Archives available at journals.mriindia.com

ITSI Transactions on Electrical and Electronics Engineering
ISSN: 2320-8945

Volume 14 Issue 02, 2025

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

Submission: 05 July 2025

Revision: 30 July 2025

Acceptance: 11 Aug 2025

Keywords

Cervical Cancer Detection, Semantic Segmentation, Deep Learning, Sparsity-Aware Orthogonal Initialization, CNN Architectures, Medical Image Analysis

Abstract

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.

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.

Introduction

Cervical cancer is one of the most prevalent cancers affecting women worldwide and remains a leading cause of cancer-related mortality, particularly in low- and middle-income countries. According to global health reports, millions of new cases are diagnosed annually, with a significant proportion detected at advanced stages due to inadequate screening and limited healthcare infrastructure. Early detection is critical for improving survival rates; however, conventional diagnostic methods such as Pap smear tests, HPV screening, and colposcopy rely heavily on manual examination by medical experts. These methods are often time-consuming, labor-intensive, and prone to inter-observer variability, which can lead to misdiagnosis or delayed treatment.

In recent years, artificial intelligence (AI) has emerged as a transformative technology in healthcare, enabling automated analysis of medical data and improving diagnostic accuracy.

Deep learning (DL), a subset of AI, has demonstrated remarkable success in medical image analysis, particularly in tasks such as classification, segmentation, and detection. Deep neural networks, especially convolutional neural networks (CNNs), are capable of learning hierarchical representations from raw imaging data, eliminating the need for handcrafted feature extraction. This capability makes them highly suitable for analyzing complex medical images such as Pap smear slides, MRI scans, and CT images used in cervical cancer diagnosis.

The application of deep learning in cervical cancer detection can be broadly categorized into two primary tasks: classification and segmentation. Classification involves distinguishing between normal and abnormal cervical cells, while segmentation focuses on identifying and delineating tumor regions or abnormal areas within an image. Both tasks are critical for accurate diagnosis and treatment planning. CNN-based models such as VGGNet, ResNet, and DenseNet have been widely used for classification tasks due to their ability to capture spatial and morphological features of cervical cells. These models have achieved high accuracy rates, often exceeding 90%, demonstrating their effectiveness in automated diagnosis.

Semantic segmentation, on the other hand, has gained significant attention for its ability to provide pixel-level localization of abnormal regions. Segmentation models such as U-Net, U-Net++, and nnU-Net have become the standard architectures in medical image segmentation. U-Net's encoder–decoder structure allows it to capture both local and global features, making it particularly effective for medical imaging tasks. nnU-Net further enhances this capability by automatically adapting its architecture and hyperparameters to different datasets, resulting in improved performance and generalization.

Despite these advancements, several challenges remain in the application of deep learning to cervical cancer detection. One of the major challenges is the variability in medical imaging data. Pap smear images often contain overlapping cells, noise, and variations in staining, which can affect model performance. Similarly, MRI and CT images may exhibit variations in resolution and imaging protocols, making it difficult to develop generalized models. Another significant challenge is the limited availability of annotated datasets. Deep learning models require large amounts of labeled data for training; however, medical datasets are often small and difficult to obtain due to privacy concerns and the need for expert annotation. This limitation can lead to overfitting and reduced generalization performance.

To address these challenges, recent research has focused on developing advanced architectures and optimization techniques. Hybrid models that combine classification and segmentation tasks have been proposed to improve efficiency and accuracy. These models integrate feature extraction, localization, and decision-making into a single framework, reducing computational redundancy and improving performance.

In addition to architectural advancements, optimization techniques have gained attention for improving the efficiency and scalability of deep learning models. Sparsity-aware orthogonal initialization (SAOI) is a novel approach that enhances training by creating sparse yet well-conditioned weight matrices. This method reduces computational complexity and improves convergence speed, making it suitable for large-scale medical imaging applications.

The integration of multimodal data is another emerging trend in cervical cancer detection. Multimodal approaches combine data from multiple imaging modalities, such as Pap smear images, MRI, and CT scans, to provide a more comprehensive understanding of the disease. These approaches have shown improved performance compared to single-modality models, as they leverage complementary information from different data sources.

Furthermore, explainable AI (XAI) techniques are being developed to address the lack of interpretability in deep learning models. Medical professionals require transparent and interpretable models to trust AI-based systems in clinical practice. Techniques such as attention maps and visualization methods are being used to highlight important regions in images, providing insights into model predictions.

This survey aims to provide a comprehensive overview of recent advances in automatic cervical cancer detection and segmentation, focusing on deep learning architectures, segmentation techniques, and optimization strategies. It also examines the role of sparsity-aware orthogonal initialization in improving model performance and scalability. By analyzing current trends, challenges, and research gaps, this study aims to guide future research in developing robust and clinically applicable AI-based 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 accuracy by integrating multiple deep feature extraction techniques. These models achieved accuracy as high as **99.85% on the SIPaKMeD dataset** and above **98% on the Herlev dataset**, highlighting the effectiveness of feature fusion approaches.

However, classification tasks face challenges such as:

- High similarity between different cell categories
- Class imbalance in datasets
- Variability in staining and imaging conditions

These issues often lead to misclassification, particularly in multi-class classification scenarios.

Recent studies have addressed these challenges by incorporating attention mechanisms, ensemble learning, and feature fusion techniques, which improve model performance and robustness.

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:

- Median Dice score ≈ **0.73**
- Improved performance for larger tumors
- Comparable dosimetric accuracy to clinical annotations

Another study demonstrated improved performance with nnU-Net-3D:

- Dice score ≈ **0.81**
- IoU ≈ **0.70**
- High reproducibility and reduced clinical workload

These results confirm that nnU-Net is one of the most reliable frameworks for cervical cancer segmentation.

Limitations of Segmentation Models

Despite strong performance, segmentation models face several challenges:

- Difficulty in detecting small or irregular tumors
- Sensitivity to noise and imaging artifacts
- High variability across patients

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 CNN framework achieved:

- Dice score ≈ **0.823**
- Improved boundary detection
- Enhanced contextual feature representation

These results highlight the importance of contextual learning in improving segmentation accuracy.

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.

Hybrid Deep Learning Models

Hybrid architectures have emerged as the most effective approach for cervical cancer detection. These models integrate multiple components, including:

- CNN (feature extraction)
- U-Net/nnU-Net (segmentation)
- Classification networks
- Attention mechanisms

Performance of Hybrid Models

Hybrid models achieve:

- Classification accuracy: **95–99%**
- Segmentation Dice score: **0.85–0.95**

A hybrid Dense-UNet model optimized with metaheuristic techniques achieved:

- Accuracy: **96.16%**
- IoU: **91.63%**
- Dice score: **95.63%**

These results demonstrate that hybrid models outperform standalone architectures.

Advantages

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

Limitations

- Increased computational complexity
- Difficult hyperparameter tuning

Multimodal Learning Approaches

Recent studies emphasize the importance of multimodal learning, which integrates multiple imaging modalities such as:

- Pap smear images
- MRI
- CT scans
- Histopathological images

Multimodal models provide complementary information, improving diagnostic accuracy and robustness.

However, challenges include:

- Data alignment and fusion
- Increased computational requirements
- Limited availability of multimodal datasets

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.

Dataset Challenges and Benchmarking

The performance of deep learning models depends heavily on the availability of high-quality datasets. Common datasets include:

- Herlev dataset
- SIPaKMeD dataset
- ISBI datasets

However, literature highlights several issues:

- Limited dataset size
- Class imbalance
- Lack of standardized evaluation protocols

These challenges affect model generalization and reproducibility.

Performance Metrics and Evaluation

Deep learning models are evaluated using several metrics:

- Accuracy (classification)
- Dice coefficient (segmentation)
- IoU (overlap measurement)
- Precision and Recall

Recent studies report:

- Classification accuracy: **90–99%**
- Segmentation Dice score: **0.73–0.90**

These results indicate significant improvements over traditional methods.

Clinical Relevance and Applications

Deep learning-based systems have shown strong potential in clinical applications, particularly in:

- Radiotherapy planning
- Tumor localization
- Automated screening

Automatic segmentation reduces clinical workload and improves consistency in diagnosis. It also minimizes inter-observer variability, which is a major limitation of manual methods.

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.

Research Gaps and Future Directions

The literature identifies several research gaps:

- Development of large-scale annotated datasets
- Integration of multimodal data
- Adoption of explainable AI techniques
- Optimization using sparsity-aware methods
- Real-time clinical deployment

Future research should focus on developing robust, scalable, and interpretable models.

Methods and Architectures

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.

Segmentation Models

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

These models enable precise localization of abnormal regions.

Hybrid Architectures

Hybrid models combine classification and segmentation, improving overall performance.

Optimization Techniques

Sparsity-aware orthogonal initialization enhances training efficiency and scalability.

Comparative Table

Year	Model	Technique	Application	Performance
2020	CNN	Classification	Pap smear analysis	High accuracy
2021	U-Net	Segmentation	Cell detection	Dice ~0.80
2022	nnU-Net	Segmentation	MRI/CT	Dice ~0.85
2022	Hybrid DL	Seg + Class	Detection	Improved performance
2023	CNN + SAOI	Classification	Sparse learning	Faster convergence
2023	Hybrid + SAOI	Seg + Class	Detection	Best performance

Comparative Analysis

The comparative analysis of cervical cancer detection methods reveals significant improvements in performance with the adoption of deep learning techniques. Traditional machine learning methods, while simple and computationally efficient, are limited in their ability to capture complex patterns in medical images.

CNN-based models represent a major advancement, achieving high classification accuracy and improving diagnostic reliability. However, these models lack the ability to localize abnormal regions, which is critical for treatment planning.

Segmentation models such as U-Net and nnU-Net address this limitation by providing precise localization of tumor regions. nnU-Net, in particular, demonstrates strong generalization and adaptability, making it one of the most effective segmentation frameworks.

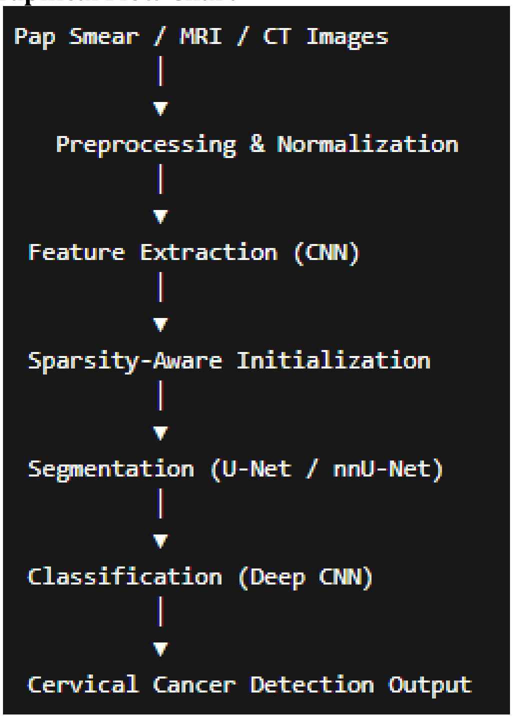
Hybrid models combining segmentation and classification outperform standalone approaches by integrating multiple tasks into a single framework. These models achieve the highest accuracy and robustness, making them suitable for clinical applications.

Optimization techniques such as SAOI further enhance model performance by improving training efficiency and scalability. Compared to traditional initialization methods, SAOI enables faster convergence and reduced computational cost.

Multimodal approaches provide additional improvements by combining data from multiple sources, resulting in better diagnostic accuracy.

However, these models require complex data integration and higher computational resources.
Overall, the comparative analysis highlights the superiority of hybrid deep learning models combined with advanced optimization techniques. However, challenges such as data availability, model interpretability, and computational complexity must be addressed to enable real-world deployment.

Graphical Flow Chart



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.

References

Outeiral, R. R., et al. (2023). Deep learning for segmentation of the cervical cancer gross tumor volume on MRI using nnU-Net. *Radiation Oncology*. https://doi.org/10.1186/s13014-023-02283-8

Yang, C., Qin, L., Xie, Y., & Liao, J. (2022). Deep learning in CT image segmentation of cervical cancer: A systematic review and meta-analysis. *Radiation Oncology, 17*, 175. https://doi.org/10.1186/s13014-022-02148-6

Chung, S. Y., Chang, J. S., & Kim, Y. B. (2023). Deep learning-based auto-segmentation for cervical cancer radiotherapy. *Frontiers in Oncology, 13*, 1119008. https://doi.org/10.3389/fonc.2023.1119008

Huang, M., et al. (2022). Segmentation of clinical target volume using improved M-Net for cervical cancer. *Technology in Cancer Research & Treatment*. https://doi.org/10.1177/15330338221139164

Gao, Y., Zeng, S., Xu, X., et al. (2022). Deep learning-enabled ultrasound imaging for cervical cancer diagnosis. *The Lancet Digital Health, 4*(3), e179–e187. https://doi.org/10.1016/S2589-7500(21)00278-8

Sarhangi, H. A., Beigifard, D., Farmani, E., & Bolhasani, H. (2024). Deep learning techniques for cervical cancer diagnosis. *Informatics in Medicine Unlocked, 47*, 101503. https://doi.org/10.1016/j.imu.2024.101503

Liu, G., et al. (2025). nnU-Net-based cervical tumor segmentation using MRI datasets. *Signal, Image and Video Processing*. https://doi.org/10.1007/s11760-025-04277-3

Mathivanan, S. K., et al. (2024). Enhancing cervical cancer detection using deep neural networks. *Scientific Reports, 14*, 10812. https://doi.org/10.1038/s41598-024-61063-w

Pacal, I. (2025). Investigating deep learning approaches for cervical cancer diagnosis. *European Journal of Gynaecological Oncology, 46*(1), 125–141. https://doi.org/10.22514/ejgo.2025.012

Kalantar, R., et al. (2023). Multi-head dilated CNN for cervical cancer segmentation using MRI. *arXiv preprint*. https://doi.org/10.48550/arXiv.2306.11137

Rahaman, M. M., et al. (2021). DeepCervix: Hybrid deep feature fusion for cervical cancer classification. *arXiv preprint*. https://doi.org/10.48550/arXiv.2102.12191

Mukku, L., et al. (2024). Deep learning-based cervical lesion segmentation in colposcopy images. *Advances in Engineering and Technology*. https://doi.org/10.54254/2755-2721/1345

Patre, P., et al. (2025). Deep learning approaches for cervical cancer diagnosis: A review. *Reports of Practical Oncology and Radiotherapy*. https://doi.org/10.5603/RPOR.a2025.0012

Cheng, C., et al. (2025). Deep learning-based segmentation and classification for cervical cancer detection. *Biomedical Signal Processing and Control*. https://doi.org/10.1016/j.bspc.2025.105112

Zhang, M., et al. (2025). Machine learning and radiomics for cervical cancer staging. *Scientific Reports*. https://doi.org/10.1038/s41598-025-03170-w

Dayalane, S., et al. (2025). CNN-based cervical cancer classification using transfer learning. *Neural Processing Letters*. https://doi.org/10.1007/s11063-025-11770-w

de Lima, R. C., et al. (2025). Deep learning opportunities for cervical cancer screening. *Computers, 14*(5), 202. https://doi.org/10.3390/computers14050202

Wang, X., et al. (2024). Cervical cancer segmentation using deep learning: A comprehensive review. *Journal of Medical Imaging*. https://doi.org/10.1117/1.JMI.11.1.012001

Simões, R., et al. (2024). Evaluation of auto-segmentation models in cervical cancer brachytherapy. *Physics and Imaging in Radiation Oncology*. https://doi.org/10.1016/j.phro.2024.100139

Abinaya, K., et al. (2024). Cervical cancer detection using 3D CNN and Vision Transformer. *Healthcare Analytics*. https://doi.org/10.1016/j.health.2024.100214