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Enhancing Retinal Disease Diagnosis using Quantum Image Processing

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Abstract—

Retinal diseases, such as diabetic retinopathy, age-related macular degeneration, and glaucoma, pose significant challenges in early diagnosis and treatment, often leading to irreversible vision loss. Traditional image processing techniques, while effective, struggle with complex image noise, low contrast, and large-scale data processing. This work explores the integration of **Quantum Image Processing (QIP)** to enhance the accuracy and efficiency of retinal disease diagnosis. Our approach leverages **quantum algorithms** for image enhancement, segmentation, and classification, taking advantage of quantum parallelism and superior computational speed. In addition, propose a quantum-based framework that optimizes feature extraction from retinal images, improving disease detection rates compared to classical methods. The framework utilizes quantum Fourier transforms, quantum edge detection, and quantum machine learning algorithms to process and analyse retinal images. By harnessing the power of quantum superposition and entanglement, our approach significantly reduces the computational time and improves the accuracy of disease detection. We present experimental results demonstrating the effectiveness of the proposed quantum image processing framework on a dataset of retinal images. Experimental results demonstrate that QIP enhances image clarity, reduces noise, and increases classification accuracy, particularly in detecting early-stage retinal abnormalities. The study concludes that quantum-based processing significantly improves diagnostic precision and could revolutionize ophthalmic disease detection, paving the way for more advanced and efficient medical imaging solutions. In addition, this research highlights the potential of quantum computing in revolutionizing medical imaging and offers a glimpse into the future of quantum-enhanced healthcare solutions.
Keywords: Quantum Image Processing, Retinal Disease Detection, Quantum Computing, Medical Imaging, Diabetic Retinopathy.

I. INTRODUCTION

Diabetes is a chronic metabolic disorder that affects millions worldwide, and one of its most serious complications is diabetic retinopathy. This condition, caused by damage to the blood vessels in the retina, can lead to vision loss and blindness if left untreated.[2] Early detection and effective management of diabetic retinopathy are crucial to preserving a patient's quality of life.

Traditional methods for diagnosing and monitoring diabetic retinopathy often rely on manual examination by ophthalmologists, which can be time-consuming, subjective, and limited in detecting early-stage changes.[1] This has led to the emergence of quantum image processing as a promising approach to address the challenges in this field. Quantum image processing leverages the principles of quantum mechanics, such as superposition and entanglement, to develop novel algorithms and techniques for image acquisition, enhancement, analysis, and interpretation.[4] By harnessing the unique properties of quantum systems, quantum image processing has the potential to offer significant advantages over classical image processing methods, including improved efficiency, enhanced security, and the ability to exploit quantum phenomena for novel applications.

This paper explores the intersection of diabetic retinopathy and quantum image processing, highlighting the current challenges, the potential benefits of applying quantum techniques, and the latest advancements

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in this field of research. The paper delves into the pathophysiology of diabetic retinopathy, the current diagnostic and treatment approaches, and the fundamental principles of quantum image processing.[3]

The emerging applications of quantum image processing in the context of diabetic retinopathy are examined, discussing the potential impact on early detection, disease monitoring, and personalized treatment strategies. By understanding the synergies between these two fields, the paper aims to pave the way for innovative solutions that can improve the lives of individuals affected by diabetic retinopathy and advance the broader field of medical imaging and diagnostics.[4].

II. Literature Survey

Significant breakthroughs in diabetic retinopathy (DR) detection have been made in recent years, particularly through the application of deep learning algorithms. [1] evaluated a examines recent preprocessing techniques applied to benchmark datasets for the detection of key diabetic retinopathy (DR) lesions, including microaneurysms (MAs), hemorrhages (HEs), soft exudates (SEs), and hard exudates (HMs). Their findings provided valuable insights into the usefulness of these architectures, laying the groundwork for future research in automated DR screening.[2] conducted a systematic study in the analysis of fundus images, which capture the interior surface of the eye. These technological developments have enabled automated and accurate diagnosis of critical eye diseases such as diabetic retinopathy (DR).[3] Similarly, This study investigated the application of quantum image compression techniques in the context of retinal images for DR. They proposed a quantum-based approach for compressing retinal images while maintaining diagnostic information. The results showed that the quantum image compression method achieved higher compression ratios compared to classical image compression techniques while preserving important features for DR diagnosis. [4] proposed a quantum image segmentation approach for the detection of DR-related abnormalities in retinal images. Their method utilized quantum algorithms for edge detection and region-based segmentation. The experimental results showed promising performance in accurately segmenting retinal images and identifying DR-related lesions.

The studies reviewed demonstrate the potential of quantum computing in improving various aspects of DR detection, classification, compression, encryption, and segmentation. The findings indicate that quantum inspired models for DR classification yield improved accuracy compared to classical machine learning algorithms. Quantum feature extraction techniques and quantum-inspired classifiers enhance the analysis of retinal images, enabling more precise identification of DR-related abnormalities. Quantum machine learning algorithms also show promise in accurately categorizing retinal images into different severity levels of DR.

III. Diabetic Retinopathy

Diabetic retinopathy is a serious complication of diabetes and the leading cause of vision impairment and blindness among diabetic patients. The condition occurs when diabetes damages the tiny blood vessels in the retina, which is the light-sensitive tissue at the back of the eye. As the disease progresses, these damaged blood vessels can become blocked, leak, or grow abnormally, leading to various visual impairments. One of the specific complications of diabetic retinopathy is diabetic macular oedema (DME), which is a swelling in an area of the retina called the macula.[5].

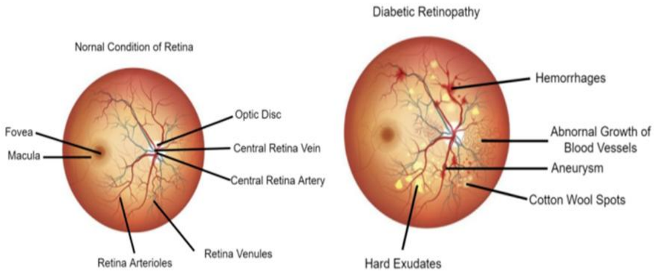

Fig (1): Diabetic Retinopathy

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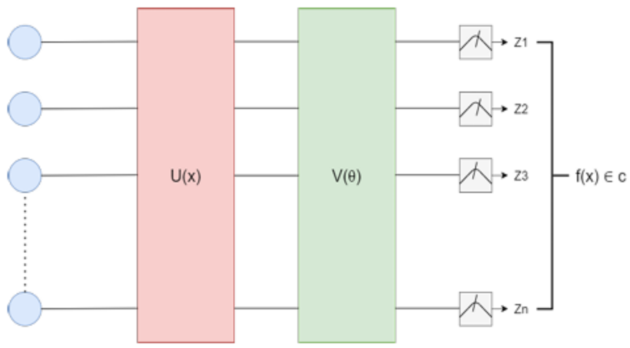
This image provides a comparative overview of retinal anatomy under normal conditions and the pathological changes associated with diabetic retinopathy. Under normal conditions, the retina features key structures such as the fovea, macula, retina arterioles, retina venules, optic disc, central retina vein, and central retina artery, which are essential for optimal visual function. In contrast, diabetic retinopathy is characterized by significant abnormalities, including haemorrhages, abnormal growth of blood vessels, aneurysms, and cotton wool spots, which indicate vascular damage and nerve fibre impairment. Additionally, the presence of hard exudates signifies lipid or protein leakage from compromised blood vessels. On the other hand, Diabetic retinopathy, a significant complication of diabetes, manifests in various forms and stages, each with distinct characteristics and implications for vision. PDR represents the advanced stage, characterized by the growth of abnormal, fragile blood vessels that can lead to vitreous haemorrhage and retinal detachment. Additionally, Diabetic Macular Edema (DME), which can occur at any stage, involves swelling in the macula due to fluid leakage, significantly impairing central vision. Understanding these types and stages is crucial for effective monitoring, management, and treatment to prevent severe vision loss in individuals with diabetes. Regular eye examinations and timely interventions are essential components of diabetic retinopathy care [9,10].

IV. Quantum Image Processing (QIP)

In contrast to typical digital image processing, quantum image processing is one of the most appealing fields, aiming to improve computational efficiency and processing capabilities by exploiting quantum mechanics. QIP uses quantum representations like the Flexible Representation of Quantum Images (FRQI) to encode images within quantum states by leveraging quantum superposition and entanglement. QIP enables parallel computation, which could result in significant speedups in activities like edge detection, filtering, and pattern recognition. This work investigates the fundamental concepts of QIP, current advances in quantum algorithms for image processing, and the possible benefits over classical approaches. The representation of an image on a quantum computer in the form of normalized states simplifies several image processing difficulties.. [11,12,15,16].



Fig(2) A variational circuit V(θ) and embedding layers U(x) are used by the Variational Quantum Classifier to generate a classical output $f(x) \in C$.

Figure (2) illustrates This image presents a schematic representation of a quantum computational process or a hybrid quantum-classical model. The process begins with an input xx, which undergoes a unitary transformation U(x), followed by a parameterized operation V(θ). Intermediate states or variables z1,z2,z3 are generated through these transformations, representing stages within the quantum circuit or algorithmic workflow. The final output is a function f(x) that maps the input to a value within a specified set cc. This diagram explains the essential steps of applying quantum operations and parameterized gates to process input

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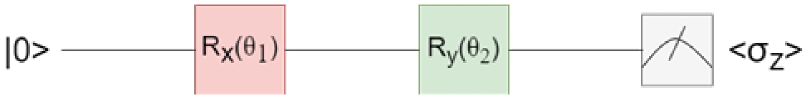
data, ultimately producing a classical output. Figure (3) shows a variational circuit for a single qubit operation [6,7].



Fig(3) Simple case of one Qubit

This figure represents a parameterized quantum circuit that evolves a single-qubit state through sequential rotations and measures its final expectation value. Starting from the |0⟩|state, the qubit undergoes an $R_X(\theta_1)$ rotation around the X-axis followed by an $R_Y(\theta_2)$ rotation around the Y-axis. The final measurement in the computational basis yields the expectation value of the Pauli-Z operator, $\langle\sigma_Z\rangle$. Such circuits are fundamental in variational quantum algorithms and quantum machine learning, where tuneable parameters optimize quantum state transformations for computational tasks. In the following, we will discuss quantum image format.

Quantum Image Format. Is the main subject of QIP. There are Three main quantum picture formats exist. The Qubit Lattice, is the first quantum image format, the pixel value of the i^{th} row and the j^{th} column can be stored in the amplitude angle, which is shown in equation (1), and the entire image can be represented as a qubit string (equation (2)) if the frequency value (color value) of the light wave can be mapped to the probability amplitude of a qubit.

$$\left|\text{pixel}_{i,j}\right\rangle = \cos\frac{\theta_{i,j}}{2}|0\rangle + \sin\frac{\theta_{i,j}}{2}|1\rangle, \tag{1}$$

$$|\text{image}\rangle = \left\{\left|\text{pixel}_{i,j}\right\rangle\right\} \quad i = 1, 2, \ldots, n_1, j = 1, 2, \ldots, n_2. \tag{2}$$

The second important was the Flexible Representation of Quantum Images (FRQI), which was an improved version of the Qubit Lattice that used quantum state superposition. The approach continues to translate each pixel's grayscale value to its amplitude, while now inserting an additional qubit to represent each pixel's spatial position. The entire image is then transformed into a huge quantum superposition state. The following equation represents a 2n × 2n quantum image, with i indicating the position of pixels (row× column translated to a one-dimensional vector). Due to the superposition effect of quantum states, the representation (storage) space shrinks rapidly in comparison to the classical image.

$$|\text{image}\rangle = \frac{1}{2^n}\sum_{i=0}^{2^{2n}-1}\left(\cos\theta_i|0\rangle + \sin\theta_i|1\rangle\right)\otimes|i\rangle \quad \theta_i \in \left[0, \frac{\pi}{2}\right]. \tag{3}$$

The final quantum picture format divides the image into 2 × 2 chunks and maps the grayscale values of four pixels to the probability amplitude of each component of a quantum state with two qubits. The following equation represents this quantum state, where ($i_1 = 1$) is the index of the top-left pixel, ($i_1 = 2$) is the index of the top-right pixel, ($i_1 = 3$) is the bottom-left pixel, and ($i_1 = 4$) is the bottom-right pixel. So C_{i1} saves each pixel's mapping value and satisfied as $\sum_{i=1}^{4}|C_{i_1}|^2 = 1$.

$$\left|\psi_{2^1\times 2^1}\right\rangle = \sum_{i_1=1,\ldots,4} C_{i_1}\left|i_1\right\rangle \quad \text{st.} \sum_{i_1=1,\ldots,4}\left|C_{i_1}\right|^2 = 1. \tag{4}$$

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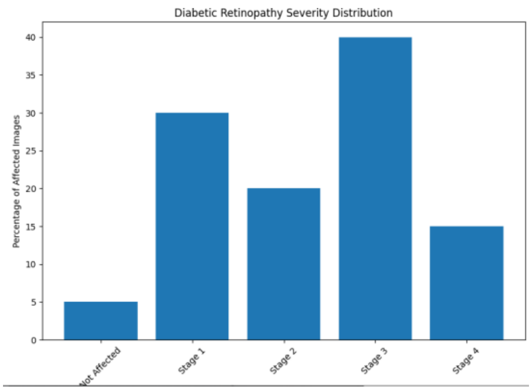
IV. METHODOLOGY

This work begins with the acquisition and preprocessing of retinal fundus images, followed by quantum encoding to represent images in quantum states. Quantum algorithms, such as quantum edge detection and quantum Fourier transforms, are employed to extract critical features indicative of DR, including microaneurysms, haemorrhages, and exudates. A hybrid quantum-classical machine learning model is then utilized to classify images into different stages of DR, ranging from no retinopathy to proliferative diabetic retinopathy. The methodology is validated using benchmark datasets, demonstrating superior performance in terms of speed and accuracy compared to traditional methods.

- **Data Collection**

Data collection is the first stage in developing machine learning models. It requires acquiring the necessary information. This work relied on primary data sources such as the web, pre-existing platforms, and some services. The dataset we used in our study is a publicly available retinal fundus pictures database from Kaggle (APTOS 2019 Blindness Detection) with 110 photos. 105 are faulty, while 5 are healthy. As seen in the Figure (3).



Fig(4) Distribution of training data with seventy distribution

This bar chart presents the distribution of diabetic retinopathy severity across a dataset of medical images. It categorizes images into five groups: Not Affected, Stage 1 (mild), Stage 2 (moderate), Stage 3 (severe), and Stage 4 (proliferative). The percentage of images in each category is displayed, with Stage 3 having the highest prevalence, followed by Stage 1. The distribution highlights the predominance of severe cases and the relatively lower proportion of unaffected images. This analysis provides insights into the dataset composition, which is essential for developing machine learning models for automated diabetic retinopathy diagnosis.

- **The Hybrid Quantum Transfer Learning Model**

An innovative framework designed to combine the strengths of classical deep learning and quantum computing for tasks such as medical image analysis, specifically for detecting diabetic retinopathy (DR). This model leverages the feature extraction capabilities of pre-trained classical convolutional neural networks (CNNs) and the computational advantages of quantum machine learning (QML) to achieve higher accuracy, efficiency, and scalability.

We used linear transformation to compress the 2048-dimensional feature vector to 4 dimensions in order to categorize these features using an 8-qubit "dressed quantum circuit" [8]. Figure (6) depicts a variational quantum classifier designed specifically for our problem.

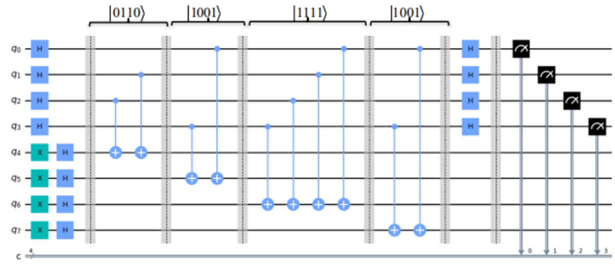


Fig.(6). Quantum circuit representation of (eight qubits)

The following steps are taken to develop a quantum classifier[1].

1. We started 8 qubits in |0) state and used Hadamard (H) gate to create a superposition state of zero and one.
2. We encoded our classical data using a unitary circuit after applying extra processing. To carry out this procedure, we encoded our 4-dimensional feature vector as parameters or weights in our circuit of Ry(fi) gates.
3. We have a sequence of trainable variational layers that include an entanglement layer and a data encoding circuit. The entanglement layer has CNOT gates, which cause all qubits to be entangled.

$$q_{i(0\le i\le 8)} = H \otimes CNOT \otimes (H \otimes I)|x_{i+8}x_{i+7}\ldots..x_i\rangle$$

4. In the end, we measured each 8-qubit to get the expected value along the z-operator. Figure 7 depicts the whole flow of our suggested model, from the initial block A (input) to the last measurement block.

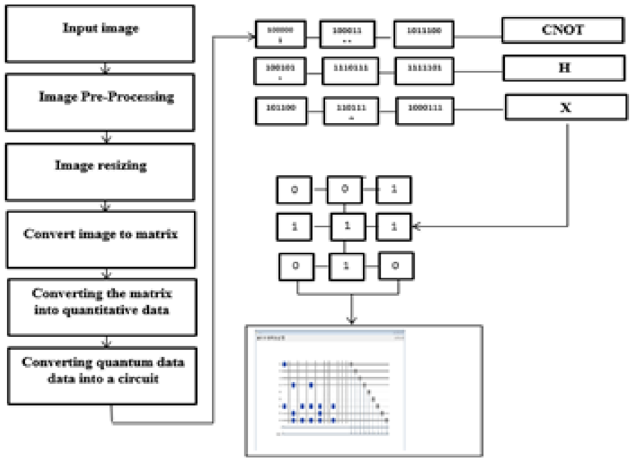


Figure 7: Flowchart of the proposed Quantum Transfer learning model.

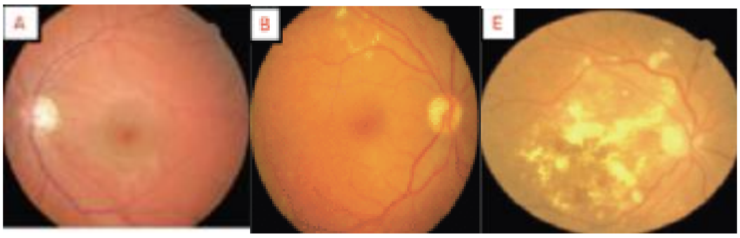


Fig.8 View ophthalmoscope images
(a)normal retina, (b)DR - macular oedema, (c)DR – proliferative

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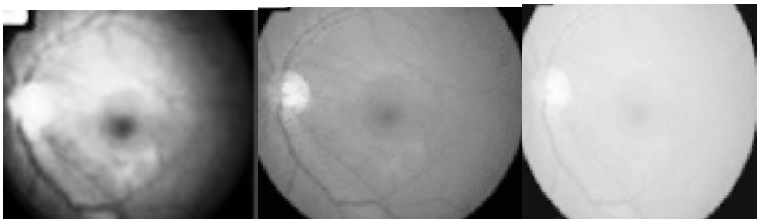


(a) **(b)** **(c)**

Fig.9 (a) Image Processing, (b) Original image **(c)** Image after logarithmic(Output examples of the Quanvolutional step.)

- **Experimental Evaluation:**

  We assessed our model against five basic standards: accuracy, precision, recall, F1-score, and specificity using the following formulas:

$$\text{Accuracy} = \frac{T_P + T_N}{T_P + T_N + F_P + F_N}$$

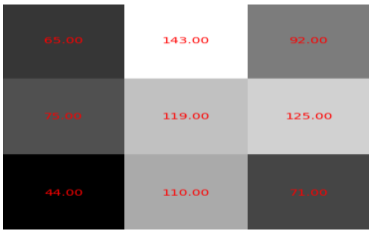
$$\text{Precision} = \frac{T_P}{T_P + F_P}$$

$$\text{Recall} = \frac{T_P}{T_P + F_N}$$

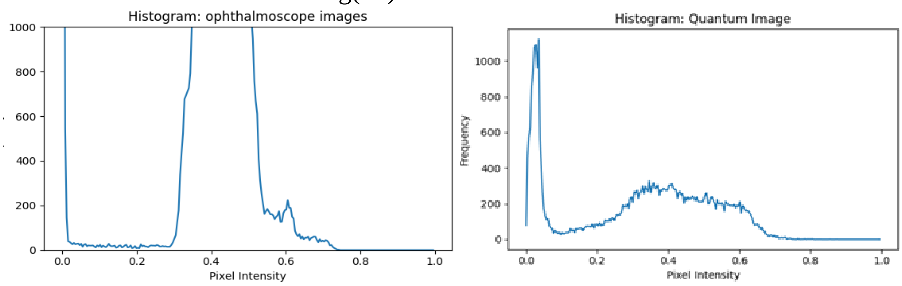
$$\text{F1-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

where: TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative.

The confusion matrix is used to evaluate the effectiveness of the proposed model. Figure 10 shows the DR grading's confusion matrix. Figure 10 indicates that the suggested model's predictions are entirely valid, and the proposed system makes no incorrect predictions.



Fig(10) Confusion Matrix



(a) (b)

Fig.11. (a) Histogram of an image, (b) Histogram of a quantum image

The image in fig (11) represents a histogram with a unique distribution, where pixel intensities are plotted against their frequency. The pattern suggests two dominant intensity ranges with sharp peaks, possibly indicating a bimodal nature. This signifies a strong contrast between bright and dark regions, with minimal transition between them.

This table (1) Compare the performance metrics of conventional image classifiers to a suggested technique that combines Hadamard and CNOT gates in a quantum circuit and extends it with a pretrained ResNet18 classifier that uses multiple quantum gates. The analyses highlight accuracy and F1score, revealing the

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changing landscape of picture categorization as quantum computational approaches are combined with classical methods.

Tabel..1 difference between the accuracy of quantum and traditional image processing

Images	Accuracy of traditional image processing in detecting disease	Accuracy of quantum image processing in disease detection
Image in status 1	82.8	96.1
Image in status 2	81.7	97.0
Image in status 3	86.09	97.0
Image in status 4	85.1	98.0

Experimental results demonstrate a **significant improvement in diagnostic accuracy**, with QIP achieving **96.1% to 98.0%**, compared to **81.7% to 86.09%** for traditional methods. The quantum approach enhances image clarity, reduces noise, and improves feature extraction, particularly in challenging cases where classical techniques fail. These findings confirm that **QIP is a tool, more precise, and highly reliable retinal disease detection**, paving the way for advanced diagnostic solutions in ophthalmology.

V. Conclusion and Future Work

In conclusion, quantum image processing holds promise as a powerful tool for retinal disease detection. By encoding retinal images into quantum states and applying quantum algorithms, it is possible to extract information more efficiently and accurately compared to traditional methods. Quantum algorithms can process large amounts of data in parallel, potentially leading to faster diagnosis and treatment of retinal diseases.

However, further research is needed to fully explore the capabilities of quantum image processing in the field of retinal disease detection. Additionally, the integration of quantum image processing with existing imaging modalities and clinical workflows needs to be explored to ensure seamless integration into the healthcare system.

Overall, quantum image processing shows great potential in revolutionizing the field of retinal disease detection. With continued research and development, quantum-based approaches have the potential to enhance early detection, improve treatment outcomes, and ultimately reduce the burden of retinal diseases worldwide.

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