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A Review on Medical Image Analysis Using Deep Learning

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Abstract - *Medical image analysis is the process of analyzing medical images using computers with the goal of finding, categorizing, and measuring patterns in clinical images. Medical image processing and analysis requires the use of a number of techniques, including segmentation, classification, detection, localization, and registration. Medical image analysis has made extensive use of deep learning, a quickly expanding area of artificial intelligence. Deep learning networks have shown successful in tasks including image identification, segmentation, and classification. Examples of these networks are convolutional neural networks (CNNs) and recurrent neural networks (RNNs). Deep learning is being used in medical image analysis to explore and analyze large amounts of data, which will increase the precision of recognizing and diagnosing medical diseases. All things considered, medical image analysis is essential to helping medical practitioners diagnose patients accurately, plan treatments, and keep track of their progress. The following areas of application research are briefly summarized: computerized pathology, neural, brain, retinal, pneumonic, bosom, heart, breast, bone, stomach, and musculoskeletal.*

Key Words: Deep Learning, Convolutional neural network, Medical image, Brain tumor.

1. INTRODUCTION

Artificial intelligence (AI) models and deep learning applications have the ability to improve people's lives in a short period of time. Computer vision, pattern recognition, image mining, and machine learning have all been integrated into medical image processing, which includes picture production, retrieval, analysis, and visualization. Deep learning has created new opportunities for medical image analysis because of its capacity to use neural networks to discover patterns in data formats. Applications of deep learning in healthcare cover a broad spectrum of problems, such as infection control, individualized therapy recommendations, and cancer detection. Modalities including PET, X-ray, CT, fMRI, DTI, and MRI are frequently used in medical images. In order to increase accuracy, deep learning networks like convolutional neural networks (CNNs) are frequently employed in medical picture processing [1].

Medical imaging helps in disease research and identification by taking pictures of internal organs for therapeutic use. Clinical research and therapy effectiveness are the main objectives of medical image analysis. Deep learning has revolutionized this sector by showing hidden patterns for flawless diagnosis and performing tasks like segmentation, registration, and classification well. Numerous deep learning techniques, such as convolutional neural networks and pretrained models, are explored to enhance medical image processing performance. These techniques are particularly useful in organ segmentation, cancer detection, and illness classification [2].

1.1 Medical Image Analysis Using Deep Learning

The main goal of medical image analysis is to identify the anatomy's diseased regions so that doctors can better understand how lesions progress. Four primary phases are involved in the analysis of a medical image: (1) preprocessing the image; (2) segmentation; (3) feature extraction; and (4) pattern identification or classification. Preprocessing is the process of enhancing image information for subsequent processing or removing undesired distortions from photographs. The technique of separating areas for additional research—such as tumors and organs—is referred to as segmentation. Feature extraction is the process of carefully selecting information from the regions of interest (ROIs) to help identify them. Classification helps to categorize the ROI based on features that are extracted [2][3].

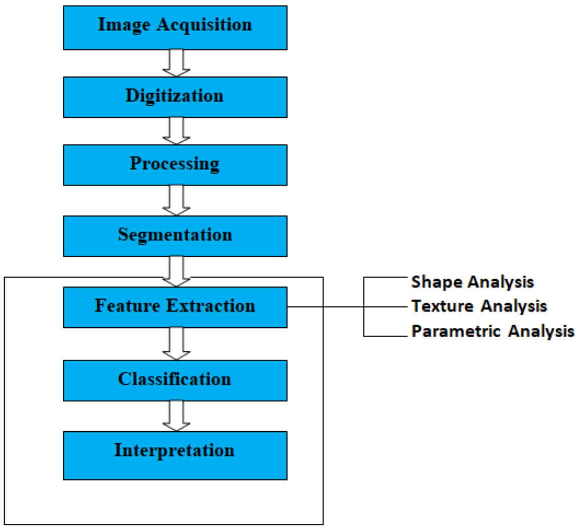

Fig1: Steps of Medical Image Analysis

1.2 Deep Learning

Deep learning is a branch of machine learning that focuses on creating deep neural networks that are modeled after the biological neural networks seen in the human brain. Recent developments in deep learning have revolutionized the interpretation of medical images, showing impressive success in terms of precision, effectiveness, stability, and scalability. By using advanced deep models, these technologies can interpret intricate patterns found in medical imaging, opening the door to more advanced clinical uses. Deep learning's hierarchical structure makes it possible to extract minute features from medical images, greatly advancing both clinical and scientific endeavors [3].

Deep learning-powered medical image analysis is revolutionizing the field of medicine. Medical image interpretation has been completely transformed by deep learning techniques like convolutional neural networks (CNNs) and recurrent neural networks (RNNs). These cutting-edge methods provide unmatched accuracy and efficiency in applications such as picture registration and anatomical and cellular research. Deep learning algorithms have recently achieved tremendous success in terms of accuracy, stability, and scalability, pushing medical image analysis to new heights [4].

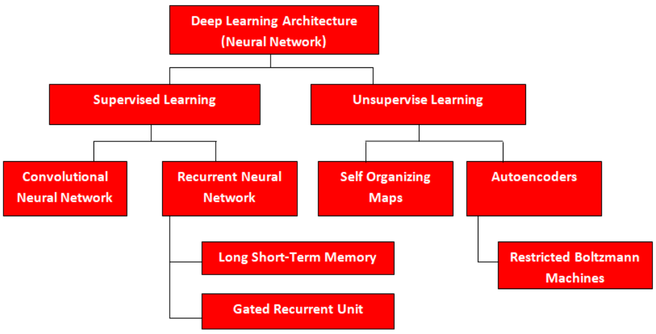

Fig 2: Deep Learning Architecture

1.3 Convolutional Neural Network

Deep convolutional neural networks (CNNs) have become a game-changer in the field of illness diagnosis when applied to medical picture classification. CNNs perform exceptionally well on tasks like picture categorization, segmentation, and illness detection by utilizing the power of deep learning. With its considerable potential to improve diagnostic precision and efficiency in medical imaging, this technology offers a bright future for better healthcare results [5]. CNNs are specialized artificial neural networks designed for computer vision, inspired by the visual cortex of the human brain. CNNs consist of convolutional, pooling, and fully connected layers and are good at extracting features. Filters are used by convolutional layers to extract features, pooling layers to minimize spatial dimensions, and fully connected layers to complete classifications. CNNs are frequently used in medical image analysis and are excellent in identifying, categorizing, and segmenting a wide range of medical diseases [6].

With a convolutional filter intended for 2D to 3D conversion, this model exhibits the best fit for handling two-dimensional input. It is very strong because of its remarkable performance strength and quick learning speed. Nonetheless, for the classification process to work well, a significant amount of labeled data must be provided. Convolutional Neural Nets (CNNs) face several notable obstacles, such as the presence of local minima, a comparatively slower rate of convergence, and a high degree of human factor interference. After AlexNet's astounding success in 2012, CNNs have become a crucial component in enhancing the efficiency of human physicians in the field of medical image processing [1][6].

1.4 Recurrent Neural Network

Particularly useful for applications involving time series or natural language processing, Recurrent Neural Networks (RNNs) are a specific kind of artificial neural network that is intended to analyze sequential input. RNNs provide a memory mechanism that enables them to capture dependencies within successive observations, which sets them apart from typical neural networks. When generating predictions or analyzing the current input, RNNs can take into account the context of earlier inputs because to this memory function. In applications like language modeling, time series analysis, and speech recognition, where the context and order of the data are critical, they perform exceptionally well [1] [3] [4].

1.5 Long short-term memory/gated recurrent unit networks (LSTM/GRU)

Recurrent neural networks (RNNs) with advanced features, such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), are employed in deep learning. In order to overcome the vanishing gradient issue that conventional RNNs have, LSTM and GRU are both made to be able to recognize long-term relationships in sequential data. The network can store and retrieve data for longer thanks to the introduction of memory cells, gates, and updating and forgetting procedures by LSTM. A less complex version called GRU is computationally more economical because it can accomplish comparable results with fewer parameters. Natural language processing, time-series analysis, and many more fields where comprehending and maintaining temporal connections are essential find use for these networks [1] [3].

1.6 Autoencoder

Deep learning algorithms that are intended for unsupervised learning are known as Autoencoder. The goal of these neural networks is to compress the input data and then use the compressed representation to recreate the original data. Autoencoders are a versatile tool that may be applied to a wide range of tasks, including data compression, denoising, and feature learning. They are effective in extracting meaningful representations from complex data [3]. One deep learning model that best illustrates the idea of unsupervised representation learning is the Autoencoder (AE), as seen in Fig. 3a. When there are more unlabelled data in the input data than labeled data, AE is helpful. In a lower-dimensional space, z, AE encodes the input, x. Through a single hidden layer, z, the encoded representation is once more decoded to an approximate representation x′ of the input x [4].

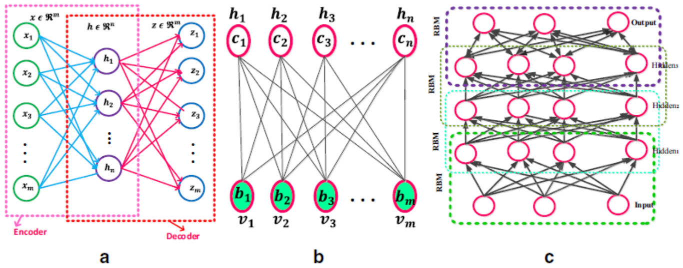

Fig 3: a Autoencoder [4] b Restricted Boltzmann Machine with m visible and n hidden units [4] c Deep Belief Networks [4]

1.7 Restricted Boltzmann Machine

An artificial neural network that is intended for unsupervised learning is called a Restricted Boltzmann Machine (RBM). RBMs are generative stochastic algorithms that may be trained to learn a probability distribution over a collection of inputs. Geoffrey Hinton invented them in 1985. RBMs have random connections between their visible and buried layers. Their applications in machine learning include collaborative filtering, feature learning, dimensionality reduction, and other areas. Natural language processing, picture recognition, and recommendation systems are just a few of the fields in which RBMs are used [1][4].

2. DEEP LEARNING TECHNIQUE OF MEDICAL IMAGING

An Overview of current techniques of DL for medical imaging followed by various specifications considered for selecting the classifiers and the analysis metrics used to evaluate classification models. The existing literature review is divided according to the disease such as brain tumor, and chronic kidney disease etc.

2.1 Brain Tumor

An abnormal growth of brain tissue is called a brain tumor. It may be malignant (cancerous) or benign (non-cancerous). The tumor could be primary (originating in the brain) or secondary (spreading from other regions of the body to the brain). Depending on where and how big they are, brain tumors can impair a variety of bodily processes. Symptoms include headaches, seizures, vision alterations, and cognitive problems [7].

Nowadays, brain tumors are a serious and concerning condition that impacts a lot of people. The primary cause of brain tumors is the aberrant functioning of brain cells. Primary and secondary brain tumors can be distinguished from one another. While tumors in the secondary stage grow larger and are referred to as malignant, early stage tumors are small and deemed benign. According to the National Brain Tumor Society, there are over 700,000 brain tumor patients in the United States, of which 30.2% have aggressive brain tumors and 69.8% have benign ones. It is reported that just 36% of people with brain tumors survive. Roughly 87,000 people received a brain tumor diagnosis in 2020 [8].

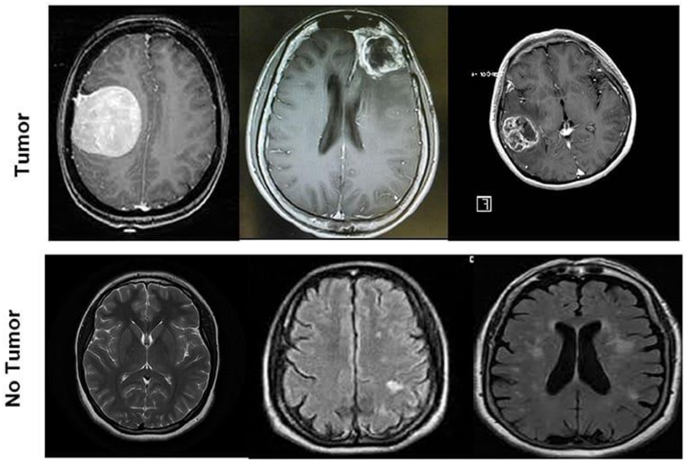

Fig 4: MRI brain images samples for two classes tumor and no tumor [25].

2.2 Chronic Kidney Disease

Chronic kidney disease (CKD) is primarily caused by diabetes and high blood pressure. Reduced renal function over time is a result of chronic kidney disease (CKD).Premature death is linked to chronic kidney disease (CKD). Preventing the advancement of chronic kidney disease (CKD) requires early diagnosis and identification. To diagnose CKD, researchers examine markers of kidney disease including the Glomerular Filtration Rate (GFR). In comparison to other modern machine learning methods, a deep learning model has been built for the early identification and prediction of CKD. To determine which traits were most crucial for CKD identification, Recursive Feature Elimination (RFE) was employed [24].

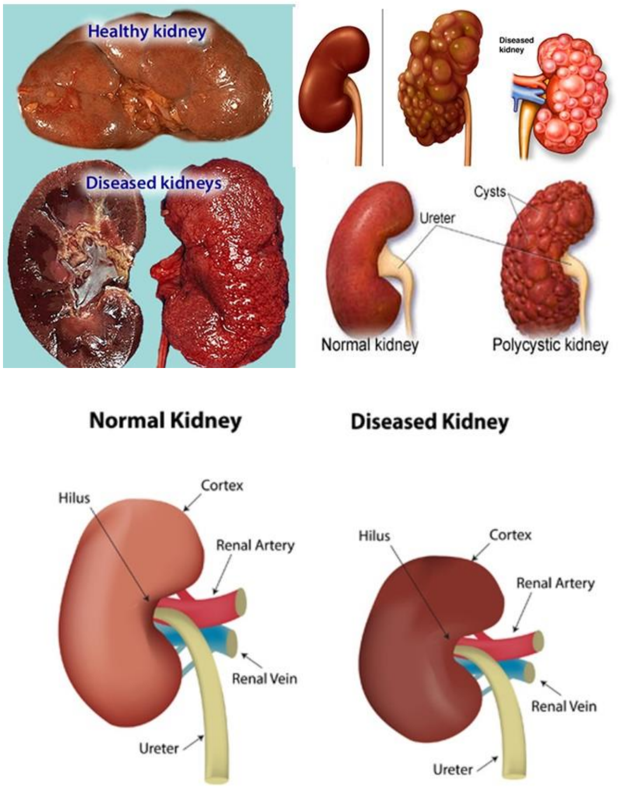

Fig 5: Images for Healthy Kidney and Diseased Kidneys [31]

3. LITERATURE SURVEY

This section covers survey studies on deep learning-based methods for medical image analysis, Brain tumor, and chronic kidney disease.

Muhammad Imran Sharif et al. [8] focus on high accuracy, research aims to improve multiclass brain tumor classification in medical imaging. We introduce an automated deep learning method based on the Densenet201 model, optimized by deep transfer learning on data that is not balanced. Extraction of features from the average pool layer obtains comprehensive tumor data. We present feature selection methods (EKbHFV and MGA) with additional refinement via a unique threshold function to overcome accuracy constraints. Using a multiclass SVM cubic classifier, our method uses a non-redundant serial-based strategy to merge these characteristics. Without augmentation, experimental validation on the BRATS2018 and BRATS2019 datasets achieves over 95% accuracy. A comparative study using alternative neural networks demonstrates the importance and performance of our suggested approach in improving the categorization of brain tumors.

Aniwat Phaphuangwittayakul, et al. [9] Conducted a systematic review of Showcasing advances in medical imaging and diagnostic applications, an ideal deep learning framework specifically designed for traumatic brain injury has been established for the detection and quantification of multi-type hemorrhagic lesions in head CT images.

Gunasekaran Manogaran, et al. [10] Introduced an enhanced machine-learning method based on orthogonal gamma distribution is presented in this study to analyze regions affected by brain tumors and identify anomalies using automatic ROI identification. Employing a machine learning technique to measure the sensitivity and selectivity parameters, the research tackles the issue of data imbalance in the abnormality zone by sampling the edge coordinates. By employing a mathematical formulation, the study verifies the algorithm's mean error rate, efficiency, accuracy, and optimal automatic identification for both tumor and non-tumor areas. With reference to MRI applications especially, the research advances the field of brain abnormalities identification and analysis in the healthcare industry.

Carlo Tappero, et al. [11] Worked on the study investigates whether post-mortem CT (PMCT) can be used to detect cerebral hemorrhages in bodies that have decomposed. With post-mortem decomposition, the study seeks to show that PMCT is still able to detect brain hemorrhages. The implications of the detrimental effects of decomposition on the consistency of brain tissue make this especially important. The study unveils the potential of PMCT imaging in forensic pathology by examining and validating its capacity to locate and diagnose cerebral hemorrhages in deteriorated remains.

JAEHAK YU, et al. [12] performed a machine learning-based system for predicting the risk of stroke using PPG and ECG biomarkers. Using machine learning approaches, the proposed system seeks to predict and semantically understand stroke prognostic signs. In order to construct this system, a variety of bio-signal data are recorded and gathered, such as electroencephalography (EEG), electrocardiography (ECG), and electromyography (EMG). Additionally, for the AI-based stroke disease prediction module, a multimodal bio-signals method is investigated.

Rohit Lamba, et al. [13] Concentrated on early detection, the scientists suggest a hybrid Parkinson's disease diagnosis method based on speech signals. To create the model with the best performance, they experiment with different feature selection strategies and classification algorithms. There are three feature selection techniques used: genetic algorithm, extra tree, and mutual information gain. There are three classifiers used: random forest, k-nearest-neighbors, and naive bayes. The best result is obtained with 95.58% accuracy when the evolutionary algorithm and random forest classifier are combined, outperforming earlier research in the literature.

S. Deepak, et al. [14] Focus on automating the classification of brain cancers from MRI pictures by combining Support Vector Machine (SVM) and Convolutional Neural Network (CNN) characteristics. The CNN was created expressly to extract pertinent features from brain MRI pictures. After that, a multiclass SVM is combined with these collected features to improve brain tumor classification performance. An open-source MRI dataset from Figshare that depicts three different kinds of brain tumors is used to assess the suggested method. A completely automated brain tumor classification system with increased accuracy is the goal of integrating CNN and SVM.

Sukhpal Kaur, et al. [15] conducted an improving Parkinson's disease diagnosis by combining transfer learning, data augmentation, and a deep Convolutional Neural Network (CNN). The study attempts to increase diagnostic accuracy by utilizing the power of a deep 25-layer CNN classifier (AlexNet). Transfer learning makes use of previously learned information for the model, and data augmentation makes the model more robust by artificially growing its dataset. The objective of the suggested methodology is to offer a sophisticated and precise Parkinson's disease diagnosis tool.

Sidra Sajid, et al. [16] proposed on deep learning method for segmenting and identifying brain tumors in MR images is presented in this work. The method merges contextual and local data using hybrid CNN architecture with a patch-based strategy. Dropout regularization and batch normalization are used to reduce over fitting. A two-phase training approach is applied to address the imbalance in data. A CNN-based feed-forward pass comes after preprocessing for image normalization and bias field correction.

Loveleen Gaur, et al. [17] focuses on workable way to identify COVID-19 from chest X-rays and differentiate between healthy individuals and those suffering from viral pneumonia. The research uses deep learning methods, more especially deep convolutional neural networks (CNNs), to examine medical images, mostly X-rays of the chest. The aim is to improve COVID-19 detection accuracy while tackling issues like differentiating COVID-19 from other respiratory disorders. The suggested method adds to the current efforts to use cutting-edge technology for quick and precise COVID-19 diagnosis using medical imaging.

Table -1: Comprehensive Analysis

Reference	Dataset	Method	Application	Result	Modality
Muhammad Imran Sharif1 et al. 2021 [8]	BRATS2018 and BRATS2019	Fine-Tuning Densenet201	Brain Tumor	BRATS2018 and BRATS2019 datasets, achieving an accuracy of over 95%.	HGG(high-grade glioma) and LGG(Low-grade glioma)
Aniwat Phaphuangwittayakul, et al. 2021 [9]	RSNA 2019, PhysioNet and CMU-TBI	Deep Learning Framework	Hemorrhagic Lesions Detection	The proposed deep learning framework achieved an average accuracy of 96.21% for the detection.	CT Images
Amin ul Haq, et al. 2023 [19]	Brain Tumor Images	Convolutional Neural Network(CNN)	Brain MR images in the IoT healthcare system	The proposed CNN model achieved High outcomes 99.89% classification accuracy	MR Images
Sidra Sajid, et al. 2019 [20]	BRATS 2013	CNN	Brain Tumor Detection and Segmentation	The deep learning-based approach obtains, for the entire tumor region, dice score, sensitivity, and specificity scores of 0.86, 0.86, and 0.91, respectively.	MRI Segmentation
Muhammad Aamir, et al. 2022 [21]	BraTS	Deep Learning	Brain tumor detection technique using MRI	When brain tumors were identified using MRI scans, the suggested technique had 98.95% classification accuracy.	MRI Images

4. METHODOLOGY

Our target topic is Medical image analysis using deep learning. We ended up using around 30 of the most recent papers related to medical image analysis using deep learning. Some of the papers examined only deep learning, while other used a combination of Machine Learning and deep learning.

To find the papers for our search, we mostly used the Scopus database. This is to keep non-refereed publications out of it. On the other hand, we show the distribution of a few chosen papers among the current databases in Figure 4. PubMed, ScienceDirect (Elsevier), IEEE, and Springer are the top four databases

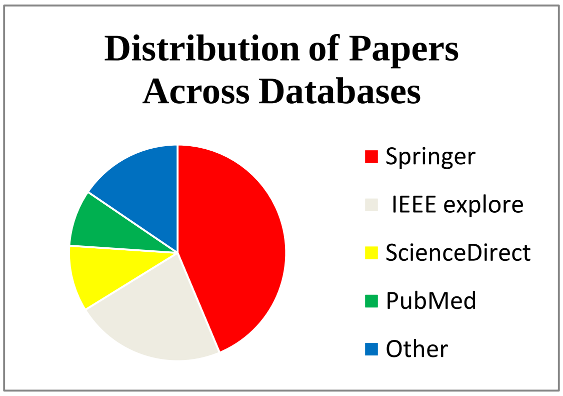

Fig 6: Distribution of Papers across Databases

It is evident that the use of deep learning for medical image analysis and brain tumor research articles peaked between 2019 and 2023. We focused solely on journal and conference articles, reducing the total number of papers to 30, and we only included studies that used genetic expression and imaging. In addition to several forms of gene expression and gene sequencing, the imaging modalities that we took into consideration included ultrasound, radiography, mammography, and magnetic resonance imaging (MRI). Our research focuses on articles that employ deep learning to implement medical image analysis and studies that forecast brain tumors using both gene and image data. For every article, we used the following eligibility standards: (1) The work is written in English; (2) It addresses the diagnosis and treatment of brain tumors; and (3) It talks about machine learning and deep learning hybrid models. (4)The study discusses deep learning only; (5) genetic expression data; (6) imaging data; (7) journal and conference publications are the only ones kept; (8) Convolutional and recurrent neural networks are covered in the paper; (9) The paper focuses on deep learning-based medical picture analysis; (10) Only papers pertaining to medicine or biomedical engineering are retained.

Please be aware that the study did not include any non-refereed papers. First, we noted the essential details, like the title of the work, the year it was published, the list of writers, and the publisher. Then, we incorporated certain data to carry out the systematic review, like the dataset, the features, the recorded accuracy and other performance assessment metrics, the algorithm employed, and if the publication talks simply deep learning or a hybrid between DL and ML, among many other columns. These standards helped us respond to our study inquiries.

5. CONCLUSION

This article provided a review of the most recent research on deep learning for medical imaging. It talks about a noteworthy contribution in the following fields. Firstly, a detailed review of the core ideas of Deep Learning is discussed. Consider this section of the review as a lesson on common medical imaging Deep Learning principles. Second, a thorough summary of Deep Learning-based methods in Medical Imaging was given by the study. Later in the paper, the main problems that Deep Learning encounters when analyzing medical images are discussed, along with potential solutions. This work assessed the progress made by CNN-based deep learning algorithms in clinical applications like object detection, segmentation, registration, and image classification. Several technical issues were covered in the research, including data problems, machine and hospital integration, robust systems, data preprocessing, ongoing model learning, and cross-system fine tuning. According to a review of the literature, the DNN classifier outperforms traditional classifiers in terms of accuracy. AI-based image evaluation can identify complicated imaging patterns that are impossible to detect using visual radiologic evaluation. The study also showed that DL tools are beneficial to radiologists and clinics. According to that study, humans who use AI perform better than those who do not.

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