

Role of Artificial Intelligence in Cervical Cancer Detection

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ABSTRACT

Cervical cancer remains a significant global health concern, particularly in low- and middle-income countries where access to expert diagnostic services is limited. The integration of artificial intelligence (AI), especially deep learning techniques, into cervical cancer screening has shown promise in enhancing diagnostic accuracy and efficiency. This paper explores the role of AI in cervical cancer detection, focusing on the analysis of colposcopic images. We discuss the critical steps involved, including image acquisition, preprocessing, segmentation, and classification, highlighting the importance of each in the AI diagnostic pipeline. Deep learning models, such as convolutional neural networks (CNNs), have demonstrated high accuracy in classifying cervical lesions, often matching or surpassing the performance of experienced colposcopists. The incorporation of multimodal data—combining colposcopic images with clinical information like patient history and cytology results—further enhances diagnostic precision. Studies have reported that AI-assisted colposcopy can achieve diagnostic accuracies exceeding 90%, underscoring its potential as a valuable tool in cervical cancer screening programs. The integration of AI into cervical cancer detection workflows holds the potential to improve early diagnosis, optimize resource utilization, and ultimately reduce the global burden of cervical cancer.

Key words: Artificial intelligence, deep learning, machine learning, cervical cancer, specular reflection, segmentation, classification

INTRODUCTION

Cervical cancer remains a significant global health challenge, ranking as the fourth most common cancer among women worldwide. Despite being largely preventable through early detection and treatment, it continues to cause substantial morbidity and mortality, particularly in low- and middle-income countries[1]. Traditional screening methods, such as Pap smears and HPV testing, have been instrumental in reducing incidence rates but are often limited by factors like variability in human interpretation, resource constraints, and accessibility issues. These limitations underscore the need for innovative approaches to enhance screening accuracy and reach, especially in underserved regions.

The advent of artificial intelligence (AI)[2] in healthcare offers promising solutions to these challenges. AI algorithms[3], particularly those utilizing deep learning, have demonstrated remarkable proficiency in analyzing medical images, enabling the automated detection of precancerous and cancerous lesions with high accuracy. For instance, AI-driven systems can evaluate cervical cytology and colposcopy images, identifying subtle abnormalities that may be overlooked by human observers. Studies have shown that such AI applications not only match but often surpass the diagnostic performance of experienced clinicians, thereby enhancing early detection and reducing diagnostic errors.

In underdeveloped regions, the integration of AI into cervical cancer screening programs is already underway. The health departments have initiated pilot projects employing AI-based screening tools to improve early detection rates and address the shortage of specialized medical personnel. These initiatives aim to expand access to quality healthcare services, particularly in rural and underserved areas, by leveraging AI's capabilities to analyze high-resolution cervical images and identify abnormalities requiring further evaluation. Such efforts exemplify the transformative potential of AI in enhancing cervical cancer detection and underscore the importance of continued research and investment in this domain.

The steps involved in cervical cancer detection using AI with supporting literature

The integration of artificial intelligence (AI) into cervical cancer detection has revolutionized traditional screening methods, offering enhanced accuracy, efficiency, and accessibility. AI-driven approaches encompass a series of systematic steps, from data acquisition to final diagnosis, each playing a crucial role in the overall effectiveness of the detection process. Understanding these steps is essential for appreciating how AI contributes to early and accurate identification of cervical abnormalities, ultimately improving patient outcomes.

This section delves into the sequential stages involved in AI-assisted cervical cancer detection. Beginning with image acquisition, where high-quality cervical images are captured, the process moves through preprocessing techniques that enhance image clarity and focus on regions of interest. Subsequent steps involve specular reflection removal, feature extraction, where pertinent characteristics are identified, followed by classification algorithms that differentiate between normal and abnormal findings. Finally, the system provides diagnostic outputs that aid clinicians in decision-making. Each of these steps is supported by contemporary research and literature, highlighting the advancements and efficacy of AI in this domain.

By systematically exploring each phase, this section aims to provide a comprehensive understanding of the AI-driven workflow in cervical cancer detection. The discussion is anchored in current studies and practical implementations, showcasing how AI not only augments traditional screening methods but also addresses challenges such as resource limitations and diagnostic variability. Through this exploration, the transformative potential of AI in enhancing cervical cancer screening and diagnosis becomes evident.

Image acquisition

Image acquisition is a foundational step in AI-driven cervical cancer detection, as the quality and consistency of input images directly influence the performance of diagnostic models. High-resolution, well-annotated colposcopic images are essential for training deep learning algorithms to accurately identify and classify cervical lesions. Variations in image quality, lighting conditions, and anatomical presentation can introduce noise and bias, potentially compromising the reliability of AI predictions. Therefore, standardized image acquisition protocols are crucial to ensure that AI systems can generalize effectively across diverse patient populations and clinical settings.

Several publicly available datasets support the development and validation of AI models in cervical cancer detection:

CeLaTis: A Large Scale Multimodal Dataset with Deep Region Network to Diagnose Cervical Cancer: It is a privately sourced dataset that contains colposcope images along with corresponding clinical data that aids in accurate classification of cervical cancer affected cases. [4]

Multistate Colposcopy Image (MSCI) Dataset: This dataset comprises 4,753 colposcopic images from 679 patients, captured in three states—acetic acid application, green filter, and iodine test. It facilitates the development of AI models capable of grading cervical intraepithelial neoplasia (CIN) with high accuracy. [5]

Atlas of Colposcopy – Principles and Practice: Developed by the International Agency for Research on Cancer (IARC), this resource offers a collection of high-quality colposcopic images accompanied by clinical data, expert impressions, and histopathological outcomes, serving as a valuable tool for training and validating AI systems.

Cervix93 Dataset: Containing 93 real image stacks with grade labels and manually annotated nuclei, this dataset is designed for evaluating nucleus detection and image classification methods in cervical cytology. [6]

Intel & MobileODT Cervical Cancer Screening Dataset: Available on Kaggle, this dataset includes a large number of cervix images labeled for cancer screening, supporting the development of AI models for automated diagnosis. [7]

Preprocessing and specular reflection removal

Preprocessing is a critical phase in AI-assisted cervical cancer detection, ensuring that colposcopic images are optimized for accurate analysis. One of the primary challenges during this phase is the presence of specular reflections—bright white spots caused by light reflecting off the moist and uneven surface of the cervix. These reflections can obscure vital anatomical details, potentially leading to misdiagnosis and hindering the performance of AI algorithms. Therefore, effective detection and removal of specular reflections are essential to enhance image quality and ensure reliable diagnostic outcomes.

Advancements in machine learning have introduced more sophisticated techniques for specular reflection removal. For instance, neural network-based methods have been developed to detect and inpaint specular regions without requiring ground truth data[8]. These models learn to reconstruct the obscured areas by analyzing patterns in the surrounding tissue, effectively restoring the anatomical structures beneath the reflections[9]. Studies have demonstrated that such approaches not only eliminate specular reflections but also preserve the color distribution and structural integrity of the original images, thereby facilitating more accurate AI-driven diagnoses[10].

Therefore, preprocessing, particularly the removal of specular reflections, is a vital step in preparing colposcopic images for AI-based cervical cancer detection. By employing both traditional image processing techniques and modern machine learning approaches, clinicians and researchers can enhance image quality, reduce diagnostic errors, and improve the overall effectiveness of cervical cancer screening programs.

Segmentation of colposcope images using artificial intelligence

Segmentation of colposcopic images using artificial intelligence (AI) is a pivotal step in enhancing the accuracy and efficiency of cervical cancer detection[11]. By delineating specific regions of interest, such as the cervix and potential lesions, AI-driven segmentation facilitates precise analysis, aiding clinicians in diagnosis and treatment planning[12].

The transformation zone is particularly significant, as over 90% of cervical precancerous lesions and cancers originate within this region. Accurate segmentation of the TZ is essential for identifying the squamocolumnar junction (SCJ) and determining the appropriate type of TZ, which directly influences biopsy decisions and treatment strategies[13][14]. Studies have demonstrated that AI-assisted segmentation of the TZ can improve diagnostic accuracy, especially in resource-limited settings where experienced colposcopists may be scarce [15][16].

Furthermore, segmentation facilitates the identification of acetowhite lesions—areas that turn white upon application of acetic acid, indicating potential abnormalities[17]. By isolating these regions, AI models can more effectively assess lesion severity and guide clinicians in selecting optimal biopsy sites. Advanced deep learning architectures, such as Dense-U-Net and DeepLabv3+, have been employed to achieve high segmentation accuracy, outperforming traditional methods and even experienced clinicians in some cases.

Classification of colposcope images using Machine learning and Deep learning

Classification of colposcopic images using artificial intelligence (AI) is a critical component in the automated detection and diagnosis of cervical cancer. This process involves categorizing cervical images into distinct classes, such as normal tissue, low-grade squamous intraepithelial lesions (LSIL), high-grade squamous intraepithelial lesions (HSIL), or invasive cancer[18][19]. Accurate classification aids clinicians in determining the severity of cervical abnormalities, guiding biopsy decisions, and formulating appropriate treatment plans. Moreover, AI-driven classification enhances diagnostic consistency and efficiency, particularly in settings with limited access to experienced colposcopists[20].

Once the region of interest is segmented, deep learning models extract features that are indicative of various cervical conditions. Convolutional Neural Networks (CNNs) [21] are particularly effective in this regard, as they can capture complex patterns related to color, texture, and morphology. For instance, models like ResNet

and EfficientNet [22] have been utilized to classify images into categories such as normal, LSIL, HSIL, or invasive cancer[23].

Convolutional Neural Networks (CNNs) have become a cornerstone in medical image classification, offering automated, accurate, and efficient analysis of complex visual data. Their architecture is particularly well-suited for identifying patterns in medical images, such as those from colposcopic examinations, aiding in the detection and diagnosis of diseases like cervical cancer. Sometimes an ensemble of multiple base CNNs are used for improved performance of deep learning classifiers [14][24].

Integration of Multimodal Data

Integrating multimodal data—specifically colposcopic images and clinical information—has emerged as a transformative approach in enhancing the accuracy and reliability of cervical cancer detection through artificial intelligence (AI)[25]. This integration leverages the strengths of both visual and non-visual data, providing a comprehensive perspective that surpasses the limitations of single-modality analyses[26].

Colposcopic images, obtained after applying agents like saline, acetic acid, and Lugol's iodine, reveal distinct visual cues indicative of cervical abnormalities. However, these images alone may not capture the complete clinical context[27]. Incorporating clinical data—such as patient age, cytology results, and HPV status—adds valuable layers of information. For instance, a study demonstrated that combining colposcopic images with cytology and HPV test results using a deep learning model significantly improved diagnostic performance[28]

CONCLUSION

The integration of artificial intelligence (AI) into cervical cancer detection, particularly through the analysis of colposcopic images, represents a significant advancement in medical diagnostics. AI methodologies, especially deep learning models like convolutional neural networks (CNNs), have demonstrated high accuracy in classifying cervical lesions, thereby enhancing early detection and treatment planning. The incorporation of multimodal data—combining imaging with clinical information—further refines diagnostic precision, offering a more comprehensive assessment of patient health. Despite these promising developments, challenges remain in standardizing AI applications across diverse clinical settings. Variations in image quality, differences in data acquisition protocols, and the need for large, annotated datasets pose hurdles to the widespread adoption of AI in cervical cancer screening. Moreover, ethical considerations, including patient privacy and the interpretability of AI decisions, necessitate careful deliberation.

REFERENCES

1. M. Lalasa and J. Thomas, "A Review of Deep Learning Methods in Cervical Cancer Detection," in International Conference on Soft Computing and Pattern Recognition, 2022, pp. 624–633.
2. L. Mukku and J. Thomas, "Media's influence on suicide: Building a safer online world for all," Asian J. Psychiatr., vol. 91, p. 103868, 2024.
3. L. Mukku and J. Thomas, "A machine learning model to predict suicidal tendencies in students," Asian J. Psychiatr., vol. 79, p. 103363, 2023, doi: <https://doi.org/10.1016/j.ajp.2022.103363>.
4. L. Mukku and J. Thomas, "CeLaTis: A Large Scale Multimodal Dataset with Deep Region Network to Diagnose Cervical Cancer," in International Conference on Intelligent Systems Design and Applications, 2023, pp. 154–163.
5. Y. Yu, J. Ma, W. Zhao, Z. Li, and S. Ding, "MSCI: A multistate dataset for colposcopy image classification of cervical cancer screening," Int. J. Med. Inform., vol. 146, p. 104352, 2021.
6. H. A. Phoulady and P. R. Mouton, "A new cervical cytology dataset for nucleus detection and image classification (Cervix93) and methods for cervical nucleus detection," arXiv Prepr. arXiv1811.09651, 2018.
7. M. Darwish, M. Z. Altabel, and R. H. Abiyev, "Enhancing cervical pre-cancerous classification using advanced vision transformer," Diagnostics, vol. 13, no. 18, p. 2884, 2023.
8. L. Mukku and J. Thomas, "Specular Reflection Removal Techniques in Cervix Image: A Comprehensive Review," in International Conference on Emerging Research in Computing,

- Information, Communication and Applications, 2023, pp. 479–490.
9. L. Mukku and J. Thomas, “A Specular Reflection Removal Technique in Cervigrams,” in 2023 IEEE International Conference on Contemporary Computing and Communications (InC4), 2023, vol. 1, pp. 1–5.
10. L. Mukku and J. Thomas, “EGMM: removal of specular reflection with cervical region segmentation using enhanced Gaussian mixture model in cervix images,” *Multimed. Tools Appl.*, pp. 1–22, 2024.
11. L. Mukku and J. Thomas, “Deep learning-based cervical lesion segmentation in colposcopic images,” *Appl. Eng. Technol.*, vol. 3, no. 1, pp. 16–25, 2024.
12. L. Mukku and J. Thomas, “Advanced Cervical Lesion Detection using Deep Learning Techniques,” in 2024 1st International Conference on Communications and Computer Science (InCCCS), 2024, pp. 1–6.
13. L. Mukku and J. Thomas, “Artificial Intelligence in Early Detection of Cervical Intraepithelial Neoplasia.”
14. L. Mukku and J. Thomas, “Early-Stage Cervical Cancer Detection via Ensemble Learning and Image Feature Integration,” in International Conference on Intelligent Systems Design and Applications, 2023, pp. 112–122.
15. L. Mukku and J. Thomas, “A Lesion Feature Engineering Technique Based on Gaussian Mixture Model to Detect Cervical Cancer,” in Congress on Intelligent Systems, 2023, pp. 63–75.
16. L. Mukku and J. Thomas, “A Review of Deep Learning Methods in Automatic Facial Micro-expression Recognition,” in International Conference on Computational Intelligence and Data Engineering, 2022, pp. 1–16.
17. M. Lalasa, S. Nithya, K. Nagalakshamma, A. Suvarnalatha, and P. Nageshwar Rao, “In Silico Platforms for Systems Toxicology,” in Proceedings of the 2nd International Conference on Computational and Bio Engineering: CBE 2020, 2021, pp. 25–31.
18. S. Nithya, M. Lalasa, K. Nagalakshamma, and S. Archana, “Computational approaches in toxicity testing: an overview,” in Advances in Computational and Bio-Engineering: Proceeding of the International Conference on Computational and Bio Engineering, 2019, Volume 2, 2020, pp. 255–261.
19. S. Mukku, M. Lalasa, K. Nagalakshamma, G. Savitri, P. Sujata, and K. S. Shanthi Sree, “The role of law and regulation on the intersection of bioprospecting and bio piracy,” in Proceedings of the 2nd International Conference on Computational and Bio Engineering: CBE 2020, 2021, pp. 129–134.
20. L. Mukku, “Vikas Burri Colorado State University, Fort Collins, Usa.”
21. L. Mukku and J. Thomas, “CMT-CNN: colposcopic multimodal temporal hybrid deep learning model to detect cervical intraepithelial neoplasia,” *Int. J. Adv. Intell. Informatics*, vol. 10, no. 2, pp. 317–332, 2024.
22. L. Mukku and J. Thomas, “Comparative Performance Analysis of Deep Learning Models in Cervical Cancer Detection,” in International Conference on Intelligent Systems Design and Applications, 2023, pp. 185–194.
23. L. Mukku and J. Thomas, “WITHDRAWN: Navigating the Data Challenge in Predictive Machine Learning Models for Precision Psychiatry,” *Asian J. Psychiatr.*, p. 104283, 2024.
24. M. Lalasa, “Threat to wildlife-exploring mass elephant die-offs and role of technology intervention,” *SGS-Engineering Sci.*, vol. 1, no. 01, 2021.
25. L. Mukku and J. Thomas, “Multimodal Early Fusion Strategy Based on Deep Learning Methods for Cervical Cancer Identification,” in Congress on Intelligent Systems, 2023, pp. 109–118.
26. L. Mukku and J. Thomas, “Hybrid Decision Fusion based Multimodal Ensemble Framework for Cervical Cancer Detection,” 2023.
27. L. Mukku and J. Thomas, “Attention Based Meta-Module to Integrate Cervigrams with Clinical Data for Cervical Cancer Identification,” in International Conference on Intelligent Systems Design and Applications, 2023, pp. 286–295.
28. L. Mukku and J. Thomas, “TelsNet: temporal lesion network embedding in a transformer model to detect cervical cancer through colposcope images,” *Int. J. Adv. Intell. Informatics*, vol. 9, no. 3, pp. 502–523, 2023.