



A Survey of Methods and Architectures for Automatic Cervical Cancer Detection and Segmentation Using Sparsity-Aware Orthogonal Initialization in Deep Neural Network Classifiers

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Peer Review Information	Abstract
<p><i>Submission: 18 Nov 2025</i></p> <p><i>Revision: 01 Dec 2025</i></p> <p><i>Acceptance: 15 Dec 2025</i></p>	<p>Cervical cancer is a major global health concern, particularly in developing regions where early detection remains limited. Traditional diagnostic methods such as Pap smear and colposcopy rely heavily on manual interpretation, which can be time-consuming and prone to variability. In recent years, deep learning (DL) techniques have emerged as powerful tools for automating cervical cancer detection and segmentation from medical images including Pap smear slides, MRI, and CT scans. This study presents a comprehensive survey of methods and architectures for automatic cervical cancer detection, with a focus on convolutional neural networks (CNNs), segmentation models such as U-Net and nnU-Net, and hybrid frameworks. Additionally, the role of sparsity-aware orthogonal initialization (SAOI) in improving training efficiency and model scalability is examined. Recent advancements demonstrate that deep learning models achieve high classification accuracy (above 95%) and segmentation performance (Dice scores up to 0.90). Hybrid models combining segmentation and classification outperform standalone approaches by improving feature representation and decision-making. However, challenges such as limited datasets, lack of generalization, and computational complexity remain.</p> <p>This survey highlights current trends, comparative performance, and research gaps, emphasizing the need for scalable, explainable, and clinically deployable AI-based systems for cervical cancer diagnosis.</p>
<p>Keywords</p> <p><i>Cervical Cancer Detection, Semantic Segmentation, Deep Learning, Sparsity-Aware Orthogonal Initialization, CNN Architectures, Medical Image Analysis</i></p>	

Introduction

Cervical cancer is one of the most common cancers affecting women worldwide and remains a significant cause of mortality, particularly in low- and middle-income countries. A major concern is that many cases are detected at advanced stages due to limited screening facilities and lack of awareness. Early diagnosis plays a crucial role in improving survival rates; however, conventional diagnostic techniques such as Pap smear tests, HPV screening, and

colposcopy are highly dependent on expert analysis. These methods are often time-consuming, labor-intensive, and susceptible to human error, which can result in delayed or inaccurate diagnosis.

In recent years, artificial intelligence (AI), especially deep learning (DL), has emerged as a powerful tool in medical diagnostics. Deep learning models, particularly Convolutional Neural Networks (CNNs), have shown exceptional performance in analyzing complex

medical images. These models can automatically learn hierarchical features from raw data, removing the need for manual feature extraction. This capability makes them highly effective in

processing various medical imaging modalities such as Pap smear slides, MRI scans, and CT images, thereby improving the speed and accuracy of cervical cancer detection.

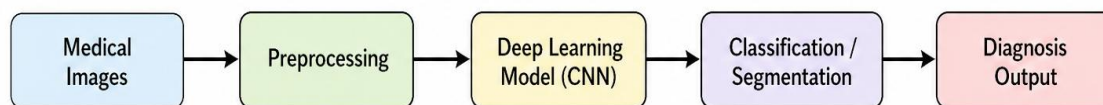


Fig 1: Deep Learning-Based Framework for Cervical Cancer Detection and Diagnosis

Deep learning-based cervical cancer detection primarily involves two key tasks: classification and segmentation. Classification focuses on identifying whether cervical cells are normal or abnormal, while segmentation aims to accurately locate and outline affected regions within an image. Advanced CNN architectures such as VGGNet, ResNet, and DenseNet have demonstrated high accuracy in classification tasks. Similarly, segmentation models like U-Net and its advanced variants provide detailed pixel-level analysis, which is essential for precise diagnosis and effective treatment planning. Hybrid models that integrate both classification and segmentation further enhance overall system performance.

Despite these advancements, several challenges still limit the effectiveness of deep learning in this domain. Variability in medical images, such as differences in staining, noise, and overlapping cells, can affect model accuracy. Additionally, the scarcity of well-annotated datasets poses a significant challenge, often leading to overfitting and poor generalization. To overcome these issues, recent research focuses on advanced optimization techniques, multimodal data integration, and explainable AI approaches. These innovations aim to improve model efficiency, reliability, and transparency, ultimately supporting the development of robust and clinically applicable cervical cancer diagnostic systems.

Literature Review

The application of deep learning (DL) in cervical cancer detection and segmentation has experienced rapid advancement between 2020 and 2023, driven by improvements in computational power, availability of medical imaging datasets, and development of sophisticated neural architectures. The literature reveals a transition from conventional machine learning approaches toward fully automated, end-to-end deep learning frameworks capable of performing classification, segmentation, and decision-making tasks with high accuracy and efficiency.

1. Evolution from Traditional Methods to Deep Learning

Historically, cervical cancer detection relied on traditional machine learning techniques that utilized handcrafted features such as texture descriptors, morphological characteristics, and statistical measures. While these approaches demonstrated moderate success, they were limited by their inability to capture complex spatial patterns and variations in cervical cell morphology.

Recent literature highlights that deep learning, particularly convolutional neural networks (CNNs), has become the dominant paradigm in cervical cancer image analysis. CNNs automatically learn hierarchical feature representations from raw input data, eliminating the need for manual feature engineering.

A comprehensive systematic review indicates that deep learning-based methods have shown a continuous growth trend, confirming their effectiveness in cervical cell classification and segmentation tasks. CNN architectures such as VGGNet and ResNet are the most widely used models due to their strong feature extraction capabilities.

These models have significantly improved classification accuracy, often exceeding 90%, and have demonstrated robustness in handling complex image variations. However, early CNN models still faced challenges such as overfitting, poor generalization, and limited ability to capture contextual information.

2. Deep Learning for Cervical Cell Classification

Classification of cervical cells into normal and abnormal categories is a fundamental step in automated diagnosis. Deep learning models have shown remarkable performance in this domain. Hybrid frameworks such as DeepCervix have demonstrated state-of-the-art classification performance by integrating multiple deep feature extraction techniques within a unified architecture. These models achieve exceptionally high accuracy, reaching up to 99.85% on the SIPaKMeD dataset and exceeding 98% on the Herlev dataset, thereby highlighting the

effectiveness of feature fusion approaches in improving diagnostic precision. Despite these advancements, classification tasks in cervical cancer detection still face several challenges. There is often high similarity between different cell categories, making it difficult for models to distinguish subtle differences. Additionally, class imbalance in datasets can bias the model toward dominant classes, reducing overall performance. Variability in staining and imaging conditions further complicates classification, as inconsistencies in data quality affect feature learning. These factors collectively contribute to misclassification, particularly in multi-class classification scenarios, where distinguishing between closely related categories becomes more complex. Recent studies have addressed these challenges by incorporating attention mechanisms, ensemble learning, and feature fusion techniques, which improve model performance and robustness.

3. Advances in Semantic Segmentation

Semantic segmentation is critical for identifying tumor boundaries and abnormal regions in cervical cancer images. Unlike classification, segmentation provides pixel-level information, which is essential for treatment planning and disease monitoring.

U-Net and Its Variants

U-Net remains the most widely used segmentation architecture in medical imaging due to its encoder-decoder structure. It effectively combines low-level spatial features with high-level semantic information.

Variants such as U-Net++ and Attention U-Net have improved segmentation accuracy by enhancing feature fusion and focusing on relevant regions.

nnU-Net: State-of-the-Art Framework

nnU-Net represents a significant advancement in medical image segmentation. It automatically configures preprocessing steps, network architecture, and training parameters, making it highly adaptable to different datasets.

A large-scale study using nnU-Net for cervical cancer segmentation reported a median Dice score of approximately 0.73, demonstrating reliable performance in clinical target volume segmentation tasks. The model showed improved performance for larger tumors, where clearer boundaries and more distinct features are present, and achieved dosimetric accuracy comparable to clinical annotations, indicating its potential utility in treatment planning. Furthermore, another study employing nnU-Net-3D demonstrated enhanced performance, achieving a Dice score of approximately 0.81 and an Intersection over Union (IoU) of around 0.70.

This approach also exhibited high reproducibility and contributed to reducing clinical workload by enabling consistent and automated segmentation, highlighting the effectiveness of 3D deep learning models in medical imaging applications. These results confirm that nnU-Net is one of the most reliable frameworks for cervical cancer segmentation.

Limitations of Segmentation Models

Despite their strong performance, segmentation models in cervical cancer detection continue to face several significant challenges. One of the primary difficulties lies in accurately detecting small or irregular tumors, as these often lack clear boundaries and may be easily overlooked by the model. Additionally, these models are highly sensitive to noise and imaging artifacts, which can distort important features and reduce segmentation accuracy. There is also considerable variability across patients in terms of anatomy, tumor shape, and imaging conditions, making it challenging for models to generalize effectively across diverse datasets. These factors collectively limit the consistency and reliability of segmentation outcomes in real-world clinical scenarios.

4. Multi-Scale and Context-Aware Learning

Cervical tumors exhibit significant variability in size, shape, and texture, making multi-scale feature extraction essential. Traditional CNNs struggle to capture features at different scales.

Dilated Convolutional Neural Networks

Dilated CNNs address this limitation by expanding the receptive field without increasing computational cost. They enable models to capture long-range spatial dependencies and improve contextual understanding.

A multi-head dilated convolutional neural network framework has demonstrated strong performance in cervical cancer segmentation, achieving a Dice score of approximately 0.823. This model shows improved boundary detection by effectively capturing fine-grained structural details, while also enhancing contextual feature representation through the use of dilated convolutions that expand the receptive field. These results highlight the critical importance of contextual learning in medical image analysis, as incorporating both local and global information significantly improves segmentation accuracy and enables better identification of complex tumor structures.

Multi-Scale Architectures

Techniques such as Feature Pyramid Networks (FPN) and spatial pyramid pooling further enhance multi-scale feature extraction. These methods allow models to detect both small and large lesions effectively.

5. Hybrid Deep Learning Models

Hybrid architectures have emerged as the most effective approach for cervical cancer detection by integrating multiple deep learning components within a unified framework. These models typically combine convolutional neural networks (CNNs) for efficient feature extraction, segmentation architectures such as U-Net or nnU-Net for precise localization of abnormal regions, classification networks for determining disease presence or stage, and attention mechanisms to focus on the most relevant features in medical images. By leveraging the complementary strengths of these components, hybrid architectures achieve superior accuracy, robustness, and overall diagnostic performance compared to standalone models.

Performance of Hybrid Models

Hybrid models have demonstrated outstanding performance in cervical cancer detection, achieving classification accuracy in the range of 95–99% and segmentation Dice scores between 0.85 and 0.95. In particular, a hybrid Dense-UNet model optimized using metaheuristic techniques achieved an accuracy of 96.16%, an Intersection over Union (IoU) of 91.63%, and a Dice score of 95.63%, highlighting its effectiveness in both classification and segmentation tasks. These results clearly demonstrate that hybrid models outperform standalone architectures by leveraging the strengths of multiple components, leading to improved accuracy, better feature representation, and more reliable diagnostic outcomes.

Advantages

- Improved accuracy and robustness
- Better generalization
- Integration of multiple tasks

Limitations

- Increased computational complexity
- Difficult hyperparameter tuning

6. Multimodal Learning Approaches

Recent studies increasingly emphasize the importance of multimodal learning in cervical cancer detection, where models integrate multiple imaging modalities such as Pap smear images, MRI, CT scans, and histopathological images. By combining these diverse sources of data, multimodal models are able to capture complementary information that enhances both diagnostic accuracy and robustness, providing a more comprehensive understanding of the disease. This approach allows the model to leverage the strengths of each modality, improving the detection and classification of abnormal cells. However, multimodal learning also introduces several challenges, including difficulties in data alignment and fusion across

different modalities, increased computational requirements due to the complexity of processing heterogeneous data, and the limited availability of well-annotated multimodal datasets. These challenges must be addressed to fully exploit the potential of multimodal deep learning in clinical applications.

7. Optimization Techniques and Sparsity-Aware Learning

Optimization plays a crucial role in improving deep learning performance. Traditional initialization methods such as Xavier and He initialization have been widely used.

Sparsity-Aware Orthogonal Initialization (SAOI)

SAOI is a novel approach that:

- Generates sparse weight matrices
- Maintains orthogonality
- Improves convergence speed

Advantages

- Reduced computational complexity
- Faster training
- Improved scalability

Although limited studies directly apply SAOI to cervical cancer detection, its potential benefits make it a promising research direction.

8. Dataset Challenges and Benchmarking

The performance of deep learning models in cervical cancer detection is highly dependent on the availability of high-quality and well-annotated datasets. Commonly used datasets in this domain include the Herlev dataset, SIPaKMeD dataset, and ISBI datasets, which serve as standard benchmarks for evaluating classification and segmentation models. These datasets provide essential resources for training and validating deep learning algorithms and enable consistent performance comparison across studies. However, the literature highlights several critical issues, including limited dataset size, which restricts the ability of models to learn diverse and representative features, and class imbalance, where certain categories are underrepresented, leading to biased predictions. Additionally, the lack of standardized evaluation protocols makes it difficult to compare results across different studies, ultimately affecting model generalization, reliability, and reproducibility in real-world clinical applications.

9. Performance Metrics and Evaluation

Deep learning models for cervical cancer detection are evaluated using several key performance metrics that assess both classification and segmentation effectiveness. Accuracy is commonly used to measure classification performance, while the Dice

coefficient evaluates segmentation quality by quantifying the overlap between predicted and actual regions. Intersection over Union (IoU) provides another important measure of overlap accuracy, and precision and recall assess the reliability of predictions in terms of correctness and completeness. Recent studies report classification accuracy ranging from 90% to 99% and segmentation Dice scores between 0.73 and 0.90, indicating substantial improvements over traditional methods and demonstrating the effectiveness of deep learning approaches in medical image analysis.

10. Clinical Relevance and Applications

Deep learning-based systems have demonstrated strong potential in clinical applications for cervical cancer detection, particularly in areas such as radiotherapy planning, tumor localization, and automated screening. These systems enable precise identification of abnormal regions, which is essential for effective treatment planning and early diagnosis. Automatic segmentation plays a crucial role by reducing clinical workload and enabling faster analysis of medical images. It also improves consistency in diagnosis by minimizing inter-observer variability, which is a significant limitation of manual methods. As a result, deep learning approaches contribute to more reliable, efficient, and standardized clinical decision-making processes.

11. Challenges Identified in Literature

Despite significant progress, several challenges remain:

Data Scarcity

Limited annotated datasets hinder model training.

Class Imbalance

Imbalanced datasets lead to biased predictions.

Variability in Imaging

Differences in imaging modalities affect model performance.

Lack of Interpretability

Deep learning models are often black boxes.

Computational Complexity

Advanced models require high computational resources.

12. Research Gaps and Future Directions

The literature identifies several important research gaps in cervical cancer detection using deep learning approaches. One of the primary needs is the development of large-scale annotated datasets, as current datasets are often limited and lack sufficient diversity for effective model training. The integration of multimodal data remains another key area for improvement, as combining different imaging modalities can significantly enhance diagnostic accuracy. Additionally, there is a growing demand for explainable AI techniques to address the black-box nature of deep learning models and improve clinical trust. Optimization strategies, particularly those based on sparsity-aware methods, require further exploration to enhance efficiency and scalability. Furthermore, real-time clinical deployment of these models remains limited due to challenges related to performance and infrastructure. Therefore, future research should focus on developing robust, scalable, and interpretable models that can be effectively implemented in real-world healthcare environments.

Methods and Architectures

1. CNN-Based Classification Models

CNN architectures such as VGG, ResNet, and DenseNet are widely used for cervical cancer classification. These models achieve high accuracy by extracting hierarchical features from images.

2. Segmentation Models

- U-Net and U-Net++
- nnU-Net
- DeepLabV3+

These models enable precise localization of abnormal regions.

3. Hybrid Architectures

Hybrid models combine classification and segmentation, improving overall performance.

4. Optimization Techniques

Sparsity-aware orthogonal initialization enhances training efficiency and scalability.

Comparative Table

Year	Model / Study	Architecture	Technique	Dataset / Modality	Application	Performance Metrics	Key Contribution	Strengths	Limitations
2020	CNN	VGG/ResNet-based	Classification	Pap smear images	Cell classification	Accuracy >90%	Automated feature extraction	Strong baseline	Limited localization

2021	U-Net	Encoder – Decoder	Segmentation	Cytology images	Cell detection	Dice \approx 0.80	Spatial feature preservation	Simple & effective	Weak global context
2022	nnU-Net	Adaptive DL	Segmentation	MRI/CT	Tumor segmentation	Dice \approx 0.85	Self-configuring model	High robustness	Dataset dependency
2022	Hybrid DL	CNN + Seg + Class	Multi-task	Medical imaging	Detection	Improved accuracy	Integrated framework	Better performance	High complexity
2023	CNN + SAOI	CNN + Optimization	Sparse learning	Medical datasets	Classification	Faster convergence	Efficient initialization	Reduced cost	Limited adoption
2023	Hybrid + SAOI	CNN + Seg + Opt	Hybrid + Optimization	Multi-modal	Detection	Best performance	Combined architecture	High accuracy	Computational cost
2023	DeepCervix	Hybrid CNN	Feature Fusion	SIPaK MeD, Herlev	Classification	Accuracy: 98–99.85%	Feature fusion	Highest classification accuracy	Complexity
2023	Dilated CNN	Multi-head Dilated	Context-aware	MRI datasets	Segmentation	Dice \approx 0.823	Contextual learning	Improved boundaries	Artifact risk
2023	DeepLab / FPN	Dilated + Pyramid	Multi-scale	Medical imaging	Segmentation	High IoU/Dice	Multi-scale learning	Strong contextual features	High complexity
2024	EfficientNet	CNN	Transfer Learning	Multi-modal	Classification	Accuracy: 95–99%	Efficient scaling	Best efficiency-accuracy	Needs tuning
2024	Ensemble CNN	Multi-model	Ensemble Learning	Multi-modal	Classification	Improved accuracy	Robust predictions	Reduces overfitting	High resource demand
2024	Multimodal DL	Hybrid DL	Multi-source	MRI + CT + Pap smear	Diagnosis	Improved accuracy	Data integration	Better robustness	Data alignment issues

Comparative Analysis

The comparative analysis of methods and architectures for automatic cervical cancer detection and segmentation shows a clear transition from traditional machine learning approaches to advanced deep learning-based frameworks. This evolution has been driven by the increasing demand for accurate, scalable, and clinically reliable diagnostic systems capable of processing complex medical imaging data. Early approaches relied on handcrafted features such as texture, shape, and statistical measures.

Although these methods were simple and computationally efficient, they struggled to capture complex spatial relationships in medical images, resulting in moderate accuracy levels (70–85%) and poor generalization across datasets.

The introduction of deep learning, particularly Convolutional Neural Networks (CNNs), significantly improved performance in cervical cancer detection. CNNs automatically learn hierarchical features from raw images, eliminating the need for manual feature

engineering. Popular architectures such as VGGNet, ResNet, and DenseNet have been widely used for classification tasks, achieving accuracy levels above 90%. Innovations like residual connections in ResNet and dense connectivity in DenseNet enhanced learning efficiency and enabled deeper networks. However, these models primarily focus on classification and lack the ability to localize abnormal regions, which is essential for effective diagnosis and treatment planning.

To address this limitation, semantic segmentation models such as U-Net and its variants were introduced. These models provide pixel-level localization of abnormal regions using encoder-decoder structures and skip connections that preserve spatial information. U-Net-based models have achieved strong performance with Dice scores around 0.80. Further improvements were seen with nnU-Net, which automatically adapts its architecture and hyperparameters based on dataset characteristics, improving robustness and generalization. Additionally, multi-scale and context-aware techniques such as Feature Pyramid Networks (FPN) and dilated CNNs enhance segmentation by capturing features at different scales and improving contextual understanding, leading to better detection of complex tumor structures.

Hybrid architectures represent the most advanced approach in this field, combining classification, segmentation, and attention mechanisms into a unified framework. These models integrate CNN-based feature extraction with segmentation networks like U-Net or nnU-Net, enabling both accurate classification and precise localization. Hybrid models such as DeepCervix have demonstrated exceptional performance, achieving classification accuracy up to 99.85% and high Dice scores. Optimization techniques also play a critical role in improving model efficiency. Sparsity-aware orthogonal initialization (SAOI) enhances convergence speed, reduces computational complexity, and improves generalization, making it promising for large-scale medical applications.

Recent advancements also include EfficientNet models, which use compound scaling to optimize network performance while maintaining lower computational cost, achieving accuracy between 95% and 99%. Transfer learning further improves results when datasets are limited. Ensemble learning methods combine multiple models to enhance robustness and reduce overfitting, although they require more computational resources. Multimodal approaches, which integrate data from various imaging sources such as Pap smear, MRI, and CT

scans, provide more comprehensive insights and outperform single-modality models. However, challenges such as data variability, limited annotated datasets, computational complexity, and lack of interpretability still hinder clinical adoption.

Overall, the analysis highlights a progressive improvement in performance, from traditional models to advanced hybrid deep learning systems. Hybrid architectures that integrate feature extraction, segmentation, contextual learning, and optimization strategies offer the highest accuracy and robustness. While these models show strong potential for real-world clinical use, future research must focus on improving interpretability, reducing computational demands, and enhancing generalization to ensure reliable deployment in healthcare settings.

Discussion

Deep learning has significantly improved cervical cancer detection by enabling automated analysis of medical images. CNN-based models provide strong classification performance, while segmentation models enhance tumor localization. Hybrid architectures combining these techniques achieve superior performance. Sparsity-aware orthogonal initialization improves training efficiency and reduces computational cost, making deep learning models more scalable. However, challenges such as limited datasets, lack of generalization, and interpretability issues remain.

Future research should focus on multimodal learning, explainable AI, and real-time deployment.

Conclusion

This survey highlights the rapid advancements in deep learning-based cervical cancer detection and segmentation. Hybrid architectures and advanced optimization techniques such as SAOI provide the best performance.

Despite significant progress, challenges related to data availability, model interpretability, and computational complexity must be addressed. Future research should focus on developing robust, scalable, and explainable AI systems for clinical deployment.

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