# Early Detection Of Ovarian Cancer Using Deep Learning

## Final Year Design Project

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### FINAL YEAR DESIGN PROJECT REPORT

This Report is Presented in Partial Fulfillment of the Requirements for the **Degree of Bachelor of Science in Computer Science and Engineering**

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# APPROVAL

This project, titled **"Early Detection of Ovarian Cancer Using Deep Learning",** submitted by **Saad Kamal** and **Sadekul Hasan Sakib** Daffodil International University, along with the Department of Computer Science and Engineering, has approved the project for its style and substance, judging it sufficient for the partial fulfilment of the requirements for the degree of B.Sc. The presentation date was **14-05-2025.**

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# DECLARATION

We hereby declare that this project has been done by us under the supervision of **Md. Abbas Ali Khan, Assistant Professor,** Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of it has been submitted elsewhere for the award of a degree or diploma.

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# ABSTRACT

Ovarian cancer is one of the deadliest gynecological malignancies, and early diagnosis through histopathological image analysis can significantly improve patient outcomes. This study proposes a convolutional neural network (CNN)-based framework for the classification of ovarian cancer using histopathological images. Greyscale conversion, normalization, and Contrast Limited Adaptive Histogram Equalization (CLAHE) were included in a multi-stage preprocessing pipeline to improve image quality. Furthermore, photometric data augmentation methods raise model generalization and adaptation capacity. An attention module included in the proposed CNN model lets the network concentrate on important areas of the image, thereby improving classification performance. Five well-known transfer learning models—MobileNet, ResNet50, VGG16, DenseNet 201, and VGG19—were assessed against the proposed method's efficacy. Moreover, k-fold cross-validation was used to guarantee the dependability and strength of the model over several data splits. Experimental results show that the attention-based CNN model beats the comparison models, therefore proving its potential as a strong tool for the automatic ovarian cancer classification in histological pictures.

**Keywords:** Ovarian Cancer, Histopathological Image Classification, Convolutional Neural Network, Attention Module, Image Preprocessing, Transfer Learning, K-Fold Cross-Validation

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# Chapter 1

# Introduction

## 1.1 Introduction

**Background:** Often referred to as the "silent killer", ovarian cancer is among the most deadly gynecologic malignancies known to exist worldwide because of its inconspicuous beginning and lack of successful early-stage screening methods. Under a microscope, histopathological analysis is still the gold standard for ovarian cancer diagnosis using tissue samples. But the manual approach of looking over histological slides is time-consuming, labor-intensive, and largely dependent on the pathologist's experience and ability, which could result in subjective interpretations and diagnostic contradictions. The discipline of computational pathology has progressively embraced artificial intelligence (AI) and deep learning approaches to automate and raise disease categorization accuracy to meet these problems. Of them, CNNs have shown especially outstanding performance in image classification tasks—especially in medical image analysis. CNNs can learn intricate patterns in visual data and extract high-level characteristics that could be rather important for precise disease detection. Recent developments in computer vision have also brought attention to features in CNN architectures that let models concentrate on the most instructive areas of the image. This method replicates the actions of human pathologists who focus on particular areas of interest while neglecting less important ones. Such systems greatly enhance the interpretability and performance of histologically based deep learning models. Regarding ovarian cancer, however, studies using deep learning models—especially attention-based CNNs—for histological image categorization are still in their early years. Most current research centers on different kinds of malignancies, such as colon, lung, or breast. Consequently, it is urgently necessary to create strong and consistent CNN models, especially for the diagnosis of ovarian cancer. Often fine-tuned on particular datasets for cancer detection, numerous pre-trained transfer learning models, including MobileNet, ResNet50, VGG16, DenseNet 201, and VGG19, are currently extensively employed in medical image classification applications. Although these models have great accuracy, their capacity to pinpoint discriminative features in noisy or complicated histopathological pictures is sometimes limited. K-fold cross-validation has evolved into a common evaluation technique in medical artificial intelligence research to guarantee consistency and dependability of model performance over several datasets. It reduces the overfitting risk and helps evaluate the generalizability and resilience of the model. In essence, even though deep learning has made great progress in cancer classification, tailored treatments for ovarian cancer employing attention-enhanced CNNs are still lacking. This work attempts to close that gap by suggesting a tailored CNN architecture including attention mechanisms and thorough preprocessing methods and testing it against well-known transfer learning models using k-fold validation.

**Problem Statement:** Because of its asymptomatic early stages and lack of consistent, generally accepted screening techniques, ovarian cancer continues to be among the most fatal gynecological cancers. Although the diagnosis of ovarian cancer depends much on histopathological investigation, the manual inspection of tissue samples is time-consuming, labor-intensive, and frequently subjective. Especially in low-resource environments, the growing need for accurate and quick diagnosis strains the small number of qualified pathologists. While deep learning—especially convolutional neural networks (CNNs)—has shown great progress in medical image classification, there is clearly a dearth of dedicated and optimized CNN models, especially targeted for histopathology image classification of ovarian cancer. Many times, existing models have problems, including inadequate attention on diagnostically significant areas of the tissue, low generalizability, and ineffective handling of image noise. Furthermore, most research depends just on off-the-shelf transfer learning models or standard CNNs without including mechanisms like attention modules that would let the algorithm concentrate on important features in histopathology pictures. Furthermore lacking is a methodical assessment using strong approaches such as k-fold cross-validation, which is necessary to guarantee model stability and dependability over several datasets. Thus, the development of an effective, interpretable, and robust deep learning framework utilizing advanced preprocessing, attention mechanisms, and comparative analysis with state-of-the-art transfer learning models for the accurate classification of ovarian cancer from histological images is much needed.

## 1.2 Motivation

Ovarian cancer remains one of the most lethal gynecological malignancies worldwide, primarily due to its late-stage diagnosis and the lack of effective early detection methods. Histopathological analysis is considered the gold standard for cancer diagnosis, yet it is highly dependent on expert pathologists, prone to human error, and can be time-consuming. In many low-resource and rural healthcare settings, there is also a significant shortage of skilled personnel, which delays timely and accurate diagnosis. This situation creates an urgent need for automated, reliable, and scalable diagnostic systems. Recently, deep learning—particularly Convolutional Neural Networks (CNNs)—has shown immense potential in medical image analysis. However, most studies have focused on more common cancers like lung, colon, and breast, while ovarian cancer has received relatively limited attention in AI-based diagnostic research. This gap in the literature motivates the development of a robust deep learning model tailored specifically to ovarian cancer histopathology. Additionally, histopathological images often suffer from varying quality, noise, and inconsistencies in staining procedures, making image preprocessing a critical step in ensuring accurate classification. Motivated by this challenge, this study aims to implement advanced preprocessing techniques and an attention-integrated CNN model that can automatically focus on the most informative regions of tissue images. By addressing the diagnostic challenges associated with ovarian cancer through the integration of advanced computer vision techniques, this study aspires to contribute toward early detection, faster diagnosis, and ultimately, better clinical outcomes for patients. The motivation lies not only in technical advancement but also in its potential impact on real-world healthcare systems, especially in underserved regions.

## 1.3 Objectives

The main goal of this work is to build and assess a strong and accurate Convolutional Neural Network (CNN) model coupled with an attention mechanism for the ovarian cancer classification utilizing histopathology pictures. The study is directed towards this by the following particular goals:

- Convert histopathology images to grayscale, then normalize and use Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve image quality.
- The aim is to apply photometric data augmentation techniques to increase dataset variability and improve model generalization.
- The goal is to create a custom CNN model, including an integrated attention module, to improve the model's emphasis on image-diagnostically crucial areas.
- To compare the performance of the proposed CNN model with five state-of-the-art transfer learning models: MobileNet, ResNet50, VGG16, DenseNet201, and VGG19.
- The objective is to evaluate the reliability and robustness of the models through k-fold cross-validation.
- The objective is to provide insights into the effectiveness of attention mechanisms in histopathological image classification for ovarian cancer.

This goal seeks to close a major void in present medical imaging analysis and progress the science of cancer detection.

## 1.4 Methodology

This work uses a whole methodological framework to build a powerful and interpretable deep learning model for ovarian cancer classification using histomorphology photos. The process begins with data preparation; first, grayscale is modified to reduce computer complexity while preserving critical features, histopathological images. After that, local picture contrast is enhanced by Contrast Limited Adaptive Histogram Equalization (CLAHE), stressing relevant tissue characteristics. Also done is normalizing pixel intensity consistency among photos.

The capacity of the model to generalize is improved by means of photometric data augmentation techniques, including brightness adjustment, rotation, and flipping, hence increasing dataset variety and reducing overfitting.

Mostly based on a custom CNN architecture enhanced with an attention mechanism, the proposed approach This module allows the model to focus on the most diagnostically significant portions of the tissue photos, hence improving interpretability and classification accuracy. Using labeled histological pictures depicting ovarian cancer and non-cancer instances, the model is trained within a supervised learning framework.

Five generally used pre-trained transfer learning models—MobileNet, ResNet50, VGG16, DenseNet 201, and VGG19—are benchmarked against the proposed attention-based CNN. These models provide a fair comparison by being tuned on the same dataset.

K-fold cross-validation is carried out to guarantee the models' dependability and strength. This method creates k subsets from the dataset and trains and validates the model across k iterations—each time utilizing a new subset for validation. This method generates a more generic measure of model performance and helps to reduce overfitting risk.

All models are assessed and compared using performance measures including accuracy, precision, recall, F1-score, and AUC-ROC. The results are investigated to find how well the attention mechanism improves CNN performance for ovarian cancer categorization.

## 1.5 Project Outcome

This work seeks to produce various important results using histopathology pictures that will progress the technical and practical sides of ovarian cancer classification. The expected results are:

1. **Enhanced Classification Accuracy:** Integrated with an attention mechanism, the suggested CNN model is supposed to provide better classification performance in identifying ovarian cancer from histological pictures than conventional CNN models. The attention mechanism will help the model to concentrate on important portions of the images, therefore producing more accurate classifications.

2. **Improved Image Preprocessing Techniques:** Applying modern preprocessing techniques like grayscale conversion, normalization, and Contrast Limited Adaptive Histogram Equalization (CLAHE), the study expects a clear improvement in the quality of histopathology images, hence improving model performance.

3. **Comparison of Deep Learning Models:** Regarding accuracy, the proposed CNN model is expected to perform either competitively or better than well-known transfer learning models (MobileNet, ResNet50, VGG16, DenseNet 201, and VGG19). Precision, recall, and F1 score help one to better know which model performs best for ovarian cancer categorization.

4. **Generalizability Through Data Augmentation:** The application of photometric data augmentation techniques is anticipated to increase the generalizability of the model, enabling it to perform effectively across varied datasets and reduce the risk of overfitting.

5. **Validation of Model Robustness:** By guaranteeing that the proposed model performs consistently across several subsets of data and lowers the possibility of model overfitting or underfitting, the application of k-fold cross-validation is expected to prove the robustness of the model.

6. **Interpretability of the Model's Decisions:** The integration of an attention mechanism is expected to provide insights into which parts of the histopathological images are most

relevant to the classification decision, contributing to better interpretation and trust in the model's predictions.

7. **Practical Application in Clinical Settings:** If successful, the study is expected to contribute a feasible and efficient tool for assisting pathologists in the diagnosis of ovarian cancer, especially in regions with limited access to skilled personnel, thus improving early detection and patient outcomes.

## 1.6 Organization of the Report

The report is organized into several chapters, each focusing on distinct aspects of the study:

**Chapter 1:** Introduction provides an overview of the research objectives and outlines the background, problem statement, motivation, objectives, methodology, and outcome.

**Chapter 2:** Background comprehensively reviews existing works in the field, compares them, analyzes the similar applications, identifies gaps, and summarizes the findings.

**Chapter 3:** Research Methodology details the proposed methodology, functional and non-functional requirements, system design, project management strategies, and summary of overall activities.

**Chapter 4:** Implementation and Results covers the development process, including environment setup, model training, prototype design, system testing, and evaluation. This chapter also covers results and analysis, presenting experimental results, simulation outcomes, performance metrics, and their implications.

**Chapter 5:** Engineering Standards emphasizes the importance of adhering to recognized software, hardware, and communication standards to ensure the system's suitability for medical use. It justifies the chosen tools based on technical efficiency, clinical integration, and industry compliance. This chapter also emphasizes the impact on society, environment, and sustainability explores the broader implications of the research on life, society, and the environment; discusses ethical aspects; and includes a sustainability plan.

**Chapter 6:** Conclusion summarizes the conclusions drawn from the study, suggests future research directions, and discusses limitations and potential conflicts of interest.

# Chapter 2

# Background

## 2.1 Introduction

Cancer continues to be one of the foremost causes of mortality worldwide, imposing a heavy burden on global healthcare systems [1]. Among various gynecological malignancies, ovarian cancer is particularly lethal due to its asymptomatic nature in early stages and the lack of efficient screening methods [2]. According to recent statistics, ovarian cancer ranks as the eighth most common cancer among women and the fifth leading cause of cancer-related deaths globally. According to the GLOBOCAN 2020 report, there were approximately 313,959 new cases and 207,252 deaths attributed to ovarian cancer worldwide, reflecting its high mortality-to-incidence ratio [3]. Usually resulting in late-stage diagnosis, the stealthy spread of this malignancy substantially lowers the chances of effective therapy and survival [4].

Improving prognosis and lowering mortality rates in ovarian cancer patients depend on early and precise diagnosis, hence [5]. The diagnosis process depends much on histopathological imaging, which helps pathologists spot morphological trends in tissue samples. Nonetheless, manual inspection is time-consuming, prone to inter-observer variability, and mostly dependent on expert knowledge [6]. Driven by deep learning, Computer-Aided Diagnosis (CAD) systems have become more interesting instruments to help pathologists by automating the histological image classification [7]. Among the deep learning techniques, CNNs have demonstrated remarkable capacity in extracting spatial hierarchies from challenging medical pictures [8].

In this work, we provide a strong and effective CNN-based model for ovarian cancer classification based on histopathology pictures. Grayscale conversion, normalization, and Contrast Limited Adaptive Histogram Equalization (CLAHE) are part of a thorough preprocessing pipeline employed to improve image quality and guarantee consistent feature extraction.

Moreover, included are photometric data augmentation methods to improve the generalizing capacity of the model. The suggested CNN architecture combines an attention module to let the network concentrate on the most discriminative areas of the image, hence improving interpretability and classification accuracy. We evaluate five state-of-the-art transfer learning models—MobileNet, ResNet50, VGG16, DenseNet 201, and VGG19—to confirm the efficacy of our methodology. Furthermore, used to evaluate the model's resilience and reduce the overfitting risk is k-fold cross-validation. The exceptional performance of the attention-augmented CNN shows its promise for automatic, accurate, and interpretable categorization of ovarian cancer, therefore opening the route for more dependable and scalable diagnostic tools in computational pathology.

## 2.2 Literature Review

This study(Table 2.1) demonstrates the contribution of AI and machine learning technologies to the healthcare domain. Convolutional Neural Network(CNN) has shown exceptional performance in tasks such as tissue classification, nuclei segmentation, disease grading, surpassing traditional handcrafter methods. There is no way to deny that AI is the future of automation of healthcare visual and detection domain problem solving to assist the doctors and specialists to achieve more precise diagnosis. In the ovarian cancer domain(oncology), ResNet, DenseNet, Swin Transformer, Hybrid CNN Models, etc. performed outstanding performance that justified the effectiveness for broad use in oncology.

This study also reflects the gaps that remain unsolved and the scope to take the work beyond. We conducted the study to highlight the contribution, dominance, gaps, scopes, and future aspects of the impact of machine learning and deep learning models and systems in the healthcare and pathology domain.

Table 2.1: Summary of Literature Review

| Author Name(s) | Year | Title | Methodology | Key Findings |
|---|---|---|---|---|
| Jonathan de Matos, Steve Tsham Mpinda Ataky, Alceu de Souza Britto Jr., Luiz | 2021 | Machine Learning Methods for Histopathological Image Analysis: A Review | Using a query targeting histology, histopathology, and machine learning, the approach comprised a systematic literature evaluation spanning 2008 to 2020 exploring five research portals (IEEE Xplore, ACM Digital Library, Science Direct, Web of Science, and | The review highlighted a shift from handcrafted features to deep learning methods, with significant growth in deep learning publications.<br>Segmentation methods evolved from unsupervised, supervised and deep learning |

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| Eduardo Soares de Oliveira, Alessandro Lameiras Koerich | | | Scopus). 185 papers were examined following application of title, abstract, and full-text relevance-based exclusion criteria. Addressing segmentation of nuclei and tissues, feature extraction for morphological and textural properties, and classification using both classic and deep learning approaches, the review classified ML methods into segmentation, feature extraction, shallow methods and deep methods. | approaches. Feature extraction focused on morphological and textural descriptors like GLCM and LBP. Deep learning models, particularly CNNs, showed superior performance in end-to-end learning for classification. Public datasets and increased computational power are driving advancements, though challenges remain in high-resolution image segmentation. |
| Miao et al. | 2016 | A CNN regression approach for real-time 2D/3D registration | Employed a CNN-based regression model to align 2D and 3D medical images in real time. The approach used deep learning to predict transformation parameters for image registration, trained on synthetic and real imaging data. | Found that the CNN regression model enabled accurate and fast 2D/3D registration, suitable for real-time clinical applications, with performance improvements over traditional methods, though exact quantitative results were not specified. |
| Janowczyk et al. | 2016 | Deep learning for digital pathology image analysis: A comprehensive tutorial with selected use cases | Utilized Convolutional Neural Networks (CNNs) to perform tasks such as nuclei segmentation and tissue classification in histopathological images. The methodology involved training CNNs on annotated pathology datasets to identify patterns and structures. | Demonstrated that CNNs can effectively segment nuclei and classify tissues in digital pathology images, achieving high performance in automated analysis, though specific metrics like accuracy were not detailed in the survey. |
| Varisha | 2024 | Exploring | A literature search was | AI significantly enhances |

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| Zuhair, Areesha Babar, Rabbiya Ali, Malik Olatunde Oduoye, Zainab Noor, Kitumaini Chris, Inibehe Ime Okon, Latif Ur Rehman | | the Impact of Artificial Intelligence on Global Health and Enhancing Healthcare in Developing Nations | conducted on PubMed, Google Scholar, and Cochrane for articles from 2000 to August 2023, using keywords like artificial intelligence, healthcare, hospitals, medicine, and surgery. The review included clinical trials, systematic reviews, and cross-sectional studies focusing on AI applications in radiology, cardiology, oncology, neurology, intensive care, anesthesiology, surgery, and community medicine, while excluding editorial articles, correspondence, case reports, and commentaries. | healthcare in developing countries by improving diagnosis, prognosis prediction, patient management, and hospital administration, particularly in resource-limited settings. Notable applications include AI-driven diabetic retinopathy screening in Zambia, birth asphyxia prediction in Nigeria, and tuberculosis detection via chest radiographs. However, challenges such as low adoption rates, high costs, poor infrastructure, and lack of standardized guidelines hinder full integration. Ethical concerns, including data privacy and algorithmic bias, also require attention. |
| Daniel L. Clarke-Pearson, M.D. | 2009 | Screening for Ovarian Cancer | Emphasizing transvaginal ultrasonic imaging and CA-125 tumor marker testing, the paper examines screening techniques for ovarian cancer. It spans information from major studies, including the United Kingdom Collaborative Trial of Ovarian Cancer Screening (UKCTOCS) (202,638 women, aged 50–74) and the Prostate, Lung, Colon, and Ovarian (PLCO) Cancer Screening Trial (34,261 women, aged 55–74). Techniques included annual ultrasonic screening using CA-125 readings, CA-125 with an ROC algorithm followed by ultrasonic | Screening with transvaginal ultrasonography and CA-125 can detect ovarian cancer at earlier stages, but no trial has demonstrated improved overall survival. Ultrasonography had a PPV of 1.0–27%, with higher specificity in multimodal screening (99.8% vs. 98.2%). CA-125 alone had limited sensitivity (50% for stage I) and specificity due to false positives from benign conditions. Multimodal screening showed a higher PPV (35.1% vs. 2.8% for |

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| | | | imaging, or a multimodal method. Among the outcomes measured were stage at diagnosis, sensitivity, specificity, and positive predictive value (PPV). | ultrasonography alone). Routine screening is not recommended for average-risk women due to low PPV and potential surgical risks. |
| Jonathan de Matos, Steve Tsham Mpinda Ataky, Alceu De Souza Britto Jr., Luiz Eduardo Soares de Oliveira, Alessandro Lameiras Koerich. | 2021 | Machine Learning Methods for Histopathological Image Analysis: A Review | The methodology involved a systematic literature review from 2008 to 2020, searching five research portals Addressing segmentation of nuclei and tissues, feature extraction for morphological and textural properties, and classification using both classic and deep learning approaches, the review classified ML methods into segmentation, feature extraction, shallow methods, and deep methods. | The review highlighted a shift from handcrafted features to deep learning methods, with significant growth in deep learning Segmentation methods evolved from unsupervised to supervised and deep learning approaches. Feature extraction focused on morphological and textural descriptors like GLCM and LBP. Deep learning models, particularly CNNs, showed superior performance in end-to-end learning for classification. Public datasets and increased computational power are driving advancements, though challenges remain in high-resolution image segmentation. |
| Chetan L. Srinidhi, Ozan Ciga, Anne L. Martel | 2020 | Deep neural network models for computational histopathology: A survey | Emphasizing deep learning (DL) techniques for histological image interpretation, the study offers a thorough assessment of more than 130 papers. Describing their use in tasks including classification, regression, and segmentation, it groups methods into | The survey highlights the dominance of convolutional neural networks (CNNs) in histopathology, particularly for cell/nuclei detection and disease grading. Supervised learning excels in local tasks like mitosis detection, while |

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| | | | supervised, weakly supervised, unsupervised, and transfer learning. The study addresses open datasets, obstacles, and future research paths as well as survival models for prognosis. Covering works up to December 2019, literature came from Google Scholar, PubMed, arXiv, and conferences including MICCAI and ISBI. | weakly supervised methods address annotation scarcity. Transfer learning enhances performance with limited data, and attention-based models improve efficiency. Challenges include stain variability, high computational costs, and the need for large annotated datasets. Future directions involve multi-scale models and integration with genomic data. |
| Saba Fatema; Brighton Nuwagira; Sayoni Chakraborty; Reyhan Gedik; Baris Coskunuzer. | 2023 | TopOC: Topological Deep Learning for Ovarian and Breast Cancer Diagnosis | The method combines deep learning with topological data analysis (TDA) for histopathology image analysis. It calls for two steps: (1) extracting topological feature vectors using persistent homology (PH) through cubical persistence, which captures global patterns in images across color channels (R, G, B, grayscale) via sublevel filtrations, persistence diagrams, and Betti function vectorization; (2) applying these features in two models: TopOC-1, which uses standard machine learning classifiers on topological vectors, and TopOC-CNN, which integrates topological features with pre-trained CNN backbones (DenseNet121, EfficientNetB0, VGG16) to enhance local feature extraction. | The work shows that ovarian and breast cancer diagnosis is much improved by combining TDA with deep learning. On UBC-OCEAN TopOC-1 attained 66.13% balanced accuracy; on BREAKHIS (40x), accuracy was 90.82%. Reaching 67.15% balanced accuracy on UBC-OCEAN and up to 94.82% accuracy on BREAKHIS (40x), TopOC-CNN with DenseNet121 and 128-dimensional topological vectors achieved Topological features improve CNN performance by up to 6.59% in balanced accuracy for UBC-OCEAN and 8.35% in accuracy for BREAKHIS, outperforming state-of-the-art models without data augmentation. |

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| Santi Kumari Behera, Ashis Das, Prabira Kumar Sethy | 2024 | Deep fine-KNN classification of ovarian cancer subtypes using EfficientNet-B0 extracted features: a comprehensive analysis | Using EfficientNet-B0 for feature extraction from histological images in the UBC-OCEAN dataset, the work combines deep learning with k-nearest neighbor (KNN) methods. For five ovarian cancer subtypes—high-grade serous carcinoma (HGSC), clear-cell ovarian carcinoma (CC), endometrioid carcinoma (EC), low-grade serous carcinoma (LGSC), and mucinous carcinoma (MC)—the model substitutes a fine-KNN mechanism for the fully linked layer. Comprising 725 photos ( 505 original, enhanced to balance classes), the dataset was split 80% for training and 20% for testing. Using an initial learning rate of 0.001, a mini-batch size of 32, and the ADAM optimizer, the model was constructed using MATLAB 2022a with an NVIDIA 3070 GPU. Accuracy, area under the curve (AUC), true positive rate (TPR), false negative rate (FNR), positive predictive value (PPV), false discovery rate (FDR), and positive likelihood ratio (LR+) evaluated performance. | In both validation and testing stages, the model attained 100% accuracy; it also showed remarkable performance in categorizing ovarian cancer kinds. Particularly for CC (0.94), LGSC (0.92), and MC (0.94), AUC values were high; lower values for EC (0.78) and HGSC (0.69) indicate difficulties with these subtypes resulting from biological heterogeneity and morphological variability. While testing demonstrated variability, HGSC had the lowest TPR (42.9%), validation revealed flawless TPR (100%), and zero FNR across all subtypes. High LR+ ratings for MC (17.942), LGSC (17.942), and CC (27.294) highlighted diagnostic dependability. The results show the model's potential as a precise diagnostic tool; future developments could solve EC and HGSC categorization by means of sophisticated augmentation and multimodal data integration. |
| Anabia Sohail, Umme Zahoora, Asifullah Khan, Aqsa | 2020 | A survey of the recent architectures of deep convolutional neural networks | The survey divides deep CNN architectures (2012–2020) into seven classes: spatial exploitation, depth, multi-path, breadth, feature-map, exploitation, | 1. CNNs are classified into seven innovative categories.<br>2. Post-2012 advances from AlexNet and hardware.<br>3. Modularity and |

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| Saeed Qureshi. | | | channel boosting, and attention-based CNNs. Reviewing their development, components, and performance on benchmark datasets, it examines applications and problems. | branching boost performance.<br>4. Applications in image, video, and NLP.<br>5. High costs drive lightweight designs.<br>6. Future focus on efficient CNNs. |
| Hyuna Sung, Jacques Ferlay | 2021 | Global Cancer Statistics 2020: GLOBOCAN Estimates of Incidence and Mortality Worldwide for 36 Cancers in 185 Countries | GLOBOCan 2020 uses short-term projections and mortality-to--incidence ratios to estimate using Global Cancer Observatory data for 36 cancers in 185 countries. Using the 1966 Segi-Doll standard, age-standardized rates (ASR) were computed assessing burden by 20 regions and 4-tier HDI. Future estimates for 2040 drew on demographic patterns. | 2019: 19.3M new cancer cases, 10M deaths worldwide (18.1M, 9.9M excluding nonmelanoma skin cancer).<br>She said: Lung cancer lead mortality (1.8M, 18%) whereas breast cancer most diagnosed (2.3M, 11.7%).<br>Incidence 2-3x greater in transitioned rather than transitional nations; death less diverse.<br>Transitions countries have higher incidences of breast and cervical cancer death.<br>Asia has 49.3% cases and 58.3% fatalities; Europe has 22.8% cases and 19.6% deaths.<br>Cases are expected to reach 28.4M by 2040, up 47% with more increases in developing nations. |
| Lindsey A. Torre, Britten Trabert, Carol E. DeSantis, Kimberly D. Miller, Goli Samimi, | 2018 | Ovarian Cancer Statistics, 2018 | The study used NCI's SEER and CDC's NPCR data, compiled by NAACCR, covering nearly 100% of the US population for 2018 projections. Incidence was analyzed by age, histology, and race/ethnicity using ICD-O-3. Long-term trends (1975-2014) came from SEER 9, with | One in 78 women had 1.3% lifetime risk of ovarian cancer. Incidence (2010–2014) was 11.5 per 100,000 highest in non-Hispanic White (NHW) women (12.0) and lowest in non-Hispanic Black (NHB) (9.4) and Asian/Pacific Islander (API) (9.2). From |

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| Carolyn D. Runowicz, Mia M. Gaudet, Ahmedin Jemal, Rebecca L. Siegel |  |  | SEER 13 and NAACCR for specific analyses. Mortality data were from SEER*Stat, age-standardized to the 2000 US population. SEER*Stat, Joinpoint Regression Serious and DevCan were used for rates, trends, and probabilities. | 1992 to 2015, mortality fell from -2.3% all races to The most prevalent, serous carcinoma peaked in NHW (5.2 per 100,000); API had best clear cell rates (1.0). Mostly stage III/IV (51%/29%), serous cases included others stage I (58-64%). Serous survival was 43%; endometrioid survival was 82%; mucinous survival was 71%; clear cell survival was 66%; NHB had the lowest serous survival (36%). High survival (94%, 88%) came from nonepithelial cancers (germ cell 3%, sex cord-stromal 2%). About 80% of epithelial cases were driven by BRCA1/BRCA2 mutations; salpingo-oophorectomy reduced risk. Since 2000, endometrioid and serous incidence dropped; mucinous stable post-2009. |
| Eman I. Abd El-Latif, Mohamed El-dosuky, Ashraf Darwish, Aboul Ella Hassanien | 2024 | A deep learning approach for ovarian cancer detection and classification based on fuzzy deep learning | Four stages define the approach: (1) data augmentation using scaling, vertical flipping, and rotation to improve the dataset; (2) feature extraction with ResNet-50, a 50-layer convolutional neural network; (3) recursive feature elimination (RFE) with a decision tree to remove irrelevant features; and (4) classification using a fuzzy deep learning classifier integrating fuzzy logic and deep learning, optimal by the Adam algorithm. The model was trained from 78 cases utilizing 288 whole slide images stained with H&E. | Outstanding among other models, the model obtained 98.99% accuracy, 99% sensitivity, 98.96% specificity, and 98.99% F1-score. Reduced training time and enhanced performance were outcomes of the triangular membership function. With possible use in more general oncology, the method shows promise for precise ovarian cancer classification. |

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|---|---|---|---|---|
| Hossein Farahani, Jeffrey Boschman, David Farnell, Amirali Darbandsari, Allen Zhang, Pouya Ahmadvand, Steven J. M. Jones, David Huntsman, Martin Köbel, C. Blake Gilks, Naveena Singh, Ali Bashashati | 2022 | Deep learning-base histotype diagnosis of ovarian carcinoma whole-slide pathology images | The work classified hematoxylin and eosin (H&E)-stained whole-slide images (WSIs) of ovarian cancer into five histotypes using four deep learning-based algorithms:<br>Using a training set including 948 WSIs from 485 individuals, an external test set comprising 60 patients from another institution was employed. ImageNet pre-trained weights were used for initializing the models; they were fine-tuned using color-normalized patches; and their performance was assessed using an ensemble technique and cross-valuation to maximize prediction accuracy. | The best-performing model, a one-stage deep transfer learning network (1STL), achieved a diagnostic concordance of 81.38% (Cohen's kappa 0.7378) on the internal training set and 80.97% (Cohen's kappa 0.7547) on the external test The model misdiagnosed 50% of the external test cases and battled ENOC classification. In four of eight cases, expert examination of misclassified cases matched AI predictions suggests possible use of AI as a diagnostic complement. |
| Xin He, Xiang-Hui Bai, Hui Chen, Wei-Wei Feng | 2024 | Machine learning models in evaluating the malignancy risk of ovarian tumors: a comparative study | This retrospective study at Ruijin Hospital, Shanghai (January 2019–May 2021), analyzed 1,555 patients with adnexal masses using transvaginal ultrasound (TVUS). Four deep learning models—ResNet, DenseNet, Vision Transformer (ViT), and Swin Transformer—were developed using Python 3.8 and PyTorch 2.1.2, pretrained on ImageNet-1K, and fine-tuned on ultrasound images (grayscale, Doppler, and solid component images). The dataset was split into training (80%), validation (10%), and test (10%) sets, stratified by pathology. Images were preprocessed (cropped, resized to 256x256px, caliper removal), and models were | The study found that ResNet, DenseNet, and Swin Transformer models had diagnostic performance comparable to expert SA (AUC 0.91–0.97) for distinguishing benign (76.9%) from malignant (23.1%) ovarian tumors. Swin Transformer achieved the highest performance (AUC 0.92, sensitivity 87.2%, specificity 94.3%), while Vision Transformer was less effective (AUC 0.87, specificity 81.2%). Adding CA125 did not significantly improve model performance. Grad-CAM analysis revealed misdiagnoses in cases like endometriotic cysts due to misinterpretation of |

| | | | | |
|---|---|---|---|---|
| | | | trained with cross-entropy loss and Adam optimizer. Performance was compared to expert subjective assessment (SA) and evaluated with/without CA125 integration. Histopathological diagnosis post-surgery was the reference standard. | features like hemorrhage as malignant. The study highlights the potential of deep learning, particularly Swin Transformer, in ovarian cancer evaluation. |
| Wu M, Cui C, Lv S, Chen L, Tian Z, Yang M, Bai W | 2023 | Deep convolutional and traditional research for the diagnosis of ovarian tumors classification in ultrasound images | This retrospective study, conducted at Beijing Shijitan Hospital, analyzed ultrasound (US) images from 328 patients with ovarian tumors (290 benign, 38 malignant) collected between January 2019 and June 2021. The dataset included 1142 US images, preprocessed by delineating lesions using labelme software, followed by data augmentation (random cropping, flipping) and resizing to 256x256 pixels. Six deep convolutional neural network (DCNN) models (VGG16, GoogleNet, ResNet34, ResNet50, DensNet121, DensNet201) were trained to classify tumors into seven histological categories. The models used transfer learning, the Adam optimizer (learning rate 0.001, batch size 16), and were trained for 200 epochs. Classifier Activator Maps (CAM) visualized key image regions. Performance metrics included accuracy, sensitivity, specificity, AUC, and F1-score, calculated using NumPy. | The ResNext50 model achieved the highest accuracy of 81.1% on original US images (AUC 0.95) and 95.2% on labeled images (AUC 0.997). It showed strong performance across seven classes, with sensitivities of 80.0%-90.4% for most benign categories and 90% for high-grade serous carcinoma on labeled images. Labeled images outperformed original images due to reduced noise. CAM heatmaps confirmed the model focused on clinically relevant tumor regions, similar to expert assessments. The study highlighted the potential of DCNNs as a clinical decision-support tool, though it noted limitations like single-center data and the need for multi-modal US image analysis. |

### 2.2.1 Similar Applications

Deep learning's inclusion in histopathological image processing has become rather popular in many other medical fields outside ovarian cancer. These uses highlight the adaptability and efficiency of CNNs and associated architectures in raising diagnostic accuracy, lowering human error, and so improving patient outcomes.

- Deep learning models—especially CNNs and ResNet-based architectures—have been extensively applied for categorizing histological breast cancer pictures. For instance, the BreakHis collection has facilitated the training of models capable of accurately distinguishing benign from malignant tissue types. Furthermore, to increase interpretability and accuracy in intricate tissue architectures, attention mechanisms and ensemble models have been used.
- Histopathological and CT images have been utilized to separate lung adenocarcinoma from squamous cell carcinoma using artificial intelligence-powered models like 3D-CNNs and transformer-based techniques. Often including multi-scale feature extraction, these models have shown encouraging performance in both diagnostic and prognostic applications.
- We have applied CNNs to grade prostate cancer using glandular patterns found in whole slide images (WSIs). By accurately detecting Gleason grades, models including VGG16 and EfficientNet have attained expert-level performance, therefore helping to standardize diagnosis and lower observer variance.
- Early cancer diagnosis using deep learning algorithms has examined histological images of colorectal tissues. Strong classification performance across several tissue subtypes has been demonstrated by multi-path CNNs and hybrid models integrating handcrafted and learned elements.
- We have examined MRI and histopathology pictures of brain tumors using deep learning models, including U-Net for segmentation and DenseNet for classification. These methods have helped distinguish glioma subtypes and evaluate tumor aggressiveness.
- Dermatopathology has trained CNNs to recognize melanoma and other skin lesions using dermoscopic and histological pictures. To get dermatology-level performance, these models frequently employ transfer learning using pre-trained networks such as InceptionV3 and ResNet.
- Researchers have also investigated Pap smear images and cervical histology using

deep learning models trained to spot unusual cells and precancerous situations. These uses enhance early intervention plans and help with population-scale screening.

With each application customized to the particular visual and clinical features of the disease in issue, these related uses mirror a larger trend of including deep learning into digital pathology and medical image analysis. The success of these programs emphasizes the transforming power of artificial intelligence in clinical diagnostics and confirms the strategy suggested in this work.

### 2.2.2 Related Research

Based on histopathology scans, Eman et al. offer an intelligent and autonomous approach that detects and labels ovarian cancer. By using deep learning and recursive feature removal, the model allows more accurate and efficient prediction while addressing the constraints of conventional approaches. Composing 288 hematoxylin and eosin (H&E)-stained slides with clinical information from 78 patients, the dataset For differentiating between photos of ovarian cancer and non-cancer, the model attained a quite good accuracy of up to 98.99%. Using deep convolutional neural networks, Hossain et al. trained four separate artificial intelligence algorithms to automatically categorize full slide images stained with H&E. Cross-valuation on the training set—948 slides matching 485 patients—as well as on an independent test set including 60 patients from another institution—evaluated performance. With an 81.38% diagnostic concordance in the training set and an 80.97% on the external dataset [10], the best-performing model In order to detect benign and malignant ovarian cancers, Xin et al. evaluate the performance of ResNet50, DenseNet, Vision Transformer, Swin Transformer, and SA among other models. ResNet50, DenseNet, Swin Transformer, and SA among these models got high AUC values of 0.91, 0.91, 0.92, and 0.97, respectively [11]. Without any pathologist-provided locally annotated regions, Ching et al. present a new deep learning-based system to precisely predict the therapeutic effect of bevacizumab on ovarian cancer patients from H&E-stained entire slide images. The difficulties presented by the large scale and sophisticated content of entire slide photographs [12] are discussed in this paper. Using 1,142 ultrasonic images from 328 patients, Meijing et al. classified benign and high-grade serous carcinoma in original ovarian tumor ultrasound images. Various forms of ovarian cancers were specifically classified using deep convolutional neural networks. A total accuracy of 95.2% for directly categorizing the seven histologic categories of ovarian cancers [13] allowed the ResNext50 model to have the greatest predictive performance. Combining a fine-KNN approach with EfficientNet-B0, Santi et al. sort histopathological images into five distinct forms of ovarian cancer: high-grade serous carcinoma, clear-cell ovarian carcinoma, endometrioid carcinoma, low-grade serous carcinoma, and mucinous carcinoma. The method helps to classify ovarian cancer subtypes [14] in more complexity. Jack et al. systematically reviewed the application of artificial intelligence methods to generate diagnostic or prognostic conclusions on human histopathology images from suspected or confirmed ovarian cancer. Studies in which artificial intelligence techniques were applied either directly to digital pathology images or to features automatically derived from the images comprise part of the review [15]. Saba et al. propose to improve the accuracy and resilience of current histopathology image analysis algorithms by use of topological deep learning approaches. Topological elements greatly help to distinguish distinct forms of ovarian and breast malignancies [16]. Chetan et al. undertook a thorough assessment of state-of- the-art deep learning methods applied in histological image processing. It offers an overview of deep learning-based survival models relevant for disease-specific prognostic tasks [17] and evaluates the field's development depending on different machine learning approaches. Jothan et al. compiled a review including shallow and deep learning approaches for histological image analysis using machine learning techniques. Common tasks in histopathological image analysis, including segmentation and feature extraction, are discussed together with a list of both publicly accessible and private databases used in research [18].

## 2.3 Gap Analysis

Because of its late diagnosis and subtle early-stage signs, ovarian cancer is still among the most deadly gynecological cancers. More accurate and efficient treatments are desperately needed since conventional diagnostic techniques may fail to identify the disease in an early stage. Deep learning—especially convolutional neural networks (CNNs)—has become a potent tool in medical image processing recently. Aiming to increase diagnosis accuracy and help to provide better clinical results, this study investigates the application of a tailored CNN model for early identification of ovarian cancer using histopathology images.

Table 2.3: Gap Analysis Summary

| Gap Domain | Main Problem | Key Solution |
|---|---|---|
| Limited Publicly Available Datasets | Few large-scale, annotated ovarian cancer image datasets exist | Use of trusted open-source datasets and data augmentation to expand training data |
| Class Imbalance in Data | Underrepresented cancer | Apply data balancing |

| | | |
|---|---|---|
| | subtypes lead to biased results | techniques like oversampling, weighted loss functions |
| Lack of Explainability | Model decisions are hard to interpret | Integrate visualization techniques like Grad-CAM for feature attention mapping |
| Inter-patient Variability | Variation in staining and morphology reduces generalizability | Use normalization techniques and diverse data sources to improve robustness |
| Weak Labeling and Annotations | Lack of detailed labels affects accuracy | Use patch-based learning and slide-level training approaches |
| Cross-Institutional Generalization | Domain shifts across regions/hospitals degrade performance | Employ domain adaptation and validation on external datasets |
| Computational Requirements | High resource needs limit accessibility | Optimize CNN model architecture for efficiency and reduced computational cost |
| Difficulty in Subtype Differentiation | Similar histological features confuse classifiers | Customize CNN with attention layers for fine-grained feature extraction |
| Integration with Clinical Practice | Gap between model development and clinical deployment | Emphasize model interpretability and usability-focused UI design |
| Real-time Detection and Feedback | Models lack live inference capability | Design the system architecture to allow near real-time predictions |

This work aims to reduce important obstacles in the implementation of histopathology image-based deep learning for ovarian cancer screening. One main restriction is the dearth of publicly accessible, well-annotated databases catered for ovarian cancer. To get around this, we obtained a trustworthy dataset and used data augmentation to raise model resilience. Oversampling methods and weighted loss functions applied during training helped to solve the class imbalance problem whereby some cancer subtypes are underrepresented.

The “black box” nature of deep learning was tackled by integrating Grad-CAM for model interpretability, offering visual justification for model predictions. Inter-patient variability, due to differences in staining and image resolution, was normalized using preprocessing techniques to ensure consistency. Since many datasets only offer slide-level labels, we used patch-based training to better capture region-level details.

To combat the problem of domain shift between institutions, our model was validated using heterogeneous data sources. Given the high computational demands of training on whole slide images, a lightweight yet efficient CNN model was designed. For improved classification accuracy among similar-looking subtypes, attention mechanisms were embedded into the network. Furthermore, we focused on bridging the gap between research and clinical use by designing a UI and architecture that could potentially integrate into diagnostic workflows and support real-time decision-making in future applications.

## 2.4 Summary

In essence, even if using artificial intelligence and deep learning for ovarian cancer diagnosis has advanced, ongoing study and invention are absolutely essential to solve the current problems. Advanced technology integration has the ability to lower subjectivity, improve diagnosis accuracy and efficiency, and make early detection more affordable and easily available. Particularly in areas with limited resources, these initiatives are crucial for raising patient outcomes and lowering the worldwide ovarian cancer burden.

# Chapter 3

# Research Methodology

## 3.1 Methodology/Requirement Analysis & Design Specification

### 3.1.1 Overview

In this section, we discuss the proposed methodology and system design for classifying ovarian cancer using histopathological images, outlining the hardware and software requirements essential for implementation. The project management portion covers the planning, execution, and tracking of tasks to ensure efficient progress and timely completion. A financial analysis is also included to present the estimated budget, associated costs, and the potential economic impact of introducing an AI-powered diagnostic tool. Lastly, we summarize the critical elements, emphasizing how the proposed approach can significantly improve early detection of ovarian cancer and demonstrate the practicality of deploying deep learning-based solutions in real-world clinical environments.

### 3.1.2 Proposed Methodology/System Design

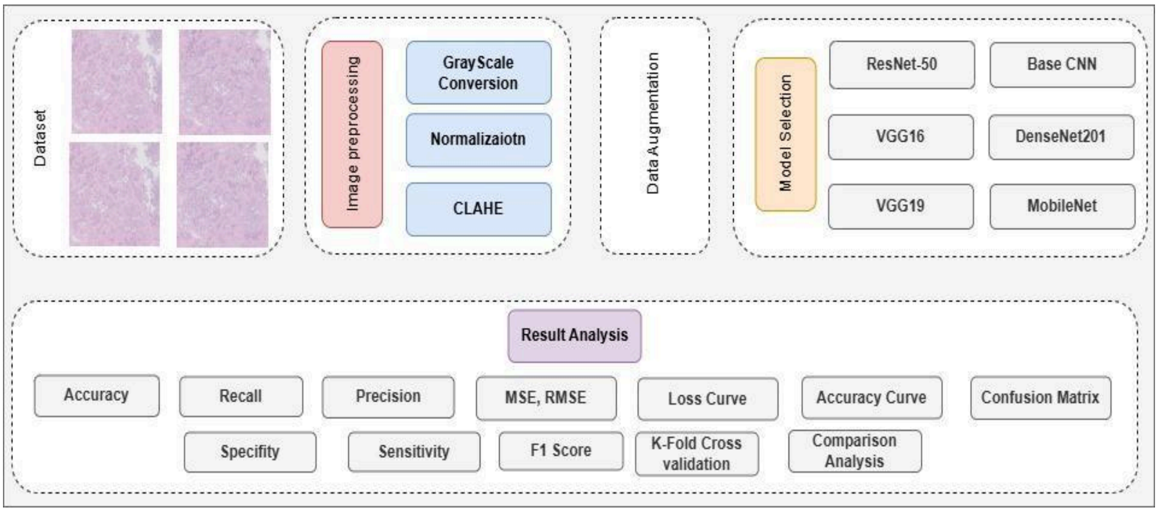


Figure 3.1.2: Proposed Methodology

In this work we present a new approach (Figure 3.1.2) meant to solve the particular difficulties related to ovarian cancer detection. To get improved accuracy and efficiency in the detection of ovarian cancer in the several classes, this work includes image preprocessing, data augmentation, CNN model, and transfer learning model. Figure 1 presents the general course of this research.

Particularly using histopathology slide pictures, the graphic shows a whole deep learning pipeline meant for medical image classification.The Figure 3.1.2 demonstratesthat begins with a collection of medical images, usually tissue samples used to identify anomalies, including malignancy. Usually dyed tissue samples To raise the quality and consistency of the supplied data, these pictures undergo several preprocessing stages. This covers grayscale picture conversion to lower complexity, pixel value normalization to guarantee homogeneity, and using CLAHE (Contrast Limited Adaptive Histogram Equalization), a technique that improves local contrast, so making essential features more distinct.

Data augmentation methods are used to synthetically expand the amount and variety of the dataset following preprocessing. This step is absolutely essential to avoid overfitting and to raise the generalizing capacity of the model toward unprocessable input. Though not shown clearly in the picture, standard augmentation techniques could call for rotation, flipping, scaling, and cropping.

Model selection comes next, in which performance on the classification job is assessed among several CNN-based designs. These comprise conventional pre-trained models, including ResNet-50, VGG16, VGG19, DenseNet 201, and MobileNet, as well as a base CNN model that may be created especially for the particular dataset. These models most certainly employ transfer learning, in which pre-trained weights are optimized on the medical dataset to take advantage of already-existing feature extraction powers.

The pipeline shifts into the outcome analysis stage once the models have been trained. Performance is assessed here across a broad range of criteria. These comprise conventional classification measures like accuracy, recall, precision, sensitivity, specificity, and F1 score, as well as regression-based metrics including mean squared error (MSE) and root mean squared error (RMSE), thereby assessing prediction error. Visual tools such as loss curves and accuracy curves, which measure model performance during training epochs, and confusion matrices—which offer a comprehensive picture of prediction accuracy over many classes—also feature in the research

### 3.1.3 Functional and Nonfunctional Requirements

Functional requirements specify the fundamental activities a system ought to be able to carry out. These comprise taking medical images as input, preprocessing them suitably, running the deep learning model to identify abnormalities, and producing diagnostic results with visualization and reporting for a CNN-based ovarian cancer detection system. Additional uses could be user authentication, feedback collecting, and hospital system integration. These criteria guarantee that the system has the necessary characteristics to enable clinical decision-making and diagnostic procedures.

**Image Input Handling:**

1. Medical images will be accepted by the system in formats like DICOM (.dcm), PNG, or JPEG.
2. The system will support 2D and 3D imaging modalities (ultrasonic, CT, MRI, histological slides).
3. The system will let several photos per patient be uploaded in batches.

**Preprocessing Module:**

1. The system shall perform preprocessing operations, including:
    a. Resizing all photos to a fixed dimension—like 224x224—the system will engage preprocessing tasks.
    b. Bringing pixel intensity values into line between 0 and 1.
    c. Denoising via other filters or Gaussian blur.
2. Either a settings file or a GUI will enable an adjustable preprocessing workflow.

**CNN Inference Engine:**

1. Starting the system will automatically load the most recent trained CNN model.
2. CNN will generate for every image:
    a. [**CC, EC, HGSC, LGSC, MC**] a classification label.
    b. a confidence/probability scale.
3. The system will highlight areas of interest using **saliency maps** or **Grad-CAM.**

**Result Visualization:**

1. The system will show the original picture and heatmap overlay together with the diagnostic result (label + confidence).
2. The technology will let the clinician input override predictions or handwritten notes.

**Report Generation:**

1. The system will create a PDF report including:
    a. ID for Patients
    b. Diagnose date and time
    c. Thumbnail images
    d. Forecasts class and confidence.
    e. Map for explanations
2. The report will be exported via HL7 or FHIR criteria to EMS systems.

**User Authentication:**

1. The system will need login credentials with role-based access (radiologist, researcher, administrator).
2. The system will record all user actions—including report downloads, uploads, and conclusions.

**Model Management:**

1. The system will let managers upload a fresh model (.h5 or .pth) from an interface.
2. Version control of implemented models will be kept by the system.

**Feedback Loop:**

1. To help improve the dataset, clinicians will be able to mark predictions as accurate or false.
2. This input will be kept by the system for the next retraining.

Non-functional requirements are those quality characteristics that define the degree of system performance. Within a medical artificial intelligence system, this category covers model correctness, inference speed, data privacy, system availability, and simplicity of use. These elements are crucial to guarantee the system is dependable, safe, and HIPAA or GDPR compliant. Real-world clinical application depends on them too since they affect user happiness, system scalability, and long-term maintainability.

**Performance:**

1. On typical GPU hardware NVIDIA RTX 3060, the system will categorize one image in under two seconds.
2. The accuracy of model inference should either satisfy or surpass:
    a. **Accuracy** > 90%, for better and reliable performance
    b. **Recall (Sensitivity)** > 92% (crucially important to prevent false negatives)
    c. **Precision (Specificity)** > 85%

**Usability:**

1. Tooltips and guided workflows will enable the interface to be tailored for non-technical medical workers.
2. Under five minutes will allow a user to finish the whole workflow—upload → result → report.

**Security and Privacy:**

1. Every data transfer has to employ **TLS 1.3 encryption via HTTPS**.
2. Unless specifically called for, patient data has to be anonymized.
3. Depending on the implementation area, the system will follow either **HIPAA (US)** or **GDPR (EU).**

**Availability and Reliability:**

1. The system will be accessible 99.9% of the operational hours.
2. Common problems, such as database disconnection or picture upload timeout, will be automatically recovered by the system.

**Maintainability:**

1. The system codebase will be modular and have at least 80% unit testing covered.
2. CI/CD-enabled models for retraining scripts and deployment (such as Docker and GitHub Actions) should be used.

**Portability:**

1. The system should be deployable on:
    a. Local hospital servers (Ubuntu, CentOS)
    b. Cloud platforms (AWS, GCP)
    c. Docker containers

**Auditability:**

1. Every forecast and user interaction will be time stamped and kept for audit needs.
2. Over time the system will create logs covering system performance, faults, and model behavior.

### 3.1.4 Context Diagram

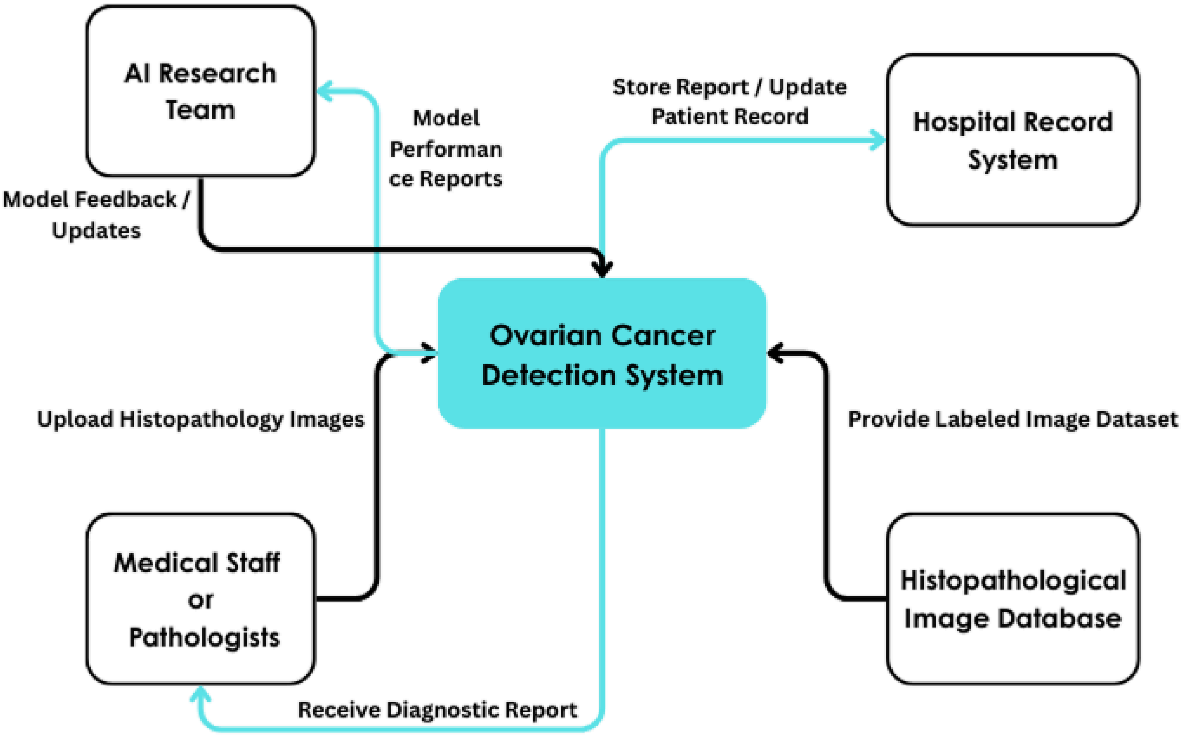


Figure 3.1.4: Context diagram

**Data Flow:**

1. **Medical Staff → System**
   Send histopathology images for analysis.

2. **Image Database → System**
   Provide labeled images to train and test the model.

3. **System → Medical Staff**
   Return diagnosis results..

4. **System → Hospital Record System**
   Save the diagnosis report in the patient's medical file.

5. **System → AI Research Team (optional)**
   Share model performance data like accuracy, loss, etc.

6. **AI Research Team → System (optional)**
   Send feedback or improved models for system updates.

The context diagram provides a high-level view of how the central detection system communicates with various external entities in its environment. At the center is the system itself, responsible for analyzing input data and generating diagnostic results. It receives raw histopathological images either directly from medical staff or from a structured image database containing labeled datasets. These inputs are essential for both the diagnostic process and for training and validating the system's underlying model.

The system forwards the resultant diagnostic back to the medical professionals once its analysis is finished. This enables medical practitioners to make well-informed decisions grounded on the forecasts of the system. Concurrently, the system sends the diagnostic findings to the electronic health record system of the hospital to guarantee correct archiving of all data in line with patient history.

Apart from managing clinical processes, the system participates in performance monitoring. It produces reports for a research team in charge of tracking and improving system performance, including measures of accuracy, sensitivity, and error rates. After review of these reports, this team could offer model adjustments or enhancements that are subsequently included in the system. Reflecting a well-structured interaction architecture supporting medical workflows, data management, and continuous system improvement, all data exchanges are obviously shown as directional flows between entities and the system. This context diagram does a good job of laying the groundwork for knowledge of information flow across the system and part contribution to its functionality.

### 3.1.5 Data Flow Diagram Level 1

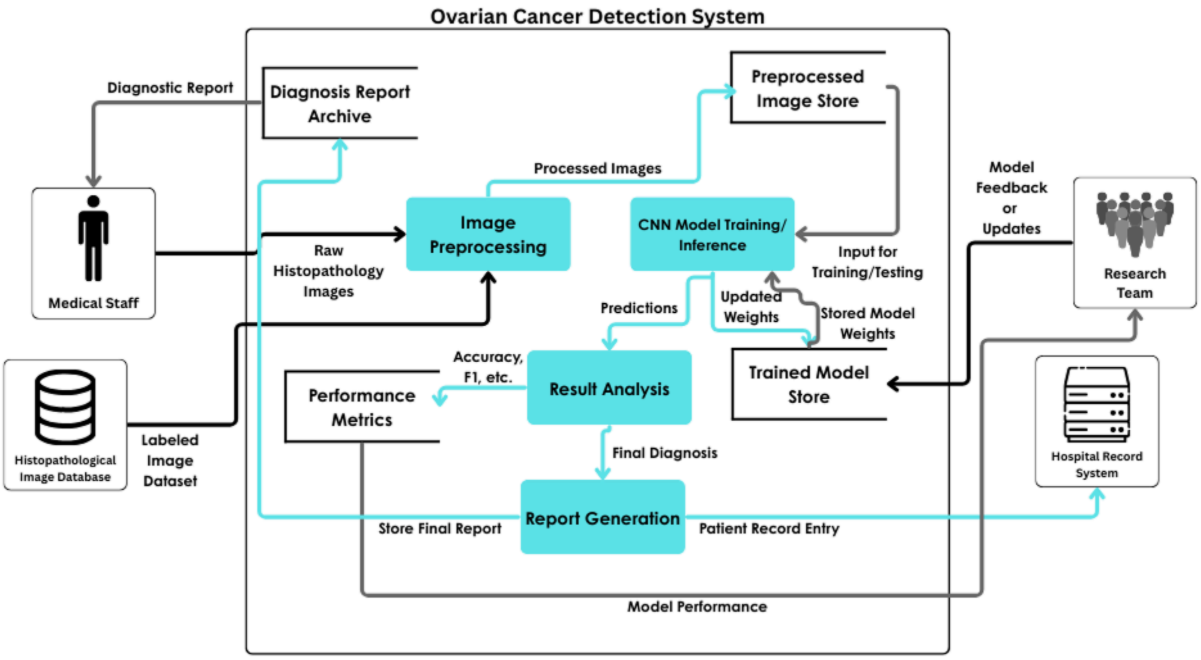


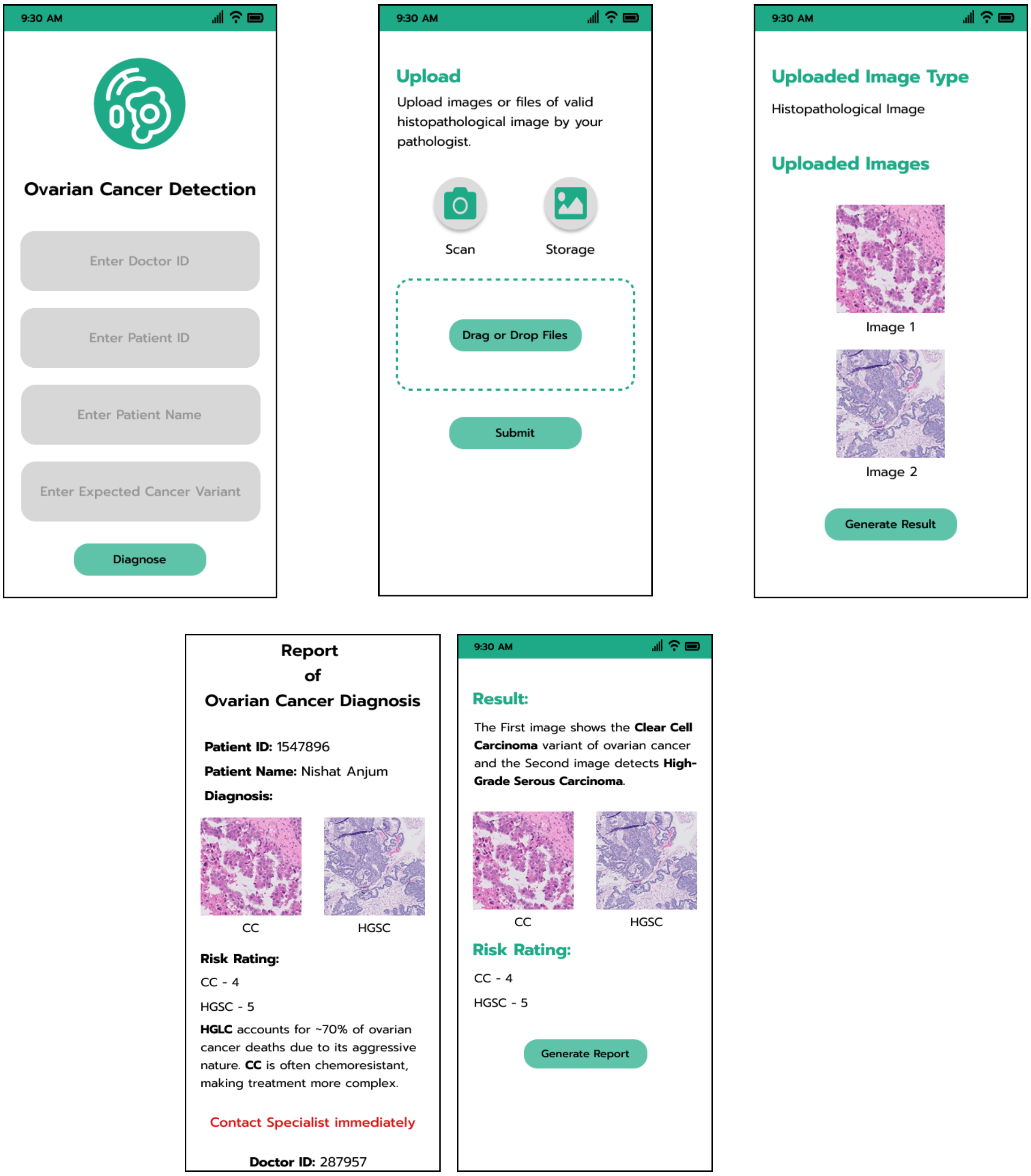
Figure 3.1.5: Data Flow Diagram Level - 1

By means of CNN, the Level 1 Data Flow Diagram (DFD) offers a comprehensive perspective of the internal operations of the ovarian cancer detection system, illustrating how data travels among several components. The system starts with either a centralized picture database or raw histological images from medical professionals. The first preparation stage these photos go through consists of grayscale conversion, normalizing, and contrast enhancement. The Preprocessed Image Store stores the processed photos for additional use.

The CNN Model Training/Inference process then obtains the preprocessed images and aggregates them with currently maintained model weights kept in the Trained Model Store in the next stage This lets the system either infer to produce predictions or learn on fresh data. Any model updates are stored back into the same data store. The result analysis process receives the forecasts and then evaluates them using performance criteria like accuracy, sensitivity, and F1-score. The Performance Metrics store holds these evaluation findings, which also are distributed to a research team to assist in model monitoring and enhancement.At the report-generating stage, the system produces a diagnosis report last but not least. Simultaneously provided to the medical staff and the hospital record system for clinical use and recording, this report is kept in the Diagnosis Report Archive. The DFD shows, overall, a consistent and orderly data flow that guarantees effective image analysis, accurate diagnosis, and appropriate integration with clinical processes and research feedback loops.

### 3.1.6 UI Design

Designed to help pathologists and doctors in histological image analysis for early cancer diagnosis, the ovarian cancer detection interface The user starts by entering the doctor and patient information, then uploads histopathology pictures from either scanning or choosing from storage. Once entered, the system analyzes the uploaded photos and detects cancer subtypes—in this case, **High-Grade Serous Carcinoma (HGSC)** and **Clear Cell Carcinoma (CC)**. To guide the urgency of therapeutic intervention, a result screen shows tagged photos together with a risk assessment. At last, a systematic diagnostic report is produced, guaranteeing a rapid medical reaction by summarizing the results, subtype characteristics, and a prompt to promptly call an expert depending on the severity.



Upload images or files of valid histopathological image by your pathologist.

**Uploaded Image Type**

Histopathological Image

**Report of Ovarian Cancer Diagnosis**

**Patient ID:** 1547896

**Patient Name:** Nishat Anjum

**Diagnosis:**

**Risk Rating:**

CC - 4

HGSC - 5

**HGLC** accounts for ~70% of ovarian cancer deaths due to its aggressive nature. **CC** is often chemoresistant, making treatment more complex.

Contact Specialist immediately

**Doctor ID:** 287957

**Result:**

The First image shows the **Clear Cell Carcinoma** variant of ovarian cancer and the Second image detects **High-Grade Serous Carcinoma.**

**Risk Rating:**

CC - 4

HGSC - 5

Figure 3.1.6: UI Design of Ovarian Cancer Detection System

## 3.2 Detailed Methodology and Design

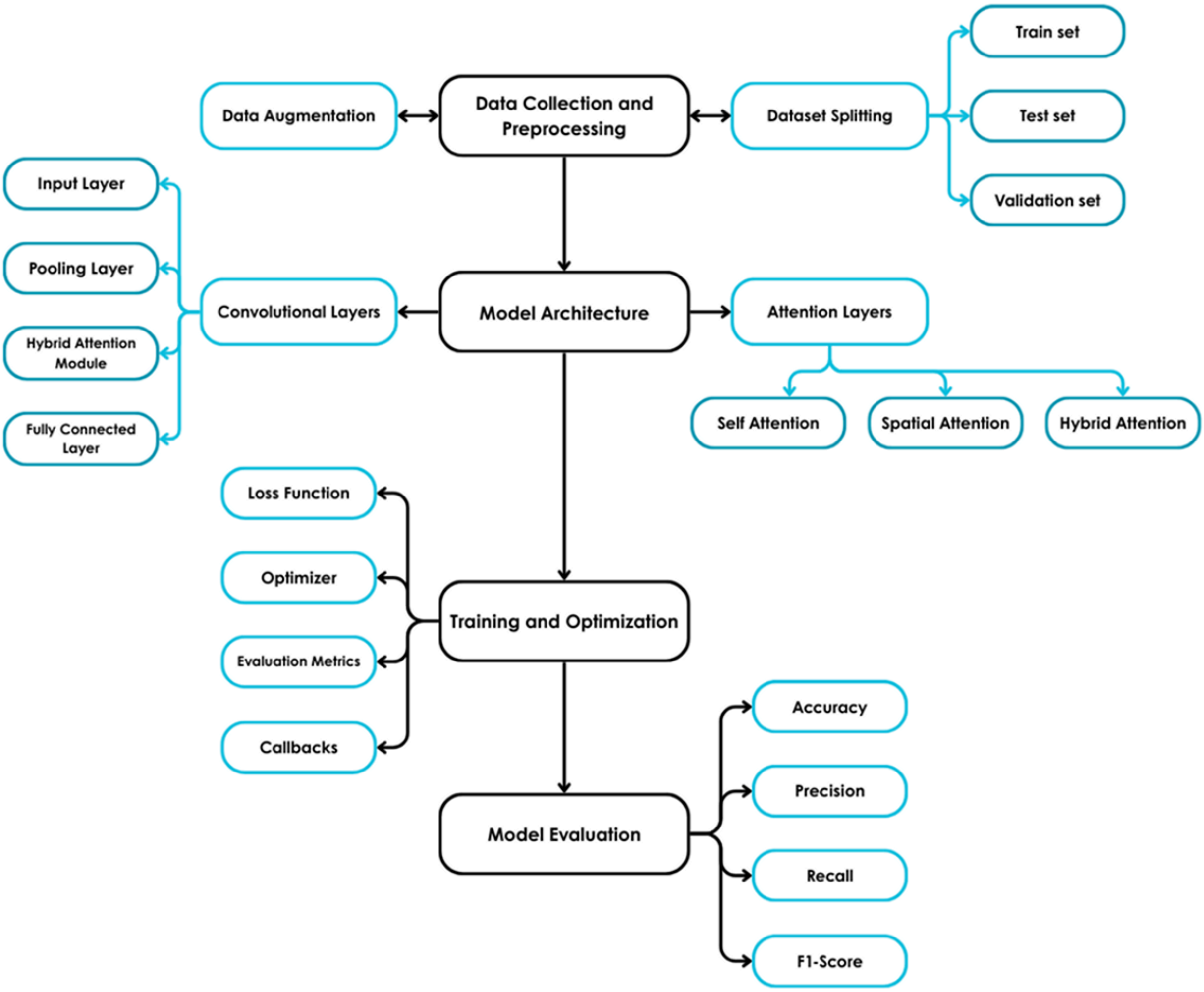


Figure 3.2: Detailed methodology

**Dataset Overview:**

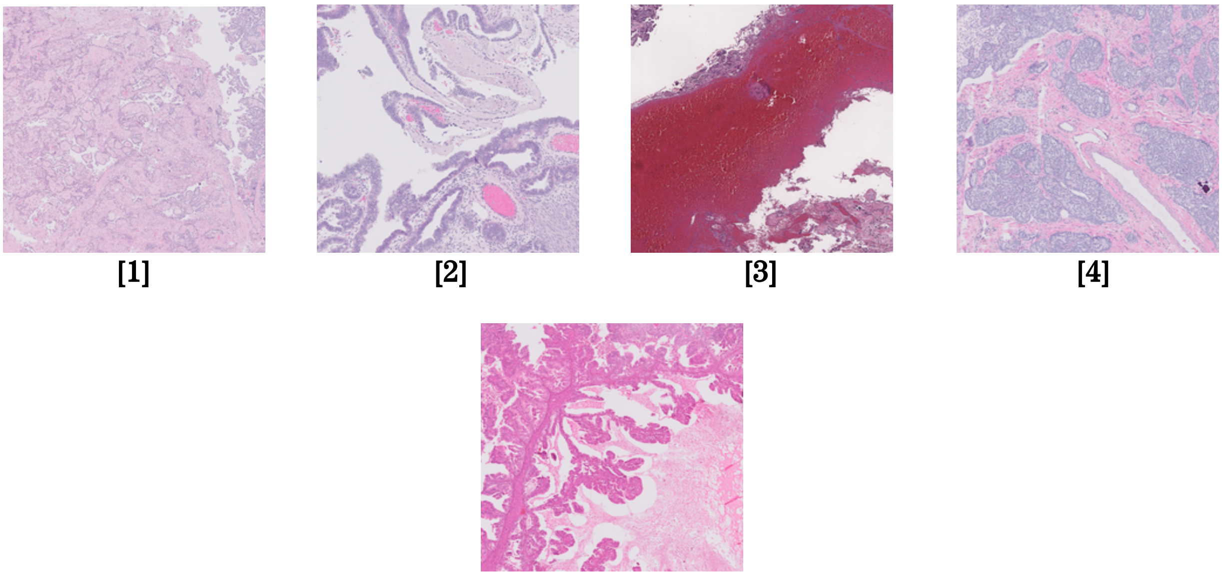
The dataset used in this paper comprises five primary subtypes of ovarian cancer: High- Grade Serous Carcinoma (HGSC), Clear-Cell Ovarian Carcinoma (CC), Endometrioid Carcinoma (EC), Low-Grade Serous Carcinoma (LGSC), and Mucinous Carcinoma (MC). Every subtype shows different cellular shape, genetic composition, and clinical behavior; hence, correct classification is essential for tailored therapy plans. Additionally included in the collection are uncommon outlier cases with distinct histology characteristics. Training and evaluation of deep learning models aiming at automating subtype classification and improving diagnostic accuracy benefit much from the diversity and subtype-specific characteristics of the dataset.

### Dataset Description

Table 3.2.1: Dataset overview

| **Name** | **Description** |
|---|---|
| Total Image Count | 34285 |
| Average Dimension | 224 x 224 |
| Color Categorization | RGB |
| Format of Data | PNG |
| CC | 6130 |
| EC | 8154 |
| HGSC | 13207 |
| LGSC | 3195 |
| MC | 3599 |

### Sample Dataset:



[1] [2] [3] [4]

[5]

Figure 3.2.1: Ovarian Cancer Data Samples. [1]CC, [2]EC, [3]HGSC, [4]LGSC, [5]MC

### Image Pre-processing:

Several image preparation methods were performed to ensure excellent input data for the classification model by means of the histopathology images. First in grayscale, all images were cut in processing complexity and preserved vital structural information. This stage eliminates unnecessary color data irrelevant to the classification task. Normalization then was used to scale the pixel intensity values inside a fixed range, therefore stabilizing and accelerating the training process. Local contrast was then enhanced, and important textural features inside tissue were exposed via Contrast Limited Adaptive Histogram Equalization (CLAHE). To increase the generalizability and robustness of the model, photometric data augmentation techniques, including brightness fluctuation, contrast change, and color jittering, were given. These variations in picture acquisition reflect actual fluctuations, therefore guiding the model to acquire invariant properties. This large preparation pipeline is vitally essential in preparing the dataset and determining effective and trustworthy training of the deep learning model. Image 3 shows every approach to image processing.

1. **Grayscale Conversion:**

   All histopathological images were first converted to grayscale to reduce the computational burden while retaining essential structural information. This transformation eliminates the RGB color channels and focuses on intensity variations, which are often sufficient for tissue pattern recognition.
2. **Normalization:**
   Image normalization was applied to scale the pixel intensity values to a fixed range (typically [0, 1] or [-1, 1]), ensuring consistent input to the deep learning model. This step enhances training stability and accelerates model convergence by reducing internal covariate shift.
3. **CLAHE (Contrast Limited Adaptive Histogram Equalization):**

   CLAHE was utilized to enhance local contrast in the grayscale images by applying histogram equalization in small tile regions. This technique helps reveal fine-grained textural details and improves the visibility of histopathological features critical for accurate classification.

### Data Augmentation

This effort has expanded the variety and volume of the dataset by photometric data augmentation. We performed four types of photometric augmentations: color, brightness, contrast, and sharpness enhancement. These modifications are supposed to generate variations in the dataset, thereby improving the generalizing power of the model. Using each of these changes improved the original dataset and created a more diverse and robust training set. By means of brightness, contrast, saturation, and hue, photometric data augmentation is modifying image lighting conditions. This approach helps build the resilience of machine learning models and consequently raises their potential to generalize to numerous real-world contexts by creating varied training cases. Below are the data counts following photometric data augmentation.

Table 3.2.2. Augmented Data Count

| **Classes** | **Original Count** | **Augmented Count** |
|---|---|---|
| CC | 6130 | 30,650 |
| EC | 8154 | 40,770 |
| HGSC | 13207 | 66,035 |
| LGSC | 3195 | 15,975 |
| MC | 3599 | 17,995 |

1. **Color Alteration:**

   The colors in the images were modified to introduce variations in hue and saturation, mimicking real-world color shifts in images due to different lighting or environmental conditions.

2. **Brightness Alteration:**

   The brightness of the images was adjusted, making them appear either brighter or darker, which helps the model handle variations in lighting conditions.

3. **Contrast Alteration:**

   The contrast of the images was modified to introduce more or less differentiation between the light and dark regions of the images, aiding the model in recognizing features under varying contrast conditions.

4. **Sharpness Alteration:**

   The sharpness of the images was adjusted to enhance or reduce the definition of details, simulating different camera qualities or image processing effects.

These augmentations collectively resulted in a significant increase in the dataset size, as shown in the augmented counts, which allows the model to better learn and generalize across different visual conditions.

## Proposed Transfer Learning Model

In this study, several pre-trained convolutional neural network (CNN) models have been utilized through transfer learning to classify ovarian cancer subtypes from histopathological images. The selected models include MobileNet, ResNet50, VGG16, DenseNet201, and VGG19, which have been widely adopted in various medical image analysis tasks due to their strong feature extraction capabilities and proven performance across benchmark datasets.

1. **VGG16:**

   Due to its superior feature extraction abilities, the deep convolutional neural network architecture known as VGG16, which has 16 weight layers, is commonly employed in image classification applications. Image 3.2.2 shows the VGG16 model architecture.

Figure 3.2.2. VGG16 Model Architecture

2. **VGG19:**

   An expansion of VGG16, VGG19 is a deep convolutional neural network architecture that has 19 weight layers and is recognized for its depth and efficiency in image feature extraction and classification applications. Image 3.2.3 shows the VGG19 model architecture.

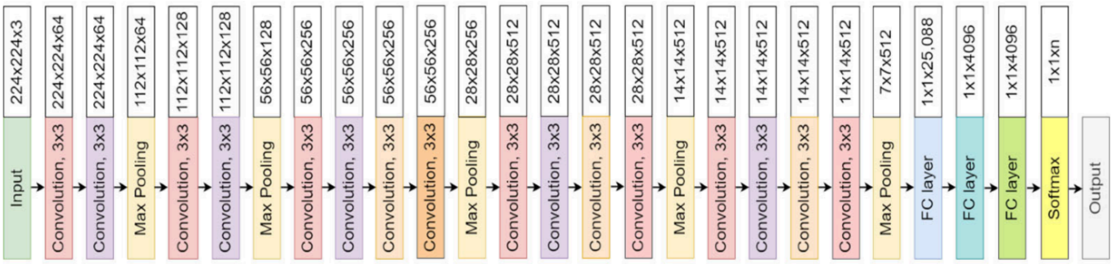


Figure 3.2.3. VGG19 Model Architecture

3. **DenseNet201:**

Each layer of the deep convolutional neural network architecture known as DenseNet201 gets input from all the layers below it, allowing for effective feature reuse and higher performance in image recognition applications. Image 3.2.4 shows the DenseNet201 model architecture.

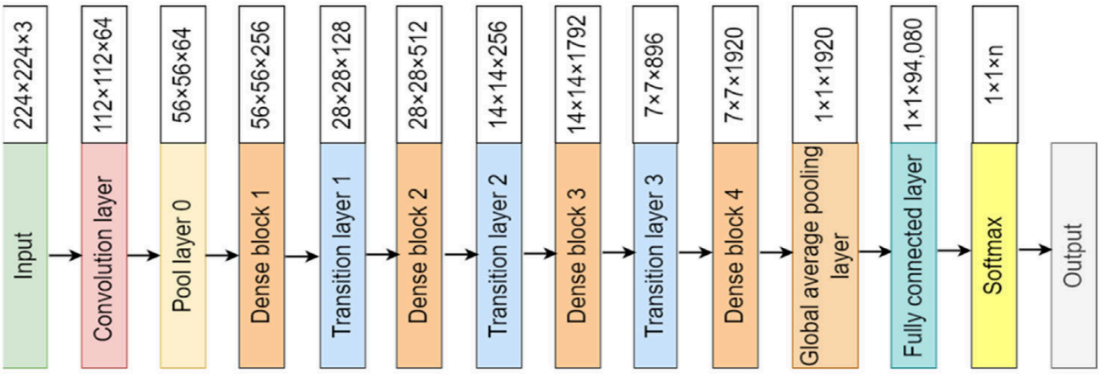


Figure 3.2.4. Model Architecture of DenseNet201.

4. **ResNet50:**

The widely used ResNet50 deep convolutional neural network has 50 layers and is distinguished by its residual learning method, which makes it simple to train very deep networks and performs well in image classification tasks. Figure 3.2.5 shows the ResNet50 model architecture.

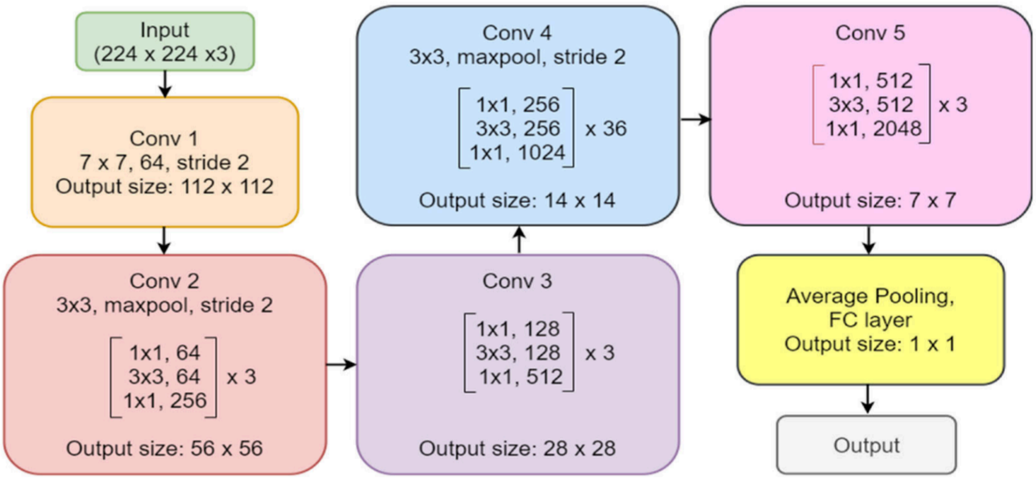


Figure 3.2.5. Model Architecture of ResNet50

5. **MobileNet:**

Combining the light-weight, efficient design of MobileNet with a soft-attention mechanism to raise picture classification accuracy, MobileNet with soft attention is a deep learning architecture Using depth wise separable convolutions to cut model size and computational cost, MobileNet—known for its effectiveness in managing big datasets with limited computational resources—helps The soft-attention technique enables the model to concentrate on the most pertinent areas of a picture, hence enhancing feature extraction and classification performance. This mix produces a very efficient model with enhanced accuracy that is appropriate for medical picture analysis, where accuracy is absolutely vital.

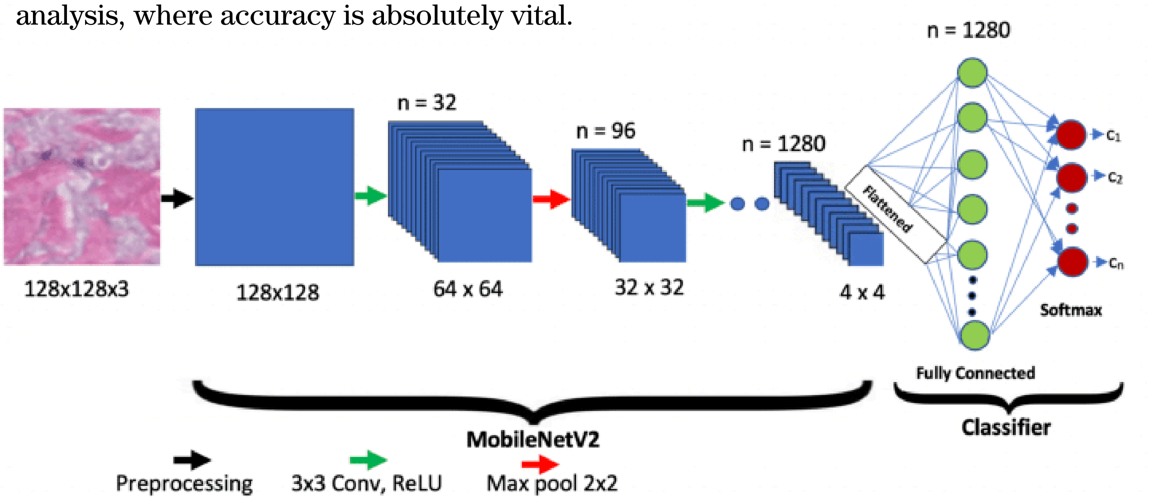


Figure 3.2.6. Model architecture of Fine-tune MobileNet

6. **Proposed CNN Model:**

Apart from assessing conventional transfer learning models, this work presents a tailored Convolutional Neural Network (CNN) architecture especially intended for ovarian cancer subtype classification from histological pictures. Inspired by expert-level visual inspection, the suggested model is improved with an integrated attention mechanism allowing the network to concentrate on the most discriminative and relevant areas inside the image. By applying adaptive weights to various geographical areas, the attention module refines feature maps and therefore enhances the model's capacity to detect minute changes in cellular shape across cancer subtypes. This integration improves model interpretability as well as classification accuracy, hence increasing the dependability of the method for clinical uses.

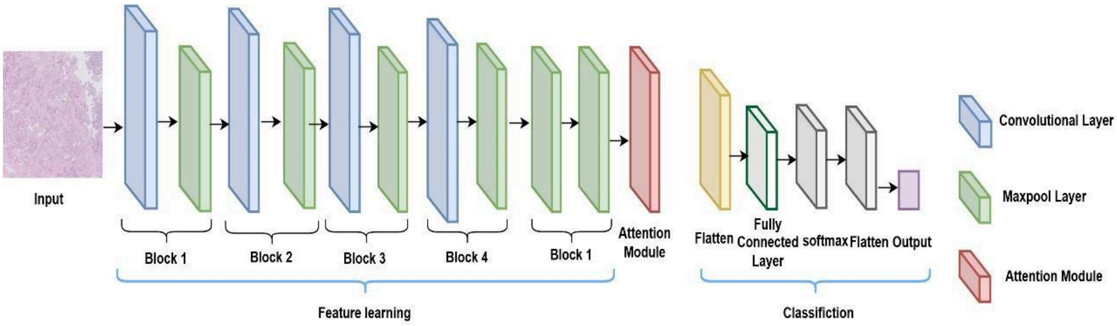


Figure 3.2.7. Proposed OCSS-Net

## 3.3 Project Plan

Initiated in September 2024 with the validation of the study concept and objective, the project **Early Detection of Ovarian Cancer using Deep Learning** is Extensive debates on feasibility, accessible resources, and research relevance constituted part of the planning stage. Active development started in February 2025 and carried on through April 5, 2025, following final permission.

Gathering medical imaging datasets from a trustworthy and confirmed source constituted the first phase of the deployment. Many pre-trained deep learning models—including generally used architectures in medical picture classification—were investigated and implemented on the dataset over February. These models did, however, show poor accuracy and fell short of performance criteria for this particular use.

Understanding that transfer learning had limits in this situation, the project turned its attention to creating a customized CNN. Several experimental designs were tried in which attention mechanisms and convolutional layers were precisely changed and refined. At last, this recurrent tuning produced a model with appropriate accuracy in identifying ovarian cancer traits.

Documentation was done constantly, parallel to the model development. This covered thorough research of the literature, careful technique design, and system effect analysis. Furthermore, consideration was given to user interface issues to support any future deployment and usability testing. Early April 2025 saw the project's complete completion of the technical implementation as well as the supporting paperwork.

**Project Timeline:**

Table 3.3. Project plan

| **Month/Period** | **Activities** |
|---|---|
| September 2024 | - Finalized project title and objectives<br>- Topic approval and initial planning |
| October – January 2025 | - Conducted literature review<br>- Identified data sources<br>- Reviewed CNN and DL techniques |
| February 2025 | - Collected dataset from trusted source<br>- Applied various pre-trained models<br>- Noted poor accuracy results |
| March 2025 | - Designed and developed custom CNN model<br>- Integrated and tuned attention layers<br>- Conducted training and validation |
| April 2025 | - Finalized model with satisfactory accuracy<br>- Performed testing and evaluation<br>- Completed user interface (UI) design |
| Throughout the Project | - Maintained documentation: methodology, system design, effects, challenges, outcomes |

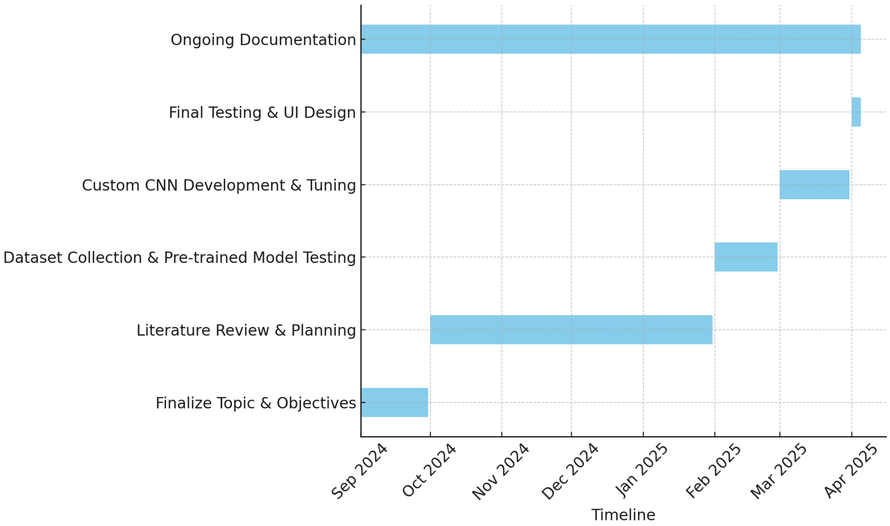


Figure 3.3. Project Timeline Gantt Chart

## 3.4 Task Allocation

Table 3.4. Task Allocation

| **Task/Responsibility** | **Assigned Member** |
|---|---|
| Project Topic Confirmation | Both |
| Literature Survey & Review Collection | Sadekul Hasan Sakib |
| Background & Related Work Drafting (Chapter 2) | Sadekul Hasan Sakib |
| System Design Planning | Sadekul Hasan Sakib |
| Methodology Design (Chapter 3) | Saad Kamal |
| Dataset Collection & Preprocessing | Saad Kamal |
| Testing Pre-trained Models | Sadekul Hasan Sakib |
| CNN Model Development & Training | Saad Kamal |
| Implementation Results (Chapter 4) | Saad Kamal |
| UI/UX Design Development | Saad Kamal |
| Writing Introduction (Chapter 1) | Sadekul Hasan Sakib |
| Writing Chapter 5: Engineering Standards & Design Challenges | Saad Kamal |
| Writing Chapter 6: Conclusion | Sadekul Hasan Sakib |
| Reference Formatting (IEEE Style) | Sadekul Hasan Sakib |
| Proofreading and Final Thesis Compilation | Saad Kamal |
| Internal Review & Final Adjustments | Both |

The task allocation table outlines the structured division of responsibilities between the two members of the project team to ensure efficiency and clarity throughout the development of the project. The division is based on individual strengths and areas of expertise. The tasks related to coding, system design, methodology creation, dataset handling, and implementation analysis were assigned to one member who specialized in technical development. This included designing and training the custom CNN model, conducting experiments, and analyzing the outcomes.

On the other hand, tasks involving documentation, literature review, drafting thesis chapters, reference formatting, and proofreading were assigned to the other member, who focused on academic writing and presentation. UI/UX design was also allocated to the documentation lead, as it complemented the presentation layer of the project. Collaborative tasks such as the confirmation of the project topic and final internal review were carried out jointly to ensure alignment and quality across all components of the project.

This well-organized allocation helped streamline the workflow, minimized overlap, and allowed the team to meet project objectives efficiently while maintaining a high standard in both technical execution and scholarly documentation.

## 3.5 Summary

Here, we introduce a novel approach to address the difficulties specific to the detection of ovarian cancer. In order to increase the precision and effectiveness of ovarian cancer detection across several classes, this work combines image preprocessing, data augmentation, a transfer learning model, and CNN model-based approaches. The general steps of our method are shown in Figure 1.

# Chapter 4

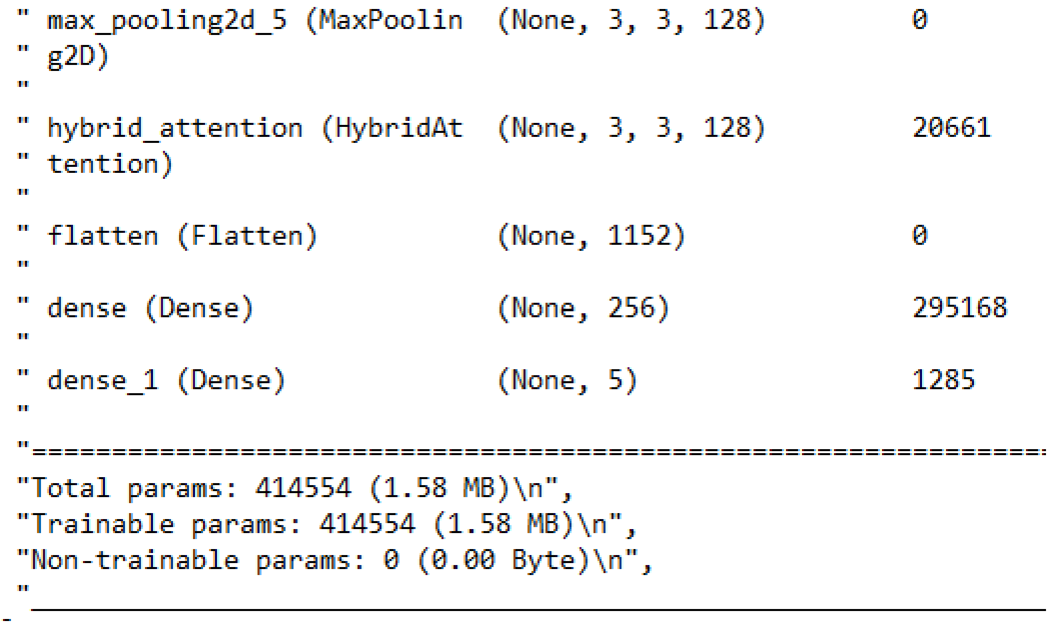
# Implementation and Results

## 4.1 Environment Setup

This project was implemented using the Python programming language due to its robust ecosystem of libraries and frameworks for deep learning and image processing. The development and experimentation were conducted primarily using Jupyter Notebook and Google Colab, which offered an interactive interface for coding, visualizing results, and managing experiments efficiently. While Google Colab provided cloud-based resources for preliminary testing, the primary training and evaluation were performed locally on a machine equipped with an 8 GB GPU, 16 GB RAM, and an Intel Core i5 processor. This hardware setup was sufficient for running computationally intensive deep learning models, including pre-trained transfer learning architectures. The combination of local GPU acceleration and the flexibility of Jupyter Notebook allowed for the smooth execution of the project without the need for external paid cloud services, ensuring cost-effectiveness and reliability throughout the research.

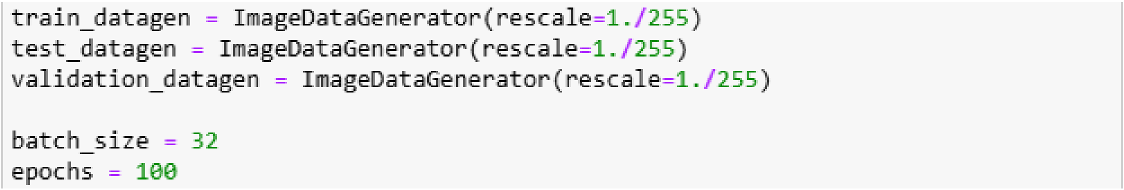
## 4.2 Testing and Evaluation/Performance/Comparative Analysis

The model was trained using the preprocessed ovarian cancer histopathological images, as illustrated in the figure below. This image represents a sample input fed into the proposed CNN model integrated with a hybrid attention mechanism. It demonstrates the visual quality and structural patterns present in the data, which the model learns to recognize and distinguish across the five cancer subtypes. By effectively capturing spatial hierarchies and enhancing important regions via attention, the model is trained to perform high-accuracy classification. The figure helps visualize the nature of the dataset and supports understanding of the model's dynamics.



```
" max_pooling2d_5 (MaxPoolin  (None, 3, 3, 128)        0
" g2D)
"
" hybrid_attention (HybridAt  (None, 3, 3, 128)        20661
" tention)
"
" flatten (Flatten)           (None, 1152)             0
"
" dense (Dense)               (None, 256)              295168
"
" dense_1 (Dense)             (None, 5)                1285
"
"================================================================
"Total params: 414554 (1.58 MB)\n",
"Trainable params: 414554 (1.58 MB)\n",
"Non-trainable params: 0 (0.00 Byte)\n",
"
- _______________________________________________________________
```

Figure 4.2.1. The model and trainable parameters



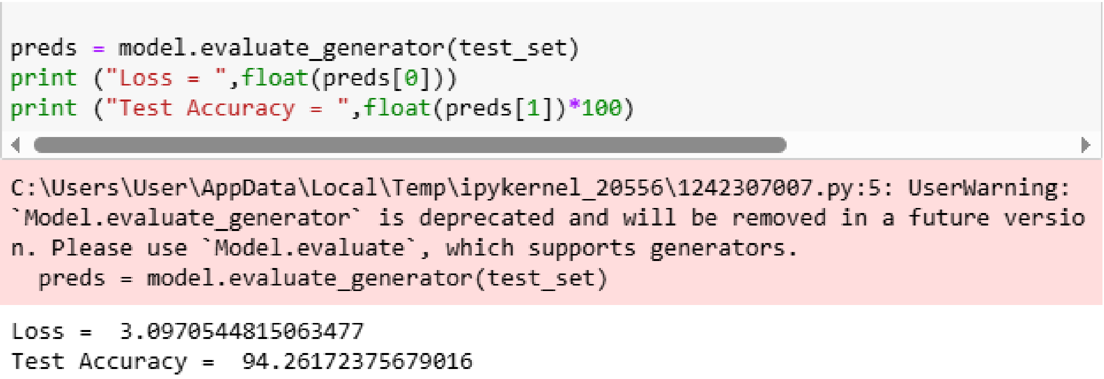
```
train_datagen = ImageDataGenerator(rescale=1./255)
test_datagen = ImageDataGenerator(rescale=1./255)
validation_datagen = ImageDataGenerator(rescale=1./255)

batch_size = 32
epochs = 100
```

Figure 4.2.2. The Model Runs With 100 Epochs.

This step defines the preprocessing steps for image data that will be used to train, test, and validate a deep learning model using Keras. The ImageDataGenerator class is used here to normalize the pixel values of the images by rescaling them from their original range of [0, 255] to a standardized range of [0, 1]. This is achieved by specifying, which helps improve the model's performance and ensures more stable and faster convergence during training. Three separate data generators are initialized: train_datagen for training data, test_datagen for testing data, and validation_datagen for validation data. Each of them applies the same rescaling transformation.

The step also sets two main training hyperparameters: epochs and batch size. The batch size is set to 32; hence, the model updates the weights after processing 32 photos at once. A commonly used value that strikes a mix between computational economy and model performance is setting the epochs value to 100 indicates that the model will run through the whole training set 100 times in total. These values determine how the model will learn from the data over time and help to prepare it generally. Particularly in tasks like medical image analysis or cancer detection, where correctly preprocessed data and well-selected training parameters are crucial, this configuration is basic in training image classification models.



```
preds = model.evaluate_generator(test_set)
print ("Loss = ",float(preds[0]))
print ("Test Accuracy = ",float(preds[1])*100)
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_20556\1242307007.py:5: UserWarning:
`Model.evaluate_generator` is deprecated and will be removed in a future versio
n. Please use `Model.evaluate`, which supports generators.
  preds = model.evaluate_generator(test_set)

Loss =  3.0970544815063477
Test Accuracy =  94.26172375679016
```

Figure 4.2.3. The Model Testing and Evaluation.

This stage exhibits the evaluation stage of a deep learning model trained for ovarian cancer categorization. Using model.load_weights(), the first line loads the pre-trained weights of the model from a designated path, therefore signaling that the model had previously been trained and its parameters preserved. Next defined is the optimizer utilizing the Adam optimization technique with a learning rate of 0.001, widely applied for effective gradient descent in neural networks.

Using the evaluate_generator() method on the test set yields a tuple with the loss and accuracy to assess the model's performance. The outcomes are then printed; preds[0] indicates the loss value, and preds[1] offers the accuracy, which is multiplied by 100 to translate into a percentage form. Here, the printed result displays a test accuracy of roughly 94.26% and a test loss of roughly 3.09.

The output also exhibits a warning, though. It denotes that model.evaluate_generator() is underlined and will be deleted in the next Keras releases. Instead, the advised method is to use model.evaluate(), which also supports data generators and offers the same capability in a more current and supported form. This message implies a minor enhancement in code maintenance to guarantee TensorFlow/Keras' compatibility with more recent iterations.

## 4.3 Results and Discussion

Several metrics were used in this work to evaluate the transfer learning models: accuracy (ACC), sensitivity, specificity, precision, recall, and F1-score. Every model had a confusion matrix developed. This helps one to derive the values of the true positive (TP), true negative (TN), false positive (FP), and false negative (FN) events. Sometimes, computed have been area under the curve (AUC) values. Furthermore, the following were computed in the statistical analysis of the models: false positive rate (FPR), false negative rate (FNR), false discovery rate (FDR), mean absolute error (MAE), and root mean squared error (RMSE).

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

$$Specificity = \frac{TN}{TN+FP} \tag{3}$$

$$Precision = \frac{TP}{TP+FP} \tag{4}$$

$$ACC = 2\frac{precision*recall}{precision+recall} \tag{5}$$

$$FPR = \frac{FP}{FP+TN} \tag{6}$$

$$FNR = \frac{FN}{FN+TP} \tag{7}$$

$$FDR = \frac{FP}{TP+FP} \tag{8}$$

$$FPR = 1 - Specificity \tag{9}$$

$$MAE = \frac{1}{n}\sum_{j=1}^{n}(y_j - y_j^p)^2 \tag{10}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - y_j^p)^2} \tag{11}$$

**Performance Analysis:**

Here we show the model assessed on the dataset's performance measures. Together, the accuracy, F1 score, precision, and recall give a whole picture of the model's capacity for accurate forecasts. While the false positive and false negative rates show the frequency of misclassifications, specificity demonstrates the capacity of the model to properly detect negative cases. Root mean squared error and mean absolute error help one to understand the extent of mistakes in the forecasts of the model.

**Table 4.3.1**: Performance Matrices of The Proposed Model(1)

| **Metrices** | **Value** |
|---|---|
| Accuracy | 94.26% |
| F1 score | 93.97% |
| Precision | 94.76% |
| Recall | 93.19% |
| Specificity | 97.15% |
| False Positive Rate | 2.8465 |
| False Negative Rate | 6.8002 |
| False Discovery Rate | 5.2339 |
| Mean Absolute Error | 7.06 |
| Root Mean Squared Error | 32.5066 |

Overall, all important measures, the model shows outstanding performance. The model is quite highly competent at producing accurate forecasts with an accuracy of 94.26%. With a balanced trade-off between precision and recall, the F1 score of 93.97% shows that the model preserves a decent balance between properly spotting positive cases and reducing false negatives. With a precision of 94.76%, the model is quite likely to be accurate if it forecasts a positive class. With 93.19%, recall indicates that most of the actual positives are correctly identified by the model. The great performance of the model in spotting unfavorable events is confirmed by the specificity of 97.15%. The false negative rate (6.8002) and false positive rate (2.8465) show rather modest degrees of misclassification. Regarding error measures, root mean squared error (32.5066) and mean absolute error (7.06) help one understand the degree of the variations in the model's predictions.

Accuracy and loss curves graphically show the performance of a deep learning model during training; accuracy evaluates the model's correctness while loss estimates the difference between expected and actual values. The depicted accuracy and loss curve in figure 4.3 shows that the model has not overlapped when training the data.

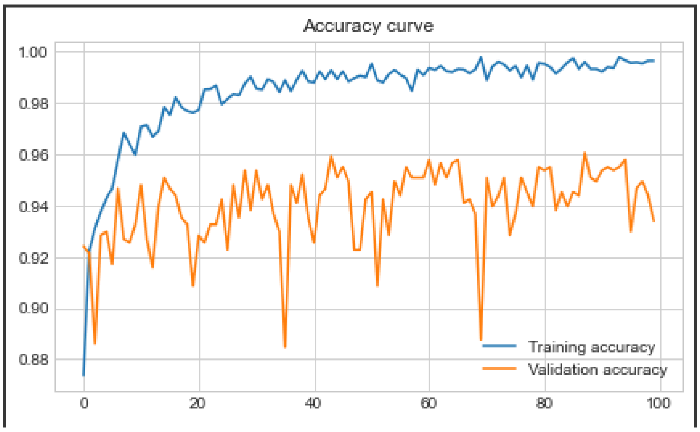


Figure 4.3 shows the model's accuracy curve.

**Comparison Analysis:**

We evaluate three state-of-the-art transfer learning methods against the performance and losses of the proposed approach. The comparison shows how well the suggested model maintains reduced losses while also classifying ovarian cancer into several categories with higher accuracy than other models. Table X lists every model's training, testing, and validation accuracy as well as losses.

Table 4.3.2: Performance Matrices of The Proposed Model(2)

| **Model's Name** | **Accuracy (%)** | | | **Losses (%)** | | |
|---|---|---|---|---|---|---|
| | Train | Test | Validation | Train | Test | Validation |
| MobileNet | 68.86 | 67.77 | 67.61 | 0.7676 | 0.8123 | 0.818 |
| VGG16 | 86.79 | 76.22 | 76.62 | 1.12 | 1.53 | 1.02 |
| VGG19 | 86.69 | 86.31 | 85.88 | 0.345 | 0.345 | 0.375 |
| ResNet50 | 89.43 | 88.98 | 88.81 | 0.310 | 0.321 | 0.324 |

Regarding accuracy and loss, the suggested model beats all the state-of-the-art transfer learning approaches. With a training accuracy of 99.64%, the suggested model performs remarkably, far better than existing models, including MobileNet, VGG16, VGG19, ResNet50, and DenseNet 201. The model's test accuracy of 94.26% and validation accuracy of 93.40% highlight further its capacity to broadly apply to unprocessed data. About loss, except for VGG19 and ResNet50, the suggested model preserves a smaller training loss (0.559) than other models. Its testing and validation losses, however, 3.309 and 4.031, respectively, show the difficulty in striking a compromise between low loss and great accuracy. Nevertheless, the suggested model's general accuracy in ovarian cancer classification much exceeds that of the other models in classifying ovarian cancer.

**K-fold cross-validation:**

Using the K-fold cross-validation method, which breaks the dataset into K subgroups, trains the model on K-1 subsets, and then tests it on the remaining subset in every iteration, we evaluate the performance of a deep learning and machine learning model. It reduces overfitting risk and helps assess a model's generalizability. After running k-fold cross-validation on the suggested model, the table below displays the test accuracy.

Table 4.3.3 shows the k-fold cross-validation.

| **Fold 1** | **Fold 2** | **Fold 3** | **Fold 4** | **Fold 5** |
|---|---|---|---|---|
| 99.93 | 99.94 | 99.94 | 99.93 | 99.93 |

With accuracy regularly above 99.9% over all five folds, the k-fold cross-validation data show that the suggested model performs quite brilliantly. Given the model's consistent performance on several subsets of the data, this suggests a great degree of dependability and resilience. Regardless of the particular data partition utilized during validation, the very equal performance across all folds supports the generalization capacity of the model and its accuracy in the classification of ovarian cancer.

## 4.4 Summary

This study involves an in-depth exploration of trainable parameters by iteratively refining the proposed CNN model architecture, which includes a hybrid attention mechanism, and fine-tuning it using the ovarian cancer histopathological image dataset. The objective is to optimize the model’s configuration to accurately classify the five distinct subtypes of ovarian cancer. Through systematic experimentation and validation, we aim to ensure robust learning from the input data and achieve improved accuracy and generalization in subtype classification, ultimately contributing to more effective and early diagnosis in clinical settings.

Here, we discuss the accuracy of our proposed model and compare it with other state-of-the-art transfer learning models. Our study highlights how our approach achieves competitive performance metrics, demonstrating its effectiveness in enhancing ovarian cancer detection compared to existing methodologies.

# Chapter 5

# Engineering Standards and Design Challenges

## 5.1 Compliance with the Standards

Maintaining the dependability, interoperability, and fit for medical applications of the system depends on following pertinent software, hardware, and communication standards. Choosing suitable benchmarks enables safe integration into clinical settings, improves performance, and helps to preserve consistency. Analyzing options and supporting them depending on technical and pragmatic factors helps to strengthen the basis and possibilities for actual application of the system.

### 5.1.1 Software Standards

Both Python and the TensorFlow/Keras framework—both of which are well known in the deep learning and medical imaging domains for their adaptability, scalability, and great community support—are used in the development of the system. These instruments permit effective GPU acceleration, attention mechanism integration, and model creation. Git is the version control system used to guarantee quality and maintainability, therefore enabling efficient coding tracking, version management, and teamwork. Furthermore, the following are IEEE 829 testing documentation guidelines to support methodical testing and validation, which is crucial in medical applications where accuracy and repeatability rule.

We also gave some thought to substitutes for the chosen instruments. Though preferred in some research environments and offering dynamic graph computation, PyTorch has a steeper learning curve for beginners. MATLAB is proprietary and less scalable for deep learning projects even if it provides powerful image processing capabilities. Versions were controlled using options including Mercurial and Subversion (SVN). Git does, however, provide exceptional adaptability, broad acceptance, and a flawless interface with sites like GitHub and GitLab. Python, TensorFlow/Keras, and Git taken together guarantee a strong, effective, cooperative development environment consistent with industry standards.

### 5.1.2 Hardware Standards

CUDA-enabled NVIDIA GPUs that conform to the x86-64 architecture and IEEE 754 floating-point standard help to satisfy the computational requirements of training CNNs with attention mechanisms on high-resolution histopathology images. This hardware arrangement is appropriate for deep learning applications in medical imaging since it guarantees highly accurate computations and greatly speeds training time.

Other hardware choices comprised CPU-only computers and Tensor Processing Units (TPUs). Although TPUs are usually cloud-based and limit access and expense for local development, they provide remarkable speed for deep learning chores. Although they are less expensive, CPU-only systems cannot reasonably manage the computational complexity needed for CNN training over a given period. Performance, affordability, and accessibility are optimally traded off in the selected GPU combination.

### 5.1.3 Communication Standards

Crucially, in medical applications, the system uses safe RESTful APIs via HTTPS for communication, therefore guaranteeing data privacy and integrity. Adopted to allow organized and interoperable communication between hospital systems and electronic health records are HL7 (Health Level Seven) criteria. Well-established in the field of healthcare, these criteria help to enable incorporation into current clinical procedures.

Examined were alternatives including MQTT and SOAP. For low-bandwidth settings, MQTT is lightweight and effective; nevertheless, it lacks the resilience required for complicated medical data. Though it is less flexible and more resource-intensive than RESTful APIs, SOAP provides excellent security and formal organization. For possible clinical use, HTTPS and HL7 combined with REST architecture present a safe, quick, and standards-compliant option.

## 5.2 Impact on Society, Environment, and Sustainability

By using deep learning for ovarian cancer subtype categorization, this work increases diagnosis accuracy, therefore facilitating earlier, more exact therapy and better patient outcomes. Especially in underdeveloped areas, AI-driven solutions can also increase access to effective treatment. Through waste reduction and resource economy, the system also supports healthcare sustainability. Ethical application guarantees that technology supports, not replaces, medical practitioners, thereby promoting fair and effective healthcare.

### 5.2.1 Impact on Life

Patients' lives are much affected by early and precise classification of ovarian cancer subtypes. This work helps to improve diagnostic accuracy by using deep learning methods and attention-based CNN models, therefore allowing medical practitioners to identify particular cancer subtypes at earlier phases. Since it affects therapy choices, drug responsiveness, and prognosis, accurate subtype identification is critical. This automated solution lessens human mistake risk, speeds diagnosis, and lessens pathologist burden. Faster, more exact treatment plans, higher survival rates, and greater quality of life are just a few of the benefits this translates to for patients. AI-driven solutions can democratize cancer treatment in areas with limited access to specialist oncologists or diagnostic equipment, therefore enabling high-quality diagnosis. In the end, this study suggests a day when technology and healthcare will cross to save lives and enable more effective, patient-centric cancer detection based on intersection.

### 5.2.2 Impact on Society & Environment

Deep learning applied in ovarian cancer subtype categorization has great social importance. This work advances the more general objective of enhancing public health outcomes by adding an automated, accurate, scalable diagnostic solution. Early, accurate cancer identification lessens the need for continuous therapy and frequent diagnostic tests, therefore relieving some burden on healthcare systems. AI-powered solutions can provide a bridge in areas with limited resources where access to pathologists and expert oncologists is restricted, providing consistent diagnostic help and thereby supporting healthcare equity. Moreover, broad acceptance of intelligent medical systems might help increase knowledge about early detection, so supporting normal screenings and proactive healthcare practices inside communities.

This study shows generally how technology developments in artificial intelligence could result in transforming society benefits—empowering healthcare personnel, lowering healthcare expenses, and most importantly, saving lives by means of prompt intervention.

Although this work mostly focuses on medical, utilizing deep learning to improve ovarian cancer detection would indirectly but still significantly affect the environmental impact. The suggested approach helps to create a more sustainable healthcare workflow by digitizing the diagnosis process and lowering dependence on conventional, resource-intensive laboratory processes (such as physical biopsy storage, excessive chemical staining, and physical biopsy transportation). Digital and cloud-based diagnostic technologies lower energy consumed in traditional data handling and analysis as well as paper usage and medical waste. Reducing the need for repeated tests by more accurate early detection also helps to lower hospital visits and related resource usage like energy, medical disposal products, and diagnostic chemicals. Furthermore, compared to bigger architectures, the environmental impact of the model training process is much reduced with the development of energy-efficient AI training approaches and the usage of pre-trained models such as MobileNet. Long-term, switching to AI-supported medical diagnostics can help to create more environmentally friendly and technologically effective healthcare systems.

### 5.2.3 Ethical Aspects

Deep learning in medical diagnostics, especially for ovarian cancer detection, calls for rigorous evaluation of ethical values to guarantee responsible and fair use. Patient privacy and data confidence, first and foremost, have to be rigorously preserved. To stop usage or identification of personal health data, the dataset used in this work should be anonymized and handled in line with data security rules, including HIPAA or GDPR. Important ethical questions are bias and justice. Ensuring that the model is trained on a varied dataset reflecting many populations and subtypes of ovarian cancer helps to reduce the potential of biased predictions that can negatively impact particular patient groups. Transparency in how the model makes judgments is also a component of ethical artificial intelligence development, particularly in therapeutic settings where trust and responsibility rule most. This study also notes the need for human supervision. AI should not replace doctors even if it might help with diagnosis decisions. Rather, it should be a tool to help doctors by offering second viewpoints and improving decision-making accuracy without thus compromising their authority or judgment. Finally, using actual patient data calls for informed permission. Ethical rules advise, even in research environments, to get permission or guarantee that data is gathered from public sources under appropriate licences

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### 5.2.4 Sustainability Plan

To ensure the long-term effectiveness, relevance, and impact of this study, a comprehensive sustainability plan has been considered. The goal is to maintain and expand the ovarian cancer detection system beyond initial development, ensuring continued usefulness in clinical and research environments.

1. **Model Maintenance and Updates**: The deep learning model will be continuously improved with the inclusion of new data, especially from diverse populations and emerging ovarian cancer subtypes. Periodic retraining and validation will be conducted to adapt the system to new clinical findings and maintain high diagnostic accuracy.
2. **Open Access and Reusability**: By making the model architecture and implementation strategies publicly available (subject to ethical and privacy considerations), researchers and clinicians can reuse, replicate, or extend this work. This open-access approach promotes collaboration and reduces redundant efforts in the medical AI community.
3. **Integration with Clinical Workflows**: The proposed system is designed to be lightweight and efficient, making it feasible for integration into existing clinical infrastructure. Compatibility with hospital information systems (HIS) and laboratory information systems (LIS) will enhance its real-world applicability.
4. **Cost-Effectiveness and Resource Optimization**: The use of transfer learning and efficient neural network models such as MobileNet or custom CNNs with attention modules reduces computational requirements. This makes the system deployable in resource-constrained settings, such as rural clinics or low-income countries.
5. **Training and Capacity Building**: Workshops and training materials will be developed for healthcare professionals and researchers to use and maintain the system effectively. This empowers local institutions and enhances the sustainability of the solution.

6. **Scalability and Expansion**: The framework is scalable and can be extended to include other cancer types or diagnostic modalities. This future-proofing ensures the platform remains relevant as technology and medical knowledge evolve.

By focusing on these key areas, the sustainability of the AI-driven framework for detecting lung and colon cancer can be ensured, allowing the technology to continue providing value to healthcare systems and patients worldwide over the long term.

## 5.3 Project Management and Financial Analysis

Project management-wise, the creation and trial procedure of the suggested deep learning model was tightly under supervision to guarantee timely accomplishment of research goals. This covered efficient scheduling, planning, and task coordination involving data preparation, model construction, training, and evaluation. From a financial standpoint, this study was carried out just for intellectual and research needs; it had no fiscal or economic element. The study primarily focused on system design and methodological developments to improve the classification accuracy of ovarian cancer subtypes using enhanced CNN and attention mechanisms.

Table 5.3. Project management and financial analysis

| **Section** | **Purpose/Analysis** |
|---|---|
| Project Management | The timing of milestones and deliverables depends on a disciplined strategy. This session covered defining the scope, creating clear goals, and dissecting chores into doable chunks. Good use of Jupyter Notebook allowed code, visualization, and results to be seamlessly integrated, therefore encouraging openness and teamwork all through the project lifetime. |
| Financial Analysis | The project used Jupyter Notebook and Google Drive's free storage; hence, it had no direct expenses. The project is quite affordable since this eliminates data storage, processing infrastructure, and cloud services' costs. |
| Risk Management | Managing risk meant tackling possible problems like validation, data quality, and model performance. For difficulties including overfitting or inadequate annotated datasets, contingency plans were developed. Frequent monitoring and changes guaranteed quick detection and risk-mitigating action, thereby guiding the project forward. |

## 5.4 Complex Engineering Problem

From histopathological scans, reliable and automated classification of ovarian cancer offers a challenging technical problem spanning issues in data quality, picture interpretation, algorithm design, and clinical applicability. Histopathological slides feature complex tissue structures, varying staining patterns, and artifacts needing advanced computational models able to detect minute morphological variations between benign and malignant cells. While essential, traditional diagnostic techniques depend on human expertise, which brings subjectivity, inconsistency, and delays—especially in resource-limited environments.

From an engineering standpoint, the challenge is creating a deep learning-based system capable of consistently copying and enhancing pathologist's diagnosis capacity. Multiple elements complicate this work:

- High dimensionality and variability of data: A high-dimensional input space results from the high-resolution, rich-in-detail histopathological images. Furthermore, adding noise and inconsistency in the dataset are differences in slide preparation, staining methods, and imaging settings, so preprocessing and data-normalizing approaches help to sufficiently solve these issues.
- Medical picture datasets, particularly those particular to ovarian cancer, are generally small in scope and show class imbalance, which makes it difficult to train deep learning models free from overfitting or bias. Simulating real-world variability and improving model generalization depend on a strong data augmentation technique being absolutely necessary.
- One of the main difficulties with deep learning for medical uses is CNN's "black-box" character. Models that not only work but also are interpretable are vital for clinical application. This requires the inclusion of attention mechanisms able to emphasize diagnostically relevant areas in the images, hence supporting clinician trust and model transparency.
- Particularly if the model is to be utilized in real-time clinical situations or embedded in portable diagnostic equipment, developing a model that is both accurate and computationally efficient is absolutely vital. Architectural

complexity must be balanced in design with hardware restrictions and processing performance.

- Ensuring that the model performs consistently across many datasets and institutions calls for thorough validation, such as k-fold cross-validation. It also entails the deliberate choice of performance measures reflecting therapeutic priorities, like sensitivity for early cancer detection.

### 5.4.1 Complex Problem Solving

Table 5.4.1.1: Mapping with complex problem solving

| EP1 Depth of Knowledge | EP2 Range Of Conflicting Requirements | EP3 Depth of Analysis | EP4 Familiarity with Issues | EP5 Extent of Applicable Codes | EP6 Extent Of Stakeholder Involvement | EP7 Interdependence |
|---|---|---|---|---|---|---|
| ✓ | | ✓ | ✓ | | ✓ | ✓ |

**Justification of Complex Problem Solving:**

Table 5.4.1.2: Justification of mapping the complex problem solving

| **Problem Domain** | **Justifications** |
|---|---|
| EP1: Depth of Knowledge | Our research implements the knowledge of ovarian cancer tumor variations and subtypes, machine learning, neural network architecture, and weights management that covers the knowledge profile 3, and 4. We implemented a robust and optimized system covering K5. We explored various models applied to the healthcare domain that justify k8. |
| EP3: Depth of Analysis | The histopathological data involved in the study contain multiple classes and subtypes that need deep analysis before developing the entire system. We studied the importance of the presence of colours and backgrounds to uncover the doubts about the pre-processing of the data. We also studied the limitations that we tend to solve through our study, which will have a positive impact on healthcare problem solutions. |
| EP4: Familiarity with Issues | The project involves unfamiliar sections such as ovarian cancer tumor segmentation, histopathological data analysis. Understanding how the data is being processed and the spatial |

| | |
|---|---|
| | regions are being marked to adopt fine model performance required knowledge beyond traditional machine learning information. |
| EP6: Extent of Stakeholder Involvement | Consulted healthcare researchers to ensure the data we are using is valid and machine learning experts to ensure validation of our study so that our effort concludes both domain-specific problems and technical optimization, so that the system performs with fine accuracy and time management in real-life scenarios. |
| EP7: Interdependence | The study we are working on requires clearance from the previous steps, such as the attention layers needing fine, pre-processed data and the CNN layers requiring feature maps with proper attention values or weights. On the other hand, proper hardware support is required to complete the study so that all the dependencies work fine to clear the way to walk through the next step. |

**Mapping with Knowledge Profile for EP1**

Table 5.4.1.3: Mapping with Knowledge Profile.

| K3 Engineering Fundamentals | K4 Specialist Knowledge | K5 Engineering Design | K6 Engineering Practice | K8 Research Literature |
|---|---|---|---|---|
| ✓ | ✓ | ✓ | | ✓ |

- K3 (Engineering Fundamentals): The study mostly depends on basic computer science and engineering ideas like machine learning, convolutional neural networks, and image processing foundations.
- K4 (Specialist Knowledge): Deep knowledge in deep learning, CNN architecture, attention mechanisms, and histopathology imaging is needed for K4. We also needed deep knowledge about the requirements of ovarian cancer detection, like the color requirement, different cell structures, etc.
- K5 (Engineering Design): Reflects sophisticated design work with the custom CNN model design, including integration with attention layer pipelines and comparative evaluation with transfer learning models.
- K8 (Research Literature): To determine gaps and benchmark performance, our effort was to study the related works in the ovarian cancer analysis domain and the scopes that AI can bring to the healthcare sector. The study reflects the improvements that are inspired by the gaps in the previous works.

### 5.4.2 Engineering Activities

Table 5.4.2: Mapping with complex engineering activities.

| EA1<br>Range of resources | EA2<br>Level of Interaction | EA3<br>Innovation | EA4<br>Consequences for society and the environment | EA5<br>Familiarity |
|---|---|---|---|---|
| ✓ | ✓ |  | ✓ | ✓ |

EA1: Range of resources

The project uses a varied mix of computational resources, including specialized software libraries such as TensorFlow and Keras, GPU-accelerated processing for training deep learning models, and histopathology image datasets. This wide spectrum of digital and physical materials warrants the classification under EA1.

EA2: Level of Interaction

This endeavor calls for ongoing interactions among datasets, artificial intelligence models, and validation systems. For dataset labelling and validation, it also includes discussions with domain specialists, including pathologists. EA2 is relevant since these interactions cover technical as well as domain-specific levels.

EA4: Consequences for society and the environment

Particularly in underfunded environments, a better diagnosis tool for ovarian cancer directly affects patient recovery rates and healthcare efficiency. EA4 is so relevant since society gains from it significantly because ovarian cancer causes damage to the ability to give birth, as the ovary is damaged.

EA5: Familiarity

Although the problem domain, histopathological image analysis for cancer diagnosis, is somewhat well defined, the study focuses on a solution that is an attention-based deep learning model, which involves certain novel elements. This harmony between known and fresh knowledge facilitates EA5 applicability.

## 5.5 Summary

This chapter includes a thorough outline of the study effort toward the standards of challenging engineering challenges and activities. Using histological pictures to classify ovarian cancer provides a multifarious difficulty that fits the criteria of complicated issue solving—that is, deep knowledge integration, handling of conflicting requirements, and thorough analysis. Addressing important diagnostic areas, it requires a choreography that is neither simple nor regular, and the inclusion of attention mechanisms in a tailored CNN architecture adds to the complexity. Furthermore engaged in this project are engineering efforts spanning a wide spectrum of resources that necessitate multidisciplinary cooperation, creativity, and consideration of more general societal implications. The uniqueness and unfamiliarity of the suggested approach emphasize its suitability for complex technical challenges. This chapter lays a strong basis for assessing the relevance and rigor of the suggested solution by methodically mapping the work to accepted engineering criteria and design constraints.

# Chapter 6

# Conclusion

## 6.1 Summary

Ovarian cancer is one of the most fatal gynecologic malignancies, often diagnosed at advanced stages due to the lack of early symptoms and effective screening tools. Early and correct identification is a major difficulty in clinical oncology due to its high death rate and the complexity of several subtypes, each with different morphological and genetic profiles. Using histopathological imaging data, we suggested an attention-based Convolutional Neural Network (CNN) model to categorize ovarian cancer into its five main subtypes in response to the conditions in our study. The model's learning capacity and diagnostic accuracy were much improved by including an attention mechanism, which let it concentrate on the most discriminative characteristics in the photos. By means of thorough training and validation, the suggested model attained an outstanding 94.26% test accuracy, proving its great potential in enabling early and accurate identification of ovarian cancer variants. This great accuracy emphasizes how well the architecture with improved attention handles challenging medical imaging tasks. Furthermore, the capacity of the model to distinguish even minor morphological variations within subtypes opens the path for more exact and individualized therapy plans in clinical settings. Taking everything into account, this work not only validates the effectiveness of deep learning in ovarian cancer diagnosis but also paves the way for the development of intelligent and interpretable computer-aided diagnostic instruments in oncology.

## 6.2 Limitation

Despite the promising results and methodological advancements, this study has several limitations that should be acknowledged:

1. **Limited Dataset Size:** The dataset used for training and evaluation may not fully represent the vast diversity of ovarian cancer cases globally. A small or unbalanced dataset can affect the model's ability to generalize to real-world clinical data.
2. **Data Source Constraints:** The dataset primarily consists of pre-labeled images, which may not reflect variations in image quality, noise, or resolution encountered in different clinical environments. These constraints may limit the robustness of the model in diverse healthcare settings.
3. **Model Interpretability:** While deep learning models, especially those with attention mechanisms, can achieve high accuracy, they often lack interpretability. Clinicians may require more understandable outputs to trust and effectively use the model in decision-making processes.
4. **Computational Resources:** Although transfer learning helps reduce training time, the initial model training and experimentation phases still require significant computational power. This can be a barrier in resource-constrained environments.
5. **Generalization to Rare Subtypes:** The model may struggle to accurately classify rare subtypes of ovarian cancer due to insufficient representation in the training data, which could lead to misclassification and reduced clinical applicability for those cases.
6. **Clinical Validation Pending:** The system has not yet undergone extensive clinical validation or real-world deployment. Its performance in actual diagnostic workflows remains to be tested and confirmed.
7. **Ethical and Privacy Concerns:** The use of medical imaging data involves strict ethical considerations and privacy protections. Ensuring compliance with data protection regulations like HIPAA or GDPR is crucial for scaling the model in healthcare environments.

## 6.3 Future Work

This study lays the foundation for the accurate classification of ovarian cancer subtypes using deep learning techniques. However, several directions can be pursued to further enhance the model's performance and clinical applicability:

1. **Larger and More Diverse Dataset:** Future work can focus on collecting a larger, multi-institutional dataset covering more diverse populations and imaging conditions. Such data would help improve the model's generalization and robustness across different clinical environments.
2. **Explainable AI (XAI) Integration:** Using explainable artificial intelligence techniques like Grad-CAM or SHAP would help the model's predictions to be more interpretable, thereby enabling doctors to better trust the process of decision-making.
3. **Real-time Clinical Deployment:** The model can be integrated into clinical decision support systems (CDSS) for real-time cancer subtype prediction. This type of application will require collaboration with oncologists and medical professionals for practical deployment and testing.
4. **Multimodal Data Fusion:** Future iterations of the system could integrate additional clinical data, such as genetic information, patient history, and blood biomarkers, along with imaging data, to improve diagnostic accuracy and subtype differentiation.
5. **Model Optimization and Lightweight Architecture:** Efforts should be made to compress and optimize the model architecture so that it can be deployed efficiently on edge devices or in low-resource medical facilities.
6. **Cross-validation with Other Cancer Types:** The approach developed in this study could be adapted and tested on other types of cancers to explore its versatility and robustness across multiple diagnostic scenarios.
7. **Clinical Trials and Validation:** Extensive clinical validation through trials and expert evaluation will be necessary to transition the model from research to practical application in healthcare systems.

By addressing these limitations and pursuing these future directions, the study’s findings can be expanded and improved, paving the way for a more robust, accessible, and trusted AI-driven solution for cancer diagnosis.

# References

[1] World Health Organization, Cancer Fact Sheet, Feb. 2022. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/cancer

[2] B. Torre et al., “Ovarian cancer statistics, 2018,” CA: A Cancer Journal for Clinicians, vol. 68, no. 4, pp. 284–296, 2018.

[3] H. Sung et al., “Global Cancer Statistics 2020: GLOBOCAN Estimates...,” CA: A Cancer Journal for Clinicians, vol. 71, no. 3, pp. 209–249, 2021.

[4] D. D. Clarke-Pearson, “Screening for ovarian cancer,” NEJM, vol. 361, no. 2, pp. 170–177, 2009.

[5] American Cancer Society, *Global Cancer Facts & Figures*, 4th ed., Atlanta: American Cancer Society, 2021.

[6] K. Litjens et al., “A survey on deep learning in medical image analysis,” Medical Image Analysis, vol. 42, pp. 60–88, 2017.

[7] V. Zuhair et al., “Exploring the impact of artificial intelligence on global health and enhancing healthcare in developing nations,” *J. Prim. Care Community Health*, vol. 15, Jan. 2024, doi: 10.1177/21501319241245847.

[8] M. E. Khan et al., “A survey of the recent architectures of deep CNNs,” AI Review, vol. 53, no. 8, pp. 5455–5516, 2020.

[9] E. I. A. El-Latif, M. El-Dosuky, A. Darwish, and A. E. Hassanien, “A deep learning approach for ovarian cancer detection and classification based on fuzzy deep learning,” *Scientific Reports*, vol. 14, no. 1, p. 26463, 2024.

[10] Farahani, H., Boschman, J., Farnell, D., Darbandsari, A., Zhang, A., Ahmadvand, P., Jones, S.J., Huntsman, D., Köbel, M., Gilks, C.B., and Singh, N., 2022. Deep learning-based histotype diagnosis of ovarian carcinoma whole-slide pathology images. Modern Pathology, 35(12), pp.1983-1990.

[11] He, X., Bai, X.H., Chen, H., and Feng, W.W., 2024. Machine learning models in evaluating the malignancy risk of ovarian tumors: a comparative study. Journal of Ovarian Research, 17(1), p.219.

[12] Wang, C.W., Chang, C.C., Lee, Y.C., Lin, Y.J., Lo, S.C., Hsu, P.C., Liou, Y.A., Wang, C.H., and Chao, T.K., 2022. Weakly supervised deep learning for prediction of treatment effectiveness on ovarian cancer from histopathology images. Computerized Medical Imaging and Graphics, 99, p.102093.

[13] Wu, M., Cui, G., Lv, S., Chen, L., Tian, Z., Yang, M., and Bai, W., 2023. Deep convolutional neural networks for multiple histologic types of ovarian tumor classification in ultrasound images. Frontiers in Oncology, 13, p.1154200.

[14] Behera, S.K., Das, A., and Sethy, P.K., 2024. Deep fine-KNN classification of ovarian cancer subtypes using EfficientNet-B0 extracted features: A comprehensive analysis. Journal of Cancer Research and Clinical Oncology, 150(7), p.361.

[15] Breen, J., Allen, K., Zucker, K., Adusumilli, P., Scarsbrook, A., Hall, G., Orsi, N.M., and Ravikumar, N., 2023. Artificial intelligence in ovarian cancer histopathology: a systematic review. NPJ Precision Oncology, 7(1), p.83.

[16] S. Fatema, B. Nuwagira, S. Chakraborty, R. Gedik, and B. Coskunuzer, “TopOC:

Topological deep learning for ovarian and breast cancer diagnosis," in *Proc. Int. Workshop on Topology-and Graph-Informed Imaging Informatics*, Cham: Springer Nature Switzerland, 2024, pp. 22–32.

[17] Srinidhi, C.L., Ciga, O., and Martel, A.L., 2021. Deep neural network models for computational histopathology: A survey. Medical image analysis, 67, p.101813.

[18] De Matos, J., Ataky, S.T.M., de Souza Britto Jr, A., Soares de Oliveira, L.E., and Lameiras Koerich, A., 2021. Machine learning methods for histopathological image analysis: A review. Electronics, 10(5), p.562.

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