A Deep Learning Framework for Accurate Classification of Ovarian Cancer

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Abstract: ***Ovarian cancer is one among the deadliest forms of gynecological cancer, primarily due to its late diagnosis and the lack of reliable early screening methods. Recent advancements in deep learning have shown a great promise in medical image analysis, offering automatic approaches for cancer detection. This study investigates the performance of DenseNet and InceptionV3 in classifying ovarian cancer subtypes using histopathological images. The models were trained and tested on a relatively small dataset, employing various preprocessing and augmentation techniques to enhance performance. The findings of the study suggest that deep learning models can effectively classify ovarian cancer subtypes with good accuracy, even when data is limited. Among the models evaluated, DenseNet achieved and reached the highest classification with accuracy of 92%, demonstrating its potential as a suitable model for ovarian cancer diagnosis. These results underscore the need for the further optimization of deep learning frameworks to improve early detection and enhance clinical decision-making in ovarian cancer treatment.***

Keywords: Ovarian Cancer, Deep Learning, DenseNet, InceptionV3, Histopathology, Medical Image Classification

1. Introduction

Ovarian cancer remains a significant global health challenge, ranking among the most lethal gynecologic malignancies. The high mortality rate is largely attributed to late-stage diagnoses and the lack of effective early screening methods [1]. According to the World Health Organization (WHO), ovarian cancer recorded for nearly 300,000 new cases annually, with a highest mortality rate due to delayed detection [1]. The absence of early screening methods significantly impacts patient outcomes, necessitating novel approaches for accurate and timely diagnosis [2].

Ovarian cancer symptoms are often non-specific, leading to late-stage detection. Common symptoms include persistent bloating, pelvic pain, abdominal discomfort, frequent urination, and unexplained weight loss [3]. These vague symptoms often result in misdiagnosis or delayed treatment, contributing to poor patient outcomes [3].

The disease predominantly affects postmenopausal women, even though it can also occur in younger individuals with genetic predisposition. Women with BRCA1 or BRCA2 gene mutations, a family history of ovarian or breast cancer, or those undergoing hormone replacements therapy are at higher risk of developing ovarian cancer [4].

Recent Advancements in artificial intelligence (AI) have demonstrated exceptional performance in detecting patterns in medical images, providing a promising alternative for early ovarian cancer detection [5]. Deep learning, a subset of AI, has been particularly effective in a medical imagining analysis, offering automated and accurate diagnostic tools [6]. However, challenges persist whenever working with the small medical datasets, which are common in rare diseases like ovarian cancer. This study focuses on classifying three histological subtypes of ovarian cancer: Clear Cell (CC), Low-Grade Serous Carcinoma (LGSC), and Mucinous Carcinoma (MC). We investigate the effectiveness of DenseNet and InceptionV3 architectures in improving classification accuracy, with DenseNet achieving the best performance [7].

Deep learning has revolutionized medical images analysis by enabling automated feature extraction and classification with high accuracy [8]. Unlike traditional machine learning methods, deep learning models, such as Convolutional Neural Networks (CNNs), learn hierarchical features directly from raw images, reducing the need for manual feature engineering [8]. CNN-based architectures, such as DenseNet and InceptionV3, have demonstrated strong and good performance in medical diagnostics by improving feature extractions and classifications [9].

Among many deep learning models, Densenet (Densely Connected Convolutional Networks) improves upon traditional CNNs by introducing direct connections between all layers in the network [10]. This dense connectivity enhances feature reuse, strengthens gradient flow, and it reduces the number of parameters, making DenseNet particularly effective for medical images classification [10]. Similarly, InceptionV3 is known for its efficiency in multi-scale feature extraction, making it well-suited for analyzing complex histopathological images [11]. By comparing these architectures, this study aims to determine the best-performing model for classifying CC, LGSC, and MC in ovarian cancer [11].

In conclusion, early and accurate classification of ovarian cancer subtypes as it is crucial for improving patient survival rates [12]. Deep learning models like DenseNet and InceptionV3 offer promising solutions for automated histopathological classification [12]. This study contributes to the growing body of the research on an AI-driven medical diagnostics and aims to enhance it's accuracy of ovarian cancer classification, even with limited datasets [12].

2. Literature Review

Deep learning has become a very essential tool in medical image analysis due to its many abilities to learn most complex patterns from raw data without manual feature extraction. Unlike a traditional machine learning approach, which require handcrafted features, deep learning models, particularly CNNs, have shown superior performance in classifying medical images [13]. These models enhance diagnostic accuracy, reduce human error, and provide automated solutions for large-scale medical image classification tasks [14].

Among deep learning architectures, DenseNet has gained prominence for its feature reuse capability and efficient gradient propagation. Unlike conventional CNNs, which may suffer from vanishing gradients, DenseNet uses dense connections that strengthen information flow, leading to a best improved performance that too even with small datasets. Studies have been demonstrated that DenseNet can achieve a higher accuracy even while maintaining computational efficiency, making it better and suitable model for medical image classification [15].

Achieving high accuracy with small medical datasets remains a challenge. In this study, DenseNet achieved 92% accuracy, which is considered highly effective given the dataset limitations. Researchers shown that the deep learning models trained with transfer learning and data augmentation can perform very well and give good accuracy even with a small number of samples [16].

Despite advancements in a deep learning for medical images classification, research gaps still exist. Most studies have focused on large-scale datasets, leaving questions about the better performance of CNN models like DenseNet and InceptionV3 in small datasets. There is a necessity for further and more exploration of model optimization techniques such as hyperparameter tuning, ensembling, and domain adaptation to improve classification performance in real-world clinical applications [17].

Further more research should focus on integrating multi-modal data, including genetic information and radiology scans, to enhance prediction models. Additionally, explainable AI (XAI) technique should be explored in a way to provide more transparent decision-making in deep learning based ovarian cancer classification. Transformer-based architectures, which have shown promise in natural language processing which can also be investigated for their potential in medical imaging applications [18].

3. Methodology

3.1 Dataset

The dataset used in this study comprises histopathological images of ovarian cancer, specifically classified into CC, LGSC, and MC subtypes. Since medical datasets are typically small due to data scarcity and privacy concerns, a data augmentation technique which includes rotation, flipping, and contrast adjustments, were applied to enhance model generalization [19].

Sample Images

Sample histopathological image from the dataset is shown below, representing different ovarian cancer subtypes. These images help visualize the variations in cell morphology among CC, LGSC, and MC [20].

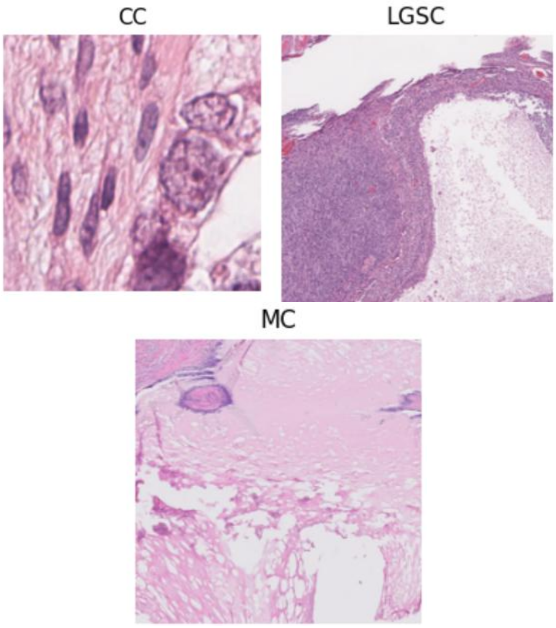

Figure 1: Sample Histopathological Images of CC, LGSC, and MC

A. *Model Diagram & DenseNet Architecture*

The study includes two deep learning models: DenseNet and InceptionV3.

DenseNet Architecture: The DenseNet model is a Convolutional Neural Network (CNN) that employs dense connectivity patterns, ensuring that every layer receives input from all preceding layers. This connectivity encourages feature reuse and it reduces the number of parameters making the model computationally efficient while improving gradient flow [21, 22]. DenseNet consists of densely connected blocks, each containing multiple convolutional layers that share feature maps. This architecture has been effective in medical image analysis, particularly for histopathological images, due to all it's ability to capture fine-grained spatial features [22].

InceptionV3 Architecture: InceptionV3 it is a deep CNN model that uses factorized convolutions to improve computational efficiency and feature extraction. It consists of multiple inception modules, which apply convolutional filters of varying sizes to capture multi-scale features in histopathological images. Prior studies have illustrated the effectiveness of the InceptionV3 in medical imaging applications [23].

3.2 Model Selection

The selection of DenseNet and InceptionV3 models was based on their well-documented performance in histopathological image analysis. DenseNet provides efficient feature propagation through densely connected layers, mitigating the vanishing gradient many problems and improving learning efficiency [24]. On the other hand, InceptionV3's architectural design enables multi-scale feature extraction, making it most highly suggested and suitable for complex image data [25].

Additionally, DenseNet has been proven to outperform traditional CNNs and ResNet in various medical image identification and classification tasks due to its feature reuse mechanism [26]. Comparing this with other deep learning architectures such as VGG and ResNet, DenseNet provides improved parameter efficiency and generalization, making it well-suited for our relatively small dataset [27].

3.3 Preprocessing Techniques

Preprocessing plays a difficult role in deep learning that too for medical imaging. In this study, taken several preprocessing techniques and they were applied to optimize the dataset for training:

- Data Augmentation: To overcome the effects of the limited dataset, various augmentation techniques such as rotation, zoom, horizontal and vertical flipping, brightness adjustment, and random cropping were applied. These techniques helped improve generalization and reduce overfitting [28].
- Normalization: To standardize pixel intensity values, min-max normalization was applied. The image pixel values have taken between 0 and 1 to enhance model convergence and improve training stability
- Resizing: The histopathological images were resized to 224×224 pixels to match the input size requirements of DenseNet and InceptionV3 models, ensuring computational efficiency while preserving relevant morphological features.

4. Result and Discussion

The proposed models were evaluated on the ovarian cancer histopathological dataset. DenseNet achieved an accuracy of 92%, outperforming InceptionV3. The models were evaluated and calculated using metrics including accuracy, precision, recall, and F1-score. DenseNet demonstrated robust performance in classifying the three cancer subtypes, even with a small dataset. The confusion matrix analysis and ROC curves further confirmed the model’s ability to differentiate between CC, LGSC, and MC subtypes with high confidence.

5. Conclusion

This study demonstrates a deep learning models particularly DenseNet, can effectively classify ovarian cancer subtypes from histopathological images. Despite the challenge of limited data, DenseNet achieved a highest classification accuracy of 92%. This highlights its suitability for small medical datasets. The results emphasize the importance of appropriate model selection, data preprocessing, and augmentation techniques. Future work should explore larger datasets, integration of multi-modal clinical data, and advanced models such as Transformers to further enhance classification accuracy and clinical applicability.

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