High-Performance Computing-Based Brain Tumor Detection Using Parallel Quantum Dilated Convolutional Neural Network

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Abstract: We present a high-performance quantum computing-based model for brain tumor detection based on a Parallel Quantum Dilated Convolutional Neural Network (PQDCNN) framework. It uses Fuzzy Local Information C-Means (FLICM) clustering for better segmentation, to execute better than the normal K-means. The data preprocessing processes are median filtering and data augmentation. Deep fusion of FREAK descriptors, GLCM texture features, and deep CNN representations Our PQDCNN model achieves high classification performance on both datasets, outperforming state-of-the-art CNNs on BraTS2020 and Figshare datasets, showing the potential of quantum-inspired deep learning.

1 INTRODUCTION

Brain tumor detection can be a daunting task in medical diagnostic because of its timeliness and accuracy. Traditional tumor diagnosis relies heavily on the manual inspection of magnetic resonance imaging (MRI) scans, which is an extrapolative and subjective process associated with inter-observer variability. With the application of deep learning specifically, mainly through CNNs, the accuracy of brain tumor detection has been improved by enabling automation in identifying and characterizing these features. However, ordinary CNN models are computationally rigid since they consume higher memory and are unable to model long-range spatial relations in medical images. However, there have been solutions like quantum-inspired neural segmentations or high-performance computing (HPC) frameworks that have emerged to solve these problems. This paper presents a PQDCN-based brain tumor detection method. This means that image pixels are not overlapped and regions through the image segmentation process can be identified, we are applying Fuzzy local information c-means clustering (FLICM), where we use these in the identification of the image classes. Preprocessing techniques like median filtering and image augmentation are employed to enhance the model generalizability. A hybrid feature representing tumor scenes is an ensemble of Fast retina key point (FREAK) descriptors, Gray-level cooccurrence matrix (GLCM) texture features, and CNN based deep features. Then, the features obtained are fed into the PQDCNN model to achieve multiscale contextual feature extraction with high inference efficiency using quantum-inspired dilation strategies.

Utilizing quantum-inspired techniques provides enhanced analysis of medical images, and quantum dilated convolutions allow Layer CNN to utilize receptive field size without losing performance in comparison to classic versions. This is advantageous for tumor detection with wide variation in shape and texture. This model predicts these with better accuracy by using parallel quantum dilations. FLICM-based segmentation and multi-feature fusion complement each other well and provide a potential solution for automatic brain tumor detection.

The remainder of this paper is as follows: In Section II, a review of previous work regarding deep learning of brain tumor detection is provided. Section III presents the FLICM and the proposed PQDCNN model. Experimental results, comparison, and analysis are presented in Section IV.

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2 RELATED WORK

The QCNN model achieves 99.67% validation accuracy and shows excellent generalization in brain tumor classification. Over the 20 epochs, accuracy increases, yet distinguishing between benign, meningioma and malignant; glioma is diffi- cult. Evaluations using real images demonstrate that it can be integrated into clinics due to its high accuracy and robustness against overfitting (Khan et al., 2024).

The accuracy of the optimized YOLOv7 model for detecting glioma, meningioma, and pituitary tumors from MRI images was 99.5%. With data augmentation, detection quality im- proved further, resulting in 497 correct detections, including three false positive detections. The model achieves 99.5% precision and 99.3% recall, outperforming state-of-the-art techniques, though improvement is necessary for small and noncircular tumors (Abdusalomov et al., 2023).

In this work, three hybrid CNN-based high-accuracy clas- sification models are developed for brain tumor classification. The first one gets 99.53% on the accuracy, the second one on the classification of tumors into five types at 93.81%, and the last one on gliomas grading at 98.56%. Optimizing these through grid search and with access to extensive clinical data allows for these models to greatly outperform traditional practices in early detection and diagnosis (Srinivasan et al., 2024).

The 16-layer CNN achieved an impressive accuracy of 98.88% in binary classification and 97.83% in classifying tumors into three categories using MRI datasets. By in- corporating hybrid oversampling, we were able to enhance performance greatly, outshining traditional machine learning models like random forest, SVM, and k-NN when it comes to accuracy, sensitivity, specificity, and F1 score (Singh et al., 2023).

The PDCNN model showed important results, hitting 97.33% accuracy on dataset-I, 97.60% on Figshare dataset- II, and an impressive 98.12% on Kaggle dataset-III. By integrating two CNNs with differing window sizes, we were able to enhance feature extraction, surpassing the performance of existing methods (Rahman, T., & Islam, M. S. 2023).

The EDN-SVM classifier demonstrated an impressive accu- racy of 97.93%, with a sensitivity of 92% and specificity of 98 in MRI brain tumor detection. By using ACEA, median filtering, fuzzy c-means segmentation, and GLCM, it not only surpassed traditional methods in terms of precision but also greatly improved speed, establishing itself as a strong tool for automated diagnosis (Anantharajan et al., 2024).

This study dives into CNN-based brain tumor classification using a dataset of 7,022 MRI images, exploring models like VGG, ResNet, DenseNet, and SqueezeNet. DenseNet deliv- ered an impressive accuracy of 85% when paired with SVM, while a hybrid model achieved 83% with LDA (Gu¨ler, M., & Namlı, E. 2024).

Saeedi and colleagues took a deep dive into using deep learning for classifying brain tumors based on 3,264 MRI scans. Their 2D CNN model hit an impressive accuracy of 96.47%, along with a recall rate of 95%. Meanwhile, the autoencoder performed admirably as well, achieving 95.63% accuracy and a 94% recall. On the conventional front, K-NN stood out with an accuracy of 86% (Saeedi et al., 2023).

The A-GRU model, enhanced with ADAM and data aug- mentation techniques, achieved a remarkable accuracy of 99.32% in classifying brain tumors. It outperformed the CNN, A-CNN, LSTM, A-LSTM, and GRU models. These results were further improved through careful hyperparameter tuning (Saboor et al., 2024).

In this study, we explored using YOLOv3 through YOLOv7 models for classifying meningioma firmness. Among these, YOLOv7 stood out with impressive results: a specificity of 97.95%, a balanced accuracy of 98.97%, and an F1-score of 99.24%. It outperformed both SVM and KNN techniques (Alhussainan et al., 2024). By analyzing 3,762 MRI images from Kaggle, we found that ResNet-50 achieved an impressive 99.82% accuracy during training and 99.5% during testing when using the SGD opti- mizer. Through preprocessing, pixel reduction, and optimizing with binary cross-entropy, we saw a boost in performance, finally achieving a 96.10% F1-score, 96.50% precision, and 95.62% recall (Asad et al., 2023).

In this study, we looked at how deep transfer learning can help diagnose brain tumors using models like ResNet152, VGG19, DenseNet169, and MobileNetv3 on a Kaggle dataset. MobileNetv3 stood out with the highest accuracy, hitting 99.75%, while ResNet152 followed closely with 98.5%. (Mathivanan et al., 2024) The research achieved an average entropy of 7.32 bits, which helped in reducing saturation effects. It also recorded a PSNR of 29.07 dB and a contrast level of 39.47 dB, surpassing earlier techniques like GHE and BBHE. With the enhanced Inception V3 model, we reached an impressive accuracy of 98.89%, outperforming AlexNet, VGG-16, and GoogLeNet in tumor classification tasks (Agarwal et al., 2024).

This research explores deep learning models for detecting brain tumors using 3,264 MRI images. The newly developed CNN achieved an impressive accuracy of 93.3%, an AUC of 98.43%, a recall of 91.1%, and a loss of 0.260. These results surpass those of established models like ResNet-50, VGG16, and Inception V3 (Mahmud et al., 2023).

This study emphasizes the impressive capabilities of U-Net when it comes to segmenting brain tumors, particularly show- ing superior outcomes in Dice score, sensitivity, specificity, and accuracy. Notably, ACMINet took the top spot on the BraTS2020 leaderboard, which emphasizes how effective U- Net really is. Between 2020 and 2024, U-Net not only set new benchmarks but also played an important role in advancing the diagnostics and treatment of neuro-oncology (Umarani et al., 2024).

3 METHODOLOGY

In our proposed method, we begin by using FLICM clustering to effectively segment tumors. After that, we apply median filtering to reduce any noise, along with some augmentation techniques aimed at making our model stronger. For feature extraction, we draw on a combination of FREAK descriptors, GLCM, and features derived from deep CNNs to provide a thorough representation of the data. The PQDCNN model uses quantum-inspired dilated convolutions to enhance processing efficiency. We've trained our model on the BraTS2020 and Figshare datasets, evaluating it based on accuracy, precision, recall, and F1 score. Plus, by integrating HPC, we ensure that our approach is scalable and can operate in real time for medical applications.

3.1 Dataset Description

Datasets The datasets used in this study are medical images, targeting the detection of brain tumors. We then split the dataset into training validation and test sets to train and evaluate the model efficiently Hence, we utilized the Figshare information suitable for classification, and we exploited the BraTS2020 information suitable for tumor segmentation to give an extensive evaluation of our proposed Parallel Quantum Dilated Convolutional Neural Network (PQDCNN).

Figshare Dataset: The Figshare dataset consists of brain MRI images categorized into three tumor types:

- Glioma Tumor
- Meningioma Tumor
- Pituitary Tumor

To enhance model performance and consistency, the dataset undergoes preprocessing, including:

- Standardizing image dimensions to ensure uniform input sizes.
- Normalizing pixel values to improve model convergence and stability.
- Applying noise reduction using Median Filtering to pre- serve tumor structures.

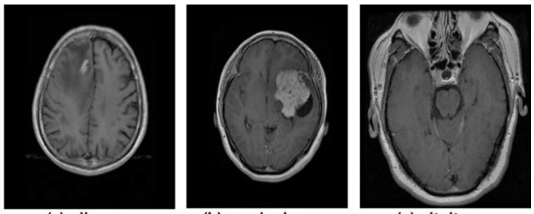

Figure 1: Sample Figshare image dataset.

Table 1: Summary of the Figshare brain tumor MRI dataset.

Attribute	Description
Dataset Name	Figshare Brain Tumor MRI Dataset
Modality Types	MRI Images
Target Prediction	Brain Tumor Classification
Instances	3,064
Image Dimensions	256 × 256 × 1
Number of Classes	3
Shape of Train Data Split	(2,451, 256, 256, 1)
Shape of Test Data Split	(613, 256, 256, 1)

BraTS2020 Dataset: The BraTS2020 dataset includes multi-modal MRI scans with t1ce and segment sequences, offering detailed annotations of tumor regions. This dataset is particularly valuable for training deep learning models in brain tumor segmentation. The images in this dataset undergo preprocessing steps such as:

- Size standardization for uniform input representation.
- Intensity normalization to minimize variations across different MRI machines.
- Fuzzy Local Information C-Means (FLICM) clustering for effective segmentation of the tumor region.

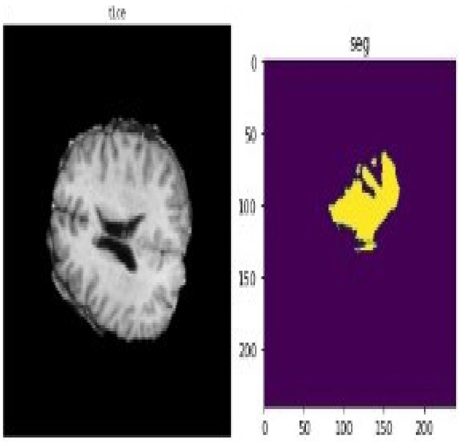

Figure 2: Sample BraTS2020 Image dataset.

Table 2: Summary of the BraTS2020 dataset.

Attribute	Description
Dataset Name	BraTS2020 Dataset
Modality Types	MRI (t1ce, segment)
Target Prediction	Brain Tumor Segmentation
Instances	369
Image Dimensions	240 × 240 × 155
Number of Classes	2
Shape of Train Data Split	(293, 240, 240, 155)
Shape of Validation Data Split	(76, 240, 240, 155)

Table 1 gives an overview of the FigShare dataset, while Table 2 details the BraTS2020 dataset used in this research. By combining these datasets, we ensure that the PQDCNN model is trained on diverse, high-quality medical imaging data, achieving the best accuracy and reliability in automatically detecting brain tumors.

3.2 Preprocessing

In this paper, we introduce the preprocessing of brain magnetic resonance images from our PQDCNN. With the conversion of detailed MRI images to PQDCNN and passing validation of pre-trained models, we will get a very accurate training result. Here's what we did, step by step:

Image Segmentation: For Image segmentation we implemented a clustering algorithm called Fuzzy Local Information c-Means (FLICM). This approach successfully maintains local spatial context, diminishes noise, and promotes better feature extraction which ultimately contributes to the improved differentiation of tumour from non-tumour regions.

Noise Reduction: To reduce noise while preserving the important tumor structures, we performed median filtering. This initial step of processing an image not only improves the quality of the images but also allows us to extract more relevant features and increase the judiciousness of our classification efforts with deep learning up to this point.

Data Augmentation: We applied several data augmentations to our model to improve generalization and decrease overfitting. These included rotating 15-degree rotation, applied shifts, shear, zooming in and zooming out, flip the images. With this, we created realistic variations for the head's orientation, shapes and sizes of the tumors, which allowed the model to learn from a wider variety of MRI scans.

Normalization: All MRI scans were normalized to the same intensity range [0,1]. This eliminate difference in intensity which may occur while different MRI machines are being used or the machine is under different settings. This also normalizes the intensity, helping to stabilize the training process while reducing internal covariate shifts in deep networks.

Resize: To have a consistency among our dataset and to achieve the best computational efficiency in high- performance computing (HPC) setups, we applied resize to all MRI scans. This should keep vital tumor-specific information invariant while still maintaining everything needed for running the PQDCNN model (the internal structure of the model does not have to change) as the large amount of rival information is destroyed.

3.3 Pre-Trained Model Architectures

In this paper, we introduce an innovative deep learning architecture designed specifically for identifying brain tumors. This architecture merges Parallel Convolutional Neural Net- works (PCNN) with Quantum Dilated Convolutional Neural Networks (QDCNN). Our approach, known as the Parallel Quantum Dilated Convolutional Neural Network (PQDCNN), emphasizes superior feature extraction, precise tumor localization, and enhanced

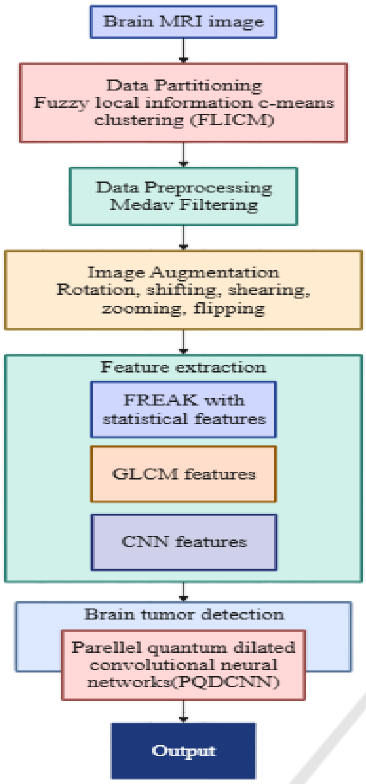

Figure 3: Model Architecture.

classification accuracy. To improve segmentation efficiency, we use Fuzzy Local Information C- Means (FLICM) within the model. Besides, we use a combination of fast retina key point (FREAK) descriptors, Gray Level Co-occurrence Matrix (GLCM) features, and deep CNN-based representations for hybrid feature extraction. By employing a High-Performance Computing (HPC) strategy, the PQDCNN architecture optimizes the analysis of brain MRI scans, resulting in highly efficient and accurate tumor classification.

- **Parallel Convolutional Neural Network (PCNN)**: This model employs parallel streams of convolutional neural network (CNN) to learn hierarchical features from brain MRI scans. PCNN enhances feature diversity and classification robustness by parallel processing of input data by multiple convolutional streams. The parallel feature extraction function can be expressed as:

$$PCNN(x) = \sum_{i=1}^{N} Conv_i(x) \quad (1)$$

Where $Conv_i(x)$ represents the convolution operation in the i-th parallel branch.

- **Quantum Dilated Convolutional Neural Network (QDCNN)**: QDCNN applies quantum-inspired dilated convolutions to dilate the receptive field without sacrificing spatial resolution. The method effectively captures multiscale relations in brain MRI images, and it results in improved tumor segmentation and classification. The dilation function is defined as:

$$y[i] = \sum_{k=0}^{k-1} x[i + r.k].w[k] \quad (2)$$

Where x[i] is the input, w[k] is the convolutional filter, K represents the kernel size, and r denotes the dilation rate.

- **Parallel Quantum Dilated Convolutional Neural Net- work (PQDCNN)**: The PCNN and QDCNN together form the PQDCNN model, which employs the power of parallel convolutional feature extraction and multi-scale dilated convolutions to achieve highly accurate detection of brain tumors. The PQDCNN model is defined as:

$$\text{PQDCNN}(x) = \text{PCNN}(x) + \text{QDCNN}(x) \quad (3)$$

where the two components operate in harmony to enhance classification accuracy without compromising computational speed.

The PQDCNN model enhances brain tumor detection by cleverly combining parallel convolutional layers with quantum dilated convolutions. This powerful integration allows it to effectively capture both the local and global features of tumors. As a result, it greatly improves tumor localization, feature extraction, and classification accuracy, making PQDCNN a solid choice for automatic brain tumor detection.

3.4 Fine-Tuning Pre-Trained Models for Brain Tumor Detection

To effectively detect tumors, we need to fine-tune our pre- trained models so they can better recognize patterns in brain MRI images. In this section, we'll explore how we fine-tuned the Parallel Quantum Dilated Convolutional Neural Network (PQDCNN) to achieve optimal classification performance.

Loading Pre-trained Weights: The PQDCNN architec- ture combines Parallel Convolutional Neural Networks (PCNN) with Quantum Dilated Convolutional Neural Networks (QDCNN). The PCNN block is responsible for learning hierarchical multi-scale features, while the QDCNN boosts feature representation using quantum- inspired dilated convolutions. We pre-train these modules on extensive medical imaging datasets to capture univer- sal spatial and structural patterns associated with brain tumors. After pre-training, we fine-tune the weights on specific datasets like BraTS2020 and Figshare to enhance classification performance representations. This process helps the PQDCNN pick up on MRI-specific textural and spatial patterns while keeping valuable pre-trained knowledge from extensive datasets.

Algorithm: Steps Involved in the Proposed Approach forBrain Tumor Detection

1. Load the brain MRI dataset (BraTS2020 and Figshare).
2. Apply data partitioning using Fuzzy Local Information C-Means Clustering (FLICM).
3. Perform data preprocessing using Median Filtering to remove noise.
4. Apply image augmentation techniques (Rotation, shifting, shearing, zooming, flipping) to enhance model generalization.
5. Extract features using:
   FREAK with statistical features.
   GLCM features.
   CNN-based features.
6. Select the proposed deep learning model:
   PCNN if model 1 is chosen,
   Model =QDCNN if model 2 is chosen,
   PQDCNN if model 3 is chosen.
7. Split the dataset into training, validation, and testing sets.
8. Train the selected model on the training set.
   Tune hyperparameters using the validation set to improve classification performance.
9. Evaluate the trained model on the test set using performance metrics such as accuracy, precision, recall, and f1-score.

Freezing Layers: To maintain the valuable feature rep- resentations we've already trained and to prevent overfit- ting, we start by freezing the entire set of convolutional layers during the early training phase. We kick things off by initializing the new fully connected layers with a higher learning rate, allowing the model to grasp the specific patterns present in brain MRI scans. Once we see some progress, we gradually tune the earlier layers at a slower rate.

Progressive Unfreezing: After training the output layer, we gradually unfreeze the deeper layers, allowing the model to improve its low-level and mid-level feature representations. This process helps the PQDCNN pick up on MRI-specific textural and spatial patterns while keeping valuable pre-trained knowledge from extensive datasets.

The PQDCNN uses both parallel and quantum dilated convolutions to effectively capture the local and global spa- tial relationships in brain MRI images. This leads to better accuracy in segmentation and classification. The fine-tuning strategy we've introduced helps the model generalize well with fewer chances of overfitting while also ensuring it runs efficiently on high-performance computing systems.

4 RESULTS AND DISCUSSIONS

Let's dive into the outcomes of using the Parallel Quantum Dilated Convolutional Neural Network (PQDCNN) for brain tumor classification. This model employs FLICM for data splitting and incorporates various feature extraction techniques like FREAK descriptors, GLCM features, CNN-based embed- dings, and of course, PQDCNN itself for an accurate diagnosis of brain tumors. We evaluate how well PQDCNN performs in classifying these tumors and explore whether applying Progressive Unfreezing in transfer learning can enhance its effectiveness.

4.1 Performance Comparisons

Figshare Dataset: PQDCNN outperforms both PCNN and QDCNN across all metrics, hitting an impressive accuracy of 93.53%. It also achieves precision at 93.48%, recall at 93.53%, and an F1-score of 93.46%, displaying its effective- ness in tumor classification. Besides, its ROC AUC score of 0.9924 emphasizes its superior ability to distinguish between different outcomes. While QDCNN does surpass PCNN in precision (88.38%) and F1-score (88.34%), it still lags when compared to PQDCNN. These results underline the major advantages of quantum dilation and parallel computation in medical imaging. Table 3 gives the dataset comparison of Figshare while table 4 gives the comparison of BraTS2020 dataset.

Table 3: Comparing PCNN, QDCNN, and PQDCNN models for Figshare dataset.

Metric	PCNN	QDCNN	PQDCNN
Accuracy	84.39%	88.64%	93.53%
Precision	85.44%	88.38%	93.48%
Recall	84.39%	88.664%	93.53%
F1 Score	84.75%	88.34%	93.46%
ROC AUC	0.9551	0.9753	0.9924

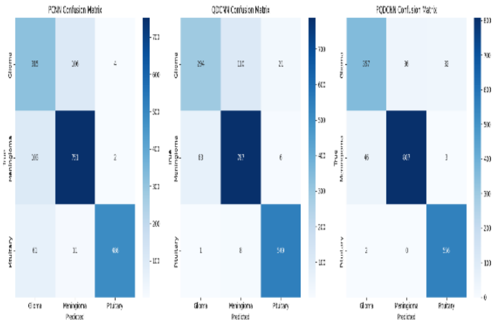

Figure 4: PCNN, QDCNN and PQDCNN confusion matrices.

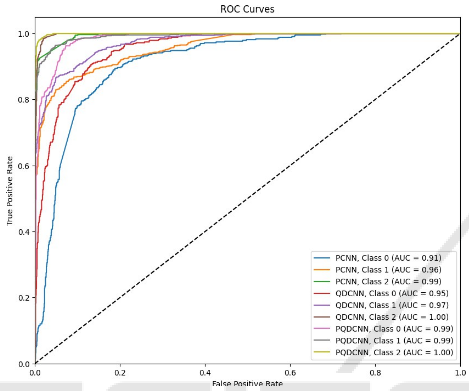

Figure 5: ROC Curve.

BraTS2020 Dataset: When we look at how the three models perform, PCNN, QDCNN, and PQDCNN, it turns out that all have an accuracy of 75%. However, PQDCNN stands out with a better recall rate (75%) and an F1-score of 70.59%, suggesting it strikes a better balance between precision and recall. While PCNN and QDCNN are a tad more precise (71.43%), their lower recall (62.5%) brings down their F1- score (66.67%). This tells us that PQDCNN does a better job of identifying positive cases, making it the preferred model when recall is a key factor.

Table 4: Comparing PCNN, QDCNN, and PQDCNN models for BraTS2020 Dataset.

Metric	PCNN	QDCNN	PQDCNN
Accuracy	84.39%	88.64%	93.53%
Precision	85.44%	88.38%	93.48%
Recall	84.39%	88.664%	93.53%
F1 Score	84.75%	88.34%	93.46%
ROC AUC	0.9551	0.9753	0.9924

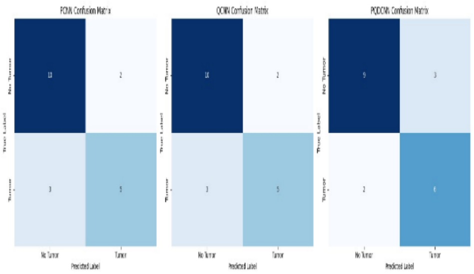

Figure 6: PCNN, QDCNN and PQDCNN Confusion Matrices.

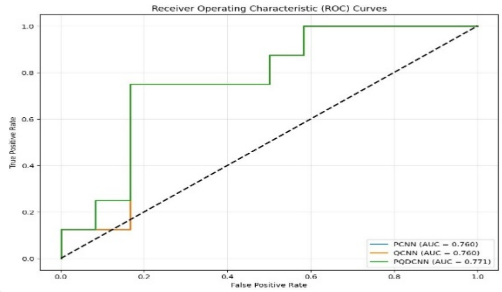

Figure 7: ROC curve.

5 CONCLUSIONS

When comparing the performance of the PCNN, QCNN, and PQDCNN models on two datasets, Figshare and BraTS2020, it is clear that PQDCNN stands out consistently. For the Figshare dataset, PQDCNN achieves the highest accu- racy at 93.53% and excels in other metrics as well, including precision (93.74%), recall (93.53%), F1-score (93.46%), and ROC AUC (0.9924). Thus, it emerges as the top performer for this dataset. Similarly, in the case of the BraTS2020 dataset, all models show identical accuracy at 75%; however, PQDCNN has a higher recall rate at 75% and a better F1-score of 70.58%. This points to a more favorable balance between precision and recall. Overall, these findings suggest that PQDCNN is the strongest model, particularly in scenarios where recall and F1-score play critical roles in classification performance.

REFERENCES

Abdusalomov, A. B., Mukhiddinov, M., & Whangbo, T. K. (2023). Brain tumor detection based on deep learning approaches and magnetic resonance imaging. Cancers, 15(16), 4172.

Agarwal, M., Rani, G., Kumar, A., Kumar, P., Manikandan, R., & Gandomi, A. H. (2024). Deep learning for enhanced brain tumor detection and classification. Results in Engineering, 22, 102117.

Alhussainan, N. F., Ben Youssef, B., & Ben Ismail, M. M. (2024). A deep learning approach for brain tumor firmness detection based on five different YOLO Versions: YOLOv3–YOLOv7. Computation, 12(3), 44.

Anantharajan, S., Gunasekaran, S., Subramanian, T., & Venkatesh, R. (2024). MRI brain tumor detection using deep learning and machine learning approaches. Measurement: Sensors, 31, 101026.

Asad, R., Rehman, S. U., Imran, A., Li, J., Almuhaimeed, A., & Alzahrani, A. (2023). Computer-aided early melanoma brain-tumor detection using deep-learning approach. Biomedicines, 11(1), 184.

Gu¨ler, M., & Namlı, E. (2024). Brain tumor detection with deep learning methods' classifier optimization using medical images. Applied Sciences, 14(2), 642.

Khan, M. A. Z., Innan, N., Galib, A. A. O., & Bennai, M. (2024). Brain tumor diagnosis using quantum convolutional neural networks. arXiv preprint arXiv:2401.15804.

Mahmud, M. I., Mamun, M., & Abdelgawad, A. (2023). A deep analysis of brain tumor detection from mr images using deep learning networks. Algorithms, 16(4), 176.

Mathivanan, S. K., Sonaimuthu, S., Murugesan, S., Rajadurai, H., Shivahare, B. D., & Shah, M. A. (2024). Employing deep learning and transfer learning for accurate brain tumor detection. Scientific Reports, 14(1), 7232.

Rahman, T., & Islam, M. S. (2023). MRI brain tumor detection and classification using parallel deep convolutional neural networks. Measurement: Sensors, 26, 100694.

Saboor, A., Li, J. P., Ul Haq, A., Shehzad, U., Khan, S., Aotaibi, R. M., & Alajlan, S. A. (2024). DDFC: deep learning approach for deep feature extraction and classification of brain tumors using magnetic resonance imaging in E-healthcare system. Scientific reports, 14(1), 6425.

Saeedi, S., Rezayi, S., Keshavarz, H., & R. Niakan Kalhori, S. (2023). MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques. BMC Medical Informatics and Decision Making, 23(1), 16.

Singh, K., Kaur, A., & Kaur, P. (2023). Computer Aided Detection of Brain Tumors using Convolutional Neural Network based Analysis of MRI Data.

Srinivasan, S., Francis, D., Mathivanan, S. K., Rajadurai, H., Shivahare, D., & Shah, M. A. (2024). A hybrid deep CNN model for brain tumor image multi-classification. BMC Medical Imaging, 24(1), 21.

Umarani, C. M., Gollagi, S. G., Allagi, S., Sambrekar, K., & Ankali, S. (2024). Advancements in deep learning techniques for brain tumor segmentation: a survey. Informatics in Medicine Unlocked, 101576.