

A Study on the Application of an AI Image Recognition-Based Early Cervical Cancer Screening System

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How to cite this paper: Qiao, H.T., Zhao, S.C., Mou, H., Guo, Y.C., Fan, C. and Liu, J.H. (2025) A Study on the Application of an AI Image Recognition-Based Early Cervical Cancer Screening System. *Health*, 17, 1058-1067.

<https://doi.org/10.4236/health.2025.179068>

Received: August 21, 2025

Accepted: September 15, 2025

Published: September 18, 2025

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Abstract

Objective: To investigate the feasibility and value of a novel early cervical cancer screening system based on Artificial Intelligence (AI) and super-high-speed cell imaging technology in clinical applications, with a focus on evaluating its sensitivity in identifying positive samples. **Methods:** This study included 2000 samples from women undergoing cervical cancer screening. A self-developed “super-high-speed cell imaging intelligent analyzer” was used for automated image acquisition and multi-dimensional feature extraction of exfoliated cervical cells. Subsequently, a deep learning-based AI model was utilized for intelligent recognition and classification of the cell images. All results judged as positive by the AI system were confirmed by histopathological examination, which served as the gold standard for calculating the system’s diagnostic sensitivity. **Results:** Among the 2000 total samples, 242 were confirmed as positive by pathology. The AI screening system successfully identified 231 of these cases, missing 11, resulting in a sensitivity of 95.45% for identifying positive samples. Analysis revealed that the system has stable and efficient recognition capabilities for mid-to-high-grade lesions, while all missed cases were low-grade lesions with a scarce number of abnormal cells and atypical features. **Conclusion:** This study confirms that the early cervical cancer screening system based on super-high-speed cell imaging and AI recognition has extremely high sensitivity. Its automation and high-throughput characteristics can effectively compensate for the shortcomings of traditional screening methods, such as strong subjectivity, reliance on manual labor, and insufficient pathologist resources in primary care. Although there is still room for improvement in identifying very early or low-burden lesions, and the system currently serves mainly

as an efficient triage tool, it has demonstrated great potential for application in large-scale cervical cancer screening. Future optimization will focus on enhancing the recognition of low-grade lesions and developing a multi-class AI model capable of lesion subtype grading to better assist in precise clinical diagnosis.

Keywords

Cervical Cancer, Artificial Intelligence, Early Screening, Deep Learning

1. Introduction

Cervical cancer is one of the most common malignant tumors among women worldwide, with high rates of both incidence and mortality, posing a serious threat to female reproductive health. According to the World Health Organization (WHO), there are approximately 600,000 new cases of cervical cancer globally each year, with over 85% occurring in developing countries [1] [2]. In China, the age of onset for cervical cancer is trending younger, and its incidence is increasing in some regions [3] [4]. Therefore, establishing an efficient, accurate, and scalable early screening system for cervical cancer is of paramount importance.

Current clinical screening methods include the ThinPrep Cytologic Test (TCT) and high-risk Human Papillomavirus (HPV) testing. Although these methods have improved the detection rate of precancerous lesions and early-stage cancer to some extent, they still suffer from issues such as high rates of missed diagnoses, reliance on manual experience, and strong subjectivity in interpretation, which limit their widespread adoption in primary healthcare institutions [5] [6]. Furthermore, traditional methods are relatively crude in terms of cell image acquisition and standardized analysis, failing to meet the demands of high-throughput, automated, and intelligent screening [7] [8]. In recent years, with the rapid development of artificial intelligence, medical auxiliary diagnostic systems based on image recognition and machine learning have been widely applied in various disease fields. Particularly in cytomorphological analysis, the introduction of deep learning algorithms has significantly improved recognition efficiency and accuracy, offering a new technological path for cervical cancer screening [9] [10].

Against this backdrop, this study developed an artificial intelligence-based early cervical cancer screening system centered on a super-high-speed cell imaging intelligent analyzer. The system combines high-speed cell imaging, liquid biopsy sample processing, multi-omics feature extraction, and an AI intelligent recognition algorithm to automatically analyze a large number of cervical cell images in a short time. We conducted a clinical application validation in 2000 cervical samples from three hospitals in Chengdu, focusing on evaluating the system's sensitivity and accuracy in identifying positive samples to provide practical evidence and technical support for intelligent early screening of cervical cancer.

2. Materials and Methods

2.1. Study Subjects

This study included a total of 2000 women, aged 21 - 65, who underwent cervical cancer screening at the People's Hospital of Qingbaijiang District, Chengdu, and two other partner medical institutions between May 2024 and April 2025. All participants signed informed consent forms and met the criteria for cervical cancer screening. Exclusion criteria included: 1) a previous clear diagnosis of cervical cancer or precancerous lesions; 2) recent cervical-related treatments; and 3) samples that did not meet quality control requirements. Key criteria for sample adequacy included ensuring a minimum of 5000 squamous epithelial cells per slide and maintaining high image clarity without excessive inflammatory cells or blood obscuring the view. All positive cases were confirmed by pathological diagnosis.

2.2. Sample Collection and Processing

Cervical scrape samples were collected from each participant using a standardized method. A disposable cell brush was used to collect exfoliated cervical cells, which were then placed in a special preservation solution, mixed, and sent to the laboratory for sample preparation and image analysis. All procedures were performed in accordance with national health industry standards, and the entire process of sample collection, transportation, and storage was completed by trained professional technicians.

2.3. Detection System and Platform

2.3.1. Image Acquisition Platform

This study used a self-developed super-high-speed cell imaging intelligent analyzer for image acquisition and feature analysis. The system integrates a laser pulse light source, fluidic control, a microfluidic chip, and a high-speed imaging module to achieve stable imaging of cells in a flowing state. By employing microfluidic technology to align cells in a single file for rapid passage through the detection area, combined with a high-frame-rate camera, the system achieves a processing throughput of up to 10,000 cells per second, significantly exceeding conventional slide-scanning systems. The system can acquire multiple morphological feature parameters for each cell, including diameter, roundness, eccentricity, major axis, minor axis, area, perimeter, and equivalent volume.

2.3.2. AI Intelligent Recognition System

After image acquisition, the cell images were automatically uploaded to a supporting server, where an AI model based on a deep learning algorithm performed recognition and classification. The AI model utilizes a Convolutional Neural Network (CNN) architecture, specifically a modified ResNet-50. The model was pre-trained on a large-scale private dataset containing over one million annotated cervical cell images, which was subsequently fine-tuned using the data from this study. Using a pre-trained discrimination model, the system can identify suspected lesion cells

with high sensitivity and generate an interpretation report. The entire analysis process is automated, and the results are presented visually, including heatmaps (e.g., diameter-roundness plots, eccentricity distribution plots), custom screening controls (multi-indicator joint settings), and image result output and archive (**Figure 1**).

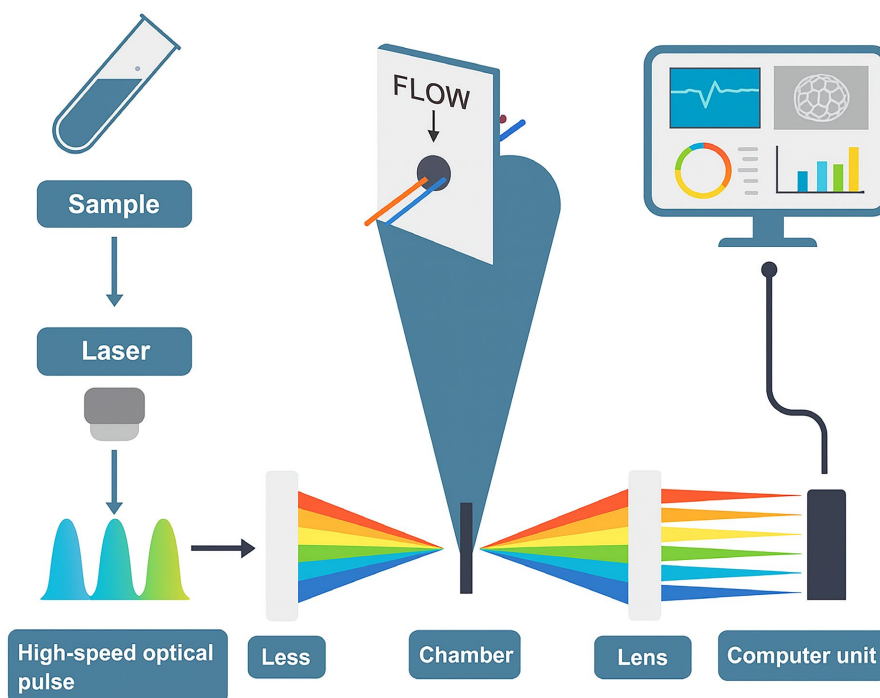


Figure 1. System schematic diagram.

2.3.3. Diagnostic Criteria and Reference Standard

Histopathological examination results were used as the gold standard for cervical cancer diagnosis in this study. Cases identified as positive by the AI system were all referred for pathological review, with the final diagnosis confirmed by two senior pathologists. In cases of disagreement, a third-party expert provided a final review. The system's recognition results were classified as follows:

- **True Positive (TP):** Identified as positive by AI and confirmed as positive by pathology.
- **False Negative (FN):** Identified as negative by AI but confirmed as positive by pathology.
- **True Negative (TN), False Positive (FP):** As this phase of the study focused on evaluating the system's sensitivity, statistics for TN and FP samples will be analyzed in subsequent research.

2.3.4. Statistical Analysis

Data were analyzed using SPSS 26.0 software. With pathological diagnosis as the gold standard, the sensitivity of the AI system was calculated as: Sensitivity = $TP / (TP + FN)$. Additionally, information such as the positive recognition success rate, misjudgment cases, and processing time was recorded. Count data were ex-

pressed as frequencies and percentages.

3. Results

3.1. Overall Detection Results

A total of 2000 cervical samples were included in this study. Among them, 242 samples were confirmed as positive by histopathology, accounting for 12.1% of the total samples. All samples were processed through the VS1000 super-high-speed cell imaging intelligent analyzer for image acquisition and AI analysis. The system operated stably throughout the process, with no records of sample loss or interruption.

3.2. Performance of the AI System on Positive Samples

Of the 242 pathologically positive samples, the AI system successfully identified 231 cases and missed 11 cases. The sensitivity for identifying positive samples was 95.45%. Details are shown in **Table 1**.

Table 1. Summary of screening results.

Indicator	Value	Description
Total Pathologically Positive (Gold Standard)	242 cases	Confirmed by histopathology
AI-Identified Positives (True Positives)	231 cases	Identified by AI and confirmed by pathology
Missed Positives (False Negatives)	11 cases	Not identified by AI but positive by pathology.
Positive Recognition Rate/Sensitivity	95.45%	$(231/242) \times 100\%$

3.3. Typical Image Analysis and Result Presentation

During the recognition process, the AI system automatically extracts morphological parameters from cell images, including but not limited to cell diameter, roundness, eccentricity, area, and major/minor axis ratio (**Figure 2**). It generates multi-dimensional scatter plot heatmaps (e.g., diameter-roundness plot, eccentricity distribution plot) to achieve automatic clustering and screening of suspected lesion cells. The system also supports multi-conditional combined screening to enhance the focusing ability on target cells. The screened abnormal cells are ultimately confirmed by liquid-based cytology and pathology (**Figure 3**).

3.4. Analysis of Misclassified Samples

All 11 missed positive samples were pathologically diagnosed as low-grade lesions. In these cases, the number of lesion cells was typically very small, and their morphological features were not prominent, making them difficult to distinguish from the background of normal cells and sheath fluid. It is speculated that the

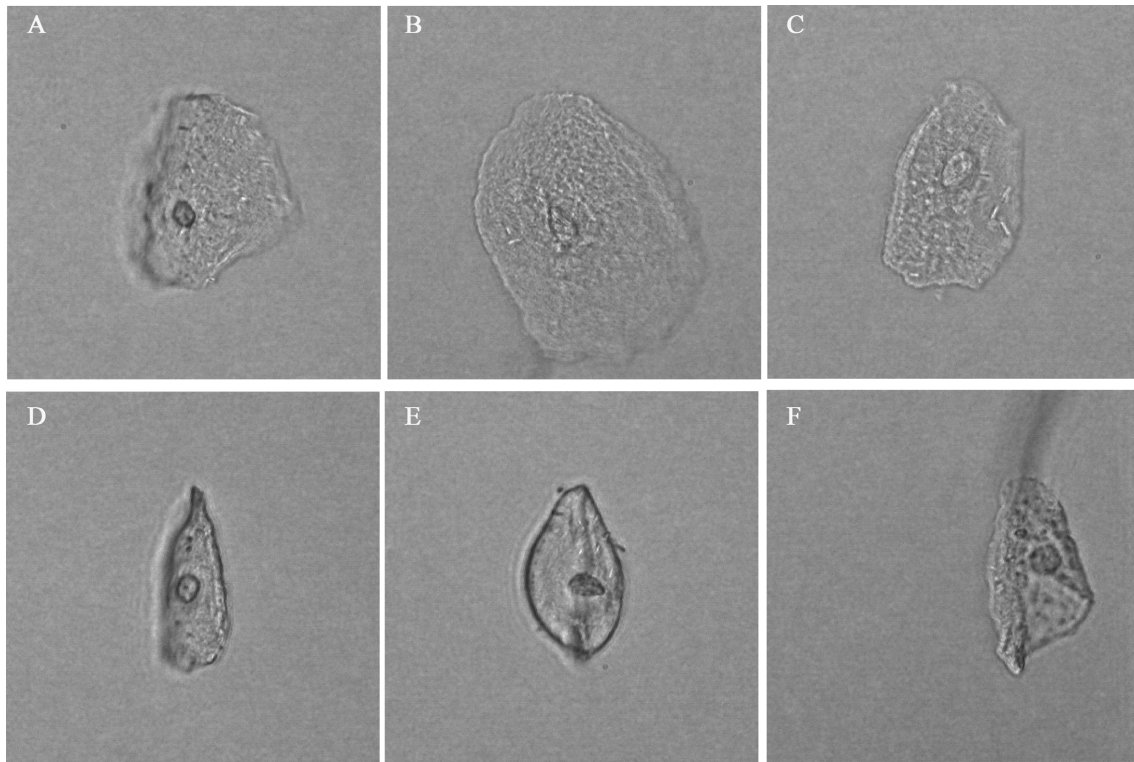


Figure 2. Screening images of normal and abnormal cervical cells from the super-high-speed AI system. (A) - (C): Normal cervical cells, showing complete cell contours, a moderate nucleus-to-cytoplasm ratio, and clearly visible nucleoli; (D) - (F): Abnormal cervical cells, showing enlarged nuclear volume, an imbalanced nucleus-to-cytoplasm ratio, uneven chromatin, and abnormal cell morphology.

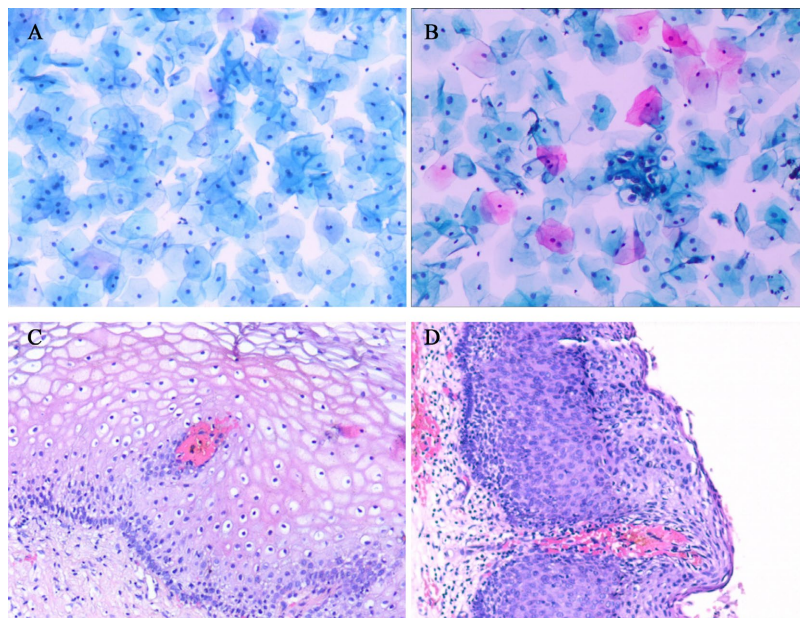


Figure 3. Liquid-based thin-layer cytology and histopathology images of normal and abnormal cervical tissues (Magnification: $\times 100$). (A) Liquid-based thin-layer cytology image of normal cervical cells, showing orderly cell arrangement, a normal nucleus-to-cytoplasm ratio, and no significant atypia; (B) Liquid-based thin-layer cytology image of abnormal cervical cells, showing some nuclei with deeper staining, an increased nucleus-to-cytoplasm ratio, and atypical changes; (C) HE staining image of normal cervical tissue, showing a well-defined epithelial structure with no atypical cell proliferation; (D) HE staining image of abnormal cervical tissue, showing epithelial proliferation, disordered cell arrangement, and significant atypia, indicative of cervical intraepithelial neoplasia.

weak signal for AI recognition was caused by these early, low-burden lesions. This result suggests that while the system is highly effective for mid-to-high-grade lesions, its ability to identify ultra-early, low-density positive cases requires further improvement.

4. Discussion

The key to preventing and controlling cervical cancer lies in early screening and accurate identification. Although conventional clinical methods such as TCT and HPV testing have been promoted at the grassroots level, they still have limitations. On one hand, TCT interpretation relies on manual experience, is highly subjective, and has poor reproducibility, making it prone to missed diagnoses, especially in early or low-grade lesions. On the other hand, while HPV testing is highly sensitive, its specificity is relatively insufficient, which can lead to false positives, increasing patients' psychological burden and unnecessary interventions [11] [12]. Recent studies further emphasize these challenges, highlighting the variability in cytological interpretation and the need for more objective screening modalities to improve accuracy and efficiency [13] [14]. Therefore, developing a high-throughput, objective, and automated intelligent auxiliary screening system is of significant clinical importance.

Based on the super-high-speed cell imaging intelligent analyzer platform, this study constructed an early cervical cancer screening system that integrates “standardized sample processing + high-speed image acquisition + multi-parameter feature extraction + AI intelligent recognition” and conducted a systematic validation in 2000 clinical cervical samples. The results showed that the system demonstrated an extremely high sensitivity of 95.45% in identifying positive samples, with stable performance, especially in mid-to-high-grade lesions (CIN II and above). This outcome is consistent with the trends in several recent studies, indicating that AI-assisted diagnostic systems can achieve or even surpass the accuracy of traditional manual reading [15] [16]. The core advantage of this system lies in its automation and high-throughput processing capabilities, which can effectively address the pain points of insufficient pathologist resources and heavy workloads in primary healthcare institutions. Meanwhile, through standardized image acquisition and objective algorithm analysis, the system eliminates subjective differences in manual reading, making it possible to achieve homogenization of screening quality.

Although this study has achieved encouraging results, its limitations must be acknowledged. First, the system's primary limitation relates to its performance on low-grade lesions. As the results showed, all 11 missed cases were pathologically identified as early-stage, low-grade lesions where the number of abnormal cells was scarce, and their morphological features were subtle. This highlights that the detection algorithm for these low-burden samples needs further optimization, for example, by introducing more advanced attention mechanism models to enhance the ability to capture features of minute lesions.

Second, a core limitation of the current system is that the AI model primarily focuses on binary classification of abnormal cells (“normal” vs. “abnormal”), with its main role being rapid initial triage. This means that all samples identified as “abnormal” by the AI still require manual review by a pathologist for final diagnosis and precise grading of lesion subtypes (e.g., ASC-US, LSIL, HSIL, SCC). As a triage tool, this AI system would integrate into the clinical workflow as a primary, rapid screening step. Samples flagged as “abnormal” by the AI would be prioritized for manual TCT review by a cytopathologist and/or reflex HPV testing. This approach allows human experts to focus their efforts on challenging or high-risk cases, significantly reducing their overall workload and improving turnaround times, while samples deemed “normal” by the AI could potentially follow a longer screening interval, subject to validation by specificity studies. In clinical practice, accurate grading of lesions is crucial for formulating subsequent treatment plans. Currently, some studies are dedicated to developing deep learning models capable of multi-class tasks and have achieved preliminary success [17] [18]. Therefore, our future research and development will focus on collecting more annotated samples with fine pathological classifications to train a multi-class AI model capable of subtype determination, thereby enhancing the system’s value in assisting with precise diagnosis and clinical decision-making.

Third, the design of this study primarily focused on evaluating the system’s sensitivity and has not yet conducted a comprehensive analysis of its specificity and false positive rate. High sensitivity accompanied by low specificity could lead to unnecessary referrals and over-treatment. Therefore, in the next phase of our research, we will include a large-scale cohort of negative samples to fully evaluate the system’s specificity and conduct a head-to-head comparative study with TCT and HPV testing to more clearly define the system’s scope of application and cost-effectiveness in different clinical scenarios.

Finally, although AI technology shows great potential, its clinical application still faces challenges such as data privacy, algorithm transparency and interpretability, and regulatory approval. As an auxiliary diagnostic tool, our system is positioned to help pathologists improve efficiency and accuracy, not to replace them completely. Building trust between doctors and AI systems and maximizing effectiveness through human-machine collaboration are key to the technology’s implementation.

In summary, this study provides preliminary validation of the feasibility and practical value of an early cervical cancer screening system based on high-speed cell imaging and AI recognition, especially in improving the positive detection rate and standardizing the screening process. With continuous technological optimization and an expanding sample size, this system is expected to be widely applied in cervical cancer census screening, secondary screening, and as a “first-line screen” in primary care settings, providing strong support for building an intelligent and accessible women’s health prevention and control system.

Authors' Contributions

Conceptualization and study design: Hongtu Qiao and Shengchun Zhao. Data collection and surgery execution: Hai Mou and Yuchao Guo. Data analysis and interpretation: Chao Fan and Jinheng Liu.

Funding

This study was supported by the Chengdu Municipal Bureau of Science and Technology's Technology Innovation Project (Project No. 2024-YF05-02594-SN) and the General Program of the Sichuan Association for the Promotion of Science and Education to Revitalize Sichuan (Project No. KJXC24-0317). The funding body had no role in the study design, data collection, analysis, interpretation, or manuscript preparation.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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