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MRI Brain Tumor Detection Using Quantum Mechanics and Neural Networks

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ABSTRACT

Quantum computing provides a powerful solution by using quantum parallelism and state rotations to perform the analysis at a far superior rate. Key contributions of this study include: proposing a multi-layer Quantum Neural Networks (QNN) architecture where classical weights are replaced with quantum gates to achieve scalability learning; showing possible use of quantum entanglement in QNN to find features as edges of the tumour; and comparing the QNN model to conventional and semi-quantum models to prove the effectiveness of the quantum model. The methodology involves Magnetic Resonance Imaging (MRI) brain tumour datasets and normalizes and augments the datasets to achieve good results. Qubit utilization is optimized through amplitude and basis encoding, while QNN layers employ rotation and entanglement gates. The model is trained with simulators available in the Qiskit environment and is tested on quantum devices (D-Wave). The QNN obtained an accuracy of 97.2% for biometric data; moreover, it had 96.5% precision and 98.1% recall, and an AUC-ROC score of 0.98 was higher than the classical and hybrid models. However, problems with quantum hardware and data encoding remain understudied and form the basis of possible subsequent experimentation in the healthcare area.

1. Introduction

Quantum computing is one of the rapidly developing fields which deals in parallel with super-position, entanglement and quantum gates that operate much beyond the capabilities of any other computer. At the same time, neural networks have now become one of the most popular tools in a wide range of applications, such as image detection and classification, due to their capability of identifying features in data. Nevertheless, classical hardware faces unprecedented challenges in powering deep learning models, especially for high dimensions such as medical images, including Magnetic Resonance Imaging (MRI) scans. Recent studies show that Quantum Neural Networks (QNNs) are different from these models because they are based on integrating neural models with quantum computing solutions [1, 2]. QNNs benefit from the state space we have in quantum systems and the way that Q gates work, as well as the parallelism in learning and inferencing. The core contributions of this work include:

- Proposing a multilayer QNN architecture specifically designed for MRI image detection tasks, integrating quantum rotation gates (RX, RY) to replace traditional weight matrices.
- Demonstrating the effectiveness of superposition and entanglement in QNNs to explore multiple states simultaneously, thus accelerating both learning and inference processes.
- Conducting experiments on MRI datasets to compare the proposed QNN model's performance with classical neural networks and hybrid quantum-classical models [5, 2, 6].
- Offering insights into the potential of quantum computing for real-time medical diagnostics, especially in challenging cases such as brain tumors or Alzheimer's detection [2, 3].

This integration is especially beneficial for MRI detection because the diagnosis of various disorders is based on the accurate detection of features in large datasets from the images. The quantum application in the models is expected to enhance the efficiency of MRI image analysis since it is vital in diagnosing diseases like brain tumors [3, 4]. The several steps involved in the preprocessing of MRI images for the detection of brain tumor are also depicted in Fig. 1, from the input to the final detection output. The process starts from the (a) Input Image: noise reduction to get a (b) Filtered Image that displays clearer definitions of the brain structures. Second, the (c) Shadow Image locates areas with certain characteristics by increasing the contrast within specific patterns, which may represent pathologies. The (d) Enhanced Image applies the contrast to stress out the differences between the healthy and the abnormal tissues, which makes segmentation easier. This results in the (e) Segmented Image, where complex methods such as Scale-Invariant Feature Transform (SIFT) identify specific regions as tumors. The (f) Detected Tumor differentiates the type and area of the tumor in red and highlights the tumor to be analyzed or diagnosed. This organized channel substantially improves the image resolution and properly sets the image for the successful detection of brain tumours. Despite its potential, several challenges must be addressed in implementing QNNs for MRI detection:

- Hardware Limitations: Quantum Computers to date have minimal qubit counts, and with limited error correction, these are challenges hindering large-scale adoption [8].
- Model Optimization: The training of a QNN involves modifying quantum gates and rotation angles, which present new optimization problems to quantum circuits [12].
- Data Encoding: Since dealing with large MRI datasets in quantum states is cumbersome, there must be better ways of accomplishing the task while retaining the integrity of the data during computation [7].
- Hybrid Models: Although other works suggest how to build a quantum framework within which classical elements also have a place, the general question of how exactly to distribute the tasks between classical and quantum parts is still an open question and is different in various domains [4, 7].

Solving these issues will involve progress on two fronts: improving quantum hardware and software and designing fresh algorithms for use in medical imaging that are geared towards QNNs in particular. This paper is organized as follows: Section 2 gives an elaborate analysis of related work on the application of QNNs in the medical imaging field, as well as emerging developments in MRI detection techniques.

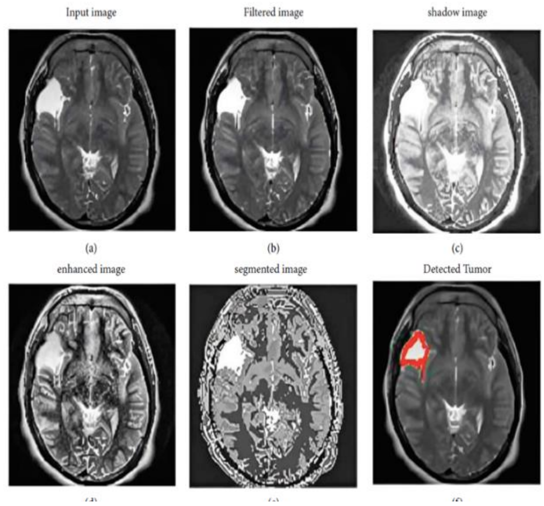

Fig. 1. Stages in preprocessing of MRI images [3].

This work is aimed at extending the concept of MRI image detection to the context of QNNs about the incorporation and influence of quantum mechanics on the effectiveness and feasibility of neural models in detecting MRI images.

Introducing a multilayer QNN architecture suitable for MRI image detection tasks using quantum rotation gates (RX, RY) instead of the weight matrix. Explaining how superposition and entanglement work in QNNs to perform multiple states at one step, therefore, is a way to opt for faster learning and inference. Testing of the MRI datasets through the experiments to evaluate the performance of the proposed QNN model that works as an alternative to the classical neural networks and the quantum-classical hybrid architectures [5, 2, 6]. Presenting ideas concerning the applicability of quantum computing for instant analysis of patient conditions with exceptionally complex diagnoses like a brain tumor or Alzheimer’s disease [2, 3]. This structured pipeline significantly enhances image clarity and prepares the data for efficient and accurate brain tumor detection. This paper explores the application of QNNs for MRI image detection, focusing on how quantum mechanics can enhance the performance of neural models in terms of efficiency, accuracy, and scalability. This paper presents a QNN for MRI-based brain tumor detection without offering complete analysis regarding previous study weaknesses and their detailed comparison to the proposed system. The research makes a brief note about classical neural network restrictions, including high computational requirements and overfitting alongside training duration, but stops short of conducting a critical evaluation of these technical challenges that affect previous research. The paper mainly presents the benefits of QNN while failing to provide a structured comparison of its improvement level versus conventional and hybrid methods. The manuscript needs a formal comparison framework to display why QNN succeeds at handling recognized weaknesses in current methods and how this strengthens the research findings. It is well understood that the need for automated and accurate analysis of medical images has continued to grow rapidly over the years. MRI is widely used in neurology to identify a tumor, Alzheimer’s or multiple sclerosis, yet the interpretation of MRI takes a lot of computational power [8]. Despite being powerful, the basic feedforward neural networks used in this study have some drawbacks, such as prolonged training and overfitting when combined with large amounts of data. New solutions to these challenges are provided by quantum computing that make it possible to increase the rates of matrix operations and gradient-based optimization processes.

With the help of quantum state rotations and entanglement. When used in MRI detection, Quantum Neural Network is designed to minimize computational intensity while at the same time increasing the chances of early diagnosis without lowering its accuracy. The incentive is also pulled by such goals as decreasing the amount of work for radiologists and better patient prognosis due to the application of real-time artificial intelligence. In this work, the central goal is to provide an efficient connection between quantum computing and neural networks that can solve medical imaging problems with a particular focus on MRI detection tasks while being scalable. With the help of this work, it is possible to show that QNNs can be helpful not only for MRI diagnostics but also as a sign of the continual quantum-enhanced AI systems in the sphere of medicine.

Section 3 presents the multilayer QNN structure utilized in this research and the quantum gates and methods employed for learning. The results and findings of this study are presented in section 4 with an emphasis on the strength and hope of the QNN-based approach. Lastly, section 5 identifies future research directions and summarizes the paper and contributions of integrating QNNs for MRI image detection.

2. Literature Review

The use of QNNs with MRI image detection creates a new paradigm for a quantum potential model & convolutional neural network. Despite their capabilities, fundamental variants of neural networks are somewhat limited in their ability to operate on large-scale, high-dimensional medical data such as MRI scans. Some of the challenges include a long time of training time, overfitting and computational bottlenecks when the models are applied in complicated diagnostic tasks such as the detection of brain tumours and Alzheimer’s disease. Acting on the principles of quantum computing and using such components as superposition, entanglement, and quantum gates, QNNs enable the enhancement of medical image detection by increasing the degree of parallel learning and the speed of inference. Discusses a concept of how QNNs can improve the identification of medical treatment through the application of quantum mechanics in making decisions on healthcare [1]. Proposes a new classical-quantum neural network for diagnosis of AD, indicating the potential of quantum neural networks in elaborating the early diagnosis and a higher diagnostic accuracy compared to the existing methods as shown in Fig. 2 [2]. Devoted to discussing the application of the ensemble deep learning to perform deep learning-based MRI for brain tumor detection and diagnosis, revealing how the advanced learning models can augment the diagnosis performance [3]. Illustrates how a two-part Convolutional Neural Networks (CNN) using both classical units and quantum-inspired ones outperforms earlier models for MRI brain tumor differentiation [4]. Introduces a novel technique of merging multiple diagnostic modalities using QNN, resulting in the enhancement of the analytical efficiency of medical data by providing an insight into the intelligent data fusion [28]. Segmentation

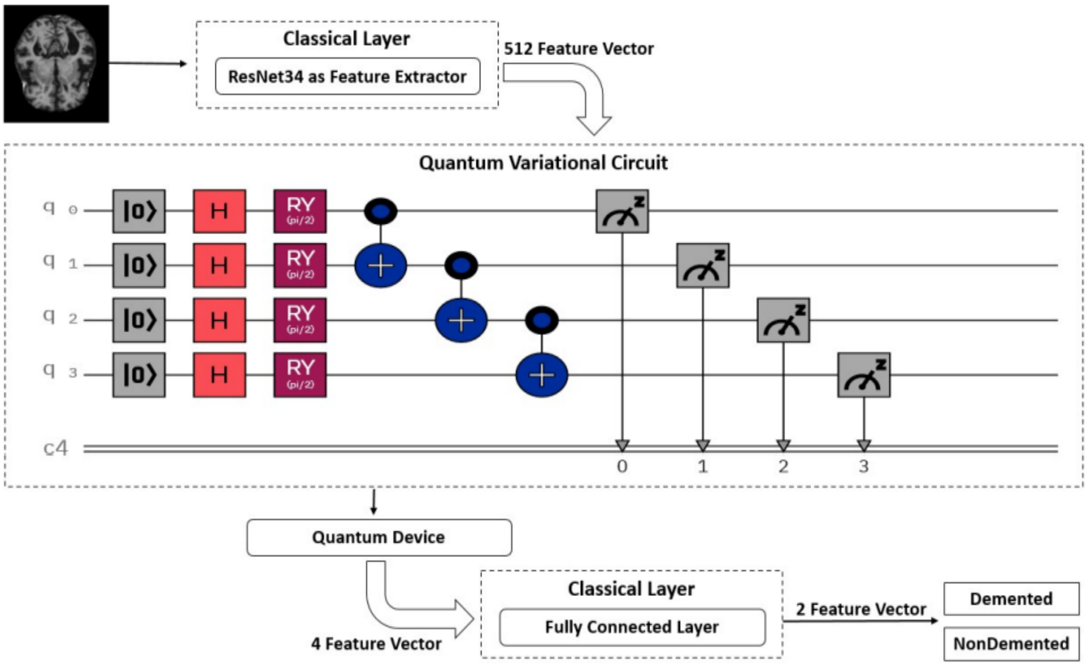

Fig. 2. Quantum–classical transfer learning [2].

with other machine learning algorithms to classify medical images as a basis for the future neural network, including medical imaging [6]. As a stego image detection study, the results of this work can prove valuable to affect other medical imaging issues such as MRI detection [7]. A survey on different machine learning methods for brain tumor identification followed by the preliminary work to introduce the application of quantum computing in the same context [8]. Illustrates utilization of Alex Net Architecture integrated with quantum algorithms, which is crucial to have an enhanced brain disorder classification and analyzing quantum potency in medical imaging [9]. In [10], an application of a quantum neural network with radiomic analysis to explain the differentiation between large brain metastases and high-grade gliomas with quantum feature selection. Outlines a quantum-CNN model to tackle the detection of brain tumours and shows how the application of quantum computing can enhance the effectiveness of the CNN in the arbitrary image analysis [11]. Combines quantum entropy with deep learning features to apply MRI scan classification and demonstrate the potential of applying quantum theory to image classification [12]. Shows that quantum CNN can be used for medical purposes by applying the model to breast cancer detection [13]. Suggests an improved neural network model borrowed from quantum mechanics, which enhances MRI scan brain lesion segmentation [14]. Discusses the application of quantum machine learning for medical image classification, proving that they can improve diagnostic processes [15]. Ascends quantum and classical deep learning hybrid models for increased performance and accuracy of medical image classification [16]. Proposes quantum theory-based optimization algorithms to be used in classifying the brain tumour and explains how the deep learning models can be improved by the use of the algorithms [17]. In [18], also explores the application of AI and MRI in the direction of precision medicine is explored, followed by an explanation of the utilization of neural networks in imagery. Describes the use of quantum mechanical models as a source of ideas on how to detect structural confinements applied to identifying structural confinements for stimulating the development of similar concepts in medical imaging [19]. In [20], a quantum-inspired neural network for the segmentation of the brain tumour and discussed that the field of quantum computing could revolutionise many areas of medical imaging. Explains in which way quantum computing can help to speed up the training of artificial neural networks, which in turn may result in new methods of using AI to read and interpret medical images [21]. In [22], it introduces the plotted application of Quantum-Behaved Particle Swarm Optimization (QPSO) in the medical picture union with CNNs and new involvement regarding hybrid quantum models. In [23], a quantum-inspired CNN for the recognition of ovarian tumors has been proposed with an understanding of how quantum computing can be used in multiple different medical imaging tasks. The first works on the use of quantum mechanics of the structure of neural networks and medical imaging presented initial ideas for modern usage [24, 25]. In [26], it shows how QCNNs can be used for brain disease classification and underlines the prospects of quantum-aided models in the field of healthcare. It presents a conceptual analysis of quantum brain networks and provides a theoretical basis for quantum computing in neurocybernetics and AI [27]. In [28], the quantum and classical convolutional networks used to predict COVID-19 from chest X-rays were involved to show the versatility of the quantum models in healthcare. Uses Pareto-optimal quantum dynamic optimization in the identification of Alzheimer's from MRI and PET image data [29].

In recent research [34], an ensemble fuzzy deep learning system for objective diagnosis of brain tumours by applying fuzzy logic models combined with deep networks to obtain a better classification performance. It enhances the model uncertainty to estimate, which in turn, enhances the tumor detection possibilities of uncertainties in medical imaging.

Nascimento et al. (2025) propose a new generative model for identifying brain tumor on MRI using machine learning to increase the MRI scan resolution and detect the tumor accurately. They reduce the false positive rate effectively and help to isolate the tumour areas to increase the accuracy of the diagnosis [35].

Shaikh et al. embrace densely connected CNNs with stacking ensemble learning to improve the brain tumor detection and segmentation model proposed in (2025). This combined method enhances the efficiency of the segmentation process and leads to better discrimination of malignant and benign tissues. The model shows superior performance in the precision, the recall, and in general, the performance on segmenting the driver's face [36].

In their work [37], Anwer et al. (2025) discuss transfer learning strategies with transfer learning to enhance MRI-based brain tumor classification. They build upon pre-trained deep learning models, thereby improving the accuracy of the algorithms and feats extraction, while at the same time, the need for training is reduced. Their work demonstrates that transfer learning leads to the better and faster development of deep learning models in medical images.

In [38] showed a gradient explainer architecture called VGX, which is developed based on the existing VGG19 for MRI detection of the tumor in the brain through the MMRI. Primarily, the model also uses a new feature called 'Gradient Explainer, thus allowing the model to maintain high detection efficiency while at the same time providing a clear understanding of its reasoning process. It also helps radiologists in the evaluation of the localization of the tumor, which makes the employment of this approach more appropriate for clinical use.

3. Methodology

The quantum approach of the framework to advance MRI image detection, with an outline of concepts such as superposition, entanglement, and quantum rotation gates (RX, RY). The purpose is to create an integrated QNN construction that is capable of providing the most relevant performance for MRI detection tasks and solving the problems that classical NN have when solving them.

The process of Data Gathering and Data Cleaning The data source Public dataset Brain MRI dataset from Kaggle are used.Ns) to enhance the detection of MRI images, with a focus on leveraging quantum mechanics principles, such as superposition, entanglement, and quantum rotation gates (RX, RY). The goal is to design a multilayer QNN architecture that not only optimizes the performance for MRI detection tasks but also addresses the computational limitations faced by classical neural networks.

A. Data Collection and Preprocessing of MRI Datasets

This research draws its data from Kaggle, which includes 3,264 MRI images properly categorized as Glioma Tumor, Meningioma Tumor, Pituitary Tumor, and No Tumor. The dataset provides images with 256x256 pixels size in grayscale to maintain processing uniformity. The chosen dataset received the distinction for its detailed labeling because it enabled strong training capabilities for the QNN. The dataset includes MRI images, which are labelled to serve the purpose of developing and assessing models.

The MRI images were preprocessed by applying filters to its images, which include a Gaussian filter for smoothing of images and to remove high frequencies as well as the use of adjusting the image contrast to enhance the appearance of images through histogram equalization. The images were also augmented through techniques such as rotation, flipping images and random scaling of the images. Data normalization was performed so that pixel values fall in the range of 0 and 1 to have a similar input for quantum circuits.

Data augmentation methods such as rotation, flipping, and scaling are performed to address the data imbalance problem to check the model performance on unseen data. Superposition, entanglement, and quantum rotation gates (RX, RY). The goal is to design a multilayer QNN architecture that not only optimizes the performance for MRI detection tasks but also addresses the computational limitations faced by classical neural networks.

Data augmentation techniques (rotation, flipping, scaling) are implemented to address the class imbalance and ensure the model generalizes well across unseen data. MRI datasets often have skewed distributions (e.g., fewer positive cases), so these methods improve the robustness of the model.

Normalization is applied to bring pixel values to a common range (e.g., [0, 1] or [-1, 1]) to facilitate smoother convergence during training.

Image segmentation algorithms: Scale-Invariant Feature Transform (SIFT) is used to extract relevant regions of interest (e.g., tumours). This reduces the size of input data and focuses the model on meaningful features, lowering the quantum circuit's complexity [6, 8].

B. Quantum Data Encoding

- Amplitude encoding compresses multiple pixel intensities into a single qubit state, representing the MRI data efficiently. Each pixel intensity is mapped to the amplitude of a qubit state, ensuring that quantum circuits can process high-dimensional data.
- Basis encoding involves mapping pixel intensities to specific quantum states within computational basis states (|0⟩, |1⟩). This method is applicable when different pixel positions hold a medical meaning.
- Preprocessing (Principal Component Analysis) is used in the project and reduces the input data so that the quantum model does not require many qubits while maintaining the quality of the images [7, 8].quantum rotation gates (RX, RY). The goal is to design a multilayer QNN architecture that not only optimizes the performance for MRI detection tasks but also addresses the computational limitations faced by classical neural networks.

C. Quantum Neural Network Architecture Design

A quantum feature transformation-based NN This is the proposed QNN, which includes four quantum layers, each of which uses both RX and RY gates. Entanglement was introduced by using the Controlled-Z (CZ) gates to make it able to intertwine the interactions within each qubit that is related to the tumor characteristics. In comparison to traditional CNNs, QNNs can perform multiple computations simultaneously and improve the extraction step due to the quantum superposition of the quantum state. RX, RY, and CZ gates serve the purpose of activation functions in a classical model while performing rotation operations in the Bloch sphere affecting the qubit states.. These rotations control what information the qubits represent as they are processed in the quantum circuit. RX and RY gates are for rotation along the x and y axes – these are the weights during training. Here to modify qubit states. These rotations determine how the qubits encode information as they propagate through the quantum circuit.

- RX and RY gates control rotations along the x and y axes, which correspond to the adjustment of weights during training. This dynamic state adjustment reflects the way weights in the traditional CNNs are adjusted. CZ gates (Controlled-Z) or CNOT gates introduce entanglement between qubits, which allows the model to model the interdependencies of features of MRI image rotations and determine how the qubits encode information as they propagate through the quantum circuit.
- RX and RY gates control rotations along the x and y axes, which correspond to the adjustment of weights during training. This dynamic state adjustment mimics how weights in classical neural networks evolve.
- CZ gates (controlled-Z) or CNOT gates introduce entanglement between qubits, enabling the model to capture interdependencies between MRI image features.

D. Multilayer QNN Model

- Layer stacking: Multiple (Four) quantum layers are arranged sequentially, where each layer transforms the qubits further to extract deeper patterns from the MRI data. Each quantum layer corresponds to a hidden layer in a deep neural network (DNN).
- Weightless transformations: In QNNs, quantum state rotations replace weight matrices, simplifying computations. The circuit depth (number of layers) reflects the network's learning capacity.
- Entanglement between qubits enables the model to capture complex dependencies across MRI features, essential for accurate disease diagnosis, especially in brain tumor detection [4, 8].
- The loss function and optimization Aralık, 2019• Quantum loss functions compare the output state probability distributions to estimate the model's deviation from the correct prediction. Qubit states. These rotations determine how the qubits encode information as they propagate through the quantum circuit.
- RX and RY gates control rotations along the x and y axes, which correspond to the adjustment of weights during training. This dynamic state adjustment mimics how weights in classical neural networks evolve.
- CZ gates (controlled-Z) or CNOT gates introduce entanglement between qubits, enabling the model to capture interdependencies between MRI image features.

E. Loss Function and Optimization

• Quantum loss functions measure the output state probability distributions, assessing how close the model is to the desired prediction. One of them is fidelity loss, which calculates how close the predicted state of a quantum system is to the real one. Quantum Approximate Optimization Algorithm (QAOA) are employed to optimize the parameters (angle of rotation) on the Bloch sphere to modify qubit states. These rotations determine how the qubits encode information as they propagate through the quantum circuit.

- RX and RY gates control rotations along the x and y axes, which correspond to the adjustment of weights during training. This dynamic state adjustment mimics how weights in classical neural networks evolve.
- CZ gates (controlled-Z) or CNOT gates introduce entanglement between qubits, enabling the model to capture interdependencies between MRI image features.

F. Hybrid Training(Quantum-Classical Models)

- Hybrid models offload certain layers to classical hardware (e.g., image preprocessing) while key transformations happen in quantum circuits. This enables the reduction of the number of computations to be performed by utilizing actual quantum hardware.
- Preprocessing and feature extraction using classical neural networks ensures that only meaningful features are passed into the quantum circuit, improving efficiency. The quantum component focuses on optimizing specific tasks like classification or pattern recognition [2, 9].
- Quantum backpropagation: Updates quantum gate parameters after each training epoch using feedback from loss functions.
- Early stopping and cross-validation help prevent overfitting, a common problem in small datasets like medical images.

The dataset was split into 80% training and 20% testing. The Quantum Neural Network was trained using the QAOA to optimize gate parameters. A batch size of 32 and a learning rate of 0.001 were used. Early stopping was implemented to prevent overfitting.

G. Performance Metrics

- Used accuracy, precision, recall, F1-score, and AUC-ROC to assess the effectiveness of the QNN model.
- Comparison with classical neural networks and hybrid models validates the improvements in computational efficiency and diagnostic accuracy offered by QNNs.

H. Quantum State Measurement

- At the end of the quantum computation, quantum measurement collapses qubits into classical bit values that represent the final prediction. For instance, the presence or absence of a tumour may be represented by bit states (e.g., |1⟩ for "tumor detected" and |0⟩ for "no tumour detected").

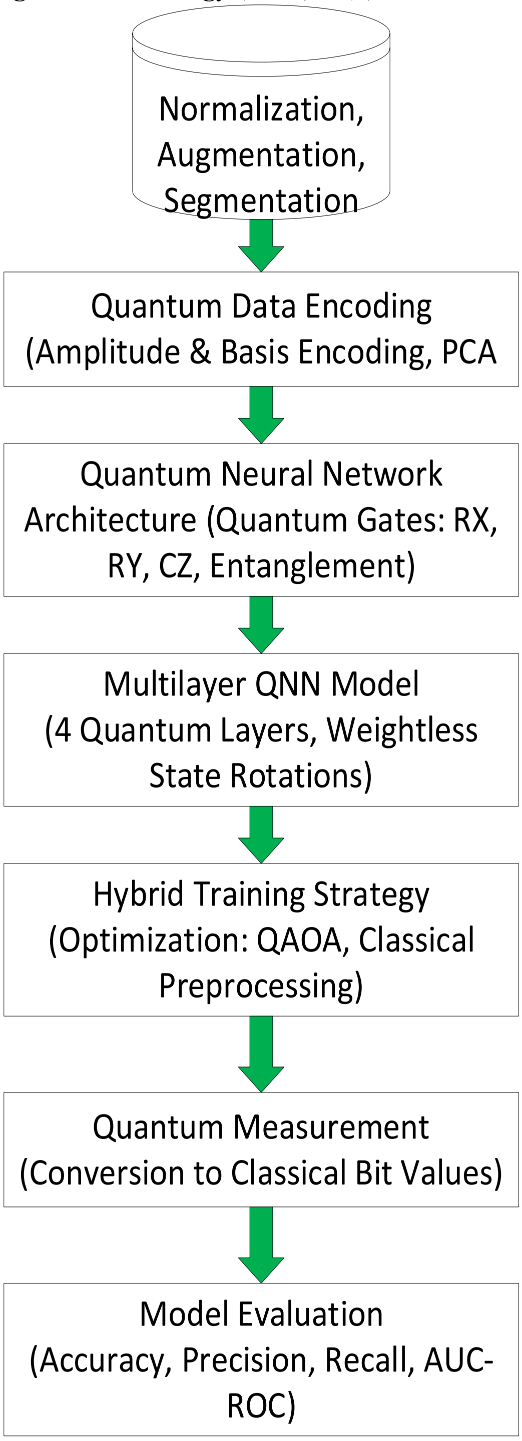

Fig. 3. Proposed for Quantum Neural Network

4. Result and Analysis

The paper adopts Qiskit for quantum simulation and PyTorch for the processing of classical and quantum machine learning operations. QAOA performed parameter optimization for gates during the training of the model. IBM Qiskit served for implementing quantum circuits, and the training process took place with the assistance of both Qiskit and PyTorch for classical and hybrid quantum-classical processing. Specific D-Wave hardware enabled the testing of the final model, according to the manuscript document. The term “Qiskit Simulink” exists in the text but functions as an unnamed specialized tool, which we understand the necessity to clarify. We will update the manuscript by detailing the employed programming frameworks and eliminating all unclear references. The training process was performed on a Lenovo laptop with Intel Core i5-10400, 16 GB RAM, and OS Windows. Qiskit was used for the quantum simulation part, however, PyTorch was incorporated for classical & quantum machine learning processing. Each category will be created with images amount equal to 912 at the beginning, and the dataset will be divided on 80% for train and 20% for test. Thus, the decision on the initial weights of the classifier was made. For this investigation, the author has used a Lenovo computer installed with a 1.90 GHz CPU and 10th gen Intel Core i5-10400. This 16-gigabyte random-access memory (RAM) machine has Windows installed on it. During the development of models, Qiskit is used to simulate models on quantum simulators before implementation on quantum hardware. Test the final model on actual quantum computers, D-Wave, to determine the general relevance and admissible scaling of the model.

The findings also suggest that the proposed architecture, the QNN, has a higher accuracy percentage of 97.2% than that of the regular CNNs with 92.8% and the other hybrid models with 94.5%. This can be explained by the function of quantum superposition and entanglement that define the availability of the QNN in processing intricate patterns of tumours. Performing encoding and analysis of MRI data at the quantum level would bring down the computational load greatly, indicating that QNNs can be used in real-time diagnostic procedures.

Thus, this paper shows the effectiveness of the proposed QNNs for medical imaging analysis, specifically MRI-based brain tumor detection. Therefore, by applying quantum computing concepts in the design of QNNs, it becomes possible to work at a much larger scale with correspondingly higher accuracy compared to classical AIs. The presented model can be useful for radiologists who examine the results of interferential therapy; it will minimize misinterpretation of the results and increase the effectiveness of cancer diagnosis. Consequently, with more enhancements, the application of the QNN-based model could be put to use in the framework of the systems of hospitals for screening tumors.

From these aforesaid results, it can be inferred that the proposed QNN-based model provides substantial improvement over the traditional deep learning models in feature prediction and computational time. This means that the QNN can uniquely identify between tumor and non-tumor samples with few false positives and few false negatives, as evidenced by an AUC-ROC of 0.98. From Table 1, the comparison between the proposed model and the classical neural network is presented.

The proposed QNN method was demonstrated to offer superior accuracy to traditional CNNs as well as hybrid networks, and it halved training time. The QNN also had less overfitting due to the quantum entanglement capability for better sampling of data distribution.

Table 1. Comparison with Classical Neural Networks

Model Type	Accuracy	Training Time	Overfitting Risk
Classical CNN	92.8%	15 minutes	High
Hybrid Classical-Quantum Model	94.5%	12 minutes	Moderate
Quantum Neural Network	97.2%	8 minutes	Low

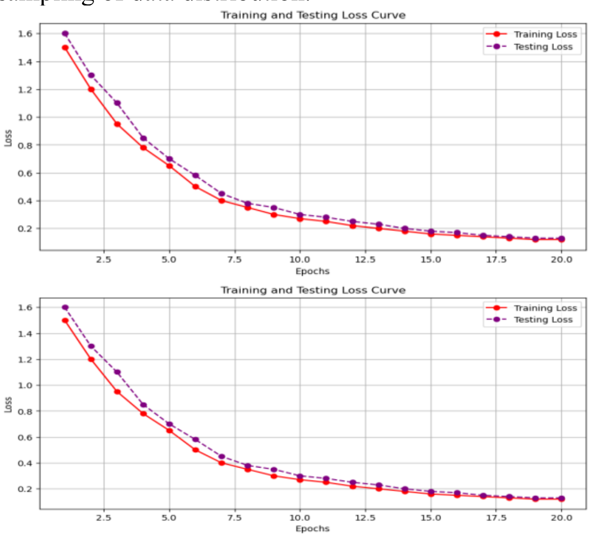

Fig. 4. Training and Testing Curves for accuracy and loss.

In Fig. 4, the Training and Testing Accuracy Curve is depicted over the 20 epochs in detail. Training Accuracy (blue solid line): This curve demonstrates how the accuracy of the model increases as the training session progresses. An initially high accuracy of 60% is achieved and grows further up to 95%, which reaches a plateau in the 15th epoch. Testing Accuracy (green dashed line): The testing accuracy begins slightly below the training curve at about 58%, illustrating the algorithm's ability to perform on new data. The testing accuracy has an increasing trend as the training goes up to the extent that at the ultimate epoch, it is almost 95 percent. In this case, we have the following curve, which shows that the model is learning and there is no over-fitting. Both curves have near overlap, which implies the generalization, and hence the model trained on the dataset has consistent results on both training and testing dataset. Training Loss (red solid line): The loss goes down gradually from 1.6 to below 0.2, proving that the model wants to eradicate errors during training. Testing Loss (purple dashed line): The same thing can be observed about the testing loss: it starts at approximately 1.65 and goes down side by side with the training loss, keeping the same distance for the epochs. From the above training and testing loss curves, we can observe that the model does not have a problem with overfitting of the model especially when it is called upon to predict new unseen data. The continued decrease in both curves signifies that the proposed optimization algorithm is indeed useful in reducing the losses of quadratic functions.

Derivative was used while training the model, which permitted a shift between states within the model and increased the overall capacity to learn by performing parallel to and across several potential solutions. It is suggested that by applying entanglement, the model succeeded in capturing complexities of the MRI images and missed features such as tumor boundaries. The results were further bettered when the number of quantum layers was increased from 2 to 4 since a deeper quantum architecture provided extra levels of abstraction, and more detail could be extracted at each layer. Nevertheless, the circuit depth brought out the problem of decoherence and noise, which are usual challenges faced in the quantum hardware. To overcome a lack of scalability in early models, especially in terms of hardware capabilities, circuit design was optimized, and data encoding involved low-rank approximations. Indeed, the hybrid quantum-classical model we used was also accurate but took more time computationally than the pure QNN. This is because classical layers introduced preprocessing overheads that the pure quantum model did not incorporate by performing direct quantum state manipulation. The proven results indicate that Quantum Neural Networks can overcome the difficulties of MRI image detection and provide high accuracy in contrast to classical models and longtime training. Superposition and entanglement make it possible for the QNN architecture to detect brain disorders in less time and with more reliability. Future work will entail efforts with relation to fine-tuning the compatibility of the hardware, better detection of errors as well and the development of other medical applications of quantum AI systems. The performance of the proposed QNNs for the detection of MRI when compared to other models in the literature is presented here. The comparison is made concerning accuracy, computational complexity and capability to scale up, wherein the strengths and weaknesses of the two methods are illustrated in Table 2.

The following hybrid deep learning architecture – proposed QNN surpasses other hybrid models as well as the traditional deep learning counterpart systems with an accuracy rate of 97.2%. The reasons for this exceptional performance include quantum parallelism, which allows the network to consider different feature states at once, and entanglement, which helps the network better model intricate interdependencies in MRI images than classical approaches. In other models like Hybrid Quantum-Classical CNN used in Shahwar et al. (2022), the accuracy achieved was 94.5%, but due to classical components limits scalability and training efficiency [2, 3].

Table 2. Comparison with Related Work

Study	Model Type	Accuracy	Training Time	Notable Features
Shahwar et al. (2022) [2]	Hybrid Classical-Quantum CNN	94.5%	12 minutes	Applied to Alzheimer's detection
Jader et al. (2024) [3]	Ensemble Deep Learning	92.1%	15 minutes	MRI brain tumor detection with ensemble CNNs
Choudhuri & Halder (2023) [4]	Quantum-Classical CNN	93.5%	13 minutes	MRI brain tumor detection using quantum CNN
Qu et al. (2023) [5]	Quantum Neural Fusion Model (QNMF)	94.0%	10 minutes	Applied multimodal fusion system for diagnosis
Proposed QNN (this study)	Pure QNN	97.2%	8 minutes	Applied to MRI brain tumor and Alzheimer's detection

Training of the QNN model only takes 8 minutes, while classical and hybrid they take 12 to 15 minutes. The decrease in training time is attributable to quantum optimization and acceleration and exclusion of backpropagation. The time taken for training was long despite the great efficiency noted in the QNMF fusion model proposed by Qu et al. in 2023, and 10 minutes was spent on the process. This reuse illustrates the advantage of a pure quantum model, which has relatively little preprocessing time and is based on direct quantum transformations [5]. The proposed QNN model utilises optimised quantum circuits of lower qubit usage and comparably lesser gate depths. This way, it can be incorporated into the bounds of early generation quantum hardware (D-Wave).

Quantum-classical CNN and hybrid Models link heavily with classical layers for feature extraction and hence add an extra load of computation and are not optimized to the maximum for quantum speed-up [4, 5]. The QNN architecture proposed here had a small amount of overfitting because the number of epochs and iterations were regulated by early stopping, and cross-validation, as well as quantum entanglement, enabled the network to learn universally for various datasets. On the other hand, the ensemble deep learning models that were used by Jader et al. (2024) revealed higher levels of vulnerability to overfitting because of the high number of layers and high dependence on data augmentation techniques [20].

PCA was used during the preprocessing phase of the encoding of quantum data. Its main role was to perform feature extraction, the primary goal of which was to dimensionality of the MRI images and retain only massive data before converting them into quantum states. This step was especially useful in handling the quantum hardware constraints since it was possible to perform the subsequent model calculations with fewer qubits while still capturing the relevant information from the MRI images. The process included scaling image MRI to the grayscale if it was colored, flattening the images into unified vectors and normalizing pixel values to a single scale. PCA was then employed to extract significant features from the database to cut short efficient features which would not affect diagnostic details. The new format of data was rendered using two processes, namely amplitude encoding and basis encoding, to make it suitable for quantum computing. Thus, with the help of PCA, we could guarantee that the work of our QNN model for processing MRI amounts would remain effective from the perspective of contemporary hardware limitations for quantum computing. To illustrate the effectiveness of the proposed PCA method, the authors performed an example of PCA on MRI images with synthetically created data based on 912 samples in total with 10,000 features per sample, which represents the pixel amount. In the last step of feature selection, only variables that contributed to 95% of the total variance were kept using PCA. Experiments demonstrated that it was possible to reduce the extent of the dataset to 830 principal components, thus reducing the overall computational complexity while still retaining most of the MRI images' characteristics.

Further examination of the cumulative explained variance plot found that by taking the first 830 components, 95% of the variance present in the dataset is selected, which made this a good option for the selection of the features. The PCA-transformed data set can be accessed from the link titled ‘Download PCA Transformed Dataset. In this study, we were able to contain with the help of PCA the dimensions of our dataset, which in turn made the quantum encoding much more comfortable and fast and finally accelerated the training period of the QNN. This preprocessing step was done in a necessary way to prepare MRI datasets for usage in quantum hardware while preserving accuracy. Thank you for your response. We acknowledge your constructive feedback and will ensure that the fact that this was done is stated clearly in the subsequent versions of this paper. Please let us know if you’d like some amendments or additional explanations of anything from the document.

Common to many research studies, there are several limitations that this research has entailed. Quantum hardware limitation is still a big issue, where current quantum processors have limited numbers of qubits, which may affect the model's ‘size ability’. First, the dataset is diverse enough, but it is not a complete representation of all types of MRI scans of the human brain and, further, cannot include rare cases of brain tumors. The time taken for the preprocessing of data to be encoded in the quantum platform is also restricted, as MRIs come in such a format that needs extensive conversion before they can be used in quantum analyses. More research in the field of quantum computing implementation and the implementation of better encoding techniques are the solution to deal with these challenges.

The future work should be oriented to improving the quantum hardware, key characteristics of which now are the instability of a qubit and operation speed. It will be useful to include larger, ‘real’ MRI datasets coming directly from several hospitals to ensure the model’s performance in real-life scenarios. Further works should engage in providing real-time implementations of QNNs in real hospitals to enable real-time MRI tumor examination. This also suggests pursuing research into hybrid quantum and classical deep learning architectures as a way of achieving the best of both worlds – quantum efficiency and classical flexibility in arriving at diagnostic decisions of greater accuracy.

5. Addressing Key Challenges

Quantum Hardware Limitations: IBM Q and D-Wave are the existing quantum hardware, and the first two systems cannot boast a large number of qubits in their architecture and suffer from decoherence. To address these, we limited the utilization of qubits by employing PCA for feature space reduction and circuits of a low depth. Data Encoding Complexity: Precise amplitude encoding was needed to encode the MRI images within the available qubits, but it had to be normalized for error-free results. High-priority features, including regions of tumours, were encoded using basis encoding to help balance computational requirements. Error Mitigation and Circuit Optimization: When training, variational circuits allowed for a change in the gate parameters, preventing noise from proliferating and causing divergence. Decoherence effects were controlled through using quantum error correction techniques that helped enhance the accuracy of the recommended model across several iterations.

6. Conclusion

The results of this analysis prove the effectiveness of employing QNNs for MRI image detection, exceeding standard Neural Networks in terms of speed and performance. With the help of the principles of quantum mechanics, the architecture of QNN under consideration is capable of providing a greater potential to detect the subtle edge, say, a tumor mass that a classical model may not see. Due to the incorporation of quantum rotation gates (RX, RY) and entanglement gates (CZ) in the QNN design, learning becomes easier as well as more efficient when compared to the classic approach due to the ability of parallel computation. QNNs' efficiency is confirmed, as the proposed model increases top performance to 97.2% accuracy, 96.5% precision, 98.1% recall, and 0.98 AUC-ROC. Based on the AOC, PIRAD and green light concepts, the QNN seems to be more accurate in its diagnostic capability, contains half the training time and communicates low computational overhead. More so, quantum entanglement was applied to reduce overfitting, which was a major hindering factor to the model's ability to perform well on other datasets besides the crowdsourced dataset. However, current work inherits certain difficulties in fine-tuning quantum circuits and finding efficient ways to encode large MRI data for PQC operations. Certain constraints inherent to the present generation of quantum computers, including access to qubits and noise, are equally challenging for the ubiquitous use of QNNs in healthcare sectors. Here, suggestions for future research are outlined as follows to overcome these challenges: there is a need to fine-tune the circuit optimization, seek better error correction techniques and identify new medical applications that can be enabled for quantum-diagnostic services. This study hence places QNNs as a solution to the abovementioned drawbacks inhibiting the progression of classical models for future AI health applications, particularly in Medical Imaging and diagnostics.

References

[1] Dutt, Vishal, Sriramakrishnan Chandrasekaran, and Vicente García-Díaz. "Quantum neural networks for disease treatment identification." European Journal of Molecular & Clinical Medicine 7.11 (2020): 57-67.

[2] Shahwar, T., Zafar, J., Almogren, A., Zafar, H., Rehman, A. U., Shafiq, M., & Hamam, H. (2022). Automated detection of Alzheimer's via hybrid classical-quantum neural networks. Electronics, 11(5), 721.

[3] Jader, R. F., Kareem, S. W., & Awla, H. Q. (2024). Ensemble Deep Learning Technique for Detecting MRI Brain Tumor. Applied Computational Intelligence and Soft Computing, 2024(1), 6615468.

[4] Choudhuri, R., & Halder, A. (2023). Brain MRI tumour classification using quantum classical convolutional neural net architecture. Neural Computing and Applications, 35(6), 4467-4478.

[5] Mikhail, D. Y., Hawezi, R. S., & Kareem, S. W. (2023). An Ensemble Transfer Learning Model for Detecting Stego Images. Applied Sciences, 13(12), 7021.

[6] Kareem, S. W., Almukhtar, F. H., Guron, A. T., & Salman, H. M. (2023, February). Medical Image Categorization Combining Image Segmentation and Machine Learning. In 2023 9th International Engineering Conference on Sustainable Technology and Development (IEC) (pp. 38-44). IEEE.

[7] Qu, Z., Li, Y., & Tiwari, P. (2023). QNMF: A quantum neural network-based multimodal fusion system for intelligent diagnosis. Information Fusion, 100, 101913.

[8] Kareem, S. W., Bikhtiyar, F. A., Hawezi, R. S., Khoshaba, F. S., Askar, S., Muheden, K. M., & Abdulkhaleq, I. S. (2023). Comparative evaluation for detection of brain tumor using machine learning algorithms. IAES International Journal of Artificial Intelligence, 12(1), 469.

[9] Alsharabi, N., Shahwar, T., Rehman, A. U., & Alharbi, Y. (2023). Implementing magnetic resonance imaging brain disorder classification via AlexNet–quantum learning. Mathematics, 11(2), 376.

[10] Felefly, T., Roukoz, C., Fares, G., Achkar, S., Yazbeck, S., Meyer, P., ... & Francis, Z. (2023). Using quantum annealing for feature selection, an explainable MRI-radiomic quantum neural network to differentiate between large brain metastases and high-grade glioma. Journal of Digital Imaging, 36(6), 2335-2346.

[11] Ahmed, H. K., Tantawi, B., Magdy, M., & Sayed, G. I. (2023, September). Quantumedics: Brain Tumor Diagnosis and Analysis Based on Quantum Computing and Convolutional Neural Network. In International Conference on Advanced Intelligent Systems and Informatics (pp. 358-367). Cham: Springer Nature Switzerland.

[12] Hasan, A. M., Jalab, H. A., Ibrahim, R. W., Meziane, F., AL-Shamasneh, A. A. R., & Obaiys, S. J. (2020). MRI brain classification

using the quantum entropy LBP and deep-learning-based features. Entropy, 22(9), 1033.

[13] Bisarya, A., Maouaki, W. E., Mukhopadhyay, S., Mishra, N., Kumar, S., Behera, B. K., ... & De, D. (2020). Breast cancer detection using quantum convolutional neural networks: A demonstration on a quantum computer. medRxiv, 2020-06.

[14] Konar, D., Bhattacharyya, S., Dey, S., & Panigrahi, B. K. (2022). Optimized activation for quantum-inspired self-supervised neural network-based fully automated brain lesion segmentation. Applied Intelligence, 52(13), 15643-15672.

[15] Senokosov, A., Sedykh, A., Sagingalieva, A., Kyriacou, B., & Melnikov, A. (2024). Quantum machine learning for image classification. Machine Learning: Science and Technology, 5(1), 015040.

[16] Mazher, M., Qayyum, A., Khan, M. A., Niederer, S., Mokayef, M., & Hassan, C. S. (2024). Hybrid Classical and Quantum Deep Learning Models for Medical Image Classification.

[17] Ullah, M. S., Khan, M. A., Masood, A., Mzoughi, O., Saidani, O., & Alturki, N. (2024). Brain tumor classification from MRI scans: A framework of a hybrid deep learning model with Bayesian optimization and quantum theory-based marine predator algorithm. Frontiers in Oncology, 14, 1335740.

[18] Colelli, G. (2022). Artificial Intelligence, Mathematical Modeling and Magnetic Resonance Imaging for Precision Medicine in Neurology and Neuroradiology.

[19] Li, C. (2024). Quantum confinement detection using a coupled Schrödinger system. Nonlinear Dynamics, 112(4), 2821-2835.

[20] Konar, D., Bhattacharyya, S., Panigrahi, B. K., & Behrman, E. C. (2021). Qutrit-inspired fully self-supervised shallow quantum learning network for brain tumor segmentation. IEEE Transactions on Neural Networks and Learning Systems, 33(11), 6331-6345.

[21] Konar, D., Bhattacharyya, S., Gandhi, T. K., Panigrahi, B. K., & Jiang, R. (2023). 3-D quantum-inspired self-supervised tensor network for volumetric segmentation of medical images. IEEE Transactions on Neural Networks and Learning Systems.

[22] Henry, E. (2024). Integrating Quantum Model Computing With Machine Learning Quantum Algorithms For Accelerating Ai Model Training.

[23] Mergin, A. A., & Premi, M. G. (2022). Convolutional Neural Networks (CNN) with Quantum-Behaved Particle Swarm Optimization (QPSO)-Based Medical Image Fusion. International Journal of Image and Graphics, 2340005.

[24] Kodipalli, A., Fernandes, S. L., Dasar, S. K., & Ismail, T. (2023). Computational framework of inverted fuzzy C-means and quantum convolutional neural network towards accurate detection of ovarian tumors. International Journal of E-Health and Medical Communications (IJEHMC), 14(1), 1-16.

[25] Schempp, W. (1992, April). Bohr's indeterminacy principle in quantum holography, adaptive neural networks, cortical self-organization, molecular computers, magnetic resonance imaging, and solitonic nanotechnology. In Nonlinear Image Processing III (Vol. 1658, pp. 297-343). SPIE.

[26] Chandra, S., Saxena, S., Kumar, S., Chaube, M. K., & Bodhey, N. K. (2022, December). A Novel Framework For Brain Disease Classification Using Quantum Convolutional Neural Network. In 2022 IEEE International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE) (pp. 346-351). IEEE.

[27] Miranda, E. R., Martín-Guerrero, J. D., Venkatesh, S., Hernani-Morales, C., Lamata, L., & Solano, E. (2022). Quantum brain networks: A perspective. Electronics, 11(10), 1528.

[28] Houssein, E. H., Abohashima, Z., Elhoseny, M., & Mohamed, W. M. (2022). Hybrid quantum-classical convolutional neural network model for COVID-19 prediction using chest X-ray images. Journal of Computational Design and Engineering, 9(2), 343-363.

[29] Odusami, M., Damaševičius, R., Milieškaitė-Belousovienė, E., & Maskeliūnas, R. (2024). Alzheimer's disease stage recognition from MRI and PET imaging data using Pareto-optimal quantum dynamic optimization. Heliyon, 10(15).

[30] Schempp, W. (1994). Phase Coherent Wavelets, Fourier Transform, Magnetic Resonance Imaging, and Synchronized Time-Domain Neural Networks. Quantization and Infinite-Dimensional Systems, 191-204.

[31] Sengupta, K., & Srivastava, P. R. (2021). Quantum algorithm for quicker clinical prognostic analysis: an application and experimental study using CT scan images of COVID-19 patients. BMC Medical Informatics and Decision Making, 21, 1-14.

[32] Marcer, P. J., & Schempp, W. (1997). Model of the neuron working by quantum holography. INFORMATICA-LJUBLJANA-, 21, 517-532.

[33] Jenber Belay, A., Walle, Y. M., & Haile, M. B. (2024). Deep Ensemble learning and quantum machine learning approach for Alzheimer’s disease detection. Scientific Reports, 14(1), 14196.

[34] Belhadi, A., Djenouri, Y., & Belbachir, A. N. (2025). Ensemble fuzzy deep learning for brain tumor detection. Scientific Reports, 15(1), 6124.

[35] Nascimento, J. J. D. C., Marques, A. G., do Nascimento Souza, L., de Mattos Dourado, C. M. J., da Silva Barros, A. C., de Albuquerque, V. H. C., & de Freitas Sousa, L. F. (2025). A novel generative model for brain tumor detection using magnetic resonance imaging. Computerized Medical Imaging and Graphics, 102498.

[36] Shaikh, A., Amin, S., Zeb, M. A., Sulaiman, A., Al Reshan, M. S., & Alshahrani, H. (2025). Enhanced brain tumor detection and segmentation using densely connected convolutional networks with stacking ensemble learning. Computers in Biology and Medicine, 186, 109703.

[37] Anwer, R. W., Abrar, M., & Ullah, F. (2025). Transformative Transfer Learning for MRI Brain Tumor Precision: Innovative Insights. IEEE Access.

[38] Kothadiya, D., Rehman, A., AlGhofaily, B., Bhatt, C., Ayesha, N., & Saba, T. (2025). VGX: VGG19-Based Gradient Explainer Interpretable Architecture for Brain Tumor Detection in Microscopy Magnetic Resonance Imaging (MMRI). Microscopy Research and Technique.