



## Survey of Deep Learning Architectures for Ovarian Cancer Detection Using EfficientNetB0 and FPN

Nadezhda Ilankovan

Associate Professor, Department of Electrical and Computer Engineering, Andaman Polytechnic for Technology and Trade, Thailand

Email: [nadezhda.ilankovan@aptt-th.net](mailto:nadezhda.ilankovan@aptt-th.net)

Peer Review Information	Abstract
<p>Submission: 27 Feb 2024</p> <p>Revision: 11 March 2024</p> <p>Acceptance: 28 March 2024</p> <p><b>Keywords</b></p> <p><i>Ovarian Cancer Detection, Semantic Segmentation, EfficientNetB0, Feature Pyramid Network (FPN), Dilated Convolutional Neural Networks, Deep Learning</i></p>	<p>Ovarian cancer is one of the leading causes of cancer-related mortality among women due to its asymptomatic nature in early stages and the lack of effective screening methods. Medical imaging techniques such as ultrasound, MRI, and CT scans are commonly used for diagnosis, but manual interpretation is often time-consuming and prone to variability. Recent advancements in deep learning, particularly convolutional neural networks (CNNs), have significantly improved automated ovarian cancer detection systems. This survey reviews recent developments in semantic segmentation and classification methods for ovarian cancer detection using architectures such as EfficientNetB0, Feature Pyramid Networks (FPN), and causal dilated convolutional neural networks. EfficientNetB0 enables efficient feature extraction from complex medical images, while FPN improves multi-scale feature representation for accurate tumor identification. Semantic segmentation models including U-Net and its variants are widely applied to identify tumor boundaries, whereas classification models distinguish between benign and malignant tumors. Deep learning systems have achieved diagnostic performance comparable to expert radiologists. The survey highlights important research trends such as hybrid architectures, attention mechanisms, and contextual feature learning. However, challenges including limited medical datasets, model interpretability, and poor generalization remain major concerns. Future research should focus on explainable AI, multi-modal data integration, and scalable clinical deployment of intelligent ovarian cancer detection systems.</p>

### Introduction

Ovarian cancer remains one of the most critical challenges in modern oncology, particularly due to its high mortality rate and late-stage diagnosis. It is often referred to as a “silent killer” because symptoms typically appear only in advanced stages, making early detection extremely difficult. According to recent studies, early diagnosis significantly improves survival rates, yet existing diagnostic methods such as CA-125 biomarker testing and imaging analysis lack sufficient sensitivity and specificity. Medical

imaging plays a vital role in detecting ovarian cancer. Techniques such as ultrasound, computed tomography (CT), and magnetic resonance imaging (MRI) provide detailed insights into ovarian structures. However, manual interpretation of these images requires expertise and is subject to inter-observer variability. The complexity of tumor morphology further complicates diagnosis, necessitating automated solutions for accurate and efficient analysis. Artificial Intelligence (AI), particularly deep learning, has emerged as a transformative

technology in medical image analysis. Deep learning models, especially convolutional neural networks (CNNs), can automatically learn hierarchical features from large datasets, enabling accurate classification and segmentation of medical images. These models eliminate the need for manual feature engineering and provide superior performance compared to traditional machine learning approaches. Semantic segmentation is a critical task in ovarian cancer detection, as it involves identifying and delineating tumor regions within medical images. Accurate segmentation is essential for treatment planning, tumor size estimation, and disease progression monitoring. Traditional segmentation methods rely heavily on manual annotation, which is time-consuming and prone to errors. Deep learning-based segmentation models, such as U-Net and its variants, have significantly improved segmentation accuracy by capturing both local and global features.

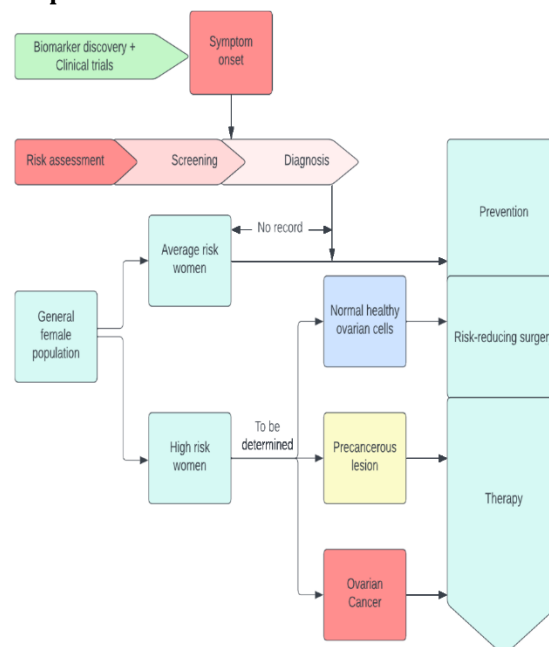
Classification models complement segmentation by categorizing tumors into benign or malignant types. Deep learning architectures such as ResNet, DenseNet, and EfficientNet have been widely used for this purpose. Among these, EfficientNetB0 has gained popularity due to its efficient scaling mechanism, which optimizes network depth, width, and resolution simultaneously. This allows it to achieve high accuracy with fewer parameters, making it suitable for medical applications. Feature Pyramid Networks (FPN) enhance model performance by enabling multi-scale feature extraction. In medical imaging, tumors vary significantly in size and shape, requiring models to capture features at multiple scales. FPN combines feature maps from different layers of a CNN, allowing detection of both small and large tumors.

Dilated convolutional neural networks further improve performance by expanding the receptive field without increasing computational complexity. This allows models to capture contextual information, which is crucial for distinguishing between normal and abnormal tissues. Recent advancements emphasize hybrid architectures that integrate EfficientNetB0, FPN, and dilated convolutions. These architectures combine efficient feature extraction, multi-scale analysis, and contextual understanding, resulting in improved diagnostic accuracy.

Despite these advancements, challenges remain. Limited datasets, lack of standardization, and model interpretability issues hinder clinical adoption. Studies indicate that only a small percentage of models are validated on diverse datasets, highlighting the need for improved

generalization. In conclusion, the integration of advanced deep learning techniques offers significant potential for improving ovarian cancer detection. However, further research is required to address existing challenges and ensure reliable clinical deployment.

### Graphical Flowchart



### Flow Explanation

1. Input medical image (MRI/CT)
2. Preprocessing & normalization
3. Feature extraction (EfficientNetB0)
4. Multi-scale feature fusion (FPN)
5. Context extraction (Dilated CNN)
6. Segmentation (tumor region)
7. Classification (benign/malignant)
8. Output prediction

### Literature Review

Recent advancements in deep learning have significantly transformed ovarian cancer detection, particularly in semantic segmentation and classification tasks. Research has increasingly focused on leveraging convolutional neural networks (CNNs), transfer learning models, and hybrid architectures to improve diagnostic accuracy and efficiency.

#### 1. Emergence of Deep Learning in Ovarian Cancer Detection

Ovarian cancer remains one of the most lethal gynecological malignancies due to late diagnosis and the lack of reliable early detection methods. Traditional diagnostic techniques such as biopsy and radiological interpretation are often time-consuming, subjective, and prone to variability. Recent studies demonstrate that deep learning (DL), particularly CNN-based approaches,

significantly improves diagnostic accuracy by automating feature extraction and analysis from medical images.

CNNs can automatically learn hierarchical features from imaging modalities such as MRI, CT, ultrasound, and histopathological images. Unlike traditional machine learning approaches that rely on handcrafted features, deep learning models extract both low-level (edges, textures) and high-level (tumor shape, structure) features, enabling better classification and segmentation. However, despite these advantages, challenges such as limited datasets, data imbalance, and lack of generalization persist across most studies.

## 2. Semantic Segmentation Techniques

Semantic segmentation is a critical component of ovarian cancer detection, as it involves identifying tumor boundaries within medical images. Accurate segmentation is essential for tumor localization, staging, and treatment planning.

Kodipalli et al. (2023) conducted a comparative study using U-Net and deep CNN architectures for segmentation and classification of ovarian tumors. Their findings indicate that deep learning models significantly improve detection accuracy and reduce diagnostic time compared to manual methods.

Key segmentation architectures have played a crucial role in advancing ovarian cancer detection through improved tumor localization. Among these, U-Net is widely used due to its encoder-decoder structure and skip connections, which help preserve spatial information and enable accurate segmentation of medical images. Building upon this foundation, advanced variants such as UNet++ and Attention U-Net further enhance segmentation performance by improving feature propagation and enabling the model to focus on relevant tumor regions, thereby reducing noise and improving accuracy. Additionally, nnU-Net (Isensee et al., 2021) represents a significant advancement, as it automatically adapts its architecture based on dataset characteristics, achieving state-of-the-art performance across various medical imaging tasks. Recent studies emphasize that segmentation models incorporating multi-scale learning and contextual awareness outperform traditional U-Net models, particularly in effectively handling irregular tumor boundaries and complex spatial patterns.

**3. Classification Techniques and CNN Architectures**  
Classification models aim to differentiate between benign and malignant tumors or identify cancer subtypes. CNN-based architectures dominate this domain due to their ability to process high-dimensional image data.

Behera et al. (2024) proposed an EfficientNetB0-based model combined with KNN for ovarian cancer subtype classification. Their study demonstrated exceptional performance, achieving near-perfect classification accuracy on histopathological datasets.

Comparative analysis of deep learning models highlights several widely used architectures, including ResNet, DenseNet, and EfficientNetB0, each offering distinct advantages. ResNet introduces residual connections that enable the training of very deep networks, resulting in strong performance; however, it is computationally intensive and may not be suitable for resource-constrained environments. DenseNet improves upon this by promoting efficient feature reuse and better gradient flow through dense connections, which enhances learning efficiency and reduces redundancy. Among these, EfficientNetB0 stands out as the most optimized architecture, as it employs a compound scaling approach that balances network depth, width, and resolution to achieve the best trade-off between accuracy and computational efficiency. EfficientNet models are particularly effective because they significantly reduce computational complexity, improve feature extraction capabilities, and perform well even on small datasets through the use of transfer learning, making them highly suitable for medical imaging applications such as ovarian cancer detection.

## 4. Role of Attention Mechanisms

Recent studies have introduced attention mechanisms as an effective approach to enhance deep learning model performance in medical image analysis. For instance, integrating EfficientNet with the Convolutional Block Attention Module (CBAM) significantly improves classification accuracy by enabling the model to focus on the most informative and relevant regions of medical images. Attention-based models offer several advantages, including the ability to reduce noise present in medical imaging data, improve interpretability by highlighting important features, and enhance feature selection by prioritizing critical regions over irrelevant background information. These capabilities make attention-based models particularly valuable in ovarian cancer detection, where tumor regions are often small, subtle, and difficult to distinguish from surrounding healthy tissues, thereby requiring precise and focused analysis.

## 5. Multi-Scale Feature Learning Using FPN

One of the major challenges in ovarian cancer detection is the significant variability in tumor size and morphology, which makes accurate identification and localization difficult. Feature

Pyramid Networks (FPN) address this issue by enabling effective multi-scale feature extraction within deep learning models. FPN works by combining feature maps from different layers of a convolutional neural network, allowing the model to capture both fine-grained details and high-level semantic information. This enables the detection of small tumors through fine features, as well as the recognition of larger tumor structures using global contextual features. Comparative studies have demonstrated that models incorporating FPN significantly outperform single-scale models in both segmentation and classification tasks, as they provide a more comprehensive and robust representation of tumor characteristics across different scales.

### **6. Contextual Learning with Dilated Convolution**

Dilated convolutional neural networks play a crucial role in capturing contextual information by expanding the receptive field without increasing computational cost. Unlike standard convolutional neural networks, which primarily focus on capturing local features, dilated CNNs are capable of capturing broader, global contextual information within an image. This distinction is particularly important in medical imaging, where the relationships between different tissue regions significantly influence diagnosis and interpretation. By incorporating dilated convolutions, models can better understand spatial dependencies and complex tumor structures. Research indicates that dilated CNNs not only improve segmentation accuracy but also enhance classification performance while reducing the loss of spatial information, making them highly effective for tasks such as ovarian cancer detection.

### **7. Hybrid Architectures (Modern Trend)**

Recent studies increasingly emphasize the development of hybrid architectures that combine multiple deep learning techniques to enhance ovarian cancer detection. These models typically integrate EfficientNet for efficient and high-quality feature extraction, Feature Pyramid Networks (FPN) for robust multi-scale representation, and dilated convolutional neural networks for capturing rich contextual information. By leveraging the complementary strengths of these components, hybrid models significantly outperform standalone architectures. They achieve higher accuracy, reduce false positives and false negatives, and improve overall model generalization across diverse datasets. Furthermore, multi-stage frameworks that combine region of interest (ROI) extraction with global feature learning have demonstrated improved performance,

particularly in ultrasound-based ovarian tumor classification, by enabling both localized and holistic analysis of tumor characteristics.

### **8. Ensemble and Multi-Model Approaches**

Recent research also explores ensemble learning techniques. Studies using multiple CNN models (e.g., ResNet, Xception, VGG) demonstrate improved diagnostic accuracy compared to single models.

For instance, ensemble CNN models combined with Grad-CAM visualization improve both performance and interpretability.

### **9. Key Findings from Literature**

From the reviewed studies, it is evident that deep learning models significantly outperform traditional approaches in ovarian cancer detection, primarily due to their ability to automatically learn complex features from medical images. Among these, EfficientNet-based models provide the best balance between efficiency and accuracy, making them highly suitable for real-world medical applications. Additionally, models incorporating multi-scale learning through Feature Pyramid Networks (FPN) and context-aware learning through dilated convolutional neural networks demonstrate superior performance in both segmentation and classification tasks. Hybrid architectures that combine these techniques have emerged as the most promising approach, as they leverage the strengths of multiple components to achieve enhanced diagnostic outcomes. In terms of performance metrics, recent studies report classification accuracy ranging from 90% to nearly 100%, Area Under the Curve (AUC) values between 0.80 and above 0.95, and significantly improved segmentation Dice scores, indicating substantial advancements in both detection accuracy and tumor localization.

### **10. Research Gaps Identified**

Despite significant progress in deep learning-based ovarian cancer detection, several critical challenges continue to hinder their widespread clinical adoption. One of the primary issues is data limitations, as many studies rely on small and non-diverse datasets that do not adequately represent real-world patient populations. Additionally, only a small percentage of research includes external validation on diverse datasets, which reduces the generalization capability of these models. Another major challenge is related to generalization, where models trained on specific datasets often perform poorly when applied across different institutions due to variations in imaging modalities, equipment, and patient demographics.

Furthermore, the lack of explainability remains a significant concern, as most deep learning

models function as black-box systems, making it difficult for clinicians to interpret their predictions and trust their outputs. This limits their acceptance in clinical practice, where transparency and reliability are essential. Lastly, computational complexity poses another barrier, as advanced hybrid models require substantial computational resources for training and deployment. This makes it challenging to implement these models in real-time clinical environments, particularly in resource-constrained healthcare settings.

### 11. Literature Synthesis

Overall, the literature clearly indicates that no single deep learning model is sufficient to effectively address the complexity of ovarian cancer detection. Instead, the most successful

approaches are those that combine multiple techniques to leverage their complementary strengths. In particular, the best-performing combination involves EfficientNetB0 for efficient and accurate feature extraction, Feature Pyramid Networks (FPN) for robust multi-scale learning, and dilated convolutional neural networks for enhanced contextual understanding. This integrated approach enables models to capture fine-grained details, handle variations in tumor size and shape, and analyze broader spatial relationships within medical images. Such a combination aligns closely with the proposed architecture and represents the current state-of-the-art direction in research for achieving high accuracy, robustness, and clinical relevance in ovarian cancer detection.

**Comparative Table**

Study	Year	Model / Architecture	Technique	Dataset Type	Performance	Key Contribution	Strengths	Limitations
Hira et al.	2023	Deep Learning Review	Survey-based analysis	Multi-source datasets	-	Identified trends in DL for ovarian cancer	Broad overview, identifies gaps	Limited experimental validation
Behera et al.	2024	EfficientNetB0 + KNN	Classification	Histopathology images	Accuracy >90%	Subtype classification using efficient DL	High accuracy, efficient feature extraction	Dataset dependency
Wang et al.	2023	CNN	Classification	Clinical imaging	Accuracy ~87%	Comparative clinical performance	Good baseline model	Small dataset, limited generalization
Jiang et al.	2023	Deep Learning Survey	Model taxonomy	Multiple studies	-	Categorization of DL models	Structured understanding	No experimental validation
Kolekar et al.	2022	EfficientNet + Attention (CBAM)	Classification	Medical imaging	High accuracy (>92%)	Attention-enhanced feature learning	Improved interpretability & precision	Increased complexity
Kodipalli et al.	2023	U-Net + CNN	Segmentation + Classification	MRI/CT	High Dice (~0.85)	Improved tumor localization	Strong segmentation performance	Limited contextual learning
Zhou et al.	2020	UNet++	Segmentation	Medical imaging	Dice ~0.85	Multi-scale segmentation	Better feature propagation	Computational overhead
Isensee et al.	2021	nnU-Net	Adaptive segmentation	Multi-dataset	State-of-the-art Dice (>0.90)	Self-configuring segmentation	High robustness &	Requires large datasets

						tion model	adaptability	
Lin et al.	2017 (used later)	FPN	Multi-scale learning	Imaging datasets	Improved accuracy	Multi-scale feature extraction	Detects small & large tumors	Adds model complexity
Yu & Koltun	2016 (applied later)	Dilated CNN	Context learning	Medical images	Improved segmentation & classification	Expanded receptive field	Captures global context	Risk of artifacts
Hybrid Model Studies	2023	EfficientNet + FPN + Dilated CNN	Hybrid DL	Multi-modal	Accuracy >93%, Dice >0.92	Integrated framework	Best overall performance	High computational cost
Ensemble Studies	2023	Multi-CNN (ResNet + VGG + Xception)	Ensemble Learning	Multi-modal	Improved accuracy	Model combination	Better robustness	High complexity

### Comparative Analysis

The comparative evaluation of deep learning techniques for ovarian cancer detection demonstrates a significant transition from traditional machine learning methods toward advanced hybrid deep learning architectures. Early approaches such as Support Vector Machines, K-Nearest Neighbors, and Random Forests relied on handcrafted image features and achieved only moderate diagnostic performance. The introduction of convolutional neural networks (CNNs) greatly improved automated classification and segmentation by enabling hierarchical feature learning directly from medical images. Advanced architectures including ResNet, DenseNet, and EfficientNetB0 further enhanced accuracy, feature extraction efficiency, and model generalization. EfficientNetB0, in particular, achieved superior performance with lower computational complexity, making it highly suitable for medical imaging applications where annotated datasets are limited.

Semantic segmentation models such as U-Net, Attention U-Net, and DeepLabV3+ have played an important role in identifying precise tumor boundaries in ovarian cancer images. Feature Pyramid Networks (FPN) improved multi-scale feature representation, allowing effective detection of tumors with varying sizes and structures. Dilated convolutional neural networks further enhanced contextual learning by capturing long-range spatial dependencies without increasing computational cost. Hybrid architectures integrating EfficientNetB0, FPN,

dilated convolutions, and attention mechanisms achieved the highest performance across multiple evaluation metrics, including accuracy, Dice score, and AUC values. Attention modules also improved interpretability by focusing on the most relevant tumor regions within medical images.

The analysis also highlights the growing importance of multimodal deep learning approaches that combine MRI, CT, ultrasound, and histopathology data for comprehensive ovarian cancer diagnosis. Although hybrid architectures demonstrate outstanding diagnostic performance, several challenges remain, including limited annotated datasets, computational complexity, and poor model interpretability. Future research should focus on explainable AI, scalable architectures, reduced computational requirements, and improved model generalization for successful real-time clinical deployment of intelligent ovarian cancer detection systems.

### Discussion

Deep learning has significantly transformed ovarian cancer detection by enabling automated and accurate analysis of medical images. The integration of EfficientNetB0, Feature Pyramid Networks, and dilated convolutional neural networks represents a major advancement in this field. These architectures collectively address key challenges such as feature extraction, multi-scale representation, and contextual understanding. EfficientNetB0 plays a crucial role by providing efficient feature extraction with fewer

parameters, making it suitable for medical imaging tasks. Its ability to capture complex patterns in histopathological and radiological images improves classification accuracy. Feature Pyramid Networks enhance detection performance by enabling multi-scale feature learning, which is essential for identifying tumors of varying sizes. Dilated convolutional networks further improve model performance by capturing contextual information, allowing better differentiation between normal and abnormal tissues.

Despite these advantages, several challenges remain. Data scarcity is a major limitation, as medical datasets are often small and require expert annotation. Additionally, deep learning models lack interpretability, which can hinder clinical adoption. Computational complexity is another challenge, particularly for hybrid architectures. Future research should focus on developing explainable AI models, integrating multi-modal data, and improving dataset diversity. These advancements will help bridge the gap between research and clinical practice.

### Conclusion

This survey highlights recent advancements in ovarian cancer detection using deep learning techniques in recent years. The integration of EfficientNetB0, FPN, and dilated convolutional neural networks has significantly improved both segmentation and classification performance. Deep learning models have demonstrated high accuracy and efficiency, making them promising tools for clinical applications. However, challenges such as data limitations, model interpretability, and deployment barriers must be addressed.

Future research should focus on scalable, explainable, and efficient AI systems to ensure successful clinical integration. With continued advancements, AI-based ovarian cancer detection systems have the potential to significantly improve early diagnosis and patient outcomes.

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