The Research of Medical Science Review

Received: 06 October, 2024
Accepted: 06 November, 2024
Published: 19 November, 2024

ISSN: 3007-1208 | 3007-1216
Volume 2, Issue 3, 2024

ROLE OF ARTIFICIAL INTELLIGENCE IN MEDICAL IMAGING: A SYSTEMATIC REVIEW

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ABSTRACT

This scholarly article provides a thorough overview of medical imaging modalities and their various uses in segmenting and classifying diseases using artificial intelligence (AI).This study provide a systematic review of research articles that use AI approaches to investigate illness classification and segmentation in various anatomical locations. Each article's results are carefully examined as part of the study, which also identifies new trends and extracts key insights. Additionally, the study provides a critical discussion of the difficulties observed in these investigations, including problems with quality and availability of data, generalization of the model, and interpretability. The objective of this study was to perform a systematic review of research publications that use AI approaches to investigate medical imaging, A database search was conducted using five online databases, including Web of Science, Scopus, Science Direct, Google Scholar, and Semantic Scholar, to identify relevant primary research on medical imaging and AI, using Boolean operators, The analysis emphasizes how important hybrid approaches are for obtaining meaningful and successful outcomes across a range of disease types. These approaches smoothly combine systematic procedures. Future research prospects in the field of medical diagnosis are made possible by the promising potential of these hybrid models. Furthermore, future research efforts should prioritize addressing the difficulties caused by the scarcity of annotated medical pictures by utilizing medical image synthesis and transfer learning approaches.

Keywords: *artificial intelligence (AI), medical imaging, classification, detection, segmentation*

INTRODUCTION

With medical imaging, doctors may now diagnose and treat a wide range of disorders with greater clarity and understanding of the human body. With the development of multiple imaging modalities, such as magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography (PET), and X-ray imaging, physicians now have access to high-resolution, high-quality images that can provide important information about physiological processes and anatomical structures [1]. However, radiologists and other medical practitioners are facing tremendous hurdles due to the growing availability and complexity of medical imaging data. Medical picture interpretation is a laborious and intricate process that calls for a high degree of skill and

substantial training. Furthermore, it may be difficult to identify minute alterations that could point to the existence of a disease due to the overwhelming amount of imaging data generated.
AI-based medical imaging can enable more precise and effective illness identification, segmentation, and classification, which could completely transform the sector. Large volumes of medical imaging data can be analysed by AI algorithms, which can then spot minute changes that can point to a disease. AI-based algorithms have demonstrated impressive performance in the identification of early-stage tumors from medical imaging, including brain, lung, and breast cancer [2, 3, 4]. Furthermore, precise diagnosis and treatment planning are made possible by the ability of AI-based segmentation and classification [5, 6, 7] approaches to precisely identify regions of interest and characterize anatomical structures [8]. Although AI-based medical imaging holds great promise, a number of issues need to be resolved before these methods can be extensively used in clinical settings. The standardization of imaging methods is a crucial task since the consistency and quality of medical pictures can be greatly impacted by differences in imaging parameters [9]. Furthermore, the creation and verification of AI models may be hampered by the scarcity of labelled data. Data security and patient privacy are ethical issues that need to be properly considered.

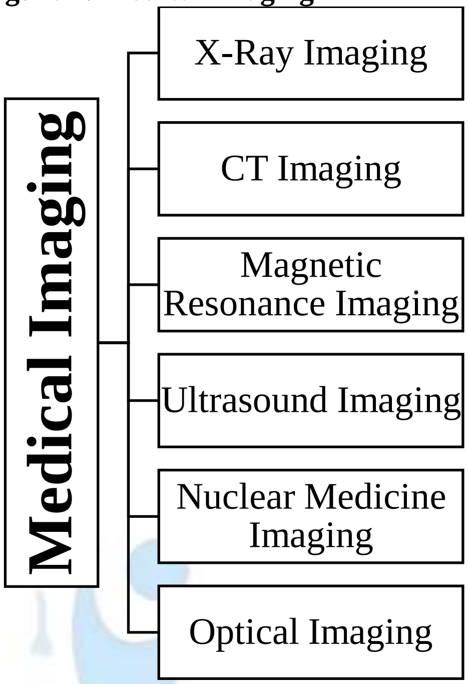
RESEARCH OBJECTIVES

The objective of this study was to perform a systematic review of research publications that use AI approaches to investigate medical imaging.

MEDICAL IMAGING

For the purposes of diagnosis and therapy, medical imaging entails the use of a variety of technologies and procedures to provide visual representations of the internal structures and functions of the human body [10]. It is a vital instrument in contemporary medicine, allowing physicians and other medical specialists to identify and diagnose a broad variety of illnesses and ailments. Medical imaging comes in several forms, such as nuclear medicine imaging (Figure 1), ultrasound, CT, MRI, X-ray, and optical imaging [11]. Each of these methods has benefits and drawbacks of its own, and based on the particular requirements of the patient and the healthcare professional, they can be applied to different imaging studies.

Figure 1: Medical Imaging



X-Ray Imaging

A strong method for non-invasively inspecting materials and things is X-ray imaging. With this imaging technique, X-rays are used to enter the item and, depending on the object's different levels of X-ray absorption, an image is produced [12]. Attenuation coefficient and contrast resolution are two important characteristics of the object being imaged that are provided by X-ray imaging. Digital imaging and communications in medicine, or DICOM, TIFF (tagged image file format), and JPEG (joint photographic experts' group) are a few of the formats in which x-ray pictures can be saved [13]. A transformative age in disease categorization and segmentation has begun with recent developments in X-ray imaging. Through the smooth integration of cutting-edge computational techniques with the characteristics of X-ray imaging, the field has made remarkable strides that have led to improved diagnostic accuracy and sophisticated understanding.
Especially, [14] led a critical breakthrough in segmentation by fusing X-ray data with convolutional neural networks (CNNs). This ground-breaking work changed the paradigm and

had a profound impact on the diagnosis and treatment of pulmonary disorders by redefining the precision of lung tissue segmentation in chest X-rays. This accomplishment establishes the groundwork for customized therapeutic interventions by utilizing CNNs' discriminative potential. Simultaneously, novel approaches have led to a rebirth in the classification of diseases. demonstrated how adversarial networks may revolutionize soft tissue segmentation accuracy and usher in a new era of structural distinction with care. To broaden these perspectives, [16] presented ensemble techniques that integrate X-ray pictures, producing incredibly precise classification results for different bone diseases and improving diagnosis comprehension. Moreover, X-ray imaging convergence using multimodal data has become a potent strategy.

Especially, [17] perfectly captured this synergy by fusing X-ray pictures with complementary imaging modalities, demographic data, and clinical profiles. This thorough method surpasses conventional classification paradigms, increasing diagnostic precision and offering new perspectives on the intricate structure of disease pathology. [18] made a daring step in leading the way in the integration of electronic health data and X-ray images, resulting in a single framework that improves disease classification and prognosis. This novel approach improves predicted accuracy by utilizing extensive patient profiles, which opens up possibilities for pre-emptive interventions and individualized patient care plans.

Computed Tomography Imaging

With the use of sophisticated computer processing and X-rays, computed tomography imaging is a medical imaging technique that produces incredibly detailed cross-sectional images of the human body. CT imaging provides important details about bones, organs, and soft tissues, giving important insights into the internal structures of the body [19]. CT imaging is characterized by three main features: temporal, contrast, and spatial resolution. CT images are usually kept in digital format, which comes in a variety of file formats. DICOM and NIfTI (neuroimaging informatics technology initiative) are two of the most widely used formats [20].

Numerous significant studies have been conducted in the field of CT imaging, which includes difficult tasks such illness segmentation and classification. Interestingly, [21] is a prime example that shows how deep learning techniques may effectively segment pulmonary nodules in CT images. This innovative work shows that nodular entities with different morphological subtleties and densities can be identified. Simultaneously, [22] provides a paradigmatic framework for integrating PET and CT imaging modalities, which leads to improved tumour grading details and cerebral neoplasm classification. Cardiovascular diagnostics has come a long way because of the ground-breaking work of [23]. They have automated the segmentation of cardiac structures in CT angiography, which is essential for precise diagnosis, by using deep learning algorithms.

A groundbreaking hybridized construct specifically designed for liver lesion segmentation in abdominal CT imaging is put forth by [24]. This architecture skilfully combines boundary-centric and region-based paradigms to provide results with strong integrity. This work, which adds even more richness to the tapestry [25], lays out a novel approach for the deep learning-based identification and categorization of cerebral hemorrhage in head CT scans. It seeks to offer quick and precise identification between various kinds of haemorrhages. The novel lung segmentation approach described by [26] for CT scans improves on later disease-specific analysis through the use of an anatomically guided and contextually aware framework. Meanwhile, [27] improves the situation by using a cascaded deep learning model that combines lesion segmentation and classification in a seamless way, increasing the accuracy of liver lesion diagnoses.

Ultrasound Imaging

High-frequency sound waves are used in ultrasound imaging, a non-invasive medical imaging technique, to create images of inside body structures [28]. Many characteristics, such as frequency, wavelength, resolution, penetration depth, and picture contrast, define ultrasound imaging. A variety of formats, including DICOM, JPEG, PNG, and BMP, are available for the storage and transmission of ultrasound images [29]. Considerable advancements have been made in the segmentation and classification of diseases in ultrasound imaging. [30] markedly improved clinical diagnostic accuracy by introducing a novel deep learning-based methodology specifically intended for the precise segmentation of liver lesions on ultrasound images. In accordance with this, [31] suggested a method based on graph-cut techniques that produced reliable kidney tumour segmentation outcomes in ultrasound scans.

Tumor border delineation accuracy is improved by this method. Simultaneously, [32] made progress in the realm of cardiac ultrasound by putting out an automated technique that makes the process of left atrial segmentation easier. When diagnosing atrial diseases, this is an important consideration. In the discipline of obstetrics, [33] put out a novel paradigm that blends generative adversarial networks and convolutional neural networks. This novel method improves fetal ultrasound image segmentation and offers insightful information for assessments of the health of the fetus. [34] went into musculoskeletal examinations by broadening the scope. A method for classifying abnormal characteristics in joint ultrasound images has been developed that combines texture analysis and machine learning. This methodology offers a non-invasive method for the assessment of musculoskeletal conditions.

Nuclear Medicine Imaging

Trace levels of radioactive materials are used in nuclear medicine imaging, a unique branch of medicine, to diagnose and treat a variety of illnesses. Usually, the radioactive substance is injected intravenously or consumed, and after that, it is scanned with the help of specialist cameras that can identify the radiation the material emits. Nuclear medicine imaging techniques come in several forms, such as planar imaging, PET, and single photon emission computed tomography (SPECT). There are a number of widely used formats for nuclear medicine imaging data, such as DICOM and NIfTI [35]. Disease segmentation and classification have advanced significantly as a result of developments in nuclear medicine imaging. [36] showed how deep learning techniques may be applied to effectively identify lung nodules in PET scans, which allows for accurate tumor localization.

Similar to this, [37] presented a novel method that combines multimodal data, such as PET and SPECT imaging, to produce a strong framework for categorizing Alzheimer's disease into several stages. [38] created a machine learning-based method for cardiovascular imaging that greatly automates the analysis of myocardial perfusion abnormalities. This development significantly improves the all-encompassing assessment of cardiac health. Concurrently, the review of oncological studies by [39] demonstrated a fusion paradigm integrating PET and MRI, validating the methods of these modalities in the diagnosis and categorization of prostate cancer. In addition, the groundbreaking work in neuro-oncology by [40] has built a radiomics-centered strategy. This method emphasizes the value of quantitative image analyses by using PET scans to categorize gliomas.

Optical Imaging

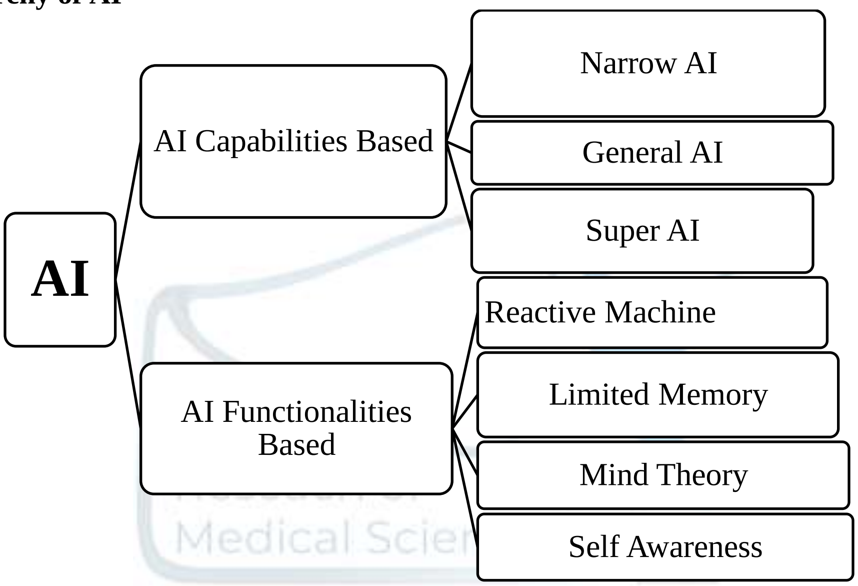
Using visible, infrared, or ultraviolet light to take pictures of objects is a commonly used technique known as optical imaging [41]. Optical imaging is characterized by several factors, such as spectral range, resolution, and depth of field. In optical imaging, a number of different formats are utilized. The JPEG format, a lossy compression format that is extensively used in digital photography, is the most commonly accepted standard [42]. Another kind is the TIFF format, which is frequently used in scientific and medical imaging and is a lossless compression format [43]. Significant progress has been made in the segmentation and categorization of diseases thanks to developments in optical imaging. Remarkably, [44] improved the accuracy of recognizing diseased characteristics by precisely segmenting retinal lesions in optical coherence tomography (OCT) images using machine learning.

A multi-modal fusion technique integrating hyperspectral and fluorescence imaging was presented by [45] in their work. The goal of this method is to increase the precision of dermatology diagnosis and improve the classification of skin lesions. An automated approach for polyp segmentation in endoscopic pictures using deep learning was given by [46] in the context of gastrointestinal imaging. The early diagnosis of colorectal problems is aided by this framework. In response to neurological difficulties, [47] developed a novel technique that uses optical fluorescence imaging to classify brain tumors, making intraoperative tumor delineation easier. Furthermore, [48] used multispectral imaging in oncology to categorize breast lesions, illustrating the potential of spectral data in enhancing disease classification.

ARTIFICIAL INTELLIGENCE

The process of building clever devices using massive amounts of data is known as artificial intelligence. These computers do tasks that are comparable to those carried out by people by using their prior experiences as a basis for learning [49]. It increases the efficacy, accuracy, and efficiency of human labor. When viewed from above, artificial intelligence can be separated into two primary categories: functionality-based AI and capability-based AI (refer to Figure 2). Furthermore, from a technological standpoint, artificial intelligence (AI) includes a number of fields, such as natural language processing, deep learning, and machine learning.

Figure 2: Hierarchy of AI



Artificial Intelligence-based on Capabilities

Based on capabilities, artificial intelligence can be divided into three main categories:

1. The first kind of AI is called narrow AI, or weak AI, and it is limited to a single task [50]. It centers on a particular set of cognitive skills and how they develop over the course of a spectrum. Narrow AI applications are becoming more commonplace in our daily lives as machine learning and deep learning approaches grow.
2. Artificial general intelligence (AGI), sometimes referred to as strong AI or deep AI, is the second type of AI. It is the ability of a computer with general intelligence to learn and use its intelligence to solve any problem [51]. Artificial General Intelligence (AGI) can demonstrate cognitive functions, understanding, and behavior that are nearly identical to human abilities in any given situation.
3. Artificial superintelligence (ASI) is the third category of AI, which is capable of thinking by itself and outperforming human intelligence through the demonstration of cognitive abilities. The most advanced, potent, and clever type of AI is called artificial superintelligence (ASI), or super AI for short. It is more intelligent than even the most sophisticated human minds. It is capable of abstract thought and interpretations that humans cannot [52].

Artificial Intelligence-based on Functionalities

Based on functionalities, AI can be divided into four categories:

1. Reactive machines are AI systems that don't remember past experiences or use them to forecast future behavior. They watch, only use info that already exists, and respond to their

surroundings. Reactive machines have limited skills and are assigned specific tasks [53].

2. AI with limited memory makes judgments by training on historical data [54]. These systems have a short-lived memory. They cannot add this past data to their experience library, but they can view it for a short time.

3. One high-level topic that is only now conceptualized theoretically is the Theory of Mind. Such AI necessitates a thorough comprehension of how one's environment, including other people and objects, might affect one's emotions and conduct [55]. It ought to be able to understand the thoughts, feelings, and emotions of people.

4. Self-aware AI, which refers to systems that comprehend their internal characteristics, emotional states, and contextual situations, including human emotions, is a completely theoretical term [56].

RESEARCH METHODOLOGY

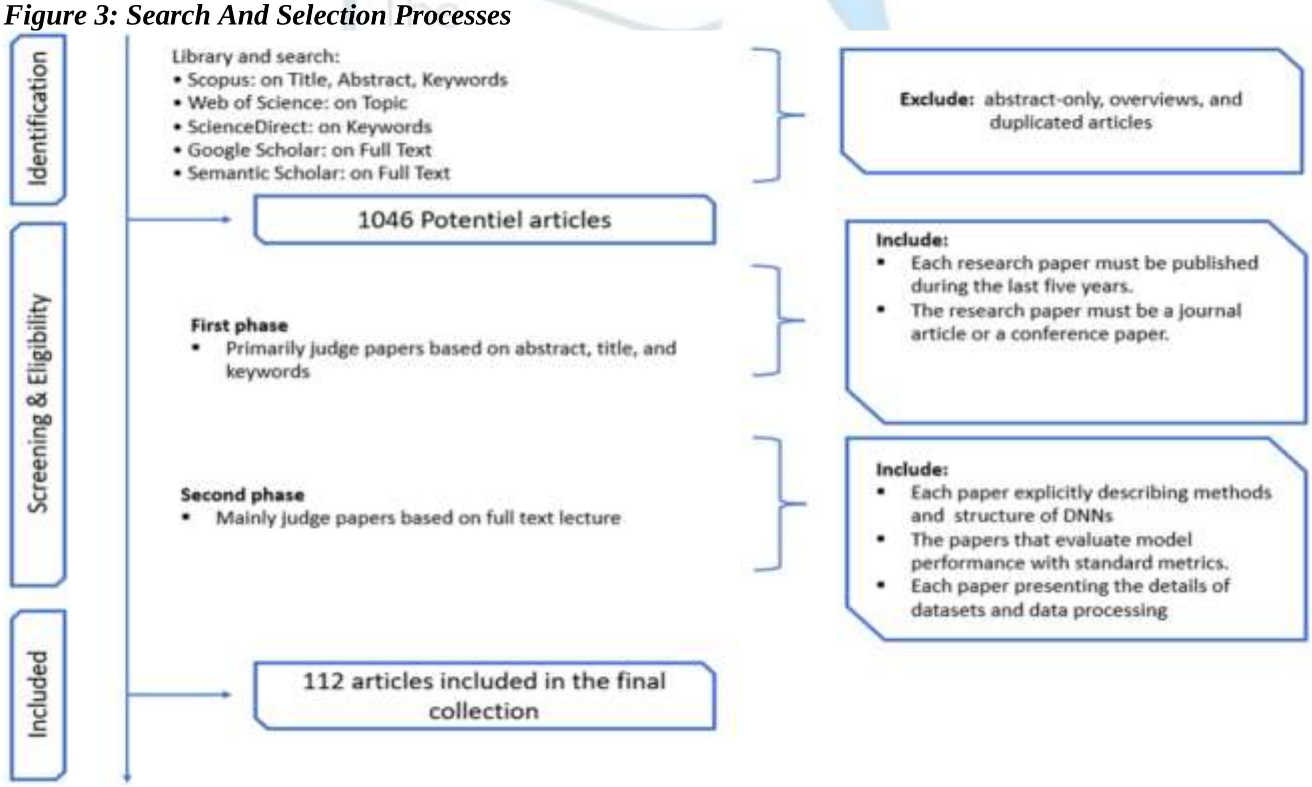
To compile current research and discussions about the useful application of AI in medical image-based diagnostics, a systematic review approach was taken. An organized database search approach was used to find the first batch of pertinent primary research. Web of Science, Scopus, ScienceDirect, Google Scholar, and Semantic Scholar are the five well-known online databases that were included in the search (Table 1).

Table 1: Results From Searched Databases

Library	Total No. of Results
Scopus	3125
Web of Science	3485
ScienceDirect	9357
Google Scholar	7458
Semantic Scholar	5749

Throughout this procedure, a collection of keywords—such as "medical imaging," and "AI" were used in a number of fields, including the title, abstract, and complete text. In order to obtain the most pertinent published papers, Boolean operators such as 'and' were inserted between the search phrases. Throughout the selection process, these papers were improved in accordance with the qualifying requirements (Figure 3).

Figure 3: Search And Selection Processes



SYSTEMATIC SEARCH RESULTS

Notable developments in recent research indicate that great progress has been made in the treatment of brain illnesses. [83] achieved an amazing accuracy rate of 0.95 in 2022 by developing a novel 3D brain slice classification method. This represented a noteworthy breakthrough in the neuroimaging area. Nonetheless, it is critical to recognize that issues with model generalization and the validation of various datasets continue to be areas of concern. The combination of SegNet and deep belief networks for the segmentation and classification of brain tumors in 2022 was another significant advancement [84]. The accuracy rates that this fusion produced were 0.933 and 0.921. Nonetheless, enduring obstacles continue, such as disparities in class and dataset diversity. [85] used a CNN-LSTM method in 2022 to identify brain tumors, and they were able to obtain a noteworthy 0.92 accuracy rate. It is important to do more thorough clinical validation. Conversely, [86] presented a deep autoencoder in 2022 for the purpose of detecting brain tumors, exhibiting a remarkable 0.97 accuracy rate. This emphasizes how crucial thorough clinical robustness is.

Turning our focus to Alzheimer's illness, it is projected that in 2022, CNNs and random forests was utilized for classification, yielding an accuracy rate of 0.926 and potentially providing an early diagnosis (87). However, there are still issues with scaling and applying this strategy to a variety of populations. In 2020, [93] presented a noteworthy deep learning model for lung disease detection using chest X-rays, particularly during the COVID-19 pandemic. With an accuracy rating of 0.989, this model highlights AI's potential for pandemic response. The availability of data and the ability to adjust to changing viral strains are persistent issues. Similarly, [94] used chest X-ray data in 2020 to diagnose lung problems using k-nearest neighbors (KNN). Their remarkable accuracy rate of 0.9809 was attained. Large datasets are necessary, though, as is the capacity to modify models in real time in response to shifting clinical circumstances.

Turning the focus from COVID-19 to lung illnesses in general, [95] classified lung nodules in 2018 using deep CNNs. Their accuracy rate came in at 0.68, and their main goals were to increase model resilience and accuracy. In 2022, [96] presented an enhanced deep learning model utilizing Bayesian principles for COVID-19 identification, attaining a remarkable 0.96 accuracy rate. On the other hand, managing a variety of datasets, reducing bias, and enhancing data accessibility are essential factors. In 2022, [98] used chest CT data to use a multi-task multi-modality SVM technique for early COVID-19 detection. With an accuracy rate of 0.89, they demonstrated the value of SVMs in the classification of COVID-19 cases. The availability of data and the requirement for additional accuracy improvements are ongoing problems. In order to maximize random forest (RF) in lung nodule localization in 2022, [99] concentrated on feature processing, resulting in a segmentation accuracy rate of 0.96.

The importance of feature engineering for this task was highlighted in this study. Obstacles can include more development and clinical implementation. In 2020, [100] introduced a unique method for unsupervised deep clustering in the stratification of lung cancer patients, using DBN and FCM. Although promising, further widespread validation and adjustment to a range of patient populations are required. Deep learning approaches have been the focus of current research in the realm of liver illnesses, with an emphasis on liver segmentation that attained high sensitivity and specificity in 2022 [101]. One of the challenges is integrating it effectively into clinical practice. NucleiSegNet attained an F1 score of 0.83 in 2021 by concentrating on segmenting images of liver cancer histology. Nevertheless, there were issues with the model's adaptability [102]. LRFNet evaluated liver reserve function in 2022 and found an AUC of 0.774 [103].

Improving precision and proving clinical significance are difficult tasks. 2019 saw the use of Gaussian mixture models and deep learning approaches for liver cancer detection, which required extensive clinical validation [104]. Achieving an accuracy of 0.96 in 2020, liver segmentation customized for fusion-guided therapies shown promising clinical applications [105]. In 2020, a 3D neural network was employed with moderate sensitivity and specificity to evaluate the burden of liver tumors with the goal of achieving enhanced accuracy [106]. In 2022, [107] introduced an atrous residual encoder for vertebrae segmentation in the realm of vertebral disorders, attaining a high degree of accuracy. This signifies a noteworthy advancement in the identification and treatment of spinal disorders. A method for identifying vertebrae from MRI scans was described in 2021 by [108], showing potential clinical utility and an outstanding accuracy of 0.955. With a Dice score of 0.91, [109], another 2021 study, concentrated on identifying lumbar vertebrae from X-ray images. This high score suggests that fractures and associated conditions might be evaluated.

Researchers used deep CNNs in 2020 [110] to categorize discs in the lumbar spine, with a high accuracy rate of 0.94. This holds out hope for more precise and effective diagnosis of diseases relating to the spine. Finally, in 2021, [111] obtained a dice score of 0.96, indicating accurate laminae segmentation. This accomplishment has a great deal of promise to advance surgical treatments for disorders of the vertebrae. In 2022, [112] presented a highly accurate automatic heart segmentation method in the field of cardiac disorders. Although there is potential for this method in the field of cardiology, there are obstacles to its integration and generalization. Deep learning was used in a study [113] from 2021 to identify cardiac illness using electrocardiogram (ECG) data. The study's remarkable accuracy rate of 0.994 demonstrates the application of AI in this industry. It did, however, also highlight how crucial it is to protect data privacy and understand outcomes produced by AI.

With an accuracy of 0.92, [114] introduced cardiac cine MRI segmentation and disease classification in the same year. This emphasizes the value of an accurate diagnosis as well as the difficulties posed by large dataset sizes. A study [115] published in 2021 showed how well deep learning works with large amounts of ECG data to identify myocardial infarction. The study's remarkable accuracy rate of 0.99 demonstrated deep learning's promise for real-time clinical applications as well as its capacity to overcome obstacles and potential biases. In 2021, [116] presented a hybrid DL technique for gland segmentation within the context of prostate disorders. With a dice score of 0.90, this method produced a noteworthy pathological progression. More clinical validation is still necessary, though. A strategy for segmenting prostate lesions was reported by [117] in 2020, and it showed promise with a dice similarity coefficient (DSC) of 0.8958. The study did, however, encounter difficulties in generalizing lesion types and guaranteeing robustness across various imaging procedures. [118], with an accuracy rate of 0.921, used 3D AlexNet for prostate tumor segmentation in 2020. This study emphasizes how AI may help with uncertainty and interpretability.

Prostate cancer was divided into segments in 2022 when [119] introduced prost attention-net. Notwithstanding the difficulties with integration, they were able to obtain a Dice score of 0.875, which is useful information for focused therapies. A study conducted in 2020 examined the application of machine learning techniques for MRI-based prostate cancer diagnosis. The study addressed challenges with standardization and validation in addition to showcasing possible clinical uses. AI plays a major role in pathology; in the case of breast illnesses, [121] attained impressive accuracy in diagnosing breast cancer from histopathology pictures in 2022. A study that used deep learning to identify MRI breast lesions was conducted in 2019 [122], showcasing advances in radiology and resolving issues with data privacy and validation.

Researchers used segmentation and classification approaches for mammography images in 2021 [123], highlighting the possibility of early detection and accurate diagnosis. Nonetheless, issues with accurate diagnosis and workflow integration must be resolved. Researchers [124] demonstrated the promise of AI in oncology in 2022 by using multi-scale feature fusion to classify breast cancer. The goal of this strategy was to tackle the problems associated with clinical testing and model complexity. The same year, [125] concentrated on using breast ultrasonography to accurately and precisely identify malignant tumors. The study focused on the difficulties and clinical significance related to image quality and integration.

Despite difficulties with validation and integration, [126] improved diagnostic capabilities in ophthalmology by achieving high accuracy in 2022 when classifying glaucoma in retinal pictures. Macular edema on OCT images was analyzed in 2022 by [127] with an astounding accuracy of 0.992. Though it also draws attention to issues with

OCT image variances and validation, this study offers insightful information about the evaluation of retinal health. The segmentation of curvilinear features in optical coherence tomography angiography (OCTA) images was the main emphasis of [128] in 2020. This study addressed problems with image quality and segmentation model generalization, which benefited the area of ophthalmology.

A study [129] published in 2021 stated that diabetic retinopathy may be detected in eye fundus pictures with an accuracy of 0.98. Although early diagnosis and intervention are made easier by this high accuracy, integration and access equity present certain difficulties. With difficulties in clinical validation and integration, [130]'s automated glaucoma detection using DL convolutional networks in 2019 demonstrated the potential of AI in ophthalmology.

CONCLUSION

This systematic review's main objective was to present a thorough analysis of AI's place in modern medical research, with a focus on how ML and DL methods are used to identify diseases. Our goal was to investigate the different approaches that are frequently utilized in scientific writing by using an interdisciplinary approach. Explicit approaches were preferred in most research, according to our thorough review, with separate implementations of ML and DL techniques. It is noteworthy, therefore, that a small percentage of research have adopted hybrid approaches, skilfully fusing the two paradigms.

After a thorough analysis of the data obtained from these different methodologies, a recurring trend was observed: the hybrid methodology consistently produced useful and applicable outputs, suggesting a promising direction for future research in the field of medical diagnostics. One major problem that surfaced during our investigation is the difficulty of finding annotated photos for certain conditions, which significantly affects the effectiveness of AI models. Our future research projects were concentrating on combining medical image synthesis and transfer learning strategies in order to proactively address this obstacle. These novel approaches have the potential to alleviate problems associated with restricted data availability and are well-positioned to significantly advance disease classification and segmentation models. Our strategic investment in this project demonstrates our commitment to developing medical AI and laying out a viable course for future research.

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