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Innovative AI model for bladder cancer diagnosis

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Abstract

Objectives Bladder cancer is one of the most common malignancies of the urinary system, and early diagnosis and treatment are crucial for improving patient prognosis.

Methods In this study, we developed an artificial intelligence (AI) model for bladder cancer diagnosis using CT imaging data from our hospital and The Cancer Imaging Archive (TCIA). The model was trained and validated using a large dataset of CT images, and its diagnostic accuracy was assessed through various performance metrics. The AI model was constructed using deep learning techniques, which can automatically learn and extract features from CT images. Retrospective CT data from our hospital and TCIA were used to train the AI model. Performance metrics were evaluated, and the Grad-CAM results were reviewed by radiologists.

Results The test–set accuracy exceeded 0.90, and Grad—CAM correctly highlighted tumors.

Conclusions The AI model offers accurate and transparent bladder—cancer detection on routine CT scans and merits prospective validation.

Keywords Artificial intelligence, Bladder cancer, Diagnosis

1 Introduction

Bladder cancer, a prevalent malignancy within the urinary system, poses significant threats to human health [1, 2]. Early and accurate diagnosis is paramount for improving patient prognosis and reducing mortality rates. Computed Tomography (CT) imaging has emerged as a crucial tool in the detection and diagnosis of bladder cancer. It offers detailed anatomical information and can visualize the size, location, and extent of tumors. However, interpreting CT images relies heavily on the expertise and experience of radiologists, and subtle lesions or complex cases may lead to variability in diagnostic outcomes.

While artificial intelligence (AI) has demonstrated potential in bladder cancer research, this field remains in its early stages, particularly concerning the interpretability of AI applications [3, 4]. Multi-omics studies highlight the urgent need for explainability by showing that post-translational modifications modulate oncogenic signalling pathways across tumour types. For example, Li et al. recently demonstrated that

SARS-CoV-2-driven phosphorylation site predictions overlap with lung cancer progression networks, highlighting the need to reconcile biological prior knowledge with black-box AI predictions to guide precise therapy [5, 6]. Extending this paradigm to bladder cancer, Grad-CAM offers a vehicle to bridge molecular insight and radiomic phenotype, an intersection that has yet to be explored. Recent studies have examined AI's role in various aspects of bladder cancer management, such as diagnosis, treatment response evaluation, and prognosis prediction [3, 4, 7–18]. For example, the use of AI-generated targets and inter-observer variation in online adaptive radiotherapy for bladder cancer was investigated by Åström LM et al., underscoring the challenges and opportunities in this domain [3]. Additionally, Baressi Šegota S et al. proposed a transfer learning method for the semantic segmentation of urinary bladder cancer masses in CT images, illustrating AI's potential to enhance diagnostic precision [4].

Furthermore, several investigations have centered on the application of radiomics and deep learning in bladder cancer [8]. A CT image-based radiomic model was developed by Cao Y et al. to detect PD-L1 expression status in bladder cancer patients, which may inform personalized treatment approaches [7]. The assessment of bladder cancer treatment response in CT using radiomics combined with deep learning was conducted by Cha KH et al., demonstrating AI's potential in monitoring treatment effectiveness [8]. Moreover, machine learning was applied by Garapati SS et al. to stage urinary bladder cancer in CT urography, showcasing AI's capacity to aid clinical decision-making [8]. Other research has focused on AI's utility in predicting prognosis and detecting metastasis [12, 14]. A machine learning-based combination of criteria was proposed by Girard A et al. to detect bladder cancer lymph node metastasis, which may improve metastasis detection accuracy [10]. A CT-based deep learning model was developed by Wei Z et al. to predict overall survival in muscle-invasive bladder cancer patients post-radical cystectomy, emphasizing AI's prognostic value [12]. Additionally, Xiong S et al. demonstrated that machine learning-based CT radiomics improves bladder cancer staging predictions, suggesting AI's potential to enhance staging accuracy and treatment planning [13].

AI has also been employed to distinguish between muscle-invasive and non-muscle-invasive bladder cancer. It was shown by Yang Y et al. that deep learning can serve as a noninvasive tool to differentiate these cancer types using CT, potentially reducing the need for invasive procedures [14]. Automated AI-based analysis of skeletal muscle volume was utilized to predict overall survival after cystectomy for urinary bladder cancer, highlighting AI's potential in identifying prognostic indicators [15].

Although AI research in bladder cancer is still in its nascent stages, especially regarding interpretability. As the field progresses, further research is required to address interpretability challenges and validate AI applications' clinical utility in bladder cancer.

Our study aims to develop an AI model for bladder cancer diagnosis using CT imaging data from our hospital and The Cancer Imaging Archive (TCIA) [19]. By leveraging deep learning techniques and incorporating Grad-CAM for region of interest identification [18–23], we strive to enhance diagnostic accuracy and provide a reliable auxiliary tool for clinicians. Specifically, recent advancements in explainable AI (XAI) have demonstrated the potential to improve diagnostic transparency and clinical trust. For instance, Chen et al. combined deep learning with Grad-CAM and radiomics to automatically localize and diagnose architectural distortion on digital breast tomosynthesis (DBT), achieving high diagnostic accuracy while providing visual explanations for clinical decision-making

[20]. Similarly, Fanizzi et al. developed an explainable prediction model for human papillomavirus (HPV) status in oropharyngeal squamous cell carcinoma patients using CNN on CT images, which not only predicted HPV status with high accuracy but also highlighted critical image features contributing to the predictions [21].

In the context of breast cancer, Huang et al. proposed an explainable AI model for predicting molecular expressions using multi-task deep learning based on 3D whole breast ultrasound, which provided insights into the biological underpinnings of imaging features [22]. Shah et al. integrated local and global attention mechanisms to enhance oral cancer detection, with explainability maps helping clinicians understand the model's focus during diagnosis [23]. Furthermore, Talaat et al. utilized Grad-CAM with a 3D Inception-ResNet V2 for breast cancer classification on mammograms, empowering radiologists with explainable insights into the model's decision-making process [24]. Lastly, Xia et al. enhanced cancer classification using Raman spectroscopy and CNN, with visualization of critical features aiding in the interpretation of spectral data [25].

Although Grad-CAM has demonstrated intriguing potential for enhancing the interpretability of AI models in many cancers, its application and efficacy in bladder cancer remain to be more thoroughly investigated [20–25]. Grad-CAM generates class-discriminative activation maps by back-propagating the gradient of the target class into the final convolutional layer, thereby highlighting the exact image regions that drive the network's decision. While there have been notable advancements in the application of AI to bladder cancer diagnosis, our understanding of how Grad-CAM can be effectively utilized in this specific context is less.

This gap in research might, in part, reflect the inherent complexities associated with bladder cancer imaging, as well as the fact that AI applications in this area are still evolving compared to more established fields.

By leveraging deep learning techniques and incorporating Grad-CAM for region of interest identification, we strive to enhance diagnostic accuracy and provide a reliable auxiliary tool for clinicians.

2 Materials and methods

The study utilized a combination of our hospital data and publicly available datasets from The Cancer Imaging Archive (TCIA) to compile a comprehensive dataset of CT images for bladder cancer diagnosis. Patients diagnosed with bladder cancer and those confirmed to be free of the disease were included.

The CT images were acquired using standardized protocols, ensuring consistency in image quality and resolution. Each image underwent preliminary inspection and annotation by experienced radiologists to identify regions of interest and potential artifacts. Data preprocessing steps included noise reduction, image enhancement, and normalization to standardize the input for the AI model. The flowchart illustrating the clinical data collection and modeling process was presented in Fig. 1.

2.1 Model construction

A deep learning-based AI model was developed using convolutional neural networks (CNNs), which are particularly effective for image recognition tasks [26–30].

Specifically, we employed a variant of the **ResNet50_v1c** architecture as our backbone network, which was pre-trained on the large-scale ImageNet dataset. This model

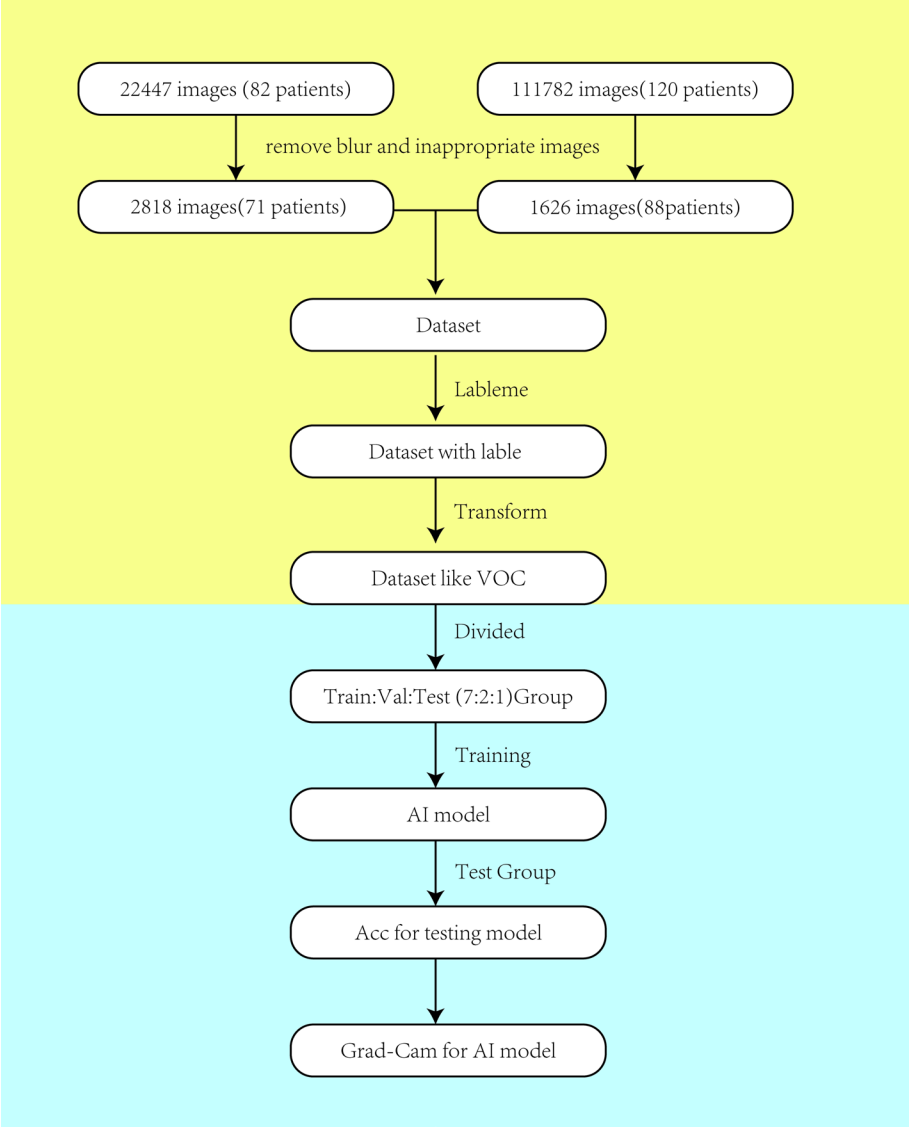

Fig. 1 Title: Flowchart of Clinical Data Collection and Modeling Process. The process involves collecting patient data, preprocessing it, building a predictive model via machine learning, and validating the model's performance

was selected for its proven efficacy in medical image analysis for several key reasons: First, the ResNet50_v1c architecture incorporates modified stem layers (a stack of 3 × 3 convolutions) compared to the original ResNet50, which allows for better retention of fine-grained details in the initial stages of feature extraction—a crucial characteristic for identifying subtle tumor boundaries and textures in CT images. Second, its residual learning framework mitigates the vanishing gradient problem, enabling the training of a deeper and more powerful network. Finally, the use of transfer learning from ImageNet weights provides a strong foundational set of features, significantly accelerating convergence and improving the model's generalization performance on our medical imaging dataset.

The model architecture was designed to process CT images and extract relevant features automatically. Transfer learning techniques were employed, leveraging pre-trained models on large-scale image datasets to accelerate training and improve performance.

The training process involved feeding the preprocessed CT images into the model, with bladder cancer diagnoses serving as labels. The model learned to associate specific imaging patterns with diagnostic outcomes through multiple iterations. To prevent overfitting, regularization techniques such as dropout layers and data augmentation were applied.

Grad-CAM (Gradient-weighted Class Activation Mapping) was integrated into the model to identify regions of interest within the CT images that are most relevant to bladder cancer diagnosis. This technique helps visualize the model's decision-making process, highlighting areas that contribute significantly to the diagnostic prediction. By focusing on these regions, the model's accuracy and reliability were enhanced.

2.2 Statistical methods

The performance of the AI model was evaluated using a variety of statistical metrics. Accuracy and Intersection over Union (IoU) were calculated to assess the model's diagnostic capability. A confusion matrix was generated to provide a detailed breakdown of true positives, true negatives, false positives, and false negatives in percentages. To ensure the robustness of the results, cross-validation techniques were applied. The dataset was divided into training, validation, and test sets, with the validation set used to tune hyperparameters and the test set reserved for final evaluation.

3 Results

3.1 Quantitative results

Figure 2 was presented to show the entire process from data collection to AI model building, explainable analysis, and further application. In the data collection phase, multi-source data, including patient basic information, medical records, and clinical examination results, was collected and strictly filtered and pre-processed to ensure quality and usability. Next, in the AI model building phase, machine-learning algorithms were employed to train the processed data, and models with high predictive and diagnostic power were obtained. The explainable analysis part involved a deep investigation into the model's internal structure and decision-making mechanism, with visualization techniques used to clarify the complex model's operation and enhance transparency and credibility. Finally, in the further application stage, the model was widely applied in clinical practice, and doctors were assisted in disease diagnosis, treatment planning, and patient prognosis assessment.

3.2 Analysis of results

Based on the results from Tables 1 and 2, we analyzed the AI model's performance in terms of IoU and accuracy.

In terms of IoU, the background class had shown consistent performance, while the bladder and bladder cancer classes exhibited slight variations between the two datasets. This may suggest that the model encounters certain challenges when identifying the bladder and bladder cancer, or that the validation set contains more challenging samples.

As for accuracy, the background class still maintains a very high level, and the accuracy of the bladder and bladder cancer classes has increased in the test set. This further confirms the potential issues the model faces when processing these two classes.

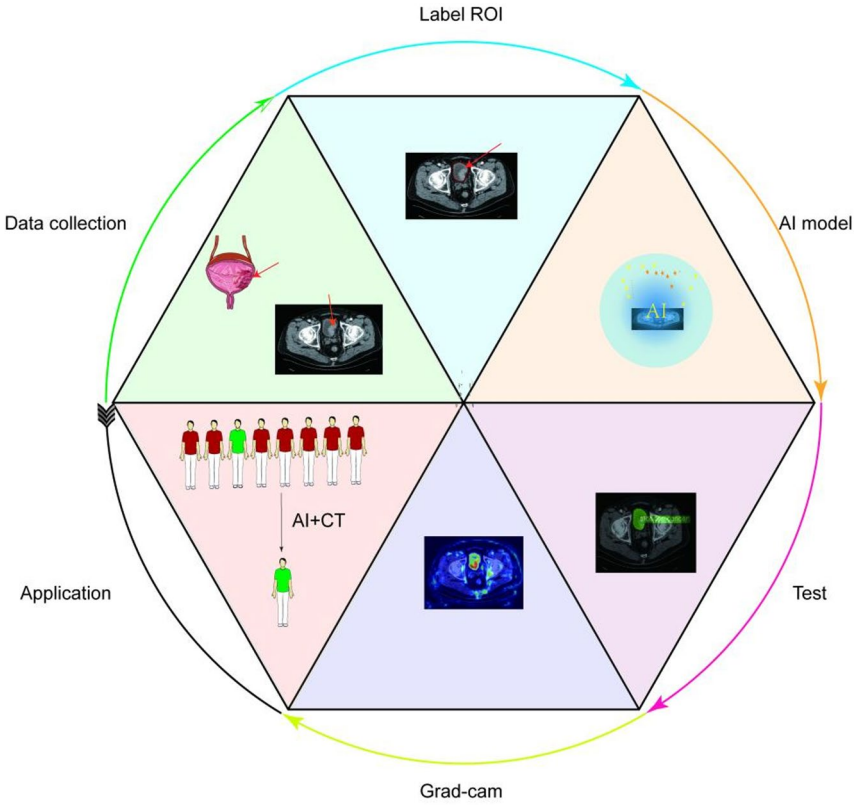

Fig. 2 Comprehensive Workflow from Data Collection to AI Model Application. This workflow encompassed data collection, AI model building, explainable analysis, and further application. In data collection, multi-source data was gathered and preprocessed. The AI model building phase used machine-learning algorithms to train data, generating models with high predictive and diagnostic power. Explainable analysis delved into the model's internal structure and decision-making mechanism, employing visualization techniques. In further application, the model was implemented clinically to aid doctors in diagnosis, treatment planning, and patient prognosis assessment

Table 1 Performance evaluation of the validation set

Class	IoU (%)	Acc (%)
Background	99.63	99.79
Bladder	91.25	98.21
Bladder cancer	84.53	91.44

Table 2 Performance evaluation of the test set

Class	IoU (%)	Acc (%)
Background	99.58	99.8
Bladder	92.04	98.65
Bladder cancer	84.61	90.18

3.3 Confusion matrices for validation and test sets in model evaluation

Figure 3 clearly showed the confusion matrices for the validation and test sets. During the model evaluation, these two confusion matrices offered rich data, helping us fully understand the model's performance. As could be seen from the figure, each confusion matrix contained a comparison between the model's predicted results and the actual labels.

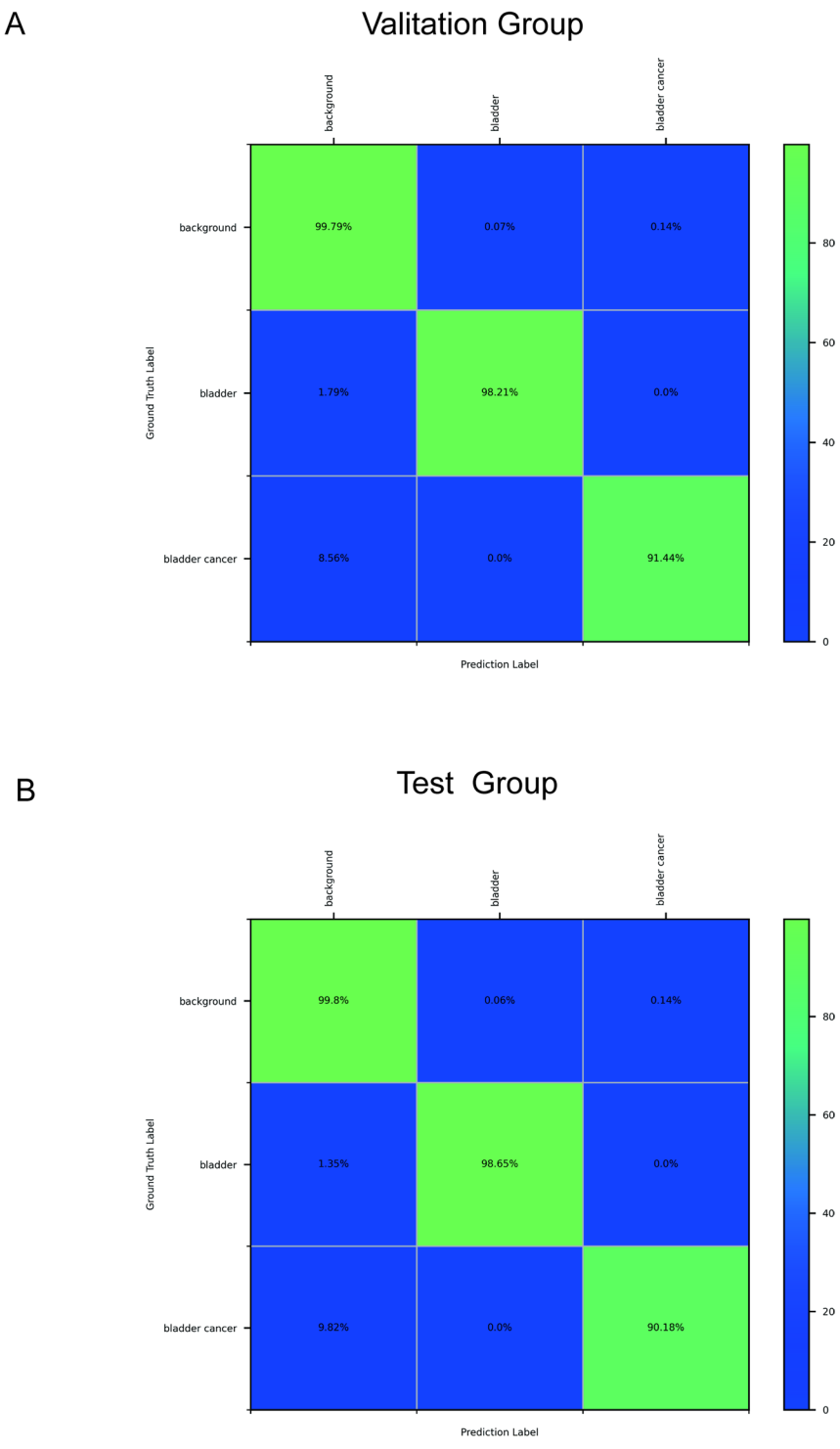

Fig. 3 Confusion Matrices for AI model Evaluation on Validation and Test Sets. Both the validation and test set confusion matrices were displayed, showing the comparison between the model's predicted results and actual labels, and offering insights into the model's performance during development and real-world application

3.4 Visualization of bladder tumor labeling and AI-Identified locations via Grad-CAM

In Fig. 4A, the labeling of bladder tumors was clearly displayed, with different colors and markers indicating various tumor types and stages. The labels were meticulously placed, ensuring accurate correspondence to the tumor regions. In Fig. 4B, the Grad-CAM AI

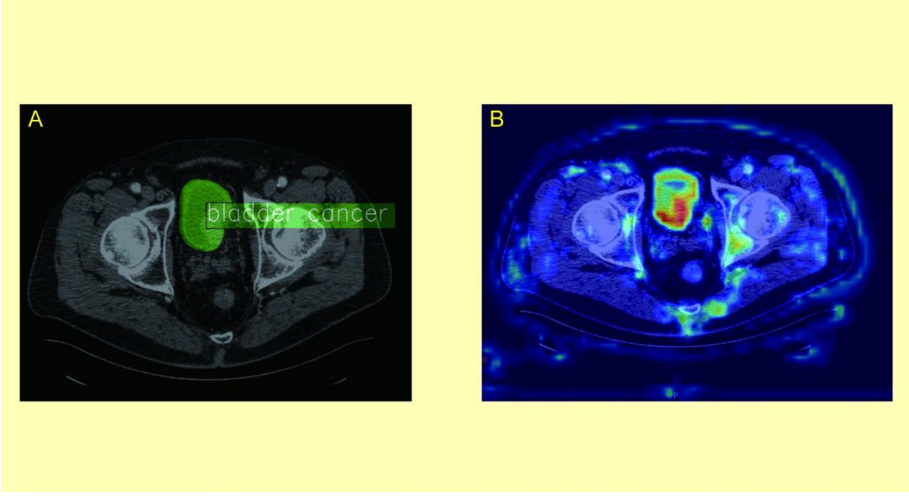

Fig. 4 Visualization of Bladder Tumor Labeling and AI-Predicted Locations

model's identified tumor locations were presented. The heat maps generated by the AI model highlighted areas of interest with varying intensity levels, reflecting the model's confidence in its predictions. These visualizations were offered, giving valuable insights into the AI's decision-making process and its alignment with actual tumor regions.

4 Discussion

Bladder cancer remains a prevalent malignancy affecting the urinary system, with a rising incidence globally [1]. This disease significantly impacts patients' quality of life and poses considerable economic burdens due to high treatment costs [1, 2]. Traditional diagnostic approaches, such as cystoscopy and biopsy, are invasive and time-consuming, often leading to patient discomfort and potential complications [31, 32]. Consequently, the need for more efficient and non-invasive diagnostic methods is urgent to enhance early detection and improve patient outcomes [33, 34]. Advances in imaging technologies and AI present promising avenues for the development of innovative diagnostic tools that can facilitate earlier diagnosis and better management of bladder cancer [35–38].

While traditional diagnostic methods such as cystoscopy and biopsy remain the gold standard, they are invasive and may not be suitable for all patients or for repeated screening. Non-invasive alternatives, including urinary cytology and molecular tests based on DNA methylation, have emerged as promising tools for detecting bladder cancer. For instance, DNA methylation biomarkers have shown potential in improving diagnostic accuracy and prognostic stratification. Recent studies by Zhang et al. and Shi et al. have identified specific methylation signatures associated with bladder cancer progression and PD-L1 expression, highlighting the role of epigenetic alterations in tumor behavior and therapeutic response [39, 40]. Additionally, the Bladder Epicheck test, a urine-based methylation assay, has demonstrated high sensitivity and specificity in detecting urothelial carcinoma, offering a clinically viable non-invasive option[41]. Similarly, Pierconti et al. validated the utility of methylation analysis within the Paris System for reporting urinary cytology, enhancing its diagnostic reliability [42]. However, these molecular approaches often require specialized laboratory setups, are cost-prohibitive in some settings, and may not yet be widely integrated into routine clinical workflows.

In contrast, our AI model leverages routinely acquired CT imaging, which is widely available and does not require additional biospecimen collection or complex molecular profiling. Unlike methylation-based tests that focus on genetic and epigenetic alterations, our approach captures radiological phenotypes that reflect underlying tumor biology and heterogeneity, as recently emphasized by Lobo et al. in their comprehensive review of molecular and histological diversity in urothelial carcinoma [43]. By integrating Grad-CAM for visual interpretation, our model also offers a level of transparency that is often lacking in "black-box" molecular classifiers, thereby facilitating clinical trust and adoption.

This study focuses on leveraging deep learning algorithms to construct an artificial intelligence diagnostic model based on CT imaging data for bladder cancer. By extracting and analyzing imaging features, the model aims to improve diagnostic accuracy and consistency, addressing the limitations of traditional methods. The findings of this research provide a foundation for the model's potential application in clinical settings, enhancing early diagnostic capabilities and offering decision support for healthcare professionals. The discussion will delve into the implications of the primary results, emphasizing the importance of AI in refining bladder cancer diagnostics and the need for further validation in diverse clinical populations.

This study highlights the significant advancements made in the application of deep learning techniques for the diagnosis of bladder cancer through CT imaging. The extraction of radiomic features from CT scans allows for a complicated understanding of tumor characteristics that traditional imaging methods may overlook. This underscores the potential of artificial intelligence to not only enhance diagnostic precision but also provide a reliable framework for clinical decision-making in bladder cancer management. The findings align with previous studies that have shown similar efficacy of deep learning algorithms in other cancer types, suggesting that AI can be a transformative tool in oncology.

Moreover, the study's robust design, which included a diverse dataset for training and validation, strengthens its findings. The high sensitivity and specificity reported for the model indicate its practical applicability in clinical settings, potentially leading to earlier detection of bladder cancer and improved patient outcomes. This is particularly crucial given the often asymptomatic nature of early-stage bladder cancer, which can lead to delayed diagnoses and poorer prognoses. The integration of deep learning in identifying critical features such as tumor texture and shape further enhances the model's capability to predict malignancy.

4.1 Limitations

Although the deep learning model in this study shows promise, several limitations must be acknowledged. The most significant constraint is the relatively small sample size, which directly impacts the model's generalizability. A limited dataset may not adequately capture the extensive heterogeneity in bladder cancer presentation, including variations in tumor size, shape, location, and stage. Consequently, while the model achieved high performance on our internal test set, it may be susceptible to overfitting and might not maintain its diagnostic accuracy when applied to populations with different demographics or to images acquired from institutions using divergent CT scanners, imaging protocols, or reconstruction kernels. This limitation is compounded by data quality concerns.

The model's performance is inherently tied to the quality of its training data. Issues such as image noise, motion artifacts, and inconsistencies in contrast administration protocols can introduce confounding variables, potentially limiting the model's robustness and real-world applicability.

4.2 Future directions

To overcome these limitations, our future work will employ targeted strategies focused on enhancing model generalizability and clinical utility. First and foremost, we will prioritize the expansion and diversification of our dataset. This will be achieved through active multi-center collaborations, which will allow us to aggregate a larger cohort that encompasses a broader spectrum of disease manifestations and imaging conditions. Secondly, to maximally leverage existing data and simulate greater diversity, we will implement more advanced data augmentation techniques specifically tailored for medical imaging, such as generative adversarial networks (GANs) for synthetic data generation. Furthermore, we plan to explore federated learning frameworks, which would enable model training across multiple institutions without sharing sensitive patient data, thereby addressing both data scarcity and privacy concerns. These concerted efforts will be crucial for refining the AI model into a reliable and widely applicable tool for bladder cancer diagnosis in routine clinical practice.

5 Conclusions

In conclusion, this research successfully developed an artificial intelligence diagnostic model based on CT imaging for bladder cancer, demonstrating its potential for improving diagnostic accuracy and prognostic assessment. The integration of radiomics features into clinical practice can provide valuable insights for personalized treatment strategies. Future efforts should focus on expanding the sample size and conducting rigorous clinical validation to establish the model's effectiveness in early diagnosis and tailored therapies for bladder cancer patients. The findings pave the way for advancements in non-invasive diagnostic methodologies that could significantly impact patient outcomes.

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Author contributions
Lei Jiang and Wenyu Ge drafted the manuscript. Lei Jiang and Wenyu Ge contributed equally. Jingru Huo and Shijie Li drew the pictures. Ruijiao Feng and Liu Ji analyzed the data. Tingting Fan reviewed and revised the manuscript. All the authors have read and approved the final version of the manuscript. All the authors contributed to the manuscript and approved the submitted version.

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Data availability
The original contributions of this study are included in the article and supplementary material. Further inquiries can be directed to the corresponding authors. The data is collected in https://www.cancerimagingarchive.net/collection/tcga-blca/.

Declarations

Ethics approval and consent to participate
Informed consent was obtained from all subjects involved in the study.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

Institutional review board statement
The study was conducted in accordance with the Declaration of Helsinki, and approved by the Institutional Review Board of Heilong Provincial Hospital.

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References

1. Bray F, Laversanne M, Sung H, Ferlay J, Siegel RL, Soerjomataram I, Jemal A. Global cancer statistics 2022: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA Cancer J Clin. 2024;74(3):229–63.
2. Siegel RL, Kratzer TB, Giaquinto AN, Sung H, Jemal A. Cancer statistics, 2025. CA Cancer J Clin. 2025;75(1):10–45.
3. Åström LM, Sibolt P, Chamberlin H, Serup-Hansen E, Andersen CE, van Herk M, et al. Artificial intelligence-generated targets and inter-observer variation in online adaptive radiotherapy of bladder cancer. Phys Imaging Radiat Oncol. 2024;31:100640.
4. Baressi Šegota S, Lorencin I, Smolić K, Anđelić N, Markić D, Mrzljak V, et al. Semantic segmentation of urinary bladder cancer masses from CT images: a transfer learning approach. Biol. 2021. https://doi.org/10.3390/biology10111134.
5. Fang Q, You C, Xiao X, Liu Y, Yang W, Li Q, et al. Mevalonate metabolic reprogramming drives Cisplatin resistance in bladder cancer: mechanisms and therapeutic targeting. Protein Pept Lett. 2025. https://doi.org/10.2174/0109298665403178250806111943.
6. Li W, Li G, Sun Y, Zhang L, Cui X, Jia Y, Zhao T. Prediction of SARS-CoV-2 infection phosphorylation sites and associations of these modifications with lung cancer development. Curr Gene Ther. 2024;24(3):239–48.
7. Cao Y, Zhu H, Li Z, Liu C, Ye J. CT image-based radiomic analysis for detecting PD-L1 expression status in bladder cancer patients. Acad Radiol. 2024;31(9):3678–87.
8. Cha KH, Hadjiiski L, Chan HP, Weizer AZ, Alva A, Cohan RH, et al. Bladder cancer treatment response assessment in CT using radiomics with deep-learning. Sci Rep. 2017;7(1):8738.
9. Garapati SS, Hadjiiski L, Cha KH, Chan HP, Caoili EM, Cohan RH, Weizer A, Alva A, Paramagul C, Wei J, Zhou C. Urinary bladder cancer staging in CT urography using machine learning. Med Phys. 2017;44(11):5814–23.
10. Girard A, Dercle L, Vila-Reyes H, Schwartz LH, Girma A, Bertaux M, Radulescu C, Lebret T, Delcroix O, Rouanne M. A machine-learning-based combination of criteria to detect bladder cancer lymph node metastasis on [(18)F]FDG PET/CT: a pathology-controlled study. Eur Radiol. 2023;33(4):2821–9.
11. Palazzo G, Mangili P, Deantoni C, Fodor A, Broggi S, Castriconi R, et al. Real-world validation of Artificial Intelligence-based Computed Tomography auto-contouring for prostate cancer radiotherapy planning. Phys Imaging Radiat Oncol. 2023;28:100501.
12. Wei Z, Xv Y, Liu H, Li Y, Yin S, Xie Y, Chen Y, Lv F, Jiang Q, Li F, Xiao M. A CT-based deep learning model predicts overall survival in patients with muscle invasive bladder cancer after radical cystectomy: a multicenter retrospective cohort study. Int J Surg. 2024;110(5):2922–32.
13. Xiong S, Fu Z, Deng Z, Li S, Zhan X, Zheng F, et al. Machine learning-based CT radiomics enhances bladder cancer staging predictions: a comparative study of clinical, radiomics, and combined models. Med Phys. 2024;51(9):5965–77.
14. Yang Y, Zou X, Wang Y, Ma X. Application of deep learning as a noninvasive tool to differentiate muscle-invasive bladder cancer and non-muscle-invasive bladder cancer with CT. Eur J Radiol. 2021;139:109666.
15. Ying T, Borrelli P, Edenbrandt L, Enqvist O, Kaboteh R, Trägårdh E, Ulén J, Kjölhede H. Automated artificial intelligence-based analysis of skeletal muscle volume predicts overall survival after cystectomy for urinary bladder cancer. Eur Radiol Exp. 2021;5(1):50.
16. Zhang G, Wu Z, Xu L, Zhang X, Zhang D, Mao L, et al. Deep learning on enhanced CT images can predict the muscular invasiveness of bladder cancer. Front Oncol. 2021;11:654685.
17. Zhang-Yin J, Girard A, Marchal E, Lebret T, Homo Seban M, Uhl M, et al. PET imaging in bladder cancer: an update and future direction. Pharmaceuticals (Basel). 2023. https://doi.org/10.3390/ph16040606.
18. Zheng Y, Shi H, Hai B, Zhang J. A commentary on 'a CT-based deep learning model predicts overall survival in patients with muscle invasive bladder cancer after radical cystectomy: a multicenter retrospective cohort study.' Int J Surg. 2024;110(8):5200–1.
19. Kirk S, Lee Y, Lucchesi FR, Aredes ND, Gruszauskas N, Catto J, Garcia K, Jarosz R, Duddalwar V, Varghese B, Rieger-Christ K, Lemmerman J. The cancer genome atlas urothelial bladder carcinoma collection (TCGA-BLCA) (Version 8) [Data set]. 2016.
20. Chen X, Zhang Y, Zhou J, Pan Y, Xu H, Shen Y, Cao G, Su MY, Wang M. Combination of deep learning Grad-CAM and radiomics for automatic localization and diagnosis of architectural distortion on DBT. Acad Radiol. 2025;32(3):1287–96.
21. Fanizzi A, Comes MC, Bove S, Cavalera E, de Franco P, Di Rito A, Errico A, Lioce M, Pati F, Portaluri M, Saponaro C, Scognamillo G, Troiano I, Troiano M, Zito FA, Massafra R. Explainable prediction model for the human papillomavirus status in patients with oropharyngeal squamous cell carcinoma using CNN on CT images. Sci Rep. 2024;14(1):14276.

22. Huang Z, Zhang X, Ju Y, Zhang G, Chang W, Song H, Gao Y. Explainable breast cancer molecular expression prediction using multi-task deep-learning based on 3D whole breast ultrasound. Insights Imaging. 2024;15(1):227.
23. Shah SJH, Albishri A, Wang R, Lee Y. Integrating local and global attention mechanisms for enhanced oral cancer detection and explainability. Comput Biol Med. 2025;189:109841.
24. Talaat FM, Gamel SA, El-Balka RM, Shehata M, ZainEldin H. Grad-CAM enabled breast cancer classification with a 3D Inception-ResNet V2: empowering radiologists with explainable insights. Cancers (Basel). 2024. https://doi.org/10.3390/cancers16213668.
25. Xia J, Li J, Wang X, Li Y, Li J. Enhanced cancer classification and critical feature visualization using Raman spectroscopy and convolutional neural networks. Spectrochim Acta A Mol Biomol Spectrosc. 2025;326:125242.
26. Alazwari S, Alsamri J, Alamgeer M, Alotaibi SS, Obayya M, Salama AS. Automated gall bladder cancer detection using artificial Gorilla troops optimizer with transfer learning on ultrasound images. Sci Rep. 2024;14(1):21845.
27. Bozkurt B, Coskun K, Bakal G. Building a challenging medical dataset for comparative evaluation of classifier capabilities. Comput Biol Med. 2024;178:108721.
28. Jian Y, Zhang N, Bi Y, Liu X, Fan J, Wu W, et al. TC-sniffer: a Transformer-CNN bibranch framework leveraging auxiliary VOCs for Few-Shot UBC diagnosis via electronic noses. ACS Sens. 2025;10(1):213–24.
29. Kurata Y, Nishio M, Moribata Y, Otani S, Himoto Y, Takahashi S, Kusakabe J, Okura R, Shimizu M, Hidaka K, Nishio N, Furuta A, Kido A, Masui K, Onishi H, Segawa T, Kobayashi T, Nakamoto Y. Development of deep learning model for diagnosing muscle-invasive bladder cancer on MRI with vision transformer. Heliyon. 2024;10(16):e36144.
30. Shalata AT, Alksas A, Shehata M, Khater S, Ezzat O, Ali KM, Gondim D, Mahmoud A, El-Gendy EM, Mohamed MA, Alghamdi NS, Ghazal M, El-Baz A. Precise grading of non-muscle invasive bladder cancer with multi-scale pyramidal CNN. Sci Rep. 2024;14(1):25131.
31. Holzbeierlein JM, Bixler BR, Buckley DI, Chang SS, Holmes R, James AC, et al. Diagnosis and treatment of non-muscle invasive bladder cancer: AUA/SUO guideline: 2024 amendment. J Urol. 2024;211(4):533–8.
32. Yang T, Luo W, Yu J, Zhang H, Hu M, Tian J. Bladder cancer immune-related markers: diagnosis, surveillance, and prognosis. Front Immunol. 2024;15:1481296.
33. Fan J, Chen B, Luo Q, Li J, Huang Y, Zhu M, et al. Potential molecular biomarkers for the diagnosis and prognosis of bladder cancer. Biomed Pharmacother. 2024;173:116312.
34. Flaig TW, Spiess PE, Abern M, Agarwal N, Bangs R, Buyyounouski MK, et al. NCCN guidelines® insights: bladder cancer, version 3.2024. J Natl Compr Canc Netw. 2024;22(4):216–25.
35. Borna MR, Sepehri MM, Shadpour P, Khaleghi Mehr F. Enhancing bladder cancer diagnosis through transitional cell carcinoma polyp detection and segmentation: an artificial intelligence powered deep learning solution. Front Artif Intell. 2024;7:1406806.
36. Lotan Y, Krishna V, Abuzeid WM, Launer B, Chang SS, Krishna V, et al. Predicting response to intravesical Bacillus Calmette-Guérin in high-risk nonmuscle-invasive bladder cancer using an artificial Intelligence-Powered pathology assay: development and validation in an international 12-Center cohort. J Urol. 2025;213(2):192–204.
37. Ma X, Zhang Q, He L, Liu X, Xiao Y, Hu J, et al. Artificial intelligence application in the diagnosis and treatment of bladder cancer: advance, challenges, and opportunities. Front Oncol. 2024;14:1487676.
38. Zhu M, Gu Z, Chen F, Chen X, Wang Y, Zhao G. Application of artificial intelligence in the diagnosis and treatment of urinary tumors. Front Oncol. 2024;14:1440626.
39. Shi ZD, Han XX, Song ZJ, Dong Y, Pang K, Wang XL, Liu XY, Lu H, Xu GZ, Hao L, Dong BZ, Liang Q, Wu XK, Han CH. Integrative multi-omics analysis depicts the methylome and hydroxymethylome in recurrent bladder cancers and identifies biomarkers for predicting PD-L1 expression. Biomark Res. 2023;11(1):47.
40. Zhang S, Zhang J, Zhang Q, Liang Y, Du Y, Wang G. Identification of prognostic biomarkers for bladder cancer based on DNA methylation profile. Front Cell Dev Biol. 2021;9:817086.
41. Fiorentino V, Pizzimenti C, Franchina M, Rossi ED, Tralongo P, Carlino A, et al. Bladder Epicheck test: a novel tool to support urothelial carcinoma diagnosis in urine samples. Int J Mol Sci. 2023. https://doi.org/10.3390/ijms241512489.
42. Pierconti F, Martini M, Cenci T, Fiorentino V, Sacco E, Bientinesi R, Pugliese D, Iacovelli R, Schinzari G, Larocca LM, Bassi PF. Methylation study of the Paris system for reporting urinary (TPS) categories. J Clin Pathol. 2021;74(2):102–5.
43. Lobo A, Collins K, Kaushal S, Acosta AM, Akgul M, Adhya AK, Al-Ahmadie HA, Al-Obaidy KI, Amin A, Amin MB, Aron M, Balzer BL, Biswal R, Mohanty S, Browning L, Chakrabarti I, Cima L, Cimadamore A, Desai S, Dhillon J, Deshwal A, Diego GG, Diwaker P, Galea LA, Magi-Galluzzi C, Giannico GA, Gupta NS, Haider A, Hirsch MS, Iczkowski KA, Arora S, Jain E, Jain D, Jha S, Kandukuri S, Kao CS, Kryvenko ON, Kumar RM, Kumari N, Kunju LP, Kuthi L, Lobo J, Lopez JI, Luthringer DJ, Maclean F, Manini C, Mannan R, Martos MG, Mehra R, Menon S, Mishra P, Moch H, Montironi R, Baisakh MR, Netto GJ, Nigam LK, Osunkoya AO, Pagliuca F, Paner GP, Panizo A, Parwani AV, Picken MM, Prendeville S, Przybycin CG, Purkait S, Queipo FJ, Rao BV, Rao P, Reuter VE, Sancheti S, Sangoi AR, Sardana R, Satturwar S, Shah RB, Sharma S, Dixit M, Verma M, Sirohi D, Smith SC, Soni S, Sundaram S, Swain M, Tretiakova M, Trpkov K, MuñizUnamunzaga G, Zhou M, Williamson SR, Lopez-Beltran A, Cheng L, Mohanty SK. Advances, recognition, and interpretation of molecular heterogeneity among conventional and subtype histology of urothelial carcinoma (UC): a survey among urologic pathologists and comprehensive review of the literature. Histopathology. 2024;85(5):748–59.

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