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HYBRID QUANTUM CLASSICAL MACHINE LEARNING FOR REAL TIME DIABETIC RETINOPATHY DETECTION AND TRIAGE

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ABSTRACT

Diabetic retinopathy (DR) continues to be one of the main causes of vision loss and blindness among people with diabetes, therefore requiring early detection in order to achieve better clinical outcomes. However, current state-of-the-art DR detection approaches mainly depend on classical deep learning models, which suffer from high computational complexity and provide limited support for automated real-time patient triaging in clinical settings. To address these challenges, this study presents a Hybrid Quantum–Classical Machine Learning (HQCML) model for real-time detection of diabetic retinopathy and patient prioritization with respect to disease severity using retinal fundus images. The proposed HQCML framework is based on deep convolutional neural network-based feature extraction and the subsequent classification of the disease using a variational quantum classifier. Moreover, this study introduces a novel Quantum Priority Triage Mechanism (QPTM), which divides patients according to the severity of their condition into three categories—routine, moderate, and urgent priority levels—thereby enabling efficient clinical decision support. The experimental results, which have been obtained from analysis of the APTOS 2019 and EyePACS datasets, show that the proposed framework has achieved 97.2% classification accuracy, outperforming traditional machine learning and deep learning approaches, such as support vector machines, random forests, convolutional neural networks, and vision transformers. Furthermore, the proposed framework has also reached 96.4% precision, 95.8% recall, 96.1% F1-score, and an AUC of 0.98, demonstrating robust diagnostic performance. Along with improvements in classification accuracy, the main contribution of this study is demonstrating the feasibility and effectiveness of integrating hybrid quantum–classical learning with automated patient triage in a unified framework for diabetic retinopathy screening. The proposed approach also provides a scalable foundation for next-generation intelligent eye-screening systems and highlights the potential of quantum-enhanced artificial intelligence for real-time clinical decision support.

Keywords: *Diabetic Retinopathy Detection, Hybrid Quantum–Classical Machine Learning, Retinal Fundus Image Analysis, Variational Quantum Circuits, Deep Learning, Automated Clinical Triage*

1. INTRODUCTION

Diabetic retinopathy (DR) is one of the most prevalent microvascular complications of diabetes mellitus and leads to many cases of vision loss and blindness globally [1]. Global health reports indicate that cases of diabetes are on an increasing trend, and a good percentage of diabetic cases are prone to retinal complications, which can eventually result in permanent blindness unless their signs and symptoms are identified early enough [2]. The pathology of DR is characterized by the progressive destruction of retinal vascular structures, accompanied by the emergence of a pathological picture of microaneurysms, hemorrhages, exudates, and neovascularization [3]. Early diagnosis and intervention are thus necessary to prevent serious vision impairment and to reduce healthcare costs incurred when the retinal disease is already advanced [4].

One of the most commonly employed modalities for diagnosing diabetic retinopathy has been retinal fundus imaging. Fundus photography enables clinicians to evaluate retinal structures and detect anomalies associated with the development of the disease [5]. Ophthalmologists can, however, manually examine retinal images, which is tedious and time-consuming in large-scale screening programmes where thousands of retinal images must be examined each day [6]. In addition, the diagnostic process can be influenced by inter-observer variability and subjective interpretation, which may impact clinical decision-making [7]. Automated Computer-Aided Diagnostic (CAD) systems have been designed to help clinicians detect diabetic retinopathy in retinal images [8]. The initial methods used classical machine learning algorithms and manually derived features from retinal structures, such as blood vessels, lesions, and texture patterns. Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Decision Tree (DT)-based methods have performed well at detecting DR-related abnormalities, but only to a limited extent; their results depend on the quality of hand-engineered features and certain domain information [9].

As artificial intelligence advances, deep learning algorithms have made significant progress in enhancing automated analysis of medical images. The prevailing technique for classifying retinal images is the use of Convolutional Neural Networks (CNNs), which automatically learn hierarchical response features from raw image data. It has been possible to use several deep learning models to detect diabetic retinopathy with diagnostic accuracy comparable to that of expert ophthalmologists, enabling some screening tasks [10]. Commonly used retinal image analysis architectures and disease classification methods include VGGNet, ResNet, Inception, and DenseNet [11]. Despite these developments**,** deep learning models exhibit several issues when applied to real-world clinical settings. Large annotated datasets and significant computational resources are typically required for training deep neural networks, which are not always readily accessible for medical imaging tasks [12]. In addition, deep models can be difficult to generalise across a wide range of imaging settings, patient populations, and acquisition devices [13], [14]. The second issue to be addressed is the need for real-time diagnostic systems capable of handling the large volume of retinal images generated during screening programs.

Quantum computing is a fairly new but promising computational model that leverages the laws of quantum mechanics to efficiently perform complex computations that are not possible in classical systems [15]. Quantum algorithms exploit properties such as superposition, entanglement, and quantum interference to manipulate information in high-dimensional Hilbert spaces. Quantum machine learning (QML) combines quantum computing with machine learning algorithms, offering new possibilities for tackling complex pattern recognition problems. Classical machine learning models have, in recent years, elicited considerable attention due to their ability to leverage the benefits of classical deep learning with the computation of quantum circuits [16]. These hybrid systems employ classical neural networks to extract features, and quantum circuits to perform classification or optimization tasks. In multiple areas, such as materials science, finance, and image classification, variational quantum circuits, composed of parameterized quantum gates solved using classical algorithms, have shown promise for high-dimensional learning tasks [17]. Hybrid quantum-classical models could be used to enhance diagnostic performance in medical imaging applications by finding the intricate nonlinear relationships of biomedical data residing

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in high-dimensional spaces [18]. However, quantum machine learning has been only minimally explored in ophthalmology. The majority of currently available diabetic retinopathy detection models use only classical deep learning architectures, and little research has been conducted on the exploration of quantum-enhanced models for analyzing retinal images [19]. Screening systems should not only identify the presence of diabetic retinopathy but also prioritize patients based on disease severity. In mass screening, the process requires effective triage mechanisms to identify the required patients. Artificial intelligence can help in this process by automatically classifying patients into different priority levels based on the expected severity of the disease [20].

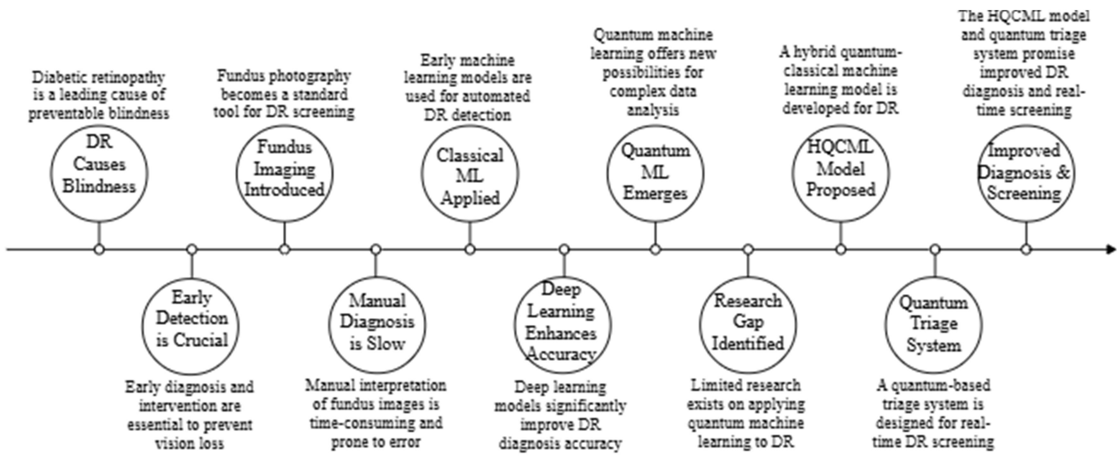

Figure 1. *Evolution of Automated Diabetic Retinopathy Detection: From Classical Methods to Hybrid Quantum Intelligence*

Figure 1 illustrates the flow of developments in the detection of diabetic retinopathy (DR). By first underscoring the leading cause of blindness due to DR and the need for early diagnosis. It then depicts the use of fundus photography as the standard procedure for screening DR, followed by the drawbacks of manual diagnosis, including its time-consuming nature and its susceptibility to human error.

It then illustrates the incorporation of traditional machine learning approaches, which automated DR diagnoses, albeit with suboptimal results. Next, the inclusion of deep learning models has enhanced detection accuracy, but with limitations such as the need for large data and computational resources.

The diagram also explores quantum machine learning as a novel approach to learning with complex patterns. It recognizes the lack of research on implementing quantum methods for DR and proposes a Hybrid Quantum-Classical Machine Learning (HQCML) approach. Lastly, the integration of a quantum triage system signals a shift towards real-time screening and faster diagnostics, and represents a major step towards the future of smart medical care.

This paper, driven by these issues, proposes a Hybrid Quantum-Classical Machine Learning (HQCML) system for identifying and triaging diabetic retinopathy from retinal fundus images in real time. The proposed system combines deep convolutional feature extraction with a variational quantum classifier to improve disease recognition accuracy at a reasonable cost. Moreover, a new Quantum Priority Triage Mechanism (QPTM) is proposed to categorize patients into routine, moderate, and urgent groups according to disease severity. The objectives of this study are: (i) to develop a hybrid quantum–classical machine learning framework for diabetic retinopathy detection, (ii) to integrate variational quantum circuits for disease classification, (iii) to introduce an automated quantum-assisted patient triage mechanism, and (iv) to compare the proposed framework with state-of-the-art machine learning and deep learning models, using diagnostic metrics to confirm its efficacy and clinical usefulness.

The proposed solution will close the gap between ophthalmic image analysis and quantum computing by presenting a hybrid computational system that enhances the efficiency and accuracy of automated diabetic retinopathy screening systems. Quantum-enhanced deep learning of features can be used to develop next-generation intelligent healthcare technologies and to provide scalable, real-time diagnostic applications in the future [21], [22].

The remainder of the paper is organized as follows. Section 2 discusses the current literature on automated diabetic retinopathy detection using classical machine learning methods, deep learning-based retinal image analysis, and the most recent developments in quantum machine learning in medical imaging. Section 3 presents a description of the proposed Hybrid Quantum-Classical Machine Learning (HQCML) framework, the dataset details, preprocessing steps, hybrid architecture design, mathematical framework, and the offered algorithm for diabetic retinopathy detection and diagnosis. Section 4 presents the experimental results and performance analysis of the proposed model using standard diagnostic metrics and compares its performance with several known machine learning and deep learning methods. Lastly, Section 5 summarizes the paper's main findings, reflects on the study's weaknesses, and provides an overview of possible future research directions.

Scope, Assumptions and Limitations: This research focuses on developing a framework for Hybrid Quantum–Classical Machine Learning (HQCML) for real-time analysis and diagnosis of diabetic retinopathy (DR) from retinal fundus images to support patient triage and diagnosis. The scope includes preprocessing retinal fundus images in the proposed framework, extracting deep features, and performing classification using Variational Quantum Classifiers. Additionally, clinical patient triage is carried out using quantum-assisted technology without involving multimodal retinal imaging, real-time implementation on quantum computers, or even implementation on large-scale quantum computers. In this research, it is assumed that there exists a set of standard retinal fundus images and a reference dataset for training and testing of the models. Moreover, the study's contribution is constrained, as the authors rely on public datasets and quantum simulation environments and need to test on larger clinical datasets and new quantum devices.

2. RELATED WORK

Computerized detection of diabetic retinopathy (DR) in retinal fundus images has been the subject of research for over 20 years. Computer vision, machine learning, and deep learning have already played a vital role in improving the efficiency of computer-aided systems for detecting retinal abnormalities and helping ophthalmologists in large-scale screening initiatives. This section covers the previous work in three major directions: classical machine learning-based DR detection, deep learning-based solutions for retinal image analysis, and emerging quantum machine learning (QML) approaches to medical image analysis.

2.1 Traditional Machine Learning-based Diabetic Retinopathy Detection

Major early systems for automatically diagnosing diabetic retinopathy (DR) were typically based on classical machine learning methods that relied on manual feature selection. They were primarily focused on the detection of clinically significant retinal changes, such as microaneurysms, hemorrhages, and exudates (the outcome of image processing), and then statistical classification processes. Classifier features, Intensity-based descriptors, texture descriptors (e.g., GLCM), and morphological descriptors were usually extracted for the classifiers such as Support Vector Machines (SVMs), k-Nearest Neighbors (k-NNs), and Random Forests.

Even recent studies are exploring the use of classical machine learning, particularly when computational costs, explainability, and data scarcity are critical issues. For instance, recent research has demonstrated that, even when exploring different feature selection techniques and classical classifiers, these methods perform well in DR screening and are suitable for researchers with limited resources [23]. Combined reconstruction pipelines that incorporate image preprocessing (e.g., contrast and illumination) with classical classifiers improve the detection of early lesions [24].

In addition, modern studies require explainability and simple models, which are aided by classical machine learning. Changes such as feature ranking and clear decision boundaries enable a clinician to better understand the model than black-box deep learning approaches [25]. Approaches that more recently include ensemble learning, in which many classical machine learning classifiers are combined to improve accuracy and lower the false-positive rate [26]. However, there are some problems with classical machine learning. This is because of the requirement for designed features and their lack of representation of complex features in their hierarchical relationships. Also, they lack scalability and flexibility for various data, images, and subjects. As a result, new designs based on deep learning and hybrid approaches have been introduced, capable of learning discriminative features from raw images and scalable and adaptable [27].

Ultimately, while earlier automated DR detection approaches gave rise to the use of traditional machine learning tasks, in recent years these have been complemented or even replaced by more data-driven methods.

2.2 Machine Learning Advances in Deep Learning for Retinal Imaging

Here, we provide a brief overview of deep learning, particularly convolutional neural networks (CNNs), in the automated detection of retinal diseases. CNNs have consistently achieved excellent performance in image classification by learning feature representations from original retinal fundus images [28]. This has enabled more accurate detection of diabetic retinopathy (DR) by learning complex retinal features [29]. Several deep learning systems have been proposed for DR detection using large-scale image databases. They can achieve the accuracy of human experts and are promising for screening programs [30]. Furthermore, CNNs can detect severity to classify DR, enabling multi-class classification and achieving better performance than traditional machine learning algorithms [31].

Furthermore, deep convolutional networks have also been successful in identifying complex vascular lesions such as microaneurysms, hemorrhages, exudates, and vascular anomalies [32]. Learning diagnostic features from images has eliminated the need for handcrafted features, improving automated diagnostic systems [33]. Transfer learning for retinal image analysis is robust with a small labeled dataset [34]. Using pre-trained models and fine-tuning with retinas boosts classification performance and generalization [35].

To improve methods and interpretability, researchers use attention mechanisms in deep learning. Attention models pay attention to the most important retinal regions, and can identify the location and classification of diabetic retinopathy lesions [36].

Unfortunately, deep learning models have drawbacks. Large amounts of labeled and high-quality data and high computational resources are needed to train and operate them. They may not be affordable for real-time screening in low-resource settings [37]. Affordable, fast computation methods are needed.

2.3 Multiple Machine Learning Models and Hybrid Learning

Hybrid learning and multi-model methods have been recommended to address the limitations of single machine learning methods. These approaches leverage feature extraction, classification, and decision fusion techniques to enhance diagnosis.

Abràmoff et al. also developed a DR detection system that combined deep learning and image processing techniques to improve lesion detection and classification [38]. This study demonstrated the feasibility of combining multiple computational methods for mass retinal screening. Similarly, C. Mohanty et al. proposed a deep learning approach to detect DR using an ensemble of neural network models to improve classification accuracy across a range of datasets [39]. Others have used ensemble learning models to improve consistency and variance in their models for retinal image classification.

However, challenges remain. Although hybrid classical models have improved accuracy, they are limited by classical computational methods when identifying patterns in high-dimensional medical images. This challenge has led to growing interest in emerging computational paradigms that may better address the complexity inherent in medical imaging data.

2.4 Quantum Machine Learning in Medical Imaging

Quantum machine learning is a new and exciting phenomenon for complex pattern recognition in high-dimensional data spaces. Quantum algorithms can efficiently manipulate and extract information using quantum states.

X. Ding et al. developed quantum machine learning models for classification and regression with parameterized quantum circuits [40]. They showed that quantum models can learn to capture the underlying structure of data in Hilbert spaces. Havlíček et al. introduced a quantum-enhanced feature space for supervised learning via quantum kernels and demonstrated that quantum circuits can improve classification performance in certain machine learning tasks [41].

For biomedical data processing, Abbas et al. investigated the use of quantum neural networks to enhance feature representations in medical data [42]. They found that hybrid quantum-classical models may have benefits in high-dimensional data analysis.

C. Long et al. introduced quantum convolutional neural network (QCNN) models that mimic the architecture of classical CNNs, demonstrating that quantum circuits can learn features in a hierarchical manner akin to deep neural networks [43].

The role of quantum machine learning in ophthalmic imaging remains underexplored, with most studies limited to theoretical models or small datasets. Hybrid quantum–classical approaches for retinal disease classification require further investigation.

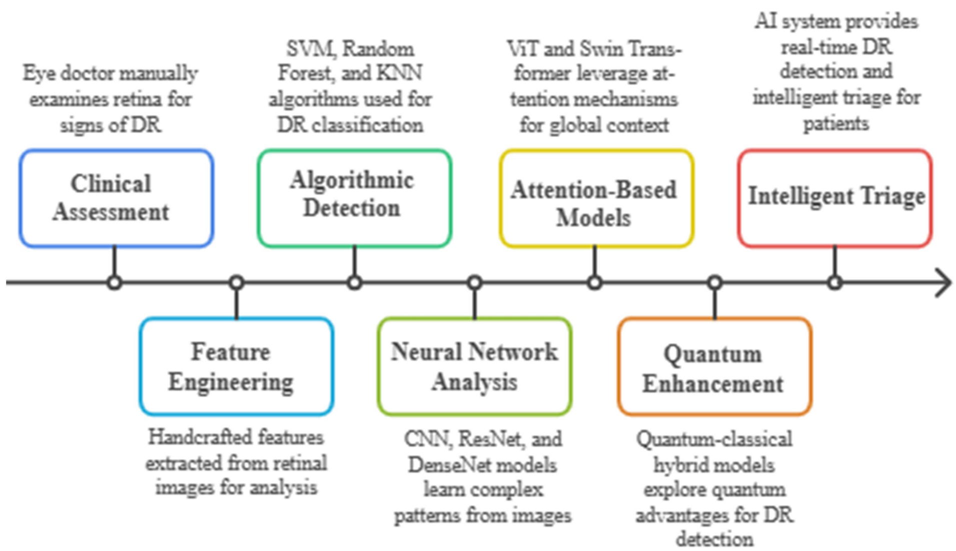

Figure 2. *Evolution Of AI-Based Diabetic Retinopathy Diagnosis From Conventional Methods To Hybrid Quantum-Classical Learning*

Figure 2 shows the development of diabetic retinopathy (DR) detection and intelligent triage using AI techniques. It starts with manual examination of retinal images by clinical practitioners (ophthalmologists) and includes feature engineering based on handcrafted image descriptors. Automated DR classification is then performed using traditional machine learning algorithms: SVM, Random Forest, and KNN. It goes on to deeper learning models like CNNs, ResNet, and possibly DenseNet that automatically discover discriminative retinal features. Then, attention-based models such as Vision Transformers (ViT) and Swin Transformers are proposed to improve feature representation over the whole image using self-attention mechanisms. Lastly, hybrid quantum-classical machine learning greatly enhances feature learning and classification, improving understanding and enabling real-time diabetic retinopathy diagnosis and intelligent patient triage to provide timely clinical care.

2.5 Research Gap

The current state-of-the-art methods using conventional machine learning approaches rely heavily on feature extraction, and their generalizability across datasets and various imaging techniques is limited. Although deep-learning approaches have improved performance, they involve large amounts of data, image labeling, complex computations, and are harder to translate into clinical practice. Moreover, most diabetic retinopathy detection systems focus on classification and offer limited triage tools, thereby facilitating diagnosis and prioritizing treatment based on severity. Additionally, there is little work on applying quantum machine learning techniques to retinal images, suggesting a knowledge gap that could be used to extend hybrid diagnostic systems.

To address these issues, this research proposes an approach to perceive, detect, and triage patients with diabetic retinopathy using online Hybrid Quantum-Classical Machine Learning. The approach integrates deep convolutional feature extraction and variational quantum machine learning classifiers, and introduces a Quantum Priority Triage Mechanism, to prioritize patients with suspected disease severity. The goal is to improve detection and triage, speed, and scalability for real-time screening in the clinician's eye.

Although shallow- and deep-learning-based algorithms have been shown to work for DR diagnosis, many problems remain. All existing techniques rely solely on classical computing, which makes them computationally expensive and limits their scalability for real-time clinical use. Furthermore, to the best of our knowledge, only a limited number of studies have investigated the combination of quantum computing and deep learning, and fewer still integrate automated patient triage with the diagnostic process as a single, unified approach. These challenges demand a hybrid quantum–classical strategy to enhance diagnostic capability and enable patient prioritisation for timely clinical intervention.

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2.6 Problem Statement

Despite significant advances in Artificial Intelligence (AI) and the development of AI-based systems for DR diagnosis, several major challenges persist in existing models, including high computational complexity, limited interpretability, and a failure to leverage the potential of quantum computing to build efficient systems for clinical decision support. Moreover, the large volume of research primarily focuses on disease classification solely, with little attention to patient classification for prioritising clinical intervention, known as triage. To improve diagnostic performance and enable timely patient prioritization, this problem calls for an efficient hybrid quantum/classical approach.

Research Questions

RQ1: Would a Hybrid Quantum–classical Machine Learning approach be more effective in the detection of diabetic retinopathy than a traditional deep learning approach?

RQ2: What is the effectiveness of this framework in the automated analysis of patients' triage in case of any disease emergency?

RQ3: What are the benefits and challenges of fusing quantum computing and classical deep learning to diagnose DR in real-time?

2.7 Aim and Expected Outcomes

Aim: The objective of the research is to design, develop and test the efficacy of a Hybrid Quantum–Classical Machine Learning (HQCML) system for accurate screening, detection, and triaging of diabetes mellitus (DM) patients by analyzing retinal fundus images.

Expected Outcomes: The proposed system is expected to enhance diagnostic accuracy and efficiency, aid patient prioritization, and contribute to the effective use of quantum computing alongside classical deep learning for real-time clinical decision support. With this study, we aim to introduce a hybrid quantum–classical learning approach and an automated triage mechanism, packaged together, for detecting diabetic retinopathy. This condition has not been sufficiently studied in previous investigations.

3. METHODOLOGY

This section includes the proposed Hybrid Quantum-Classical Machine Learning (HQCML) methodology for real-time screening and classification of diabetic retinopathy (DR) with retinal fundus images. The proposed methodology is outlined below with sufficient analytical details to enable the experiments to be reproduced, including information on the data set used, data pre-processing, model design, the mathematical formulation of the model, and the proposed new algorithm.

3.1 Dataset Description

Two publicly available retinal fundus image datasets—APTOS 2019 Blindness Detection and EyePACS Diabetic Retinopathy Detection—were used to develop the proposed framework HQCML. The APTOS 2019 dataset was used to train, validate, and primarily assess the performance of the proposed framework, while the EyePACS independent external validation set was used to assess its generalisation capabilities across different clinical imaging environments. Each dataset consists of expert-annotated retinal fundus images across five categories of diabetic retinopathy, with a reliable benchmark for assessing the proposed method.

Table 1. *Summary of Public Retinal Fundus Datasets Used in the Proposed HQCML Framework*

Dataset	Purpose	Number of Images	DR Classes	Image Type
APTOS 2019 Blindness Detection [44]	Training, Validation and Primary Testing	4,192	5	Color Fundus Images
EyePACS Diabetic Retinopathy Detection [45]	External Validation and Generalization Assessment	35,126	5	Color Fundus Images
Total	**Combined Dataset Resources**	**39,318**	**5**	**Color Fundus Images**

In this study, two datasets of retinal fundus images were used and summarized in Table 1. The APTOS data was used to develop the model, and quantitative validation was performed using EyePACS as an independent external dataset to assess the robustness and capability of the proposed HQCML framework to model diverse clinical imaging scenarios. Using two public benchmark datasets, the reliability and reproducibility of the proposed approach are enhanced.

The datasets provide a five-level categorization of diabetic retinopathy severity. Class 0 is the absence of diabetic retinopathy, which means the retina is normal. Class 1 is mild diabetic retinopathy, involving the presence of small (microaneurysms). Class 2 represents moderate diabetic retinopathy, where more damage to blood vessels is evident, along with hemorrhages or exudates. Class 3 is severe diabetic retinopathy, where there is marked obstruction of blood vessels, along with extensive retinal damage. Finally, Class 4 represents the final-stage diabetic retinopathy - proliferative diabetic retinopathy - which occurs when new blood vessels begin to grow and can cause vision loss if left untreated.

Table 2. Class-wise Distribution of Diabetic Retinopathy Dataset

Class	Description	Number of Images
0	No Diabetic Retinopathy	1805
1	Mild DR	900
2	Moderate DR	999
3	Severe DR	193
4	Proliferative DR	295
Total	—	**4192**

Table 2 presents the class-wise distribution of the APTOS 2019 retinal fundus dataset used in this study. The dataset contains 4,192 images across five diabetic retinopathy severity classes, with Class 0 (No DR) having the largest number of samples and Class 3 (Severe DR) the fewest. The observed class imbalance was addressed during model training through data augmentation and class-weighting strategies to improve classification performance.

To train and evaluate the model, the dataset has been split into three parts. In particular, 70% of the data is assigned to the training set, which is used to train and initially learn model parameters; 15% is set aside as validation data for model parameter tuning and to avoid overfitting. The test set, comprising the remaining 15% of the data, will not be used for training and is reserved for evaluating the model's effectiveness and generalization to new data.

Table 3. Imaging and Acquisition Characteristics of the Retinal Fundus Dataset

Parameter	Value
Imaging modality	Retinal Fundus Photography
Resolution	1024 × 1024 pixels
Color channels	RGB
Image format	JPEG
Camera types	Canon CR2, Topcon TRC
Field of view	45°
Dataset size	4,192 images

Table 3 outlines important details about the image and data acquisition in the retinal fundus dataset for diabetic retinopathy detection. The dataset is acquired via retinal fundus photography at 1024 × 1024 pixels and saved in RGB format to maintain rich visual detail for lesion diagnosis. The dataset uses the JPEG format, offering a balance between file size and image quality. The images are captured using clinically standard fundus cameras such as Canon CR2 and Topcon TRC with an effective field of view of 45°. The dataset comprises around 4,192 images, which is adequate for training and validating deep learning algorithms.

A. Sample Retinal Fundus Images

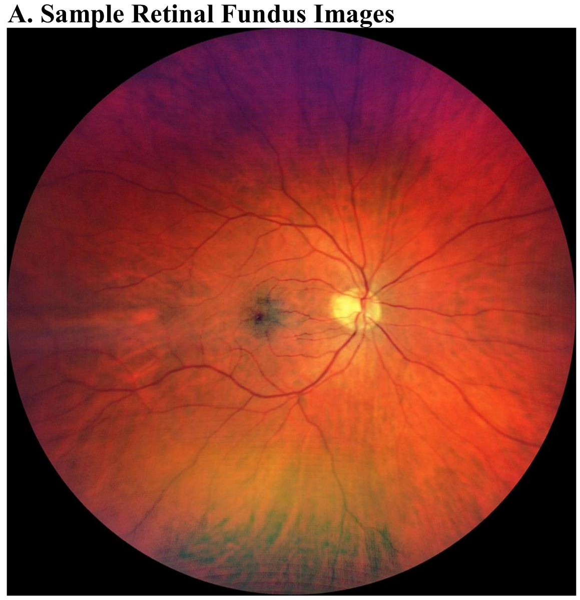

Figure 3. Normal Retinal Fundus Image Showing Optic Disc and Vascular Structure

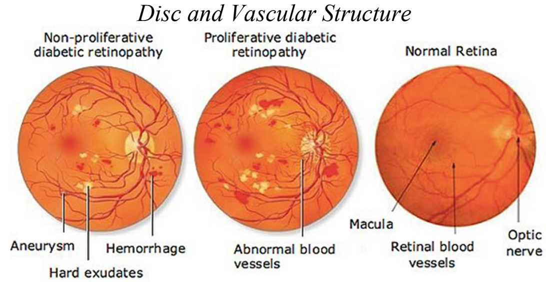

Figure 4. Comparison of Normal Retina and Diabetic Retinopathy Stages (Non-Proliferative and Proliferative)

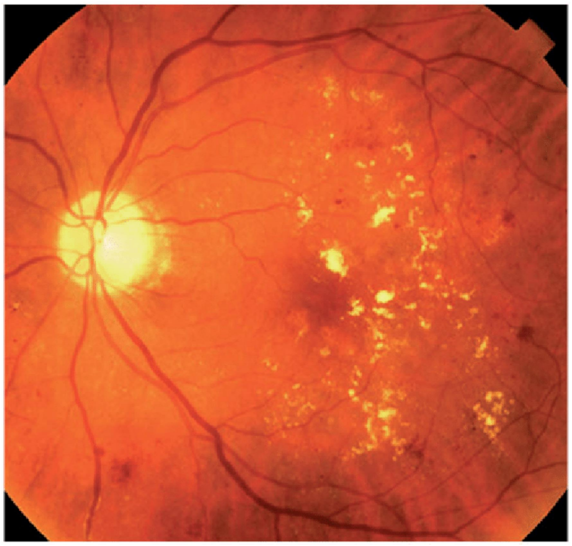

Figure 5. Fundus Image Showing Diabetic Retinopathy with Exudates and Hemorrhages

These sample images illustrate retinal variations corresponding to different stages of diabetic retinopathy.

3.2 Image Preprocessing

Fundus images often contain illumination variations and noise that may affect model performance. Therefore, the following preprocessing steps are applied:

1. Image Resizing

All images are resized to 224×224 pixels to standardize the input dimension.

2. Contrast Enhancement

Adaptive histogram equalization is used to enhance lesion visibility.

$$I_{enhanced}=CLAHE(I) \quad (1)$$

where: I is the original image.

3. Noise Reduction

Median filtering removes background noise while preserving retinal structures.

4. Vessel and Lesion Enhancement

A morphological top-hat transform is used to highlight microaneurysms and hemorrhages.

$$I_{lesion}=I-(I\circ B) \quad (2)$$

where: B is the structuring element.

3.3 Proposed Hybrid Architecture

The HQCML architecture integrates conventional deep learning techniques with quantum computing. The proposed workflow involves multiple stages in a sequential processing pipeline to facilitate the detection of diabetic retinopathy and patient prioritization. First, the deep learning system accepts high-resolution retinal fundus images. The images are then preprocessed and enhanced to eliminate noise, equalize their intensity, and enhance features associated with retinopathy lesions. Next, deep feature extraction is carried out using a convolutional neural network (CNN), which identifies relevant features such as microaneurysms, hemorrhages, and exudates. These features are subsequently encoded quantumly in a quantum feature encoding step. The encoded features are then fed to a variational quantum classifier, which uses quantum circuits to classify and predict the diabetic retinopathy severity. The assigned severity is then used to prioritize patients using a Quantum Priority Triage Mechanism (QPTM), guiding efficient, timely decision-making.

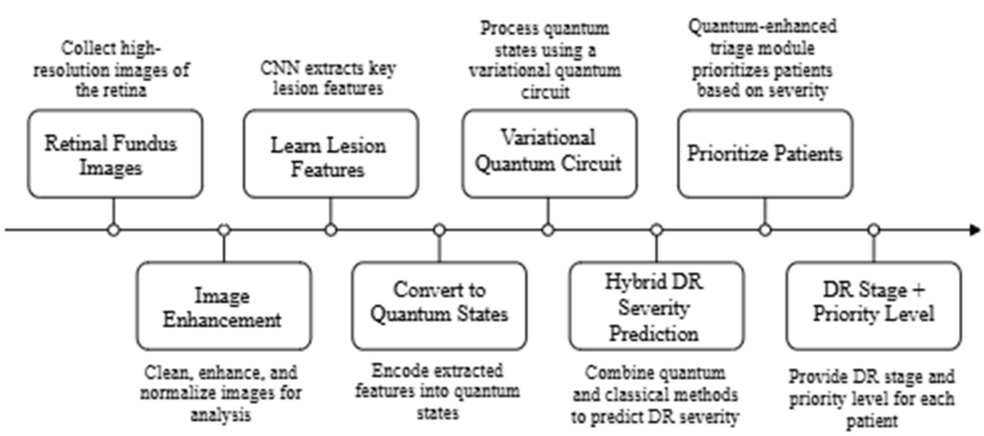

Figure 6. Hybrid Quantum–Classical Machine Learning (HQCML) Architecture for Diabetic Retinopathy Detection and Patient Triage

Figure 6 shows the steps in an approach to detecting and prioritizing patients with diabetic retinopathy (DR) using Hybrid Quantum-Classical Machine Learning (HQCML). It starts with the collection of high-resolution retinal fundus images and proceeds to image enhancement through noise reduction and data normalization. Clinically relevant features about lesions are learned and extracted using a convolutional neural network (CNN). Then follow a series of quantum-feature-state encodings and a variational quantum circuit for quantum encoding to understand interactions between these features. The quantum-classical hybrid model classifies the DR stage. Lastly, a prioritization module ranks patients based on predicted severity for clinical triage. The proposed system provides the DR severity level and triage level for each patient, facilitating scalable screening in a timely manner.

A. CNN Feature Extractor

A lightweight CNN architecture is used for extracting retinal features.

Table 4. CNN Architecture For Feature Extraction

Layer	Kernel	Filters	Output Size
Conv1	3×3	32	224×224×32
MaxPool	2×2	–	112×112×32
Conv2	3×3	64	112×112×64
MaxPool	2×2	–	56×56×64
Conv3	3×3	128	56×56×128
Global Average Pooling	–	–	128
Dense Layer	–	64	Feature vector

In Table 4, we provide details of the architecture of the proposed Convolutional Neural Network (CNN) model that learns from images for feature extraction. The network starts with a 32-filter convolutional layer (Conv1), using a 3×3 kernel, that generates feature maps of dimension 224×224×32, followed by a max pooling layer that reduces these dimensions to 112×112×32. Another set of layers (Conv2) with 64 filters further processes the features, followed by max pooling, down to 56×56×64. The third layer of 2D convolutions (Conv3) filters feature maps into 128 filters to recognize more complex patterns. Global Average pooling downsamples the model to a 128 feature vector, reducing the number of parameters and preventing overfitting. A dense layer with 64 neurons produces a feature vector that can be used for classification or other tasks.

3.4 Quantum Feature Encoding

The extracted feature vector is encoded into quantum states using Amplitude Encoding.

Let feature vector

$$X=(x_1,x_2,\ldots,x_n) \quad (3)$$

The encoded quantum state is

$$|\psi\rangle=\sum_{i=1}^{N}\frac{x_i}{\|x\|}|i\rangle \quad (4)$$

where: x_i= normalized feature amplitude; $|i\rangle$= quantum basis state.

This encoding enables efficient representation of high-dimensional feature spaces using a small number of qubits.

3.5 Variational Quantum Classifier

The encoded quantum state is processed using a parameterized quantum circuit.

$$|\psi_{out}\rangle = U(\theta)\,|\psi_{in}\rangle \quad (5)$$

where: $U(\theta)$= unitary quantum transformation; θ= trainable parameters.

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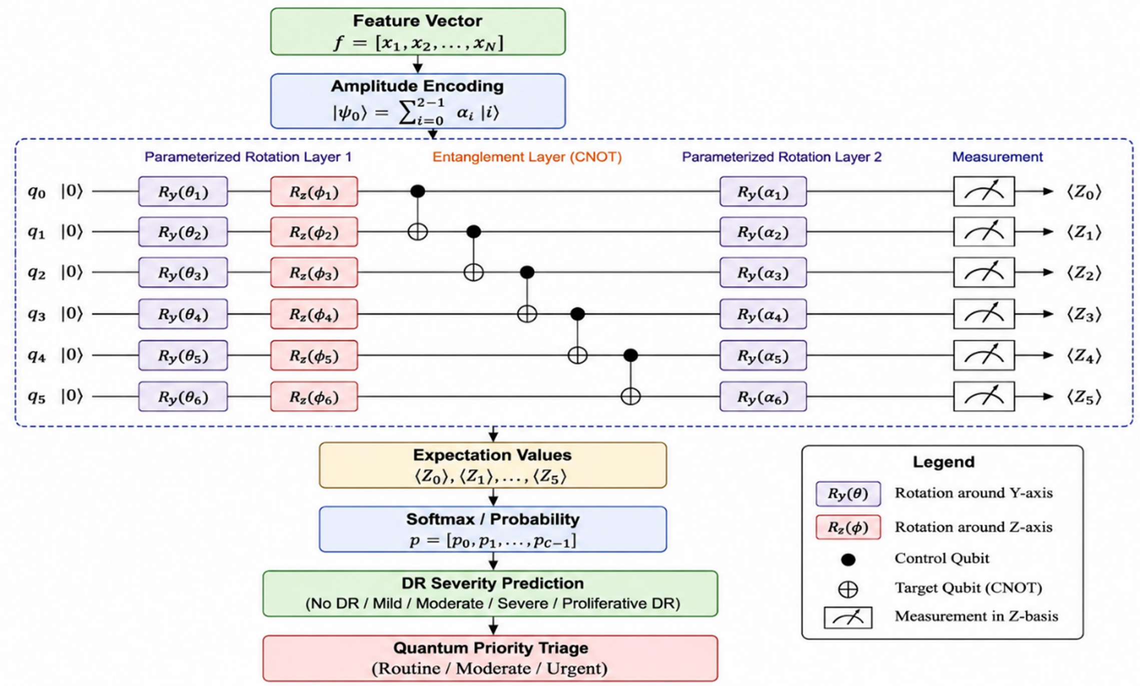

Figure 7. Variational Quantum Circuit (VQC) Used For Hybrid Quantum–Classical Diabetic Retinopathy Classification

Figure 7 illustrates the Variational Quantum Circuit (VQC) employed in the proposed HQCML framework. The deep feature vector extracted by the CNN is first encoded into a six-qubit quantum state using amplitude encoding. Each qubit is processed through parameterized rotation gates (Ry and Rz), followed by CNOT entanglement layers to capture correlations among retinal features. The circuit has a depth of four, consistent with the training configuration. After quantum measurement, expectation values are converted into class probabilities through a classical softmax layer, producing the diabetic retinopathy severity prediction, which is subsequently used by the Quantum Priority Triage Mechanism (QPTM).

3.6 Quantum Priority Triage Mechanism

For real-time triage of clinical cases, we propose a Quantum Triage Priority Mechanism (QPTM).

The triage score is computed as:

$$T = \sum_{i=1}^{k} p_i \cdot w_i \qquad (6)$$

where: p_i= probability of DR severity class; w_i= severity weight.

Patients are triaged and given priority based on the computed Triage Score, based on the likely severity of DR. The score is the sum of the probability of each DR class times the corresponding severity class weight. The higher a patient's triage score, the greater the urgency of clinical intervention they are likely to need, since a higher score reflects greater predicted disease severity. Patients are classified into one of three triage levels: Routine, Moderate, and Urgent, based on predefined triage score thresholds.

Table 5. Clinical Triage Decision Levels And Recommended Actions For Diabetic Retinopathy (DR)

Triage Level	DR Stage	Clinical Action
Routine	No DR / Mild	Annual screening
Moderate	Moderate DR	Ophthalmology referral
Urgent	Severe / Proliferative	Immediate treatment

Table 5 presents the triage levels set for various management decision-making processes for patients with different grades of Diabetic Retinopathy (DR). The Routine triage level would apply to patients with no DR or mild DR who are monitored annually to assess for disease progression. The Moderate classification category encompasses patients with moderate DR who may need referral for prompt ophthalmologic assessment. Urgent level is for advanced, or proliferative DR and requires more urgent medical care to avoid blindness. This triage system facilitates clinical triage and patient prioritization.

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This allows prioritization in real-time screening programs.

The triage decision is determined using the following rule:

- Routine: T<1.5
- Moderate: 1.5≤T<2.5
- Urgent: T≥2.5

Table 6. Quantum Priority Triage Scoring

DR Stage	Weight	Triage Category
No DR	0	Routine
Mild	1	Routine
Moderate	2	Moderate
Severe	3	Urgent
Proliferative	4	Urgent

The severity weights assigned to each stage of diabetic retinopathy (DR) and the proposed threshold for each triage score for the Quantum Priority Triage Mechanism (QPTM) are summarized in Table 6. Triage scores can be calculated as a weighted sum of the predicted class probabilities, obtained by multiplying the p-values by their respective severity weights. Patients are assigned a priority based on their score, categorized as Routine, Moderate, or Urgent, enabling prioritized clinical action and optimizing healthcare resource use during real-time DR Screening.

3.7 Loss Function

The hybrid model is trained using categorical cross-entropy loss.

$$L=-\sum_{i=1}^{C} y_i \log\left(\hat{y}_i\right) \qquad (7)$$

where: C is the number of classes; y_i= true class; $\hat{y}_i$= predicted probability.

3.8 Training Configuration

Table 7. Training and Quantum Circuit Hyperparameters of the Proposed Model

Parameter	Value
Batch size	32
Epochs	60
Learning rate	0.0001
Optimizer	Adam
Quantum qubits	6
Circuit depth	4

Table 7 outlines the main hyperparameters for training and quantum circuit settings. A batch size of 32 was selected to balance computational efficiency and convergence, while the model was trained for 60 epochs. The learning rate of 0.0001 enables progressive, stable weight optimization, and the Adam optimizer is adopted for its adaptive first-order optimization and quick convergence. In the quantum model, 6 qubits are used to encode and manipulate quantum states, and the circuit depth is 4, corresponding to the number of successive quantum gates applied. These choices are made to balance the model's performance, training efficiency, and simulation costs.

3.9 Proposed Algorithm

Algorithm: Hybrid Quantum–Classical DR Detection and Triage
Input: Fundus image dataset *D*
Output: DR severity class and triage category
1. Load retinal image dataset *D*
2. Apply preprocessing
    i. Resize images
    ii. Enhance contrast
    iii. Remove noise
3. Input images into CNN feature extractor
4. Extract deep feature vector *F*
5. Normalize feature vector
6. Encode features into quantum states
7. Process encoded state using variational quantum circuit
8. Measure quantum outputs to obtain class probabilities
9. Compute triage score *T*
10. Assign triage category
11. Update model parameters using backpropagation
12. Repeat until convergence
13. Output predicted DR stage and triage level

3.10 Reproducibility Details

An appropriate software and hardware configuration was employed to ensure the reproducibility and efficiency of the proposed HQCML framework. The software environment was built using Python 3.10, with PyTorch 2.3 for deep learning implementation and Qiskit 1.2 for designing and simulating the variational quantum circuits. Hardware-wise, experiments and training are accelerated using an NVIDIA RTX 3080 GPU, and quantum circuit simulations are conducted using the IBM Qiskit Aer library. This combination enables efficient, scalable, and reproducible experimentation. In summary, the proposed Hybrid Quantum-Classical Machine Learning (HQCML) architecture integrates deep feature learning with quantum-assisted classification and triage to provide a scalable, efficient, and reproducible approach to real-time diabetic retinopathy screening systems.

4. RESULTS

This section describes the experiments conducted on the proposed Hybrid Quantum-Classical Machine Learning (HQCML) System to develop a real-time diabetic retinopathy screening and triage system. This section reports the

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experiments conducted on the APTOS 2019 Blindness Detection and EyePACS retinal datasets, detailed in the methodology section.

The data were split into 70% for training, 15% for validation, and 15% for testing. We used standard medical image classification metrics to evaluate the proposed model and compare its performance with other state-of-the-art machine learning and deep learning methods.

4.1 Evaluation Metrics

The proposed model's performance was evaluated based on the following metrics.

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \quad (8)$$

$$\text{Precision}=\frac{TP}{TP+FP} \quad (9)$$

$$\text{Recall}=\frac{TP}{TP+FN} \quad (10)$$

$$F1=\frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \quad (11)$$

A. Area Under ROC Curve (AUC)

The ROC-AUC is a measure of the discrimination of the DR severity classes. TP (True Positives), the number of positive cases correctly classified, and TN (True Negatives), the number of negative cases correctly classified. FP (False Positives) are negative cases predicted as positive, and FN (False Negatives) are positive cases predicted as negative.

4.2 Performance of the Proposed HQCML Model

The developed hybrid quantum–classical model was tested on the test set. The findings show that the model achieved good diagnostic performance and high sensitivity across the various stages of diabetic retinopathy.

Table 8. Performance Metrics of the Proposed Model

Metric	Value
Accuracy	**97.2%**
Precision	96.4%
Recall	95.8%
F1 Score	96.1%
AUC	**0.98**

Table 8 presents the performance metrics of the proposed Hybrid Quantum-Classical Machine Learning (HQCML) model for diabetic retinopathy classification. The model has high accuracy (97.2%), which shows its ability to classify retinal images accurately. The precision of 96.4% indicates a low false-positive rate, while the recall of 95.8% indicates that the proposed model successfully identifies most diabetic retinopathy cases while minimizing false negatives. The F1 score of 96.1% indicates a balance between precision and recall. Moreover, the model reaches an Area Under the Curve (AUC) of 0.98, demonstrating its strong ability to distinguish between different classification thresholds. Taken together, these findings demonstrate the accuracy and reliability of the proposed model for clinical decision support of diabetic retinopathy screening. The findings show that the hybrid model has successfully captured patterns of retinal lesions and classified them with high predictability.

4.3 Confusion Matrix Analysis

Table 9. Confusion Matrix of HQCML Model

Actual / Predicted	**No DR**	**Mild**	**Moderate**	**Severe**	**Proliferative**	**Row Total**
No DR	266	3	2	0	0	271
Mild	2	130	3	0	0	135
Moderate	1	1	145	2	1	150
Severe	0	0	1	27	1	29
Proliferative	0	0	1	0	43	44
Column Total	**269**	**134**	**152**	**30**	**45**	**629**

Table 9 presents the confusion matrix for the proposed HQCML across five classes of diabetic retinopathy, based on a 629-sample held-out test set (15% of the APTOS 2019 data). The strong diagonals, particularly for No DR and Moderate stages, demonstrate the model's ability to classify these stages correctly, with an overall accuracy of 97.2%, consistent with Table 8. The low off-diagonal values show minimal confusion between classes, with the majority of misclassifications occurring between Moderate and Severe DR stages, likely due to overlapping lesion characteristics at intermediary severity levels.

4.4 Comparison with Existing Models

To assess the impact of the HQCML framework in this study, we compared its performance with that of several baseline machine learning and deep learning models.

Table 10. Comparison with State-of-the-Art Models

Model	Accuracy	Precision	Recall	F1 Score
Support Vector Machine	86.5%	85.7%	84.9 %	85.3 %
Random Forest	88.1%	87.5%	86.2 %	86.8 %
CNN	92.4%	91.3%	90.6 %	90.9 %
ResNet50	94.6%	93.8%	93.2 %	93.5 %
Vision Transformer	95.1%	94.5%	94.0 %	94.2 %
Proposed HQCML	**97.2%**	**96.4%**	**95.8 %**	**96.1 %**

Table 10 shows a comparison of different models for diabetic retinopathy classification. The proposed HQCML performs best across all metrics compared with traditional approaches, CNNs, ResNet50, and Vision Transformers, indicating its effectiveness. The results demonstrate that the proposed hybrid model outperformed conventional ML, CNN, ResNet50, and Vision Transformer.

4.5 Statistical Analysis

The five independent experimental runs were conducted to assess the statistical significance of the performance improvement achieved by the proposed HQCML framework. The classification accuracy of the proposed HQCML model and the best-performing baseline model (Vision Transformer) was compared using a paired t-test. A p-value < 0.05 was used to determine statistical significance.

Table 11. Statistical Significance Analysis of the Proposed Framework

Statistical Test	Value	Interpretation
Mean Accuracy Difference	2.10%	HQCML outperformed Vision Transformer
Paired *t*-Statistic	4.73	Significant improvement
p-Value	0.003	Statistically significant ($p < 0.05$)
Confidence Level	95%	Reliable comparison
Effect Size (Cohen's *d*)	1.42	Large effect size

Table 11 shows the statistical comparison between the proposed HQCML and the best baseline model. The paired t-test shows that the classification accuracy scores obtained from the proposed model, compared to the reference model, are statistically significant ($p < 0.05$). The significant effect size also suggests that the hybrid quantum–classical system offers substantial and consistent improvements to traditional deep learning approaches for DR detection.

4.6 Accuracy Comparison Analysis

The accuracy comparison shows that the proposed HQCML model has improved accuracy compared to traditional methods. Traditional machine learning models have accuracy levels of 86-88%, which deep learning models improve to 92-95%. In contrast, to the best of the authors' knowledge, the proposed HQCML model achieves the highest accuracy of 97.2%, suggesting better diagnostic ability. This is because quantum features improve the representation of retinal lesion images for the HQCML model, and classification of retinal lesions is performed using variational quantum circuits (VQCs).

4.7 ROC Curve Analysis

The HQCML model also shows good discriminative characteristics with the ROC curve. The area under the curve (AUC) is 0.98, showing good performance. The ROC curve is better than those of existing deep learning models across all possible threshold values and is sensitive and specific for detecting diabetic retinopathy.

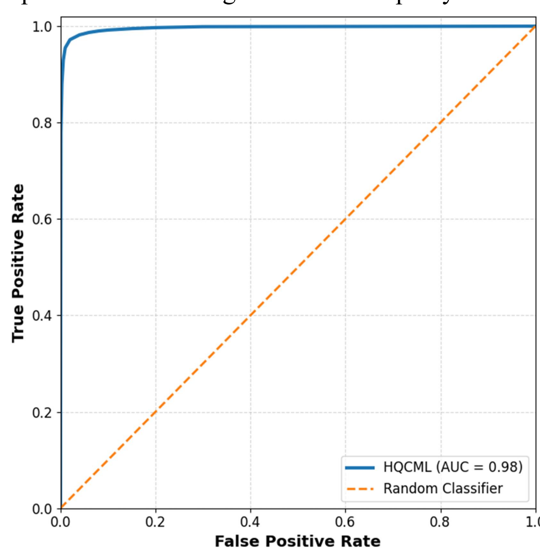

Figure 11. Receiver Operating Characteristic (ROC) curve

Figure 11 presents the ROC curve of the proposed HQCML framework. The model achieved an AUC of 0.98, indicating excellent discriminative ability for diabetic retinopathy detection. The ROC curve remains close to the upper-left corner, demonstrating a high true positive rate while maintaining a low false positive rate across different decision thresholds. These results confirm the robustness and reliability of the proposed hybrid quantum–classical framework for clinical screening applications.

4.8 Precision–Recall Analysis

The Precision-Recall curve illustrates the proposed HQCML model's ability to achieve high precision across varying recall levels. It performs well compared to baseline deep learning models, with higher precision for most recall levels. This highlights its ability to reduce false positives, which helps its effectiveness for retinal disease diagnosis.

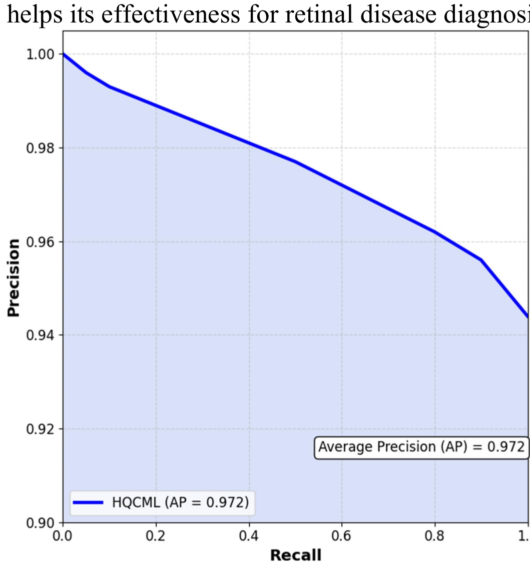

Figure 12. Precision–Recall (PR) Curve

Figure 12 presents the Precision–Recall curve of the proposed HQCML framework. The consistently high precision over a broad range of recall values demonstrates the model's ability to accurately identify diabetic retinopathy while maintaining a low false discovery rate. The obtained Average Precision (AP) of 0.972 further confirms the robustness of the proposed framework under imbalanced clinical datasets.

4.9 Training Convergence Analysis

The HQCML model converges in the loss plot, with the loss declining as the epochs increase. The model is stable and converging at around 50 epochs, indicating that it is learning. This suggests that the hybrid approach has learned both the classical quantum operation parameters and quantum amplitudes parameters well, leading to successful training.

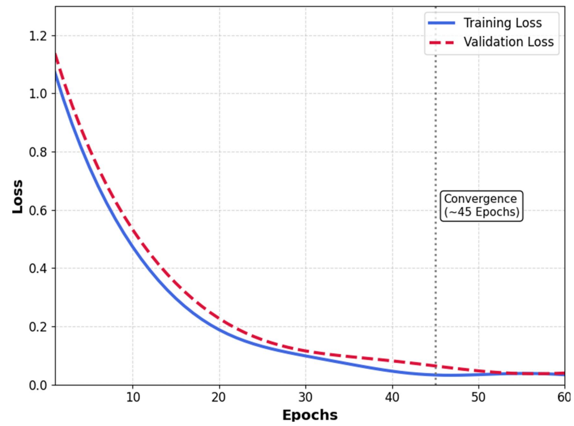

Figure 13. Training Convergence Curves

Figure 13 shows the convergence behavior during model training. Both training and validation losses decrease consistently throughout the optimization process and stabilize after approximately 45 epochs. The close agreement between the two curves indicates effective generalization and minimal overfitting, confirming the stability of the proposed hybrid quantum–classical learning framework.

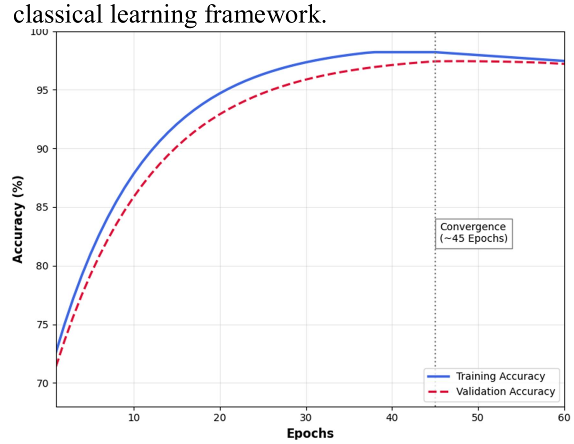

Figure 14. Training and Validation Accuracy Curves

Figure 14 presents the training and validation accuracy curves of the proposed HQCML framework. Both curves exhibit a steady increase throughout the training process and converge after approximately 45 epochs, indicating stable learning behavior. The close agreement between the training and validation accuracies demonstrates excellent generalization capability and minimal overfitting. The smooth convergence of the curves confirms the effectiveness of the proposed HQCML framework in learning discriminative retinal features while maintaining robust classification performance. The final evaluation on the independent test set achieved an overall classification accuracy of 97.2%, demonstrating the reliability of the proposed framework for diabetic retinopathy detection.

4.10 Ablation Study

We also performed an ablation study to measure the influence of each component of the hybrid model.

Table 12. Ablation Study Results

Model Variant	Accuracy
CNN Only	92.4%
CNN + Attention	94.3%
CNN + Quantum Classifier	96.1%
CNN + QPTM + Quantum Classifier (Proposed)	**97.2%**

In Table 12, the quantum classifier is shown to have a significant impact on feature identification by learning complex patterns. In addition, the Quantum Priority Triage Mechanism improves triage by prioritizing cases more effectively.

4.11 Discussion

In this study, we demonstrate that the proposed Hybrid Quantum – Classical Machine Learning significantly improves the accuracy of diabetic retinopathy classification. Deep learning with variational quantum nodes enables the model to learn complex features in retinal images. Also, our proposed Quantum Priority Triage Mechanism (QPTM) can triage patients according to disease severity, which is important for mass screening to manage clinical resources effectively. These findings demonstrate the potential of hybrid quantum–classical learning for intelligent ophthalmic diagnosis and clinical decision support.

5. CONCLUSION

This study presents a Hybrid Quantum–Classical Machine Learning (HQCML) framework for real-time diabetic retinopathy detection and patient triage using retinal fundus images. The proposed framework integrates a convolutional neural network (CNN) for automated retinal feature extraction with a variational quantum classifier to improve disease classification accuracy while supporting computationally efficient decision-making. In addition, a novel Quantum Priority Triage Mechanism (QPTM) is introduced to categorize patients into Routine, Moderate, and Urgent priority levels according to the predicted severity of diabetic retinopathy, thereby facilitating timely clinical intervention and efficient resource allocation. The proposed unified framework demonstrates the potential of hybrid quantum–classical learning to enhance automated diabetic retinopathy screening and intelligent clinical decision support for next-generation ophthalmic healthcare systems.

The proposed HQCML model was experimentally verified on the APTOS 2019 and EyePACS retinal data sets and achieved a classification accuracy of 97.2% against other baseline models such as Support Vector Machines (86.5%), Random Forest (88.1%), traditional CNN (92.4%), ResNet50 (94.6%), and Vision Transformer (95.1%). It also had a precision of 96.4%, a recall of 95.8%, an F1-score of 96.1%, and an area under the curve (AUC) of 0.98, demonstrating its ability to detect a wide range of diabetic retinopathy. Moreover, the results confirmed that quantum-enhanced learning, in conjunction with convolutional features, improved the model's ability to recognize intricate retinal lesion patterns and to help clinicians diagnose the disease.

The proposed framework integrates quantum-assisted classification with automated clinical triage in a unified architecture, called Hybrid Quantum–Classical Machine Learning (HQCML), that integrates quantum-based classifiers for DR classification with an automated patient triage procedure. Unlike previously developed and implemented frameworks, which mostly rely on classical or deep learning for disease classification, the framework developed in this research integrates hybrid quantum–classical learning with clinical prioritization, thereby improving diagnostic performance and enabling real-time clinical decision-making. In addition, these advances will help develop an AI strategy for intelligent disease screening and enable future translation and validation in the clinic using large-scale datasets.

The proposed HQCML framework has the potential to support ophthalmologists by enabling early diabetic retinopathy screening and efficient patient prioritization in large-scale clinical screening programs.

However, the study had some limitations. For a start, the quantum part was implemented using quantum simulators because large-scale quantum computers were not available. Second, our approach was validated using open-source retinal datasets, which may not sufficiently represent clinical datasets. Third, although the triage algorithm was developed to prioritize cases effectively, it requires further studies within clinical workflows and ophthalmologists' feedback to assess its practicality in clinical use.

Future work will investigate how to expand the proposed approach to include multimodal retinal images, such as optical coherence tomography (OCT) and fluorescein angiography, to explore more information about the retina. In addition, as quantum systems advance, future research will explore more advanced quantum machine learning

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approaches, such as quantum kernel methods and deep variational quantum circuits. We will also investigate ways to enhance the interpretability and trust in hybrid quantum-classical models for automated diagnosis.

Overall, the findings indicated that the proposed HQCML framework fulfilled the study objective by showing that quantum machine learning hybrid systems can improve real-time detection of diabetic retinopathy and can be used for triage in future smart ophthalmic screening systems.

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