

Quantum-Enhanced Deep Learning Approach for Lung Tumor Identification

Anusheebha K.^{1*}, Blessed Prince P.²

¹Research Scholar, Department of Information Science, School of Computer Science and Engineering, Presidency University, Bangalore, India.

²Professor & Head, Department of Computer Science and Engineering, School of Computer Science and Engineering, Presidency University, Bangalore, India.

E-mail: ^{1*} ANUSHEEBHA.20223CSC0008@presidencyuniversity.in, ²blessedprince@presidencyuniversity.in

Orcid ID: ^{1*} 0009-0002-6721-3759, ²0000-0002-0337-2841

Abstract

Lung cancer is one of the leading causes of cancer-related deaths worldwide, affecting millions of people every year. Early and accurate detection is significant for providing suitable treatment and improving patient survival. Computed Tomography (CT) scan images are widely utilized in lung cancer diagnosis because they provide detailed information about lung tissues and abnormalities. Recently, quantum computing has also been explored in medical image analysis owing to its potential to process complex and high-dimensional data more efficiently. Therefore, this study introduces a Quantum Computing-based Framework for Enhanced Lung Cancer Detection (QCF-ELCD) using CT images. The proposed QCF-ELCD framework involves advanced pre-processing steps to enhance the image quality and uniformity within the data. The hybrid feature extraction process integrates ConvNext architecture along with an efficient channel attention mechanism. This combination extracts highly discriminative features, which are then forwarded to the quantum fidelity-based classification algorithm. The classifier enhances the model's performance by identifying the class with the maximum quantum fidelity match. Moreover, the AdaBelief optimizer is employed to improve model parameters during training, contributing to improved classification performance. Additionally, Grad-CAM++ is utilized to visualize the discriminative regions learned by the proposed QCF-ELCD, thereby improving model interpretability and clinical transparency. The experimental analysis of the QCF-ELCD framework is conducted using the IQ-OTH/NCCD Lung Cancer Dataset and LIDC-IDRI Dataset, achieving promising classification accuracy of 95.13% and 94.23%, respectively. Consequently, the proposed QCF-ELCD framework demonstrates its potential as an effective tool for automatic lung cancer classification, outperforming existing models.

Keywords: Lung Cancer Detection, Computed Tomography, Efficient Channel Attention Mechanism, Quantum Computing, AdaBelief Optimizer.

1. Introduction

Lung Cancer (LC) is a widespread cause of cancer-related deaths globally, which makes timely diagnosis significant to enhance patient outcomes [1]. The disease may cause multiple symptoms, namely fatigue, weight loss, loss of appetite, chest pain, persistent coughing, and hemoptysis. Meanwhile, numerous risk factors are relevant to LC, including

smoking, radon exposure, chemical exposure, air pollution, and second-hand smoke. Therefore, timely intervention in LC is essential for aiding clinical intervention, which can significantly improve the survival rate [2]. Conventional diagnostic techniques mostly depend on the manual examination of medical imaging using computed tomography (CT) images. CT scans offer significant information in the assessment of a lung nodule, which supports clinicians in the process of diagnosis. Although the analysis of CT scans provides detailed information about the disease, it is time-consuming and susceptible to human error. Such traditional methods are utilized to detect and classify the tumor stage, though each method has a specified limitation.

Recently, Artificial Intelligence (AI) has been commonly leveraged in the medical field to effectively capture non-linear relationships and complex interaction effects within medical data. Currently, Machine Learning (ML), a branch of AI, is extensively adopted in several healthcare domains, which improves clinical decision-making, health services management, and patient data analysis. The advancement of Deep Learning (DL) algorithms has shown remarkable success in examining medical images and complex pattern identification, making it suitable for LC classification [3]. In addition, the DL model can accurately detect subtle nodules and lesions in medical images, which leads to a more reliable and accurate screening method. By using the advanced learning ability of the DL model, valuable insights are offered and support clinical decision-making. Such advanced technology has emerged as an important innovation, resulting in significant improvement in medical diagnosis. Moreover, the incorporation of DL with a large dataset can improve the performance of LC classification and provide a reliable solution for effective healthcare.

1.1 Motivation and Paper Contribution

The increasing development of medical imaging techniques and deep learning approaches has significantly enhanced lung cancer analysis. However, lung cancer is still a major factor in cancer-related deaths because of its delayed diagnosis. Many existing CT-based techniques depend on conventional or fundamental deep learning features that often fail to obtain subtle nodule differences and intricate lung tissue patterns. Accordingly, it can be difficult to correctly differentiate between normal, benign, and malignant conditions at early stages. Also, dissimilarities in CT image quality and patient-related factors further decrease the consistency of existing approaches, thus emphasizing the requirement for more advanced methods. To address these limitations, this article proposed a Quantum Computing-based Framework for Enhanced Lung Cancer Detection (QCF-ELCD) using CT images. The key contributions of the study are as follows:

- A novel hybrid classical-quantum algorithm learns image features utilizing an advanced ConvNeXt network, strengthens key details with channel attention, and sorts the data inside a quantum fidelity architecture rather than employing a traditional layer of computer classification.
- Proposes an attention-guided quantum classification strategy for lung CT scans. This framework uses channel-wise refinement to emphasize emerging patterns prior to employing quantum state encoding and fidelity-related class distribution.
- An optimized and explainable learning system is built using AdaBelief for better parameter tuning and Grad-CAM++ for visual explanations. This helps the model train better and identify important image areas for diagnosis.

The novelty of the proposed QCF-ELCD method lies in integrating these existing components. The proposed framework applies a classical-quantum learning method where the ConvNeXt backbone learns strong image features. These features are refined using channel-wise attention and further transformed into a quantum representation for fidelity-based class discrimination. The AdaBelief-based optimizer enables adaptive parameter learning throughout the framework, while Grad-CAM++ adds an explainability component that helps interpret the model's predictions. Thus, the methodological contribution lies in the proposed feature-refinement-to-quantum-fidelity learning pathway and its application to lung CT classification, rather than claiming novelty for the individual constituent algorithms.

2. Related Works

This section discusses a concise overview of existing literature on lung cancer classification using CT, along with identified research gaps. Khan et al. [4] investigated tuning an effective CNN-driven approach, specifically EfficientNet-B0, to identify Lung Cancer (LC) from CT scans across three types: Malignant, Benign, and Normal. Rao and Pappala [5] examined the Multi-Stage Cross-Element Attention Quantum Convolutional Transformer with Group Aggregation Network (MSEGA-Net), an advanced multitask system designed for segmenting multimodal lung cancer images. Shatnawi et al. [6] introduced the design of an automated classifier and predictor for lung cancer using employing CT scans, using DL models, especially CNNs, to enable rapid and accurate image diagnosis. Tawfeek et al. [7] explored a novel methodology to classify and distinguish pulmonary disorders such as tuberculosis, pneumonia, and LC by investigating traditional X-ray and CT scan images.

Güraksın and Ozdemir et al. [8] recommended a hybrid DL system that incorporates CNNs with ViTs. To optimize and integrate the grid and block attention system with InceptionNeXt blocks, the presented method successfully extracts lightweight and large-scale attributes in CT images. Güraksın and Kayadibi [9] presented a hybrid Lung Ensemble CNN (LECNN) framework for the computer-aided timely analysis of LC through CT images. The presented hybrid methodology combines a TL system with EL based on majority voting. Crasta et al. [10] introduced a new DL framework for classifying LC in input CT images. It leverages a 3D-VNet system for precise segmentation of pulmonary nodules and a 3D-ResNet technique deployed for their categorization. Existing LC recognition employing CT images still encounters challenges in obtaining fine-grained nodular features and subtle tissue variances. Numerous techniques rely on conventional DL or handcrafted feature-based methods that cannot proficiently capture complex spatial patterns in lung structures. There is an incomplete analysis of advanced feature fusion techniques, which have increased discriminatory learning between conditions like benign and malignant. Moreover, most models struggle with robustness under varying dataset heterogeneity and image quality. These gaps underscore the necessity for the most innovative and stable framework for accurate recognition of LC.

3. Methodological Framework

The proposed QCF-ELCD model follows a multi-stage pipeline for the detection and classification of LC using CT images, as illustrated in Figure 1. Initially, the input images undergo preprocessing, which includes non-local means denoising, ACLAHE-based contrast enhancement, z-score normalization, and image augmentation. These steps aim to improve image quality, standardize intensity values, and enhance dataset variability. Moreover, the

hybrid feature extraction method, combining ConvNeXt with the ECA mechanism, is used to extract rich and discriminative features. A quantum fidelity-based classification approach then compares the similarity between quantum-encoded CT image features to categorize images into normal, benign, and malignant LC classes. The AdaBelief optimizer is utilized for hyperparameter tuning and model parameter updates during training. Finally, Grad-CAM++ is employed to identify the pulmonary regions that contribute to the classification results, helping to understand the areas of model prioritizes.

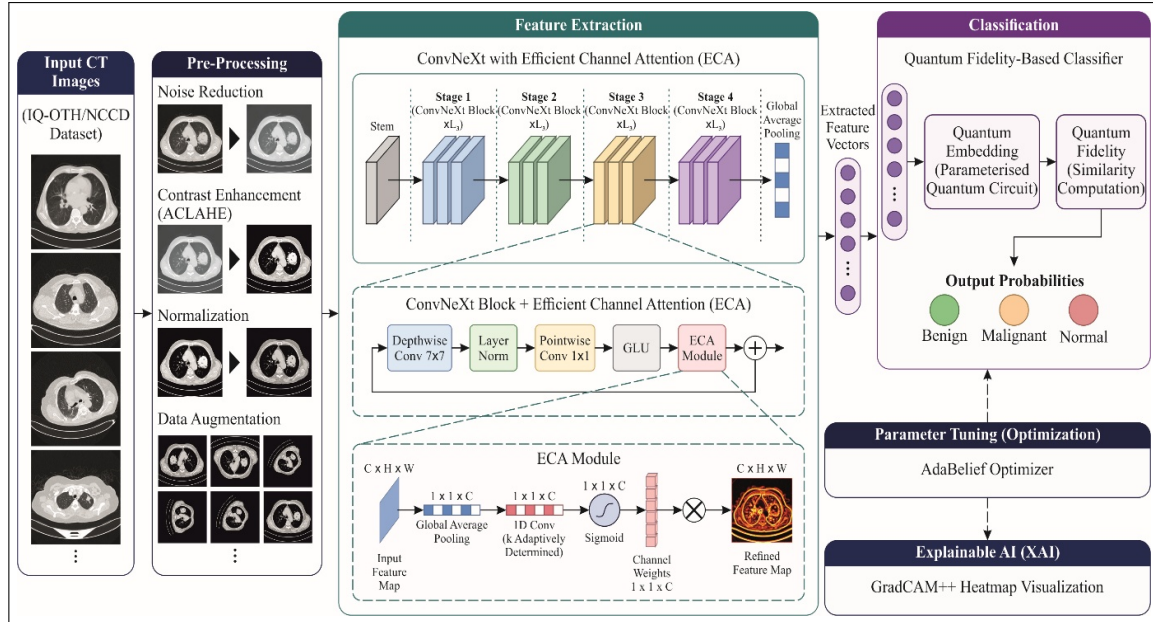


Figure 1. Complete workflow of proposed QCF-ELCD model

3.1 Image Preprocessing

The CT images are first denoised using Non-Local Means (NLM) filtering. Then, ACLAHE is applied to improve image contrast, followed by Z-score normalization to standardize the intensity values. Rotation, flipping, and scaling are applied to the training images to increase the number of samples and reduce overfitting.

Noise Removal using NLM: The NLM filtering process minimizes image noise by substituting each pixel with the weighted mean of similar patches throughout the images, which helps decrease random noise while efficiently maintaining significant structural information [11]. A general mathematical representation of the NLM filtering process is defined as follows:

$$\hat{I}(x) = \sum_{y \in \Omega} w(x, y) I(y) \quad (1)$$

In the above formula, $I(y)$ implies the observed intensity at position, $\hat{I}(x)$ denotes the denoised image intensity at position x , the term $w(x, y)$ refers to the normalized similarity weight based on patch similarity, and the symbol Ω signifies the search window.

ACLAHE-based Enhancement: Adaptive Contrast Limited Adaptive Histogram Equalization (ACLAHE) is applied for contrast enhancement, which enhances local image contrast by performing histogram equalization on small image regions using an adaptive clip limit to control noise amplification. This adaptive contrast enhancement mechanism improves

structural information in low-contrast regions while preserving image quality and effectively suppressing background noise and artifacts.

Z-score Normalization: This normalization is commonly referred to as standardization, a broadly applied normalization approach. It transforms the data, ensuring and ensures the mean value becomes zero, and the standard deviation value becomes one.

$$x' = \frac{x - \text{mean}(x)}{\text{Std}(x)} \quad (2)$$

Here, the term $\text{mean}(x)$ and $\text{std}(x)$ represent the mean and SD of the feature x , respectively, and the terms x and x' denote the original and normalized value, respectively.

Image Augmentation: An image augmentation technique is employed to improve the diversity of training samples through transformations, namely rotation, flipping, and scaling, thus enhancing model performance and generalization ability. Such a process supports the model in effectively handling variation in orientation, viewpoint, and object dimension, thus improving its generalization performance on unseen data.

3.2 Hybrid Feature Representation

ConvNeXt enhances the CNN model through the improvement of conventional techniques and the combination of design principles from hierarchical vision transformers (ViT), encompassing Swin Transformer. While retaining a fully convolutional model, it improves feature extraction through architectural improvements like inverted bottlenecks, larger convolution kernels, and innovative training methods [12]. In this research, the ConvNeXt-Base framework has been utilized for CT image analysis owing to its effective feature representation ability, efficiency, and scalability. The framework encompasses four hierarchical phases, each accountable for learning higher-level feature representations. All stages begin with a downsampling layer that decreases spatial resolution while improving channel depth, thus permitting efficient multi-scale feature representation from medical image data. The feature extraction approach of ConvNeXt is determined by:

$$F_c = \text{ConvNeXt}(I_{CT}) \quad (3)$$

In the above-mentioned expression, I_{CT} represents the input CT image, and F_c characterizes the deep feature maps that can be extracted through the ConvNeXt-Base framework. In the proposed system, ConvNeXt is highly effective at capturing structural irregularities and textural variations present in CT images, including nodules, tissue density variations, and mass boundaries. To improve distinctive feature extraction, an attention mechanism (AM) is combined among the final ConvNeXt phase and the global average pooling (GAP) layer, thus allowing the model to highlight the most important feature mappings before classification.

ECA is an effective AM developed to improve CNNs by adaptively modeling channel-wise dependency without incurring considerable computational cost. Different conventional AMs include SENet, which is based on dimensionality reduction across fully connected (FC) layers; ECA evades parameter-heavy functions and instead uses a faster one-dimensional convolution approach. It refines feature extraction by creating channel-wise attention weights via global contextual aggregation accomplished by local cross-channel relationships. With the input feature mapping X , the process of AM is expressed as:

$$s = F_{eca}(X, \theta) = \sigma(\text{Conv1D}(\text{GAP}(X))) \quad (4)$$

$$Y = s \cdot X \quad (5)$$

Here, $\text{GAP}(X)$ implies GAP, Conv1D obtains a local cross-channel relationship, and σ represents the sigmoid activation function utilized to create standardized attention weights. The final attention vector is then employed to rescale the original feature mapping X , improving meaningful channels while controlling less significant ones. The main benefit of ECA is its adaptive kernel dimensional representation that measures the level of local channel relationship. The kernel dimension k has been calculated as:

$$k = \psi(C) = \left\lfloor \frac{\log_2(C)}{\gamma} + \frac{b}{\gamma} \right\rfloor_{\text{odd}} \quad (6)$$

In Eq. (6), the parameter C denotes the number of input channels, while γ and b denote hyperparameters. The “odd” constraint ensures symmetric convolution across all channels. Conversely, ECA enhances ConvNeXt feature mappings by emphasizing diagnostically significant channels related to lesion features, such as spiculated margins, heterogeneous intensity functions, and irregular nodule shapes. These distinct advantages improve the model’s sensitivity to pathological variances, thereby increasing classifier robustness.

The proposed method integrates ConvNeXt, ECA, quantum fidelity-derived classification, and AdaBelief optimization within a sequential learning architecture. ConvNeXt first learns hierarchical feature representations from CT images, and ECA then adaptively recalibrates these attributes by highlighting diagnostically significant channels. The refined features are subsequently encoded into quantum states and classified using a quantum fidelity-based classifier. During the training process, the AdaBelief optimizer modifies the learnable parameters of the ConvNeXt and ECA models by diminishing classification loss, enhancing feature discrimination and method stability.

3.3 Quantum-based Lung Cancer Classification Module

In quantum-inspired healthcare image analysis, similarity-based learning approaches have been obtained by improving attention because of their capability to manage higher-dimensional and intricate data exchanges [13]. The proposed quantum-based model was executed utilizing a quantum simulator, and no experiments were conducted on real quantum hardware. In particular, quantum fidelity offers a theoretically grounded evaluation for assessing encoder data extraction in Hilbert space. A quantum fidelity-driven classifier model for lung cancer identification using CT images. The proposed system maps CT scan image data into a higher-dimensional quantum Hilbert space, while classification is performed based on the resemblance among quantum states. It allows the method to capture intricate and non-linear interactions in clinical imaging data more efficiently than conventional distance-driven methods. The ConvNeXt-Base-ECA feature extraction stage generates 768-dimensional feature vectors, which are then reduced to 8 dimensions using a trainable fully connected (FC) projection layer before quantum encoding. Following dimension reduction, each projected feature is linked with eight individual qubits and encoded through an angle-driven parameterized quantum circuit (PQC), providing the classical-to-quantum interface for subsequent fidelity-related classification. Let all CT imaging be represented by a feature vector x , obtained after pre-processing and feature representation. These features are encoded into a quantum state

using a parameterized quantum circuit $(PQC)U(x)$, which serves as a feature mapping. The quantum embedding of a CT image is represented as:

$$|x\rangle = U(x)|0\rangle \quad (7)$$

Consider the extracted feature vector representation is defined as $f \in \mathbb{R}^{768}$, and its dimensionality reduction process is expressed as:

$$z = W_p f + b_p, \quad (8)$$

In Eq (8), $W_p \in \mathbb{R}^{8 \times 768}$ refers the learnable weight matrix and $b_p \in \mathbb{R}^8$ denotes the corresponding bias vector. As a result, the 768-dimensional features vectors are reduced and transformed into eight representations $z \in \mathbb{R}^8$.

The PQC is created as a sequence of feature-encoding rotation operations and parameterized entanglement operations. The rotation operations encode the decreased feature values into individual qubits, whereas the entanglement operations develop relationships among the encoded attributes.

To describe the embedded procedure, the PQC is determined as a sequence of combined transformations used to differentiate features:

$$U(x) = \prod_{i=1}^d U_i(x_i) \quad (9)$$

In Eq. (9), x_i implies the i -th CT image feature, and $U_i(x_i)$ indicates the quantum gate encoder that encodes the features into the quantum state. The PQC involves feature-encoding operations and learnable quantum operations that produce the respective quantum-state representations. In the training process, the learnable parameters of the presented model are optimized through classification loss with the AdaBelief optimization algorithm. The projection layer reduces the dimension to eight compact representations, which are then fed into the quantum circuit, in which quantum classification supports the computation of fidelity-driven class scores. Following the embedding of CT-image features into quantum Hilbert space, the similarity among two CT-image representations is computed through a quantum fidelity kernel, which is formulated as:

$$K(x_i, x_j) = |\langle x_i | x_j \rangle|^2 \quad (10)$$

This measure of fidelity refers to the squared overlap between the pair of quantum states. A high-fidelity score highlights the maximum similarity among the respective CT-image representations, while a low value indicates increased dimensionality. Better fidelity implies more resemblance in the CT imaging. In clinical image analysis, this property is very helpful since subtle differences in intensity distribution, tissue texture, and structural patterns is efficiently obtained by quantum state overlaps. It enables the method to differentiate between abnormal and normal lung structures with enhanced sensitivity. To perform classification, the test CT-image is compared with the labeled training samples, and the corresponding average quantum fidelity is computed independently for each class as:

$$F(x) = \frac{1}{M} \sum_{k=1}^M |\langle x | x_k \rangle|^2 \quad (11)$$

Let M imply the overall count of training instances, and $|x_k\rangle$ represent the training

CT images as quantum states. To improve interpretability and enhance decision stability, the fidelity values could be standardized to process a probability-like outcome employing a softmax-inspired equation:

The fidelity scores are estimated separately for each class (Normal, Benign, and Malignant) as:

$$S_c(x) = \frac{1}{N_c} \sum_{i: y_i=c} |\langle x | x_i \rangle|^2 \quad (12)$$

where $S_c(x)$ represents the class-wise fidelity score, and c denotes the consistent class labels.

$$P(c|x) = \frac{e^{S_c(x)}}{\sum_{j \in C} e^{S_j(x)}} \quad (13)$$

Where $P(c|x)$ denotes the probability for every class (Normal, Benign, and Malignant). The final prediction is obtained as:

$$\text{Class}(x) = \arg \max P(x) \quad (14)$$

The presented model classifies CT-images based on quantum-state similarity instead of directly relying on traditional Euclidean distance. The 768-dimensional ConvNeXt-Base-ECA vector representation is initially reduced to a 7-dimensional vector and further encoded using eight qubits. These encoded features are processed by the quantum circuit to obtain higher-dimensional Hilbert space representations, in which the Normal, Benign, and Malignant categories are accurately separated based on their quantum-state fidelity. This fidelity-based classification strategy offers a compact and nonlinear representation for multi-class lung cancer categorization. Figure 2 denotes the architecture of the quantum fidelity-based classification module.

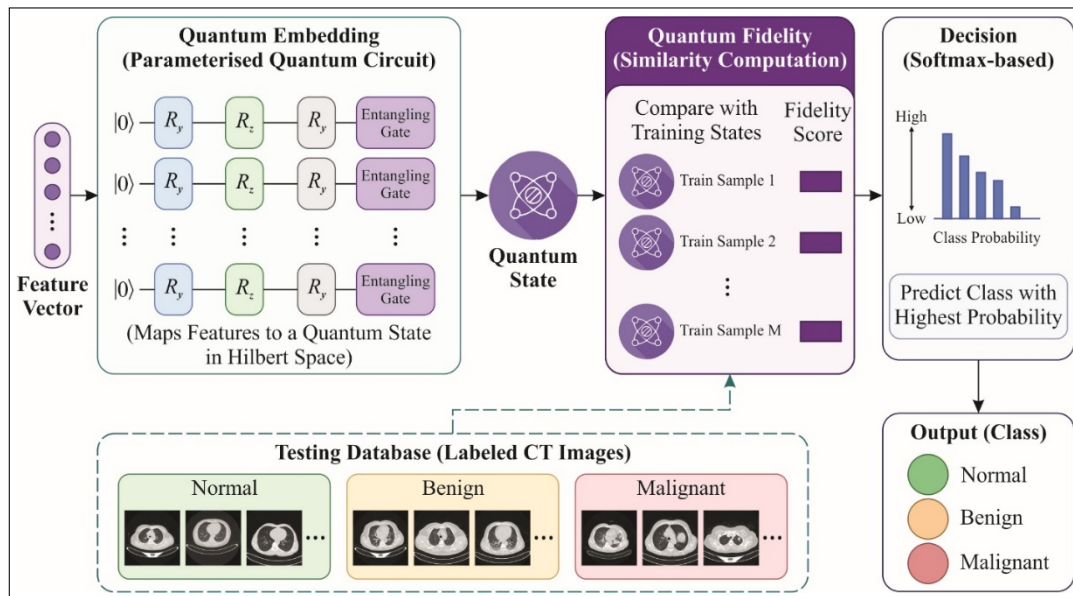


Figure 2. Architecture of quantum fidelity-based classification module

3.4 Hyperparameter Tuning Strategy

The AdaBelief optimization algorithm is an advanced form of the Adam optimizer, which is widely employed to improve convergence, enhance training stability, and boost the

overall performance of models [14]. This process adjusts parameter updates based on the reliability of gradient predictions, which enables the model to learn effectively using CT images. AdaBelief regulates weight updates and relies on the concept of belief. In this method, a new feature s_t represents the weighted moving average of $(g_t - m_t)^2$, here $g_t - m_t$ denotes the gradient deviation. A small modification between g_t and m_t indicates strong belief, which leads to higher weighted updates, and weaker belief results in lower variances. This adaptive upgrade mechanism allows the network to effectively learn distinctive characteristics of lung nodules and cancerous regions from CT scan images, thus preserving stable convergence during training.

$$s_t = \beta_2 s_{t-1} + (1 - \beta_2)(g_t - m_t)^2 + \varepsilon \quad (15)$$

$$\hat{s}_t = \frac{s_t}{1 - \beta_2^t} \quad (16)$$

and the upgrade rule of Adabelief optimizer is stated

$$w_{t+1} = w_t - \frac{\eta}{\sqrt{\hat{s}_t} + \varepsilon} \hat{m}_t \quad (17)$$

The AdaBelief employed in the proposed framework enables efficient optimization of network parameters, which improves training stability and the overall performance of the model.

Table 1. Parameter settings

Component	Parameter	Value
Dataset	Dataset Name	IQ-OTH/NCCD Lung Cancer Dataset and LIDC-IDRI Dataset
	Image Modality	Computed Tomography (CT) Images
Preprocessing	Input Image Size	$224 \times 224 \times 3$
	Noise Reduction	NLM Filtering
	Contrast Enhancement	ACLAHE
	Normalization	Z-score Normalization
	Data Augmentation	Rotation, Flipping, and Scaling
Feature Extraction	Backbone Model	ConvNeXt
	Feature Extraction Stages	4
	Feature Dimension	768
Efficient Channel Attention (ECA)	Attention Kernel Size	3
	Channel Attention	Adaptive 1D Convolution
Quantum Fidelity-Based Classifier (QFC)	Number of Qubits	8
	Quantum feature dimension	8
	Quantum circuit	Parameterized Quantum Circuit (PQC)
	Quantum Encoding	Angle Encoding
	Fidelity Measurement	Quantum State Fidelity
AdaBelief Optimizer	Initial Learning Rate	1×10^{-4}
	β_1	0.9
	β_2	0.999
	Epsilon	1×10^{-8}

Training	Batch Size	32
	Epochs	50
	Loss Function	Cross-Entropy Loss
	Train-Test Split	80:20 and 70:30

Table 1 depicts the experimental setup utilized in the proposed structure for CT image analysis from the IQ-OTH/NCCD Lung Cancer Dataset and LIDC-IDRI Dataset. The input CT imaging is pre-processed employing resizing, noise mitigation with NLM filtering, contrast enhancement through ACLAHE, standardization, and data augmentation models. Feature representation is carried out utilizing the ConvNeXt backbone, and then ECA to enhance channel-wise feature modification. The classifier phase uses a Quantum Fidelity-Based Classifier with 8 qubits and angle encoding, and the method has been optimized by applying the AdaBelief optimizer. The quantum fidelity classifier utilizes an 8-qubit circuit with angle encoding. Through the integration of the quantum module only in the final classification phase after dimensional feature representation, the system decreases the size of the quantum circuit and its overall computational requirement. Training is performed by employing a batch size of 32 for 50 epochs with cross-entropy loss. The datasets have been divided at the patient level using two train-test split strategies: 80% training and 20% testing, and 70% training and 30% testing. Data augmentation is accomplished only after splitting and is applied to the training set to prevent data leakage.

4. Result Analysis

This section presents the empirical evaluation of the proposed QCF-ELCD framework using the IQ-OTH/NCCD Lung Cancer Dataset. The proposed QCF-ELCD approach was executed using Python 3.11 with TensorFlow/Keras on a system prepared with an NVIDIA GeForce RTX 3080 GPU (10 GB memory), an Intel Core i7 processor, and 16 GB RAM. The outcomes exhibit its efficiency and applicability for consistent lung cancer identification. The presented quantum circuit is used entirely on a quantum simulator, with no experimentation conducted on physical quantum hardware. Thus, the reported outcomes respect simulator-based quantum execution.

4.1 Data Description

The experimental evaluation of the QCF-ELCD method can be examined using the IQ-OTH/NCCD - Lung Cancer Dataset [15] and the LIDC-IDRI Dataset [16]. The IQ-OTH/NCCD database was chosen because of its clinical significance and suitability for the multi-class categorization of lung CT images. Even though several larger lung CT databases exist, IQ-OTH/NCCD offers three relevant diagnostic classes: Normal, Benign, and Malignant, which directly correspond to the objective of this study. The original IQ-OTH/NCCD dataset includes 1,097 CT images gathered from 110 cases, including 416 normal, 120 benign, and 561 malignant images. To handle this class imbalance problem, data augmentation was employed to the benign class, producing 360 additional images. Thus, the final dataset utilized for experimentation includes 1,457 images: 416 normal, 480 benign, and 561 malignant. The cases were gathered at special clinical centers and subsequently reviewed by clinical experts who provided clinically meaningful information for model development and assessment. In addition, the open availability and established application of this dataset supports effective classification of multi-class lung cancer. Hence, this dataset was chosen according to multiple

considerations such as its diagnostic class structure, clinical relevance, quality of annotation, and comparability with existing studies instead of solely on dataset size. To evaluate the performance of the presented model across varied data-partition settings, the dataset was assessed through two training and testing configurations, such as 80:20 and 70:30 splits. These two configurations offer complementary assessment settings for investigating the steadiness and reliability of the resulting classification performance.

This dataset is a collection of CT scan images gathered from Iraqi oncology centers, established for investigation in automated lung cancer classification. It comprises images from benign, malignant, and normal instances, generating it suitable for multi-class classifier tasks in medical imaging. This database is broadly utilized in DL analysis to develop and evaluate models for accurate and timely lung cancer detection. The benign classes are further improved by augmentation methods, including flipping, rotation, and scaling (zooming), to enhance model performance and improve training diversity. Table 2 presents the three diverse categories with an overall count of 1,457 instances. Figure 3 shows representative sample images of normal, benign, and malignant classes. Figure 4 represent samples of preprocessed images and Figure 5 denotes sample of feature maps.

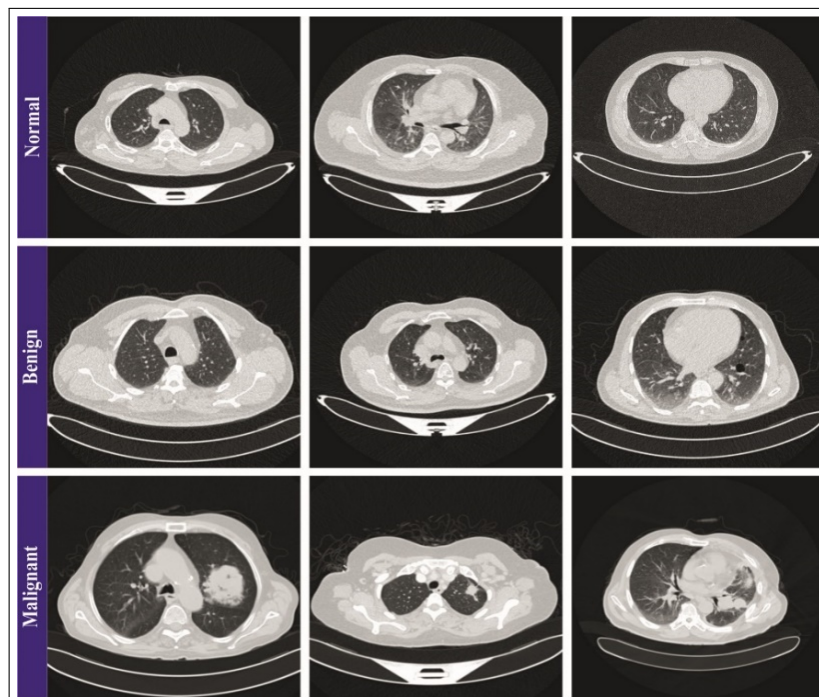


Figure 3. Representative sample images of normal, benign and malignant classes on IQ-OTH/NCCD - lung cancer dataset

To assess a model's robustness to cross-device and multi-center variability, three datasets with distinct acquisition features are utilized. IQ-OTH/NCCD comprises CT scans obtained from the Iraq Oncology Teaching Hospital and National Center for Cancer Diseases employing a Siemens SOMATOM scanner with 1-mm slice thickness. LIDC-IDRI contains CT analyses gathered from a collaboration between seven academic centers and eight healthcare image sectors, with multi-radiologist annotations. NLST further improves LDCT and cross-device variability, containing scans acquired utilizing eight CT scanner techniques manufactured by four vendors with reconstructed slice thickness ranging from 2 to 5 mm. Therefore, the three datasets collectively encompass variability in institutional setting, scanner

manufacturer, acquisition protocol, annotation setting and slice thickness, allowing a more complete evaluation of model robustness through heterogeneous CT information.

Table 2. Details of the IQ-OTH/NCCD - lung cancer dataset

Classes	Number of Count
Normal	416
Benign	480
Malignant	561
Total Count	1457

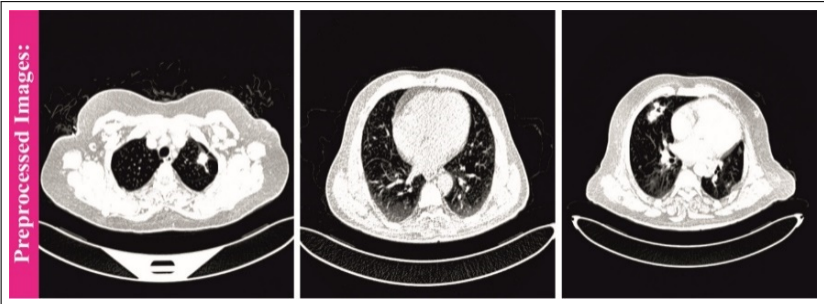


Figure 4. Samples of preprocessed image on IQ-OTH/NCCD - lung cancer dataset

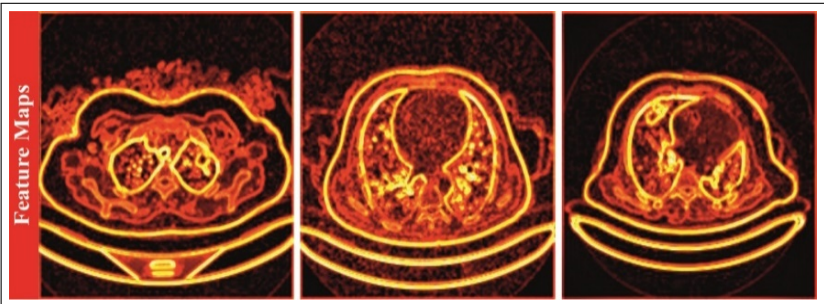


Figure 5. Sample of feature maps with IQ-OTH/NCCD - lung cancer dataset

4.2 Classification Results and Analysis

Figure 6 shows the confusion matrices of the QCF-ELCD method using an 80:20 split, which accurately classifies most CT image samples with minimal misclassification among the three classes, representing the efficiency of the lung cancer classification methods.

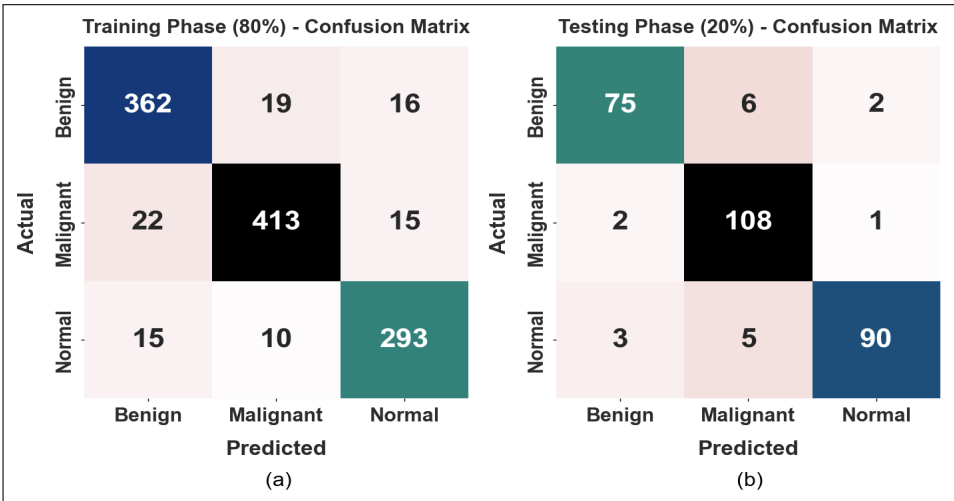


Figure 6. Confusion matrix of the QCF-ELCD method with 80:20 split on IQ-OTH/NCCD - lung cancer dataset

Figure 7 presents the ROC analysis of the QCF-ELCD approach with 80:20 splits, indicating that the system offers efficient classification across each class. This reliable trend of enhanced ROC values across different class labels indicates the capable performance of the QCF-ELCD algorithm in predicting classes, emphasizing its robust nature during the identification process.

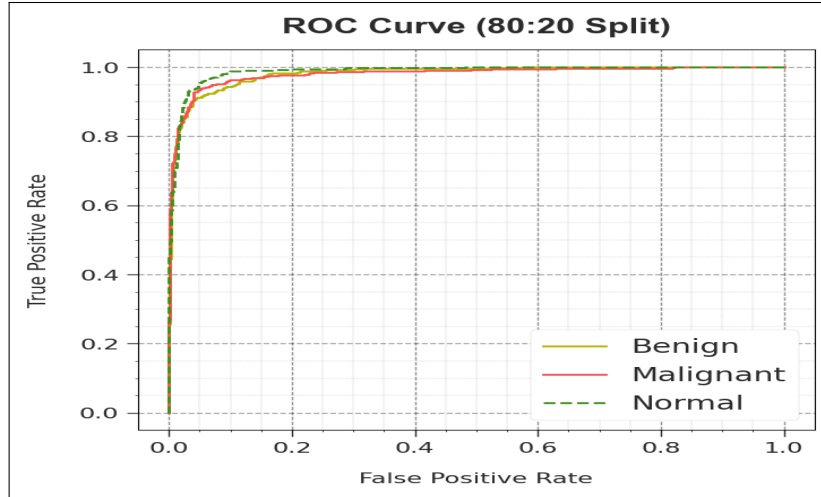


Figure 7. ROC curve of the QCF-ELCD method with 80:20 split in IQ-OTH/NCCD - lung cancer dataset

Table 3 exhibits the lung cancer classifier outcome of the QCF-ELCD method with an 80:20 split. The proposed QCF-ELCD approach achieved value with $accuracy$ of 91.67% in TRAIP and $accuracy$ 93.49% in TESTP, demonstrating an effective classifier in the lung cancer detection system.

Table 3. Lung cancer classifier result of the QCF-ELCD approach with 80:20 with IQ-OTH/NCCD - lung cancer dataset

Class Labels	Training Phase (TRAIP) (80%)	Testing Phase (TESTP) (20%)
Accuracy ($accuracy$)	91.67	93.49
Precision ($precision$)	91.53	93.76
Recall ($recall$)	91.7	93.17
F1-Score ($F1_{score}$)	91.61	93.39
MCC	87.42	90.20

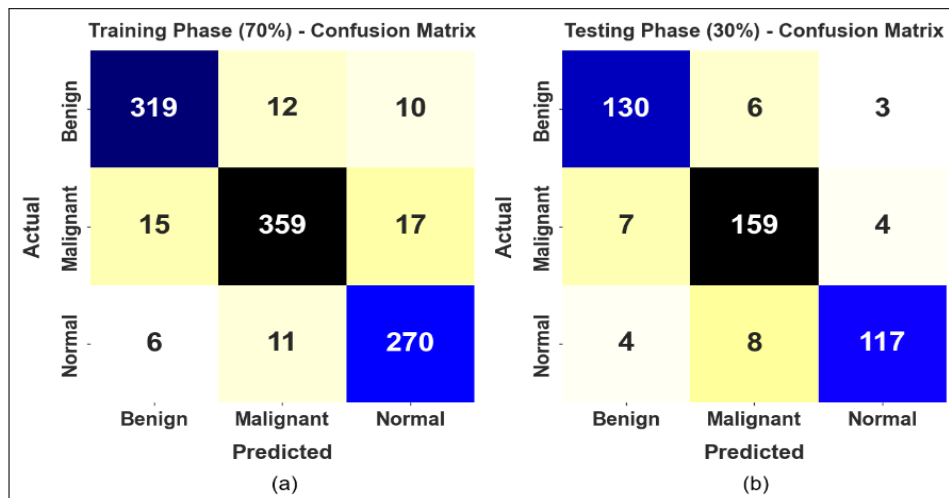


Figure 8. Confusion matrix of the QCF-ELCD method with 70:30 split in IQ-OTH/NCCD - lung cancer dataset

Figure 8 reveals the confusion matrices of the QCF-ELCD approach, which precisely categorizes most CT image instances with fewer misclassifications between the three classes, denoting the usefulness of the lung cancer detection approaches.

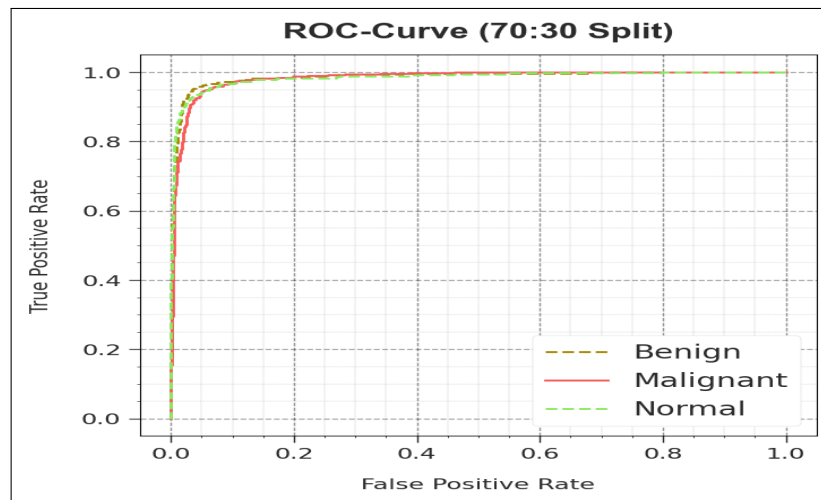


Figure 9. ROC curve of the QCF-ELCD method with 70:30 split in IQ-OTH/NCCD - lung cancer dataset

Figure 9 presents the ROC analysis of the QCF-ELCD approach with a 70:30 split, indicating that the system offers efficient classification across all classes. The enhanced ROC values for all class labels indicate the efficiency and reliability of the QCF-ELCD method in class prediction.

Table 4. Lung cancer classifier result of the QCF-ELCD approach with 70:30 with IQ-OTH/NCCD - lung cancer dataset

Class Labels	TRAIP (70%)	TESTP (30%)
Accuracy	93.03	92.69
Precision	92.9	92.82
Recall	93.15	92.58
F1-Score	93.01	92.69
MCC	89.51	89.96

Table 4 displays the lung cancer classifier results of the QCF-ELCD approach with a 70:30 split. The QCF-ELCD method attained value with $accuracy$ of 95.35% and 95.13% for the TRAIP and TESTP, signifying the efficient classifier in the lung cancer diagnosis system.

4.3 Comparative Performance Evaluation

Table 5 presents the comparison outcome of the QCF-ELCD system with other methodologies utilizing evaluation measures [17-21]. The performance indicated that the ConvNeXt and InceptionV3 approaches gained worse performance, whereas the TL-TesNet, Ensemble deep learning, DCNN, and U-Net with ResNet methods achieved slightly greater values. Also, the Hybrid CNN + Swin Transformer, Vision Transformer, DenseNet121 with LSTM and ResNet50 systems have obtained moderate and reasonable solutions. On the other hand, the proposed QCF-ELCD method has achieved higher performance with $accuracy$ of 93.49%, $precision$ of 93.76%, $recall$ of 93.17% and $F1_{score}$ of 93.39%. This study emphasizes the outstanding performance of the QCF-ELCD system, proving its potential as an extremely strong and consistent approach for lung cancer detection.

Table 5. Comparative analysis of the QCF-ELCD approach with IQ-OTH/NCCD - lung cancer Dataset

Models	Accur _y	Preci _n	Recal _l	F1 _{score}
Hybrid CNN + Swin Transformer	90.96	89.23	87.10	88.73
TL-TesNet	88.00	90.57	91.00	91.26
Vision Transformer	92.30	90.50	92.80	92.10
ResNet50	94.50	93.10	76.40	85.20
Ensemble deep learning	89.77	89.50	90.10	89.80
DCNN	89.30	88.90	89.40	89.10
U-Net with ResNet	90.00	88.00	84.00	86.00
ConvNeXt	87.00	86.70	89.50	88.00
InceptionV3	76.90	48.50	91.20	77.10
DenseNet121 with LSTM	92.00	89.00	87.00	88.00
QCF-ELCD	93.49	93.76	93.17	93.39

Table 6 displays the processing time outcomes of the QCF-ELCD method compared with existing approaches. The results imply that the QCF-ELCD approach demonstrates the fastest execution time at 14.2ms, while other models, such as Hybrid CNN + Swin Transformer, TL-TesNet, Vision Transformer, ResNet50, Ensemble Deep Learning, DCNN, U-Net with ResNet, ConvNeXt, InceptionV3, and DenseNet121 with LSTM, obtain slower execution times ranging from 15.6 ms to 27.3ms, signifying increased difficulty. The QCF-ELCD system has been developed as the most effective method, indicating a smaller processing time while preserving a robust classifier model.

Table 6. Processing time of the QCF-ELCD approach with IQ-OTH/NCCD - lung cancer dataset

Model	Processing Time (ms)
Hybrid CNN + Swin Transformer	18.38
TL-TesNet	22.07
Vision Transformer	19.65
ResNet50	21.40
Ensemble Deep Learning	24.80
DCNN	18.90
U-Net with ResNet	27.30
ConvNeXt	16.80
InceptionV3	15.60
DenseNet121 with LSTM	22.70
QCF-ELCD (Proposed)	14.20

Table 7 depicts the sensitivity analysis of various learning rates and batch sizes for the proposed QCF-ELCD method. The outcomes specify that the method maintains stable performance under dissimilar hyperparameter settings. The configuration with a learning rate of 0.001 and batch size of 32 achieved the maximal accuracy of 94.02%, while a learning rate of 0.0001 and a batch size of 32 generated a higher F1-score of 93.39%, showing the consistency of the proposed framework.

Table 7. Sensitivity analysis of hyperparameter settings for the proposed QCF-ELCD model

Experiment	Learning Rate	Batch Size	Accuracy (%)	F1-Score (%)
1	0.01	16	92.76	90.94
2	0.001	16	93.68	91.89
3	0.0002	16	93.95	92.13
4	0.0001	32	94.02	92.22
5	0.001	32	93.17	93.39

Table 8 demonstrates the comparison outcome of the QCF-ELCD technique with other algorithms utilizing evaluation measures on the LIDC-IDRI dataset [22, 23]. The performance specified that the CNN, CLSTM, DLNmet, and MV-KBC DNN models achieved worse performance, while the VGG-16, and VGG-19 techniques reached moderate and reasonable outcomes. On the other hand, the proposed QCF-ELCD algorithm attained maximum performance with $accu_r_y$ of 93.49%, $prec_i_n$ of 93.76%, $recal_l$ of 93.17% and $F1_{score}$ of 93.39%.

Table 8. Comparative analysis of the QCF-ELCD approach on LIDC-IDRI dataset

Models	Accur _y	Preci _n	Recal _l	F1 _{score}
CNN	87.00	88.00	90.00	89.00
VGG-16	95.00	96.00	95.00	95.00
VGG-19	92.00	91.00	93.00	92.00
CLSTM	84.00	81.93	79.04	81.88
DLNmet	86.00	81.88	79.55	79.77
MV-KBC DNN	75.62	79.06	79.47	80.86
QCF-ELCD	93.49	93.76	93.17	93.39

To examine the robustness of the proposed model under real-time image-quality variations, an additional image degradation analysis was performed under conditions of Gaussian noise, Gaussian blur, and reduced-contrast. These variations were added to simulate common image-quality issues that may occur during medical image acquisition and processing. The efficiency of the proposed framework was subsequently validated under every degraded condition, and the respective Peak Signal-to-Noise Ratio (PSNR) values were computed to quantify the degree of image distortions. Table 9 demonstrates the performance analysis of the proposed model under diverse image-quality variations and the results exhibited reliable performance, exhibiting its capability in tolerating moderate variations in image quality. These results provide additional evidence of the robustness of the proposed framework beyond the evaluation performed on the original images.

Table 9. Robustness analysis of the proposed model under different image quality conditions

Condition	Accur _y	Preci _n	Recal _l	F1 _{score}	PSNR (dB)
Original images	93.49	93.76	93.17	93.39	-
Gaussian noise	91.76	89.41	90.91	90.15	21.3697
Gaussian blur	89.02	91.47	91.09	91.28	34.3985
Reduced contrast	90.82	90.75	90.34	90.54	11.6568

External assessment is performed utilizing the NLST dataset [24], which consists consist of low-dose CT analyses understood by radiology professionals. Therefore, 403 radiology specialists participated in interpreting NLST CT studies, with every examination explained by

each radiologist as per the normalized NLST screening protocol. The incorporation of NLST offers an externally obtained, medically interpreted low-dose CT experimental condition. These experiments collectively offer evidence of model consistency and external applicability. Table 10 exhibits the comparison study of the QCF-ELCD approach with existing methodologies for the NLST dataset using various metrics. The results imply that the MCTformer, TimeSformer, MViT, SIFA, ResNet50, DenseNet121, and InceptionV3 approaches obtain performance with $accur_y$ value ranging from 61.48% - 82.69%, while the proposed QCF-ELCD model achieves performance with $accur_y$ of 95.13%, $prec_i_n$ of 92.82%, $recal_l$ of 92.58% and $F1_{score}$ of 92.69%.

Table 10. Comparative analysis of the QCF-ELCD method with other approaches using NLST dataset

Methods	Accur _y	Preci _n	Recal _l	F1 _{score}
MCTformer	82.69	80.74	79.86	80.30
TimeSformer	79.34	77.82	76.91	77.36
MViT	75.91	74.38	73.62	74.00
SIFA	78.86	76.94	75.83	76.38
ResNet50	63.72	61.84	60.73	61.28
DenseNet121	61.48	59.76	58.91	59.33
InceptionV3	68.16	66.42	65.37	65.89
QCF-ELCD	95.13	92.82	92.58	92.69

4.4 Discussion

Table 11 presents the sensitivity analysis results of the proposed framework under different preprocessing configurations. The model without preprocessing achieves the lowest accuracy of 89.72%. The integration of the NLM model improves the accuracy to 91.38%, while CLAHE increases it to an accuracy of 92.41%. Then, Z-score normalization achieves an accuracy of 91.76%, whereas the combination of NLM and CLAHE further improves the accuracy to 94.27%. Lastly, the proposed NLM + CLAHE + Z-score configuration attains the highest performance, accomplishing 95.13% accuracy, 92.82% precision, 92.58% recall, and 92.69% F1-score, showing the efficiency of the integrated preprocessing phases in enriching the classification performance.

Table 11. Sensitivity analysis on preprocessing methods

Preprocessing Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Without preprocessing	89.72	87.95	86.84	87.31
NLM only	91.38	89.76	88.94	89.32
CLAHE only	92.41	90.83	90.16	90.47
Z-score normalization only	91.76	90.12	89.43	89.71
NLM + CLAHE	94.27	92.31	91.58	91.92
NLM + CLAHE + Z-score (Proposed)	95.13	92.82	92.58	92.69

An ablation analysis assesses a model by eliminating or changing its components to understand their individual contributions. It aids in identifying which parts are more dynamic for performance and directs model improvement and optimization. Table 12 presents the ablation results of the QCF-ELCD method with various metrics. The findings showed that ConvNeXt (Baseline), ConvNeXt + ECA, ConvNeXt + ECA + AdaBelief, ConvNeXt + Quantum Fidelity

Classifier, and ConvNeXt + ECA + Quantum Fidelity Classifier approaches obtained minimal values across various metrics, whereas the QCF-ELCD (ConvNeXt + ECA + Quantum Fidelity Classifier + AdaBelief) method achieved maximal values with $accu_r_y$ of 93.49%, $preci_n$ of 93.76%, $recal_l$ of 93.17%, and $F1_{score}$ of 93.39%. Additionally, to calculate the efficiency of the proposed quantum fidelity model, the same ConvNeXt+ECA features were classified utilizing SVM, XGBoost, and MLP. The comparison illustrates the maximum of the proposed quantum fidelity classifier under specify feature demonstration.

Table 12. Ablation study of the QCF-ELCD approach with IQ-OTH/NCCD - lung cancer dataset

Model Variant	Accur _y	Preci _n	Recal _l	F1 _{score}
ConvNeXt (Baseline)	89.84	88.72	87.96	88.33
ConvNeXt + ECA	91.43	90.18	89.65	89.91
ConvNeXt + ECA + AdaBelief	93.28	91.84	91.27	91.55
ConvNeXt + Quantum Fidelity Classifier	94.12	92.46	92.03	92.24
SVM + ConvNeXt + ECA	92.74	91.16	90.72	90.94
XGBoost + ConvNeXt + ECA	93.31	91.88	91.46	91.67
MLP+ConvNeXt + ECA	94.08	92.51	91.98	92.24
ConvNeXt + ECA + Quantum Fidelity Classifier	95.01	93.14	92.68	92.91
QCF-ELCD (ConvNeXt + ECA + Quantum Fidelity Classifier + AdaBelief)	93.49	93.76	93.17	93.39

Table 13 describes the statistical analysis of the QCF-ELCD framework with the baseline approaches using 10 independent runs. The proposed model accomplished the maximal mean accuracy with lower standard deviation, representing constant outcomes. The Wilcoxon signed-rank test gives 10 positive ranks and no negative ranks for all comparisons, with $p = 0.0051$ (< 0.05), ensuring that the performance improvement of QCF-ELCD over the baseline methods is statistically significant.

Table 13. Statistical comparison of QCF-ELCD with baseline models using the wilcoxon signed-rank test

Method	Mean $\pm$ SD (%)	Positive Ranks	Negative Ranks	Wilcoxon Statistic (W)	p-value
QCF-ELCD vs ConvNeXt	94.23 $\pm$ 0.11 vs 91.87 $\pm$ 0.10	10	0	0	0.0051
QCF-ELCD vs EfficientNet	94.23 $\pm$ 0.11 vs 90.95 $\pm$ 0.10	10	0	0	0.0051
QCF-ELCD vs ResNet50	94.23 $\pm$ 0.11 vs 89.79 $\pm$ 0.13	10	0	0	0.0051

Table 14 shows the computation efficiency of QCF-ELCD method with other algorithms. Based on inference time, the QCF-ELCD model denotes minimum value of 3.89ms, Flops of 0.80G and GPU of 893M whereas the CapsNet, EfficientNetB0, ResNet50, Exception, NASNet Large, and MobileNet CapsNet methods achieve maximum time of 15.53ms, 12.21ms, 14.29ms, 5.06ms, 10.76ms, and 9.01ms, correspondingly.

Table 14. Computational complexity of the proposed QCF-ELCD method

Methods	FLOPs (G)	GPU (M)	Inference Time (ms)
CapsNet	0.28	5292	15.53
EfficientNetB0	0.11	5900	12.21
ResNet50	10.89	2179	14.29
Exception	1.79	5913	5.06

NASNet Large	20.56	2752	10.76
MobileNet CapsNet	0.98	2513	9.01
QCF-ELCD	0.80	893	3.89

Table 15 demonstrates the K-fold cross validation of the proposed system. In fold 1, the model accomplished an $accur_y$ of 95.08%, $preci_n$ of 93.14%, $recal_l$ of 92.55%, $F1_{score}$ of 92.78%, MCC of 89.52%, and $kappa$ value of 89.47%. Conversely, fold 2 acquired an $accur_y$ of 94.92%, $preci_n$ of 92.98%, $recal_l$ of 92.41%, $F1_{score}$ of 92.63%, MCC of 89.34%, and $kappa$ value of 89.29%. Furthermore, fold 3 recorded the higher performance among the initial folds with an $accur_y$ of 95.13%, $preci_n$ of 93.20%, $recal_l$ of 92.67%, $F1_{score}$ of 92.89%, MCC of 89.61%, and $kappa$ value of 89.56%. Similarly, fold 9 attained an $accur_y$ of 95.10%, $preci_n$ of 93.16%, $recal_l$ of 92.60%, $F1_{score}$ of 92.83%, MCC of 89.57%, and $kappa$ value of 89.52%. Lastly, fold 10 presented an $accur_y$ of 94.89%, $preci_n$ of 92.95%, $recal_l$ of 92.37%, $F1_{score}$ of 92.60%, MCC of 89.31%, and $kappa$ value of 89.26%. The average outcomes based on all folds, gets an $accur_y$ of 94.99%, $preci_n$ of 93.05%, $recal_l$ of 92.49%, $F1_{score}$ of 92.71%, MCC of 89.43%, and $kappa$ value of 89.38%, when the standard deviation remained lower, representing enriched model performance.

Table 15. K-Fold cross validation of the proposed QCF-ELCD framework

Fold	Accur _y	Preci _n	Recal _l	F1 _{score}	MCC	Kappa
1	95.08	93.14	92.55	92.78	89.52	89.47
2	94.92	92.98	92.41	92.63	89.34	89.29
3	95.13	93.20	92.67	92.89	89.61	89.56
4	94.87	92.91	92.34	92.56	89.28	89.23
5	95.02	93.08	92.48	92.72	89.45	89.40
6	94.81	92.84	92.26	92.49	89.19	89.14
7	95.16	93.24	92.71	92.94	89.68	89.63
8	94.95	93.02	92.46	92.67	89.38	89.33
9	95.10	93.16	92.60	92.83	89.57	89.52
10	94.89	92.95	92.37	92.60	89.31	89.26
STD	±0.12	±0.13	±0.15	±0.15	±0.16	±0.16
Average	94.99	93.05	92.49	92.71	89.43	89.38

Figure 10 presents the Grad-CAM++ activation maps generated by the proposed QCF-ELCD model for three representative chest CT images. The overlaid heatmaps reveal that the architecture predominantly attends to the lung parenchyma and abnormal tissue regions while suppressing irrelevant background structures. Higher-intensity activation regions, denoted by red and yellow, are associated with areas that contributes most considerably to the lung cancer classification decision, although lower-importance regions are shown in green, blue, and purple. The reliable localization of diagnostically significant pulmonary attributes cross various CT slices exhibits that QCF-ELCD effectively captures meaningful spatial features associated with lung cancer, thus increasing model interpretability and prediction reliability. The Grad-CAM++ visualizations offers qualitative evidence that the proposed model bases its predictions on clinically important regions instead of diverse anatomical structures.

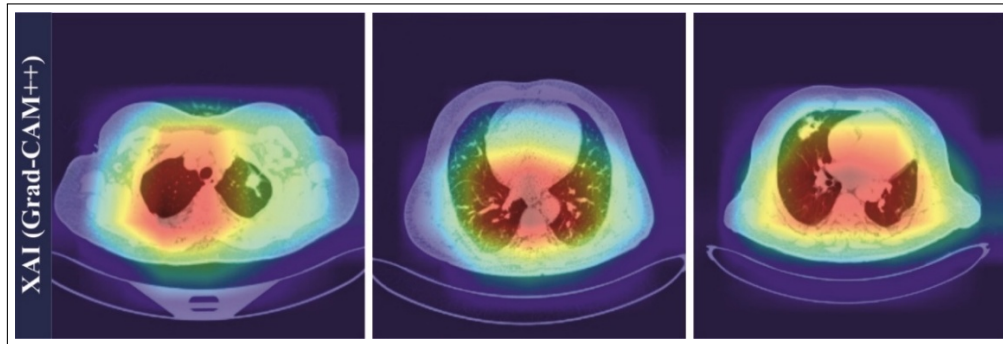


Figure 10. Grad-CAM++ visualization of QCF-ELCD method

The proposed QCF-ELCD framework enhances the identification of lung cancer using CT images from the IQ-OTH/NCCD dataset. First, the technique involves effective pre-processing steps that enhance the visual quality for better feature representation. The integration of the ConvNext structure with ECA as the feature extractor captures complex spatial representation, underscoring the more instructive channel characteristics. In addition, the classifier process uses a Quantum Fidelity-based classification algorithm to evaluate the similarity among quantum encoded feature vectors to achieve strong class discrimination across benign, normal and malignant classes. Furthermore, the AdaBelief optimization algorithm is applied to enhance convergence efficiency and training stability, resulting in improved diagnostic results. Finally, Grad-CAM++ is utilized to enhance the interpretability of the proposed QCF-ELCD by identifying and visualizing the most informative pulmonary regions influencing its diagnostic predictions.

5. Conclusion and Future Work

In this study, a new QCF-ELCD approach has been designed to efficiently classify lung cancer into benign, normal, and malignant classes, assisting clinicians in providing suitable treatment. The proposed QCF-ELCD framework includes advanced pre-processing steps to enhance visual quality and uniformity among the data. The feature extraction process integrates ConvNext architecture with ECA, a hybrid process that captures significant discriminative features. Furthermore, the quantum fidelity-based classifier improves model performance by recognizing the class with the maximum quantum fidelity match. Moreover, the AdaBelief optimization algorithm is used to improve network parameters during the training process. Additionally, Grad-CAM++ is used to validate the decision-making process of the proposed QCF-ELCD by highlighting clinically relevant regions that drive its lung cancer classification outcomes. The experimental analysis confirms the efficiency of the proposed model by attaining enhanced classification accuracies of 95.13% and 94.23% on the IQ-OTH/NCCD Lung Cancer Dataset and LIDC-IDRI Dataset, respectively. Therefore, the proposed QCF-ELCD model demonstrates significant potential for automatic lung cancer classification over existing approaches. Even though the QCF-ELCD model shows excellent performance in identifying lung cancer, it faces challenges associated with modifications in CT images and the need for higher computational resources. Future research may concentrate on extending the model by incorporating multimodal data, including clinical and radiological reports, for improving diagnostic accuracy. The incorporation of lightweight models can be developed to reduce computational cost and make it well-suited for practical clinical deployment. Moreover, novel quantum-assisted and hybrid learning methodologies can be investigated to further improve classification effectiveness across various medical imaging conditions. In addition, future

studies will assess the QCF-ELCD approach on lower-dose CT scans, multi-center datasets, and images extracted from diverse CT devices to analyze its robustness with differing medical imaging states. In future evaluations, the proposed quantum module will be assessed using realistic quantum noise models and, where feasible, on physical quantum hardware to evaluate its practical performance and reliability. These evaluations will provide further insights into the more reliable, scalable, and suitable future clinical deployment potential of the proposed model.

Declarations

Data Availability Statement

The data that support the findings of this study are openly available in Kaggle repository at <https://www.kaggle.com/datasets/adityamahimkar/iqothnccd-lung-cancer-dataset>, reference number [15], cancer imaging archive at <https://www.cancerimagingarchive.net/collection/lidc-idri/> [16], and NLST dataset at <https://www.cancerimagingarchive.net/collection/nlst/> [24].

Competing Interests and Funding

The authors did not receive support from any organization for the submitted work.

Funding Statement

The authors received no funding for this study.

Human Participants and/or Animals

Not applicable

Ethics Approval

Not Applicable

Conflict of Interest

The authors declare that they have no conflict of interest. T

Consent to Participate

Not applicable.

References

- [1] Sivaprakash, P., K. Subhashini, Francis H. Shajin, and P. Rajesh. "Computer-aided Lung Cancer Classification on Computed Tomography Imaging Using Optimized Heterogeneous Bi-Directional Recurrent Neural Network." *Expert Systems with Applications* (2026): 132007.
- [2] Alshmrani, Goram. "AI in Lung Health: Advanced Automated Solutions for Lung Cancer Diagnosis and Prognosis Using Multimodality of Medical Data." PhD diss., Lancaster University (United Kingdom), 2026.
- [3] Kumar, U., Thakral, G., and Gambhir, S. "A Systematic Review of Segmentation and Classification Techniques for Lung Cancer Detection on LDCT Scan Images." *International Journal of Research Publication and Reviews* 2026. 6(9). 3231-3240.

- [4] Khan, Arsalan, Taimoor Ali Shah, Wajihullah Khan, Younas Nazir Khan, Tariq Nawaz, Said Khalid Shah, and Muhammad Ayaz. "Lung Cancer Classification from CT-scan Images Using an Efficient CNN With Transfer Learning." *Spectrum of Engineering Sciences* 4, no. 2 (2026): 465-479.
- [5] K. G. K. Rao and L. K. Pappala, "Early-Stage Multimodal Lung Cancer Detection Using Attention-Based Feature Fusion," in *IEEE Access*, vol. 14, 2026, 48374-48393.
- [6] Shatnawi, Mohammad Q., Qusai Abuein, and Romesaa Al-Quraan. "Deep Learning-Based Approach to Diagnose Lung Cancer Using CT-scan Images." *Intelligence-Based Medicine* 11 (2025): 100188.
- [7] Tawfeek, Medhat A., Ibrahim Alrashdi, Madallah Alruwaili, Warda M. Shaban, and Fatma M. Talaat. "Enhancing the Efficiency of Lung Cancer Screening: Predictive Models Utilizing Deep Learning from CT Scans." *Neural Computing and Applications* 37, no. 17 (2025): 11459-11477.
- [8] Ozdemir, Burhanettin, Emrah Aslan, and Ishak Pacal. "Attention Enhanced Inceptionnext-Based Hybrid Deep Learning Model for Lung Cancer Detection." *IEEE Access* 13 (2025): 27050-27069.
- [9] Güraksın, Gür Emre, and Ismail Kayadibi. "A Hybrid LECNN Architecture: A Computer-Assisted Early Diagnosis System for Lung Cancer using CT Images." *International Journal of Computational Intelligence Systems* 18, no. 1 (2025): 35.
- [10] Crasta, Lavina Jean, Rupal Neema, and Alwyn Roshan Pais. "A Novel Deep Learning Architecture for Lung Cancer Detection and Diagnosis from Computed Tomography Image Analysis." *Healthcare Analytics* 5 (2024): 100316.
- [11] Buades, Antoni, Bartomeu Coll, and J-M. Morel. "A Non-Local Algorithm for Image Denoising." In *2005 IEEE computer society conference on computer vision and pattern recognition (CVPR'05)*, vol. 2, IEEE, 2005, 60-65.
- [12] Liu, Zhuang, Hanzi Mao, Chao-Yuan Wu, Christoph Feichtenhofer, Trevor Darrell, and Saining Xie. "A Convnet for the 2020s." In *2022 IEEE/CVF conference on computer vision and pattern recognition (CVPR)*, IEEE, 2022, 11966-11976.
- [13] John, Manuel, Julian Schuhmacher, Panagiotis Barkoutsos, Ivano Tavernelli, and Francesco Tacchino. "Optimizing Quantum Classification Algorithms on Classical Benchmark Datasets." *Entropy* 25, no. 6 (2023): 860.
- [14] Zhuang, Juntang, Tommy Tang, Yifan Ding, Sekhar C. Tatikonda, Nicha Dvornek, Xenophon Papademetris, and James Duncan. "Adabelief Optimizer: Adapting Stepsizes by the Belief in Observed Gradients." *Advances in neural information processing systems* 33 (2020): 18795-18806.
- [15] <https://www.kaggle.com/datasets/adityamahimkar/iqothnccd-lung-cancer-dataset>
- [16] <https://www.cancerimagingarchive.net/collection/lidc-idri/>
- [17] Chang, Ya-Han, Yi-Hui Lin, Hsing-Chen Meng, Shawn Wu, Yen-Yu Lin, and Chun-Rong Huang. "Spatiotemporal Deformable Transformer for Lung Cancer Risk Prediction Using Low-Dose CT Images." *IEEE Transactions on Radiation and Plasma Medical Sciences* (2026)

- [18] Meeradevi, T., S. Sasikala, L. Murali, N. Manikandan, and Krishnaraj Ramaswamy. "Lung Cancer Detection with Machine Learning Classifiers with Multi-Attribute Decision-Making System and Deep Learning Model." *Scientific Reports* 15, no. 1 (2025): 8565.
- [19] Durgam, Revathi, Bharathi Panduri, V. Balaji, Adil O. Khadidos, Alaa O. Khadidos, and Shitharth Selvarajan. "Enhancing Lung Cancer Detection Through Integrated Deep Learning and Transformer Models." *Scientific Reports* 15, no. 1 (2025): 15614.
- [20] Thakur, Neha, Pradeep Chouksey, Ashok Sharma, Mayank Chopra, Parveen Sadotra, and Sunil Kumar. "Binary Classification of Lung Cancer Using Vision Transformer Models on CT Images." *Discover Computing* 29, no. 1 (2026): 66.
- [21] Vemula, Suseela Triveni, Maddukuri Sreevani, Perepi Rajarajeswari, Kumbham Bhargavi, Joao Manuel RS Tavares, and Sampath Alankritha. "Deep Learning Techniques for Lung Cancer Recognition." *Engineering, Technology & Applied Science Research* 14, no. 4 (2024): 14916-14922.
- [22] Javed, Rabia, Tahir Abbas, Ali Haider Khan, Ali Daud, Amal Bukhari, and Riad Alharbey. "Deep Learning for Lungs Cancer Detection: A Review: Javed et al." *Artificial Intelligence Review* 57, no. 8 (2024): 197.
- [23] Bhattacharee, Ananya, Abhishek Bhattacharjee, Ranjit Prasad Swain, and Ram Kumar Sahu. "Multiclass Lung Cancer Detection Using a Hybrid Capsule Inspired Deep Neural Network." *Scientific Reports* (2026).
- [24] <https://www.cancerimagingarchive.net/collection/nlst/>.