic resonance imaging (MRI) study in autistic children," *J. Child Neurol.*, vol. 21, no. 12, pp. 1051–1058, Dec. 2006.
[19] E. Pappas *et al.*, "A new polymer gel for magnetic resonance imaging (MRI) radiation dosimetry," *Phys. Med. Biol.*, vol. 44, no. 10, pp. 2677–2684, Oct. 1999.
[20] S. Aime, D. D. Castelli, S. G. Crich, E. Gianolio, and E. Terreno, "Pushing the sensitivity envelope of lanthanide-based magnetic resonance imaging (MRI) contrast agents for molecular imaging applications," *Acc. Chem. Res.*, vol. 42, no. 7, pp. 822–831, Jul. 2009.
[21] A. Aljarbouh, "Accelerated simulation of hybrid systems: method combining static analysis and run-time execution analysis." Rennes 1, 2017.
[22] T. M. Mayhew and D. R. Olsen, "Magnetic resonance imaging (MRI) and model-free estimates of brain volume determined using the Cavalieri principle," *J. Anat.*, vol. 178, pp. 133–144, Oct. 1991.
[23] Z. Bai, R. Yang, and Y. Liang, "Mental task classification using electroencephalogram signal," *arXiv preprint arXiv:1910.03023*, 2019.
[24] Z. I. Wang *et al.*, "Voxel-based morphometric magnetic resonance imaging (MRI) postprocessing in MRI-negative epilepsies," *Ann. Neurol.*, vol. 77, no. 6, pp. 1060–1075, Jun. 2015.
[25] A. Panigrahy and S. Blüml, "Neuroimaging of pediatric brain tumors: from basic to advanced magnetic resonance imaging (MRI)," *J. Child Neurol.*, vol. 24, no. 11, pp. 1343–1365, Nov. 2009.
[26] A. Aljarbouh, "Non-standard zeno-free simulation semantics for hybrid dynamical systems," 2019, pp. 16–31.
[27] G. M. Villeirs and G. O. De Meerleer, "Magnetic resonance imaging (MRI) anatomy of the prostate and application of MRI in radiotherapy planning," *Eur. J. Radiol.*, vol. 63, no. 3, pp. 361–368, Sep. 2007.

[28] N. Houssami, R. M. Turner, and M. Morrow, "Meta-analysis of pre-operative magnetic resonance imaging (MRI) and surgical treatment for breast cancer," *Breast Cancer Res. Treat.*, 2017.
[29] R. A. Pugliesi, "Deep Learning Models for Classification of Pediatric Chest X-ray Images using VGG-16 and ResNet-50," *Sage Science Review of Applied Machine Learning*, vol. 2, no. 2, pp. 37–47, 2019.
[30] M. Rudwaleit, A. G. Jurik, and K. G. A. Hermann, "Defining active sacroiliitis on magnetic resonance imaging (MRI) for classification of axial spondyloarthritis: a consensual approach by the ASAS/OMERACT MRI …," *Annals of the*, 2009.
[31] C. K. Kuhl, S. Schrading, K. Strobel, H. H. Schild, R.-D. Hilgers, and H. B. Bieling, "Abbreviated breast magnetic resonance imaging (MRI): first postcontrast subtracted images and maximum-intensity projection-a novel approach to breast cancer screening with MRI," *J. Clin. Oncol.*, vol. 32, no. 22, pp. 2304–2310, Aug. 2014.
[32] X. Wu, Z. Bai, J. Jia, and Y. Liang, "A Multi-Variate Triple-Regression Forecasting Algorithm for Long-Term Customized Allergy Season Prediction," *arXiv preprint arXiv:2005.04557*, 2020.
[33] M. R. Torkzad, L. Påhlman, and B. Glimelius, "Magnetic resonance imaging (MRI) in rectal cancer: a comprehensive review," *Insights Imaging*, vol. 1, no. 4, pp. 245–267, Sep. 2010.
[34] N. Houssami and D. F. Hayes, "Review of preoperative magnetic resonance imaging (MRI) in breast cancer: should MRI be performed on all women with newly diagnosed, early stage breast cancer?," *CA Cancer J. Clin.*, vol. 59, no. 5, pp. 290–302, Aug. 2009.
[35] A. Aljarbouh, A. Duracz, Y. Zeng, B. Caillaud, and W. Taha, "Chattering-free simulation for hybrid dynamical systems," *HAL*, vol. 2016, 2016.
[36] M. Østergaard *et al.*, "The OMERACT Rheumatoid Arthritis Magnetic Resonance Imaging (MRI) Scoring System: Updated Recommendations by the OMERACT MRI in Arthritis Working Group," *J. Rheumatol.*, vol. 44, no. 11, pp. 1706–1712, Nov. 2017.
[37] D. Pflugfelder, R. Metzner, D. van Dusschoten, R. Reichel, S. Jahnke, and R. Koller, "Non-invasive imaging of plant roots in different soils using magnetic resonance imaging (MRI)," *Plant Methods*, vol. 13, p. 102, Nov. 2017.
[38] A. Aljarbouh, M. Fayaz, and M. S. Qureshi, "Non-Standard Analysis for Regularization of Geometric-Zeno Behaviour in Hybrid Systems," *Systems*, vol. 8, no. 2, p. 15, 2020.
[39] N. Kitayama, V. Vaccarino, M. Kutner, P. Weiss, and J. D. Bremner, "Magnetic resonance imaging (MRI) measurement of hippocampal volume in posttraumatic stress disorder: a meta-analysis," *J. Affect. Disord.*, vol. 88, no. 1, pp. 79–86, Sep. 2005.
[40] O. Sitburana and W. G. Ondo, "Brain magnetic resonance imaging (MRI) in parkinsonian disorders," *Parkinsonism Relat.*

Disord., vol. 15, no. 3, pp. 165–174, Mar. 2009.

[41] A. Chavez, D. Koutentakis, Y. Liang, S. Tripathy, and J. Yun, "Identify statistical similarities and differences between the deadliest cancer types through gene expression," *arXiv preprint arXiv:1903.07847*, 2019.

[42] M. Fatahi and O. Speck, "Magnetic resonance imaging (MRI): A review of genetic damage investigations," *Mutation Research/Reviews in Mutation Research*, 2015.

[43] A. R. Aron, T. E. Behrens, S. Smith, M. J. Frank, and R. A. Poldrack, "Triangulating a cognitive control network using diffusion-weighted magnetic resonance imaging (MRI) and functional MRI," *J. Neurosci.*, vol. 27, no. 14, pp. 3743–3752, Apr. 2007.

[44] D. Nelson-Gruel, Y. Chamaillard, and A. Aljarbouh, "Modeling and estimation of the pollutants emissions in the Compression Ignition diesel engine," 2016, pp. 317–322.

[45] R. Collins *et al.*, "Duplex ultrasonography, magnetic resonance angiography, and computed tomography angiography for diagnosis and assessment of symptomatic, lower limb peripheral arterial disease: systematic review," *BMJ*, vol. 334, no. 7606, p. 1257, Jun. 2007.

[46] G. B. C. Vasbinder *et al.*, "Accuracy of computed tomographic angiography and magnetic resonance angiography for diagnosing renal artery stenosis," *Ann. Intern. Med.*, vol. 141, no. 9, pp. 674–82; discussion 682, Nov. 2004.

[47] A. Duracz *et al.*, "Advanced hazard analysis and risk assessment in the ISO 26262 functional safety standard using rigorous simulation," 2020, pp. 108–126.

[48] F. Eckstein, F. Cicuttini, J.-P. Raynauld, J. C. Waterton, and C. Peterfy, "Magnetic resonance imaging (MRI) of articular cartilage in knee osteoarthritis (OA): morphological assessment," *Osteoarthritis Cartilage*, vol. 14 Suppl A, pp. A46-75, May 2006.

[49] A. Aljarbouh and B. Caillaud, "Chattering-free simulation of hybrid dynamical systems with the functional mock-up interface 2.0," 2016, vol. 124, pp. 95–105.

[50] A. Prasad, "Making Images/Making Bodies: Visibilizing and Disciplining through Magnetic Resonance Imaging (MRI)," *Sci. Technol. Human Values*, vol. 30, no. 2, pp. 291–316, Apr. 2005.

[51] G. Katti, S. A. Ara, and A. Shireen, "Magnetic resonance imaging (MRI)–A review," *International journal of dental clinics*, 2011.

[52] V. S. Khoo, D. P. Dearnaley, D. J. Finnigan, A. Padhani, S. F. Tanner, and M. O. Leach, "Magnetic resonance imaging (MRI): considerations and applications in radiotherapy treatment planning," *Radiother. Oncol.*, vol. 42, no. 1, pp. 1–15, Jan. 1997.

[53] J. C. Richardson, R. W. Bowtell, K. Mäder, and C. D. Melia, "Pharmaceutical applications of magnetic resonance imaging (MRI)," *Adv. Drug Deliv. Rev.*, vol. 57, no. 8, pp. 1191–1209, Jun. 2005.

[54] J. F. Schenck, "The role of magnetic susceptibility in magnetic resonance imaging: MRI magnetic compatibility of the first and second kinds," *Med. Phys.*, vol. 23, no. 6, pp. 815–850, Jun. 1996.