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Overview of medical analysis capabilities in radiology of current Artificial Intelligence models

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Abstract

Judgment is fundamental in medicine, particularly when combining complex data layers with detailed decision-making processes. Radiology processes present a distinct challenge for medical decisions due to the data amount and shortage in time and personnel capable of analyzing images.

Additionally, it's crucial to consider each patient's specific situation, including their current state and disease history. Despite advancements in technology, there are still significant hurdles in accurately analyzing radiology data. Radiographic assessments, which are predominantly based on visual inspections, could greatly benefit from enhanced computational analyses. Artificial intelligence (AI) in particular holds the potential to significantly improve the qualitative interpretation of imaging by medical experts - automating and even replacing some parts of their work. This article will be an overview of possibilities and challenges associated with introducing new technology into medical spaces. Doctors are struggling with time and it limits how much care they can show for each patient. The image can be marked for most important parts, AI can produce a more user friendly version of the description, suggesting what might be the problem for later human evaluation. Understanding the possibilities of automating or cutting down time spend by radiology experts on analyze will allow faster deliver of radiologic image description for doctors dealing with patient treatment.

Material and methods

In this study, we employed a comprehensive search strategy to identify relevant literature on the application of artificial intelligence (AI) in radiology. We primarily utilized Google Scholar and PubMed, recognized academic databases for scholarly publications. Our search queries incorporated keywords terms encompassing "artificial intelligence," "radiology," "deep learning," "machine learning," "natural language processing (NLP)," "large language models (LLMs)," "convolutional neural networks (CNNs)," and "neural networks." Additionally, we reviewed reference lists of pertinent articles to uncover further relevant publications. This multifaceted approach ensured the capture of a broad spectrum of academic research on AI techniques, such as LLMs, CNNs, and neural networks, within the domain of radiology.

Keywords

“artificial intelligence”, “medicine”, “radiology", "deep learning”, "machine learning” “large language models”, "neural networks”

Artificial Intelligence - definition and capabilities

Artificial intelligence (AI) is a vast range of algorithms that are connected by trying to mimic some of human capabilities in terms of analyzing data, speaking, seeing and understanding.
It can be defined as

> *Intelligence exhibited by machines. This intelligence is achieved through complex algorithms that enable machines to learn from data, reason, solve problems, and make decisions that would typically require human-like cognitive abilities*[1]

To understand how it can be used in a medical application we first need to explore different types of algorithms, how they work and what their limitations are.
The first one will be - Convolutional Neural Networks (CNN) is an architecture of Neural Network specifically designed to better understand complicated data inside the image itself. Firstly let's start with defining what is a Neural Network and how the convolutional one differs from the classic approach. The definition presented in „Deep learning in neural networks: An overview" gives a proper definition of them

> *A neural network is a computational model inspired by the structure and function of the biological brain. It consists of interconnected nodes, called artificial neurons, that process information by transmitting signals to each other.* [2]

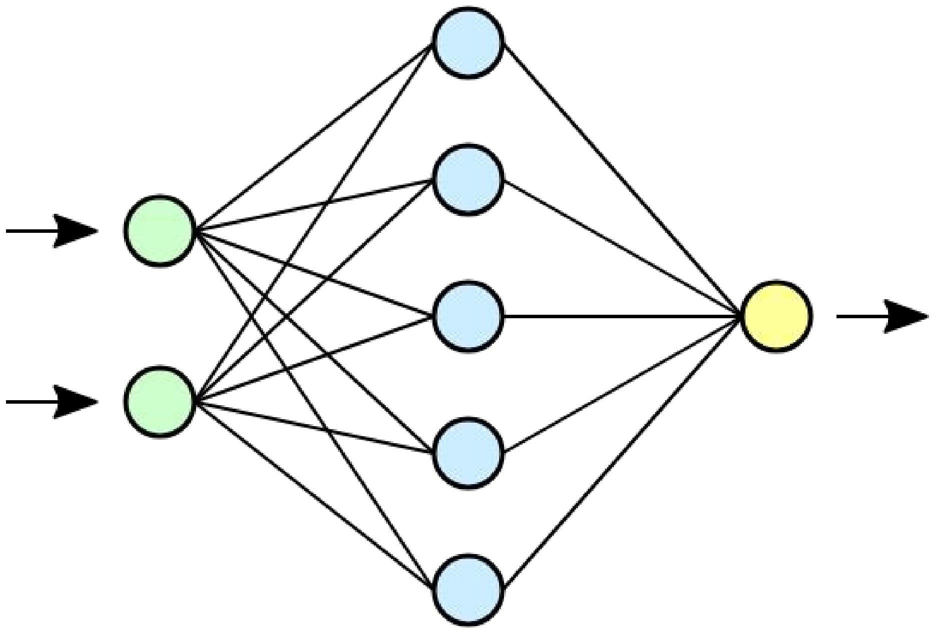

Figure 1 Visualization of simple Neural Network with two input neurons one layer and one output neuron[3]

[1] McCarthy, John, et al. "What is artificial intelligence?" Communications of the ACM 50.1 (2007): 36-44, https://doi.org/10.1007/s10796-016-9641-2
[2] Schmidhuber, Jürgen. "Deep learning in neural networks: An overview." Neural networks 61 (2015): 850-874, https://doi.org/10.48550/arXiv.1404.7828
[3] https://pl.wikipedia.org/wiki/Sie%C4%87_neuronowa

Artificial neural networks are characterized by their layered architecture. Each layer comprises interconnected artificial neurons, mimicking the biological structure of the brain. These connections are not simply binary on/off switches; instead, they are weighted. The weight associated with a connection determines the strength of the signal transmitted between „neurons".

During the training process, these weights are meticulously adjusted based on the network's performance. This optimization process allows the network to learn complex relationships within the data and ultimately perform tasks like image recognition or medical diagnosis.

Convolutional Neural Networks (CNNs) represent a specialized sub architecture within the broader field of Neural Networks (NNs). They excel at processing visual data, such as images and videos, due to their unique structure inspired by the biological visual cortex. Unlike standard Artificial NNs with fully connected layers, CNNs incorporate convolutional layers that employ filters to scan the input image. These filters act as feature detectors, identifying specific patterns like edges, shapes, or textures within the image. By applying these filters across the entire image, the CNN can efficiently extract relevant visual information. Additionally, CNNs share weights across similar regions of the image, reducing the number of connections needed and improving training efficiency. This optimized architecture makes CNNs particularly adept at tasks like image recognition (identifying objects in pictures) and medical image analysis (detecting abnormalities in X-rays or MRIs).

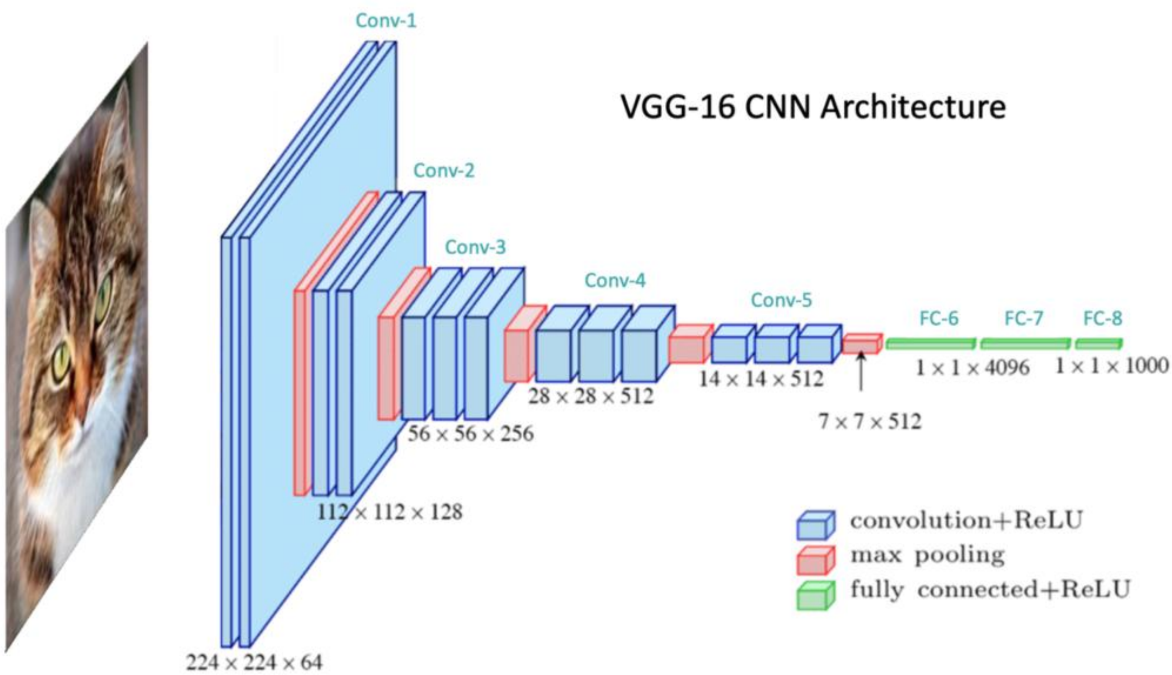

Figure 1 Visualization of a VGG-16 CNN architecture containing multiple filters pooling and convolution layers [4]

This example architecture starts with five convolutional blocks, which form the feature extraction part of the model.

[4]https://learnopencv.com/understanding-convolutional-neural-networks-cnn/

A convolutional block typically refers to a series of layers in a Convolutional Neural Network (CNN) that are often repeated to help extract features from inputs. After the feature extraction phase, there's a classifier section which converts these features into class predictions, outputting them through the final layer. The VGG-16 model, specifically, was trained using the ImageNet dataset that includes 1,000 different classes. Consequently, the final output layer comprises 1,000 neurons, each representing the likelihood that the input image matches one of these classes. The class corresponding to the highest probability becomes the predicted class.[5][6]

While both CNNs and standard ANNs utilize interconnected processing units (artificial neurons) that learn through training, they differ significantly in their approach to data processing, particularly visual data. Standard ANNs typically employ fully connected layers where each neuron in a layer connects to all neurons in the subsequent layer. This dense connectivity can be computationally expensive, especially when dealing with high-dimensional data like images. In contrast, CNNs leverage their convolutional layers and weight sharing to achieve superior efficiency in processing visual information. This specialization allows CNNs to extract relevant features from images with fewer connections and often achieve superior performance in image-related tasks compared to traditional ANN architectures. [7]

They are designed to mimic our vision system resembling the mammalian neuron architecture. Algorithm combine three main concepts:[8]

- Local Receptive Fields - focusing on feature (color, brightness, density) of the pixels or parts of the image that are the nearest to the currently analyzed part. The size of the neighboring pixel parts are determined by the size of the filter in the CNN
- Shared Weights and Translation Invariance: To ensure consistent feature extraction regardless of location within the image, CNNs employ shared weights. The same filter is applied across the entire image, promoting translation invariance. This means the network can identify the same feature (like a vertical edge) irrespective of its position in the image.
- Subsampling and Building Higher-Level Features: After extracting features through convolutions, CNNs utilize a technique called subsampling to reduce the dimensionality of the data. This is often achieved through max-pooling, which selects the most significant feature from a small region of the image.

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[5] Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition.https://doi.org/10.48550/arXiv.1409.1556

[6]Ganatra, Nilay & Patel, Atul. (2018). A Comprehensive Study of Deep Learning Architectures, Applications and Tools. International Journal of Computer Sciences and Engineering. 6. 701-705. http://dx.doi.org/10.26438/ijcse/v6i12.701705

[7] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. Advances in neural information processing systems, 25, 1097-1105.

[8] Jonas Teuwen, Nikita Moriakov "Convolutional Neural Network", J in Handbook of Medical Image Computing and Computer Assisted Intervention, 2020

As the network progresses through subsequent convolutional and pooling layers, the extracted features become more complex, combining the lower-level features into higher-level representations that are crucial for object recognition or image classification.

While both CNNs and ANNs are powerful tools in the AI arsenal, CNNs offer a more efficient and optimized approach for handling visual tasks.
Their unique architecture, inspired by the visual cortex, allows them to extract key features from images with remarkable accuracy, making them the preferred choice for image recognition, object detection, and various medical image analysis applications.
Large language models (LLMs) are another type of AI algorithms that have revolutionized natural language processing (NLP) by leveraging their massive training on text data. They are currently one of the most promising parts of computer science in terms of using them to generate text on pair with the one produced by a professional from a certain field.
Liu et al. (2023) define LLMs in their review paper as "statistical language models trained on massive amounts of text data to learn long-range dependencies and generate coherent text".[9] These models, essentially complex neural networks, learn by analyzing patterns and relationships between words within this data. This empowers them to perform a vast array of language-related tasks, including:

- Understanding and Responding Naturally: LLMs can process user queries and generate human-quality text responses, mimicking conversation or crafting creative text formats like poems or code.
- Extracting Information from Text: They can analyze documents and identify key information or categorize them based on content.
- Answering Knowledge-Based Questions: Through ingesting vast amounts of text data, LLMs build a comprehensive knowledge base and answer factual inquiries with impressive accuracy.
- Summarization - they can effectively summarize a long text by understanding the key parts of it.

One of the key factors enabling LLMs to achieve such remarkable capabilities lies in their ability to process and understand the underlying "encodings" of language. A simplified version of generating text by a Large Language Model consist of 3 phases - tokenization, embedding layed and transformer architecture.
The initial step of tokenization involves breaking down text data into smaller units called tokens. These tokens can be individual words, sub-words, or even characters depending on the specific LLM architecture.
Embedding layer i where each token is assigned a numerical representation, its "embedding," within a high-dimensional vector space. This embedding captures the semantic meaning and relationships between the token and other words in the vocabulary. Imagine a vast map where each word is a location, and its position reflects its relationship to other words.

[9] Liu, Y., Wu, Y., Wang, Y., Zhou, M., Li, S., Zheng, Z., & Huang, M. (2023). A Comprehensive Survey of Large Language Models: Technologies, Applications, and Societal Impact, https://arxiv.org/abs/2306.07255

While a detailed explanation of transformers is beyond the scope of this discussion, it's important to acknowledge their crucial role in LLMs. Transformers are a specific type of neural network architecture that excels at analyzing relationships between tokens within a sequence, even if they are not directly adjacent.
They achieve this by employing attention mechanisms, which essentially allow the model to focus on specific parts of the input sequence when generating an output.
These models excel at various tasks, including extracting information from documents, generating human-quality text formats, and answering knowledge-based questions with impressive accuracy, even performing well on standardized medical exams like the USMLE.[10]
This growth coincides with advancements in parallel computing hardware, allowing efficient training on vast datasets. Beyond traditional NLP, LLMs exhibit unexpected capabilities like few-shot learning (adapting to tasks with minimal training data) and even zero-shot learning (performing tasks without any specific training).
In the medical field, LLMs hold immense potential for clinical and research applications due to their ability to process and understand medical text. Potential benefits include improved efficiency through automated tasks like report generation, enhanced cost-effectiveness through streamlined workflows, and potentially elevated quality of care by assisting radiologists in interpreting medical images and identifying abnormalities. However, limitations exist, including hallucinations (generating factually incorrect information), knowledge cutoff (limited by training data), potential for bias, and limitations in complex reasoning. Moving forward, strategies like grounding LLMs in external data, prompt engineering, and fine-tuning can optimize these models for safe and effective use in clinical settings. As LLM technology continues to evolve, the potential for improved efficiency, cost-effectiveness, and quality of care in radiology is significant, but rigorous validation and ongoing research are essential for responsible and reliable implementation.

Radiology - current state of knowledge

Radiology is a medical specialty that employs various imaging modalities to diagnose and treat diseases visualized within the human body. Techniques such as X-ray radiography, computed tomography (CT)[11], magnetic resonance imaging (MRI)[12], ultrasound, and nuclear medicine, including positron emission tomography (PET), are utilized to capture images of the internal composition of the body, highlighting contrasts between different tissues and obtain detailed images of the anatomical structures and physiological processes of the body. Beyond its crucial role in medical diagnostics, radiology is instrumental in therapeutic interventions.

[10] Wang, et al. (2023). Capabilities of GPT-4 on Medical Challenge Problems, https://doi.org/10.48550/arXiv.2303.13375

[11] Haijo Jung (2021) "Basic physical principles and clinical applications of computed tomography." Progress in Medical Physics, 1-17 https://doi.org/10.14316/pmp.2021.32.1.1

[12] Kose, K. (2021). Physical and technical aspects of human magnetic resonance imaging: present status and 50 years historical review. Advances in Physics: X, 6(1). https://doi.org/10.1080/23746149.2021.1885310

It guides minimally invasive procedures such as angioplasty, biopsy and tumor ablation. Radiology also facilitates radiation therapy, where high-energy radiation is used to shrink tumors and kill cancer cells. This dual functionality of diagnosis and treatment underscores the integral role of radiology in comprehensive patient care.[13]
One of the basic imaging tests is X-ray. It utilizes the differential absorption properties of body tissues to produce diagnostic images. X-rays, a form of electromagnetic radiation, penetrate body tissues and are absorbed at varying degrees, creating contrasts in the resulting images.
This imaging technique is fundamental in medical diagnostics, allowing for non-invasive examination of the internal anatomy to detect abnormalities such as fractures, tumors, and other pathologies.[14] The operation of systems involves generating a beam of X-rays, which are directed through the body and captured on a detector on the opposite side. The image produced reflects the varying degrees of absorption by different tissues, with denser tissues such as bone appearing whiter due to higher absorption rates. This technology not only supports diagnostic procedures but is also crucial in guiding therapeutic and surgical interventions, enhancing the precision and safety of these procedures.[15]
The next important imaging test is Computed Tomography (CT) utilizes X-ray attenuation to generate detailed cross-sectional images of the body without using harmful wave exposure for patient.[16] Unlike conventional X-ray, CT employs a more sophisticated technique. An X-ray source and detectors rotate around the patient, acquiring data from numerous angles as the X-ray beam traverses the body. This multi-angular data acquisition allows for the capture of X-ray intensity variations due to tissue density differences. Complex mathematical algorithms then process this wealth of projection data to reconstruct a high-resolution, three-dimensional image of the scanned region. Tissue densities are depicted using Hounsfield Units (HU), a scale based on water attenuation (0 HU), with air having significantly lower values (-1000 HU) and bone exhibiting higher values (+1000 HU). This non-invasive technique offers a powerful diagnostic tool for visualizing and differentiating various tissue types within the body.[17]
One of the most accurate imaging methods is magnetic resonance imaging. MRI is a non-invasive diagnostic tool that utilizes powerful magnetic fields and radio waves to produce detailed images of internal body structures without the use of harmful ionizing radiation, making it a safer alternative to computed tomography (CT). The core mechanism behind MRI involves the precession of atomic nuclei with magnetic moments—found in atoms with an odd number of protons or neutrons—under the influence of an external magnetic field.
When these nuclei are exposed to radio waves at a specific frequency, they "tip" out of alignment with the magnetic field. Once the radio waves are stopped, the nuclei return to their

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[13] Britannica, The Editors of Encyclopaedia. "radiology". Encyclopedia Britannica, 17 Apr. 2024, https://www.britannica.com/science/radiology.

[14] Haijo Jung (2021) “Basic physical principles and clinical applications of computed tomography.” Progress in Medical Physics, 1-17 https://doi.org/10.14316/pmp.2021.32.1.1

[15] National Institutes of Health (US).” X-ray Imaging - Medical Imaging Systems - NCBI Bookshelf”. Maier A, Steidl S, Christlein V, et al., editors. Cham (CH): Springer; 2018.

[16] KALRA, Mannudeep K., et al. Strategies for CT radiation dose optimization. Radiology, 2004, 230.3: 619-628. https://doi.org/10.1148/radiol.2303021726

[17]Nadrljanski M, Campos A, Chieng R, et al. Computed tomography. Reference article, Radiopaedia.org https://doi.org/10.53347/rID-9027

original orientation and emit a radio signal that is captured by the MRI machine. This process, along with the unique T1 and T2 relaxation times of different tissues, which dictate how quickly nuclei realign after excitation, allows MRI to distinguish between various tissue types, providing essential anatomical and functional insights.[18] MRI offers superior tissue contrast compared to CT but has lower spatial resolution and is more prone to motion artifacts. This contrast advantage allows MRI to detect tumors that are invisible in CT scans.[19]

One of the least invasive is ultrasound imaging Ultrasound, also known as sonography, utilizes high-frequency sound waves to generate real-time visual images of the internal aspects of the body. This process involves a device known as a transducer that both emits and receives sound waves. When the emitted waves encounter internal tissues, they reflect back to the transducer as echoes, which a computer then processes to create visual images displayed on a monitor. This technique is particularly beneficial because it does not involve ionizing radiation, making it a safe option for various medical assessments, including during pregnancy[20]

The last imaging techniques presented will be nuclear tomographic imaging modalities. SPECT (Single Photon Emission Computed Tomography) and PET (Positron Emission Tomography) utilize radioactive tracers to capture functional insights within the body by tracking the emitted radiation from these tracers, revealing cellular and biochemical activity essential for diagnosing various conditions. Since both techniques inherently provide limited anatomical detail, they are often combined with anatomical imaging technologies like CT (Computed Tomography) or MRI (Magnetic Resonance Imaging). These hybrid systems enrich the functional insights from SPECT or PET with precise anatomical information from CT or MRI, significantly enhancing the utility in diagnosis and treatment management. However, combining these modalities introduces technical challenges, particularly with MRI integration, due to the interference between the MRI's electromagnetic fields and the nuclear imaging components.[21] [22]

Artificial Intelligence in Radiology

This chapter delves into the specific applications of AI models in radiology and broader medical environments, highlighting the transformative capabilities and the diverse range of algorithms employed.

We will focus on three main groups of algorithms that have shown promising results in this domain: Convolutional Neural Networks (CNNs), Large Language Models (LLMs), and a

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[18] Kulczycki, Jerzy, et al. "Wartość rezonansu magnetycznego w diagnostyce różnicowej zmian naczyniopochodnych w mózgu." Archives of Medical Science [AMS] 18.8 (2022): 1830-1835

[19] Cieszanowski, A. (2023). Zastosowanie badania rezonansu magnetycznego w onkologii [The use of magnetic resonance imaging in oncology]. SP CSK, II Zakład Radiologii Klinicznej, Warszawski Uniwersytet Medyczny.

[20] Prado-Costa, R., Rebelo, J., Monteiro-Barroso, J. et al. Ultrasound elastography: compression elastography and shear-wave elastography in the assessment of tendon injury. Insights Imaging 9, 791–814 (2018). https://doi.org/10.1007/s13244-018-0642-1

[21] Maki, J. H., & Marinelli, M. R. (2000). Single-photon emission computed tomography (SPECT)/computed tomography (CT) myocardial perfusion imaging for the diagnosis of ischemic heart disease. Journal of nuclear medicine technology, 28(2), 89-99.

[22] Trotter J, Pantel AR, Teo BK, „Positron Emission Tomography (PET)/Computed Tomography (CT) Imaging in Radiation Therapy Treatment Planning: A Review of PET Imaging Tracers and Methods to Incorporate PET/CT" Adv Radiat Oncol. 2023;8(5):101212. Published 2023 Mar 27. doi:10.1016/j.adro.2023.101212

combination of statistical and basic machine learning techniques. Each category offers unique strengths—CNNs excel in image data interpretation, LLMs such as RaDialog innovate in report generation and interactive communication, and statistical machine learning techniques provide foundational methods for pattern recognition and predictive analytics.

Through comprehensive exploration of these technologies, this chapter aims to illuminate their distinct roles and synergistic potentials in reshaping radiological practices and improving clinical outcomes.

First I want to mention a use case of LLM in building comprehensive radiology reports. Large Language Models can be multimodal - it means that they can understand input data other than only text - for example videos and images.

This can be extremely useful as we can ask a question and attach an image that can be processed by an AI model to answer it referring to the attached picture. RaDialog[23] is such a multimodal LLM. It exemplifies the transformative potential in medical diagnostics, particularly in the field of radiology. This advanced vision-language model automates and enhances the generation of radiology reports by integrating structured pathology findings and visual image features with the robust textual capabilities. As a standout implementation, RaDialog not only streamlines the creation of clinically accurate radiology reports but also introduces an interactive dimension where users can engage in dialogues-asking questions, requesting clarifications, or seeking report modifications. This model dramatically improves efficiency and accuracy in diagnosing through chest X-rays, demonstrating the broader utility of LLMs in integrating complex data types to support critical healthcare functions. Through RaDialog, LLMs show promise in reshaping medical imaging diagnostics by providing tools that are not only reactive but also adaptive to the nuanced needs of clinical environments.

Another application of artificial intelligence (AI) in summarizing medical documentation, particularly in radiology reports, exemplifies significant advancements in making complex medical information more accessible to patients. Recent data indicates that doctors can spend up to two hours on documentation for each hour of patient interaction.[24] LLM's are instrumental in transforming dense medical jargon into simplified, patient-friendly summaries. For instance, the RaDialog system utilizes a tailored version of the T5 model[25], fine-tuned to generate understandable summaries for patients with varying medical knowledge. This process involves collecting extensive datasets, adapting the model through staged training with initially noisy data for accuracy, and rigorous dual evaluations with both medical experts and laypersons to ensure clarity and reliability.

Despite the promise of these technologies, challenges such as maintaining accuracy, avoiding data bias, ensuring model interpretability, and navigating regulatory landscapes are critical considerations. These AI-driven summarizations aim to improve patient engagement and

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[23]Pellegrini, C., Özsoy, E., Busam, B., Navab, N. & Keicher, M., 2023. RaDialog: A Large Vision-Language Model for Radiology Report Generation and Conversational Assistance.
https://doi.org/10.48550/arXiv.2311.18681

[24] Sinsky, C., Colligan, L., Li, L., Prgomet, M., Reynolds, S., Goeders, L., Westbrook, J., Tutty, M. & Blike, G. Allocation of physician time in ambulatory practice: a time and motion study in 4 specialties. Annals of internal medicine 165, 753–760 (2016).

[25] Raffel, C., Shazeer, N., Roberts, A., Lee, K., Narang, S., Matena, M., Zhou, Y., Li, W., & Liu, P. J. (2019). Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer
https://doi.org/10.48550/arXiv.1910.10683

compliance by providing clearer insights into medical findings and recommended treatments, showcasing a pivotal shift towards patient-centered healthcare facilitated by advanced AI tools.[26]

In the medical field, convolutional neural networks (CNNs) are used to analyze medical images for the purpose of diagnosis.

In this study[27] researchers built a machine learning model to rule out COVID-19 in patients before they are admitted to the hospital. The model was trained on a dataset of chest CT scans, clinical examination findings, and laboratory test results from 4437 patients. The model that included all three types of features (chest CT, clinical examination, and laboratory test) performed the best, achieving a sensitivity of 0.89 and a specificity of 0.89. This means that the model was able to correctly identify 89% of the patients who had COVID-19 and 89% of the patients who did not have. The addition of chest CT features to the model significantly improved its performance compared to a model that only included clinical examination and laboratory test features. These results suggest that CNNs can be a valuable tool for diagnosing COVID-19 and other diseases. Even if they are not precise enough to make the final diagnosis they can take a lot of valuable time from doctors. They can function as a first filter especially while hospital capacity is overwhelmed.

Another study published in Digital Signal Processing[28] delves into the potential of convolutional neural networks (CNNs) for medical image segmentation, a technique crucial for various medical image analysis tasks. This approach can solve problems associated with medical image segmentation, including high dimensionality, inherent variability within anatomical structures, and the presence of noise or artifacts. These factors can hinder traditional image segmentation methods as the complexity of the data makes the model not accurate enough. The proposed framework utilizes CNNs' exceptional ability to learn complex patterns from image data. By training the CNN on a large dataset of labeled medical images, the network learns to identify and segment specific anatomical structures within the image. However, there is a need to acknowledge a significant hurdle in CNN-based medical image segmentation: the limited availability of labeled medical image datasets. To overcome this we can expand the dataset using data augmentation techniques. It involves artificially manipulating existing medical images to create new variations. These variations can include rotations, flips, cropping, and intensity scaling.

By incorporating these augmented images into the training dataset, we can improve the generalization capabilities of the CNN model. This mitigates overfitting, a phenomenon

[26] Patient Centric Summarization of Radiology Findings using Large Language Models
Amara Tariq, Sam Fathizadeh, Gokul Ramaswamy, Shubham Trivedi, Aisha Urooj, Nelly Tan, Matthew T. Stib, Bhavik N. Patel, Imon Banerjee
doi: https://doi.org/10.1101/2024.02.01.24302145

[27] Kramer, M., Ingwersen, M., Teichgräber, U., & Güttler, F. (2023). Added value of chest CT in a machine learning-based prediction model to rule out COVID-19 before inpatient admission: A retrospective university network study. European Journal of Radiology, 163, 110827. https://doi.org/10.1016/j.ejrad.2023.110827

[28] Aljabri, M., & AlGhamdi, M. (2022). A review on the use of deep learning for medical images segmentation. Neurocomputing, 468, 311-335. [doi: 10.1016/j.neucom.2022.07.070]

where the model performs well on the training data but fails to generalize to unseen data. But it's a solution that doesn't permanently solve a problem - lack of well labeled datasets. [29]
The technological innovation of Neural Networks is eloquently demonstrated in a study that utilizes MRI data from The Cancer Imaging Archive and genetic information from The Cancer Genome Atlas. Here, CNNs, particularly a DenseNet-121 model, are trained to non-invasively predict risk stratification based on a prognostic three-gene signature.
The process begins with detailed image preprocessing where MRIs are standardized, normalized, and segmented to highlight regions of interest. This is crucial because the accuracy of CNN predictions depends heavily on the quality and consistency of the input data. The CNN model is then trained in two phases—initially to recognize basic image features and subsequently to associate these features with clinical outcomes such as patient survival rates and tumor progression. Technically, this involves adjusting numerous hyperparameters like the number of convolutional layers, kernel sizes, and activation functions to optimize the learning process. This dual-phase training allows the model to develop an internal representation of what different genetic risk profiles look like on MRIs. For instance, CNN learns to correlate certain image features with the presence of genes like WEE1, CRTAC1, and SEMA4G, which are known to affect tumor behavior. In practical terms, this CNN application enhances both patient and doctor experiences by providing a rapid, non-invasive tool for risk assessment. Doctors can access detailed prognostic information without the need for invasive biopsy procedures, leading to quicker decision-making regarding treatment plans. For patients, this means a potential reduction in procedural risks and a personalized treatment approach based on their tumor's genetic makeup. By automating part of the diagnostic process, CNNs also free up valuable time for radiologists and oncologists, allowing them to focus more on patient care rather than the manual interpretation of MRIs. Additionally, this model serves as a proof of concept that can be expanded to other types of cancer or diseases, broadening the scope of precision medicine. In essence, this use case exemplifies how deep learning can bridge the gap between radiomic phenotypes and genomic data, paving the way for integrated diagnostics that enhance clinical workflows and patient care strategies. The potential for such technologies to be incorporated into routine clinical practice heralds a new era in the application of artificial intelligence in medicine.[30]
The integration of convolutional neural networks (CNNs) in radiology, particularly in the assessment of coronary artery disease (CAD) through coronary computed tomography angiography (CCTA) images, represents a significant technological advancement in medical diagnostics. This sophisticated application of CNNs involves a detailed process that begins with the meticulous preparation and preprocessing of CCTA images. Initially, images are annotated semi-automatically to delineate vessel lumens and identify areas of calcified and noncalcified plaques.
These annotations are critical as they serve as the ground truth for training the CNN. The technical core of this process employs a two-step training methodology using a DenseNet-121

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[29] Yu, L., Chen, H., Yan, Q., Liu, X., Xu, Y., & Wang, D. (2018). Addressing the challenges of limited labeled data for deep learning in healthcare applications.
[30] Karabacak, M., Ozkara, B.B., Senparlak, K., & Bisdas, S. (2023) 'Deep Learning-Based Radiomics for Prognostic Stratification of Low-Grade Gliomas Using a Multiple-Gene Signature', Applied Sciences, 13(6), pp. 3873. Available at: https://doi.org/10.3390/app13063873

architecture, a decision informed by its success in handling large-scale image data. In the first step, the entire network is trained with a preliminary endpoint - typically early revascularizations to refine the model's ability to recognize basic patterns in the imaging data. Subsequently, the feature layer of the network undergoes further training, focusing exclusively on a primary endpoint such as major adverse cardiac events. This dual-phase training helps in fine-tuning the network to enhance its predictive capabilities significantly.
During model training, a variety of hyperparameters are optimized, including the number of epochs, batch size, and learning rate, to ensure the CNN learns effectively from the training dataset without overfitting.

The training dataset itself is carefully curated to include a diverse array of patient images stratified by factors like age, gender, and scanner generation to make the model robust across different patient demographics and technical specifications of CCTA scans. After training, the CNN's efficacy is evaluated based on its area under the curve (AUC)[31]statistic, which measures the model's ability to predict cardiovascular events accurately. The integration of CNN analysis with traditional clinical risk assessments and CT-based parameters like the extent of CAD (eoCAD) and Morise score is particularly noteworthy. It not only enhances the AUC but also demonstrates the CNN's capacity to integrate and augment traditional diagnostic frameworks with high-dimensional data insights that are typically imperceptible to the human eye. This complex interplay of image processing, machine learning training, and statistical evaluation encapsulates the cutting-edge nature of CNN applications in medical imaging, setting a new standard for how radiological data can be leveraged to improve diagnostic accuracy and patient outcomes in cardiology.[32]
In the realm of radiology, the integration of neural networks (NNs) like convolutional neural networks (CNNs) can substantially enhance the capabilities of medical practitioners by streamlining and improving the accuracy of diagnostic processes. A particular focus of recent advancements involves the use of AI to facilitate values-based shared decision-making in clinical settings. This approach aligns AI's analytical prowess with the core values and concerns of patients, such as trust, privacy, autonomy, and equity, which are crucial for patient-centered care. The application of a values-based guide for shared decision-making, as discussed in the article "The Use of Artificial Intelligence in Clinical Care: A Values-Based Guide for Shared Decision Making" from Current Oncology, provides a framework for clinicians to integrate patient values into the decision-making process effectively. This guide suggests structured dialogues where clinicians and patients discuss various treatment options facilitated by AI insights.
The AI systems analyze complex medical data to present options that not only align with medical best practices but also resonate with individual patient values and preferences, thus enhancing the personalization of care. In practical terms, this means that during a radiological

[31] N. Seliya, T. M. Khoshgoftaar and J. Van Hulse, "A Study on the Relationships of Classifier Performance Metrics," 2009 21st IEEE International Conference on Tools with Artificial Intelligence, Newark, NJ, USA, 2009, pp. 59-66, doi: 10.1109/ICTAI.2009.25.
[32] Adolf, R., Nano, N., Chami, A., von Schacky, C.E., Will, A., Hendrich, E., Martinoff, S.A., & Hadamitzky, M. (2023) 'Convolutional neural networks on risk stratification of patients with suspected coronary artery disease undergoing coronary computed tomography angiography'

assessment, AI can help interpret imaging data and suggest diagnostic outcomes that are then discussed in a patient-centric consultation. The clinician uses the AI-generated information to inform the patient about potential health scenarios and treatment pathways, ensuring that the patient's values guide the final decision-making. This process not only improves diagnostic accuracy but also enhances patient trust and satisfaction by making healthcare interactions more transparent and tailored to individual needs.
Such AI-enhanced decision-making processes in radiology not only streamline diagnostics but also ensure that care pathways are comprehensively aligned with what matters most to the patient, thus embodying a truly patient-centered approach to healthcare.[33]

Conclusions

The integration of Artificial Intelligence into the field of radiology marks a pivotal advancement in medical diagnostics and treatment, offering a transformative approach to enhancing healthcare delivery and accessibility. This paper has delineated the current state of knowledge in radiology, illustrating the capabilities of technologies such as Neural Networks and Large Language Models in medical imaging and documentation. Through this exploration, have identified numerous opportunities for AI to augment the diagnostic precision and operational efficiency in radiology, while also acknowledging the associated challenges that must be navigated to realize its full potential.
AI role in the medical field is grounded in ability to analyze vast quantities of imaging and language data with accuracy and speed surpassing that of human capabilities. CNNs, in particular, have demonstrated efficacy in enhancing image interpretation, providing detailed analyses that support radiologists in making more informed diagnostic decisions. The integration of CNNs in clinical settings exemplifies how AI can reduce the workload on medical personnel by performing preliminary analyses, thereby allowing radiologists to focus on more complex diagnostic tasks. This capability not only streamlines the diagnostic process but also potentially reduces waiting times for patients, thereby improving the overall efficiency of medical services. With correct implementation it will massively help especially those countries that struggle with numbers of doctors and their accessibility for their population. Furthermore, LLMs have revolutionized the way medical documentation is handled, by automating the generation of radiology reports and making medical information more accessible to patients through simplified summaries. These advancements facilitate better patient understanding and engagement, which is crucial for effective healthcare delivery. The ability to convert technical medical jargon into patient-friendly language enhances communication between healthcare providers and patients, promoting a more patient-centric approach to care.

Despite these advancements, AI in radiology is not without its challenges. Issues such as data privacy, potential biases, and the need for significant datasets for training models are critical concerns that need addressing. Additionally, the integration of AI systems into existing medical infrastructures requires careful consideration to ensure compatibility and

[33] Macri, R. and Roberts, S.L., The Use of Artificial Intelligence in Clinical Care: A Values-Based Guide for Shared Decision Making, doi: 10.3390/curroncol30020168

functionality. The ethical implications, including the delegation of tasks and the reliability of AI-driven decisions, also warrant thorough examination to maintain trust and integrity in medical practices. Collaborative efforts between researchers, medical professionals, and ethical boards are crucial to guide the development of applications that are effective, human friendly and ethically sound.

Educational programs aimed at equipping healthcare professionals with knowledge to utilize AI tools effectively will be vital in creating an environment where technology will help them.

In conclusion, AI presents a significant opportunity to reshape the landscape of radiology and, more broadly, medicine. By enhancing diagnostic accuracy, streamlining processes, and improving patient engagement, AI can significantly contribute to a more efficient and patient-centered healthcare system. However, successful integration into healthcare will depend on addressing the technological, ethical, and operational challenges that accompany its implementation. With careful management and continued innovation, AI has the potential to not only complement but also significantly enhance the capabilities of medical professionals, thus ensuring that the medical system evolves in alignment with the needs and values of society

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