Advancements in Cancer Detection: An Artificial Intelligence-Based Approach Using PET/CT Datasets

Faten Imad Ali[1*], Hadeel K. AlJobouri[2], Ali M. Hasan[3]

Authors affiliations:
1*) Department of Biomedical Engineering, Al-Nahrain University, College of Engineering, Baghdad, Iraq.
faten.imad@nahrainuniv.edu.iq

2) Department of Biomedical Engineering, Al-Nahrain University, College of Engineering, Baghdad, Iraq.
hadeel.k.aljobouri@nahrainuniv.edu.iq

3) Physiology and Medical Physics Department, Al-Nahrain University, College of Medicine, Baghdad, Iraq.
alialwaeli@nahrainuniv.edu.iq

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Abstract

Artificial intelligence (AI) is rapidly advancing as a valuable tool in oncology for enhancing detection and management of cancer. The integration of AI with PET/CT imaging presents significant scenarios for improving efficiency and accuracy of cancer diagnosis. This study examines the current applications of AI with PET/CT imaging, highlighting its role in diagnosing, differentiating, delineating, staging, assessing therapy response, determining prognosis, and enhancing image quality. A comprehensive literature search was conducted in six data-bases to get the most recent works, use Springer, Scopus, PubMed, Web of Science, IEEE, and Google Scholar in the last five years (2019-2024), identifying 80 studies that met the criteria for inclusion that focused on AI-driven models applied to PET/CT data in various cancers, with lung cancer being the most studied. Other cancers examined include head and neck, breast, lymph nodes, whole body, and others. All studies involved human subjects. The findings indicate that AI holds promise in improving cancer detection, identifying benign from malignant tumors, aiding in segmentation, response evaluation, staging, and determining the prognosis. However, the application of AI-powered models and PET/CT-derived radiomics in clinical practice is limited because of issues of data normalization, reproducibility, and the requirement of large multi-center data sets for improving model generalizability. All these limitations have to be solved to guarantee the dependable and ethical use of AI in day-to-day clinical activities.

Keywords: Artificial Intelligence (AI), Deep Learning (DL), Machine Learning (ML), Precision Oncology, Positron Emission Tomography/Computed Tomography (PET/CT), Radiomics.

التطورات في الكشف عن السرطان: نهج قائم على الذكاء الاصطناعي باستخدام مجموعات بيانات التصوير المقطعي بالإصدار البوزيتروني/التصوير المقطعي المحوسب

فاتن عماد علي، هديل قاسم الجبوري ،علي مجيد حسن

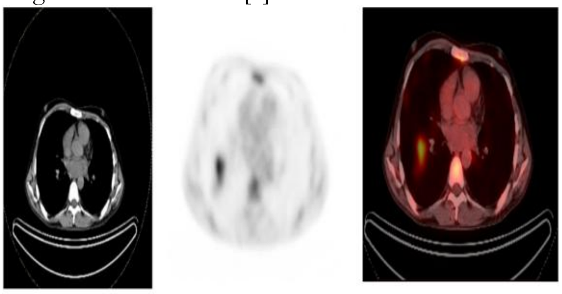
الخلاصة:

الذكاء الاصطناعي بسرعة كأداة قيمة في علم الأورام لتعزيز اكتشاف السرطان وإدارته. يقدم دمج الذكاء الاصطناعي مع التصوير المقطعي بالإصدار البوزيتروني/التصوير المقطعي المحوسب سيناريوهات مهمة لتحسين كفاءة ودقة تشخيص السرطان. تدرس هذه الدراسة التطبيقات الحالية للذكاء الاصطناعي مع التصوير المقطعي بالإصدار البوزيتروني/التصوير المقطعي المحوسب، وتسلط الضوء على دوره في التشخيص والتمييز والترسيم وتحديد المرحلة وتقييم استجابة العلاج وتحديد التشخيص وتحسين جودة الصورة. تم إجراء بحث شامل في الأدبيات في ست قواعد بيانات للحصول على أحدث الأعمال واستخدام Springer وScopus وPubMed وWeb of Science وIEEE وGoogle Scholar في السنوات الخمس الماضية (٢٠١٩-٢٠٢٤)، وتحديد ٨٠ دراسة استوفت معايير الإدراج التي ركزت على النماذج التي يقودها الذكاء الاصطناعي والمطبقة على بيانات التصوير المقطعي بالإصدار البوزيتروني/ التصوير المقطعي المحوسب في أنواع مختلفة من السرطان، وكان سرطان الرئة هو الأكثر دراسة. تشمل

أنواع السرطان الأخرى التي تم فحصها الرأس والرقبة والثدي والغدد اللمفاوية والجسم كله وغيرها. شملت جميع الدراسات مواضيع بشرية. تشير النتائج إلى أن الذكاء الاصطناعي يحمل وعدًا في تحسين اكتشاف السرطان، وتحديد الأورام الحميدة من الخبيثة، والمساعدة في التجزئة، وتقييم الاستجابة، وتحديد المرحلة، وتحديد التشخيص. ومع ذلك، فإن التنفيذ السريري الروتيني للنماذج القائمة على الذكاء الاصطناعي والتصوير المقطعي بالإصدار البوزيتروني/التصوير المقطعي المحوسب لا يزال محدودًا، وخاصة بسبب متطلبات التقنيات القياسية والقابلة للتعميم والقابلة للتكرار والدقيقة.

1. Introduction

Positron Emission Tomography/Computed Tomography (PET/CT) is a sophisticated medical imaging technology which fuses the anatomical information offered by CT with the functional imaging features of PET Figure.1. This hybrid imaging modality has become an indispensable tool in modern medicine, particularly in the field of oncology, for its ability to provide comprehensive diagnostic information [1].



(a) (b) (c)

Figure (1): Slices from (a) CT scan, (b) PET scan, and (c) fused PET/CT scan, where the PET and CT images have been aligned and combined. [2]

PET is a nuclear imaging method that measures cellular metabolic activity by injecting a radiotracer, commonly 18F-FDG, which accumulates in high-metabolism areas like cancer cells. The PET scan detects gamma rays produced when positrons from the radiotracer collide with electrons, creating a 3D image that highlights areas of increased activity. CT imaging, on the other hand, uses X-rays to create detailed cross-sectional images of the body's internal structures, providing precise anatomical localization. fusing CT and PET technologies to create PET/CT technology provide fused the advantages of both (anatomical features from CT and metabolic insights from PET) that outfit highly infallible diagnosing, monitoring and staging diseases such as cancer [3].

latest advances, such as AI integration and new radiotracers, have further improved PET/CT's diagnostic capabilities. AI improves image analysis that providing more accurate and efficient to the process. PET/CT diagnosing is complicate and tend to variability among specialists' experience. In spite of AI provide high efficiency and consistency, it requires inclusive training with expert-annotated and high-quality datasets [4,5]. Processing of high-dimensional PET/CT data can be more efficiently by AI models, especially deep learning (DL) which reducing losses in information produced by conventional machine learning. However, challenges remain, such as requirement for accurate expert-annotations, lack training data, and the intricacy of PET/CT images [6,7].

2. 2. PET/CT Imaging for Various Malignancy: Related Work and AI Application

AI with PET/CT imaging has attracted considerable attention in recent years, leading to diagnosis, leading, staging, sharing, diagnostic determination and reaction assessment for different applications in oncology. However, despite the growing number of studies, there are several restrictions that prevent the adoption of AI in PET/CT image.

In this section, we explore the range of diseases for which AI-supported PET/CT diagnostic systems have been developed. We also provide an overview of the AI technologies employed to create these decision support systems.

2.1 Lung

Several studies have shown the use of AI-operated techniques for PET/CT imaging in various cancers, with the largest test of lung cancer. For example, Tang et al. [15] discussed the accuracy of ^{18}F-FDG PET/CT scans diagnostic for various sizes pulmonary nodules, using 100 scans of solitary pulmonary nodules (SPNs) patients. Their results showed the particularly effectiveness of ^{18}F-FDG PET/CT in recognizing SPNs of 11 to 20 mm in diameter, outperforming other diagnostic methods. In addition, the study referred to the outperforming of ^{18}F-PET/CT in sensitivity than CT alone in recognizing pulmonary nodules [16, 17], making it particularly invaluable in diagnostic lung diseases as non-small cell lung cancer (NSCLC) by identifying sites of disease which could identified as normal on CT [18, 19].

For pulmonary nodules evaluation, key factors involve density, metabolic activity, and size which typically estimated utilizing the maximum standardized uptake value (SUVmax). In general, pulmonary nodules size range (4-30 mm), with those larger than 3 cm often classified as lung masses and supposed malignant [20-21]. commonly ,^{18}F-PET/CT nodules include three categories (malignant nodules, benign nodules, and indeterminate nodules). Moreover, major malignant nodules are located in the upper lobes (specifically the right side) [22-30]. SUVmax, which represents the maximum concentration of ^{18}F-FDG in the region of interest (ROI), is a crucial metric in PET/CT. An SUVmax of 2.5 or over typically denotes malignancy in cases of pulmonary involvement, offering a consistent method of interpretation [31-43].

2.2 Head and neck

Functional imaging, particularly with PET/CT and PET/MRI, continues to offer valuable insights in neurology, helping detect brain tumors early and track conditions like Alzheimer's and Parkinson's. While FDG is the primary radiotracer for monitoring glucose metabolism, newer tracers like FDOPA and FET now help assess dopaminergic activity and amino acid uptake. Brain-PET is also crucial for diagnosing malignancies, tracking metastasis, and guiding epilepsy surgery [44-50]. In head and neck cancers, PET/CT has become the preferred method for detecting, staging, and monitoring treatment, effectively distinguishing between inflammation and tumor recurrence. AI have shown promising consequences in head and neck tumor segmentation and treatment response evaluation. For instance, Naser et al. [47] developed a multimodal AI-based totally segmentation framework for PET/CT scans, which carried out excessive segmentation accuracy. However, a crucial venture on this domain is the shortage of diverse datasets that embody versions in tumor characteristics and imaging protocols [51-54]. Most AI models educated on PET/CT images for head and neck most cancers depend upon constrained datasets from single establishments, elevating worries approximately their robustness and external validity [56-65].

2.3 Breast

Although mammography is the primary imaging tool for detecting and screening breast cancer, other imaging techniques like MRI, ultrasound and PET/CT are frequently utilized in follow-up evaluations [70-73]. PET/CT is used as an additional imaging modality in the evaluation of patients with breast cancer. FDG PET/CT has demonstrated clinical utility in the staging of recurrent or metastatic breast cancer as well as in evaluating the efficacy of treatment in locally advanced breast cancer cases, both pre- and post-treatment [74-75].

Many studies, such as Takahashi et al. [76] and Chen Y et al. [77] have leveraged deep learning and radiomics to enhance diagnostic accuracy in breast cancers PET/CT imaging. However, these approaches often require extensive functional engineer, making them less favorable for clinical settings for real world. In addition, there are limited researches, focusing on the integration of PET/CT with other imaging forms such as MRIs to increase clinical accuracy [78-85].

2.4 Lymph node

PET scans are essential for identifying lymph node malignancy, even though CT scans are usually the most practical way to find lymph nodes. PET/CT imaging excels in detecting and assessing metastatic lymph nodes across various cancers, including lung, breast, bladder, and cervical cancers [66,67]. AI-more suitable PET/CT imaging has been especially treasured for steering preliminary remedy strategies in lymphoma by organizing baseline staging and presenting vital prognostic data [68-69].

2.5 Others

For the diagnosis, staging, and treatment of a number of malignancies, including uterine sarcomas, cervical, pancreatic, and soft-tissue sarcomas (STS), PET/CT imaging is crucial. Using radiomics and metabolic information from ^{18}F-FDG PET/CT images, PET/CT is major for identifying mass-forming pancreatic lymphoma from pancreatic carcinoma and for separating autoimmune pancreatitis from pancreatic ductal adenocarcinoma [89]. Integration of AI provide advances prognostic and diagnostic PET/CT, making it a crucial technique for pancreatic cancer patient care [90]. PET/CT improves patient outcomes and treatment planning in cervical cancer by predicting the chance of far metastasis and local relapse [91]. Furthermore, AI techniques combined with PET/CT imaging help predict metastatic soft tissue tumors, allowing for more personalized treatment for patients at risk [92]. In addition, in uterine sarcoma, PET/CT plays an established role in staging, treatment planning, and monitoring response to therapy across different sarcoma types, demonstrating its versatility and importance in oncologic imaging [93,94].

3. Methods

Despite progress, many challenges remain uncontrolled in literature. First, the reproducibility of AI-based PET/CT model is interrupted by imaging protocols, scanner specifications and variation in the patient population. Most studies are unable to provide detailed openness, which makes it difficult to repeat the conclusions. Secondly, large, multicenter datasets are required to improve the generality of the AI model. Many existing studies are performed using retrospects of single-centers, which cannot completely represent the asymmetry seen in the clinical practice of the real world. In addition, PET/CT imaging studies have major concerns for AI adoption. Black-box Deep Learning models lack spontaneous logic, making it challenging for doctors to rely on AI-powered decisions. The development of clear AI-techniques can address this problem.

In this study, six databases were used to conduct a comprehensive literature evaluation including Springer, Scopus, PubMed, Web of Science, IEEE, and Google Scholar, with the search terms: "positron emission tomography/computed tomography (PET/CT)"; "oncology"; "artificial intelligence (AI)"; "machine learning" and "deep learning (DL)". Date restrictions were applied in the period (2019-2024). The number of studies on the application of AI for PET/CT scans during the past five years is illustrated in Figure.2.

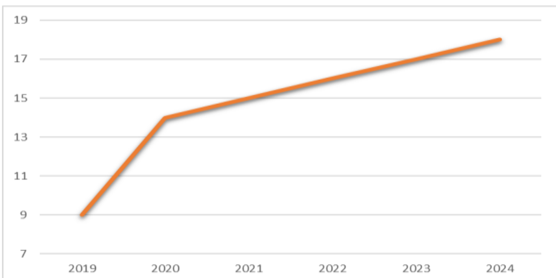


Figure (2): The number of studies on the application of AI for PET/CT scans during the past five years.

This review identified 90 studies that were screened against the requirements for inclusion, which concentrated on studies that established AI models with PET/CT data to help diagnose, differentiation, delineation, staging, therapy response assessment, prognosis determination, or image quality enhancement. A flowchart of the study selection procedure is shown in Figure.3. After screening for titles and abstracts, ten studies were eliminated for the entirety of the review (5 for not utilizing PET/CT data for input into the AI model, 3 for not evaluating AI models, and 2 for being Irrelevant studies). Ultimately, 80 studies met the inclusion criteria.

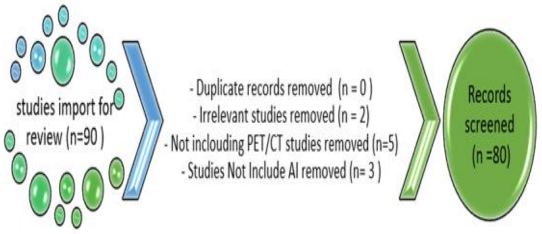


Figure (3): Study Selection Diagram.

The studies reviewed employed a whole lot of AI strategies, such as: Deep Learning (DL) (Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based fashions) were regularly used for characteristic extraction and classification. Hybrid Approaches blended CNNs with attention mechanisms or multi-modal learning frameworks (such as: PET/CT fusion) to improve interpretability and accuracy. Radiomics and Machine Learning (ML) for function-based machine getting to know fashions, consisting of Support Vector Machines (SVMs) and Random Forest classifiers, have been used along radiomics-derived PET/CT capabilities for tumor characterization and outcome prediction. Self-Supervised and Few-Shot Learning Models had been leveraged to compensate for the confined availability of annotated PET/CT datasets Figure.4 AI workflow diagram depicting the prevalent stages from obtaining information to processing AI-assisted diagnostics in PET/CT imaging [90].

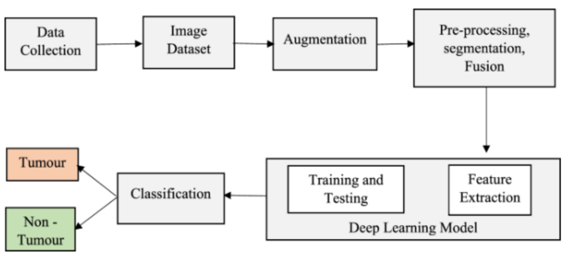


Figure (4): AI workflow for PET/CT image processing in cancer detection.

4. Results

In this study, a comprehensive compilation of studies on using AI-driven PET/CT algorithms for different cancer types was compiled. Table.1 provides a categorized list of the studies included sorted according the type of cancer. The most common disease to be assessed using AI models was lung cancer, followed by head and neck, lymph nodes, breast, whole body and others cancers.

Table (1): A list of the included research (arranged according to the type of cancer).

NO.	Cancer Type	Number of Studies	The Most Performed Task	AI Models Used	Ref.
1	lung	30	(12) Prediction and Classification, (10) Diagnostic Accuracy and Improvement, (7) Image Fusion and Multi-modality Approaches, (11) AI Screening and Early Detection	CNNs, Transformers, Random Forest, SVMs	14-43
2	head and neck	22	(8) Segmentation, (9) Prognostic Evaluation, (6) Image Fusion and Multi-modality Approaches, (7) Survival Analysis and Outcome Prediction	U-Net, 3D CNNs, Attention-based Models	44-65
3	lymph nodes	4	(3) Detection and Diagnosis, (1) Response Assessment	CNNs, Decision Trees, Hybrid Models	66-69
4	Breast cancer cell	16	(6) Diagnostic Accuracy and Techniques, (4) Prediction, (6) Imaging and Radiomics	CNNs, SVMs, Radiomics-based AI	70-85
5	whole body	3	(2) Classification and Localization, (1) Detection and Segmentation	Transformers, GANs, Few-Shot Learning Models	86-88
6	others	5	(3) Differentiation and Diagnosis, (2) Prediction	Hybrid AI Models, Multi-modal Learning	89-93

The table gives details about the types of cancer that have been investigated, how many studies have been conducted, what task has been done the most, and references. The table shows that, with 30 studies conducted on lung cancer and 22 on brain cancer, lung cancer is the most often examined cancer type in PET/CT imaging research. Regardless of cancerousness, three studies out of the many investigations used the most readily available PET/CT images to investigate the specific task. Figure 4. Using AI and PET/CT images, the examined cancer kind is depicted. According to the table, the organs that are most commonly researched in this context are the lungs and disorders associated to them.

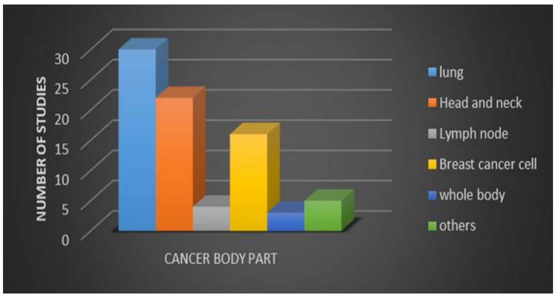


Figure (4): The studied cancer type using AI and PET/CT images.

In addition to the various types of cancer and activities done in this study, a comparation is made to compare the AI approaches in relation to the performance metrics of different application areas, which are segmentation (traditional tumor marking methods were outperformed by attention-based CNN models for segmentation tasks), diagnosis and classification (highly malignant lesions were better detected by radiologists using hybrid transformer models), and performance prognosis (SVM and random forest radiomic machine learning models performed exceptionally well on treatment outcome predictions).

The studies that were reviewed used a various of performance indicators to determine how effective the AI model was including: Accuracy, Sensitivity, and Specificity (used in the diagnostic AI models for differentiating malignant and benign lesions), Dice Similarity Coefficient(DSC) (for segmentation activities which captures the overlap between the predicted and actual tumor boundaries), Area Under the Receiver Operating Characteristic Curve (AUC-ROC) (to assess the classification effectiveness of AI adopted predictive models), F1-Score and Precision-Recall Curves (to evaluating model effectiveness on heterogeneous data), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) (to assessing AI techniques for quantitative assessment of PET/CT image data).Employing these AI strategies helped the researchers to enhance the accuracy and efficiency of the diagnosis provided by PET/CT scanners while overcoming some of its limitations.

5. Discussion

The integration of AI with PET/CT imaging is a major advancement in cancer care, offering new possibilities for improving detection, diagnosis, and treatment planning. This review highlights AI's broad applications in common cancers such as lung, head and neck, and breast, where it has already demonstrated improved image interpretation, automated lesion detection, and diagnostic accuracy. However, there are also emerging opportunities for AI in less-explored areas, particularly rare cancers like pancreatic and soft-tissue sarcomas, where data scarcity limits clinical AI adoption. AI holds the potential to revolutionize the early detection of cancers by identifying subtle features in PET/CT images that may go unnoticed with traditional methods. Early intervention greatly improves patient outcomes, but to maximize the effectiveness of AI-based tools, larger and higher-quality datasets are needed. The need for standardized protocols and reliable datasets, especially in underrepresented cancers, remains a critical challenge. Collaboration between radiologists, oncologists, and data scientists is critical to overcoming these barriers and expanding the clinical impact of AI.

As AI technology evolves, it is likely to become a vital tool in addressing gaps in cancer care, from diagnosis to prognosis, and enhancing both personalized treatment planning and patient outcomes. Future research should focus on the continued development of generalizable and robust AI models across different cancer types, and ensuring that AI systems are ethically and safely integrated into routine clinical workflows.

In addition, AI operated PET/CT image contains the real applications beyond oncology. AI-enhanced PET/CT model can be used in neurology for early identification of neurodiznerative diseases such as Alzheimer's and Parkinson's, where physical changes occur before metabolic changes in the brain. In cardiology, AI-controlled PET/CT analysis can help identify myocardial spraying of abnormalities and guidance treatment for cardiovascular disease. In addition, AI has potential applications in the handling of infectious disease, where it can help detect inflammatory patterns associated with conditions such as tuberculosis and covid -19.

6. Conclusions

AI has shown significant capacity in improving PET/CT imaging for cancer detection, staging and evaluation of treatment response. This study highlights the AI ability to increase clinical accuracy, automatic lesion segmentation and support making clinical decision. The most tested type of cancer in AI-assisted PET/CT imaging is lung cancer, followed by head and neck, breasts, lymph nodes and other deformities. The AI-driven PET/CT model has successfully differentiated the malignant from a benign tumor, predicted the reaction of treatment and facilitates early cancer detection, which led to several individual treatment strategies.

However, many challenges prevent the adoption of AI in PET/CT image. These include data standardization problems, large dataset requirements for multicenters, variation in imaging protocols and lack of clarity in intensive learning models. Many existing studies depend on individual centers of datasets, limiting the generality of the AI model. In addition, regulatory and moral ideas meet AI implementation in clinical workflows open challenges that require further explorations.

Future research should focus on installing standardized evaluation matrix, developing strong AI models that can generalize in different populations, and doctors can improve the model interpretation to increase confidence. In addition, integration of PET/CT imaging such as other methods such as MRI and multimodal AI approaches can provide more comprehensive analysis for cancer diagnosis and diagnosis. Collaborative efforts between radiologists, oncologists and AI researchers will be important for meeting these challenges and ensuring that AI-controlled PET/CT image can be effectively translated into clinical practice. Cleaning these challenges can revolutionize cancer, first and more accurate diagnosis, improvement results and eventually increase the patient's survival rate. In order to unlock the full potential of AI-controlled PET/CT imaging in oncology, AI function, data set markets and continuous progress in interdisciplinary cooperation are necessary.

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