A Review Based On Deep Learning Techniques Of Ovarian Cancer Detection

Ms.Minu Cherian
Computer Science and Engineering
Amal Jyothi College of Engineering, Autonomous
Kanjirapally, Kottayam, India
minucherian@amaljyothi.ac.in

Ms.Sivakami Sudesh
Computer Science and Engineering
Amal Jyothi College of Engineering, Autonomous
Kanjirapally, Kottayam, India
sivakamisudesh2026@cs.ajce.in

Ms.Sivani M Kumar
Computer Science and Engineering
Amal Jyothi College of Engineering, Autonomous
Kanjirapally, Kottayam, India
sivanimkumar@cs.ajce.in

Ms.Sneha J Kannan
Computer Science and Engineering
Amal Jyothi College of Engineering, Autonomous
Kanjirapally, Kottayam, India
snehajkannan2026@cs.ajce.in

Ms.Sneha Rose Vinod
Computer Science and Engineering
Amal Jyothi College of Engineering, Autonomous
Kanjirapally, Kottayam, India
sneharosevinod2026@cs.ajce.in

Abstract—**Ovarian cancer remains one of the most lethal gynecological malignancies, primarily due to delayed diagnosis and the disease's histological heterogeneity. Recent advancements in artificial intelligence (AI) and deep learning (DL) have demonstrated significant promise in improving early detection and accurate classification of ovarian tumors through non-invasive imaging modalities. This study synthesizes findings from four contemporary AI-based research approaches utilizing ultrasound and multi-parametric magnetic resonance imaging (mpMRI) for early ovarian cancer diagnosis. A systematic review and meta-analysis revealed that AI-enhanced ultrasound achieved pooled sensitivity and specificity rates of 81% and 92%, respectively. Another approach developed a DL model leveraging multi-sequence mpMRI data, which effectively distinguished high-grade serous carcinoma from clear cell carcinoma with an AUC of 91.62%. A deep learning radiomics nomogram (DLR_Nomogram) derived from ultrasound images outperformed the traditional O-RADS classification, achieving AUCs as high as 0.985. Additionally, a multiclassification framework incorporating multiple DL models and explainable AI (XAI) techniques, including InceptionV3, achieved up to 97.96% accuracy, while enhancing model interpretability. Collectively, these AI-driven strategies demonstrate powerful potential for improving diagnostic accuracy, enabling precise subtype identification, and advancing personalized treatment planning in the early detection of ovarian cancer.**

Keywords- Deep learning (DL), Ultrasound imaging, Multiparametric MRI (mpMRI), Radiomics, Explainable Artificial Intelligence (XAI), Tumor classification, Medical image analysis.

I. Introduction

Ovarian cancer is one of the leading causes of cancer-related deaths among women worldwide. The disease is often diagnosed at an advanced stage because early symptoms are mild and difficult to identify. Early detection plays a crucial role in improving the survival rate of patients.

Medical imaging techniques such as ultrasound, computed tomography (CT), and magnetic resonance imaging (MRI) are commonly used to diagnose ovarian cancer [4]. However, manual interpretation of these images may lead to misdiagnosis due to human error and the complexity of tumor structures.

Recent advancements in artificial intelligence and deep learning have improved the accuracy of cancer detection. Deep learning models are capable of automatically extracting features from medical images and classifying tumors as benign or malignant. This paper presents a survey of various deep learning techniques used for ovarian cancer detection and analyzes their effectiveness.

Medical research has focused on improving early detection methods to increase survival rates. Early diagnosis can significantly improve treatment outcomes and reduce mortality rates among patients. However, traditional diagnostic approaches rely heavily on the expertise of medical professionals, and analyzing complex medical images manually can sometimes lead to inconsistencies in diagnosis.

With the rapid advancement of artificial intelligence technologies, computer-based diagnostic systems are becoming increasingly popular in the healthcare sector. Deep learning techniques have demonstrated remarkable performance in image recognition tasks, making them suitable for analyzing medical images such as ultrasound, CT scans, and MRI images. These models can automatically learn patterns from large datasets and assist doctors in identifying abnormal tissues more efficiently.

II. Overview of Ovarian Cancer

Ovarian cancer develops in the ovaries and is categorized into several types based on the type of cells affected.

Major Types of Ovarian Cancer

- **Epithelial [8] Tumors**
  - Most common type
  - Includes High Grade Serous Carcinoma (HGSC)
- **Germ Cell Tumors**
  - Rare type
  - Usually affects younger women
- **Stromal Tumors**
  - Develop in hormone-producing tissues
- **Small Cell Carcinoma**
  - Rare but aggressive cancer

Early detection is essential for effective treatment and improved patient outcomes. Ovarian cancer [4] can originate from different types of cells within the ovary. Among these, epithelial ovarian cancer is the most common form and accounts for the majority of diagnosed cases. This type usually develops from the cells that cover the outer surface of the ovary. Because of its aggressive nature, epithelial ovarian cancer often spreads quickly to nearby organs and tissues.

The risk factors associated with ovarian cancer include genetic mutations, family history of cancer, increasing age, hormonal imbalance, and lifestyle factors. Certain inherited gene mutations such as BRCA1 and BRCA2 significantly increase the risk of developing ovarian cancer. Understanding these risk factors helps researchers and healthcare professionals develop improved screening and prevention strategies.

Early detection methods include pelvic examinations, ultrasound imaging, and blood tests such as the CA-125 marker test. However, these methods alone may not always provide accurate results. Therefore, integrating advanced technologies like artificial intelligence with traditional diagnostic techniques can help improve the accuracy of ovarian cancer detection.

III. Literature Survey

Several studies have explored the use of artificial intelligence and deep learning techniques for the detection and classification of ovarian cancer using medical images.

Researchers have applied convolutional neural networks to analyze ultrasound and MRI images for tumor detection. CNN [2] models have demonstrated strong performance in extracting relevant features and distinguishing between benign and malignant tumors.

Some studies have used pre-trained deep learning models such as VGG16, VGG19, and ResNet50 through transfer learning techniques. Transfer learning allows models trained on large datasets to be adapted for medical image analysis tasks, improving accuracy even with limited datasets. Other research works have explored hybrid approaches combining machine learning algorithms with deep learning models. For example, feature extraction using CNNs [2] followed by classification using Support Vector Machines (SVM) or K-Nearest Neighbor (KNN) classifiers.

Additionally, several researchers have investigated the use of radiomics and deep learning frameworks to improve ovarian cancer diagnosis using multiparametric MRI images. These approaches combine imaging features with clinical data to achieve better prediction performance. Several research studies have explored the use of deep learning algorithms to enhance the performance of ovarian cancer detection systems. Many of these studies focus on analyzing medical images using convolutional neural networks due to their strong capability in feature extraction and pattern recognition.

In addition to CNN-based approaches, researchers have also experimented with transfer learning techniques where pre-trained models are fine-tuned for medical image classification tasks. This approach helps improve performance when only a limited number of medical images are available for training. Transfer learning models such as ResNet, VGG, and Inception architectures have demonstrated promising results in various medical imaging applications.

Furthermore, some studies combine deep learning with traditional machine learning algorithms to improve classification accuracy. In such hybrid systems, deep learning models first extract important image features, which are then used by classifiers such as Support Vector Machines (SVM) or Random Forest algorithms. These integrated approaches have shown improved performance in distinguishing between benign and malignant ovarian tumors.

Despite these advancements, many studies face limitations such as small dataset sizes, lack of diversity in medical images, and challenges in model interpretability.

IV. Deep Learning Techniques Used for Ovarian Cancer Detection

Deep learning has become an important tool for analyzing medical images and detecting diseases automatically.

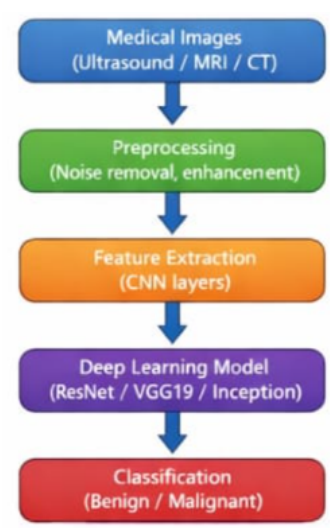

Fig. 1: General Workflow of deep learning for ovarian cancer detection

Several deep learning models have been applied for ovarian cancer detection.

- **Convolutional Neural Networks (CNN)**

Convolutional Neural Networks are one of the most commonly used deep learning architectures for image analysis. CNNs [2] consist of convolution layers, pooling layers, and fully connected layers. These layers work together to extract important features from images and classify them effectively.

CNN models are widely used in medical imaging because they can automatically learn complex patterns from large datasets.

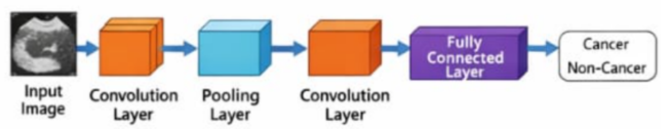

Fig. 2: Basic Architecture of Convolutional Neural Networks

- **ResNet**
  Residual Networks (ResNet) are deep neural networks designed to overcome the problem of vanishing gradients in very deep models. ResNet introduces skip connections that allow information to pass directly between layers.
  ResNet models have achieved high accuracy in many medical image classification tasks and are often used in cancer detection systems.
- **VGG19**
  VGG19 is a deep convolutional neural network consisting of 19 layers. It uses small convolution filters and a simple architecture, making it easy to implement. VGG19 has shown good performance in image classification tasks and is frequently used as a baseline model in medical imaging research.
- **InceptionV3**
  InceptionV3 is another powerful deep learning architecture designed to improve computational efficiency while maintaining high accuracy. The model uses multiple convolution filters of different sizes to capture both local and global features in images. Deep learning techniques are particularly useful for medical image analysis because they eliminate the need for manual feature extraction. Instead of relying on handcrafted features, deep learning models automatically learn relevant patterns from large datasets during the training process. This capability enables them to identify subtle variations in medical images that may not be easily visible to the human eye.
  Another advantage of deep learning models is their ability to process large volumes of medical data efficiently. Modern healthcare systems generate a significant amount of imaging data, and analyzing this data manually can be time-consuming. Automated deep learning systems can analyze images quickly and assist doctors in making faster diagnostic decisions.
  In addition, deep learning models can be integrated with computer-aided diagnostic systems to support radiologists during clinical analysis. These systems can highlight suspicious regions in medical images and provide probability scores indicating the likelihood of cancer. Such assistance helps reduce diagnostic errors and improves the reliability of medical decision-making.

V. Performance Evaluation Metrics

To evaluate the performance of deep learning models in ovarian cancer detection, several evaluation metrics are commonly used.

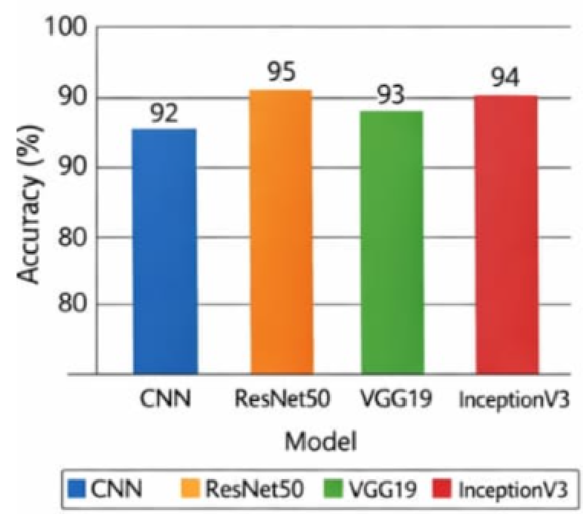

Fig. 3: Comparison of different Deep Learning models

- **Accuracy:** Accuracy measures the overall correctness of the model in predicting the correct class.
- **Precision:** Precision indicates the proportion of correctly predicted positive cases among all predicted positive cases.
- **Recall (Sensitivity):** Recall measures the ability of the model to correctly identify actual positive cases.
- **F1-Score:** F1-score is the harmonic mean of precision and recall and provides a balanced measure of model performance.
  These metrics help researchers compare different models and determine their effectiveness in cancer detection.

Performance evaluation metrics are essential for measuring how effectively a deep learning model performs in medical diagnosis tasks. Since incorrect predictions in healthcare applications can have serious consequences, it is important to use multiple evaluation metrics to assess the reliability of the model.

In addition to accuracy, precision, recall, and F1-score, researchers often use other metrics such as the Area Under the Receiver Operating Characteristic Curve (AUC-ROC). The AUC-ROC value provides an overall measure of the model's ability to distinguish between different classes. A higher AUC value indicates better classification performance.

These evaluation metrics allow researchers to compare different deep learning models and determine which architecture performs best for ovarian cancer detection. Proper evaluation also ensures that the model can generalize well to new medical images that were not included in the training dataset.

VI. Challenges and Limitations

Although deep learning techniques have achieved significant improvements in medical image analysis, several challenges still exist.

- Limited Medical Datasets
  Many medical datasets are small and lack diversity, which can affect the performance and generalization of deep learning models.
- High Computational Cost
  Deep learning models require powerful hardware resources and large computational power, which may not be available in all healthcare environments.
- Lack of Model Interpretability
  Deep learning models often operate as black-box systems, making it difficult for doctors to understand how predictions are made.
- Data Imbalance
  Medical datasets often contain more normal cases than abnormal cases, which can cause bias during model training.

Another important challenge in applying deep learning techniques to medical diagnosis is the availability of high-quality labeled datasets. Medical data collection requires strict ethical approvals and expert annotations, which can make dataset creation time-consuming and expensive. As a result, many studies rely on relatively small datasets that may not fully represent real-world clinical scenarios.

Privacy and security concerns also play a significant role in medical data usage. Patient data must be protected according to healthcare regulations, which can limit data sharing among research institutions. This restriction may affect the development of more robust and generalized deep learning models.

Additionally, implementing deep learning systems in real healthcare environments requires collaboration between computer scientists, radiologists, and medical professionals. Without proper integration into clinical workflows, the practical use of these technologies may remain limited.

VII. Conclusion

This survey reviewed various deep learning techniques used for ovarian cancer detection. Models such as CNN [2], ResNet, VGG19, and InceptionV3 have shown promising results in medical image classification and tumor detection. However, challenges such as limited datasets and high computational costs still exist. Future research should focus on improving model accuracy, developing better datasets, and implementing explainable AI techniques for reliable medical diagnosis. Overall, the application of deep learning techniques has significantly improved the ability to analyze medical images for ovarian cancer detection. Advanced neural network architectures [2] are capable of identifying complex patterns and features that may not be easily recognized through traditional diagnostic approaches. As a result, deep learning models provide a promising solution for supporting early diagnosis and improving clinical decision-making.

The studies reviewed in this survey demonstrate that deep learning models such as CNN [2], ResNet, VGG19, and InceptionV3 have achieved high accuracy in tumor detection and classification tasks. These models can automatically extract meaningful features from ultrasound and MRI images, reducing the need for manual analysis. By assisting medical professionals in identifying cancerous tissues more accurately, these technologies can contribute to faster diagnosis and more effective treatment planning.

Despite these advancements, there are still several challenges that need to be addressed before these systems can be widely adopted in real clinical environments. Issues such as limited medical datasets, computational requirements, and the lack of interpretability of deep learning models remain significant concerns. Addressing these challenges will require continued research, collaboration between healthcare experts and data scientists, and the development of more efficient and transparent algorithms.

In conclusion, deep learning has the potential to transform the field of medical image analysis and significantly improve the detection of ovarian cancer. With further improvements in model performance, data availability, and explainability, AI-based diagnostic systems may become valuable tools in supporting healthcare professionals and enhancing patient outcomes in the future.

VIII. Future Work

Future research in ovarian cancer detection using deep learning can focus on several important directions.

One important area is the development of larger and more diverse medical datasets to improve model training and generalization. Researchers can also explore combining multiple medical imaging modalities such as ultrasound, CT scans, and MRI to provide more comprehensive diagnostic information.

Another promising direction is the integration of Explainable Artificial Intelligence (XAI) techniques to improve the transparency of deep learning models. Explainable models can help medical professionals better understand and trust automated diagnostic systems.

Additionally, future studies can focus on developing lightweight deep learning models that require less computational power while maintaining high accuracy. Such models would enable real-time diagnostic applications and improve accessibility in resource-limited healthcare settings. Future research can also focus on integrating multimodal medical data to improve the accuracy of ovarian cancer detection systems. Combining information from medical images, clinical reports, genetic data, and patient history may provide a more comprehensive understanding of the disease and improve predictive performance.

Another promising direction is the development of real-time diagnostic systems that can assist doctors during medical examinations. With the help of cloud computing and advanced hardware technologies, deep learning models can be deployed in hospitals to provide instant analysis of medical images.

Furthermore, continued research in explainable artificial intelligence (XAI) will play an important role in increasing trust in automated diagnostic systems. By providing clear explanations for predictions, these models can help doctors better understand the reasoning behind the decisions made by deep learning algorithms.

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