What are the Opportunities, Challenges, and Best Practices Regarding Computer-Aided Diagnoses in Tumour Detection for Lung Cancer?

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Abstract

Background:

Lung cancer is the leading cause of cancer-related mortality globally and in Canada. Early detection is associated with better health outcomes but traditional screening methods, such as low dose computed tomography, are limited by human error and increasing workload demands. Computer-aided diagnosis (CAD) systems, powered by deep learning (DL) and convolutional neural networks (CNNs), which are subfields within artificial intelligence (AI), have emerged as tools for enhancing lung cancer screening and diagnosis.

Objectives:

The objective of this paper is to explore the role of CAD systems in lung cancer detection, assessing their performance, with a focus on CNN-based approaches and to examine the impact of AI on Canadian radiologists, medical students, and healthcare implementation, addressing challenges and best practices for integration.

Methods:

A literature review was conducted using Ovid MEDLINE to analyze studies from 2019 to 2025 and clinicaltrials.gov to analyze Canadian clinical trials. The first objective focused on CAD systems and DL applications in lung cancer imaging, while the second examined AI's influence on radiology professionals and implementation considerations.

Results:

CAD systems demonstrate high sensitivity in lung nodule detection, segmentation, and classification, reducing false positives and improving diagnostic precision. CNN-based models

such as ResNet and DenseNet enhance feature extraction, while transfer learning addresses challenges posed by limited medical imaging datasets. However, there are still many concerns regarding data bias, model interpretability, patient privacy, and liability. Medical students express anxiety about AI's impact on radiology careers, highlighting the need for greater education and leadership within the field. The Canadian Association of Radiologists has issued guidelines to regulate AI implementation, focusing on data privacy, liability, and deployment.

Conclusion:

AI has the potential to revolutionize lung cancer diagnostics, complementing radiologists and improving early detection. However, challenges related to data quality, ethical considerations, and professional adaptation must be addressed through interdisciplinary collaboration and policy development. Future efforts should prioritize model explainability, improved datasets, and education for medical professionals.

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Introduction

Lung cancer is a disease that is caused when lung cells begin to grow abnormally in uncontrollable ways.[1] A group of cancerous cells forms tumours, which can cause severe harm and death.[1] Lung cancer is a significant public health concern.[1] In 2020, it was the number one cause of cancer deaths worldwide at 1.8 million deaths.[1] In Canada, lung cancer remains the second most diagnosed cancer and is the leading cause of death from cancer.[2,3] In 2024, it was estimated that 32,100 Canadians were diagnosed with lung cancer, representing 13% of all new cancer cases. Of these cases, an estimated 20,700 die, representing 23% of all cancer deaths.[2,3]

There are many risk factors for developing lung cancer. Smoking tobacco (e.g., cigarettes, cigars, and pipes) is the main risk factor.[1] However, non-smokers can still develop lung cancer through exposure to secondhand smoke, occupational hazards, air pollution, hereditary cancer syndromes, and previous chronic lung disease.[1] Primary prevention focuses on minimizing these risks through healthy behaviours such as avoiding tobacco, exposure to secondhand smoke, occupational hazards, and air pollution.[1] Secondary prevention emphasizes early detection through screening, which improves treatment outcomes by identifying cancer before it spreads.[1] Common screening methods include physical examination, imaging (chest X-rays, computed tomography [CT], and magnetic resonance imaging [MRI]), bronchoscopy, biopsy, and molecular testing.[1] Among these, low-dose computed tomography (LDCT) is preferred due to its high spatial resolution, cost effectiveness, wide availability, and non-invasiveness.[1,4] CT and X-Rays use ionizing radiation, so they can harm the human body and cannot be used many times.[5] Additionally, the average wait time for an MRIs in Canada is 63 days, so it might not be viable for everyone.[6]

Imaging results are interpreted and analyzed by radiologists. They aim to detect pulmonary nodules, as they are the initial manifestation of lung cancer.[7] They are round lung opacities or irregular lung lesions ranging from 3-30mm and can appear alone or in groups.[7] However, pulmonary nodules can vary in diameter, position, mass, and volume.[7] Additionally, they can be easily missed if they are close to pleura or blood vessels and many small nodules are benign.[7,8] Radiologists can perform medical image analysis; however, they are limited compared to the demand.[5] Additionally, human error, burnout, experience and distraction, and perceptual error in conjunction with the aforementioned challenges with lung nodules, further decrease diagnostic accuracy.[4,5] These medical errors can lead to incorrect diagnoses and even delayed illness, which poses a threat to patient health.[5] As such, there is a need to study a way for computers to perform medical image analysis to improve efficiency and accuracy.

Computer-aided diagnosis (CAD) systems are those that help clinicians interpret medical images and are often seen as a "second opinion".[9,10] They can be used to provide an assessment of the disease, disease type, severity, stage, progression, or regression.[9] CAD systems often make use of artificial intelligence (AI), which is the ability for computers to mimic human intelligence.[10,11] The most well-known type is machine learning (ML), which allows computers to analyze training data, identify patterns, and then apply those patterns to similar scenarios in the future, also known as testing data.[11] In medical image analysis, the most common type of AI is deep learning (DL), which consists of algorithms to create an artificial neural network, mimicking how neurons in the brain work.[11] Much like ML, it allows the network to learn patterns in the training data and make decisions on testing data.[11] Convolutional Neural Networks (CNNs), have been very powerful for lung cancer screening, including lung segmentation, nodule detection, false positive (FP) reduction, nodule classification, and prognosis.[7]

As such, the research question I aim to answer is: What are the opportunities, challenges, and best practices regarding CAD systems in tumour detection for lung cancer. This topic was chosen for two reasons. First, my late grandfather had lung cancer, which sparked my interest in health care. Second, one of my goals in this program was to develop stronger technical skills related to AI. The objective of this paper is twofold. The first objective is to explore and examine the use of CAD systems, specifically those that use DL and CNNs, in lung cancer image analysis. The second objective is to explore how AI impacts Canadian radiologists and other medical learners and implementation considerations. This topic is relevant to eHealth, which integrates engineering, health sciences, and business. The first objective satisfies the engineering and health sciences pillars through the application of AI on lung cancer imaging. The second objective satisfies the business pillar through the impact on stakeholders and health systems.

Methods

Separate literature searches were conducted for each section. For the first objective, exploring and examining the use of CAD systems and DL in lung cancer image analysis, a literature review of English studies published between 2019 and 2025 was performed using Ovid MEDLINE using Medical Subject Headings (MeSH) terms: Lung Neoplasms; Diagnosis, Computer-Assisted; Tomography, X-Ray Computer; Magnetic Resonance Imaging; X-Rays.

For the second objective, how AI impacts Canadian radiologists and other medical learners and implementation considerations, a literature review was conducted for English studies using Ovid MEDLINE using keywords and MeSH terms: Canad*; Radiolog*; Artificial Intelligence.

Clinical trials were searched through clinicaltrials.gov using the terms “Lung Cancer”, “Artificial Intelligence” and filtered for “In Canada”.

Objective 1: AI in Lung Cancer

Computer-Aided Diagnosis Systems

CAD systems help radiologists with visualization, detection, and characterization of lung cancer images.[12] Visualization allows radiologists to enhance certain parts of the images, allowing them to see areas in more detail.[12] Detection allows radiologists to identify suspicious regions within the image data.[12] Characterization is the processing of selected suspicious regions to provide more specific diagnostic information.[12] CAD systems have fast calculations, allowing for precise, quantitative, and reproducible measurements.[12] The data is always increasing, giving it more training data for robustness and is not susceptible to fatigue, unlike radiologists.[12]

The general system for CAD for nodule characterization has five stages: data acquisition, pre-processing, segmentation, feature extraction, and nodule classification.[12,13]

For data acquisition, LDCT is the most medical imaging modality because of its high spatial resolution, cost effectiveness, wide availability, and non-invasiveness.[4] As for databases to obtain these images, it is difficult to come across large datasets of high quality, labeled medical images.[5,13] Usually, researchers use public databases such as the Lung Image Database Consortium (LIDC), Lung Image Database and Image Database Resource Initiative (LIDC-IDRI), Lung Nodule Analysis 2016 (LUNA16), and early Lung Cancer Action Program (ELCAP).[13] For the purposes of comparing the performance CAD systems between different researchers, private databases and hospital databases are not recommended.[4]

Image preprocessing typically focuses on removing noise and increasing contrast.[14] It is considered in the following areas: image contrast enhancement, spatial filtering, threshold filtering, and geometric filtering.[12] There are many types of noises.[14] Noise is affected by the number of photons reaching the detector and can be improved by using larger voxels, increasing the radiation dose (not advisable), or using smoothing filters.[14] Artifacts can occur during machine calibration, scanning, and reconstruction of the image and may sometimes be corrected with recalibrating the detector.[14] Streaks can be caused by motion and edge effects, which includes involuntary and voluntary movement from the patient.[14] Techniques that enhance image contrast are usually only beneficial to human observers because there is no difference for a computer as it only “sees” one numeric range over another.[12]

In the context of nodule characterization, nodule segmentation aims to remove irrelevant information such as the trachea, bronchi, and pulmonary vessels as nodule segmentation is necessary for the next step, feature extraction and selection.[13,14] When curating these datasets, it requires the radiologists to label the nodules. In fact, how radiologists trace regions for nodules can affect the performance of CAD software.[15] However, the models performance, measured with the competition performance metric, were better when using integrated annotations from multiple radiologists than annotations from a single radiologist.[15] Some segmentation methods include optimal threshold, Otsu algorithm, pixel-based segmentation, and Watershed transform.[13] However, in DL models, network can learn deep features, so the segmentation module is not necessary.[13] Intensity values of voxels in CT images are correlated with the density of the scanned material.[12] However, malignant nodules do not have a unique density; furthermore, main bronchi and blood vessels may have similar density values.[12] So, this represents another challenge, however, the shapes of nodules, bronchi, and blood vessels differ significantly.[12] This can work well for isolated nodules, but nodules are frequently attached to blood vessels or the pleural surface, which can further complicate segmentation. When nodules are attached to a vessel, Reeves et al.[12] developed a sequence of 3D morphologic filters that remove long cylindrical vessels from 3D images without blurring surface details of the nodule.[12] When nodules are attached to the pleural surface, the orientation of the surface is determined and then a directed morphologic filter kernel is applied.[12]

Feature extraction and selection aim to extract and select certain features that identify the nodules.[13] Features are divided into deep and traditional features. Deep features are extracted by deep neural networks (NNs).[13] Traditional features include shape, texture, intensity, size, margin, and morphology and are mainly calculated by feature descriptors.[13] Feature extraction aims to reduce the number of FPs.[14,16] Most of the time, the nodule is detected at a high sensitivity and is followed up with FP reduction, which tends to maximize the performance.[8] This is because lung datasets tend to be unbalanced between the number of non-malignant and malignant nodule samples.[8] Thus, applying detection and classification together might confuse the classifier with too many negative samples at different locations.[8] After detecting nodules, a consequent classifier or detector can be trained only on positive and similar FP samples, reducing FP.[8]

Nodule classification has always been a challenge because not all nodules are cancerous.[16] There are several ways to characterize nodules. For example, the LIDC-IDRI database has a 1-5 level rating.[13] If the level is above 3, then they are classified as malignant and benign if not. If the level is equal to 3, then it is uncertain.[13] This ranking has been used by several researchers including Zhao et al.[17] and Liu et al.[18] Nodules can also be classified by shape, size, texture, and morphology distribution.[16] Support vector machines (SVM) is the most popular traditional classifier and is commonly paired with DL.[13] Overall, SVM and DL networks have similar performance, but SVM edge out DL for nodule classification based on metrics such as area under curve (AUC) on the receiver operating characteristic (ROC) and accuracy.[13] Still, the best predictor of nodule malignancy is rate of growth, which is calculated through repeated scans.[12]

Convolutional Neural Networks

CNNs are the most common application of DL in medical imaging analysis.[7] In lung cancer screening, CNNs have been used for lung segmentation, nodule detection, FP reduction, nodule classification, and prognosis.[7]

A CNN is organized in layers, where the output of the previous layer becomes the input of the next.[7] They contain multiple layers of convolution, where the image passes through and becomes a representation through each layer, transforming it into a more and more abstract representation of the original image.[7] The goal of the convolutional layers is to extract deep features from the layers.[5] By processing these deep features, CNNs can perform a variety of tasks on the medical images, including segmentation, detection, classification, and disease prediction.[5]

CNN Structure

In a CNN, the image starts in the input layers, moves through the middle, or hidden layers, then ends up at the output, where it is classified. Convolutional layers, the most fundamental part of a CNN, follow the input layers to extract features.[5] Each convolutional layer has a kernel that is a filter that slides over the image that is sensitive to a specific feature.[5] Generally, the first few convolutional layers extract basic features, while the latter ones extract more advanced features.[5] For example, the first layers may extract edges and lines while the latter ones extract the textures of a lung nodule.[5]

It may seem like having more features is a good thing.[5] However, additional features may contain information that is not necessary and can slow down the CNN.[5] Pooling down-samples the extracted feature maps, which compresses the resolution and only retains important feature information.[5] There are two main types of pooling.[5] Max pooling selects the maximum value from the local domain of the image as the representative, which can preserve texture features of the image.[5] Average pooling selects the average value as the representative from a local domain of the image, which can better preserve the features of the overall image's data.[5]

Activation functions introduce nonlinearity into the CNN.[5] Data is not linearly separable and without activation functions, it is difficult for CNNs to achieve a good effect on linearly indivisible data.[5] Earlier renditions of activation functions were sigmoid and tanh, however now most CNNs use rectified linear unit (ReLU).[5]

The fully connected layers come after the convolutional layers and are the "classifiers" in the whole CNN.[5] The fully connected layers weigh all the characteristics from the neural networks at the same time and reduce the spatial dimensionality.[5] Another method is to use global average pooling, which can apply average pooling on the entire feature space which produces a one-dimensional vector.[5] Regardless, both layers allow for the final softmax layer to output the classification probability.[5] Additionally, having too many parameters in the fully connected layer can make the model too bloated and prone to overfitting.[5]

Since practical problems are challenging, it often leads to tendencies to use deeper and deeper NN structures.[5] However, deep NNs can have issues with slow learning because either the upper network is constantly adjusting to the change of the input data and/or the activation functions fall into the gradient saturation.[5] Batch normalization is a technique that normalizes the output signal into an ideal range.[5] This allows the data input into each layer to be within a certain range through normalization, so latter layers do not have to constantly adjust to the inputs, increasing learning speed.[5] The model also becomes less sensitive to parameters in the NN, which improves the learning stability.[5] It also adds random noise to the NN, which brings regularization.[5]

Overfitting is another common issue in DL and occurs when the training sample is small, the network is complex, or has too many parameters.[5] Dropout is a technique where, usually 50%, of the nodes in the hidden layers are set to 0, which ignores 50% of the feature detectors, alleviating overfitting.[5] This results in weakened interactions between nodes and punishes neurons that are too prominent and reduces reliance on those neurons.[5]

Transfer Learning

CNNs hold many advantages as they can be applied to not just lung medical images, but many other scans as well. They have a high accuracy and fast analysis speed.[5] However, some shortcomings include the long, difficult, and expensive training process.[5]

To overcome the problem with small and sparse datasets, a process called transfer learning has been implemented.[5] The theory goes as follows: if a CNN can solve a problem, then it likely learned something and can solve a different problem even faster.[5] It begins with the source domain, which is the existing knowledge, and applying those patterns to a target domain, or the new knowledge.[5] It uses a pre-trained model as its base, which greatly saves the training time and reduces the difficulty of training.[5] It requires less data and is less prone to overfitting as creating a model from scratch.[5] There are two common strategies for applying transfer learning using pre-trained models: fine-tuning and feature extractor.[5] Some common pre-trained CNNs are AlexNet, VGGNet, ResNet, and DenseNet.[5,13]

In fine-tuning, the tagged medical image data is used to train the pre-trained CNN on the last few layers.[5] The hidden layers used to extract features and the final output layers of the pre-trained model are retained.[5] After fine-tuning, the network has stronger classification performance and stronger feature extraction ability for the target data domain.[5]

In feature extractor, the hidden layers are frozen except for last few layers.[5] Then, its own classifier is spliced into the model (such as SVM, reconstructing a new network model.[5] It can also be powerful, enabling new networks to earn the powerful feature extraction performance from the pre-trained network with a low training cost.[5] In general, if there is a lot of labeled data, then fine-tuning could work well, otherwise, try feature extractor.[5]

Pretrained Models

ResNet is a CNN that uses residual blocks and skip connections.[8,13] The skip connection encourages feature reuse but is not as robust in exploring new features.[13] It is popular because it is easy to converge to in training.[8] Usually, the number of layers follows the name, for example, ResNet-18 contains 18 layers, but it often ranges from 18 to 152.[8,13,19]

DenseNet is another valid CNN because each layer has direct access to the gradients from the loss function and the original input signal, which leads to deep supervision and easy training.[8] However, it is computationally demanding and requires a large training set.[8]

Researchers often build off these pre-trained models. DenseBTNet is a CNN that is 50 layers and inherited properties of DenseNet and improved the classification performance.[13] However, it can suffer from feature redundancy due to the dense connections.[13] 3D DPN is another CNN that has 92 layers and attempts to integrate the advantages of DenseNet for exploring new features and ResNet for feature reuse.[13] Xu et al.[20] used dual skip connection upsampling to locate nodules, which surpassed the performance from a single skip connection and single-scale feature map model. This architecture uses DenseNet and ResNet in parallel, which could be useful for exploring new potential features, preventing vanishing gradients, and reducing FPs.[20]

CAD System Performance versus Physicians

In a CAD system with DL capabilities, it improved the less experienced radiologists' detection sensitivity for nodules of all sizes.[21] There was a significant improvement in their abilities to detect small nodules (3-6mm in diameter) and medium nodules (6-10mm in diameter) while reducing their reading time.[21] CAD systems should not replace physicians, but rather assist less-experienced radiologists from overlooking nodules by improving their sensitivity.[21] There will always be a need for human oversight due to the complexities in anatomical structures and the heterogenous nature of the disease.[13]

In a retrospective study with 570 subjects, lung nodules were examined from LDCT scans by radiologists, oncologists, and thoracic physicians, as well as CAD based on 3D CNN based on DenseNet and evaluated on AUC ROC.[22] This system was InferRead CT Lung (IRCL), a CAD system developed in China.[22] It used a region-based CNN to detect nodules.[22] IRCL demonstrated high consistency with the panel's evaluation in nodule detection.[22] The comparison of solid nodules' attenuation characteristics also showed acceptable consistency.[22] Additionally, there was no significant difference between the AUC ROC for the panel and IRCL for patients with lung cancer.[22] Both the panel and IRCL saw maximum diameter, solid nodules, subsolid nodules, spiculation sign, and lobulation signs as statistically significant as interpreters of cancerous nodules.[22]

Objective 2: AI's impact on Canadian Medical Learners and Radiologists

Medical Students and Residents

In March 2018, Gong et al.[23] distributed an anonymous online survey to all 17 Canadian medical schools that shed light on medical students' perspectives on AI. Of the 322 respondents, 70 (21.7%) students considered radiology as their top specialty choice, and 133 (41.3%) rated radiology among their top three choices.[23]

Anxiety about AI was a contributing factor with lowered preferences for radiology.[23] 16.7% of respondents shared that they would have otherwise ranked radiology as their first choice if AI did not cause so much anxiety.[23] AI anxiety was also prevalent among first-choice respondents, as 48.6% agreed AI caused anxiety.[23] Interestingly, it was not a lack of intrinsic interest in radiology that pushed respondents away from radiology.[23] Moreover, this anxiety did not seem to stem from "replacement" of radiologists, rather "displacement".[23] 29.3% of respondents agreed AI would replace radiologists in the foreseeable future, but 67.7% agreed that AI would reduce the demand for radiologists.[23]

Significant exposure to radiology through research, conferences, or rotations and electives led to a lower frequency of agreement with anxiety statements.[23] Exposure to AI through courses, conducting computer science or radiology research projects involving AI had no significant effect on the frequency of agreement with anxiety statements.[23] Respondents did not agree that the anxiety statements demonstrated higher level confidence in their understanding of AI.[23]

To assess the students' understanding of AI, Gong et al.[23] also included a five question True/False quiz on AI. Only 14% of respondents got 5/5 and 30.7% got 0/5.[23] This suggests a gap between self and objective assessment of the students' understanding of AI.[23] However, having a degree in CS or prior exposure to AI was strongly associated with higher test scores.[23]

The students had a few recommendations on how the radiology community can help medical students.[23] There were several proposed solutions that mainly centered around education and leadership.[23] For education, the students' proposal involved inviting more experts to provide opinions on the impact of AI, more discussions on AI in preclinical radiology lectures, and offering courses in AI.[23] For leadership, the students proposed publishing position statements of radiology organizations and explaining the perspectives of radiologists in general media.[23]

While the survey by Gong et al.[23] provided many valuable insights into medical students' attitudes towards AI, these trends were corroborated by data published from Canadian Resident Matching Service (CARMS) annual data reports from 2010-2020.[24] But, this does not mean that AI and AI anxiety were the only contributing factors to these trends.

The number of available radiology residency positions decreased from 84 to 81.[24] The proportion of applicants with radiology as their first choice decreased from 4.5% to 3.1% and the number of applicants applying exclusively to radiology decreased from 39 to 16.[24] There were fewer applicants with diagnostic radiology as their first choice or only choice in the match as more students looked towards diversifying to avoid going unmatched.[24] However, there was no change in the overall number of students applying to diagnostic radiology.[24] The disparity and match data could be due to efforts to increase exposure to radiology during medical school.[24]

The match numbers corroborate recent reports of increased workload burnout, declining reimbursement, and uncertainty regarding radiology with respect to AI.[24] Some other factors that could have played a role in the declining number of applicants are lifestyle changes and workload increases due to the growth of imaging volumes, partly from the aging population.[24]

Another study with 152 residents showed that more recent graduates are more concerned about technology replacing radiologists, and radiology applicants are less concerned about AI replacing radiologists.[25] Much like the suggestions given by Gong et al,[23] positive interactions with radiologists and mentorship are key influencers to giving a more positive outlook on the field.[25]

The Canadian Association of Radiologists and AI

Currently, the Canadian Association of Radiologists (CAR) recognizes AI as a growing part of the field and has worked towards developing legal and ethical guidelines for the development and use of AI.[26] There are a few key lessons that the CAR outlined.

Canada is a public healthcare system, so there is the opportunity to develop CAD systems using population-wide training data, which is a massive advantage since large databases are difficult to come by.[26] These advancements will cause a shift in the value of data.[26]

With the rise of electronic health records (EHRs), ownership of medical records and the secondary use of de-identified medical data is complex and will depend on the type of use.[26] CAR has determined that the healthcare provider that produced the medical record owns the physical record and the patient has a right of access to it.[26] There are still ethical challenges regarding beneficence and justice (improving public health through the secondary use of a patient’s medical data) and autonomy (free and ongoing consent to use the medical data).[26]

To protect patients, there must be safeguards at every level. Beginning with the data itself, there must be tools and policies to standardize the anonymization of medical images.[26] Onto patient consent, there needs to be more specific uses of consent like “broad consent”, “opt-out consent”, and/or “presumed consent” to more general data uses.[26] For health communication, there need to be public education campaigns to educate the public on the benefits that come with sharing anonymized personal health data.[26] For implementation, there needs to be guidelines prior to the deployment of AI in hospitals to minimize the potential harm and liability for malpractice in the case of medical errors involving AI.[26]

The CAR and Radiology Society’s Recommendations

Data Privacy

Privacy is one of the fundamental rights for Canadians, as per the Constitution Act of Canada.[26] Privacy is the individual’s right to be free from intrusion or interference from others and exercising control over the information pertaining to the individual and consent for others to use that information.[26] Personal information in the context of radiology consists of medical images and is very personal and sensitive.[26]

The CAR recommends advocating for public education programs to increase public awareness of the benefits of sharing anonymized personal health data and harm reduction strategies.[26] They also advocated for the general adoption of revised forms of consent (such as “broad consent”) for appropriately safeguarded secondary use of health data.[26] Lastly, CAR is looking to develop a framework for security, anonymization, and secondary use of radiology data.[26]

Technical Aspects of Implementing Data Privacy

De-identification refers to the removal of personal identifiable information.[26] In contrast, anonymization refers to data that can never be re-identified and pseudo-anonymization refers to replacing personal identifiers with artificial identifiers.[26] In radiology, re-identification can occur from inadequately processed Digital Imaging and Communications in Medicine (DICOM) image headers.[26] Radiology databases consist of DICOM files, which contain the images and metadata within.[26] Some of the metadata fields include ".studydate = 20250305" and ".PatientName = Jane Doe".[26] Each radiologic manufacturer also adds their own proprietary DICOM header fields, which may contain more identifying data in unexpected or undocumented locations.[26]

Thus, the CAR recommends that there must be a clear protocol demonstrating how DICOM data is truly deidentified and non-re-identifiable.[26] For data transfer between stakeholders, CAR recommends that a clear protocol is developed demonstrating its security.[26] They also recommend advocating to radiologists that medical images that already meet DICOM standards should be standardized and easily removable in the case of future anonymization.[26] Lastly, CAR should provide links to reputable DICOM anonymization software tools.[26]

Role of Data Custodian: Data Sharing

A data custodian is one who deals with the sensitive personal health information, such as a hospital or regional health authority.[26] They play a vital role in gatekeeping which AI projects are ethically appropriate to perform.[26] Usually, a research ethics board grants approval towards a research protocol and/or data transfer agreement.[26]

The CAR should assist radiology data custodians by developing clear guidelines for their role and preparing sample templates of data sharing agreements for common AI-related scenarios.[26]

They should also educate stakeholders on the importance of the data custodian role in the absence of explicit consent.[26] Lastly, CAR should work to set budget guidelines for departments when granting access to third parties.[26]

Role of the Radiologist: Liability

The integration of AI within the radiologist workflow has interesting implications for how liability will be spread.[26] There needs to be a balance between justice with expected positive consequences (reducing harm and increasing happiness).[26] AI can function at different levels of autonomy, and as such, CAR has identified several levels with different liabilities.[26]

The CAR should work together with other stakeholders, such as the provincial Ministries of Health and the Canadian Medical Protective Association (CMPA) to develop guidelines for appropriate deployment of AI within hospital settings.[26] These guidelines should aim to minimize harm and institutional liability for malpractice in the case of medical errors involving AI.[26] Lastly, AI should not replace human expert judgement as radiologists should be aware of its limitations and use AI appropriately within scope.[26]

The CAR, alongside the American College of Radiology (ACR), the European Society of Radiology (ESR), the Royal Australian and New Zealand College or Radiologists (RANZCR), and the Radiological Society of North America (RSNA) published guidelines and considerations for augmentative and autonomous AI.[27] Augmentative AI operates with human oversight and autonomous AI operates without direct human oversight.[27] While by strict definition, this would imply augmentative AI is level 0-4 and autonomous AI is level 5 on Appendix 1, there could be an argument to be made that the lines are blurred within levels 3-4, where they could be either.

Augmentative AI can lead to human-computer bias, where humans tend to favour AI decisions and disregard conflicting data or human opinions.[27] This can lead to both overreliance and under-reliance of AI if the radiologist trusts or does not trust the AI's outputs, respectively.[27] Both of these examples may lead to increased FPs and false negatives.[27] These challenges are further compounded by negative workplace attitudes, burnout, and high workloads.[27] These challenges may be mitigated with more training and more robust AI models with higher accuracy, which would reduce the bias.[27]

Autonomous AI, although level 5 might not ever be possible, is still necessary to examine as there are more significant safety and ethical considerations at play.[26] Autonomous AI is more likely to be used in communities that have access to fewer radiology services.[27] However, these systems could lack the nuance that human judgement can provide.[27] These systems require more stringent performance standards and continuous testing to ensure reliability and accuracy for these systems.[27] Moreover, should these systems be deemed not up to standard, then there needs to be failure modes in place to stop the AI.[27] Training healthcare providers on recognizing failure modes and offering a simple mechanism to disable autonomous AI systems is the bare minimum.[27] This is a reactive measure, which means that the system has provided a series of inaccurate results over time before someone could confirm the inaccuracies.[27] To be more proactive, there must be a way to gain earlier insights on accuracy.[27] For example, using additional tools for assessing expected AI outcomes or comparing the results of one AI model to another model simultaneously should be explored and employed.[27]

Development, Purchasing, Implementation, and Monitoring of AI

Before purchasing an AI tool, hospitals should verify its certifications to ensure compliance with IT standards and privacy laws (e.g., Personal Health Information Protection Act [PHIPA]).[27] Its intended use, clinical value, risks, and economic impact must also be examined.[27] The commercial claims will also need to be verifiable and monitored to ensure it meets hospital needs.[27] Lastly, the users must be trained, and the psychological effects of AI-human-interactions must be accounted for before purchasing an AI tool.[27]

To ensure the long-term stability and safety of AI tools, there are several considerations.[27] For instance, there will be naturally occurring data drift, which causes AI models' performance to degrade over time.[27] As such, users should anticipate this and have countermeasures in place, such as monitoring strategies.[27] At minimum, these monitoring strategies should include a yearly re-evaluation of the performance of all AI models being used in clinical practice so that appropriate measures can be taken to ensure the patients' safety and health.[27] These monitoring methods can be used more frequently for parameters that are associated with the data drift.[27] If there is a need for more continuous AI monitoring, then this monitoring should capture model performance, examination parameters, and patient demographics in data registries that provide reports to end-users and developers.[27] This would be more robust and offer faster insights towards data drift compared to periodic re-evaluation but requires more overhead and oversight.[27] While it might not be necessary for some AI models, it could be necessary if the AI is considered high or full automation (Appendix 1).[27]

Discussion

From the basic structure of a CNN to how CAD systems can match the performance of a panel of radiologists and other medical professionals, this paper attempts to look at CAD systems from a micro to macro level. It may seem like CAD systems could only be beneficial to the field, however there are still many implications and limitations to explore from different perspectives.

We will describe the limitations first and but also demonstrate the effort researchers are making in terms of performing clinical trials with AI models in lung cancer.

Limitations for Data

A key limitation of AI is its reliance on high-quality, representative training data. AI trained on biased data can promote or harm group-level subsets based on gender, sexual orientation, ethnic, social, environmental, or economic factors.[27] This would not be a problem, however, medical image databases are notorious for having a lack of high quality, labeled images for training and testing.[5] Even though there are many public lung databases, the data is often heterogeneous, noisy, unbalanced between malignant and benign pulmonary nodules, and poor quality, which negatively affects training.[5,13] This often constrains the training for models and parameter optimization, resulting in overfitting, which reduces generalizability to testing data.[5] To combat for overfitting, one can use dropout and regularization methods or transfer learning.[5] Additionally, data augmentation such as translation, rotation, clipping, scaling, and changing contrast can be used to generate new images from the training set.[5,13,28] Expanding the training samples can increase the model's performance, even when on small and unbalanced datasets.[29] These databases could also cause clinical confounding bias, where AI might be biased by clinical confounders such as comorbidities.[27] This can be ameliorated by having more training data so that confounders make up a smaller percentage of the training and testing data. Additionally, some medical databases have medical data that lacks labels.[5] This defeats the purpose of AI as it will not be able to train. This can be solved by either producing more labeled data through self-supervised learning, which also involves AI, or by performing transfer learning on the target domain.[5] Self-supervised learning could produce labels with non-labeled original data from scratch without human annotation.[5]

Patient health information is highly sensitive and personal, so it naturally raises issues surrounding patient privacy.[28] Many researchers have generated and published their DL models, which include parameters that may include sensitive data.[28] It may be possible to reverse engineer sensitive information from these parameters, threatening patient privacy.[28] However, proper de-identification guidelines, as laid out by the CAR, could combat this issue.

To address these issues, the best-case scenario is to have more high-quality, public databases. It would address biases within the data like different ethnic representation and clinical confounders. Ideally, these databases would also include different nodules types such as those less than 5mm in diameter, irregularly shaped nodules, isolated nodules, and juxta-pleural or juxta-vascular nodules.[13] However, because of PHIPA and other patient privacy laws, it has always been difficult to curate these databases. CAR released guidelines for de-identifying patient data, and these guidelines should be followed by those looking to curate public databases for lung cancer imaging. Moreover, these images should be annotated by multiple physicians to provide the best diagnostic power for any models trained on that database. For the time being, should these public databases remain the way that they are, researchers should look towards data augmentation to increase the amount of training data because it is beneficial irrespective of the type of model.

Limitations for CAD systems and AI

While CAD systems and AI are not the same thing, they have similar limitations. However, CAD systems are higher level, while AI is lower level. Some limitations in CAD systems include limited accuracy, and low sensitivity and specificity.[13,30] To improve accuracy, there are a few solutions. First, there is a need to develop new DL techniques to diagnose nodules for lung cancer and optimize existing techniques.[13] Another solution is to integrate multi-modal data into

CAD systems, such as patient clinical data from EHRs.[31] This may provide more comprehensive, holistic lung cancer detection which can increase accuracy and provide more sensible clinical practice decision-making, but brings in further concerns about patient privacy.[31] Another way to improve accuracy, low sensitivity, and low specificity would be to procure more high-quality databases, which was previously mentioned. There is also more research on CAD systems utilizing FP reduction systems, which can improve specificity.[32] Xie et al.[33] used a two-stage method to detect nodules and reduce FPs. The nodule detection used faster region-based CNN architecture and a 2D CNN architecture for FP reduction.[33]

An AI-specific limitation is hyperparameter optimization, which are values that the parameters of network changes to “learn”.[28] It is a challenge for DL algorithms because more optimized hyperparameters create better generalizability costs more time and computing power.[28] AI research has always struggled with this problem as there is always a balance to strike between model size and training time. Another limitation is the environmental impact, as they consume a lot of energy during training and operations, contributing to a large carbon footprint.[34]

Using pre-trained models and implementing transfer learning can vastly decrease the number of hyperparameters to tune as only few layers are accessed and modified at once. There also needs to be more memory-efficient model architectures, such as the Tensor-Train compression technique, which achieves more than 100x memory reduction with negligible training time and accuracy trade-off to improve the carbon footprint.[34] In general, physician-scientists should continue collaborating with AI researchers to understand trends within the field, so they can apply newer, more robust AI models to help with lung cancer image analysis.[13]

Limitations for Patients

CT scans can also be challenging for patients because they require a patient to hold their breath as they lie on a scan table.[12,35] The limitations include radiation dose and the continuous scan time.[12,35] Many patients with lung cancer are either of advanced age or have other chronic lung diseases, so they may have trouble with the required breath-holds.[12,35] There is a balance between the resolution, acquisition time, and radiation dose.[12,35] To obtain images of the highest possible resolution, a technician must use an acceptable radiation dose during a tolerable single breath-hold.[12,35] However, there are more protocols now that can produce detailed images without needing much breath-hold and should be explored for these patients.[12,35]

Another limitation for patients is data security and ownership as they may uneasy about their data being used without explicit consent and when it is shared with third-party developers. To mitigate these concerns, there needs to be work done on developing DICOM anonymization protocols, policies supporting different types of consent, and public education campaigns on data usage should be followed, as per the CAR recommendations.[26]

Limitations for Medical Students

The medical students' concerns lie in anxiety related to AI in radiology. This has caused downstream effects like affecting residency matching, however, there are many other confounders at play too. Much like the suggestions laid out by the medical students, there needs to be a bigger focus on education and leadership. Education needs to focus on bringing in radiology and AI experts to provide opinions and educate medical students on the implications of AI in radiology. This could further be extended to AI in medicine as there are many other fields that are affected by AI too, such as dermatology and pathology. This should be implemented into the curriculum for all medical students. Leadership should focus on publishing more position statements and sharing the perspectives of radiology leaders in the general media.

Limitations for Residents and Physicians

Residents and physicians will be lumped together in this section as their responsibilities are more similar than those of medical students. Residents and physicians are already in the field, and as such, their needs, with respect to AI, are different than those of medical students, who are mostly focused on dealing with the anxiety on radiologist displacement.

Automation bias is the phenomenon where humans tend to favour AI decisions, holding it of a higher standard than data or human opinions that suggest otherwise.[27] This can lead to errors of omission, where humans fail to notice or disregard the error in the AI tool, and commission, when someone erroneously accepts the AI's faulty decision despite the contrary evidence.[27] This may be mitigated with more training and more robust AI models with higher accuracy.

Model interpretability is also an issue as CNNs and AI in general is a "black box" because it cannot explain its findings.[5,28] This is important because physicians need to be able to explain findings to a patient should they base a diagnosis or treatment plan based off an AI's decision.[28] This can be mitigated through model transparency, which is a growing field within AI, especially with the advent of DeepSeek-R1 and its ability to explain its reasoning.[36] While DeepSeek-R1 is a large language model and most CAD systems are CNNs, it is not entirely transferable, so more research should be done on explainable AI in general as it has been an issue within the field.

It should be part of the physician's duty to assess their and their patient's comfort levels with AI. AI should only be used in the diagnosis procedure should both parties agree. Physicians should not force AI onto unwilling patients, and if a physician is unwilling, then they should be able to connect pro-AI patients with AI-literate physicians.

Policy and Implementation Implications

While CAD systems offer clear clinical and technical benefits, their adoption into healthcare settings requires policy and implementation strategies. The CAR has already identified a liability framework for CAD systems. In the case of shared liability, better physician training and more robust AI models can mitigate these concerns. Much like the CAR suggested, in the case of shared liability, AI should only remain a partner for physicians, rather than a replacement. On the other hand, in the case of autonomous AI, there need to be failure options to protect patients.

Translating guidelines into clinical policy requires coordination with provincial Ministries of Health, hospital administrators, and legal stakeholders such as the CMPA. When deploying a CAD system, there need to be considerations on malpractice coverage, patient consent mechanisms, and staff readiness. Without clearly established guidelines and protocols on handling procurement, data sharing, and AI use, the implementation of CAD systems could be inconsistent across patients and legally risky.

Hospital leadership must also invest in change management processes. This includes training staff to understand CAD system outputs, standardizing workflows to incorporate CAD systems, and engaging in patients on its use. The hospitals must also consider data drift, as model performance may degrade over time due to shifts in population health or imaging protocols. Thus, there is a need for continuous monitoring, training, and policy and governance.

Due to the levels of autonomy, there could be a phased rollout that seeks to start at level 1 before advancing towards level 5. The first phase should focus on low-risk, high-support environments such as academic medical centres. They generally have access to better data infrastructure and physician-scientists who may be more technologically literate and willing. This phase should focus on building trust on level 1-2 AI systems, understanding real-world workflow integration, and integrating radiologist, patient, and hospital administrator feedback to improve guidelines. The second phase could focus on urban hospitals and community imaging centres and should look towards improving access of care and reducing radiologist workload. The third phase should focus on underserved areas, such as rural hospitals. Here, the learnings from phases 1 and 2 can be used to develop policies that best support rural physicians, who suffer from the most workload pressures. The final phase should be a cycle of continuous monitoring and feedback. This should focus on evolving policies on ethical issues, such as data drift, and focus on expanding to higher levels of autonomy.

While a phased rollout provides a structured path to AI adoption, its success hinges on other factors including hospital information technology infrastructure, training, and readiness, which may be lacking in underserved or rural areas.[37] It is vital to support underserved and rural areas, otherwise it could exacerbate health inequities. While Khan et al.[37] looked at the deployment of virtual healthcare services in rural Saskatchewan, the applications are quite similar to CAD systems as they are both eHealth products. Their key recommendations include creating detailed community profiles, assessing digital literacy, and assessing community readiness to meet infrastructure and clinical needs.[37] Additionally, they used a weighted prioritization framework to ensure efficient resource allocation and partnered with Indigenous-led institutions to support local healthcare assistants with virtual care delivery.[37] It is important to adopt a community-centred approach to address community-specific issues, such as upholding Indigenous data sovereignty principles, to ensure success in the recommended phased approach.[37,38]

Prospective Clinical Trials

Despite the limitations and concerns surrounding of AI use, there have been notable efforts to conduct clinical trials related to the application of AI in lung cancer imaging. In Canada, there were three clinical trials on clinicaltrials.gov that were recruiting (1) or completed (2) that met the search criteria. All three trials use endobronchial ultrasound transbronchial needle aspiration (EBUS-TBNA) as the imaging modality, and all have the same principal investigator.

The first completed clinical trial was a single-centre, prospective study that compared NeuralSeg, a U-Net style CNN, against an expert endosonographer and the gold standard of pathology, a pathologic specimen from surgery.[39] The outcome was predicting nodal metastasis.[39] When compared to the expert endosonographer, NeuralSeg displayed moderate accuracy of 73.78% (95% CI, 68.40-78.68), specificity of 84.34% (95% CI, 79.22-88.62), and sensitivity of 18.37% (95% CI, 8.76-32.02).[39] When compared to the gold standard, NeuralSeg was found to have a diagnostic accuracy of 72.87% (95% CI, 63.46-80.98), specificity of 90.79% (95% CI, 81.94-96.22), and sensitivity of 28.12% (95% CI, 13.75-46.75).[39] These results were moderate, with NeuralSeg's accuracy and specificity within the ranges of 56%-91% and 23%-93%, respectively, that the authors found in their literature search.[39] The other completed clinical trial was a single-centre, prospective trial.[40] The authors compared NeuralSeg against the gold standard, which achieved an overall accuracy of 70.59% (95% CI, 63.50-77.01), sensitivity of 43.04% (95% CI, 31.94-54.67), and specificity of 90.74% (95% CI, 83.63-95.47). While the accuracy and specificity may be moderate, the sensitivity was lower than what was found in existing literature.[40] The other clinical trial is currently recruiting which attempts to measure malignancy prediction between NodeAI and surgeons.

Conclusion

CAD systems have proven to show similar performance to radiologists, as such, has potential to improve cancer image analysis by enhancing early detection, reducing radiologist workload, and improve diagnostic accuracy. CNNs have a unique structure that allows them to extract features, and many pre-existing models, such as ResNet, that increase their performances.

Despite these benefits, there are still many challenges within this field. These challenges are not limited to just AI and the data, but also stakeholders such as patients, medical students, residents, and physicians. The CAR has taken many proactive steps to address guidelines and recommendations for purchasing, implementation, and use of AI. However, there should be continued efforts to create standardized policies that balance stakeholder needs while considering ethical issues such as patient privacy and data security.

A phased rollout of CAD systems represents a practical and ethical approach that integrate the recommendations put forth from CAR. Starting with the implementation in academic hospitals and gradually expanding to urban hospitals and underserved populations. This iterative cycle should focus on level 1-2 systems, before gradually moving towards level 4-5. This allows for careful monitoring, iterative improvement, and policy refinement. Additionally, there is a need for transparency, equitable data representation, and continuous education at all levels of medical professionals to build confidence and competency with AI. Future efforts should focus on the interdisciplinary collaboration between radiologists, AI researchers, and policymakers to overcome challenges such as datasets, explainable AI, refining clinical policy, and education. By addressing these concerns, CAD systems will be able to play a larger role in lung cancer image diagnosis, leading to earlier treatments and better patient outcomes.

Appendix

Appendix 1: CAR levels of autonomy for AI. This is a full reproduction of the original table.[26]

CAR level	Name	Description	Liability
0	No automation	Interpretation/intervention is done solely by the radiologist.	Radiologist/ Clinician
1	Physician assistance	Interpretation/intervention is done primarily by the radiologist with AI providing secondary oversight.	Radiologist/ Clinician
2	Partial automation	Interpretation/intervention is done primarily by the AI with radiologist providing secondary oversight.	AI/ Radiologist/ Clinician
3	Conditional automation	Interpretation/intervention is done solely by the AI for a specific indication with the expectation that radiologist will intervene if the results are positive or indeterminate.	AI
4	High automation	Interpretation/intervention is done solely by the AI for a specific indication without the expectation that the radiologist will intervene. The AI can arrive at a differential diagnosis and recommend management autonomously.	AI
5	Full automation	Interpretation/intervention is done solely by the AI for all indications expected of radiologists. It can arrive at a differential diagnosis and recommend management autonomously.	AI

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