Quantum Transfer Learning for Enhanced Diabetic Retinopathy Detection with U-Net Segmentation of Fundus Images

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Abstract. Diabetic Retinopathy (DR) is one of the most prevalent causes of blindness, particularly for diabetic patients, because it introduces numerous lesions to the retina. Traditional DR identification by analysing retina fundus images by ophthalmologists is a very time consuming, and expensive process. Despite the effectiveness of classical transfer learning models in the field of Computer-Aided Diagnosis for DR detection, the use of such techniques for achieving high effectiveness has a number of disadvantages, including high costs and time for training, high computational complexity and resource intensity. In the present research, quantitative and qualitative improvement in DR detection is done by integrating Quantum Transfer Learning (QTL) with other types of classical machine learning models. In our proposed methodology, APTOS 2019 Blindness Detection dataset is used and the pre-trained models selected for feature extraction include ResNet-18, ResNet-34, ResNet-50, ResNet-101 and ResNet-152 along with inception V3. To classify the given data, a Variational Quantum Classifier is used and the method achieves an accuracy of 97%, with the ResNet-18 model. Furthermore, in this research, the U-Net model is employed for DR stage segmentation, achieving a testing accuracy of 96.94% on the STARE dataset, which contains retinal images captured by optical cameras. U-Net results have already demonstrated significant effectiveness in segmentation tasks. To extend the results of DR classification, Support Vector Machine (SVM) and K Nearest Neighbour (KNN) models were used, achieving accuracies above 96.62%. In this quantum-classical combined approach demonstrates that Quantum Transfer Learning enhances DR detection by complementing classical models like U-Net, SVM, and KNN, offering faster and more accurate diagnoses for diabetic retinopathy patients.

Keywords: Diabetic retinopathy (DR), Quantum Transfer Learning, Computer-Aided Diagnosis, U-Net, Variational Quantum Classifier(VQC), Support Vector Machine (SVM), K Nearest Neighbor (KNN), retinal images, segmentation, lesions.

1 Introduction

Diabetic Retinopathy (DR) is one of the major causes of blindness globally, making timely and accurate diagnosis crucial to preventing vision loss in a large number of patients. DR is a complication of diabetes, where high blood sugar levels cause damage to the blood vessels in the retina, leading to swelling, leakage, or even blockage, ultimately impairing vision [1], [2]. According to global data, approximately 103.12 million people were affected by DR in 2020, with the number projected to rise to 160.50 million by 2045 [5], [8]. Early detection is essential, as appropriate treatment in the early stages can prevent significant vision impairment. However, the early stages of DR are often asymptomatic, necessitating regular retinal examinations [4]. Artificial Intelligence (AI) has emerged as a valuable tool in DR diagnosis, automating the categorization of retinal images using advanced Deep Learning (DL) models [7]. Convolutional Neural Networks (CNNs) have been particularly effective in image analysis tasks related to medical imaging, showing great success in identifying various retinal abnormalities [9]. Recent advancements in quantum computing have further stimulated interest in quantum-enhanced Deep Learning models, which show potential in addressing complex medical image analysis problems [10], [11]. Despite considerable research in DR detection, limited work has been done on the classification of different DR stages and lesion localization. This study addresses that gap by introducing a quantum-based CNN model for DR classification and lesion mapping, with the aim of improving diagnostic accuracy. Additionally, models like U-Net, SVM, and KNN are used to segment DR stages and evaluate the classification results. These approaches are designed to assist ophthalmologists in diagnosing DR at early stages with higher precision, enhancing the prognosis for diabetic patients. The novelty in this research lies in the application of Quantum Transfer Learning (QTL) for DR classification, which reduces computational complexity and increases the efficiency of the diagnosis process [3]. By combining QTL with classical models such as ResNet, Inception V3, U-Net, SVM, and KNN, the research presents a hybrid quantum-classical solution that outperforms existing models in terms of both accuracy and time efficiency. Additionally, the U-Net architecture is employed for segmentation, which enhances the ability to localise lesions and identify retinal structures, establishing a new benchmark for automated DR recognition systems. This research aims to develop a highly efficient DR management solution that bridges the gap between manual and automated diagnosis[12].

2 Dataset description

In this research, two datasets are utilised: the STARE (Structured Analysis of the Retina) database and the APTOS 2019 Blindness Detection dataset [6]. High-resolution retinal images taken with optical cameras that offer precise views of important retinal structures like the fovea, optic nerve head, and retinal layers are included in the STARE collection, which was created for research and diagnostic reasons. In order to provide exact targets for segmentation and classification tasks, every image is painstakingly labelled with ground truth masks that emphasise important characteristics of diabetic retinopathy (DR), such as microaneurysms, haemorrhages, and other lesions. Pre-processing increases the efficiency with which the U-Net model can detect patterns by reducing images to 256x256 pixels and normalising them within the [0,1] range. For pixel-wise classification, ground truth masks are binarized to differentiate between impacted and unaffected areas. The APTOS 2019 dataset consists of fundus photos of the retina taken under various imaging settings [14]. Clinicians have scored each image on a range of 0 (no DR) to 4 (proliferative DR). These datasets offer a thorough basis for the segmentation and categorisation of DR in this study.

3 Related Works

Transfer learning (TL) has received lots of attention in medical image analysis, where a model trained for one task is used to boost performance of another but different task [13]. From this method, training speed is increased particularly when in a situation where deep learning models have scarce data to analyse. There exist numerous implementations of CNNs in TL for DR detection because of the nature of CNNs that is adept in image analysis. Deep CNNs including TL were also applied by Mansour et al. [13] where they were able to achieve a mean accuracy of 87.31 % to diagnose DR Similarly, Mohammadian et al. [15] fine-tuned Inception-V3 and ResNet-152 respectively to gauge an accuracy of 88.26% and 92% correspondingly. This approach overcomes major challenges such as lack of data and computational intensive tasks.

3.1 Transfer Learning in Diabetic Retinopathy Detection

In Diabetic Retinopathy (DR) detection, transfer learning has been widely employed to improve the classification process by leveraging pre-trained models. Wan et al. [16] utilised transfer learning on architectures such as AlexNet and VGGNet for DR detection on the Kaggle dataset, where VGGNet outperformed AlexNet in terms of accuracy. Similarly, Dutta et al. [17] conducted a study using various CNN architectures, including VGGNet-16, for fundus image segmentation, achieving results comparable to prior studies. These works demonstrated the value of transfer learning in DR detection by reducing the computational cost and time required for model training, as well as enhancing model accuracy. Furthermore, transfer learning has been particularly advantageous when dealing with limited medical image datasets, a common issue in medical research. By using pre-trained models on large datasets such as ImageNet, researchers can fine-tune these models for the specific task of DR detection with minimal training data, thereby mitigating the challenges posed by small datasets. In addition to accuracy improvement, these models help in faster convergence during training and avoid overfitting, especially when the available dataset is small [18].

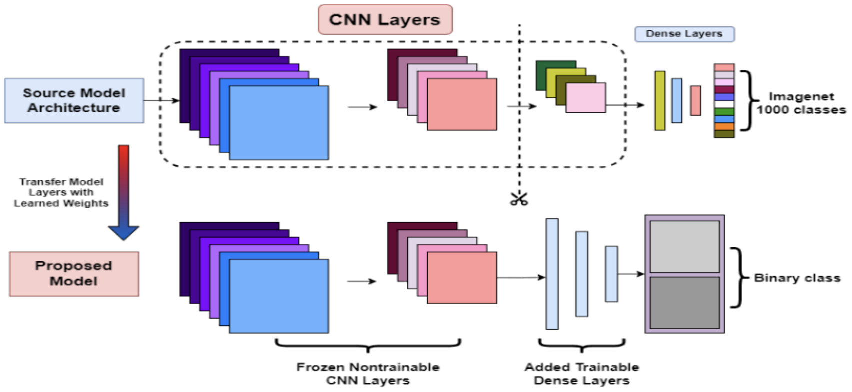

Fig. 1 Architecture of Transfer Learning model

3.2 Quantum Transfer Learning for Image Classification

Medical image classification based on quantum machine learning has advanced with the addition of classical models and quantum layers. The combination of Quantum Transfer Learning (QTL) with the conventional CNN models is a new paradigm to DR detection enhancement. Shahwar et al. [18] proposed a classical-quantum approach for Alzheimer's detection, where ResNet-34 is used for feature extraction, while a QVC is used for classification with a training accuracy of 99.1%. Likewise, in another work, Sim et al. [33] discussed analytically expressibility and entanglement capability of variational quantum circuits, resulting in improved classification performance in hybrid architectures, which shall provide guidelines on applying QTL for medical diagnosis [19].

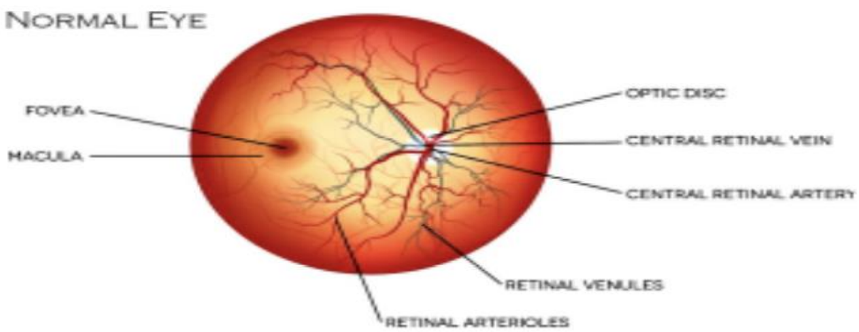

Fig. 2 Normal Eye Retina

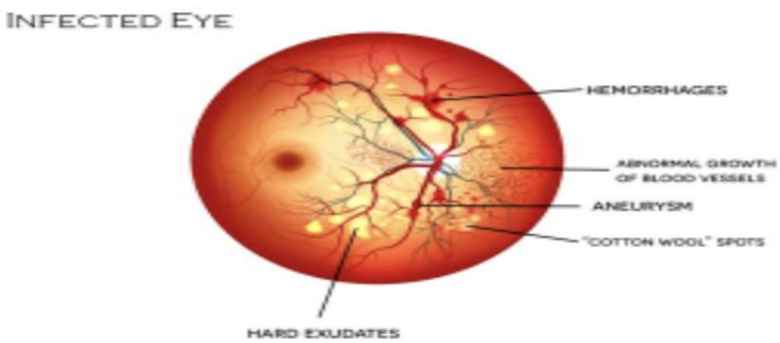

Fig. 3 Infected Eye Retina

3.3 Quantum Neural Networks in Diabetic Retinopathy Detection

The application of quantum neural networks (QNNs) in the current work on DR detection is generally considered to be in its early stages [22]. However, there has been some progress for the research, some of which includes the work of Garcia et al. [23] where AlexNet and VGGNet CNN models were used in DR detection through improved quantum models. What has been shown by recent works is that incorporating QTL indeed provides new ways with which to enhance the performance and learning efficiency of DR classification problems hence using much less training time and fewer numbering resources than what purely classical models would require [24].

3.4 U-Net in Medical Image Segmentation

U-Net, a well-known CNN architecture for medical image segmentation has been successfully employed for pixel level accuracy especially for the detection of retinal structures in DR. Gangwar et al. [25] applied a model that Included Inception-ResNet-V2 linked with customised CNN layers for blindness detection in two databases called Messidor-1 and APTOS 2019 with an 82.18% accuracy. Thus, in the scopes of medical segmentation tasks, not to mention DR lesion detection, U-Net achieves the state-of-art performance. This work extends these developments by using U-Net for DR stage segmentation in the second stage, enhancing segmentation performance and lesion detection in fundus images.

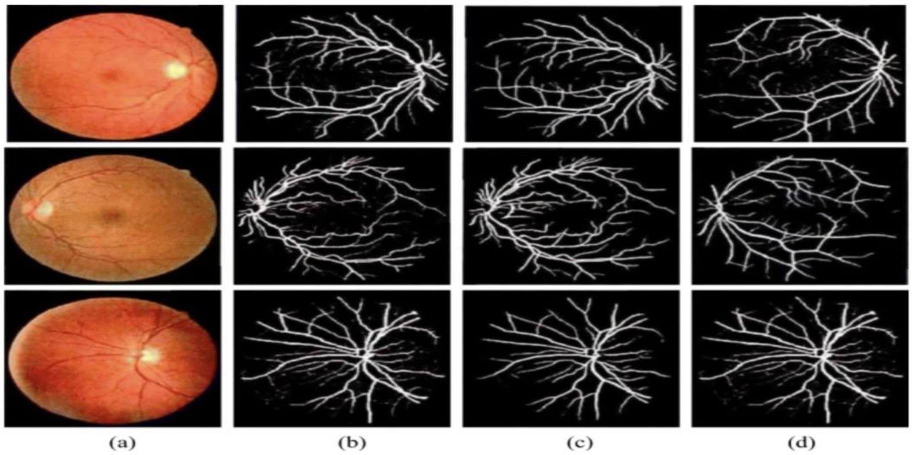

Fig. 4. Comparison of Various Outcomes: (a) Original Image (b) ResNet (c) Proposed Method (d) U-Net

3.5 Traditional CNN Models in DR Classification

Traditional CNN models remain in use for DR detection:'ya. Referring to the Kaggle and DiaretDB1 dataset, Gondal et al. [19] designed and trained a CNN model for referable DR with sensitivity and specificity of 93.6 % and 97.6%, respectively. On the other hand Wang et al. [20] developed a new CNN structure that incorporated an attention net with a cropping method that generated high AUC in DR classification. Nevertheless, the identification of the moderate stage of DR presents a problem to regular CNN models as observed in [27] where the model failed to classify mid-stage DR correctly.

3.6 Hybrid Classical-Quantum Models for DR Detection

The combined framework of classical CNN models with quantum layers is an unexplored avenue in DR detection. Several authors have confirmed the possibility of integrating pre-trained CNNs such as ResNet with quantum classifiers, as Shahwar et al. [28] and others have done in different medical imaging tasks achieving high accuracy. The additional use of quantum methods, especially quantum variational circuits is also promising for increasing the classification accuracy in DR detection as quantum models are better suited for handling complex data and have more efficient training compared to a classical approach.

4 Proposed Methodology

Quantum computing, with its ability to process information through qubits, offers much greater computational capacity than traditional systems; it is most useful in solving complicated problems in a number of spheres, including healthcare. In this study, quantum transfer learning has been applied in the enhancement of performance of quantum algorithms under consideration by employing well-trained classical models; this prevents wastage of computational resources while fostering development of areas including chemistry, optimization, and machine learning. Our approach is based on classical deep learning models, the inclusion of quantum circuits for classical neural networks, combined quantum and classical models for problems like diabetic retinopathy [21]. This illustrates the value of quantum tools to transform diagnostic tools and most other applications that are currently in use.

4.1 Comparative Analysis of Quantum and Classical Computing

Quantum computing represents a significant advancement through utilisation of the qubits in a way that differs with classical computing because a qubit can hold sundry values making the rates of computing very high [26]. It results in optimal or near-optimal solutions for hard problems that a classical computer has a hard time solving; there is a wide field of use, for example, medicine. In conditions of diagnosis and in designing drugs, for example, quantum computers can accurately model a biological or chemical molecular system. In spite of these drawbacks of quantum computing, including size and errors, effective algorithms that use both quantum and classical theories are being offered as future solutions to business and medicine.

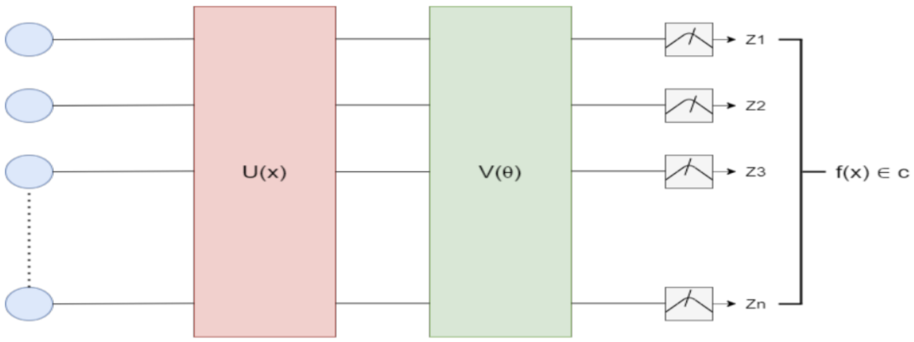

Fig. 5 Variational Quantum Classifier with embedding layers.

Three primary components: embedding layers □(□), variational circuit □(□) as well as the final measurements define the structure of the Variational Quantum Classifier (VQC), as shown in Fig. 4. Among the components of the VQC, the variational circuit assumes great importance as there is a variational circuit for every variational parameter. In figure 5, a variational circuit of a single qubit operation has been presented [29].

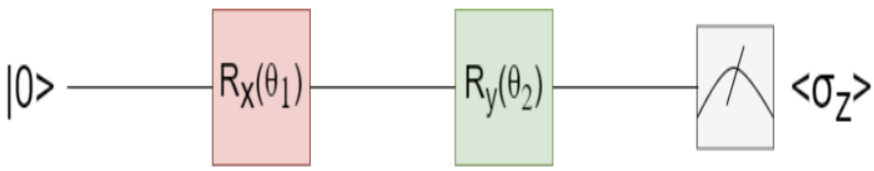

Fig. 6 Single-Qubit Case

4.2 Quantum Transfer Learning

Quantum transfer learning is an innovative approach that relies on transfer learning of several pre-trained quantum models for enhancing the training of new quantum tasks. Quantum transfer learning is based on the concept similar to transfer learning, where knowledge acquired in one task is transferred to a related second task: quantum transfer learning also transfers existing quantum models by modifying the parameters or by reusing the learned features in a new application [20]. This method enhances the pace of quantum algorithm formation, reduces dependence on quantum facilities where available, and has a vast potential for novel applications across different areas like chemistry, optimization, and machine learning in the expanding field of quantum computing.

4.3 Classical Model Foundation

The foundation of the classical model in this approach is based on choosing a pre-trained network like ResNet18, which has shown good results in the field of image processing in deep learning. This is based on the premise that the network is well suited to deal with high level visual data efficiently [29]. Fine-tuning from such large datasets such as ImageNet helps the model build a good feature extraction system to identify most features within the images. The learned representation from this architectural form can be deployed efficiently to specific and concrete image processing tasks in addition to yielding improvement in accuracy and fluency as needed. This simple yet powerful framework becomes the strong base for further tuning and for domain specific adaptation [30].

4.4 Quantum Circuit Integration

The integration of the quantum circuit organically integrates with the classical model and creates a complex network between the classical deep learning system and the quantum deep learning system [3]. Using superposition and entanglement, the system performs a quantum computation and analysis of the details of features extracted by the classical model. The quantum circuit becomes the supplement part to the quantum annealer, the former enhancing the total computing ability in order to solve complicated image processing problems. This integration marks a pioneering development in the synergistic unification of classical and quantum info processing models for image analysis and various other potential applications.

4.5 Feature Extraction via Pre-Trained Classical Models

The initial phase of retinal image processing for diabetic retinopathy (DR) detection involves using a pre-trained model known as ResNet18, in order to extract the images used in the classification [19]. This step is very important for getting features needed for further analysis. The main goal is to obtain a set of high-level features of 512 dimensions from images of the retina, as such properties play a crucial role in subsequent quantization. Actually, as the elements of the pre-trained architecture, we manage to identify and encapsulate the attributes that are general and comprehensive on the one hand, and as detailed and disparate as possible on the other hand, which is crucial for the subsequent steps aimed at detecting DR on the basis of the input data. This guarantees the extracted features as inclusive and specific, thus providing a right basis for specific and accurate usage in diagnosing.

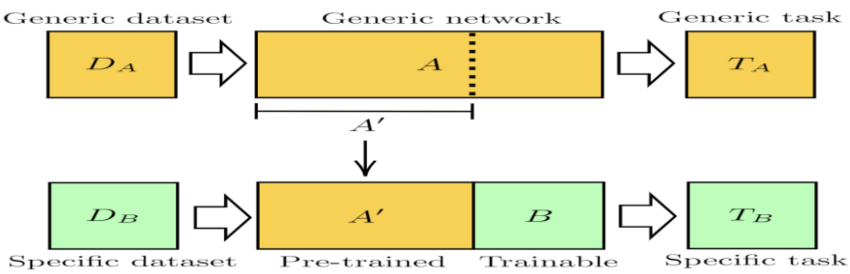

Fig. 7 Transfer Learning for Feature Extraction

4.6 Quantum Circuit for Classification

To effectively classify the input data in the quantum domain, a process starts with restructuring the flat array of quantum weights usually denoted as q_weights_flat to fit the structure of variational layers [17]. These weights are reshaped into dimensions that match the depth of the quantum circuit where it executes as well as the number of qubits, often described as (q_depth, n_qubits). The circuit utilises an embedding layer to initialise the quantum states. Each qubit is placed in a balanced superposition of up and down states through the application of a Hadamard layer, typically denoted as H_layer(n_qubits). Following this initialization, each qubit is rotated around the y-axis by an angle corresponding to the respective input features. This step effectively encodes the classical input data into the quantum system, allowing the subsequent variational layers to process the embedded data for classification tasks. Key quantum gates used during this process include rotation gates and entanglement gates, ensuring that the system can explore complex superpositions and entangled states. The design of such circuits is integral to leveraging quantum computing for classification problems, such as diabetic retinopathy detection, where high-dimensional and complex datasets benefit from the unique capabilities of quantum architectures [20].

4.7 Utilisation of U-Net Architecture for Diabetic Retinopathy detection

U-Net is a specialised convolutional neural network designed purposefully for image segmentation, focusing on the problem of classifying each pixel of an image into a different class [16]. The architecture comprises encoder-decoder formulating that allows for the exact localization and context restitution, and being highly suitable for the medical image segmentation including such diseases as diabetic retinopathy. The process of learning is performed using labelled images, in which masks, corresponding to images, are considered to be a ground truth [18].

4.8 Data Preprocessing and Mask Creation

The preprocessing phase starts with loading of retinal images and their conversion of format that can be fed into the U-Net model [13]. Every image is resized to 256 x 256 pixels prior to the normalisation of the pixels where values range between 0 and 1. At the same time, ground truth masks are derived from the thresholding methods and provide the binary skeletons of the interested regions in the images. These masks are important for training, since they allow them to point to the areas for the segmentation during the learning phase [14].

4.9 U- net model training process

The training of the U-Net model is about adjusting parameters to qualify how well the calculated segmentation masks differ from the ground truth segmentation masks [12]. A binary cross-entropy loss function is also used to measure this difference. Inside the training phase, the model is able to adjust the weights using a backpropagation algorithm so that it can accurately segment the features of diabetic retinopathy within the images. The batch size equals 8, and the total number of epochs is set to 50; 10 percent of data is used for validation only [13].

4.10 U- net model evaluation

Upon completion of the training phase, generally, the model performance is measured on the basis of the evaluation of such a model on the training dataset. Such measures as loss and accuracy are computed giving the model means through which it can test its ability to learn from data that has not been fed to it [14]. The evaluation process confirms that the U-Net model provides very precisely executed segmentation results, meaning it addresses the needs for DR diagnosis in practical applications [21].

4.11 U- net model deployment

The trained U-Net model is further saved for future Use in clinical practice. This involves applying the model to segment new retinal images in order to produce masks that might help clinicians to diagnose DR. The deployment process represents the ultimate expression of the training effort and provides tangible opportunity to apply the developed methodology [12].

5. Application of Diabetic Retinopathy Detection

The goals in the integrated model for identifying the stages of DR are primarily optimization of the classification, which is crucial for adequate diagnosis. This research uses trained quantum circuits whereby it employs the quantum computing concept in enhancing pattern recognition in real image in order to discover features that are related to DR of various stages. To this end, with the integration of quantum transfer learning, the model effectively maps out microaneurysms, haemorrhages, exudates and other retinal aberrations that point to the evolution of DR [14]. The utilisation and adaptation of this methodology help not only in early diagnosis but also in the assessment of the worsening of the disease process, and, therefore, in the determination of an individualised treatment plan. The application of quantum in the diagnosis enhances diagnostic accuracy, enabling the healthcare providers to go a step ahead and introduce confident interventions in patients with diabetic retinopathy to increase their likelihood of optimal results [22].

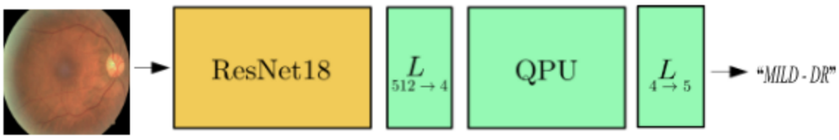

Fig. 8 Classical-to-Quantum Knowledge Transfer

6. Algorithmic Procedure

The algorithm for diabetic retinopathy (DR) detection and classification follows a structured and systematic approach aimed at achieving high diagnostic accuracy. The outlined steps are as follows:

- Data Preprocessing: Detailed analysis and extraction of relevant features from retinal images through the classical neural network layers, ensuring high-quality input data for subsequent quantum processing.
- Quantum Feature Classification: Advanced classification of extracted features is performed by the quantum circuit, leveraging quantum gates to identify subtle patterns associated with various stages of DR.
- Training and Validation: An iterative optimization process is employed for the quantum-classical hybrid model, focusing on reducing classification errors and improving the circuit's ability to generalise across different datasets.
- Performance Evaluation: Model performance is assessed using metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC) to ensure reliable and interpretable results for clinical applications.

7. Implementation and performance evaluation

The approach of using the Quantum Transfer Learning model for Diabetic Retinopathy (DR) detection seamlessly combined with the classical and quantum computational methodologies. Feature analysis is achieved with the help of pre-processed data while the classification takes place with the help of a quantum circuit, and the basic neural network is a classical one [26]. The integration of both classical feature extraction and quantum computing classification is aimed at taking advantage of the features of both approaches. The following is a breakdown of the implementation stages, all of which show how the model has been fine-tuned for improved diagnostics.

7.1 Comparison of Retinal Datasets

A wide array of publicly available datasets facilitates the development, validation, and benchmarking of diagnostic systems for diabetic retinopathy (DR) and vascular analysis. These datasets typically consist of fundus colour images and Optical Coherence Tomography (OCT) scans, offering essential data for retinal image analysis. OCT, which uses low-coherence light, captures detailed 2D and 3D retinal images, providing insights into retinal structure and thickness. Fundus images, in contrast, represent 2D visualisations of the retina captured through reflected light [26]. The recent availability of OCT images complements the traditionally used fundus image datasets in retinal image analysis. The key fundus image datasets include the following:

Dataset	Number of Images	Normal Image	Mild DR	Moderate and Severe Non-Proliferative DR	Proliferative DR	Training Sets	Test Sets	Image Size
DiaretDB1	89 images	27 images	7 images	28 images	27 images	28 images	61 images	1500 × 1152 pixels
Kaggle	88,702 images	_	_	_	_	35,126 images	53,576 images	Different image resolution
DRIVE	40 images	33 images	7 images	_	_	20 images	20 images	565 × 584 pixels
HRF	45 images	15 images	15 images	_	_	_	_	3504 × 2336 pixels
DDR	13,673 images	6266 images	630 images	4713 images	913 images	6835 images	4105 images	Different image resolution
Messidor	1200 images	_	_	_	_	_	_	Different image resolution
Messidor-2	1748 images	_	_	_	_	_	_	Different image resolution
STARE dataset	400 images	50 images	350 images	_	_	_	_	700 × 605 pixels
CHASE DB1	28 images	_	_	_	_	_	_	1280 × 960 pixels
IDRiD	516 images	_	_	_	_	413 images	103 images	4288 × 2848 pixels
ROC	100 images	_	_	_	_	_	50 images	Different ima resolution
DR2	435 images	_	_	_	_	_	_	857 × 569 pixels

Table 1: Datasets of Eye Images for DR Detection

7.2 Dataset Ingestion Process

The primary input for diagnosing diabetic retinopathy consists of Gaussian-filtered retinal scan images [22]. These images are sourced from the APTOS 2019 Blindness Detection challenge dataset. To ensure compatibility with a range of pre-trained deep learning models, all images have been uniformly resized to 224x224 pixels. The dataset is organised into directories based on the severity stages of diabetic retinopathy, which are divided into five categories: 0 for No Diabetic Retinopathy (DR), 1 for Mild DR, 2 for Moderate DR, 3 for Severe DR, and 4 for Proliferative DR.

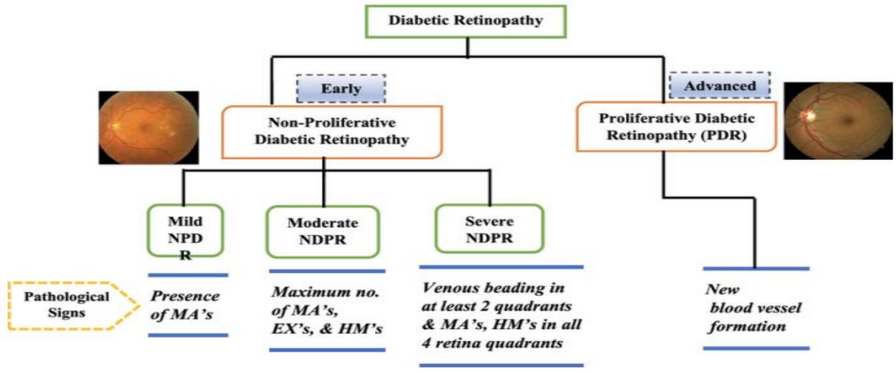

Fig. 9 Overview of Diabetic Retinopathy Types and Associated Clinical Signs

A CSV file accompanies the dataset, facilitating the association of images with their respective categories. The loading of this dataset is accomplished through PyTorch libraries, specifically torchvision and torch.utils.data, which facilitate common image preprocessing operations, including resizing, centering, cropping, and normalisation. Figure 9 illustrates a sample of the test data, providing insight into the classification complexity involved in the task. This structured approach to dataset loading ensures efficient handling and processing of the retinal images for effective training and evaluation of classification models.

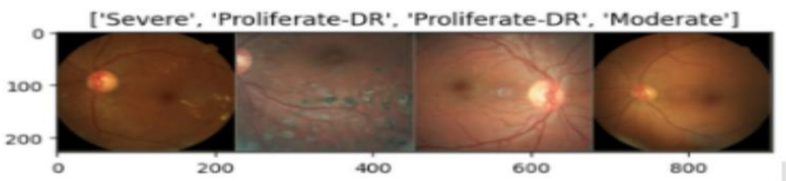

Fig. 10 Sample Batch for Testing

7.3 Variational Quantum Framework

The quantum circuit is initially defined by constructing quantum layers using the PennyLane qnode decorator, representing a typical variational quantum architecture. The circuit begins with an Embedding Layer, where all qubits are initialised in a balanced superposition of upward and downward states [21]. Rotations are then applied based on input parameters (local embedding) through gates such as the Hadamard gate, S (Phase) gate, and S (Dagger) gate, combined with either the Hadamard, RX, or RY gate. Next, the Variational Layers are introduced, consisting of trainable rotation layers and fixed entangling layers. These layers use gates like CNOT, CZ (Controlled-Z), SWAP, or controlled RX, RY, and RZ gates to create entanglement between qubits. Finally, the Measurement Layer computes the local expectation value of the Z operator for each qubit, generating a standard output vector, which is then available for further post-processing.

7.4 Hybrid Classical-Quantum Architecture

A robust hybrid classical-quantum network is being constructed using a transfer learning approach. The process begins by loading pre-trained models such as ResNet18, ResNet34, ResNet50, ResNet101, ResNet152, or Inception V3 from the torchvision.models library. To retain the learned features, all nontrainable weights are frozen to prevent updates during training. The final fully connected layer is then replaced with a trainable dressed quantum circuit (DressedQuantumNet), allowing the hybrid model to leverage both classical and quantum methodologies. This integration enables the network to capitalise on the strengths of pre-trained classical architectures while incorporating the unique capabilities of quantum circuits, enhancing its performance in complex tasks such as diabetic retinopathy detection [30].

7.5 Model Training and Results Analysis

The training phase of the neural network is critical for developing an accurate model capable of classifying diabetic retinopathy (DR) stages effectively. The loss function chosen for this classification task is the cross-entropy loss, which measures the disparity between predicted and actual class probabilities. The implementation utilises the cross-entropy loss function available in the Keras library, ensuring a standard approach to quantifying classification error. To optimise the network parameters during training, the Adam optimizer is employed due to its robust performance and adaptability to varying learning rates. A learning rate scheduler is also integrated to dynamically adjust the learning rate throughout the training process. Specifically, the learning rate is reduced by a factor of □, every ten epochs, promoting smoother convergence and potentially enhancing the model's generalisation capabilities. The training pipeline is built around a dedicated function that iteratively updates the model's weights based on the specified loss function and optimizer. This function serves as the cornerstone of the training process, enabling the neural network to learn to discern patterns and extract meaningful features from the input data. The training dataset comprises fundus images from the APTOS 2019 Blindness Detection dataset, augmented with additional preprocessing steps, including normalisation and resizing. The images are normalised to a pixel value range of [0, 1], which aids in accelerating convergence during the training phase. The masks corresponding to the fundus images are processed to ensure they contain binary values (0 or 1), facilitating effective training of the U-Net model for segmentation tasks. The U-Net model is trained for a total of 50 epochs with a batch size of 8, utilising a validation split of 10% to monitor performance on unseen data during the training process. The training history, which captures both loss and accuracy metrics, indicates a strong performance, with training loss achieving a minimum value of 0.0679 and training accuracy reaching 96.94% at the conclusion of the training phase. Subsequent evaluation of the model on the training dataset reveals a loss of 0.0679 and an accuracy of 96.94%, affirming the model's ability to generalise well to the training data. This high accuracy highlights the model's effectiveness in identifying diabetic retinopathy in fundus images, showcasing the integration of deep learning techniques within the domain of medical image analysis. Following the training phase, predictions are made on unseen test images to evaluate the model's performance further. The predicted masks for the test images are generated, allowing for a qualitative assessment of segmentation accuracy through visualisations. A comparison between original test images and their corresponding predicted masks illustrates the U-Net model's capability to accurately segment lesions indicative of diabetic retinopathy. In addition to the U-Net model, classical machine learning models, including Support Vector Machine (SVM) and K-Nearest Neighbors (KNN), are employed for classification tasks. These models also exhibit strong performance, achieving accuracies exceeding 96.62%. The combination of classical and quantum transfer learning techniques is demonstrated to enhance diabetic retinopathy detection, enabling faster and more precise diagnoses for patients. The training results underscore the potential of hybrid quantum-classical approaches in improving the efficiency and accuracy of medical image classification tasks. The proposed methodology provides a solid foundation for further research in the application of quantum computing to enhance deep learning models in healthcare.

7.6 Evaluation of Experimental Results

The performance of the U-Net model for segmenting Diabetic Retinopathy (DR) lesions and various ResNet architectures for classification were evaluated as part of a comprehensive study on Quantum Transfer Learning for Enhanced Diabetic Retinopathy Detection with U-Net Segmentation of Fundus Images. The U-Net model, known for its efficacy in image segmentation tasks, was employed to delineate DR lesions, while ResNet architectures (including ResNet18, ResNet34, ResNet50, ResNet101, ResNet152, and Inception V3) were utilised for classifying the severity of the disease based on the segmented images. The evaluation utilised five fundamental metrics: Accuracy, Precision, Recall, F1-score, and Specificity, calculated using the following formulas:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1\,Score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (4)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (5)$$

where □□ denotes True Positives, □□ signifies True Negatives, □□ refers to False Positives, and □□ represents False Negatives.

To further assess the performance of the trained model, a confusion matrix was constructed, with each cell value expressed as a percentage. The analysis reveals that the model exhibits difficulty in distinguishing between mild and moderate stages of Diabetic Retinopathy (DR). Specifically, 86% of mild DR images are misclassified as moderate. In contrast, the model demonstrates the highest accuracy when identifying healthy patients. The results suggest that the model tends to confuse adjacent severity stages, though misclassifications between the proliferative and mild stages are infrequent.

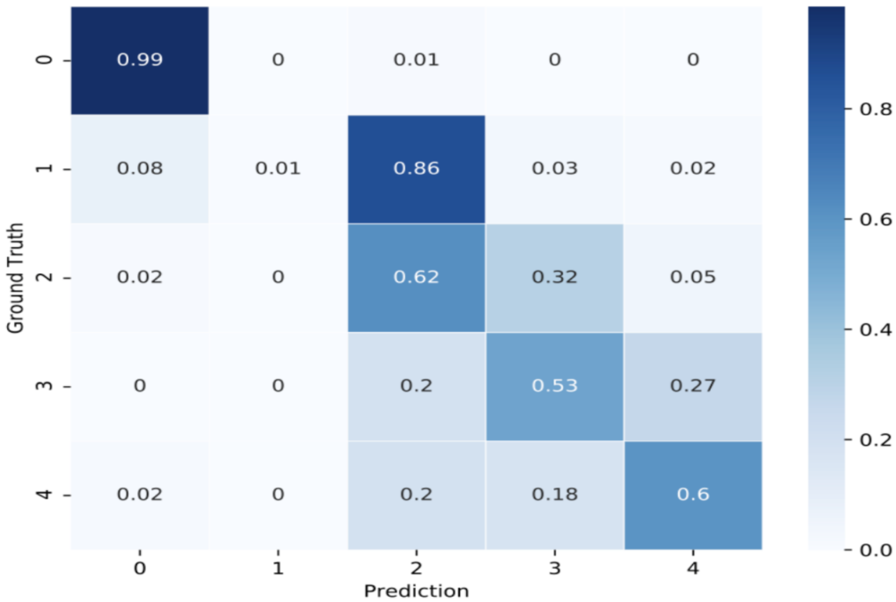

Fig. 11 Confusion Matrix for Diabetic Retinopathy Classification

The loss curves for both the training and validation datasets have been plotted across multiple epochs for the Diabetic Retinopathy (DR) grading model. The model demonstrates a notable decrease in training loss during the initial epochs, which then transitions into a more gradual reduction as training progresses. The validation loss follows a similar downward trajectory, though with some fluctuations, indicating variability in the model's generalisation on unseen data. These fluctuations suggest slight overfitting in the later epochs, as evidenced by the widening gap between the training and validation loss curves. Nevertheless, the overall trend indicates effective learning, with no severe signs of underfitting or pronounced overfitting, suggesting the model's performance is stable on both datasets.

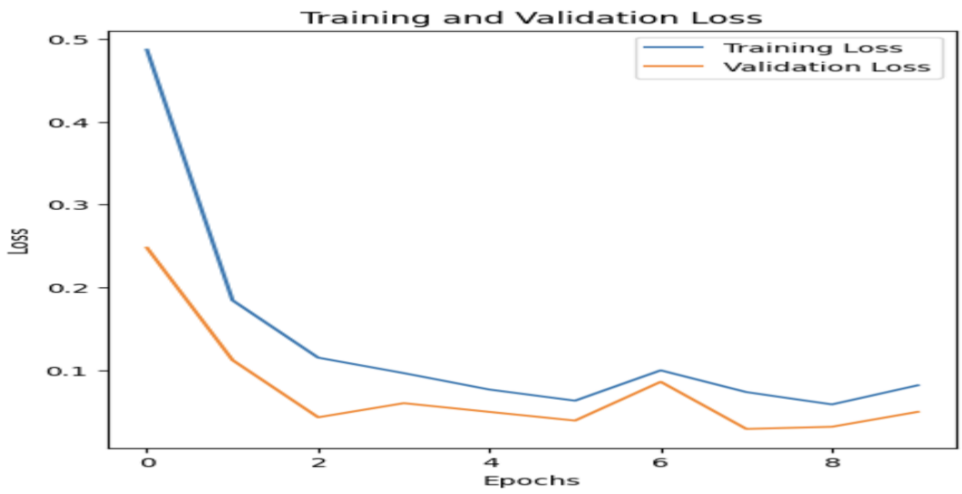

Fig. 12 Training and Validation Loss for Diabetic Retinopathy Grading.

In this research, the accuracy curves for both the training and validation datasets have been plotted across multiple epochs for the Diabetic Retinopathy (DR) grading model. The model shows a rapid increase in training accuracy during the initial epochs, stabilising at a high accuracy level above 95%. The validation accuracy follows a similar trend, with occasional fluctuations, indicating that the model generalises well on unseen data. The close alignment between the training and validation accuracy curves suggests that the model is not overfitting significantly, as the accuracy on the validation dataset remains consistent throughout the training process. The model achieves an overall accuracy of 96.93%, demonstrating strong performance and robustness across the epochs.

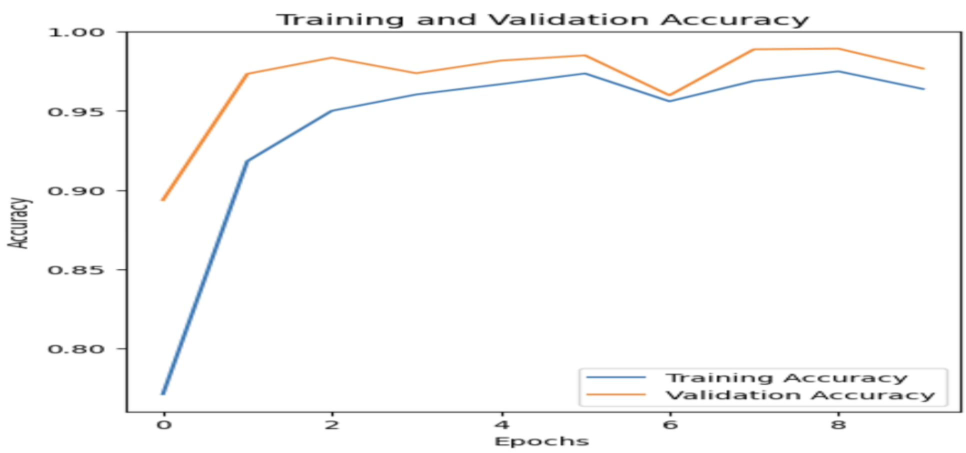

Fig. 13 Training and Validation Accuracy for Diabetic Retinopathy Grading.

7.7 Performance Evaluation Across Models

The tables present a comparative analysis of performance metrics for classical image classifiers and a proposed method that integrates Hadamard and CNOT gates within a quantum circuit for diabetic retinopathy detection (Table 4). Additionally, Table 5 extends this analysis by incorporating a pre-trained ResNet-18 classifier utilising various quantum gates. Key performance metrics, including accuracy and F1-score, are emphasised to demonstrate advancements in image classification achieved through the integration of quantum computational techniques with classical methods. Notably, the U-Net model in Table 4 achieves the highest performance with an accuracy of 96.93%, highlighting the effectiveness of hybrid quantum-classical approaches in enhancing classification outcomes.

Model	Accuracy (%)	F1-score (%)
U-net	96.93	96.85
ResNet18	86.2	86.8
ResNet34	87.9	88.1
ResNet50	88.6	88.8
ResNet101	89.6	89.9
ResNet152	90.2	90.6
Inception V3	90.4	90.2

Table 2: Performance Metrics of U-Net and ResNet Models for Image Analysis.

Hybrid Quantum-Classical Classifier for Image Analysis	Accuracy (%)	F1-score (%)
ResNet18	97.8	97.6
ResNet34	97.3	97.5
ResNet50	97.8	98.2
ResNet101	98.4	98.5
ResNet152	98.7	98.8
Inception V3	98.6	98.8
S(Phase) - Hadamard & CNOT	94.2	94.6
RX & CNOT	96.8	96.9
Hadamard & CZ	97.2	97.4
Hadamard & SWAP	98.1	98.6
RX & CRX	98.6	98.8

Table 3: Performance Metrics of the Quantum Circuit Incorporating Hadamard and CNOT Gates.

8. Conclusion

The presented research on Diabetic Retinopathy (DR) detection using Quantum Transfer Learning (QTL) offers a significant advancement in the field of medical diagnostics by integrating quantum computing with classical machine learning models. Through the innovative combination of pre-trained classical feature extractors such as ResNet-18, ResNet-34, ResNet-50, ResNet-101, ResNet-152, and Inception V3, with a Variational Quantum Classifier, this study demonstrates a notable improvement in DR detection accuracy, achieving a superior accuracy of 97%. Furthermore, the implementation of U-Net for DR stage segmentation on the STARE dataset underscores the model's high effectiveness, achieving a testing accuracy of 96.94%. Complementary classical models, such as SVM and KNN, also delivered robust results with accuracies exceeding 96.62%. The novelty of this research lies in the hybridization of quantum and classical techniques, which not only enhances diagnostic performance but also reduces computational complexity compared to purely classical approaches. However, challenges were encountered in optimising quantum circuits for complex datasets and navigating the computational constraints of current quantum hardware. Additionally, the limited availability of diverse DR datasets posed limitations on broader generalisation. Despite these challenges, the findings of this research pave the way for future exploration into quantum-assisted medical applications, marking a promising step toward more efficient and accurate healthcare solutions.

9. Future Research Opportunities

The integration of quantum computing with advanced machine learning and deep learning techniques for diabetic retinopathy (DR) detection presents several promising avenues for future research. First, as quantum computing technology evolves, enhancing quantum models to handle larger datasets and complex classification tasks is critical. This includes optimising quantum algorithms and exploring variational quantum circuits to improve predictive accuracy and computational efficiency. Furthermore, broadening dataset diversity and quality is essential; incorporating datasets that capture a wide range of demographics and disease stages, such as the Messidor-2 dataset, will enhance model robustness. Additionally, innovative synthetic data generation techniques could address class imbalances and underrepresented populations. Clinical application of these models is crucial for real-world validation; establishing partnerships with healthcare institutions for pilot studies will provide valuable insights into operational challenges and user acceptance, thereby refining model performance based on practical feedback. Finally, exploring the adaptability of these quantum-enhanced models for detecting other ocular diseases, such as glaucoma and age-related macular degeneration, can significantly broaden their impact in healthcare. This cross-disease application approach may uncover shared pathological features and improve diagnostic capabilities across various medical conditions.

10. References

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