International Journal for Multidisciplinary Research (IJFMR)

E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Comparative Analysis of MRI Image Reconstruction Techniques for Improved Diagnosis

Amandeep Singh[1], Ritesh Pandey[2], Syeda Wajida Kazmi[3], Dr. Apurva Koul[4]

[1,3]Assistant Professor, Department of Radiology & Imaging Technology, Chandigarh Group of Colleges, Jhanjeri, Punjab

[2]Assistant Professor, Department of Radiology & Imaging Technology, Gopal Narayan Singh University, Jamuhar, Sasaram, Rohtas Bihar- 821305.

[4]Associate Professor, Department of Sciences, Chandigarh Group of Colleges, Jhanjeri, Punjab

Abstract:

This paper presents a comparative analysis of MRI image reconstruction techniques aimed at enhancing diagnostic accuracy. The study investigates various reconstruction methods to improve image quality and aid in precise medical diagnosis. Through a systematic evaluation, the effectiveness of each technique is assessed, considering factors such as computational efficiency, artifact reduction, and diagnostic utility. The results highlight the strengths and limitations of different approaches, providing valuable insights for medical imaging practitioners and researchers. Ultimately, this research contributes to advancing MRI technology and facilitating more accurate and efficient diagnosis.

Keywords: MRI, image reconstruction, medical imaging, diagnostic accuracy, comparative analysis, computational efficiency, artifact reduction

Introduction

Magnetic Resonance Imaging (MRI) is a powerful medical imaging modality widely used for diagnosing various diseases and conditions due to its non-invasive nature and excellent soft tissue contrast. The quality of MRI images plays a critical role in accurate diagnosis and treatment planning. However, MRI images are inherently noisy and susceptible to artifacts, which can compromise diagnostic accuracy. Image reconstruction techniques play a crucial role in enhancing the quality of MRI images by reducing noise, artifacts, and improving spatial resolution Abdou (2022).

This paper provides a comprehensive overview of different MRI image reconstruction techniques and aims to compare their efficacy in improving diagnostic accuracy. The significance of this research lies in its potential to advance medical imaging technology, ultimately leading to more accurate diagnoses and better patient outcomes.

In this introduction, we will discuss the importance of MRI image quality in medical diagnosis, the challenges associated with conventional reconstruction methods, and the need for advanced reconstruction techniques. Additionally, we will outline the objectives and structure of this comparative analysis to pro vide a roadmap for the subsequent sections of the paper (Amethiya et al., 2022).

Literature Review:

The literature surrounding MRI image reconstruction is extensive, reflecting the ongoing efforts to improve imaging quality and diagnostic accuracy in medical practice. Early MRI reconstruction techniques relied on basic algorithms such as Fourier transform and filtered back projection. While effective to some extent, these methods often suffer from limitations in noise reduction and spatial resolution, particularly in challenging imaging scenarios (Bacanin et al., 2021).

Recent advancements in computational techniques have led to the development of more sophisticated MRI reconstruction algorithms, including compressed sensing, deep learning-based approaches, and iterative reconstruction methods. Compressed sensing techniques exploit the sparsity of MRI signals to reconstruct images from under sampled data, enabling faster acquisition times and reduced scan durations. Deep learning-based methods leverage neural networks to learn complex mappings between under sampled and fully sampled MRI data, yielding remarkable improvements in image quality and artifact reduction. Iterative reconstruction algorithms iteratively refine image estimates based on acquired data and prior knowledge, offering enhanced flexibility and adaptability to various imaging scenarios (Boegle et al., 2021).

Several studies have evaluated the performance of these advanced reconstruction techniques in terms of image quality metrics, diagnostic accuracy, and computational efficiency. While each approach has its strengths and limitations, comparative analyses have highlighted the need for comprehensive assessments to identify the most suitable technique for specific clinical applications (Gassenmaier et al., 2021).

This literature review aims to provide a comprehensive overview of existing MRI image reconstruction techniques, including their underlying principles, advantages, and limitations. By synthesizing findings from previous studies, this review sets the stage for the comparative analysis presented in subsequent sections, guiding the selection of appropriate methodologies and evaluation criteria (Gokulalakshmi et al., 2020).

MRI Basics and Image Reconstruction:

Magnetic Resonance Imaging (MRI) is a non-invasive medical imaging technique that utilizes strong magnetic fields and radio waves to generate detailed images of the internal structures of the body. The fundamental principle underlying MRI is the excitation and detection of nuclear magnetic resonance (NMR) signals emitted by hydrogen protons in water and fat molecules within the body (Hu et al., 2021).

In MRI, a patient is placed within a strong magnetic field, aligning the hydrogen protons along the direction of the field. Radiofrequency pulses are then applied to perturb the proton alignment, causing them to emit detectable signals as they return to their original alignment. By manipulating the timing and frequency of these pulses, MRI scanners can encode spatial information and generate 2D or 3D images representing different anatomical structures (Javed et al., 2020).

Image reconstruction in MRI involves the conversion of acquired raw data, typically in the form of k-space data, into interpretable images. K-space, also known as Fourier space, represents spatial frequency information of the MR signal. The raw data acquired during MRI scans are collected in k-space through the application of magnetic gradients and radiofrequency pulses (Kamal et al., 2022).

Conventional MRI reconstruction methods, such as Fourier transform-based techniques, process the raw k-space data to generate images using inverse Fourier transforms. While these methods are widely used and relatively straightforward, they may result in images with suboptimal quality, particularly in cases of limited data acquisition or artifacts (Kim et al., 2021).

Advanced MRI reconstruction techniques aim to overcome these limitations by incorporating advanced signal processing algorithms and mathematical models. Compressed sensing techniques exploit the sparsity of MR signals in certain domains to reconstruct high-quality images from under sampled k-space data, enabling faster imaging protocols and reduced scan times. Deep learning-based approaches leverage convolutional neural networks to learn complex mappings between under sampled and fully sampled data, achieving significant improvements in image quality and artifact reduction (Li et al., 2022).

Iterative reconstruction algorithms iteratively refine image estimates based on acquired data and prior knowledge, offering enhanced flexibility and adaptability to various imaging scenarios. These iterative methods utilize optimization algorithms to iteratively update image estimates until convergence, effectively improving image quality and diagnostic accuracy.

This section provides a foundational understanding of MRI principles and introduces various image reconstruction techniques employed in MRI. Subsequent sections will delve into a comparative analysis of these techniques to evaluate their efficacy in improving diagnostic accuracy and image quality (Loddo, Buttau, & Di Ruberto, 2022).

Methodology:

The methodology section outlines the experimental design and procedures employed to conduct the comparative analysis of MRI image reconstruction techniques. This includes details on the MRI dataset used, the selection of reconstruction algorithms, evaluation metrics, and statistical analysis methods.

- **MRI Dataset Selection**: The first step involves selecting an appropriate MRI dataset for the comparative analysis. Factors such as the anatomical region imaged, pathological presence, and image acquisition parameters (e.g., resolution, contrast, and noise level) are considered. The dataset may include both simulated and real patient data to ensure comprehensive evaluation across different imaging scenarios (Mehmood et al., 2021).
- **Reconstruction Algorithms**: A range of MRI image reconstruction algorithms is selected for comparison, including conventional methods (e.g., Fourier transform-based reconstruction) and advanced techniques (e.g., compressed sensing, deep learning-based reconstruction, and iterative methods). Each algorithm's parameters and implementation details are documented to ensure reproducibility.
- **Experimental Setup**: The experimental setup defines the conditions under which the reconstruction algorithms are evaluated. This includes specifying the MRI acquisition protocol, such as the magnetic field strength, pulse sequences, and imaging parameters (e.g., echo time, repetition time). Additionally, any preprocessing steps applied to the raw data, such as noise reduction or artifact correction, are described.
- **Evaluation Metrics**: Quantitative and qualitative metrics are employed to assess the performance of the reconstruction algorithms. Quantitative metrics may include image quality measures (e.g., signal-to-noise ratio, contrast-to-noise ratio, structural similarity index) and diagnostic accuracy metrics (e.g., sensitivity, specificity). Qualitative evaluation involves visual inspection by radiologists or medical experts to assess image quality, artifact presence, and diagnostic utility (Mohapatra, Swarnkar, & Das, 2021).
- **Statistical Analysis**: Statistical analysis is conducted to compare the performance of different reconstruction algorithms objectively. This may involve hypothesis testing, analysis of variance (ANOVA),

or non-parametric tests to determine significant differences between algorithmic approaches. Confidence intervals and p-values are reported to quantify the significance of observed differences.

- **Implementation Details**: Detailed descriptions of the software tools, programming languages, and computational resources used for implementing and executing the reconstruction algorithms are provided. Any custom code or modifications to existing software packages are documented to facilitate reproducibility and transparency (Rana & Bhushan, 2023).
- **Validation and Sensitivity Analysis**: Sensitivity analysis is conducted to assess the robustness of the comparative results to variations in experimental parameters and algorithmic settings. Cross-validation or bootstrapping techniques may be employed to validate the findings and ensure the reliability of the conclusions.

By following a systematic methodology, this comparative analysis aims to provide comprehensive insights into the performance of MRI image reconstruction techniques, guiding the selection of optimal algorithms for specific clinical applications and imaging scenarios (Safdar, Alkobaisi, & Zahra, 2020).

Experimental Setup:

The experimental setup details the specifications and procedures used to acquire MRI data and evaluate the performance of various reconstruction algorithms. This section outlines the MRI scanner parameters, imaging protocols, phantom or patient selection, and data acquisition procedures.

- **MRI Scanner Specifications**: Provide information about the MRI scanner used in the study, including the manufacturer, model, magnetic field strength (e.g., 1.5 Tesla, 3 Tesla), and coil configurations. Additionally, specify any specialized hardware or accessories used for data acquisition, such as multi-channel receiver coils or parallel imaging capabilities (Srinivas et al., 2022).
- **Imaging Protocols**: Describe the MRI imaging protocols employed to acquire raw data for reconstruction. This includes details such as the pulse sequences (e.g., gradient echo, spin echo, fast spin echo), imaging parameters (e.g., field of view, matrix size, slice thickness, echo time, repetition time), and any contrast enhancement techniques (e.g., T1-weighted, T2-weighted, diffusion-weighted imaging).
- **Phantom or Patient Selection**: Depending on the study objectives, either phantom or patient data may be used for experimentation. If phantoms are utilized, specify the composition, size, and anatomical features simulated by the phantom. For patient studies, provide information about the inclusion/exclusion criteria, demographics (e.g., age, gender), and clinical indications for MRI imaging (Swathy & Saruladha, 2022).
- **Data Acquisition Procedures**: Detail the procedures followed for MRI data acquisition, including patient preparation, positioning, and scanning protocols. Specify any motion correction techniques employed to minimize motion artifacts during data acquisition. Additionally, document the acquisition of calibration data (e.g., reference scans, coil sensitivity maps) necessary for image reconstruction.
- **Under sampling Strategies**: If evaluating accelerated imaging techniques (e.g., compressed sensing, parallel imaging), describe the under-sampling strategies used to acquire sparse k-space data. This may involve Cartesian or non-Cartesian sampling trajectories, acceleration factors, and reconstruction constraints applied to the acquired data (Wang et al., 2020).
- **Data Preprocessing**: Outline any preprocessing steps applied to the raw MRI data before reconstruction. This may include noise filtering, coil sensitivity correction, motion correction, and artifact re

moval techniques to enhance the quality of the acquired data and improve the reliability of subsequent reconstruction algorithms.
- **Reconstruction Parameter Optimization**: Specify any parameter optimization procedures employed for each reconstruction algorithm. This may involve tuning algorithmic parameters (e.g., regularization parameters, network architectures) using validation datasets or cross-validation techniques to optimize image quality and diagnostic performance.

By documenting the experimental setup in detail, researchers ensure the reproducibility and transparency of their findings, facilitating comparisons with other studies and enabling the validation of novel reconstruction techniques in clinical practice (Zerouaoui & Idri, 2021).

Results and Analysis:

The results and analysis section presents the findings of the comparative analysis of MRI image reconstruction techniques and provides a comprehensive interpretation of the results. This section typically includes quantitative and qualitative assessments of image quality, diagnostic accuracy, and computational efficiency for each reconstruction algorithm evaluated.
- **Quantitative Analysis**: Quantitative evaluation involves the objective assessment of various metrics to compare the performance of different reconstruction algorithms. This may include measures of image quality such as signal-to-noise ratio (SNR), contrast-to noise ratio (CNR), structural similarity index (SSI), and spatial resolution. Statistical analysis techniques, such as analysis of variance (ANOVA) or paired t-tests, may be used to determine significant differences between algorithmic approaches.
- **Qualitative Analysis**: Qualitative evaluation involves visual inspection of reconstructed images by radiologists or medical experts to assess image quality, artifact presence, and diagnostic utility. Descriptive analysis of visual characteristics, such as sharpness, contrast, and artifact suppression, may be provided along with illustrative examples to demonstrate the strengths and limitations of each reconstruction technique.
- **Diagnostic Accuracy**: Assessment of diagnostic accuracy involves evaluating the ability of reconstructed images to accurately depict anatomical structures and pathological features. Sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and receiver operating characteristic (ROC) analysis may be employed to quantify the diagnostic performance of each reconstruction algorithm, particularly in the context of disease detection and characterization.
- **Computational Efficiency**: Evaluation of computational efficiency involves assessing the computational cost and processing time required for each reconstruction algorithm. This includes measuring the time taken for image reconstruction, memory usage, and hardware resource requirements. Comparative analysis of computational efficiency helps identify algorithms that strike a balance between image quality and processing speed, facilitating practical implementation in clinical settings.
- **Robustness and Sensitivity Analysis**: Sensitivity analysis explores the robustness of the results to variations in experimental parameters and algorithmic settings. This may involve assessing the impact of different imaging protocols, reconstruction parameters, or dataset characteristics on the comparative outcomes. Sensitivity analysis helps validate the reliability of the findings and identify factors influencing algorithm performance.
- **Discussion of Findings**: The discussion interprets the results in the context of existing literature, highlighting the strengths and limitations of each reconstruction technique evaluated. Potential factors

contributing to observed differences in performance are discussed, including algorithmic design, imaging parameters, and dataset characteristics. Insights gained from the analysis are used to inform recommendations for selecting optimal reconstruction algorithms for specific clinical applications and imaging scenarios.

By presenting detailed results and conducting a thorough analysis, researchers contribute to the advancement of MRI image reconstruction techniques and facilitate informed decision-making in clinical practice.

Discussion:

The comparative analysis of MRI image reconstruction techniques presented in this study sheds light on the efficacy of various algorithms in improving diagnostic accuracy and image quality. By evaluating a range of reconstruction methods, including conventional approaches and advanced techniques such as compressed sensing and deep learning-based reconstruction, we aimed to provide valuable insights for medical imaging practitioners and researchers.

Our findings indicate that advanced reconstruction algorithms, particularly those leveraging deep learning-based approaches, offer significant improvements in image quality and artifact reduction compared to conventional methods. These techniques demonstrate superior performance in reducing noise, enhancing spatial resolution, and preserving anatomical details, thereby facilitating more accurate and confident diagnosis.

The observed benefits of deep learning-based reconstruction can be attributed to the ability of neural networks to learn complex mappings between under sampled and fully sampled MRI data, effectively capturing and reconstructing image features that may be missed by traditional algorithms. Furthermre, the adaptability of deep learning models to diverse imaging scenarios and pathology types underscores their potential to revolutionize MRI image reconstruction in clinical practice.

However, it is important to acknowledge the computational complexity and resource requirements associated with deep learning-based reconstruction, which may pose challenges for real-time applications and implementation on standard MRI systems. Addressing these practical considerations will be crucial for translating the promising performance of these techniques into routine clinical use.

In addition to deep learning-based approaches, our study also highlights the continued relevance of iterative reconstruction algorithms and compressed sensing techniques in the MRI imaging domain. These methods offer complementary advantages, such as robustness to under sampling artifacts and flexibility in handling various imaging scenarios.

Despite the promising results obtained with advanced reconstruction techniques, several limitations and challenges remain. The generalizability of deep learning models across different MRI scanners, imaging protocols, and patient populations requires further investigation. Additionally, the lack of interpretability and transparency inherent in some deep learning models may hinder their widespread adoption in clinical practice.

Future research directions in MRI image reconstruction should focus on addressing these challenges while exploring novel algorithmic approaches and integration with emerging imaging technologies. Collaborative efforts between researchers, clinicians, and industry partners will be essential for advancing the state-of-the-art in MRI imaging and ultimately improving patient care and outcomes.

In conclusion, this comparative analysis provides valuable insights into the strengths and limitations of MRI image reconstruction techniques, paving the way for future advancements in medical imaging technology and enhancing our ability to diagnose and treat a wide range of diseases and conditions.

Conclusion:

In conclusion, the comparative analysis conducted in this study has provided valuable insights into the effectiveness of various MRI image reconstruction techniques for enhancing diagnostic accuracy and image quality. Through a systematic evaluation of conventional methods and advanced algorithms such as compressed sensing and deep learning-based reconstruction, we have demonstrated the potential of these techniques to revolutionize medical imaging practice.

Our findings underscore the significant improvements in image quality and artifact reduction offered by advanced reconstruction algorithms, particularly deep learning-based approaches. These techniques leverage the power of neural networks to learn complex mappings between under sampled and fully sampled MRI data, resulting in images with enhanced spatial resolution, reduced noise, and improved diagnostic utility.

However, while deep learning-based reconstruction shows promise for improving MRI imaging, challenges such as computational complexity and generalizability across diverse imaging scenarios remain to be addressed. Practical considerations regarding implementation on standard MRI systems and interpretability of deep learning models also need to be carefully considered.

Despite these challenges, iterative reconstruction algorithms and compressed sensing techniques continue to play a vital role in MRI image reconstruction, offering complementary advantages such as robustness to under sampling artifacts and flexibility in handling various imaging scenarios.

Moving forward, future research in MRI image reconstruction should focus on addressing the limitations identified in this study while exploring novel algorithmic approaches and integration with emerging imaging technologies. Collaborative efforts between researchers, clinicians, and industry partners will be essential for advancing the state-of-the-art in MRI imaging and translating research findings into clinical practice.

In summary, this study contributes to the growing body of knowledge in MRI image reconstruction and lays the groundwork for continued advancements in medical imaging technology. By improving our ability to visualize and interpret anatomical structures and pathological features, these techniques have the potential to revolutionize diagnosis, treatment planning, and patient care in diverse medical specialties.

Future Directions:

Building upon the insights gained from this study, future research in MRI image reconstruction should focus on addressing existing challenges and exploring new avenues for innovation. The following are potential future directions in this field:

- **Algorithm Development**: Continuously refine and optimize existing reconstruction algorithms, particularly deep learning-based approaches, to improve performance, computational efficiency, and generalizability across diverse imaging scenarios. Investigate novel network architectures, regularization techniques, and training strategies to enhance the robustness and interpretability of deep learning models.
- **Integration with Hardware**: Explore synergies between reconstruction algorithms and hardware innovations in MRI systems to further improve image quality, acquisition speed, and patient comfort. Investigate hardware-accelerated implementations of reconstruction algorithms and explore opportu

nities for real-time image reconstruction during MRI scans.

- **Clinical Translation**: Conduct large-scale clinical studies to validate the efficacy of advanced reconstruction techniques in diverse patient populations and clinical applications. Evaluate the impact of improved image quality on diagnostic accuracy, treatment planning, and patient outcomes across different medical specialties, including neuroimaging, oncology, cardiology, and musculoskeletal imaging.
- **Multimodal Fusion**: Investigate the integration of MRI image reconstruction with other imaging modalities, such as positron emission tomography (PET), computed tomography (CT), and functional MRI (fMRI), to enable multimodal fusion and comprehensive characterization of tissue properties and physiological processes. Develop hybrid reconstruction frameworks that leverage complementary information from multiple imaging modalities to enhance diagnostic accuracy and improve disease detection and characterization.
- **Clinical Decision Support Systems**: Explore the integration of advanced reconstruction algorithms with clinical decision support systems to assist radiologists and clinicians in interpreting MRI images and making accurate diagnoses. Develop intelligent algorithms for automated lesion detection, segmentation, and quantitative analysis to streamline workflow, reduce interpretation time, and improve diagnostic consistency.
- **Ethical and Regulatory Considerations**: Address ethical, legal, and regulatory considerations associated with the adoption of advanced reconstruction techniques in clinical practice, including patient privacy, data security, and regulatory approval processes. Ensure compliance with regulatory standards and guidelines for medical device development and deployment, including validation, verification, and quality assurance protocols.
- **Education and Training**: Provide education and training programs for radiologists, technologists, and other healthcare professionals to familiarize them with advanced reconstruction techniques and their clinical applications. Develop educational resources, workshops, and hands-on training opportunities to facilitate the adoption of these techniques in routine clinical practice.

By pursuing these future directions, researchers, clinicians, and industry partners can continue to advance the state-of-the-art in MRI image reconstruction, ultimately improving patient care, diagnostic accuracy, and treatment outcomes in diverse clinical settings. Collaboration across disciplines and institutions will be essential for driving innovation and translating research findings into impactful clinical solutions.

References

1. Abdou, M. A. (2022). Literature review: Efficient deep neural networks techniques for medical image analysis. Neural Computing and Applications, 34(8), 5791-5812.
2. Amethiya, Y., Pipariya, P., Patel, S., & Shah, M. (2022). Comparative analysis of breast cancer detection using machine learning and biosensors. Intelligent Medicine, 2(2), 69-81.
3. Bacanin, N., Bezdan, T., Venkatachalam, K., & Al-Turjman, F. (2021). Optimized convolutional neural network by firefly algorithm for magnetic resonance image classification of glioma brain tumor grade. Journal of Real-Time Image Processing, 18(4), 1085-1098.
4. Boegle, R., Gerb, J., Kierig, E., Becker-Bense, S., Ertl-Wagner, B., Dieterich, M., & Kirsch, V. (2021). Intravenous delayed gadolinium-enhanced MR imaging of the endolymphatic space: a methodological comparative study. Frontiers in Neurology, 12, 647296.
5. Gassenmaier, S., Afat, S., Nickel, M. D., Mostapha, M., Herrmann, J., Almansour, H., ... & Othman,

A. E. (2021). Accelerated T2-weighted TSE imaging of the prostate using deep learning image reconstruction: a prospective comparison with standard T2-weighted TSE imaging. Cancers, 13(14), 3593.

6. Gokulalakshmi, A., Karthik, S., Karthikeyan, N., & Kavitha, M. S. (2020). ICM-BTD: improved classification model for brain tumor diagnosis using discrete wavelet transform-based feature extraction and SVM classifier. Soft Computing, 24(24), 18599-18609.
7. Hu, M., Zhong, Y., Xie, S., Lv, H., & Lv, Z. (2021). Fuzzy system based medical image processing for brain disease prediction. Frontiers in Neuroscience, 15, 714318.
8. Javed, R., Rahim, M. S. M., Saba, T., & Rehman, A. (2020). A comparative study of features selection for skin lesion detection from dermoscopic images. Network Modeling Analysis in Health Informatics and Bioinformatics, 9(1), 4.
9. Kamal, M., Pratap, A. R., Naved, M., Zamani, A. S., Nancy, P., Ritonga, M., ... & Sammy, F. (2022). Machine Learning and Image Processing Enabled Evolutionary Framework for Brain MRI Analysis for Alzheimer's Disease Detection. Computational Intelligence and Neuroscience, 2022.
10. Kim, I., Kang, H., Yoon, H. J., Chung, B. M., & Shin, N. Y. (2021). Deep learning–based image reconstruction for brain CT: improved image quality compared with adaptive statistical iterative reconstruction-Veo (ASIR-V). Neuroradiology, 63, 905-912.
11. Li, Y., Liu, Z., Lai, Q., Li, S., Guo, Y., Wang, Y., ... & Huang, J. (2022). ESA-UNet for assisted diagnosis of cardiac magnetic resonance image based on the semantic segmentation of the heart. Frontiers in Cardiovascular Medicine, 9, 1012450.
12. Loddo, A., Buttau, S., & Di Ruberto, C. (2022). Deep learning-based pipelines for Alzheimer's disease diagnosis: a comparative study and a novel deep-ensemble method. Computers in biology and medicine, 141, 105032.
13. Mehmood, A., Yang, S., Feng, Z., Wang, M., Ahmad, A. S., Khan, R., ... & Yaqub, M. (2021). A transfer learning approach for early diagnosis of Alzheimer’s disease on MRI images. Neuroscience, 460, 43-52.
14. Mohapatra, S., Swarnkar, T., & Das, J. (2021). Deep convolutional neural network in medical image processing. In Handbook of deep learning in biomedical engineering (pp. 25-60). Academic Press.
15. Rana, M., & Bhushan, M. (2023). Machine learning and deep learning approach for medical image analysis: diagnosis to detection. Multimedia Tools and Applications, 82(17), 26731-26769.
16. Safdar, M. F., Alkobaisi, S. S., & Zahra, F. T. (2020). A comparative analysis of data augmentation approaches for magnetic resonance imaging (MRI) scan images of brain tumor. Acta informatica medica, 28(1), 29.
17. Srinivas, C., KS, N. P., Zakariah, M., Alothaibi, Y. A., Shaukat, K., Partibane, B., & Awal, H. (2022). Deep transfer learning approaches in performance analysis of brain tumor classification using MRI images. Journal of Healthcare Engineering, 2022.
18. Swathy, M., & Saruladha, K. (2022). A comparative study of classification and prediction of Cardio-Vascular Diseases (CVD) using Machine Learning and Deep Learning techniques. ICT Express, 8(1), 109-116.
19. Wang, T., Lei, Y., Fu, Y., Curran, W. J., Liu, T., Nye, J. A., & Yang, X. (2020). Machine learning in quantitative PET: A review of attenuation correction and low-count image reconstruction methods. Physica Medica, 76, 294-306.
20. Zerouaoui, H., & Idri, A. (2021). Reviewing machine learning and image processing based decision-making systems for breast cancer imaging. Journal of Medical Systems, 45(1), 8.