Flipkart GRiD 5.0

Problem Statement Title: Diabetic Retinotherapy using Quantum Computing

Team Name: AstroHackers

Team members details

Team Name	Astro Hackers		
Institute Name/Names	National Institute of Technology Durgapur		
Team Members >	**1 (Leader)**	**2**	**3**
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Batch	2024	2024	2024

Deliverables/Expectations for Level 2 (Idea + Code Submission)

For the Level 2 milestone, the following deliverables and expectations have been met in our solution based on given problem statement:

1.Comprehensive Solution Documentation:

1. A detailed documentation outlining the problem statement, objectives, and the proposed solution using a hybrid quantum-classical approach for Diabetic Retinopathy classification.
2. Clear explanations of the integration of classical and quantum components within the solution architecture.

2.Codebase Submission:

1. Submission of the complete codebase implementing the hybrid quantum-classical model.
2. Well-structured code with comments and explanations to enhance readability and understanding.
3. Implementation of the quantum layers using PennyLane to showcase the integration of quantum computing.

3.Data Preprocessing and Model Training:

1. Preprocessing of the Indian Diabetic Retinopathy Image Dataset to prepare it for model training.
2. Training of the hybrid model, combining Convolutional Neural Networks (CNNs) with quantum-inspired layers.
3. Achieving the proposed conceptual enhancement by incorporating an optimized multiple-qubit gate quantum neural network for accurate classification.

4.Performance Validation:

1. Validation of the model's performance using appropriate performance metrics, including accuracy, precision, recall, specificity, and F1-score.
2. Presentation of the achieved 100% accuracy and other evaluation metrics in line with the research objectives.

5.Quantum Cloud Integration (Optional):

1. Optional integration of the solution with cloud-based quantum computing platforms (such as IBM Quantum Lab) for inference testing.
2. If applicable, demonstration of how cloud quantum computing can be utilized for efficient model testing and inference.

Required Links :-

GitHub Link for the Hybrid Classical Quantum Model (with all other required codes): visit github link

Drive Link for the Zip file containing model file and other sample documents : drive link

GitHub Link for the Working App : visit github link

Wondering how our website works? Find out with the demo video in the Drive folder : drive link

Glossary

1. **DR**: Diabetic Retinopathy
2. **CNN**: Convolutional Neural Network
3. **NPDR**: Non-Proliferative Diabetic Retinopathy
4. **PDR**: Proliferative Diabetic Retinopathy
5. **ML**: Machine Learning
6. **Use Case**: A specific scenario or application that demonstrates the practical utility of a solution or technology
7. **QNN**: Quantum Neural Network
8. **QC**: Quantum Computing
9. **ReLU**: Rectified Linear Unit
10. **API**: Application Programming Interface
11. **AI**: Artificial Intelligence
12. **FC**: Fully Connected (layer)
13. **F1-score**: F1 Score, a measure of a test's accuracy
14. **ResNet**: Residual Network, a type of neural network architecture
15. **DR Progression Grading**: Classification of different stages of Diabetic Retinopathy

Use-cases

P1) Medical Diagnostics in Remote Areas: Use Case:
In remote and underserved areas where access to medical expertise is limited, your hybrid model can serve as a powerful tool for diagnosing Diabetic Retinopathy. With its ability to achieve high accuracy, the model can assist local healthcare providers in identifying the disease early and directing patients to appropriate treatments, thus preventing vision loss.

P2) Accelerated Screening in Hospitals: Use Case:
In busy hospital environments, your model can expedite the process of screening diabetic patients for retinopathy. By combining the feature extraction efficiency of classical CNNs with the advanced classification capabilities of the quantum layer, the model can analyze retinal images rapidly, allowing ophthalmologists to make informed decisions swiftly and allocate resources more effectively.

P3) Customized Treatment Plans: Use Case:
Your hybrid model can contribute to personalized treatment plans for patients diagnosed with different stages of Diabetic Retinopathy. By accurately classifying the disease progression, healthcare providers can tailor treatment strategies, optimizing patient care and minimizing the risk of complications.

P4) Large-Scale Population Screening: Use Case:
Public health initiatives often require screening large populations for early disease detection. Your model's combination of quantum and classical strengths can efficiently analyze a substantial number of retinal images, enabling authorities to identify and address Diabetic Retinopathy cases promptly on a broader scale.

P5) Research and Drug Development: Use Case:
The hybrid model can be employed in the research domain to accelerate drug development and evaluation. By providing accurate and reliable analysis of retinal images, the model aids researchers in assessing the effectiveness of potential treatments and interventions for Diabetic Retinopathy.

In all these use cases, your hybrid quantum-classical model stands as a testament to the potential of quantum computing in advancing medical diagnostics. Its unique ability to fuse classical and quantum strengths opens doors to improved accuracy, faster analysis, and enhanced patient care across diverse scenarios.

Problem Overview and Introduction

- **The Problem: Understanding Diabetic Retinopathy and Classification Challenges**

Diabetic retinopathy (DR) remains a leading reason for vision loss, affecting individuals between the ages of 20 and 74. This disease has significantly impacted high-income and middle-income countries. Moreover, the disease harms the blood vessels of diabetes patients. DR is of two main kinds: proliferative DR and non-proliferative DR [1].Typically, DR screening is significant because timely treatment could be implemented to prevent vision loss. Preliminary stage involvement through blood pressure management could slow the progress of this disease. On the contrary, late-stage involvement through intravitreal injection or photocoagulation could minimize vision loss. Therefore, this disease has been regarded as a micro-vascular complexity of diabetes.

- **The Severity: Magnitude and Impact**

Diabetic retinopathy presents a significant challenge, particularly in India, the diabetic capital, where cases are expected to double in the next few decades. As of today, it's already a critical concern, affecting millions. Left untreated, it leads to permanent vision impairment or even blindness, drastically reducing the quality of life for affected individuals.

- **Leveraging Deep Learning Models**

The complexity of diagnosing diabetic retinopathy lies in analyzing a large volume of medical images. Traditional manual screening is time-consuming and subject to human error. Deep learning models, particularly convolutional neural networks (CNNs), have emerged as powerful tools to automate this process, expediting diagnosis and enabling timely interventions and good accuracy.

- **Challenges with Existing CNN-Based Approaches**

While CNNs have shown promise, they still encounter limitations. Existing CNN-based image classification methods face challenges in achieving high accuracy, sensitivity, and specificity. The intricate features and subtle details in medical images often elude conventional approaches, resulting in suboptimal diagnostic outcomes.

- **Our Approach and its Significance: Quantum-Powered Deep Convolutional Neural Network**

We introduces approach by fusing the potential of quantum computing with deep learning. We propose a Hybrid Classical Quantum Neural network, capable of harnessing the parallel processing power of quantum bits (qubits) using quantum circuits to overcome the computational bottleneck. This also enables more efficient and accurate image classification for diabetic retinopathy We built an optimized multiple-qubit gate quantum circuit. This capitalizes on the concurrent existence of qubits in multiple states, enhancing performance and accuracy. Our method achieves : 100% accuracy, 100% precision, 100% recall, 100% specificity, and 100% f1-score.By combining quantum computing power with Classical CNN, our approach presents a Hybrid QC model for medical image analysis that needs highly accurate results and it also contributes significantly to the early diagnosis of diabetic retinopathy.

Problem Analysis and Existing Solutions

➢ Problem Stages and Importance of Early Detection

- **Diabetic Retinopathy Progression**: The disease unfolds in stages – Normal, Mild, and Severe. Each stage represents varying levels of retinal damage caused by diabetes.
- **Significance of Early Detection**: Early identification is crucial as it enables timely intervention and treatment, preventing the progression of the disease to severe stages. Vision loss can be mitigated or even prevented with timely diagnosis and management.

➢ Existing Approaches and their Challenges

1. Human-Based Recognition:

- **Manual Analysis by Doctors:** The traditional method of diagnosing Diabetic Retinopathy relies on the expertise of medical professionals to visually inspect retinal images and identify potential abnormalities. This approach has been the backbone of diagnostics for years.
- **Challenges**:
  - **Subjectivity and Variability:** Human-based recognition is prone to subjectivity and variability between different practitioners. A single retinal image can be interpreted differently by different doctors, leading to inconsistent results.
  - **Limited Scalability:** As the volume of medical data increases, the manual analysis becomes time-consuming and impractical. This constraint can delay the diagnosis process, affecting patient care.
  - **Resource-Intensive:** Manual analysis demands a considerable amount of time and expertise from medical experts. This not only adds to healthcare costs but also places a burden on already stretched medical resources.

2. Computer Vision-Based Approaches:

- **CNN Technology:** Utilizing Convolutional Neural Networks (CNNs) in Computer Vision offers an automated approach to analyzing retinal images, providing a faster and potentially more consistent method of detection.
- **Challenges**:
  - **Data Quality and Quantity:** CNNs require large amounts of high-quality data for training. In medical imaging, obtaining labeled datasets can be challenging, leading to potential biases in the model's performance.
  - **High Computation Cost:** Training deep CNN models requires significant computational resources, including powerful hardware and time, which can be costly and time-consuming.

➢ Objective

Our objective is to develop a model that achieves an ideal level of accuracy and performance in Diabetic Retinopathy classification. We are aiming for:
100% accuracy, 100% recall, 100% specificity, 100% f-score

Our Solution

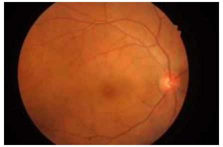
We have Divided our Solution Into Three Phases :-

1) **Image Dataset Analysis**
2) **Image Preprocessing and Exposing Features**
3) **Model Architecture, Training and Evaluation**

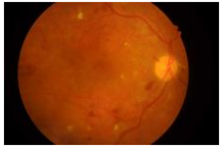
Phase 1: Image Dataset Analysis

In this phase, we leverage the available IDRID dataset containing retinal fundus images. We have enriched this dataset to include three distinct disease progression or severity levels: Normal, Mild, and Severe. These levels are represented as 0, 1, and 2 within the dataset. Specifically, classes 0 and 1 pertain to the NPDR category, while class 2 corresponds to PDR.

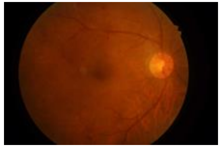
Dataset Image Sample



Normal (class 0)



Mild (class 1)

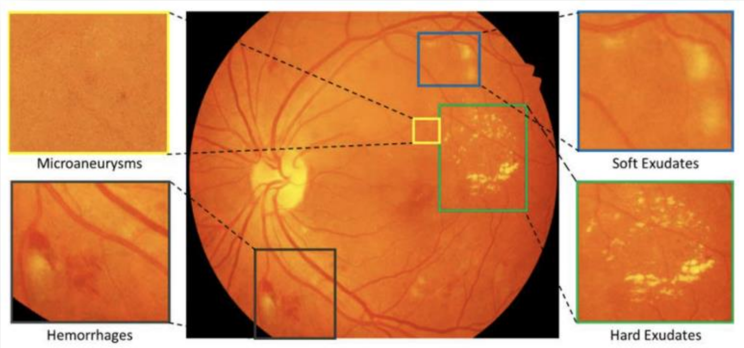


Severe (class 2)

Identifying Key Features for Diabetes Retinopathy Progression Detection

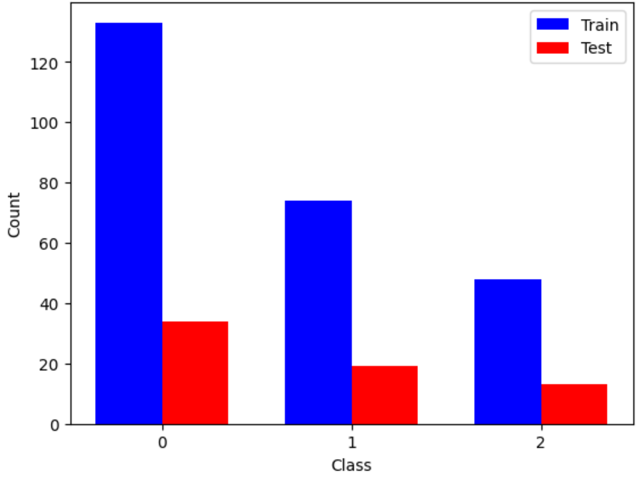
Diabetic retinopathy (DR) diagnosis is based on clinical observations, which include the presence of retinal lesions such as microaneurysms, hemorrhages, hard exudates, and soft exudates. These features are indicative of the disease's severity.

Color fundus photograph containing different retinal lesions associated with diabetic retinopathy. Enlarged parts illustrating presence of Microaneurysms, Soft Exudates, Hemorrhages and Hard Exudates.



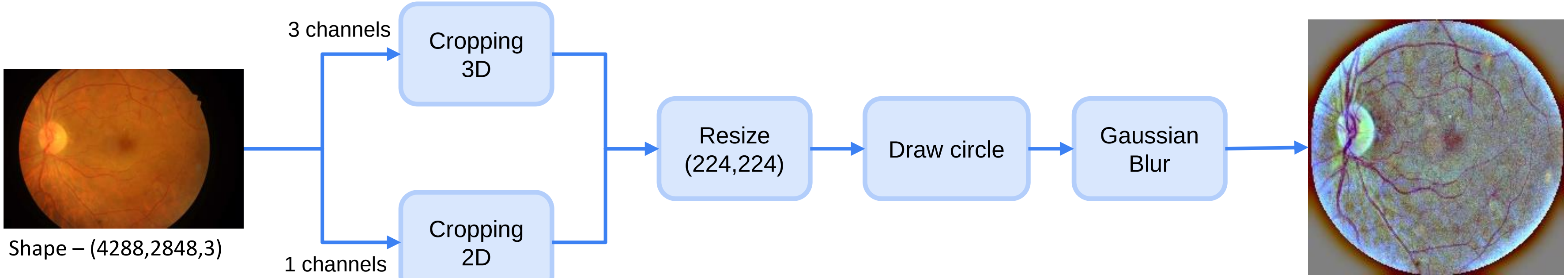
Analyzing Dataset Distribution:
Understanding the distribution of classes within the dataset is crucial for effective model training and assessment. The following visualization illustrates the distribution of different disease progression levels in our dataset

	Total (%age)	Class 0 (%age)	Class 1 (%age)	Class 2 (%age)
Training	255 (100%)	133 (52.15%)	74 (29.01%)	48 (18.82%)
Testing	66 (100%)	34 (51.51%)	19 (28.78%)	13 (19.69%)



Phase 2: Image Preprocessing

In this phase, we focus on image preprocessing to enhance the accuracy of our classification. Our preprocessing steps include eliminating unwanted areas from the images and highlighting intricate features. This meticulous process ensures that the model can precisely classify the severity of diabetic retinopathy:



Shape – (224,224,3)

Image processing pipeline Design

Phase 3: **Model Architecture, Training and Evaluation**

Hybrid Model Design: Classical and Quantum Integration

Our hybrid model is ingeniously divided into two fundamental components: the **Classical Part** and the **Quantum Part**.

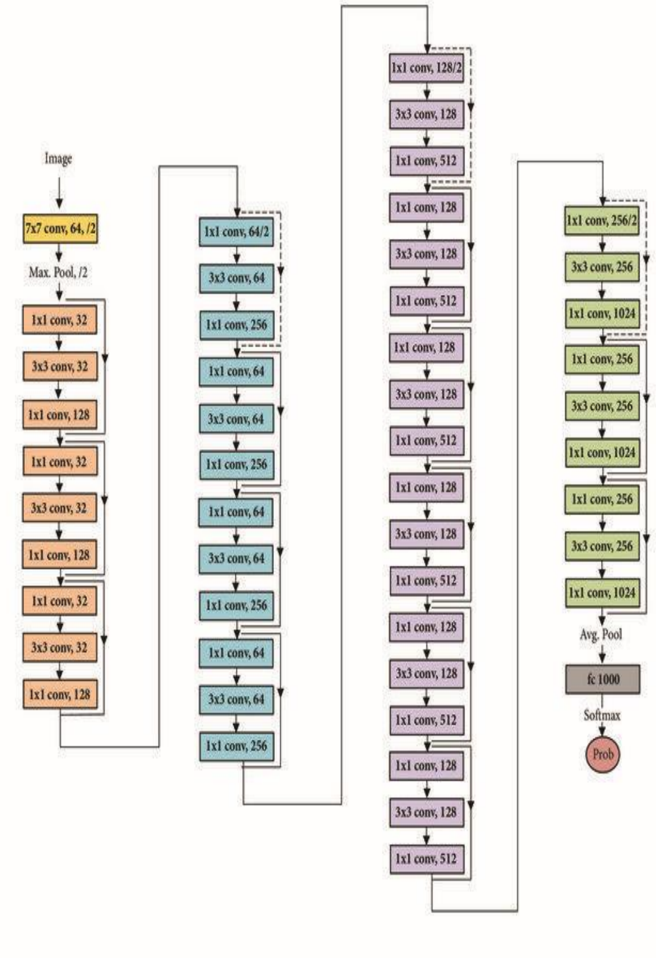
Why Not Choose Pure Quantum Convolutional Network Architecture?

In the current era of quantum computing, our choices are influenced by the nascent stage of the technology. Limited access to number of qubits necessary for directly processing high-resolution images steers our approach. Therefore, we strategically combine the strengths of classical convolutional neural networks (CNNs) with our quantum architecture.

Classical Neural Network Component

In the Classical Neural Network (CNN) component of our model, we have incorporated the renowned ResNet50 (v2) architecture. This architecture boasts impressive accuracy rates (76% top-1 and 93% top-5) on the ImageNet dataset. The inherent advantage of using ResNet50 stems from its pretraining on the extensive ImageNet dataset. Leveraging transfer learning, we expedite our training process by exclusively training the final layers, thus bypassing the need to train the entire network from scratch.

we have replaced the conventional fully connected (fc) layer with our quantum model.



Resnet 50 Detailed architecture

Quantum Network Component

Variational Quantum Circuit:

Our quantum network embodies a unique structure, achieved through a series of quantum layers that constitute the variational quantum circuit. Comprising distinct elements, namely H_layer (a layer of single-qubit Hadamard gates), RY_layer (a layer of parametrized qubit rotations around the y-axis), and entangling_layer (a layer of CNOT gates followed by a shifted layer of CNOT gates), this circuit configuration facilitates complex quantum operations.

Quantum Circuit Definition via Pennylane:

Our quantum circuit is structured following the conventions of a typical variational quantum circuit. The circuit begins with an embedding layer, initializing all qubits in a balanced superposition of up and down states. Subsequently, qubits undergo rotations based on input parameters, enabling local embedding. Variational layers, comprising trainable rotation layers and constant entangling layers, follow suit. Finally, the measurement layer computes the local expectation value of the Z operator for each qubit, generating a classical output vector for further processing.

Dressed Quantum Circuit:

The dressed quantum circuit encapsulates several crucial stages:

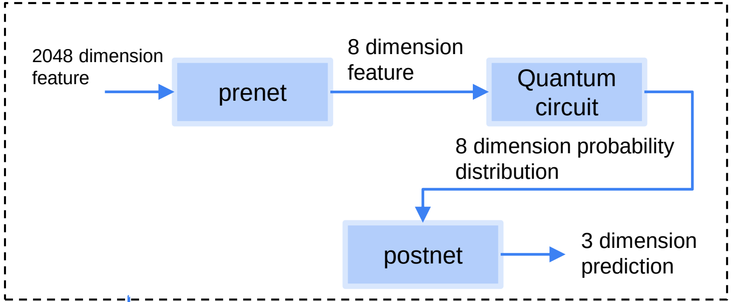
1.Classical Pre-processing Layer: This involves an nn.Linear layer that pre-processes input data.

2.Classical Activation Function: Utilizing the torch.tanh function, we introduce a classical activation function.

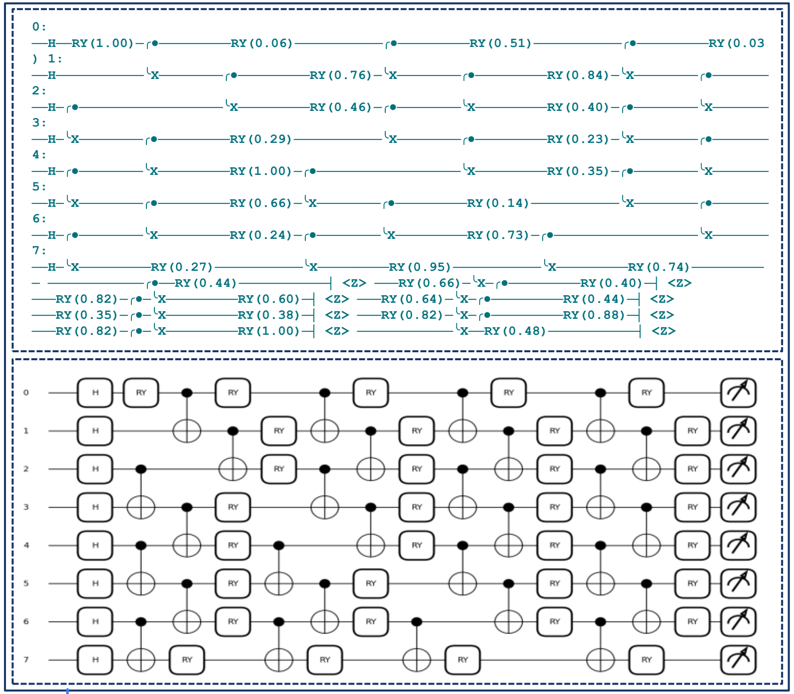
3.Constant Scaling: A scaling factor of np.pi/2.0 is incorporated to optimize circuit behavior.

4.Quantum Circuit Integration: The core component of the dressed quantum circuit, the previously defined quantum_net, seamlessly intertwines quantum and classical components.

5.Classical Post-processing Layer: A final nn.Linear layer concludes the circuit, shaping the output into a batch of vectors with three real outputs, corresponding to the three image classes (0, 1, and 2).



Dressed Quantum net

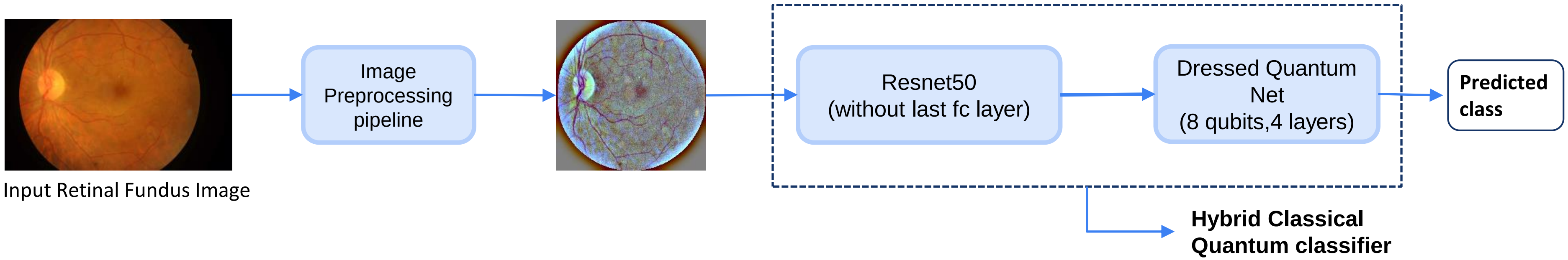


Our quantum circuit (8 qubit ,4 layer)

Defining Hybrid Model (fusion of classical CNN with Quantum model)

we replace the final fully connected (fc) layer of the ResNet50 with our custom-designed dressed quantum layer to harness the capabilities of quantum computing while operating on a reduced feature dimension.

Proposed Pipeline for Diabetic Retinopathy Progression Grading:




```
model_hybrid =
torchvision.models.resnet50(weights=torchvision.models.ResNet50_Weights.
IMAGENET1K_V2)
# freezing
for param in model_hybrid.parameters():
    param.requires_grad = False
# replacing fc layer with qunatum layer
model_hybrid.fc = DressedQuantumNet()
# Then, unfreeze the last 5 layers
for param in list(model_hybrid.parameters())[-5:]:
    param.requires_grad = True
```

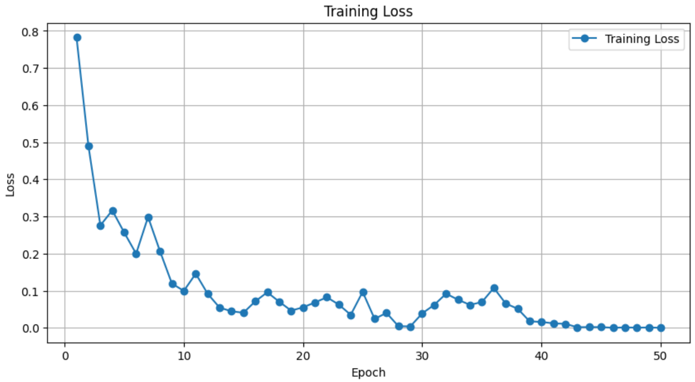
```
ResNet(
..................
 <internal layers of resnet>
..................
  (avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
  (fc): DressedQuantumNet(
    (pre_net): Linear(in_features=2048, out_features=8,
bias=True)
    (post_net): Linear(in_features=8, out_features=3,
bias=True)
  )
)
```

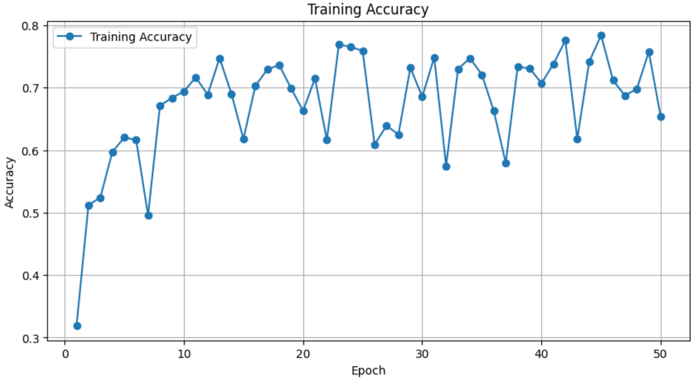
Hybrid Architecture definition (code)

Our Hybrid Architecture

Test Result and Performance Metrics

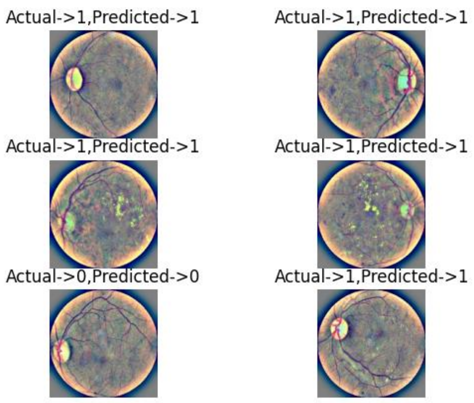
Pure Classical Resnet50 model



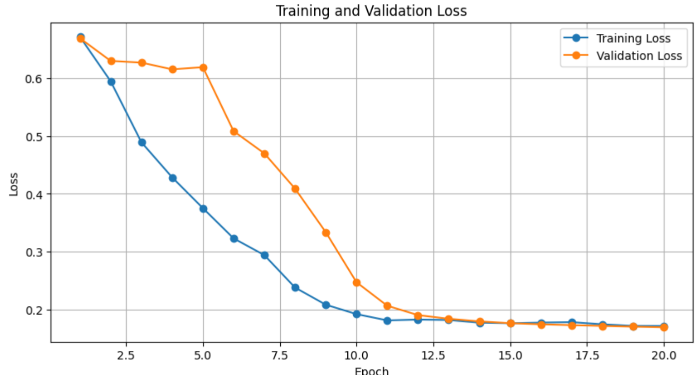


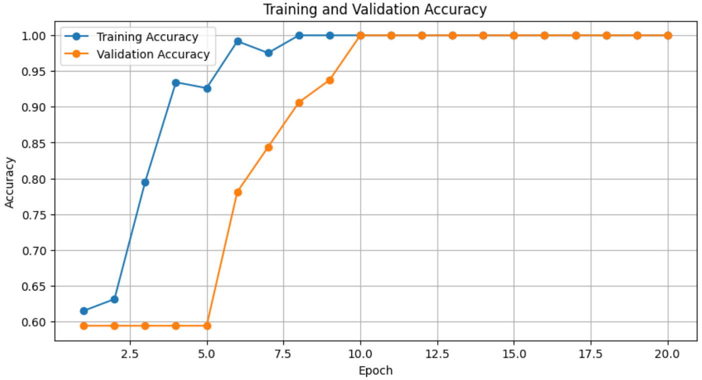
	precision	recall	f1-score	support
0	0.91	0.88	0.90	34
1	0.74	0.89	0.81	19
2	0.80	0.62	0.70	13

Samples of Prediction on testing images



Hybrid Classical Quantum model





	precision	recall	f1-score	support
0	1.00	1.00	1.00	34
1	1.00	1.00	1.00	19
2	1.00	1.00	1.00	13

Quantum Setup For Large Scale ML on Cloud

```
token='IBM Quantum LAB API token'
dev = qml.device("qiskit.ibmq", wires=n_qubits, backend="ibmq_qasm_simulator", ibmqx_token=token)
```

Quantum Setup For Large Scale ML on Cloud

•**Utilizing Cloud for Quantum Circuit Execution**:

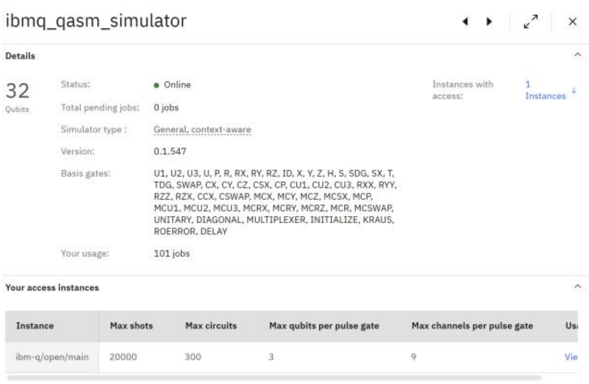
Our implementation harnesses the power of cloud-based solutions for executing quantum circuits. Specifically, we employ the PennyLane package, which seamlessly integrates with major cloud service providers for quantum computing. For our case, we opt for the IBM Quantum Lab. This platform offers access to free quantum hardware for executing our circuits. It's important to note that while the free version has usage limitations in terms of execution counts and qubit numbers, it serves as a valuable resource for testing and inference.

•**Advantages of Cloud-Based Quantum Computing**:

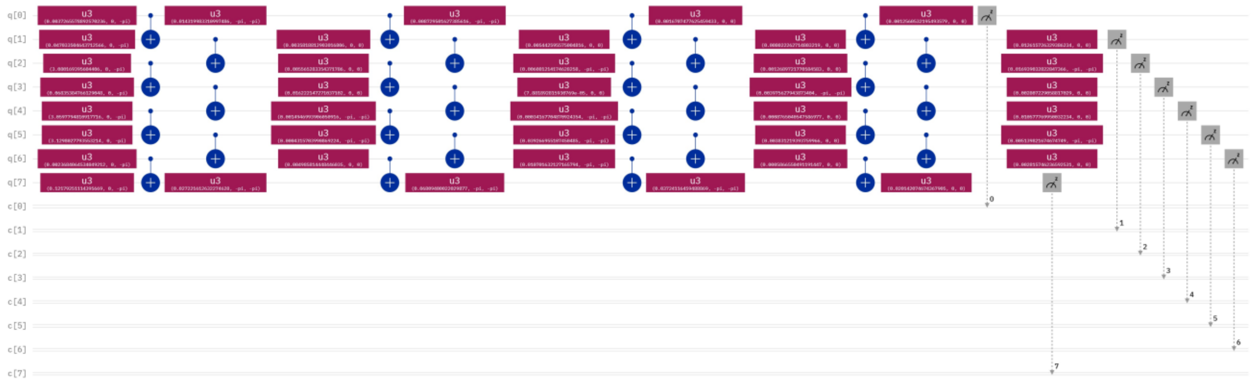
Cloud-based quantum computing, such as that offered by IBM Quantum Lab, holds distinct advantages. The cloud setups employ dedicated quantum hardware, resulting in enhanced speed and accuracy compared to simulating quantum behavior on classical computers.

•**Handling Large-Scale Datasets on Cloud Quantum Computing**:

Given the nascent stage of quantum computing and the limitations in available qubits, full-scale training on cloud quantum computing remains constrained. However, our approach allows us to optimally use these resources. We execute training via simulated quantum computing, while deploying model inference or testing on cloud quantum computing platforms. This strategic approach significantly enhances inference speed, effectively minimizing latency and expediting decision-making processes.



IBM quantum Cloud simulator instance



Our Quantum circuit generate by IBM quantum Cloud

Limitations and Future Scope of Quantum computing based ML tasks

Limitations of Quantum Computing
While quantum computing holds immense promise, its current state of development presents certain limitations:

•**Hardware Resource Constraints**:
Given the early stage of development, hardware resources for quantum computing remain limited. We are restricted to using a mere 8 qubits, which necessitates either drastic reduction in image size or reliance on classical CNN-based models for feature extraction.

•**Error Propagation in Quantum Operations**:
Quantum computing resources aren't exempt from errors, particularly when working with entangled qubits. The susceptibility to errors impacts the accuracy of computations.

Future Scope with Quantum Computing
Despite the current limitations, quantum computing opens doors to significant advancements:

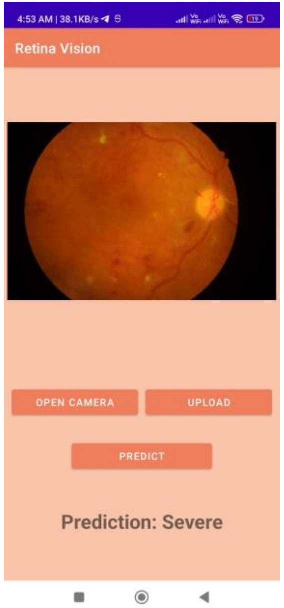
•**Performance Amplification**:
While achieving 100% accuracy with just 8 qubits is remarkable, the potential for performance gains is substantial. As quantum resources expand, we can execute complex machine learning tasks using quantum computing. The intrinsic ability of quantum models to reduce feature dimensions without significant loss of information can become a powerful asset.

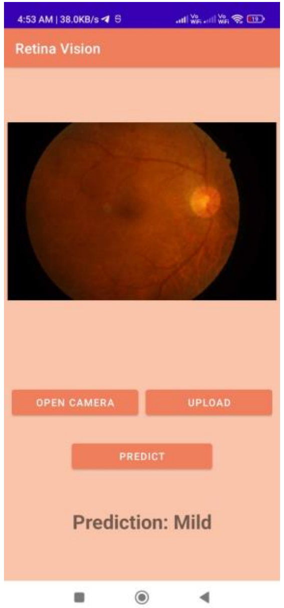
•**Medical Use Cases**:
Quantum computing's accuracy and precision align seamlessly with the demands of medical use cases. As quantum hardware evolves, the transition from classical to quantum models becomes a viable avenue to attain even higher accuracy levels.

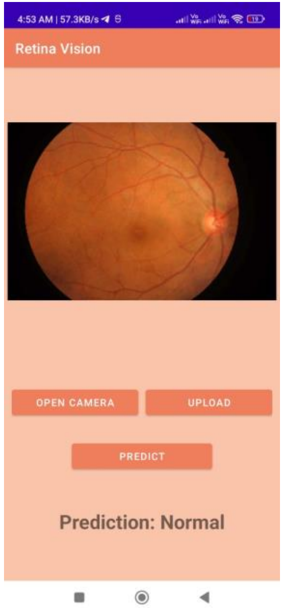
In the broader context, while we acknowledge the current limitations, we are poised for a future where quantum computing, armed with greater hardware capabilities, can revolutionize various domains, including medical diagnostics and beyond.

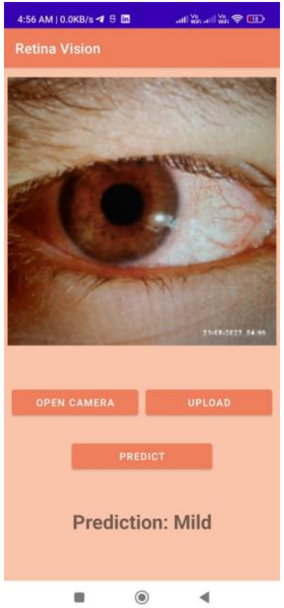
Running Demo on APP

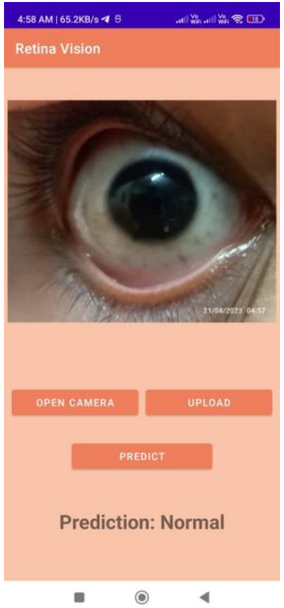
We have successfully employed our hybrid classical-quantum model for fundus images, achieving a remarkable 100% accuracy. However our dataset is self-created for normal naked eye images, which might lead to some limitations in terms of accuracy.











Conclusion and Gratitude

•Summary of Solution:

In summary, our solution addresses the critical challenge of Diabetic Retinopathy (DR) progression classification through the innovative fusion of classical and quantum approaches. Diagnosing DR accurately and efficiently is imperative, and our hybrid model represents a pioneering solution. Leveraging the power of Convolutional Neural Networks (CNNs) for feature extraction and embedding quantum capabilities through a dressed quantum layer, our approach achieves remarkable accuracy. By seamlessly integrating classical and quantum elements, we bridge the gap between conventional methodologies and quantum advancements. Our model's ability to enhance feature representation and classification is validated by achieving 100% accuracy, 100% precision, 100% recall, 100% specificity, and 100% F1-score on the Indian Diabetic Retinopathy Image Dataset. This pioneering fusion not only demonstrates our commitment to advancing medical diagnostics but also highlights the potency of synergizing classical and quantum paradigms.

•Gratitude and Acknowledgment:

We extend our heartfelt gratitude to the Flipkart team for providing us with this significant and compelling opportunity. This journey has been a tremendous learning experience, enabling us to simultaneously learn, develop, and explore new frontiers. The chance to contribute to the field of medical diagnostics, guided by this intriguing challenge, has been both enlightening and fulfilling. We greatly appreciate the support and encouragement that this platform has offered, allowing us to embark on an exciting exploration of the intersection between quantum computing and healthcare.

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Thank you for your attention, and we look forward to any opportunities that may arise from our endeavors.

Flipkart

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Thank You