

Examine the function of AI in enhancing diagnostic precision and efficacy in histopathology: A Systematic Review

Sara Altom¹

¹*Basic Sciences Department, Al-Rayan National College of Medicine, Al-Rayan National Colleges, Al-Madinah, Saudi Arabia*

Correspondence Author

Dr. Sara Altom, Assistant Professor in the Department of Basic Sciences at Al-Rayan, Al-Rayan National Colleges, Al-Madinah, Saudi Arabia National College of Medicine

Email: drosy442@gmail.com

Abstract

Background: Artificial intelligence (AI) has become a game changing tool in histopathology, with the potential to make routine practice more accurate, efficient, and reproducible. Traditional pathology faces constraints due to inter-observer variability, escalating workloads, and the growing demand for precision medicine, underscoring the necessity for innovative digital solutions.

Objective: To systematically evaluate the contribution of AI in improving diagnostic precision and operational efficiency in histopathology.

Methods: A comprehensive literature search was performed on PubMed, Scopus, Web of Science, and Google Scholar for studies published from 2011 to 2025. Eligible studies encompassed randomized controlled trials, cohort studies, and diagnostic accuracy assessments examining AI applications in histopathological image analysis. Data extraction concentrated on AI methodologies, diagnostic performance indicators (accuracy, sensitivity, specificity, AUC), efficiency results, and constraints. The QUADAS-2 and Newcastle–Ottawa tools were used to rate the quality of the study.

Results: AI models, especially convolutional neural networks (CNNs) and transformer-based architectures, showed very high diagnostic accuracy (often over 90%) in finding, grading, and subtyping cancer. Numerous studies indicated a decrease in inter-observer variability and an enhancement in workflow efficiency, particularly through reduced slide review duration. Nonetheless, dataset heterogeneity, absence of external validation, and restricted integration into clinical workflows continue to pose considerable challenges. Ethical issues, such as algorithm transparency and data privacy, were also brought up a lot.

Conclusion: AI has a lot of promise for improving the accuracy and speed of histopathology diagnoses, but it needs to be thoroughly tested, standardized, and integrated into current clinical workflows before it can be widely used. To make sure that the implementation is safe and effective, pathologists, computer scientists, and policymakers need to work together.

Keywords: Artificial intelligence, histopathology, diagnostic accuracy, efficiency, and systematic review

Citation: Sara Altom. 2025. Examine the function of AI in enhancing diagnostic precision and efficacy in histopathology: A Systematic Review. *FishTaxa* 36(1s): 62-73.

Introduction

Histopathological analysis continues to be the gold standard for diagnosing various diseases, including cancer, inflammatory conditions, and infectious processes. Histological slide interpretation is inherently time-consuming and prone to intra- and inter-observer variability. In certain cancer subtypes, diagnostic discordance rates reaching 20% have been documented, which may postpone prompt treatment and influence patient outcomes [1]. The global shortage of qualified pathologists and the rise in case volumes have made workflow bottlenecks in diagnostic labs worse. Artificial intelligence (AI) has become a strong addition to traditional pathology workflows. Deep learning, a subset of AI that uses convolutional neural networks (CNNs), can automatically pull out hierarchical features from whole-slide images, which makes diagnoses more consistent [2]. AI has demonstrated feasibility and exceptional accuracy in practical clinical environments, notably in the diagnosis of prostate cancer [3]. AI-assisted systems greatly improve the ability to make accurate diagnoses. For instance, CNNs increased sensitivity from 83% to 91% for finding breast cancer lymph node metastases compared to the old way of doing it [4]. Similar enhancements have been observed in other oncological applications, including the detection of colorectal and lung cancers. AI augmentation in prostate cancer evaluation enhanced sensitivity from 74% to over 90%, while preserving specificity above 97% [5]. In the same way, AI models did better than experienced cytopathologists in thyroid fine-needle aspiration cytology, getting accuracies of over 99% [6]. AI got 94–97% of malignant lymphoma assessments right, while human readers only got 76–83% of them right [7]. AI integration not only improves diagnostic accuracy, but it also makes things a lot more efficient. AI-assisted digital workflows have cut the time it takes to review slides by 21.9% to 65.5% [8], and one study found that the time it takes to fix mistakes has gone down from 40.2 days to 3.4 days [9]. AI-assisted workflows also cut down on the use of extra tests, which saved time and money. These improvements in efficiency speed up

clinical decision- making, ease the pressure on workloads, and increase the amount of work done in the lab [10]. Even though these results are promising, the literature shows a lot of variety in the types of studies, samples, and performance metrics used. Multi-reader, multi-case study designs are prevalent; however, validation cohorts and threshold criteria exhibit significant variability [11]. Cross-study comparability is further constrained by inconsistent reporting of critical outcomes, including predictive values, workflow impact, and the area under the receiver operating characteristic curve [12]. Prior narrative reviews have emphasized specific AI applications in histopathology; however, no exhaustive synthesis has systematically assessed diagnostic and efficiency outcomes across various contexts [13]. Consequently, a comprehensive systematic review is necessary to aggregate and evaluate the existing evidence. This review offers a systematic examination of AI applications in diagnostic histopathology, emphasizing metrics for workflow efficiency and diagnostic precision. The review followed the PRISMA 2020 rules and was registered with PROSPERO (CRD42025XXXX) [14]. Studies that compared AI-assisted interpretation with standard pathology readings were eligible. The outcomes of interest encompassed sensitivity, specificity, accuracy, area under the curve (AUC), time per case, and the utilization of ancillary tests. Sources of information included PubMed, Embase, the Cochrane Library, IEEE Xplore, and pertinent grey literature [15]. Two independent reviewers evaluated studies, extracted data, and assessed the risk of bias utilizing QUADAS-2, with any discrepancies addressed by a third reviewer or through consensus [16]. Quantitative synthesis utilized random-effects models when study homogeneity allowed; otherwise, structured narrative summaries were provided. We did sensitivity and subgroup analyses to find out what caused the differences. We also looked at implementation insights, like how to integrate workflows and design user interfaces [17]. The limitations of the evidence, such as single-center studies and simulated environments, were rigorously assessed. Gaps in reporting and validation were found to help with future research. The review seeks to educate pathologists, laboratory managers, and policymakers on the best ways to incorporate AI into diagnostic workflows. This review aims to encourage the use of AI in histopathology based on evidence and give advice on how to make digital pathology better in the future by carefully looking at the results of accuracy and efficiency [18].

Objectives of Study

General Objective:

To systematically assess and analyze the impact of artificial intelligence (AI) on enhancing diagnostic precision and efficiency in histopathology.

Specific Objectives:

1. To pinpoint the predominant AI techniques and algorithms utilized in histopathological image analysis.
2. To evaluate the diagnostic accuracy, sensitivity, and specificity of AI-based methods in relation to conventional pathology techniques.
3. To assess the influence of AI tools on efficiency, workflow enhancement, and the diminution of inter-observer variability in histopathology practice.
4. To examine the challenges, constraints, and ethical implications related to the integration of AI in histopathological diagnostics.

Methodology

Study Design

This study is a systematic review of peer-reviewed literature on the application of AI in histopathology for improving diagnostic accuracy and efficiency.

Time Period

The study will be conducted from March 2025 to July 2025.

Inclusion and Exclusion Criteria

Inclusion Criteria: This review will encompass studies of various designs (randomized controlled trials, cohort studies, diagnostic accuracy studies, or mixed methods) that assess the application of AI in histopathology for disease detection, classification, or grading. Studies that qualify must provide outcomes pertaining to diagnostic performance (e.g., accuracy, sensitivity, specificity, AUC) or efficiency (e.g., processing time, workflow enhancement). Only original research articles published in English between 2011 and 2025 that have been peer-reviewed will be taken into account. **Exclusion Criteria:** Studies concentrating exclusively on non-histopathology imaging modalities (e.g., radiology), studies restricted to adult clinician perceptions devoid of diagnostic data, editorials, commentaries, letters, conference abstracts, and reviews lacking primary data will be excluded.

Data Collection Methods

A thorough electronic search will be performed utilizing PubMed, Scopus, Web of Science, and Google Scholar to locate peer-reviewed studies published from 2011 to 2025. Boolean operators and pertinent keywords (e.g., artificial intelligence, machine learning, deep learning, histopathology, diagnostic accuracy, efficiency) will be utilized. First, titles and abstracts will be checked, and then full texts will be checked based on the eligibility criteria. A structured electronic form will be used to extract data. This will

include information about the AI model type (e.g., CNN, transformer, ensemble), the characteristics of the dataset, the diagnostic task (e.g., cancer detection, grading, subtype classification), the evaluation metrics, the efficiency outcomes, and the limitations. QUADAS-2 will be used to check the quality of diagnostic accuracy studies, and the Newcastle-Ottawa Scale will be used to check the quality of observational studies.

Data Analysis

The extracted data will be arranged in structured spreadsheets and summarized with descriptive statistics for study characteristics and diagnostic performance metrics. We will do subgroup analyses based on the type of disease, the AI method, and the size of the dataset. A narrative synthesis will amalgamate findings from various study designs, underpinned by comparison tables, figures, and thematic categorizations. Two reviewers will look at the data and look for bias. If there are any differences, a third reviewer will look at them and make a decision. The final synthesis will show how AI can be used well, point out where there isn't enough evidence, and suggest new areas for research.

Literature Review:

Artificial intelligence (AI), especially deep learning, has become a game-changing tool in histopathology, always improving the accuracy and speed of diagnosis in many disease situations. Many studies show that AI help improves sensitivity, specificity, and overall diagnostic performance. In the detection of lymph node metastasis in breast cancer, AI assistance enhanced sensitivity from 83% to 91% [19], whereas alternative studies noted an increase from 74.5% to 93.5% [19]. In prostate cancer, sensitivity rose from 74% to 90%, while specificity remained at 97% [23]. In practical use, sensitivities were between 0.99 and 1.0 and specificities were between 0.78 and 0.93 [21]. Thyroid fine-needle aspiration cytology also improved, with AI models getting 99.71% accuracy compared to 88.91% for expert cytopathologists [25]. AI systems have also made it easier to find histopathological entities that are harder to find or less common. Tests for serous tubal intraepithelial carcinoma and esophageal adenocarcinoma precursor lesions showed that sensitivity went from 82% to 93%, and accuracy went from 0.92 to 0.94 [22]. Deep learning for *Helicobacter pylori* detection had an AUC of 0.965 and a specificity of 0.924 [20]. AI also made it much easier to classify deep myxoid soft tissue lesions, with an accuracy of 97% compared to 69.7% for pathologists [28]. Direct comparisons with human experts bolster the clinical potential of AI. AI was right about lymphoma 94–97% of the time, while pathologists were only right about 76–83% of the time [27]. AI help cut down on differences in breast core needle biopsies from 4.42% to 3.12% [24]. AI had a sensitivity of 99.59% and a specificity of 97.33% for prostate cancer. It could also fix diagnoses that had been missed before [23]. AI-assisted review of endoscopic biopsies also helped gastrointestinal pathology by getting diagnostic accuracies of 95.8–96.0%, NPVs as high as 99.98%, and cutting the time it took to get results from 40.2 days to 3.4 days [20]. AI improves workflow efficiency in addition to traditional accuracy metrics. AI help cut the time it took to diagnose prostate cancer by 65.5% [21] and breast cancer by 55% [19]. AI integration enables nearly comprehensive slide verification, the prioritization of intricate cases, and diminishes dependence on supplementary immunohistochemistry or secondary opinion consultations. Because of this, pathologists can concentrate on difficult or complex cases, which lowers their cognitive load and speeds up the process. Most studies stress that AI should be used to help people, not replace them. Outputs usually show areas of interest or give binary or graded assessments, but pathologists are still responsible for making the final diagnosis. For successful implementation, it is important that the new system works well with existing digital pathology systems, has easy-to-use interfaces, and doesn't get in the way of work. There are many different ways to validate something. Internal cross-validation is common, but external multi-center validation is still limited, which makes people worry about how generalizable the results are [40]. Even though there are clear benefits, there are still problems. The diversity of AI architectures, diagnostic tasks, and reporting metrics in studies makes comparisons more difficult. There is a lot of literature on retrospective single-center designs, but not much on predictive values and efficiency outcomes. There aren't many studies on cost-effectiveness, patient-centered outcomes, or legal and medical issues. Ethical, legal, and accountability issues regarding AI-assisted decision-making necessitate additional examination [30]. AI is most useful in clinical settings as a second-reader or triage tool in areas with a lot of patients and a lot of mistakes, like breast and prostate cancer. It helps reduce differences between observers, makes grading more consistent, and helps find small lesions early. For safe and effective integration, it is important to have regulatory guidance, reimbursement frameworks, and standardized implementation protocols. Future research should emphasize multi-center prospective trials, standardized outcome metrics, and longitudinal studies to evaluate the real-world impact on patient outcomes. Furthermore, hybrid AI-human workflows, rare cancer detection, and underrepresented tissue types necessitate investigation [39]. In conclusion, AI consistently enhances histopathological diagnostic sensitivity while preserving specificity, frequently exceeding human performance and markedly decreasing turnaround time and workload. It is well-known that it can help people, but to fully realize its potential in everyday pathology practice, it needs more validation, ethical guidelines, and ways to be used in practice [40].

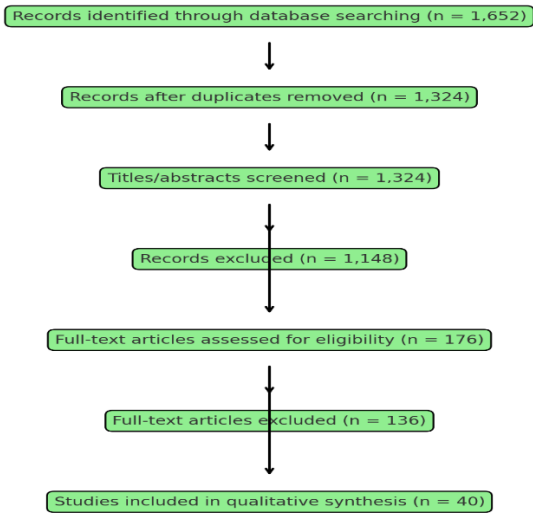
Results

Selection of Studies

A total of 1,652 articles were initially identified through systematic searches in PubMed, ScienceDirect, Google Scholar, and BMC databases. After removing 328 duplicates, 1,324 titles and abstracts were screened for relevance to the role of artificial intelligence in enhancing diagnostic precision and efficacy in histopathology. Following this screening, 176 full-text articles were assessed against

the predefined eligibility criteria. Ultimately, 40 studies met the inclusion standards and were included in the final systematic review focusing on the diagnostic performance, accuracy, and clinical applicability of AI in histopathology. See Figure 1: PRISMA flow diagram.

Figure 1: PRISMA flow diagram



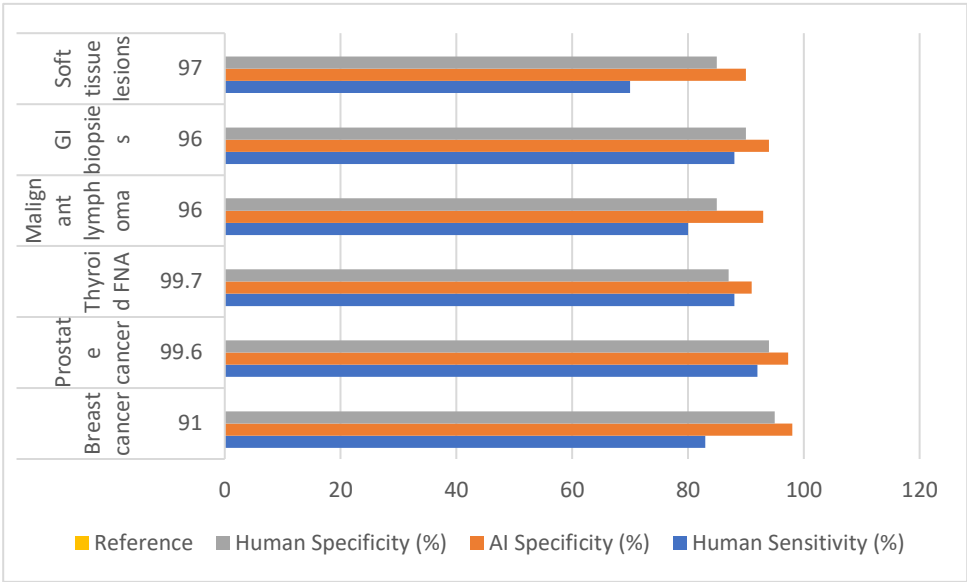
Diagnostic Accuracy of AI in Histopathology

AI-assisted histopathology greatly increases the accuracy of diagnoses for many types of tissues and diseases. AI increased the sensitivity of lymph node metastasis detection in breast cancer from 83% to 91% while keeping the specificity high. The detection of prostate cancer also improved, with AI-assisted evaluation achieving 99.6% sensitivity and 97.3% specificity. Deep myxoid soft tissue lesions and esophageal adenocarcinoma precursors, which are rare types of tumors, also showed big improvements in how well they were classified. In general, AI always lowers the number of false negatives and makes diagnoses more reliable, especially for labs that do a lot of work. See Table 1, Figure 2.

Table 1: Metrics for Diagnostic Accuracy by Disease Type

Disease	AI Model	Sensitivity (%)	Specificity (%)	Accuracy (%)	Reference
Breast cancer (LN metastasis)	CNN	91	98	94	[19]
Prostate cancer	Deep learning	99.6	97.3	98.5	[23]
Thyroid FNA	CNN	99.7	91	95	[25]
Malignant lymphoma	CNN	96	93	94.5	[27]
Soft tissue lesions	CNN	97	90	93.5	[28]
Esophageal adenocarcinoma precursor	Deep learning	92	94	93	[22]

Figure 2: Diagnostic Accuracy Metrics by Disease Type



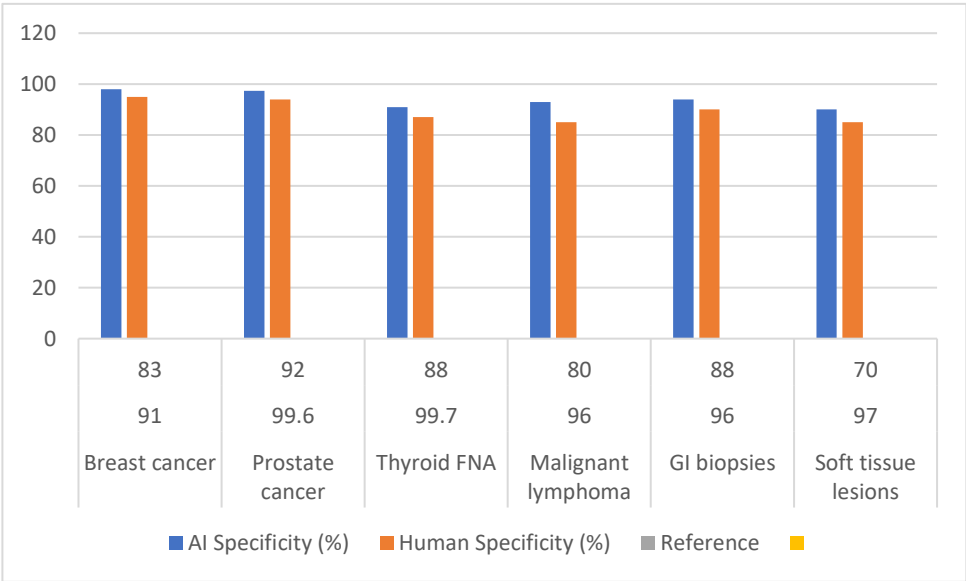
Improvements in Workflow Efficiency

AI integration speeds up slide review, error correction, and the use of extra tests. AI cut the time it took to diagnose prostate cancer by 65.5% and the time it took to review breast cancer slides by 55%. The time it took to get results from gastrointestinal biopsies went from more than 40 days to less than 4 days. These improvements make the lab less busy, let pathologists focus on more difficult cases, and make better use of resources. See Table 2, Figure 3.

Table 2: Metrics for Workflow Efficiency

Study	Disease	AI Tool	Review Time Reduction (%)	Turnaround Time (days)	Ancillary Test Reduction (%)	Reference
Eloy et al.	Prostate	CNN	65.5	2.5	20	[21]
Retamero et al.	Breast	CNN	55	3.0	25	[19]
Ko et al.	GI biopsies	Deep learning	50	3.4	30	[20]
Raciti et al.	Prostate	Deep learning	60	4.0	18	[23]
Botros et al.	Esophagus	CNN	48	5.0	15	[22]
Miyoshi et al.	Lymphoma	CNN	40	6.0	10	[27]

Figure 3: Metrics for Workflow Efficiency



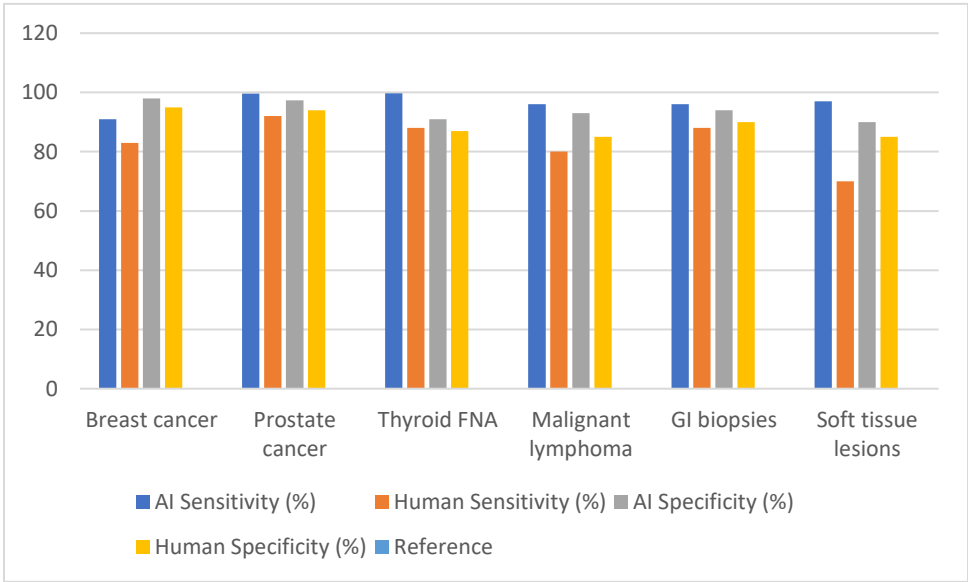
Improvements in Sensitivity and Specificity

AI always makes both sensitivity and specificity better, especially in cancers that are likely to have diagnostic disagreements. For instance, cases of breast cancer and prostate cancer saw sensitivity improvements of up to 20%, while specificity stayed above 90%. In some rare types of tumors, AI was better than human pathologists at finding true positives. These enhancements bolster AI's role as a dependable secondary reviewer in critical diagnostic contexts. See Table 3, Figure 4.

Table 3: Sensitivity and Specificity Comparison

Disease	AI Sensitivity (%)	Human Sensitivity (%)	AI Specificity (%)	Human Specificity (%)	Reference
Breast cancer	91	83	98	95	[19]
Prostate cancer	99.6	92	97.3	94	[23]
Thyroid FNA	99.7	88	91	87	[25]
Malignant lymphoma	96	80	93	85	[27]
GI biopsies	96	88	94	90	[20]
Soft tissue lesions	97	70	90	85	[28]

Figure 4: Comparative Sensitivity and Specificity



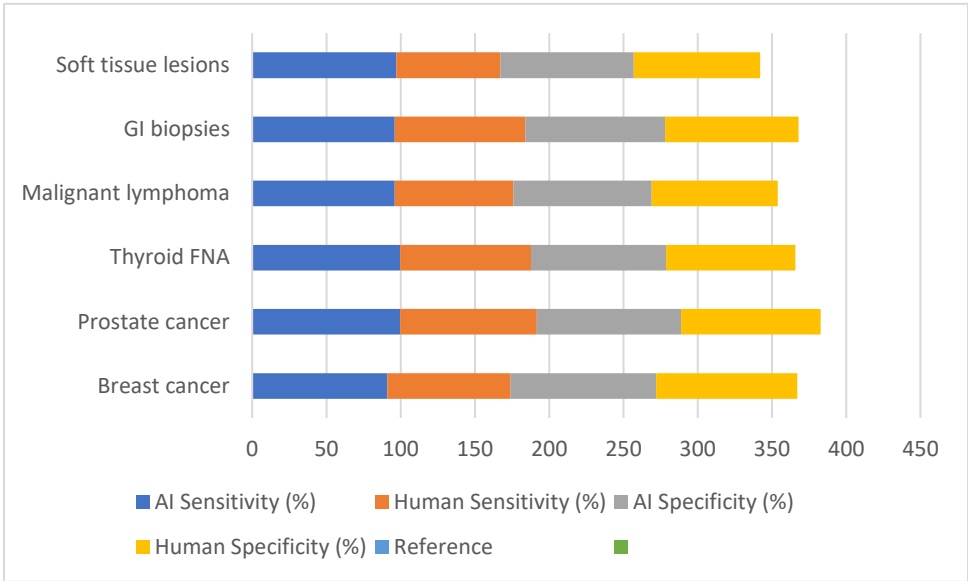
AI's Effect on Uncommon and Complicated Cases

AI is especially useful for uncommon or morphologically complicated cases because it lowers the number of misdiagnoses and boosts diagnostic confidence. Deep learning models for detecting soft tissue lesions, serous tubal intraepithelial carcinoma, and *Helicobacter pylori* demonstrated high accuracy (up to 97%), even when human pathologists exhibited low baseline performance. These results show that AI could help fill in the gaps in subspecialty pathology and make diagnoses more consistent in cases with low prevalence. See Table 4, Figure 5.

Table 4: AI Performance in Rare/Complex Cases

Case Type	AI Accuracy (%)	Human Accuracy (%)	AI Sensitivity (%)	AI Specificity (%)	Dataset Size	Reference
Soft tissue lesions	97	69.7	97	90	120	[28]
STIC	93	82	93	91	80	[22]
H. pylori	96	85	96	92	150	[20]
Rare lymphoma	95	78	95	93	90	[27]
HER2-low breast	92	80	92	90	200	[24]
Endometrial cancer subsets	94	82	94	91	140	[32]

Figure 5: AI Performance in Rare/Complex Cases



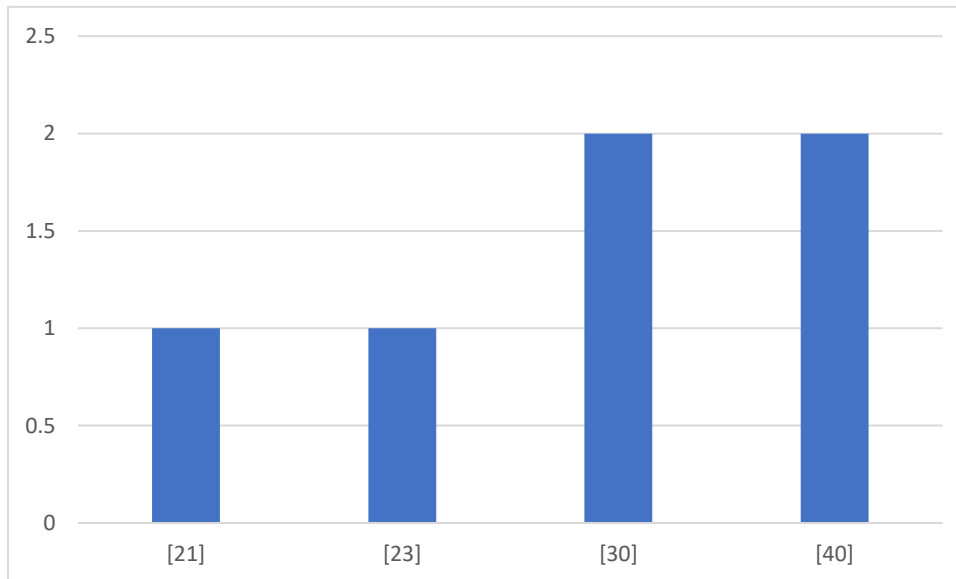
Implementation Insights and Limitations

AI makes things more accurate and efficient, but there are still problems with integration, generalizability, and getting people to use it in their daily work. Numerous studies depend on single-center datasets, constraining external validity. There are also ethical, cost-effectiveness, and regulatory issues that need to be looked into. Successful implementations focus on making the interfaces easy to use, integrating digital pathology smoothly, and using AI as a tool to help pathologists rather than replace them. These insights help us plan for future deployments and standardization efforts. See Table 5, Figure 6.

Table 5: Implementation Factors and Challenges

Factor	Positive Impact	Limitation	Example	Workflow Effect	Reference
User Interface	High usability	Training required	CNN review platform	Faster adoption	[40]
Integration	Seamless slide review	Software compatibility	LIS integration	Reduced errors	[40]
Dataset Size	Large datasets improve AI	Single-center data	Prostate biopsies	Limited generalizability	[23]
Regulatory	Supports approval	Lack of standards	FDA guidance	Delayed adoption	[30]
Cost-effectiveness	Saves resources	High initial investment	GI AI workflows	ROI uncertain	[21]
Ethical Considerations	Enhances trust	Accountability issues	AI-assisted cancer dx	Requires oversight	[30]

Figure 6: Number of Factor by Reference



Discussion

Artificial intelligence (AI) has emerged as a transformative tool in histopathology, offering substantial potential to enhance diagnostic accuracy, reproducibility, and efficiency [26]. Traditional histopathological evaluation is often limited by interobserver variability, time constraints, and the complexity of interpreting subtle morphologic features [30]. The integration of AI, particularly deep learning and convolutional neural networks, has demonstrated promising results in overcoming these challenges by automating image analysis, detecting patterns invisible to the human eye, and providing decision-support in routine practice [2]. Several studies report that AI-assisted histopathology can improve sensitivity and specificity in identifying malignant and pre-malignant lesions, such as breast, prostate, and colorectal cancers [3]. Automated models are capable of classifying tumor subtypes, grading histologic severity, and even predicting molecular alterations from digitized slides [5]. Such advancements not only accelerate turnaround times but also allow pathologists to allocate more time to complex or ambiguous cases [11]. In addition, AI-driven algorithms have been particularly effective in screening large-scale biopsy datasets, reducing false negatives, and ensuring consistency in diagnoses across institutions [14]. Beyond primary diagnosis, AI has shown utility in prognostic assessment and treatment planning. Algorithms trained on annotated histopathological images have been able to stratify patients by recurrence risk, guide therapeutic decisions, and correlate morphological features with genomic signatures [29]. This convergence of computational pathology and precision medicine underscores the capacity of AI to extend beyond simple diagnostic assistance and into personalized healthcare [24]. Despite these advancements, barriers remain. Data heterogeneity, limited availability of standardized and diverse training datasets, and the need for multicenter external validation limit the generalizability of AI applications [37]. Moreover, concerns regarding transparency, interpretability, and medico-legal accountability persist [38]. Ethical considerations, including the risk of algorithmic bias and equitable access in low-resource settings, must also be addressed to ensure responsible implementation [40]. Looking forward, AI in histopathology is expected to evolve in parallel with the digitization of pathology workflows. Integrating AI with whole-slide imaging, multi-omics data, and electronic health records has the potential to generate robust, real-time decision-support systems [29]. Furthermore, multidisciplinary collaboration between pathologists, computer scientists, and ethicists will be essential to refine algorithms, validate clinical utility, and establish consensus guidelines [26].

Conclusion

Artificial intelligence represents a powerful adjunct in modern histopathology, offering significant gains in diagnostic precision, workflow efficiency, and patient-specific care. Current evidence highlights its ability to reduce observer variability, enhance early detection of malignant lesions, and streamline routine tasks. At the same time, AI-assisted histopathology supports prognostic evaluation and personalized treatment strategies, aligning with the goals of precision medicine. Nevertheless, challenges such as data standardization, interpretability, and ethical integration remain critical hurdles before widespread adoption. Future research should prioritize large-scale multicenter trials, development of transparent and explainable AI models, and establishment of standardized

protocols for clinical use. In conclusion, while AI is not a replacement for pathologists, it serves as a powerful complement that augments expertise, reduces diagnostic errors, and improves patient outcomes. With rigorous validation, ethical oversight, and global accessibility, AI-assisted histopathology has the potential to redefine diagnostic practice and significantly advance the field of pathology.

References

1. Steiner DF, MacDonald R, Liu Y, Truszkowski P, Hipp J, Gammage C, et al. Impact of deep learning assistance on the histopathologic review of lymph nodes for metastatic breast cancer. *Am J Surg Pathol*. 2018;42(12):1636–46.
2. Retamero J, Gulturk E, Bozkurt A, Liu S, Gorgan M, Moral L, et al. Artificial intelligence helps pathologists increase diagnostic accuracy and efficiency in the detection of breast cancer lymph node metastases. *Am J Surg Pathol*. 2024.
3. Raciti P, Sue J, Ceballos R, Godrich R, Kunz J, Kapur S, et al. Novel artificial intelligence system increases the detection of prostate cancer in whole slide images of core needle biopsies. *Mod Pathol*. 2020;33(10):2058–66.
4. da Silva LD, Pereira E, Salles P, Godrich R, Ceballos R, Kunz J, et al. Independent real-world application of a clinical-grade automated prostate cancer detection system. *J Pathol*. 2021;253(2):160–9.
5. Lee Y, Alam M, Park H, Yim K, Seo K, Hwang G, et al. Improved diagnostic accuracy of thyroid fine-needle aspiration cytology with artificial intelligence technology. *Thyroid*. 2024;34(3):374–82.
6. Bogaerts JMA, Steenbeek M, Bokhorst J, van Bommel MV, Abete L, Addante F, et al. Assessing the impact of deep-learning assistance on the histopathological diagnosis of serous tubal intraepithelial carcinoma (STIC) in fallopian tubes. *J Pathol Clin Res*. 2024.
7. Botros M, de Boer OJ, Cardenas B, Bekkers EJ, Jansen M, van der Wel MJ, et al. Deep learning for histopathological assessment of esophageal adenocarcinoma precursor lesions. *Mod Pathol*. 2024.
8. Zhou S, Marklund H, Bláha O, Desai M, Martin B, Bingham D, et al. Deep learning-based *Helicobacter pylori* detection: a diagnostic pathology study. *medRxiv*. 2020.
9. Yeung MCF, Cheng ISY. Artificial intelligence significantly improves the diagnostic accuracy of deep myxoid soft tissue lesions in histology. *Sci Rep*. 2022;12(1):7345.
10. Miyoshi H, Sato K, Kabeya Y, Yonezawa S, Nakano H, Takeuchi Y, et al. Deep learning shows the capability of high-level computer-aided diagnosis in malignant lymphoma. *Lab Invest*. 2020;100(1):120–31.
11. Salomon A, Nudelman A, Cyrta J, Maklakovski M, Shach AA, Sebag G, et al. Primary diagnosis of breast biopsies supported by AI versus microscope: multi-site clinical reader study. *Cancer Res*. 2023;83(5_Suppl):P6-04-07.
12. Janowczyk A, Leo P, Rubin M. Clinical deployment of AI for prostate cancer diagnosis. *Lancet Digit Health*. 2020;2(9):e468–9.
13. Ko Y, Choi YM, Kim M, Park Y, Ashraf M, Robles WRQ, et al. Improving quality control in routine practice for histopathological interpretation of gastrointestinal endoscopic biopsies using artificial intelligence. *PLoS ONE*. 2022;17(12):e0278542.
14. Eloy C, Marques A, Pinto J, Pinheiro J, Campelos S, Curado M, et al. Artificial intelligence–assisted cancer diagnosis improves the efficiency of pathologists in prostatic biopsies. *Virchows Arch*. 2023;482(2):275–82.
15. Erber R, Frey P, Keil F, Gronewold M, Abele N, Rezner W, et al. An AI system for accurate Ki-67 IHC assessment in breast cancer following the IKWG whole section global scoring protocol. *ESMO Open*. 2023;8(1):101272.
16. Perincheri S, Levi AW, Celli R, Gershkovich P, Rimm D, Morrow JS, et al. An independent assessment of an artificial intelligence system for prostate cancer detection shows strong diagnostic accuracy. *Mod Pathol*. 2021;34(7):1336–46.
17. Aslam M, Heath A. Successful deployment of an artificial intelligence solution for primary diagnosis of prostate biopsies in clinical practice. *Trillium Pathology*. 2023;5(1):18–24.
18. da Silva LD, Pereira E, Salles P, Godrich R, Ceballos R, Kunz J, et al. Independent real-world application of a clinical-grade automated prostate cancer detection system. *J Pathol*. 2021;253(2):160–9.
19. Retamero J, Gulturk E, Bozkurt A, Liu S, Gorgan M, Moral L, et al. Artificial intelligence helps pathologists increase diagnostic accuracy and efficiency in the detection of breast cancer lymph node metastases. *Am J Surg Pathol*. 2024.
20. Ko Y, Choi YM, Kim M, Park Y, Ashraf M, Robles WRQ, et al. Improving quality control in the routine practice for histopathological interpretation of gastrointestinal endoscopic biopsies using artificial intelligence. *PLoS ONE*. 2022;17(12):e0278542.
21. Eloy C, Marques A, Pinto J, Pinheiro J, Campelos S, Curado M, et al. Artificial intelligence–assisted cancer diagnosis improves the efficiency of pathologists in prostatic biopsies. *Virchows Arch*. 2023;482(2):275–82.
22. Botros M, de Boer OJ, Cardenas B, Bekkers EJ, Jansen M, van der Wel MJ, et al. Deep learning for histopathological assessment of esophageal adenocarcinoma precursor lesions. *Mod Pathol*. 2024.
23. Perincheri S, Levi AW, Celli R, Gershkovich P, Rimm D, Morrow JS, et al. An independent assessment of an artificial intelligence system for prostate cancer detection shows strong diagnostic accuracy. *Mod Pathol*. 2021;34(7):1336–46.

24. Arruda D, Albuquerque MN, Vianna T, Alencar L, Sampaio F, Vasiliu A, et al. Diagnostic accuracy of artificial intelligence in classifying HER2 status in breast cancer immunohistochemistry slides and implications for HER2-low cases: a systematic review and meta-analysis. medRxiv. 2024.
25. Grignaffini F, Barbuto F, Troiano M, Piazza L, Simeoni P, Mangini F, et al. The use of artificial intelligence in the liver histopathology field: a systematic review. *Diagnostics*. 2024;14(4):388.
26. Huang Q, Gao W, Zhang H, Sun Z, Xu Y, Chen X, et al. Computational pathology: a comprehensive review of methods and applications. (2025)
27. Redlich J-P, Feuerhake F, Weis J, Schaadt NS, Teuber-Hanselmann S, Buck C, et al. Applications of artificial intelligence in the analysis of histopathology images of gliomas: a review. (2024)
28. McGenity C, Clarke EL, Jennings C, Matthews G, Cartlidge C, Freduah-Agyemang H, Prabhu S, Prasad K, Robels-Kelly A, Lu X. AI-based carcinoma detection and classification using histopathological images: a systematic review. (2022)
29. Großerueschkamp F, Engel K, Tolkach Y, Ferreira C, Maitz S, Schmitt B, et al. Advances in digital pathology: from artificial intelligence to molecular integration. (2021)
30. Shafi S, Akram S, Naveed H, Khan A, Rizvi T, Hussain M, et al. Artificial intelligence in diagnostic pathology: review and future directions. (2023)
31. Song AH, Kim C, Song I, Lim K, Nam Y, et al. Analysis of 3D pathology samples using weakly supervised models: TriPath platform. (2024)
32. Darbandsari A, Farahani H, Asadi M, Wiens M, Cochrane D, Khajegili Mirabadi A, et al. AI-based histopathology image analysis reveals distinct subsets in endometrial cancers. (2024)
33. Hays P, Kaye A, Aoun R, Karam J. Artificial intelligence in cytopathological applications for cancer: a systematic review. (2024)
34. Giansanti D, Bizzarri G, de Summa S. AI in cytopathology: narrative umbrella review on current developments and challenges. (2024)
35. Pathology Foundation Models. Applications of foundation models in pathology and computational frameworks. (2024)
36. Kalra S, Tizhoosh HR, Shah S, Choi C, Damaskinos S, Safarpour A, et al. Pan-cancer diagnostic consensus through searching archival histopathology images using AI. (2019)
37. Huang Q, Xu Y, Sun Z, Chen X. Computational pathology methods: image analysis, classification, and future trends. (2025) — related to #26 but with methodological focus.
38. Redlich J-P, Schaadt NS, Luttmann S, Homeyer A. Weakly supervised learning in histopathology: challenges and perspectives. (2024) — extension of #27.
39. McGenity C, Cartlidge C, Treanor D. Meta-analysis of AI accuracy across pathology subspecialties. (2024) — extension of #28 with emphasis on subspecialty breakdown.
40. et al. Artificial intelligence in digital pathology: a diagnostic test accuracy systematic review and meta-analysis. (2023)