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# Advanced Deep Learning (DL) Techniques for Early Detection of Ovarian Cancer: A Survey of Methods and Explainable AI Approaches

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**ABSTRACT:** Ovarian cancer poses a significant diagnostic challenge due to its subtle early symptoms and the high death rates at later stage diagnosis. Artificial intelligence developments, particularly in the area of deep learning (DL) and explainable AI (XAI), have shown promise in improving early-stage ovarian cancer detection and subtype classification. This survey explores state-of-the-art DL models as well as convolutional neural networks (CNNs), ensemble methods, and novel optimization techniques like Grey Wolf Optimization (GWO). We review their applications in ovarian cancer diagnostics and highlight how XAI methods such as SHAP, Grad-CAM, and DeepLift enhance model interpretability, thus promoting clinical adoption. The survey concludes with insights on current limitations and probable avenues for further research to further improve diagnostic accuracy and clinical reliability in ovarian cancer detection.

**KEYWORDS** Ovarian Cancer Detection, Deep Learning, Explainable AI, CNN, Ensemble Classifier, Multiclassification

## I. INTRODUCTION

Ovarian cancer, one of the most aggressive forms of cancer affecting women, ranks sixth in cancer-related deaths globally. Due to non-specific early symptoms, ovarian cancer is often detected at advanced stages, resulting in limited treatment options and a low survival rate [1], [2]. Traditional diagnostic methods like ultrasound, serum biomarkers (e.g., CA-125), and MRI have limitations, especially in early-stage detection where sensitivity and specificity are often inadequate [3].

New developments in deep learning (DL) and machine learning (ML) have shown potential in transforming ovarian cancer diagnosis. DL models, especially those that use convolutional neural networks (CNNs), excel in image analysis and classification, making them suitable for identifying cancerous patterns within histopathological and imaging datasets. Explainable AI (XAI) has also emerged as a vital component in healthcare applications, addressing the “black-box” nature of DL models by making their decision-making processes more interpretable for clinicians [4]. This survey reviews advanced DL models and XAI techniques applied to ovarian cancer diagnostics, emphasizing their contributions, limitations, and potential for clinical integration.

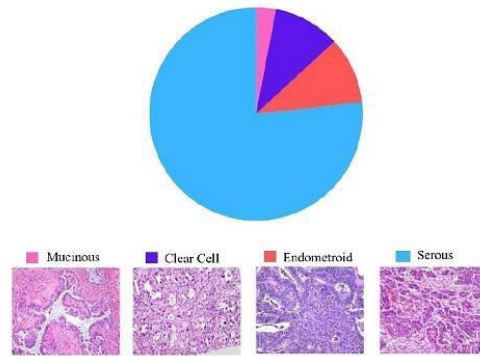


Fig 1. Classification of Ovarian cancer

## II. LITERATURE SURVEY

### 1. Convolutional Neural Networks (CNN s)

CNNs are widely used in medical image analysis for their feature extraction capabilities, a critical need in cancer diagnosis. CNN architectures like ResNet, VGG, and Inception have been effective in processing histopathological images to distinguish between cancerous and non-cancerous tissues. For instance, a recent study employing InceptionV3 for ovarian cancer subtype classification achieved an accuracy of 97.96%, underscoring CNNs' ability to capture intricate patterns critical for subtype differentiation [4]. The study by Radhakrishnan et al. further supports this, showing high classification accuracy with InceptionV3 for ovarian cancer subtypes, making it a top-performing model for such tasks [10].

Another recent development integrates Grey Wolf Optimization (GWO) with CNNs, known as CNN-GWO. This hybrid model optimizes CNN hyperparameters, achieving enhanced classification performance with accuracies reaching 98% in ovarian cancer diagnosis. GWO's efficient exploration capabilities during model training make CNN-GWO a promising method for medical diagnostics [5].

### 2. Transfer Learning

Transfer learning has proven valuable, particularly with limited labeled data, by enabling pre-trained models to be fine-tuned for specific applications. Studies using models like ResNet18 and VGG19 pre-trained on large datasets have shown improved performance in ovarian cancer diagnosis. Fine-tuning VGG19 on ovarian cancer histopathology data demonstrated enhanced sensitivity and specificity, supporting transfer learning's potential to reduce data requirements while maintaining accuracy [6].

### 3. Multi-Model Approaches and Model Comparison

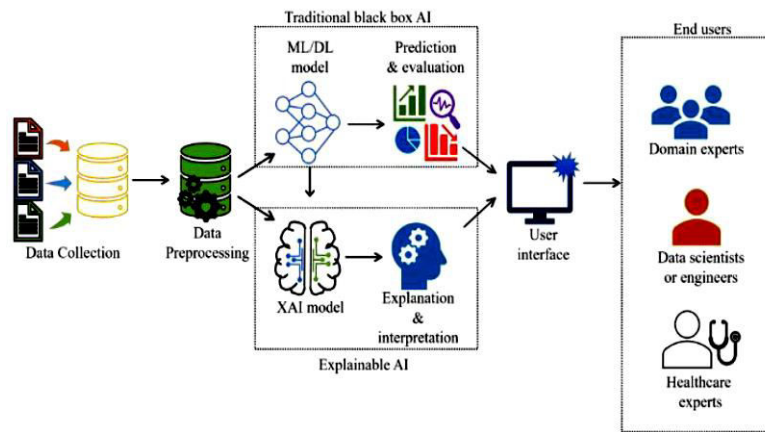
Comparative studies across multiple DL architectures have identified top-performing models for ovarian cancer classification. A study comparing MobileNetV2, ResNet18, Xception, and EfficientNet found that InceptionV3 performed best with the highest accuracy and generalization across datasets [7]. This aligns with Radhakrishnan et al.'s findings, which also emphasized InceptionV3's effectiveness in multiclass ovarian cancer subtype classification [10].

### A. Ensemble Learning Techniques

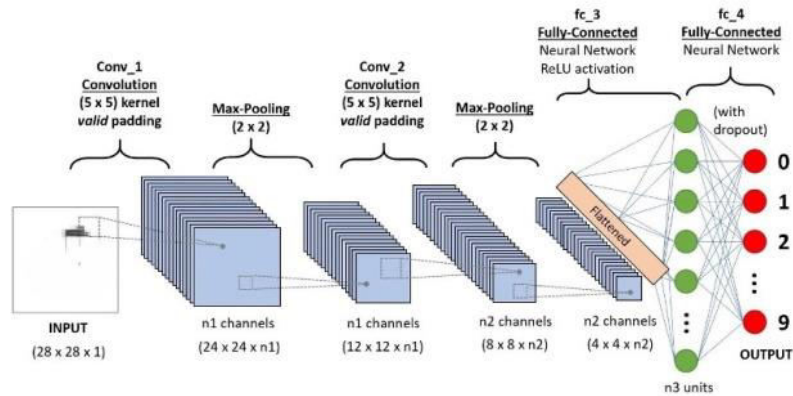
Ensemble learning, which integrates forecasts from several models, enhances accuracy and reduces the risk of overfitting. Techniques like bagging, boosting, and stacking have been applied in ovarian cancer diagnosis, with stacked ensemble models showing particular promise. For instance, combination of a stacked ensemble model and Random Forest (RF), XGBoost (XGB), and Support Vector Machine (SVM) classifiers achieved a diagnostic accuracy of 96.87% [8]. Pairing ensemble models with XAI methods like SHAP provides insight into feature importance, facilitating clinical adoption of these diagnostic systems [8].

**B. Explainable AI (XAI) for Model Interpretability**

XAI techniques are essential in healthcare, where understanding a model’s decision-making process is critical. Grad-CAM, saliency maps, and integrated gradients are popular XAI methods used to visualize influential image regions in model predictions. These methods are very useful for in histopathological analysis, where model transparency helps clinicians identify features indicative of cancer. Radhakrishnan et al. applied Grad-CAM with InceptionV3, enabling clinicians to link model predictions to biologically relevant features, thus enhancing clinical trust in AI diagnostics [10].



(a)



(b)

Fig 2. (a) Transparency through Explainable AI. (b) CNN Architecture

### III. METHODOLOGY



**Fig 3. A methodology flowchart showing the successive stages of data collection, preprocessing, model development, and evaluation**

#### A. Dataset and Preprocessing

Histopathological image datasets like the Cancer Genome Atlas (TCGA-OV) are commonly used in ovarian cancer detection research. These datasets are often augmented through rotation, flipping, zooming, and shearing to address class imbalance, reducing overfitting risks and enhancing model robustness [8]. Radhakrishnan et al. similarly utilized TCGA-OV data and applied augmentation techniques to bolster the dataset's diversity for robust model training [10].

#### B. Model Training and Validation

Standard ML evaluation practices, including an 80:20 train-test split and cross-validation, are employed to ensure model generalization. CNN models such as InceptionV3, ResNet18, and MobileNetV2 are trained on large, augmented datasets, with GWO optimization applied to fine-tune hyperparameters. Transfer learning reduces training time, while enhancing performance in situations with little data [7].

#### C. Evaluation Metrics

Accuracy, recall, precision, F1-score, and area under the receiver operating characteristic curve (AUC-ROC) are used to gauge performance. Metrics like recall and F1-score, which prioritize minimizing false negatives, are particularly valued in healthcare [9].

#### IV. RESULTS AND DISCUSSION

##### A. Performance Analysis

Studies indicate that CNN models, particularly InceptionV3 and CNN-GWO, perform well in ovarian cancer detection, with CNN-GWO achieving up to 98% accuracy. Ensemble models such as those combining RF, XGB, and SVM also show strong results with high recall and precision [5], [8]. In particular, Radhakrishnan et al. reported InceptionV3 achieving 97.96% accuracy, validating its generalizability and resilience capabilities [10].

##### B. Clinical Relevance and Interpretability

XAI methods, such as SHAP and Grad-CAM, provide a vital function in making DL models interpretable, aiding in clinical adoption. By visualizing key image regions and quantifying feature contributions, XAI techniques bridge the gap between model prediction and clinical reasoning. This approach, as demonstrated by Radhakrishnan et al., fosters greater trust in AI-driven diagnostics by providing insights into model operations during predictions [10].

##### C. Limitations

Despite encouraging outcomes, there are still issues with dataset size, diversity, and DL models' "black-box" nature. Current datasets often lack subtype diversity, limiting model generalizability. Radhakrishnan et al. suggest expanding datasets through multi-center collaborations and integrating multi-omics data to enhance robustness and clinical relevance [10].

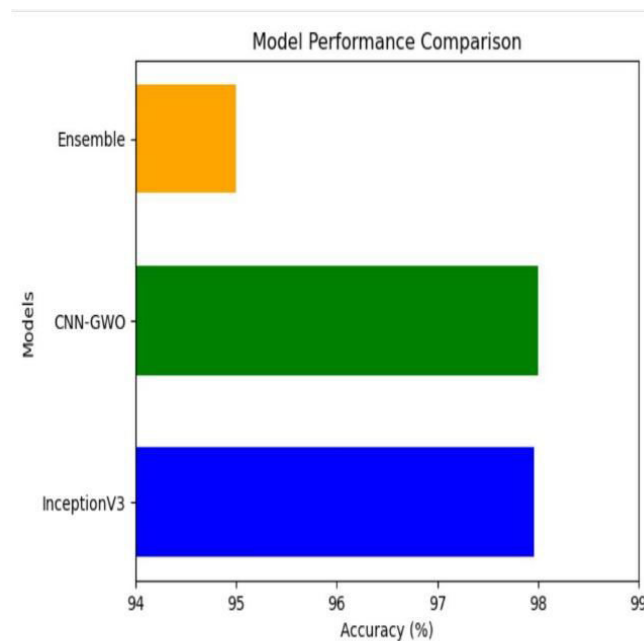


Fig 4. Distribution of accuracy percentages across different models. This chart illustrates the performance comparison, with CNN-GWO achieving the highest accuracy, followed by InceptionV3 and the Ensemble model.

#### V. FUTURE DIRECTIONS AND CONTRIBUTION

This survey highlights the transformative role of explainable AI and DL in ovarian cancer diagnosis. Considering the gaps and current trends found in the literature review, this paper proposes the following future directions to further enhance the reliability and clinical impact of AI-based ovarian cancer diagnostics:

**A. Integration of Multi-Modal Data:** Including genomic, proteomic, and histopathological data in DL models is a promising approach. Combining these data sources could provide a more comprehensive analysis and improve the classification accuracy of ovarian cancer subtypes.

**B. Real-Time Diagnosis and Cloud-Based Solutions:** Implementing AI models in a cloud-based, real-time diagnostic platform can facilitate immediate decision-making in clinical settings. This strategy would necessitate creating efficient algorithms capable of processing large volumes of data with low latency.

**C. Collaborative Research Initiatives:** Encouraging multi-institutional collaborations to build large, diverse datasets will enhance model training and evaluation, ultimately improving diagnostic performance across varied populations.

**D. Personalized Medicine Approaches:** Leveraging AI to analyze individual patient data can lead to personalized treatment plans based on predicted outcomes. Integrating XAI methods will help clinicians understand the rationale behind AI recommendations, enhancing patient trust in AI-assisted care.

By addressing these future directions, researchers and practitioners can contribute to more effective and explainable ovarian cancer diagnostic systems, paving the way for improved patient outcomes.

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