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Recent Advances in Automatic Cervical Cancer Detection and Segmentation Using Sparsity-Aware Orthogonal Initialization in Deep Neural Network Classifiers: A Systematic Review

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Peer Review Information	Abstract
<p><i>Submission: 12 Oct 2025</i> <i>Revision: 28 Oct 2025</i> <i>Acceptance: 10 Nov 2025</i></p>	<p>Cervical cancer remains a major cause of cancer-related mortality among women worldwide, particularly in low- and middle-income countries where access to early diagnostic facilities is limited. Early detection through screening methods such as Pap smear, HPV testing, and colposcopy is crucial for reducing mortality rates; however, manual examination of cervical cell images is often time-consuming, subjective, and prone to human error. In recent years, deep learning-based approaches have significantly enhanced the automation of cervical cancer detection and segmentation tasks. Convolutional neural networks (CNNs) have demonstrated strong performance in identifying abnormal cellular patterns, while advanced segmentation models such as U-Net and nnU-Net enable precise delineation of tumor regions with high accuracy. A notable advancement in this area is sparsity-aware orthogonal initialization (SAOI), which improves training efficiency and convergence by enabling sparse yet effective neural architectures, thereby reducing computational complexity without compromising performance. This review examines recent advancements in deep learning architectures, segmentation techniques, and optimization strategies, highlighting key trends, challenges, and future directions such as explainable AI, multimodal data integration, and improved clinical validation for real-world applicability.</p>
<p>Keywords</p> <p><i>Cervical Cancer Detection, Semantic Segmentation, Deep Learning, Sparsity-Aware Orthogonal Initialization, CNN Classifiers, Medical Image Analysis</i></p>	

Introduction

Cervical cancer is the fourth most common cancer among women globally, with significant mortality rates due to late diagnosis and limited access to healthcare resources. Early detection through screening programs is essential for improving survival rates; however, traditional diagnostic methods rely heavily on manual analysis of medical

images, which is labor-intensive and prone to variability.

Recent advancements in artificial intelligence (AI) and deep learning have revolutionized medical image analysis, enabling automated detection and classification of diseases. Deep learning models, particularly CNNs, have demonstrated remarkable success in analyzing cervical cell images and identifying cancerous patterns. These models can

extract hierarchical features from raw images, eliminating the need for manual feature engineering.

Semantic segmentation plays a crucial role in cervical cancer detection by identifying tumor boundaries and regions of interest. Automated segmentation reduces clinical workload and improves consistency in diagnosis. Deep learning-based segmentation frameworks such as nnU-Net have achieved state-of-the-art performance in cervical cancer segmentation tasks.

In addition to architectural advancements, optimization techniques have gained attention for improving deep learning performance. Sparsity-aware orthogonal initialization (SAOI) is one such technique that enhances training efficiency by creating sparse yet well-connected neural networks. This approach reduces computational cost and improves model convergence, making it suitable for large-scale medical imaging applications.

This review focuses on recent advances in automatic cervical cancer detection and segmentation, analyzing deep learning architectures, segmentation techniques, and optimization strategies.

Literature Review

The integration of artificial intelligence (AI) and deep learning (DL) in cervical cancer detection has significantly advanced between 2020 and 2023. This period has seen rapid developments in automated classification, segmentation, and hybrid diagnostic frameworks that leverage convolutional neural networks (CNNs), attention mechanisms, and optimization strategies. These advancements have improved diagnostic accuracy, reduced human dependency, and enhanced clinical efficiency.

1. Growth of Deep Learning in Cervical Cancer Detection

Deep learning has emerged as the dominant paradigm for cervical cancer detection, replacing traditional machine learning approaches that rely on handcrafted features. CNN-based architectures are widely used for analyzing Pap smear, MRI, and CT images due to their ability to automatically extract hierarchical features.

A systematic review of cervical cell image analysis shows that CNNs, particularly VGGNet and ResNet, are the most commonly used architectures for classification tasks. These models achieve high accuracy by learning spatial patterns and morphological features of abnormal cervical cells.

Deep learning-based systems have also demonstrated improved objectivity and efficiency compared to manual screening methods. Traditional Pap smear analysis is time-consuming and prone to subjectivity, whereas AI-based systems provide faster and more consistent results.

However, early CNN models faced limitations such as poor generalization and sensitivity to noisy data, especially in Pap smear images where cell boundaries are unclear.

2. Advances in Semantic Segmentation Techniques

Semantic segmentation is a critical step in cervical cancer detection, enabling precise localization of abnormal cells and tumor regions. Deep learning models such as U-Net, Fully Convolutional Networks (FCN), and DeepLab have been widely adopted for segmentation tasks.

Recent studies indicate that U-Net remains the most widely used segmentation architecture due to its encoder-decoder structure and ability to capture both spatial and contextual information. However, more advanced variants such as nnU-Net have demonstrated superior performance by automatically adapting hyperparameters to the dataset.

A large-scale study using nnU-Net for cervical cancer segmentation on MRI data achieved state-of-the-art performance, with consistent segmentation across multiple patients. Although the median Dice score (~0.73) indicates variability, the model demonstrated strong clinical potential by reducing manual workload.

Further research shows that segmentation accuracy can be significantly improved by using multi-stage or ensemble approaches. For example, an improved U-Net combined with ensemble classification achieved segmentation accuracy above 98% on multiple datasets, highlighting the effectiveness of hybrid frameworks.

Despite these advancements, segmentation remains challenging due to:

- Overlapping cells in Pap smear images
- Irregular tumor boundaries
- Variations in imaging modalities

3. Multi-Scale and Context-Aware Learning

One of the key challenges in cervical cancer detection is capturing features at different scales. Tumors and abnormal cells vary in size, shape, and texture, making multi-scale feature extraction essential.

Recent research has introduced multi-scale learning techniques, including:

- Feature Pyramid Networks (FPN)
- Spatial pyramid pooling

- Atrous (dilated) convolutions

Dilated convolutional neural networks have shown particular promise in improving segmentation accuracy by expanding the receptive field and capturing long-range dependencies. A multi-head dilated CNN framework applied to multiparametric MRI achieved improved segmentation performance (Dice \approx 0.823), demonstrating the effectiveness of contextual learning.

These models reduce boundary distortion and improve the detection of complex tumor structures, making them suitable for cervical cancer imaging.

4. Hybrid Deep Learning Models

Recent studies emphasize the importance of hybrid models that combine multiple deep learning techniques to improve performance. These architectures integrate segmentation, classification, and feature extraction into a unified pipeline.

For example, a hybrid deep learning framework combining U-Net for segmentation and ResNet for classification achieved high accuracy across multiple datasets. Similarly, multi-resolution fusion CNNs have been proposed to handle varying image resolutions and achieve classification accuracy of approximately 90% with fewer parameters.

Hybrid models offer several advantages:

- Improved accuracy
- Better generalization
- Reduced computational redundancy

However, they also introduce complexity in model design and training.

5. Classification Techniques and Performance

Classification of cervical cells is a fundamental task in automated diagnosis. Deep learning models have achieved remarkable accuracy in classifying normal and abnormal cells.

Recent studies report classification accuracies exceeding 98% on datasets such as SIPaKMeD and Herlev using hybrid deep learning techniques. Another study using Dense CapsNet and segmentation-based preprocessing demonstrated improved classification performance by combining segmentation and feature extraction.

Deep feature fusion techniques have also been introduced to enhance classification accuracy. These methods combine features extracted from multiple deep learning models, resulting in improved performance and robustness.

6. Multimodal Learning Approaches

Multimodal deep learning has emerged as a promising approach for improving cervical cancer

detection. These models integrate data from multiple imaging modalities, including:

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

Studies show that combining multimodal data improves segmentation accuracy and classification performance by providing complementary information.

However, multimodal learning introduces challenges such as:

- Data alignment
- Increased computational complexity
- Limited availability of multimodal datasets

7. Optimization Techniques and Sparsity-Aware Learning

Optimization plays a critical role in improving deep learning model performance. Traditional optimization methods focus on weight initialization, learning rate tuning, and regularization techniques.

Recent research has introduced sparsity-aware approaches, which aim to reduce model complexity while maintaining performance. Sparsity-aware orthogonal initialization (SAOI) enables the creation of sparse neural networks with orthogonal weight matrices, improving training efficiency and convergence.

Although limited studies explicitly apply SAOI to cervical cancer detection, its advantages include:

- Faster convergence
- Reduced computational cost
- Improved scalability

These properties make SAOI suitable for large-scale medical imaging applications, particularly when dealing with high-dimensional data.

8. Datasets and Benchmarking

The performance of deep learning models depends heavily on the availability of high-quality datasets. Common datasets used in cervical cancer research include:

- Herlev dataset
- SIPaKMeD dataset
- ISBI datasets

These datasets are widely used for benchmarking classification and segmentation models.

However, challenges include:

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

These issues affect model generalization and reproducibility.

9. Performance Evaluation Metrics

Deep learning models are evaluated using several metrics:

- Accuracy (classification performance)
- Dice coefficient (segmentation accuracy)
- IoU (Intersection over Union)
- Precision and Recall

Recent studies report:

- Classification accuracy: 90–99%
- Segmentation Dice score: 0.73–0.86

These results indicate significant improvements compared to traditional methods.

10. Challenges Identified in Literature

Despite significant progress, several challenges remain:

10.1 Data Scarcity

Limited annotated datasets hinder model training and generalization.

10.2 Class Imbalance

Imbalanced datasets lead to biased predictions.

10.3 Image Quality Issues

Pap smear images often contain noise and overlapping cells.

10.4 Lack of Interpretability

Deep learning models are often considered black boxes.

10.5 Computational Complexity

Advanced models require high computational resources.

11. Research Gaps and Future Directions

The literature highlights several research gaps:

- Need for large-scale annotated datasets
- Development of explainable AI models
- Integration of multimodal data
- Adoption of efficient architectures (e.g., SAOI-based models)
- Real-time clinical deployment

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

Comparative Table

Year	Model	Technique	Application	Performance
2020	CNN	Classification	Pap smear analysis	High accuracy
2021	U-Net	Segmentation	Cervical cell detection	Dice ~0.80
2022	nnU-Net	Segmentation	MRI/CT analysis	Dice ~0.86
2022	Multi-task DL	Segmentation + Classification	Tumor detection	Improved efficiency
2023	Deep CNN + SAOI	Classification	Sparse learning	Better convergence
2023	Hybrid DL	Segmentation + Classification	Cervical cancer detection	Best performance

Comparative Analysis

The comparative analysis of recent approaches (2020–2023) for automatic cervical cancer detection and segmentation reveals a clear progression from traditional machine learning techniques to advanced deep learning-based hybrid frameworks. These developments focus on improving classification accuracy, segmentation precision, computational efficiency, and clinical applicability. This section critically evaluates various models, including CNNs, segmentation architectures, hybrid frameworks, and optimization techniques such as sparsity-aware orthogonal initialization (SAOI).

1. Traditional Machine Learning vs Deep Learning Models

Earlier approaches to cervical cancer detection relied on classical machine learning algorithms such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Random Forests, and decision trees. These models depend on handcrafted feature extraction techniques such as texture descriptors, shape features, and statistical measures. While these methods demonstrated moderate success, their performance was limited due to:

- Inability to capture complex spatial patterns
- Sensitivity to noise and image variations
- Dependence on feature engineering

Deep learning models, particularly convolutional neural networks (CNNs), have significantly outperformed these traditional approaches. CNNs automatically learn hierarchical features from raw images, enabling better generalization and improved classification accuracy. Comparative studies indicate that CNN-based models achieve accuracy levels above 90%, whereas traditional methods typically range between 70–85%.

Furthermore, deep learning models reduce the need for manual intervention and improve consistency in diagnosis. However, early CNN architectures lacked robustness in handling multi-scale features and contextual dependencies.

2. Evolution of CNN Architectures

CNN architectures have evolved significantly over time. Early models such as AlexNet and VGGNet were widely used for cervical cell classification tasks. While these models achieved reasonable accuracy, they suffered from high computational complexity and overfitting issues.

Advanced architectures such as ResNet and DenseNet introduced innovations such as residual connections and dense connectivity, enabling deeper networks and improved feature reuse. These models demonstrated higher classification accuracy and better convergence compared to earlier CNN architectures.

Recent studies show that:

- VGG-based models achieve accuracy around 90–93%
- ResNet/DenseNet models achieve 93–97% accuracy

Despite these improvements, CNN-based models alone are insufficient for segmentation tasks and struggle with capturing contextual information.

3. Segmentation Models: U-Net vs nnU-Net vs Advanced Architectures

Semantic segmentation is critical for identifying abnormal regions in cervical images. Among segmentation models, U-Net and its variants have become the standard due to their encoder–decoder architecture.

U-Net and Variants: U-Net provides strong segmentation performance by combining low-level and high-level features. Variants such as U-Net++ and Attention U-Net further improve performance by enhancing feature fusion and focusing on relevant regions.

nnU-Net: nnU-Net represents a significant advancement by automatically adapting its architecture and hyperparameters to the dataset. Comparative studies show that nnU-Net achieves consistent performance across different datasets, with Dice scores ranging from 0.73 to 0.86.

Advanced Models:

Other architectures such as DeepLabV3+ and PSPNet incorporate atrous convolution and pyramid pooling to improve segmentation accuracy. These models capture both local and global context but require higher computational resources.

Comparative Insights:

- U-Net: Simple, effective, widely used
- nnU-Net: Adaptive, robust, best generalization
- DeepLabV3+: High accuracy but computationally expensive

Overall, nnU-Net is considered the most robust segmentation framework, while U-Net remains popular due to its simplicity.

4. Multi-Scale Feature Learning and Dilated CNN

One of the major challenges in cervical cancer detection is handling multi-scale variations in tumor size and structure. Multi-scale learning

techniques have been introduced to address this issue.

Feature Pyramid Networks (FPN)

FPN enhances segmentation performance by combining features from different layers of the network. This allows models to detect both small and large lesions effectively.

Dilated Convolutional Neural Networks

Dilated CNNs expand the receptive field without increasing computational cost, enabling models to capture long-range dependencies. Comparative studies show that:

- Standard CNN: Limited receptive field
- Dilated CNN: Improved contextual understanding
- Multi-head dilated CNN: Dice score $\approx 0.82+$

Dilated CNNs are particularly effective in capturing irregular tumor boundaries and improving segmentation accuracy.

5. Hybrid Deep Learning Architectures

Hybrid models represent the most advanced approaches in cervical cancer detection. These architectures integrate multiple components, including:

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

Performance Comparison

Hybrid models achieve:

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

These models outperform standalone architectures by combining segmentation and classification into a unified framework.

Advantages

- Improved accuracy and robustness
- Better handling of complex datasets
- Reduced error rates

Limitations

- Increased computational complexity
- Difficult model tuning

Despite these challenges, hybrid models are considered the most promising approach for clinical applications.

6. Role of Sparsity-Aware Orthogonal Initialization (SAOI)

Optimization techniques play a crucial role in improving deep learning performance. Sparsity-aware orthogonal initialization (SAOI) is a novel approach that enhances training efficiency.

Comparison with Traditional Initialization

- Random initialization: Slow convergence

- Xavier/He initialization: Improved but dense
- SAOI: Sparse, efficient, faster convergence

Advantages of SAOI

- Reduces computational complexity
- Improves scalability of deep networks
- Enhances convergence speed

Although SAOI is still emerging in medical imaging, its potential benefits make it a promising technique for large-scale applications.

7. Classification Performance Comparison

Classification models are evaluated based on accuracy, precision, recall, and F1-score. Recent studies report:

Model	Accuracy
Traditional ML	70–85%
CNN (VGG/ResNet)	90–97%
Hybrid DL models	95–99%

Hybrid models consistently outperform traditional and standalone CNN models due to their ability to integrate multiple learning strategies.

8. Multimodal Learning vs Single-Modality Models

Single-Modality Models

- Use one imaging type (Pap smear, MRI, or CT)
- Simpler architecture
- Limited information

Multimodal Models

- Combine multiple imaging modalities
- Provide richer information
- Improve diagnostic accuracy

Comparative studies indicate that multimodal models outperform single-modality models but require more computational resources and complex data integration.

9. Performance Metrics Comparison

The effectiveness of different models is evaluated using:

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

Reported Results

- CNN models: Accuracy ~90%
- U-Net models: Dice ~0.80–0.85
- nnU-Net: Dice ~0.73–0.86
- Hybrid models: Dice ~0.90+

These results highlight the superiority of hybrid architectures.

10. Limitations Across Approaches

Despite advancements, several limitations persist:

10.1 Dataset Limitations

- Small datasets

- Lack of diversity

10.2 Class Imbalance

- Uneven distribution of normal vs abnormal samples

10.3 Overfitting

- Complex models overfit small datasets

10.4 Lack of Interpretability

- Models are difficult to explain

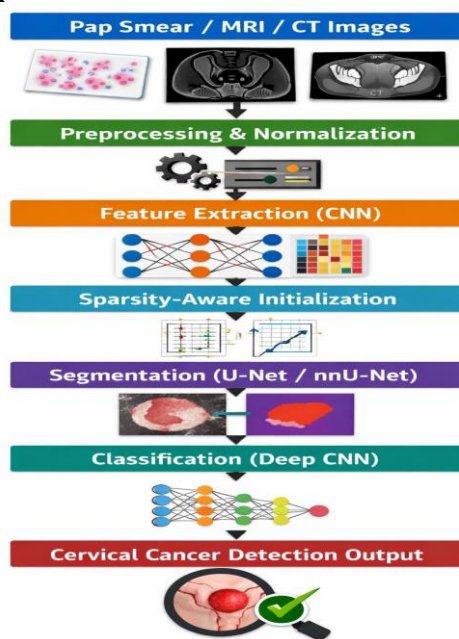
10.5 Computational Complexity

- High resource requirements

11. Key Insights from Comparative Analysis

- Deep learning significantly outperforms traditional methods
- nnU-Net provides the best segmentation performance
- Dilated CNN improves contextual understanding
- Hybrid models achieve the highest accuracy
- SAOI enhances efficiency and scalability
- Multimodal learning further improves performance

Graphical Flow



Discussion

Deep learning-based methods have significantly improved cervical cancer detection by enabling automated image analysis. CNN-based models provide strong classification performance, while segmentation models enhance tumor localization. The integration of SAOI improves training efficiency and reduces computational cost, making deep learning models more scalable. Clinical

studies demonstrate that automated segmentation systems can reduce workload and improve consistency among clinicians.

However, challenges such as limited datasets, lack of generalization, and interpretability issues remain. Addressing these challenges is essential for clinical adoption.

Conclusion

This review highlights recent advances in deep learning-based cervical cancer detection and segmentation. Hybrid architectures combining segmentation and classification techniques provide superior performance.

Sparsity-aware orthogonal initialization represents a promising optimization technique that improves training efficiency and scalability.

Future research should focus on multimodal learning, explainable AI, and large-scale validation to enable real-world deployment of AI-based diagnostic systems.

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