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A DIABETIC RETINOPATHY DETECTION THROUGH QUANTUM-TRANSFER LEARNING

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ABSTRACT
This study explores the performance of advanced architectures, specifically the ResNet family, and hybrid quantum-classical models for classifying diabetic retinopathy images. Classical models, particularly ResNet18, achieved a baseline accuracy of 78.69% and an F1-score of 78.54%. Through the integration of transfer learning, ResNet18's performance improved significantly, with accuracy reaching 81.91% and an F1-score of 80.94%. Furthermore, the proposed hybrid quantum classifier, incorporating various quantum gate configurations such as Hadamard & CZ, demonstrated competitive accuracy of 81.91%, matching the best-performing classical model. However, during testing, the hybrid model achieved an F1-score of 0.7021, suggesting room for improvement, particularly in reducing false positives. Overall, this research highlights the potential of combining classical deep learning and quantum computing to enhance medical image classification, underscoring the importance of further innovation in medical diagnostics.

Keywords:
Dibetic Retinapathy, DR, Quantum Transfer Learning

I. Introduction
Diabetes affects approximately 415 million people globally, with nearly 45% of diabetic patients developing diabetic retinopathy (DR), a condition caused by prolonged high blood sugar damaging the small blood vessels in the retina, leading to vision impairment and potentially permanent blindness. Early detection of DR is crucial to prevent severe vision loss, as the disease progresses through various stages characterized by abnormalities like microaneurysms, hemorrhages, exudates, and cotton wool spots. Traditional machine learning (ML) techniques have been widely used in computer-assisted diagnostic systems for DR detection, but they often require significant manual effort for feature extraction and domain expertise. In contrast, deep learning (DL) offers automated data representation, eliminating the need for manual feature extraction and showing significant potential in predictive analysis when trained on large, well-annotated datasets. While supervised DL models are crucial for accurate predictive tasks, unsupervised learning (UL) techniques, such as clustering, provide exploratory data analysis by identifying hidden patterns in data without requiring labelled outcomes. UL is particularly useful in medical fields where annotation is labor-intensive, helping reveal complex relationships in high-dimensional medical imaging data. However, challenges such as parameter tuning and validation persist in UL, emphasizing the need for careful interpretation. Deep clustering algorithms like Deep Embedded Clustering (DEC) combine the strengths of both DL and clustering, enhancing performance by integrating feature learning with cluster assignments. Given the rising prevalence of diabetes, the demand for ophthalmologists is expected to grow, with projections estimating 780 million people affected by 2045, of which 35% will suffer from DR, highlighting the urgent need for advanced diagnostic tools to mitigate the global burden of sight-threatening retinopathy.
Diabetic retinopathy (DR) is a severe complication of diabetes, affecting nearly 45% of diabetic patients worldwide. It occurs when high blood sugar levels cause damage to the small blood vessels in the retina, leading to vision impairment and potentially blindness if left untreated. Early detection is critical in preventing severe vision loss, and the Early Treatment Diabetic Retinopathy Study (ETDRS)

scale is widely used to classify DR severity. The disease progresses through various stages, from mild non-proliferative DR (NPDR) characterized by microaneurysms to proliferative DR (PDR), where abnormal blood vessels form in the retina, posing a high risk of blindness. As the global prevalence of DR increases, particularly in developing countries with limited access to ophthalmologists, there is a growing need for automated detection systems that can assist in identifying and categorizing DR at its early stages, reducing the burden on healthcare professionals.

Traditional methods for DR detection rely heavily on manual examination by ophthalmologists, which can be labor-intensive and time-consuming, especially with large datasets. Automated systems offer a solution by utilizing advanced image processing techniques and artificial intelligence (AI) to detect early signs of DR in retinal images. These systems analyze key features such as microaneurysms, hemorrhages, and exudates, classifying images based on DR severity. Deep learning (DL) models, particularly Convolutional Neural Networks (CNNs), have shown great promise in automating DR classification, reducing the workload on specialists and enabling faster diagnosis. With the advent of quantum computing, there is growing interest in integrating quantum techniques with DL to enhance performance further. This study proposes a quantum-based CNN for fully automated DR screening, which not only detects DR but also localizes lesions and categorizes the disease into five distinct stages. By leveraging quantum neural networks, the system aims to improve classification accuracy, offering a powerful tool for early DR detection and aiding ophthalmologists in managing this vision-threatening disease.

II. Literature

Numerous studies have made progress in DR detection by utilizing various machine learning and DL models, improving the accuracy and efficiency of diagnoses. This review examines several of these studies and summarizes their findings. R. Taylor and D. Batey [1] noted that diabetes is a condition where the body fails to produce enough insulin, leading to elevated blood glucose levels. This condition affects several organs, including the retina. K. Boyd discussed diabetic retinopathy (DR), a complication of diabetes where blood and fluids leak from the retinal blood vessels.

According to Z. L. Teo et al. [4,5], DR affected approximately 103.12 million people globally in 2020, with projections indicating an increase to 160.50 million by 2045. S. Qummar et al. [6] explained that DR affects around 22.27% of diabetics, with proliferative DR (6.96%) and diabetic macular edema (6.81%) being key stages. Early detection enables effective management, but regular ocular fundus examinations are necessary, as DR is often asymptomatic in its early stages. The two main types of DR are proliferative and non-proliferative.

V. Bellemo et al. [7] highlighted that AI-based algorithms have been successfully applied to detect multiple retinal diseases, including DR. W. L. Alyoubi et al. [8,9] emphasized that manually diagnosing DR from retinal images is time-consuming and complicated by a lack of medical professionals. Therefore, creating automated DR detection systems is crucial for assisting healthcare workers in overcoming these challenges. CNNs, as explained by W. L. Alyoubi et al. [9] and S. Gayathri et al. [10], are widely used in image analysis and have significantly enhanced automated object detection and classification.

N. Mathur et al. [11] pointed out that quantum deep learning techniques are gaining attention, with quantum parametric circuits being used to classify traditional data. S. Mangini et al. [12] explained that quantum computers have shown superior accuracy in certain applications, especially when sampling complex probabilities, making them promising for image classification tasks.

Research by Mir et al. [14] demonstrated that a hybrid quantum-classical model using the Inception-V3 architecture and a Variational Quantum Classifier achieved accuracy rates between 93% and 96%, outperforming the 85% accuracy of the classical model. This emphasizes the potential of hybrid quantum approaches in DR detection. Similarly, Mohammadian et al. [15] achieved accuracies of 87.12% and 74.49% by fine-tuning pre-trained models such as Inception-V3 and Xception, underscoring the importance of model selection and fine-tuning in improving performance.

Wan et al. [16] applied transfer learning and hyperparameter tuning to pre-trained models such as AlexNet, VggNet-s, VggNet-16, VggNet-19, GoogleNet, and RestNet, with VggNet-s achieving the highest accuracy at 95.68%. Dutta et al. [17] compared various neural networks on a dataset of 300 images, with deep neural networks yielding an accuracy of 86.3%, illustrating the advantages of deeper networks. Gangwar and Ravi [8] used a pre-trained Inception-ResNet-V2 model with custom CNN layers to achieve an accuracy of 82.18% on the APTOS 2019 dataset, demonstrating the effectiveness of custom CNN layers.

T. Shahwar et al. [18] proposed a hybrid classical-quantum model that utilized ResNet 34 and a quantum variational circuit, achieving an accuracy of 99.1%, further demonstrating the potential of quantum computing in DR detection. Gondal et al. [19] achieved clinical-level accuracy in DR detection with CNNs, reporting a sensitivity of 93.6% and specificity of 97.6% using the DiaretDB1 dataset. Wang et al. [20] used the Inception model and reported AUC values of 0.978 for normal DR and 0.960 for referable DR, indicating strong detection capabilities but room for improvement in specificity.

Chanrakumar and Kathirvel [21] attained a 94% accuracy using CNNs with dropout regularization, while Memon et al. [22] achieved a kappa score accuracy of 0.74, highlighting the need for validation in model assessment. Garcia et al. [23] used the VGG16 model, achieving 93.65% specificity, 54.47% sensitivity, and 83.68% accuracy, showcasing the model's efficiency in DR detection. Kumar et al. [24] and Thomas et al. [25] demonstrated effective methods using neural networks and fundus imaging, respectively, to improve DR detection rates. Gupta et al. [26], Georgios et al. [27], and Manuel et al. [28] also explored machine learning and computer-aided diagnostic (CAD) systems for DR, further advancing the field.

Welikala et al. [29] used a combination of multi-layered perceptron networks and SVM classifiers to achieve improved DR detection, while Shanthi and Sabeenian [30] and Zago et al. [31] achieved high precision and sensitivity using CNN models.

In summary, while traditional deep learning models have been effective in DR detection, limitations persist in identifying various stages and lesion types. Quantum Transfer Learning presents a new opportunity for enhancing accuracy and efficiency in DR detection, combining classical feature extraction with quantum-based classification. This study contributes to the field by offering a quantum-based approach that automates DR detection and improves lesion identification and stage classification. As quantum computing progresses, it has the potential to revolutionize medical image analysis, providing faster, more accurate, and cost-effective solutions for diseases like DR. This research underscores the promise of quantum deep learning in medical diagnostics, paving the way for future developments in the field.

III. Methodology

The problem of Diabetic Retinopathy (DR) detection is both critical and complex due to the necessity of identifying early symptoms to prevent irreversible vision loss. DR, a leading cause of blindness in diabetic patients, results from prolonged high blood sugar levels that damage the blood vessels in the retina. The challenge is compounded by the fact that DR often remains asymptomatic in its early stages, with progression leading to blindness if not diagnosed and treated early. DR is a multistage disease, typically divided into five phases: No DR, Mild Non-Proliferative DR, Moderate Non-Proliferative DR, Severe Non-Proliferative DR, and Proliferative DR. Identifying and categorizing lesions, such as microaneurysms, hemorrhages, and exudates, which form on the retina during DR progression, is crucial for determining its phase. However, differentiating between these lesions is challenging due to their subtle differences and varying appearances across patients. While manual diagnosis using retinal fundus images is highly reliant on skilled ophthalmologists, it is time-consuming, expensive, and challenging, particularly in regions with limited access to specialized healthcare.

To address these limitations, the proposed solution introduces a Quantum Transfer Learning (QTL) approach for DR detection. The hybrid model leverages both classical and quantum computing

paradigms to create a powerful and efficient system. Classical feature extraction is performed using pre-trained CNNs, such as ResNet or Inception, which reduces the need for large amounts of labeled DR data. These extracted features are then passed into a Variational Quantum Classifier (VQC), optimized to handle complex decision boundaries, leading to more efficient and accurate classification. By integrating quantum computing, the proposed model aims to enhance the speed, accuracy, and scalability of DR detection, providing comprehensive diagnostic information, including lesion identification and disease staging. This hybrid approach has the potential to outperform traditional deep learning models while aligning with future advancements in quantum hardware.
Quantum computing stands apart from classical computing due to its use of qubits, which allow for exponentially increased processing power. This feature is particularly advantageous for addressing complex problems in various fields, including healthcare, by providing the ability to perform simultaneous computations through quantum superposition and entanglement. The integration of Quantum Transfer Learning (QTL) into quantum computing is a significant advancement, as it builds on pre-trained classical models to enhance the efficiency of quantum algorithms. This approach conserves computational resources and accelerates the development of solutions in domains such as chemistry, optimization, and machine learning. Specifically, this study focuses on combining classical neural networks for feature extraction and quantum circuits for classification, applying this hybrid model to the detection of diabetic retinopathy (DR). By leveraging the strengths of both classical and quantum computing, the hybrid model demonstrates the potential to revolutionize medical diagnostics, offering faster, more accurate results and enabling more complex problem-solving capabilities in healthcare.
In implementing this hybrid quantum-classical model, the study utilizes the APTOS 2019 Blindness Detection dataset, which consists of retinal fundus images labeled with various stages of DR. Initial feature extraction is carried out using pre-trained classical models like ResNet and Inception, which have been trained on large datasets like ImageNet. These extracted features, represented as high-dimensional vectors, are then fed into a quantum variational classifier (VQC) for final classification. The quantum classifier is designed using layers of quantum gates, such as Hadamard and RX gates, to process the data efficiently and deliver the classification outcome. The integration of these two systems—classical and quantum—creates a scalable, efficient model capable of addressing the limitations of existing deep learning techniques in DR detection. Through this approach, the hybrid model not only aims to enhance accuracy but also provides a forward-looking framework that aligns with future advancements in quantum hardware.

IV. Experimental Evaluation

The hardware requirements include a high-performance CPU like Intel Core i7, 16 GB of RAM, 1 TB SSD, high-speed internet, and backup storage for efficient quantum computation. Software needs include Windows, Linux, or macOS with Python 3.7+, quantum SDKs like IBM Qiskit or Google Cirq, and deep learning libraries such as TensorFlow or PyTorch. The APTOS 2019 dataset is sourced from Kaggle, containing 3,662 retinal fundus images for diabetic retinopathy detection. Data preprocessing involves resizing images, normalization, and augmentation, with balanced train-test splits. Model hyperparameters include learning rate, batch size, and epochs, while quantum circuit parameters involve qubits, gates, and optimizers. Implementation starts with data import using libraries like Pandas, PyTorch, and NumPy, followed by structured data loading, augmentation, and pipeline configuration for training and evaluation.
The process begins by loading the CSV files containing image filenames and corresponding labels into pandas DataFrames for training, validation, and testing datasets. The images are then preprocessed through resizing to 224x224 pixels, conversion to tensors, and normalization to ensure compatibility with pre-trained deep learning models like ResNet. A custom dataset class is created to manage image loading and apply these transformations, while DataLoaders handle batching, shuffling, and sequential loading for training, validation, and testing. Sample images from batches are visualized using

Matplotlib to confirm that data preprocessing has been correctly applied. Feature extraction is then performed using pre-trained ResNet models, with extracted features saved for future use in hybrid classical-quantum modeling.

The next phase integrates transfer learning with a hybrid quantum-classical model. Pre-extracted ResNet features are fed into a quantum circuit using Pennylane to create a hybrid model for diabetic retinopathy detection. Different quantum gate combinations, such as Hadamard and CNOT, are tested to evaluate their impact on accuracy and F1-score. These hybrid models are trained and evaluated using various quantum circuits, with results compared to identify the best-performing model. The pre-trained hybrid models are then tested on unseen data, where test images are processed, and predictions are evaluated for accuracy and F1-score. Finally, individual images are tested using the hybrid model, showcasing how quantum-enhanced models can be used for medical image classification.

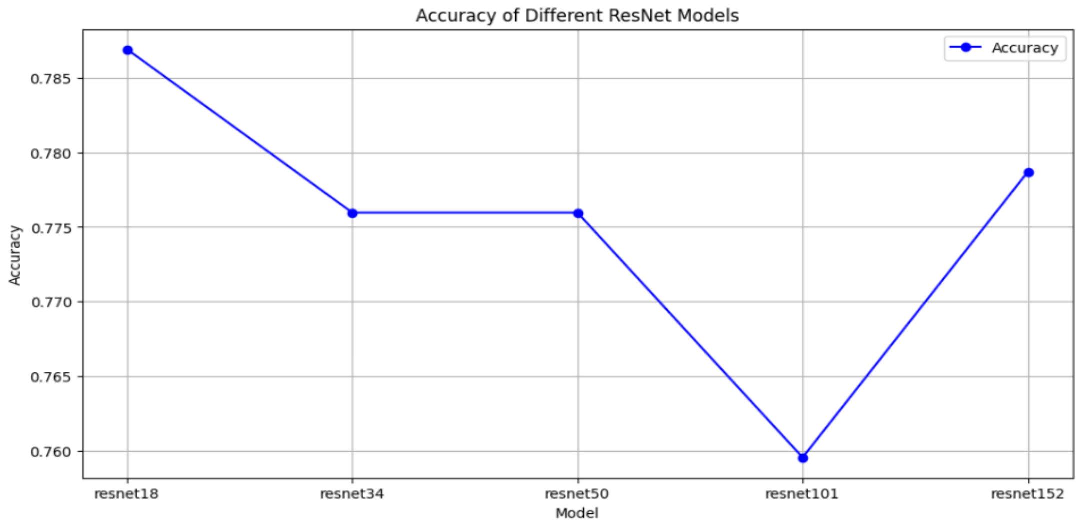
V. Results and Discussion

5.1 Classical Model Foundations

ResNet18 emerged as the top performer among the evaluated models for classifying diabetic retinopathy images, achieving an accuracy of 78.69% and an F1-score of 78.54%. ResNet34 and ResNet50 both had 77.60% accuracy with slightly lower F1-scores, while ResNet101 showed a performance drop with 75.96% accuracy. ResNet152 performed similarly to ResNet18, with 77.87% accuracy and a 77.72% F1-score.

Table 5.1 Performance Summary

Model	Accuracy	F1-score
ResNet18	0.7869	0.7854
ResNet34	0.776	0.7745
ResNet50	0.776	0.7761
ResNet101	0.7596	0.7582
ResNet152	0.7787	0.7772



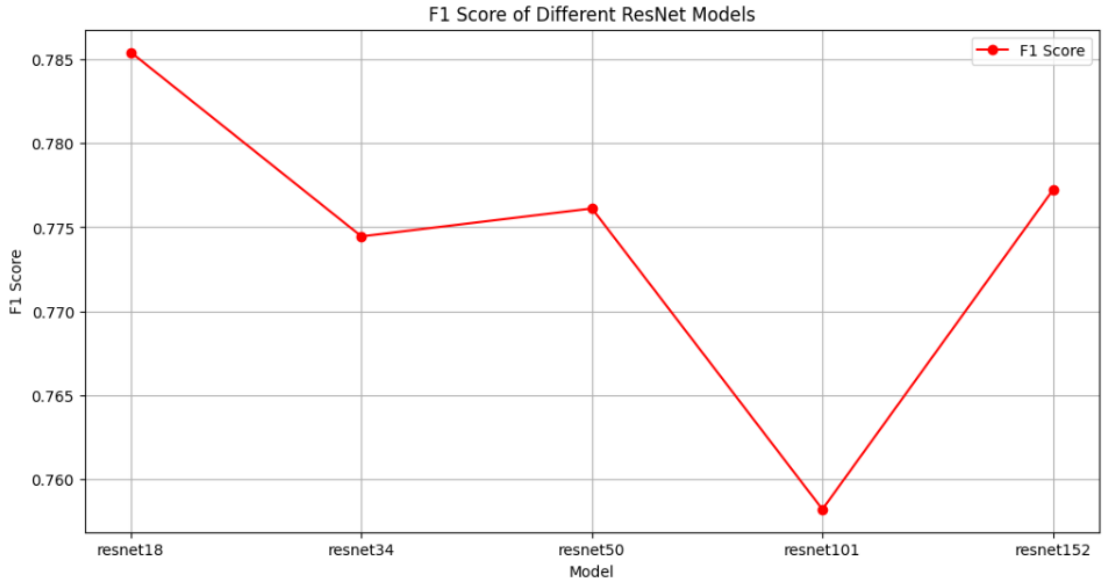


Fig. 5.1 performance results of various classical models based on the ResNet architecture.

5.1.1 Results after Integration of Transfer Learning

The integration of transfer learning significantly improved the accuracy and F1-scores across various ResNet architectures for diabetic retinopathy grading. The training and validation loss plots showed a decreasing trend over epochs, indicating effective learning and successful optimization. Both training and validation losses consistently decreased, suggesting good model fitting and minimal overfitting.

Table 5.2 Accuracy and F1-Score after Integration of Transfer Learning

Model	Final Accuracy	Final F1-score
ResNet18	0.8191	0.8094
ResNet34	0.8055	0.7944
ResNet50	0.814	0.8023
ResNet101	0.7952	0.7818
ResNet152	0.8038	0.7949

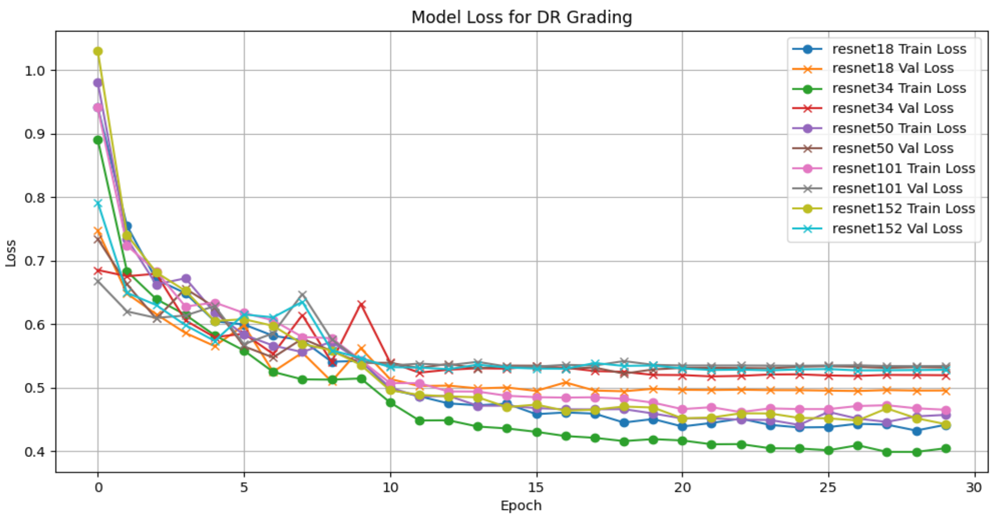


Fig. 5.2 plot of training and validation loss over epochs

Model Accuracy

The accuracy plot across epochs highlights the performance of each model in classifying images accurately. Each model exhibits a rising accuracy trend, with ResNet18 achieving the highest final accuracy of approximately 81.91%, followed closely by ResNet50 at 81.40%. These results confirm that transfer learning effectively enhances the capability of deeper networks to classify diabetic retinopathy images.

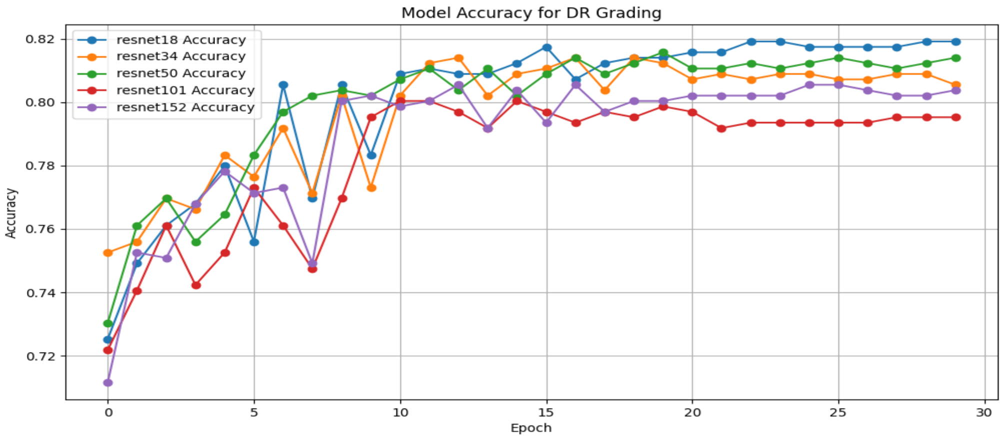


Fig. 5.3 Accuracy plot across epochs

Accuracy vs Different Models

The bar chart comparing the final accuracy of each model clearly illustrates ResNet18's superior performance in the context of DR grading, followed by ResNet50 and ResNet34. This visualization emphasizes the effectiveness of different ResNet architectures, confirming that deeper networks generally yield better classification results.

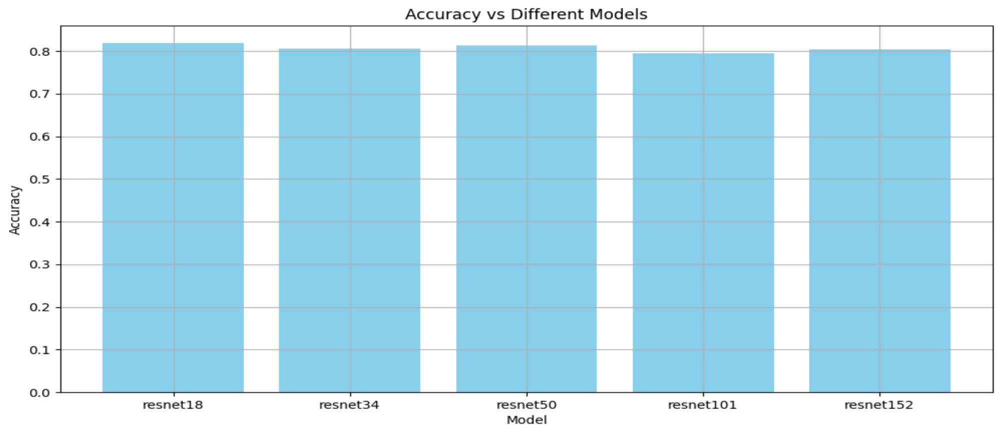


Fig. 5.4 Bar chart comparing the final accuracy of each model

F1 Score vs Different Models

Similarly, the F1 score results demonstrate how well the models balance precision and recall. ResNet18 again led the group with an F1 score of approximately 80.94%,
indicating not only high accuracy but also reliability in its predictions, particularly in the context of imbalanced classes.

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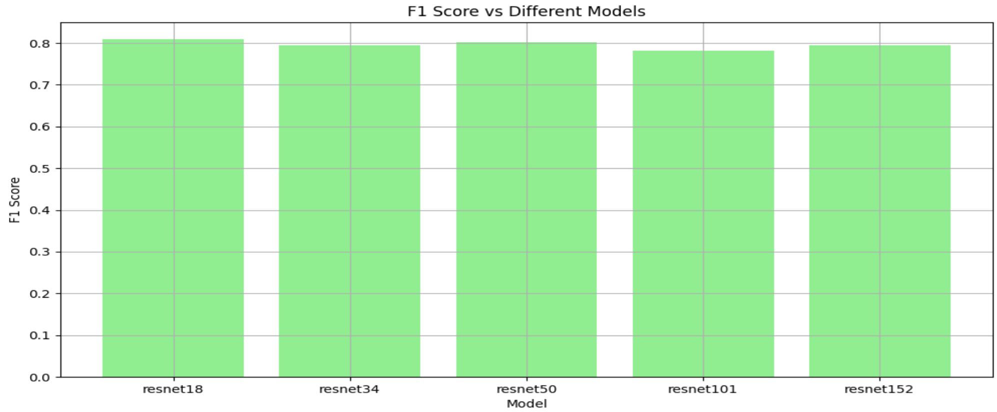


Fig. 5.5 F1 score results of each model

Confusion Matrix for ResNet18

The confusion matrix for ResNet18 visualizes the classification performance, showing the true positive, false positive, and false negative predictions across different classes. This matrix helps identify specific areas where the model excels or struggles, providing insights for further refinement

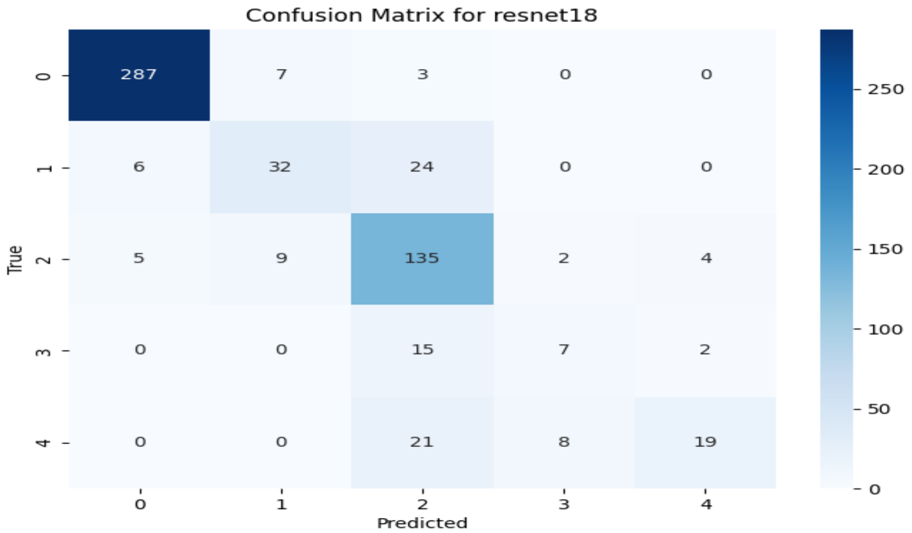
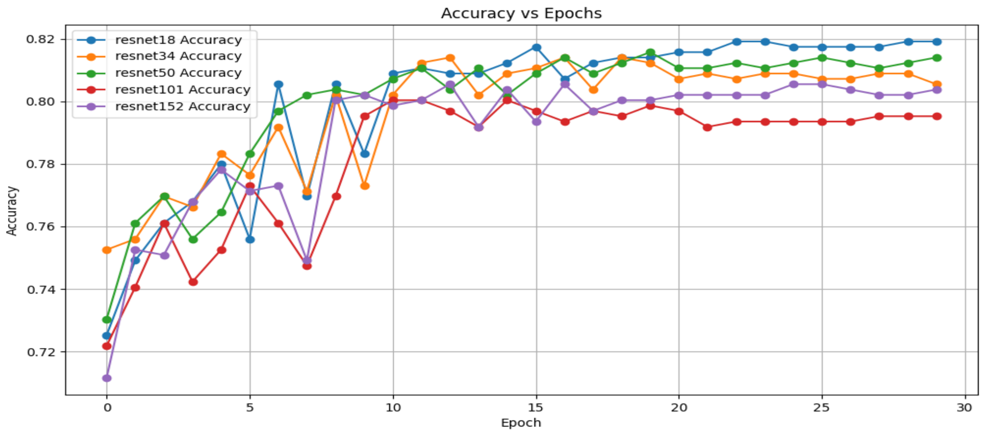


Fig. 5.6 Confusion Matrix for ResNet18

Accuracy vs Epochs and F1 Score vs Epochs

The plots for accuracy and F1 score against epochs further substantiate the performance trends observed earlier. Each model's consistency in improving metrics over training epochs highlights the effectiveness of transfer learning and the robustness of the employed architectures



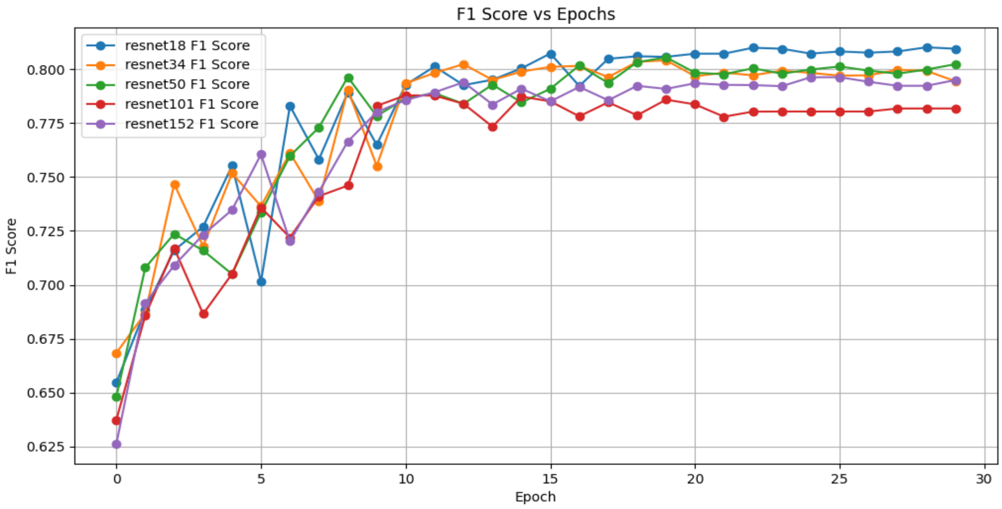


Fig.5.7 plots for accuracy and F1 score against epochs

5.1.2 Evaluation of the Proposed Hybrid Quantum Classifier with Different Quantum Gate Configurations

In this section, we evaluate the proposed hybrid quantum classifier by analyzing its performance across various quantum gate configurations using the ResNet architectures. The evaluation metrics include accuracy and F1 score for each configuration.

Accuracy Metrics

The following results summarize the accuracy achieved by the hybrid quantum classifier utilizing different gate combinations for the ResNet models as shown in table 3.

Table 5.3 summarize the accuracy achieved by the hybrid quantum classifier

Model	Gate Configuration	Accuracy
resnet18	Hadamard & CNOT	0.8157
	Hadamard & CNOT Dagger	0.8089
	RX & CNOT	0.8089
	Hadamard & CZ	0.8191
	Hadamard & SWAP	0.8106
	Hadamard & CRX	0.814
	RX & CRX	0.8089
resnet34	Hadamard & CNOT	0.8123
	Hadamard & CNOT Dagger	0.8089

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	RX & CNOT	0.8072
	Hadamard & CZ	0.8123
	Hadamard & SWAP	0.8055
	Hadamard & CRX	0.8157
	RX & CRX	0.8072
resnet50	Hadamard & CNOT	0.814
	Hadamard & CNOT Dagger	0.8157
	RX & CNOT	0.8106
	Hadamard & CZ	0.8123
	Hadamard & SWAP	0.8089
	Hadamard & CRX	0.8208
	RX & CRX	0.8157

F1 Score Metrics

The following results present the F1 score attained by the hybrid quantum classifier with various quantum gate configurations for the ResNet models as shown in table 4.

Table 5.4 results present the F1 score attained by the hybrid quantum classifier with various quantum gate configurations

Model	Gate Configuration	F1 Score
resnet18	Hadamard & CNOT	0.8064
	Hadamard & CNOT Dagger	0.7997
	RX & CNOT	0.7997
	Hadamard & CZ	0.808
	Hadamard & SWAP	0.801
	Hadamard & CRX	0.8047
	RX & CRX	0.7976
resnet34	Hadamard & CNOT	0.8023
	Hadamard & CNOT Dagger	0.7992
	RX & CNOT	0.7975
	Hadamard & CZ	0.8029
	Hadamard & SWAP	0.7959
	Hadamard & CRX	0.8066
	RX & CRX	0.7982
resnet50	Hadamard & CNOT	0.8028
	Hadamard & CNOT Dagger	0.8048
	RX & CNOT	0.7985
	Hadamard & CZ	0.7991
	Hadamard & SWAP	0.7968

	Hadamard & CRX	0.8104
	RX & CRX	0.8041

5.1.3 Testing

The testing phase involved evaluating the hybrid quantum classifier on a dedicated test dataset by loading and preprocessing the images, followed by predictions using the pre-trained model. Each image was processed to extract features and input into the hybrid model, which combines classical and quantum components for classification. The evaluation metrics focused on the F1 score, which was calculated to be 0.7021, indicating a moderate balance between precision and recall in the model's predictions. This result suggests that while the classifier demonstrates reasonable performance, there is potential for further improvements in identifying true positive cases and reducing false positives in future iterations.

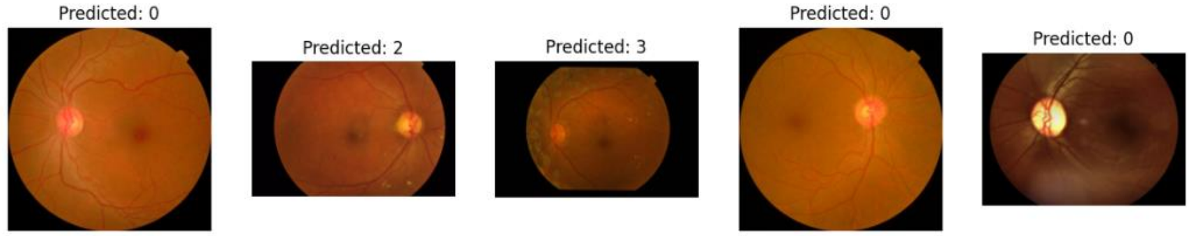

Fig. Fig 5.8 Prediction Result

VI. Conclusion

The evaluation of classical models, particularly those based on the ResNet architecture, highlighted ResNet18 as the top performer for classifying diabetic retinopathy images, achieving an accuracy of 78.69% and an F1-score of 78.54%. The use of transfer learning further improved the model’s performance, with ResNet18’s accuracy increasing to 81.91% and its F1-score reaching 80.94%. This demonstrates the effectiveness of leveraging pre-trained models to enhance performance in specialized medical imaging tasks like diabetic retinopathy grading.

The integration of a hybrid quantum classifier showed promising results, particularly with configurations like Hadamard & CZ, which yielded an accuracy of 81.91% for ResNet18. However, during the testing phase, the hybrid model achieved an F1-score of 0.7021, indicating a reasonable balance between precision and recall but also highlighting areas for improvement, such as reducing false positives. Overall, the study underscores the potential of advanced architectures and hybrid quantum-classical approaches to improve medical image classification, while pointing to the need for further innovation in medical diagnostics.

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