

Artificial Intelligence for Cervical Cancer Histopathology in Sub-Saharan Africa: A Systematic Review of Segmentation, Classification Techniques, and Barriers to Deployment

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Systematic Review

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Abstract

Background and Objective

Cervical cancer remains a major cause of morbidity and mortality in Sub-Saharan Africa (SSA), where access to pathology expertise, screening, tissue diagnosis and digital pathology infrastructure is uneven. Histopathological examination remains central to confirming cervical neoplasia, grading lesions and guiding management. Artificial intelligence (AI) offers opportunities to support pathologists by automating image segmentation and classification, but evidence on clinical generalisability and deployment in SSA is fragmented. This systematic review synthesizes AI techniques for cervical histopathology segmentation and classification and examines barriers to translation into routine practice in SSA.

Methods

A structured systematic evidence synthesis was prepared and reported with reference to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020). Contemporary evidence was identified from PubMed/MEDLINE, Scopus, Web of Science, IEEE Xplore and Google Scholar searches and from reference chaining of relevant systematic reviews. Eligible evidence addressed cervical histopathology or closely related cervical image-analysis tasks involving segmentation, feature learning, classification, whole-slide analysis, clinical validation or deployment. The synthesis focused on 49 substantive publications spanning classical image processing, machine learning, CNNs, transfer learning, U-Net-family and other segmentation methods, attention/transformer models, whole-slide analysis, African studies and digital-pathology implementation.

Results

The evidence shows a transition from thresholding, clustering, watershed, active contours and handcrafted morphological/texture features toward CNN-based segmentation and classification, transfer learning, multiple-instance learning, attention models and transformer/foundation-model approaches. Early studies were frequently based on small, pre-segmented public datasets, whereas newer studies increasingly use histology images and whole-slide images. African evidence remains limited but is expanding. An Ethiopian study used 915 histopathology images and EfficientNetB0, reporting 94.5% test accuracy for cervical cancer classification. A 2026 Rwandan study used 885 patient-level H&E cervical biopsy images and reported EfficientNetB0 accuracy of 0.99 with ROC-AUC 0.99 on a held-out test set. A Ugandan study used 5,966 cervical histopathology images acquired with smartphone-assisted microscopy and DeepLabV3 + with a ResNet34 encoder for 21-feature segmentation, reporting validation mIoU of approximately 75.8% and Dice of approximately 93.1%.

Conclusion

AI has substantial potential to augment cervical histopathology in SSA, but reported algorithmic performance should not be interpreted as evidence of clinical readiness. The dominant evidence gaps are external validation, prospective evaluation, multi-institutional datasets, standardised staining and imaging, transparent reporting, calibration, explainability, workflow integration and implementation economics. Future research should prioritize locally representative datasets, lightweight and edge-capable models, patient-level validation, human-in-the-loop decision support and implementation studies conducted within African pathology workflows.

1.0 Introduction

Cervical cancer is a major global health problem with marked geographic inequalities. Contemporary global estimates show that the disease burden is disproportionately concentrated in low- and middle-income countries, including countries in Sub-Saharan Africa. The World Health Organization global elimination strategy emphasizes prevention, screening, diagnosis and treatment as interconnected components of cervical cancer control. In SSA, these components are

constrained by limited laboratory capacity, shortages of specialist personnel, delayed presentation, uneven access to screening and treatment, and differences in health-system infrastructure [1–4].

Histopathology is an essential component of the diagnostic pathway when tissue is obtained. Conventional assessment requires fixation, processing, sectioning, staining, microscopic examination and interpretation by trained personnel. Although the method remains indispensable, manual interpretation is time-intensive and can be affected by interobserver and intraobserver variability, particularly in borderline lesions. These constraints have stimulated interest in digital pathology and AI-assisted image analysis [5–9].

Cervical image-analysis systems can be conceptualized as workflows involving image acquisition, preprocessing, segmentation or localization, feature learning and classification. Earlier studies frequently relied on curated or pre-segmented datasets, whereas more recent research increasingly evaluates models on histopathology and whole-slide images. This review therefore focuses specifically on tissue histopathology, segmentation, classification and deployment considerations in Sub-Saharan Africa.

AI in histopathology has evolved from handcrafted measurements of size, shape, colour and texture to end-to-end deep learning. CNNs can learn hierarchical image representations without explicit feature engineering, while residual networks, DenseNet, EfficientNet, attention mechanisms, multiple-instance learning and transformers have expanded model capacity. Whole-slide imaging has also enabled slide-level analysis, although the gigapixel scale of pathology images introduces challenges in storage, patch selection, computational cost and weak supervision [10–18].

The relevance of these developments to SSA is twofold. First, AI could potentially increase access to specialist-level decision support where pathology workforce capacity is limited. Second, the infrastructure needed to digitise, store, transmit and process pathology images can itself be difficult to sustain in low-resource settings. Therefore, a useful review must assess not only algorithmic performance but also whether the underlying technologies are compatible with local laboratory workflows.

1.1 Cervical Histopathology and Diagnostic Features

Cervical histopathology evaluates architectural and cytological changes across the spectrum from normal epithelium through cervical intraepithelial neoplasia (CIN) to invasive malignancy. Relevant image features include nuclear enlargement, hyperchromasia, pleomorphism, abnormal mitotic activity, altered nuclear-to-cytoplasmic ratio, epithelial maturation, architectural disorganization, keratinisation, glandular patterns, stromal invasion and the relationship between epithelial and stromal compartments. AI systems can model these features at cell, region, patch or whole-slide levels [3, 7, 13, 19–24].

Segmentation is important because it establishes the spatial units from which morphological features are learned. Depending on the task, segmentation may target nuclei, cytoplasm, epithelium, tumour regions, glands, keratin pearls, abnormal mitoses or broader tissue compartments. Classification can then operate on segmented objects, image patches or whole-slide representations.

1.2 Image Analysis Features and Data Sources

Early cervical image-analysis studies commonly used open datasets such as Herlev and related Pap-smear collections. These studies provided important benchmarks for segmentation and classification, but their images were often highly curated and did not necessarily represent the variation encountered in routine histopathology laboratories. Histopathology studies increasingly use H&E-stained biopsy images, region-of-interest patches and whole-slide images. African studies add an important dimension by providing data acquired within local laboratory environments rather than exclusively from public datasets [7, 8, 25].

Variation can occur at multiple levels: fixation, tissue processing, section thickness, H&E staining, scanner optics, magnification, camera settings, compression, image resolution, tissue artefacts, disease prevalence and case mix. These factors can cause domain shift between development and deployment sites. Patient-level splitting is therefore essential to prevent the same patient's morphology or staining characteristics appearing in both training and test datasets.

1.3 Automated Histopathology Analysis

The general AI-assisted histopathology workflow consists of image acquisition, preprocessing, segmentation or region localization, feature learning, classification and clinical interpretation. This workflow provides a useful framework for describing contemporary AI systems, although modern deep learning can combine feature extraction and classification within a single model. For whole-slide images, a practical system commonly adds tissue detection, tiling, patch-level inference and aggregation to a slide-level prediction. (Table 1).

1.3.1 Stages and Techniques Used in Automated Histopathology

Image acquisition may use conventional microscopy coupled to a camera, whole-slide scanners or lower-cost smartphone-assisted microscopy. Preprocessing may include resizing, colour normalization, stain normalization, background removal, artifact filtering and augmentation. Segmentation methods range from thresholding, clustering, watershed, active contours and graph cuts to U-Net, DeepLabV3+, fully convolutional networks, attention networks and transformer-based models. Classification approaches include support vector machines, random forests, k-nearest neighbours, conventional neural networks, ResNet, DenseNet, EfficientNet, Xception, ensemble models, multiple-instance learning and transformer architectures [10–18, 26–33].

2.0 Methods

This review was prepared as a structured systematic evidence synthesis and was reported with reference to the PRISMA 2020 statement [50]. The review question, eligibility criteria, information sources, data items and synthesis approach were defined around AI-assisted cervical histopathology, image segmentation, classification and implementation in Sub-Saharan Africa.

Search sources included PubMed/MEDLINE, Scopus, Web of Science, IEEE Xplore and Google Scholar, supplemented by backward and forward reference checking of relevant systematic reviews. Search concepts combined terms relating to artificial intelligence, cervical cancer, cervical intraepithelial neoplasia, histopathology, digital pathology, whole-slide imaging, segmentation, classification, deep learning, convolutional neural networks, transformers and Sub-Saharan Africa.

Studies were considered relevant when they reported development, evaluation, validation or implementation of AI/image-analysis methods for cervical tissue histopathology or closely related cervical microscopic image analysis. Evidence addressing segmentation, lesion classification, whole-slide analysis, explainability, clinical validation, digital pathology implementation and resource-limited deployment was included where it directly informed the review question. Purely genomic or non-image predictive models were not considered part of the core histopathology evidence. Cytology and colposcopy studies were used selectively when they provided evidence about deployment, workflow, validation or technology requirements relevant to tissue-based pathology.

Data extracted included publication year, country, image modality, dataset type, task, segmentation approach, classification architecture, validation design, reported metrics, explainability, hardware requirements and implementation barriers. Because the literature is heterogeneous in task definitions, datasets and outcome measures, a narrative synthesis was used rather than pooling accuracy estimates across incomparable studies.

The original search-export and deduplication records were not available for retrospective reconstruction. Consequently, exact database-specific record counts are not reported in this version rather than being estimated or fabricated. This

limitation should be considered when interpreting the review as a systematic evidence synthesis.

3.0 Results

Forty-nine substantive publications were synthesized across four overlapping evidence domains: (1) cervical histopathology classification and whole-slide analysis; (2) cervical cell/tissue segmentation and representation learning; (3) clinical validation and human-in-the-loop AI; and (4) digital pathology implementation and resource-limited deployment. The evidence shows a clear technological progression from handcrafted image processing to deep learning and increasingly integrated digital pathology workflows. (Table 2).

3.1 Survey of Existing Literature on Automated Cervical Histopathology Analysis

Early work established the importance of segmentation before classification. Song et al. developed a multiscale convolutional network with graph partitioning for cervical cytoplasm and nucleus segmentation, demonstrating the value of multiscale contextual features and coarse-to-fine refinement [44]. Sornapudi et al. subsequently introduced EpithNet for automated epithelium segmentation in cervical histology [45]. Hussain et al. combined a U-Net-derived architecture with residual and densely connected blocks and shape information for simultaneous nuclei segmentation and classification [46]. These studies illustrate the transition from explicit image-processing rules toward learned representations.

Histopathology classification has similarly progressed from conventional machine learning to transfer learning. Habtemariam et al. evaluated EfficientNetB0 using 915 histopathology images and reported a 94.5% test accuracy for cervical cancer classification, demonstrating the feasibility of transfer learning in an Ethiopian setting [7]. The study is important because it combines local data and a lightweight architecture rather than relying solely on high-resource datasets.

Whole-slide analysis has addressed the limitations of patch-level classification by aggregating information across very large digital slides. Cheng et al. reported a robust deep-learning framework for cervical cancer screening from whole-slide images, while later reviews documented the evolution of WSI pipelines toward multiscale analysis, attention and weak supervision [13, 11, 12]. The technical advantage of WSI analysis is broader tissue coverage; its disadvantages include very large files, high computational requirements and complex annotation.

Recent studies increasingly compare compact CNNs and use patient-level evaluation. A 2026 Rwandan study evaluated 885 H&E cervical biopsy images from the University Teaching Hospital of Kigali using ResNet50, EfficientNetB0 and DenseNet121. EfficientNetB0 achieved test accuracy 0.99, sensitivity 0.98, specificity 1.00 and ROC-AUC 0.99, while ResNet50 and DenseNet121 achieved lower accuracy and similar AUC values. The authors emphasized that the results remain a feasibility study requiring external, multicentre and prospective validation [8].

Ugandan evidence provides an example of a technology-appropriate segmentation pathway. Nakasi et al. used smartphone-assisted microscopy and DeepLabV3+ with a ResNet34 encoder on 5,966 cervical histopathology images from the Uganda Cancer Institute. The model targeted 21 histopathological feature classes and achieved validation mIoU of about 75.8% and Dice of about 93.1%, outperforming a U-Net baseline under the reported evaluation setting. Importantly, the authors characterize the work as proof of concept and call for independent multicentre validation [9].

Table 1
Evolution of AI Techniques for Cervical Histopathology Image Analysis

Generation	Typical techniques	Primary task	Strengths	Limitations
1. Classical image analysis	Thresholding, K-means/FCM, watershed, active contours, graph cuts	Nucleus/cytoplasm segmentation	Low computational burden; interpretable	Sensitive to staining, overlap and hand-tuned parameters
2. Conventional ML	KNN, SVM, random forest, decision trees	Feature-based classification	Works with small datasets; relatively simple	Requires handcrafted features; limited representation learning
3. Early CNN	CNN, MSCN, FCN, EpithNet	Segmentation and cell classification	Learns image features automatically	Often trained on small/curated datasets
4. Transfer learning CNN	ResNet, DenseNet, EfficientNet, Xception	Patch/ROI classification	Good performance with moderate data; efficient models available	Domain shift; risk of overfitting
5. Attention/WSI learning	MIL, attention, multiscale WSI models	Slide-level diagnosis	Uses broader tissue context	High compute and annotation complexity
6. Transformer/hybrid models	ViT, Swin, CNN-transformer hybrids	Classification/segmentation	Global contextual modelling	Data and computational requirements
7. Technology-appropriate AI	Lightweight CNNs, smartphone microscopy, edge AI	Local screening/triage	Potentially deployable with limited infrastructure	Requires rigorous local validation and workflow integration

Table 2
Representative Evidence Matrix of AI for Cervical Cancer and Digital Histopathology

No.	Evidence	Modality/task	AI/technical approach	Relevance to review
1	Li et al., 2025	Global cervical cancer burden	Epidemiology	SSA burden and inequalities
2	Singh et al., 2023	Global cervical cancer	WHO elimination initiative	Public-health context
3	Wang et al., 2024	Cervical image diagnosis	AI precision diagnosis	Modern AI trajectory
4	Liu et al., 2025	CIN/cervical cancer	Systematic review/meta-analysis	Performance evidence
5	Hou et al., 2022	Cervical screening/diagnosis	AI review	Technical landscape
6	Allahqoli et al., 2022	Cervical cancer/pre-cancer	AI systematic review	Evidence synthesis
7	Habtemariam et al., 2022	Cervical histopathology	EfficientNetB0	Ethiopian evidence
8	Nyabyenda et al., 2026	Cervical histopathology	ResNet50/EfficientNetB0/DenseNet121	Rwandan evidence
9	Nakasi et al., 2026	Cervical histopathology	DeepLabV3+/ResNet34	Ugandan segmentation
10	Cheng et al., 2021	Cervical WSI	Deep learning	WSI robustness
11	Sambyal & Sarwar, 2023	Cervical WSI	Deep learning review	Models/challenges
12	Khare et al., 2024	Cervical AI	Systematic review	Research gaps
13	Kanavati et al., 2022	Cervical WSI/cytology	Deep learning	WSI analysis
14	Ouh et al., 2024	CIN screening	AI software	Validation
15	Egemen et al., 2024	Cervical screening	Clinical AI testing	Translation lessons
16	Xue et al., 2023	Cervical squamous cells	Human-in-loop AI	Workflow support
17	Du et al., 2023	Cervical cytology	AI-assisted workflow	Efficiency
18	Bao et al., 2020	CIN/invasive cancer	Multicentre AI cytology	Clinical validation
19	Bai et al., 2024	Cervical cytology	AI assistive system	Clinical performance
20	Khamparia et al., 2020	Cervical cells	Transfer learning	Deep-learning development
21	Chandran et al., 2021	Cervix images	Ensemble deep learning	Ensemble approach

No.	Evidence	Modality/task	AI/technical approach	Relevance to review
22	Zhang et al., 2025	Cervical cells	Improved DenseNet121	Recent classification
23	Bhavsar & Shrimali, 2025	Cervical images	Transfer-learning ensemble	Hybrid models
24	Sarhangi et al., 2024	Pathology/colposcopy	Deep learning	Multimodal evidence
25	Mehedi et al., 2024	Cervical cancer types	Lightweight deep learning	Low-resource relevance
26	Jeleń et al., 2025	Cervical cancer	Feature selection/deep learning	Model optimization
27	Taddese et al., 2024	Gynaecological cancer images	Systematic review/meta-analysis	Performance synthesis
28	Sulaieva et al., 2024	Cancer pathology	Digital pathology implementation	Deployment
29	Zarella et al., 2023	Digital pathology	AI deployment review	Clinical integration
30	Xu et al., 2024	Digital pathology	Whole-slide foundation model	Foundation models
31	Qiao et al., 2022	Digital pathology	Multimodal AI	Multimodal future
32	Waqas et al., 2024	Oncology pathology	Multimodal learning	Data integration
33	Dellino et al., 2024	Cervical screening	AI review	Opportunities/challenges
34	Go, 2022	Digital pathology	AI applications	Infrastructure context
35	Xue et al., 2020	LMIC cervical screening	AI solutions	Resource-limited settings
36	Shen et al., 2023	Cervical screening	Cost-effectiveness	Economic evidence
37	Vargas-Cardona et al., 2024	Cervical screening	Scoping review	Global evidence map
38	Wu et al., 2024	Cervical screening	AI review	Implementation context
39	Giansanti et al., 2025	Cervical cytology	AI review	Recent models
40	Glučina et al., 2023	Cervical diagnosis	ML/class balancing	Data imbalance
41	Escalera et al., 2025	Cervical cytology	Low-cost platform	Low-resource design
42	Wang et al., 2025	Cancer pathology	AI review	Challenges/future
43	Aggarwal et al., 2025	Digital pathology	Reality-check review	Translation caution

No.	Evidence	Modality/task	AI/technical approach	Relevance to review
44	Song et al., 2015	Cervical microscopy	MSCN + graph partitioning	Segmentation
45	Sornapudi et al., 2020	Cervical histology	EpithNet	Epithelium segmentation
46	Hussain et al., 2020	Pap-smear microscopy	Shape-context FCNN/U-Net variant	Segmentation + classification
47	Srinidhi et al., 2021	Computational histopathology	Deep neural network survey	Methodological context
48	Campanella et al., 2019	WSI pathology	Weakly supervised DL	WSI/weak supervision
49	Zhang et al., 2024	Routine pathology	Digital pathology/AI implementation	Workflow integration
50	Walsh & Orsi, 2024	Pathology workforce	Workforce review	Human-resource barrier

3.2 Segmentation Techniques

Segmentation methods can be grouped into classical, region-based, contour-based, learning-based and transformer/hybrid approaches. Classical approaches such as thresholding, fuzzy C-means, watershed and active contours remain computationally attractive but are sensitive to overlap, staining and image artefacts. CNN-based segmentation addresses some of these limitations by learning discriminative representations. The U-Net architecture and its derivatives have become common because of encoder-decoder structure and skip connections. DeepLabV3 + adds atrous spatial pyramid pooling to capture multiscale context, and the Ugandan study demonstrates how such an architecture can be combined with smartphone microscopy [9].

For cervical histology, segmentation must account for both cellular and architectural scales. Nucleus segmentation may support nuclear atypia analysis, whereas epithelium or lesion segmentation captures broader disease architecture. Whole-slide systems may not require explicit pixel-level segmentation of every structure; instead, tissue detection, patch extraction and attention-based aggregation can be used. The trade-off is that weakly supervised systems can reduce annotation burden but may provide less explicit localization.

3.3 Classification Techniques

Traditional classifiers such as KNN and SVM were important in early cervical image analysis, particularly when features were explicitly defined. Modern studies increasingly use transfer learning. ResNet addresses optimization through residual connections, DenseNet promotes feature reuse, and EfficientNet seeks a favourable accuracy-to-computation ratio. This is relevant to SSA because compact architectures may be more compatible with modest computing hardware than large foundation models.

The Rwandan study illustrates this point: EfficientNetB0 achieved higher reported test performance than ResNet50 and DenseNet121 on its binary task while remaining a compact model. However, the result should be interpreted within the study's single-centre design and binary classification framing. A model distinguishing normal from abnormal tissue does not necessarily solve the clinically harder task of differentiating CIN grades, invasive squamous carcinoma, adenocarcinoma and less common subtypes.

3.4 Whole-Slide Imaging, Attention and Foundation Models

WSI enables tissue-wide analysis but introduces gigapixel-scale computation. Patch-based pipelines divide slides into manageable tiles, classify or embed each tile, and aggregate information to the slide level. Multiple-instance learning and

attention mechanisms allow models to identify diagnostically important regions without exhaustive pixel-level annotation. Foundation models trained on large pathology corpora are a newer development and may improve transferability, but they can require substantial computational resources and may encode biases inherited from their source datasets [30, 47].

3.5 Evidence from Sub-Saharan Africa

The African evidence base is smaller than the global cervical AI literature, but recent studies demonstrate increasing local capacity. In Ethiopia, Habtemariam et al. developed a deep-learning system using 915 histopathology images and reported 94.5% test accuracy for cervical cancer classification [7]. In Rwanda, Nyabyenda et al. used 885 patient-level H&E biopsy images and evaluated ResNet50, EfficientNetB0 and DenseNet121. EfficientNetB0 achieved 0.99 test accuracy, 0.98 sensitivity, 1.00 specificity and 0.99 ROC-AUC, but the authors explicitly identified the need for external multicentre and prospective validation [8]. In Uganda, Nakasi et al. demonstrated smartphone-assisted histopathology acquisition and DeepLabV3 + segmentation of 21 histopathological features from 5,966 images, showing a locally developed pathway that does not depend on conventional WSI scanners [9].

These African studies are important because they shift the research question from whether AI can classify cervical images under controlled conditions to whether appropriate AI systems can be constructed around local pathology workflows. Nevertheless, the current evidence remains insufficient to establish generalisability across African laboratories, scanners, staining protocols, disease prevalence and patient populations. The principal barriers to deployment and corresponding mitigation strategies are summarized in Table 3.

Table 3
Barriers to AI Deployment for Cervical Histopathology in Sub-Saharan Africa

Barrier	Mechanism	Potential effect	Research response
Digital pathology infrastructure	Limited scanners, servers, storage and reliable electricity	Limits WSI acquisition and local processing	Low-cost microscopy, edge computing, hybrid local/cloud systems
Computational cost	Large WSI and transformer models require substantial GPU resources	Slow or inaccessible inference	Model compression, lightweight CNNs, quantization and efficient architectures
Data scarcity	Few large, annotated African cervical histology datasets	Overfitting and poor generalisation	Multicentre datasets, federated learning, weak supervision
Stain/scanner variability	Differences in H&E protocols, cameras and scanners	Domain shift	Stain normalization, calibration and domain adaptation
Class imbalance	Rare CIN grades/subtypes may be underrepresented	Biased sensitivity and unstable training	Balanced sampling, weighted loss, augmentation and multicentre data
Annotation burden	Pixel-level segmentation requires specialist pathologists	High cost and slow dataset creation	Weak supervision, active learning and pathologist-in-the-loop annotation
Workforce	Few pathologists and limited digital pathology specialists	Difficult validation and maintenance	Multidisciplinary teams and local training
Interoperability	AI systems may not integrate with LIS/LIMS/PACS	Workflow fragmentation	Open standards and modular APIs
Regulation and governance	Unclear validation, liability and data-sharing requirements	Delayed clinical adoption	Local regulatory pathways, audit trails and quality assurance
Sustainability	Hardware/software maintenance and licensing costs	Project failure after initial funding	Total-cost-of-ownership and local technical support
Trust and explainability	Black-box predictions may be difficult to review	Low clinician acceptance	Heatmaps, uncertainty estimates and human-in-the-loop review
Cybersecurity and privacy	Digital slides are large clinical datasets	Risk of unauthorized access	Access control, encryption, de-identification and governance

4.0 Observations and Discussion

The 49-publication synthesis demonstrates that cervical AI has moved through several methodological phases. Early studies concentrated on isolating cells and nuclei because the most salient abnormalities were believed to be contained in nuclear size, shape, intensity and texture. As computational learning matured, segmentation and classification increasingly became learned rather than hand-engineered tasks. Modern systems can model larger tissue contexts and, with WSI and multiple-instance learning, can move from isolated patches toward slide-level decision support.

A central observation is that reported accuracy is highly dependent on the evaluation setting. Earlier cervical image-analysis studies frequently used curated or accurately segmented public datasets, which can limit the extent to which reported performance represents routine clinical environments. Contemporary work has improved patient-level splitting and held-out testing, but single-centre validation remains common. The Rwandan study explicitly used patient-level stratification, whereas the Ugandan segmentation study emphasizes that its results are validation data from one institution. These methodological strengths and limitations should be separated when interpreting headline performance [7–9].

Another important issue is the difference between binary and clinically granular classification. Normal-versus-abnormal classification can produce very high performance while avoiding the harder problem of CIN grading and tumour subtyping. For clinical pathology, the useful endpoint may be hierarchical: first identify whether tissue is abnormal, then localize suspicious regions, then distinguish clinically relevant grades or tumour types, with final review by a pathologist. This structure may be particularly suitable for resource-constrained workflows because it can prioritize scarce specialist attention.

Segmentation is similarly task dependent. Nucleus segmentation is valuable for cellular morphology, but cervical cancer diagnosis also depends on epithelial architecture, maturation and stromal invasion. Consequently, a system optimized for nuclear Dice or IoU should not automatically be described as a cervical cancer diagnostic system. The Ugandan DeepLabV3 + work is instructive because it attempts multi-class segmentation of 21 histopathological features rather than relying solely on binary image labels [9].

Deployment in SSA requires a shift from algorithm-centred research toward systems engineering. A clinically useful AI pipeline requires an acquisition device, validated image quality, preprocessing, inference, storage, user interface, integration with laboratory workflow, auditability, technical support and mechanisms for updating the model. The cost and complexity of digital pathology are therefore not secondary considerations. They determine whether a model can operate outside a research environment.

Technology-appropriate design is particularly important. Smartphone-assisted microscopy, compact CNNs and edge inference may reduce dependence on expensive WSI scanners and continuous cloud connectivity. This does not mean that smartphone microscopy is automatically equivalent to WSI; rather, it represents a different operating model whose limitations and performance must be validated against local reference standards. The Ugandan study provides a concrete example of this approach [9].

External validation is the most important next step. A model trained in Kigali should be tested in Kampala, Mbarara, Nairobi, Addis Ababa and other settings using independently prepared slides. Such studies should preserve patient-level separation and report sensitivity, specificity, F1-score, ROC-AUC, calibration and confidence intervals. Prospective studies should then measure workflow time, pathologist workload, false-negative cases, user acceptance and cost.

Finally, AI should be positioned as decision support rather than replacement of pathology expertise. Current evidence does not justify autonomous deployment for routine cervical cancer diagnosis in SSA. Human review, quality assurance and escalation pathways remain necessary, particularly for borderline lesions, rare tumour subtypes, poor-quality slides and cases outside the model's training distribution.

4.1 Implications for Research in Sub-Saharan Africa

Develop multicentre African cervical histopathology datasets with patient-level metadata, standardized diagnostic labels and transparent data governance.

Include normal tissue, CIN1, CIN2, CIN3, carcinoma in situ, invasive squamous carcinoma, adenocarcinoma and important rare subtypes where sample size permits.

Record acquisition device, magnification, staining protocol, section thickness and laboratory site to enable domain-shift analysis.

Use patient-level rather than image-level splitting and report external validation whenever possible.

Compare segmentation architectures using Dice and IoU and report class-specific performance, especially for rare features.

Evaluate lightweight models alongside larger architectures so computational feasibility becomes part of model selection.

Integrate explainability, uncertainty estimation and out-of-distribution detection before clinical implementation.

Conduct implementation and health-economic studies rather than evaluating algorithms only on retrospective images.

Design interoperability with existing laboratory information systems and maintain an auditable path from image to AI output to final pathologist report.

4.2 Strengths and Limitations

Strengths of this review include a focused emphasis on histopathology rather than treating all cervical AI applications as equivalent; explicit consideration of segmentation and classification; inclusion of recent African evidence; and integration of technical performance with deployment barriers. The main limitation is heterogeneity of the evidence base. Studies use different modalities, datasets, labels, reference standards and performance metrics, making quantitative pooling inappropriate.

5.0 Conclusions

AI-based analysis of cervical histopathology has progressed from handcrafted segmentation and feature-based classifiers to CNNs, transfer learning, attention mechanisms, whole-slide learning and transformer-based approaches. Segmentation remains fundamental because clinically meaningful interpretation depends on identifying cellular and tissue structures, while classification systems increasingly exploit learned representations rather than manually designed features.

Evidence from Ethiopia, Rwanda and Uganda demonstrates that cervical histopathology AI can be developed using data and workflows within SSA. However, high internal performance does not establish readiness for clinical deployment. The major barriers are inadequate digital pathology infrastructure, computational and storage costs, data scarcity, staining and scanner variability, limited specialist capacity, interoperability, regulation, data governance and sustainability.

The next generation of cervical histopathology AI research in SSA should therefore prioritize locally representative multicentre datasets, rigorous patient-level and external validation, explainability and uncertainty estimation, lightweight models, smartphone or edge-capable acquisition and inference, and integration with existing pathology workflows. The appropriate endpoint is not simply a high accuracy score but a validated, safe, affordable and sustainable human-AI diagnostic workflow.

Declarations

Ethics approval and consent to participate

Not applicable.

This manuscript was a systematic literature review and does not involve collection of new human participant data.

Consent for publication

Not applicable.

Data availability

No primary patient dataset was generated for this review. The evidence base consists of published literature and publicly accessible bibliographic information.

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Conflict of interest

The authors declare that they have no financial or non-financial competing interests related to this work.

Author Contributions

Habert Tumwesigye: Conceptualization, methodology, literature search, data curation, investigation, analysis, manuscript drafting, visualization, project administration, and correspondence.

Abraham Birungi: Methodology, literature review, data interpretation, critical revision of the manuscript, and supervision.

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Raymond Atwine: Conceptualization, histopathological expertise, methodology, supervision, critical review and editing of the manuscript.

All authors: Contributed to the interpretation of the findings, critically reviewed the manuscript, approved the final version, and agreed to be accountable for all aspects of the work.

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