Investigating Hybrid Quantum-Assisted Classical and Deep Learning Model for MRI Brain Tumor Classification

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***Abstract*—Brain tumors pose significant diagnostic and therapeutic challenges and are associated with high rates of illness and death. Magnetic Resonance Imaging provides detailed images of the brain's structure, making it an essential tool for identifying abnormalities, including tumors. However, accurately categorizing different types of tumors still poses a considerable difficulty. Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have shown promising results in the precise classification of brain tumors via MRI data processing. Nevertheless, the effectiveness of CNNs might be constrained by the magnitude and intricacy of the dataset. This study illustrates the application of Hybrid Quantum-Classical Convolutional Neural Network (HQC-CNN) and DenseNet121 model on the brain tumor classes namely meningioma glioma, and pituitary tumors. The experimental results indicate that the models attained accuracies of 88% and 94% in categorizing brain tumor images, respectively, with the HQC-CNN model and DenseNet121.**

***Keywords*—quantum convolutional neural networks, classical convolutional neural networks, quantum hybrid-classical, densenet121, quantum computing, brain tumor, Magnetic Resonance Imaging (MRI)**

I. Introduction

The American Cancer Society's research [1] reveals that in 2020, a total of 308,102 individuals worldwide who were diagnosed with the cancerous tumors of the brain and spinal cord. Also, in 2023, a total of 24,810 adults in Ohio, United States, were diagnosed with cancerous tumors of the brain and spinal cord. So, there is a need of more studies in this field. Currently, the diagnosis of a brain tumor involves multiple tests and procedures from taking out a tissue sample through surgery to neurological evaluation or MRIs. The genetic characterization of the tumor can be determined by these techniques, which may last several weeks. This delay in discovery can further complicate the treatment process. Our study involves a Quantum Deep Learning model that can identify and categorize tumors. This approach is less intrusive and has the potential to reduce the need for surgeries and improve the precision of therapy. However, the number of brain tumor categories exceeds 100. Therefore, we made the decision to focus our efforts on three prevalent types of cancers: meningioma, glioma, and pituitary tumors.

Meningioma, a primary brain cancer, that originates from the meninges, the layers of tissue that surround and protect the brain and spinal cord. Glioma is the second most common tumor of brain after those with meningiomas, and it represents one third of all cases. This tumor starts from the glial cell which wraps and assists neurons in brain. A pituitary tumor is an abnormal growth located in the pituitary gland, which is situated in the brain. The body's endocrine system produces hormones that have a significant impact on various glands and bodily functions.

Due to the advancement of artificial intelligence techniques, the medical sector is also undergoing significant transformations. Convolutional Neural Networks (CNNs), category of neural network architecture, suitable for computer vision and image processing tasks, have also various applications in the study of medical images for diagnosis and prognosis [2–4].

Classical CNNs suffer from the limitation of not being able to effectively learn global and distant semantic information, among other drawbacks. Hence, a logical progression would involve integrating another flourishing technology, such as Quantum based Convolutional Neural Networks (QCNNs) have a strong tendency to accurately learn the probability distributions of the training data, including both relevant patterns and irrelevant noise and outliers. QCNNs have the potential to be less susceptible to overfitting because of their wider feature areas. As the complexity and amount of the image collection increase, CNNs become restricted in their ability to convey and capture the full range of information. QCNNs are the

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development of CNNs with Quantum deep learning. Quantum properties such as superposition and entanglement are used for a higher level of expressiveness. It is a promising area, but still early in developing and regarded as a research interest within quantum machine learning, capable of reshaping all the fields requiring complex data processing.

This study utilizes a hybrid quantum classical model and DenseNet121 model to accurately classify brain tumors using an open-source brain tumor imaging dataset. The research has two main motivations:

1. Design of a Hybrid Quantum Classical Model (HQCM) and DenseNet121 model to classify the brain tumor features.
2. The experiments on MRI brain tumor datasets to evaluate the performance of both models.

As an outline of the rest of the paper, as follows: Section II discusses the literature review and Section III outlines datasets that are considered along with methodology, and Section IV describes presents the experimental results and discussions, and Section V concludes the paper.

II. Literature Review

In this section, we highlight significant works that have inspired our research work, which have utilized Quantum Deep Learning (QDL) for brain tumor classification tasks and provide a quick overview of the achieved outcomes.

In Ref. [5], the progression of a study, which is devoted to reducing the processing time of already abundant image datasets used in diagnostics, especially brain tumor images, and ensuring the protection of patient confidentiality, as the main goals are discussed. The authors also commented on their encryption-decryption technique for MRI data and solving a difficult 2-qubit tumor classification model. Dice Similarity Coefficient (DSC) was used as a validation metric, and the above model, which is still based on the side problem, managed to reach 98%. Nevertheless, the study was also dedicated to the process of brain tumor classification model creation combined with cryptographic aspects.

Dong *et al.* [6] proposed a novel Hybrid Quantum-Classical Convolutional Neural Network (HQC-CNN) model for brain tumor classification. The principal improvements of the proposed network included its high classification accuracy accompanied by 97.8%. In this study, the classification problem in a quaternary model was analyzed, with four types of conditions, meningioma, gliomia, pituitory and no tumor.

Raza [7] examined the efficacy of two pre-trained transfer learning techniques, InceptionV3 and DenseNet121, in successfully classifying several forms of brain tumors. The experimental findings indicate that the DenseNet-121 model, utilizing the transfer learning approach, surpassed other models in terms of accuracy in detecting and categorizing brain cancers, obtaining exceptional accuracy rate of 99.95%.

Amin *et al.* [8], utilize deep features from the commonly adopted inceptionV3 model, as well as a parametric quantum circuit on an input feature that has four classes as well. In this study, the authors evaluated the proposed hybrid approach using three benchmark datasets. The results demonstrated that the hybrid approach outperformed traditional CNNs, achieving an accuracy of over 90%.

The objective of the study [9] was to develop a precise and strong system that can differentiate between brain tumors and normal brain images. This was accomplished by utilizing the DenseNet121 architecture, resulting in a training accuracy of 94.83%.

Bauer *et al.* [10], however, uses an MRI dataset to develop a brain tumor model with an X-ray variant Quantum Neural Network (QNN) for metrics. The workflow performed a feature selection using mutual information that allowed to transform it into an optimization problem, deploying the combinatorial stochastic optimization methods. The problem was then solved on a D-Wave machine where the scheduled quantum annealer performing the task. This is not based on CNN model or any alteration of it but still this methodology offer flexibility in approach and yielded comparable accuracies with conventional ones.

Maqsood *et al.* [11] involves the U-Net based automated brain tumor detection & classification using edge detection and fuzzy logic. They performed the broad assessment of their method in accuracy, sensitivity and specificity using Dice coefficient index which showed that it could manage variety types of tumors on MRI. Wahlang *et al.* [12] investigated different deep learning architectures, including Convolutional Neural Networks (CNNs), Deep Neural Networks (DNNs), LeNet, AlexNet, and ResNet, along with traditional methods like Support Vector Machines (SVM), to classify brain MRI data. Their research highlighted the importance of gender and age as key elements in enhancing the accuracy of classification, with their proposed methodology outperforming existing techniques. Younis *et al.* [13] utilized the VGG-16 model within a CNN to identify brain tumors. Interestingly, the results of their study indicate that gender and age could add a key differential herein to facilitate classification at its best, surpassing other existing techniques. Younis *et al.* [13] used the CNN architecture of VGG-16 model for brain tumor detection. Their model scored the highest accuracy among other models with an astonishing 98.5 % accuracy score.

Agarwal *et al.* [14] illustrates the five machine learning classifiers and the proposed CNN model outperforming with accuracy values 99.58% for the classification of brain tumors in MRI. Kumar *et al.* [15] achieved the accuracy of 92.50% for the CNN model for the extraction and identification of tumor from brain MRI scans.

Additional literary works are included in the previously mentioned sections, and it would be pointless to merely reiterate the discoveries. DenseNet121 model showed best results in the previous studies which is one of the reasons to apply this model for the brain tumor dataset. However, it is clear that the hybrid approach, which involves enhancing the Quantum Convolutional Neural Network (QCNN) with important features from the traditional CNN, as stressed in the literature, serves as the main reason for taking a Hybrid Quantum Classical Model (HQCM) approach to the classification of brain tumor in this paper.

III. Materials and Methods

A. Dataset Overview and Splitting Strategy

This section provides a detailed summary of the dataset and its strategic division into training, validation, and testing sets. This division is essential for conducting a thorough analysis and evaluation of the study.

This study used a set of 3064 enhanced images from a pool of 233 patients [16]. In this dataset, images are in three types, one is particularly for the menigioma that consists of 708 slices, the second class is for the glioma that is made up of 1,426 slides and the third is for the pituitary tumor that comprises 930 slides. This brain tumor dataset contains T1-weighted contrast-enhanced images with three kinds of brain tumor. This study does not involve the segmentation of input tumor images as the dataset is already curated one. This research is focused on classification of three classes of brain tumor. Fig. 1 shows the sample images from the dataset, which are the segmented manually inside tumor region. This enables progress and evaluation of robust image processing and machine learning models for brain cancer classification [17, 18].

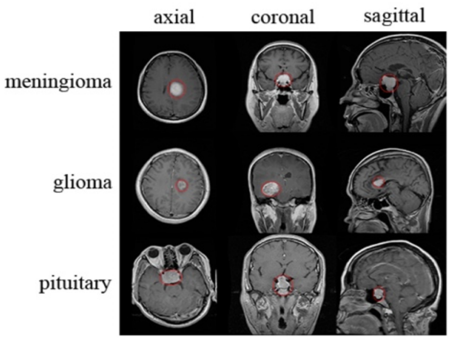

Fig. 1. Brain tumor images for three prevalent types of cancers.

B. Data Splitting

The dataset partition is comprising 70%, 10%, and 20% of the data accordingly, the three independent subsets that the dataset was split into were training, validation, and testing.

C. Data Preprocessing

This stage involves loading the dataset and extracting the image data, tumor labels, and other relevant data. Subsequently, the images are transformed into a format that is appropriate for quantum circuit processing [19]. The data processing for the HQCM model includes rescaling and normalization. The dimensions of the original image are 512×512 pixels. The image is resized to 25% of its original dimensions, resulting in a size of 128×128 pixels. We standardized the data to ensure consistency in the range of pixel values across all images. The original image matrix is divided by 255 to obtain the normalized image matrix, resulting in a conversion of the image size to 64×64. The input image for the DenseNet12 model is a rescaled image with dimensions of 128×128.

D. Experimental Modeling

This section describes the key tools and libraries used in the experimental modeling of the research work, including Pennylane for quantum machine learning, Tensorflow for classical machine learning, OpenCV for image processing, Pandas for data manipulation, Numpy for matrix manipulation, Scikit-Learn for classical machine learning, and Matplotlib for plotting.

E. Simple CNN Model

A CNN model given in Fig. 2 is a customized deep learning model designed specifically for processing visual data, such as images and videos. The architecture comprises two primary types of layers: the convolution layer, which emphasizes fine-grained features, and the pooling layer, which reduces complexity to capture the broader context.

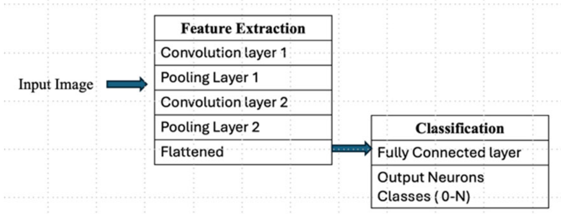

Fig. 2. Simple CNN.

F. Simple Quantum CNN model (QCNN)

QCNN is the implementation of CNN based on quantum computation. It uses the key features and structures of classes of CNNs in quantum systems [20, 21]. Fig. 3 shows that quantum computing uses qubits as the unit of information.

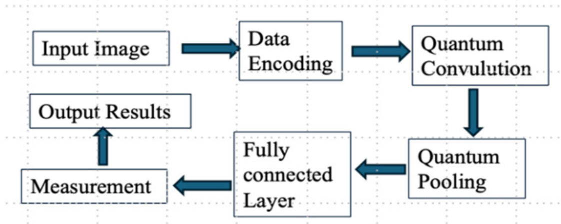

Fig. 3. Simple QCNN.

G. Proposed Hybrid Quantum Classical CNN model (HQCM)

Hybrid Quantum Classical Model (HQCM) is shown in Fig. 4.

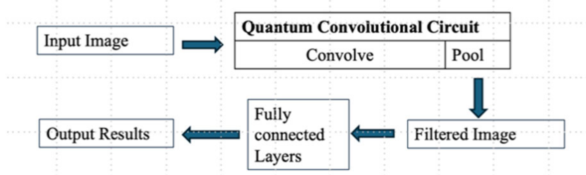

Fig. 4. Hybrid quantum-classical model.

HQCM model design spans three major phases:

1. Image processing for feature extraction on a quantum convolutional circuit after input image is detected.
2. Train the processed image with fully connected layers.
3. Classify the image.

Images shown in Fig. 5 are input to the quantum convolution circuit for the feature extraction.

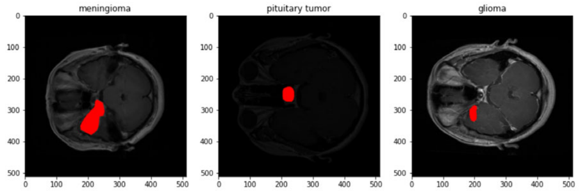

Fig. 5. Preprocessed brain tumor image categories.

The following Fig. 6 shows the output of the quantum convolutional circuit used for this study. Rx and Rz are gates representation in the quantum circuit and Z is the filtered image.

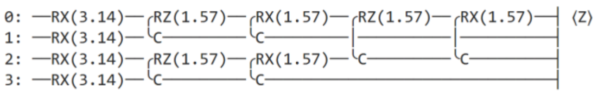

Fig. 6. Quantum circuit.

The quantum filtered image is shown in Fig. 7.

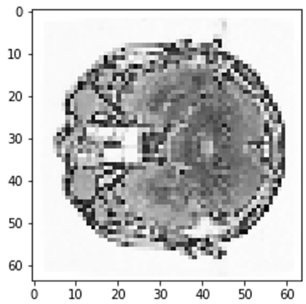

Fig. 7. Quantum filtered image.

A Quantum version of a fully connected layer receivs an input in the form of a filtered image. The implementation is done by performing the quantum SWAP test [17]. The SWAP test is a method that evaluates the degree of similarity between two quantum states. The output of the quantum pooling is then passed to a Fully Connected Layer (FCL). FCL has neurons which are structured in a feed-forward manner. It implies that every neuron interacting with all the neurons that come just after it. Just as in the case of quantum pooling, the final action to execute is a measurement. Determination of the final classification of a brain tumor image is done using the method.

H. DenseNet121 Model

One of the most effective DCNN was DenseNet [22] (~121 layers), which is a deep convolutional neural network.

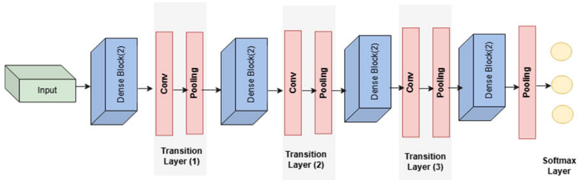

Fig. 8. DenseNet-121 architecture.

In the DCNN, the layers are connected with the dense blocks, so each layer uses the input from all previous layers to create the feature map and send data to all following layers. The DenseNet121, which consists of Four Dense Block Layers and Three Transition Layers, is presented in Fig. 8.

IV. Result and Discussion

We analyzed the performance metrics of our integrated model in this section and provide a comparative assessment with a HQCM and DenseNet121 model. The latter analysis is become a visual demonstration of our model's feasibility for the accurate classification of brain tumor.

Evaluation of model performance metrics analysis started with the derivation of several metrics, each providing an insight into a separate aspect of our model's performance. We present each metric, alongside its mathematical representation and a comprehensive explanation, in Table I.

TABLE I. Description of the Evaluation Metrics

Name of the Metrics	Formula
Accuracy	$\frac{(TP+TN)}{(TP+TN+FP+FN)}$
Precision	$\frac{TP}{(TP+FP)}$
Recall	$\frac{TP}{(TP+FN)}$
F1-Score	$\frac{2\times(Precision\times Recall)}{(Precision+Recall)}$
True Positive (TP)	Actual =1 Predicted =1
True Negative (TN)	Actual =0 Predicted =0
False Positive (FP)	Actual =0 Predicted =1
False Negative (FN)	Actual =1 Predicted =0

The proposed model was developed using Tensorflow 2.0 and keras environment. HQCM model is designed using QML simulator. Fully connected layer has one Flatten layer, one dense layer with "relu" activation and dropout layer with 0.5 value and followed by a dense layer with "SoftMax" activation function. The model has been compiled with "Adam" optimizer with 0.1 value and "sparse categorical crossentropy" for loss function.

DenseNet121 model is designed using predefined application "DenseNet12" in Keras. The model has been compiled with "Adam" optimizer with 0.1 value and 'sparse categorical crossentropy' for loss function. Also, batch size has value 16 and epochs is set to 20.

To assess the model's performance, we used different metrics like F1-Score, recall, precision, and accuracy based on the confusion matrix from the classification.

A confusion matrix is a performance measurement tool that one may use in classification tasks. The end result is that the distributions of predicted and actual class labels can be seen in much more granular detail for each matrix. The confusion matrices of HQCM model and DenseNet121 model are shown in Figs. 9 and 10 respectively.

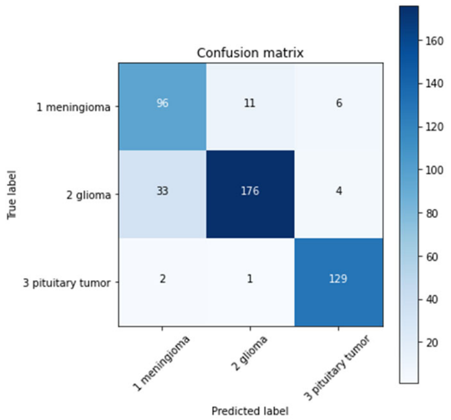

Fig. 9. Confusion Matrix for HQCM model

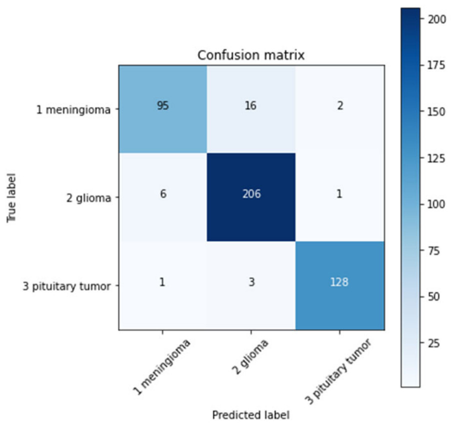

Fig. 10. Confusion Matrix for DenseNet121 model.

It appears that DenseNet121 is effective in recognizing brain tumor, as the number of true positives is higher than for ResNet50. Similarly, there is a lower number of false positives, which means that the model has higher precision and is unlikely to make mistakes in its classification.

The accuracy and loss value of the HQCM model on brain tumor classification are given in Figs. 11 and 12 respectively.

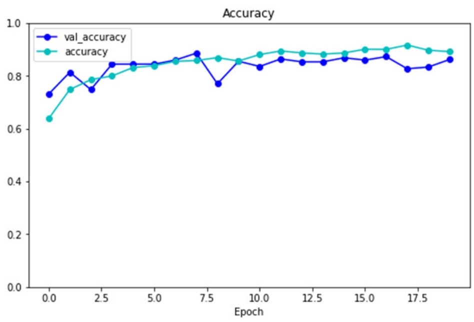

Fig. 11. Accuracy Graph for HQCM model.

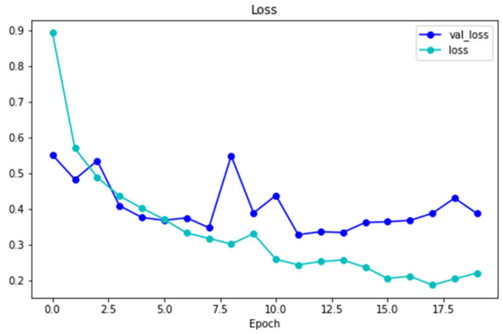

Fig. 12. Loss Graph for HQCM model.

The accuracy and loss value of the DenseNet121 model on brain tumor classification are given in Figs. 13 and 14 respectively.

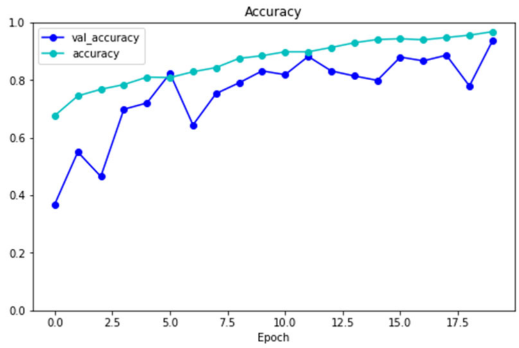

Fig. 13. Accuracy Graph for DenseNet121 model.

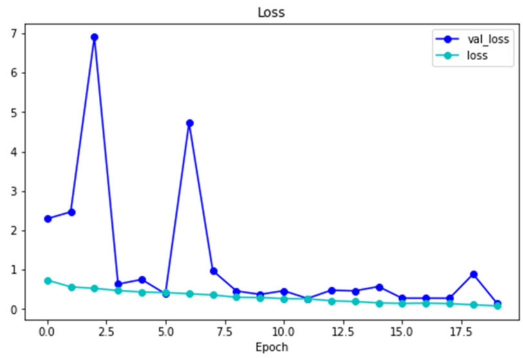

Fig. 14. Loss Graph for DenseNet121 model.

The high performance of the DenseNet121 model is consistently observed when analyzing the models' accuracies and loss values against HQCM model.

Table II provides testing and training metrics. Decnet121 seems to be performing exceptionally well and proves to be a formidable feature extractor and classifier.

TABLE II. Classification Report on Testing Data

Model	Class*	Accuracy	Precision	Recall	F1-Score
HQCM	1	0.88	0.73	0.85	0.79
	2	0.88	0.94	0.83	0.88
	3	0.88	0.93	0.98	0.95
DenseNet 121	1	0.94	0.93	0.84	0.88
	2	0.94	0.92	0.97	0.97
	3	0.94	0.98	0.97	0.97

Note: *Meningioma: class 1; Glioma: class 2; Pituitary tumor: class 3.

To sum up, the results of the DenseNet121 model in this study shows Table II that it is a powerful analytical tool in medical imaging, and it can be revolutionary in clinical diagnostics. The high level of accuracy of the model in the image classification of brain tumor implies that is is a precise and credible tool. The fact that the HQCM can effectively handle complex images and interpret them implies that they are sophisticated and versatile. Therefore, higher speed and accuracy of image processing can save many lives, making quantum neural networks seemingly highly promising in these sense-demanding tasks.

The proposed quantum classical model represents an innovative and investing approach to brain tumor image classification. While the results may be lesser than existing deep learning models, this work serves as a valuable exploration of the potential of quantum computing in this domain. But we found that DenseNet121 model achieved the good accuracy results. Rather than enhancing the results at this stage, we believe it is important to present the findings as-is to highlight the unique insights and limitations of the quantum-based approach. This will inform future studies that can build upon these initial findings and further optimize the performance of quantum models for brain tumor image classification. We will improve the proposed quantum model in our future work.

V. Conclusion

In this study, we employ a Hybrid Quantum Classical Model (HQCM) alongside a DenseNet121 model for classifying brain tumors using a publicly available brain tumor image dataset. Our main goal was to improve on standard methods for brain tumor classification, and our results with the DenseNet121 model were notable. We achieved accuracies of 88% and 94% for the HQCM and DenseNet121 models, respectively. This research presents an effective feature extraction method through the DenseNet121 architecture. It aids medical image analysis by simplifying the identification of important features in brain tumor images, thereby decreasing the need for manual feature extraction, which is time-consuming.

Moreover, applying a quantum simulator to implement the model and produce results marks an important advancement in practical Quantum Deep Learning (QDL) applications. The results of this study underline that a quantum approach offers improvements over classical methods, as shown by the accuracy rates in classifying complex medical images. This strengthens the argument for the effectiveness of the HQCM model. The results of this research add to the expanding knowledge of how QDL can address real-world challenges, especially in medical diagnostics. Additionally, this lays the groundwork for future studies that could investigate other complex tasks.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Anandhavalli Muniasamy; data collection: Salma A. S. Alquhtani, Arshiya Begum; analysis and interpretation of results: Anandhavalli Muniasamy, Afnan H. Alshehri, Asfia Sabahath; draft manuscript preparation: Anandhavalli Muniasamy. All authors reviewed the results and approved the final version of the manuscript.

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References

[1] R. L. Siegel, A. N. Giaquinto, and A. Jema, "Cancer statistics, 2024," *CA: A Cancer Journal for Clinicians*, 2024. https://doi.org/10.3322/caac.21820

[2] U. Ullah and B. Garcia-Zapirain, "Quantum machine learning revolution in healthcare: A systematic review of emerging perspectives and applications," *IEEE Access*, 2024. https://doi.org/10.1109/ACCESS.2024. 3353461

[3] M. Vatandoost and S. Litkouhi, "The future of healthcare facilities: How technology and medical advances may shape hospitals of the future," *Hospital Practices and Research*, vol. 4, no. 5, 2019. https://doi.org/10.15171/hpr.2019. 01

[4] D. Menegatti *et al.*, "CADUCEO: A platform to support federated healthcare facilities through artificial intelligence," *Healthcare*, vol. 11, no.15, 2023. https://doi.org/10.3390/healthcare11152199

[5] J. Amin, M. A. Anjum, N. Gul, and M. Sharif, "A secure two-qubit quantum model for segmentation and classification of brain tumor using MRI images based on blockchain," *Neural Computing and Applications*, vol. 34, no. 20, 2023. https://doi.org/10.1007/s00521022-07388-x

[6] Y. Dong, Y. Fu, H. Liu, X. Che, L. Sun, and Y. Luo, "An improved hybrid quantum-classical convolutional neural network for multi-class brain tumor MRI classification," *Journal of Applied Physics*, vol. 133, no. 6, 2023. https://doi.org/10.1063/5.0138021

[7] A. Raza, M. Alshehri, S. Almakdi, A. A. Siddique, M. Alsulami, and M. Alhaisoni, "Enhancing brain tumor classification with transfer learning: Leveraging DenseNet121 for accurate and efficient detection," *Int. J. Imaging Syst. Technol.*, vol. 34, no. 1, e22957, 2024. doi:10.1002/ima.22957

[8] J. Amin, M. A. Anjum, M. Sharif, S. Jabeen, S. Kadry, and P. MorenoGer, "A new model for brain tumor detection using ensemble transfer learning and quantum variational classifier," *Computational Intelligence and Neuroscience*, 2022. https://doi.org/10.1155/2022/3236305

[9] Zebari *et al.*, "Enhancing brain tumor classification with data augmentation and DenseNet121," *Academic Journal of Nawroz University*, vol. 12, pp. 323–334, 2023. doi: 10.25007/ajnu.v12n4a1985

[10] B. Bauer, S. Bravyi, M. Motta, and G. K. L Chan, "Quantum algorithms for quantum chemistry and quantum materials science," *Chemical Reviews*, vol. 120, no. 22, 2022. https://doi.org/10.1021/acs.chemrev.9b00829

[11] S. Maqsood, R. Damasevicius, and F. M. Shah, "An efficient approach for the detection of brain tumor using fuzzy logic and U-NET CNN classification," in *Proc. Computational Science and Its Applications—ICCSA*; Springer International Publish: Cham, Switzerland, 2021, pp. 105–118.

[12] I. Wahlang, A. K. Maji, G. Saha, P. Chakrabarti, M. Jasinski, Z. Leonowicz, and E. Jasinska, "Brain magnetic resonance imaging classification using deep learning architectures with gender and age," *Sensors*, vol. 22, no. 5, P. 1766, 2022.
[13] A. Younis, L. Qiang, C. O. Nyatega, M. J. Adamu, and H. B. Kawuwa, "Brain tumor analysis using deep learning and VGG-16 ensembling learning approaches," *Applied Sciences*, vol. 12, no. 14, P. 7282, 2022.
[14] R. Agarwal, S. D. Pande, S. N. Mohanty, S. K. Panda, "A novel hybrid system of detecting brain tumors in MRI," *IEEE Access*, vol. 11, pp. 118372–118385, 2023. doi: 10.1109/ACCESS.2023.3326447
[15] P. Kumar, A. Katti, S. Nandan Mohanty, S. N. Senapati, "A deep learning-based approach for an automated brain tumor segmentation in MR images," in *Pattern Recognition and Data Analysis with Applications. Lecture Notes in Electrical Engineering*, D. Gupta, R. S. Goswami, S. Banerjee, M. Tanveer, and R. B. Pachori, Eds. Springer, Singapore, vol. 888, 2022. https://doi.org/10.1007/978-981-19-1520-8_7
[16] J. Cheng, "Brain tumor dataset," *Figshare*. *Dataset*, 2017. https://doi.org/10.6084/m9.figshare.1512427.v5
[17] J. Cheng *et al.*, "Enhanced performance of brain tumor classification via tumor region augmentation and partition," *PLOS One*, vol. 10, no. 12, e0144479, 2015. https://doi.org/10.1371/journal.pone.0140381
[18] J. Cheng *et al.*, "Retrieval of brain tumors by adaptive spatial pooling and fisher vector representation," *PLOS One*, vol. 11, no. 6, e0157112, 2016. https://doi. org/10.1371/journal.pone.0157112
[19] M. Khan *et al.*, "Brain tumor diagnosis using quantum convolutional neural network," arXiv Print, arXiv: 2401.15804, 2024.
[20] M. Gado and A. Younes, "Optimization of reversible circuit using toffoli decompositions with negative controls," *Journal Symmetry*, vol. 13, no. 6, 1025, 2021. doi.org/10.3390/sym13061025
[21] S. Oh, J. Choi, and J. Kim, "A tutorial on Quantum Convolutional Neural Network (QCNN)," arXiv Print, arXiv: 2009.09423, 2020.
[22] G. Huang, Z. Liu, L. V. D. Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in *Proc. the IEEE Conference on Computer Vision and Pattern Recognition*, 2017, pp. 4700–4708.