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Review Article

Recent advances in computed tomography and magnetic resonance imaging techniques for cancer detection with artificial intelligence and machine learning integration

Mohd Faraz[1], Zeeshan Akram[1], Saqib Zameer[2], Urooj Fatima[1], Kasib Zafar[1], Mohd Fazil Ansari[3], Afsha[4], Mudassir Alam[5]*

[1]Department of Radiodiagnosis, J. N. Medical College, Paramedical College, Faculty of Medicine, Aligarh Muslim University, Aligarh, Uttar Pradesh, India
[2]Department of Microbiology, J. N. Medical College, Paramedical College, Faculty of Medicine, Aligarh Muslim University, Aligarh, Uttar Pradesh, India
[3]Department of Surgery and Anaesthesiology, J. N. Medical College, Paramedical College, Faculty of Medicine, Aligarh Muslim University, Aligarh, Uttar Pradesh, India
[4]Department of Radiodiagnosis, Arogyam Institute of Paramedical and Allied Science, Roorkee, Uttarakhand, India
[5]Department of Biological Sciences, Indian Biological Sciences and Research Institute (IBRI), Noida, Uttar Pradesh, India

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***Correspondence:**
Dr. Mudassir Alam,
E-mail: syedalamalig@gmail.com

ABSTRACT

Cancer is one of the leading causes of death all over the world. The International Agency for Research on Cancer (IARC) estimated 20 million new cancer cases in 2022. However, detecting cancer is difficult because it shows symptoms in the final stage. Diagnostic imaging plays a vital role in the early detection of cancer. Advanced imaging technology includes X-ray mammography, ultra-low-dose computed tomography (ULDCT), and dual-source CT, which uses two X-ray sources and improves the resolution of images. Radiomics is another advanced approach that converts medical images into quantitative data and deep learning methods (DL) using Artificial intelligence (AI), which tremendously increases the accuracy of tumor detection. Several automated and semi-automated methods are proposed to detect pulmonary nodules using DL methods such as Conventional neural network (CNNs), which include ResNet-50, VGG16, and InceptionV3. In addition to techniques that involves ionizing radiation, this review also explains the magnetic resonance imaging (MRI) techniques for cancer detection. MRI uses radio-frequency (RF) pulses to form images with high spatial resolution. Diffusion-weighted imaging (DWI), functional magnetic resonance imaging (fMRI), and MR spectroscopy (MRS) are the MRI sequences generally used for cancer detection. The aim of this paper is to provide an overview of modern CT and MR imaging techniques integrating with AI and machine learning for cancer detection.

Keywords: Artificial intelligence, Deep learning, Diagnostic imaging, Radiomics, Tumor detection

INTRODUCTION

Almost one in six deaths (16.8%) and one in four deaths (22.8%) from non-communicable diseases (NCDs) worldwide are caused by cancer.[1] Early detection of cancer is important to overcome this problem.[2,3] Diagnostic imaging procedures including positron emission tomography (PET), magnetic resonance imaging (MRI), ultrasound (USG), computed tomography (CT), and X-ray mammography are frequently employed for early disease and cancer identification.[4] CT imaging is based on ionizing radiation although useful and referred to as the best modality for lung cancer detection.[5] Non-ionizing modality such as Magnetic resonance imaging (MRI) uses the magnetic field for image acquisition. Advanced techniques such as MR spectroscopy (MRS), Dynamic contrast-enhanced (DCE) MRI, and functional MRI (fMRI) are commonly used for cancer detection.[6] Different morphologic and functional imaging properties are measured using current-generation hybrid imaging, which can provide additional information about the tumor environment.[7] However, deep learning models, especially convolutional neural networks (CNNs), have shown great achievement in automating the detection and diagnosis of diseases.[8] It improved diagnostic accuracy, faster decision-making, and better outcomes for patients. It's time to switch towards hybrid imaging models (PET-CT and PET-MRI) and quantitative data (radiomics) to form multi-parametric models for personalized diagnosis and treatment plans for different diseases.[9] Images contain different intensities in anatomical structures that may cause difficulty in distinguishing between normal cells and the tumor cell. In the early detection of cancers CT imaging and MRI have become very reliable.[10] Usually, low-dose CT is used for lung cancer and optical imaging for esophageal, skin, or colorectal cancer detection. Conventionally, the approach was qualitative in early detection involving the radiologist's visual interpretation of images.[11] The detection depended on the experience of the clinician or radiologists. In the last few years, quantitative approaches (radiomics) have been developed to convert images (qualitative data) into quantitative mineable data with the help of computerized tools.[12] It aims to improve the existing data using mathematical and analysis methods of artificial intelligence (AI). It increases cancer detection accuracy and helps radiologists and clinicians distinguish between benign and malignant tumors. Radiomics data is shown in statistical form as first-order, second-order, and higher-order.[13] These data and bio-informative tools together developed several models that increased the accuracy of cancer detection and helped clinicians make better clinical decisions and the process of radiomics is mentioned in Figure 1.[14] In MRI conventionally, longitudinal relaxation (T1), transverse relaxation (T2), diffusion-weighted imaging (DWI), and proton density (PD) imaging sequences are used for cancer detection. It also measures the volume of the tumor cells and provides images with high anatomical resolution. Intravenous (IV) contrast media enable the enhancement of cancerous cells.[15] Recent advancements in deep learning (DL) have greatly improved the accuracy of cancer detection. Tumor detection methods include convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid models.[16]

Many studies have explored traditional, manual methods of interpreting medical images for cancer detection. However, there is still no complete review that brings together all the key developments in CT and MRI techniques supported by artificial intelligence, as well as automated and semi-automated diagnostic methods. This paper fills that gap by combining and reviewing these different approaches in one place, giving a clear and comprehensive view of current methods and future trends in AI-based cancer imaging.

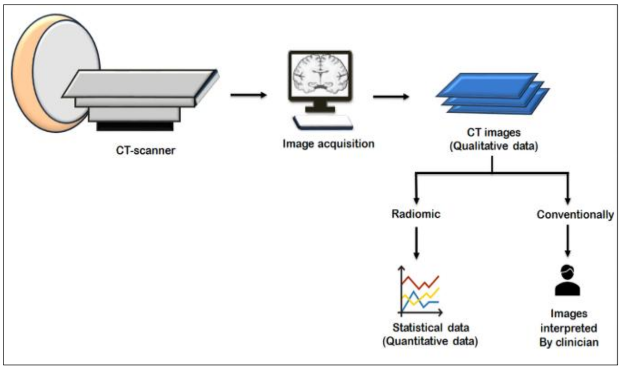

Figure 1: Represents the radiomics procedure: conversion of medical images into statistical data for better cancer detection.

TECHNOLOGICAL ADVANCEMENTS IN CT IMAGING

Role of CT scan in cancer detection

CT scans help to detect tumors in different organs such as the lungs, liver, kidney and brain. Traditional, iodinated contrast media is injected to enhance the blood vessels and organs.[17,18] Tumor cells typically have abnormal vascularization that highlights prominently with contrast media. Low-dose computed tomography (LDTC) is primarily used for lung cancer detection at an early stage.[19] National lung screening trial (NILST) has shown that low-dose CTs can improve the detection accuracy of lung cancer by comparing their size and shape.[20] Dual-energy (CT) is another advanced technique used in cancer diagnosis and evaluate the treatment process.[21] In this, two sets of X-ray sources (tubes) and detectors are used in one gantry as shown in Figure 2. More photon scattering occurred that caused excessive noise due to the two sources, advanced algorithms have been developed to overcome scattering and noise problems.[22] A study of 599 patients with known malignancies undergone the CT examination in 2019 showed that the cancer-related complication majorly was seen in the thorax (265/599) followed by the abdomen (229/599), head, and neck (105/599) regions.[23]

Nodule detection methods in CT imaging

Several automated and semi-automated methods are proposed to detect pulmonary nodules. All these methods include four basic steps: image acquisition, image enhancement, image segmentation, and data extraction.[24] as mentioned in Figure 3. The primary aim of image acquisition is to obtain images of high quality and high resolution. Image enhancement is done by using different types of filtering techniques such as median filtering (removes the noise while keeping the structure intact), wiener filtering (adaptive filtering to reduce the specific type of noise), Gaussian filter (smooths the image while preserving edges), bilateral filtering (smooth the image keeping edges Sharpe), specific high-pass filter (enhance the edges).[25] These techniques reduce the patient dose and noise in the images. To enhance the pulmonary nodules in CT imaging, Bae et al used a morphological filter although Ochs et al, and Paik et al used a spherical enhancement filter. Image segmentation is a process of dividing the lung regions into multiple regions such as lungs, airways, and nodules to improve the detection.[24]

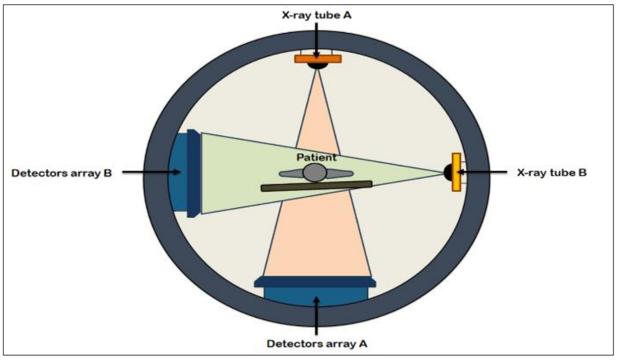

Figure 2: Schematic illustration of dual source (X-ray tube) CT, mounted in a single gantry at an angle of 90 degrees.

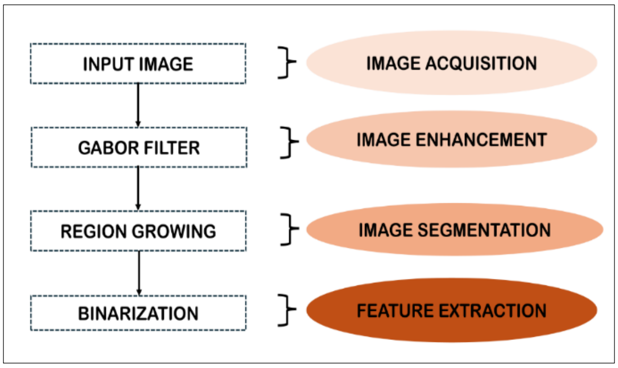

Figure 3: Image processing for lung cancer detection stages.

Various approaches have been developed for lung segmentation and can be classified as 2D and 3D approaches. Region growing is a segmentation technique that extracts the region of interest (ROI) using different filters. Gabor filter is a linear 2D filter, based on edge detection. It detects the boundaries between the different organs by comparing their tissue intensity.[26] The schematic diagram of high-resolution computed tomography (HRCT) thorax represents the input image and the results after being enhanced by the Gabor filter in Figure 4. Similarly, segmentation using 3D-Region growing is a technique that can help in the extraction of the desired area in an image.[27] It is based on initiating a set point (seed) and then expanding it across the required area as shown in Figure 5.

Binarization is the process of feature extraction to differentiate between benign (non-cancerous) and malignant (cancerous) nodules. It converts the grayscale color pixel into two classes, black and white. The quantity of black and white received after the segmentation is compared with the threshold value to identify the condition of the lungs.[28] If the black pixel number is more than the threshold, it indicates normal lungs but if it is less than the threshold, it is an indication of cancer. In a study, 17178 is taken as a threshold value for a normal lung and compared with data from five patients and result as shown in Figure 6.[24]

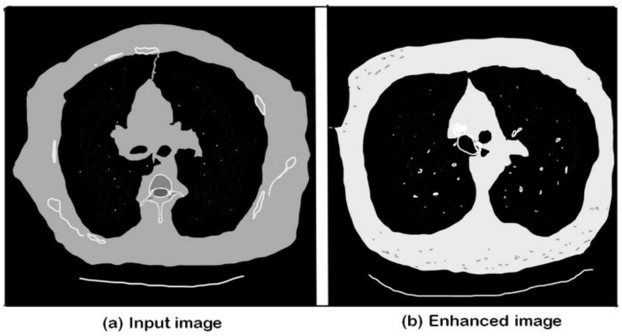

Figure 4: The schematic diagram of high-resolution computed tomography (HRCT) scan shows the input image and output image (enhanced) by the Gabor filter.

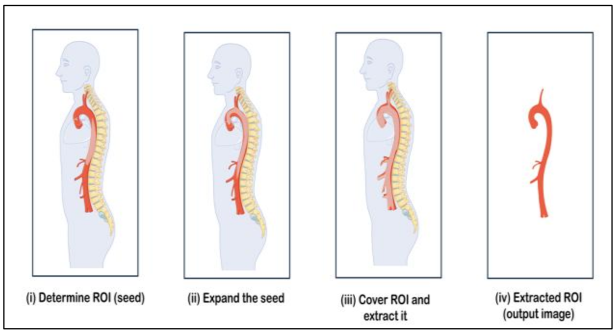

Figure 5: Steps of 3D Region growing technique to extract the desired area.

INNOVATIONS IN MRI IMAGING FOR CANCER DETECTION

MRI has an essential role in cancer detection. T1, T2, DWI, and PD were conventionally used and for better visualization of the tumor, gadolinium-based contrast media is used. Dynamic contrast-enhanced (DCE) MRI is supposed to be more effective in the case of peritoneal metastases.[29] A study was conducted with thirty-four patients to compare the accuracy of conventional MRI sequences with DEC MRI sequences. The result shows that a small volume of mesenteric tumor is better on DEC as compared to conventional MRI.[30] Another approach is functional MRI (fMRI) is widely used to measure changes in brain metabolism activities. It is based on blood oxygen level-dependent (BOLD) signal changes. Tumor affects brain activities such as altered blood flow or functional activities and fMRI measures these altered changes.[31] DWI plays a significant role in tumor detection. It detects areas of restricted diffusion due to cancer growth. A study was conducted to distinguish between benign and malignant tumors in sixty histologically proven cases of superficial soft tissue masses by using the conventional method alone and the conventional method along 5 of 8 with DWI. The result shows that the conventional method used with DWI accuracy increased by 8.3%.[32] One more technique is used to classify types and grades of tumors, magnetic resonance spectroscopy (MRS) is a non-invasive imaging diagnostic method that measures the concentration of different metabolites in gliomas and other tumors.[33] There are several metabolites that MRS can identify but only a few of them have clinical significance in the diagnosis of gliomas including N-acetylaspartate (NAA), choline (Cho), creatine (Cr), myo-inositol (ml), lactate (Lac), lipids (Lip) and glutamate and glutamine (Glx).[34] These are present in very trace amounts in the body, and routine MR sequences cannot detect them. MRS uses high radio frequency (RF) pulses and forms a graph that represents the concentration of different metabolites.[35] The concentration of different metabolites is fixed in normal tissue, a change in concentration is an indication of an abnormality in the tissue. It is useful for radiotherapy treatment planning as it can detect the areas of high metabolic activities that may linked with cancerous cell proliferation.[36,37]

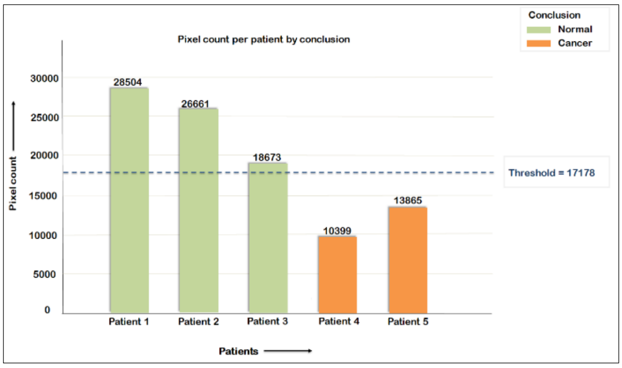

Figure 6: Shows the comparison of white and black pixel values of five patients with threshold value and classifies them as normal and cancerous. If the pixel value is more than the threshold then patient is normal and less than the threshold is consider as cancerous.

INTEGRATION OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

Cancer detection has significantly evolved with the integration of AI and machine learning (ML) in diagnostic radiology. In the current scenario, DL models are becoming a revolutionary method for cancer detection and classifying them into benign and malignant.[38] In thorax CT scans, these models can detect pulmonary nodules. Shin et al formed a CNN-based DL model that can detect lung cancer automatically.[39] CNN technique is used to identify pancreatic lesions in CT scans, and they found highly remarkable results.[40] CNNs are the most widely used DL models for image classification and object detection tasks. They are especially efficient in tumor detection from medical images because of their capability to extract and interpret spatial hierarchies in image data. Commonly CNN models used in tumor detection include ResNet-50, VGG16, and InceptionV3.[41] Additionally, recent advancements in 3D CNNs have allowed for three-dimensional medical imaging. Fully convolutional networks (FCNs) is another recently developed model for pixel-wise segmentation.[42] In the FCNs model a segmentation map is formed for each image, this helps in marking tumor boundaries. These DL methods tremendously reduced the workload and increased the efficiency and accuracy of work for radiologists and clinicians.[43] Another technique integration of multi-modal Data, which is based on a combination of multiple imaging modalities (e.g., combining CT and MRI) and provides more elaborated data. Zhou et al proposed using both CT and MRI data in combination improved the detection accuracy of liver tumors as compared with information provided by each modality independently.[44]

CLINICAL CHALLENGES AND CONSIDERATIONS

While CT imaging and MRI have shown many advances in cancer detection. Several challenges remain and cause hindrances in the accurate detection, characterization, and monitoring of cancers despite improved technologies.45 The primary challenge is the lack of large, annotated datasets. Many datasets used for DL are limited in size and narrow range and require expert knowledge to use. Another challenge is the interpretability and explainability also known as the 'black box issue'.[46] DL provides data based on predictions without explanations, which may cause trust issues among radiologists. Computational complexity is a limitation in the development of DL AI-based models. It required large databases and high-performance hardware systems which are generally not available in small hospitals.[47] During MRI sometimes patients suffer from claustrophobia. Sedation and additional sequences (after sedation) might be required for these patients in order to complete the examination.[48]

FUTURE PERSPECTIVES IN CT AND MRI IMAGING

There is a relationship between radiation exposure and oncogenesis but it is not clear yet. When the patient is under examination of ionizing radiation dose limits should be used as "As Low As Reasonable Achieved" is the ALARA principle, it decreases the over and under exposures.[49] International Commission of Radiologic Protection (ICRP) mentioned three basic principles of radiation: justification; dose optimization; and dose limitation. In the future, optimizing the education of clinicians and patients on ionizing radiation is necessary.[50] Several approaches such as photon-counting CT (PCCT) use photon counting detectors instead of conventional detectors as it provides a better spatial resolution and reduces the patient's dose.[51] Similarly, ultra-low-dose CT (ULDCT) is an advanced technique, that allows imaging with very low radiation generally used for paediatric imaging and lung screening.[52]

Additionally, spectral or dual CT reduces the chances of multiple scans and provides fast imaging. Integration of AI techniques such as 2D-CNN and 3D-CNN reduces the noise and helps in tumor detection. Another model is hybrid imaging which combines CT with photon emission tomography (PET) and MRI with PET and improves the diagnostic accuracy.[53] The advancements in MRI such as high-field and ultra-high field MRI using 7 Tesla (T), provide very high resolution. MRI sequences (example; fast-spin sequences) are integrated with AI and improve image acquisition and quality.[54] These are some advancements in medical imaging technology that improved the healthcare system. Explainable AI (XAI) models are another DL technique, that aims to make deep learning algorithms more transparent and interpretable to clinicians.[55]

CONCLUSION

Tumor analysis techniques have evolved over the last decade. This review summarises advanced tumor detection techniques in diagnostic imaging focusing on CT and MRI. Radiomics are useful in converting 6 of 8 qualitative data into quantitative data for cancer detection. Segmentation method plays an important role in lung nodule detection although use for other structures also. fMRI and MRS can measure brain activity and concentration of different metabolites respectively. DL revolutionizes tumor detection using models such as ResNet-50, U-Net, and 3D CNN. The combination of PET with CT or MRI offers a hybrid imaging model that guides the segmentation process. In CT and MRI system AI algorithms are also being developed and play a very important role in early tumor detection and better image acquisition. These models are capable of analyzing large volumes of medical data efficiently and with high accuracy, potentially assisting clinicians in making quicker and more accurate diagnoses. Continued efforts to improve the reliability, transparency, and efficiency of these models will be pivotal in advancing their adoption for routine medical use.

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