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PAPER

Artificial Intelligence Techniques in Medical Imaging: A Systematic Review

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ABSTRACT

This scientific review presents a comprehensive overview of medical imaging modalities and their diverse applications in artificial intelligence (AI)-based disease classification and segmentation. The paper begins by explaining the fundamental concepts of AI, machine learning (ML), and deep learning (DL). It provides a summary of their different types to establish a solid foundation for the subsequent analysis. The prmary focus of this study is to conduct a systematic review of research articles that examine disease classification and segmentation in different anatomical regions using AI methodologies. The analysis includes a thorough examination of the results reported in each article, extracting important insights and identifying emerging trends. Moreover, the paper critically discusses the challenges encountered during these studies, including issues related to data availability and quality, model generalization, and interpretability. The aim is to provide guidance for optimizing technique selection. The analysis highlights the prominence of hybrid approaches, which seamlessly integrate ML and DL techniques, in achieving effective and relevant results across various disease types. The promising potential of these hybrid models opens up new opportunities for future research in the field of medical diagnosis. Additionally, addressing the challenges posed by the limited availability of annotated medical images through the incorporation of medical image synthesis and transfer learning techniques is identified as a crucial focus for future research efforts.

KEYWORDS

artificial intelligence (AI), machine learning (ML), deep learning (DL), medical imaging, classification, detection, segmentation

1 INTRODUCTION

Medical imaging has played a crucial role in diagnosing and treating various diseases, offering clinicians valuable insights into the human body. With the advent of several imaging modalities, including X-ray imaging, computed tomography (CT), positron emission tomography (PET), and magnetic resonance imaging (MRI),

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clinicians have access to high-quality, high-resolution images that can reveal critical details about anatomical structures and physiological functions [1].

However, the increased availability and complexity of medical imaging data have posed significant challenges for radiologists and other healthcare professionals. The interpretation of medical images is a complex and time-consuming task that requires a high level of expertise and extensive training. Moreover, the sheer volume of imaging data produced can make it challenging to detect subtle changes that may indicate the presence of a disease. Artificial intelligence (AI) has emerged as a promising solution to address these challenges, utilizing machine learning (ML) algorithms to automatically analyze and interpret medical images. AI-based medical imaging has the potential to revolutionize the field by enabling more accurate and efficient disease detection, segmentation, and classification. AI algorithms can analyze vast amounts of medical imaging data and identify subtle changes that may indicate a disease.

For instance, AI-based algorithms have shown remarkable performance in detecting early-stage cancers, such as lung, brain, and breast cancer, from medical images [2, 3, 4, 5, 6, 7]. Moreover, AI-based segmentation and classification techniques can accurately delineate anatomical structures and identify regions of interest, thereby facilitating precise diagnosis and treatment planning [8]. Despite the significant promise of AI-based medical imaging, several challenges must be addressed before these techniques can be widely adopted in clinical practice. One critical challenge is the standardization of imaging protocols, as variations in imaging parameters can significantly affect the quality and consistency of medical images [9]. Additionally, the limited availability of annotated data can hinder the development and validation of AI models. Ethical considerations regarding patient privacy and data security must also be carefully addressed.

This paper provides a comprehensive review of state-of-the-art AI-based medical imaging techniques for disease detection, including segmentation and classification methods. It also discusses the challenges of applying AI to medical imaging and proposes potential solutions to address these challenges.

The remainder of the paper is structured as follows: Section 2 provides a comprehensive overview of medical imaging. This section includes clear definitions, an exploration of different imaging modalities, and an examination of recent advancements in AI-based disease classification and segmentation within each modality. In Section 3, the definition of AI is provided, along with a taxonomy that summarizes the main categories within the field. Section 4 defines ML and outlines its various types. Additionally, a taxonomy is presented to concisely summarize the main subdivisions within ML. Section 5 focuses on deep learning (DL), providing clear definitions and outlining the various types of DL. Similarly, a taxonomy is introduced to encapsulate the main classifications within this domain. Section 6 provides insights into the methodologies applied in the reviewed research studies. It also compiles the relevant findings from these studies and discusses the challenges encountered during their implementation. In Section 7, a comprehensive comparative analysis is conducted, systematically evaluating and contrasting the relevant results obtained from various approaches. Additionally, this study explores potential future research directions, emphasizing areas that are ready for further investigation and advancement in the field.

2 MEDICAL IMAGING

Medical imaging involves the application of various technologies and techniques to create visual representations of the internal structures and functions of the human body for the purposes of diagnosis and treatment [10]. It is an essential tool in modern medicine, enabling doctors and other healthcare professionals to detect and diagnose a wide range of diseases and conditions. There are several types of medical imaging, including X-ray, CT, MRI, ultrasound, optical imaging, and nuclear medicine imaging [11] (see Figure 1). Each of these techniques has its own advantages and limitations and may be used for various imaging investigations, depending on the specific needs of the patient and the healthcare provider.

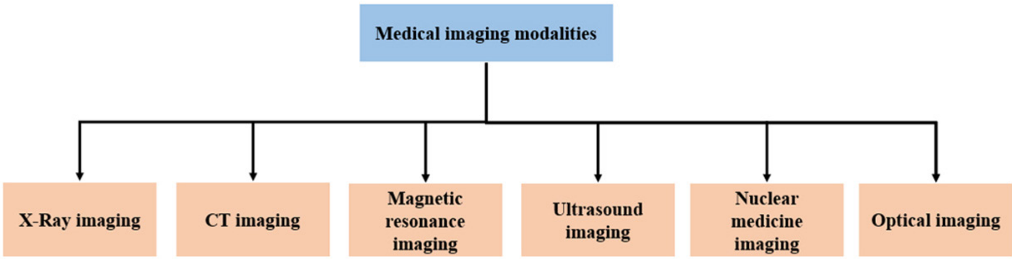

Fig. 1. Medical imaging modalities

2.1 X-ray imaging

X-ray imaging is a powerful technique that enables non-invasive inspection of objects and materials. This imaging method uses X-rays to penetrate the object and create an image based on the varying degrees of X-ray absorption within the object [12]. X-ray imaging provides valuable characterizations of the object being imaged, including the attenuation coefficient and contrast resolution. X-ray images can be stored in various digital formats, including DICOM (digital imaging and communications in medicine), TIFF (tagged image file format), and JPEG (joint photographic experts group) [13].

Recent advancements in X-ray imaging have ushered in a transformative era in the fields of segmentation and disease classification. By seamlessly integrating state-of-the-art computational methodologies with the inherent attributes of X-ray imaging, the discipline has witnessed unprecedented progress, resulting in heightened diagnostic precision and nuanced insights. Notably, [14] spearheaded a pivotal advancement in segmentation by combining convolutional neural networks (CNNs) with X-ray data. This groundbreaking work redefined the accuracy of lung tissue segmentation in chest X-rays and led to a paradigm shift with significant implications for the diagnosis and management of pulmonary diseases. By harnessing the discriminative potential of CNNs, this achievement lays the foundation for personalized therapeutic interventions. In parallel, disease classification has undergone a renaissance propelled by innovative strategies. [15] showcased the transformative potential of adversarial networks in enhancing the precision of soft tissue segmentation, inaugurating an era of meticulous structural differentiation. Expanding these horizons, [16] introduced ensemble methods that combine X-ray images, resulting in highly accurate classification outcomes for various bone pathologies, thereby enhancing diagnostic understanding. Furthermore, the convergence of X-ray imaging with multimodal data has emerged as a powerful approach. [17] epitomized this synergy by seamlessly integrating clinical profiles, demographic characteristics, and complementary imaging techniques with X-ray imagery. This comprehensive approach goes beyond traditional classification paradigms, improving diagnostic accuracy and providing insights into the complex nature of disease pathophysiology.

In a bold move, [18] led the way in integrating X-ray images with electronic health records, creating a unified framework that enhances disease prediction and classification. By capitalizing on comprehensive patient profiles, this innovative approach enhances predictive accuracy, providing opportunities for proactive interventions and personalized patient care strategies.

2.2 Computed tomography imaging

Computed tomography imaging is a medical imaging modality that uses X-rays and advanced computer processing to generate highly detailed cross-sectional images of the human body. CT imaging offers valuable insights into the internal structures of the body, providing crucial information about bones, organs, and soft tissues [19]. Characterizations of CT imaging include spatial resolution, contrast resolution, and temporal resolution. CT images are typically stored in a digital format, with several different file formats available. The most common formats include DICOM and NIfTI (neuroimaging informatics technology initiative) [20].

In the field of CT imaging, which involves complex tasks such as disease segmentation and classification, a series of important studies have emerged. Significantly, [21] stands as an exemplar, highlighting the effectiveness of deep learning methodologies in accurately segmenting pulmonary nodules within CT images. This groundbreaking effort demonstrates the ability to identify nodular entities that vary in terms of their morphological nuances and densities. Concurrently, [22] presents a paradigmatic framework that integrates CT and PET imaging modalities, resulting in an enhanced ability to classify cerebral neoplasms and provide more detailed tumor grading. The field of cardiovascular diagnostics has advanced rapidly thanks to the groundbreaking work of [23]. They have utilized deep learning techniques to automate the segmentation of cardiac structures in CT angiography, which is crucial for accurate diagnosis. Meanwhile, [24] proposes a seminal hybridized construct tailored to liver lesion segmentation in abdominal CT scans. This construct adeptly amalgamates region-based and boundary-centric paradigms to yield outcomes of robust fidelity. Further enriching the tapestry [25], this study charts an innovative course toward the detection and classification of intracranial hemorrhage in head CT scans using deep learning. It aims to provide rapid and accurate differentiation across different types of hemorrhages. The innovative methodology proposed by [26] for lung segmentation in CT scans enhances subsequent disease-specific analyses by utilizing an anatomically guided and contextually informed framework. Concomitantly, [27] elevates the landscape through a cascaded DL model that seamlessly integrates lesion segmentation and classification, thereby bolstering diagnostic precision for liver lesions.

2.3 Ultrasound imaging

Ultrasound imaging is a non-invasive medical imaging method that uses high-frequency sound waves to generate images of internal body structures [28]. Ultrasound imaging is characterized by various parameters, including frequency, wavelength, resolution, penetration depth, and image contrast. Ultrasound images can be stored and transmitted in various formats, such as DICOM, JPEG, PNG, and BMP [29].

In the field of ultrasound imaging, significant progress has been made in the areas of disease segmentation and classification. [30] introduced a groundbreaking deep learning-based methodology designed specifically for the accurate segmentation of liver lesions in ultrasound images, providing a noticeable improvement in clinical diagnostic accuracy. Correspondingly, [31] proposed an approach based on graph-cut techniques, providing robust segmentation results for kidney tumors in ultrasound scans. This approach enhances the accuracy of tumor boundary delineation. In parallel, [32] advanced the field of cardiac ultrasound by proposing an automated algorithm that facilitates the segmentation of the left atrium. This is a crucial factor in the diagnosis of atrial pathologies. Within the obstetric field, [33] proposed a groundbreaking framework that combines convolutional neural networks and generative adversarial networks. This innovative approach enhances the segmentation of fetal ultrasound images, providing valuable insights into prenatal health evaluations. By expanding the scope, [34] ventured into musculoskeletal investigations. A methodology combining texture analysis and machine learning has been developed for the classification of pathological features in joint ultrasound images. This approach provides a non-invasive means of evaluating musculoskeletal disorders.

2.4 Nuclear medicine imaging

Nuclear medicine imaging is a distinct medical specialty that utilizes trace amounts of radioactive substances to diagnose and manage a wide range of diseases. The radioactive material is typically administered intravenously or ingested and then imaged using specialized cameras that detect the radiation emitted by the material. There are several types of nuclear medicine imaging techniques, including PET, single photon emission computed tomography (SPECT), and planar imaging. In terms of formats for nuclear medicine imaging data, there are several commonly used formats, including NIfTI and DICOM [35].

Advancements in nuclear medicine imaging have led to significant progress in disease segmentation and classification. [36] demonstrated the effective application of deep learning methodologies in accurately delineating lung nodules within PET scans, thereby enabling precise tumor localization. In a similar vein, [37] introduced an innovative approach that integrates multimodal data, including PET and SPECT images, resulting in a robust framework for classifying different stages of Alzheimer's disease. Within the field of cardiovascular imaging, [38] developed a machine learning-based approach that significantly automates the analysis of myocardial perfusion defects. This advancement greatly enhances the comprehensive evaluation of cardiac health. Meanwhile, the examination of oncological investigations by [39] revealed a fusion paradigm combining PET and MRI, confirming the techniques of these modalities in the identification of prostate cancer classification. Moreover, the pioneering endeavors of [40] in the field of neuro-oncology have established a radiomics-centered approach. This approach utilizes PET scans to classify gliomas, highlighting the importance of quantitative image analyses.

2.5 Optical imaging

Optical imaging is a widely used technique that involves capturing images of objects using visible, infrared, or ultraviolet light [41]. Various characterizations are associated with optical imaging, including resolution, depth of field, and spectral range. In terms of formats, there are several formats used in optical imaging. The most common standard is the JPEG format, which is a lossy compression format widely used in digital photography [42]. Another type is the TIFF format, which is a lossless compression format that is often used in scientific and medical imaging [43].

Advancements in optical imaging have led to significant strides in disease segmentation and classification. Notably, [44] utilized machine learning to achieve precise segmentation of retinal lesions in optical coherence tomography (OCT) images, thereby improving accuracy in identifying pathological features. In their study, [45] introduced a multi-modal fusion approach that integrates hyperspectral and fluorescence imaging. This approach aims to improve the classification of skin lesions and enhance diagnostic accuracy in dermatology. Within gastrointestinal imaging, [46] presented an automated framework that utilizes deep learning for polyp segmentation in endoscopic images. This framework contributes to the early detection of colorectal abnormalities. Addressing neurological challenges, [47] proposed a groundbreaking method that employs optical fluorescence imaging for brain tumor classification, thereby facilitating intraoperative tumor delineation. Additionally, within the field of oncology, [48] utilized multispectral imaging to classify breast lesions, demonstrating the potential of spectral data in improving disease discrimination.

3 ARTIFICIAL INTELLIGENCE

Artificial intelligence is the process of constructing intelligent machines using vast amounts of data. These machines learn from their past experiences and accomplish tasks similar to those performed by humans [49]. It improves the efficiency, precision, and effectiveness of human efforts. From an upper view, AI can be subdivided into two main categories: capability-based AI and functionality-based AI-based on functionalities (see Figure 2). In addition, from a technical perspective, AI encompasses various disciplines, including machine learning, deep learning, and natural language processing.

3.1 Artificial Intelligence-based on capabilities

There are three primary classifications for artificial intelligence based on capabilities:

The first type is narrow AI, also known as weak AI, which focuses on a specific task and has limited abilities [50]. It focuses on a specific set of cognitive abilities and their development across the spectrum. With the expansion of machine learning and deep learning methodologies, narrow AI applications are becoming increasingly prevalent in our daily lives.

The second kind of AI is artificial general intelligence (AGI), often known as strong AI or deep AI refers to a machine that possesses general intelligence and is capable of learning and applying its intellect to solve any problem [51]. AGI possesses the capability to exhibit cognitive abilities, comprehension, and behavior that are virtually indistinguishable from those of a human being in any context.

The third type of AI is artificial superintelligence (ASI), which surpasses human intelligence by exhibiting cognitive abilities and developing its own thinking capabilities. ASI, also known as Super AI, is the most sophisticated, powerful, and intelligent form of AI, surpassing the intelligence of even the sharpest human minds. It can think of abstractions and interpretations that humans are incapable of [52].

3.2 Artificial intelligence based on functionalities

There are four types of AI based on functionalities:

Reactive machines are a form of AI that do not keep track of memories or utilize previous actions to predict future actions. They only work with existing data, observe, and react to the environment around them. Reactive machines are assigned specific tasks and do not possess any additional capabilities [53].

Limited memory AI trains on previous data to make decisions [54]. The memory of such systems is short-lived. They can access this historical data for a limited period, but they are unable to add it to their experience library.

The Theory of Mind represents a high-level concept that currently exists only as a theoretical idea. Such AI requires a comprehensive understanding of how people and objects in one's surroundings can influence one's emotions and behavior [55]. It should be able to comprehend people's feelings, emotions, and thoughts.

Self-aware AI is a purely speculative concept, referring to systems that have an understanding of their internal attributes, emotional states, and contextual circumstances, including human emotions [56].

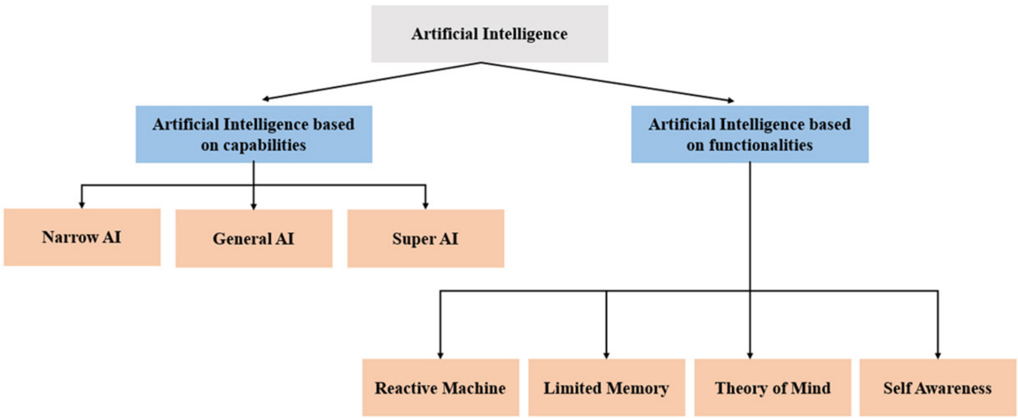

Fig. 2. Hierarchy of artificial intelligence

4 MACHINE LEARNING

Machine learning is a subfield of AI that focuses on the advancement of machines that learn and improve their performance based on the data they process [57, 58]. Anything that can be saved digitally as data can be employed by ML. By identifying patterns in this data, the algorithms learn and improve their efficiency in performing a specific task. ML can be divided into four primary classifications: supervised learning, semi-supervised learning, unsupervised learning, and reinforcement learning [59].

4.1 Supervised learning

Supervised learning is an approach defined by the use of labeled datasets (see Figure 5a). These datasets are curated to facilitate the training of algorithms, enabling precise data classification and predictive modeling [60]. The process of supervised learning is illustrated in Figure 3, where the input consists of observations and their corresponding labels. The objective is to develop a predictive model that can accurately map the input observations to their corresponding labels. This process involves training the model using a labeled dataset, where the model learns the underlying patterns and relationships between the input features and the target labels. Once the model is trained, it can be used to make predictions on new, unseen data by applying the learned mapping.

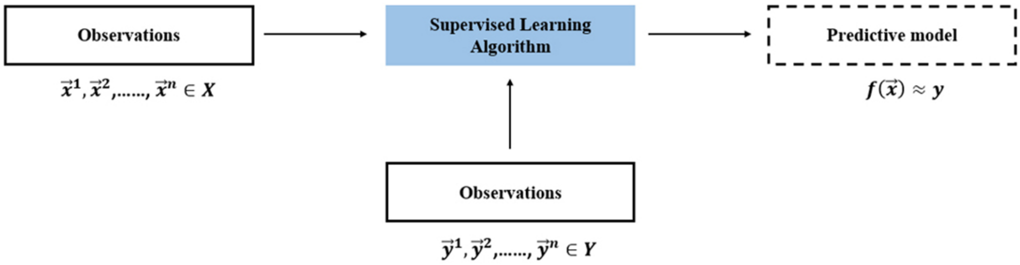

Fig. 3. Supervised learning

Supervised learning can be categorized into two fundamental problem types: classification and regression.

Classification is a supervised learning approach that uses training data to identify and assign incoming observations to specific predefined categories. A program leverages a provided dataset or collection of observations to acquire knowledge and subsequently categorize new observations into numerous classes or categories. [61].

There are primarily three types of classification tasks (refer to Figure 4).

- Binary classification refers to the task of classifying observations within a dataset into two distinct classes, based on a predefined classification rule [62].
- Multi-class classification involves classifying observations into more than two classes. Each observation can only be labeled with one class [63].
- Multilabel Classification is a classification task in which each observation can be assigned multiple target labels, rather than just one, as in multiclass classification [64].

In the literature, the most common classification algorithms are Naive Bayes, Random Forest, Support Vector Machines (SVM), Decision Trees, and K-Nearest Neighbors.

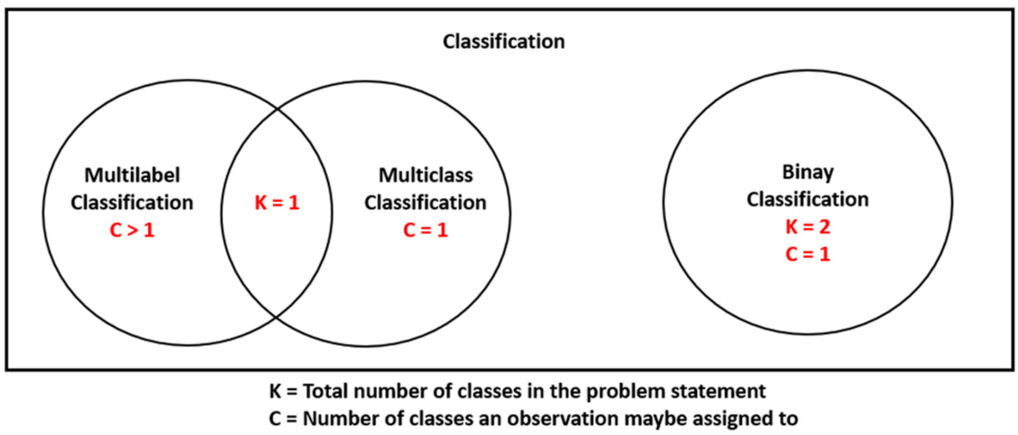

Fig. 4. Classification overview

Regression is a supervised machine learning technique used to predict continuous real values. In simpler terms, regression is used to determine the relationship between observations. i.e., mapping the input variables to a continuous function in order to predict the results as a continuous output [65].

The most frequently used algorithms for regression problems are as follows: linear regression, polynomial regression, robust regression, support vector regression, decision tree regression, random forest regression, logistic regression, and lasso regression.

4.2 Semi-supervised learning

Semi-supervised learning is a machine learning approach that involves integrating a limited quantity of labeled data with a substantial volume of unlabeled data during the training phase [66]. A notable benefit of this approach is its ability to circumvent the need for labeling all training examples, which is especially relevant in situations where data collection is straightforward (see Figure 5b).

4.3 Unsupervised learning

Unsupervised learning is used when the data provided to train the model is neither classified nor labeled (see Figure 5c). The goal of this type of ML is not only to make predictions but also to capture the inherent structure or distribution within the analyzed data. This enables a more profound understanding and exploration of the data [67].

Unsupervised learning includes two main categories of algorithms: clustering and dimensionality reduction algorithms.

- Clustering is a process that enables similar data to be brought together. This type of analysis allows for the identification of groups with different profiles and simplifies the data analysis by highlighting commonalities and differences. This, in turn, reduces the number of variables in the data [68]. The most common clustering algorithms used in machine learning are K-means, DBSCAN, mean-shift, Gaussian mixture model, BIRCH, and agglomerative hierarchical clustering.
- Dimensionality reduction consists of reducing the number of variables in the training data in order to improve efficiency in terms of results and analysis time [69]. Among the best-known algorithms for dimensionality reduction are LDA (linear discriminant analysis), PCA (principal component analysis), and SVD (singular value decomposition).

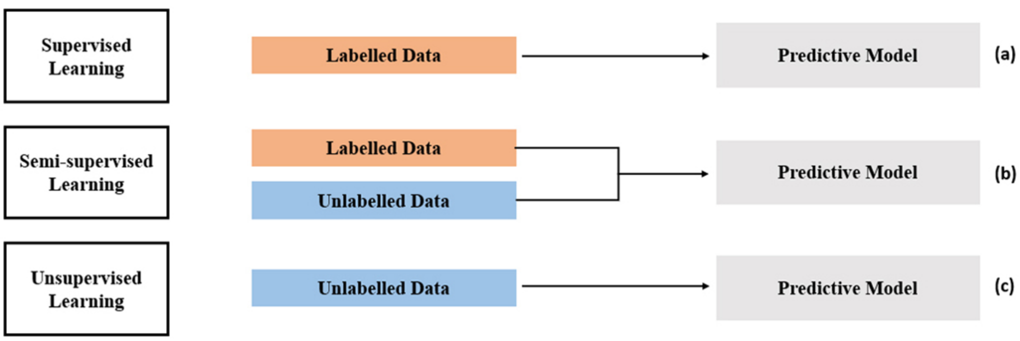

Fig. 5. Data in supervised, semi-supervised and unsupervised learning

4.4 Reinforcement learning

In the realm of reinforcement learning, the learning system has the capacity to engage with its environment and execute actions, subsequently receiving rewards in response.

These rewards can have a positive value if the action was deemed favorable or a negative value if it was considered unfavorable [70]. In certain instances, the reward may occur following an extended sequence of actions, as observed in systems that learn complex games such as Go or chess. Consequently, the learning process involves establishing a policy—a systematic strategy aimed at consistently obtaining the most optimal reward (see Figure 6). Among the important learning algorithms in reinforcement learning are Q-learning, DQN, and TD learning.

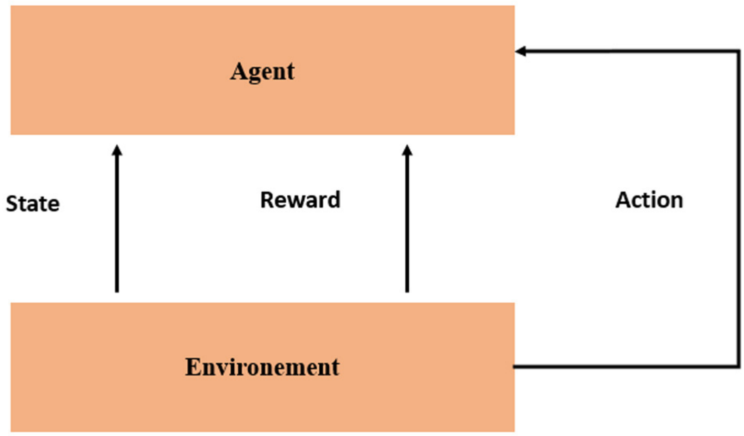

Fig. 6. Reinforcement learning overview

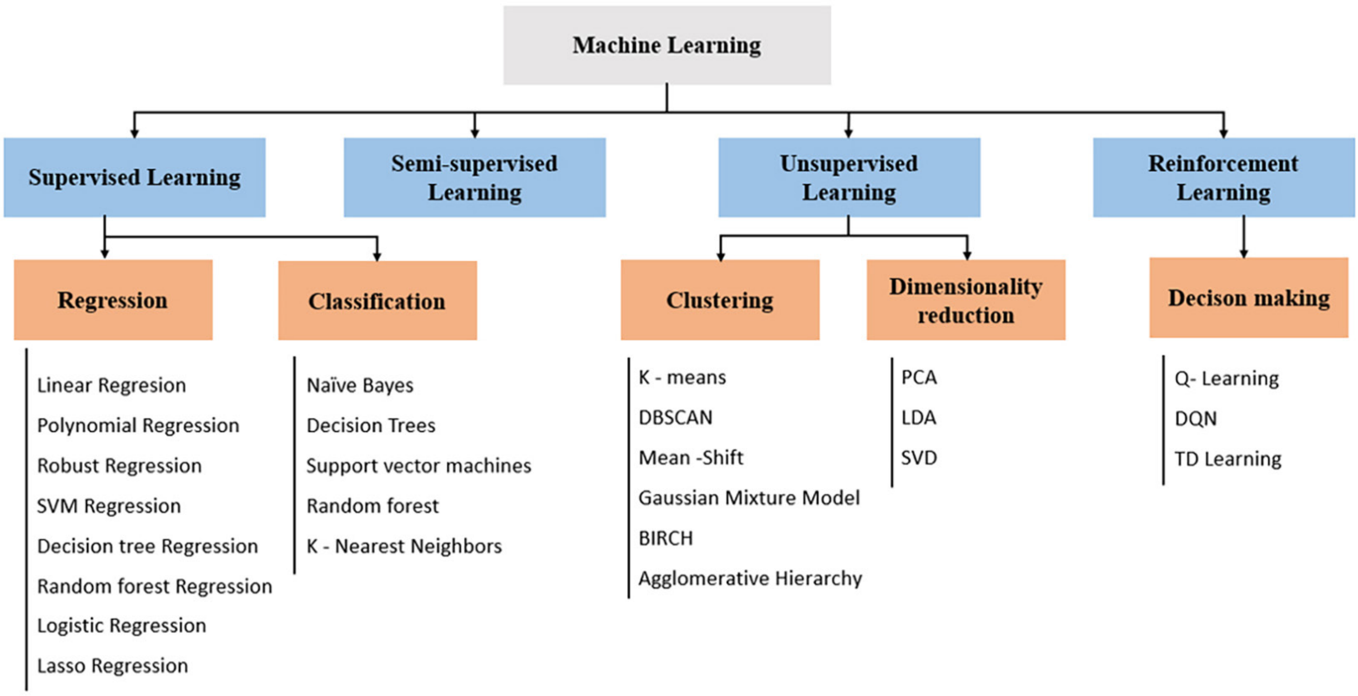

Fig. 7. Taxonomy of machine learning algorithms

To conclude, Figure 7 presents a taxonomy showcasing several widely utilized ML algorithms that are commonly implemented in practical applications.

5 DEEP LEARNING

Deep learning is a sub-branch of AI that is derived from ML. It encompasses all ML techniques that are based on mathematical approaches and are used to model data. It relies on artificial neural networks that are inspired by the structure and functioning of the human brain. These networks are composed of many layers of interconnected neurons. Each neuron receives and processes data from the previous layer through convolutional operations, extracting features and patterns. This information is then passed through subsequent layers, progressively analyzing problems or scenarios similar to past occurrences. By leveraging learned features, CNNs examine potential solutions and iteratively address challenges in an optimized manner [71]. In the literature, DL models utilize various algorithms in the learning process (see Figure 13).

5.1 Convolutional neural networks

Convolutional neural networks are feed-forward artificial neural networks that take inspiration from the functioning of the visual cortex of animals. They are generally used in image processing and computer vision [72]. The most common architectures for convolutional neural networks are AlexNet, VGG, ResNet, Inception, and Xception. CNNs typically comprise the following layers (see Figure 8):

The convolution layer (CONV) employs filters that traverse the input data based on its dimensions, performing convolution operations. The filter size (F) and stride (S) can be adjusted to configure this layer. The resulting output (O) from this operation is referred to as a feature map or activation map [73].

The pooling layer (POOL) is a downsampling procedure commonly implemented after a CONV in neural networks. It aims to reduce the spatial dimensions of the feature maps. Max pooling and average pooling are the predominant forms of pooling, where the maximum and average values, respectively, are selected to represent the pooled region [74].

The fully connected layer (FC) is applied to a flattened input, where each input is connected to all neurons within the layer. FC are typically positioned towards the end of CNN architectures and play a crucial role in optimizing objectives, such as class scores [75].

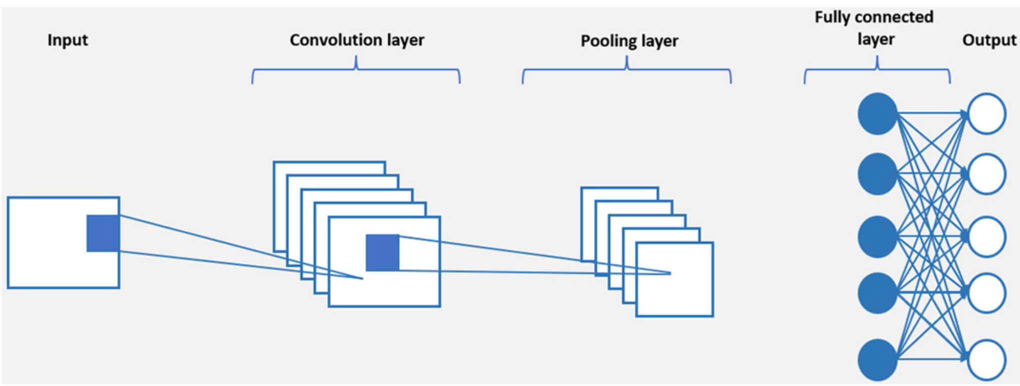

Fig. 8. CNN architectures

5.2 Recurrent neural networks (RNNs)

Recurrent neural networks (RNNs) are a widely used type of neural network in the field of deep learning. RNNs use previous outputs as inputs while maintaining hidden states, making them well-suited for processing sequential data [76]. The most well-known RNNs are LSTM, BI-LSTM, and GRU, and they are generally presented as follows (Figure 9).

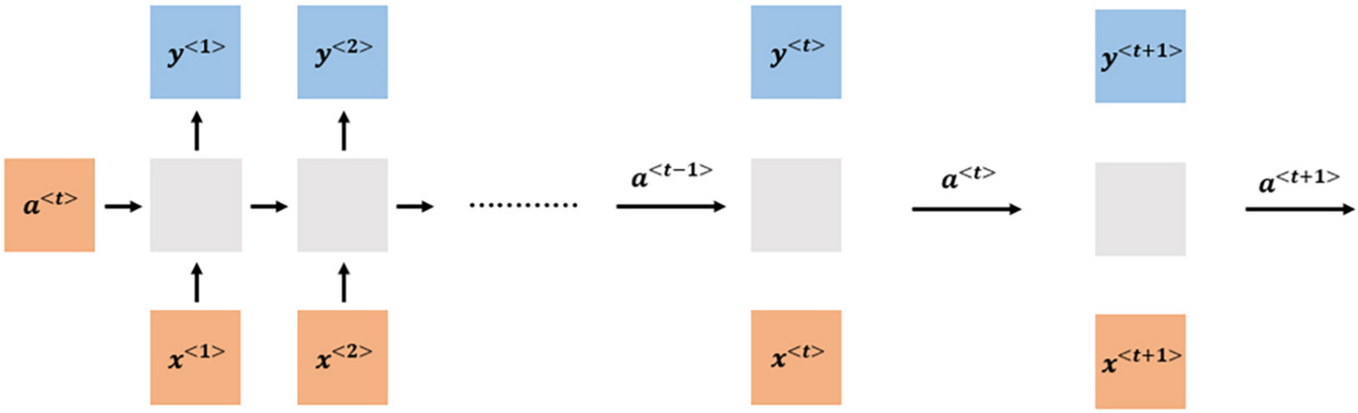

Fig. 9. RNN mechanism

At each time ***t,*** the forward pass is modeled by the following equations:

$$a^{<t>} = g_1(W_{aa}a^{<t-1>} + W_{ax}x^{<t>} + b_a) \quad (1)$$

$$y^{<t>} = g_2(W_{ya}a^{<t>} + b_a) \quad (2)$$

Where x_t and a_t are the input vector and activation vector at time t, g_1, g_2 are activation functions. The b and W are the biases and weights, respectively, to be learned during network training.

The output value at time t, $y^{<t>}$ is determined by equation (2), which is based on the activation value $a^{<t>}$ calculated by equation (1).

5.3 Auto-encoders

Auto-encoders are a type of unsupervised learning algorithm used, particularly in DL. They consist of a specific deep neural network in which the output layer must be identical to the input layer in order to create a new data representation (see Figure 10). In other words, autoencoders train themselves to extract the most important parts of an input by ignoring noises. They then generate an output that has fewer descriptors and is closer to the input [77]. The most well-known types of autoencoders are the denoising autoencoder (DAE), sparse autoencoder (SAE), variational autoencoder (VAE), deep autoencoder, convolutional autoencoder (CAE), contractive autoencoder, and undercomplete autoencoder.

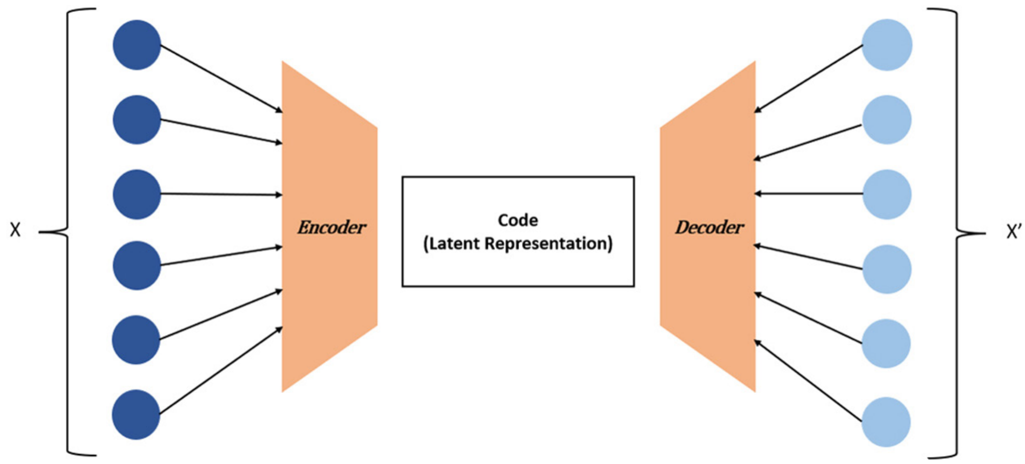

Fig. 10. Auto-encoders architectures

5.4 Generative adversarial networks

Generative adversarial networks (GANs) represent a powerful category of neural networks that are extensively applied in unsupervised learning. They are composed of a pair of neural network models engaged in a competitive interaction, enabling them to analyze, capture, and replicate inherent variations within a given dataset (see Figure 11). Among the best-known types of GANs are conditional GAN (cGAN), vanilla GAN, deep convolutional GAN (DCGAN), laplacian GAN (LAPGAN), and super resolution GAN (SRGAN).

Within the context of GANs, two key components are present: the generator and the discriminator. The generator is responsible for producing synthetic data samples, such as images or sounds, and aims to deceive the discriminator. Conversely, the discriminator aims to discern and differentiate between real and synthesized samples. In the training phase, both the generator and the discriminator function as neural networks, engaging in a competitive relationship. The iterative process is repeated multiple times, enabling the generator and discriminator to progressively enhance their performance in their respective tasks with each iteration [78, 79]. The operation can be visualized in the diagram below:

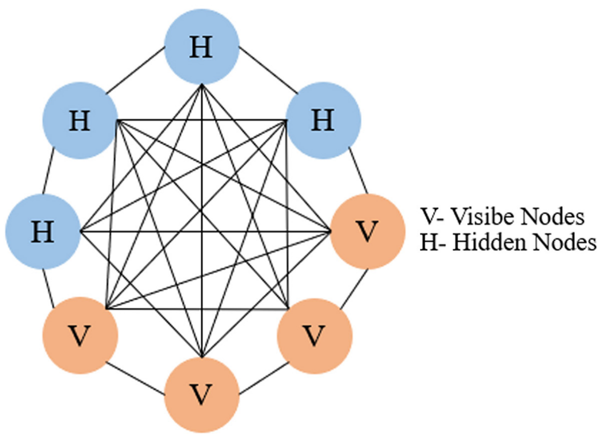

Fig. 11. GANs architectures

5.5 Boltzmann machines

Boltzmann machines, characterized by their random and generative nature, belong to the category of neural networks that are proficient in learning internal representations. These machines have the capability to effectively represent and solve complex combinatorial problems. BMs embody a neural network structure characterized by intricate interconnections among all neurons. This architecture comprises two primary node categories: visible nodes (input nodes) and hidden nodes, with a notable absence of output nodes [80] (refer to Figure 12). Among the most famous types of boltzmann machines are restricted Boltzmann machines (RBMs), deep belief networks (DBNs) and deep Boltzmann machines (DBMs).

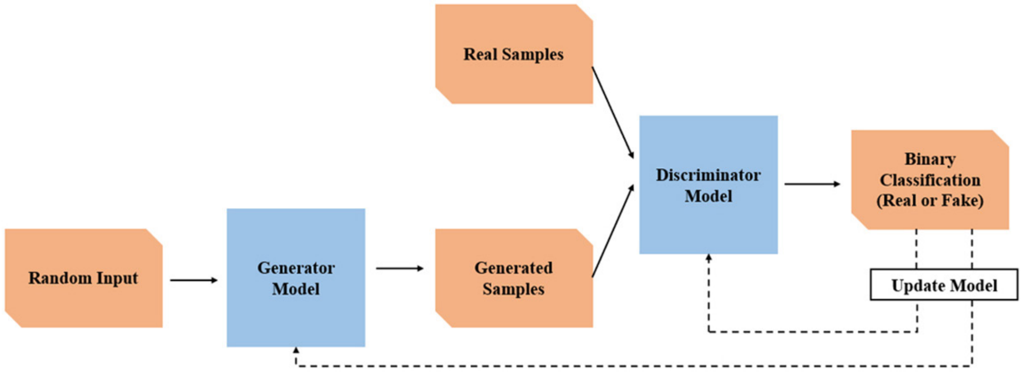

Fig. 12. Boltzmann Machine architecture

5.6 Self-organizing map

The self-organizing map (SOM) is a form of unsupervised learning method commonly employed in deep learning to analyze the structure of a data set. A SOM consists of a map of neurons arranged in two dimensions. These neurons establish connections with neighboring neurons based on topological connections, also referred to as neighborhood connections. The dataset chosen for analysis serves as the foundation for organizing the SOM, taking into account the topological constraints imposed by the input space. Consequently, a mapping is established between the input space and the map space, ensuring a coherent alignment between the two. Notably, when two observations in close proximity within the input space are encountered, they are expected to activate either the same neuron or neighboring neurons within the SOM. To verify these constraints, the neighboring neurons surrounding the most representative neuron undergo an update of their prototype with the aim of improving the representation of the respective data. The significance of this update becomes more pronounced when considering that the neurons involved are in close proximity to the reference neuron [81, 82]. The learning of the SOM can be seen as the minimization of a cost function.

$$\tilde{\boldsymbol{R}}(\omega) = \frac{1}{N}\sum_{k=1}^{N}\sum_{i=1}^{M} K_{iu^*(x^{(k)})} \left\| x^{(k)} - \omega_i \right\|^2$$

with $\boldsymbol{N}$ the number of data, $\boldsymbol{M}$ the number of neurons of the map, $\boldsymbol{u}^*(\boldsymbol{x}^{(k)})$ is the neuron $\boldsymbol{i}$ whose prototype vector $\boldsymbol{\omega}_i$ is the closest to the data $\boldsymbol{x}^{(k)}$

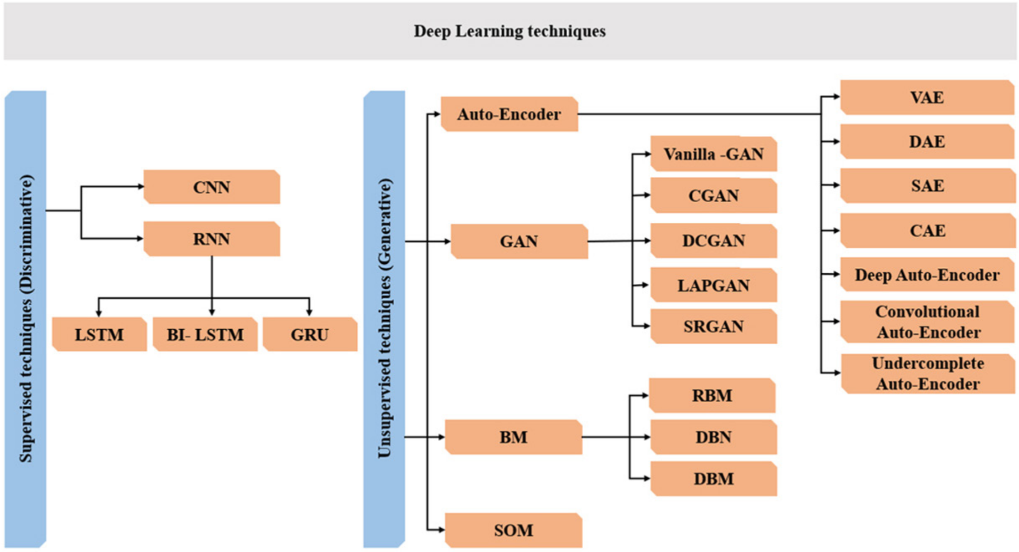

Fig. 13. Taxonomy of deep learning algorithms

6 RESEARCH METHODOLOGY

A systematic literature review approach was adopted to synthesize existing knowledge and recent debates regarding the practical implementation of ML and DL algorithms in medical diagnostics using medical images. The paper's search process was based on well-known review protocols and the most recommended guidelines for this purpose.

6.1 Search and selection

A structured database search strategy was employed to obtain the initial set of relevant primary studies. The search covered five prominent online databases, namely Web of Science, Scopus, ScienceDirect, Google Scholar, and Semantic Scholar (Table 1). In this process, a set of keywords, including "medical imaging", "deep learning", and "machine learning" were applied across various fields, including the title, abstract, and full text. Boolean operators like 'and' were used between the search keywords to acquire the most relevant published papers. These papers will be refined throughout the selection process based on the eligibility criteria (see Figure 14).

Table 1. Results from searched databases

Library	Total number of results
Scopus	4093
Web of Science	6099
Science Direct	31254
Google Scholar	36700
Semantic Schcolar	191000

Our selection process consists of two distinct phases. In the initial phase, papers are filtered based on specific criteria. These criteria encompass the publication date, which must be within the last five years, and the nature of the articles. Papers that consist solely of abstracts, offer mere overviews, or are duplicates from other sources are excluded. In the subsequent phase, a thorough examination of the complete papers is conducted. This examination aims to verify that the key terms "medical imaging," "deep learning," and "machine learning" are included in the paper's content. Furthermore, it ensures that the papers explicitly delineate the application of deep or ML techniques, provide reports on model performance using standard metrics, and furnish comprehensive information regarding data sets and data processing. In the initial primary research, 1046 titles were retrieved. and collected for the title and abstract review, and finally, only 117 papers are qualified that focus on medical diagnosis using deep learning via medical imaging.

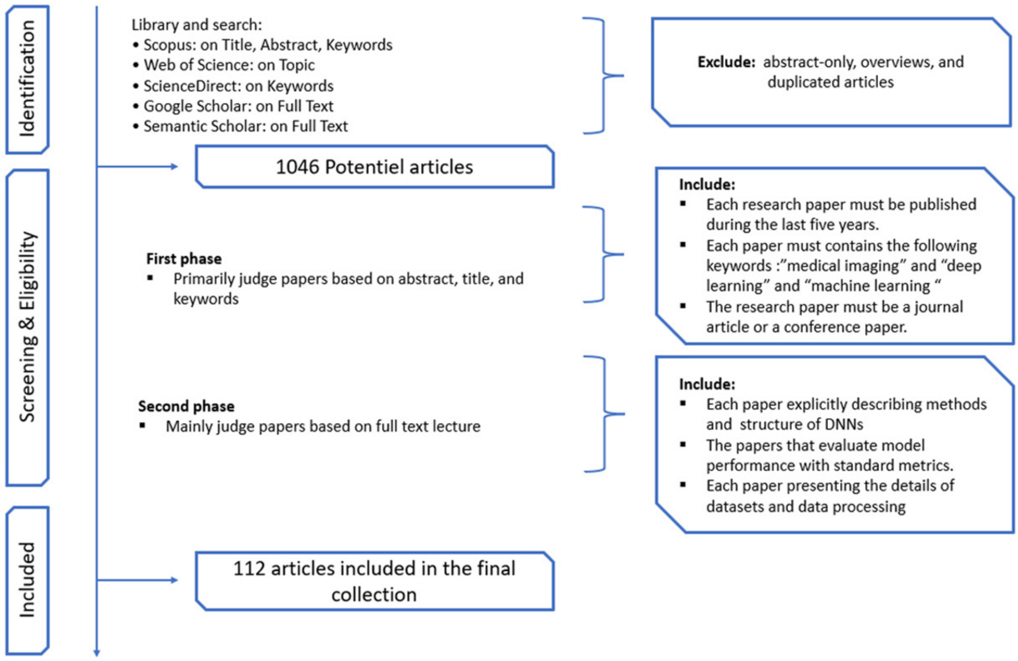

Fig. 14. Search and selection processes

6.2 Systematic search results

In the field of treatment for brain diseases, significant progress has been made, as evidenced by notable advancements in recent research. [83] pioneered a groundbreaking 3D brain slice classification approach in 2022, achieving an impressive accuracy rate of 0.95. This marked a significant advancement in the field of neuroimaging. However, it is imperative to acknowledge that challenges concerning model generalization and the validation of diverse datasets persist as areas of concern. Another notable breakthrough was the fusion of SegNet and deep belief networks for brain tumor segmentation and classification in 2022 [84]. This fusion achieved yielding accuracy rates of 0.933 and 0.921. However, persistent challenges remain, including dataset diversity and class imbalances. [85] adopted a CNN-LSTM approach in 2022 for brain tumor identification, achieving a notable accuracy rate of 0.92. Further rigorous clinical validation is essential. In a different vein, [86] introduced a deep autoencoder for brain tumor detection in 2022, demonstrating an impressive accuracy rate of 0.97. This highlights the importance of comprehensive clinical robustness. Shifting our attention to Alzheimer's disease, [87] CNNs and random forest will be used for classification in 2022, achieving an accuracy rate of 0.926 and offering potential for early diagnosis. Nevertheless, challenges persist in terms of scaling and generalizing this approach to diverse populations.

In the field of lung diseases, especially during the COVID-19 pandemic, [93] introduced a significant deep learning model in 2020 for detecting infections through chest X-rays. This model achieved an accuracy rate of 0.989, emphasizing the potential of AI in responding to pandemics. Persistent challenges involve the availability of data and adaptability to evolving virus strains. Similarly, in 2020, [94] utilized k-nearest neighbors (KNN) for diagnosing lung conditions using chest X-ray data. They achieved an impressive accuracy rate of 0.9809. However, challenges include the need for large datasets and the ability to adapt models in real-time to changing clinical conditions. Shifting the focus beyond COVID-19 to lung diseases in general, [95] utilized deep CNNs in 2018 for the classification of lung nodules. They achieved an accuracy rate of 0.68, with the primary objectives being to enhance accuracy and improve model robustness. For COVID-19 detection, [96] introduced an optimized deep learning model based on Bayesian principles in 2022, achieving an impressive accuracy of 0.96. However, addressing diverse datasets, mitigating bias, and improving data availability are indispensable considerations. [98] employed a multi-task multi-modality SVM approach in 2022 for early COVID-19 diagnosis using chest CT data. They achieved an accuracy rate of 0.89, highlighting the significance of SVMs in COVID-19 case classification. Ongoing challenges include the availability of data and the need for further accuracy improvements. [99] focused on feature processing for optimizing random forest (RF) in lung nodule localization in 2022, achieving a segmentation accuracy rate of 0.96. This study emphasized the significance of feature engineering for this task. Challenges may involve further refinement and clinical application. [100] presented a novel approach in 2020 that combined DBN and FCM for unsupervised deep clustering in the stratification of lung cancer patients. While showcasing potential, broader validation and adaptation to diverse patient populations are needed.

In the field of liver diseases, recent research has focused on liver segmentation using deep learning techniques, which achieved high sensitivity and specificity in 2022 [101]. Challenges include effective integration into clinical practice. In 2021, NucleiSegNet focused on segmenting liver cancer histopathology images and achieved an F1 score of 0.83. However, the model faced challenges related to its versatility [102]. In 2022, LRFNet assessed liver reserve function and obtained an AUC value of 0.774 [103]. Enhancing accuracy and establishing clinical relevance pose challenges. In 2019, deep learning and Gaussian mixture model techniques were employed for the detection of liver cancer, which necessitated thorough clinical validation [104]. In 2020, liver segmentation tailored for fusion-guided interventions achieved an accuracy of 0.96, highlighting promising clinical applications [105]. Lastly, in 2020, a 3D neural network was used to assess liver tumor burden with moderate sensitivity and specificity, aiming to achieve refined accuracy [106].

In the domain of vertebral diseases, [107] introduced an atrous residual encoder in 2022 for vertebrae segmentation, achieving a high level of accuracy. This represents a significant stride forward in the diagnosis and management of vertebral diseases. In 2021, [108] presented a method for recognizing vertebrae from MRI images, demonstrating an impressive accuracy of 0.955 and showcasing potential clinical utility. [109], also in 2021, focused on detecting lumbar vertebrae from X-ray images and achieved a Dice score of 0.91. This high score indicates the potential for evaluating fractures and related conditions. In 2020, [110] researchers employed deep CNNs to classify lumbar spine discs, achieving a high accuracy rate of 0.94. This offers promise for improved diagnostic accuracy and efficiency in spine-related pathologies. Lastly, [111] achieved precise laminae segmentation in 2021, with a dice score of 0.96. This achievement holds significant potential for improving surgical interventions related to vertebral diseases.

In the field of cardiac diseases, [112] introduced an automatic heart segmentation approach in 2022 with high accuracy. This approach shows promise in the field of cardiology, but it also faces challenges in terms of generalization and integration. In 2021, a study [113] utilized deep learning to detect heart disease using electrocardiogram (ECG) data. The study achieved an impressive accuracy rate of 0.994, showcasing the potential of AI in this field. However, it also emphasized the importance of interpreting AI-generated results and ensuring data privacy. In the same year, [114] introduced cardiac cine MRI segmentation and disease classification, achieving an accuracy of 0.92. This highlights the significance of precise diagnosis and the challenges associated with dataset size. In 2021, a study [115] demonstrated the effectiveness of deep learning in detecting myocardial infarction using extensive ECG data. The study achieved an impressive accuracy rate of 0.99, highlighting the potential of deep learning in real-time clinical applications and its ability to overcome challenges and potential biases.

Within the domain of prostate diseases, [116] introduced a hybrid DL approach for gland segmentation in 2021. This approach yielded a dice score of 0.90, which represents a significant advancement in pathology. However, further clinical validation is still required. In 2020, [117] presented a methodology for segmenting prostate lesions with a promising dice similarity coefficient (DSC) of 0.8958. However, the study faced challenges in generalizing lesion types and ensuring robustness across different imaging protocols. [118], in 2020, employed 3D AlexNet for prostate tumor segmentation, achieving an accuracy rate of 0.921. This study highlights the potential of AI in addressing interpretability and uncertainties. In 2022, [119] introduced prost attention-net for the segmentation of prostate cancer. They achieved a Dice score of 0.875, providing valuable information for targeted interventions despite the challenges of integration. In 2020, a study focused on diagnosing prostate cancer through MRI using machine learning methods. The study showcased potential clinical applications while also addressing standardization and validation issues.

In the context of breast diseases, [121] achieved commendable accuracy in classifying breast cancer from histopathology images in 2022, highlighting the significant role of AI in pathology. In 2019 [122], a study successfully utilized deep learning to detect MRI breast lesions, demonstrating advancements in radiology and addressing concerns related to data privacy and validation. In 2021, [123] researchers employed mammography image segmentation and classification techniques, which highlighted the potential for early detection and precise diagnosis. However, challenges related to workflow integration and diagnostic accuracy need to be addressed. In 2022, researchers [124] employed multi-scale feature fusion to classify breast cancer, highlighting the potential of AI in oncology. This approach aimed to tackie the challenges of model complexity and clinical testing. In the same year, [125] focused on classifying malignant tumors in breast ultrasound with high sensitivity and specificity. The study emphasized the clinical relevance and challenges associated with image quality and integration.

In the field of eye diseases, [126] achieved high accuracy in classifying glaucoma in retinal images in 2022, improving diagnostic capabilities in ophthalmology despite facing challenges in validation and integration. In 2022, [127] analyzed macular edema on OCT images with an impressive accuracy of 0.992. This study provides valuable insights into retinal health assessment, although it also highlights challenges related to OCT image variations and validation. In 2020, [128] focused on segmenting curvilinear structures in optical coherence tomography angiography (OCTA) images. This research contributed to the field of ophthalmology by addressing issues related to segmentation model generalization and image quality. In 2021, a study [129] reported a detection accuracy of 0.98 for diabetic retinopathy in eye fundus images. This high accuracy facilitates early diagnosis and intervention, but there are challenges related to integration and equity in access. In 2019, [130] automated glaucoma detection using DL convolutional networks, showcased the potential of AI in ophthalmology, with challenges in clinical validation and integration.

All papers have been meticulously summarized and are presented in Table 2, which provides a comprehensive overview of the key findings obtained from these studies.

7 FINDINGS AND FUTURE DIRECTIONS

In this section, we conduct a comprehensive analysis of the different articles selected during our research process. This analysis is based on the following criteria:

Method: Based on these criteria, the aim is to categorize the various techniques used in medical diagnostics into three groups: deep learning-based techniques, machine learning-based techniques, and a hybrid approach that combines both techniques.

Context or DataSet: It is the collection of datasets used during the training, testing, and validation phases of the created model.

Modalities: It is the various types of medical imaging used for each research study.

Result or Feature: This criterion identifies the various evaluation metrics for the approach used.

The "Accuracy" metric, for instance, is used to determine the ratio of correct predictions to the total number of input samples. "Precision and Recall" is a concept in which Precision is defined as the proportion of relevant samples that were correctly identified, and Recall is the proportion of relevant samples that were identified.

"Specificity" is the ratio of correctly classified negative predictions to the actual number of as negative cases, while "F1-score" is defined as the harmonic mean of precision and recall.

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP+TN}}{\boldsymbol{TP+TN+FP+FN}} \qquad \boldsymbol{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FP}}$$

$$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}} \qquad \boldsymbol{Specifity} = \frac{\boldsymbol{TN}}{\boldsymbol{TN+FP}}$$

$$\boldsymbol{F_1 = 2.\frac{Precision\,.\,Recall}{Precision + Recall}}$$

True Positives (TP): Number of samples correctly predicted as "positive"
False Positives (FP): Number of samples wrongly predicted as "positive"
True Negatives (TN): Number of samples correctly predicted as "negative"
False Negatives (FN): Number of samples wrongly predicted as "negative"

Table 2. Summary of recent AI-based advances in medical imaging

Paper	Title	Method	Context/Dataset	Modalities	Result/Feature	Year	Comments
Brain Diseases							
[83]	3D brain slice classification and feature extraction using Deformable Hierarchical Heuristic Model	Deep Learning CNN + DDRN	RIDER dataset - 70,220 REMBRANDT dataset 110,020 TCGA-LGG dataset 241,183	MRI	Accuracy 0.95	2022	Classification
[84]	SegNet and Salp Water Optimization-driven Deep Belief Network for Segmentation and Classification of Brain Tumor	Deep Learning SegNet + DBN	BRATS, 2018 datasets BRATS, 2020 datasets	MRI	Accuracy 0.933 Accuracy 0.921	2022	Segmentation + Classification
[85]	A Brain Tumor Identification and Classification Using Deep Learning based on CNN-LSTM Method	Deep Learning CNN + LSTM	Kaggle dataset - 3264	MRI	Accuracy 0.92	2022	Classification
[86]	A deep autoencoder approach for detection of brain tumor images	Deep Learning deep autoencoder	Kaggle dataset - 3000	MRI	Accuracy 0.97	2022	Classification
[87]	DTI based Alzheimer's disease classification with rank modulated fusion of CNNs and random forest	Deep Learning + Machine Learning CNN + RF	ADNI dataset	DTI	Accuracy 0.926	2022	Classification
[88]	An Adaptive Eroded Deep Convolutional neural network for brain image segmentation and classification using Inception ResnetV2	Deep Learning AEDCNN + Inception resnetV2	TCIA - Brain tumour dataset	MRI	Accuracy 0.97	2022	Segmentation + Classification
[89]	A Hybrid CNN-SVM Threshold Segmentation Approach for Tumor Detection and Classification of MRI Brain Images	Deep Learning + Machine Learning CNN + SVM	BRATS 2015 dataset	MRI	Accuracy 0.984	2022	Segmentation + Classification
[90]	An Efficient Technique to Segment the Tumor and Abnormality Detection in the Brain MRI Images Using KNN Classifier	Machine Learning KNN	59 MRI	MRI	Accuracy 0.96	2020	Classification
[91]	MRI brain tumor image classification with support vector machine	Machine Learning SVM	3064 MRI	MRI	Accuracy 0.99	2022	Classification
[92]	Brain Tumor MRI Images Identification and Classification based on the Recurrent Convolutional Neural Network	Deep Learning RNN	Kaggle dataset 3264	MRI	Accuracy 0.95	2022	Classification
Lung Diseases							
[93]	A Novel Medical Diagnosis model for COVID-19 infection detection based on Deep Features and Bayesian Optimization	Deep Learning CNN	2905 chest X ray	CXR	Accuracy 0.989	2020	Classification
[94]	New machine learning method for imagebased diagnosis of COVID-19	Machine Learning KNN	1 560 chest X ray	CXR	Accuracy 0.9809	2020	Classification

(Continued)

Table 2. Summary of recent AI-based advances in medical imaging *(Continued)*

Paper	Title	Method	Context/Dataset	Modalities	Result/Feature	Year	Comments
[95]	Computer-aided diagnosis of lung nodule classification between benign nodule, primary lung cancer, and metastatic lung cancer at different image size using deep convolutional neural network with transfer learning	Deep Learning CNN	1236 CT	CT	Accuracy 0.68	2018	Classification
[96]	Bayesian-based optimized deep learning model to detect COVID-19 patients using chest X-ray image data	Deep Learning CNN	10848 chest X-ray	CXR	Accuracy 0.96	2022	Classification
[97]	COVID-19 disease identification from chest CT images using empirical wavelet transformation and transfer learning	Deep Learning CNN	2 482 chest X-ray	CXR	Accuracy 0.85	2022	Classification
[98]	Multi-task multi-modality SVM for early COVID-19 Diagnosis using chest CT data	Machine Learning SVM	4000 CT	CT	Accuracy 0.89	2022	Classification
[99]	Features processing for random forest optimization in lung nodule localization	Machine Learning RF	2124 CT	CT	Accuracy 0.96	2022	Segmentation
[100]	Joint DBN and Fuzzy C-Means unsupervised deep clustering for lung cancer patient stratification	Deep Learning + Machine Learning DBN + FCM	LIDC-IDRI datasets - 1018	CT	DBI 2.35 SC 0.68	2020	Classification
Liver Diseases							
[101]	Liver segmentation from computed tomography images using cascade deep learning	Deep Learning UNET	LITS dataset 131 CT	CT	Sensitivity 0.95 specificity 0.99 Dice 0.95	2022	Segmentation
[102]	NucleiSegNet: Robust deep learning architecture for the nuclei segmentation of liver cancer histopathology images	Deep Learning NucleiSegNet	KMC liver dataset - 80	HIS images	F1 score 0.83	2021	Segmentation
[103]	LRFNet A deep learning model for the assessment of liver reserve function based on Child-Pugh score and CT image	Deep Learning LRFNet	1022 CT	CT	AUC 0.774	2022	Classification
[104]	Deep learning based liver cancer detection using watershed transform and Gaussian mixture model techniques	Deep Learning + Machine Learning DNN + GMM	225 CT	CT	Accuracy 0.99	2019	Segmentation + Classification
[105]	Deep learning-based liver segmentation for fusion - guided intervention	Deep Learning MIMO-FAN	70 CT	CT	Accuracy 0.96	2020	Segmentation
[106]	Three-Dimensional Neural Network to Automatically Assess Liver Tumor Burden Change on Consecutive Liver MRIs	Deep Learning U-Net + ResNet-18	64 MRI	MRI	Sensitivity 0.85 Specificity 0.92	2020	Segmentation

(Continued)

Table 2. Summary of recent AI-based advances in medical imaging *(Continued)*

Paper	Title	Method	Context/Dataset	Modalities	Result/Feature	Year	Comments
Vertebrae Diseases							
[107]	Atrous residual interconnected encoder to attention decoder framework for vertebrae segmentation via 3D volumetric CT images	Deep Learning Atrous-ResUNet	10 CT	CT	Accuracy 0.9910	2022	Segmentation
[108]	Automatic vertebrae recognition from arbitrary spine MRI images by a Category-Consistent self-calibration detection framework	Deep Learning Can-See	450 MRI	MRI	Accuracy 0.955	2021	Segmentation
[109]	Automatic detection and segmentation of lumbar vertebrae from X-ray images for compression fracture evaluation	Deep Learning M-net	160 lumbar X-ray	XR	Dice 0.91	2021	Segmentation
[110]	Lumbar spine discs classification based on deep convolutional neural networks using axial view MRI	Deep Learning VGG16	1 736 MRI	MRI	Accuracy 0.94	2020	Classification
[111]	Precise laminae segmentation based on neural network for robot-assisted decompressive laminectomy	Deep Learning SegRe-Net	35 CT	CT	Dice 0.96	2021	Segmentation
Heart Diseases							
[112]	An automatic approach for heart segmentation in CT scans through image processing techniques and Concat-U-Net	Deep Learning Concat-U-Net	36 CT	CT	Accuracy 0.99	2022	Segmentation
[113]	Heart disease detection using deep learning methods from imbalanced ECG samples	Deep Learning GAN-LSTM	400 ECG	ECG	Accuracy 0.994	2021	Classification
[114]	Automatic cardiac cine MRI segmentation and heart disease classification	Deep Learning CNN	150 MRI	MRI	Accuracy 0.92	2021	Segmentation
[115]	Hybrid CNN-LSTM deep learning model and ensemble technique for automatic detection of myocardial infarction using big ECG data	Deep Learning CNN-LSTM	MIT-BIH dataset	ECG	Accuracy 0.99	2021	Classification
Prostate Diseases							
[116]	A hybrid deep learning approach for gland segmentation in prostate histopathological images	Deep Learning RINGS	1500 RGB	RGB	Dice 0.90	2021	Segmentation
[117]	Prostate lesion segmentation in MR images using radiomics based deeply supervised U-Net	Deep Learning 2D U-Net	3 245 MRI	MRI	DSC 0.8958	2020	Segmentation
[118]	Medical image segmentation and reconstruction of prostate tumor based on 3D AlexNet	Deep Learning 3D AlexNet	500 MRI	MRI	Accuracy 0.921	2020	Segmentation

(Continued)

Table 2. Summary of recent AI-based advances in medical imaging *(Continued)*

Paper	Title	Method	Context/Dataset	Modalities	Result/Feature	Year	Comments
[119]	ProstAttention-Net: A deep attention model for prostate cancer segmentation by aggressiveness in MRI scans	Deep Learning ProstAttention-Net	219 MRI	MRI	Dice 0.875	2022	Segmentation
[120]	A new approach to diagnosing prostate cancer through magnetic resonance imaging	Deep Learning + Machine Learning MLP + SVM + KNN	271 MRI	MRI	Accuracy 0.80	2020	Classification
Breast Diseases							
[121]	Classification of breast cancer from histopathology images using an ensemble of deep multiscale networks	Deep Learning DAMCNN + CSAResnetx	BreakHis dataset	HIS images	Accuracy 0.99	2022	Classification
[122]	Detection and characterization of MRI breast lesions using deep learning	Deep Learning CNN	335 MRI	MRI	AUC 0.816	2019	Segmentation
[123]	Deep learning in mammography images segmentation and classification: Automated CNN approach	Deep Learning modified U-Net model and Inception V3	DDSM dataset	MAMMO images	Accuracy 0.98	2021	Segmentation + Classification
[124]	MultiNet: A deep neural network approach for detecting breast cancer through multi-scale feature fusion	Deep Learning DenseNet-201 + NasNetMobile, + VGG16	BreakHis dataset	RGB images	Accuracy 0.99	2022	Classification
[125]	Classification of malignant tumors in breast ultrasound using a pretrained deep residual network model and support vector machine	Deep Learning + Machine Learning ResNet-101 + SVM	2099 US images	US images	Sensitivity 0.94 Specificity 0.93	2021	Classification
Eye Diseases							
[126]	Deep learning-based classification network for glaucoma in retinal images	Deep Learning CoG-NET	Drishti-GS dataset RIM-Onedataset REFUGE dataset	Retinal images	Accuracy 0.935	2022	Classification
[127]	DeepOCT: An explainable deep learning architecture to analyze macular edema on OCT images	Deep Learning DeepOCT	ZhangLab dataset	OCT images	Accuracy 0.992	2022	Segmentation
[128]	CS2-Net: Deep Learning Segmentation of Curvilinear Structures in Medical Imaging	Deep Learning CS2-Net	OCTA dataset	OCTA images	Accuracy 0.9183	2020	Segmentation
[129]	Diabetic retinopathy detection and stage classification in eye fundus images using active deep learning	Deep Learning ADL-CNN	EyePACS dataset	Fundus images	Accuracy 0.98	2021	Segmentation
[130]	Automated detection of Glaucoma using deep learning convolution network (G-net)	Deep Learning G-net	DRISHTI-GS dataset	Fundus images	Accuracy 0.958	2019	Segmentation

Examination of the various articles listed in Table 2 reveals a diversity of techniques employed in the field of medical diagnostics. These techniques include the implementation of DL approaches [83, 84], the use of ML methods [94, 98], and the adoption of hybrid approaches that combine ML and DL methodologies [87, 89].

In our comparative analysis of the outcomes achieved with various evaluation metrics, it becomes apparent that the hybrid approach, which integrates both ML and DL techniques, stands out as the approach yielding the most accurate, efficient, and robust models [89, 104, 125].

Furthermore, it is noteworthy to mention the limited prevalence of the hybrid approach in the field of medical diagnosis. The majority of papers tend to focus on explicit methods, particularly DL approaches.

Additionally, it is crucial to emphasize the limited availability of annotated images for specific diseases, which significanty rises the performance of the proposed models. These models typically rely on extensive datasets during the training and validation phases to achieve higher levels of accuracy and reliability [119, 122].

Moreover, a significant observation is that the majority of the research primarily focuses on a specific imaging modality, often disregarding the importance of disease detection through multimodal medical imaging. This omission is significant, given the substantial advancements made in enhancing clinical accuracy through the utilization of multimodal approaches.

In light of these observations, it is necessary to prioritize the datasets used as input for the classification and segmentation of medical image synthesis or transfer learning techniques. By doing so, we can address the challenges associated with the limited number of annotated images, which may result in models overfitting. Subsequently, future research can be directed towards improving the performance of models used in disease classification and segmentation. This can be achieved through the exploration of hybrid techniques that integrate both DL and ML approaches. These approaches are expected to provide more accurate results.

8 CONCLUSION

The primary goal of this systematic review was to provide a comprehensive perspective on the role of AI in contemporary medical research, with a particular emphasis on the utilization of ML and DL techniques for disease detection. Employing an interdisciplinary approach, our aim was to explore the various methodologies commonly used in scientific literature. Our comprehensive analysis revealed a predominant preference for explicit approaches in the majority of studies, with independent applications of ML and DL techniques However, it is noteworthy that a minority of studies have embraced hybrid methodologies, seamlessly combining both paradigms. Through a meticulous examination of outcomes across these various approaches, a consistent pattern emerged: the hybrid methodology consistently yielded effective and relevant results, indicating a promising avenue for further exploration in the field of medical diagnosis. A critical issue that arosed during our analysis is the significant challenge posed by the scarcity of annotated images for specific diseases, which has a substantial impact on the performance of AI models.

To proactively address this challenge, our upcoming research initiatives will focus on integrating medical image synthesis and transfer learning techniques. These innovative strategies hold promise for mitigating issues related to limited data availability and are poised to make substantial contributions to the advancement of disease classification and segmentation models. Our strategic commitment to this endeavor underscores our dedication to advancing the field of medical AI and charting a promising path for ongoing investigations.

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