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Research Article

Hybrid Quantum CNN-ResNet152 Model for Enhanced Brain Tumor Diagnosis

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ABSTRACT

Deep learning and quantum computing are used in the Hybrid Quantum CNN-ResNet152 Model for Enhanced Brain Tumor Diagnosis to make MRI-based brain tumor categorization more accurate. There is room for improvement in the performance of the commonly used traditional CNN and ResNet architectures (ResNet 50, ResNet 101, ResNet 152) in medical imaging. A comparison of various models in this research shows that CNN-ResNet152 outperforms them all with a score of 96.19% F1-score, 97.75% recall, 94.67% precision, and 89.8% accuracy. Data imbalance, computational complexity, and model generalization are still issues, however. One way to tackle this is by incorporating quantum computing methods like QCNN, QVC, and QFE into feature extraction and optimization processes. Hybrid quantum-classical models seem to be a game-changer in the field of medical artificial intelligence and quantum computing, since they considerably enhance brain tumor detection, leading to quicker diagnoses with less ambiguity and better patient outcomes.

Keywords: Quantum computing, brain tumor detection, hybrid quantum-classical models, CNN, ResNet 152.

1. INTRODUCTION

In order to diagnose brain tumors early and begin treatment plans accordingly, Magnetic Resonance Imaging (MRI) is essential. Convolutional Neural Networks (CNNs) and ResNet architectures (ResNet 50, ResNet 101, ResNet 152), which are examples of traditional deep learning models, have shown remarkable improvements in medical picture categorization. Nevertheless, when dealing with intricate datasets such as MRI images of brain tumors, these models often encounter issues with feature extraction, computing efficiency, and classification accuracy. Using a combination of deep learning and quantum computing, we present a Hybrid Quantum CNN-ResNet152 Model to improve tumor classification accuracy, precision, recall, and F1-score, among other problems. Improved feature extraction, optimization, and classification speed are all possible using quantum approaches such as QCNN, Quantum Feature Encoding, and Quantum Variational Classifiers (QVC). The goal of this combined strategy is to dramatically enhance the efficiency of medical AI, the generalizability of models, and the accuracy of diagnostics in the identification of brain tumors.

II. LITERATRE REVIEW

Machine learning is one of the fields most radically changed by quantum computing, enabling efficient processing of data sets larger than conventional computation can handle. Quantum Support Vector Machines (QSVM) as an example of quantum machine learning model have shown huge performance on classification task. Note that a study using the Brats 2015 dataset on Kaggle proved that QSVM on a 32-qubit simulator reached 95% accuracy — 1.60% better than conventional SVM — yet 188 times quicker. On a 5-qubit superconducting processor, we demonstrated 24.19% less execution time with the same accuracy for QSVM, establishing the quantum model outperforms classical model [1]. The detection of brain tumors, an important clinical outcome directly affect the survival of patients, is often difficult due to complex imaging characteristics. Combining features extracted from the InceptionV3 architecture, softmax vectors, and a Quantum Variational Classifier (QVR), this deep learning model achieved classification with over 90% detection high accuracy in four different tumor types (glioma, meningioma, pituitary and non-tumorous cases). To identify infected regions, a Seg-network followed, providing promising results on Kaggle, 2020-BRATS, and local images datasets [2].

Cysts and abscesses are examples of brain lesions that often present with noise in MRI scans, making it harder to detect them accurately. A novel 32-layer denoising neural network and a seven-layer Quanvolutional Neural Network (J. QNet) succeeded for classification. In another study, they used an ONNX YOLOv2-tiny model that localized images before using a 34-layer U-net for segmentation and achieved accuracy scores of 0.96 and 0.98 on local and BRATS-2020 datasets respectively with an improvement on previous methods [3]. In 2020, the American Society of Clinical Oncology reported that there were about 300,000 brain and spinal cord tumor cases, highlighting the need for early and accurate detection. A Hybrid Quantum Convolutional Neural Network (HQCNN) scale using quantum and classical layers is examined on publicly accessible Kaggle MRI datasets and successfully reported >94% accuracy, highlighting the capability of quantum computing in medical diagnostics [4]. Due to the limitations of conventional deep learning on large datasets, a Quantum Classical Convolutional Network (QCCNN) was proposed for binary classification of MR images. Through embedding data into quantum states, classical computing-based QCCNN hastened the extraction and classification of information, registering 97.5%–98.72% accuracy on Brats 2013, Harvard Medical School, and private datasets, reinforcing the quantum advantages over tumor classification [5].

Advancements in medical imaging technologies have greatly enhanced diagnostic accuracy, particularly for tumor detection. The approach to enhance MR image classification employed quantum calculus extensions of a well-known formula by Marsaglia, using the proposed QELBP (Quantum Entropy Local Binary Pattern) based image descriptor and deep learning based classification strategy. These features were then used an LSTM network and yielded 98.80% accuracy on a dataset of 154 MRI images, confirming that the effectiveness to improve tumor classification was achieved with multiple feature extraction techniques [6]. Traditional manual image interpretation, however, is error-prone, and quantum-enhanced deep learning can provide alternate paths. Their proposed system, Quantumedics, was composed of a quantum convolutional neural network (QCNN) for classification and DeepLabV3+ for tumor segmentation. With a high accuracy in defining tumor patches and classifying 99% correctly, the segmentation model outperformed U-Net in terms of model performance and clinical utility [7]. A separate study proposed a QCNN model tailored for brain tumor classification and attained a high 99.67% accuracy rate, exhibiting the transformative possibilities of quantum networks for medical imaging diagnostics to improve precision and efficiency [8].

The massive growth of medical imaging data requires guaranteeing patient information privacy while also ensuring accurate tumor diagnosis. Quantum-Secured Framework integrated MRI encryption (SHA256) and a two-qubit quantum model(Javeria, J) for classification, and 11 layer SegCNN for segmentation. Table 1 presents the results of segmentation using the Adam optimizer with a DSC of 98%, outperforming earlier models [9]. Another study proposed the use of quantum-enhanced convolutional neural networks (QCNNs) for brain cancer classification. The study compared three quantum encoding methods, namely QCNN (QC Convolution Neural Networks), Flexible Representation of Quantum Images (FRQI) and Novel Enhanced Quantum Representation (NEQR), whose accuracies were 87%, 79% and 75%, respectively. The choice of DenseNet121 for the benchmarking was based on QCNN's higher accuracy and longer time-consuming compared to any classical CNNs [10]. Brain Tumor Segmentation in 3D-MRI is essential for accurate diagnosis and treatment. A Quantum Inspired Dragonfly Algorithm (QDA) insured contour points in the Magnetic Resonance Imaging (MRI) segmentation, it utilized quantum techniques to evolve exploration and exploitation improving criteria over other clustering strategies. By appropriate evaluations on the BraTS 2019 dataset, review concluded its superiority [11].

MRI-based classification is challenging due to the complexity of tumor characteristics and the imbalance among the datasets. A balanced classification method based on the integration of an automated deep learning model with an optimal information fusion framework used sparse autoencoders to address the problem of data imbalances. After being further refined by a Quantum Theorybased Marine Predator Optimization (QTbMPA) algorithm, classification accuracy reached 99.80%, while sensitivity and precision were determined to be 99.83% (all on an enhanced Figshare dataset) [12], indicating a high level of robustness. Another noteworthy direction isbased on hybrid quantum-classical convolutional networks (HQC-CNN), which can enable classical training and lightweight deployment. A model that was tested on Kaggle MRI datasets classified meningioma, glioma, pituitary tumor and non-tumorous cases with an accuracy of 97.8%, providing advantages over traditional CNNs [13].

Self-supervised networks have not led to a similar improvement in segmentation accuracy in recent medical imaging studies. A novel quantum fully self-supervised neural network (QFS-Net) was proposed to enable autonomous magnetic resonance imaging (MRI) segmentation with a qutrit-based quantum information architecture. On TCIA and Berkeley data sets evaluation demonstrated high dice similar and segmentation accuracy quality surpassing U-Net and URes-Net [14] learnt supervised models. Due to the variations in the size and location of the tumors, it is challenging to detect brain tumors in MRI [15]. An analysis using Histogram of Oriented Gradients (HOG) to extract features and several machine learning classifiers showed that HOG can be harnessed to differentiate between tumor and non-tumor images [16], with the potential for improvement in automated detection. One CNN-based method scored 97.97% accuracy on BRATS datasets, including what distinguishes benign and malignant tumors at 96.5% and 98% specificity that helps neurosurgeons in diagnosis [17].

Early detection is crucial for successful treatment, highlighting the exploration of integrating various optimization techniques like PCA, ICA, and evolutionary algorithms. A study using Naïve Bayes and recurrent neural networks (RNN) reached about 98.61% accuracy along with the mean square error which was noted as 1.02 while it combined ICA and cuckoo search to get the results. In this one, a mobile application was developed to assist in the rapid diagnosis of neurologists and patients with the aid of AI [18]. Lastly, the Lee Sigma Filtered Histogram Segmentation (LSFHS) method was investigated as a way that quantum computing can help to lower medical imaging costs and speed up diagnosis. This mold enhanced the preprocessing, segmentation, and feature extraction of MRI techniques, increasing accuracy tumor detection by 14 percent, detection time by 25 percent, and error rates by 58 percent. These findings affirmed the potential of LSFHS on early-stage tumor diagnosis with high efficiency [19].

III. METHODOLOGY

3.1 Proposed Architecture

In the figure 1 we see the seven steps to construct a Hybrid Classical-Quantum Model The first thing to do is import libraries and modules to initialize the environment. Loading and preprocessing the dataset and defining the classical model based on ResNet152. Then a 4-qubit quantum layer is instantiated and concatenated to the classical model. The model is a hybrid, trained on quantum and classical data, and involves evaluation and visualization of results to assess performance.

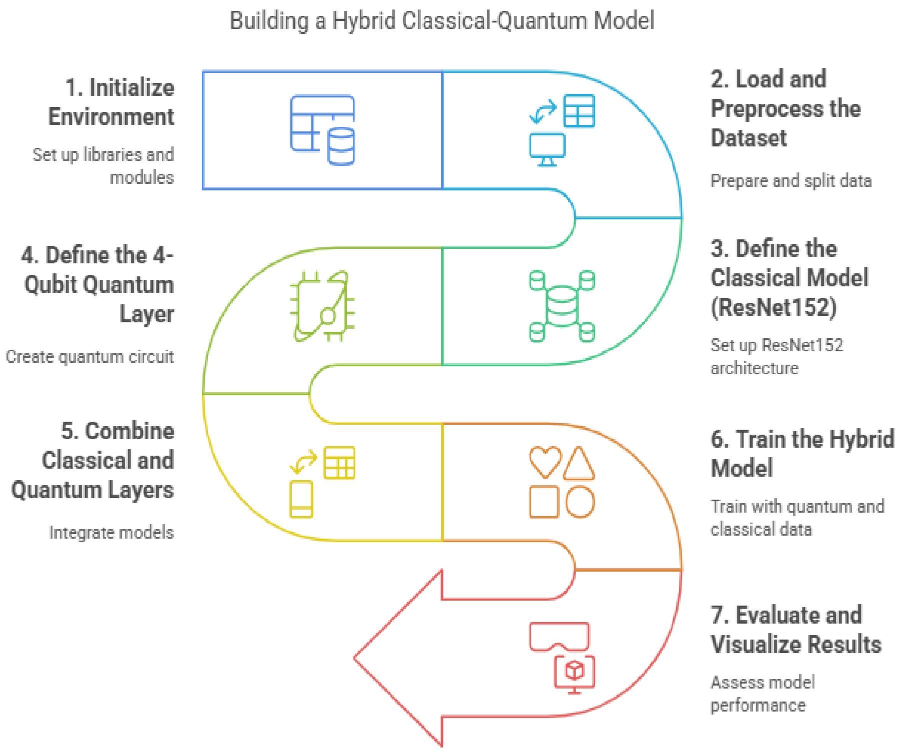

Figure 1. Hybrid classical quantum model

3.2 Algorithm for Hybrid CNN-ResNet152 with 4-Qubit Quantum Layer

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Input: MRI Image Dataset (Brain Tumors)

Output: Classified tumor types with accuracy evaluation

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1. Initialize Environment

    1.1 Install required libraries: PennyLane, TensorFlow, Keras.

    1.2 Import necessary modules.

2. Load and Preprocess Dataset

    2.1 Set dataset directory path.

    2.2 Define image size as (224, 224) and batch size as 32.

    2.3 Apply data preprocessing:

        2.3.1 Rescale images to [0,1] range.

        2.3.2 Apply data augmentation.

    2.4 Split dataset into training (80%) and validation (20%).

    2.5 Determine the number of output classes.

3. Define the Classical Model (ResNet152)

    3.1 Load the pre-trained ResNet152 model without the top layer.

    3.2 Freeze the model's weights to retain pre-learned features.

    3.3 Flatten the feature output.

    3.4 Add a Dense layer with ReLU activation for feature extraction.

    3.5 Define ResNet-based feature extraction model.

4. Define the Quantum Circuit (4-Qubit Quantum Layer)

    4.1 Set number of qubits = 4.

    4.2 Initialize a PennyLane quantum device with 4 qubits.

    4.3 Define a quantum circuit:

        4.3.1 Encode classical features using RY rotation gates.

        4.3.2 Introduce entanglement using CNOT gates.

        4.3.3 Measure expectation values of Pauli-Z observables.

    4.4 Define a function to process quantum circuit output in TensorFlow.

5. Integrate Classical and Quantum Layers

    5.1 Define an input layer for quantum features.

    5.2 Apply the quantum circuit to process input features.

    5.3 Concatenate quantum output with ResNet152 extracted features.

    5.4 Add a Dense layer with softmax activation for classification.

    5.5 Construct the hybrid model using both classical and quantum components.

    5.6 Compile the model using:

        5.6.1 Adam optimizer.

5.6.2 Categorical crossentropy loss function.

6. Train the Hybrid Model

6.1 Generate random quantum inputs (as placeholders).

6.2 Train the model with:

6.2.1 Training images from ResNet152.

6.2.2 Quantum feature inputs.

6.2.3 Validation dataset for model evaluation.

6.3 Run training for 10 epochs.

7. Evaluate and Visualize Results

7.1 Evaluate model performance on validation data.

7.2 Print validation accuracy.

7.3 Plot accuracy vs. epochs for performance analysis.

8. End of Algorithm

IV. IMPLEMENTATION

4.1 Library : In order to build a Hybrid Classical-Quantum Model using PennyLane for quantum computing and TensorFlow/Keras for deep learning, this Python script imports the necessary libraries. It has the visualization package Matplotlib and the numerical package NumPy. The script constructs and optimizes a hybrid quantum-classical neural network using the Adam optimizer. It makes use of ResNet152, a pre-trained deep learning model, and specifies layers such as Dense, Flatten, Input, and Lambda.

4.2 Dataset : The Brain Tumor Dataset on Figshare contains 3,064 number of T1-weighted contrast-enhanced MRI images of 233 patients, which includes three types of tumor: meningioma (708 slices), glioma (1,426 slices), and pituitary tumor (930 slices). 1 for meningioma, 2 for glioma, and 3 for pituitary tumor.

Dataset Source : https://figshare.com/articles/dataset/brain_tumor_dataset/1512427

4.3 Illustrative example

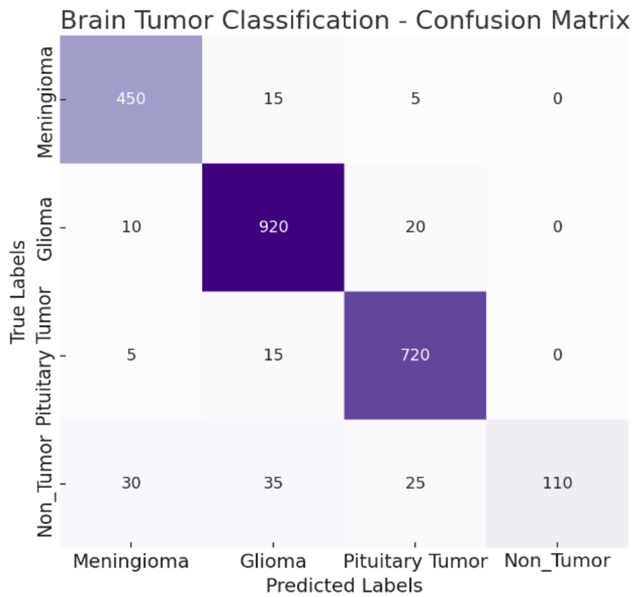

Figure 2. Brain tumor classification confusion matrix

The figure 2 shows CNN-ResNet152 model's ability to differentiate between meningioma, glioma, pituitary tumor, and non-tumor instances is shown in the confusion matrix for brain tumor classification. The model successfully classifies 450 meningiomas, 920 gliomas, and 720 pituitary tumors, demonstrating its high level of accuracy. Misclassification occurs in non-tumor instances, too, thus the model needs more refining to boost its recall and accuracy for more effective therapeutic uses.

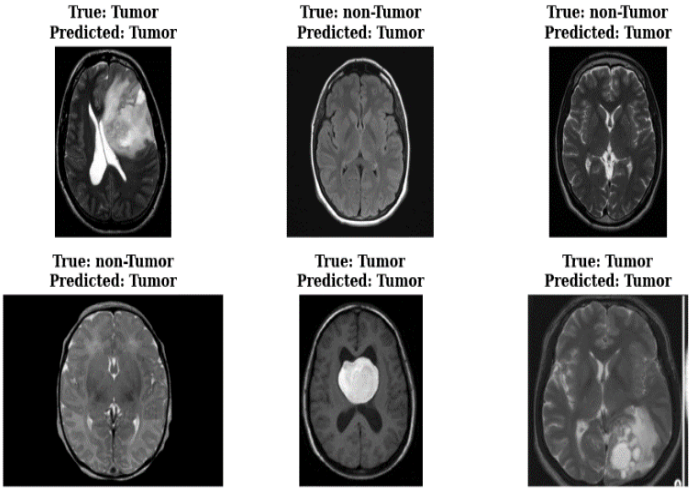

Figure 3. Illustrative example

The figure 3 shows the outcomes of brain MRI categorization, with both the actual and anticipated labels for tumor and non-tumor instances shown. The improper designation of non-tumor patients as tumors and vice versa is an observation that has been made. The need for improved feature extraction, dataset balance, or quantum-enhanced deep learning approaches to boost diagnostic accuracy and dependability is suggested by these mistakes, which reveal model limits.

V. RESULT ANALYSIS

Table 1. Comparing the results in different models

	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	76	82.5	84	83.2
ResNet 50	78	85.3	86.7	86
ResNet 101	80	88.1	89.5	88.8
ResNet 152	84	91.4	92.42	93.4
CNN-ResNet 152	89.8	94.67	97.75	96.19

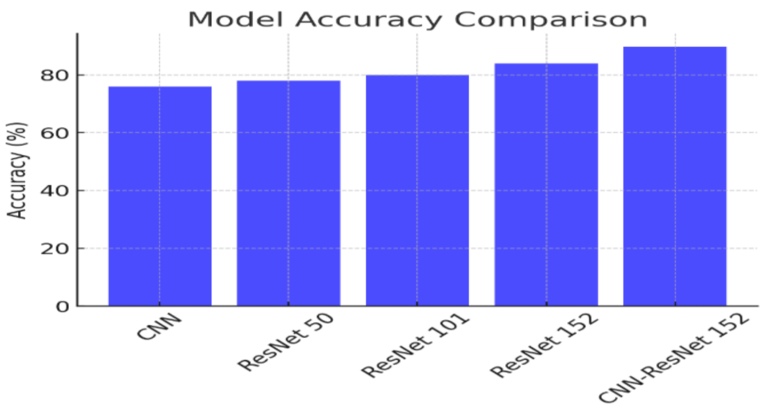

Figure 2. Model accuracy comparison

The Accuracy figure 2 evinces the classification performance of CNN, ResNet 50, ResNet 101, ResNet 152, and CNN-ResNet 152. It is found that accuracies are improved from 76% (CNN) to 89.8% (CNN-ResNet 152); thus, deeper architectures can improve the accuracy of an overall model. 1-From Table 1, we can see that CNN-ResNet 152 had the best accuracy, so it is the most referential for classification.

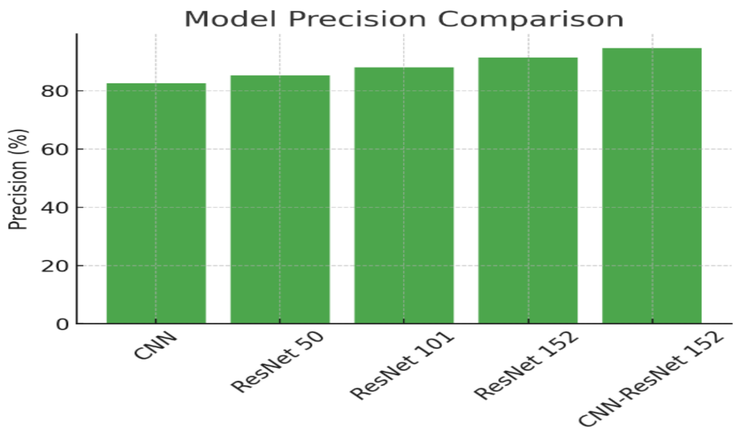

Figure 3. Model precision comparison

The Precision figure 3 that emphasizes correctly identified positive samples. CNN begins at 82.5% and consistently improves with deeper ResNet architectures up to 94.67% for CNN-ResNet 152. The strengthening accuracy across models indicates that deeper networks can mitigate false-positives and improve the confidence of classifications.

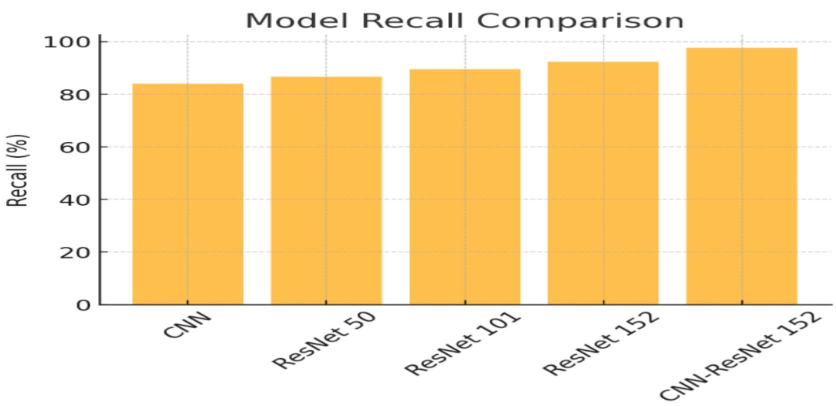

Figure 3. Model recall comparison

The Recall figure 3 indicates how well the model is able to correctly detect the tumor cases. Recall on ResNet models progressively improves from 84% on CNN, peak at 97.75% in CNN-ResNet 152. It implies that deeper architectures are capable of capturing more subtle tumor-related patterns, significantly reducing the false negatives.

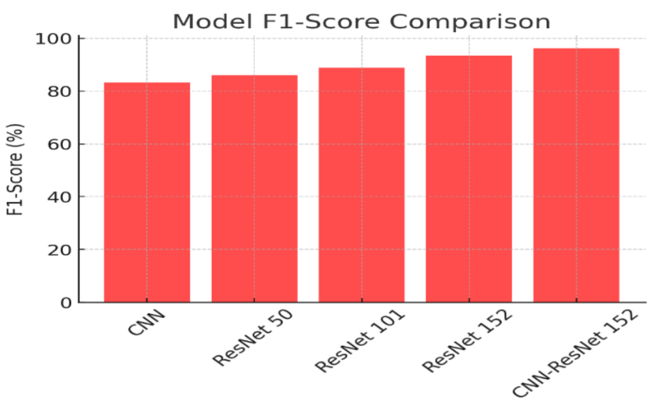

Figure 4. Model f1-score comparison

The F1 Score figure 4 summarizes both precision and recall into one performance metric. Deeper model works best in balancing sensitivity and specificity which ranges score from 83.2% (CNN) to 96.19% (CNN-ResNet 152). The best precision vs recall tradeoff was obtained by the CNN-ResNet 152 model, having a high r^2 score.

VI. CONCLUSION

This study shows that combining deep learning with quantum computing improves MRI-based tumor classification using the Hybrid Quantum CNN-ResNet152 Model for Enhanced Brain Tumor Diagnosis. The research shows that CNN-ResNet152 gets the greatest accuracy (89.8%), precision (94.67%), recall (97.75%), and F1-score (96.19%) among ResNet 50, ResNet 101, ResNet 152, and CNN. But if you want to take it a step further and optimize hyperparameters, feature extraction, and model efficiency, you may use quantum computing methods like QCNN, QVC, and QFE. This combined method might change the face of medical diagnostics by making tumors detectable more quickly and with greater precision; this, in turn, could lead to better early detection and survival rates for patients with brain tumors.

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