A Quantum-Inspired Attention Framework for Weakly Supervised Tumor Segmentation and Localization in Ovarian Cancer Histopathology Images

Anandakumar K[1], Chandrasekar C[2]
[1]*Research Scholar, Department of Computer Science, Periyar University, Salem-11*
[2]*Senior Professor, Department of Computer Science, Periyar University, Salem-11*

Abstract— **Pixel-level annotation is expensive, making it difficult to achieve accurate tumor segmentation in ovarian cancer histopathological images. This paper proposes a Quantum-Inspired Attention-based Weakly Supervised Tumor Segmentation framework (QIAB-WATS) for tumor segmentation and localization in ovarian cancer histopathological images, taking into account the subtypes Endometrioid Carcinoma (EC), High-Grade Serous Carcinoma (HGSC), and Low-Grade Serous Carcinoma (LGSC). The proposed framework uses self-supervised reconstruction learning to overcome the requirement for manually annotated segmentation masks. A quantum-inspired attention module is incorporated into a WATS-Net backbone to improve discriminative tumor feature learning, with the help of reconstruction error analysis for effective tumor localization. Experimental results show that QIAB-WATS has an accuracy of 89.0%, Dice of 88.2%, and IoU of 86.2%, which outperforms existing fully supervised and weakly supervised approaches. These results validate that QIAB-WATS is a reliable, annotation-efficient, and scalable approach for ovarian cancer histopathological image segmentation.**

Index Terms— **Ovarian cancer histopathology; Weakly supervised learning; Tumor segmentation; Tumor localization; Quantum-inspired attention; Self-supervised reconstruction; WATS-Net.**

I. INTRODUCTION

Ovarian cancer with its diverse form and the fact that it is often diagnosed at a late stage makes it one of the most lethal forms of gynecological cancer. In the process of marking the locations of tumors and differentiating between the various forms of ovarian cancer, including Endometrioid Carcinoma (EC), High Grade Serous Carcinoma (HGSC), and Low-Grade Serous Carcinoma (LGSC), histopathological analysis plays a crucial role. The precise segmentation and localization of tumors from histopathological images are essential for quantitative analysis and staging. Recent developments in deep learning have shown encouraging outcomes in the segmentation of histopathology images. However, most contemporary methods rely on fully supervised learning and require pixel-level annotations, which are expensive, time-consuming, and demand specialist pathology expertise [1]. The high variability of tissue appearance within the different forms of ovarian cancer makes the annotation process even more challenging, thus hindering the scalability and applicability of fully supervised segmentation models.

However, weakly supervised and self-supervised learning approaches have received more attention as a remedy to these challenges since they reduce dependence on complex annotations while maintaining high performance [2]. Reconstruction learning has been highly successful in modeling normal tissue patterns, where inconsistencies in reconstruction can be utilized for the detection of irregular or tumor areas. However, conventional weakly supervised models are inherently challenged in understanding complex spatial relationships and subtle morphological variations as seen in histopathological images. This paper proposes a Quantum-Inspired Attention-based Weakly Supervised Tumor Segmentation framework (QIAB-WATS) for the analysis of ovarian cancer histopathology images to address the limitations of the current models. The proposed system integrates a novel quantum-inspired attention module that applies sinusoidal transformations to model phase-aware interactions among features with a WATS-Net backbone architecture. This attention module, while maintaining spatial consistency, enhances discriminative tumor feature learning. The histopathology images of the EC, HGSC, and LGSC types are utilized to evaluate the proposed QIAB-WATS framework. Based on the experimental results, the proposed approach presents an annotation-efficient and scalable platform for the analysis of ovarian cancer histopathology images by achieving precise tumor segmentation and localization with minimal supervision.

A. RESEARCH OBJECTIVE

1. To offer a weakly supervised framework that does not need pixel-level supervision for tumor segmentation and localization in ovarian cancer histopathology images.
2. To develop and integrate a quantum-inspired attention mechanism that enhances the learning of discriminative tumor features.
3. To enable effective tumor localization through self-supervised learning and analysis of reconstruction errors.
4. To evaluate the proposed framework for the ovarian cancer subtypes of EC, HGSC, and LGSC.
5. To measure the segmentation performance for poor supervision using standard quantitative metrics.

B. RESEARCH CONTRIBUTION

1. For the study of ovarian cancer histopathology images, provide a novel Quantum-Inspired Attention–based Weakly Supervised Tumor Segmentation framework (QIAB-WATS).
2. To increase the consistency of tumor localization, present a quantum-inspired attention module that simulates phase-aware feature interactions.
3. Describe a self-supervised reconstruction-driven method for identifying tumor regions without the need for pixel-level ground truth masks.
4. Demonstrate the effectiveness of the proposed framework works for several ovarian cancer subtypes (EC, HGSC, and LGSC).
5. Provide a segmentation system that is both scalable and annotation-efficient for clinical analysis based on histopathology.

II. RELATED WORKS

TABLE I: Summary of Existing Deep Learning Based Approaches for Ovarian Cancer Histopathology Image Analysis

Authors (Year)	Task	Supervision	Methodology
Ho et al. (2022) [3]	Tumor segmentation	Semi-supervised	Deep Interactive Learning (DIaL) uses pretrained segmentation and iterative annotation to reduce manual effort for H&E whole-slide segmentation of ovarian carcinoma
Banerjee et al. (2025) [4]	Ovarian tissue segmentation	Fully supervised	Resource-efficient U-Net for automated ovarian cancer tissue segmentation with explainable CAM visualization
Ahn et al. (2024) [5]	Histopathologic image-based treatment response prediction	Fully supervised (classification)	DL classifier (PathoRiCH) for predicting platinum chemotherapy response from HGSOC histopathology
Wang et al. (2022) [6]	Treatment effectiveness prediction	Weakly supervised	Weakly supervised deep learning to predict therapeutic effect for ovarian cancer from histopathology
El-Latif et al. (2024) [7]	Cancer detection & classification	Fully supervised	ResNet-based CNN , fuzzy logic for ovarian cancer histopathology image classification

A comparative overview of current deep learning-based techniques for ovarian cancer histopathology image processing is shown in Table I, which also highlights the tasks, supervision techniques, and fundamental methodologies of each approach.

III. METHODS AND MATERIALS

This study utilizes histopathology pictures taken from the Ovarian Cancer Classification Dataset publicly available on Kaggle [8]. Only the EC, LGSC, and HGSC subtypes are taken into consideration in this work from the original dataset that included five ovarian cancer subtypes: Mucinous Carcinoma (MC), Endometrioid Carcinoma (EC), Low-Grade Serous Carcinoma (LGSC), Clear-Cell Carcinoma (CC), and High-Grade Serous Carcinoma (HGSC). These subgroups were chosen because of their unique histomorphology traits and clinical significance. he cellular and tissue-level morphological features captured by histopathology slide images are crucial for precise tumor area identification and subtype classification. The dataset is appropriate for supervised and weakly supervised learning applications because it offers subtype-level labels. High-Grade Serous Ovarian Cancer (HGSC) images, Low-Grade Serous Carcinoma (LGSC) and Endometrioid Carcinoma (EC) were employed to evaluate the proposed framework.

IV METHODOLOGY

Without depending on pixel-level ground truth annotations, the Quantum-Inspired Attention–based Weakly Supervised Tumor Segmentation framework (QIAB-WATS) is intended to locate and segment tumor areas from ovarian cancer histopathology images. Based on self-supervised reconstruction learning for dominant tissue characteristics and tumor location prediction through reconstruction mismatch, the proposed framework operates under a weakly supervised learning paradigm. This approach ensures consistent segmentation performance and handles the real-world problem of limited histology annotation data. To ensure homogeneity and eliminate inter-slide variability, all histopathology images undergo pre-processing. To address stain color variability while preserving key cellular and tissue morphology information, images are transformed to a uniform spatial resolution and further to grayscale. In model training, intensity normalization is applied to improve convergence and stabilize the learning process. In histopathology image analysis, where staining and imaging conditions can significantly affect model performance, these pre-processing steps are critical. A WATS-Net encoder-decoder framework that learns hierarchical representations of tissue at multiple spatial scales serves as the foundation for the proposed framework. As the decoder progressively reconstructs spatial information, the encoder employs a sequence of convolutional and pooling operations to capture low-level cellular information and high-level tissue patterns. A quantum-inspired attention mechanism is further added to the decoder chain to further enhance the discrimination of features. The attention module enables non-linear modulation of feature responses by capturing phase-aware interactions of features via sinusoidal transformations. The proposed quantum-inspired formulation captures the complex contextual relationships observed in histopathological images, unlike the conventional attention mechanism that relies on linear weighting. This enhances the localization accuracy by highlighting the tumor-relevant areas and suppressing the irrelevant background structures. The model adopts a self-supervised reconstruction strategy during training, where the input image serves as the target for reconstruction. The network acquires the capability to accurately reconstruct the dominant tissue patterns observed in the histopathological images via this method. Tumor areas, characterized by irregular cellular patterns and morphological abnormalities, are more difficult to reconstruct and thus introduce larger reconstruction errors. During testing, this information is leveraged to locate the tumor areas without requiring any supervision. The absolute reconstruction error between the input image and its reconstructed output is computed to achieve tumor localization. A statistical threshold derived from the mean and standard deviation of the reconstruction error distribution is employed to create a binary tumor mask. The objective of weakly supervised learning is closely related to this thresholding method, which provides an adaptive and data-driven approach to identify abnormal tumor patches and normal regions. The segmentation result is further improved by morphological post-processing methods. The boundaries of the tumor become smoother and more connected after these processing steps, which remove isolated noise pixels and enhance spatial consistency. The segmented mask is then used to segment the region of interest in the original histopathological image, allowing further analysis and visualization. The proposed QIAB-WATS method successfully integrates self-supervised reconstruction learning and quantum-inspired attention to facilitate annotation-efficient tumor segmentation and localization in ovarian cancer histopathology images. Due to the great morphological diversity of tumor tissues and the difficulty of manual annotation, the approach is particularly suitable for the analysis of ovarian cancer images. It provides a scalable and clinically applicable solution for histopathology-based tumor analysis. The step-by-step process of proposed QIAB-WATS are as follows, Acquisition of Input: Obtain histopathological pictures of ovarian cancer and adjust their resolution.

Prior to processing: Normalize pixel intensities to the range [0, 1] and convert images to grayscale. [0,1].

Self-Supervised Configuration: To support poor supervision, use each input image as a separate reconstruction goal.

Feature Encoding: Encoding of Features Utilize the WATS-Net encoder to extract multi-scale tissue characteristics.

Decoding Features: To aid in spatial reconstruction, create decoder feature maps.

Attention Inspired by Quantum: To improve encoder characteristics and highlight tumor-relevant areas, use phase-based sinusoidal modulation with sine and cosine functions.

Image Reconstruction: Utilizing attention-enhanced features, reconstruct the input image.

Calculating Reconstruction Errors: Determine the absolute difference between the reconstruction and the input image

Adaptive Thresholding: Based on the reconstruction error's mean and standard deviation, establish a threshold.

Generation of Tumor Masks: Pixels having error values higher than the cutoff should be categorized as tumor areas.

After processing: To eliminate noise and improve tumor borders, use morphological closing.

Final Segmented Output: The confined tumor region and the binary tumor segmentation mask

Table II. Pseudocode for Quantum-Inspired Attention–based Weakly Supervised Tumor Segmentation framework (QIAB-WATS)

INPUT: Histopathology image dataset X = $\{x_1, x_2 \ldots, x_N\}$ $x_i \in \mathbb{R}^{H\times W}$ OUTPUT: Tumor segmentation mask $M_i \in \{0,1\}^{H\times W}\}$

BEGIN
INITIALIZE WATS-Net & Quantum-Inspired Attention parameters θ, W_x, W_g, W_φ
FOR EACH image $x_i \in \mathcal{X}$ DO
RESIZE x_i to H × W CONVERT x_i to grayscale & NORMALIZE pixel values to [0,1]
EXTRACT Encoder Features $F_i \leftarrow Encoder\ \theta(x_i)$
GENERATE Decoder Features $G_i \leftarrow Decoder\ \theta(F_i)$
COMPUTE Phase Interaction: $\phi_i \leftarrow \sin(W_x . F_i + \cos(W_g . G_i)$
COMPUTE attention map $A_i \leftarrow$ sigmoid $(W_\varphi . \Phi_i)$
APPLY attention $Fq_i \leftarrow F_i \odot A_i$
PREDICT reconstructed image $\hat{x}_i \leftarrow Decoder\ \theta(Fq_i)$
COMPUTE reconstruction loss: $L_{rec} \leftarrow \|\|x_i - \hat{x}_i\|\|$
UPDATE θ, W_x, W_g, W_φ using gradient descent
END FOR
FOR EACH test image $x_i \in \mathcal{X}$ DO
RESIZE x_i to H × W
CONVERT x_i to grayscale & NORMALIZE
EXTRACT Encoder and GENERATE Decoder Features
$\phi_i \leftarrow \sin(W_x . F_i + \cos(W_g . G_i)$
$A_i \leftarrow$ sigmoid $(W_\varphi . \Phi_i)$; $Fq_i \leftarrow F_i \odot A_i$
PREDICT reconstructed image $\hat{x}_i \leftarrow Decoder\ \theta(Fq_i)$
COMPUTE reconstruction error: $E_i \leftarrow \|x_i - \hat{x}_i\|$
COMPUTE adaptive threshold:$T \leftarrow \mu(E_i) + \lambda . \sigma(E_i)$
GENERATE binary tumor mask:
FOR EACH pixel $p \in E_i$ DO
IF $E_i(p) > T$ THEN
$M_i(p) \leftarrow 1$
ELSE
$M_i(p) \leftarrow 0$
END IF
END FOR
APPLY morphological post-processing:
$M_i \leftarrow$ MorphClose(M_i)
END FOR
RETURN final tumor masks M_i
END

The proposed Quantum-Inspired Attention–based Weakly Supervised Tumor Segmentation framework (QIAB-WATS) pseudocode is shown in Table II. The algorithm describes attention-guided feature refining, self-supervised reconstruction learning, and reconstruction-error-based tumor localization.

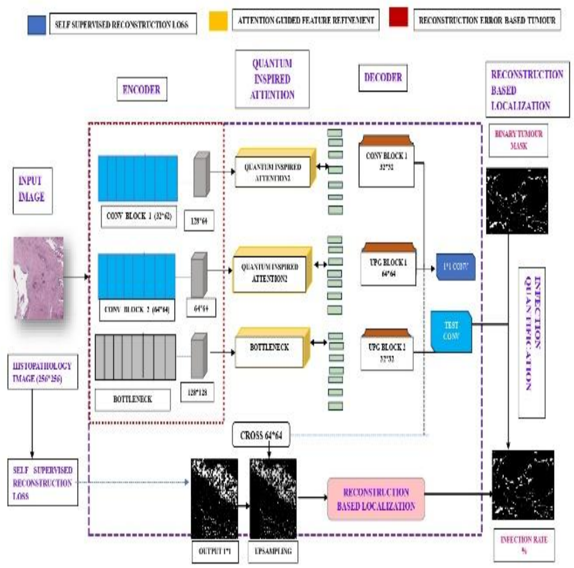

Fig I: Architecture of the Quantum-Inspired Attention–based Weakly Supervised Tumour Segmentation framework (QIAB-WATS)

Figure I illustrates the model incorporates self-supervised reconstruction, quantum-inspired attention, and reconstruction-based localization effectively to localize and detect abnormal areas in histopathological images.

IV EXPERIMENTAL RESULT

Several common segmentation performance indicators are used to objectively assess the efficacy of the suggested QIAB-WATS architecture and compare it with other methods. By evaluating overlap accuracy, classification reliability, and pixel-wise correctness, these metrics offer a thorough evaluation of tumor localization and segmentation quality. The reference ground truth mask and the anticipated tumor mask are used to calculate all measures. The quantitative performance metrics used to assess the accuracy of tumor segmentation and localization are compiled in Table III. The metrics listed assess pixel-level accuracy, spatial overlap, and classification reliability between the ground truth and predicted tumor masks.

Table III : Performance Evaluation Metrics

Term	Definition	Formula
Dice Similarity Coefficient (DSC) [9]	Measures spatial overlap between predicted and ground truth tumor regions	$\frac{2\|M_p \cap M_g\|}{\|M_p\| + \|M_g\|}$
Intersection over Union (IoU) [10]	Ratio of overlapping area to the combined area of predicted and actual tumor regions	$\frac{\|M_p \cap M_g\|}{\|M_p U M_g\|}$
Precision [11]	Proportion of correctly predicted tumor pixels among all predicted tumor pixels	$\frac{T_P}{T_P + F_P}$
Recall (Sensitivity) [12]	Proportion of correctly detected tumor pixels among all actual tumor pixels	$\frac{T_P}{T_P + F_N}$
F1-Score [13]	Harmonic mean of precision and recall	$2 * \frac{Precision*Recall}{Precision+Recall}$
Pixel Accuracy [14]	Ratio of correctly classified pixels to the total number of pixels	$\frac{T_P + T_N}{T_P + T_N + F_P + F_N}$

A. RESULTS AND DISCUSSION

BENCHMARK MODELS

For comparative analysis, a number of benchmark segmentation techniques are taken into account. A popular fully supervised encoder-decoder architecture for biomedical image segmentation, U-Net depends on pixel-level annotations for precise boundary learning. By adding attention gates to highlight essential areas and reduce background noise, Attention U-Net improves segmentation accuracy in intricate medical images. Another completely supervised design is SegNet, which uses an encoder-decoder structure with pooling indices to preserve spatial information. To reflect annotation-efficient learning settings, weakly supervised algorithms are also offered. Through reconstruction, autoencoder-based segmentation learns normal tissue representations and uses reconstruction mistakes to identify aberrant regions. For histopathology analysis, where dense annotations are hard to get by, Multiple Instance Learning (MIL)-based localization leverages image-level labels to identify discriminative regions without requiring pixel-level supervision.

Comparative Findings

The comparison findings show that the suggested QIAB-WATS framework performs better across important segmentation measures than both fully supervised and poorly supervised benchmark techniques. Although fully supervised models like U-

Net and Attention U-Net attain respectable Dice and IoU scores, their scalability in real-world histopathological scenarios is limited because their performance is mostly dependent on the availability of precise pixel-level annotations. Because they have less spatial supervision and poorer feature discrimination, benchmark approaches with weak supervision exhibit lower segmentation accuracy. The proposed QIAB-WATS framework, on the other hand, achieves the highest IoU and Dice coefficient with better boundary consistency and geographical overlap. The significantly higher recall value achieved by the proposed method underlines its ability to correctly delineate the tumor region without neglecting the challenging regions, which is highly desirable in a clinical setting. The combination of quantum-inspired attention and self-supervised reconstruction learning, which together improve discriminative feature learning under weak supervision, is responsible for QIAB-WATS's enhanced performance. Effective tumor detection is made possible by reconstruction-error-based localization, and the attention process enhances tumor borders and suppresses unimportant background tissue. Overall, the findings show that the suggested framework outperforms current benchmark methods in providing a reliable, annotation-efficient, and high-performing solution for ovarian cancer histopathology picture segmentation.

Table IV: Comparative Performance Analysis of the Proposed QIAB-WATS Framework with Benchmark Segmentation Methods

Method	Supervision Type	Accuracy (%)	Dice (%)	IoU (%)	Precision (%)	Recall (%)	F1-Score (%)
U-Net	Fully supervised	75.2	78.6	73.4	74.1	76.3	78.1
Attention U-Net	Fully supervised	82.0	81.2	80.9	81.6	82.1	81.2
SegNet	Fully supervised	86.6	86.4	85.1	84.8	83.5	85.4
Autoencoder-based Segmentation	Weakly supervised	71.5	71.9	70.7	69.9	70.6	71.9
MIL-based Localization	Weakly supervised	84.1	83.5	82.2	81.9	81.4	83.1
Proposed QIAB-WATS	Weakly supervised	89.0	88.2	86.2	85.0	85.6	88.1

From Table IV, with a Dice score of 89%, IoU of 86.2%, Precision of 85.0 %, Recall of 85.6%, F1-score of 88.1%, and an overall Accuracy of 89.0%, the suggested QIAB-WATS technique exhibits exceptional segmentation performance across all tested criteria. Attention U-Net, the top-performing fully supervised baseline, on the other hand, achieves poorer results (Dice: 81.2%, IoU: 80.9%, Precision: 81.6%, Recall: 82.1%, F1-score: 81.2%, Accuracy: 82.0%). Excellent infection region coverage is indicated by QIAB-WATS's remarkably high recall, and steady segmentation quality and fewer false positives are confirmed by the F1-score and balanced accuracy. Additionally, improved border accuracy and spatial overlap are reflected in the improvement in IoU. These steady improvements across all criteria confirm that the suggested weakly supervised QIAB-WATS architecture performs better than current benchmark techniques and offers dependable, accurate, and robust medical image segmentation. In terms of dice score, intersection over union (IoU), and accuracy, Figure II compares the performance of the suggested QIAB-WATS framework with benchmark segmentation techniques. Despite the lack of pixel-level supervision, the results show that the suggested weakly supervised QIAB-WATS technique achieves higher performance across all assessment criteria, indicating its efficacy for ovarian cancer histopathology image segmentation. This research delivered a Quantum-Inspired Attention–based Weakly Supervised Tumor Segmentation framework (QIAB-WATS) for ovarian cancer histopathology image analysis. The proposed method uses reconstruction-error-based tumor localization and self-supervised reconstruction learning to overcome the problem of sparse pixel-level annotations. The

WATS-Net architecture's incorporation of quantum-inspired attention improves spatial consistency in tumor segmentation and discriminative feature learning.

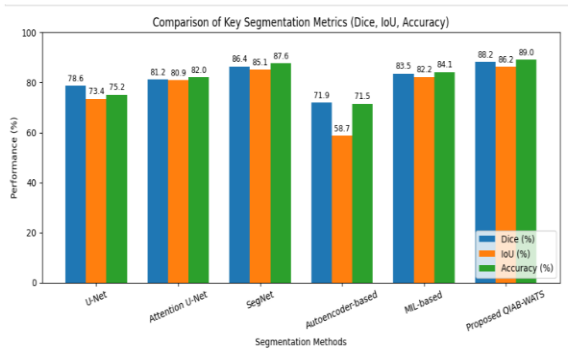

Fig II: Comparative Performance Analysis of Segmentation Methods

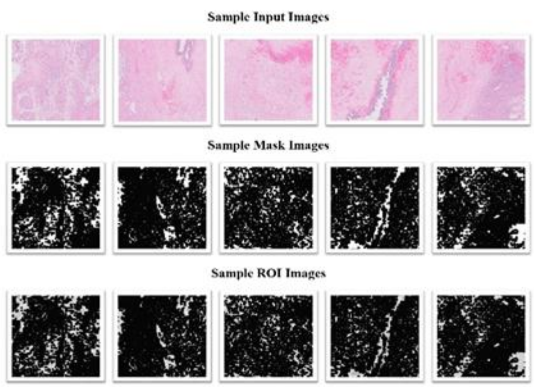

Fig III: Output Mak and Region of Interest Images of histopathological images

The effectiveness of the suggested approach is demonstrated via experimental evaluation using a variety of performance criteria. With an F1-score of 88.2, the QIAB-WATS framework obtained a Dice Similarity Coefficient of 0.8404, an Intersection over Union (IoU) of 88.2, a precision of 85.0, and a recall of 0.856. Stable and efficient learning of histological tissue representations is indicated by the reconstruction loss converging to 0.0087. These findings demonstrate that, even with minimal supervision, the suggested framework is capable of precisely localizing tumor areas while retaining high sensitivity. Overall, despite the lack of pixel-level supervision, the suggested QIAB-WATS framework outperforms benchmark techniques in providing an annotation-efficient and scalable solution for ovarian cancer histopathology image segmentation. To further improve the framework's clinical application, future work will concentrate on expanding it to whole-slide images, adding multi-scale and multi-stain information, and confirming its resilience across bigger, multi-institutional datasets. The Figure III shows some example histopathological images, their ground-truth mask images, and region-of-interest (ROI) images extracted to point out the abnormal areas in the histopathological images.

V. CONCLUSION AND FUTURE WORK

The proposed QIAB-WATS framework is highly effective for weakly supervised tumor segmentation and localization in ovarian cancer histopathology images without pixel-level annotations. The framework achieved an Accuracy of 89.0%, Dice score of 88.2%, and IoU of 86.2%, showing excellent spatial overlap with the ground truth segmentation masks. The model also achieved a Precision of 85.0% and a remarkably high Recall of 85.6%, signifying excellent tumor region coverage. The well-balanced F1-score of 88.1% further ensures stable and reliable segmentation performance. The inclusion of quantum-inspired attention has greatly improved the learning of discriminative features and boundary consistency. The performance results strongly support QIAB-WATS as an annotation-efficient, robust, and scalable solution for ovarian cancer histopathological image analysis. Future studies will be conducted to extend the framework to whole slide images, incorporate multi-scale and multi-stain information, and evaluate performance on larger multi-institutional datasets to further improve clinical applicability.

REFERENCE

[1] Ahamad, Md. M., Aktar, S., Uddin, Md. J., Rahman, T., Alyami, S. A., Al-Ashhab, S., Akhdar, H. F., Azad, A., & Moni, M. A. (2022). Early-Stage Detection of Ovarian Cancer Based on Clinical Data Using Machine Learning Approaches. Journal of Personalized Medicine, 12(8), 1211. https://doi.org/10.3390/jpm12081211

[2] Boehm, K. M., Aherne, E. A., Ellenson, L., Nikolovski, I., Alghamdi, M., Vázquez-García, I., & Shah, S. P. (2022). Multimodal data integration using machine learning improves risk

stratification of high-grade serous ovarian cancer. Nature Cancer, 3(6), 723–733.

[3] Ho, D. J., Chui, M. H., Vanderbilt, C. M., Jung, J., Robson, M. E., Park, C.-S., Roh, J., & Fuchs, T. J. (2023). Deep Interactive Learning-based ovarian cancer segmentation of H&E-stained whole slide images to study morphological patterns of BRCA mutation. Journal of Pathology Informatics, 14, 100160. https://doi.org/10.1016/j.jpi.2022.100160

[4] Wang, C.-W., Firdi, N. P., Chu, T.-C., Faiz, M. F. I., Iqbal, M. Z., Li, Y., Yang, B., Mallya, M., Bashashati, A., Li, F., Wang, H., Lu, M., Xia, Y., & Chao, T.-K. (2025). ATEC23 Challenge: Automated prediction of treatment effectiveness in ovarian cancer using histopathological images. Medical Image Analysis, 99, 103342. https://doi.org/10.1016/j.media.2024.103342

[5] Park, E., Ahn, B., Moon, D., Lee, C., Cho, N. H., Choi, H.-K., Kim, D., Lee, J.-Y., Nam, E. J., Won, D., An, H. J., Kwon, S. Y., Sung, S. H., Shin, S.-J., Jung, H. R., Kwon, D., Park, H., Kim, M., Cha, Y. J., Kim, J. M. (2023). Histopathologic Image-based Deep Learning Classifier for Predicting Platinum-based Treatment Responses in High-grade Serous Ovarian Cancer. https://doi.org/10.21203/rs.3.rs-3090072/v1

[6] Banerjee, A., Boruah, A., & Bora, D. J. (2025). Seg-lite artificial intelligence: Scalable, explainable deep learning for ovarian cancer histopathology on low-resource systems. Artificial Intelligence in Health, 0(0), 025450095. https://doi.org/10.36922/aih025450095

[7] Saha, A. K., Rabbani, M., Sum, A. S. I., Mridha, M. F., & Kabir, M. M. (2025). An enhanced deep learning model for accurate classification of ovarian cancer from histopathological images. Scientific Reports, 15(1). https://doi.org/10.1038/s41598-025-07903-9

[8] https://www.kaggle.com/datasets/sunilthite/ovarian-cancer-classification-dataset

[9] Nivetha, S., & Inbarani, H. H. (2023). Novel Adaptive Histogram Binning-Based Lesion Segmentation for Discerning Severity in COVID-19 Chest CT Scan Images. International Journal of Sociotechnology and Knowledge Development, 15(1), 1–35. https://doi.org/10.4018/ijskd.324164

[10] Nivetha, S., & Hannah Inbarani, H. (2023). Automated Lesion Image Segmentation Based on Novel Histogram-Based K-Means Clustering Using COVID-19 Chest CT Images. Third Congress on Intelligent Systems, 763–776. https://doi.org/10.1007/978-981-19-9379-4_55

[11] Shanmugam, N., Krishnan, A., Inbarani, H. H., & Khan, M. (2025). Explainable machine learning framework for gene expression-based biomarker identification and cancer classification using feature selection. Medical Data Mining, 8(3), 19. https://doi.org/10.53388/mdm202508019

[12] Nivetha, S., & Inbarani, H. H. (2022). Neighborhood Rough Neural Network Approach for COVID-19 Image Classification. Neural Processing Letters, 54(3), 1919–1941. https://doi.org/10.1007/s11063-021-10712-6

[13] Nivetha, S., & Hannah Inbarani, H. (2023). Novel Hybrid Genetic Arithmetic Optimization for Feature Selection and Classification of Pulmonary Disease Images. International Journal of Sociotechnology and Knowledge Development, 15(1), 1–58. https://doi.org/10.4018/ijskd.330150

[14] Nivetha, S., & Hannah Inbarani, H. (2023). Novel Hybrid Genetic Arithmetic Optimization for Feature Selection and Classification of Pulmonary Disease Images. International Journal of Sociotechnology and Knowledge Development, 15(1), 1–58. https://doi.org/10.4018/ijskd.330150