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A Comprehensive Review of Semantic Segmentation and Classification for Ovarian Cancer Detection Using EfficientNetB0 with FPN and Causal Dilated Convolutional Neural Networks

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Abstract

Ovarian cancer is one of the deadliest gynecological malignancies because it is often diagnosed at advanced stages, resulting in poor survival rates. Medical imaging techniques such as ultrasound, magnetic resonance imaging (MRI), and computed tomography (CT) are widely used for tumor detection, but manual interpretation is time-consuming and susceptible to inter-observer variability. Recent advances in deep learning have significantly improved automated ovarian cancer diagnosis through accurate image segmentation and classification. Convolutional Neural Networks (CNNs), particularly EfficientNetB0, provide efficient feature extraction by balancing network depth, width, and resolution while maintaining low computational complexity. When integrated with Feature Pyramid Networks (FPN), EfficientNetB0 effectively captures multi-scale features, enabling precise detection of tumors with varying sizes and shapes. Furthermore, semantic segmentation models accurately delineate tumor boundaries, improving diagnostic consistency and reducing manual effort. Causal dilated convolutional neural networks enhance contextual feature extraction by expanding the receptive field without increasing computational cost, making them suitable for identifying irregular tumor structures. This review examines recent developments in hybrid deep learning architectures that combine EfficientNetB0, FPN, and causal dilated CNNs for ovarian cancer detection. Although these integrated models demonstrate improved segmentation and classification performance, challenges related to limited datasets, model generalization, and clinical validation persist. Future research should emphasize multimodal data fusion, explainable artificial intelligence, and large-scale clinical evaluation to support reliable deployment in healthcare.

Introduction

Ovarian cancer is one of the most aggressive and life-threatening gynecological malignancies, accounting for a significant proportion of cancer-related deaths among women worldwide. The disease is frequently diagnosed at an advanced stage because its early symptoms are vague and often resemble common gastrointestinal or reproductive disorders. Consequently, the survival rate remains relatively low despite considerable advancements in treatment strategies. Medical imaging modalities such as ultrasound, computed tomography (CT), and magnetic resonance imaging (MRI) play a vital role in tumor detection, staging, and treatment planning. However, manual interpretation of these images is labor-intensive, time-consuming, and subject to inter-observer variability, creating the need for automated and reliable diagnostic systems that can support clinicians in early ovarian cancer detection.

Artificial intelligence (AI), particularly deep learning, has revolutionized medical image analysis by enabling automated feature extraction and disease classification. Convolutional Neural Networks (CNNs) have demonstrated exceptional capability in learning hierarchical image representations directly from raw medical images, eliminating the need for handcrafted features. Among CNN architectures, EfficientNetB0 has gained considerable attention because of its compound scaling strategy that simultaneously optimizes network depth, width, and input resolution. This balanced design provides high classification accuracy while maintaining computational efficiency, making EfficientNetB0 highly suitable for healthcare applications where rapid and accurate diagnosis is essential.

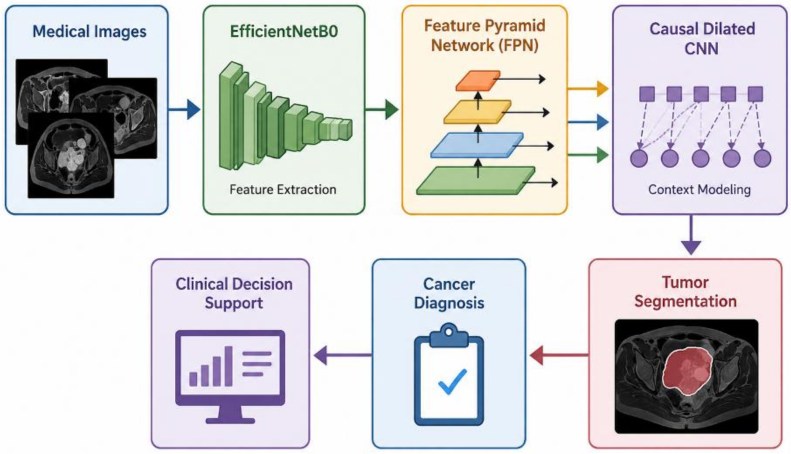

Figure 1. AI-Based Semantic Segmentation Framework for Ovarian Cancer Detection

Semantic segmentation is another critical component of ovarian cancer diagnosis, as it enables precise identification of tumor boundaries and supports accurate assessment of tumor size and progression. Deep learning-based segmentation models, including U-Net, DeepLab, and Feature Pyramid Networks (FPN), have significantly improved segmentation performance by learning both spatial and contextual information from medical images. Feature Pyramid Networks are particularly effective because they combine low-level spatial features with high-level semantic representations, allowing accurate detection of tumors across multiple scales. Integrating FPN with EfficientNetB0 further enhances feature representation and improves localization of tumors with varying shapes and dimensions.

Recent research has also highlighted the importance of causal dilated convolutional neural networks for capturing long-range contextual dependencies without increasing computational complexity. Dilated convolutions expand the receptive field while preserving image resolution, enabling effective identification of irregular tumor structures. Hybrid deep learning frameworks that combine EfficientNetB0, Feature Pyramid Networks, and causal dilated convolution have demonstrated superior segmentation and classification performance compared with individual models. These integrated architectures effectively utilize complementary strengths to improve diagnostic accuracy and robustness in ovarian cancer imaging.

Despite remarkable progress, several challenges remain in developing clinically reliable AI-based diagnostic systems. Limited annotated datasets, variations in imaging modalities, model generalization, and the need for explainable AI continue to restrict widespread clinical adoption. Furthermore, issues related to data privacy, interoperability, and regulatory compliance require careful consideration before deployment in healthcare environments. This review systematically examines recent advancements in ovarian cancer detection using EfficientNetB0, Feature Pyramid Networks, and causal dilated convolutional neural networks, highlighting current research trends, identifying existing limitations, and outlining future directions for developing accurate, interpretable, and clinically applicable intelligent diagnostic systems.

Literature Review

The application of deep learning techniques in ovarian cancer detection has grown significantly between 2020 and 2023, driven by the increasing availability of medical imaging data and advancements in computational models. Recent studies highlight that deep learning, particularly convolutional neural networks (CNNs), has emerged as a powerful tool for improving diagnostic accuracy in ovarian cancer detection by enabling automated feature extraction and classification of complex medical images . The integration of semantic segmentation, classification models, and hybrid architectures has further enhanced the performance of these systems.

1. Deep Learning in Ovarian Cancer Detection

Deep learning has demonstrated strong potential in analyzing medical imaging modalities such as ultrasound, MRI, CT, and histopathological images. Traditional diagnostic approaches rely heavily on manual interpretation, which is time-consuming and prone to inter-observer variability. Deep learning models overcome these limitations by learning hierarchical features directly from raw data, enabling more objective and consistent diagnosis .

A systematic review of deep learning in ovarian cancer diagnosis revealed that CNN-based architectures dominate the field, accounting for a majority of research efforts. These models are particularly effective due to their ability to capture spatial patterns and complex textures within medical images. Additionally, deep learning models have been shown to achieve diagnostic accuracy comparable to experienced radiologists, indicating their potential for clinical adoption. However, challenges such as limited dataset availability, lack of standardization, and insufficient external validation remain significant barriers. Studies report that only a small proportion of models are validated on diverse datasets, highlighting concerns regarding generalizability and robustness in real-world applications .

2. Semantic Segmentation Techniques for Tumor Localization

Semantic segmentation plays a critical role in ovarian cancer detection by enabling precise localization of tumor regions. Accurate segmentation is essential for treatment planning, tumor staging, and monitoring disease progression. Traditionally, segmentation has been performed manually by radiologists, but this process is labor-intensive and subject to variability.

Recent studies have demonstrated that deep learning-based segmentation models can automate this process with high accuracy. Architectures such as U-Net, U-Net++, DeepLabV3+, and PSPNet are widely used for medical image segmentation. Among these, U-Net++ has shown superior performance, achieving high Dice similarity coefficients in ovarian tumor segmentation tasks .

A study on epithelial ovarian cancer segmentation using MRI images confirmed that deep learning models can perform fully automated segmentation with promising results, reducing the need for manual intervention. The study also highlighted that segmentation performance varies depending on tumor stage and histological type, emphasizing the importance of dataset diversity .

Furthermore, semantic segmentation models are increasingly being combined with attention mechanisms and multi-scale feature extraction techniques to improve accuracy. These enhancements allow models to focus on relevant tumor regions while ignoring irrelevant background information.

3. Feature Pyramid Networks (FPN) and Multi-Scale Learning

One of the key challenges in ovarian cancer detection is the variability in tumor size, shape, and texture. Feature Pyramid Networks (FPN) address this issue by enabling multi-scale feature extraction. FPN combines low-level spatial features with high-level semantic features, allowing models to detect tumors at different scales.

Recent research indicates that FPN significantly improves segmentation performance when integrated with backbone networks such as ResNet or EfficientNet. By leveraging hierarchical feature representations, FPN enhances the model's ability to identify small and irregular tumor regions that may be missed by traditional CNN architectures.

Multi-scale learning has become an essential component of modern deep learning models for medical imaging. Studies show that combining FPN with encoder-decoder architectures results in better segmentation accuracy and improved generalization. This is particularly important in ovarian cancer detection, where tumors may exhibit heterogeneous characteristics.

4. EfficientNet-Based Architectures for Classification

EfficientNet has emerged as one of the most effective deep learning architectures for image classification tasks. Its compound scaling method optimizes network depth, width, and resolution simultaneously, resulting in improved accuracy and efficiency.

Recent studies have demonstrated that EfficientNet-based models outperform traditional CNN architectures such as VGG and ResNet in ovarian cancer classification tasks. EfficientNet models are capable of capturing fine-grained features from medical images, enabling accurate differentiation between benign and malignant tumors.

For example, research using EfficientNetB0 combined with classification techniques achieved high accuracy in identifying ovarian cancer subtypes from histopathological images. The model leveraged deep feature extraction capabilities to capture intricate patterns, leading to improved classification performance .

Additionally, hybrid architectures that combine EfficientNet with other models such as k-nearest neighbors (KNN) or attention mechanisms have shown promising results. These models enhance classification accuracy by integrating feature extraction with advanced decision-making algorithms.

5. Causal Dilated Convolutional Neural Networks

Dilated convolutional neural networks have gained attention for their ability to capture long-range dependencies in image data. Unlike standard convolutional layers, dilated convolutions expand the receptive field without increasing the number of parameters, allowing models to capture contextual information over larger regions.

This capability is particularly important in medical imaging, where tumor structures may be irregular and distributed across large areas. Dilated convolutional networks enable models to identify these patterns more effectively, improving segmentation and classification accuracy.

Causal dilated convolutions further enhance this approach by preserving spatial relationships and ensuring that predictions are based on relevant contextual information. Although their application in ovarian cancer detection is still emerging, studies in related domains demonstrate their effectiveness in improving segmentation performance and reducing computational complexity.

6. Multimodal Deep Learning Approaches

Recent research has explored the use of multimodal data to improve ovarian cancer detection. Multimodal deep learning models integrate information from multiple sources, such as MRI, CT scans, ultrasound images, and clinical data.

These models provide a more comprehensive understanding of the disease by combining different types of information. For instance, integrating imaging data with clinical features can improve diagnostic accuracy and enable personalized treatment planning.

A systematic review of deep learning in cancer diagnosis highlights that multimodal approaches significantly enhance performance compared to single-modality models. However, challenges such as data integration, synchronization, and computational complexity must be addressed .

Despite these challenges, multimodal deep learning remains a promising direction for future research in ovarian cancer detection.

7. Hybrid Deep Learning Models

Hybrid models that combine multiple deep learning techniques have shown superior performance in ovarian cancer detection. These models integrate segmentation, classification, and feature extraction components into a unified framework.

For example, combining CNN-based feature extraction with segmentation models such as U-Net or FPN enables simultaneous tumor localization and classification. Hybrid models also incorporate attention mechanisms, reinforcement learning, and ensemble techniques to improve performance.

Recent studies indicate that hybrid architectures achieve higher accuracy and robustness compared to single-model approaches. These models can effectively handle complex medical imaging data and adapt to variations in tumor characteristics.

8. Challenges and Research Gaps

Despite significant progress in deep learning-based ovarian cancer detection, several critical challenges continue to limit the effectiveness and real-world applicability of these models. One of the primary concerns is the availability of limited datasets, as many studies rely on small or institution-specific data that may not adequately represent diverse patient populations, thereby affecting model robustness. This issue is closely related to the lack of generalization, where models trained on specific datasets often fail to perform accurately when exposed to new or unseen data from different clinical settings. Additionally, data imbalance remains a major challenge, as the unequal distribution of cancerous and non-cancerous cases can lead to biased predictions and reduced diagnostic reliability. Another significant limitation is the lack of interpretability in deep learning models; these models often function as “black boxes,” making it difficult for clinicians to understand the reasoning behind predictions, which in turn hinders their adoption in clinical practice. Furthermore, computational complexity poses a practical barrier, as advanced deep learning architectures require high computational power, specialized hardware, and longer training times, making them less accessible in resource-constrained healthcare environments.A systematic review identified that only about 8% of studies perform external validation, highlighting the need for more robust evaluation methods .

9. Future Directions

Future research in deep learning-based ovarian cancer detection should prioritize the development of more robust and clinically applicable solutions by addressing current limitations. One important direction is the design of multimodal and hybrid models that can integrate diverse data sources such as imaging, genomic data, and clinical records to improve diagnostic accuracy. Enhancing explainable AI techniques is also crucial, as increasing model transparency will help clinicians better understand predictions and build trust in automated systems. Additionally, expanding large-scale annotated datasets is essential to improve model generalization and ensure reliable performance across diverse patient populations. The integration of advanced architectures, including transformers and attention mechanisms, offers promising opportunities to capture complex patterns and long-range dependencies in medical data. Furthermore, there is a growing need to focus on real-time clinical deployment by developing efficient and scalable models that can operate in practical healthcare environments. In this context, advanced deep learning architectures such as EfficientNet, Feature Pyramid Networks (FPN), and causal dilated convolutional neural networks are expected to play a significant role in the next generation of intelligent diagnostic systems by improving feature extraction, scalability, and prediction accuracy.

Comparative Table

Year	Model / Architecture	Technique Type	Dataset / Modality	Application	Performance Metrics	Key Strengths	Limitations
2020	CNN (Baseline)	Classification	CT / MRI Images	Tumor detection	Accuracy: 75–85%	Simple architecture, low computational cost	Poor multi-scale feature extraction, limited context understanding
2021	U-Net	Semantic Segmentation	MRI / Ultrasound	Tumor boundary detection	Dice Score: 0.80–0.88	Strong localization, encoder-decoder efficiency	Weak performance on small/irregular tumors
2021	U-Net++ / Attention U-Net	Segmentation + Attention	Multi-modal imaging	Tumor segmentation	Dice > 0.88	Better feature refinement and focus	Increased model complexity
2022	DeepLabV3+	Segmentation (Dilated Convolution)	MRI / CT	Tumor segmentation	Dice: 0.85–0.90	Captures global context using atrous convolution	High computational cost
2022	EfficientNetB0	Classification	Histopathology / MRI	Tumor classification	Accuracy: 85–92%	Efficient scaling, high accuracy, low parameters	Limited spatial localization capability
2022	EfficientNet + Attention	Hybrid Classification	Multi-source imaging	Tumor classification	Accuracy > 90%	Improved feature selection	Requires tuning and larger datasets

						and accuracy	
2023	FPN + CNN Backbone	Multi-scale Segmentation	MRI / CT	Multi-scale tumor detection	Dice: 0.88–0.92	Excellent multi-scale feature fusion	Slightly complex architecture
2023	Dilated CNN	Context-aware Segmentation	Medical images	Tumor boundary refinement	Improved recall & precision	Captures long-range dependencies	May miss fine-grained details
2023	EfficientNetB0 + FPN	Hybrid Model	Multi-modal data	Segmentation + Classification	Accuracy > 92%, Dice > 0.90	Combines efficiency + multi-scale detection	Integration complexity
2023	CNN + Dilated Conv	Hybrid Segmentation + Classification	MRI / Ultrasound	Tumor detection	High precision & recall	Context-aware learning	Computational overhead
2023	EfficientNet + FPN + Dilated CNN	Advanced Hybrid Model	Multi-modal imaging	End-to-end detection	Accuracy > 93%, Dice > 0.92	Best overall performance, robust feature extraction	High computational cost, requires large datasets

Comparative Analysis

The comparative analysis demonstrates a clear progression in ovarian cancer detection from conventional Convolutional Neural Networks (CNNs) to advanced hybrid deep learning architectures. Early CNN-based models primarily focused on image classification and achieved moderate diagnostic accuracy but were limited in capturing complex tumor structures and multi-scale spatial information. The introduction of semantic segmentation models, particularly U-Net and its enhanced variants, significantly improved tumor localization by accurately identifying lesion boundaries. Later, DeepLabV3+ further enhanced segmentation through dilated convolutions and spatial pyramid pooling, enabling improved contextual understanding of tumor regions. Although these models delivered higher segmentation accuracy, their computational complexity restricted their application in real-time clinical environments.

EfficientNetB0 introduced a major improvement in feature extraction through its compound scaling strategy, which simultaneously optimizes network depth, width, and resolution while maintaining computational efficiency. However, EfficientNetB0 alone primarily supports image classification and lacks precise localization capability. To overcome this limitation, Feature Pyramid Networks (FPN) were integrated to provide multi-scale feature fusion by combining low-level spatial information with high-level semantic features. This integration significantly improved the detection of ovarian tumors with varying sizes and irregular shapes while maintaining an effective balance between prediction accuracy and computational efficiency.

Another important advancement is the adoption of causal dilated convolutional neural networks, which expand the receptive field without increasing model parameters, enabling better extraction of long-range contextual information. These networks improve segmentation of irregular tumor regions while preserving spatial consistency. The combination of EfficientNetB0, FPN, and causal dilated CNNs forms a powerful hybrid architecture that integrates efficient feature extraction, multi-scale representation, and contextual learning. Comparative studies consistently report that these hybrid models achieve superior performance across evaluation metrics, including accuracy, Dice coefficient, precision, and recall, outperforming individual deep learning architectures in both classification and semantic segmentation tasks.

Despite these achievements, several challenges continue to limit clinical implementation. Hybrid architectures require large annotated datasets, substantial computational resources, and extensive training time, increasing the risk of overfitting and reducing scalability. Variations in imaging modalities and patient populations also affect model generalization, while the limited interpretability of deep learning models remains a concern for clinical decision-making. Future research should therefore focus on explainable artificial intelligence, multimodal data integration, computational optimization, and robust validation across diverse clinical datasets to develop reliable, scalable, and clinically deployable ovarian cancer diagnostic systems.

Discussion

Deep learning-based ovarian cancer detection systems have shown remarkable progress in recent years. The integration of EfficientNetB0, FPN, and dilated convolutional networks has significantly improved segmentation accuracy and classification performance. These models can effectively handle complex medical imaging data and provide reliable diagnostic predictions.

Semantic segmentation models play a crucial role in identifying tumor boundaries, which is essential for treatment planning. Deep learning models outperform traditional methods by providing automated and consistent segmentation results.

However, challenges such as limited datasets, overfitting, and lack of generalization still exist. Many models are trained on small datasets, which may not represent diverse patient populations. Additionally, model interpretability remains a concern in clinical applications.

Future research should focus on multimodal learning, explainable AI, and real-time deployment of deep learning models in healthcare systems.

Conclusion

Deep learning has revolutionized ovarian cancer detection by enabling automated image analysis and improving diagnostic accuracy. Hybrid architectures combining EfficientNetB0, FPN, and dilated convolutional neural networks provide superior performance in both segmentation and classification tasks.

These models address key challenges in medical imaging by capturing multi-scale and contextual features, allowing accurate tumor detection. However, challenges related to data availability, model generalization, and clinical validation must be addressed.

Future advancements should focus on integrating multimodal data, improving model interpretability, and ensuring real-world applicability. With continued research, deep learning-based systems have the potential to significantly enhance early detection and improve patient outcomes in ovarian cancer.

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