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Analysis of Medical Image Processing using Machine Learning Applications - A Review

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ABSTRACT

Intelligent health systems and a range of patient care can benefit from the help of artificial intelligence. In the medical field, artificial intelligence methods from machine learning to deep learning are widely used for patient risk assessment, medication development, and illness diagnosis. To accurately detect illnesses using artificial intelligence approaches, a variety of medical data sources are needed, including computed tomography scans, genomes, mammograms, ultrasound, magnetic resonance imaging, and more. Additionally, artificial intelligence mainly improved the experience of patients in the hospital and expedited the process of getting them ready to continue their recovery at home. This article discusses a thorough analysis of artificial intelligence-based methods for diagnosing a wide range of illnesses, including cancer, diabetes, Alzheimer's disease, chronic heart disease, stroke, cerebrovascular, hypertension, skin, and liver disease. We carried out a thorough analysis that included the medical imaging dataset that was utilized, as well as the feature extraction and classification procedure for making predictions. For the purpose of early prediction of various disease types using artificial intelligence-based methods, articles published up until October 2020 on the Web of Science, Scopus, Google Scholar, PubMed, Excerpta Medical Database, and Psychology Information are chosen based on preferred reporting items for systematic reviews and Meta-Analysis guidelines.

Key words: Medical Image Processing; Machine Learning; Deep Learning; X-Ray; Symptoms.

1. INTRODUCTION

Medical image processing is one of the most essential tasks when it comes to the diagnosis of diseases. Recently, researchers have used advanced methods of machine learning and deep learning to interpret, analyze, and modify medical images which help in diagnosis and treatment [1]. From the first decade of the 2000s new technologies in machine learning, deep learning, and big-data technologies have greatly affected the medical image processing field. Specifically, machine learning algorithms have matured, coupled with the increased access to large repositories of medical images [2], leading to faster growth worldwide and greater reliance on more consistent, accurate, and comprehensive solutions in oncology, radiology, and cardiac science[3]. The progress of medical image technology has also run hand-in-hand with healthcare needs for the accuracy of images. The main focus of early studies conducted in this area was the different image processing methods such as feature extraction, segmentation, and classification. The emergence of machine learning systems, most particularly deep learning seems to have accelerated the pace of these models and their attendant studies. Since 2010, cloud computing and the big-data era have progressed and this area has expanded further with cloud picture processing technology, massive data, and improved performance all contributing towards advancement. This era also marked the growth of artificial intelligence AI [4].

More studies have recently focused on the development of operable robotic systems for telemedical surgeries, multi-modal imaging, and cloud-based collaborative model training. These advancements are new frontiers in precision medicine which allow treatment to be tailored to individuals and increase the knowledge of complicated diseases [5].

We aim in this survey to provide a comprehensive overview of studies in medical image processing from 2000 to the present. By examining the technologies, applications, and future trends, this paper aims to give researchers, developers, and clinicians an in-depth understanding of past and current developments, as well as insights into future opportunities in this rapidly advancing field

Benefits for illness diagnosis are associated with the use of artificial intelligence (AI). The healthcare system is a dynamic, ever-evolving setting [2]. And medical professionals always encounter fresh difficulties due to shifting duties and regular disruptions [3]. This diversity frequently causes medical professionals to see illness diagnosis as a secondary concern.

Furthermore, it is a cognitively demanding effort to analyze medical information clinically. This is true for both seasoned professionals and performers with little or no experience, such young assistant physicians [6]. Diagnostics is a very difficult procedure because medical specialists often have limited time and because illnesses and patient dynamics may alter over time [7]. Nonetheless, early treatment and, consequently, safe and successful patient care depend heavily on an accurate diagnosis procedure. Our primary goal in this study is to provide an overview of the most recent research on deep learning applications for medical image processing [8, 9].

Since building systems become more feasible, the role of AI in the diagnostic process has been progressively growing [10]. AI continues to generate excitement and buzz [11], and both practitioners and researchers give this technology equal attention from a variety of angle. AI is defined as "the ability of a machine to perform cognitive functions that we associate with human minds, such as perceiving, reasoning, learning, interacting with the environment, problem solving, decision making, and even demonstrating creativity", though there is no agreed-upon definition for the term [12]. The main contribution of the current study lies in investigating a wide range of illness symptoms and exploring how AI methods can be utilized for their detection. This report is particularly noteworthy for its detailed discussion on various illness diagnoses and projections, derived from a comprehensive survey of detection methods.

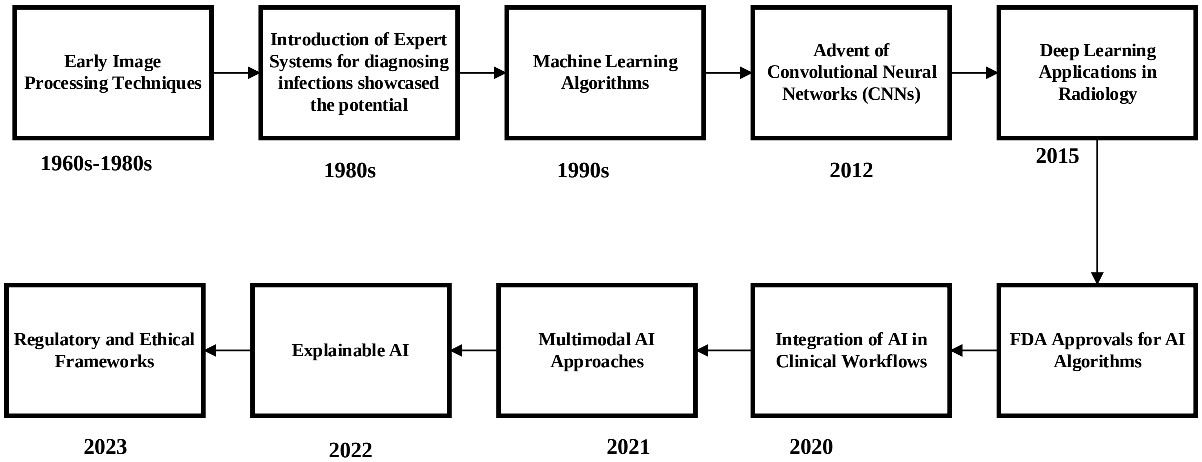

Figure 1: A historical overview of advancements in medical image processing.

2. FUNDAMENTALS OF MEDICAL IMAGING

The evolution of contemporary medical imaging technology, from Wilhelm Roentgen's groundbreaking invention of X-ray technology in 1895 to today's most sophisticated methods, exemplifies the unrelenting quest for scientific progress and its profound impact on radiology [13] (Figure 1).

A major turning point was the introduction of computed tomography in 1973 by Sir Godfrey Hounsfield and Allan Cormack, which went beyond the constraints of 2D imaging by introducing a three-dimensional (3D) format[14]. In order to reconstruct 3D volumetric data from the gathered 2D images, computed tomography combines the fundamental idea of differential absorption with the synchronized rotation of X-ray sources and detectors around the patient's body, along with advanced computational algorithms [13]. A vital component of the complex machinery of multidisciplinary medical teams is radiology. A comprehensive, patient-focused healthcare strategy is facilitated by radiologists' quick and accurate imaging reports, which improve communication between specialists and help shape important choices [15]. As important consultative partners, radiologists provide crucial information about how to select and interpret appropriate imaging studies, contributing to radiation safety and dose control while their knowledge clarifies the clinical picture and provides information that can significantly impact patient care [15, 16].

2.1 Medical Imaging Techniques Types

Medical imaging techniques vary in their underlying technology, applications, and the type of information they provide. Here are some of the most commonly used types:

- X-ray A diagnostic method called radiography uses ionizing electromagnetic radiation, like X-rays, to see things. With a wavelength of 0.01 to 10 manometers, X-rays are high intensity electromagnetic radiation that may ionize gases and penetrate materials [17] as shown in Figure 2.

Figure 2: X-Ray images example

- Magnetic Resonance Imaging (MRI) is a diagnostic technique that images bodily tissues and tracks bodily chemistry using magnetic and radio frequency fields.The MRI's capacity to identify variations in proton density and magnetic spin relaxation times both of which are indicative of the environment the sick tissue presents is what allows it to visualize morphological abnormalities[18] as show in Figure 3.

- **Computed Tomography** (CT) is a diagnostic technique that creates pictures of cross sections of the human body by combining X-ray equipment, a computer, and a cathode ray tube display as shown in Figure 4. A detector that measures the X-ray profile takes the role of the radiography film. The CT scanner is a revolving frame with the detector positioned on one side and an X-ray tube mounted on the other [19].

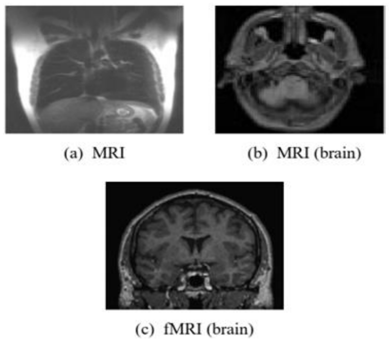

Figure 3: MRI images example

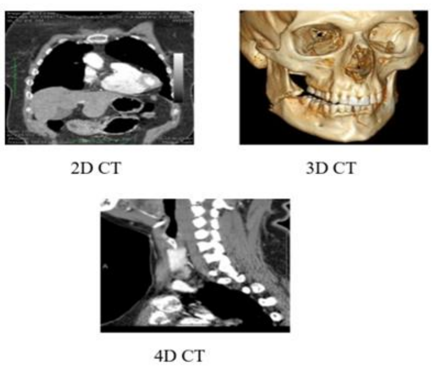

Figure 4: CT images example

- **Ultrasound** the first technique to do elastography was ultrasound elastography, which is now extensively researched for clinical diagnostic applications to scan soft tissue biomechanical characteristics [20]. as shown in Figure 5

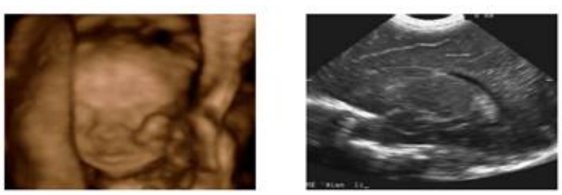

Figure 5: Ultrasound images example

- **PET** provide details on a disease's metabolic processes. PET imaging uses isotopes that decay due to positron emission. After only a short distance, the released positron experiences an annihilation event, producing two photons that move in opposing directions to each other [21]. As illustrated in Figure 6.

- **Single Photon Emission Computed Tomography** (SPECT) is a method of imaging that uses medications labeled with atoms that, upon decay, release at least one gamma ray. It is required to put a collimator in front of the detector so that only gamma rays released in the detector's direction may be detected because gamma rays are typically emitted equally in all directions [21].

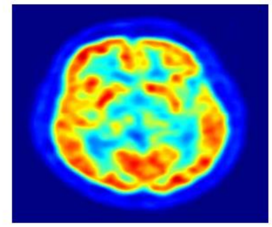

Figure 6: PET for brain image

- **Image Acquisition and Preprocessing**

Other methods, in which predicting a result becomes exponentially more efficient than relying solely on visual diagnosis, are utilized for normal image-based diagnoses of diseases such as skin cancer [22], Cardiovascular diseases [23], Lung diseases [24], Jaundice diseases [25],and so on.

2.2 Numerical data

Other approaches use numerical data for disease diagnosis, such as laboratory test results (e.g., blood pressure, heart rate, oxygen saturation, and temperature) [26]. In these methods, the input is provided as numerical values, and the output is the estimated risk of these diseases [27].

The dataset utilized in this way is sourced from the Central Person Registry (CPR) and includes illness trajectories from the Danish National Patient Registry (DNPR) , encompassing 229 million hospital diagnoses [28].

2.3 Baseline for medical image processing

Typically, most medical image processing pipelines (see Figure 7) follow a series of key steps:

- **Image Categorization**: Organizing images into relevant categories based on characteristics or intended analysis.
- **Image Pre-Processing**: Preparing images by correcting artifacts, resizing, or standardizing formats for consistent input.
- **Image Enhancement**: Improving image quality by adjusting contrast, reducing noise, and sharpening details to highlight key features.
- **Segmentation**: Partitioning images into meaningful regions or structures, such as organs or lesions, for focused analysis.
- **Feature Extraction**: Identifying and isolating significant features or patterns within the images that are relevant to the diagnosis.
- **Feature Selection**: Selecting the most important features to reduce data complexity and enhance the performance of the analysis.
- **Classification**: Assigning labels or categories to images or regions based on extracted features, often to detect or diagnose specific conditions.

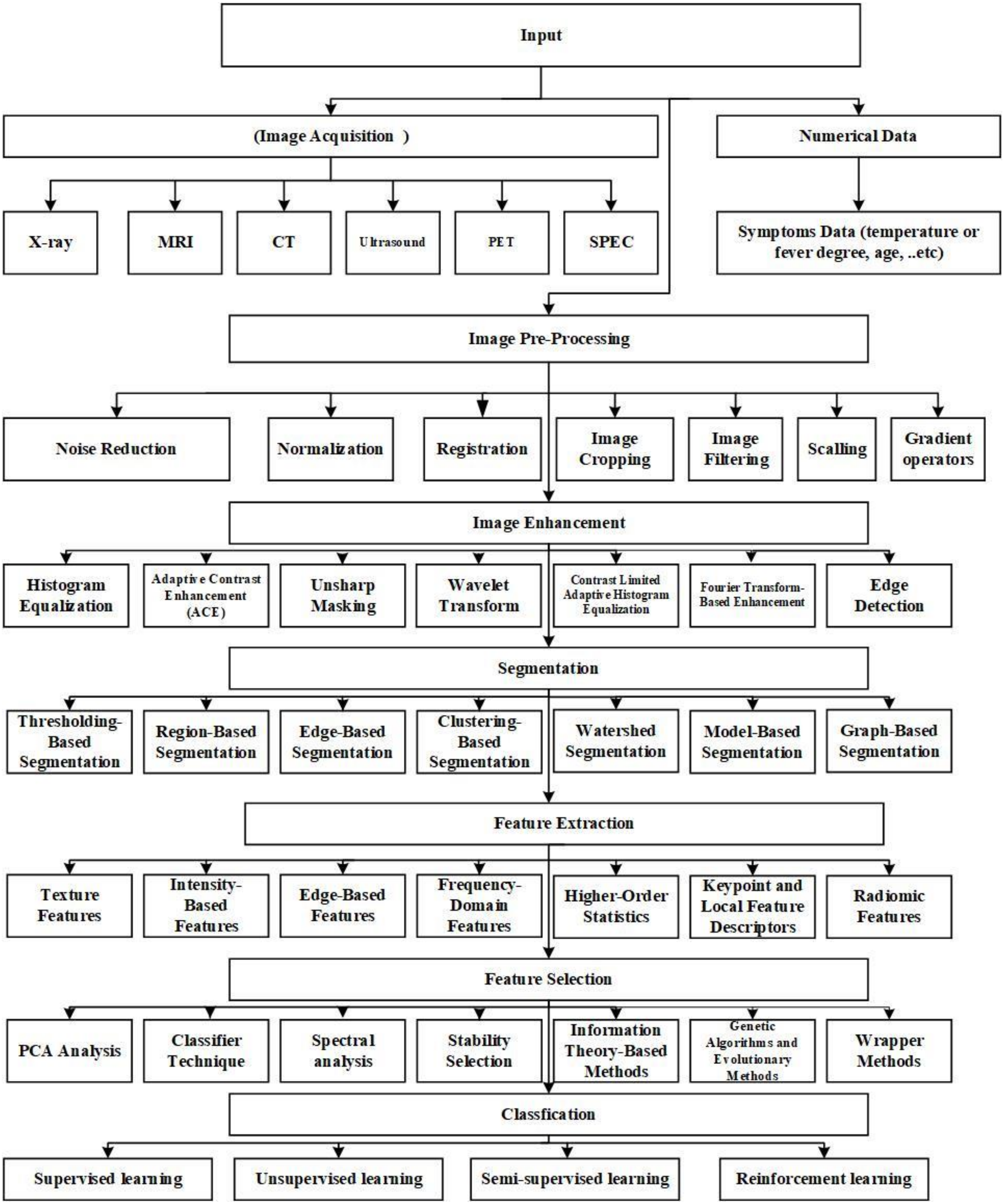

Figure 7: The pipeline of medical image processing

3. MEDICAL IMAGE PROCESSING BY MACHINE LEARNING TECHNIQUES

Recently, machine learning approaches, together with artificial intelligence (AI) models, clinical data, and image analysis, have shown significant potential to improve people's lives in a relatively short period [29]. Below, we list the main approaches for disease diagnosis:

3.1 Deep learning approaches

Many approaches and algorithms that allow computers to learn from data form the foundation of machine learning. Supervised and unsupervised learning are the two main types of machine learning that underpin this field.

1) Supervised learning

One popular machine learning technique is supervised learning, which uses input-output pairs as training data or pre-existing examples. The goal is to develop a function that maps input data to corresponding outputs, allowing for accurate prediction or classification of new data. Essential algorithms in supervised learning include decision trees, logistic regression, and linear regression [30]. Supervised learning addresses a scenario where a model is trained to learn a relationship between input samples and a target variable [26]. Systems that use examples of input vectors along with their corresponding target vectors in the training data are referred to as supervised learning systems. The two main categories of supervised learning problems are classification and regression [27]. In classification, the task is to predict a class label, whereas in regression, the objective is to predict a numerical value as the target variable [28].

Most supervised methods use common networks, such as:

- **AlexNet** : In 2012, Krizhevsky et al. [31] developed AlexNet to tackle the ILSVRC-2010 objective of categorizing 1.5 million images into 1000 classes. AlexNet is based on the LeNet-5 architecture, with some modifications: it consists of eight layers, with the first five dedicated to feature extraction and the final three for classification.

- **The Visual Geometry Group (VGG)** model was developed in 2014 by Simonyan and Zisserman [32] for classification and localization tasks. With approximately twice as many convolutional layers as AlexNet, VGG extends the depth of the CNN to 16 layers (VGG-16) and 19 layers (VGG-19).

- **GoogleNet** [33] was developed for detection and classification tasks. It expands the CNN's width and depth while keeping the computational budget constant, with 12 times fewer parameters than AlexNet. GoogleNet's primary innovation is the inception module, which replaces the fully connected convolutional layer with a sparsely connected layer. Including pooling layers, inception modules, and auxiliary classifiers, GoogleNet comprises a total of 100 layers, with 22 convolutional layers.

- **The deep residual network (ResNet)** : In 2016, He et al. [34] introduced ResNet for tasks such as segmentation, classification, detection, and localization. ResNet addresses the vanishing gradient problem that occurs with increasing network depth by incorporating residual blocks. It is eight times deeper than VGG while maintaining lower complexity (fewer parameters), as the residual mapping does not require additional parameters.

- **Conventional Neural Network (CNN):** To perform well and generalize effectively, CNNs require a large number of labeled examples. Creating a high-quality dataset with many samples can be costly and challenging, especially when labeling requires human involvement, as is often the case with medical datasets.

- **Region-Based Convolutional Neural Network (R-CNN)** was proposed by Girshick et al. [35] for object segmentation, detection, and localization. R-CNN combines the power of a CNN, a region proposal method, and a support vector machine (SVM). The CNN extracts feature from each candidate region box generated by the region proposal method, known as selective search. The SVM then predicts a class and creates a bounding box for each potential object.

- **Faster R-CNN**: To increase the speed of R-CNN, Girshick [36] developed the fast region-based convolutional neural network (Fast R-CNN. Fast R-CNN extracts visual features using a single CNN. Following CNN's computation of the feature maps, Fast R-CNN converts each suggested region's size into a fixed length using the ROI pooling layer.

- **Mask R-CNN**: To recognize an object and simultaneously generate a segmentation mask, He et al. [37] introduced Mask R-CNN for instance segmentation.

- **Fully Convolutional Network (FCN)**: The FCN was proposed by Long et al. [38] for semantic segmentation. An FCN is a CNN that consists of two sections: downsampling and upsampling paths, and it replaces all dense layers with convolutional layers. A CNN (including convolutional layers, ReLU, and pooling layers) is used in the downsampling path for feature extraction. Transposed convolution layers (also known as deconvolution) are included in the upsampling path to recover the spatial information of feature maps.

- **U-Net**: U-Net was developed by Ronneberger et al. [39] for biomedical semantic segmentation. The U-Net architecture has a U-shape, with two symmetrical paths (contracting and expanding). The contraction (downsampling) path uses a conventional CNN for feature extraction. The expanding path, also known as upsampling, preserves spatial information. Skip connections are used to link the two paths, ensuring that spatial properties from the early layers are maintained. Figure 8 shows the accuracy of supervised networks.

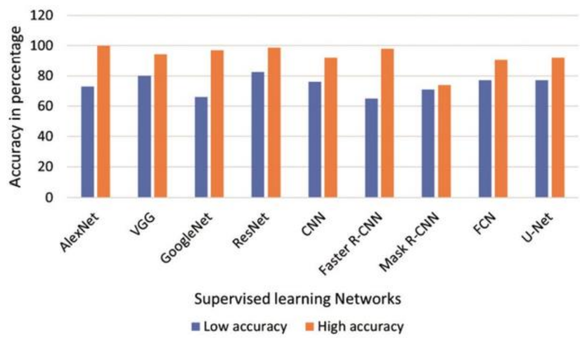

Figure 8: Accuracy of supervised learning networks: lowest and highest [40]

2) *Unsupervised learning*

In this section, we formally present unsupervised deep learning architectures used in medical image analysis. Unsupervised learning is a computational method in which computers identify hidden structures and patterns in unlabeled data without the use of output labels. Unlike supervised learning, where labeled examples are available, the model in unsupervised learning must discern inherent relationships and groupings within the data to facilitate classification and interpretation [41]. Selecting unsupervised learning is advantageous when the objective is to explore and understand the intrinsic structure of data. This approach is ideal for tasks where explicit output labels are either challenging to obtain or unnecessary, as well as in situations where labeled data is scarce or unavailable [42]. In medical imaging research, unsupervised learning is highly effective in various classification tasks, such as distinguishing between benign and malignant tumors [43, 44], enabling domain adaptation in cardiac arrhythmia classification [45], identifying brain diseases [46], and detecting masses in breast cancer [47]. Unsupervised learning's ability to uncover hidden patterns and correlations, revealing subtle differences in images, is a critical advantage in medical image processing and analysis. This capability enhances understanding of complex clinical and anatomical phenomena.

Unsupervised learning enables creating new ideas and hypotheses through the grouping of unlabeled data into clusters. In addition, odd distance transform and other dimensionality reduction techniques enhance the interpretability of the data that would otherwise be visually difficult to analyze due to the high dimensionality. But there are also unintended consequences raised by the unsupervised models that are capable of noise capturing resulting in creation of classification that is clinically uninformative. Thus, using unsupervised learning must be complemented with thorough validation, clinical judgement, and knowledge of its limitations [41].

3) *Reinforcement Learning*

In such mechanisms of learning, it is possible to have complex imaging procedures and even more complex patients rendering such imaging for optimal decision-making in case of changing conditions. It is useful with regard to problems for which there is a solution but that is not known at the very beginning and has to be built up through time. Such an approach is preferred when the model is to learn from its actions and from the experiences, one is required to make some decisions amid uncertainty. In the literature, such aspects have been attributed, for instance, autonomous driving systems [48], robotic control [49], and game playing [50].Reinforcement learning is applied in medical image processing and analysis for tasks such as automating the exploration of different imaging sequences [51], developing patient-specific treatment plans [52], and optimizing imaging parameters during acquisition [53]. Additionally, by customizing post-processing algorithms to each patient's unique characteristics, reinforcement learning improves image quality and enhances diagnostic accuracy [54]. In anatomical and biological landmark detection [55], modality-invariant landmark localization, and minimizing the time to locate landmarks using a continuous action space [56], reinforcement learning is essential for accurately identifying landmarks across various imaging modalities. It is also valuable for applications like breast lesion detection in object identification and extraction tasks.

4) *Semi-Supervised Learning*

Semi-supervised learning is a combination of both unsupervised and supervised learning. In this method, the models are provided with a tiny portion of labeled data along a huge dataset with no labels as the models draw relations between the labeled data and try to learn the structure of the unlabeled data. In situations where one aims to utilize the maximum usages of unlabeled examples present in the data while having an additional value from the labeled examples, semi supervised approach should be utilized. This method is mostly popular in the fields like natural language processing [57] and automated speech recognition [58]. In the case of medical image processing and analysis, Semi-Supervised Learning and its variants are being employed to meet challenges resulting from the limited availability of annotated medical datasets leading to better evaluation and better understanding. It is often used in image manipulation tasks such as artificial image synthesis [59], segmentation [60] and classification [61]. The main benefit of semi supervised learning is enhanced generalization and robustness of the models where typically only a small amount of labeled data is available while shallow regions are sought in large unlabeled data sets. However, a model always requires careful attention to the factors that dictate the proportion between such labeled and unlabeled datasets [41].

In Figure 9, statistical data on the use of machine learning in medical image processing is presented.

In Table 1, we present a summary of the most important research studies that have used machine learning in medical image processing.

Table 1: Comparative evaluation of several disease detection methods

Author	Disease type	Dataset	Method	Accuracy	Code
Li et al. [62]	Coronary Artery	Phonocardiogram (PCG) and Electrocardiogram (ECG) images	CNN that combines feature extraction in these signals.	Highest result 93.69%	Python (Keras framework)
Jasti et al. [63]	Breast Cancer	MIAS and DDSM dataset	Machine learning (AlexNet) with a geometric mean filter	Highest result 95%	-
Ucar et al. [64]	COVID-19	COVIDx dataset	Deep Squeeze Net	98.30%	MATLAB
Heidari et al [65]	COVID-19	SARS-COV-2 CT scan dataset	Long short-term memory networks (LSTM)	89%	Pytorch and MATLAB
Solayman et al.[66]	COVID-19	The authors collected a private dataset	The hybrid CNN-LSTM algorithm	96.34%	-
Nithya et al. [67]	Kidney	Kidney ultrasound images	K-means clustering, ANN, Segmentation based linear and quadratic	99.61%	MATLAB
Khan et al. [68]	Gastrointestinal	The authors collected a private dataset through IoT	Deep Learning (VGG 16, ANN)	98.4%	-
Gouda et al. [69]	COVID-19	disease CT scan dataset	Deep learning	90.9%	-
Arsalan et al. [70]	Hypertension	DRIVE, CHASE-DB1, STARE	Vess-net Method, Semantic Segmentation	96.55%	MATLAB R2019a
Lai et al. [71]	Tuberculosis	a private dataset from “Taipei Medical university”	ANN, Random Forest	88.67%	-
Gao et al. [72]	Tuberculosis	100 CT TB images	Deep Learning (ResNet)	85.29 %	Python
Keenan et al. [73]	Detection of Retinal Fluid	scan data (1127 SDOCT)	AI (software tool)	80.5 %	AI software tool
Sarao et al. [74]	Detection of Retinopathy	Real time data of 165 patients	Image Analysis Software (AI software tool)	90.8%	AI software tool
Ljubic et al. [75]	Alzheimer	EMR and SCRP dataset	deep learning models (LSTM, RNN)	98-99%	Python
Khan et al. [76]	Alzheimer	OASIS-database	Machine learning, Pipeline, Pattern Recognition		
Janghel et al. [77]	Alzheimer	ADNI-database	KNN, SVM, Decision Tree	73.46 %	Python
Isravel et al. [78]	Heart	Health-dataset	Naïve Bayes, KNN, ECG signals, Decision Tree	80 %	Python
Bibault et al.[79]	obstructive pulmonary	ECLIPSE-dataset	AI (software tool)	88.6 %	AI software tool
Rodrigues et al. [80]	Skin Lesion	ISIC-dataset	CNN (VGG Net), Random, Forest KNN, SVM	96.805%	Python
Memon et al. [81]	Breast cancer	Dataset From Wisconsin Diagnostic Breast Cancer Center	SVM and Machine Learning	99 %	Python
Chu et al. [82]	Oral cancer	408 of OSCC (patients)	PCA, Decision Tree, KNN, SVM	70.59%	MATLAB
Hosseinzadeh et al. [83]	Thyroid	MRI-dataset	ANN	99%	Python
Ostovar et al. [84]	Covid 19	Dataset from Laboratory of RTPCR	Deep learning	60–70%	Python
Yadav et al. [85]	Thyroid	3710 thyroid cases (patients)	Random Forest, Decision Tree, Regression Tree, and Classification	Decision tree: 98% Random forest:99%	Python
Tengnah et al. [86]	Hypertension	Real time dataset	Multi-Layer Perceptron, Fuzzy logic, SVM, Decision Tree	90.48%	Python
Ali et al. [26]	Respiratory	Real time dataset	Fuzzy logic	95 %	MATLAB
Chang et al. [87]	Disease of Scalp	Dataset gathered from a physiotherapist who treats scalp hair	Deep learning (RNN)	97.41–99.09%	MATLAB
Morabito et al. [88]	Disease of Scalp	Data based on AD and EEG	CNN with Multi-Layer Perceptron	80%	MATLAB
Jo et al. [89]	Alzheimer	AD-dataset	Deep learning (RNN)	96.0%	Python
Ani et al. [90]	Disease of Chronic	191 patients with and without stroke	Random forest, KNN, Naïve Bayes, Classification	93%	MATLAB

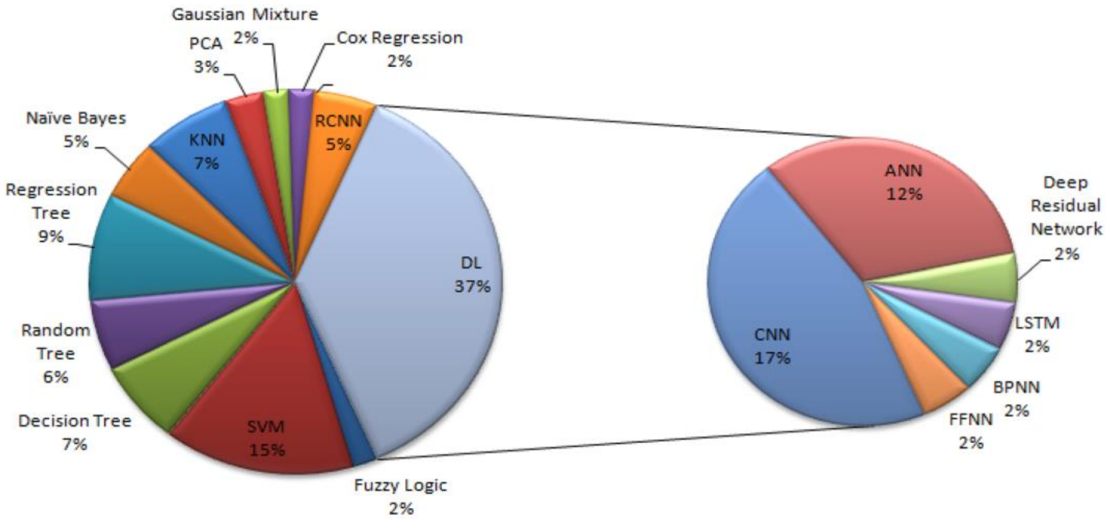

Figure 9: Prediction Approaches by Artificial intelligence [91]

3.2 Limitations, Challenges, and Future Directions

AI's growth in healthcare, especially in diagnostic radiology, has created previously unheard-of chances to improve patient care's effectiveness and quality. The "black box" conundrum, the need for sufficient data volume and quality, integration into clinical practice, and ethical issues are only a few of the numerous obstacles that accompany this quick expansion. This section analyzes these problems and suggests possible solutions that might help radiologists adopt and use AI responsibly while taking into account a number of technological, infrastructure, legal, and human considerations [92].

4. THE QUANTITY QUALITY FOR DATA

Artificial intelligence (AI) algorithms, which are essentially mathematical mirrors of reality, rely on comprehensive datasets that accurately reflect a range of patient demographics, including age, sex, ethnicity, and disease stages, in addition to their training datasets and accuracy [93, 94].

Due to the use of limited demographic groupings or particular clinical contexts, representation biases sometimes hinder the creation of such datasets [95]. In order to address data scarcity and guarantee dataset variety and balanced representation during model training, techniques such as data augmentation, oversampling, and undersampling are frequently used [96]. Given that poor management might unintentionally reinforce health inequities and produce AI models that perform poorly in particular patient populations, it is critical to identify and mitigate the risks associated with biased or unrepresentative data. The lack of transparency in AI models, known as the "black box" problem, makes it more difficult to identify bias and uncover errors, which has a negative impact on therapeutic utility and underrepresented populations [97].

5. CONCLUSION

A summary of the most important discoveries, revolutionary possibilities, and future directions of the complex link between AI and medical imaging is provided in the review's conclusion. AI is essential to modern radiology and offers several benefits, including increased diagnostic precision, streamlined workflow, and individualized patient care. These developments, which include computer-aided diagnosis, picture segmentation, classification, and novel diagnostic and prognostic tools powered by radiomics and predictive analytics, portend a bright future for bettering patient outcomes. However, issues with security, data privacy, and the "black box" nature of AI models still need to be resolved. Notwithstanding these challenges, the future appears bright as new architectures and algorithms expand the use of medical image analysis.

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