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Problem Statement Title: Diabetic Retinotherapy using Quantum Computing

Team Name: Misfits

Team members details

Team Name	Misfits		
Institute Name/Names	National Institute of Technology, Rourkela		
Team Members >	**1 (Leader)**	**2**	**3**
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Batch	2024	2024	2024

Glossary

- **Ref** - Reference
- **DSC** - Depthwise Separable Convolution
- **CNN** - Convolutional Neural Network
- **Resnet** - Residual Network
- **EfficientNet** - Efficient Neural Network
- **DR** - Diabetic Retinopathy
- **FLOPs** - Floating Point Operations
- **IDRiD** - Indian Diabetic Retinopathy Fundus Image
- **ConvBnAct** - Convolution-BatchNormalization-Activation
- **MBConvN** - Mobile Inverted Residual Bottleneck Convolutional Block N
- **CZ** - Controlled-Z Gates

Solution statement:

Steps	Description
Dataset	Made a **balanced dataset** out of a highly skewed large dataset
Pre-processing	Augmenting images catering to all input edge-cases and applying some well known **ben-graham crop and gaussian-filter**.
Quantum Circuit on Cloud	A class ‘MyQuantumCircuit’ running on **QiskitRuntime** having a parameterized circuit is defined, whose probabilistic outcomes is used for feature-enhancement.
Transfer Learning	Following a hybrid-CNN approach, Quantum circuit integrated with our **EfficientNet** neural model has been implemented to process and classify images with high accuracy.
Testing	Model has been tested on Indian Diabetic Retinopathy Fundus Image Dataset which is similar to **Smartphone Fundus photography** [Ref]
Accuracy	**Test data: 0.8454 Recall: 0.7636** **Precision: 0.8527 F1-Score: 0.7968**
Deployment	https://drdetection.streamlit.app/ https://github.com/Dibyansika/Deployment

Dataset :

Dataset	No. of Fundus images	Balanced (Y/N) / No_DR (percentage)	Accuracy after training the model
IDRID	513	Balanced - N No_DR% = 32.59	50.25%
Diabetic Retinopathy (resized)	35126	Balanced - N No_DR% = 73.48	67.41%
Gaussian filtered APTOS dataset	3662	Balanced - Y No_DR% = 49.29	68.23%
Ours (pre-processed and balanced dataset)	20126	Balanced - Y No_DR% = 53.71	84.54%

- The dataset was highly skewed(75% of total was from NO_DR).
- Further, we have pre-processed the images by Ben-graham crop method[Ref], gaussian filter for
  - smoothing & reducing noise
  - highlighting the details[Ref] of Haemorrhages, Hard Exudates, Aneurysm, “COTTON WOOL” spot and abnormal growth of blood vessels

Image Pre-processing :

Code	Changes implemented
cv2.COLOR_BGR2RGB	converting the image from BGR to RGB to pass in crop_image_from_gray function We have found by experimenting that color image performs better than gray
crop_image_from_gray	• We have further modified this function to take RGB image instead of grayscale image for better accuracy (from experiment) • Converts the input color(RGB) image to grayscale, crops the corresponding channels. • If too dark, it returns the original image. [Ref]
cv2.GaussianBlur(image, (0,0), 10)	Gaussian blur is a smoothing technique that reduces noise and details in the image. [Ref]
cv2.addWeighted (image,4, cv2.GaussianBlur(image , (0,0) , 10) ,-4 ,128)	• weighted combination of two images: the original image and its Gaussian-blurred version. • -4: This is the weight or beta value for the Gaussian-blurred image. • 128: This is the gamma value or the scalar added to the weighted sum. It helps control the brightness of the final image. [Ref]

(Demo) Pre-processing

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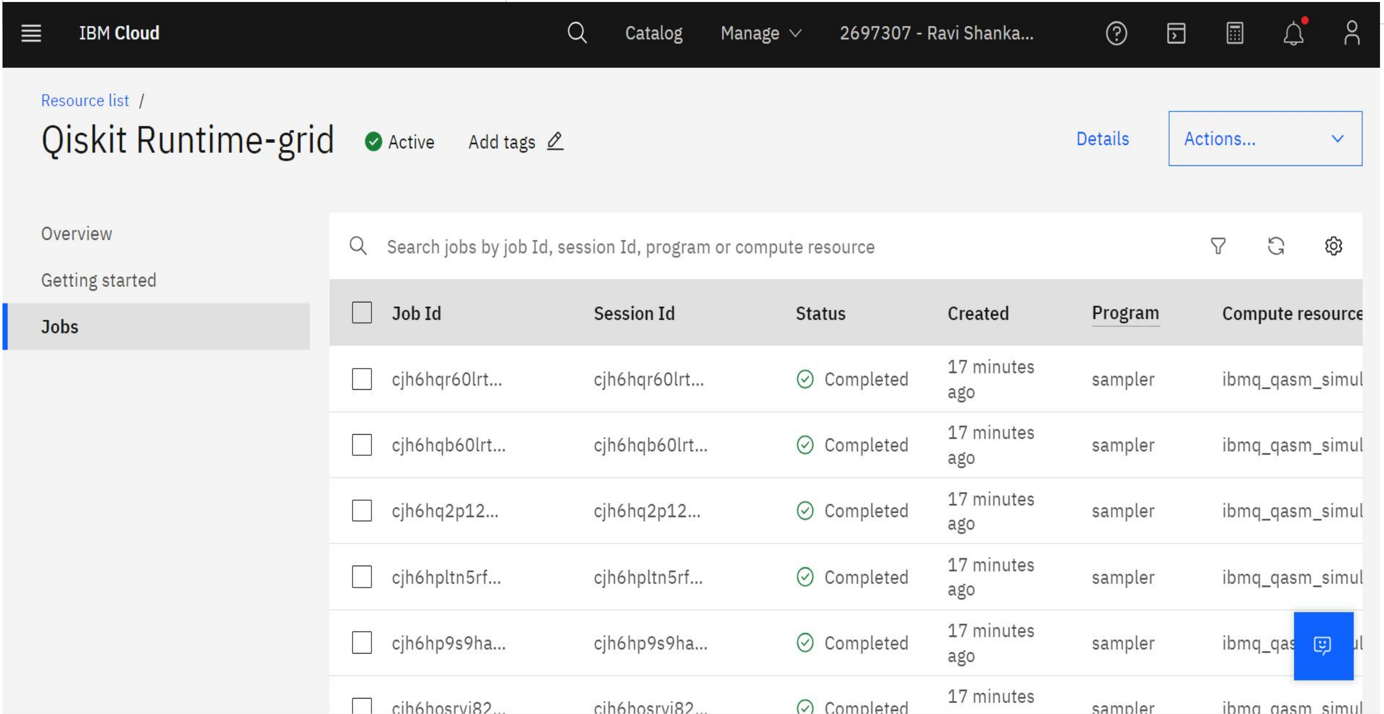
After PreProcessing

Quantum Circuit Components	Description
Encoded Quantum States	Microaneurysms, Haemorrhages, and Exudates are encoded into 3 quantum states (qubits). Additional features can be added with higher complexity and cost.
Hadamard Gate	Creates a superposition of the $\|0\rangle$ and $\|1\rangle$ states by transforming the initial quantum state $\|\psi\rangle$ of the qubit: $H\|\psi\rangle = 1/\sqrt{2}(\|0\rangle + \|1\rangle)$.
Subsequent R_Y Gates	Introduces variations in superposition amplitudes, encoding probabilistic feature distribution based on angles. Mathematically: $R_Y(\theta)\|\psi\rangle = \cos(\theta/2)\|0\rangle + e^{i\phi}\sin(\theta/2)\|1\rangle$.
Controlled-Z (CZ) Gates	Used between qubits 0-1 and 1-2 to introduce **entanglement**, capturing correlations between different parts of an image.
Probability Distributions	Insights gained from probability distributions from Sampler helps identify strongly correlated bitstrings with image features, like indicating abnormalities like blood vessel issues.
Feature Extractor Method	Probabilities associated with bitstrings are used as weights or constraints in the feature extractor method.

Term	Description
Qiskit Runtime[Ref]	A cloud-based service by Qiskit enabling execution of quantum programs on IBM Quantum cloud infrastructure. Improves efficiency with containerized execution environment.
Backpropagation[Ref]	Shifts parameters and calculates gradients by comparing results obtained from the params passed after running in circuit.



Here is the screenshot of the job instances that ran on IBM Cloud using Qiskit Runtime which ran the circuit on a quantum simulator and delivered probabilistic outputs using Sampler Primitive.

Why Transfer Learning with Efficient Net?

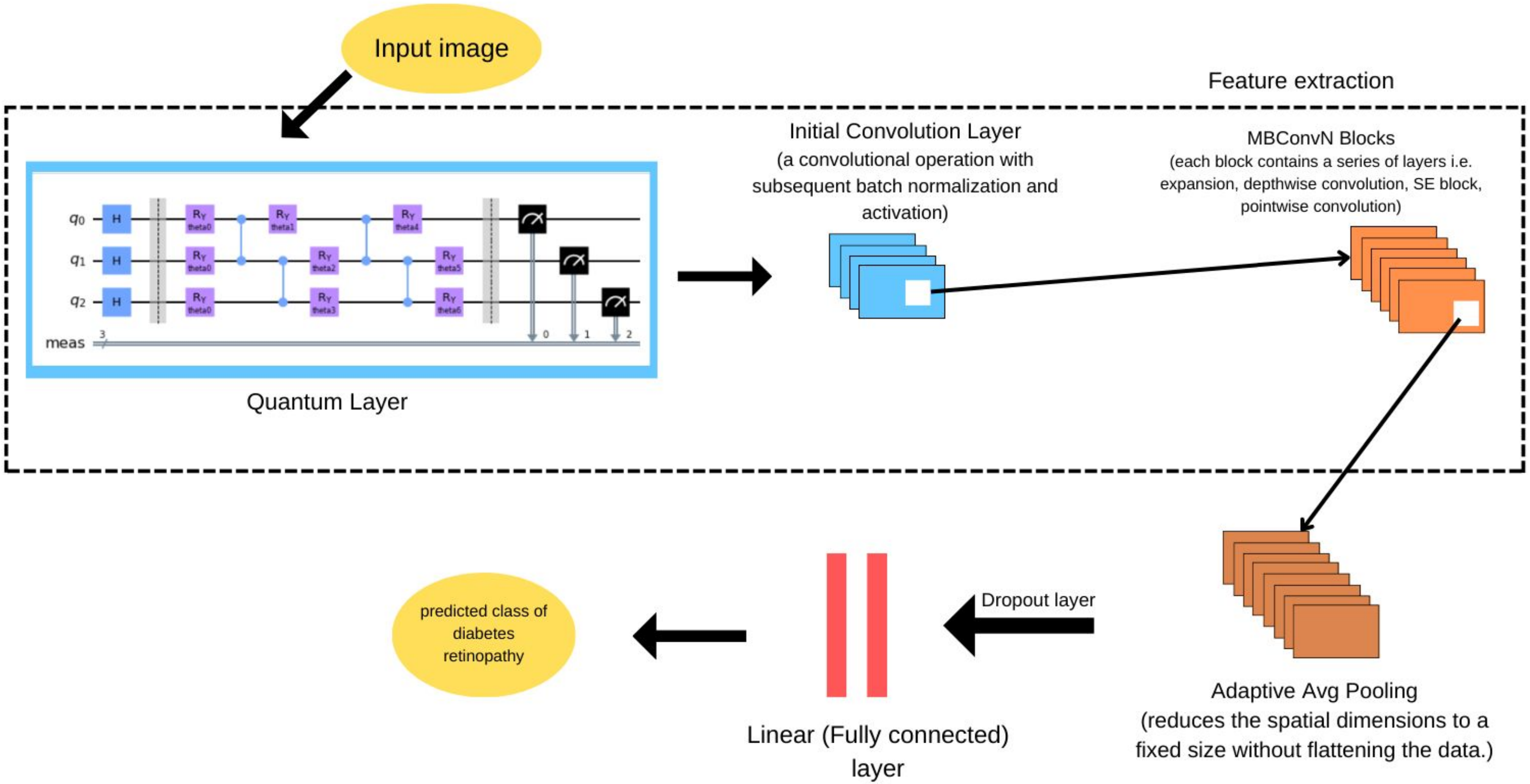
We are using transfer Learning model because they are pretrained on large image dataset and we can further finetune the model using fundus image.

Aspect	EfficientNet	Resnet	Vanilla (from scratch)
Compound Scaling	EfficientNet scales depth, width, and resolution together	Resnet scales in terms of depth or width , not simultaneously	It has no predefined compound scaling method, so it do not scales depth and width together
Performance-Size Efficiency	84.54% accuracy on my dataset while testing. fewer parameters and FLOPs	58.23% accuracy on my dataset while testing. more parameters required and FLOPs for similar performance	44.16% accuracy on my dataset while testing. Performance-size balance varies
Adaptability	We trained on different learning rates and fine-tuning perform very well	On the same fine-tuning parameters ,gradient of loss function was very steep which result in 48% (very low) accuracy despite 93% accuracy while training	It was worst in this case. Even our best Model converges to 44% and did show mild tuning.

Model Architecture :

Class	Features	Uses	Functions
EfficientNet	• QuantumLayer • Adaptive avg. pooling	Main class constructing the EfficientNet model	• QuantumLayer • Apply adaptive average pooling
ConvBnAct	• Computation cost reduced	DSC is one of the tricks which makes efficient nets, efficient	• Depthwise followed by Pointwise convolution
SqueezeExcitation	• provides a different weight for each channel	Enhance important information	• emphasizes the important channels
StochasticDepth	• train short and use deep networks at test time	This is one of the tricks to accelerate the training of the model.	• subset of layers is randomly dropped & bypass them with identity function
MBConvN	• Pointwise convolution	depthwise convolution	• Expand input

Block Diagram of Model



Testing and Deploying

- Dataset used: IDRiD dataset (as it is similar to the resolution that we will receive in case of **Smartphone Fundus photography** [Ref])

- Images of the dataset has been pre-processed in the same way as described in Slide 6.

- Created an UI using Streamlit library, for uploading the image and predicting the level of diabetes retinopathy and deployed the web app in Streamlit cloud

Limitations to mitigate in Future:

- The current DR classifications rely only on 7 standard field photographs to grade the severity of DR. However, these standard photographic fields only cover about 30% of the total retinal surface area [Ref]
- We have run our quantum circuit on simulator whereas Real hardware introduces noise and errors which reflects real-world effects.
- The free account of IBM Quantum/Cloud comes with a lot of logistics issues from their end, with multiple time account suspension at intervals.

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Thank You