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Artificial Intelligence for Diagnostic Radiology: Early Detection of Cancer

Background and Context

The field of radiology is one that is ever-changing, primarily focusing on the use of rays, typically x-rays, to create images of our internal organs and tissues. The practice of diagnostic radiology involves physicians who interpret the images captured to diagnose illnesses and aid in treatment (Davidson 3042). One major disease that relies heavily on radiologic imaging is cancer. Images of cancerous masses can be evaluated to visualize abnormalities and determine their location within the body (Dupler 475). Cancer is a potentially fatal disease where abnormal cells grow uncontrollably in the body, and in many instances manifest into masses known as tumors (Dupler 471). Christina A. Clarke, a cancer epidemiologist at GRAIL and associate professor at the University College of London, writes that in the United States alone, the number of new cancer diagnoses have "increased over the last decade by 24% in men to more than 1 million cancers per year, and by 21% in women to more than 900,000 cases per year" (Clarke et al. 900). However, early cancer detection allows for early treatment, which can increase patient prognoses. Clarke et al. found that even detection of stage IV cancers at stage III would cause a 15% reduction in cancer-related deaths, while stage IV cancers detected at stages I, II, and III could result in a total reduction of 24% of overall cancer-related mortality (Clarke et al. 895). For colon, skin, breast, and prostate cancer, the difference in survival rates between stage I and stage

IV diagnosis are more than 60%, with skin, breast, prostate, and testicular cancer having a 99% or higher survival rate when diagnosed at stage I or earlier (5 Things). Detecting any form of cancer before it spreads to other parts of the body (progressing the stage of cancer) would greatly reduce its societal burden by reducing cancer-related deaths. Thus, early detection of cancer is a heavily studied topic, one for which Clarke et al. claim that “new and innovative approaches are urgently needed” (Clarke et al. 900). Emerging radiologic technology can aid early detection, providing a possible solution for this issue.

To understand new radiologic technology, it is important to review its progression throughout history. Radiologic technology originated in 1895 with the discovery of the x-ray, which would pass through the body differentially and create an image on a treated screen (Davidson 3043). Beginning in the 1970s, other imaging techniques developed with computing power, such as computed tomography (CT), which employs the use of 360-degree x-ray scans to create cross-sectional scans of the body, allowing for diagnoses to be made (Hage 361). Another technique, which doesn't use any radiation, is magnetic resonance imaging (MRI), which uses radio waves and magnets to generate images and produces better photos of soft tissues than x-rays (Davidson 3044). Improved computers in the 1980s allowed for diagnostic x-ray images to be recorded digitally, allowing for easier and immediate access to images (Davidson 3043). Stronger computing power also allows for radiologic images to be converted into mineable data by extracting quantitative features, and analysis of this data can be used for diagnostic purposes, this practice is known as radiomics (Gillies et al. 563). Robert Gillies, who was chair of Cancer Physiology at the Moffitt Cancer Center, claims that “conversion of digital images to mineable data will eventually become routine practice” (Gillies et al. 563). Radiomics allows for medical images to be computationally analyzed rather than traditionally visually analyzed, meaning information in the images that could be overlooked can be taken into consideration. With constantly improving and evolving computing technology, radiologic images will be interpreted using online resources more than visually, which could accelerate result turnaround and aid radiologists.

Artificial Intelligence as an aid

Images produced by radiologic techniques must be interpreted in order to determine diagnosis and treatment, but before thorough processing, it can be hard to visually understand an image. Advancements in technology and computing power allow for these images to be processed more quickly and provide clearer images. An emerging and revolutionary technology being used in radiologic imaging is artificial intelligence (AI), which can be used in image normalization, noise reduction, and enhancement (Marques 62). Oge Marques is a researcher and professor of computer and biomedical science at Florida Atlantic University. Marques writes that "AI in radiology typically encompass two main categories: detection, where AI aids in identifying abnormalities in radiological images, and classification, where AI helps categorize these detected anomalies based on their characteristics" (Marques 97). Artificial intelligence can serve as a major guide to physicians when examining radiologic images, especially through the use of radiomics. Bettina Baeßler, a radiologist and professor at The Julius Maximilian University of Würzburg, writes that "radiomic features capture intricate patterns and subtle variations within the images that may elude a pure visual image inspection" (Baeßler et al. 504). These small details in radiologic photos are captured in radiomic data, which can be fed through AI algorithms to "analyze these features to generate knowledge, define novel imaging biomarkers, and support diagnostic decision-making and outcome prediction" (Baeßler et al.

504). Artificial intelligence can identify easily missed details by examining images quantitatively, looking for inconsistencies in data, and removing the time required by humans to data-mine the images. Anusree Majumder and Debraj Sen, who are professors and researchers at Command Hospital and Army Hospital respectively, write that AI systems “significantly improve the accuracy of image detection for cancer by removing human subjective biases which may ensue from lack of adequate experience, training, or due to time constraints” (Majumder and Sen 483). Through AI deep learning models, accuracy and precision of analyzing radiologic images and radiomics data is improved, and thus AI use in radiology ultimately comes as a benefit.

With greater computing power and novel radiologic technology, the ability to detect cancer before metastasis is greater than ever. Through further research and development, the use of artificial intelligence in diagnostic radiology may be able to greatly reduce the mortality rate of cancer and lighten its burden on society.

Most Significant Findings

AI Technologies versus Human Radiologists

AI models are becoming increasingly adept at detecting tissue lesions, sometimes outperforming human radiologists. A statistic called the average area under the receiver operating characteristic curve (AUC) is used to quantify radiologist and AI model image evaluation performance, with AUC values closer to one indicating increased performance. A study conducted by medical doctor Quinlan D. Buchlak and his research team examined the performance of an AI model compared to radiologists assisted by the same model and unassisted radiologists. Their focus was on non-contrast computed tomography brain scans (NCCTB), a radiologic method for imaging brain tissue. Buchlak and his team found that "The [AI] model demonstrated an […] (AUC) of 0.93 across 144 NCCTB findings and significantly improved radiologist interpretation performance. Assisted and unassisted radiologists demonstrated an average AUC of 0.79 and 0.73 across 22 grouped parent findings and 0.72 and 0.68 across 189 child findings, respectively" (Buchlak et al. 810). The AI model alone earns an AUC of 0.93, indicating near perfect interpretation performance. Radiologists assisted by the model earned higher AUC scores than those who interpreted scans without the model's assistance. Thus, Buchlak and his team's findings suggest that radiologists assisted by an AI model can reach higher interpretation efficacy than those unassisted by a model. While Buchlak's study focuses on NCCTB scans, another study done by Thomas Schaffter, a former postdoctoral researcher at the International Business Machines Corporation, and his research team targets the performance of AI and AI-assisted radiologists in mammography. This study utilized a dataset of 144,231 mammograms obtained from 85,580 US women and 166,578 mammograms from 68,008 Swedish women, resulting with AI-assisted radiologists in the US achieving an AUC of 0.942 and seeing an increase in specificity from 90.5% unassisted to 92% assisted (Schaffter et al. 1). Specificity is the measure of the true negative rate, or in other words, the likelihood a diagnostic test will be negative for someone without disease or injury. Thus, higher specificities indicate lower false positive rates for these tests. The AI-assisted radiologist AUC score of 0.942 indicates excellent detection accuracy. Schaffer's study also found that "no single algorithm outperformed radiologists" (Schaffter et al. 1), underscoring that AI models don't always outperform radiologists. Overall, an AI model's performance compared to that of an unassisted radiologist's appears to be case dependent, with some scenarios yielding lower AI performance while others yield higher AI performance. However, AI-assisted radiologists have consistently outperformed unassisted radiologists, suggesting the most pragmatic approach for future radiologic technology should include an AI component.

<u>The Importance of Quality Training Datasets: What is Needed?</u>

While some AI models may exhibit high efficacy in identifying tissue lesions, this efficacy means nothing if the model's training dataset is inadequate. Ideal training datasets are large, reliable, and contain variety: this ensures inherent bias isn't carried out in the model's evaluation of new data. This applies to radiology because AI models used to evaluate radiologic imaging are trained on a dataset containing radiologic images, and if this dataset is biased, the model's evaluation—and thus its tissue lesion detection—will be biased as well. For example, an AI model trained solely on scans from one demographic would be less effective when evaluating a random patient compared to a model trained on scans from a broad spectrum of demographics. The model trained on scans from one demographic is incapable of accounting for demographic differences, rendering it ineffective when evaluating diverse groups of patients. A mass analysis of publications discussing healthcare related AI model databases performed by Cambridge University researcher Anmol Arora and his team provides an accurate synthesis of the topic. Arora's study discusses the common findings across "10,646 unique records" of which "30 relevant records were included" (Arora et al. 2930). Dataset validity in healthcare is clearly a prevalent topic, emphasizing its importance. The main commonalities between these documents can be categorized into three areas: representative/diverse data, use of metrics, and data standardization. Representative/diverse data is data that represents all members of a population, accounting for their differences in socioeconomic status, gender, race, etcetera rather than ignoring some or all of these factors. The use of metrics calls for a number to be created that measures the validity of a dataset. Data standardization highlights the importance of legal standards regarding datasets (Arora et al. 2931-2934). The findings from Arora's study underscore how crucial each of these dataset components are when preventing bias in AI models, as they appear frequently across related scholarly work. Another comprehensive study led by Caitlin Kuhlman, a PhD computer scientist, explains why these dataset components are so important. To discuss the need for diverse datasets, Kuhlman's study criticizes two AI models trained on datasets lacking diversity. When examining the first model, the study found that "due to a lack of representation of both female faces and dark-skinned faces in the training datasets used, prediction rates […] suffered greatly for these groups" (Kuhlman et al. 5). The second model, specifically related to medicine, "show[ed] that at the same health risk score, black patients are considerably sicker than whites due to the way the risk score is attributed to different illnesses that occur disparately" (Kuhlman et al. 5). The findings from Kuhlman's study provide examples of issues that can arise when a dataset doesn't have representative/diverse data: the same theme mentioned by Arora's study. The other two themes—the use of metrics and data standardization—can be used to counteract possible dataset biases shown in Kuhlman's study. By creating a number that measures the validity of a dataset (use of metrics), the dataset's quality becomes transparent to other researchers seeking data or evaluating the capabilities of an AI model trained on the data. The standardization of datasets would further this notion. Having strict guidelines for how data is collected and implemented into AI model training will further dataset transparency. Ultimately, this would benefit researchers and radiologists as data transparency would allow for decreased levels of bias for training datasets used in radiologic AI technologies by allowing these professionals to evaluate a dataset's validity. Thus, AI-assisted radiologists can take advantage of models that cater to a diverse range of patients, which can improve tissue lesion detection.

Weaknesses of AI in Radiology

In theory, the implementation of AI models in radiologic technology can be beneficial by increasing a radiologist's tissue lesion detection rate. However, these models also have weaknesses regarding their implementation into clinical practice. These weaknesses stem from the lack of proper datasets and regulations (underscored in the Quality Training Datasets section) and patient perceptions of AI capabilities. A comprehensive study led by Albert T Young, a medical doctor, analyzes patient attitudes towards AI model implementation in healthcare. The participants of Young's study "perceived one of AI's primary weaknesses to be a less accurate diagnosis, such as the concern of missing less common health conditions" (Young et al. 608). Participants also "perceived that AI had a risk of miscommunication, increased patient anxiety, […] increased healthcare disparities, […] [and] risks to privacy" (Young et al. 608). The participants in Young's study harbored distrust and even fear towards AI models being used for clinical practice and diagnosis. AI models are clearly not ready to be implemented into clinical practice as patient trust is crucial for successful healthcare outcomes. To change patient perceptions of AI models, patients must be educated on their functionality. A set of standard regulations for AI data usage must be created to assure patient data can be kept secure and training datasets can be viable (per the Quality Training Datasets section). While AI currently lacks patient trust, its flaws also extend into tissue lesion detection. Buchlak's study mentions that "NCCTB deep learning systems developed, however, have been limited in scope, capable of detecting just a single or a small number of clinical findings" (Buchlak et al. 811). This finding shows how AI models used for screening are not currently capable of performing the same tasks as a human radiologist, emphasizing their need for improvement. Considering Young and Buchlak's studies, both the scope of AI model detection ability and patient trust towards AI must be improved before radiologists can utilize AI models in clinical practice. While these flaws are apparent, there are solutions. Patient education and reassurance from clinical professionals can help instill trust between patients and AI assisted radiologists. A standard set of privacy regulations regarding AI's use of patient data can be created on top of another set that oversees the creation and use of training datasets for AI models (underscored in the Quality Training Datasets section). These regulations would improve patient trust in AI assisted radiology and tissue lesion detection rates, respectively. Overall, AI is not ready for clinical implementation just yet. However, with further research, development, and legislation, AI's clinical implementation has the potential to revolutionize radiologic technology.

Benefits

AI Improves Early Cancer Detection

Artificial intelligence (AI) is transforming the way early cancers are detected by enhancing the accuracy and efficiency of detection to save more lives. Medical researchers Jörg Kleeff and Ulrich Ronellenfitsch stress the extraordinary precision of AI, stating, "The algorithm achieved a sensitivity of 92.9% and a specificity of 99.9% for the identification of pancreatic lesions, with an area under the curve (AUC) of 0.986–0.996" (Kleeff et al. 3002). This amount of accuracy drastically reduces the risk of misdiagnosis to ensure patients receive timely and effective treatments. Early detection is critical in determining a patient's survival chances, as Douglas Dupler, a professor at the University of Colorado Boulder, emphasizes, "For all types of cancer, the earlier a cancer is diagnosed and treated, the better the chance of surviving it" (Dupler 474). AI's ability to analyze vast amounts of imaging data allows medical professionals to catch cancer in its infancy, providing an opportunity for more successful interventions before the disease progresses. Likewise, radiology expert Kun Cao and his team ran a large-scale study illustrating AI's supremacy in breast cancer screening, reporting that a controlled trial of 80,000 randomized women going through a mammography screening specifically for breast cancer found that AI was able to outperform radiologists, having an outcome of reducing workloads by more than 40% and enhancing detection rates from 5.1 to 6.1 per 1000 participants (Kleeff et al. 3002). The power of AI alongside radiologists reduces radiologist workload and improves cancer detection rates. The U.S. Preventive Services Task Force (USPSTF) stresses the urgency of early diagnosis, emphasizing that "early detection is key to preventing and treating many cancers as it provides doctors a better chance to outline effective treatment and ensure better survival rates" (*"*Screening*"* 1030). These findings highlight the life-changing role AI has in modern medicine. Its role is to detect early cancer, increase survival rates, and eventually change the outcome of patients' lives. Additionally, researcher and professor of radiology at Imperial College London, Andrea G. Rockall, highlights the potential benefits of AI by unveiling that "the potential benefits of gaining additional information from the images already obtained for diagnostic purposes is very appealing" (Rockall et al. 81). This supports the idea that one of AI's biggest strengths is its ability to catch what the human eye may miss. Artificial Intelligence (AI) can uncover subtle details in medical images that could change the entire prognosis of a diagnosis. By providing a transparent, more detailed, and accurate picture, AI not only improves early cancer detection but also reduces the chances of human error

Ways AI Reduces False Positives and False Negatives when Detecting Tumors

Not only does AI help improve cancer detection, but it also drastically reduces false positives and negatives, promising a more accurate diagnosis while minimizing unnecessary stress for patients. One of the main ways AI accomplishes this is through its ability to enhance tumor characterizations. Artificial Intelligence does this by pinpointing subtle patterns within imaging data that could go unnoticed by human radiologists. Oncology imaging expert Kaustav Bera and colleagues explain that “DL strategies leverage deep neural networks for pattern recognition, which typically comprise a series of trainable nonlinear operations, known as layers, each of which transforms input data into a representation that facilitates pattern recognition” (Bera et al. 132). This in-depth approach allows AI to differentiate between malignant and benign tumors with pronounced precision, reducing the chances of misidentification. False positives can create extensive psychological and financial weight on patients, often leading to unnecessary invasive procedures and emotional turmoil. As Kleeff and Ronellenfitsch highlight, “False-positive findings startle patients and entail costly and often invasive further diagnostic measures. Accurate informed consent of patients is therefore paramount, and the possible consequences of a positive, but also a negative, finding on AI-based screening must be well explained” (Kleeff et al. 3003). By improving accuracy, AI helps reduce these burdens, ensuring that only those who truly need further intervention undergo additional testing. As Rockall stated in her research, “Standardizing the way such information is presented allows for more direct comparisons between and replicability across studies focusing on different AI systems” (Rockall et al. 81). At the same time, reducing false negatives is equally important, as missed diagnoses may delay life-saving treatment. AI’s ability to decrease both types of errors represents a major breakthrough in oncological screening, supporting its role as an essential tool in modern cancer diagnostics.

AI Leads to Better Prognosis and Survival Rates

AI’s ability to improve early detection and reduce diagnostic errors directly translates into better prognosis and higher survival rates for cancer patients. Detecting cancer at earlier stages allows doctors more time to intervene with effective treatments, often leading to better outcomes. Kun Cao and his research team also emphasize the critical role of AI in pancreatic cancer detection, stating that its accuracy is “superior to those of several acknowledged screening methods such as Pap smears for cervical cancer or mammography for breast cancer” (Kleeff et al. 3002). Specifically, pancreatic cancer is difficult to diagnose early, often leading to poor survival rates. However, AI-driven imaging can catch tumors at an earlier, more treatable stage, providing patients with a significantly better chance of survival. This is particularly crucial because “Survival rates of different types of cancer vary substantially” (Dupler 471). This means that an earlier diagnosis can dramatically shift the odds of a patient’s outcome. Beyond detection, AI is also transforming cancer predictions by helping doctors forecast disease progression and formulate treatments accordingly. A study on radiomics and AI-assisted imaging explains, “A prognostic biomarker conveys information pertaining to the risk of a disease-related end-point. In oncology, prognostic biomarkers are used to determine the risk profile of a patient with cancer on the basis of tumor characteristics” (Bera et al. 132). These AI-driven biomarkers allow oncologists to assess a patient’s risk level with extraordinary accuracy, guiding treatment decisions that can maximize survival chances. Furthermore, radiologists are becoming essential contributors to AI’s success, as highlighted by Rockall: “Radiologists will need to become important partners in testing the diagnostic accuracy of such tools, and their role in outcome prediction and prognosis including feedback on how well these integrate into clinical practice and the impact on patient care” (Rockall et al. 81). By providing a more precise understanding of tumors, as well as risk profiles of patients, AI is transforming cancer care: ensuring that patients receive a faster, personalized treatment that will help improve their overall prognosis and quality of life.

Conclusion

Artificial intelligence has the potential to revolutionize radiology. AI assisted radiologic technology has many applications across diagnostic imaging and can aid physicians in early cancer diagnosis, ultimately improving cancer survivability. AI assisted radiologists consistently demonstrate higher accuracy when detecting tissue lesions from radiologic images than humans alone, meaning AI models combined with radiomics allow for details missed by human radiologists to be identified. However, as Mamjuder and Sen wrote, "AI cannot be a foolproof panacea to all our problems nor can it completely replace the role of humans" (Majumder and Sen 490). This is said because AI models still have poor detection rates in some cases and patient attitudes towards AI are skeptical. AI models are also subject to biases that arise from their training datasets. Thus, AI should be an aid to radiologists rather than the sole diagnostician and should be consistently checked by human radiologists to prevent possible biases and harm that arise from improper training databases.

With cancer rates continuing to rise, especially in the United States, it is crucial that AI is implemented into radiologic technology. For this to happen, these steps need to be taken: further research and development must be conducted on AI model detection ability. This will ensure AI models can assist radiologists with all types of diseases rather than a select few. Legislation must be created to support the proper creation of training datasets to begin eliminating biases within these models, furthering their efficacy. The relationship between patients and AI must be improved through education, transparency, and data privacy, and more before clinical implementation is possible. If these steps are taken to progress AI model clinical implementation into radiology, it is likely that a decrease in cancer related deaths will be seen. The burden of cancer needs to be stopped, and the advent of artificial intelligence technology in radiology serves as a catalyst for this change.

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