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DEEP LEARNING MODELS FOR DIGITAL MEDICAL IMAGING

***Eng. Osama Awwad Alhawawshah, Eng. Hanin Amin Al Qaraleh, Eng. Baraa'h Jalal Alzboun, Eng. Khaled Mohammad Alrousan, Eng. Mohammad Ahmad Abu Shaqra**

Medical Devices Technology Institute, Royal Medical Services, Al-Balqa Applied University, P.O. Box: 15008, Amman 11134, Jordan.

***Corresponding Author: Eng. Osama Awwad Alhawawshah**

Medical Devices Technology Institute, Royal Medical Services, Al-Balqa Applied University, P.O. Box: 15008, Amman 11134, Jordan. **DOI:** https://doi.org/10.5281/zenodo.18093504

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ABSTRACT

Digital medical imaging has become a significant revolution in modern healthcare. This technology aims to help medical staff in the early diagnosis of various diseases, support doctors in planning treatments, and assist specialists in accurately and thoroughly monitoring different diseases. Additionally, this new advancement can help radiologists write patients' reports specifically and professionally. Deep learning models, particularly Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), have demonstrated significant performance in understanding multifaceted medical images, whether for pediatric patients or adult patients. This study provides an overview of how deep learning models are provided in digital medical imaging, their assistance, challenges, and applications.

KEYWORDS: Deep Learning, Digital, Medical Imaging, Healthcare Solutions.

1. INTRODUCTION

Medical imaging technologies like X-Ray (Porto-Álvarez, Barnes et al. 2023), Computed Tomography (CT) (Dourado Jr, Da Silva et al. 2019), Magnetic Resonance Imaging (MRI) (Wang, Gong et al. 2021), and ultrasound imaging (Jamshed, Mehra et al. 2025) are important imaging modalities in clinical practice. In fact, X-ray is a form of high-energy electromagnetic radiation with a wavelength shorter than that of ultraviolet rays and longer than that of gamma rays. In like manner, CT refers to an investigative imaging procedure that employs X-rays to generate comprehensive cross-sectional images of the body, meaningfully supporting the diagnosis and treatment of numerous medical conditions. By the same token, MRI refers to a medical imaging procedure utilized in radiology to produce images of the anatomy and the physiological processes inside the body. MRI scanners utilize robust magnetic fields, magnetic field gradients, and radio waves to create images of the organs in the body. Correspondingly, ultrasound is a noninvasive imaging test that addresses structures inside the body by means of high-intensity sound waves. Healthcare providers utilize ultrasound tests for numerous determinations, including during pregnancy, for diagnosing conditions, and for image supervision throughout surgical procedures. Also, ultrasound allows healthcare providers to examine particulars of soft tissues inside the body without making any incisions. And unlike X-rays, ultrasound does not use radiation.

However, studying these medical images and taking important decisions based on them needs professional knowledge and is often time-consuming. Recently, deep learning - an advanced form of machine learning depending on artificial neural networks in which several layers of processing are utilized to extract higher-level specifications from data - has appeared to be a prevailing result for automating image analysis. In general, deep learning networks can recognize outlines and anomalies in medical images with high accuracy, frequently resembling or surpassing human experts.

This paper addresses the studies interested in the same topic in Section two, which is the "Literature Review" section. In Section three, the "Deep Learning in Medical Imaging" section, some models and important definitions are presented. Section four states deep learning applications in healthcare, especially in digital medical imaging. Section five provides some benefits and challenges of deep learning in digital medical imaging. The last section (i.e., Section six) concludes the paper.

2. Literature Review

Deep learning and its applications in medical imaging, particularly in aiding the detection and treatment of diseases, garner significant interest in contemporary literature. When faced with common diseases, deep learning models can deliver diagnostic answers at a far faster rate than professionals while maintaining consistent accuracy. (Liu, Wang et al.) analyze the present use of deep learning models in medicine and identify problems from an "input-model-output" approach. The study addresses key concerns in the medical arena, such as data quality and model. Also, the paper states that architecture design and application scope suggest refinement strategies while summarizing effective methodologies. Not only that, but also the study focuses on understudied areas such as integrating interdisciplinary expert knowledge, developing unique medical models, evolving non-solid tumor models, and establishing integrated multi-data web platforms. The paper addresses that the introduction of these potential research avenues has significant clinical and research implications, providing novel exploration pathways for future researchers and helping to address current gaps in integrated development, fostering the continuous advancement of deep learning in the medical domain.

(Gulakala and Stoffel 2025) propose a novel third-generation neural network framework, the Neuromorphic Medical Diagnostic (NMD) network, as a medical imaging diagnosis approach. The developed technique is offered as a deployable rapid diagnostic tool due to the high hit rate of 99% of the fully trained network model and low power consumption. At the same time, the dataset is utilized to evaluate the performance which allowed for extremely good accuracy and precision in distinguishing between Covid-19, pneumonia, and healthy lungs. The low prerequisites of the framework, united with extremely competent neuromorphic hardware, can enable clinical distribution of the anticipated hardware. Together with, it addresses a medical study from daily clinical practice that would be suitable to explore the planned basis in combination with the hardware. The study affords a background and a technique for overcoming the high computational and energy requirements of second-generation networks, bringing us one step closer to enabling the deployment of neural networks in medical imaging systems.

(Aslan 2019) seek to provide a broad overview of deep learning applications in digital medical imaging. Until recently, traditional machine learning methods suffered from a shortage of huge amounts of labeled data to adequately train and test learning algorithms. (Sun, Shrivastava et al.) find that using a larger dataset of 300 million photos from Google enhances algorithm performance. Also, medical image analysis lacks publicly available and tagged data. (Cho, Lee et al. 2015) explore the optimal amount of data for training an algorithm for medical image analysis. Generative models like VAEs and GANs use artificial medical data to address this issue. (Guibas, Virdi et al. 2017) use fabricated data and a two-phase segmentation method to successfully generate retinal fundus images.

As a matter of fact, major depression disorder (MDD) is a common psychiatric condition that can result in continuous melancholy and loss of interest, as well as a significant reduction in life quality. To early diagnose and treat MDD, a 3D deep learning network, 3D-DenseNet, is suggested and first deployed to the classification task for MDD and HC based on MRI data in (Wang, Gong et al. 2021). The strategy of this paper converts the 2D densely connected network into a 3D version to completely mine the feature variations in brain anatomy between MDD patients and HCs. Furthermore, a transfer learning procedure dubbed ADNI-Transfer is intended to address the issue of insufficient data. Experimental results demonstrate that the common brain lesion sites of MDD patients are where brain structure changes are considerable.

In the same way, (Seeram 2019) states that imaging informatics is increasingly commonly used in the imaging field, replacing the term medical imaging informatics. It also addresses that the Society of Imaging Informatics in Medicine (SIIM) defines imaging informatics as the use of information and communication technologies to acquire, manipulate, analyze, and distribute image data. The paper defines the indispensable machinery as the essentials of computers and communication technologies that are the basic blocks for an understanding of imaging informatics.

3. Deep Learning in Medical Imaging

Different deep learning networks automatically learn specifications from data without manual feature extraction (Zhang and El-Gohary 2021). It also deploys informed choices from massive volumes of unstructured data. Moreover, the dataset's hidden patterns and relationships are learned using an artificial neural network architecture. Deep learning necessitates a greater bulk of dataset compared to machine learning. While supervised learning models rely on structured, labeled input data to produce reliable results, deep learning models can use unsupervised learning. Deep learning models can use unsupervised learning to extract the traits, features, and relationships required to provide correct results from raw, unstructured data. Furthermore, these models can analyze and update their results for greater accuracy.

Deep learning models in digital medical imaging are mainly used for.

- Classification: The models of deep learning here play a significant role in recognizing whether an image comprises signs of a disease, like during the COVID -19 pandemic, where the deep learning models were employed to competently forecast this disease. However, classification is a supervised machine learning method in which the model attempts to predict the correct label for a given input data. In classification, the model is fully trained on training data and then evaluated on test data before being used to predict new data (Panda, Ramesh et al. 2024).
- Segmentation: Deep learning models detect and outline structures or lesions like tumors in brain MRI. It assigns a class to every pixel of the image, where the model provides much more detailed information about the image. Image segmentation supports understanding the entire mystery of the image and is a very imperative subject in image processing and computer vision. It has several claims, such as image compression and scene understanding (Liu, Song et al. 2021).
- Detection: Models associated with deep learning locate abnormalities or regions of interest such as lung nodules. It is a powerful computer vision approach for identifying and labeling things in photos, videos, and even live footage. To accomplish object detection, models are trained with many annotated visuals before being used with new data. It becomes as simple as providing input images and obtaining a completely marked-up output visual (Rana and Bhushan 2023).
- Reconstruction: Improving image quality or reconstructing images from raw data. It quickly reconstructs images with low noise, desired noise texture, and preserved spatial resolution while affording the prospect to decrease radiation dose up to 71% (Yaqub, Jinchao et al. 2022).

Many deep learning models can be used to enhance digital medical imaging. One of the most popular models is the Convolutional Neural Network (CNN). This model has three impressive layers, which are the convolutional layer, the pooling layer, and the fully connected layer (Kshatri and Singh 2023). The Recurrent Neural Network (RNN) is another deep learning model that is widely used in digital medical imaging. This model preserves a hidden state that detects data about previous inputs (Masson, Sharma et al. 2024). Long Short-Term Memory network (LSTM) is a very important deep learning model that is utilized in many healthcare applications. It is considered to avoid the long-term dependence issue. It has a cell state, input gate, forget gate, and output gate (Čepová, Elangovan et al. 2024).

Generative Adversarial Networks (GANs) have been utilized to generate representative images, videos, and audio. This deep learning model produces genuine data by training two neural networks in a competitive situation. It works via a generator network, a discriminator network, and a training process (Ali, Ali et al. 2025). Moreover, Transformer Networks (TNs) are new deep learning models that employ input data utilizing a self-attention, permitting parallelization and enhanced supervision of long-range needs. These models work using a self-attention mechanism, a positional encoding, and an encoder-decoder architecture that comprises an encoder that develops the input arrangement and a decoder that produces the output arrangement. Each contains numerous layers of self-attention and feed-forward models (Shaik, Cherukuri et al. 2024).

Autoencoders are unsupervised learning models used for applications such as data compression, denoising, and feature extraction. They learn how to encode data into a lower-dimensional representation and then decode it back to its original form. These models work using encoder, latent space, decoder, and training (Shvetsova, Bakker et al. 2021). Additionally, Deep Belief Networks (DBNs) are deep learning models that are used in digital medical imaging. DBNs are multiplicative networks composed of manifold layers of stochastic, latent parameters. They are utilized for specification withdrawal and dimensionality decrease. These models work via layer-by-layer training and fine-tuning (Lavuri, Leelashyam et al. 2025).

Deep Q-Networks (DQNs) apply deep learning with Q-learning, which is a strengthening learning process, to switch settings with high-dimensional state spaces. They have been effectively assigned duties like directing robots. These networks work using Q-learning, a deep neural network, an experience replay, and a target network (Stember and Shalu 2022). Variational Autoencoders (VAEs) are generative networks that utilize variational inference to produce new data points comparable to the training data. They are performed for generative duties and irregularity detection. These networks work using an encoder, a latent space sampling, a decoder, and a training (Dustakar, Rao et al. 2023). Furthermore, Graph Neural Networks (GNNs) simplify neural networks to graph-structured data. They are utilized for communal network investigation, molecular structure examination, and commendation arrangements. They work via a graph representation, a message passing, and a readout function (Zhang, Zhao et al. 2023).

4. Deep Learning Applications in Healthcare, Especially in Digital Medical Imaging

Incorporating deep learning has been effectively applied in several fields of healthcare. Deep learning has a very fruitful impact in the radiology field. It can be used to detect fractures and help the medical team to professionally diagnose fractured bones as well as skull fractures. Most deep learning models in radiology process two-dimensional (2D) images, even when the image datasets are three-dimensional (3D). Increased availability of medical 3D image datasets is likely to drive the evolution and optimization of 3D CNN architectures. Alternatives to 3D CNNs include combining 2D CNNs with neural networks specialized for sequence data to process successive 2D photos of a 3D volume (Cheng, Montagnon et al. 2021).

(Naik and Edla 2021) created a lung nodule classification and identification model for computed tomography (CT) images. The CT scans required a computer-aided detection system to classify the lung nodule as benign or malignant, as well as the highest level of accuracy to avoid a diagnostic delay. Deep learning approaches for categorizing lung nodules outperform other methods. When the mutations were integrated into the deep learning architecture, the classification system's accuracy improved dramatically. The deep learning method was employed to specify the new impacts in nodule classification, as well as to distinguish the preliminary stage of a malignant lesion.

One of the research hotspots in artificial intelligence and computer vision is the use of deep learning technologies to make cancer diagnoses based on medical images. Because of the rapid development of deep learning methods, cancer detection requires very high accuracy and timeliness, as well as the inherent specificity and complexity of medical imaging. MRI offers obvious advantages in identifying liver cancer, and the performance of liver cancer magnetic resonance is quite specific. Liver cancer cases show typical imaging performance features on magnetic resonance (Vasireddi, Leo et al. 2022). Magnetic resonance contains several sequences, each with a specific importance in the diagnosis of liver cancer. Magnetic resonance allows for the detection of very small liver cancer lesions (Yang, Yu et al. 2020, Shao, Wang et al. 2021). Furthermore, MRI is effective in diagnosing various types of abdominal cancer, such as pancreatic cancer and kidney cell carcinoma. MRI has the potential to be a biomarker for the diagnosis, therapy, and prognosis of renal cell carcinoma.

Likewise, segmenting target volumes and organs at risk (OARs) is a fundamental component of radiation planning. This procedure takes a large amount of physician and staff time away from patients to outline structures before dosimetry therapy planning. Accurate segmentation is heavily reliant on the underlying imaging to guide it, which opens the possibility of automating the entire process: auto-segmentation (Savjani, Lauria et al. 2022). Before deep learning, computer vision and machine learning were used to try auto-segmentation. These approaches frequently needed knowledge of image features to aid manual parameter selection, such as contrast-based thresholding, edge detector definition, or cluster determination. They tended to function well for specific datasets or patients but did not always generalize well to other centers and had an upper limit to their utility. Deep learning provided a unique approach in which parameters could be generated through data training and neural network weight optimization. Recently, an excellent study was published on the evolution of deep learning algorithms for medical imaging segmentation (Haque and Neubert 2020, Liu, Song et al. 2021).

Undoubtedly, RNNs are commonly employed in machine learning or deep learning applications that require time. Image diagnostics can utilize several time stamps to track illness progression and patient response to treatments. Most research has based its classification tasks on an RNN, which is usually combined with a CNN for the feature extraction stage. Table 1 below shows RNN applications in digital medical imaging.

Table 1: Recurrent Neural Network Applications.

Reference	**Imaging Modality**	**Task**	**CNN Feature Extraction**	**Disease**	**Model Used**
(Rajeev, Samath et al. 2019)	MRI	Classification	Yes	Alzheimer's	BGRU
(Yao, Bai et al. 2024)	Histopathological images	Classification	No	Breast Cancer	None
(Cui, Liu et al. 2019)	MRI	Classification Segmentation	No	Brain Tumor	LSTM
(Zhang and Qie 2023)	MRI	Segmentation	Yes	Aorta	LSTM
(Anbalagan and Balasubramanian 2024)	MRI	Classification Localization	Yes	Knee ligament	LSTM
(Shobayo and Saatchi 2025)	IRT	Classification	Yes	Diabetes Mellitus	LSTM
(Kim, Hong et al. 2018)	CT	Image Denoising	No	Lungs	LSTM
(Zhu, Chen et al. 2022)	MRI	Registration	Yes	Brain Cancer	LSTM

5. Benefits and Challenges of Deep Learning in Digital Medical Imaging

In this section, we will start with the benefits of deep learning. This new technology (i.e., deep learning) has a lot of advantages that add significant value to healthcare in many ways. However, deep learning in radiology has the potential to improve healthcare by enhancing diagnostic imaging and workflow efficiency. Accurate and prompt diagnosis is crucial in healthcare because it informs treatment decisions and, ultimately, improves patient outcomes. Deep learning improves radiological diagnosis accuracy and efficiency through enhanced picture processing and pattern identification. Deep learning in radiology automates processes like image interpretation, lesion detection, and classification that were previously manually handled by radiologists. Automation saves time and decreases human error, leading to more reliable diagnostic results (Khalifa and Albadawy 2024).

It is important to mention that deep learning does not replace medical experts; rather, it acts as a strong tool to supplement existing expertise and improve patient outcomes. Standardization of care is one feature that can help to improve the quality of healthcare. When various users interpret the same medical image differently, it can lead to diagnosis variability and potentially jeopardize patient care. Deep learning-powered solutions aid in the early detection of diseases by evaluating past patient data and identifying trends that may suggest potential health problems. These predictive analytics help healthcare providers initiate faster interventions, which ultimately lead to better patient outcomes and lower healthcare expenditures. Deep learning could reduce the number of examinations and lab tests by analyzing trends and patterns in patient data, allowing for more targeted and efficient testing (Meng, Li et al. 2022).

Deep learning-driven automation improves radiological workflows by automating common tasks like image preparation and report production. This automation enables radiologists to focus on complex patients, shortens reporting times, and improves overall clinical efficiency. Radiologists are focusing on deep learning workflow efficiency and automation to manage the growing complexity and amount of medical imaging data. Deep learning technologies can expedite radiology processes, increase efficiency, and improve patient care. Deep learning algorithms can automatically preprocess and enhance medical photos, resulting in higher quality and consistency. (Arafah, Khatoon et al. 2023) found that reducing the requirement for manual changes by radiologists saves time and ensures high-quality images for reliable interpretation.

Deep learning algorithms can be trained to identify and categorize various visual artifacts. This helps medical physicists determine the source of artifacts, including equipment, patient placement, and other factors. Deep learning can evaluate past quality assurance data and trends to detect performance decline or improvement over time. This information allows medical physicists to make informed judgments about equipment maintenance and calibration schedules. Deep learning can enhance patient-specific dosimetry by assessing anatomy, radiation therapy planning, and treatment delivery parameters. While deep learning has the potential to improve quality assurance in radiology, its application requires thorough validation, integration, and continual monitoring (Bejarano 2023).

Despite deep learning's enormous promise for early disease detection, various challenges must be addressed, including data privacy problems, ethical considerations, regulatory permissions, and the necessity for rigorous validation of deep learning algorithms. Collaborations among healthcare practitioners, deep learning researchers, and regulatory agencies are critical to ensuring that deep learning technologies are properly integrated into clinical practice while maintaining the highest levels of patient care and safety (Shinners, Grace et al. 2022). This recent advanced technology in radiology can improve diagnosis and workflow efficiency, leading to better healthcare outcomes.

Not forgetting that the need for large and high-quality labeled datasets is another challenge that makes deep learning face some issues while providing help to healthcare. Another issue that faces deep learning is the risk of bias due to unbalanced training data. Furthermore, the difficulty in explaining model decisions (i.e., black-box nature) is a key issue that deep learning suffers from. Also, there is an important challenge, which is the regulatory and ethical concerns that might affect the workflow of the models and networks associated with deep learning.

6. CONCLUSION

Deep learning has considerably enhanced the field of digital medical imaging, providing strong diagnostic tools that are both accurate and efficient. While problems still exist, further development and careful integration of these models into clinical procedures have the potential to change patient care. In the future, study in the medical image analysis field is anticipated to remain with tasks of prediction, content-based image acquisition, image reports or subtitle generation, manipulation of physical objects, and surgical robots.

7. REFERENCES

1. Ali, M., M. Ali, M. Hussain and D. Koundal (2025). "Generative adversarial networks (GANs) for medical image processing: recent advancements." Archives of Computational Methods in Engineering, 32(2): 1185-1198.
2. Anbalagan, V. and V. Balasubramanian (2024). "HBO-GMRNN: Honey badger optimization based gain modulated recurrent neural network for classification of breast cancer." Biomedical Signal Processing and Control, 91: 105910.
3. Arafah, A., S. Khatoon, I. Rasool, A. Khan, M. A. Rather, K. A. Abujabal, Y. A. H. Faqih, H. Rashid, S. M. Rashid and S. Bilal Ahmad (2023). "The future of precision medicine in the cure of Alzheimer's disease." Biomedicines, 11(2): 335.
4. Aslan, Z. (2019). "On the use of deep learning methods on medical images." The International Journal of Energy and Engineering Sciences, 3(2): 1-15.
5. Bejarano, A. (2023). "The benefits of artificial intelligence in radiology: transforming healthcare

through enhanced diagnostics and workflow efficiency." Rev Contemp Sci Acad Stud, 3(8): 1-4.
6. Čepová, L., M. Elangovan, J. V. N. Ramesh, M. K. Chohan, A. Verma and F. Mohammad (2024). "Improving privacy-preserving multi-faceted long short-term memory for accurate evaluation of encrypted time-series MRI images in heart disease." Scientific Reports, 14(1): 20218.
7. Cheng, P. M., E. Montagnon, R. Yamashita, I. Pan, A. Cadrin-Chênevert, F. Perdigón Romero, G. Chartrand, S. Kadoury and A. Tang (2021). "Deep learning: an update for radiologists." Radiographics, 41(5): 1427-1445.
8. Cho, J., K. Lee, E. Shin, G. Choy and S. Do (2015). "How much data is needed to train a medical image deep learning system to achieve necessary high accuracy?" arXiv preprint arXiv:1511.06348.
9. Cui, R., M. Liu and A. s. D. N. Initiative (2019). "RNN-based longitudinal analysis for diagnosis of Alzheimer's disease." Computerized Medical Imaging and Graphics, 73: 1-10.
10. Dourado Jr, C. M., S. P. P. Da Silva, R. V. M. da Nobrega, A. C. d. S. Barros, P. P. Reboucas Filho and V. H. C. de Albuquerque (2019). "Deep learning IoT system for online stroke detection in skull computed tomography images." Computer Networks, 152: 25-39.
11. Dustakar, S. R., L. K. Rao and B. Vipparthi (2023). "An automated medical image segmentation framework using deep learning and variational autoencoders with conditional neural networks." International Journal of Advanced Computer Science and Applications, 14(8).
12. Guibas, J. T., T. S. Virdi and P. S. Li (2017). "Synthetic medical images from dual generative adversarial networks." arXiv preprint arXiv:1709.01872.
13. Gulakala, R. and M. Stoffel (2025). "A sustainable neuromorphic framework for disease diagnosis using digital medical imaging." Computer Methods and Programs in Biomedicine Update, 7: 100171.
14. Haque, I. R. I. and J. Neubert (2020). "Deep learning approaches to biomedical image segmentation." Informatics in Medicine Unlocked, 18: 100297.
15. Jamshed, A., P. S. Mehra, D. Samanta, T. Gupta and B. Bhardwaj (2025). Introduction to Digital Imaging. Computer-Assisted Analysis for Digital Medicinal Imagery, IGI Global, 1-28.
16. Khalifa, M. and M. Albadawy (2024). "AI in diagnostic imaging: revolutionising accuracy and efficiency." Computer Methods and programs in biomedicine update, 5: 100146.
17. Kim, J., J. Hong and H. Park (2018). "Prospects of deep learning for medical imaging." Precision and Future Medicine, 2(2): 37-52.
18. Kshatri, S. S. and D. Singh (2023). "Convolutional neural network in medical image analysis: a review." Archives of Computational Methods in Engineering, 30(4): 2793-2810.
19. Lavuri, N. R., V. Leelashyam, B. Shankar, V. S. Kumar, N. Nallametti and G. K. Reddy (2025). Brain Tumour Identification using Deep Belief Networks: A Resilient Deep Learning Technique. 2025 7th International Conference on Intelligent Sustainable Systems (ICISS), IEEE.
20. Liu, B., X. Wang, Y. Cong, X. Cong, L. Cong, S. Tang and H. Chen "Deep Learning Models for Digital Medical Imaging: A Survey." Available at SSRN 5033167.
21. Liu, X., L. Song, S. Liu and Y. Zhang (2021). "A review of deep-learning-based medical image segmentation methods." Sustainability, 13(3): 1224.
22. Masson, P., D. Sharma, K. Yadav and T. Sethi (2024). Enhancing Medical Image Segmentation with Recurrent Neural Network Architectures. 2024 2nd International Conference on Disruptive Technologies (ICDT), IEEE.
23. Meng, Q., B. Li, P. Gao, W. Liu, P. Zhou, J. Ding, J. Zhang and H. Ge (2022). "Development and validation of a risk stratification model of pulmonary ground-glass nodules based on complementary lung-RADS 1.1 and deep learning scores." Frontiers in public health, 10: 891306.
24. Naik, A. and D. R. Edla (2021). "Lung nodule classification on computed tomography images using deep learning." Wireless personal communications, 116(1): 655-690.
25. Panda, S. K., J. V. N. Ramesh, H. Ghosh, I. S. Rahat, A. Sobur, M. H. Bijoy and M. Yesubabu (2024). "Deep Learning in Medical Imaging: A Case Study on Lung Tissue Classification." EAI Endorsed Transactions on Pervasive Health & Technology, 10(1).
26. Porto-Álvarez, J., G. T. Barnes, A. Villanueva, R. Garcia-Figueiras, S. Baleato-González, E. Huelga Zapico and M. Souto-Bayarri (2023). "Digital medical x-ray imaging, cad in lung cancer and radiomics in colorectal cancer: Past, present and future." Applied Sciences, 13(4): 2218.
27. Rajeev, R., J. A. Samath and N. Karthikeyan (2019). "An intelligent recurrent neural network with long short-term memory (LSTM) BASED batch normalization for medical image denoising." Journal of medical systems, 43(8): 234.
28. Rana, M. and M. Bhushan (2023). "Machine learning and deep learning approach for medical image analysis: diagnosis to detection." Multimedia Tools and Applications, 82(17): 26731-26769.
29. Savjani, R. R., M. Lauria, S. Bose, J. Deng, Y. Yuan and V. Andrearczyk (2022). Automated tumor segmentation in radiotherapy. Seminars in radiation oncology, Elsevier.
30. Seeram, E. (2019). "Medical imaging informatics: an overview." Digital Radiography: Physical Principles and Quality Control, 165-183.
31. Shaik, N. S., T. K. Cherukuri, N. Veeranjaneulu and J. D. Bodapati (2024). "Medtransnet: advanced gating transformer network for medical image

classification." Machine Vision and Applications, 35(4): 73.
32. Shao, Y.-Y., S.-Y. Wang, S.-M. Lin, K.-Y. Chen, J.-H. Tseng, M.-C. Ho, R.-C. Lee, P.-C. Liang, L.-Y. Liao and K.-W. Huang (2021). "Management consensus guideline for hepatocellular carcinoma: 2020 update on surveillance, diagnosis, and systemic treatment by the Taiwan Liver Cancer Association and the Gastroenterological Society of Taiwan." Journal of the Formosan Medical Association, 120(4): 1051-1060.
33. Shinners, L., S. Grace, S. Smith, A. Stephens and C. Aggar (2022). "Exploring healthcare professionals' perceptions of artificial intelligence: Piloting the Shinners Artificial Intelligence Perception tool." Digital Health, 8: 20552076221078110.
34. Shobayo, O. and R. Saatchi (2025). "Developments in Deep Learning Artificial Neural Network Techniques for Medical Image Analysis and Interpretation." Diagnostics, 15(9): 1072.
35. Shvetsova, N., B. Bakker, I. Fedulova, H. Schulz and D. V. Dylov (2021). "Anomaly detection in medical imaging with deep perceptual autoencoders." IEEE Access, 9: 118571-118583.
36. Stember, J. N. and H. Shalu (2022). "Reinforcement learning using Deep Q Networks and Q learning accurately localizes brain tumors on MRI with very small training sets." BMC Medical Imaging, 22(1): 224.
37. Sun, C., A. Shrivastava, S. Singh and A. Gupta "„Revisiting Unreasonable Effectiveness of Data in Deep Learning Era,"4 August 2017." arXiv preprint arXiv:1707.02968.
38. Vasireddi, A. K., M. E. Leo and J. H. Squires (2022). "Magnetic resonance imaging of pediatric liver tumors." Pediatric Radiology, 52(2): 177-188.
39. Wang, Y., N. Gong and C. Fu (2021). "Major depression disorder diagnosis and analysis based on structural magnetic resonance imaging and deep learning." Journal of integrative neuroscience, 20(4): 977-984.
40. Yang, J., S. Yu, L. Gao, Q. Zhou, S. Zhan and F. Sun (2020). "Current global development of screening guidelines for hepatocellular carcinoma: a systematic review." Zhonghua liu Xing Bing xue za zhi= Zhonghua Liuxingbingxue Zazhi, 41(7): 1126-1137.
41. Yao, W., J. Bai, W. Liao, Y. Chen, M. Liu and Y. Xie (2024). "From cnn to transformer: A review of medical image segmentation models." Journal of Imaging Informatics in Medicine, 37(4): 1529-1547.
42. Yaqub, M., F. Jinchao, K. Arshid, S. Ahmed, W. Zhang, M. Z. Nawaz and T. Mahmood (2022). "Deep learning-based image reconstruction for different medical imaging modalities." Computational and Mathematical Methods in Medicine, 2022; 1: 8750648.
43. Zhang, H. and Y. Qie (2023). "Applying deep learning to medical imaging: a review." Applied Sciences, 13(18): 10521.
44. Zhang, L., Y. Zhao, T. Che, S. Li and X. Wang (2023). "Graph neural networks for image-guided disease diagnosis: A review." Iradiology, 1(2): 151-166.
45. Zhang, R. and N. El-Gohary (2021). "A deep neural network-based method for deep information extraction using transfer learning strategies to support automated compliance checking." Automation in Construction, 132: 103834.
46. Zhu, K., Y. Chen, X. Ouyang, G. White and G. Agam (2022). "Fully RNN for knee ligament tear classification and localization in MRI scans." Electronic Imaging, 34: 1-6.