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A STRUCTURED FRAMEWORK FOR AUTOMATED ULTRASOUND-BASED UTERINE FIBROID CLASSIFICATION USING A HYBRID QUANTUM-CLASSICAL CONVOLUTIONAL NEURAL NETWORK

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Abstract

An accurate and early detection of uterine fibroid is important for effective clinical treatment and prevention of delays in diagnostics. Sometimes classical learning models face difficulties due to complex feature representation and generalization, specifically when trained under limited medical datasets. To work through with such problems, this study proposes an organised pipeline with hybrid quantum classical convolutional neural network that incorporates classical feature extraction with parameterized variational quantum circuit for enhanced high-dimensional feature representation and classification. The proposed work was evaluated along with a classical CNN under both non-augmented and augmented training constraints. Experimental results under non-augmented constraints, the structured pipeline achieved ACC, AUC, SE, SP of 89%, 96%, 98%, 77% for hybrid QCNN and 63%, 69%, 72%, 51% for CNN. Similarly, under augmented conditions, achieved ACC, AUC, SE, SP of 90%, 96%, 96%, 83% for hybrid QCNN and 67%, 75%, 67%, 67% for CNN respectively. In both constraints, sensitivity and specificity was improved in hybrid model and it reduces false negative cases. Throughout epochs, the hybrid model showed faster convergence and improved generalization stability compared to classical CNN. These outcomes highlight the effectiveness of quantum-based approaches into classical learning for complex image classification by improving diagnostic reliability, reducing false negatives, false positives and supporting more accurate uterine fibroid detection systems.

Keywords:

Hybrid Quantum Convolutional Neural Network, Uterine Fibroid, Preprocessing, Segmentation, Data Augmentation

1. INTRODUCTION

Fibroids are also known as uterine leiomyomas, the most common non-cancerous tumours affecting women of reproductive age. Their growth is influenced by hormonal factors, particularly Estrogen and Progestrone and they start from soft tissues of uterus. Irregular menstrual bleeding, lower back discomfort, bowel problem, pelvic pain, frequent urination, a sense of urgency and constipation are some of the symptoms. Fibroids may vary on size, and location depends on patient’s age. Myomectomy, hysterectomy, uterine artery embolization, and MRI focused ultrasound surgery are all part of diagnostic procedures of fibroid [1].

Although many advanced medical imaging techniques are developed to generate images for different parts of anatomy. But ultrasound scan technique is a preferred imaging method for finding the fibroids. Because it is mostly used and efficient tool for imaging the soft tissues in organs due to its visible benefits including effective cost, speed, ease of use, compactness, safety and absence of ionizing radiation [2].

In the early phases of abnormality, recognising symptoms in medical imaging is quite subtle and varied in appearance, so specialists face difficulties in making diagnoses. Finding the soft tissues from ultrasound image is complex problem due to that images affected by speckle noise, low contrast that degrades scan images into poor quality. Because anatomical inconsistencies, varied size of tissues and location leads to difficulty for the process of feature extraction and segmentation. Usually, radiologists manually checks the fibroids and mark its edges from ultrasound images, this process often time consuming and dependent on radiologist. So, the implementation of stable pre-processing and segmentation algorithms in fibroid detection has significant improvement in treatment planning [3].

Particularly in tasks involving prediction, segmentation and classification, recent developments of classical learning in medical image analysis have shown promising outcomes. But their performance in ultrasound fibroid detection is still limited due to noise, large volume of data requirements and computational conditions. Emerging applications such as quantum machine learning offer significant advantages in handling high-dimensional information, complex feature extraction, computational cost and limited amount of data motivating the investigation of uterine fibroid.

The uniqueness of this study lies in the creation of a hybrid quantum-classical convolutional neural network for automated detection of uterine fibroids using ultrasound images. Unlike traditional CNN methods, the novel approach uses a combination of classical convolution features and variational quantum circuit to change and distinguish the learned features in quantum feature space. The model will also be analyzed with regard to non-augmented and augmented training to investigate the robustness of the approach in case of insufficient training data. The quantum element in this work was chosen based on previous studies where hybrid quantum-classical CNN models were shown to be applicable in image classification for medical and radiological applications.

The key objectives of the current study are:

- To design an automated system for automatic detection of uterine fibroids from ultrasonic images.
- To preprocess and segment the input images in order to get a better image representation.
- To extract discriminative features from the image by applying classical Convolution Neural Network (CNN).
- To incorporate a parametrized variational quantum circuit into the architecture of the classical CNN.
- To examine the effect of data augmentation on the performance of the proposed model.
- To compare the proposed hybrid quantum/classical model (QCNN) with classical CNN on the basis of ACC, AUC, sensitivity, and specificity.

- To reduce false negatives during automated detection of uterine fibroids.

The primary contributions of this study are as follows:

1. To enhance the model classification performance, this study develops a structured framework involving preprocessing, segmentation and augmentation techniques.
2. A hybrid quantum convolutional neural network is proposed for uterine fibroid classification from ultrasound images by combining classical convolutional feature extraction with parameterized quantum circuits.
3. The advantages of proposed HQCNN model in uterine fibroid classification is compared to classical CNN using standard evaluation metrics to validate its effectiveness, especially the trade-off between sensitivity and specificity.
4. This work demonstrates the ability of hybrid quantum architectures to achieve improved performance under limited dataset conditions, emphasizing their capability for real-world clinical settings.

2. LITERATURE REVIEW

Kaur et al. [4] reviewed the highlights effective preprocessing or denoising techniques directly influences the performance of feature extraction and classification in improving reliability of diagnoses before applying machine learning algorithms. Therefore, preprocessing methods form a foundational step in analysis of medical images to assure reliable segmentation and categorization.

The importance of preprocessing and feature selection techniques was highlighted due to the challenges of noise, dataset size requirements, data irregularity and dataset bias discussed by Rana and Bhushan [5]. Similarly, Shivakumar et al. [6] explored segmentation methods that facilitates the contour to initialize far from object boundaries and gradually converge toward complex regions due to degraded image quality of ultrasound imaging. Additionally, Sadullaeva et al. [7] discussed about segmentation of ultrasound image to find uterine fibroid is a complex problem and built threshold-based segmentation to compare the brightness value of each pixel of images to find homogeneity.

Shahzad et al. [8] demonstrated that the use of data augmentation would improve the learning capability of models to accurate the diagnostic process and effectiveness. To reduce overfitting, Raimondo et al. [9] applied data augmentation techniques to find uterine adenomysis. Similarly, [2] applied augmentation techniques within training data for the model to learn objects located under various constraints for improving generalization in real-world clinical data.

Varoquaux et al. [10] discussed about significant limitations in machine learning for medical imaging. The study specifically mentioned that the availability of datasets would affects the evaluation of models due to small and biased datasets. Also states the use of standard evaluation metrics for evaluating model performance.

Nowadays, machine learning algorithms are widely used for automate the task of classification, segmentation and anamoly detection in medical images. To find the characteristics of images Dinesh et al. [11] utilized the algorithms including logistic regression, support vector machines, K-nearest neighbour, Decision trees and Random forest for breast cancer identification. Zhang et al. [12] used the ML based algorithms such as linear regression, LR, SVMs, RFs and multilayer perceptron for prediction fibroids after HIFU ablation. Although, these methods shown good performance in early computer-assisted diagnosis, their effectiveness depends on manual pre-processing and feature extraction techniques.

With improvements of analysing raw images, the deep learning algorithms become a significant method to gradually replaces the traditional ML algorithms in medical imaging. Suganyadevi et al. [13] given the brief outline about the DL techniques including DNN, CNN, RNN, DBN, AEs, SAEs, LSTM and its implementation frameworks. Further described about the process of medical image analysis including segmentation, localization, detection and object classification. Also states about the types of anatomical abnormalities are implemented using DL algorithms. Especially CNN based models shows classification accuracy by enhanced segmentation techniques by Andrea Tinelli et al. The CNN based algorithms DeepBreastCancerNet [14], Dual Path CNN [8], attention based EfficientNetB0 [3] showed better classification accuracy in medical image analysis. This study employed data augmentation techniques to expand the dataset size to address data insufficiency and mitigate the problem of overfitting. Similarly, to accurate the classification performance these study uses segmentation techniques to gain accurateness.

Although deep learning models have shown remarkable achievements in medical image classification and segmentation processes, challenges including large-scale data requirements, high computational resources and limited generalization in small datasets remain a problem. In response to these conditions, Quantum Machine Learning has progressed as an assuring paradigm that integrates quantum computing principles with machine learning techniques.

Ullah et al. [15] reviewed the QML revolution in healthcare based on characteristics and its applications. QML and QDL algorithms have been developed to address underlying challenges of classical learning by using the computational ability of QC. Different QML models, including QNN, QCNN, QSVM and VQC have been described for the applications of healthcare sectors including drug development and discovery, radiotherapy and early-stage diagnosis assistance. This review shows that QML model achieved comparable, in some cases higher performance compared to classical learning in healthcare-related studies. Beyond these investigations, various experimental works have implemented QML models for image classification tasks.

Vann et al. [16] used QNN model in cancer (500 images) and heart disease (500 images) to pattern recognition. QNN model showed the optimal accuracy (92%) under limited dataset conditions in accordance with efficient processing speed and low computational resources. In relation to previous work, A hybrid QNN model was implemented by Senokosov et al. [17] to classify MNIST and CIFAR-10 datasets. The model shows better learning ability and classification using fewer parameters.

In addition to these, Chen et al. [18] designed QCNN using TensorFlow quantum model that shows improved performance in classification when compared with CNN. Relatedly, an adaptive hybrid Quantum CNN was implemented by Ajlouni et al. [19]

with parameterized quantum circuits to classify brain tumour in an MRI dataset consisting of 7000 images. The test results show the HQCNN model converges faster and reach better performance in fewer epochs. Similarly, Xiang et al. [20] executed QCCNN model on three breast cancer datasets, GBSG, SEER and WDBC to validate the generalization of model performance. Here, the QCCNN model shows good classification with improved processing speed and efficient pattern learning.

Despite these promising results, the uses of quantum machine learning in clinical image diagnostics are still in its initial stage. The QML based research is still limited, particularly in uterine fibroid analysis of ultrasound. Moreover, the QML based studies remain constrained by limited qubit availability, hardware requirements and noisy quantum devices. It highlights the need for furthermore investigation in medical imaging applications to develop a balanced hybrid quantum architecture.

While deep learning methods used to detect uterine fibroids have performed well, several limitations are still present. First, CNN algorithms usually require vast amounts of training data and could experience reduced generalization when the dataset size or heterogeneity is low. Moreover, ultrasound-based studies are mostly based on internal datasets, which makes it hard to apply the algorithm in other hospitals, with other ultrasound machines and on different populations. A systematic review has found that many studies on benign gynecological ultrasound using AI have a high risk of bias associated with subject selection and lack of external validation. Another limitation is that most current fibroid detection algorithms mainly utilize classical deep learning networks, such as CNN, EfficientNet, MobileNet, attention networks and generative augmentation. The use of quantum-classical learning is not explored enough in uterine ultrasound imaging. There are a few studies which have applied hybrid architectures in medical imaging and found that quantum methods work, but their performance is no better than classical networks' one, and hence there is a need for validation on application-specific datasets instead of assuming a quantum advantage on any kind of dataset.

3. METHODOLOGY

The study methodology describes the structured pipeline to execute the quantum-based model using quantum circuits for the classification of uterine fibroids in ultrasound scan images. in this part, In-depth description of used techniques is described thoroughly. The Fig.1 presents the proposed pipeline of classification of uterine fibroid using quantum-based learning.

3.1 PREPROCESSING

In this study, an organised preprocessing techniques was applied to improve ultrasound scan image quality and enhance feature illustration before entering into model training. Ultrasound images is naturally affected by speckle noise, different intensity and low contrast. Therefore, multiple enhancement techniques were applied including gaussian smoothing, median filtering, contrast enhancement using CLAHE, spatial normalization using resizing and pixel normalization. Let the given input ultrasound image be represented as $I_X\left(x,y\right)$. Initially, gaussian filtering was applied to reduce high-frequency noise while preserving anatomical boundaries of medical image. The obtained gaussian filtered image is represented as:

$$I_G = I\left(x,y\right) * G\left(x,y\right) \tag{1}$$

Where * denotes convolution operation and $\mathrm{G}\left(\mathrm{x},\mathrm{y}\right)$ is gaussian kernel defined as

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

where σ controls the smoothing intensity.

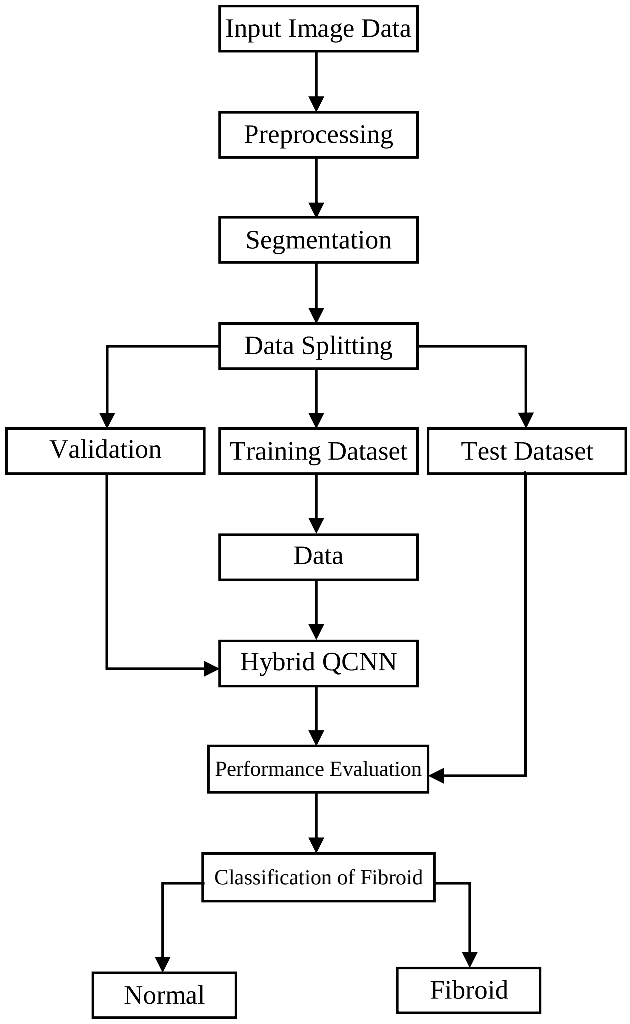


Fig.1. Proposed Pipeline of classification of uterine fibroid using quantum-based learning

Followed by median filtering was applied to reduce speckle noise, which commonly existed in ultrasound imaging. it median intensity values calculated from its nearby pixels. The filtered image is obtained by replacing each pixel with the median value is represented as

$$I_M\left(x,y\right) = \text{median}\{I_G\left(i,j\right) | \left(i,j\right) \in N_{x,y}\} \tag{3}$$

where $N_{x,y}$ is neighbourhood pixel values centered as x, y.

To improve local contrast and visibility of fibroid, CLAHE was applied. The computed histogram probability distribution is represented as

$$P(r_k) = \frac{n_k}{N} \tag{4}$$

where n_k denotes the number of pixels at intensity level k and N denotes the total number of pixels. The histogram cumulative distribution functions is computed as

$$CD(r_k) = \sum_{j=0}^{k} P(r_j) \tag{5}$$

The enhanced intensity value is obtained as:

$$I_c = (L-1) \times CD(r_k) \tag{6}$$

where L is number of gray intensity levels.

Afterwards, all images were resized to a fixed spatial resolution 224 ×224 pixels to ensure dimensional consistency to images for passing as a model input. The resized image is represented as

$$I_R = Resize(I_c, 224, 224) \tag{7}$$

Finally, to regulate the pixel intensity values throughout all sample images, intensity normalization method was performed using min-max normalization. The normalized image is computed as

$$I_N = \frac{I - I_{min}}{I_{max} - I_{min}} \times (B - A) + A \tag{8}$$

where A = 0, B = 255 define the output intensity range and I_{min}, I_{max} represent the minimum and maximum intensity values of the image.

This organised preprocessing technique improves noise reduction, enhances lesion visibility and input feature consistency, thereby supporting stable feature leaning in implemented model.

3.2 SEGMENTATION

The region-of-interest based segmentation framework was implemented to improve lesion localization and reduce irrelevant characteristics in ultrasound images. The applied segmentation combines global thresholding, adaptive edge detection, morphological refinement and contour-based filtering to create high-quality pseudo-masks for ultrasound images to enable the model to learn better.

Initially, preprocessed input grayscale images were converted into 8-bit intensity representation to assure consistency with thresholding and edge detection algorithms. Gaussian smoothing is applied to 8-bit converted image prior to move segmentation process for stabilizing intensity dissemination and minimizing high-frequency noise. To automatically regulates the optimal threshold value by minimizing intra-class variance, a global threshold process was implemented using Otsu's segmentation method. The threshold value was reserved within an experimental defined range to improve stability among all intensity distributions of ultrasound images. It is represented as:

$$\sigma_\omega^2(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t) \tag{8}$$

where ω_1, ω_2 are class probabilities and σ_1^2, σ_2^2 represents the variance of classes.

Adaptive canny edge detection was applied to enhance boundary detection and improves strength across varying brightness and contrast level observed in ultrasound imaging. The lower and upper thresholds were dynamically calculated based on the median pixel intensity is represented as

$$T_{low} = 0.66 \times Median(I) \tag{9}$$

$$T_{high} = 1.33 \times Median(I) \tag{10}$$

The binary mask acquired from otsu was added with the edge map using local union operation to maintain intensity information and boundary characteristics. Following this mask fusion, morphological operations such as opening and closing was applied to eliminate thin noise formations and smooth ROI boundaries. These opening and closing operation is represented as

$$I_{\text{open}} = (I \ominus B) \oplus B \tag{11}$$

$$I_{\text{close}} = (I \oplus B) \ominus B \tag{12}$$

Here B is the structuring element for morphological operations. To identify anatomically relevant structures, contour detection method was performed to images for finding larger contours to do further processing. Area based contour filtering is represented as

$$A_{min} = 0.015 \times H \times W \tag{13}$$

Here H and W represents image height and width. A pseudo-mask was generated, where the mask values are defined between 0 and 1.

$$Mask(x, y) \in \{0, 1\} \tag{14}$$

Finally, the ROI enhanced image was obtained using all the above masking process

$$I_{ROI} = I_N \times Mask \tag{15}$$

The resulting pseudo-masks enable ROI based feature learning to improve classification stability in both classical and hybrid quantum architectures.

3.3 DATA AUGMENTATION

A structured augmentation methods was implemented to improve model generalization and reduce overfitting problem connected with limited medical datasets. This augmentation methods were executed on ROI-based segmented images to sustain clinically related structures while extending size of dataset. The methods added in this study is geometric transformations such as random horizontal flip and small angle rotations, intensity variations using color jitter (brightness and contrast) and inject stochastic noise to reproduce real-world image acquisition characteristics without affecting original anatomical features of ultrasound. Initially, randomly selected controlled rotation with an angle $\theta \in [-15°, +15°]$ was applied to simulate variations in positioning and scanning angles of image during acquisition. It is denoted by $I_R(x,y)$ and is written by Eq.(1)

$$I_R(x, y) = I_{ROI}\ (x\cos\theta - y\sin\theta,\ x\sin\theta + y\cos\theta), \quad \theta \in [-15^\circ, +15^\circ] \tag{16}$$

Afterwards, random horizontal flipping with probability $P(F) = 0.5$ was applied to the rotated image to help improve invariance orientation differences in scanning. The horizontally flipped image is represented by $I_F(x,y)$ and Eq.(2) is formulated as

$$I_F(x,y) = I_R(W-x-y, \quad y), P(F) = 0.5 \tag{17}$$

where W denotes width of an image. Thereafter, to stimulate intensity variations instigated by ultrasound acquisition conditions brightness and contrast methods was introduced. The intensity applied image is represented by $I_{BC}(x,y)$ and formulated as Eq.(3)

$$I_{BC}(x,y) = \alpha I_F(x,y) + \beta \tag{18}$$

where α is contrast scaling factor and β is brightness adjustment factor. At the end, stochastic noise was injected to mimic ultrasound specific acquisition noise and improve stability of input images against real-world imaging noises. The noise applied images is represented as $I_A(x,y)$ and the Eq.(4) is expressed as

$$I_A(x,y) = clip\left(I_{BC}(x,y) + N\left(0,\sigma^2\right), 0,1\right) \tag{19}$$

Where $N\left(0,\sigma^2\right)$ is gaussian distributed noise with variance and clip(.) constraints pixel intensities from 0 to 1. Importantly, augmentation method was only applied to the training dataset where validation and test datasets had remained unaltered to assure unbiased model evaluation and maintain clinical reliability of performance evaluation metrics.

3.4 NEURAL NETWORK FEATURE EXTRACTION

In this work, Similar convolutional neural network feature extraction methodology was implemented for both CNN and hybrid QCNN models to assure a fair architectural evaluation of performance comparison. This feature extraction network consists of three convolution blocks followed by max-pooling layers for hierarchical feature extraction and spatial dimensionality reduction.

Following convolutional feature extraction, adaptive average pooling was applied to create a fixed length feature representation suitable for following classification layers. The convolutional blocks increasingly learn texture features, important structural patterns and complex lesion representations from ultrasound ROI images. Table 1. below is the structure with output shape and parameters.

Table.1. Neural network feature extraction used in CNN and HQCNN

Layer Type	Output Shape	Trainable Parameters	Non-Trainable Parameters
Input Image (1, 224, 224)	224×224×1	0	0
Conv2D (1 → 64, 3×3)	64×224×224	640	0
MaxPool2D (2×2)	64×112×112	0	0
Conv2D (64 → 32, 3×3)	32×112×112	18,464	0
MaxPool2D (2×2)	32×56×56	0	0
Conv2D (32 → 16, 3×3)	16×56×56	4624	0
MaxPool2D (2×2)	16×28×28	0	0
AdaptiveAvgPool2D (1×1)	16×1×1	0	0
Flatten Layer (Reshape)	16	0	0

3.4.1 Convolutional Neural Network:

In medial image analysis, the convolutional neural network is widely applied due to its ability to learn spatial and hierarchical features from given images. In this work, CNN is used as a base architecture for feature extraction and classification of fibroids from uterine ultrasound images. The CNN is consists of convolutional layer, pooling layer and fully connected layer to classifying images. Here, convolutional layer learns texture and structural information, while pooling layer helps to reduce dimensionality. The fully connected layer performs classification of uterine fibroid.

3.5 HYBRID QUANTUM CONVOLUTIONAL NEURAL NETWORK

Even though the CNN models achieve better performance in image classification, they may face some difficulties in understanding highly complex features present in medical images. As well as CNN models requires large amount of data to improve generalisation and avoid overfitting problem. Due to this problem, a hybrid QCNN architecture is introduced. This design integrates classical deep learning and quantum-based learning to improve feature representation using quantum entanglement and parameterized quantum gate operations.

The hybrid QCNN consists of three functional phases: classical convolutional feature extraction, classical-to-quantum feature transformation and variational quantum convolution-based learning followed by classification. First phase is used to learn spatial structure, boundary and structural characteristics of fibroid. In the second phase, the extracted features were mapped to quantum feature space using fully connected layer. This phase is used to converts classical features into quantum parameters corresponding to the number qubits in the quantum circuit.

The quantum circuit works on an initialized and all qubits were set to zero state. The parameterized rotation gates RX and RZ are used to encode classical features into quantum states. This method transforms classical feature amplitudes into quantum probability amplitudes enabling quantum state representation of classical image features. Following this, quantum convolutional block is applied.

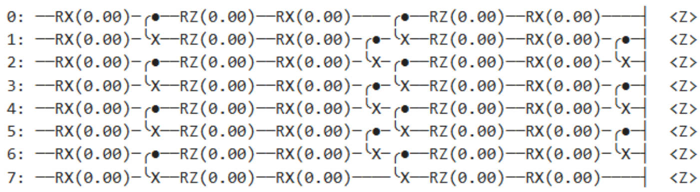


Fig 1. Even-Odd Entangled Quantum circuit

Controlled-NOT gates are applied between the qubits in an alternating pattern to allows quantun states to share information using even-odd entanglement is represented in Fig.1 This entanglement enables local feature interaction between qubits. After entanglement, RX and RZ rotation gates are applied to each qubit for learning optimal quantum states transformations during model training. These rotations are used to increase circuit processing and allow to map non-linear features in high dimensional space. After this process, pauli-Z expectation measurement is used to collapses the quantum state into classical transformed feature information. Finally, the quantum enhanced feature vector passed to classical fully connected layers for final classification and produces predicted results.

4. SIMULATION AND EXPERIMENTAL RESULTS

In this study, CNN and HQCNN model is trained to compare the advantages of quatum based learning in the classification of uterine fibroid based on the data augmentation techniques.

4.1 EXPERIMENTAL DESIGN

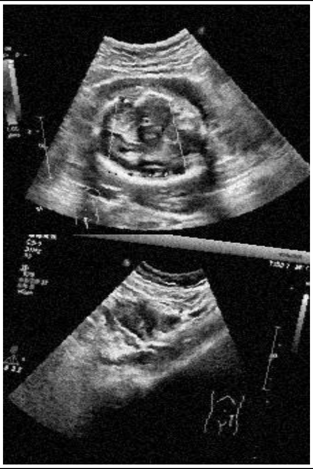
The model experiments in this study demonstrate the advantages hybrid QCNN algorithm, specifically its improved generalization performance over classical CNN architectures based on augmented and non augmented dataset. To ensure a fair comparison of perfomance, both the CNN and HQCNN models are implemented with similar configurations and training parameters. The HQCNN models uses the Classical CNN as a support for extracting hierarchical feature of images, followed by quantum layer implemented using a 8-qubit quantum circuit with rotation and entanglements gates. The quantum putputs are passed to classical fully connected layers for classification. Finally, the CNN and HQCNN model is evaluated and the performance is compared with augmented and non augmented dataset.

4.2 TRAINING SETUP

The execution of model in this study used a Redmi Book 15 Pro Laptop. The configuration of this laptop is an 11th Gen Intel(R) Core(TM) i5-11300H CPU model running at a clock speed of 3.10GHz (3.11 GHz). The laptop runs on Windows 11 64-bit operating system with size of 8GB RAM. The implementation is executed using Anaconda3 2025.06-0 (Python 3.10.19, 64-bit), Jupyter Notebook 7.5.0, PyTorch 2.5.1, and PennyLane 0.42.3. To make sure consistent computational performance in model, the system is connected to AC power supply.

Table.1. Dataset Preparation Pipeline for Uterine Fibroid Ultrasound Images

Stage	Representative Image	Processing Description	Objective
Original Ultrasound Image	 	Raw grayscale B-mode ultrasound image acquired from the uterine fibroid dataset. The image contains fibroid tissues along with surrounding anatomical structures, speckle noise, acoustic shadows, and varying intensity levels.	To preserve the original clinical information before image enhancement.
Pre-processed Image	 	Image preprocessing includes grayscale normalization, median filtering, Gaussian smoothing, image resizing (e.g., 224 × 224 pixels), and Contrast Limited Adaptive Histogram Equalization (CLAHE). These operations reduce speckle noise while improving contrast and preserving lesion boundaries.	To improve image quality, suppress noise, and enhance tissue visibility for reliable feature extraction.

Segmented Image		The fibroid region is isolated using image segmentation techniques such as thresholding, region growing, morphological operations, or deep learning-based segmentation. The Region of Interest (ROI) excludes unnecessary surrounding tissues.	To focus the learning model on the uterine fibroid region while reducing background interference and computational complexity.
Augmented Image		Data augmentation generates additional training samples through rotation (±15°), horizontal/vertical flipping, scaling, translation, zooming, brightness adjustment, and slight cropping while preserving diagnostic labels.	To increase dataset diversity, prevent overfitting, balance class distribution, and improve model generalization.

The uterine fibroid ultrasound dataset underwent a four-stage image preparation pipeline prior to classification. Initially, raw ultrasound images containing anatomical structures, fibroid lesions, speckle noise, and imaging artifacts were collected. During preprocessing, image normalization, filtering, contrast enhancement, and resizing improved visual quality and standardized the dataset. Segmentation was subsequently performed to isolate the uterine fibroid Region of Interest (ROI), allowing the model to focus on diagnostically relevant tissue while minimizing background information. Finally, data augmentation techniques, including rotation, flipping, scaling, translation, and brightness variation, generated multiple realistic training samples from each original image. This processing pipeline enhanced feature representation, reduced overfitting, and significantly improved the performance of the proposed Hybrid Quantum Convolutional Neural Network (QCNN), resulting in higher classification accuracy, sensitivity, and specificity compared with the conventional CNN.

5. DATASET DESCRIPTION

The images used for this study is gathered from openly available sources of Mendely, including 1990 original medical images, has been already separated into folders as normal and fibroid. The available dataset is having 1594 for training and 396 testing sets. The testing set (20%) is reserved from the original dataset to ensure normalized performance valuation. However, the original dataset didn't have a validation set, so the training dataset (80%) is used for development and further divided into training and validation sets in 90:10 ratio to increase training samples while maintaining enough samples for validation. This resulted in approximate total distribution on 72% training, 8% validation and 20% testing while maintaining class balance across subsets. All images are goes through similar preprocessing and segmentation steps while data augmentation techniques only applied to training set. Validation and test sets remained unmodified to assure proper performance evaluation on distribution of data.

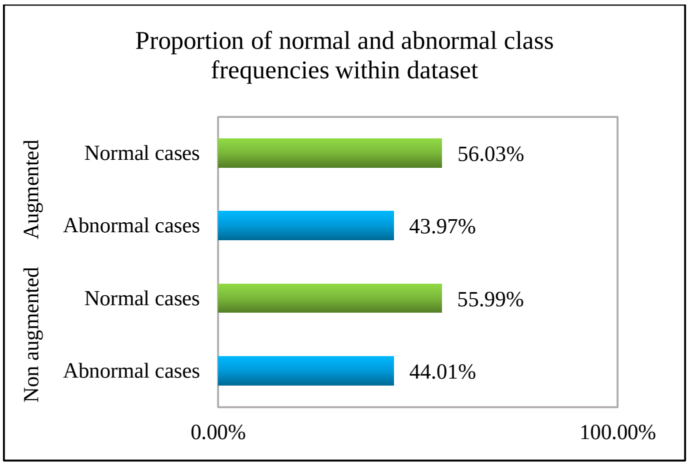


Fig.1. Proportion of normal and abnormal class frequencies within dataset

It mainly helps to improve dataset size and model generalization. The augmented dataset is created using techniques such as rotation, flips, brightness and gaussian noise to process various image characteristics. The augmented number of images in the training set is increased to 4035 images respectively. The non-augmented and augmented datasets show near-balanced class distributions, ensuring minimal bias during model training and evaluation, with only small variations approximately normal (56%) and abnormal (44%) cases. The class imbalance percentage is shown in Fig 1.

6. PERFORMANCE EVALUATION

The trained models were evaluated on an openly availabe dataset of uterine fibroid to assess their accuracy, precision, F1 score, recall (sensitivity), specificity, approximate precision (PR - AUC) and AUC from ROC curve. The definition of evaluation metrics used in this study are mentioned below.

- **Accuracy**: It represents the ratio of anomalous images thar are correctly classified from the test dataset.
- **Precision**: It represents the ratio of correctly classified positive cases with the number of cases predicted as positive.
- **Recall**: It represents the ratio of correctly classified positive cases with the number of actual positive cases.
- **F1 Score**: It is a balanced measure of the model performance and it represents the harmonic mean of precision and recall.
- **Specificity**: It represents the ratio of correctly finding the negative cases among all actual negative cases in the dataset.
- **AUC**: The overall capacity of model to differentiate between positive and negative cases across all classification levels.

Approximate precision (PR - AUC): A measurement that represents the model's overall ability to identify positive cases across different precision - recall thresholds, especially useful for evaluating performance on imbalanced datasets.

7. RESULTS AND DISCUSSION

This study evaluation process involved the performance and effectiveness of the hybrid QCNN and CNN architectures for analysing uterine fibroid classification using standard classification metrics. The performance evaluation of the CNN and hybrid QCNN under two experimental conditions such as non-augmented and augmented.

Table.2. Classification results of CNN and HQCNN

Models	Precision		Recall		F1 Score		Accuracy	
	Non Aug	Aug	Non Aug	Aug	Non Aug	Aug	Non Aug	Aug
CNN	65.85 %	72.46 %	72.64 %	67.26 %	69.08 %	69.76 %	63.38 %	67.17 %
HQCNN	72.64 %	88.16 %	98.20 %	96.86 %	91.06 %	92.30 %	89.14 %	90.90 %

The Table.2 represents the comparative performance of CNN and hybrid QCNN models under data augmentation settings. In non-augmented conditions, hybrid QCNN shows good results compare to CNN. The Hybrid QCNN model improved its performance under augmentation, accomplishing better results. based on the evaluation metric results the hybrid QCNN model consistently performs better than classical CNN. The performance improvement indicates enhanced capability of hybrid QCNN in detecting fibroid cases.

Similarly, data augmentation improved the performance of both CNN and hybrid QCNN models. However, the result was significantly higher in hybrid QCNN compared to classical CNN. This implies that the hybrid model benefits from augmentation techniques due to increasing the training samples for generalization. This result confirms that integration of quantum-based learning improves complex feature representation and classification ability compared to classical deep neural networks.

The learning behaviour of the CNN and hybrid QCNN model shows difference between the accuracy of training and validation curve on generalization. Under the non-augmented data conditions, CNN indicates the limited generalization capability where hybrid QCNN shows gradual convergence indicates strong performance in generalization. Under the augmented data conditions, CNN shows stabilized generalization where hybrid QCNN model achieves 87% validation accuracy in 20 epochs, shows faster convergence and improved stability.

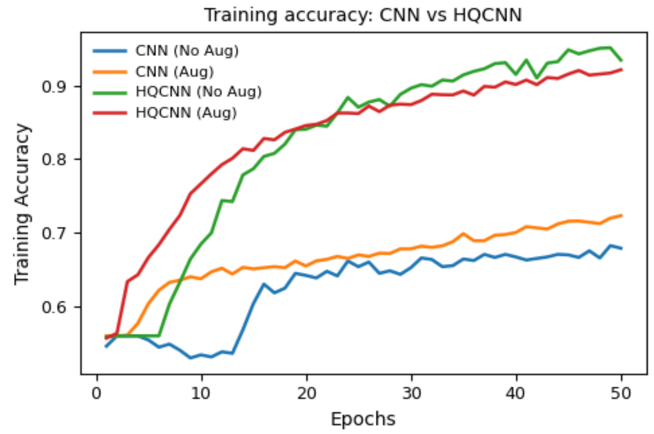


Fig.2. Convergence curve (Training accuracy) of CNN and HQCNN when executed under Non Augmented and Augmented dataset

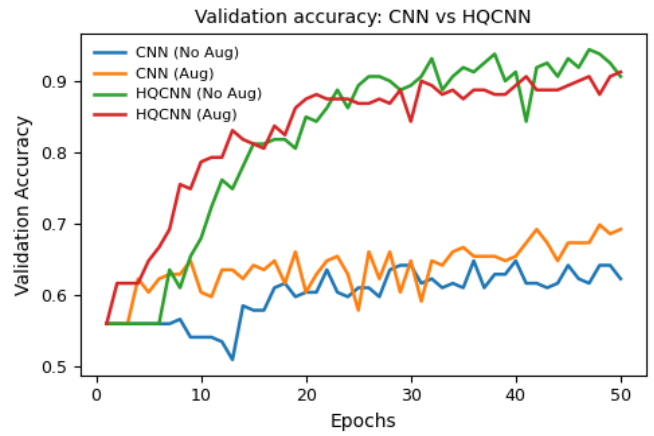


Fig.3. Convergence curve (Validation accuracy) of CNN and HQCNN when executed under Non Augmented and Augmented dataset

The Table.3 presents a performance comparison of detailed confusion matrix between both models. Based on this comparison, in both conditions the hybrid QCNN model reduces the number of false negative cases. Because a higher false negative in fibroid detection may leads to delayed diagnosis. The hybrid model shows significant improvements in false positive and false negatives cases which is more important for improving diagnostic reliability.

Table.3. Confusion Matrix parameters

Models	True Positive		True Negative		False Positive		False Negative	
	Non Aug	Aug	Non Aug	Aug	Non Aug	Aug	Non Aug	Aug
CNN	162	150	89	116	84	57	61	73
HQCNN	219	216	134	144	39	29	4	7

The Table.4 shows the trade-off between sensitivity and specificity. These evaluation metrics is crucial in clinical diagnostic systems to correctly identifying healthy and diseased cases respectively. According to these results, CNN model was moderately capable of finding fibroids, resulting in a high false positive rate. But the overall diagnostic reliability still in limited conditions. In contrast, the hybrid QCNN shows the improved diagnostic challenge in both non-augmented and augmented conditions. The higher sensitivity in hybrid model indicates that maximum all fibroid cases were identified correctly with minimum false negative cases.

Table.4. Comparison of Sensitivity vs Specificity trade-off

Models	Sensitivity		Specificity	
	No Aug	Aug	No Aug	Aug
CNN	72.64%	67.26%	51.44%	67.05%
HQCNN	98.20%	96.86%	77.45%	83.23%

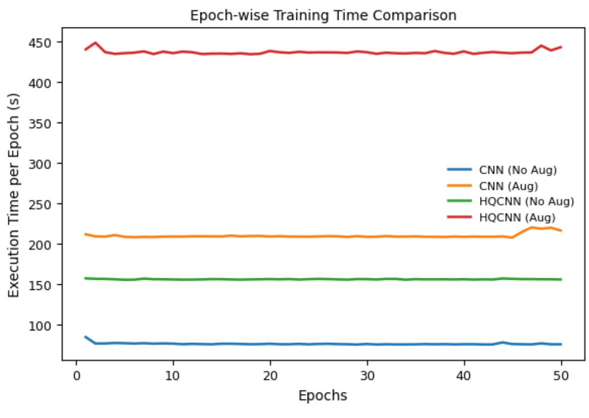


Fig.4. Convergence speed per epochs for CNN and HQCNN model under Non-Augmentated and Augmented dataset

The Fig.4 illustrates the epoch-wise training time comparison between both models under both non-augmented and augmented settings. Here in both conditions CNN model execution time is 85s and 220s. similarly for hybrid QCNN execution time is 160s and 450s. Both models training time is relatively stable across epochs, shows consistent computational ability and stable optimization behaviour in both non-augmented and augmented conditions. It is important to note that this hybrid model is executed in classical hardware system. Therefore, the computational gap between the model expected to reduced while this model executed in quantum-based processors.

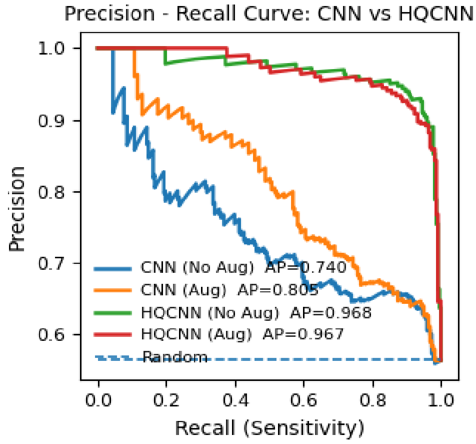


Fig.5. Precision - Recall curve analysis of CNN and HQCNN under non-augmented and augmented dataset

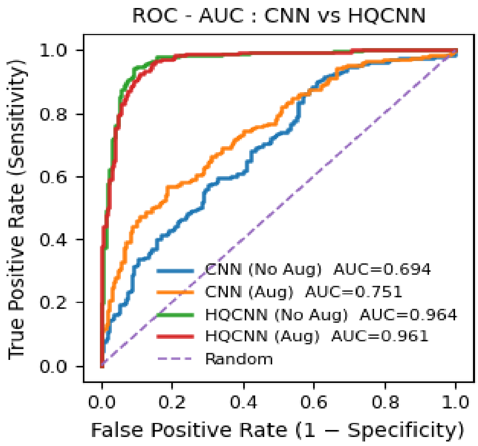


Fig.6. ROC - AUC curve analysis of CNN and HQCNN under non-augmented and augmented dataset

Based on the experimental results the hybrid QCNN model offers good classification performance, improved sensitivity and specificity, reduced false-negatives, faster convergence and better generalization compared to the classical CNN in both conditions. The hybrid quantum-classical learning model is a promising approach for medical diagnostic applications to captures complex features in ultrasound.

8. CONCLUSION

This study presented a hybrid QCNN with an organized pipeline for automated uterine fibroid classification using ultrasound images and compared its performance against with classical CNN model under both non-augmented and augmented conditions. The experimental results states that the hybrid QCNN achieves better results compared to CNN model in all the evaluation metrics. The hybrid QCNN achieved sensitivity

(98.20% - non-augmented, 96.86% - augmented), indicating its strong ability in correctly identifying fibroid case with minimal false negatives. Additionally, the confusion matrix analysis confirmed that the hybrid CNN model minimized both false positive and false negative cases in both experimental settings. Overall, the integration of quantum-based learning in classical convolutional feature extraction enables improved feature learning ability and regions, making hybrid QCNN model is promising framework for advanced medical image classification tasks.

Further research will include validating the proposed QCNN through larger and multi-center/multi-device datasets to evaluate the performance of the framework under the generalization setting. The framework can also be used for automatic localization, segmentation, size estimation, and fibroid subtype classification rather than being limited to binary classification. Further research can explore quantum encoding methods, more depth quantum circuits, quantum attention methods, and noise-aware quantum models. Validation with external datasets from different hospitals and different manufacturers of ultrasound devices is essential to evaluate the clinical robustness of the framework. Techniques of explainable AI can be applied to visualize the contribution areas of the proposed model. Finally, implementation on actual quantum computers and evaluation of computational resources, latency, energy efficiency, and model complexity compared to classical CNNs will demonstrate the advantages of the proposed quantum-classical framework.

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