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REVIEW

Artificial intelligence advances in cystoscopy and imaging for bladder cancer: a narrative review

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Bladder cancer (BCa) diagnosis relies heavily on cystoscopy and imaging. Both have limited sensitivity and accuracy, particularly for muscle-invasive disease. Artificial intelligence (AI) has emerged as a promising tool for improving detection, grading, and staging by extracting imaging features that exceed human perception. We conducted a narrative review of peer-reviewed, English-language studies published between 2015 and 2025. We identified 75 articles and synthesized data from 35 key studies retrieved via PubMed, Google Scholar, Scopus, and Embase. Data were synthesized narratively, emphasizing diagnostic performance, clinical relevance, and study limitations. In cystoscopy, AI models achieved high accuracy in tumour detection and grading, including carcinoma in situ, and in some studies reduced missed lesions by >20% compared with expert urologists; CystoNet-T reported an average precision of 91.4%. Performance varied across studies, with inconsistencies driven by methodological factors: endoscopic acquisition conditions (illumination quality; white-light vs. enhanced imaging), variation in ground truth and annotation (histopathology vs. expert-labelled frames), dataset size and class imbalance, model architecture and preprocessing pipelines, and validation strategy (internal splits vs. external testing). Most evidence remains limited by retrospective, single-center datasets, which restrict generalizability. In imaging, AI applications showed modality-dependent performance. CT-based radiomic and deep-learning models demonstrated the most consistent improvements for grading, staging, and recurrence prediction across several studies. MRI and radiogenomic models demonstrated proof-of-concept associations between imaging features and molecular profiles. However, clinical readiness is limited by small cohorts and a lack of prospective validation. Results were also affected by scanner heterogeneity and reader dependence. Evidence for PET/CT remains sparse and preliminary. Many approaches outperformed conventional clinical models, including a vision transformer (ViT)-based MRI model for muscle invasiveness prediction (AUC = 0.872). Methodological heterogeneity restricted generalisability. AI shows potential to reduce diagnostic variability and improve initial treatment planning in BCa. Nonetheless, prospective multicentre trials with standardised methodology are essential before clinical integration. In parallel, regulatory approval of AI as medical software, real-time workflow integration within cystoscopy suites and radiology systems, data governance and patient privacy, and ongoing post-deployment performance monitoring must be addressed to ensure safe and effective clinical use.

Key Words: Bladder cancer, artificial intelligence, machine learning, cystoscopy, imaging

Introduction

Bladder cancer (BCa) is one of the most prevalent urinary tract cancers, with a worldwide incidence of 900,000 new cases per year. Approximately 25% are muscle-invasive BCa (MIBC), while the rest are non-muscle-invasive (NMIBC).[1] The five-year survival

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rate for NMIBC is around 90%. In contrast, survival rates decrease for patients with MIBC as the cancer advances.[2] Early, accurate staging and diagnosis are critical to improving patient outcomes. The key unmet clinical need is reliable identification of MIBC at initial presentation. Earlier, accurate diagnosis could expedite treatment and improve outcomes. The current diagnostic workup relies heavily on cystoscopy and cross-sectional imaging. White-light cystoscopy (WLC) can miss flat lesions, such as carcinoma *in situ* (CIS) and small papillary tumours. Missed rates can approach 30%,[3] and incomplete transurethral resection of the bladder (TURBT) is a common occurrence. Imaging with ultrasonography, computed tomography (CT), and magnetic resonance imaging (MRI) faces inter-observer variability. These techniques have limited ability to detect microscopic muscle invasion or early extravesical extension, leading to inaccurate staging and delayed treatment.[4] Inaccurate preoperative staging remains a major clinical problem, with up to 30% of patients with muscle-invasive bladder cancer receiving inappropriate or suboptimal treatment because staging fails to correctly identify the extent of invasion.[3] MRI-based pathway performance is heterogeneous and depends on reader expertise.

Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), enables computers to recognize complex patterns in medical images. By training on large datasets, these models can perform tasks such as detecting tumours, tumour segmentation, and classification with high Accuracy. In other cancers, AI has already improved radiological interpretation, reduced observer variability, and supported personalized treatment planning. AI is increasingly being applied to BCa diagnosis to address the limitations of cystoscopy and imaging.[5–8] By analysing visual and radiological data with high Precision, AI models can identify subtle patterns and anomalies that may be overlooked by clinicians. In cystoscopy, this includes improved detection of flat lesions such as CIS. In imaging, AI-enhanced analysis of CT and MRI has shown potential to improve tumour staging and to differentiate benign from malignant lesions with greater Sensitivity and Specificity. These applications highlight the promise of AI in strengthening diagnostic Accuracy and supporting earlier clinical decision-making. This narrative review aims to critically evaluate recent advances in AI for cystoscopy and imaging in diagnosing BCa.

Methods

Search strategy

We conducted a narrative review of the literature following standardised principles for synthesis. Searches were performed in PubMed and Google Scholar for studies published between January 2015 and January 2025. The search strategy combined the following terms using Boolean operators: "bladder cancer" OR "urothelial carcinoma" AND ("artificial intelligence" OR "machine learning" OR "deep learning") AND (cystoscopy OR endoscopy OR CT OR MRI OR PET OR imaging OR diagnosis). The search terms were expanded to include "radiogenomics," "radiogenomic profiling," and "real-time cystoscopy" to ensure comprehensive identification of emerging AI applications.

The search identified 431 records, of which 404 remained after duplicate removal. Titles and abstracts were screened (n = 219), and 185 were excluded because the full text was not accessible, the article was a conference abstract, preprint, or case report, or the content was clearly unrelated to AI-based bladder cancer diagnostics.

160 full-text articles were assessed for eligibility. Of these, 85 were excluded because they did not contain relevant information on cystoscopy-based AI, cross-sectional imaging AI, or BCa diagnostic applications. A total of 75 articles were included in the narrative synthesis. These encompassed studies across cystoscopy (white-light, blue-light, RGB [red, green, blue]-enhanced), CT, MRI, PET/CT (positron emission tomography/computed tomography), and hybrid modelling approaches.

Following the literature search, studies were assessed for relevance in a stepwise manner. Titles and abstracts were reviewed to identify publications addressing artificial intelligence–based approaches to bladder cancer diagnosis using cystoscopy or cross-sectional imaging. Full-text articles were examined where eligibility was unclear. Studies were excluded if they were not focused on bladder cancer, did not involve AI-based diagnostic methods, or did not contribute meaningful clinical or methodological insight relevant to the aims of this review.

Inclusion criteria were peer-reviewed original research or comprehensive reviews; English language; human subjects or clinical imaging data; application of artificial intelligence (machine learning, deep learning, segmentation, detection, or prediction models) to BCa diagnosis; full-text availability; and sufficient methodological detail to allow narrative synthesis. Two independent reviewers (UK, NS) conducted the screening

and cross-validated all inclusion decisions, with disagreements resolved by consensus with a senior reviewer (DB). As narrative reviews are not eligible for PROSPERO registration, this review was not registered. Exclusion criteria were conference abstracts, preprints, case reports, veterinary or non-human studies, inaccessible full texts, and studies lacking clinically meaningful AI diagnostic components.

To enhance methodological transparency, we distinguished cystoscopy-based AI (direct endoscopic visualisation) from cross-sectional imaging AI (CT, MRI, PET/CT). Study quality considerations were summarised narratively using principles derived from QUADAS-2 and PROBAST-AI, focusing on risks of bias related to retrospective design, ground-truth assignment, data handling, validation strategy, and model generalisability.[9,10]

Bias and quality appraisal

To evaluate methodological robustness, we conducted a structured bias and quality appraisal of the included studies using principles adapted from QUADAS-2 (for diagnostic Accuracy research) and PROBAST-AI (for prediction-model studies).[9,10] Each study was assessed for risks of bias across patient selection, reference standard, data handling, model development, and validation design.

Common concerns included:

- Retrospective single-centre design, limiting external validity
- Selection and spectrum bias, particularly exclusion of difficult or borderline cases
- Inconsistent or unclear reference standards, especially variable histopathology confirmation
- Potential data leakage due to inadequate separation of training, validation, and test sets
- Lack of blinding during annotation or outcome assessment
- Underpowered or small test sets, including the absence of external validation
- Heterogeneous reporting, limiting reproducibility and comparison across studies

These assessments informed the narrative synthesis by highlighting methodological gaps that affect the reliability and generalisability of current AI-based diagnostic tools.

A flowchart demonstrating our search process has been included as a figure (Figure 1).

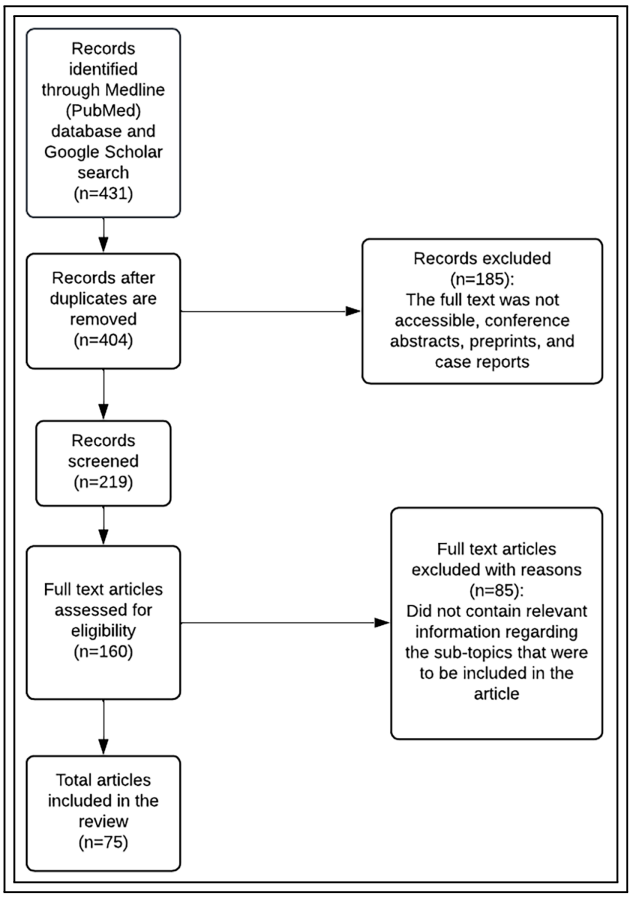

FIGURE 1. Flow chart of the study

Results

Across the included studies, AI approaches were applied to four distinct tasks: lesion detection/segmentation, histologic grade prediction, muscle-invasiveness assessment, and recurrence-risk stratification, and findings are summarized within these task categories.

Endourology

For clarity, cystoscopy-based AI methods are grouped into three technical pathways: (1) convolutional neural networks (CNN)-based systems, (2) attention mechanism-enhanced systems, and (3) colour/narrow band imaging (NBI)-enhanced approaches. Cystoscopy is pivotal in BCa diagnosis. White-light cystoscopy (WLC) has imperfect sensitivity and may miss a clinically relevant proportion of lesions, particularly flat disease such as carcinoma *in situ*. In addition, suboptimal resection quality remains common, with incomplete TURBT rates reported as approaching 50%, which may

contribute to early recurrence and the need for repeat procedures.[11]

CNN-based systems

CNN-based systems form the most mature category, offering strong lesion detection Accuracy with real-time feasibility but limited by single-centre training and variable generalisability. Wu et al. developed an AI-based diagnostic system (cystoscopy artificial intelligence diagnostic system, CAIDS) that achieved high Accuracy for BCa detection, including CIS, with a performance comparable to that of expert urologists (Sensitivity 95.4%, Specificity 93.9%), suggesting AI-based white-light cystoscopy (WLC) could reduce missed lesions and improve diagnostic consistency.[4] To enhance bladder tumour detection during WLC, Jia et al. developed CystoNet-T, a model that improves recognition of subtle or flat lesions and provides real-time visual alerts during procedures. After being trained on 510 images, CystoNet-T outperformed well-known models (Faster R-CNN [Region-based CNN] and YOLO [You Only Look Once]), with an average Precision of 91.4, demonstrating its potential as an effective instrument in BCa diagnosis, with a relatively low computational cost.[12] DL-augmented cystoscopy can optimise tumour localisation, intraoperative navigation, and surgical resection. Shkolyar et al. described CystoNet, a CNN facilitating automated bladder tumour identification during cystoscopy. CystoNet was prospectively validated, revealing 39 of 41 papillary tumours and all three flat BCas, reaching a Sensitivity of 90.9% and Specificity of 98.6%, respectively, highlighting its impact on diagnostic Accuracy. However, validation in larger multicentre trials is required before widespread adoption.[13] Chang et al.'s study assessed the applicability of real-time CystoNet integration within cystoscopy and TURBT. With tumour-bounding boxes, the cystoscopy video systems were able to provide on-screen alerts during procedures. This achieved a per-frame tumour Specificity of 98.8% during clinic cystoscopy, with a median error rate of 3.6, displaying its feasibility in enhancing intraoperative tumour detection within the operating theatre. While feasible, these findings were from a single-centre study and require validation across different surgical settings.[14] A meta-analysis carried out by Hengky et al. aimed to assess five studies for their application of AI in cystoscopic BCa detection. The study yielded strong diagnostic performance with the area under the summary receiver operating characteristic (SROC) curve (0.988), and the pooled Sensitivity and Specificity achieved 95.3% and 95.7%. This meta-analysis supports strong diagnostic performance of AI-assisted cystoscopy, though the included studies were heterogeneous and largely limited to small cohorts.[15] Unless otherwise specified, cystoscopy models reported performance on a per-frame or per-lesion basis, with ground truth derived from histopathology for resected lesions and expert endoscopic consensus for unresected lesions. Because cystoscopy studies reported heterogeneous metrics (area under curve [AUC], Sensitivity/Specificity, Precision), results were interpreted within each metric group rather than directly compared across metrics. From the perspective of external validity, Wu et al.'s[4] CAIDS study provides the strongest evidence: it used consecutively collected cystoscopy images from multiple hospitals and explicitly demonstrated improved detection of flat lesions, including CIS. In contrast, CystoNet was evaluated in a single-centre prospective pilot by Shkolyar et al.,[13] and a small real-time feasibility study by Chang et al.,[14] and CystoNet-T was trained and tested on archived white-light cystoscopy data from a single institution, which limits generalisability beyond the original centres.

Additional CNN models and classifiers

Ikeda et al.[16] developed a CNN-based support system for cystoscopy, achieving high diagnostic Accuracy (Sensitivity 89.7%, Specificity 94.0%, AUC 0.98) in distinguishing tumour from normal urothelium. This represented an improvement on their earlier classification model, which had shown lower Specificity (83.7%).[17] Importantly, these results suggest AI can provide reliable real-time decision support during cystoscopy, potentially reducing diagnostic variability between operators. Accurate tumour detection is critical for efficient TURBT. However, WLC misses up to 30% of BCa. Blue light cystoscopy-based photodynamic diagnosis is helpful in small and flat lesions, typically missed by WLC. Ali et al. applied AI to blue light cystoscopy, classifying tumour and healthy urothelium images using deep CNN models. By investigating the performance of various CNNs, the authors pre-trained four CNNs to predict malignancy, invasiveness, and grading, showing a Sensitivity of 95.77% and a Specificity of 87.84%. Sensitivity and Specificity reached 88% and 96.56%, respectively, for tumour invasiveness, demonstrating that AI can enhance blue light cystoscopy, particularly for small or flat lesions, often missed with WLC.[18] Lee et al.[19] evaluated multiple convolutional neural network models for bladder tumour classification using 3731 cystoscopic images from 543 bladder tumour cases and 219 normal cases. EfficientNetB0 was selected as the best-performing model, achieving

a balanced accuracy of 81%, sensitivity of 88%, specificity of 74%, and an AUC of 0.92 on test data, and it was benchmarked against urologists and medical students. These results support the potential utility of automated cystoscopy image classification, although the evaluation was image-based and retrospective, prospective validation in real-time clinical workflows remains necessary before implementation.

Attention-based and hybrid segmentation systems

Attention-enhanced and hybrid segmentation frameworks can highlight relevant mucosal regions and improve boundary delineation, though performance remains constrained by modest dataset size and heterogeneous annotation quality. Numerous DL models have also been explored for polyp segmentation in cystoscopy. Despite these frameworks demonstrating a level of feasibility, Precision rates were modest (55%), suggesting early limitations in clinical readiness without further optimisation. This highlights promising proof of concept, but insufficient Accuracy for direct clinical use.[20] DL was used in a separate study to divide and categorise BCa lesions based on their nature (normal, papillary, flat, mixed). Segmentation was performed using a Deeplab v3+ model (an AI system designed to draw precise borders around lesions), while classification, or lesion identification, was carried out with VGG19 (a well-established image-recognition network that progressively extracts visual features). This approach allowed the model to pick out fine details and consistently distinguish between different lesion types. The classification model achieved 91.2% Accuracy, while the segmentation model reached 95.1%. There was a significant level of agreement between the AI results and expert visual assessment, indicating that such systems can reliably differentiate lesion subtypes and support more accurate endoscopic characterisation.[21] For instance, U-Net, a deep learning tool that outlines bladder lesions in images, was tested on cystoscopy images from 120 patients, achieving good segmentation performance (Sensitivity 88.5% and Specificity 86.7%).[22] Accurate delineation of tumour borders could support more complete resections. In contrast, another study using a cystoscopy atlas, essentially a large reference library of labelled cystoscopy images used to train AI, showed much lower Specificity (30–45%), although Sensitivity remained high. Within this study, MobileNet (a lightweight AI model designed for fast, real-time image recognition) and PlexusNet (a network tailored to detect complex visual patterns) performed best for identifying tumours during live cystoscopy. These findings highlight that while deep learning can enable real-time AI support, further optimisation and validation are required before such systems can be applied in routine clinical practice.[23] To enhance bladder tumour detection during cystoscopy, Zhang et al.'s study presented an attention-based cystoscopic segmentation (ACS) model, which functions by removing irrelevant information while combining fine details with a broad view of the tumour area, achieving a detection Accuracy of 82.7%, and showcases its potential utility for enhanced tumour recognition during routine cystoscopy, though further refinement is required.[24] Segmentation performance was assessed using the dice similarity coefficient (DSC), which is not directly comparable to classification metrics; therefore, findings were interpreted within the segmentation domain only.

Colour/narrow-band/RGB-enhanced systems

Colour- and NBI-based models improve contrast between malignant and normal mucosa, supporting grade prediction and subtle lesion recognition, but require optimised lighting and are sensitive to acquisition variability. Another study evaluated a DL-based AI model for BCa detection utilising white-light and narrow-band imaging with tumour grade prediction using colour analysis with the red-green-blue method. The model was trained on nearly 11,000 cystoscopic images, focusing on identifying regions suggesting tumour presence through high-precision contours. The model had a strong diagnostic performance with 95.0% Sensitivity, 93.7% Specificity, and 94.1% Accuracy. Colour analysis revealed significant red and blue value differences linked to tumour grade, enabling accurate differentiation between benign and malignant tumours with over 98% Accuracy. These findings demonstrate the high Accuracy of AI-assisted cystoscopy based on colour analysis.[25]

Imaging

Computed tomography (CT)

Imaging efficacy depends on the modality in use. CT gives an overview of BCa characteristics, allowing staging and localisation. Staging CT of the abdomen and pelvis has limited Accuracy, mainly due to its inability to identify microscopic extravesical tumour extension or lymph node (LN) metastases.[26] Researchers applied CT-based DL radiomic nomograms (DLRN) to predict the preoperative pathological grade of BCa. DLRN involves extracting quantitative features, including the shape and intensity of the tissue, which DL models then analyse. This visual information from images is converted

into measurable data that reveals hidden patterns, assisting models in making more accurate predictions regarding tumour characteristics and their potential behaviour. Combining the most applicable radiomics and DL features, an AUC of 0.943 was achieved. The DLRN outperformed the clinical model, achieving training and external test AUCs of 0.961 and 0.947, underscoring its capability to distinguish high- and low-grade BCa. These results highlight AI's ability to outperform standard clinical models in grade prediction, though findings were based on retrospective, single-centre data.[27] Imaging-based studies predominantly reported metrics on a per-patient basis, with ground truth obtained from postoperative histopathology when available or from expert radiologist consensus where tissue confirmation was not obtained. Wang et al. explored AI's abilities for the postoperative prediction of BCa recurrence using 3-phase enhanced CT images. The DL device reported a strong predictive power for recurrence, with a concordance index (measuring how well the model's predicted risk ranking agrees with actual patient outcomes) of 0.869 and an AUC of 0.889 in the validation set, ranking superior to other models. By defining cutoff values, recurrence-free survival and overall survival were stratified into high and low-risk groups, allowing for cumulative recurrence risk calculation and as a guide for personalised Precision therapy. However, external validation was lacking, and the model's utility in prospective clinical practice remains untested.[28] CT studies predominantly reported AUC and concordance indices; we therefore evaluated them within their own metric class rather than against detection-based Accuracy metrics used in cystoscopy.

Biomarkers

Companion diagnostics, tests used to identify patients most likely to respond to a therapy, are essential in selecting candidates for immunotherapy, with Programmed Death-Ligand 1 (PD-L1) being an extensively studied biomarker. Cao et al. aimed to predict the expression of PD-L1 in BCa patients through a CT-based radiomic model. Using five ML algorithms, the training set AUCs ranged from 0.92 to 1.00, and validation sets from 0.753 to 0.766, proving the model's effectiveness in distinguishing high PD-L1 expression.[29] Chen et al. developed a deep learning radiomic signature (DLRS) to predict muscle invasion, achieving strong performance (AUC 0.973 training, 0.844 test). Clinical usefulness was confirmed with decision curve analysis, showing the model would add greater value in practice than the radiomics-only model. This suggests AI could non-invasively predict PD-L1 status, though external validation was limited and performance dropped notably between training and validation.[30] Two CT-based studies provided multi-centre evidence: Song et al.[27] developed a deep-learning radiomics nomogram for pathological grade in a multicentre cohort, and Wang et al.[28] reported a multiphase CT deep-learning signature for recurrence prediction across several institutions. By contrast, other CT radiomics and deep-learning models, such as those by Cao et al.[29] and Chen et al.[30], were derived from single-centre retrospective datasets without independent external validation.

Multidetector row computed tomography (MDCT)

Multidetector row computed tomography (MDCT) urography is an effective imaging tool for detecting urinary tract conditions through a fusion of unenhanced corticomedullary, nephrographic, and excretory phase series.[31] Ma et al. used a U-Net model to automatically segment the bladder on CT urography, outperforming earlier models that required manual input. The U-Net model breaks down images into smaller parts with more details. It facilitates BCa detection through an accurate bladder outline, which aids in identifying suspicious areas. Using 81 cases for training and validation, and 92 cases for testing, the U-Net DL was compared to a previous DL model, which required the operator to manually draw a box around the region of interest for tracking and defining object boundaries in images, helping separate tumour regions more accurately. Unlike its predecessor, the U-Net DL generated bladder likelihood maps without requiring operator input. The best 2D U-Net DL model outperformed the 3D version of the baseline models in all Accuracy metrics, indicating that U-Net DL provides more accurate and fully automated bladder segmentation for computed tomography urography (CTU) imaging.[32]

Computed tomography urography (CTU)

CT urography–based work has extended AI applications beyond traditional T-stage stratification into both invasion prediction and molecular profiling. In a dual-energy CT urography (DECTU) cohort of 202 patients, Hu et al.[33] developed an intratumoral–peritumoral radiomics nomogram for preoperative muscle invasion prediction and reported test AUC 0.886, with accuracy 0.836, sensitivity 0.737, and specificity 0.881, outperforming a DECT-parameter-only model (AUC 0.763). Separately, Jiao et al.[34] used excretory-phase CTU from 97 bladder cancer patients to predict HER2 status using radiomics and an MLP model, reporting AUC 0.79 in training and AUC 0.73

in validation; while performance remained moderate and data were single-centre, this illustrates how CTU may support non-invasive biomarker enrichment alongside anatomical assessment.

Magnetic resonance imaging (MRI)

MRI offers superior soft tissue contrast, eliminating exposure to ionising radiation and reliably differentiating bladder wall layers with tumour invasion assessment and extravesical extension depth.[35] One study explored AI-augmented bladder segmentation using CNN, utilising radiomic features generated automatically from apparent diffusion coefficient (ADC) maps. Feature reproducibility was confirmed with a high intraclass correlation, indicating consistent extraction across images. The approach that combined multiple image types performed best, achieving an average AI-expert segmentation match (DSC) of 0.83 for training data, 0.79 for validation data, and a median of 0.81 for test data (with most results falling between 0.70 and 0.88). Furthermore, radiomics features showed good reproducibility, indicating that the modified U-net model provides exact BCa segmentation with a high reproducibility of radiomics features.[36]

To enhance BCa staging, researchers assessed the possibility of increasing staging Accuracy by fusing MRI-based radiomics with RNA sequencing and AI. 40 formalin-fixed paraffin-embedded (FFPE) tissue samples and matched MRI images were examined in the study, with FFPE samples subjected to bulk RNA sequencing. Radiomic features were then extracted from MRI scans and integrated with RNA profiles. This combined model effectively differentiated between intra- and extra-vesical disease with a Sensitivity of 94%, Specificity of 88% (overall Accuracy 92%), suggesting that MRI-based radiogenomics may provide a more accurate method for BCa staging than models that were just based on genetic or imaging characteristics. However, the small sample size ($n = 40$) limits generalisability, and findings remain exploratory.[37] To determine the extent of BCa invasion before surgery, Chen et al.'s study created and verified a predictive model utilising full-sequence MRI with data from 445 patients. Radiomic features were selected and modelled from preoperative MRI scans. The models' respective AUCs for pathological and muscle invasion prediction were 0.808 and 0.828, highlighting the potential for full-sequence MRI models to enhance preoperative assessment of BCa infiltration.[38]

A retrospective study carried out by Huang et al. aimed to improve the prediction rate for 5-year recurrence in patients with NMIBC, where existing techniques such as the European Organisation for Research and Treatment of Cancer (EORTC) model frequently fall short, due to its reliance on clinical and histopathological data. MRI features from 191 patients were analysed, incorporating tumour and peritumoural regions. After testing four prediction models, the one that combined DL, radiomics, and clinical data scored highest, with the model attaining a high level of Accuracy (AUC = 0.909). This outperformed the EORTC model, though the retrospective design limits immediate clinical application.[39]

Differentiating between pure urothelial carcinoma and urothelial carcinoma with squamous cell differentiation in MIBC is imperative, given their distinct treatment approaches. Huang et al.'s study tackled the difficulty of differentiating between them prior to surgery by using 119 patients' clinical data and MRI scans to create an automated ML model, integrating tumour size, texture, and nodal features. It accurately distinguished between the two forms of cancer (AUC of 0.955 in training and 0.932 in testing). By detecting more aggressive cancer subtypes early, this non-invasive technique may assist physicians in making better treatment decisions before surgery.[40]

Kurata et al. developed a Vision Transformer (ViT) model for MRI-based detection of MIBC, designed to capture complex oncological patterns more effectively than conventional CNNs. Diagnostic and segmentation models were built, with the ViT and CNN models compared using AUC analysis. The model's performance on the test dataset was validated using manual and auto-generated regions of interest. It was compared to assessments made by three senior and three young radiologists using Vesical Imaging Reporting and Data System scores. Among 170 patients in the training set and 53 in the test set, ViT-based models outperformed CNNs, with a mean AUC of 0.831 vs. 0.713 to 0.812. The ViT achieved an AUC of 0.872 with manual region of interests (ROIs), comparable to junior radiologists, and 0.815 with automated ROIs, both outperforming CNN-based models. However, performance still fell short of expert radiologists, and further prospective validation is required before clinical adoption.[41]

Yu et al.[42] proposed a Cascade Path Augmentation U-Net (CPA-U-Net) for multi-regional segmentation on T2-weighted MRI, targeting the bladder inner wall, outer wall, and tumour. Using 1545 T2-weighted MRI scans, CPA-U-Net achieved strong segmentation performance in the test set, reporting Dice similarity coefficients of 98.19% for the inner wall, 82.24% for the outer wall, and 87.40% for the tumour, supporting its utility as a segmentation backbone for downstream computer-assisted assessment of muscle invasion. A

2D CNN was used by Hammouda et al.[43] to segment T2W MRI images. They incorporated patient-specific shape information into a CNN, improving segmentation of bladder walls and tumour (DSC up to 0.99). The segmentation performance was greatly improved using adaptive shape and contextual information.[43] They further enhanced their research in 2020 by expanding its use to T2W MRI for 3D bladder segmentation. In a 2020 extension, a 3D CNN with noise reduction methods further improved segmentation compared to the U-Net, highlighting advancement in data conclusions.[44]

Comparative evidence between AI-based MRI models and established radiologic scoring systems, such as Vesical Imaging-Reporting and Data System (VI-RADS), remains limited. However, Kurata et al.'s[41] study reported diagnostic performance comparable to junior radiologists applying VI-RADS, while senior radiologists continued to outperform both groups, supporting a role for AI as an assistive rather than replacement tool. Similarly, Li et al.[45] demonstrated that radiomics and deep-learning models achieved diagnostic Accuracy for muscle invasion comparable to that reported in the VI-RADS literature, though no direct head-to-head comparisons were performed. Recent MRI radiomics reviews also highlight that AI shows promise as a complementary decision-support approach, but that high-quality reader-comparison studies are still lacking. Overall, current evidence suggests that AI can approximate or modestly support VI-RADS-based interpretation, but robust comparative trials of reader performance with and without AI assistance are needed before definitive conclusions can be drawn.

MRI studies frequently used DSC for segmentation and AUC for staging prediction; these were examined separately to avoid cross-metric comparisons. For MRI, Moribata et al.[36] and Kurata et al.[41] both used data from two institutions, providing somewhat broader validation for tumour segmentation and muscle-invasion diagnosis, respectively. However, most radiomics and radiogenomic MRI models, including those by Qureshi et al.[37] and Huang et al.[39], remain small, retrospective, and effectively single-centre, with internal rather than external validation.

Positron Emission tomography/computed tomography (PET/CT)

Only one AI study to date has applied ^{18}F-FDG PET/CT to BCa. Girard et al.[46] developed a machine-learning model for nodal metastasis prediction using PET/CT-derived morphological and metabolic features. Performance metrics in PET/CT studies were reported on a per-patient basis, with histopathology serving as the primary reference standard. AI may enhance PET/CT interpretation by recognising subtle patterns beyond human perception, potentially reducing subjectivity in image reading. Enhancement in pelvic LN staging is crucial for tumour invasion status in MIBC. To enhance LN identification, Girard et al.[46] trained an ML model through PET/CT imaging data from 173 patients who had preoperative [^{18}F] FDG PET/CT. Important predictive characteristics were identified, including the primary tumor's dimensions, the size of the largest LN, and the highest metabolic activity of the most active LN. The model showed substantial agreement with expert radiologists ($K = 0.66$) and performed similarly in the validation set (AUC 0.59 *vs*. 0.64). Table 1 compares imaging modalities used in bladder cancer alongside their AI applications, highlighting key use cases, strengths, and limitations.

The AI techniques described in our review are summarised in Table 2.

Table 3 provides a summary comparing key features from the studies included in this review.

Discussion

AI has opened new avenues to increase efficiency and Accuracy in BCa diagnosis. However, key challenges must be addressed for these frameworks to adapt appropriately. Wu et al.[4] pointed out that AI trained on narrow datasets may not generalise well, as variability in disease frequency, presentation, and treatment response can lead to diagnostic errors. Scaling models across populations may require costly retraining. Developing rigorous evaluations on diverse datasets is imperative to ensure equal outcomes.

Prospective studies that remove bias and introduce standardised data collection are key to Accuracy. One benefit of prospective studies is assessing AI systems' predictive performance in real-world clinical conditions, providing more realistic evidence of their capabilities. Testing AI models in diverse populations reduces selection bias and leads to more broadly applicable results.[4,28]

The included studies reported performance using diverse metrics (Accuracy, AUC, Sensitivity/Specificity, DSC), which limits direct comparability. We therefore interpreted results within each metric category rather than comparing absolute values across different metrics. Where possible, findings were stratified by modality and task (detection, segmentation, staging) to maintain methodological consistency, although full

TABLE 1. **Comparison of AI application scenarios across computed tomography (CT), CT urography (CTU), magnetic resonance imaging (MRI), and positron emission tomography/CT (PET/CT)**

Modality	Primary AI tasks	Strengths	Limitations
CT	Grading, staging, and recurrence prediction	Widely available; strong radiomics performance	Limited soft-tissue contrast; mostly retrospective evidence
CTU	Bladder segmentation, T-stage stratification	Automated segmentation feasible (U-Net, CLASS)	Boundary ambiguity; operator-dependent variability
MRI	Muscle invasion prediction, radiogenomics	Superior soft-tissue delineation; Vision Transformer (ViT) outperforms convolutional neural networks (CNN)	High variability across scanners; requires large datasets
PET/CT	Lymph node (LN) metastasis prediction	Integrates metabolic + morphological signals	Limited bladder cancer (BCa) evidence; small sample sizes

normalization was not feasible given heterogeneity in study design and reporting.

AI applications in BCa vary substantially by task, and the strength of supporting evidence differs accordingly. Lesion detection and segmentation, especially in cystoscopy, represent the most mature area, supported by multiple prospective or multi-centre evaluations reporting consistently high Sensitivity and Specificity. Histologic grade prediction and muscle-invasiveness assessment show promising performance, mainly based on radiomics and MRI, but evidence remains largely retrospective and single-centre. Recurrence-risk prediction is the most preliminary domain; despite encouraging AUC values, studies are limited by small cohorts, model overfitting, and lack of external validation. These distinctions highlight that while detection models are approaching clinical readiness, staging, grading, and prognostic models require further validation before integration into practice.

A narrative appraisal of methodological quality revealed several recurrent sources of bias across the included studies. Most models were developed using retrospective, single-centre datasets, introducing substantial risks of selection and spectrum bias, as previously highlighted in evaluations of diagnostic and predictive modelling studies.[47] Many imaging and cystoscopy studies also lacked predefined analysis plans or adequate reporting structure, a limitation consistent with methodological weaknesses commonly observed in medical AI literature.[48] Data leakage was a notable concern, particularly in radiomics and deep learning workflows, where images from the same patient or acquisition may unintentionally appear in both training and test subsets, leading to inflated performance estimates.[49,50] Test sets were frequently small, underpowered, or insufficiently external, which limits confidence in the generalisability of reported AUC, DSC, or Accuracy values.[47] Blinding procedures were rarely specified; in several studies, it remained unclear whether reviewers were blinded to clinical information or to the model outputs during annotation, introducing risks of observer and incorporation bias.[49] Ground-truth labels also varied, with some studies using histopathology, others expert consensus, and some relying on a single annotator, creating heterogeneity in reference standards and potential inconsistency in classification.[47] These issues mirror the types of limitations systematically identified in formal appraisal frameworks such as QUADAS-2 and PROBAST, reinforcing the need for prospective, multi-centre datasets, clear separation of training/validation/testing cohorts, robust external validation, transparent blinding procedures, and standardised reporting in future AI-based BCa diagnostics.[9,10] Ground-truth quality represents another ceiling on achievable model performance. For cystoscopy-based systems,

TABLE 2. **A summary of the AI techniques mentioned**

AI technique	Application	Key findings	Clinical application phase (Based on included studies)
Machine Learning (ML)	Cystoscopy & Imaging	Improves diagnostic classification and reduces inter-observer variability.	Retrospective development
Deep Learning (DL)	Cystoscopy & Imaging	Learns complex visual/radiomic patterns enabling tumour detection or staging.	Retrospective development
Convolutional Neural Networks (CNNs)	Cystoscopy (e.g., CystoNet)	High Sensitivity and Specificity for tumour detection.	Prospective pilot/feasibility (single-centre)
ResNet/ResNeXt-101	Cystoscopy image processing	Enhances tumour recognition and grade differentiation.	Retrospective development
Feature Pyramid Network (FPN)	Tumour size/detection	Detects tumours across multiple spatial scales.	Retrospective development
U-Net	Contrast Urography segmentation	Provides accurate and automated bladder segmentation.	Retrospective development with external testing
Vision Transformer (ViT)	Magnetic Resonance Imaging (MRI)-based Muscle Invasive Bladder Cancer (MIBC) detection	Outperforms Convolutional Neural Networks (CNNs) for muscle invasion prediction.	Multicentre retrospective validation
Radiomics/DLRN	Computed Tomography (CT)-based tumour grading	Strong predictive performance for tumour grade or invasion.	Multicentre retrospective validation
Multilayer Perceptron (MLP)	Muscle invasion prediction	Distinguishes Muscle Invasive Bladder Cancer (MIBC) vs. Non-Muscle Invasive Bladder Cancer (NMIBC) with high Accuracy.	Retrospective development
MA-Net/ResNet34	Cystoscopy segmentation	High-Precision tumour segmentation with fewer false positives.	Retrospective development

pathology sampling error can lead to discordance between visual appearance and the histologic reference standard, meaning the 'true' label itself may contain uncertainty. For imaging models, particularly MRI staging, inter-reader variability is substantial; differentiating T1 from T2 lesions or identifying early muscle invasion is known to have only moderate reproducibility even among expert radiologists, which inherently constrains the upper limit of algorithmic Accuracy. When reference labels are noisy or inconsistent, improvements in model architecture cannot fully translate into higher performance. Future studies would benefit from consensus ground-truthing approaches, such as dual-reader annotation with adjudication, pathology–radiology correlation sessions, or structured multi-reader panels, to reduce label noise and create more reliable targets for training. These strategies are essential for ensuring that model performance reflects the true biological signal rather than variability in human interpretation or sampling.[51,52]

TABLE 3. **A summary table comparing key studies and results**

Author (Year)	Modality	AI model/ Approach	Cohort size	Centres	Ground truth	Validation type	Primary metrics	Clinical endpoint
Wu et al.[4] (2022)	White-light cystoscopy	CAIDS (PSPNet)	10,729 patients	Multicentre	Histopathology/ cystoscopic confirmation	Internal test set	Sensitivity 95.4%, Specificity 93.9%, AUC 0.978–0.991	Lesion detection
Ikeda et al.[16] (2020)	White-light cystoscopy	CNN classifier	2102 images	Single-centre	Expert-labelled frames	Internal test set	Sensitivity 89.7%, Specificity 94.0%, AUC 0.98	Lesion classification
Shkolyar et al.[13] (2019)	White-light cystoscopy	CystoNet (CNN)	95 patients	Single-centre	Histopathology/ cystoscopic confirmation	Internal test set	Sensitivity 90.9%, Specificity 98.6%	Lesion detection
Ali et al.[18] (2021)	Blue-light cystoscopy	Deep CNN (transfer learning)	216 images	Multicentre	Histopathology/ cystoscopic findings	Internal test set	Sensitivity 95.8%, Specificity 87.8%	Lesion detection
Yoo et al.[25] (2022)	Cystoscopy (RGB)	ResNeXt-101	10,991 images	Multicentre	Expert segmentation	Internal test set	Sensitivity 95.0%, Specificity 93.7%, Accuracy 94.1%, DSC 74.7	Lesion segmenta-tion/detection
Song et al.[27] (2023)	CT	Deep Learning Radiomic Nomogram (DLRN)	688 patients	Multicentre	Postoperative pathology	Internal test set	AUC = 0.961	Muscle invasiveness prediction
Wang et al.[28] (2023)	Multiphase enhanced CT	Deep learning signature	874 patients	Multicentre	Postoperative pathology	Internal test set	AUC = 0.889	Recurrence prediction
Chen et al.[30] (2022)	CT	Multilayer Perceptron (MLP)	173 patients	Single-centre	Postoperative pathology	Internal split (train/test)	AUC = 0.973 (train), 0.844 (test)	Muscle-invasion/grade prediction
Kurata et al.[41] (2024)	MRI	Vision Transformer	223 patients	Multicentre	Postoperative pathology	Internal test set	AUC = 0.872	Muscle invasiveness prediction

External validity varied substantially between studies. The multicentre CAIDS cystoscopy system reported by Wu et al. offers the most convincing real-world evidence, drawing on consecutively collected data from multiple hospitals and demonstrating improved detection of challenging flat lesions, including CIS.[4] Single-centre prospective evaluations of CystoNet by Shkolyar et al.[13] and the real-time pilot by Chang et al.[14] support feasibility and local performance but are underpowered for broad generalisation. Among imaging studies, CT-based deep-learning nomograms from Song et al.[27] and Wang et al.[28] incorporated multicentre cohorts and independent validation, lending stronger support for the generalisability of grade and recurrence prediction.[27,28] In contrast, many other CT and MRI radiomics or deep-learning models, such as those by Qureshi et al.[37], Chen et al.[38], and Huang et al.[39], were developed using retrospective single-centre datasets without robust external testing, and rarely stratified performance for subtle or early lesions.[37–40] Overall, external validity is currently strongest for multicentre cystoscopy and CT models, whereas most MRI and prognostic applications remain preliminary and require larger multi-centre, multi-vendor prospective validation.

Emerging evidence suggests a gradual shift toward more clinically relevant research, with prospective and multi-institutional work starting to become more available despite robust external validation remaining uneven. In cystoscopy, a recent prospective, workflow-oriented diagnostic study recruited collected 102 white-light cystoscopy videos, with 33,657 frames manually annotated. The deep-learning segmentation system achieved test-set sensitivity 91.6% and precision 91.3% (mDice 80.3%), with marked dependence on image quality (high-resolution sensitivity/precision 94.8%/94.4% vs. low-resolution 75.6%/74.8%), reinforcing that real-time performance is strongly constrained by video clarity and acquisition conditions.[53] Multi-institutional cystoscopy evidence is also emerging, though still largely retrospective. A three-institution evaluation using 5670 cystoscopy images reported a sensitivity of 0.973, specificity of 0.92, and accuracy reaching, showing tumour-localisation performance is broadly comparable to clinicians. This supports improved generalisability when data

are pooled across site.[54] In MRI, a multi-center T2-weighted deep learning model demonstrated strong discrimination internally (AUC 0.931 in validation; 0.907 in internal test) but performance fell substantially on external testing (AUC 0.721; accuracy 81.6%; sensitivity 57.1%; specificity 87.1%), highlighting persistent domain-shift limitations despite multi-center design.[55] Finally, the release of multicentre annotated MRI resources from four centres with pathology confirmed muscle-invasion labels and pixel-level tumour contours should accelerate reproducible external benchmarking and federated/multi-site training approaches, which are critical to reducing generalizability.[56] Beyond methodological considerations, real-world deployment of AI systems introduces several practical constraints that are rarely addressed in current studies. Endoscopy-based models must operate with low inference latency to enable real-time overlay of bounding boxes or heatmaps during cystoscopy, yet most published systems do not report performance on clinical-grade hardware. Integration into endoscopy suites requires compatibility with heterogeneous video processors and the ability to run on compact GPU-enabled units without interrupting the existing workflow. Similarly, imaging-based AI tools must interface smoothly with picture archiving and communication system (PACS) for automated retrieval and return of annotated studies and should support either a real-time assistive mode or a second-reader paradigm that complements, rather than replaces, radiologist interpretation. Human-in-the-loop designs are essential to mitigate automation bias, ensuring that clinicians retain situational awareness and can override erroneous outputs when necessary. These deployment-level considerations are critical for clinical translation, yet few studies provide detailed reports on hardware requirements, workflow integration, or latency testing, underscoring an important gap between algorithmic performance and practical usability.[57]

From a clinical translation perspective, successful deployment will also require regulatory pathway alignment. Current AI-based diagnostic systems used in urology would fall under FDA Software as a Medical Device (SaMD) and analogous EMA regulations, requiring evidence of safety, performance consistency, and post-market monitoring. Integration into existing cystoscopy towers and PACS requires vendor interoperability, low-latency execution, and hardware-agnostic device compatibility. Early economic analyses from endoscopic AI systems in other specialties suggest cost benefits driven by reduced repeat procedures, shorter reading times, and improved detection rates, though formal health-economic modelling remains absent in BCa AI. A key technical factor is the differential performance of ViTs vs. CNNs: ViT models achieved superior AUC in MRI-based muscle invasion prediction due to stronger long-range spatial attention, but at the cost of requiring larger, more diverse datasets to avoid overfitting, limiting immediate clinical scalability.

Robust governance is essential if AI tools for BCa are to be deployed safely. Dataset curation should include explicit consent pathways or appropriate waivers, clear rules for re-use of archived cystoscopy video and imaging, and procedures for de-identifying protected health information in endoscopy streams and PACS exports. Ongoing monitoring for model drift will be needed as case mix, imaging hardware and surgical practice evolve, with periodic re-evaluation against contemporary data rather than one-off validation. Governance frameworks should also mandate equity analyses, reporting performance across sex, age, ethnicity, and other relevant subgroups to detect differential error rates that might exacerbate existing disparities in BCa outcomes. Future studies would benefit from aligning their design and reporting with established AI-specific guidelines: TRIPOD+AI for prediction model development and validation, SPIRIT-AI and CONSORT-AI for clinical trial protocols and reports, and DECIDE-AI for early, live evaluations of decision-support systems.[58–60] These standards provide concrete checklists for documenting data provenance, handling of patient information, human–AI interaction, and post-deployment surveillance, and can help ensure that safety and governance considerations are embedded from the outset rather than added retrospectively.

Formal use of AI-specific reporting frameworks such as CLAIM, TRIPOD-AI, and CONSORT-AI was not explicitly documented in the BCa AI studies included in this review. Our observations are consistent with a recent systematic evaluation of imaging-based MIBC prediction models, in which He et al. applied CLAIM, RQS, and PROBAST and found generally suboptimal reporting quality and a high overall risk of bias across 21 studies, with calibration statistics and decision-curve analyses reported in only a minority of cases.[61] As prospective AI-assisted clinical studies emerge, aligning imaging studies with CLAIM, prediction models with TRIPOD-AI, and future interventional trials with CONSORT-AI, alongside routine inclusion of calibration and decision-curve analysis, will be essential to ensure transparent and clinically meaningful evaluation.

Recent reviews in oncology reinforced that the translational barriers identified in bladder cancer

AI are not unique to uro-oncology. For example, a 2025 review on artificial intelligence in colorectal cancer outlines how AI is increasingly positioned as a workflow-facing adjunct across screening and diagnosis, but emphasises recurring challenges in dataset heterogeneity, external validation, and the need for implementation-oriented evaluation before widespread adoption, mirroring the bottlenecks observed in cystoscopy-and imaging-based bladder cancer models.[62] In parallel, a 2025 review focused on AI for cancer detection highlights that clinical uptake is often limited less by headline performance than by trust, interpretability, and governance, noting that many cancer-AI studies still underreport interpretability and security considerations. Taken together, these works support a cross-cutting conclusion that future bladder cancer AI studies should not only standardise acquisition and ground-truthing but also embed interpretable outputs and human–AI interaction design, aligning evaluation with regulated clinical expectations rather than research-grade benchmarking.[63]

Improving the generalisability of BCa AI models will require coordinated development strategies across centres and vendors. Emerging approaches such as federated learning, which allow collaborative model training on distributed datasets without sharing patient-level data, reduce privacy barriers while capturing greater population heterogeneity.[64] Domain adaptation methods can mitigate scanner-, protocol-, and population-specific distribution shifts and improve performance when deploying models across new institutions. Building multicentre atlases that follow FAIR (Findable, Accessible, Interoperable, and Reusable) principles is increasingly recognised as essential for robust medical-AI development.[65] As a minimum specification for future datasets, multi-institutional cohorts with paired imaging and pathology, consistent annotation protocols (e.g., voxel-level segmentation for MRI, frame- or lesion-level labelling for cystoscopy), and clearly separated training, validation, and external test sets should be adopted. Such frameworks would support more robust benchmarking and facilitate community-wide model development.[64,65]

To generate practice-changing evidence, future evaluations of AI for BCa should follow a structured clinical trial roadmap. Early-phase studies ought to compare AI-assisted cystoscopy or imaging interpretation directly against current standard-of-care workflows (for example, WL-cystoscopy alone or radiologist/uro-radiologist reading with VI-RADS) using patient- or list-level randomisation. Primary endpoints should extend beyond per-image Accuracy to include clinically meaningful outcomes such as changes in complete resection rates, reduction in pathological upstaging at repeat TURBT or cystectomy, time-to-recurrence or progression, and procedure-level measures such as reading time and list throughput. Randomised trials of AI-assisted colonoscopy already provide a template for such designs, using adenoma detection rate, miss rate, and procedure time as key endpoints, and similar principles can be adapted for BCa AI.[66] Health-economic outcomes, including incremental cost per recurrence or progression avoided and theatre or radiology resource use, will be important to support adoption. Sample size calculations should be based on realistic effect sizes, which will often require several hundred patients per arm or multicentre cluster-randomised designs. Trial protocols and reports should align with SPIRIT-AI and CONSORT-AI guidance so that the AI intervention, workflow integration, and human–AI interaction are specified in sufficient detail for replication and critical appraisal.[67,68]

Given the diversity of AI models and their architectures, some models may mimic actual pathological characteristics, whilst others may generalise, resulting in benign lesions being flagged as malignant. Borna et al. reported that models reach high Precision but occasionally fail to capture the full extent of some lesions. However, in a separate case, the FPN-ResNet34 model identifies and outlines polyps by combining image details from different scales, but its focus on clear, confident regions often causes it to miss subtle or faint edges, leading to smaller or incomplete segmentations. This reflects the common trade-off between Precision and recall in AI systems. Consistent performance is essential, as underdiagnosis risks missed cancers, and overdiagnosis can lead to unnecessary interventions. Standardisation, rigorous validation, and comparative analysis of models are critical to identifying reliable tools for clinical use.[20]

Chen et al.'s study highlighted that ML models built solely using radiomics features performed poorly compared to other studies, possibly due to the imbalance between NMIBC and MIBC in the training sample. This imbalance reduced the model's ability to differentiate invasive from non-invasive disease. Therefore, studies could utilise oversampling or undersampling to balance the dataset and use evaluation metrics that better account for class imbalance, such as the F1 score (which balances Sensitivity and Precision).[29] The relatively modest number of manual 3D bladder outlines employed in Hadjiiski et al.'s study constituted a separate restriction, impacting

how well the model generalises. The CLASS technique also struggled with low-contrast boundaries, occasionally extending contours into adjacent normal tissue.[32] These issues emphasise the need for larger, balanced datasets and more robust segmentation criteria to improve model generalisability. The future of disease management in NMIBC can focus on AI-based models to reduce bias and interobserver variability. This will require large, high-quality datasets to train reliable models.[69]

Other studies regarding the incorporation of AI in uro-oncology highlight the need for a greater agreement between the algorithm and the human reader to enhance user interface and workflow integration. For example, in prostate cancer, zonal differences limit the transferability of AI-derived imaging features across tumour sites.[70] For training models, data quality and annotation are crucial at first, but acquiring high-quality medical data and precise annotations is still difficult and time-consuming. Second, clinical practitioners must comprehend and have faith in the predictive outcomes of AI models, which makes interpretation a persistent difficulty. Furthermore, to guarantee the security and compliance of patient data, concerns like privacy and security must be thoroughly considered. It is envisaged that as medical technology continues to progress, the use of AI in urologic oncology, including diagnosis, treatment planning, and rehabilitation monitoring, will be further extended to offer patients more extensive medical care.[71] Despite these challenges, the consistent finding across studies is that AI can extract clinically meaningful patterns from cystoscopy and imaging data.

Across medicine, several AI systems have already moved beyond retrospective validation into regulated, real-world clinical use, offering a practical benchmark for what deployment-ready automated technology can look like. In ophthalmology, IDx-DR became the first FDA *De Novo*–authorized autonomous AI diagnostic system, designed to detect more-than-mild diabetic retinopathy without clinician interpretation, illustrating that fully automated diagnostic pathways can reach routine clinical deployment when indications, workflow, and accountability are tightly defined.[72] In acute stroke care, Viz.ai received FDA clearance for CT/CTA-based detection and alerting for suspected large-vessel occlusion and is used operationally as a care-coordination layer in hospital systems, demonstrating a common near-term deployment pattern for AI as triage and pathway acceleration rather than definitive diagnosis.[73] In pathology, Paige Prostate received FDA *De Novo* authorization as assistive AI for prostate biopsy review, showing that regulated AI is also entering digitised diagnostic specialties where it functions as quality-assurance within established reporting structures.[74] Finally, population screening is increasingly testing AI in live service settings: the Mia breast-screening system is CE-marked and has been evaluated in prospective clinical service use, exemplifying how AI can be deployed as a second reader to address workforce constraints while remaining within governed screening pathways.[75] Collectively, these deployed examples indicate that the most clinically mature AI tools tend to succeed when they have a clear intended use, regulatory positioning, and well-defined workflow integration, typically operating as autonomous diagnosis only in tightly constrained settings or more commonly as triage/assistive decision support embedded into routine clinical systems.

Limitations

This narrative review has some limitations that should be acknowledged. First, the literature search was limited to studies published in English and indexed in PubMed and Google Scholar, which may have led to selection bias and the exclusion of relevant studies. Additionally, the review did not adopt a systematic methodology, which introduces the possibility of subjective bias in study selection, data extraction, and interpretation.

The heterogeneity among the included studies, such as differences in AI models, imaging modalities, datasets, and validation techniques, limited our ability to conduct a quantitative synthesis or meta-analysis. Many of the studies reviewed were retrospective, single-centre, or based on small sample sizes, which restricts generalisability. Moreover, as this is a rapidly evolving field, some emerging technologies or very recent publications may not have been captured within the time frame of our search.

A further challenge is the inconsistency of results reported. Some AI models deliver excellent Accuracy in small retrospective datasets but fail to generalise, while others perform well with radiologists without offering a clear clinical advantage. These conflicting outcomes underscore the current early status of AI in BCa imaging.

Finally, while we aimed to provide a comprehensive overview, our focus on AI applications in cystoscopy and imaging means that other promising areas of AI in BCa management (e.g., genomics, treatment response prediction) were not explored in depth.

Conclusions

AI has shown promising potential in improving the Accuracy and efficiency of BCa diagnosis, particularly through advancements in cystoscopy and imaging techniques. Early studies suggest that AI may assist in reducing misdiagnosis and improving lesion detection, thereby supporting clinicians in making more informed and timely decisions. Additional benefits include the potential for workflow optimization, reduced interobserver variability, and enhanced diagnostic consistency. However, the current evidence base is still limited in scope, sample size, and clinical diversity. Metric heterogeneity limited direct numerical comparison, so results were synthesized within metric categories. Key priorities for harmonisation include standardisation of imaging acquisition protocols, particularly cystoscopy illumination conditions and magnetic resonance imaging sequence selection, consistent ground-truth definitions anchored to histopathology or adjudicated expert consensus, uniform outcome definitions at both lesion- and patient-level, and adoption of robust validation frameworks incorporating external and prospective testing. To ensure safe and effective integration into routine clinical practice, further validation is needed through large-scale, multicenter studies across varied populations and care settings.

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Author Contributions

The authors confirm contribution to the paper as follows: Usman Khalid and Nikhil Shah conceptualised the paper and collected the data. Usman Khalid and Deepak Batura wrote the manuscript. Deepak Batura and Rajesh Kavia supervised the paper. All authors reviewed and approved the final version of the manuscript.

Availability of Data and Materials

Data are openly available in a public repository. The data that support the findings of this study are openly available in PubMed and Google Scholar at https://pubmed.ncbi.nlm.nih.gov/ and https://scholar.google.com/.

Ethics Approval

Not applicable.

Informed Consent

This study is a narrative review of previously published literature and did not involve human participants, patient data, or identifiable personal information. Therefore, informed consent was not required.

Conflicts of Interest

The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript

AUC	Area Under the Curve
AI	Artificial Intelligence
BCa	Bladder Cancer
CNN	Convolutional Neural Network
CIS	Carcinoma *in situ*
CT	Computed Tomography
CTU	CT Urography
DLRN	Deep Learning Radiomic Nomogram
DL	Deep Learning
DLRS	Deep Learning Radiomic Signature
FPN	Feature Pyramid Network
FFPE	Formalin-Fixed Paraffin-Embedded
ICC	Intraclass Correlation Coefficient
IoU	Intersection over Union
LN	Lymph Node
MDCT	Multidetector Computed Tomography
MIBC	Muscle-Invasive Bladder Cancer

ML	Machine Learning
MLP	Multilayer Perceptron
MRI	Magnetic Resonance Imaging
NMIBC	Non-Muscle-Invasive Bladder Cancer
PET	Positron Emission Tomography
PD-L1	Programmed Death-Ligand 1
RGB	Red Green Blue
ROC	Receiver Operating Characteristic
SROC	Summary Receiver Operating Characteristic
TURBT	Transurethral Resection of Bladder Tumour
Tumour ViT	Vision Transformer
WLC	White-Light Cystoscopy

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