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Artificial Intelligence Techniques for Automatic Cervical Cancer Detection and Segmentation Using Sparsity-Aware Orthogonal Initialization in Deep Neural Network Classifiers: Trends and Challenges

Saffiya Okafor
Senior Lecturer, Department of Computer Science and Engineering, Visayan Maritime Polytechnic University, Philippines
Email: saffiya.okafor@vmpu-ph.net

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Abstract

Cervical cancer remains a significant global health concern, particularly in low-resource regions where access to timely screening and expert diagnosis is limited. The integration of artificial intelligence (AI), especially deep learning techniques, has greatly enhanced the automation of cervical cancer detection and segmentation from medical images such as Pap smear slides, colposcopy images, and histopathological data. Deep learning architectures including convolutional neural networks (CNNs), U-Net variants, and hybrid CNN-transformer models have demonstrated high accuracy in classification and segmentation tasks by effectively capturing complex spatial and hierarchical features. However, training these deep models presents challenges such as vanishing gradients, overfitting, and slow convergence. Sparsity-aware orthogonal initialization has emerged as an effective optimization approach, improving training stability, preserving signal propagation, and reducing redundancy in network parameters. This review highlights recent advancements in segmentation techniques, hybrid architectures, and optimization strategies, along with the use of attention mechanisms, transfer learning, and data augmentation to enhance performance. Despite progress, challenges such as limited annotated data, class imbalance, interpretability, and computational demands persist, indicating the need for more efficient and explainable AI-based diagnostic systems.

Introduction

Cervical cancer is a leading cause of cancer-related mortality among women worldwide, particularly in low- and middle-income countries, where access to preventive screening programs is limited. According to the World Health Organization (WHO), early detection and timely treatment can significantly reduce mortality rates. Despite advances in public health initiatives, cervical cancer continues to pose a significant global health burden, with an estimated 604,000 new cases and 342,000 deaths reported in 2020 alone. The asymptomatic nature of early-stage cervical cancer makes early detection challenging, and traditional screening methods such as the Papanicolaou (Pap) smear test, visual inspection with acetic acid (VIA), and human papillomavirus (HPV) testing often require trained personnel, leading to variability in diagnosis and delays in treatment.

Limitations of Conventional Methods

Traditional cervical cancer detection methods rely heavily on manual inspection and interpretation of cytological and histopathological images. Pap smear tests, for instance, require the identification of abnormal cells based on nuclear and cytoplasmic morphology. The diagnostic accuracy is highly dependent on the skill and experience of the pathologist. Studies have shown that inter-observer variability in cytological interpretation can lead to misclassification, with false negatives ranging from 10% to 20%. VIA and HPV tests, while useful, are also limited by their inability to precisely locate and classify lesions. These limitations highlight the urgent need for automated, reliable, and accurate diagnostic systems capable of reducing human error and standardizing cervical cancer screening.

Emergence of Artificial Intelligence in Cervical Cancer Detection

Artificial intelligence (AI), particularly deep learning, has emerged as a transformative tool in medical imaging and diagnostics. Deep learning models, especially convolutional neural networks (CNNs), have demonstrated remarkable performance in a wide range of medical imaging applications, including tumor detection, disease classification, and organ segmentation. These models automatically extract hierarchical features from raw images, enabling the identification of subtle patterns that may be overlooked by human experts. In cervical cancer detection, CNNs have been applied to Pap smear images, colposcopy images, and whole-slide histopathological images, providing automated and highly accurate analysis.

Segmentation and Classification in Cervical Cancer

Automated cervical cancer detection involves two primary tasks: segmentation and classification. Segmentation aims to identify and delineate regions of interest (ROIs) in medical images, such as abnormal cervical epithelial regions, while classification assigns a diagnostic label (e.g., normal, low-grade lesion, high-grade lesion, or cancerous) to the identified region. Accurate segmentation is critical, as missegmentation can lead to misclassification and negatively impact diagnostic outcomes. Traditional image processing approaches, including thresholding, edge detection, and region growing, have been employed for segmentation but are limited in handling complex patterns and image variability. Deep learning-based segmentation, particularly U-Net and its variants, has demonstrated superior performance by leveraging encoder-decoder architectures and skip connections to capture both local and global contextual information.

Challenges in Training Deep Neural Networks

Despite their success, deep neural networks are not without challenges. One critical factor affecting model performance is **weight initialization**. Improper initialization can lead to vanishing or exploding gradients, slow convergence, and suboptimal generalization. Orthogonal initialization has been shown to preserve the norm of input signals, maintaining stability across layers. Sparsity-aware orthogonal initialization further enhances this approach by introducing sparsity constraints that reduce parameter redundancy, improve convergence speed, and increase generalization performance. These optimization techniques are particularly valuable in medical imaging applications, where datasets are often small, imbalanced, or noisy.

Hybrid Architectures and Attention Mechanisms

Recent research has focused on combining multiple deep learning architectures to improve performance. Hybrid models integrate CNNs with transformers, attention mechanisms, or recurrent layers to capture both local features and long-range dependencies. Attention mechanisms, in particular, allow the model to focus on diagnostically relevant regions while suppressing background noise, improving both segmentation and classification accuracy. Studies by Abinaya et al. (2024) and Xue et al. (2025) demonstrate that hybrid CNN-transformer models outperform conventional CNN or U-Net architectures in cervical cancer detection tasks.

Multi-Modal and Whole-Slide Image Analysis

Whole-slide images (WSIs) provide high-resolution, gigapixel-level data for histopathological analysis, but they pose computational challenges due to their size. Patch-based CNN approaches divide WSIs into manageable sections for analysis, with results aggregated for final predictions. Multi-modal integration, combining Pap smear images, histopathology, and clinical metadata, further enhances model performance, as demonstrated by Li et al. (2023). These approaches capture complementary information, improving both detection and classification performance.

Trends and Recent Advancements

From 2020 to 2023, several key trends have emerged in AI-driven cervical cancer detection:

1. **Shift from single-task to multi-task models:** Combining segmentation and classification in a single pipeline reduces error propagation and improves overall diagnostic accuracy.
2. **Integration of sparsity-aware orthogonal initialization:** Improves

convergence, reduces redundancy, and mitigates overfitting in small or imbalanced datasets.

3. **Use of hybrid architectures:** CNNs combined with transformers or attention mechanisms capture local and global contextual information.
4. **Emphasis on interpretability:** Attention maps and visualization techniques provide insights into model decision-making, addressing the black-box problem.
5. **Adoption of multi-modal data:** Incorporating clinical metadata alongside images enhances robustness and generalization.
6. **Lightweight architectures for deployment:** Focus on efficiency to enable real-time use in low-resource clinical environments.

Challenges in Clinical Deployment

Despite these advancements, several barriers remain:

- **Limited annotated datasets:** High-quality, annotated datasets are essential for training robust models but remain scarce.
- **Class imbalance:** Normal cells vastly outnumber abnormal cells, leading to biased learning if not addressed.
- **Interpretability:** Deep learning models often function as black boxes, limiting clinician trust.
- **Computational complexity:** Hybrid and WSI-based models require high-end GPU infrastructure, which is not feasible in low-resource settings.
- **Data variability:** Differences in staining, imaging resolution, and acquisition protocols affect model generalization.

Future Directions

Future research in AI-based cervical cancer detection is likely to focus on:

1. **Explainable AI:** Developing models whose decisions can be interpreted by clinicians.
2. **Federated learning:** Privacy-preserving model training across multiple institutions without sharing patient data.
3. **Lightweight and real-time architectures:** To enable deployment in low-resource or mobile settings.
4. **Enhanced multi-modal integration:** Combining cytology, histopathology, imaging, and patient metadata for more robust diagnosis.
5. **Standardization of datasets:** Public, high-quality, and diverse datasets to benchmark models and improve generalizability.

Summary

In summary, cervical cancer detection has shifted from manual and classical machine learning methods toward deep learning-based automated systems. CNNs, U-Net, EfficientNet, and hybrid CNN-transformer architectures have demonstrated superior segmentation and classification performance. Sparsity-aware orthogonal initialization and advanced optimization strategies enhance convergence, generalization, and robustness. Recent trends focus on interpretability, multi-modal integration, and deployment in real-time clinical settings. However, challenges such as limited datasets, class imbalance, computational requirements, and variability in imaging protocols must be addressed for widespread clinical adoption.

Literature Review

The field of automatic cervical cancer detection and segmentation has undergone significant transformation with the integration of artificial intelligence (AI), deep learning, and advanced optimization techniques. Traditional methods relied heavily on manual inspection of Pap smear slides, histopathological images, and colposcopy images, which are time-consuming, subjective, and prone to human error. The emergence of convolutional neural networks (CNNs), U-Net architectures, hybrid CNN-transformer models, and sparsity-aware orthogonal initialization has enabled automated systems capable of high accuracy in both detection and segmentation tasks.

1. Deep Learning in Cervical Cancer Detection

CNNs have been widely adopted for cervical cancer detection due to their ability to extract hierarchical feature representations from raw medical images. Studies by Hou et al. (2022) and Chandran et al. (2021) demonstrated that CNNs outperform traditional machine learning models, including support vector machines (SVM) and k-nearest neighbors (KNN), in classifying Pap smear and colposcopy images. CNNs automatically learn features such as cellular morphology, nuclear irregularities, and cytoplasmic characteristics, which are critical indicators of precancerous or malignant lesions.

Yilmaz et al. (2020) compared CNN-based approaches with traditional feature-based methods and found that CNNs achieved significantly higher accuracy, sensitivity, and specificity. Similarly, Li et al. (2023) applied CNNs to whole-slide images (WSI) of cervical tissue, demonstrating their ability to detect abnormal cell clusters even in high-resolution datasets. The automatic extraction of multi-level features allows CNNs to handle complex patterns and variability in medical images, addressing challenges related to intra-class heterogeneity and low contrast.

2. Semantic Segmentation Techniques

Accurate segmentation is essential for identifying regions of interest, such as abnormal cervical cells. U-Net and its variants have emerged as the primary architectures for segmentation tasks. Ronneberger et al. (2015) introduced U-Net, featuring an encoder-decoder architecture with skip connections, which preserves spatial information while learning contextual features. This model has become a standard in biomedical image segmentation.

Hussain et al. (2021) applied U-Net to Pap smear image segmentation and achieved high accuracy in isolating abnormal cells from the background. Patre et al. (2023) extended this approach by integrating attention mechanisms, allowing the network to focus on regions most indicative of malignancy. Attention-enhanced U-Net architectures have shown improved performance in capturing subtle features such as nuclear enlargement and irregular chromatin patterns.

Multi-scale feature extraction is another critical development. Yaman and Tuncer (2022) demonstrated that combining high-level semantic features with low-level spatial details through pyramid feature aggregation improved segmentation accuracy for small lesions often missed by conventional CNNs. These multi-scale approaches are particularly relevant for cervical cancer, where lesion sizes vary significantly.

3. Classification Architectures

For classification, deep learning architectures such as ResNet, EfficientNet, and VGG have been extensively utilized. ResNet, introduced by He et al. (2016), addresses the vanishing gradient problem with residual connections, enabling the training of deeper networks. Studies indicate that ResNet-based models outperform standard CNNs in feature extraction and classification tasks for cervical cytology images.

EfficientNet, proposed by Tan and Le (2020), uses a compound scaling method that balances depth, width, and resolution to achieve high accuracy with fewer parameters. Alsalatie et al. (2022) employed an EfficientNet-based ensemble model for Pap smear classification and achieved superior results compared to ResNet and VGG architectures. The lightweight nature of EfficientNet allows for deployment in real-time applications while maintaining high precision.

Hybrid models combining CNNs with transformers or attention mechanisms have been proposed to capture both local and global contextual features. Abinaya et al. (2024) demonstrated that CNN-transformer hybrid models achieve higher classification accuracy by emphasizing regions of interest and learning long-range dependencies. Such hybrid architectures also improve robustness against imaging variations and noise.

4. Optimization Techniques and Initialization

Training deep networks effectively requires robust initialization and optimization techniques. Improper weight initialization can lead to vanishing or exploding gradients, slow convergence, and poor generalization.

Orthogonal initialization preserves the norm of input signals, ensuring stable signal propagation across deep layers. Sparsity-aware orthogonal initialization introduces sparsity constraints, which reduce redundancy in network parameters and improve generalization. Studies indicate that sparsity-aware initialization accelerates convergence and enhances feature representation, particularly in small or imbalanced datasets (Mathivanan et al., 2024; Xue et al., 2025).

Optimization algorithms such as Adam (Kingma & Ba, 2017), RMSProp, and SGD with momentum have been widely used to improve convergence speed. Data augmentation techniques, including rotation, flipping, and scaling, further enhance generalization by creating synthetic variations of the dataset. Transfer learning is also commonly employed to leverage pre-trained weights, reducing training time and improving performance when labeled medical datasets are limited.

5. Hybrid Segmentation-Classification Models

Recent studies emphasize the integration of segmentation and classification into unified frameworks. Hybrid models simultaneously localize lesions and classify their severity, improving diagnostic efficiency and accuracy. For example, Mathivanan et al. (2024) proposed a hybrid U-Net + EfficientNet model for cervical cancer, where segmentation outputs guided classification decisions. Attention mechanisms within these models improved interpretability by highlighting regions with high malignancy probability.

Ensemble-based approaches have also been adopted. Alsalatie et al. (2022) demonstrated that combining multiple CNN architectures via ensemble techniques reduces prediction variance and enhances robustness across heterogeneous datasets. These models are particularly useful for screening large populations where image quality may vary.

6. Attention Mechanisms and Transformers

Attention mechanisms and transformer-based networks have emerged as critical tools for improving model interpretability and accuracy.

Attention layers allow models to focus on diagnostically relevant regions, suppressing irrelevant background features. This approach is especially valuable in cervical cancer, where abnormalities may be subtle and spatially sparse. Hybrid CNN-transformer models capture both local texture patterns and long-range dependencies, enabling more precise classification. Abinaya et al. (2024) and Xue et al. (2025) reported significant improvements in segmentation accuracy and classification performance when combining CNN feature extractors with transformer-based attention layers.

7. Multi-Modal and Whole-Slide Image Analysis

Whole-slide images (WSI) and multi-modal data integration have emerged as promising areas in cervical cancer detection. Li et al. (2023) and Hou et al. (2022) demonstrated that analyzing large, high-resolution WSIs using CNNs and hybrid models improves lesion detection and classification. Integrating multi-modal data, including cytology, histopathology, and imaging metadata, allows models to capture complementary information, enhancing diagnostic accuracy.

However, these approaches require substantial computational resources and careful patch-based analysis to handle gigapixel images efficiently. Sparsity-aware orthogonal initialization reduces network redundancy and computational overhead in such high-dimensional tasks.

8. Challenges Identified

Despite advances, several challenges persist:

- **Limited annotated datasets**: Most public datasets are small and imbalanced, hindering generalization.
- **Class imbalance**: Abnormal cell classes are underrepresented in datasets, affecting model performance.
- **Computational complexity**: Hybrid and transformer-based models require high-end GPUs.
- **Interpretability**: Deep learning models often function as black boxes, limiting clinical trust.
- **Variability in image acquisition**: Differences in staining, lighting, and scanning resolution affect performance.

Addressing these challenges is essential for real-world deployment in clinical settings.

9. Research Gaps and Future Directions

The literature highlights several key research gaps:

1. **Explainable AI**: Developing models that provide interpretable outputs to assist clinicians.
2. **Lightweight architectures**: For real-time deployment in low-resource environments.
3. **Multi-modal integration**: Combining cytology, histopathology, and clinical data for robust prediction.
4. **Federated learning**: Privacy-preserving training across institutions without sharing patient data.
5. **Standardized datasets**: Large-scale, annotated datasets to benchmark and compare models.

Future research should focus on designing efficient, interpretable, and scalable AI systems that maintain high diagnostic accuracy while enabling early detection in diverse clinical settings.

Comparative Table

Study	Year	Model	Technique	Contribution
CNN Study	2021	CNN	Classification	Feature extraction
U-Net Study	2022	U-Net	Segmentation	Tumor localization
Hybrid Model	2023	CNN + Transformer	Hybrid	Improved accuracy
Optimization Study	2023	DNN	Orthogonal Init	Faster convergence

Comparative Analysis

The comparative analysis of recent studies on automatic cervical cancer detection and segmentation demonstrates significant advancements in AI and deep learning architectures, with particular emphasis on CNNs, U-Net variants, hybrid CNN-transformer models, and sparsity-aware orthogonal initialization. The analysis focuses on segmentation accuracy, classification performance, training efficiency, generalization, and interpretability across different approaches.

1. Traditional Machine Learning vs Deep Learning

Earlier cervical cancer detection relied on classical machine learning methods, including Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Random Forests. These methods required handcrafted features such as nuclear morphology, texture descriptors, and cytoplasmic characteristics. Studies like Yilmaz et al. (2020) indicate that while traditional approaches achieve moderate classification accuracy (~75–80%), they are highly sensitive to feature selection and variability in imaging conditions.

In contrast, CNN-based deep learning models automatically learn hierarchical representations from raw images, significantly outperforming traditional models in both segmentation and classification. Hou et al. (2022) and Chandran et al. (2021) reported that CNN architectures improved sensitivity and specificity by over 15% compared to classical models, especially for detecting small or subtle lesions.

2. Standard CNN Architectures vs EfficientNet

Standard CNN architectures, including VGG and ResNet, have been widely used for classification tasks. ResNet's residual connections allow deeper network training, improving feature extraction. However, these models often require extensive computational resources and large datasets to achieve optimal performance.

EfficientNet, introduced by Tan and Le (2020), offers a compound scaling method that balances network depth, width, and input resolution. Alsalatie et al. (2022) and Mathivanan et al. (2024) demonstrated that EfficientNet-based models achieve higher accuracy (up to 96–98%) with significantly fewer parameters and faster convergence compared to standard CNNs. EfficientNet also handles high-resolution Pap smear images efficiently, making it suitable for both segmentation-guided classification and end-to-end diagnostic pipelines..

3. Segmentation: U-Net vs Attention-Based and Multi-Scale Models

Accurate segmentation of abnormal cervical regions is critical for improving classification accuracy. U-Net architectures remain the benchmark for biomedical image segmentation, as highlighted by Hussain et al. (2021). U-Net provides high segmentation accuracy due to skip connections and encoder-decoder design, but struggles with multi-scale features, particularly when lesions vary in size.

FPN-enhanced U-Net and attention-based variants address these limitations. Yaman and Tuncer (2022) showed that multi-scale feature fusion improved segmentation of small lesions by ~7–10%, while attention mechanisms enhanced focus on regions most indicative of malignancy. These approaches significantly reduce false positives in segmentation tasks.

4. Hybrid Models vs Single-Architecture Approaches

Hybrid architectures integrating CNNs with transformer layers or attention mechanisms have emerged as state-of-the-art. Abinaya et al. (2024) reported that CNN-transformer hybrids achieved higher segmentation accuracy (IoU ~0.92) and classification accuracy (~98%) compared to standalone CNNs or U-Net models. These hybrid models capture both local texture patterns and long-range dependencies, making them robust against noise and variability in Pap smear or histopathology images.

Ensemble methods also improve robustness. Alsalatie et al. (2022) demonstrated that combining multiple CNN models reduces prediction variance, leading to more stable performance across heterogeneous datasets.

5. Optimization Techniques: Sparsity-Aware Orthogonal Initialization vs Standard Initialization

Weight initialization is critical for training deep networks efficiently. Traditional random or Xavier initialization often leads to vanishing/exploding gradients, slower convergence, and overfitting in small medical datasets.

Sparsity-aware orthogonal initialization, as described by Mathivanan et al. (2024) and Xue et al. (2025), preserves the norm of input signals while introducing sparsity constraints. This reduces parameter redundancy, improves feature representation, and accelerates convergence. Models using sparsity-aware orthogonal initialization converge up to 30% faster than randomly initialized networks while achieving higher accuracy (~2–3% improvement in classification).

6. Attention Mechanisms vs Standard CNNs

Attention layers enhance performance by weighting relevant regions of the input image. Abinaya et al. (2024) demonstrated that integrating attention mechanisms into EfficientNet-U-Net hybrid models improved detection of high-grade lesions and reduced misclassification rates by ~5%.

Compared to standard CNNs, attention-based models provide:

- Improved interpretability (highlighting abnormal regions)
- Better feature selection
- Higher classification accuracy

However, attention layers increase computational complexity and may require more training data.

7. Multi-Modal and Whole-Slide Image Analysis

Whole-slide image (WSI) analysis presents unique challenges due to gigapixel resolution. Li et al. (2023) and Hou et al. (2022) developed patch-based CNN and hybrid architectures capable of handling WSIs. Multi-modal integration, including combining cytology, histopathology, and patient metadata, improved classification performance by up to 4–5%.

8. Comparative Metrics Across Studies

Study	Year	Architecture	Dataset	Segmentation Accuracy	Classification Accuracy	Optimization/Init
Yilmaz et al.	2020	CNN	Pap smear	0.78	0.80	Random Init
Hussain et al.	2021	U-Net	Pap smear	0.87	—	Xavier
Alsalatie et al.	2022	EfficientNet Ensemble	Pap smear	0.89	0.95	Adam + Transfer Learning
Abinaya et al.	2024	CNN + Transformer	WSI	0.92	0.98	Sparsity-Orthogonal
Mathivanan et al.	2024	EfficientNet-U-Net	Pap smear	0.91	0.96	Sparsity-Orthogonal + Adam

9. Key Insights

1. Deep learning models outperform classical machine learning approaches, particularly in detecting subtle abnormalities.
2. EfficientNet architectures balance computational cost and feature extraction performance.
3. Hybrid architectures (CNN + Transformer + Attention) achieve state-of-the-art performance in segmentation and classification.
4. Sparsity-aware orthogonal initialization significantly accelerates training and improves generalization, particularly on limited datasets.
5. Attention and multi-scale mechanisms improve segmentation of heterogeneous lesions.
6. Multi-modal and WSI-based approaches increase clinical applicability, though they demand high computational efficiency.

10. Limitations and Challenges

- Limited availability of annotated datasets and class imbalance remain significant bottlenecks.
- High computational requirements for hybrid and WSI-based models hinder real-time deployment.
- Black-box nature of deep learning models reduces interpretability, affecting clinical trust.
- Model generalization across different imaging protocols is still challenging.

11. Future Research Directions

- Development of lightweight, explainable hybrid architectures.
- Integration of multi-modal data including histopathology, cytology, and clinical metadata.
- Use of federated learning for privacy-preserving AI across institutions.
- Standardization and expansion of public cervical cancer datasets.
- Implementation of real-time screening tools suitable for low-resource clinical environments.

Summary

The literature clearly demonstrates that hybrid deep learning architectures, especially when combined with sparsity-aware orthogonal initialization, provide the most effective solution for automatic cervical cancer detection and segmentation. These models achieve higher segmentation and classification accuracy, faster convergence, and improved robustness compared to traditional methods or standard CNNs. Future research should focus on interpretability, efficiency, and multi-modal integration for clinical translation.

Discussion

Artificial intelligence techniques have significantly transformed cervical cancer detection by enabling automated analysis of medical images with high accuracy. Deep learning architectures such as CNNs, U-Net, and hybrid models have demonstrated strong capabilities in both segmentation and classification tasks. These models can effectively capture complex spatial patterns, leading to improved identification of abnormal cervical cells.

One of the key advancements in recent studies is the incorporation of **sparsity-aware orthogonal initialization**, which enhances training stability and accelerates convergence. By preserving signal propagation and reducing parameter redundancy, this approach improves model generalization, particularly in scenarios with limited datasets. Additionally, optimization techniques such as transfer learning, data augmentation, and adaptive optimizers have contributed to improved performance.

Despite these advancements, several challenges remain. The lack of large annotated datasets limits model training, while class imbalance affects performance. Moreover, the black-box nature of deep learning models raises concerns about interpretability and clinical trust.

Future research should focus on developing explainable AI systems, lightweight architectures, and multimodal data integration to improve clinical applicability.

Conclusion

This review highlights the significant progress in artificial intelligence techniques for automatic cervical cancer detection and segmentation. Deep learning models, particularly CNN-based architectures and hybrid frameworks, have demonstrated superior performance in medical image analysis tasks. The integration of sparsity-aware orthogonal initialization further enhances model efficiency by improving convergence, stability, and generalization.

Despite these advancements, challenges such as data scarcity, computational complexity, and lack of interpretability remain barriers to clinical adoption. Addressing these challenges is essential for developing reliable and scalable AI-based diagnostic systems.

Future research should focus on explainable AI, lightweight models, and real-time deployment in clinical settings. The integration of multimodal data sources, including imaging and clinical data, is also expected to improve diagnostic accuracy.

In conclusion, AI-based systems have the potential to revolutionize cervical cancer screening and diagnosis, enabling early detection and improved patient outcomes.

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