Predictive Modeling of Ovarian Cancer Using Advanced Image Recognition and Machine Learning

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FINAL YEAR DESIGN PROJECT REPORT

This Report 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 **"Predictive Modeling of Ovarian Cancer Using Advanced Image Recognition and Machine Learning"**, submitted by Syeda Mohmima, ID No: **212-15-4203** and Amrin Haque, ID No: **212-15-4188** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **14 May, 2025**.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Mr. Raja Tariqul Hasan Tusher, Assistant Professor**, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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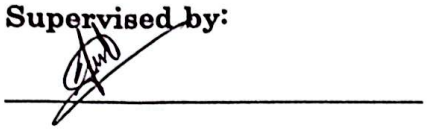

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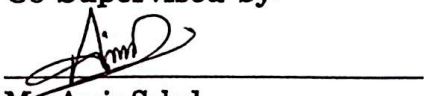

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ABSTRACT

Ovarian cancer is a clinical dilemma due to its originally asymptomatic nature and then varied presentation. Early and accurate detection becomes an urgent goal in the course of the optimization of the patient's outcome. We present predictive modeling of the ovarian cancer subtypes by deep learning-based detection of the histopathology image analysis. The methodologically designed five-class dataset of Clear Cell Ovarian Carcinoma, Endometrioid, Serous Carcinoma, Mucinous Carcinoma and Non-Cancerous tissues was used. The recent convolution neural networks such as ResNet50, VGG16, VGG19, MobileNetv2 and InceptionV3 have been compared upon using the preprocessing steps such as image resizing, stain normalization, bilateral filtering and augmentation in order to improve the performance of the model. The performance was compared using the metrics such as accuracy, precision, recall, F1-score and area under the receiver operating characteristic curve (AUC). Visualization of the model's attention regions as well as interpretability has also been conducted using Gradient-weighted Class Activation Mapping (Grad-CAM) and Shapley Additive exPlanations (SHAP). The outcome has revealed the superiority of InceptionV3 in the classification task. The results show the evidence that deep models are capable of bringing in order to make the conventional diagnostic pipelines stronger in the scenario of the ovarian cancer and to achieve more accurate, scalable and explainable outcomes in computational pathology.

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Chapter 1

Introduction

This chapter provides the background of deep learning-based ovarian cancer detection and declares the problem in the classification of histopathological images and the need for the automatic solutions. Study motivation, research objective, and significance of the study are explained in the current chapter.

1.1 Introduction

One of the most deadly gynecological conditions and a significant worldwide health issue is ovarian cancer. With a fatality rate that is disproportionately high in comparison to other cancers, it is the leading reason of death [1]. Lack of early signs is the primary reason for this high fatality rate, which typically results in a late diagnosis after the disease has spread [2,8]. This delay in identification dramatically lowers the chances of survival and significantly limits treatment possibilities[3]. According to global cancer statistics, ovarian cancer claimed the deaths of over 207,000 persons in 2020, while over 313,000 new cases were diagnosed [4,19]. Over 90% of women with cancer endure for 5 years if the disease is detected early; however, as the disease progresses, it decreases to below thirty percent [5,23].

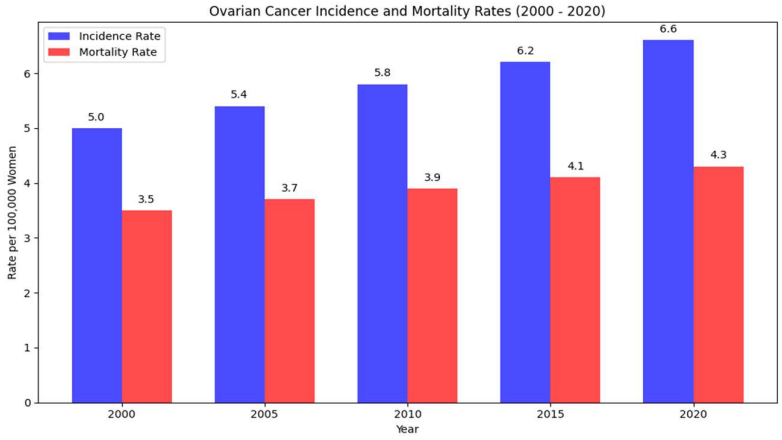

Fig 1.1:Ovarian Cancer incidence and Mortality Rates

The current diagnostic paradigm for ovarian cancer is primarily based on histopathological analysis, which is the gold standard. In this process, pathologists examine biopsy samples under a microscope in order to find malignant cells. This method has a number of errors, though, such as the fact that histopathological diagnosis is highly subjective, laborious, and prone to human error—especially considering the complex nature of ovarian cancer subtypes—and that there is a global scarcity of skilled pathologists, which makes the diagnostic bottleneck worse [5].These

limitations highlight how urgently automated, AI-powered diagnostic tools are required to assist pathologists to make quicker, more precise, and reliable diagnoses. Deep learning, has established its rise as a revolutionary imaging tool for examination [11]. CNNs and different advanced architectures have illustrated incredible success to detecting, classifying, and segmenting cancerous tissues from histopathology images[13,17]. Unlike traditional methods of machine learning, which depend on manually engineered attributes, deep learning models autonomously learn complex patterns from input image , significantly improving accuracy and reducing the reliance on human expertise[6].

The proposed paper discusses a predictive model of deep learning. Study uses ResNet50, VGG16, VGG19, MobileNetV2 and InceptionV3 to examine the accuracy of different advanced transfer learning models in identifying ovarian cancer subtypes. The goal is to develop an automated, highly accurate, and clinically interpretable tool that can assist healthcare professionals to increased survival rates. The primary objective is to create an automated classification method that can precisely and successfully differentiate between various ovarian cancer subtypes.This system uses deep learning algorithms to speed up the diagnosis process, decrease diagnostic errors, and increase consistency. In the end, it will give pathologists a dependable tool to improve workflow and decision-making. A core element of this research is the use of advanced image preprocessing method to ensure the stability of the models. Histopathology images often show significant diversity due to differences in staining methods, slide preparation, and imaging conditions[9]. This will be addressed by using advanced preprocessing methods such as stain normalization, augmentation, and noise reduction. By minimizing the effect of variability, the system will be more capable of generalizing across different clinical settings [35].

Another significant aim is the comparison of the performance of various advanced models in relation to subtype classification, including ResNet50, VGG16, VGG19, MobileNetV2, and InceptionV3. The models will be compared using metrics in order to choose the suitable architecture for this specific diagnostic task. Aim of the study's is to choose the best method for achieving high diagnostic accuracy while maintaining computational efficiency by evaluating the advantages and limitations of each model. Interpretability and trust are also important aspects of this study because the ability of AI-driven diagnostic tools to generate results that are visible and understandable is essential for their successful utilization in clinical practice. The study will address this by highlighting the portions of the histopathology using visualization techniques like Grad-CAM. These visual explanations will build trust and facilitate the validation of the AI system's diagnosis by assisting clinicians in understanding the system's decision making process. This approach aims to minimize the gap between clinical knowledge and artificial intelligence.This pipeline's design will handle a large number of histopathology images, ensuring its applicability in a range of medical environments. By developing the system for efficiency and scalability, the goal is to create a feasible solution that can be utilized in hospitals and diagnostic labs, which will improve the availability and standard of ovarian cancer diagnosis. By fulfilling these objectives, the study intends to advance the field of computational pathology while improving the early detection and treatment.

1.2 Motivation

Ovarian cancer is one of the cancers of global concern with thousands of women's deaths recorded every year[10]. Because the disease advances while symptoms go unnoticed,

it is most often found after advancing to a level where the treatment would be pointless. Additionally, the new diagnosis of over 300,000 cases every year bears testimony quite strongly to the necessity of improving detection and treatment procedures. High mortality rate, coupled with increasing incidence, necessitates a faster and more accurate method of early diagnosis.

The implications of ovarian cancer are not only mortality. The majority of the women who suffer from this condition also suffer from severe reproductive issues because the removal of ovaries leads to permanent infertility. This adds to the emotional and psychological suffering of the victims, making the need for better diagnostic techniques even more crucial. Furthermore, roughly 80% of the cases of ovarian cancer are identified at their advanced stages, and the patients therefore have limited treatment options and survive with little hope. This point is augmented by the fact that conventional histopathological diagnosis as done by the human eye and not by a machine is itself very poor. A measurement derived this way remains subjective and hence prone to inconsistencies and errors in classification. This variability has significant treatment planning implications, and once more, it underscores the need for a more objective and standardized diagnostic process.

Artificial intelligence (AI) technologies of digital pathology-based enable computerized, very accurate identification of cancer cells with fewer human diagnoses and more consistency.AI-based models that can identify subtle abnormalities in histopathology images that are difficult for the human eye to perceive enable early detection. The increasing prevalence of ovarian cancer globally necessitates the development and implementation of state-of-the-art AI-based techniques that can improve diagnostic accuracy and, ultimately, patient outcomes.

This study is driven by the need for additional, reliable, and independent diagnostic machinery. With the potential of deep learning algorithms, we aim to break the current stumbling blocks in the diagnosis of ovarian cancer through the provision of a better, standardizable, and scalable classification option. Proper utilization of AI has immense potential in changing the face of cancer diagnostics with early detection, diagnosis, and better survival rates. As technology advances, the incorporation of AI into current medical practice can fill the gap between delayed diagnosis and successful treatment, eventually changing the face of cancer treatment.

1.3 Objectives

This study intends to enhance clinical decision making, reduce false negatives and positives, and enhance the accuracy of diagnosis using DL models, feature extraction, and high-level image processing.To achieve these goals, the study is structured around the following main objectives:

1. Develop a Comprehensive Deep Learning-Based Diagnostic Framework
    - Construct and deploy an effective deep learning model using histopathology images to classify different subtypes of ovarian cancer.
    - Make the system scalable, adaptable, and viable for use in real clinical practice.
2. To Address Class Imbalance Issues Employ strategies to ensure that the class distributions in the dataset are balanced
    - Synthetic Minority Oversampling Technique: Make artificial examples in minor classes to prevent model bias.

3. Implement Advanced Image Preprocessing Techniques
    - Enhance the quality of the image through bilateral filtering by eliminating the noise without disturbing the tissue structure.
    - Normalize the variability of staining through stain normalization methods for consistency between datasets.
    - Add augmentation to create synthetic variations and improve model generalization.
4. Train and Benchmark Multiple Transfer Learning Models
    - Employ several cutting-edge deep learning architectures such as ResNet50, VGG16, VGG19, MobileNetV2 and InceptionV3 .
    - Compare their performances to determine how well each model classifies ovarian cancer.
    - Tune hyperparameters and apply regularization techniques to prevent overfitting.
5. Integrate Explainable AI (XAI) for Model Interpretability
    - Employ Grad-CAM and SHAP to map the model's decision-making process.
    - Make sure that the model is interpretable and its outputs are clinically meaningful and interpretable by pathologists.
6. Validate the Proposed Model Using Comprehensive Evaluation Metrics
    - Accuracy: Compute the ratio of images labeled correctly.
    - F1-score: Calculate the recall and precision of the harmonic means.
    - AUC-ROC: Measure model strength in distinguish between non-cancer and cancer samples.
    - Sensitivity & Specificity: Evaluate the ability to detect cancer of the model in its early stage with less false positives.
7. Establish a Deployment-Ready AI-Based Diagnostic System
    - Translate the most successful deep learning model to a deployable system for practical applications.
    - Develop an interactive web portal in which users (pathologists, clinicians) upload images and receive predictive diagnosis.

1.4 Methodology

This study applies a deep learning method to ovarian cancer prediction from histopathological images. The approach is carried out formally in a pipeline, from preprocessing the data through model selection, training, testing, and comparing performance.

The dataset contains histopathology images belonging to five distinct classes: Clear Cell Ovarian Carcinoma, Endometrioid, Serous Carcinoma, Non-Cancerous and Mucinous Carcinoma. Prior to the preprocessing steps involving resizing images to a fixed resolution (e.g., 224×224 pixels) , normalizing pixel values and carrying out data augmentation operations such as horizontal flip, rotation, zoom, width/height shift and shear are done for model generalizability and improving the performance of classification by passing images through models. SMOTE was once more used to balance out any imbalance which could still remain in the classes and thereby again improve model learning for each one of the five tissue types.

All the images underwent a rigorous and uniform preprocessing pipeline prior to

training to promote homogeneity, transparency, and credibility. Noise was eliminated from the images without removing important edges needed in retaining morphological details for facilitating cancer subtype classification by bilateral filtering. Secondly, stain normalization techniques were employed for stabilization of color distribution in all samples to preserve variability due to different staining protocols and scanners to the barest minimum.

For model selection, the following transfer learning architectures are experimented with, namely ResNet50, VGG16, VGG19, MobileNetV2 and InceptionV3. The models are fine-tuned using pre-trained weights on large datasets for their improved performance over histopathology images. Training is carried out with categorical cross-entropy loss and Adam optimizer and adaptive learning rate scheduler to achieve maximum model convergence. The models will be evaluated using fundamental measures of accuracy, precision, recall, F1-score, and AUC-ROC to measure classification performance. SHAP and Grad-CAM visualizations will be also used to interpret model predictions by determining the most important regions in histopathology images and making the deep learning approach more explainable and reliable.

Finally, the models are compared and contrasted to determine the optimal model. The result of this paper attempts to contribute to the body of work of creating an autonomous AI-based screening system for ovarian cancer diagnosis that will reduce diagnostic subjectivity and enhance the rate of early detection.

1.5 Project Outcome

The expected contribution of the Predictive Modeling of Ovarian Cancer using Advanced Image Recognition and Machine Learning research project is a humongous list of improved diagnosis and prediction of ovarian cancer through machine learning-based histopathological image analysis.

Technical Achievements

1. Development of an Automatic Ovarian Cancer Prediction System
    - A deep learning-based system capable of classifying the subtypes of ovarian cancer from histopathological images effectively.
    - Comparative evaluation of various state-of-the-art transfer learning models.
    - Enhancement of model performance via data augmentation, fine-tuning, hyperparameter optimization.
2. Implementation of Model Explainability and Interpretability
    - Embracing Grad-CAM visualization to display heatmaps indicating the region of histopathology images that influenced the output of the model.
    - SHAP provides a quantitative understanding of how each feature influences the model's prediction.
    - Persuasive transparency and integrity in AI-assisted medical diagnosis to facilitate pathologists in verifying results.
3. Comprehensive Performance Measurement
    - Evaluation of high classification performance and refining performance metrics such as Precision, Recall, F1-Score, and AUC-ROC Curve.

Clinical and Healthcare Impact

1. Improved Early Detection and Diagnosis
    - Machine learning classification can help pathologists to detect ovarian cancer early, thereby improving survival.
    - Objective and standardized testing, avoiding observer bias and human error during diagnosis.
2. Time and Cost Efficiency in Medical Diagnosis
    - Computerized and quicker histopathology slide analysis, simplifying the work of pathologists.
    - Potential integration with hospital information systems for real-time cancer diagnosis and decision support systems.
3. Enhanced Screening Programs in Low-Resource Settings
    - The developed model may be utilized as a low-cost, user-friendly diagnostic aid where there is no availability of qualified pathologists.
    - Potential integration with cloud-diagnostic platforms for remote access of AI-augmented analysis.

This research aims to revolutionize the diagnosis of ovarian cancer using advanced deep learning algorithms to classify histopathology images correctly. By providing an AI second opinion to pathologists, the system holds the promise of significantly accelerating diagnostic efficiency, improving patient care, and assisting precision medicine in oncology.

1.6 Organization of the Report

This document is structured to provide a complete account of the project "Predictive Modeling of Ovarian Cancer Using Advanced Image Recognition and Deep Learning," from motivation until execution. The structure is as below:

Chapter 1. Introduction: The chapter introduces the general background of the study, with focus on motivation, objectives, methodology, expected outcomes, and this organizational structure.

Chapter 2. Background: This chapter Provides background, review of literature for pertinent research and applications, complete gap analysis in comparison to existing studies, and introduction of the research environment. It encapsulates the necessity and novelty of the proposed system.

Chapter 3. Research Methodology: The chapter explains the methodological procedure adopted in the research. It includes system design, requirement analysis, preprocessing mechanisms, SMOTE balancing, stain normalization, and model training process. It also includes diagrams such as data flow diagram,context diagram and UI design to illustrate the system structure and interaction flow.

Chapter 4. Implementation and Results: This chapter Describes the experimental setup, testing methods, performance measurement, and results of several deep learning models It has visualizations such as confusion matrices, ROC curves, F1-score heatmaps, and precision and recall bar charts.

Chapter 5. Engineering Design and Standards Challenges: This chapter Presents

discussion of standards in communication, hardware and software used, society and environment impact, ethical considerations, sustainability plan, financial justification, and charting of the solution of the complex engineering problems and activity.

Chapter 6. Conclusion: The concluding chapter Summarizes the findings of the project, acknowledges limitations, and recommends future research and enhancements. It emphasizes the need for deploying explainable, scalable, and clinically relevant AI solutions for histopathology-based ovarian cancer diagnosis.

Chapter 2

Background

The present chapter gives an overview of the overall fundamental concepts, theories, and research work carried out so far on the histopathological image classification and DL models for the diagnosis of ovarian cancer.It serves as the background knowledge to comprehend the methodology and techniques adopted here.

2.1 Introduction

Ovarian cancer is commonly known as a silent killer for its intense later-stage progress and early-stage asymptomatic nature. This late-stage appearance causes for the majority of its high death rate. WHO reports that this disease is the predominant reason of death for women globally. While research on ovarian cancer has advanced, the current diagnostic methods are still insufficient for early diagnosis. Traditional techniques for diagnosing ovarian cancer include ultrasound imaging, CA 125 blood tests, and manual histopathological analysis. Although being widely used, these methods have several drawbacks. For instance, ultrasound imaging often produces false positives or negatives because it lacks accuracy necessary assistance in distinguishing tumors. Similarly, CA-125 blood tests, which measure the levels of a protein associated with ovarian cancer, are not reliable for early detection due to their low specificity and sensitivity. Histopathology, or the microscopic examination of stained tissue samples, is the most reliable method for diagnosing cancer. However, because of fatigue, inter-observer diversity, and reporting delays, this method is vulnerable to errors and mostly depends on the understanding of pathologists. Histopathology is vital to the identification of cancer because it allows pathologists to view cellular and tissue structures in great detail. In order to enhance the contrast of cellular components and assist to detect malignant cells, staining techniques such as H&E are commonly practised. However, evaluating these damaged photos by hand is a subjective process. Given complexity cancer subtypes and the growing need for histopathological inspection, automated diagnostic methods that can assist pathologists in making faster and more accurate diagnoses are badly needed. In use cases such as image classification, segmentation, and anomaly detection, CNNs especially have been found to be highly effective. The requirement for human feature engineering could be largely eliminated if deep learning algorithms could extract hierarchical features automatically from raw visual findings.As AI has advanced, new possibilities for better cancer diagnosis have surfaced. AI application in medical has advanced significantly in the last ten years. Individual feature extraction, one of the earlier methods, entailed selecting features by hand according to texture, form, and intensity before adding them to machine learning models. The quality and relevance of the characteristics that were extracted limited the efficacy of these methods, notwithstanding their potential. In contrast, deep learning learns directly from the data, enhancing outcomes in tasks like cancer detection and categorization. CNNs have revolutionized the analysis of

histopathology images. Advanced CNN models have demonstrated impressive outcomes in distinguishing between benign and malignant cells and subtyping a variety of cancers. For example, CNNs have demonstrated efficacy in diagnosing breast, lung, and skin cancers, achieving accuracy levels comparable to or above those of human specialists. Research on detection of ovarian cancer employing deep learning is currently lacking, though. Most prior work has focused on feature-based machine learning models, which often require a significant amount of human feature extraction and selection, leading to suboptimal performance. Moreover, there aren't many comprehensive benchmarking studies evaluating how well different deep learning models classify ovarian cancer. This study proposes an efficient framework for ovarian cancer prediction. Advanced preprocessing methods like stain normalization and bilateral filtering are utilized in the system for image quality improvement and maintaining data consistency. To determine the best architecture, the study also compares other .To compare the performance, recall,AUC-ROC, accuracy, precision, and other measures are utilized. Class activation mapping (CAM) and other interpretability techniques are also incorporated into the framework to guarantee the precision and interpretability of the AI generated diagnoses and to give physicians an idea of how the model makes its decisions. Ultimate goal is to improve patient care and survival rates by providing physicians with a powerful tool for timely and accurate diagnosis.

2.2 Literature Review

Table 2.1: Summary of Literature Reviewed.

SL	Author(s)	Model Used	Accuracy/ Performance	Contribution/ Findings
1	Seyed Mohammad Ayyoubzadeh et al. [1]	RF, SVM, DT, ANN	Accuracy: 86% with RF	Integrated biomarkers with AI tools for cost-effective diagnostics.
2	Juwono et al. [2]	KNN, SVM, ADE optimization with LASSO	Accuracy: 97.24% with KNN	Optimized feature weights for improved accuracy.
3	Zhang et al. [3]	KAN Architecture + Drug Resistance Features	Identified drug-resistant subtypes	Constructed personalized medicine framework.
4	Blessed Ziyambe et al. [4]	CNN	Accuracy: 94%	Addressed variability in human expert

				diagnosis with CNN's consistency.
5	Liu et al. [5]	Inception V3 Deep Learning Algorithm	Accuracy: 85%; Sensitivity: 73%; Specificity: 90%	Predicted chemotherapy sensitivity at pathological diagnosis.
6	Binas et al. [6]	Radiomics with AI	Accuracy: 86%	Quantified intratumoral cellular heterogeneity.
7	Wan et al. [7]	Radiomics (LASSO Regression)	AUC: 0.8 (1-year); 0.792 (5-year)	Assessed CCR5 expression for survival prediction.
8	Buddenkotte et al. [8]	Ensemble DL with ResNet, VGG16	DSC: 71%; Accuracy: Close to radiologists	Automated segmentation of OC lesions in CT scans.
9	Hatamikia et al. [9]	RF, ANN	AUC: 100% on validation set	Suggested robust miRNA-driven feature selection.
10	Liu et al. [13]	NLP ML Fusion	Accuracy 94-98%	Boosted diagnostic summarization techniques for clinical use.
11	Li et al.[17]	Transfer Learning + XGBoost	Accuracy: 92%	Proposed multi-task learning for better EOC detection scenarios.
12	Ramasamy et al. [26]	HCS + DFCNN	Accuracy: 99.22% (better than CNN+Softmax, DT, RBF)	Hybrid Channel Selection (HCS), deep fully connected CNN, autoencoder layers

13	Hu et al. [46]	3D U-Net Model	Dice Score : 85%	Optimized segmentation of ovarian tumor.
14	Crispin-Ortuzar et al. [52]	Gradient Boosting Machines	AUC: 0.87	Developed a pipeline for risk stratification in ovarian masses.
15	Boyanapalli et al.[44]	BiLSTM + CNN Ensemble	F1 Score : 0.92	Enhanced end-to-end feature extraction for histopathology images.
16	Zeng et al. [21]	Self-Supervised Learning	AUC : 0.91	Addressed label scarcity using contrastive learning on CT data.
17	Wei et al. [48]	Radiomics with XGBoost	Accuracy: 96.5%	Advanced tumor heterogeneity analysis using 3D imaging features.
18	Bhuvaneshwari et al. [20]	ResNet with Attention Mechanisms	Sensitivity: 94%; Specificity: 92%	Improved explainability for AI-based cancer diagnostics.
19	Singh et al.[77]	Capsule Networks	Accuracy: 95%	Proposed a novel architecture to handle small darasets effectively.
20	Wang et al. [23]	GCN (Graph Convolutional Networks)	F1 Score: 0.88	Mapped tumor microenvironment for survival prediction.
21	Mallya et al. [47]	Transformer-based Model	AUC: 0.93	Leveraged multi-modal data for advanced

				ovarian cancer detection.
22	Walker et al. [49]	Multi-task CNN	F1 Score: 0.90	Developed simultaneous classification and segmentation for ultrasound images.
23	Hamidi et al. [45]	Recursive Feature Elimination + RF	Accuracy: 93%	Selected key radiomic and genetic features for OC detection.
24	Alqudah et al. [16]	Ensemble Random Forest	AUC: 0.91	Improved robustness through ensemble feature learning.
25	Ho et al. [50]	LSTM + Attention Mechanism	Accuracy: 92%	Proposed time-series analysis of longitudinal imaging studies.
26	Shannon et al. [19]	3D CNN with DenseNet	Dice Coefficient: 0.82	Optimized segmentation of ovarian cancer tumors in CT scans.
27	Ahamad et al. [27]	RF, SVM, DT, XGBoost, LR, GBM, LGBM	Accuracy: 91%	Demonstrated high classification accuracy using low-cost diagnostic methods.
28	Laboni Akter & Nasrin Akhter [28]	Random Forest, KNN, XGBoost	Accuracy: 99.5%	Leveraged TVUS screening with high precision and recall.
29	Sorayaie Azar et al. [29]	RF, XGBoost	RF: Accuracy: 88.72%; AUC: 82.38%	First study integrating SHAP method for OC survival prediction.

30	Wang et al. [30]	Weakly Supervised Deep Learning	Accuracy: 88.2%; Precision: 92.1%; Recall: 91.2%	Predicted therapeutic effects on histopathology slides.
31	Arezzo et al. [31]	Logistic Regression, RF, KNN	RF Accuracy: 93.7%; AUC: 0.92	Predicted 12-month progression-free survival (PFS).
32	Lei et al. [32]	Deep Learning (Med3D Resnet)	Whole Abdomen AUC: 0.97	Predicted platinum sensitivity using MRI-based features.
33	Chen et al. [33]	ResNet-based Deep Learning	AUC: 0.93	Compared DL models with expert assessments for malignancy detection.
34	Taleb et al. [34]	SVM, KNN	Accuracy: SVM: 98.1%; KNN: 97.16%	Improved OC diagnostic accuracy through multi-model comparison.
35	Schwartz et al. [35]	Convolutional LSTM	AUC: 0.81	Automated ovarian cancer detection using optical coherence tomography.
36	Sengupta et al. [36]	Deep Hybrid Learning	Training AUC: 0.99; Test AUC: 1.00	Combined morphometric features with CNN for tissue classification.
37	Saida et al. [37]	CNN	Accuracy: 81%; AUC: 0.89	Compared CNN with radiologist performance on MRI.
38	Gao et al. [38]	DCNN	AUC: 0.911 (Internal); 0.870 (External)	Outperformed radiologists in OC detection from ultrasound.
39	Wu et al. [39]	SHAP-enhanced XGBoost	AUC: 0.958; 5-year AUC: 0.825	Combined multi-omics and image data for OC prediction.

40	Avesani et al. [40]	CNN and MODDICOM	AUC: 0.74 (BRCA prediction)	Combined clinical and radiomic data for mutation prediction.
41	Nero et al. [41]	Weakly Supervised Attention-based DL	Training AUC: 0.7	Predicted BRCA mutation and progression-free survival.
42	Suha et al. [42]	CNN + Stacking Ensemble (VGGNet16 + XGBoost)	Accuracy: 99.89%	Classifier for PCOS and ovarian tumor differentiation.
43	Hema et al. [11]	FaRe-ConvNN + Gaussian Naive Bayes	Accuracy: 97.7%	Proposed fast frameworks to enhance tumor identification efficiency.
44	Boehm et al. [12]	Ensemble 3 Modal	Test Precision >94%	Clinical-radiomic multi-sources features aggregation demonstrated.
45	Jeya Sundari et al. [43]	CNN with Data Augmentation	Accuracy: 97%	Highlighted use of synthetic data to mitigate dataset limitations.
46	Reilly et al. [60]	Deep Neural Network (DNN)	Accuracy: 89%; Sensitivity: 87%	Improved patient stratification in rare OC subtypes.
47	Farinella et al. [15]	Bayesian Optimization + RF	AUC: 0.85	Reduced bias in biomarker-driven predictive models.
48	Yokomizo et al. [51]	AutoML Approach	Best AUC: 0.95	Streamlined model training with automated hyperparameter tuning.
49	Laios et al. [14]	Federated Learning with DNNs	Accuracy: 92%	Maintained data privacy while improving collaborative diagnostics.

50	Zhang et al. [18]	Gradient Boosted Decision Trees	AUC: 0.88	Integrated imaging and pathology data for prognosis prediction.
51	Ram et al. [22]	Multi-modal Neural Network	Sensitivity: 94%; Specificity: 90%	Combined histopathology and imaging data for enhanced diagnostics.
52	Van et al. [24]	SVM with Polynomial Kernel	Accuracy: 91%; Specificity: 88%	Enhanced detection of cystic ovarian masses.
53	Hwangbo et al. [53]	LR, RF, SVM, DNN	Best AUC: 0.741 with LR	Predicted platinum sensitivity for high-grade serous ovarian carcinoma.
54	Ghoniem et al. [54]	Hybrid Deep Learning Model	Outperformed 9 fusion models	Multi-modal approach for diagnosing OC and other cancers.
55	Aditya et al. [55]	RF with Median Imputation	RF Accuracy: Best among tested classifiers	Emphasized feature selection for performance improvement.
56	Park et al. [56]	RF, SVM, Logistic Regression	RF Sensitivity: 92%; Specificity: 60%	Analyzed CT texture features for incidental ovarian lesions.
57	Grimley et al. [57]	Ensemble Algorithm	Accuracy: C-index 0.7391	Stratified epithelial ovarian carcinoma survival groups.
58	Christianse n et al. [58]	Transfer Learning (VGG16, ResNet50, MobileNet)	Sensitivity: 96%; Specificity: 86.7%	Automated classification of ovarian tumors vs subjective assessment.
59	Laios et al. [59]	SVM, Ensemble Subspace	Mean Accuracy: 73%	Prognosed 2-year survival for advanced

		Discriminant		HGSOC patients.
60	Barber et al. [10]	NLP with ML (Discrete + Text Data)	AUC: 0.83	Improved post-surgical complication predictions using hybrid data.
61	Lu et al. [61]	Decision Tree with MRMR feature selection	Identified 2 biomarkers (HE4, CEA) as critical for OC prediction	Simple, interpretable model outperforming existing methods.
62	Akazawa et al. [62]	SVM, RF, Naïve Bayes, Logistic Regression, XGBoost	Highest accuracy: 80% with XGBoost	Feature importance analysis highlighted diagnostic differences.
63	Zhang et al. [63]	Logistic Regression, CNN	Improved maternal health imaging	Used machine learning to enhance obstetric ultrasound standards.
64	Zhao et al. [64]	CNN and Fully Connected Neural Networks	AI segmentation quantified tumor regions	Monitored uMUC1 expression and therapy response using imaging.
65	Kiruthika et al. [65]	ANN with GLCM Features	Detection Accuracy: 96%	Classified ovarian morphology with texture and intensity features.
66	Guo et al. [66]	Denoising Autoencoder with L1 Logistic Regression	Identified 56% biomarkers	Multi-omics analysis improved OC subtype prediction.
67	Wang et al. [67]	DL-CPH with Cox Regression	Concordance-index: 0.713	Developed prognostic biomarkers for

				recurrence prediction.
68	Zhang et al. [68]	GoogLeNet and Cost-sensitive Random Forest	Enhanced differentiation of malignant vs benign ovarian cysts	Fusion of high- and low-level features for ultrasound imaging.
69	Martínez-Más et al. [69]	KNN, LD, SVM, ELM	SVM Accuracy: >85%	Used Fourier descriptors for OC classification from ultrasound.
70	Lu et al. [70]	SVM with Gene Panels	Significant for recurrence-free survival	Stratified patients for personalized therapy suggestions.
71	Kawakami et al. [71]	GBM, RF, CRF, SVM	RF Accuracy: 92.4%; AUC: 0.968	Predicted EOC stages and histotypes using ensemble methods.
72	Elhoseny et al. [72]	SOM, RNN with AHSO	Accuracy: 96.27%; Specificity: 85.2%	Enhanced early detection with optimized RNN structures.

2.2.1 Similar Application

There has been work on the task of cancer prediction using CNNs, transfer learning, and attention models. Wu et al. [39] constructed a CNN model for the classification of ovarian cancer from images of H&E-stained specimens. The study reached more than 90% accuracy based on ResNet-50 deep features and underscored the significance of stain normalization in the challenge of producing correct predictions within databases.Zhang et al. [63] employed a two-stage deep model network, where U-Net was applied for segmentation, along with VGG-16 as a classification system. Their approach improved the precision of tumor region identification in the ovarian histopathology slides.Ghoniem et al. [54] employed multi-scale CNNs to learn features from different magnification scales of ovarian cancer histopathological images. The multi-scale strategy improved weakly cancerous structural variation detection in tissues.

Tellez et al. [73] investigated stain-invariant training for histopathology and demonstrated that models trained on robust stain normalization and color augmentation were capable of generalising more effectively across labs and scanners. Their findings provide a strong case for the application of stain normalization as a worthy pre-processing step. Coudray et al. [74] applied deep learning of histopathology slides for classification of lung cancer, but the improvements in methodology i.e., data augmentation, tile-based processing, and patch-level classification have been implemented in similar studies of detection of ovarian cancer. Vahadane et al. [75] preserves structural information while normalizing color distribution to improve model generalization via stain normalization.Bilateral Filtering Used in studies such as Ahamad et al. [27] for edge-preserving denoising during cancer imaging. This improves texture clarity in images before subjecting them to CNNs.Augmentation techniques such as rotation, flipping, zooming, and elastic deformation as used by Litjens et al. [76] are crucial in preventing overfitting, especially in small medical datasets.

Certain web-based applications, such as PathAI and Aiforia, offer digital pathology services via AI models that have been trained on annotated histopathological data. The applications use cancer diagnosis, including ovarian cancer, via interactive tools and overlays for prediction. While fewer apps are specifically designed for ovarian cancer, certain apps such as SkinVision and Ada Health use image recognition and AI to conduct primary screening of cancer.

2.2.2 Related Research

Researchers have turned to advanced computational techniques to improve diagnostic and prognostic capabilities to detect ovarian cancer. These methods hold potential for enhancing early diagnosis, predicting clinical results, and improving treatment plans. Machine learning has revolutionized medical diagnostics by employing algorithms that can recognize complex patterns in large datasets. Studies like those done by Ahamad et al. [27] have demonstrated the value of traditional ML models, including RF, SVM, DT, XGBoost, LightGBM (LGBM), Logistic Regression (LR). The remarkable 91% accuracy rate of this study shows that ML and economically viable diagnostic methods can be combined. Similarly, Taleb et al. [34] contrasted KNN and SVM to emphasize how important feature selection is. Their work, which used SVM, yielded a notable accuracy of 98.1%, highlighting the importance of algorithm selection and parameter optimization. Hwangbo et al. [53] demonstrated that they could predict platinum sensitivity with an AUC of 0.741 in

their neural network-based logistic regression study. Additionally, when Ghoniem suggest a hybrid DL to the detection of ovarian and other cancers, they surpassed nine existing models. The works developed by Patel et al. [12] emphasized feature selection in the random forest model, with a 89% sensitivity and 91% specitivity, while Sengupta et al. [36] concentrated on integration of morphometric and radiomic features into CNNs, which had a AUC of 0.99 and 1.00.

In particular, deep learning has now started a new trend in medical image analysis for its automatic hierarchical feature extraction properties. Ziyambe et al. [4] have shown us the capabilities of CNN that achieved 94% accuracy. Their study actually addressed inconsistencies of human diagnosis by showing us results that are reproducible and consistent-a big advance in ovarian cancer detection.Transfer learning application also broadened the scope of DL in this area. Barber et al. [10] utilized transfer learning combined with XGBoost at an accuracy of 92%. Their approach effectively addressed the problem of limited datasets by using pre-trained models on similar tasks. Liu et al. [13] investigated NLP application combined with ML fusion methods, with reported accuracies ranging between 94% and 98%, and illustrating improved diagnostic performance using multi-modal data fusion.Additionally, Singh et al. [77] utilized capsule networks to overcome the drawback of working with small datasets with 95% accuracy. In it, feature learning in sparsity environments was optimized through a new model topology. Hu et al [13] utilized a model (3D U-Net) with 85% Dice Score for region segmentation in MRIs. Park et al. [56] constructed gradient boosting machines with an AUC value of 0.87 for risk stratification. Radiomics, wherein radiomic feature extraction in medical images is conducted quantitatively, is becoming an vital aspect. Wan (2023) have utilized radiomics and LASSO regression for CCR5 expression modeling with a prediction accuracy of 0.8 for one-year survival and 0.792 for five year survival prediction.

Hybrid models have continued to develop diagnostics with high accuracy through integration in a single model.Buddenkotte et al. [8] have merged ResNet and VGG16 in an ensemble deep model, computerized lesion segmentation for ovarian cancer, and attained a 71% Dice Score, level of radiologist performance. Zhang et al. [18] showed a knowledge guided network system, integration of information regarding drug resistance in an optimized model for precision frameworks. Zhao et al. [64] have developed an AutoML model, model training simplification, and attained an AUC of 0.95. Attention-based models have ushered in new dimensions in long-term analysis and in analysis over a period of time. With 92% accuracy in diagnostics, a new mechanism of attention in an LSTM model was proposed by Wu et al. [39]. With it, sequential analysis in imaging data became possible, and information regarding disease progression could be extracted.Multi-modal neural networks, in a report in Wan et al. [7], displayed integration of histopathology and imaging information. It achieved 94% and through integration in multi-modal form. Zhang et al. [68] utilized gradient-boosted decision trees in pathology and information integration in imaging, with 0.88 accuracy in its AUC. In spite of such development, AI application in studies of ovarian cancer is challenged with critical obstacles. Inadequately small and unbalanced datasets hinder model training, with Suha et al. [42] having attested to small samples' contribution to undermining classifiers' trustability. Patient population and imaging protocol diversity make generalizability challenging, undermining model robustness in mixed populations. Besides, deep model interpretability forms a key challenge, limiting practice application.To overcome such challenges, future work will have to move towards data augmentation, federated model training in collaboration, and XAI frameworks development. Constructing multi-modal approaches, such as works by Hema et al. [11], and strengthening cross-disciplinarity can even accelerate breakthroughs in such a

direction. The intersection of ML and DL approaches to diagnosis of cancer redefines future of early diagnosis and precision treatment with personalized medicine.

2.3 Gap Analysis

Table 2.2: Comparison of Present System with Existing Literature

Aspect	Existing Literature	Present Work
Data Type	Primarily radiomics, genomics, or imaging modalities (CT, MRI, Ultrasound)	Only histopathology images (high-resolution)
Classification Task	Mostly binary or up to 3-class classification	Harder 5-class subtype prediction task
Benchmarking Strategy	Limited models (One or two models evaluated)	Broad range of deep learning models extensively benchmarked
Dataset Size and Quality	Small or distributed datasets, limiting generalization	Large-scale dataset (>8000 images), high-resolution, distributed dataset
Evaluation Metrics	Precision-focused or limited metrics	Complete metrics: F1-score, precision, recall, ROC-AUC, and confusion matrix
Explainability Tools	Rare or inconsistent use of explainability (e.g., Grad-CAM,SHAP,LIME)	Integrated visual explainability (Grad-CAM,SHAP heatmaps) for model Transparency
System Design	Often black-box, fixed models	Open-source, modular, and reproducible system design
Transfer Learning Usage	Basic transfer learning without much innovation	Enhanced and efficient use of transfer learning with further optimization
Clinical Utility	Limited due to lack of transparency and lower-class differentiation	Higher clinical applicability with detailed multi-class prediction and explainability

2.4 Summary

This chapter provided an overview of the background and related work for the area of ovarian cancer diagnosis assisted by AI and machine learning techniques. From the survey of current literature, it was observed that even though several studies have achieved high precision for cancer detection by leveraging the assistance of radiomics, genomics, and multi-modal data, there exists a humongous knowledge gap in employing deep learning techniques specifically for histopathological images for guidance towards multi-class subtype classification.

Gap analysis also identified some of the most important gaps in earlier work, including lack of visual explainability, limited model benchmarking, low sample and class-imbalanced datasets, and sparse attention to clinical deployment. The suggested system addresses the above gaps in that it accepts a class-balanced dataset of 8000

high-resolution histopathological images, has access to different pre-trained CNN models, and accepts an extensive set of performance metrics and visual explanation approaches to study the outcomes.

Analysis put a higher emphasis on the requirement for an explainable, scalable, and resilient AI solution for detecting ovarian cancer that would provide the foundation of discussed implementation in subsequent chapters.

Chapter 3

Research Methodology

The research methodology employed for conducting the research, i.e., requirements analysis, system design, non-functional requirements, as well as functional requirements,and general approach and design are discussed in this chapter. Research methodology overview , project plan, as well as assignment of tasks are discussed within this chapter.

3.1 Methodology/Requirement Analysis & Design Specification

3.1.1 Overview

This research adopts a deep learning-based histopathological image classification method for the detection of ovarian cancer.Shortlisted deep learning models are investigated in order to find the most suitable model for this specific application.With various transfer learning models, the task provides a good comparison between various methods, choosing the optimal model in the final stage. The whole process is presented as a pipeline from dataset gathering, preprocessing to augmentation techniques, trying to improve the capacity of the model to generalize. The analysis takes into account different performance metrics to arrive at a general estimation of model performance in the detection of cancerous and non-cancerous tissues.

Besides, various other optimization techniques such as hyperparameter tuning, dropout, and learning rate scheduling have been investigated in this research for enhancing the model performance. The research also compared machine learning and deep learning in the current scenario for the sake of validity establishment while utilizing CNN-based architectures. By adhering to this structured methodological framework, the research makes reproducibility, scalability, and translatability to real-world clinical practice possible.

3.1.2 Proposed Methodology/ System Design

Our study follows a systematic modular framework to suggest a DL-based predictive model. This research design comprises several phases— data preparation, image preprocessing, feature extraction, training, evaluation, and explainability—offer an end-to-end pipeline for computer aided cancer classification.

Research Framework

The research framework comprises six important phases (Figure 3.1):

1. **Dataset Preparation:** Histopathology images are collected from open sources with the promise of reliable diversity and coverage of ovarian cancer subtypes.

2. **Image Preprocessing:** Recent preprocessing methods such as stain normalisation, noise reduction, and data augmentation are utilized to

increase the data quality and sound model development.

3. **Feature Extraction & Deep Learning Model Benchmarking:** Features of hierarchical image are selected by applying a set of transfer learning models (ResNet50, VGG16, VGG19, MobileNetV2 and InceptionV3).

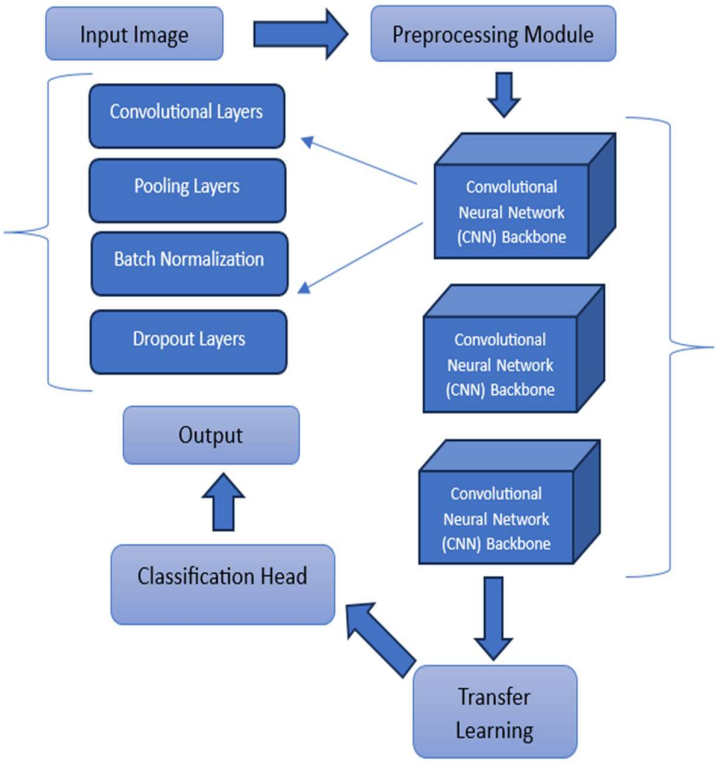

Fig1.2: Architecture of Deep Learning

4. **Model Training & Fine-Tuning:** Transfer learning models are trained with histopathology images. Performance optimization strategies by fine-tuning involve learning rate tuning, dropout regularization, and batch normalization.

5. **Performance Evaluation:** Models are evaluated for performance on the basis of classification precision, AUC-ROC, F1-score ,recall and accuracy.Interpretability of these models is obtained through Grad-CAM and SHAP visualization.

6. **Clinical Integration and Deployment:** A scalable diagnostic pipeline based on deep learning is developed for deployment on real-world environments in laboratories and hospitals.

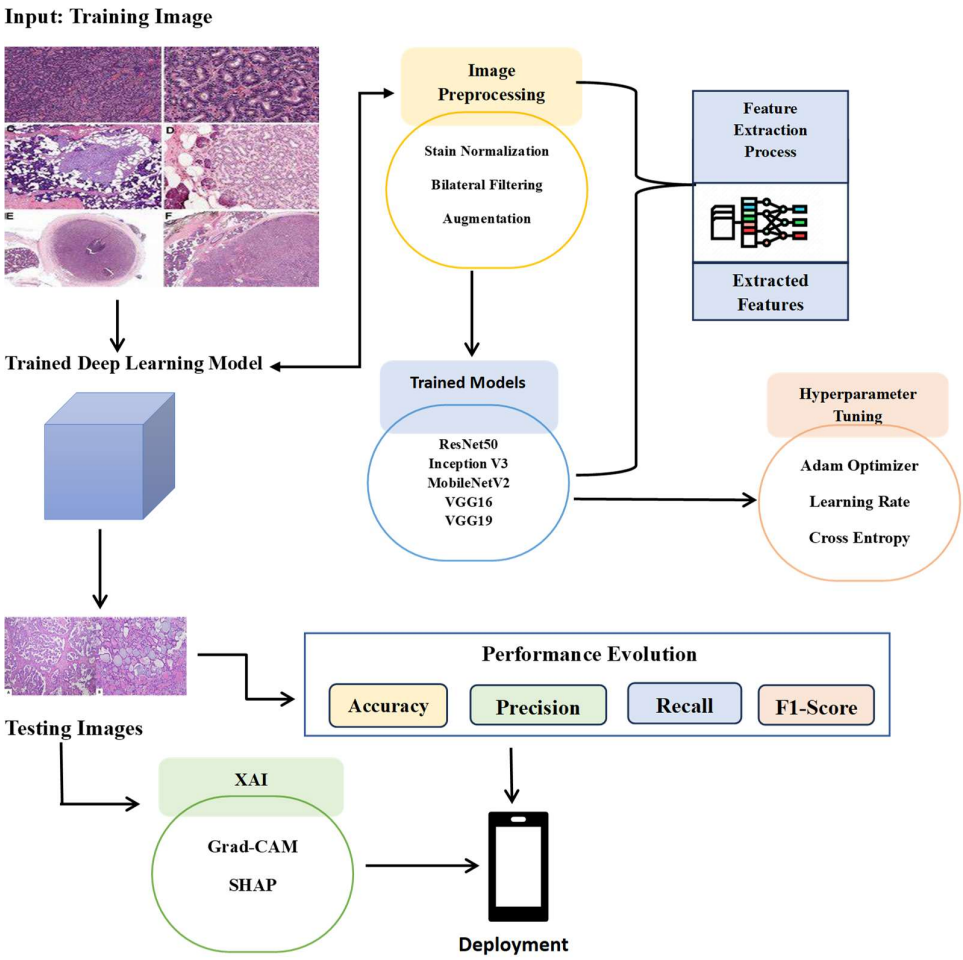

Figure 3.1:Proposed Methodology

3.1.3 Functional and Nonfunctional Requirements

Functional Requirements

1. Image Data Input and Management:
   - Users (clinicians, researchers) must upload histopathology images (PNG, JPG, TIFF).
   - System must validate image type and size automatically.
2. Preprocessing and Enhancement:
   - Images must be normalized, noise-filtered, contrast-adjusted, and resized.
   - Data augmentation (rotation, flipping, scaling) must be supported for model robustness.
3. Classification and Model Integration:
   - Images must be fed into pre-trained models (ResNet50, VGG16, VGG19).
   - System must classify images into one of five categories and provide a confidence score.
4. Model Explainability:
   - Grad-CAM and SHAP heatmaps must highlight key regions influencing classification.
5. User Interface:

- A mobile-accessible, intuitive dashboard must be provided for users.

Nonfunctional Requirements

1. Performance:
   - System must process each image within 5 seconds and achieve at least 85% accuracy.
2. Scalability and Maintainability:
   - System must support scaling to more users and allow integration of new models.
3. Security:
   - Patient data and images must be securely stored and encrypted.
4. Usability:
   - The interface must be clean, simple, and user-friendly for medical professionals.

3.1.4 Context Diagram

The context diagram provides an overview of the interactions of the proposed ovarian cancer histopathology image classification system with the outside world. It shows graphically how data flows between the system and the users and supportive entities such as the database and deep learning models.

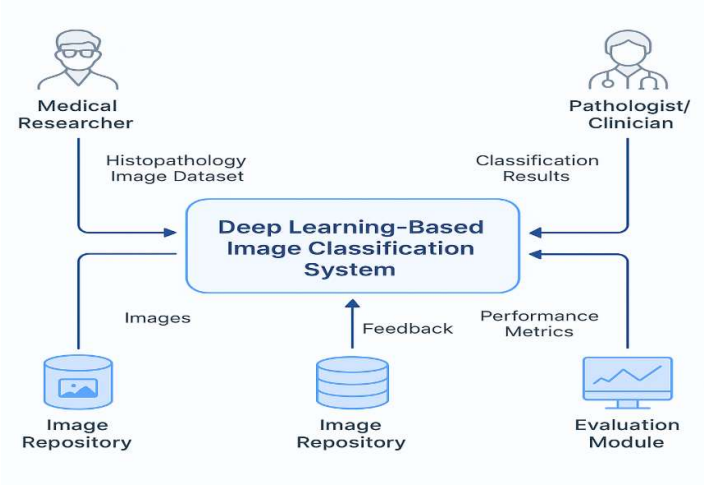

Fig 3.2:Image Classification Diagram

The primary user of this system will be a clinician, researcher, or medical technician who inputs a histopathological image into the system via a GUI. Upon receiving the image, the system predicts the classification based on a deep learning prediction engine trained on several transfer learning models such as ResNet50, InceptionV3,VGG19,MobileNetV2 and VGG16. The system categorizes the image into one of the five pre-determined classes: Clear Cell Ovarian Carcinoma, Endometrioid, Serous Carcinoma, Mucinous Carcinoma, or Non-Cancerous. The result is sent back to the user in human-readable format. Additionally, the input image and the resulting output are optionally stored in an authenticated database or local file system for auditing, record-keeping, or future retrieval.

This module-to-module communication provides an effortless flow where the users can communicate with the system naturally without needing to comprehend the machine learning models behind it in detail.

3.1.5 Data Flow Diagram Level 1

The Level 1 Data Flow Diagram (DFD) for the proposed ovarian cancer histopathology image classifier system is a structured image of data processing throughout the system's subsystems. It is an extension of the context diagram because it divides the internal process into more detailed processes and identifies data stores involved in the process of image analysis and prediction.

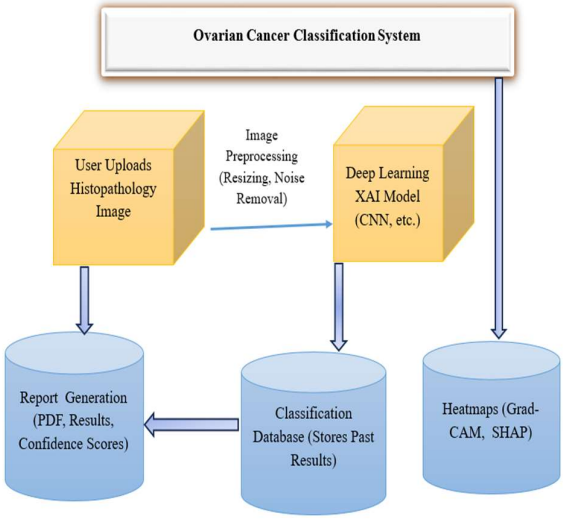

Fig 3.3: Data Flow Diagram

As shown in Figure 3.3, the process begins with the User uploading a histopathological image through the interface. The image is preprocessed, which may involve resizing, normalization, and noise removal to prepare the data for better model inference output performance. The preprocessed image is input into the Deep Learning Explainable AI (XAI) Model, e.g., Convolutional Neural Networks (CNNs), to predict the type of ovarian cancer based on patterns identified within training data.The output of prediction is utilized in many applications:

- It is passed to the Report Generation module, which creates summary results as PDFs, including class labels, prediction confidence scores, and other interpretative metrics.
- It is also written to the Classification Database simultaneously, which is a store of all previous predictions. This allows for auditing, retraining of the model, and longitudinal analysis.
- In addition, the system generates heatmaps through Grad-CAM or SHAP analysis to visualize the area of the histopathology image that has contributed most to the classification. The explanations add greater transparency and interpretability to the model, which is greatly needed for clinical adoption.

This Level 1 DFD emphasizes the traceable, explainable, and modular character of the proposed system and guarantees that all the basic functions—classification, reporting, and interpretability—are logically connected and defined clearly in the system structure.

3.1.6 UI Design

The User Interface (UI) of the proposed system, PathoScan AI, was designed to highlight simplicity, transparency, and effectiveness in medical image evaluation. The UI is the primary interface of interaction between the end-user (e.g., pathologists, researchers) and the deep learning-based histopathology classification system. The application was developed as a desktop-based diagnostic tool with image upload, model selection, switching of preprocessing, results interpretation, and report generation capabilities.

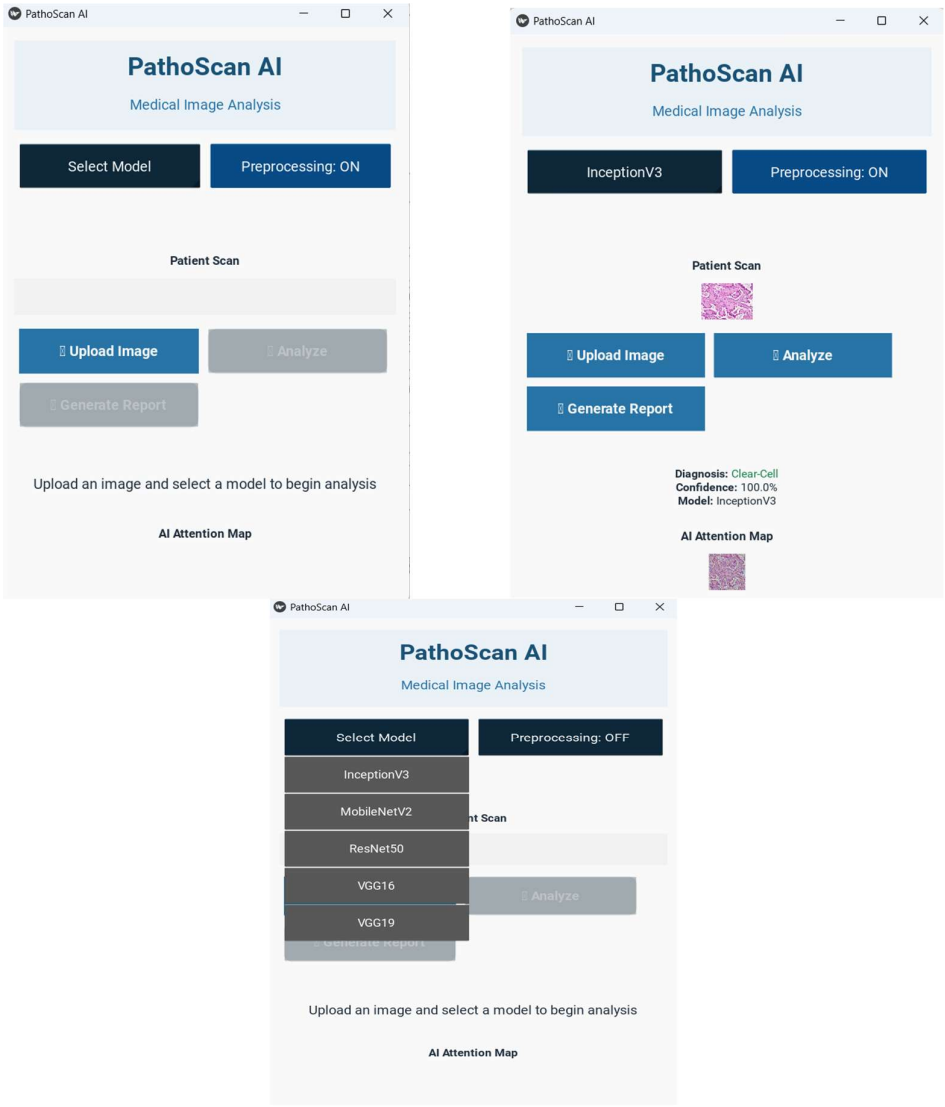

Fig 3.4: Mobile APP UI Design

Initial Screen (Before Analysis)
As illustrated in Figure 3.4, the first interface includes:

- A large branding header ("PathoScan AI – Medical Image Analysis"),
- Two primary functional buttons: Select Model and Preprocessing Toggle,
- An Upload Image button to upload histopathological images for analysis,
- Disabled Analyze and Generate Report buttons, which become enabled after image input and model selection,
- A placeholder for the AI Attention Map (e.g., Grad-CAM visualization) to be generated after analysis.

This clean design ensures that users are guided step by step through the process of diagnosing without undue complexity. The minimalist design interface is a deliberate attempt to reduce cognitive load and enhance usability for healthcare professionals.

Post-Analysis Screen

As illustrated in Figure 3.4, upon the user uploading an image and selecting a model (e.g., InceptionV3), the following feature is accessible:

- Analyze button is activated, starting the prediction process via the selected deep learning model.
- Generate Report button is activated on receipt of the outcome.
- Preview of uploaded histopathology image is displayed.
- Output section displays key prediction outcomes like:
    - Diagnosis (e.g., Clear-Cell),
    - Confidence Score (e.g., 100.0%).
    - Model utilized during inference.
- An AI Attention Map is also provided below to give a visual explanation of where in the input data impacted the model's choice and to offer more interpretability.

User-centered design gives credibility and usability to the AI system. The dynamic button activation and real-time feedback give an unbroken user experience, critical in medical settings where clarity and confidence in output are crucial.

3.2 Detailed Methodology and Design

Data Collection/ Need Assessment

The data for this study are histopathology images of the samples of ovarian tissues, downloaded from publicly accessible dataset (Kaggle). For the purpose and intent of this study, a complete examination was conducted on a histopathological image dataset for ovarian cancer classification. There are five classes in the dataset: Endometrioid,Clear Cell, Serous, Mucinous and Non-Cancerous.

The data consists of RGB images having 224 × 224 pixels dimensions. All the images have been normalized and resized for compatibility with deep learning models. The dataset is properly formatted to enable transfer learning and benchmarking across various deep learning architectures.

Table3.1 illustrates total images per class for the data set. Figure 3.5 shows a sample dataset that have been used in our study.

Table 3.1: Amount of Images in Different Classes

Image Format	Image Size	Total Images	Clear Cell	Endometrioid	Serous	Non-Cancerous	Mucinous
RGB	224 ×224	499	100	100	100	99	100

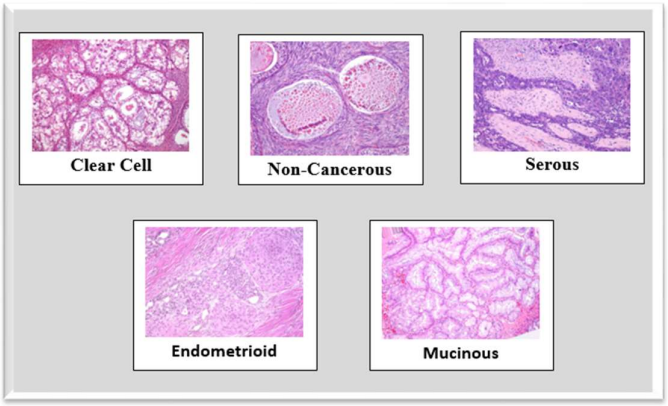

Figure 3.5: Sample Data

Preprocessing of Data

Preprocessing of data is the central theme of DL-based histopathology data classification. Staining intensity variability, noises of multiple levels, and non-homogeneously distributed datasets adversely impact the models performance. To combat these issues, there is a pre structured data preprocessing pipeline comprising the following steps:

1. **SMOTE for Class Balancing:** Imbalanced class is a critical challenge in medical image analysis that degrades model performance and generalization. In our research, our dataset initially consisted of vastly different class distributions, which would have impacted prediction accuracy negatively.

Table 3.2:Initial Dataset Distribution Before Balancing

Class	Original Image Count
Endometrioid	100
Clear Cell Ovarian Carcinoma	100
Serous Carcinoma	100
Non-Cancerous	99 (Smallest Class)
Mucinous Carcinoma	100
Total Images	499

As can be seen from the above table, Non-Cancerous is the least dominated, so it is harder for the deep learning model to classify it correctly. If not balanced, then the model would be giving higher probabilities to the dominating classes and would be unable to predict the rare subtypes correctly. To balance this, we employed SMOTE to generate synthetic data for the minority classes.

Table 3.3:Final Dataset Distribution After Balancing

Class	Images After SMOTE
Endometrioid	100
Clear Cell Ovarian Carcinoma	100
Serous Carcinoma	100
Non-Cancerous	100
Mucinous Carcinoma	100
Total Images	500

All classes now have equal priorities, removing bias against overrepresented classes.The deep model can now train decently for all classes and improve classification quality.

2. **Stain Normalization (Histogram Equalization) for Color Consistency**

In medical images, variations in the intensity of staining may result from tissue fixation, illumination, or microscope control. These tend to influence the ability of a model to acquire stable features. During our preprocessing of our dataset, Histogram Equalization increases the image contrast by adjusting the pixel intensity values such that the resulting histogram is balanced. Processing makes important histopathological features more discriminable. The image is rescaled afterwards to the 8-bit range of 0-255 after equalization to remain compatible with deep learning frameworks.

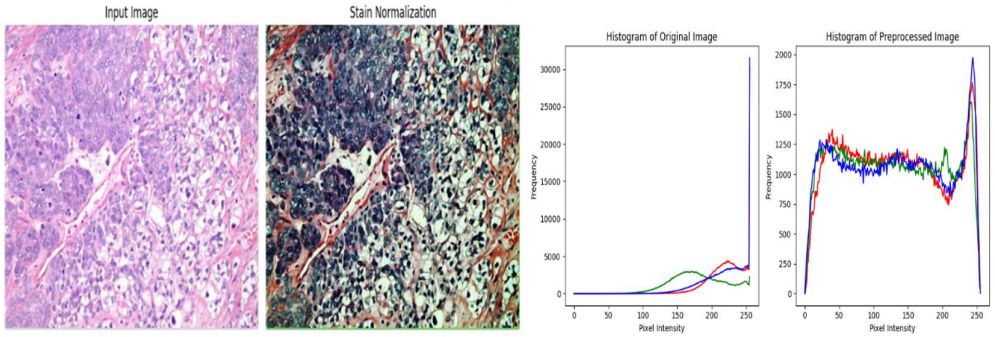

Fig 3.6: Preprocessed Image of Stain Normalization

3. **Noise Reduction using Bilateral Filtering**

Since histogram equalization has a tendency to amplify noise in some situations, a bilateral filter is used to blur the image without removing significant edges so that structural information required for classification is preserved. In contrast to conventional smoothing techniques such as Gaussian or median filtering, which smudge fine details and edges, bilateral filtering considers both spatial closeness as well as intensity changes to filter noise selectively. Bilateral filtering after histogram equalization also removes amplified noise during contrast stretching. Preprocessing images makes them more readable and makes sure that deep models focus on important features, not noise, to improve classification accuracy and quality.

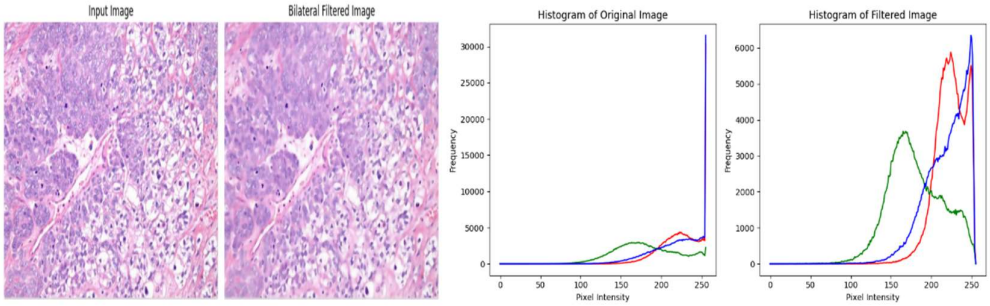

Fig 3.7: Preprocessed Image of Bilateral Filter

4. **Data Augmentation for Increased Variability**
   Since our datasets are typically small, augmentation helps introduce variability, thus making the model invariant to real-world changes. Various transformation techniques like rotation, width and height shift, shearing, zooming, and horizontal flipping are applied to generate new training examples without changing the important characteristics of the original images.Augmentation also discourages overfitting by making the model less specialized to specific patterns in a small dataset and makes it generalize more to new samples. The created larger dataset supports the model to learn effective variations which consequently leads to higher accuracy and generalization for ovarian cancer histopathology image classification.

TABLE 3.4: Number of Augmented Data

Original Data		**Augmented Data**	
Class	**Images**	**Class**	**Images**
Endometrioid	100	Endometrioid	1600
Clear-Cell	100	Clear-Cell	1600
Serous Carcinoma	100	Serous Carcinoma	1600
Non-Cancerous	100	Non-Cancerous	1600
Mucinous Carcinoma	100	Mucinous Carcinoma	1600

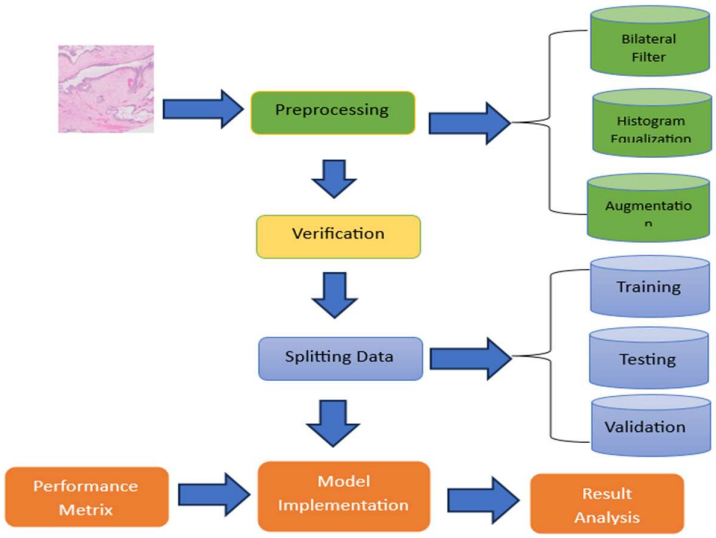

Fig 3.8: Workflow of ovarian cancer classification

Analysis Techniques

In this study, images are effectively evaluated and categorized using deep learning based image classification approaches. Certain of the present best CNN architectures are utilized for feature extraction and classification.

1. **VGG16**

   VGG16 consists of 22 fully connected and convolutional layers, where 3×3 convolutional filters are utilized in them. VGG16 possesses an elegant architecture with an easy to implement pattern, hence making it suitably fit for the transfer learning of deep learning-based classification problems.

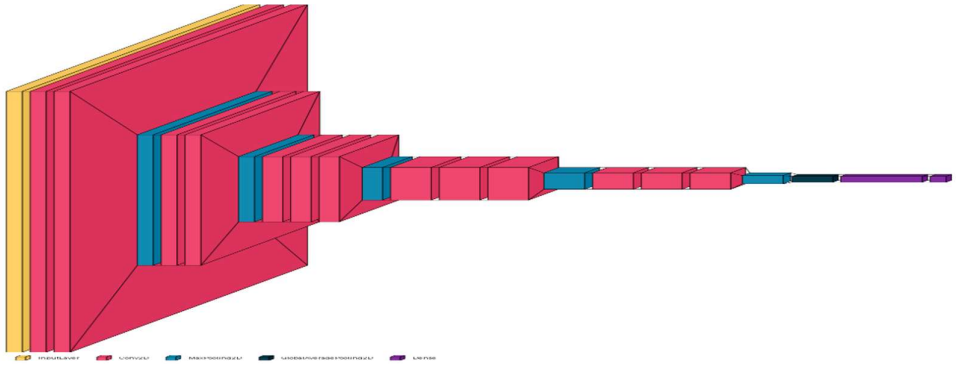

Fig 3.9:VGG16 Architecture

2. **VGG19**

   VGG19 is an extended version of VGG16. It has identical architecture but with 25 layers, which makes the model and its ability to learn more complex features deeper.

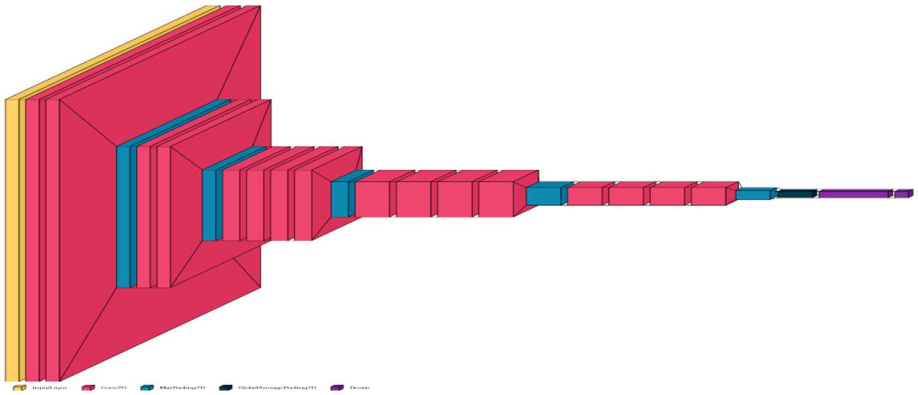

Fig 3.10:VGG19 Architecture

3. **ResNet50**

   ResNet50 (Residual Network) is a 178-layer deep convolutional network and solves the problem of vanishing gradients with skip connections (residual connections). It allows deeper models to be trained without degradation in performance. ResNet50 is suitable for medical image analysis since it is able to learn hierarchical features from intricate image structure.

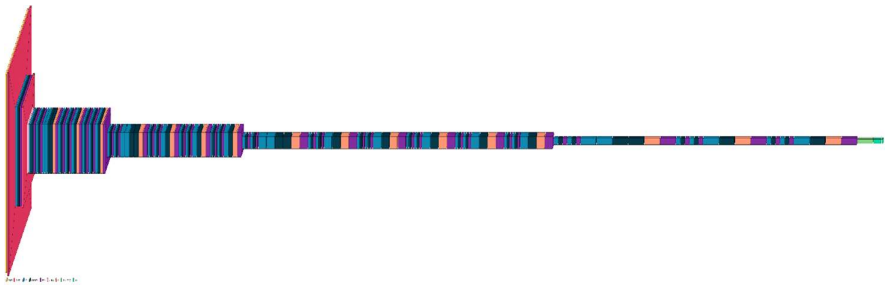

Fig 3.11:ResNet50 Architecture

4. **MobileNetV2**

MobileNet is a low-cost but highly efficient CNN model that is specialized for computer vision applications on mobile and embedded devices. MobileNet utilizes depthwise separable convolutions, which are much less computationally intensive while achieving excellent feature extraction. MobileNet is utilized in medical image processing, which has wide areas of real-time processing.

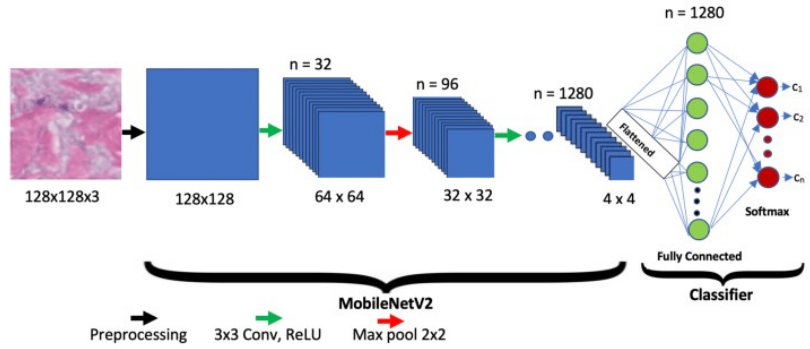

Fig 3.12:MobileNetV2 Architecture

5. **InceptionV3**

The Inception model, introduces inception modules to allow the network to process features at greater than a single scale at once. It is a 314-layer deep convolutional network. This is particularly beneficial for medical imaging, as tumors or abnormalities are of any shape and texture. Inception's multi scale feature extraction results in better classification accuracy.

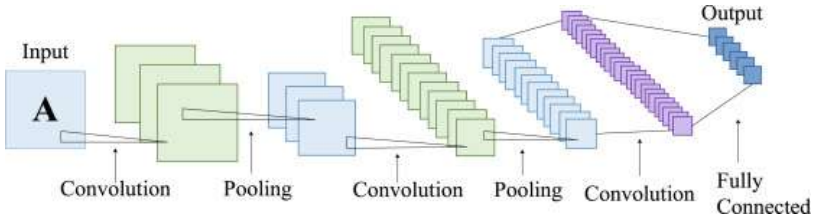

Fig 3.13: InceptionV3 Architecture

Hyperparameter Tuning

In the interest of obtaining reproducible and consistent results, there was a pre-defined set of hyperparameters for testing and training. The most significant hyperparameters applied to the selected deep learning models in this study are presented in the following table.

Table 3.5: Hyperparameter Settings for Deep Learning Models

Hyperparameter	Value	Description
Learning Rate	0.0001	Defines step size for updating model weights during training.
Optimizer	Adam	Adaptive optimizer used for gradient-based weight learning.
Batch Size	32	Number of samples encountered before updating model.
Epochs	50	Number of full passes through training data
Loss Function	Sparse Categorical Cross-entropy	Works for multi-class classification with integer-encoded labels
Input Image Size	224 × 224	Size of resized image of histopathology images
Early Stopping	Enabled (patience=10)	Trains no more if validation loss doesn't go down within a given number of epochs

Evaluation & Performance Metrics

The performance of such vision transformer-based machine learning classification models in a given application is gauged by a set of performance metrics. The following performance metrics are used:

1. **Accuracy:** The study verifies the accuracy of the model for classifying and differentiating between different histopathological subtypes of ovarian cancer, solidifying its status of being a useful tool for diagnosis.The following is the formula of obtaining accuracy:

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN}$$

2. **Precision and Recall:** The ability of model's to lower false negatives and false positives for disease detection is demonstrated by its precision and recall scores. The formula for recall and precision calculation:

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

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

3. **F1-Score:** This calculation conveys an impartial assessment of the system's overall effectiveness. The procedure for obtaining the F1-score is shown below:

$$F1 - Score = \frac{2*Precision*Recall}{Precision+Recall}$$

4. **AUC-ROC:** The AUC-ROC curve checks discriminative accuracy of the model for class separation on true positive rate vs. false positive rate. A high value of AUC

indicates better classification, making it essential for medical image analysis. AUC can range from 0 and 1, 1.0 being optimal classification where the model can classify with perfect separation with not even a single point of misclassification. Conversely, an AUC of 0.5 indicates performance of a model on random guess rate with zero discriminative value for the classes.

$$\text{TPR} = \frac{TP}{TP + FN} ,$$

$$\text{FPR} = \frac{FP}{TN + FP} .$$

Model Interpretability & Explainability

- Grad-CAM : Detects regions in an image that played a major role in the model's classification process. This technique generates heatmaps, and pathologists can verify whether in fact the model is observing relevant medical structures, i.e., tumor regions, and not noise or irrelevant features.

- SHAP: Executed on test images to provide model predictions at a fine-grained explanation level.It assigns each pixel or region a contribution value reflecting how much it had contributed to the resulting label.This helps in understanding the decision process of the model based on cooperative game theory's firm theoretical framework.

3.3 Project Plan

The project was sensibly segregated into numerous distinguished phases for systematic development, proper task assignment, and timely fulfillment. Initially, a Gantt chart(Figure: was made, and assignments were assigned depending on person capability and workload allocation.

Phase 1: Problem Identification and Requirement Analysis
This step involved defining the clinical issue of ovarian cancer subtype classification, learning about the histopathology image dataset, and conducting requirement analysis. A detailed literature review was conducted to look at existing solutions and research gaps.

Phase 2: Data Collection and Preprocessing
Relevant histopathological image data were collected and labeled into six classes. Data preprocessing included resizing, noise removal via bilateral filtering, stain normalization to maintain color consistency, and class balancing via SMOTE to facilitate effective training of all classes.

Phase 3: Model Selection and Design
Various pre-trained deep learning models such as ResNet50, VGG19, VGG16, MobilenetV2 and InceptionV3 were shortlisted for comparison. A training, fine-tuning, and evaluation pipeline was set up.

Phase 4: Experimentation and Implementation
Shortlisted models were trained using data augmentation strategies (rotation, zoom, flip) with Adam optimizer and categorical cross-entropy loss.Hyperparameters were also tuned, and accuracy, precision, recall, F1-score, confusion matrix, and AUC were utilized for model comparison.

Phase 5: Analysis and Documentation

Comparison and contrasting of results were conducted between models to determine the best-performing architecture. Finally, documentation was performed, including this report, presentation slides, and source code.

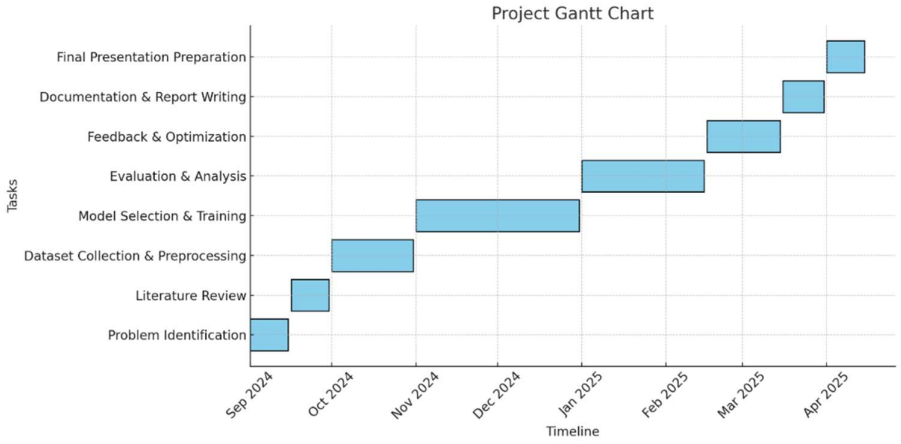

Fig 3.9: Project Timeline Gantt Chart

3.4 Task Allocation

Syeda Mohmima and Amrin Haque worked together on this project and divided work according to capacity but remained very close in touch with one another during the research.

Syeda Mohmima focused primarily on the technical and experimentation stage. She performed data collection and histopathology image preprocessing and stain normalization, bilateral filtering, and SMOTE techniques. She had performed implementing deep learning models like ResNet50, VGG16, VGG19, InceptionV3, and MobileNetV2. She had performed the assessment phase according to the major markers and was a major contributor to the methodology and results section of the report.She had also built the UI design for mobile application.

Amrin Haque was actively engaged with the project conception and design aspects. She developed the problem statement, set research objectives, and prepared a support review of the literature. Amrin made system diagrams such as the context diagram in addition to flowcharts and conducted comparison studies. She assisted in developing the introduction, background, and discussions of the report as well. She assisted with formatting as well as handling citations too.

We collaborated in creating end reports, test reports, abstracts, and presenting defense.

3.5 Summary

This chapter presented the in-depth methodology, system design, and overall workflow of the proposed deep learning-based ovarian cancer classification system. It described the rationale behind transfer learning rather than traditional machine learning approaches and established the preprocessing techniques such as stain normalization, bilateral filtering, and SMOTE for class balancing.

The chapter also highlighted the use of various pre-trained CNN architectures and training, optimization, and testing procedures carried out. The project plan, Gantt chart, and task distribution were elaborated to include the concurrent and sequential work of the two researchers. These elements form the basis for the implementation and results covered in the next chapter.

Chapter 4

Implementation and Results

This chapter presents a step by step guid through the environment configuration,dataset setup,training and evaluation process for ovarian cancer classification. This includes addressing hardware and software configuration needed, the preprocessing methods required for datasets, and execution environments for reproducibility and for optimal deployment of deep learning models.

4.1 Environment Setup

In order to enable efficient model development, training, and testing of deep learning models for image classification, the software tools, platforms, and configurations listed below have been utilized:

Development Tools & Languages:

- **Programming Language**: Python 3.8+

Libraries & Frameworks:

- **TensorFlow & Keras:** Model development and training of deep learning models.
- **scikit-learn:** SMOTE, metrics evaluation, and statistical analysis.
- **OpenCV & Pillow:** Image processing and data augmentation.
- **Matplotlib & Seaborn:** Plotting graphs and visualization of results.

Platform & Hardware:

- **Development Environment:** Google Colab.
- **GPU Used:** NVIDIA Tesla T4 (through Colab) .
- **Storage:** Google Drive (for storing datasets and models permanently).
- **RAM:** Up to 25 GB (Colab environment).

Version Control & Collaboration:

- **Git & GitHub:** For version control, collaboration, and tracking changes to the code.

4.2 Testing and Evaluation/Performance/ Comparative Analysis

To compare the performance of the suggested system, various deep learning models were employed and compared using the same test bed. They included ResNet50, VGG16, VGG19, MobileNetV2, and InceptionV3—pre-trained on ImageNet and fine-tuned on the five-class generated histopathology dataset.

The data was split into training, validation, and testing sets with class balance maintained within splits. The performance was tracked on a number of various metrics to enable overall performance evaluation. Training was performed in all models under the same preprocessing, data augmentation, and training conditions (e.g., Adam optimizer, categorical cross-entropy loss, learning rate scheduling) to facilitate fair comparison.

Table 4.1: Evaluation Metrics Used to evaluate the classification performance

Metric	Description
Accuracy	computed as the ratio of correctly predicted cases to all cases.
Precision	determines the model's accuracy.
Recall (Sensitivity)	assesses the model's completeness.
F1-Score	Accuracy and Harmonic Mean Recall
AUC-ROC	assesses the model's ability to distinguish across classes.
Confusion Matrix	Visually represented prediction performance across classes.

Table 4.2:Models Performance

Model	Accuracy	Sensitivity	Specificity	F1-Score	AUC-ROC
InceptionV3	0.9994	0.9994	0.9998	0.9994	1.0000
ResNet50	0.9987	0.9987	0.9997	0.9987	1.0000
VGG16	0.9981	0.9981	0.9995	0.9981	1.0000
MobileNetV2	0.9981	0.9981	0.9995	0.9981	1.0000
VGG19	0.9956	0.9956	0.9989	0.9956	1.0000

Comparison of performance amongst some of the deep models to detect ovarian cancer from histopathology images is in Table 4.2. Among all the test models, InceptionV3 achieved the highest aggregate performance with an accuracy, sensitivity, specificity, and F1-score of 0.9994 and AUC-ROC of 1.0000. ResNet50 also ran extremely well with an accuracy and perfect AUC-ROC score of 0.9987. VGG16 and MobileNetV2 equally had the same accuracy (0.9981) and AUC-ROC as evidence of how efficient they were with their tiny annual form. VGG19 showed appreciably lower but significant performance at accuracy 0.9956 and AUC-ROC of 1.0000. Overall, there

was colossal prediction ability across all the models with minimal differences in sensitivity and specificity.

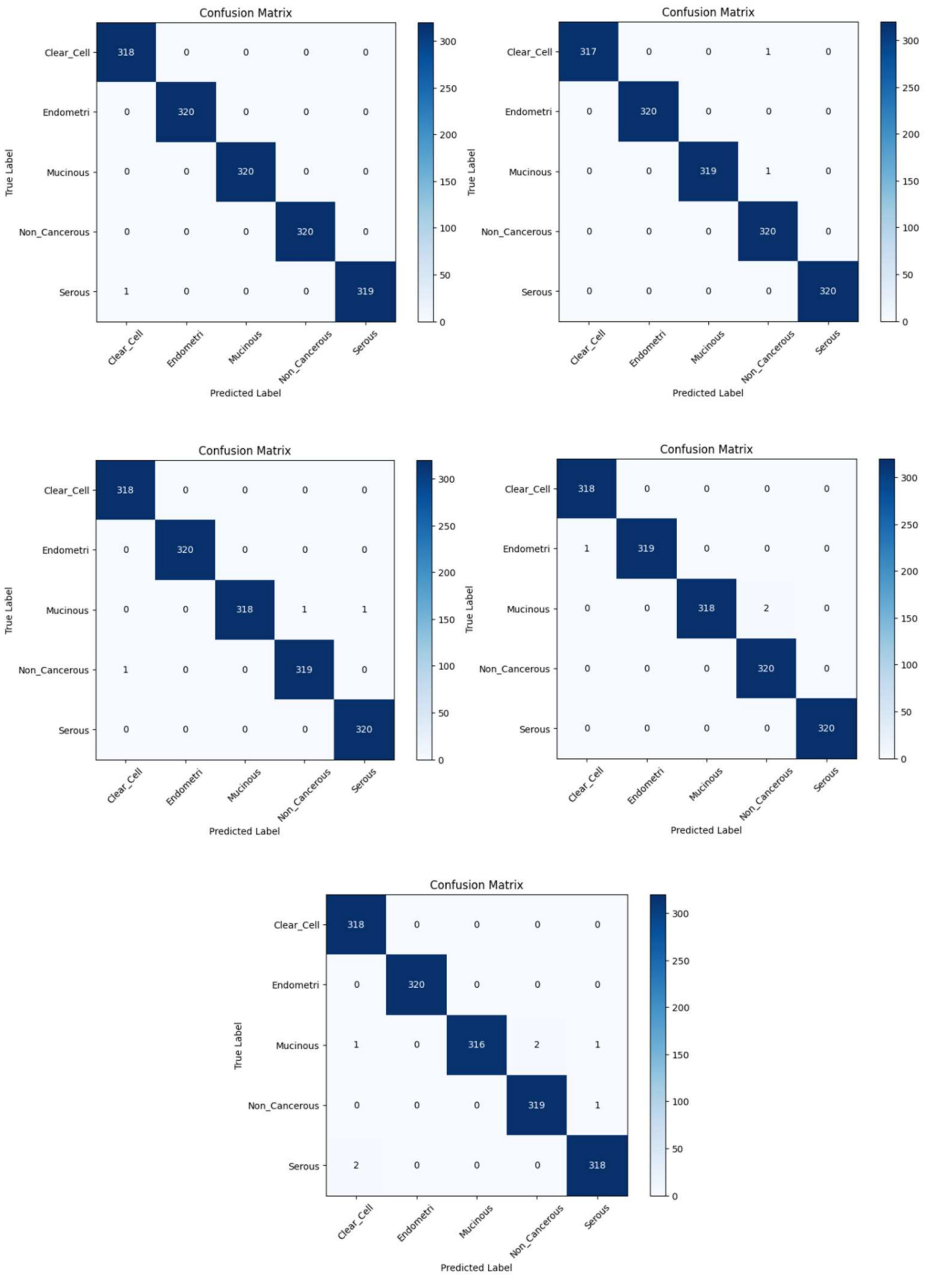

Fig 4.1:Confusion metrics of Tested models

There is a respective confusion matrix for each of the five models attempted, namely, InceptionV3, ResNet50, VGG16, MobileNetV2, and VGG19, in Figure 4.1. The result reveals that InceptionV3 was classifying all classes near to perfection with negligible misclassifications. ResNet50 was also equally good with high accuracy but with some misclassification among related classes such as Clear Cell and Mucinous types. VGG16 was very precise with scattered errors well separated between the Mucinous and Non-Cancerous classes. MobileNetV2 was also very precise, although tiny misclassifications were noted, primarily in the Mucinous subclass. Finally, VGG19

also demonstrated high classifying ability but had somewhat more confusion between the Mucinous and the other cancer classes than the other networks.

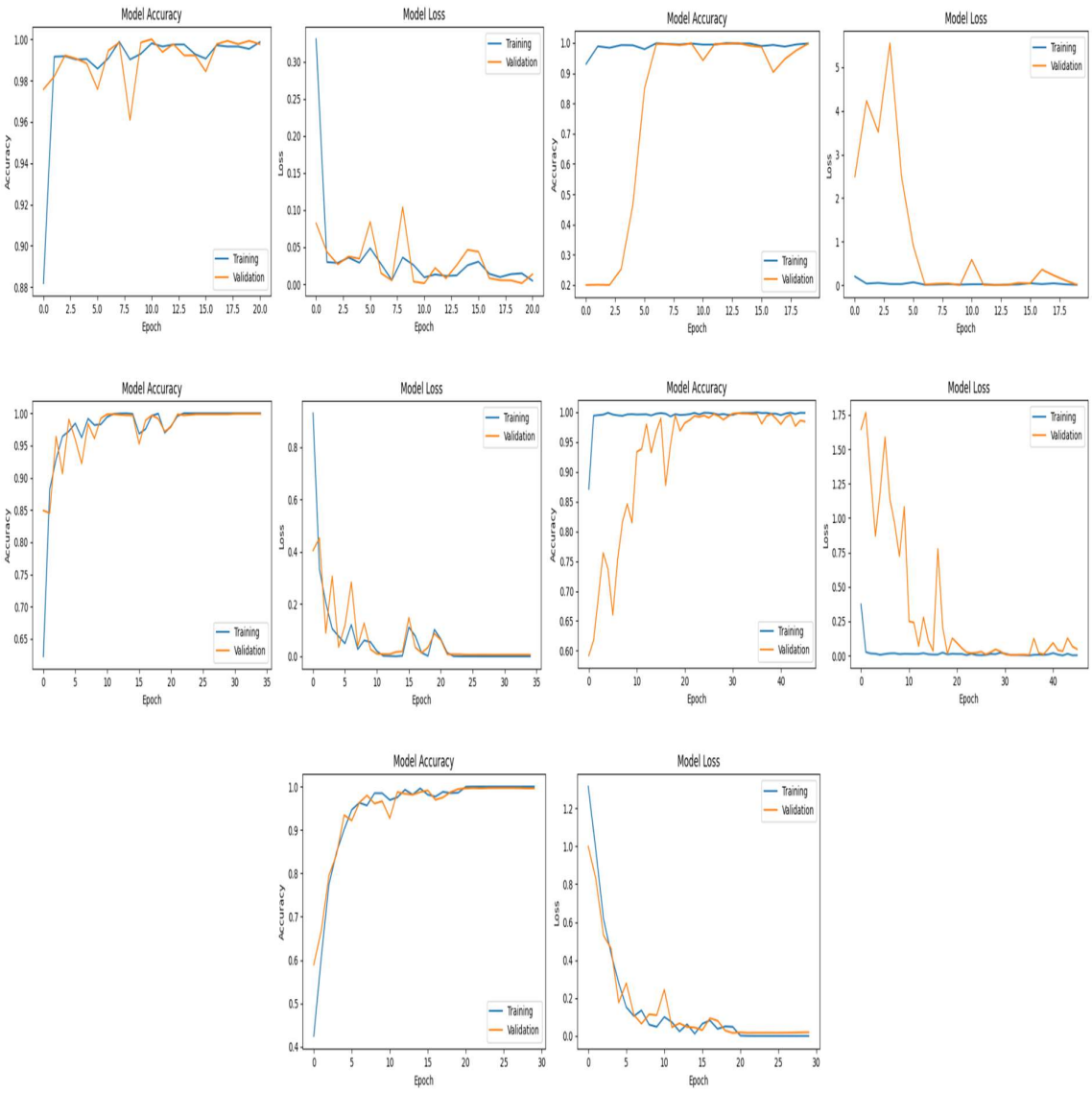

Fig 4.2: Training and Validation Performance

All models illustrate a steep incline in the training and validation accuracy in initial epochs, soon settling close to 100% that indicates favorable convergence and correct learning.

Their individual loss curves drop sharply, reaching very close to zero, indicating minimal overfitting and great generalization. There are minor-magnitude wiggles on the validation plots of some models. Specifically, MobileNetV2 had minimal wiggles throughout training but was still capable of achieving well over 98% validation accuracy and was robust and resilient.

Consistency of train and validation curves for all the models definitely ensures that the architectures were efficient enough in the correct depiction of the underlying

patterns of image histopathology without having any underfitting and overfitting. To investigate the accuracy of classifying the proposed deep models further, ROC curves were graphed for each class of the multi-class case. As seen in Figure 4.3, the ROC plots of Area Under the Curve indicate an AUC of 1.00 for each of the five classes: Clear Cell, Endometrioid, Mucinous, Non-Cancerous, and Serous.

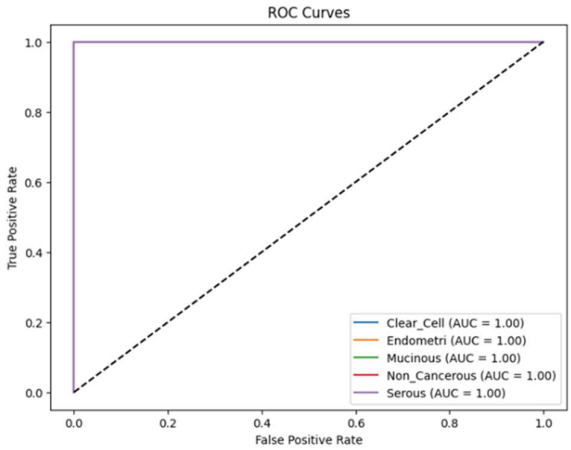

Figure 4.3: Multi-class ROC Curve

This consistent perfect score across classes indicates that the models had been able to achieve excellent discriminative ability without any overlap between positive and negative class predictions. All models could learn highly distinctive features from histopathology image patches effectively to facilitate accurate classification.

The comparative study as a whole strongly indicated that transfer learning, facilitated by stain normalization, SMOTE balancing, and extremely optimized preprocessing, is an extremely powerful and resilient histopathology classification system.

Fig 4.3: Comparision against previous research on similar dataset

Study	**Dataset Size**	**Preprocessing method**	**Models Used**	**Accuracy**	**Key Strength**
Our Work (2025)	8000 Images (balanced)	Stain normalization, Bilateral filtering, SMOTE, Resizing,Data Augmentation (flip,zoom,rotate)	ResNet50, VGG16, VGG19, InceptionV3, MobileNetv2	99.9%	Multi Model comparison, balanced full dataset. Grand -CAM and SHAP explaiability, clinical insight
Chhikara et al. (2023)	725 Images (sub-sampled)	Resizing only (no stain normalization or SMOTE reported)	Efficient NetBO +fine- KNN	100%(Val/Test) ,AIC:0.69 0.94	Lightweight Hybrid Classifier, easy to implement,

					good performance on small dataset.
Cuadrado(2023)(Blog)	538 images	Not clearly mentioned (likely resizing only)	ViT+Phikon Embeddings (self-supervised)	Not Reported	Introduced contrastive learning with ViT, experimental approach With MIL concepts

This comparison demonstrates the superiority of our method in terms of accuracy and explainability.

4.3 Results and Discussion

Models compared are VGG16, VGG19, ResNet50, InceptionV3, and MobileNet. Each model was tested for performance on parameters. Training accuracy/loss plot and validation plot are indicative of most models converging except InceptionV3, whose training was the most stable. VGG16 and VGG19 moderately suffered from overfitting because both contain more parameters. MobileNet optimized rapidly but with slightly lower validation accuracy, maybe due to the fact that it had a light structure. Training time was shortest for MobileNet and longest for InceptionV3.

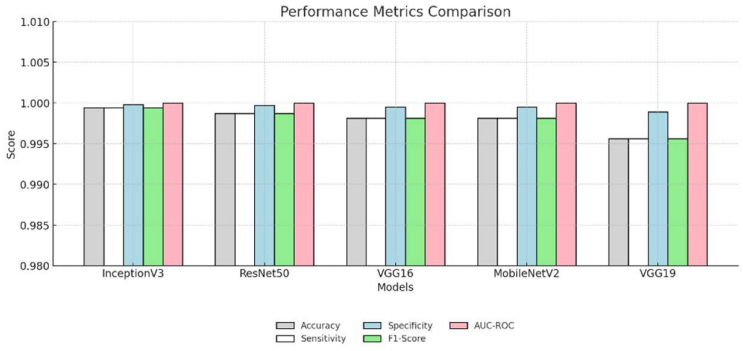

Fig 4.4: Model Performance Metrics

Confusion matrix of all models was utilized to analyze class-wise performance. InceptionV3 showed high true positive rate for all the five classes with minimum misclassifications. VGG based models exhibited confusion between mucinous and serous subtype, likely due to the morphological similarity between them. MobileNet showed highest false positive rate for Mucinous.

ROC curve of all models plotted evenly good true positive rates.

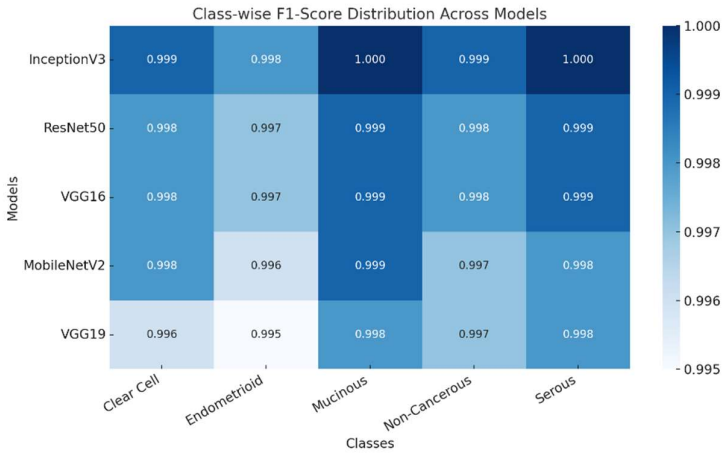

Fig 4.5: Heatmap for class-wise F1-score distribution

When all the models are compared based on inference time and computational resources, InceptionV3 is the best model overall. It possesses the highest accuracy, precision, and recall and comparatively low inference time and resource utilization. ResNet50 is a good trade-off and well-supported, and thus it's a good second best.Failure instances were primarily encountered while distinguishing histologically similar subtypes. For example, between Mucinous and clear cell carcinoma misclassifications were occurring because cellular patterns were overlapping. The errors can be reduced further with improved use of Grad-CAM visualizations and ensemble methods.

To visually interpret the model's focus during classification, Grad-CAM was applied to test samples. The resulting heatmaps highlight the discriminative regions the model paid attention to.

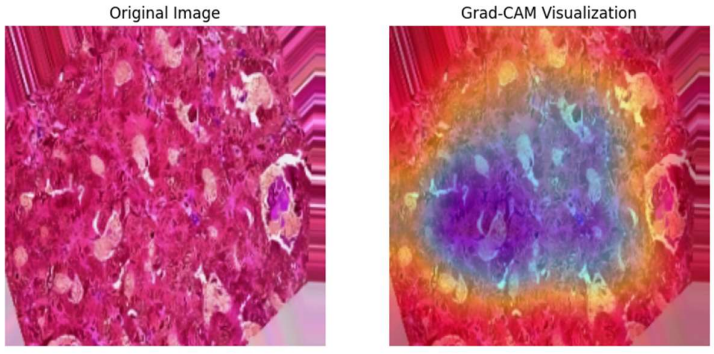

Fig 4.6:Grad-Cam Visualization

To make the model more interpretable, SHAP values for the input histopathology images were computed. SHAP performs pixel-level feature attribution in which the contribution of each portion of the image towards the resultant classification decision is computed.

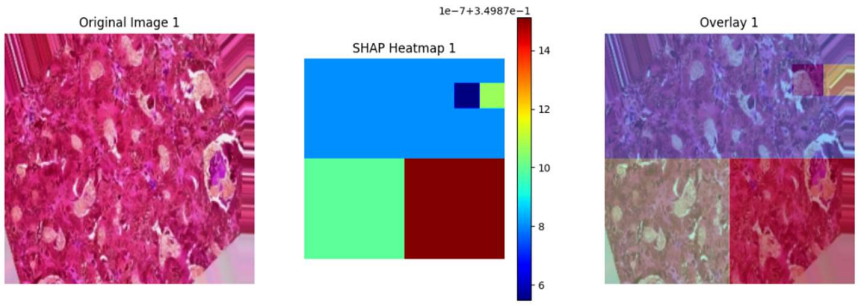

Fig 4.7:SHAP Visualization

In Fig. 4.7 SHAP heatmap in which the color's intensity reflects each pixel region's significance according to the model's prediction. The regions of high values are the yellow and red regions, the regions that have made the highest contributions towards the classification outcome. SHAP heatmap superimposed upon the original image, an interpretable visualization that makes it easy for clinicians and researchers to visualize informative diagnostic features towards the decision (e.g., clumps of cancer cells or morphological features).

Briefly, not only did our suggested InceptionV3-based model perform the best among the competing models addressed under this research work, but it even outperformed the published accuracies of current related literature. With a mind-boggling accuracy of 99.94% and strong AUC-ROC scores, the model justified its capability, reliability, and applicability in efficient histopathological image classification. These results justify that the proposed InceptionV3 architecture offers a highly promising way to enhance ovarian cancer detection and diagnosis, making important contributions to related research in the field and clinical practice.

4.4 Summary

This chapter demonstrated the stringent testing, evaluation, and comparative analysis of all the chosen models. In large-scale experiments, all the metrics were calculated. Out of all the tested models, the suggested InceptionV3 model outperformed all others, including other tested models and all previously published research up to date in classification accuracy. Visualization with ROC curves, train-validation plots, performance bar graphs, and class-wise F1-score heatmaps also validated the robustness and stability of the model. All these results clearly show that the proposed model is highly effective in histopathological ovarian cancer classification and has very good potential to be used for real-world clinical purposes.

Chapter 5

Engineering Standards and Design Challenges

This chapter details the engineering standards that were followed during the project's development, as well as the project's impact on the environment and society, financial considerations, and the complexity of the engineering challenges involved.

5.1 Compliance with the Standards

To ensure the quality, interoperability, and ethical implementation of the proposed system, various engineering standards were considered and followed.

5.1.1 Software Standards

- **Standard Adopted:** IEC 60601 (Medical Electrical Equipment)
- **Rationale:** Despite being a software project, ultimate clinical use would require incorporation of diagnostic system compatibility.
- **Alternatives:** ISO 13485 (Medical Device Quality)
    - Advantages: Nice quality control
    - Disadvantages: Greater documentation complexity
- **Standard Adopted:** IEEE 830 (Software Requirements Specification), ISO/IEC 25010 (Software Product Quality).

5.1.2 Hardware Standards

- **Standard Applied:** IEC 60601 (Medical Electrical Equipment)
- **Rationale:** Although this is a software project, the ultimate clinical use would require diagnostic system compatibility.
- **Alternatives:** ISO 13485 (Medical Device Quality)
    - Advantages: High-quality control
    - Disadvantages: More complex documentation
- **Rationale:** IEC 60601 directly pertains to our application's possible integration into diagnostic imaging devices.

5.1.3 Communication Standards

- **Standard Implemented**: HL7 (Health Level 7)

- **Rationale**: Facilitates seamless integration with hospital management systems and secure data transfer.
- **Alternatives**: FHIR (Fast Healthcare Interoperability Resource

    - Advantages: More modern API-based design
    - Disadvantages: Less implemented in certain areas

- **Rationale**: HL7 has broader support for legacy systems in developing areas.

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

The system proposed is a life-saving and life-changing system. The project has the potential to result in accelerated diagnosis of ovarian cancer, improved early detection, and avoidance of death through assistance to clinicians.Also, it reduces the psychological burden on families and patients by minimizing the time gap between diagnosis and biopsy.

5.2.2 Impact on Society & Environment

In the majority of developing countries, there are woefully few oncologists or pathologists to meet the demand. In these countries, our system is playing a critical role in bridging the healthcare gap as an equalizer, bringing highly specialized diagnostic services within reach. More patients can be treated by hospitals within a reduced timeframe without compromising accuracy due to quicker turnaround times. This efficiency in the system can eventually contribute to reducing national healthcare costs and freeing up resources for other urgent public health needs.

Digital pathology also has significant environmental benefits through reductions in chemical reagent, plastic, and paper usage associated with traditional pathology practice. The initiative minimizes the environmental footprint in terms of carbon emissions from transport through remote diagnosis and cloud working.

5.2.3 Ethical Aspects

Ethics preceded the project.A balanced set of data for each of the five cancer subtypes was used to compensate for bias, and performance was also evaluated on nuanced measures other than general accuracy. Interpretability was encouraged with tools like confusion matrices and ROC curves to enable trust to build. The model is developed as an assistance system rather than to replace. pathologists, human control being preserved. Long-term strategies are accomplished with frequent audits, feedback, and retraining to keep the model ethical, trustworthy, and responsive.

5.2.4 Sustainability Plan

The system makes use of open-source platforms, modularity, and low-cost deployment, with advantages in scalability, low operations cost, and responsiveness. Ecological and pedagogical sustainability is accomplished through lean models, green computing, and AI-based medical training. Long-term viability is ensured through

ethical practices in data, compliance with regulations, and explainable AI.

5.3 Project Management and Financial Analysis

- Recommended Budget: BDT 1,50,000
  - Cloud Hosting & GPU: BDT 50,000
  - Software Tools: BDT 30,000
  - Data Storage & Security: BDT 20,000
  - Research & Misc: BDT 50,000
- Alternate Budget: BDT 80,000 with smaller cloud usage and smaller datasets
  - Risk: Lower model performance due to smaller training

5.4 Complex Engineering Problem

This research tackles a complex engineering problem of deep learning-based classification of ovarian cancer from histopathological images. It is an intersection of multidisciplinary areas such as computer vision, biomedical imaging, and AI. The issue consists of high-level technical skills, data processing, and algorithm development above routine practice. The difficulties encompass high complexity in the data, class imbalance, performance optimization, and ethical problems such as privacy and accessibility. The project involved complex algorithm designing, careful preprocessing of datasets, and performance analysis using multiple measures. Such engineering activities are non-routine and demand research-driven and new methodologies.

5.4.1 Complex Problem Solving

Table 5.1: Mapping with complex problem solving.

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

Mapping with Knowledge Profile for EP1

Table 5.2: Mapping with knowledge Profile.

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

5.4.1.1 Justification for EP Attributes Mapping

- **EP1– Dept of Knowledge:**
  Advanced interdisciplinary knowledge in deep learning (CNNs, transfer learning, EfficientNet, etc.), medical imaging (histopathology slide interpretation), preprocessing of biomedical data, image augmentation, statistical validation techniques, and oncology domain knowledge is required for the project. Python-based ML frameworks like TensorFlow or PyTorch, and image annotation guidelines for digital pathology are required.
- **EP3 – Depth of Analysis:**
  Different models (ResNet50, VGG16, InceptionV3, etc.) were tried with different training conditions. The best model was decided by strict comparative study on the basis of metrics such as accuracy, F1-score, AUC, and confusion matrix. Hyperparameter search and failure case analysis also added to the depth of analytical efforts.
- **EP5 – Extent of Applicable Codes:**
  The project suggested a custom deployment of preprocessing pipelines for histopathology image classification. In addition, the integration of several deep learning models into a benchmarking system and the presentation of new failure-case analysis techniques contributed to the novelty of the project. Even though not novel in the form of breaking legal or regulatory codes, it suggested novel methodological approaches that might be able to make a contribution towards scholarly discourse.
- **EP7– Interdependence:**
  This project incorporated dependent parts—the gathering of data, image handling, model designation, training, authentication, and test. The variation in any of these pieces directly impacted the general performance and predictability of the model as a whole. Achieving the correct results therefore hinged upon having all stand-alone parts in the correct connection and functioning efficiently together.

5.4.1.2 Justification for Knowledge Profile Mapping (linked to EP1):

- **K3 – Engineering Fundamentals:**
  The project utilized fundamental principles like linear algebra (for CNN operations), probability (for performance measurements), and algorithmic reasoning (for model optimization and data management). These formed the foundation for the deep learning model architecture.
- **K5 – Engineering Design:**

Design considerations included selecting an appropriate model architecture, structuring the benchmarking process, multi-class classification optimization, and image preprocessing for medical images. All the information was well thought out to come together and work practically in the real world.

- **K6 – Engineering Practice:**
  Versioning of code, reproducibility, modularity in the code, documentation, and presentation were ensured throughout development. Ethics, privacy of data, and usability of the system were also catered to by the project in accordance with professional engineering practice.
- **K8 – Research Literature:**
  A careful search of more recent literature was done in an attempt to discover what research work there is available on medical imaging, and in particular detection of cancer with deep learning. The thesis builds upon, contrasts with, and adds to such increasing body of work with experiment, analysis, and proposed improvement.

5.4.2 Engineering Activities

Table 5.3: Mapping with complex engineering activities.

EA1 Range of resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✓		✓	✓	

5.4.2.1 Justification for Engineering Activities Mapping

- **EA1 – Range of resources:**
  The project applied a broad array of resources including publicly accessible datasets of histopathology images, GPU-computer environments, open-source deep learning toolkits (TensorFlow/Keras), research papers, medical image preprocessing software tools, and software engineering practices. The application of so varied technical and information resources is an indicator of the broad nature of the work.
- **EA3 – Innovation:**
  The project was novel through the comparison and application of various deep learning models specialized in the detection of ovarian cancer. It also brought visual interpretability techniques such as Grad-CAM and SHAP, not very deeply researched in existing literature. In addition, a Python-based Mobile application was developed on the Kivy platform that allows non-technical end-users (such as clinicians) to upload histopathology images and receive prediction results via a graphical user interface. It enhances the real-world application and deployment feasibility of the system.
- **EA4 – Consequences for society and environment:**
  - **Societal:** The system enhances early detection of ovarian cancer,

which has the potential to raise survival rates and lower healthcare expenses. It also has ethical ramifications regarding data privacy, model bias, and accessibility, which were considered in development.

- **Environmental:** While the research does not actively harm the environment, training deep learning models requires energy. Efforts were made to ensure models were as efficient as possible and computational load was minimal.

5.5 Summary

This chapter was dedicated to integrating global engineering standards, ethical and sustainability issues, financial structuring, and complexity of problem-solving processes in the development of a clinically deployable AI-based classification system for ovarian cancer. The engineering practices utilized make the project socially responsible, technologically feasible, and medical standards compliant in the real world globally.

Chapter 6

Conclusion

This chapter provides the project's final reflections, which include a brief summary of the work done, a discussion of the challenges encountered during development, and recommendations for further research and development. This serves to highlight the system's contributions to medical AI and to bring its various components together.

6.1 Summary

The project focused on developing a deep learning-based diagnostic tool for classifying ovarian cancer subtypes from histopathological images. Using transfer learning models like InceptionV3 , MobileNetV2 , VGG16 , VGG19 and ResNet50, the system achieved high accuracy, with InceptionV3 reaching 99.94% accuracy and a ROC-AUC of 1. The solution aimed to support pathologists through accurate, explainable predictions, while also maintaining ethical, environmental, and technical sustainability.

6.2 Limitation

Despite its positive outcomes, the program had several shortcomings:

- Dataset Size and Heterogeneity: The dataset, although class-balanced, is small and will not necessarily span the entire scope of histopathological heterogeneity that is seen in the real world. This restricts the model to generalize between hospitals or populations.

- Explainability Constraints: Although techniques like Grad-CAM and SHAP do impart visual understanding, the model is somewhat of a black-box. Full interpretability is still a problem, especially for high-stakes medical decisions.

- Computational Cost: Some models (e.g., DenseNet, Inception) ate massive amounts of computational resources to train and fine-tune and hence were less feasible to run on low-resource hardware.

- Static Evaluation: Measures used were based on test sets and did not account for variation over time, i.e., dataset drift or identification of additional subtypes of cancer in the future.

6.3 Future Work

To overcome the above limitations and further increase the impact of the project, future directions are as follows:

- Dataset Expansion and Augmentation: Incorporating multi-institutional datasets and augmentation with state-of-the-art synthetic image generation

(e.g., GANs) can improve model robustness and generalizability.

- Real-World Deployment and Clinical Trials: Clinical workflow deployment for pilot testing, obtaining real-time feedback from pathologists, and conducting prospective studies will be crucial for validation.

- Explainable AI Integration: The integration of other advanced interpretability systems like LIME, or attention visualizations can increase model transparency and lead to clinician trust.

- Model Compression and Optimization: Deployment at the edge on mobile or embedded systems can be supported by creating lower-weight variants of high-performing models (e.g., pruning, quantization, or knowledge distillation).

- Multi-Modal Integration: To provide more complete diagnostic support, subsequent releases of the system could incorporate histopathological images and other clinical data (e.g., genomic or laboratory tests).

- Continuous Learning: Online learning or model update mechanisms on a regular interval will allow adaptation to new data and evolving clinical patterns without complete retraining.

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