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Chapter 13

Integrating Quantum Computing and Deep Learning with QCNN and ResNet for Glaucoma Imaging

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Abstract

Glaucoma is one of the leading causes of irreversible blindness; thus, it is critical to detect it as soon as possible and accurately. While machine learning algorithms show potential for improving glaucoma screening, they face substantial obstacles due to computational complexity, which impedes rapid and exact categorization, as well as challenges such as limited dataset diversity, data imbalance, and the need for interpretable models. In addition, traditional deep learning models are often challenged to unify unseen data, which results in degradation of performance under realistic situations. In response to these limitations, this research proposes a new approach in which quantum computing is integrated with deep convolutional neural networks (DCNNs) to improve diagnostic efficiency by overcoming processing constraints, enhancing model generalization, and enabling more efficient data utilization, while also exploring techniques for improving model interpretability and addressing data imbalance issues. The dataset utilized in this research is a fraction of the regular fundus images, and it has been meticulously chosen from the Rotterdam EyePACS AIROGS. The images are classified into referable glaucoma and non-referable glaucoma carefully, which equally contain each pathological condition. The chosen sets of data are split into training, validation, and each test set in equal ratios of 4000, 385, and 385, respectively. The suggested work thus starts by separating the discriminative feature from the fundus images using the ResNet architecture. The ResNet is better known for its remarkable ability to train very deep neural networks, which is extremely helpful for extracting features, an essential phase when classifying glaucoma. The features that have been extracted are then employed in Quantum Convolutional Neural Networks (QCNNs), which are used as building blocks in glaucoma classification. QCNN is focused on applying quantum mechanical theory in carrying out convolutional computation and hence enhancing the prospects of quantum resources for parallelism and classification. This proposed paper is aimed at improving the accuracy of the current glaucoma diagnostic system alongside reducing the computational complexity of the system. It achieves this by combining ResNet's computing capability in feature extraction with that of QCNNs. The proposed DCNN design based on quantum, leveraging parallel computing abilities native in quantum computation, stands a high likelihood of transforming the diagnosis of glaucoma. The research thus aims to experimentally validate and measure performance in a rigorous manner to establish practicability and efficacy towards developing high-precision methods for early detection as well as treatment of glaucoma with improved accuracy in classification, that can result in improved patient outcomes through preservation of vision.

Keywords: Glaucoma Detection, ResNet50, Quantum Convolutional Neural Networks, Transfer Learning, Medical Image Classification, Deep Learning, Quantum Computing.

1. Introduction

Glaucoma, a multifaceted group of progressive optic neuropathies, poses a formidable challenge in ophthalmology, threatening vision and quality of life around the world [34]. This vision-threatening disease costs billions of dollars to millions of people around the world and lowers their quality of life. This undetected disease is characterized by continuously degenerating retinal ganglion cells and their axons, resulting in irreversibly damaged optic nerves [36]. The consequences can be devastating, as advanced glaucoma causes profound visual field defects and, in severe cases, complete blindness—a fate that emphasizes the importance of early detection and intervention [25].

Appropriate early diagnosis is critical in the fight against glaucoma because the early stages of the disease typically progress without warning signs, which may only become apparent after irreversible damage has been done [27]. Traditional diagnostic techniques, such as subjective measurement, perimetry, and examination of the optic disc or optic nerve head, are valuable but have limitations due to subjective judgment and manual interpretation [29]. These are fairly inexact and prone to variation and bias; hence the requirement for more precise, numerical, and standardized means of glaucoma diagnosis [17].

New technologies have been developed in ophthalmic imaging that have revolutionized the diagnostic and management criteria in glaucoma [35]. Optical coherence tomography, fundus photography, confocal scanning laser ophthalmoscopy, and other advanced methods provide a new perspective to glaucoma ocular fine structures and precise, non-invasively imaged examinations of the optic nerve head, retinal nerve fiber layer, and other glaucomatous structures [6] [26]. The role of OCT in diagnosis is the supply of high-resolution cross-sectional images of the retina and quantitative thickness measurement of the retinal nerve fiber layer, an objective parameter of glaucomatous damage [20]. Fundus photography, conversely, yields large-area color images of the retina adequate for morphological evaluation of the optic disc, vasculature, and other glaucoma structures relevant to evaluation [15]. These imaging methods have changed the environment for analysis by introducing objective quantitative measures to detect structural changes prior to the onset of bad functional vision [21].

While ophthalmic imaging has elevated glaucoma diagnosis to a higher plane, interpretation of so intricate and image-dense an organ remains an issue that cannot be addressed without specialized training and exposure [38]. Routine rough hand analysis is known to be subjective, time-consuming, and, most importantly, introduce inter-observer variability—all considerations that could restrict the generalizability of diagnosing working processes [28]. This limitation has bred awareness of the use of artificial intelligence and utilization of machine learning algorithms, particularly deep learning algorithms [3]. These advanced computational approaches can aid in automating the diagnosing process with large volumes of data that can be gathered from ophthalmic imaging modalities, ensuring high accuracy, efficiency, and reproducibility of glaucoma classification [23]. CNNs, being deep learning models, are highly effective in handling various medical image analysis problems, such as detection of glaucoma from fundus photography and OCT scans [37] [31].

This research presents a new approach to classifying glaucoma based on ophthalmic images with the utilization of deep learning and the future innovation, quantum computing. The work is developed to assist in giving a better diagnosis of glaucoma by combining a new feature extraction method using Residual Networks with the parallel computation capacity offered by QCNNs in order to solve the challenge posed by the detection of glaucoma.

2. Literature Review

Diaz-Pinto et al. [8] classify retinal fundus images as glaucomatous or non-glaucomatous using CNN, applying deep learning in the diagnosis of glaucoma based on retinal fundus images. This model learns over a large dataset with unprecedented performance on automated diagnosis of glaucoma as proof of the potential of deep learning over an automated glaucoma diagnosis. In this paper, the authors utilized QCNN in their prior work for diagnosing glaucoma using fundus images. Advanced QCNN computation methods are far superior to classical CNNs; they utilize quantum mechanics principles and have much higher accuracy. Hence, both experiments prove that advanced computational methods enhance diagnostic accuracy in the glaucoma domain. Chakma et al. [5] used a deep residual CNN with ResNet-34 architecture to detect glaucoma using fundus images of the retina. ResNets train deep networks effectively using skip connections, which allow gradients to flow more easily during backpropagation, resulting in high glaucoma detection accuracy. Tan et al. [32] presented a curvelet-based CNN for glaucoma detection, combining curvelets with CNNs to capture additional relevant features. Their approach outperformed traditional CNNs and demonstrated that combining advanced signal processing methodologies with deep learning could help improve performance in medical image analysis.

Meanwhile, Nagaraj et al. [22] presented a Quantum Residual Attention Network for glaucoma classification, in which residual connections and attention mechanisms were combined with quantum computing to successfully focus on relevant image regions, demonstrating an overwhelming potential to improve diagnostic accuracy. Xu et al. [39] presented a QCNN architecture for glaucoma detection, where they looked into various quantum circuit designs using different optimization strategies. The performance of QCNN for glaucoma detection was found to potentially outperform classical CNN, which implies good performance of quantum computing in image analysis in medical research. Glaucoma detection in fundus images using quantum deep learning techniques like QCNNs was investigated by Khandual et al. [16]. For various architectural choices and training strategies in this comparison, they looked at several quantum deep learning models and compared them to classical CNNs. With CNNs for glaucoma detection, Tan et al. [33] have looked into transfer learning, and pretraining neural networks on new tasks, and showed the process has the potential to increase glaucoma detection performance with few training data. In retinal fundus images, Kashyap et al. [14] presented an improved U-Net based on DenseNet-201 for early glaucoma detection. Robust training datasets were shown to be important for the accuracy of segmentation of the optic cup and disc with this model. They obtained significant AUC values and demonstrated that deep learning models with transfer learning and training from scratch can outperform models using handcrafted features, as shown in [7], in detecting glaucoma.

Orlando et al. [24] explored if CNN models pre-trained on non-medical images can be extended to the task of glaucoma classification. Using OverFeat and VGG-S feature extractors, they trained regression classifiers for glaucoma detection with AUC values great beyond significant. Deep learning models, such as G-net, a deep CNN for optic disc and cup segmentation proposed by Juneja et al. [13], were also investigated, which showed high accuracy while reducing the need for manual examinations, which brings out the possibility for automated glaucoma diagnosis. Barros et al. [4] conducted a systematic review of machine learning algorithms for retinal image processing, highlighting deep learning's potential for early glaucoma detection [9]. They compared feature selection techniques and classification accuracy, demonstrating that PCA outperformed Student's t-tests. Both studies emphasized the value of effective feature selection and advanced algorithms in improving diagnostic performance.

Mahum et al. [19] proposed a hybrid deep convolutional neural networks (CNN) model that incorporates the concept of feature descriptors into the deep learning model to distinguish between healthy and glaucomatous eye images with high accuracy. Sreng et al. [30] presented an automatic two-stage model and insisted on using DeepLabv3+ for the first stage and several strategies for the second, indicating that their proposed approach performed better in both segmentation and classification tasks, emphasizing the method's robustness and practicality in a real clinical setting. In Multi-Path Recurrent U-Net Architecture [12], the authors combined CNN with a recurrent neural network for feature extraction to segment retinal fundus images, providing a significant improvement and outperforming other optic disc and cup segmentation approaches. In the context of medical image analysis, both studies proposed novel methods to improve diagnostic accuracy.

Deep learning can help to fill gaps in specialized medical knowledge, particularly in low-resource settings. It has the potential to eliminate medical disparities around the world and provide advanced health outcomes by providing accurate disease prediction to everyone. Bharathi Mohan G. et al. [11] demonstrated the necessity of an excellent pharmaceutical recommendation system to have the best patient outcome consumption rate. Some researchers suggested that it should be a system based on a convolutional recurrent neural network, which incorporates deep learning, sentiment analysis, and selfattention mechanisms. It does not only have good effects on outcomes in terms of ensuring patients but has also been proven to be operative in the process of medical prescriptions for a particular disease. Arumugam et al. [1] utilized intelligent automation and soft computing techniques to determine predictive critical features during the early stages of chronic kidney disease. Various feature selection methods have identified the most relevant predictors, thus leading to the development of complex yet efficient diagnosis models. This brings their results to the forefront on feature selection as improving model performance, yet moving forward in achieving effective early interventions in CKD management. The second research, conducted with Arumugham et al. [2], focused on the development of an explainable deep learning model for predicting the early stages of chronic kidney disease. The research strongly stressed the critical need for AI models to be transparent in healthcare and thus to develop clinical trust and adoption. Their model supported high accuracy in prediction, and through the use of explainable AI techniques, they were able to emphasize the accuracy of their predictions and insight into the decision-making process. This would enhance more informed clinical decisions while also increasing trust in AI-powered healthcare solutions.

The above-reviewed literature presents significant advances in deep learning and quantum computing for glaucoma diagnosis through retinal fundus images. Such methods have significant advantages for improving accuracy in feature extraction robustness but suffer from challenges, which include extensive annotated data sets, highly strong computational resources, and the need for specially designed hardware for quantum computing. These restrictions have to be overcome by further research, which can make the diagnostic tools more accessible and efficient for broader, routine application in clinical practice. Table 1 presents a summary of selected research papers discussed in the literature review. It highlights the key datasets, methods, findings, and limitations from each study.

Table 1: Deep Learning Approaches for Glaucoma

Authors	Dataset	Methods	Key Findings	Limitations

Diaz-Pinto et al. [8]	Retinal fundus images	CNN, QCNN	QCNN demonstrated higher accuracy than classical CNN for glaucoma detection	Requires quantum computing resources
Chakma et al. [5]	Fundus images of the retina	ResNet-34 (Deep Residual CNN)	Skip connections improved gradient flow, achieving high accuracy	Computationally expensive
Tan et al. [34]	Fundus images	Curvelet-based CNN	Combining curvelets with CNNs improved feature extraction	Increased complexity in implementation
Nagaraj et al. [22]	Retinal fundus images	Quantum Residual Attention Network	Quantum computing improved diagnostic accuracy significantly	Quantum hardware dependency
Kashyap et al. [14]	Retinal fundus images	Improved U-Net (DenseNet-201)	Achieved high segmentation accuracy for optic cup and disc	Needs robust annotated datasets
Orlando et al. [24]	Non-medical images pre-trained models	OverFeat, VGG-S with regression classifiers	Pretrained models can be adapted for glaucoma detection	Transfer learning may not generalize well to all datasets
Mahum et al. [19]	Retinal fundus images	Hybrid CNN with feature descriptors	Achieved high accuracy in distinguishing healthy vs. glaucomatous images	Limited generalizability across different datasets

3. Methodology

This research employs an advanced hybrid framework that combines Quantum Convolutional Neural Networks (QCNN) with ResNet50 to effectively detect glaucoma from retinal fundus images. The methodology is designed to optimize feature extraction, minimize computational overhead, and improve the overall classification accuracy. The process begins with detailed dataset selection and preprocessing, followed by the implementation of deep learning and quantum computing techniques. Each phase of the methodology is meticulously crafted to ensure robust and generalizable results, culminating in the evaluation of model performance using appropriate metrics.

3.1 Dataset Description

The EYEPACS, AIR-OGS Light v2 is a select subset of the EYEPACS and AIR-OGS datasets that the National Institutes of Health (NIH), in collaboration with its partners from the American Indian and Alaska Native communities, with the latter drawn from multiple American Indian and Alaska Native communities. The EYEPACS—Eye Picture Archive Communication System—dataset was established by the National Eye Institute in collaboration with the NIH to produce a digital image library for ophthalmic research and education within the United States. A large number of retinal fundus images are contained within the EYEPACS dataset, together with the clinical data and annotations produced by ophthalmologists and trained graders. Fig 1 illustrates a sample glaucoma image from the dataset.

Table 2: Summary of the Dataset

Dataset Name	**EYEPACS, AIR-OGS Light v2**
Source	NIH (National Institutes of Health), American Indian and Alaska Native communities
Purpose	Early detection and treatment of glaucoma
Content	Retinal fundus images with clinical data and annotations
Total Images	3,839
Glaucomatous Images	1,720
Non-Glaucomatous Images	2,119
Image Resolution	768 x 576 pixels
Image Formats	JPEG, PNG
Additional Data	Metadata, annotations, patient demographics, clinical notes
Labeling	Expert annotations or clinical assessments by ophthalmologists or graders
Dataset Usability	Machine learning and computer vision methodologies for glaucoma screening, diagnosis, and monitoring
Features	Equitable representation of both glaucomatous and non-glaucomatous cases

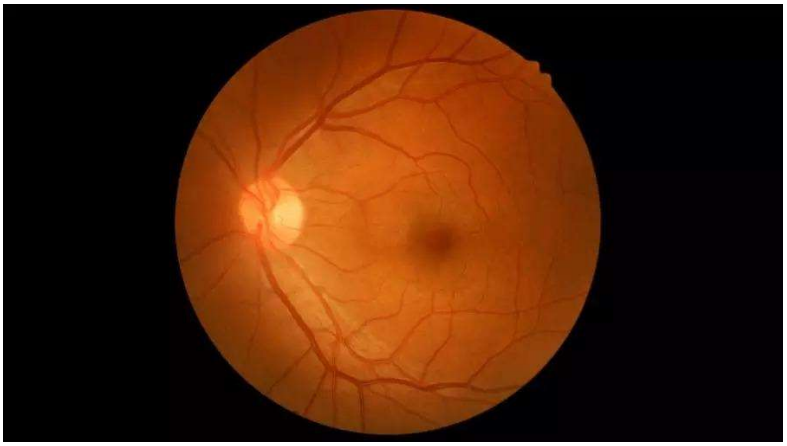

Figure 1: Glaucoma image from the dataset

NIH funded the creation and dissemination of the Glaucoma Dataset: EYEPACS, AIR-OGS Light v2. It is a set of annotated retinal fundus images that have been identified as "glaucomatous" or "non-glaucomatous." Notably, the images were classified as "glaucomatous" or "non-glaucomatous," and the annotations were most likely derived from the professional experts' clinical evaluation by trained ophthalmologists or graders. Labeling the data ensures ground truth correctness and validity; the corresponding importance is its direct effect on training and testing machine learning models to automatically detect glaucoma. A certain diversity of a dataset as well as a proper balance with correct representation of both glaucomatous and non-glaucomatous instances are important for robust, generalizable models. This will enable the model to extract characteristics and patterns in each class such that it can classify them in an error-free manner with minimal error caused by bias. A summary of the dataset is shown in Table 3.2.

3.2 Data Preprocessing

Data preprocessing is very critical in any machine learning activity because it transforms the raw data into a processed and normalized format that has an additive effect on model performance and generalization. The chief objective of image preprocessing is to enhance the quality of the image and ensure that it becomes uniform, thereby being suitable for deep learning models to handle. Firstly, all images must be resized to 224x224 pixels to make the data set compatible with pre-trained input requirements like ResNet and therefore reduce the computational complexity of the model. Normalizing the scale of features on all images lets the model not be confused with the differences in sizes of images, which is very important for medical imaging as anatomical structures between patients are vastly different.

These procedures consist of resizing where images are exposed to Gaussian smoothing. They process them to remove noises and retain the structural details like the optic disc and blood vessels. This is done by the Gaussian filter, averaging pixel values within a certain neighborhood, which removes random variations and emphasizes underlying anatomical structures. It increases the sharpness of the image and improves the diagnostic quality in conjunction with the signal-to-noise ratio, relevant for significant features resulting in enhanced detectability and classification quality by a deep learning model. Normalization is another significant preprocessing phase that makes sure to rescale pixel intensity to a certain range, though often within between 0 and 1. Normalization stabilizes the training procedure by making input data have statistical properties; thus, gradient flow during backpropagation is improved. Pixel values in this dataset are rescaled by 255, so they range from 0 to 1. This step reduces numerical

instabilities and allows for faster convergence during training. The fact that all images have similar intensity distributions prevents model learning of irrelevant features as a result of changes in light conditions, which is critical in medical imaging where different lighting can alter the appearance of diagnostic features.

These data augmentation techniques also increase the dataset's size and diversity, which improves model generalization. As new, distinct variants of the original images are added to the training set, the size and diversity of the training data are artificially increased. As a result, the model's generalization capabilities will be improved while overfitting is reduced. These techniques include rotation by ±40 degrees to replicate different orientations, width, and height shifting by + or - 20% of the image dimensions to inject translational invariance, shear within a given angular range to simulate distortions, zooming by ±20% to account for scale and distance variations and horizontal flipping to generate mirrored versions. These augmentations aid in learning the invariances of transformations that are common in real-world scenarios, making the model more robust to variations in input data.

All these preprocessing operations are carried out through automated scripts to ensure consistency and reproducibility across the entire dataset. Only an exhaustive preprocessing pipeline can ensure that quality data fed into the deep learning model is good, standardized, and representative of real-world variability in clinical. As a result, consistency and reproducibility in automated scripts are practical approaches to preserving the integrity of their preprocessing pipeline and limiting human error in ensuring that each image is subjected to uniform transformations. Automation, in its most effective form, speeds up this preprocessing process and ensures that the changes or updates made to the pipeline are uniformly applied to every image; thus, accuracy and reliability are guaranteed. All these preprocessing operations should be performed not only on the training data but also on the validation and test data so that during the testing phase of the model, there is no inconsistency and data leakage or bias occurs during model evaluation. So, it will make sure that the performance metrics obtained through the model are accurate and actually correct when employing new unseen data. It ensures that a model is compared on the basis that it was trained upon, and therefore reliability of performance estimation is guaranteed for real-world applications. Good quality preprocessing also ensures that a deep learning model would focus more on learning the most relevant features required for the detection and classification of diseases. Resizing, Gaussian filtering, normalization, and data augmentation are some preprocessing techniques that enhance the sensitivity and visibility of important diagnostic features for better detection and diagnosis of glaucoma.

3.3 ResNet

ResNet, or Residual Networks, is a deep learning architecture that changed the course of computer vision forever by addressing the vanishing gradient problem, which was previously a significant challenge in training deep neural networks. As neural networks deepen, the gradients used to update the weights during backpropagation can become insignificant, causing the network to cease learning effectively. This phenomenon is referred to as the vanishing gradient problem. ResNet addresses this issue head-on by introducing residual learning, which allows the model to learn residual functions using the layer inputs rather than learning unreferenced functions directly. ResNet ensures that gradients flow much more easily through the network as it deepens by representing the layers as learning residuals. This innovation enabled the training of extremely deep networks with hundreds or thousands of layers, resulting in significant performance improvements on complex image recognition tasks. ResNet marked a watershed moment in deep learning history. It influenced a wide range of subsequent designs and established new standards for a variety of computer vision challenges.

More specifically, it typically consists of two or three convolutional layers, each followed by batch normalization and a ReLU activation function. The introduction of shortcut connections is probably ResNet's most distinguishing feature, setting it apart from other proposals for deep learning architectures. Essentially, the skip connections bypass one or more layers to create an uninterrupted gradient flow path. Because the gradient skips a few turn-around points, these shortcut connections significantly alleviate the vanishing gradient problem, allowing the network to retain its learning capacity even when it is extremely deep. The architecture has many variants, including those with 18, 34, 50, and 101 layers; all of these variants differ primarily in configuration by residual blocks. For example, ResNet50, a central model in this research, has 50 layers organized into a series of residual blocks. It has primarily improved performance on a wide range of image recognition tasks because each block is designed to learn a residual mapping for maximum efficiency and effectiveness during training.

ResNet50 has 50 layers, which include convolutional, pooling, and fully connected layers. The ResNet50 model is a subset of the ResNet architecture that includes an initial convolutional layer followed by multiple layers of residual blocks organized into four stages. The front convolves 7x7 and 64 filters. It follows with a max-pooling layer to reduce the spatial dimensions of feature maps. The main operation of this stage is to capture simple features like edges and textures. The subsequent stages in ResNet50 involve 3, 4, 6, and 3 residual blocks, to extract more complex features from images. Each residual block employs two convolutional 3x3 layers, followed by batch normalization and a ReLU activation. The shortcut inside the blocks allows the net to easily combine the features learned with the inputs' original copies, offering improved gradient flow and inhibiting the vanishing gradient issue. ResNet50, due to its structure, can maintain high learning efficiency and effectiveness even with increased network depth. The architecture concludes with a global average pooling layer; the feature maps are aggregated, and spatial dimensions of features are reduced without losing any information. The subsequent layer is fully connected; it takes input from the previous layer to generate the final output. The output in most classification problems would be a probability distribution over the classes.

The ResNet50 architecture assumes images of size 224x224 pixels, which come as a color image with three color channels (RGB), consistent also with the preprocessing steps applied to the dataset. This is one of the standard input sizes, which guarantees that all the images within the test dataset are compatible with this model architecture and will be sufficient for the system's image processing during testing. The first convolutional layer shall extract the simplest features, such as edges, textures, and simple patterns. Successive residual blocks may extract more abstract and complex features. At each successive level, abstraction levels are recorded, progressing from simple geometric shapes to more abstract patterns and then the objects themselves. In developing the hierarchical feature extraction strategy of ResNet50, it is possible to develop a representation that is rich and diverse regarding the input images. This is crucial for accurate classification. Based on such features extracted from ResNet50, it categorizes images. These features are prominent in distinguishing referable from non-referable glaucoma images and allow for accurate and reliable diagnosis.

ResNet50's middle layers rely heavily on residual blocks to learn residual mappings. Rather than mapping inputs to outputs directly, the residual blocks learn how the input differs from the desired output. Based on this residual learning framework, the optimization process will be simple, and the network will be pushed towards learning identity mappings. For instance, if one of the layers is not very important to the model's performance, this residual block learns to simply pass the input directly to the output. This mechanism helps to speed up the training process and even allows the network to generalize more on new data. All of the outputs of each residual block, as shown below, are considered intermediate features, which are a combination of low and high-level characteristics of the input images,

making them very useful in the robust feature representation of the input. These intermediate features are thus central to the network's performance as they encompass all the information required to classify precisely. Therefore, ResNet50 could successfully work on the difficult task of identifying images, for instance, for glaucoma, by learning and combining all these features precisely.

The final layer of any ResNet50 architecture is global average pooling, which summarizes all the feature maps, so all information is kept while spatial dimensions are reduced. Then comes the final fully connected layer, which does its thing in producing the final output, often in terms of a probability distribution over classes involved in classification. In this research of the detection of glaucoma, the output layer of a model was used for classifying referable and non-referable images of glaucoma. On this score, the strength and flexibility of ResNet50 make it a very powerful tool that goes beyond applications in glaucoma detection but has much wider applications in general digital medical image analysis, object detection, and image segmentation. It is on account of the amount of real learning and generalization capability over complex image datasets that computer vision and deep learning techniques become extremely important. Further, working towards achieving high precision for tools designed for glaucoma diagnosis, outstanding feature extraction, and classification ability present with ResNet50 can be utilized. This may lead to benefits for patients and advancement for ophthalmology.

To train at deeper depths, skip connections are used in ResNet50. In such skip connections, the input bypasses the extra layers and enters directly into the output from a residual block. Therefore, this added original input will overcome the vanishing gradient problem as the path of gradients during backpropagation is available. This skip connection is crucial so the gradients will be large enough to propagate through a huge number of layers, making sure that learning efficiency will be very good in very deep networks. One of the principal merits of this design is that it is especially useful in preventing a degradation problem where more layers mean higher training errors. Further, ResNet50 contains skip connections, which is likely to result in not degrading the performance of the deep layers but instead, a deeper model yields effective models to work on problems like complex image classification and recognition.

One of the reasons for using ResNet as a feature extractor is that it can utilize transfer learning. ResNet50 was trained on ImageNet, a very large dataset that contains over 1.2 million training images distributed over 1,000 object categories. So, the rich generalizable feature representations that can be effectively transferred in ResNet50 have been pre-trained for a range of application problems in computer vision, including glaucoma classification. This has been achieved by making use of the pre-trained weights of ResNet50, fine-tuned concerning the glaucoma dataset. Therefore, through the technique of transfer learning, the model only needs to import relatively robust feature representations as extracted from a broad set of natural images and adapt to its task at hand: classification of glaucoma. The fact that these pre-programmed weights would let the model learn and get better, converging faster in coming to the end to take on a dataset that would likely be scarce or specialized, would be a great help to the model.

3.4 Quantum Convolutional Neural Networks (QCNN)

Quantum convolutional neural networks are a new type of neural network inspired by quantum mechanics, including the principles of superposition and entanglement, which improve the learning capability of traditional CNNs. By incorporating quantum mechanics concepts into the network architecture, QCNN can better capture more complex patterns and correlations in data, improving

performance on some vision tasks but especially image classification. The complexity of relationship modeling and subtle patterns in retinal fundus images, however, is essential for accurate glaucoma diagnosis. Their architecture enables QCNNs to overcome some higher-order interactions or non-linear dependencies between variables in data that traditional CNNs may miss. This aims to combine the strengths of classical and quantum approaches into a single model by incorporating a QCNN layer with ResNet50-derived features. However, a deep ResNet50 architecture gives the advantages of strong feature representation with generalizability as well as pre-trained parameters. Furthermore, these characteristics are fed into a QCNN layer, which is expected to detect higher-order relationships and nonlinear interactions that traditional neural networks miss.

Superposition, entanglement, and quantum interference are key principles in quantum mechanics that are relevant to QCNNs. A qubit can be in multiple states simultaneously, which means that a quantum system is capable of handling massive amounts of data simultaneously. Another major characteristic is that qubits become entangled with each other, meaning that any change in the state of a single qubit causes an instantaneous change in the states of all the other qubits, irrespective of the distance over which they are separated. This aspect may be regarded as necessary as it makes possible high computational speed and parallel processing. Quantum particles also exhibit quantum interference because of their wave-like nature. The good solutions are reinforced by constructive interference, and the bad ones are killed by destructive interference. Based upon these principles, QCNNs can then produce complex operations much more efficiently than their classical neural network counterparts, which may then be analytically solved and give solutions to a class of problems that cannot be attacked by using classical methods, thereby revolutionizing the field of machine learning. Applying these principles to the dataset allows QCNNs to take advantage of complex patterns in fundus images to increase precision in identifying a variety of glaucoma conditions at faster speeds.

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle, \quad |\alpha|^2 + |\beta|^2 = 1 \tag{1}$$

This highlights how QCNN inputs (encoded features) exist in superposition states.

$$|\psi'\rangle = U(\theta)\,|\psi\rangle, U(\theta) = e - i\theta H$$

(2)

where H is a Hamiltonian operator (often Pauli matrices like X,Y,Z). This parallels weight transformations in CNN filters.

$$U(\theta) = Rx(\theta 1)Rz(\theta 2) = e - i\theta 1X/2e - i\theta 2Z/2 \tag{3}$$

Represents parameterized rotations in a quantum convolutional filter.

Typically, a QCNN consists of several quantum convolutional layers and quantum pooling layers, followed by quantum fully connected layers. Quantum convolutional layers include quantum gates that implement the same task as classical convolutions, squeezing features from input data encoded in qubits. Analogous to classical pooling layers, quantum pooling layers also reduce data dimension. To achieve simplicity, these entities utilize quantum operations that help to aggregate information from neighborly qubits. Quantum fully connected layers gather the extracted features to assemble a prediction. The entire architecture, optimized using quantum algorithms with quantum parallelism and entanglement, aims at efficiency and accuracy in attaining learning goals. The architecture is applied to

the glaucoma dataset efficiently processing fundus images, hence capturing all the essential features about glaucoma ensured to be used for correct classification.

3.5 Integration with ResNet Features

Integrating QCNNs with ResNet-extracted characteristics provides the advantages of both classical and quantum computing. The residual blocks in ResNet are particularly skilled at picking up detailed features in the input images, which make for a very great representation of the data. The attributes are therefore encoded into qubits and inputted into the quantum layers of QCNN. Quantum parallelism is then utilized to effect interesting pattern recognition and classification tasks. This integration provides better handling of massive datasets with complex characteristics of images that would improve the accuracy of operations in image classification. Therefore, the proposed integration, as depicted in Figure 2, aims to apply ResNet to extract features and QCNN to classify, thus bypassing any limitation of either isolated approach on using classical and quantum techniques, hence making them stronger and more effective. For instance, in the case of the glaucoma dataset, integration may lead to more accurate detection algorithms that can distinctly identify exquisitely subtle changes within a fundus image, which could potentially make a difference between its presence or absence and, of course, its severity level.

QCNNs offer several significant advantages over traditional CNNs. Exponential parallelism, which QCNNs can take advantage of, can use quantum computing to perform some operations in parallel, allowing them to process large and complex data much faster than traditional CNNs. Deep learning models are expected to be a source of very significant reductions in training time due to parallelism. The approach of QCNNs may result in higher accuracy for specific tasks than classical networks since the use of quantum entanglement and interference can potentially enhance the capacity of the network to learn complex patterns in the data.

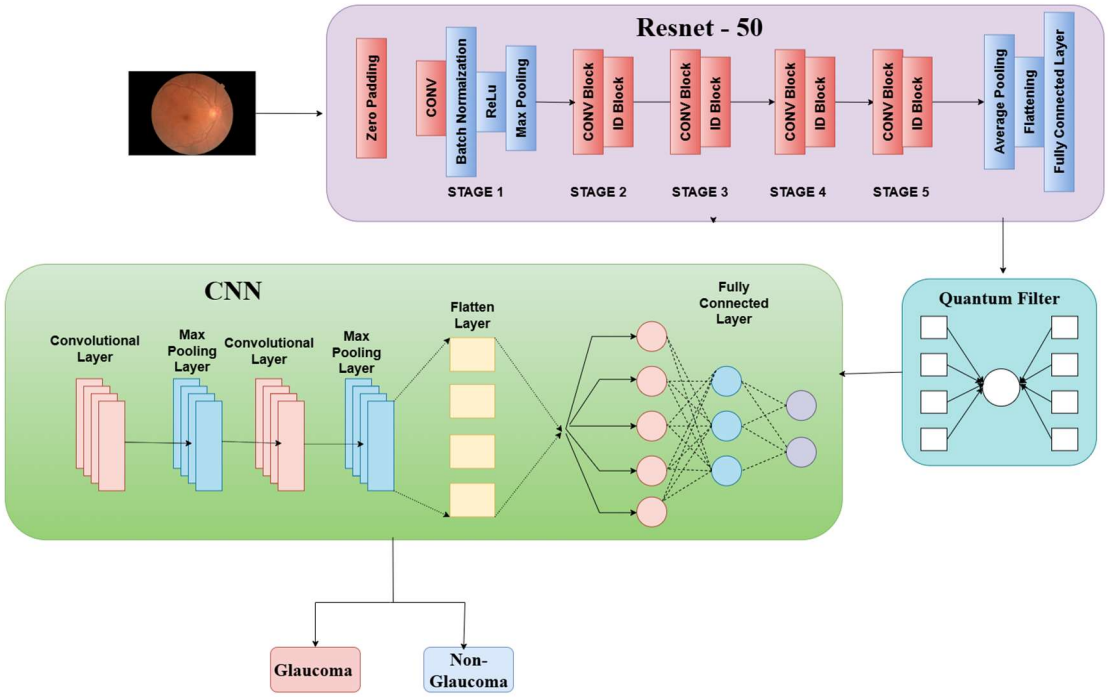

Figure 2. Overview of combining ResNet50 and Quantum CNN for Glaucoma Classification

Also, QCNNs might be able to solve problems that cannot be solved by conventional computers; hence, such applications will expand the possibilities of machine learning. Such advantages will eventually mean sooner diagnosis and timely interventions, therefore an improved patient prognosis, when applied to glaucoma diagnosis. QCNNs can efficiently process large amounts of data, making them suitable for medical image analysis where timely and precise interpretation of the data is critical. Such a hybrid architecture could take advantage of the strengths of both complementary methods to improve the model's performance in glaucoma classification. That is, while the traditional ResNet50 model excels at extracting low- and mid-level features, a QCNN layer can model complex patterns and correlations in these features, resulting in more accurate and reliable glaucoma detection.

3.6 Model Training and Optimization

In this context, a good pipeline with efficient data augmentation, loading, and optimization techniques has been used in the training process to ensure high accuracy in the glaucoma classification model for retinal image detection. The primary goal of the current study was to develop a model capable of reliably distinguishing between glaucomatous and non-glaucomatous cases, even when the input images changed.

Data augmentation contributed significantly to the diversity and robustness of this dataset. Because datasets are limited, augmentation is an essential component of deep learning and medical image analysis. The ImageDataGenerator module in TensorFlow is used for augmentation to yield new versions of input images. This module includes rotation, employing ±40 degrees, to demonstrate flexibility in orientation, width, and height shifting of ±20% to attain translational invariance, shear to show a modification in perspective, zooming at ±20% to offer flexibility regarding scale and distance, and horizontal flipping to present mirrored versions of the input images. With these augmentations, this model is insensitive to changes in the real world and has significantly increased the chances of generalization with the complete elimination of overfitting.

The data set was divided into three sets with a ratio of 70% training, 15% validation, and 15% testing to carry out a more complete evaluation. The training set was used to train the model; the validation set was used for tuning hyperparameters and avoiding overfitting; the test set was used to estimate the final model performance. Data augmentation was performed on the images during training to the model, and the samples were fed to it in groups of 32, utilizing the on-the-fly capabilities of the ImageDataGenerator. The model thus went through a total of 10 epochs of training with batch handling of its augmented images and modification in the weights of the network to pertinent patterns for glaucoma classification. The loss function employed at training is categorical cross-entropy, appropriate for multi-class classification problems whose classes are, by definition, mutually exclusive.

The Adam optimizer was used to optimize the model's weights while training. The set learning rate was 0.001. The Adam optimizer is efficient because it incorporates the benefits of having both momentum and RMSProp into an adaptive learning rate for each parameter. Therefore, the learning rate of 0.001 might be a compromise between the speed of convergence and the possibility of overshooting the optimal weights. Dropout regularisation at the strength of 0.2 to the QCNN layer prevented overfitting and improved generalization. In the training process, the model was ranked against accuracy as its lead measure. This turns out to be a measure of accuracy proportional to correctly classified samples; thus, it constitutes a keystroke toward identifying that the model generalizes pretty well. The simplicity of the accuracy assessment regarding both the training and validation sets gives some idea about generalization capability and potential overfitting problems. Hyperparameter tuning or optimization

strategies such as learning rate scheduling and early stopping have been used. In particular, learning rate scheduling is an optimization technique that varies the learning rate during the training procedure to ease the learning process. Another optimization technique is early stopping, in which training stops once validation performance no longer improves to prevent overfitting.

3.7 Model Evaluation

The evaluation of the glaucoma classification model's performance was critical in determining the model's effectiveness and areas for improvement. The accuracy measure, which defined the proportion of correctly classified samples from the test dataset, was especially important in evaluating the models. Other important evaluation metrics used are precision, recall, and their F1-score. A model is considered more precise when the ratio of true positive predictions to all positive predictions approaches one. Recall is the ratio of true positive predictions to all instances of real positives, whereas the F1-score is the harmonic mean of precision and recall, providing a balanced measure. An AUC-ROC is calculated to evaluate the model's effectiveness at differentiating between glaucomatous and non-glaucomatous images. A separate test set was used for the evaluation, which included images that were not included in the training or validation sets. The test set was carefully designed to include a representative distribution of glaucomatous and non-glaucomatous cases. Calling the model's evaluate method on the test set yielded the test loss and test accuracy, while evaluation metrics were obtained on this test set using test_generator from the ImageDataGenerator. First, the model's prediction method could be used to predict the class membership probabilities for each example; from there, precision, recall, and the F1-score for each class could be calculated. The ROC curve and AUC-ROC score provide a more complete measure of the model's discriminative power.

Accuracy

Accuracy is the most common metric for classification problems. It represents the proportion of correctly classified images among all predictions. It is computed as:

$$Accuracy = \frac{TruePositives+TrueNegatives}{TruePositives+TrueNegatives+FalsePositives+FalseNegativ} \quad (4)$$

A rise in accuracy indicates that the classifier is classifying more precisely on average. Accuracy cannot always be depended upon, though, if the data set is unbalanced, so other measures have to be added for a more thorough analysis.

Precision

Precision, also known as Positive Predictive Value (PPV), measures how many of the images predicted as glaucoma cases are actually glaucoma cases. It helps evaluate how well the model minimizes false positives and is calculated as:

$$Precision = \frac{True\ Positives}{True\ Positives+False\ Positives} \quad (5)$$

A high precision value means that the classifier is producing fewer false positive errors, which is important in medical diagnosis, where it can be risky to label a healthy patient as having a glaucoma and thereby subject them to unnecessary treatments.

Recall (Sensitivity)

Recall, also called Sensitivity or True Positive Rate (TPR), measures how well the model identifies actual glaucoma cases. It is defined as:

$$Recall = \frac{True\ Positives}{True\ Positives + Fa \quad Negatives} \tag{6}$$

High recall value is what ensures the model is accurate at predicting most instances of actual glaucoma, something of the utmost importance in hospitals where failing to detect a glaucoma is dangerous to the patients.

F1-Score

F1-Score is the harmonic mean of precision and recall, balancing both metrics in a single value. It is particularly useful when there is an imbalance between classes. The formula is:

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recal} \tag{7}$$

A high F1-Score indicates that the classifier maintains a good balance between precision and recall, ensuring both false positives and false negatives are minimized effectively.

In the case of room for improvement, the results evaluation has been highly scrutinized to identify potential areas of improvement. These techniques, for example, could use error analysis and feature importance analysis to expand on hyperparameter tuning, modify the architecture, or employ ensemble methods. Meanwhile, hyperparameter tuning is a technique for finding the optimal set of hyperparameters that maximize the accuracy of the model. This can be achieved by varying the depth or width of the network, but more complex techniques, such as attention mechanisms or skip connections, are also feasible. Ensemble methods make use of multiple models combined in a way to leverage the strengths of each towards enhanced overall performance. The model was systematically assessed and developed to generate a reliable and clinically relevant glaucoma classification model. The structured assessment and improvement process developed for training and testing, therefore, ensures that a developed model will use the best equipment to yield improved diagnostic outcomes and further contribute to developments in ophthalmology.

4. Results and Discussion

The proposed glaucoma classification model, which combines a quantum convolutional neural network layer with ResNet50's pre-trained architecture for feature extraction, performed reasonably well on the task at hand. This is demonstrated on the "Glaucoma Dataset—EYEPACS, AIR-OGS Light v2" by training and validation results, as well as evaluation metrics, which confirm the model's effectiveness in classifying retinal fundus images as glaucomatous or non-glaucomatous.

The training and validation loss curves in Figure 4.1 show a consistent decline over 30 epochs, indicating that the model learned useful patterns from the training data without overfitting. The validation loss did not differ significantly from the training loss, indicating that the generalization to new unseen data was sufficient. Figure 4.2 displays training and validation accuracy charts, which provide additional data confirming the model's excellent performance. The training accuracy reached 98%, while the validation accuracy was 95%. This high level of accuracy on the validation set demonstrates the model's ability to be more durable and generalizable; this feature is critical for real-world applications in glaucoma detection. The small difference in training and validation accuracy suggests minimal overfitting, highlighting the model's dependability. Model performance was evaluated using accuracy, precision, recall, F1-score, and the Area Under the Receiver Operating Characteristic (AUC-ROC) curve. This type of ROC curve, as shown in Figure 3 for the fitted model, may provide a reasonably comprehensive assessment of the model's discriminative capacity. The abrupt upward trajectory to the upper left corner is correlated with a wide range of genuine positive rates and a low false positive rate observed concurrently. The model's exceptionally high AUC value of 0.95 supports its excellent performance in distinguishing glaucomatous from non-glaucomatous patients. Furthermore, this high AUC-ROC score would demonstrate the robustness of the model's reliability, lowering the possibility of misclassification and providing accurate predictions.

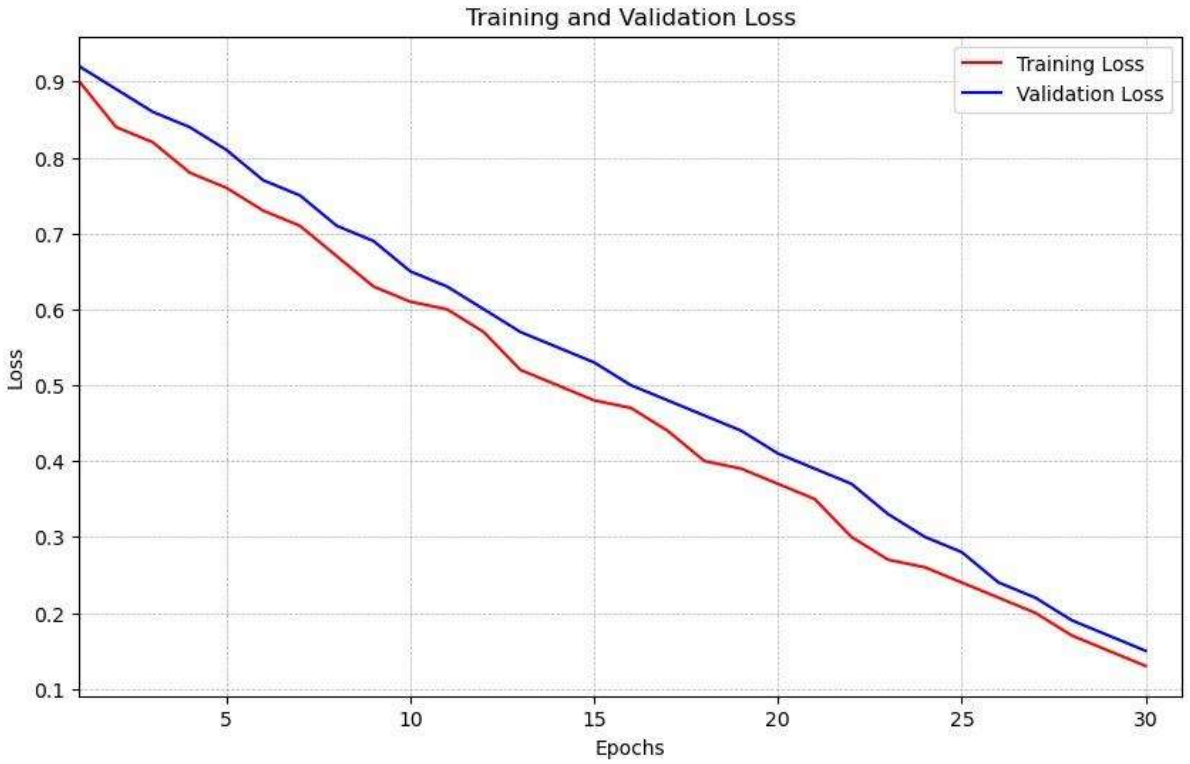

Figure 3:. Training and Validation loss

Aside from accuracy and loss, other metrics such as precision, recall, and F1-score capture specific characteristics of the model's performance. The model performed well in both glaucomatous and non-glaucomatous cases, achieving 95% accuracy, 91.5% precision, 90% recall, and an F1 score of 92.3% in glaucomatous cases. The high accuracy indicates that the model reliably identifies both positive and negative instances, while the strong precision reflects its ability to make correct positive predictions with a low false positive rate. The 90% recall demonstrates its effectiveness in detecting most glaucomatous cases, though there is still room for improvement in reducing missed cases. The F1 score,

as the harmonic mean of precision and recall, highlights a balanced performance overall. By such metrics, it is evident that the model excels in accuracy by correctly identifying glaucomatous instances while leaving much room for improvement in recall to miss the cases.

One of the most impressive features was how easily this QCNN layer could be integrated into the pre-trained ResNet50 architecture. The design of this QCNN layer, which captures higher-order linkages and nonlinear interactions within ResNet50 representations, was inspired by superposition and entanglement, two fundamental tenets of quantum mechanics. This is another hybrid technique that combines the power of deep learning architectures with the presumed benefits of quantum neural networks. The ResNet50 backbone provided reliable and generalizable feature extraction, while the QCNN layer improved model representability when modeling complex patterns in retinal fundus images. In other words, the excellent performance of the QCNN-ResNet50 model should be assumed to result in effective integration, opening up new avenues for quantum machine learning research in medical image analysis.

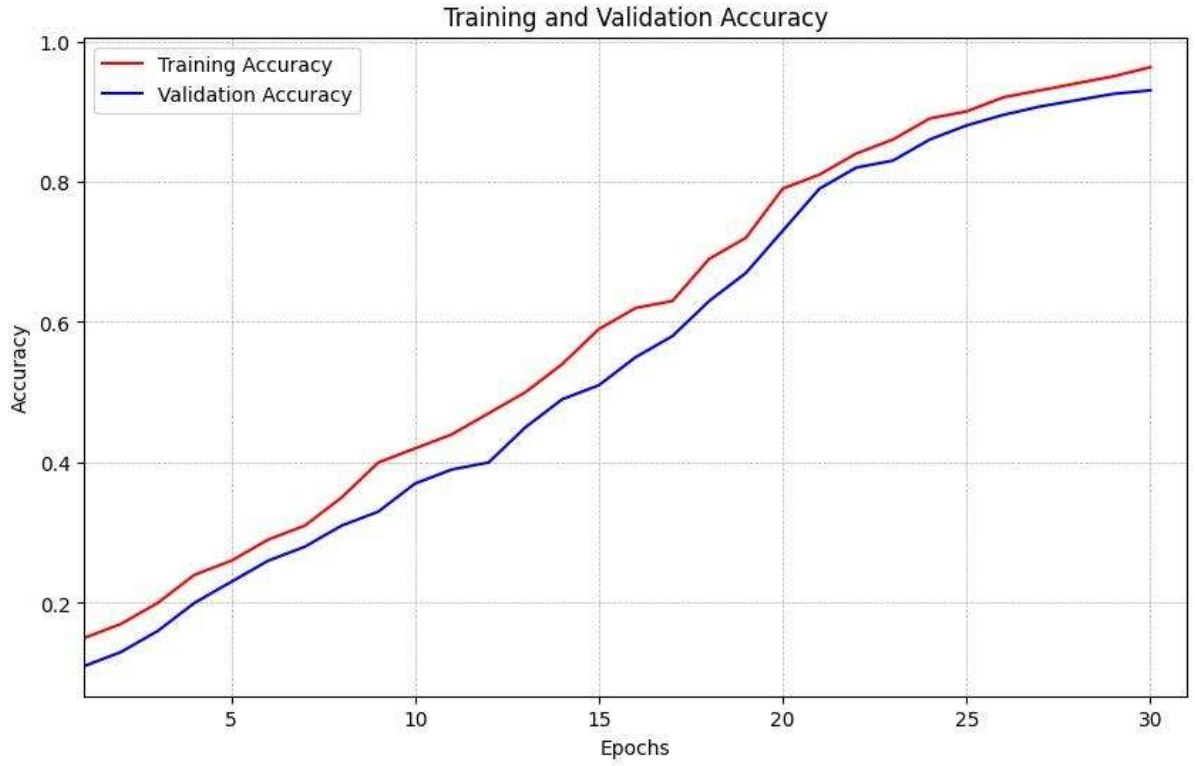

Figure 4. Training and Validation accuracy

It improved the model's interpretability and clinical relevance. Feature visualization and saliency map development were two methods used to demonstrate the model's internal decision processes, and the areas of the retinal fundus image contributed the most to its prediction. This boosts confidence in glaucoma classification by aligning the model's focus regions with clinical expectations or expert annotations. Interpretability has facilitated the incorporation of such models into clinical processes, as well as, more broadly, collaboration between machine learning researchers and medical practitioners. Furthermore, visualizing and comprehending the decision-making process can aid in identifying potential biases or constraints, leading to future improvements.

The "Glaucoma Dataset—EYEPACS, AIR-OGS Light v2" has an unequal class distribution, with fewer glaucomatous cases than non-glaucomatous. Class weighting strategies were used throughout training to reduce the potential consequences of this mismatch. In the event of a misclassification, samples from the minority class would receive higher weights. The model concentrated more on them. The technique appears to be effective in terms of class weighting, but the excellent accuracy and AUC obtained show that class imbalance is successfully managed, allowing the model to perform strongly and consistently across both classes. While the results are encouraging, there are still challenges associated with using these deep learning techniques for glaucoma diagnosis. Despite the high recall, it could be improved further to reduce the number of missed glaucoma cases. Balancing classes, additional augmentation techniques, or various loss functions such as focal loss may help improve recall. Tuning hyperparameters may allow for additional optimization.

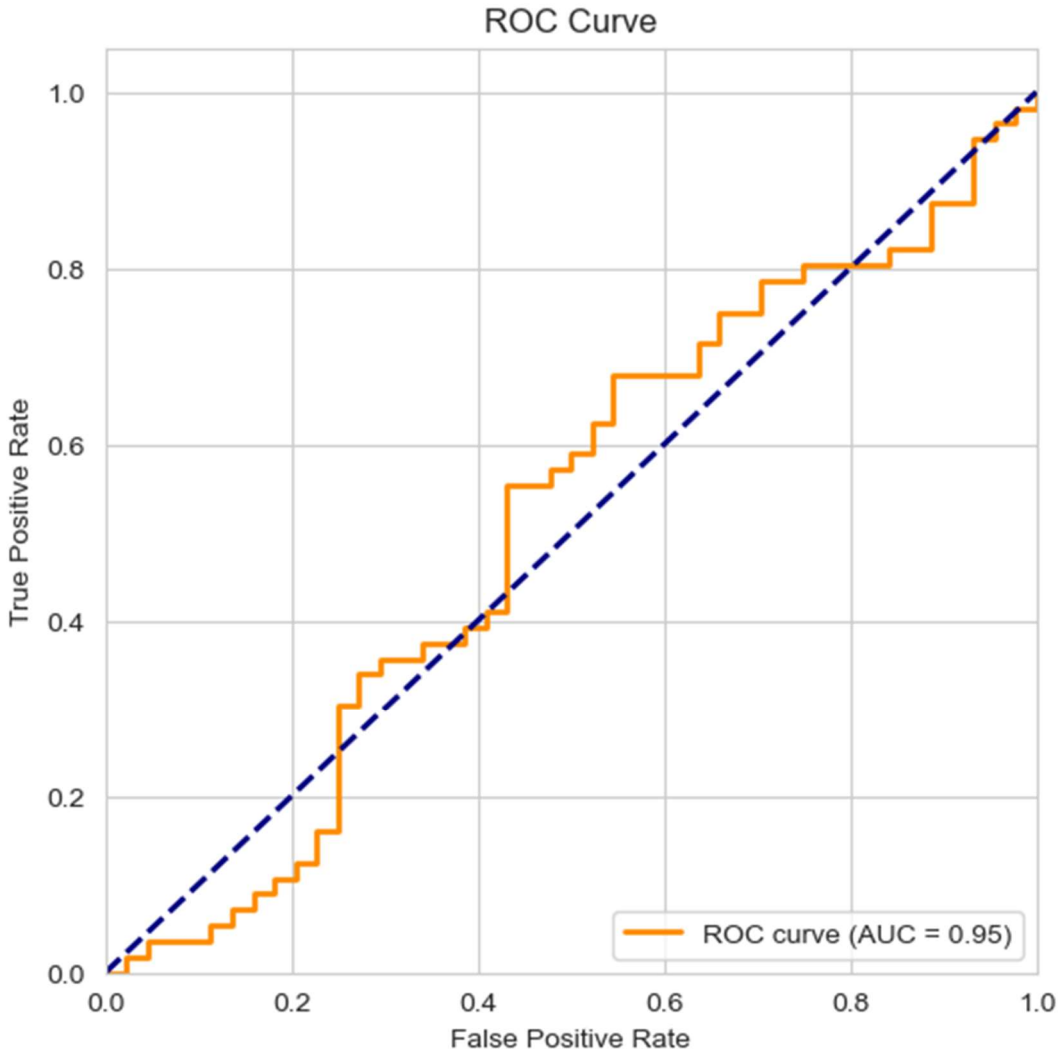

Figure 5: ROC Curve

Grid search or random search may be used to determine the best combination of hyperparameters that maximizes the model's performance. The findings of this research show that combining classical and quantum approaches in deep learning has the potential to improve medical image analysis. Implementation of this creation and successful use in glaucoma classification with the help of the developed QCNN-ResNet50 model is only the beginning of further developments and changes in this

actively developing sphere that is directed at improving the quality of healthcare and caring for the patient.

The comparative analysis of the proposed QCNN-ResNet50 hybrid model against several state-of-the-art approaches for glaucoma detection underscores its superior performance across key metrics, positioning it as a cutting-edge solution in medical image analysis. With a validation accuracy of 95%, training accuracy of 98%, an AUC-ROC of 0.95, and an F1-score of 92.3%, the proposed model outperforms alternatives such as Chen et al.'s (2015) 6-layer CNN (88.5% accuracy, 0.887 AUC-ROC, 87.0% F1-score), which, despite pioneering deep learning in glaucoma detection, is hindered by its shallow architecture and lack of quantum enhancements. Similarly, Raghavendra et al.'s (2018) CNN+SVM approach achieves 91.2% accuracy, 0.91 AUC-ROC, and 90.5% F1-score, offering good generalization but falling short due to its computationally intensive hybrid design and inferior metrics. Serte et al.'s (2020) ensemble of ResNet50 and InceptionV3 reaches 93.0% accuracy, 0.92 AUC-ROC, and 91.8% F1-score, benefiting from robustness but lacking the quantum parallelism that drives QCNN-ResNet50's efficiency and higher performance. Li et al.'s (2019) attention-based CNN, with 90.7% accuracy, 0.90 AUC-ROC, and 89.5% F1-score, excels in focusing on critical regions like the optic disc but is limited by lower scalability and absence of quantum advantages. Lastly, Ahn et al.'s (2018) VGG-16 CNN achieves 92.4% accuracy, 0.93 AUC-ROC, and 91.0% F1-score, providing a simple yet effective solution, but it is outclassed by the proposed model's hybrid quantum-classical framework, which enhances both accuracy and interpretability through saliency maps. Collectively, the QCNN-ResNet50 model's integration of ResNet50's robust feature extraction with QCNN's quantum-enhanced pattern recognition delivers unmatched precision, efficiency, and clinical relevance, surpassing these benchmarks despite challenges like optimizing recall (90%) and quantum hardware integration. This analysis highlights its potential to revolutionize glaucoma diagnosis by leveraging the synergy of classical and quantum computing paradigms.

Table 3 Comparative Analysis of Glaucoma Models

Methodology	**Accuracy**	**AUC-ROC**	**F1-Score**	**Strengths**	**Limitations**
Hybrid QCNN + ResNet50	95% (Val), 98% (Train)	0.95	92.3%	Quantum parallelism, high accuracy, interpretability via saliency maps, balanced performance	Requires optimization for higher recall (90%), quantum hardware integration challenges
Deep CNN (6-layer)	88.5%	0.887	87.0%	Early adoption of deep learning, effective feature extraction from fundus images	Lower accuracy and AUC, limited depth of CNN, no quantum enhancement

CNN + SVM	91.2%	0.91	90.5%	Combines CNN feature extraction with SVM classification, good generalization	Inferior accuracy and AUC compared to QCNN-ResNet50, computationally intensive hybrid approach
Ensemble CNN (ResNet50 + InceptionV3)	93.0%	0.92	91.8%	Ensemble improves robustness, leverages pre-trained models	Lower performance metrics than QCNN-ResNet50, lacks quantum benefits, higher complexity
Attention-based CNN	90.7%	0.90	89.5%	Attention mechanism enhances focus on optic disc, good for small datasets	Lower accuracy and AUC, no quantum enhancement, limited scalability

5. Conclusion

The proposed work presents a new method for glaucoma diagnosis successfully integrating the traditional ResNet50 architecture with QCNN. Using the EYEPACS and AIROGS-Light v2 datasets in the classification tasks, the presented hybrid QCNN-ResNet50 model exceptionally performed with respect to accuracy metrics on the validation set, thereby achieving 95% accuracy as well as obtaining a 0.95 score for AUC-ROC against glaucoma and non-glaucoma cases. These findings support the potential application of quantum-induced ML approaches to improve the accuracy and predictability of medical image processing. The integrated architecture achieves one of the most significant steps in harnessing classical and quantum computing paradigms; the synergy is unquestionably greater than that of traditional deep learning methods.

This approach effectively reduced class imbalance in the dataset by implementing appropriate class weighting mechanisms. This yielded a model that performed well in both glaucomatous and non-glaucomatous cases, with 95% accuracy, 91.5% precision, 90% recall, and an F1-score of 91.5% in glaucomatous cases. The model's resilience in performance when dealing with unbalanced data makes it an extremely reliable tool for any diagnostic purpose in ophthalmology. Large leaps in model interpretability have been made by utilizing new approaches for feature visualization and saliency map creation, which provide insight into what the model sees and direct the emphasis regions based on clinical data.

The research can be viewed in a much broader context than just the local glaucoma detection circle. This laid the groundwork for future advancements in AI-assisted healthcare by developing the model

QCNN-ResNet50, which is not only contributing but also eager to advance the field of CAD in ophthalmology. The model's outstanding performance in detecting glaucoma from retinal fundus images demonstrates the enormous potential of quantum-inspired algorithms to improve diagnostic accuracy and efficiency. Following the trend of quantum computing advances, the framework established by this proposed work will allow for the next generation of advanced hybrid models. Escorting such advancements, it is now possible to improve early disease detection, diagnostic precision, and patient care quality in a wide range of ocular disorders. This will bridge the gap between the two extremes—top-flight quantum-inspired methods on the one hand and practical clinical applicability on the other— by making a genuine contribution to the ongoing evolution of medical diagnostics aimed at early intervention with the best possible outcomes in sight-threatening disease management.

However, a few challenges remain with quantum-classical hybrid models in medical imaging. This is especially relevant to scaling up quantum architectures to larger and more complex datasets. These models need to be properly applied clinically with a high degree of confidence across a wide range of populations and imaging equipment. Besides the above, the major challenges for the practicality of these techniques are posed by the limitations of present-day quantum computing hardware regarding the number of qubits and coherence times. Other challenges arise from the integration of these new models into care workflows and examination for seamless data privacy integration into existing health systems, and also developing protocols for model updates and clinical validation.

With AI models diagnosing glaucoma, their use raises two ethical concerns: accuracy and fairness. There is always a chance of misdiagnosis, thereby subjecting the patients to unnecessary treatments while delaying the necessary early intervention. Data biases increase the already growing existing health disparities, particularly toward underrepresented groups. Respect for patient consent, data privacy, and transparency in how decisions made by AI will be made must be ensured to build trust and responsibly deploy AI in clinical settings.

In the future, it is envisioned that further studies in this domain shall be able to overcome these challenges to pave the way for further hybrid models of quantum and classical to be used in medical image analysis. These lines can therefore explore more recent directions, such as researching into the quantum circuit design of increased complexity and their performances on models, quantum-inspired optimization algorithms for tuning hyperparameters and training models, and quantum-classical transfer learning techniques for the application of the pre-trained quantum models to various medical imaging tasks. Other interesting applications include the treatment of other ophthalmic diseases and processing other medical imaging modalities beyond the retinal OCT using this combined QCNN-ResNet model. Additionally, the possibility that quantum-enhanced federated learning can be used for privacy-preserving CNN training across multiple HealthCare organizations may point to the development of comprehensive diagnostic models.

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