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Study on Machine Learning and Deep Learning in Medical Imaging Emphasizes MRI: A Systematic Literature Review

Saeed Alqahatani[1*]

[1]*Department of Radiological Sciences, College of Applied Medical Sciences, Najran University, Najran, 61441, Saudi Arabia.*

***Email:** salqahtani@nu.edu.sa*

ABSTRACT

Due to the fast growth of medical imaging technologies over the last decade, medical practitioners and radiologists find it increasingly difficult to analyze and categorize medical images. Diagnosing, surgery planning, education, and inquiry benefit immensely from the abundance of information in medical images. The objective of our study was to use Machine learning (ML), and deep learning approaches have been applied for medical image analysis; this study focuses on ML for MRI evaluation (MRI). We provide a brief overview of the advances in medical image processing and image analysis utilizing machine and deep learning, and a few related issues.
This study paper is limited to two digital databases: (1) Science Direct and (2) Google Scholar. This research report reviewed and discussed research publications. Our findings are based on a systematic literature review in which thematic analysis is done, and based on themes, we extract a comprehensive literature review on various issues, including image localization, segmentation, detection, and classification. DL approaches to analyzing brain MRI data have been extensively studied by performing a systematic review. Deep learning (DL)and machine learning techniques based on convolutional neural networks outperform traditional medical image classification, identification, and segmentation methods.

Key words: *Machine learning, Deep learning, Medical imaging, MRI*

INTRODUCTION

Medical imaging is essential for treatment planning as it provides crucial information about a patient's condition [1]. It has potential applications in the fields of education and research. Several groups, including businesses, universities, and the general public, are very interested in the recent explosion of progress in machine learning. The most current and cutting-edge solutions to computer vision, predictive modeling, and robotics challenges rely on these models. As neural networks outperformed other techniques on prestigious image analysis benchmarks, machine learning became more popular in computer vision [2].
Machine learning is feasible for integrating, analyzing, and making predictions from large, disparate data sets (health informatics) [3]. One-dimensional biosignal analysis, seizure and cardiac arrest prediction, computer-assisted detection, and diagnosis assisting in clinical decision-making, predictive modeling, drug discovery as a tool for therapy selection and improved operational efficiency [4], stratified care delivery, and analysis of electronic health records are all examples of how deep learning is used in the healthcare industry. Researchers face the difficult task of learning the concepts of physics from scratch due to a lack of relevant mathematical models. Its purpose is to adapt to data in instances where the underlying mathematical model is insufficient (think noise).

While deep learning's application to healthcare is still in its infancy, several prominent academic programs and many large companies are researching machine learning-based healthcare initiatives [5]. Companies like Google Brain, DeepMind, Microsoft, and IBM are included, as well as those in the medical technology sector. Manually analyzing medical images is a time-consuming and error-prone operation (human error). Machine learning (DL) has been demonstrated to assist several medical image processing applications such as segmentation, classification, detection, registration, biometric evaluation, and quality analysis. Nobody exceeds the accuracy of medical imaging in early cancer detection [6]. When malignant cells form in brain tissue, such as a brain tumor, the condition, caused by unregulated cell division, can spread to and affect all body regions.

Moreover, primary and secondary brain tumors exist. The repetitive process typically develops in the brain. At the same time, the second type occurs when abnormal cells spread from other organs to the brain (frequently referred to as a metastatic brain tumor). A glial cell-derived glioma is a common form of primary brain tumor. Patients with brain cancer would benefit from earlier diagnosis and treatment [7]. According to Eurostat, 1 in 10 Europeans undergo a yearly CT scan, and 1 in 13 undergo an MRI. MRI images were widely employed in earlier research.

Previous studies have classified and segmented brain tumors using supervised machine learning (ML) techniques (hand-designed features). The conventional ML approach is utilized by these methods that use feature engineering. Instead, they build a task-adapted algorithm that uses a hierarchy of more advanced capabilities to acquire knowledge about the topic. The results of DL networks were superior to those of conventional ML methods. Previous studies have shown that DL is the best data analysis strategy.

According to Zakaria *et al*. (2022), there has been an explosion in the publication of studies on the issue of automatically identifying and segmenting brain tumors. DL has been successfully implemented in several settings and is now considered a state-of-the-art technique for medical image analysis. The analysis of brain images is a common application for deep neural networks (DNNs). According to the literature, most image analyses are performed by DNNs [8].

The research question

This systematic review began with formulating a research question and then identifying existing literature on medical imaging analysis by machine learning. Then, a data search was conducted to narrow the search toward finding relevant evidence. In this systematic review approach, asking the right research question is imperative for MRI through the lens of machine learning and deep learning. The initial search results will be screened against defined inclusion and exclusion criteria, focusing on the topic under review [9]. The selected evidence will be critically reviewed and synthesized to find themes used to inform recommendations.

The CIMO framework was used to guide the understanding of the problem under consideration to design a research question. The CIMO comprises context, intervention, process, and outcomes.

The context or population of interest is MRI. The intervention that will be explored the medical image analysis and machine learning. The mechanism is the systematic review of research studies collected across several databases relevant to MRI. The desired outcome is to answer the research questions is to provide evidence.

Based on the CIMO framework in **Figure 1**, the research question for this systematic review is:

"How Machine learning and deep learning have been applied to the entire process of medical image analysis focusing on MRI."

Literature review

Deep learning, medical imaging, and MRI

Abdou *et al*. (2022) discussed that deep learning has a vast and growing list of applications in clinical practice. We will not attempt a comprehensive analysis of deep learning in medical imaging before moving on to a more organized discussion of deep learning in MRI. Convolutional neural networks can be utilized to improve the efficiency of radiology practices by selecting protocols depending on how short texts are arranged [3]. Bharati (2022) is another critical application in advanced deformable picture registration [9].

Currie *et al*. (2019) discussed that this is just one of many minor medical imaging problems that deep learning may help [10]. Zakaria *et al*. (2022) focused on considering the field of MRI scanning, where deep learning is widely used, from taking an image to gathering, sorting, and recognizing medical data about a patient [8].

Castiglioni *et al*. (2021) evaluated that in MRI, deep learning is typically used to segregate and sort reconstructed magnitude images from photographing to registering them. It made its way into the lower levels of the MRI.

MRI fingerprinting involves taking MRI images, processing the signals, reducing noise, enhancing resolution, and synthesizing the images [11].

Image registration

Datta *et al*. (2019) elaborated that image registration is becoming more critical in MR. Image registration tasks have typically been split along numerous axes, such as prospective versus retrospective image registration, geometry versus intensity, rigid versus deformable, intra versus inter-modality, intra versus inter-subject, etc. Registering is a complex mathematical problem since it requires knowledge from numerous domains [12].

Image registration is assembling two images so that the same anatomical points are shown in the same place in each image. One definition of image registration suggests that it is "the process of finding a one-to-one mapping between the coordinates in one space and those in another." Deep learning algorithms are now used to make image registration faster and more accurate [13].

MATERIALS AND METHODS

This section focuses on the technique utilized in this research and highlights the significance of an evidence-based framework as the research method's basis. An evidence-based research approach collects and critically examines relevant literature to gain new knowledge or corroborate prior findings for better decision-making. The evidence-based research technique is used to answer the following research questions:

"How Machine learning and deep learning have been applied to the entire process of medical image analysis focusing on MRI.?"

This study explains limiting the research to only papers addressing the study issue. This section also discusses the inclusion and exclusion criteria and the quality assessment utilized to access the study. This study collects relevant literature, conducts a critical review, summarises and analyses data, and identifies emergent themes using an evidence-based research strategy**.**

Systematic reviews are essential to evidence-based practice because they identify, assess, synthesize, and report the best available data. Systematic reviews are required for policymakers, scholars, and practitioners who need the most recent and relevant research findings. The rigor and transparency of the overall review process demonstrate the benefits of the systematic review technique. Systematic reviews seek, evaluate, and synthesize empirical material that meets established qualification criteria to answer a research problem. The following are the steps of the systematic review process:

- The research question that can be answered.
- Find and read any relevant literature.
- Search and evaluate the results for inclusion by predefined criteria.
- Extract relevant data and information using the quality evaluation procedure.

The evidence-based research method was directed toward answering the question by creating a research question using the CIMO framework.

Context: MRI

Intervention: Medical Image Analysis and Machine Learning

Mechanism: Systematic Review of Evidence Relevant to Medical image analysis

Outcomes: Medical Image analysis by Machine Learning

Search strategy

A systematic review includes evidence searches and retrieval and is critical in accumulating relevant articles to address the research question. The search approach included keywords and concepts to gather relevant studies, which were evaluated for quality.

Search process and terms

A database search was carried out using different library resources and external databases. A search string was generated to retrieve the relevant search results for the research question. A search string comprises keywords, truncation symbols, and Boolean operators that the user enters to discover the best search result. Every research study aims to find relevant results that can be filtered using specified delimiters and filters. The researcher can use Boolean Logic to narrow or broaden the scope of the study. Boolean Logic employs three operators- OR, AND, and NOT to connect words and phrases in the search string. In Boolean Logic, "AND" narrows the search results, "OR" allows for a more broad search, and "NOT" rejects any publication that contains a specified search word. "OR" produces a comprehensive search in Boolean Logic. At the same time, "AND" gives a defined search, while "NOT" excludes any publication that contains a certain search word. The search string comprised keywords and concepts from the study question, such as Machine Learning, Deep Learning, MRI, and Medical image analysis. (Machine Learning* OR Deep Learning OR MRI* OR Medical Image OR "analysis*") AND systematic Review (ML* OR MRI*).

Inclusion and exclusion criteria

A set of criteria" was used to guide the search and keep the thematic emphasis on the search process. The results of searches in the OneSearch library and Google Scholar included scholarly peer-reviewed journals, business periodicals, articles about Machine learning and MRI, and other scientific material. The initial phase of the search involved concentrating on MRI, machine learning, deep learning, and exploitation of the Medical image analysis. After that, the search was limited to articles released between 2015 and 2022. This period was selected to contain current and essential information on the issue.

Method of quality appraisal of the included studies

Weight of Evidence is a tool for evaluating the quality of research evidence to make qualitative judgments based on the available evidence, quality evaluation, and application of the findings. The final selected publications were evaluated for rigor, transparency, and bias using Weight of Evidence (WoE) and TAPUPAS quality evaluation procedures. The WoE grading system assigned each article a score ranging from high to low based on the following criteria received high marks, while nine obtained mediocre marks.

Weight of evidence (WoE) procedures were developed due to judicial decisions to conclude from highly varied sources of evidence in various sectors. While making an evidence-based decision, the weight of the evidence is demonstrated by meticulously connecting numerous pieces of information to the supporting aspects of the premise. Applying the WoE can increase the consistency, accuracy, and transparency of WoE methods compared to ad hoc and narrative-based techniques.

To evaluate ten articles, the Transparency, Accuracy, Purposefulness, Utility, Purpositivity, Accessibility, and Specificity (TAPUPAS) technique was utilized. The articles were critically examined using the TAPUPAS criteria, and scores ranging from 1 to 3 were assigned for each criterion, with 3 representing the highest standards met, 2 representing the majority of standards met with no flaws, and 1 representing some standards met with flaws discovered but not compromising the evidence. The total TAPUPAS score was calculated by adding the individual scores.

The TAPUPAS criteria mentioned were used to evaluate the various research initiatives. The appropriateness, transparency, and degree of rigor are considered for quality evaluation.

PRISMA diagram

A Preferred Reporting Item for Systematic Reviews and Meta-Analyses (PRISMA) diagram depicts a possible evidence search progression from the first stage to the final selection of relevant studies. The PRISMA flow diagram illustrates the flow of search information through the various stages of a systematic review, including the number of records detected, included, and excluded and the reasons for exclusions. The PRISMA flow chart depicts the search for data in databases and other primary and secondary sources during the identification stage of the search process.

Google Scholar yielded a total of 3335 articles. This comprised 2500 papers from the OneSearch collection and 835 items from Google Scholar, both of which were accessible for this review. After duplicates were removed, the results were reduced to 335 peer-reviewed articles published between 2015 and 2022. The PRISMA diagram ** sign denotes the route or path's end. Exclusion criteria resulted in the exclusion of 135 articles. The abstracts of the remaining 200 results were then analyzed, decreasing the number of publications to 80 and eliminating 120 based on the abstract. The 80 full-text scholarly publications were evaluated for qualitative review eligibility and relevance to the study topic; 70 articles were removed. The critical evaluation for this study includes the final 10 papers.

Figure 1 depicts the PRISMA flow diagram, which shows the procedures from article identification to final quality evaluation selection.

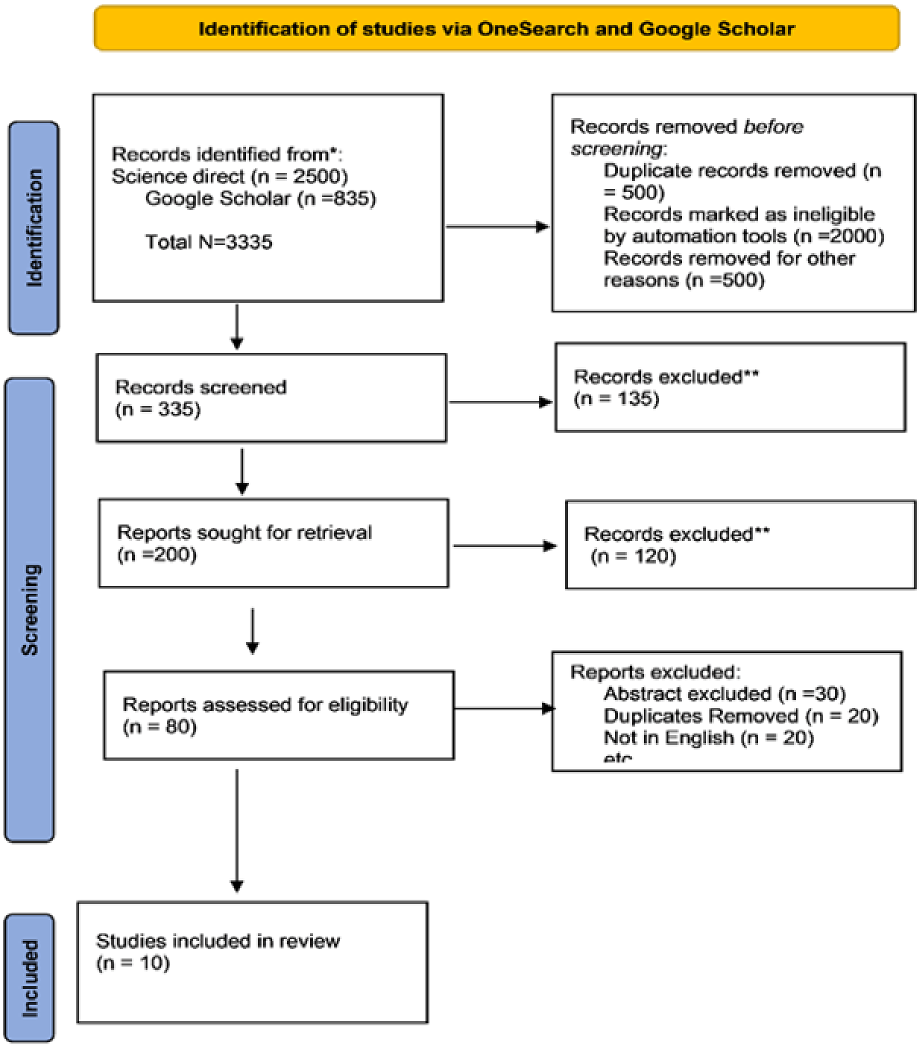

Figure 1. PRISMA Flow Diagram

Tools utilized for data management and qualitative synthesis

Mendeley Reference Manager, a free web and desktop tool, allows users to store, organize, and search for references from any library. Mendeley Reference Manager was used to categorize all the studies chosen for inclusion in this analysis. To reference and cite studies, Mendeley Reference Manager was also used. The Mendeley Reference Management library has to be subsequently exported to ATLAS.ti. ATLAS.ti performs qualitative analysis on large text databases. This study's qualitative data analysis was organized using Google Drive and Microsoft Excel.

Analysis and synthesis methodology

The thematic synthesis method was used in this analysis. The primary purpose of this research was to analyze, assess, and synthesize the articles based on the themes revealed in the results. Hence the thematic synthesis approach was suitable.

Data extraction

The process of determining the essential components of each article included in the qualitative synthesis is known as data extraction. The study's primary components were the title, author, publication year, and findings. The findings contained the sections of the original research that addressed the research question. The information extracted from the data aided in the data synthesis and analysis of the findings. For the data extraction table, see sample table for one article below **(Table 1)**:

Table 1. Article Data

Article: **Author:** Al-Galal *et al*.	**Publication date:** 2021	**Research design:** Systematic Review.	**Sector Population:** Healthcare
Sample size: n – 18	**Level of confidence(quality)** A	**Effect size** High	**Outcome Measures:** Qualitative image analysis
Main findings: Al-Galal *et al*. (2021) examined that image segmentation, the process of dividing an image into parts with similar properties, is the peak of qualitative image analysis because it allows for localization and measurement.			

Coding process

Coding is the labeling and organization of qualitative data to identify themes and relationships between research articles. A descriptive approach was utilized to create codes. Descriptive coding is a first coding cycle approach that involves reading qualitative data and categorizing that data into sections by content. Descriptive codes are often in the form of a word or phrase which captures the article's essence. This study's thematic synthesis involved developing themes by systematically analyzing articles that passed a quality evaluation. These themes emerged from the coding of the articles. The codification process required identifying level one codes, level two descriptive themes, and level three analytical themes.

The diagram below **(Figure 2)** illustrates the thematic synthesis steps.

Figure 2. Cloud form of coding from Atlas.ti

The codes are:

1. Machine Learning 2. Detection
3. Deep Learning 4. Image Localization
5. MRI 6. Classification
7.Segmentation 8. Disease Prediction
9. Medical Imaging 10. Image Registration

The 11 open codes were combined into two themes as two-level descriptive themes. **Table 2** depicts how to open codes were connected to establish a related category or level two descriptive themes.

The level two descriptive themes were produced. These descriptive themes indicated that data was not coded but re-coded to construct core categories based on linked open concepts.

The reassessment of the level two descriptive and their relationship to one another provides the framework for constructing thematic or selective codes. While previous coding cycles consisted of detecting text or short phrases with similar general ideas, thematic coding reflects a topic recognized in more than one study. It may be further enhanced or restricted in its abstract. The level three analytical in this study comprised three themes. Correlating integrating these essential concepts into a common theme resulted in these two areas of interest.

The initial 11 codes and three descriptive themes summarized to form two analytical themes for the study were the followings:

1. From Image Segmentation to Diagnosis and Prediction
2. Content-Based Image Retrieval

RESULTS AND DISCUSSION

This section discusses the relevance of the level three analytical themes to the research question. Thematic synthesis of coding is given below in **Table 2**.

Table 2. Thematic synthesis of coding

Level One Coding	Level 2 Descriptive Themes	Level Three Analytical Themes
1. Machine Learning 2. Image Localization 3. Image Segmentation		
	Machine Learning and Image Segmentation	
4. MRI 5. Prediction 6. Diagnosis 7. Deep Learning		From Image Segmentation to Diagnosis and Prediction
	MRI Prediction, diagnosis, and Deep Learning	
8. Disease prediction 9. Image Retrieval		Content-Based Image Retrieval
	Content-based retrieval of Medical Imaging and Disease Prediction	
10. Content-Based 11. Medical Imaging		

Theme 1: From Image Segmentation to Diagnosis and Prediction

Image segmentation, the process of dividing an image into parts with similar properties, is the peak of qualitative image analysis because it allows for localization and measurement. It's been 50 years, and deep-learning techniques are now used to improve medical imaging. Multispectral tissue classification, which used statistical pattern recognition techniques, was one of the most prominent research studies that opened the way for using machine learning in medical image segmentation today (and NASA satellite image processing software) [14]. We had the opportunity to contribute during this critical period by using supervised and unsupervised machine-learning algorithms for tissue categorization and MR image segmentation. Deep learning techniques like CNNs are increasingly utilized in MR picture segmentation software [15].

Since training deep learning models on medical imaging datasets is challenging because they're frequently unbalanced and have few unexpected results, these image synthesis generative models can disguise identities and improve current datasets. When the authors segmented tumors using synthetic data instead of clinical samples for training, they discovered comparable findings. In a related endeavor, coarse-to-fine GANs were applied to segment brain cancers. To handle the retinal fundus images, the researchers deployed a pair of GANs, a two-stage pipeline, and a web-based repository (SynthMed) to develop synthetic medical images.

Theme 2: Content-Based Image Retrieval

In radiology, content-based image retrieval (CBIR) aims to show similar medical images to a specific image to assist physicians in making decisions. Algorithms that rapidly and accurately match and retrieve the most similar images and annotations from a sample database are frequently used. Standard tools include large case databases, innovative image representations, disease diagnoses, and disease classification. For many years, medical imaging researchers have been actively investigating many different elements of CBIR, including its numerous applications, imaging modalities, organs, and methodological approaches.

Deep learning and Machine learning techniques have also been used to apply CBIR on a larger scale outside of the medical area at organizations such as Microsoft, Apple, Facebook, and Google (reverse image search). In 2015, a Network was trained to perform CBIR using a dataset of over a million randomly selected MRI and CT images. However, the results were inadequate when evaluated on a separate test set of labeled images (the true positive rate was 20%). In terms of CBIR, this was one of the first medical-related applications of deep learning. On the other hand, deep learning algorithms have recently become the industry standard in medical CBIR. Pizarro *et al*., for example, created a convolutional neural network (CNN) to automatically estimate the contrast of MRI scans based on the visual intensity of several segments. Deep learning approaches have recently been used to automate the preparation of radiological reports. These methods frequently use long short-term memory (LSTM) network models to index over 30 billion images [11].

Machine learning in medical imaging requires open science and rigorous research. Machine learning progress is currently exceeding the capabilities of the traditional peer-review process. Even if their discoveries are widely publicized and incorporated into the work of other researchers, many of the most recognized and influential works in machine learning released in the preceding few years are only available as preprints or in conference proceedings. There are, of course, costs to not submitting work for peer review. Nonetheless, researchers' willingness to share code and data helps to reduce these challenges.

Many relevant data sets are available for free download from various web databases. This establishes the framework for a large-scale machine-learning project. Competitions have also arisen as a fascinating part of modern machine learning and data science, with the ImageNet ILSVRC competition driving progress in deep learning for computer vision since 2012. Each competition attracts many competitors, and state-of-the-art outcomes frequently advance. Competitions not only stimulate new ideas but also, serve as simple entry points into the world of modern machine learning. It's fascinating to see deep learning-based models completely dominate all image-based competitions. Other models or approaches that attempt to replicate machine learning's performance but fall short have been mainly surpassed by machine learning itself.

Challenges, limitations, and future perspectives

Deep neural networks outperform when making informed decisions based on vast, complex datasets. Yet, they come with essential limits that researchers must work with. Some are more general, such as issues caused by excessive hype and excitement and technical difficulties caused by a lack of mathematical and theoretical foundations for many central deep learning models and techniques, making it difficult to determine precisely what makes one model superior to another. Some are more generalists, while others specialize in a specific topic. In recent years, deep learning has developed robust models and a set of best practices for typical computer vision applications such as object detection and localization. While work is still being done rapidly, numerous issues have been temporarily resolved [15].

Another problem is that medical images are often in 3D, although 2D convolutional neural networks have matured to compete with their 3D counterparts. Researchers are developing several solutions to the memory and computation consumption issues that arise when utilizing CNNs on higher-dimensional image data. Cutting-edge 2-D graphics CNNs can be extended to three dimensions, but adding a third spatial dimension presents new limitations.

Deep learning for medical data analysis is here to stay. Although deep learning is employed in the medical industry, it has a long way to go before it can be used effectively in the treatment of patients. Several high-impact studies on deep learning in medical imaging that have appeared in peer-reviewed publications provide evidence. When researchers and practitioners gain more knowledge of machine learning, it will be easier to classify problems according to the most appropriate technique for resolving them [8].

It is best to use deep learning methods throughout, and it is even better to combine deep learning with other methods. Considering the current emphasis on machine learning in medical imaging, we provide a way for medical academics and practitioners to share computational ideas.

CONCLUSION

DL approaches that analyze brain MRI data have been extensively studied by performing a systematic review. Deep learning(DL) and machine learning techniques based on convolutional neural networks outperform traditional medical image classification, identification, and segmentation methods. When it comes to DL approaches, a common cause of the challenge is a lack of data or labels, which can be solved via methods like data augmentation and classification techniques. However, the resources gathered for this study are expected to be used for various issues. DL is predicted to continue actively processing MRI images of brain tumors and CT scans.

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REFERENCES

1. Singh GP, Attavar SH, Kavuri S. Application of cone-beam computed tomography in diagnosis and treatment of multiple canals- A case report. Ann Dent Spec. 2022;10(2):15-8.
2. Al-Galal SA, Alshaikhli IF, Abdulrazzaq MM. MRI brain tumor medical images analysis using deep learning techniques: a systematic review. Health Technol. 2021;11:267-82.
3. Abdou MA. Literature review: efficient deep neural networks techniques for medical image analysis. Neural Comput Appl. 2022;34(8):5791-812.
4. Wal A, Wal P, Verma N, Srivastava A, Rai AK, Kosey S. A Comprehensive Review of Irritable Bowel Syndrome Screening Models for Drug Research and Development. Pharmacophore. 2022;13(2):17-25. doi:10.51847/jC8Hjh9XUF
5. Dal MB. Surgical Treatment Results in Obstetric and Iatrogenic Anal Sphincter Injuries. Arch Pharm Pract. 2022;13(1):58-60. doi:10.51847/2IkoQrhZDJ
6. Nath SG, Raveendran R, Perumbure S. Artificial Intelligence and Its Application in the Early Detection of Oral Cancers. Clin Cancer Investig J. 2022;11(1):5-9. doi:10.51847/h7wa0UHoIF
7. Arikawe O, Morrissey H, Ball P. Community pharmacy brief screening intervention to improve health outcomes for patients diagnosed with chronic diseases. J Adv Pharm Edu Res. 2022;12(3):1-8. doi:10.51847/bmamIaRVB8
8. Zakaria R, Abdelmajid H, Zitouni D. Deep Learning in Medical Imaging: A Review. Appl Mach Intell Eng. 2022:131-44.
9. Bharati S, Mondal M, Podder P, Prasath VB. Deep learning for medical image registration: A comprehensive review. arXiv preprint arXiv:2204.11341. 2022.
10. Currie G, Hawk KE, Rohren E, Vial A, Klein R. Machine learning and deep learning in medical imaging: intelligent imaging. J Med Imaging Radiat Sci. 2019;50(4):477-87.
11. Castiglioni I, Rundo L, Codari M, Di Leo G, Salvatore C, Interlenghi M, et al. AI applications to medical images: From machine learning to deep learning. Phys Med. 2021;83:9-24.
12. Datta P, Rohilla R. An Introduction to Deep Learning Applications In MRI Images. In2019 2nd International Conference on Power Energy, Environment and Intelligent Control (PEEIC) 2019 Oct 18 (pp. 458-465). IEEE.
13. Jyothi P, Singh AR. Deep learning models and traditional automated techniques for brain tumor segmentation in MRI: a review. Artif Intell Rev. 2023;56(4):2923-69.
14. Murtaza G, Shuib L, Abdul Wahab AW, Mujtaba G, Mujtaba G, Nweke HF, et al. Deep learning-based breast cancer classification through medical imaging modalities: state of the art and research challenges. Artif Intell Rev. 2020;53:1655-720.
15. Renard F, Guedria S, Palma ND, Vuillerme N. Variability and reproducibility in deep learning for medical image segmentation. Sci Rep. 2020;10(1):1-6.