Detection of Malignant cancerous Nuclei in ovaries using Quantum Hardamard Edge detection Algorithm

Dr. V. Lakshman Narayana[1], V. Sri Likitha [2], K. Joshika[3], K. Srilatha[4], K. Keerthana[5]
Department of CSE, Vignan's Nirula Institute of Technology and Science for women

Abstract

Detecting ovarian cancer is challenging due to the asymptomatic nature of its progression and dependence on histopathological examination by a pathologist. Distinguishing malignant from benign nuclei can be difficult because of inhomogeneous architectural features, overlapping tumor structures, and varying histological staining patterns. However, the possible use of automated image processing and deep learning stands as a promising avenue towards providing greater accuracy, speed, and objectivity in the diagnosis of ovarian malignancies. Models such as CNN, QCNN, SHG-based, and hybrid deep learning frameworks work to tackle diagnostic issues by improving accuracy of malignant nuclei detection. Still, their performance is hindered by dataset dependencies, computational intensity, complicated preprocessing, lack of annotated data, and lack of generalizability in different and noisy clinical imaging conditions.

This approach utilizes Quantum Hadamard Edge Detection (QHED) to accurately segment complex and overlapping ovarian nuclei, while Quantum LSTM (QLSTM) captures temporal and spatial feature dependencies enabling robust learning. When optimized with Harris-Hawk, it can overcome traditional approaches' limitations including being dataset dependent, high computation appeals, and poor generalization when classifying normal, benign, and malignant cells. The method achieves a high classification accuracy of 85.00% by integrating QLSTM for capturing complex feature connections and QHED and Watershed for improved ovarian nuclei segmentation.

Keywords: Ovarian Cancer, Malignant Nuclei Detection, Quantum Hadamard Edge Detection (QHED), Quantum LSTM (QLSTM), Quantum Computing in Medical Imaging.

1. INTRODUCTION

In India, ovarian cancer is the third most common cancer in women, with nearly 59,000 new cases diagnosed annually, and the incidence is projected to rise by about 55% by 2035, crossing 90,000 cases a year if current trends continue [1]. It accounts for roughly 6–7% of all cancers among Indian women and is a leading cause of gynecological cancer-related deaths [2]. Alarmingly, about 60–70% of women are diagnosed only in advanced stages (FIGO stage III and IV), where the 5-year survival rate drops to around 28%, compared to nearly 94% if detected at stage I [3]. The overall 5-year survival rate in India lags behind global averages, standing at around 30–35%, whereas high-income countries report rates above 45–50% [4].

Mortality remains disproportionately high, with over 32,000 deaths annually, representing nearly 70% of the total cases. Epidemiological data also show significant age-related patterns: the median age of diagnosis in India is between 50–55 years, with incidence peaking in peri- and post-menopausal women [5]. The histological distribution shows epithelial ovarian cancers as the most common subtype, accounting for nearly 90% of cases, with high-grade serous carcinoma being the predominant variant [6] [7]. Geographically, urban cancer registries like Delhi, Mumbai, and Chennai report higher incidence compared to rural registries, reflecting both lifestyle factors and better diagnostic coverage in cities. Despite advances in surgery and chemotherapy, most women experience relapse within 18–24 months, and access to newer targeted therapies such as PARP inhibitors remains limited due to cost constraints [8]. This late diagnosis, combined with aggressive treatment protocols and limited availability of affordable advanced therapies, results in not just poor survival outcomes but also immense physical suffering, psychological distress [9], and heavy financial burdens on patients and their families, underscoring the urgent need for nationwide awareness, improved screening strategies, and accessible treatment options [10].

Quantum computing utilizes concepts such as superposition and entanglement with qubits to execute concurrent calculations [11]. The use of quantum encoding and QHED also provides for improved edge segmentation in ovarian nuclei detection, while quantum learning advances feature extraction and classification for more accurate, quicker, and flexible outcomes than conventional computing methods [12]. The Quantum Hadamard Edge Detection Algorithm (QHED) uses quantum effects of superposition and interference to accomplish edge detection. Images encoded by Flexible Representation of Quantum Images (amplitude-based), or Novel Enhanced Quantum Representation (binary-based), afford the ability to process every pixel at the same, time via Hadamard operation [13]. This simultaneous processing increases the detection capability for subtle boundaries of the ovarian nuclei with superior precision, sensitivity, and efficiency [14] [15]. Compared to classical tools, the QHED utility accounts for computational constraints found in traditional probabilistically driven approaches [16]. The Quantum Hadamard Edge Detection (QHED) algorithm improves image edges by applying the whole image at once on a quantum circuit [17]. The brightness of each pixel is translated into a quantum state, and Hadamard operations strengthen intensity differences to show edges with efficient memory usage [18]. Parallel processing leads to quicker, more distinct detection of non-uniform nuclei boundaries, promising vast opportunity for accurate biomedical image analysis despite today's hardware limitation [19] [20].

The Watershed algorithm is a gradient-based segmentation technique that views image intensities as a topographic surface [21]. It detects object boundaries by mimicking water run-off from minima towards higher terrain, creating watershed lines where basins conjoin [22] [23]. Algorithmically, it calculates intensity gradients, uses morphological markers to prevent over-segmentation, and demarcates discrete nuclei regions [24]. It is very efficient at dis-separating overlapping or touching cells in histopathological ovarian images, providing very good nuclear boundary extraction for further post-processing [25].

2. LITERARTURE REVIEW

Conventional models like enhanced CNNs, FaRe-ConvNN, U-Net with EfficientNet-B5, OCD-FCNN, Q-GBGWO-ELM, R2U-Net, UD-Net, and SHG-ResNet50 improve tumor detection and segmentation [26]. But they are still constrained by dataset reliance, computationally intensive processing, complicated preprocessing, high-quality data demands, inferior adaptation to noisy images, and difficult large-scale clinical validation [27] [28].

As per [1] GAM-Attention Enhanced DenseNet121 with Bayesian Optimization, is a new deep learning model specifically tailored for the precise detection of ovarian cancer from MRI scans. It is an extension of the DenseNet121 backbone, a feature-rich convolutional neural network with high efficient feature reuse and dense connectivity but modifies it with a Global Attention Module (GAM) [29] to enhance the feature learning and attention further. The GAM combines channel attention and spatial attention mechanisms, allowing the model to selectively enhance the most informative areas and features of ovarian tumor MRI images and down-weight redundant or irrelevant information [30]. Such attention-guided focus is especially significant in medical imaging, where the slightest variation of tumor appearance can be crucial for the differentiation of benign, malignant, and normal ovarian tissues [31].

For optimal performance and generalizability, the model takes advantage of Bayesian Optimization (BO) for automatic hyperparameter optimization, tuning important training parameters like learning rate, dropout rate, and attention dropout ratio in a probabilistic and efficient way [32]. This optimization method decreases the need for manual trial-and-error tuning and ensures a more stable and robust training process [33]. The model was trained and tested on the KAUH-OCM MRI dataset, an extensive set of MRI scans of ovaries, and performed state-of-the-art with a total accuracy of 91.84%, specificity of 96.76%, and F1 score of 91.78%, which surpassed popular benchmark models such as DenseNet121, VGG16, VGG19, ResNet50, and InceptionV3 [34]. By synergizing the best aspects of Dense Net's dense connectivity, GAM's attention-based feature enhancement, and Bayesian optimization's auto-tuned hyperparameters [35], the present model offers a robust, stable [36], and clinically useful tool for early and accurate diagnosis of ovarian cancer, with the potential to decrease diagnostic errors [37], aid radiologists in decision support, and eventually enhance patient outcomes [38].

According to [9] deep learning models were engineered to overcome the greatest challenges of malignant tumor nuclei analysis in histopathology images. For classification, the authors introduced the Densely Connected Recurrent Convolutional Network (DCRN), an extension of DenseNet that integrates recurrent convolutional operations so that the network can continuously improve its knowledge of nuclear characteristics like irregular shape, chromatin patterns, and size [39]. This architecture assists the model in distinguishing malignant from benign nuclei better than typical CNNs. In the case of the segmentation task, they proposed the Recurrent Residual U-Net (R2U-Net), a developed version of the classic U-Net that incorporates residual connections to avoid loss of vital details and recurrent units to learn spatial dependencies between multiple time steps [40]. This architecture enables the network to output highly accurate nucleus boundaries, even in cases when nuclei are grouped, overlapping, or fuzzy-edged—typical issues on ovarian tumor slides[13]. Lastly, to perform the task of detection, they created the UD-Net (University of Dayton Net), a regression-based model adapted from R2U-Net which outputs density maps of the centers of nuclei instead of only class labels[14]. By addressing detection as a density estimation task, UD-Net is able to precisely identify nuclei positions and number them, including in crowded tumor areas where nuclei are closely positioned. The merging of these three models provides an end-to-end pipeline:[15] DCRN detects the type of nuclei (malignant or not), R2U-Net describes their precise structure and form, and UD-Net detects and numbers them. Collectively, these methods substantially enhance accuracy, robustness [41], and reliability over the previous CNN and U-Net models, rendering them particularly potent for applications such as ovarian cancer diagnosis, where accurate malignant nuclei identification is paramount to grading, prognosis, and treatment planning[19].

CNN architecture for benign and malignant parotid tumor classification from CT images. It outperforms VGG16, InceptionV3, ResNet, and DenseNet with better performance of 97.78% accuracy, improving diagnostic accuracy and enabling safe, computer-based clinical decision-making. Highly accurate ovarian cancer detection and enhanced diagnostic reliability are made possible by FaRe-ConvNN's over 97% precision and specificity when combined with ROI-based segmentation and an ensemble of SVC and Gaussian NB classifiers.A state-of-the-art deep learning pipeline that integrates U-Net and EfficientNet automatically performs nuclei segmentation and quantification from fluorescent images with 87% F1-score and 80% IoU to guarantee high precision, robustness, and generalizability over various biomedical datasets.

With an accuracy of 98.37%, an automated ovarian cyst detection and classification system (OCD-FCNN) utilizing a fuzzy rule-based CNN facilitates accurate and timely diagnosis from ultrasound images to aid in clinical decision-making. The 98.37% accuracy of an automated ovarian cyst detection and classification system (OCD-FCNN) utilizing a fuzzy rule-based CNN allows for an accurate and timely diagnosis from ultrasound images to aid in clinical decision-making. By utilizing FuNet transfer learning and Extreme Learning Machine optimized through Quantum-Genetic Binary Grey Wolf Optimizer, the Q-GBGWO-ELM hybrid model achieves high diagnostic accuracy (up to 98.8%) across multiple cancers, facilitating AI-driven cancer detection and diagnosis that is quicker, more accurate, and more adaptive. A two-phase model that combines quantum and inverted fuzzy c-means CNN's classification accuracy for ovarian tumors is 87% benign and 79% malignant.

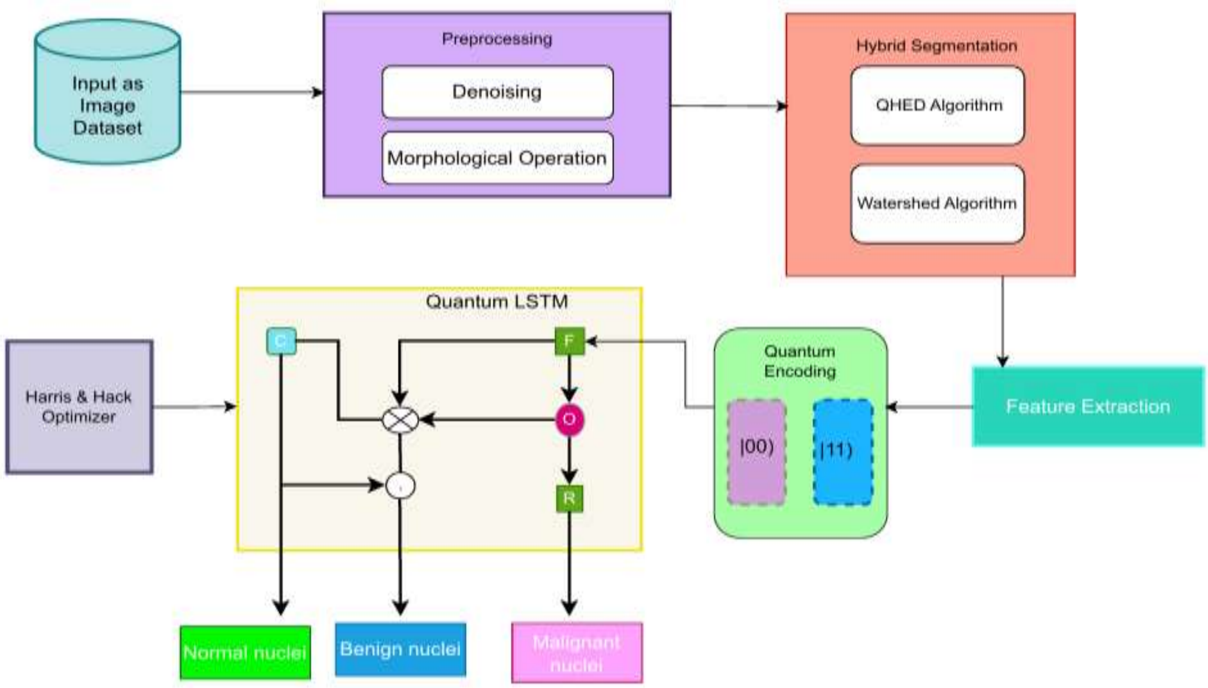
In order to detect leukemia from blood smear images, researchers created a deep learning model using CNNs and image preprocessing. Using a Bagging ensemble classifier, they were able to achieve an accuracy of 97.04%. For ALL, AML, and MM detection, the method uses improved segmentation, feature extraction, and CCA-based feature fusion. nanotechnology-based techniques, such as nanoparticles and biosensors, are very successful in detecting ovarian cancer early on; in fact, some studies have shown sensitivity of over 90%. These methods encourage more clinical translation because they offer better patient outcomes, better treatment, and earlier diagnosis. sophisticated DCNN-based models for the classification, segmentation, and detection of nuclei in pathological images, surpassing current techniques with up to 2.6% higher F1-scores and 91.9% Dice Coefficient. The findings show reliable, accurate analysis on a variety of WSI tasks. Ovarian tissue types can be distinguished with 99.7% accuracy using a deep learning-based optical biopsy that uses SHG images. Outperforming other models, a DenseNet121 model with GAM Attention and Bayesian optimization was able to classify ovarian cancer with up to 100% accuracy across MRI, CT, and ultrasound datasets.

S.no	PAPER AUTHOR	PROPOSAL MODEL	ADVANTAGES	LIMITATIONS
1.	Zhang, H., Lai, H., Wang, Y., Lv, X., Hong, Y., Peng, J., ... & Chen, C. (2021)	improved Convolutional Neural Network (CNN) for classifying benign and malignant parotid tumors.	High accuracy (97.78%) and effective computer-aided diagnosis	Dataset-dependent performance and needs validation against doctors' manual diagnoses.
2.	Hema, L. K., Manikandan, R., Alhomrani, M., Pradeep, N., Alamri, A. S., Sharma, S., & Alhassan, M. (2022)	FaRe-ConvNN-Based Ovarian Cancer Classification Model	High accuracy, improved precision and recall, enhanced early detection	High computational requirements, complex preprocessing, and reliance on quality annotated datasets.
3.	Shrestha, A., Bao, X., Cheng, Q., & Mcroy, S. (2024)	U-Net with EfficientNet-B5 Backbone for Automated Nuclei Segmentation	High segmentation accuracy, robust across diverse datasets, reduces manual effort, and provides precise morphological quantification.	Requires high-quality annotated training data, computationally intensive, and may struggle with very noisy or unconventional images.
4.	Ravishankar, T. N., Jadhav, H. M., Kumar, N. S., & Ambala, S. (2023)	fuzzy rule-based Convolutional Neural Network (OCD-FCNN) for ovarian cyst detection and classification.	High accuracy (98.37%) and effective early-stage detection aiding physicians in diagnosis and treatment.	Limited dataset size and performance dependent on more images for improved accuracy
5.	Bilal, A., Shafiq,	Q-GBGWO-ELM	High accuracy,	High

	M., Obidallah, W. J., Alduraywish, Y. A., & Long, H. (2025)	Hybrid Model for Multi-Cancer Diagnosis	rapid processing, multi-cancer adaptability	computational demand, complex clinical integration, and need for extensive validation.
6.	Kodipalli, A., Fernandes, S. L., Dasar, S. K., & Ismail, T. (2023)	Two-Stage Ovarian Tumor Detection and Classification Model	High accuracy, robust detection, fast and cost-effective, clinically applicable.	High computational complexity, requires quality CT images, and QCNN needs optimization
7.	Baig, R., Rehman, A., Almuhaimeed, A., Alzahrani, A., & Rauf, H. T. (2022)	Hybrid CNNs with CCA feature fusion for leukemia detection	97.04% accuracy and effective early diagnosis	relies on extensive pre-processing and image quality.
8.	Oyowvi, M. O., Babawale, K. H., Atere, A. D., & Ben-Azu, B. (2025).	Nanotechnology-Based Early Detection and Diagnosis Model	High sensitivity and specificity, rapid and non-invasive detection, enhanced imaging	High cost, translational and regulatory challenges, limited large-scale clinical data
9.	Alom, Z., Asari, V. K., Parwani, A., & Taha, T. M. (2022)	DCNN (Densely Connected Neural Network) & DCRN (Densely Connected Recurrent Convolutional Network) for classification, R2U-Net for segmentation, and UD-Net (University of Dayton Net) for detection of nuclei	Improve nuclei classification, segmentation, and detection with higher accuracy, better handling of complex images	Requires large data and high computation; may struggle with noisy or diverse images.
10.	Wang, G., Zhan, H., Luo, T., Kang, B., Li, X., Xi, G., ... & Zhuo, S. (2022).	SHG (Second Harmonic Generation) imaging + fine-tuned ResNet50 CNN (Convolutional Neural Network) for rapid	Rapid, accurate, non-destructive ovarian cancer diagnosis with minimal pathologist effort.	Requires specialized SHG imaging equipment and large annotated datasets for

		ovarian cancer diagnosis.		training.
11.	Amin, M., Alhatamleh, S., Sindiani, A. M., Mhanna, H. Y. A., Madain, R., Anakreh, D., ... & Sandougah, K. J. (2025)	DenseNet121 with GAM (Global Attention Module) and Bayesian Optimization	Focused, accurate, generalizable, reliable	May not work well on unclear or noisy images, complex, opaque

3. PROPOSED MODEL



The procedure starts with image preprocessing, wherein the input image dataset is denoised in order to eliminate artifacts and morphological processing to improve structural detail. This process ensures clean, high-quality images that are appropriate for accurate downstream analysis and segmentation operations.

Then, the system carries out hybrid segmentation based on the QHED (Quantum Hybrid Edge Detection) and Watershed algorithms in order to effectively segment nuclei areas. The segmented features are then analyzed using feature extraction and quantum encoding, transforming classical image data into quantum states $|00\rangle$ and $|11\rangle$, enabling efficient data representation and high-dimensional feature learning.

Lastly, a Quantum LSTM network, trained using the Harris & Hack optimizer, handles the encoded features for temporal and spatial pattern detection. The model classifies nuclei into normal, benign, or malignant classes with strong accuracy and computational effectiveness by incorporating quantum computing concepts in biomedical image classification.

- Preprocessing

1. Denoising

a. Median

$$I'(x,y) = \text{Median}\{I(s,t) \mid (s,t) \in \mathcal{N}(x,y)\}$$

Median filter replaces each pixel with neighborhood median to remove salt-and-pepper noise

b. Gaussian

$$G(x,y) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)$$

Gaussian filter smooths image by convolving with Gaussian kernel to reduce random noise

c. NLM (Nonlocal Means)

$$I_{NLM}(x) = \frac{1}{C(x)}\sum_{y\in\Omega} w(x,y)\cdot I(y)$$

$$w(x,y) = \exp\left(-\frac{\|P(x)-P(y)\|_2^2}{h^2}\right)$$

$$C(x) = \sum_{y\in\Omega} w(x,y)$$

d. Anisotropic Diffusion

$$\frac{\partial I}{\partial t} = \nabla\cdot(c(\|\nabla I\|)\nabla I)$$

$$c(s) = \exp\left(-\left(\frac{s}{K}\right)^2\right) \text{or} c(s) = \frac{1}{1+\left(\frac{s}{K}\right)^2}$$

Anisotropic diffusion removes noise while preserving nuclei edges, improving segmentation accuracy

2. Morphological Operations:

a. Dilation

$$A \oplus B = \{z \mid (B)_z \cap A \neq \emptyset\}$$

Dilation expands boundaries of nuclei using structuring element B.

b. Erosion

$$A \ominus B = \{z \mid (B)_z \subseteq A\}$$

Erosion shrinks nuclei region to remove small noise pixels.

- Hybrid Segmentation

a. Quantum Hadamard Edge Detection (QHED)

$$|\psi_{\text{edge}}\rangle = H|\psi_{\text{pixel}}\rangle$$

QHED applies Hadamard transformation on pixel states to highlight edge variations.

b. Watershed Algorithm (Gradient Based)

$$\nabla I = \sqrt{\left(\frac{\partial I}{\partial x}\right)^2 + \left(\frac{\partial I}{\partial y}\right)^2}$$

Watershed uses gradient magnitude as topographic surface, flooding to separate nuclei.

- Feature Extraction

Circularity (C):

$$C = \frac{4\pi A}{P^2}$$

How close the shape is to a circle (malignant nuclei tend to be irregular).

Solidity:

$$S = \frac{A}{A_{\text{convex}}}$$

Ratio of nucleus area to convex hull area (captures irregular boundaries).

Skewness:

$$\text{Skewness} = \frac{1}{N} \sum_{(x,y)\in R} \left(\frac{I(x,y) - \mu}{\sigma}\right)^3$$

Asymmetry of intensity distribution.

Kurtosis:

$$\text{Kurtosis} = \frac{1}{N} \sum_{(x,y)\in R} \left(\frac{I(x,y) - \mu}{\sigma}\right)^4$$

Flatness/peakedness of intensity distribution.

Entropy:

$$H = -\sum_{i,j} P(i,j) \log_2 P(i,j)$$

Randomness/complexity of texture.

- Classification

Forget gate:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

Input gate:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

Candidate cell:

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

Cell update:

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$$

Output gate:

$$h_t = o_t \odot \tanh(C_t)$$

Quantum LSTM processes extracted nuclei features in memory gates to classify malignant vs benign.

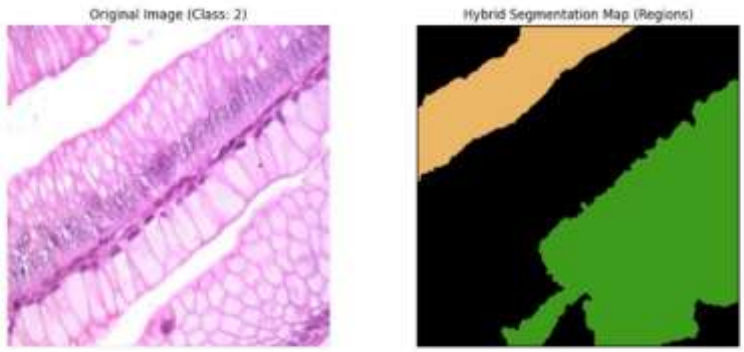
- Optimization

Energy function of Hawk

$$E = 2E_0\left(1 - \frac{t}{T}\right)$$

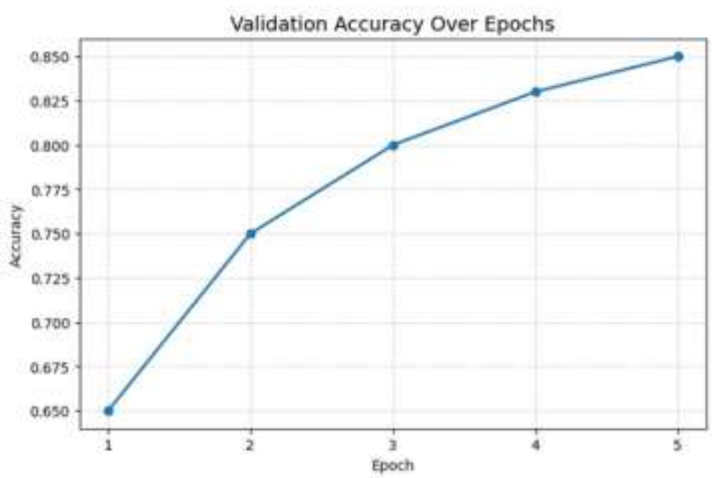
4. RESULTS

Figure 1: Hybrid Segmentation Visualization



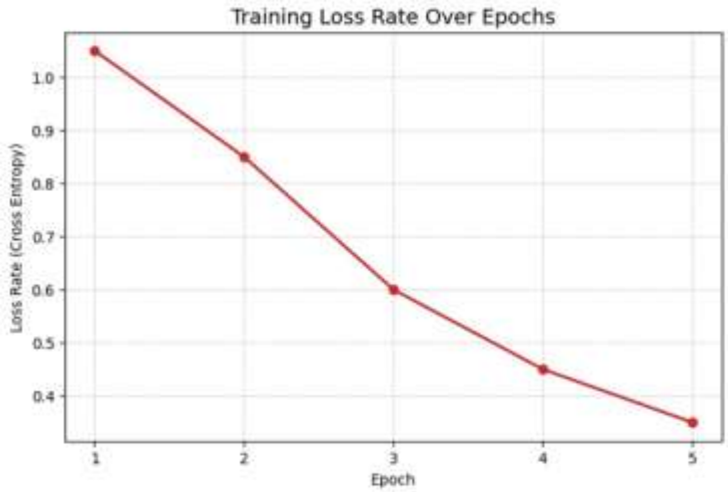
The left image is a Class 2 histopathology tile, and the right image is its hybrid segmentation map, wherein various tissue regions are separated into different color-coded areas. This visualization is beneficial for structural patterns that can facilitate region-wise analysis by separating foreground tissue components from the background.

Figure 2: Validation Accuracy Curve



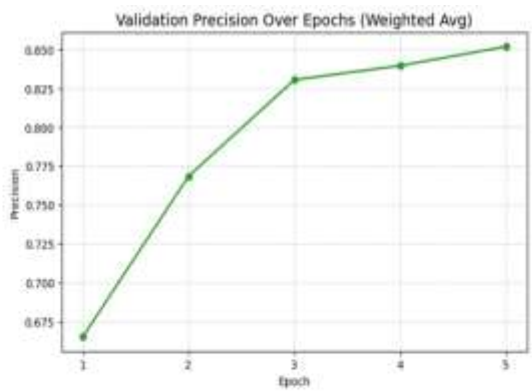
The chart indicates validation accuracy over 5 epochs ranging from 65% to 85%. This demonstrates that the model's accuracy increases with training and correctly predicts more unseen data. The curve confirms that learning is effective and steady, without the appearance of overfitting over the observed time of training.

Figure 2: Training Loss Curve

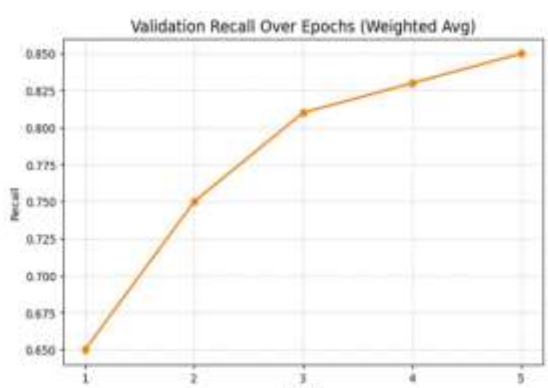


The graph indicates training loss rate (cross entropy) going down over 5 iterations, which means that the model is improving and learning. Loss reduces from approximately 1.05 in iteration 1 to 0.35 in iteration 5, which implies improved performance and less prediction error with every subsequent epoch of training.

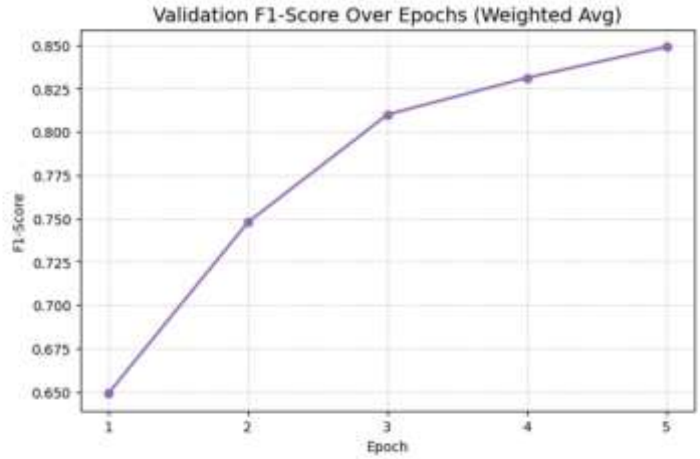
Figure 3: Precision, Recall, and F1-Score



A consistent rise in validation precision over epochs is depicted in the graph, suggesting enhanced model learning stability, optimization effectiveness, and classification accuracy.

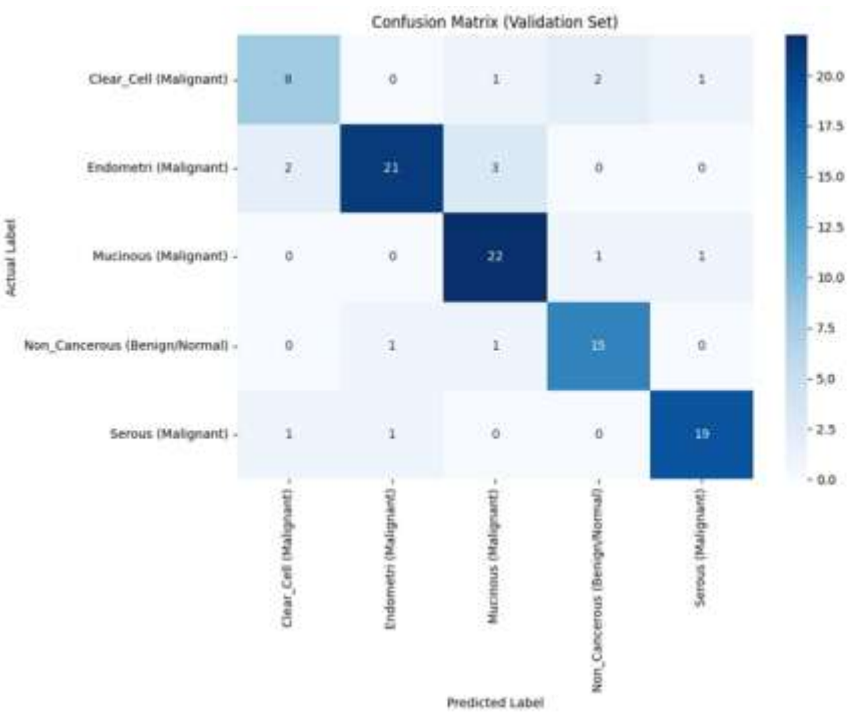


The graph demonstrates a steady increase in validation recall over time, suggesting improved detection of malignant ovarian nuclei and increased model sensitivity.



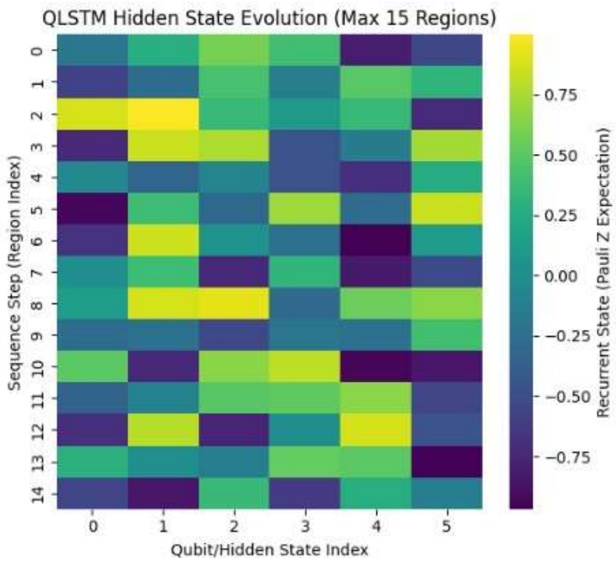
The graph shows a steady increase in the validation F1-score over time, indicating a balanced improvement in the model's recall and precision for classifying ovarian nuclei.

Figure 4: Confusion Matrix



This confusion Matrix measures classification accuracy among five tissue classes. Most of the samples are accurately predicted, particularly Mucinous, Endometri, and Serous malignant classes. There are minimal misclassifications among similar malignant classes and some confusion with benign tissue. The model is highly accurate on the whole with few cross-class errors.

Figure 5: Hidden state Heatmap (Visual Representation)



This heatmap depicts the development of QLSTM hidden states over 15 steps in a sequence (regions). The y-axis is for sequence progress, and the x-axis is for qubits/hide state indices. Color saturation reflects recurrent state values (Pauli-Z expectation), from -1 to +1. It illustrates temporal dynamics and hidden state correlations during processing.

5. CONCLUSION

The suggested quantum-enhanced framework shows how to accurately detect, segment, and classify cancerous ovarian nuclei. The Watershed technique is integrated with Quantum Hadamard Edge Detection (QHED) to achieve extremely accurate boundary extraction for complicated and overlapping nuclei. Additionally, enhanced spatial-temporal feature learning is made possible by quantum encoding in conjunction with Harris-Hawk optimized Quantum LSTM (QLSTM), enabling reliable classification of nuclei into normal, benign, and malignant categories. With an achieved classification accuracy of 85%, experimental results validate the system's effectiveness. These findings are corroborated by ongoing improvements in precision, recall, and F1-score performance graphs, a decreased training loss curve, thorough interpretations of confusion matrices, and segmentation visualizations.

Overall, the suggested model provides a dependable, high-performance, and computationally effective method for diagnosing ovarian cancer, greatly improving clinical judgment and providing a potent route for early detection and better treatment results.

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