Review Article

Can artificial intelligence aid the urologists in detecting bladder cancer?

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ABSTRACT

Introduction: The emergence of artificial intelligence (AI)-based support system endoscopy, including cystoscopy, has shown promising results by training deep learning algorithms with large datasets of images and videos. This AI-aided cystoscopy has the potential to significantly transform the urological practice by assisting the urologists in identifying malignant areas, especially considering the diverse appearance of these lesions.

Methods: Four databases, the PubMed, ProQuest, EBSCOHost, and ScienceDirect were searched, along with a manual hand search. Prospective and retrospective studies, experimental studies, cross-sectional studies, and case–control studies assessing the utilization of AI for the detection of bladder cancer through cystoscopy and comparing with the histopathology results as the reference standard were included. The following terms and their variants were used: "artificial intelligence," "cystoscopy," and "bladder cancer." The risk of bias was assessed using the Quality Assessment of Diagnostic Accuracy Studies-2 tool. A random effects model was used to calculate the pooled sensitivity and specificity. The Moses–Littenberg model was used to derive the Summary Receiver Operating Characteristics (SROC) curve.

Results: Five studies were selected for the analysis. Pooled sensitivity and specificity were 0.953 (95% confidence interval [CI]: 0.908–0.976) and 0.957 (95% CI: 0.923–0.977), respectively. Pooled diagnostic odd ratio was 449.79 (95% CI: 12.42–887.17). SROC curve (area under the curve: 0.988, 95% CI: 0.982–0.994) indicated a strong discriminating power of AI-aided cystoscopy in differentiation normal or benign bladder lesions from the malignant ones.

Conclusions: Although the utilization of AI for aiding in the detection of bladder cancer through cystoscopy remains questionable, it has shown encouraging potential for enhancing the detection rates. Future studies should concentrate on identification of the patients groups which could derive maximum benefit from accurate identification of the bladder cancer, such as those with intermediate or high-risk invasive tumors.

INTRODUCTION

As science and technology continues to advance, the increase in the volume of data, along with its higher dimensionality, has significantly contributed to the improvements in the recognition rate, accuracy, and success rate of artificial intelligence (AI),[1] enabling insights that would be otherwise challenging to obtain through manual methods.[2,3] This has lead to the application of AI in problem-solving and has transformed AI into intelligent decision support system.[1,4,5]

AI has found applications in various contexts, including the medical field, such as its utilization in endoscopic diagnostic systems to achieve precise and efficient diagnoses. The current ongoing research aims to explore the potential of AI for the detection of bladder cancer through cystoscopy, and

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has shown promising results.[6] Cystoscopy is the standard diagnostic and surveillance tool for the detection of bladder cancer, which is the fifth commonest cancer contributing to mortality among all the cancers in men (375,304 deaths; 6.8%) according to the Global Cancer Registry 2020.[7] When suspicious lesions are detected on cystoscopy, transurethral resection of the bladder tumor (TURBt) is performed for the pathological diagnosis, staging, and planning the subsequent management. Despite being a standard diagnostic procedure, urologists might overlook some of the bladder cancer lesions, resulting in incomplete resection and misdiagnosis. The reported misdiagnosis ranges up to 43%, across different cases.[8-10] Flat cancerous lesions such as carcinoma *in situ* (CIS) or extremely small tumors might not be identified on white light (WL) cystoscopy resulting in 25.2%–53.1% incidence of residual tumors.[11] Nevertheless, it is crucial to identify and remove all the tumors to accurately assess the risk and make clinical decisions, as this approach is highly effective in preventing the recurrence. Therefore, the utilization of AI during cystoscopy is being developed to improve the sensitivity of cystoscopy, aiding the urologists in differentiating the diverse bladder cancer lesions. We aimed to systematically investigate the recent research on the use of AI in aiding the detection of bladder cancer from the images taken during cystoscopy and calculate the diagnostic accuracy.

METHODS

This systematic review was performed according to the Preferred Reporting Items for Systematic Review and Meta-analysis of Diagnostic Test Accuracy[12,13] and was registered in PROSPERO (CDR42023441159).

Eligibility criteria

Studies were eligible for inclusion if they fulfilled the following criteria:

1. Design: prospective and retrospective studies, experimental studies, cross-sectional studies, and case–control or nested-case–control studies were eligible for inclusion in this review. Case series or case reports were excluded.
2. Population: human adults aged 18 years or above who underwent cystoscopic examination
3. Index test: AI tool that identifies potentially malignant lesions from images or videos taken during the cystoscopy examination
4. Reference standard: we included studies that used histopathology results to confirm the bladder cancer and histopathology was taken as the reference standard
5. Outcomes: The reported diagnostic accuracy, including true positive (TP), false negative (FN), false positive (FP), and true negative (TN) were the outcome measures.

Information sources and search strategy

Using the medical subject headings and free text terms associated with AI-aided cystoscopy for the diagnosis of bladder cancer, we devised search techniques to identify the relevant studies. The search was conducted on a variety of databases including PubMed, EBSCO, ProQuest, and ScienceDirect. A manual review of the reference lists of the included articles in addition to a thorough search on the Google Scholar was performed to identify any potentially overlooked article. Our search covered the synonyms and variations for "artificial intelligence," "cystoscopy," and "bladder cancer" without being limited by the year of publication [Supplementary File 1].

Data management, selection, collection, and extraction

We used Zotero to manage the studies identified during the search. The initial compilation of studies involved removing the duplicates and screening them for eligibility based on their titles and abstracts. This was done independently by two co-authors (AH and SKL). Potentially relevant studies underwent a full-text assessment after the initial screening. In case of any disagreement during the selection process and quality assessment, it was discussed with the another co-author (CK). Data from the selected studies was extracted and cross-checked for qualitative synthesis. We extracted the following data: author, year of study, country, study design, number of samples, number of participants, and diagnostic accuracy (TP, FN, FP, and TN). In the event of any missing data, we attempted to establish contact with the corresponding author of the selected study to procure the relevant information.

Risk of bias assessment

The Quality Assessment of Diagnostic Accuracy Studies (QUADAS-2) tool,[14] a validated tool for assessing the quality of diagnostic accuracy studies, was used to evaluate the quality of each study. Patient selection, index testing, reference standards, and flow and timing are the four major categories in which this instrument assesses the risk of bias and application issues. Each domain is assessed for concerns regarding bias and applicability using the signalling questions. The results of the QUADAS-2 assessment were employed to evaluate the overall quality of the studies and to guide any further analyses or interpretations of the findings.

Data analysis and synthesis

The systematic qualitative synthesis of the included articles was performed, with the information presented in both the text and the tables to describe and explain the study's characteristics and conclusions. Meta-analysis using a random effects model was conducted to yield pooled sensitivity, specificity, and diagnostic odds ratio (DOR). The Moses–Littenberg model was used for deriving a summary receiver operating characteristics (SROC) curve. Sources of heterogeneity were examined by the subgroup analysis and was qualitatively synthesized. Relevant data were combined and calculated using the statistical software RevMan 5.4. (Revman 5.4, Copenhagen: The Nordic Cochrane Centre, The Cochrane Collaboration)

RESULTS

Study characteristics

Through a comprehensive database search, 371 studies were initially identified [Figure 1]. After removing the duplicates, 357 studies remained, out of which 343 were excluded based on the inclusion criteria, leaving 14 studies for further assessment of eligibility. Ultimately, 5 studies were selected for the final analysis and quantitative synthesis.[6,15-18] All included studies were case–control in design [Table 1]. All the studies involved samples taken from human observers and the images were processed as training, validation, and test sets. All the studies used histopathology results as the reference standard.

Diagnostic accuracy

The quality of the included studies showed a high risk of bias and high applicability concerns for the domain of patient selection [Figure 2]. The forest plot of the meta-analysis for diagnostic accuracy is presented in Figure 3. Pooled sensitivity and specificity were 0.953 (95% confidence interval [CI]: 0.908–0.976) and 0.957 (95% CI: 0.923–0.977), respectively. Pooled DOR was 449.79 (95% CI: 12.42–887.17). The SROC curve showed an area under the curve (AUC) of 0.988 (95% CI: 0.982–0.994) [Figure 4]. A subgroup analysis showed a higher diagnostic accuracy (AUC 0.995, 95% CI: 0.994–0.996) when blue light cystoscopy was excluded [Figure 5].

Variation among studies

Our review revealed a significant amount of diversity in the approach and reporting across the studies in all the fields. The primary factors commonly observed in these studies were related to the problems with dataset quality, size and type of data, and the validation methods used. Most of the studies followed a case–control study design, with only one study adopting a prospective design and obtaining data in a consecutive manner. In addition, one out of the five studies utilized videos instead of images, and there were variations in the image resolution across the studies. Besides, flat lesions were excluded from one study.

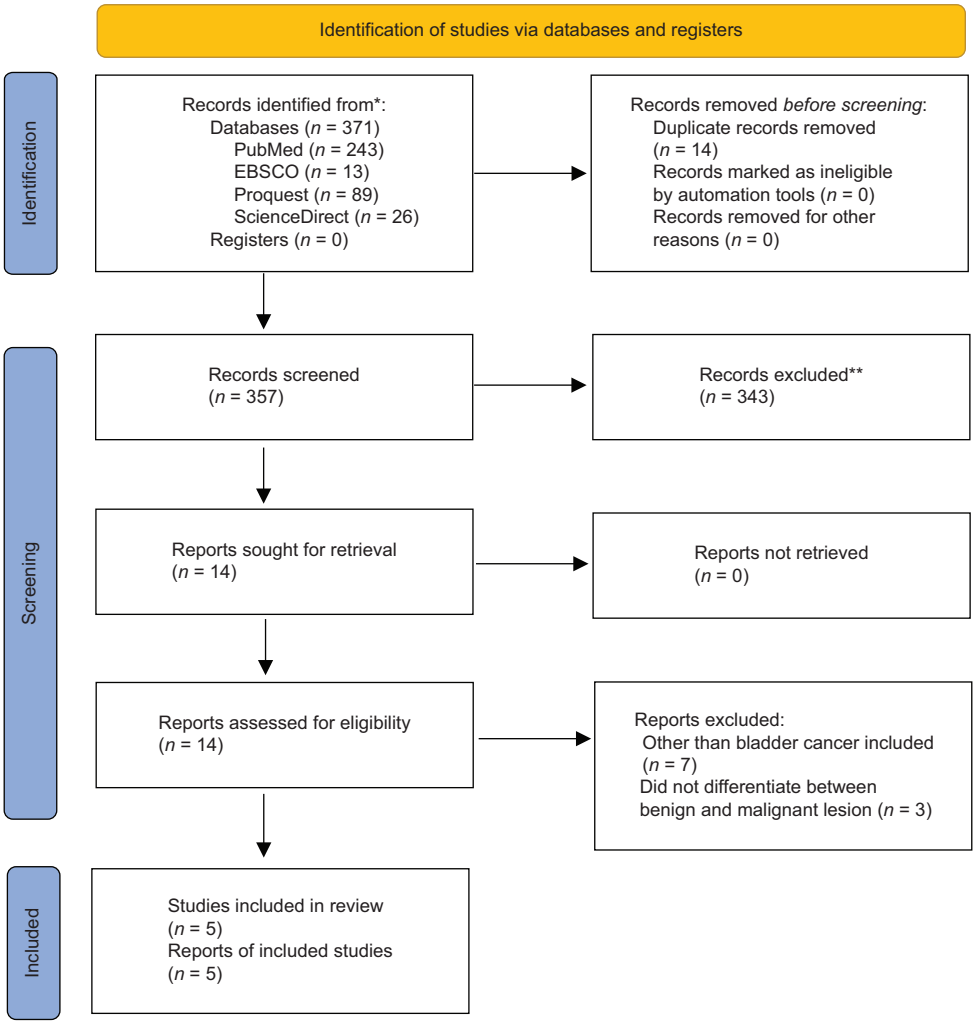

Figure 1: Preferred Reporting Items for Systematic Review and Meta-analysis flow diagram 2020

Table 1: Summary of studies

Author, year	Country	Cystoscopy type	ML model	Image quality	Type of lesion included	Comparison	Train/test split	Total samples included
Ali *et al.*, 2021[15]	Germany	Blue light (Tricam II® system and a 30° Hopkins II optic [Karl Storz, Tuttlingen, Germany])	CNN (VGG16, ResNet50, MobileNetV2, and InceptionV3)	244×244 pixels	Not specified	AI detection versus physician versus pathology	L10PO-CV: 10 images as test set, 10 images as validation set, and remaining images as training set	216 images, each from 1 patient
Ikeda *et al.*, 2021[16]	Japan	White light (CYF-VHA; Olympus Medical System, Co., Ltd., Tokyo, Japan)	CNN (GoogleNet)	1350×1080 pixels	Elevated, flat, and mixed lesions	AI detection versus pathology	Training and test set ratio is 8:2, with 1680 in training set and 422 in test set	2102 images from 109 patients (97 men and 12 women)
Shkolyar *et al.*, 2019[6]	US	White light (not specified)	CNN (CystoNet)	Not specified	Flat lesions were excluded	AI detection versus pathology	In development data set, 136 videos containing 2752 frames from 95 patients were included as training set, while 5 videos containing 1213 frames from 5 patients were included as test set. In further validation, 54 patients (57 videos or) were included	198 videos (55,938 frames) from 154 patients
Wu *et al.*, 2022[17]	China	White light (not specified)	CNN (PSPNet)	256×256 pixels	Not specified	AI detection versus physician versus pathology	Training and internal validation set ratio is 8:2 (63,452 images from 9302 patients) and other set of data for external validation set (5752 from 1427 patients)	69,204 images from 10,729 patients
Yoo *et al.*, 2022 [18]	Korea	White light (CYF-V2, Olympus Medical Systems Corporation, Tokyo, Japan)	CNN	Varied (480-1080 pixels)	Not specified	AI detection versus pathology	Training set (8244 images), validation set (1847 images), and test set (900 images)	10,991 images

Author, year	Pathological classification in total samples involved		Prediction results				
	Benign	Malignant	Classification Model	Pathology results	Benign	Malignant	Sensitivity (%)
Ali *et al.*, 2021	74 images	142 images	InceptionV3	Benign	57	17	95.07
				Malignant	7	135	
			MobileNetV2	Benign	65	9	95.77
				Malignant	6	136	
			ResNet50	Benign	61	13	91.55
				Malignant	12	129	
			VGG16	Benign	65	9	93.66
				Malignant	9	133	
			Physician 1	Benign	39	35	88.03
				Malignant	17	125	
			Physician 2	Benign	41	33	87.32
				Malignant	18	124	
Ikeda *et al.*, 2021	1671 images	432 images	ML model	Benign	315	20	89.7
				Malignant	9	78	
Shkolyar *et al.*, 2019	55,310 frames	8170 frames	Tumor cohort (31,330 frames)	Benign	23,382	406	90.9
				Malignant	685	6857	

Contd...

Table 1: Contd...

Author, year	Pathological classification in total samples involved		Prediction results				
	Benign	Malignant	Classification Model	Pathology results	Benign	Malignant	Sensitivity (%)
Wu *et al.*, 2022	62,283 images	6921 images	SYSMH and RJH (internal validation set)	Benign	10,849	275	98.7
				Malignant	16	1,245	
			SZSH (external validation set)	Benign	204	0	87.5
				Malignant	1	6	
			STCH (external validation set)	Benign	428	8	97.7
				Malignant	1	35	
			AMUFH (external validation set)	Benign	61	1	95.8
				Malignant	2	45	
			NJFH (external validation set)	Benign	525	2	95.1
				Malignant	5	103	
Yoo *et al.*, 2022	4262	6729	Test set (900 images)	Benign	562	38	95.0
				Malignant	15	285	

PSPNet=Pyramid Scheme Parsing Network, CNN=Convolutional neural network, AI=Artificial intelligence, US=United States, ML=Machine learning

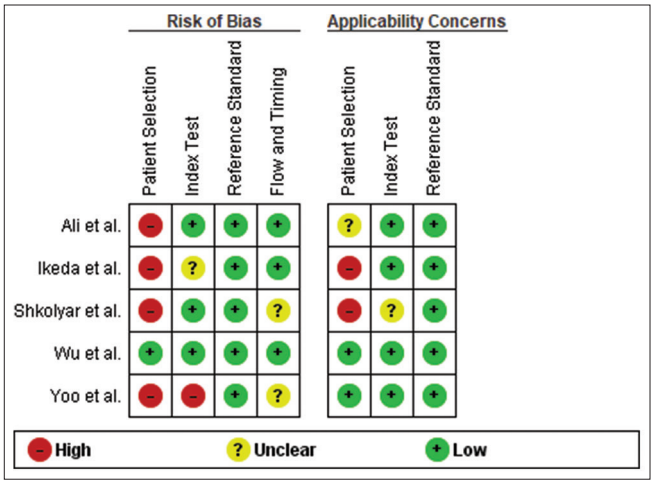

Figure 2: Quality Assessment of Diagnostic Accuracy Studies-2 summary

DISCUSSION

Diagnostic accuracy is a critical aspect of any diagnostic tool, and the pooled sensitivity and specificity reported in this meta-analysis are notably high, with the sensitivity at 0.953 and the specificity at 0.957. The pooled DOR was also substantial, indicating that the imaging technique shows promising potential for accurately diagnosing the bladder cancers. Furthermore, the SROC showed an impressive AUC of 0.989, indicating a strong overall diagnostic performance for discriminating benign or normal bladder lesions from the malignant ones.

Fluorescence cystoscopy and narrow-band imaging techniques have been developed and are currently being utilized to enhance the detection rates of bladder cancer. These methods involve the extraction of microimaging structures and the identification of pixel-level features not perceived by the human eye, serving a diagnostic purpose. The use of fluorescence cystoscopy (photodynamic diagnosis [PDD]) results in improved sensitivity (92% vs. 71%),[9] and higher detection of papillary (7%–29%), and flat CIS (20%–30%) lesions, along with a 20% reduction in the residual tumor rate after TURBt.[11] However, one study using PDD showed a lower specificity and the subgroup analysis demonstrated a higher diagnostic accuracy when the findings of blue light cystoscopy were disregarded. Researchers and physicians assessing the efficacy of the various types of cystoscopy for the detection of bladder cancer may find this helpful.

One of the studies excluded flat lesions and this may influence how broadly the bladder cancer type is represented in the analysis and may also have an impact on how accurately the AI-guided cystoscopy can make the diagnosis. One challenging lesion that can benefit from the use of AI are the flat lesions; rather than excluding them, flat lesions should be the lesions of particular interest.

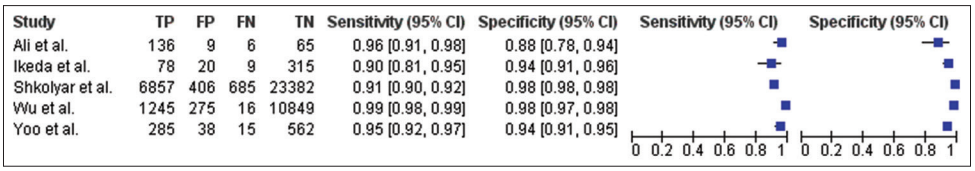

Figure 3: Forest plot

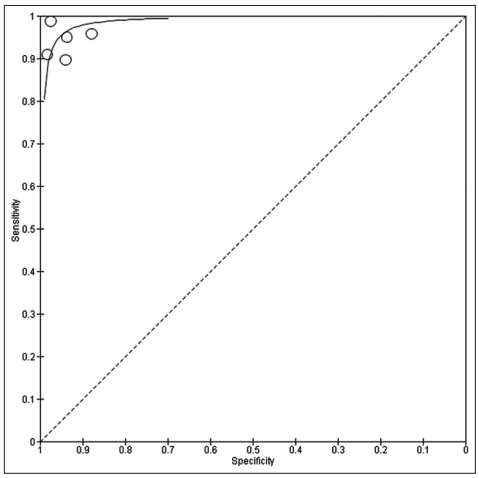

Figure 4: Summary receiver operating characteristic plot

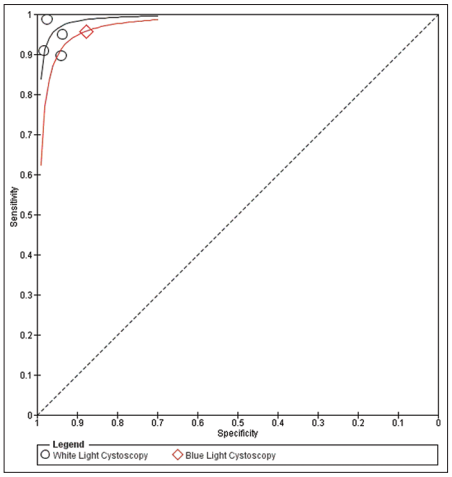

Figure 5: Summary receiver operating characteristic Plot based on cystoscopy type

Failure to accurately classify cystoscopic images or videos (FPs or FN) can be attributed to several factors. One of the issues is data annotation; for example, inflammation-induced changes in the bladder mucosa were not included in the model's learning process, so the model could not learn to recognize them.[16] Another issue that might contribute to the failure is model development, including but not limited to the unbalanced sample (positive and negative results), insufficient training data sets, and differences in processing the data.[6,15-18] Technical problems, such as the variations in the turbidity of the urine, issues with focus, or the distance of the camera from the site of the lesion, also affects the accuracy of the classification.[16] The size of the lesion is another important factor. Ikeda *et al.* reported that only around 10% of the learning sets contained small lesions, which may have contributed to inaccurate classification.[16] Differences in the imaging modalities, as shown by Yoo *et al.*, indicate that WL imaging performed better than the narrow-band imaging.[18] The limited wavelength range of narrow-band imaging may restrict the differentiation of the tumor's intrinsic color.

The discussion does, however, also draws attention to certain significant problems with the included studies. A high risk of bias and application issues were found throughout the QUADAS-2 assessment, particularly regarding the patient selection, which could have an impact on how generalizable the results are. Only 2 out of the 5 included studies specify the pathological grading of the included tumor. When employing the AI for the detection of bladder cancer, the emphasis should also be on considering the patient's quality of life and risk stratification rather than solely focusing on the detection rates.[19,20] For the patients with low-risk bladder cancer, the probability of progression is 0.06%, 0.93%, and 3.7% at 1, 5, and 10 years, respectively, whereas those with intermediate, high, and very high risk have 1.0%, 3.5%, and 16% probability to progress within 1 year, respectively.[19] Around 54% of the patients with CIS will progress to muscle-invasive cancer.[21] CIS is a flat, high-grade cancer, often multifocal, that could be missed or misinterpreted during the examination if not biopsied. In situations involving truly low-risk, nonmuscle invasive bladder cancer, these tumors are unlikely to progress to life-threatening muscle-invasive disease.[20-22] Detecting patients with low-risk diseases through AI may lead to unnecessary treatment, instead of active surveillance,[19] and add financial burden to these individuals.

The identified issues concerning the size, kind, and quality of the dataset may potentially introduce bias and consequently influence the overall validity of the results. Furthermore, the variety in the study design, especially given that most of the studies used a case–control strategy, may make it difficult to demonstrate causation or extrapolate the findings to different populations. It is also difficult to compare the results because one study included videos, and another had different image resolution. When interpreting the findings and applying them in actual clinical situations, it is essential to keep these limitations in mind. All fields showed diversity in approach and reporting, suggesting that areas of standardization and uniformity in data collection and reporting require improvement. A meta-analysis by Aggarwal *et al.* reported

that some studies used the STARD-2015 checklist to standardise the reporting, although this checklist is not specifically designed for studies related to AI.[3] Most of the studies on AI also have a high risk of bias and tend to deviate from the reporting guidelines.[23] We believe that further research on AI in the field of medicine might improve with strict adherence to the reporting standards specifically designed for studies related to AI.

Another essential concern was that the AI models were generally fed specific input variables, selected by clinicians based on their known or suspected clinical relevance to the outcome of interest.[24] Recent reports suggest that biases present in the training data used to develop AI models could have adverse effects on certain populations.[25,26] It is evident that the overall performance of an AI model relies not only on its accuracy in the training and test data but also on its reliability and ability to generalize effectively to different settings and populations.

Study strengths and limitations

Although our findings show that AI aided cystoscopy performs well for the detection of bladder cancer and has high diagnostic accuracy, its clinical suitability and applicability remain challenging to ascertain. This difficulty arises, in part, from the considerable diversity and potential biases observed in the existing literature.

Future suggestions

To improve AI-guided cystoscopy for the detection of bladder cancer and ensure its clinical effectiveness, several key points should be considered. These include the inclusion of large, diverse, and anonymized datasets; the focus on populations that would genuinely benefit from the detection of bladder cancer, such as those with moderate or high-risk bladder cancer or unequivocal lesions; and adherence to specific reporting standards for research on AI.

CONCLUSIONS

Based on the recent research, the diagnostic accuracy of AI for the detection of malignant lesions on images or videos of cystoscopy is high, however, it is difficult to conclude whether AI can aid the urologists, particularly during the live-cystoscopy for the detection of bladder cancer due to the diversity in the included population, study design, and reporting standards. AI has the potential to improve the detection and outcomes of bladder cancer detection if further research focuses on identifying the populations who might benefit from the identification of the bladder cancer, such as those with intermediate-or high-risk invasive tumors.

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Supplementary File 1: Search strategy			
Key concepts	**Concept 1** **AI**	**Concept 2** **Cystoscopy**	**Concept 3** **Bladder cancer**
Controlled vocabulary terms/Subject terms	"Artificial Intelligence" [MeSH Term] OR "Neural Networks, Computer" [MeSH Term] OR "Decision Support Systems, Clinical" [MeSH Term] OR "Expert Systems"	"Cystoscopy" [MeSH Term] OR "Transurethral Resection of Bladder" [MeSH Term] OR "Cytology" [MeSH Term] OR "Histopathology" [MeSH Term] OR "Endoscopy" [MeSH Term]	"Urinary Bladder Neoplasms" [MeSH Term] OR "Non-Muscle Invasive Bladder Neoplasms" [MeSH Term]
Free text terms/natural language terms	"Pattern Recognition" [Text Word] OR "Learning Algorithm*" [Text Word]	"Bladder Endoscopy" [Text Word] OR "Cystoscopic Examination" [Text Word] OR "Diagnostic Cystoscopy" [Text Word] OR "Flexible Cystoscopy" [Text Word] OR "Rigid Cystoscopy" [Text Word] OR "Video Cystoscopy" [Text Word] OR "Flat Lesion" [Text Word] OR "Papillary" [Text Word]	"Bladder Cancer" [Text Word] OR "Urothelial Carcinoma" [Text Word] OR "Bladder Tumor" [Text Word] OR "Bladder Carcinoma" [Text Word] OR "Bladder Malignancy" [Text Word]

Draft Entry EBSCO Search (Identified Articles: 13)		
Entry	**Filter**	**Total findings**
SU (MM "Artificial Intelligence") OR SU (MM "Neural Networks, Computer") OR SU (MM "Decision Support Systems, Clinical") OR SU (MM "Expert Systems") OR TX "Pattern Recognition" OR TX "Learning Algorithm*"	None	65,410
SU (MM "Cystoscopy") OR SU (MM "Transurethral Resection of Bladder") OR SU (MM "Cytology") OR SU (MM "Histopathology") OR SU (MM "Endoscopy") OR TX "Bladder Endoscopy" OR TX "Cystoscopic Examination" OR TX "Diagnostic Cystoscopy" OR TX "Flexible Cystoscopy" OR TX "Rigid Cystoscopy" OR TX "Video Cystoscopy" OR TX "Flat Lesion" OR TX "Papillary"	None	2412
SU (MM "Urinary Bladder Neoplasms") OR SU (MM "Non-Muscle Invasive Bladder Neoplasms*") OR TX "Bladder Cancer" OR TX "Urothelial Carcinoma" OR TX "Bladder Tumor" OR TX "Bladder Carcinoma" OR TX "Bladder Malignancy"	None	11,454
S1 AND S2 AND S3	None	13

Draft Entry ProQuest Search (Identified Articles: 89)		
Entry	**Filter**	**Total findings**
MAINSUBJECT.EXACT("Artificial Intelligence") OR MAINSUBJECT.EXACT("Neural Networks, Computer") OR MAINSUBJECT.EXACT("Decision Support Systems, Clinical") OR MAINSUBJECT.EXACT("Expert Systems") OR fulltext("Pattern Recognition") OR fulltext("Learning Algorithm*")	None	859,685
MAINSUBJECT.EXACT("Cystoscopy") OR MAINSUBJECT.EXACT("Transurethral Resection of Bladder") OR MAINSUBJECT.EXACT("Cytology") OR MAINSUBJECT.EXACT("Histopathology") OR MAINSUBJECT.EXACT("Endoscopy") OR fulltext("Bladder Endoscopy") OR fulltext("Cystoscopic Examination") OR fulltext("Flexible Cystoscopy") OR fulltext("Rigid Cystoscopy") OR fulltext("Video Cystoscopy") OR fulltext("flat lesion") OR fulltext("papillary")	None	2255
MAINSUBJECT.EXACT("Urinary Bladder Neoplasms ") OR MAINSUBJECT.EXACT("Non-Muscle Invasive Bladder Neoplasms ") OR fulltext("Bladder Cancer") OR fulltext("Urothelial Carcinoma") OR fulltext("Bladder Tumor") OR fulltext("Bladder Carcinoma") OR fulltext("Bladder Malignancy")	None	162,263
S1 AND S2 AND S3	None	89

Draft Entry PubMed Search (Identified Articles: 243)		
Entry	**Filter**	**Total findings**
(((((Artificial Intelligence[MeSH Terms]) OR (Neural Networks, Computer[MeSH Terms])) OR (Decision Support Systems, Clinical[MeSH Terms])) OR (Expert Systems[MeSH Terms])) OR (Pattern Recognition[Text Word])) OR (Learning Algorithm*[Text Word])	None	284,196
((((((((((((Cystoscopy[MeSH Terms]) OR (Transurethral Resection of Bladder[MeSH Terms])) OR (Bladder Endoscopy[Text Word])) OR (Cystoscopic Examination[Text Word])) OR (Diagnostic Cystocopy[Text Word])) OR (Flexible Cystoscopy[Text Word])) OR (Rigid Cystoscopy[Text Word])) OR (Video Cystoscopy[Text Word]))) OR (cytology[MeSH Terms])) OR (histopathology[MeSH Terms])) OR (endoscopy[MeSH Terms])) OR (flat lesion)) OR (papillary)	None	2,086,672
((((((Urinary Bladder Neoplasms[MeSH Terms]) OR (Non-Muscle Invasive Bladder Neoplasms[MeSH Terms])) OR (Bladder Cancer[Text Word])) OR (Urothelial Carcinoma[Text Word])) OR (Bladder Tumor[Text Word])) OR (Bladder Carcinoma[Text Word])) OR (Bladder Malignancy[Text Word])	None	83,688
S1 AND S2 AND S3	None	243

Draft Entry ScienceDirect Search (Identified Articles: 26)		
Entry	**Filter**	**Total findings**
(Artificial Intelligence) AND ((Cystoscopy) OR (Transurethral Resection of Bladder) OR (Cystoscopic Examination)) AND ((Urinary Bladder Neoplasms) OR (Bladder Cancer))	None	307
(Artificial Intelligence) AND ((Cystoscopy) OR (Transurethral Resection of Bladder) OR (Cystoscopic Examination)) AND ((Urinary Bladder Neoplasms) OR (Bladder Cancer))	Research Article	26