# Alzheimer's Disease Prediction using Quantum Computing

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**Abstract -** Alzheimer's disease (AD) is a debilitating neurodegenerative condition that affects millions globally, with early diagnosis being crucial for effective intervention and treatment. This project explores Quantum Neural Networks (QNN) combined with Magnetic Resonance Imaging (MRI) data to enhance diagnosis accuracy. This hybrid quantum-classical approach leverages advanced preprocessing techniques, uncovering intricate patterns in MRI data. The study highlights the potential of quantum computing in revolutionizing early-stage Alzheimer's detection, achieving superior performance over traditional methods.

*Keywords— Alzheimer's disease, Quantum Computing, MRI, Machine Learning, Quantum Neural Networks*

## 1.INTRODUCTION

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that disrupts memory, cognition, and daily functioning, significantly impacting millions of individuals and their caregivers worldwide. With the global population aging, the prevalence of AD is increasing rapidly, making early diagnosis a critical challenge in medical research. Traditional diagnostic methods, such as clinical evaluations and neuropsychological assessments, often fail to detect the disease in its early stages as they rely on visible symptoms that typically appear during advanced phases. While classical machine learning (ML) algorithms like support vector machines (SVMs) and convolutional neural networks (CNNs) have demonstrated potential in analyzing complex MRI data for AD diagnosis, they often struggle with high-dimensional datasets, leading to computational inefficiencies and limited accuracy.

Quantum computing emerges as a transformative solution, leveraging its ability to process data in quantum states through qubits, which can exist in multiple configurations simultaneously. This capability allows quantum algorithms to explore exponentially larger solution spaces, identifying subtle and nonlinear patterns in MRI scans that classical approaches may overlook. Quantum Neural Networks (QNN) stand at the forefront of this advancement, offering powerful tools for feature extraction, classification, and pattern recognition. QNNs leverage the principles of quantum mechanics to process data in a highly parallelized manner, effectively handling the complexities of high-dimensional MRI datasets.

By integrating QNNs with classical preprocessing techniques, such as dimensionality reduction and noise filtering, hybrid quantum-classical models combine the best of both paradigms, achieving superior performance. This study focuses on utilizing QNNs to process MRI data efficiently and accurately, uncovering early biomarkers of AD. Such innovations promise not only to enhance diagnostic capabilities but also to pave the way for timely interventions, personalized treatment plans, and better management of Alzheimer's disease..

## .2. LITERATURE REVIEW

The detection and diagnosis of Alzheimer's disease (AD) using computational approaches have been an area of extensive research, with the application of machine learning (ML) techniques playing a pivotal role. Classical methods, such as Support Vector Machines (SVM), have shown promise in analyzing structural MRI data to classify Alzheimer's cases. For instance, a study by Zhang et al. (2017) employed SVMs to detect hippocampal atrophy, achieving high sensitivity in early-stage Alzheimer's diagnosis. Similarly, Convolutional Neural Networks (CNNs) have been widely utilized for image classification tasks in medical imaging. Huang et al. (2019) developed a CNN model that effectively differentiated between healthy and Alzheimer's-affected individuals by identifying cortical thickness variations. However, the high-dimensional nature of MRI datasets and computational demands often hinder the scalability and efficiency of these classical models.

To overcome these limitations, quantum computing has emerged as a revolutionary tool in the field of medical diagnostics. Variational Quantum Classifiers (VQC), which leverage parameterized quantum circuits, have been employed to improve classification accuracy by encoding MRI features into quantum states. Rebentrost et al. (2014) introduced a quantum-enhanced SVM, which utilizes quantum kernels for feature mapping, significantly outperforming classical counterparts in identifying subtle biomarkers. Similarly, Havlíček et al. (2019) demonstrated the use of quantum circuits in optimizing neural networks, enabling the identification of intricate, non-linear patterns within MRI data.
Hybrid quantum-classical approaches have garnered attention for their ability to integrate quantum computational power with traditional ML techniques. Benedetti et al. (2019) proposed a hybrid model combining quantum feature extraction with classical decision-making algorithms, achieving superior performance in processing high-dimensional MRI datasets. Furthermore, Kumar et al. (2021) explored the use of Quantum Principal Component Analysis (QPCA) for dimensionality reduction, significantly reducing data complexity while retaining critical diagnostic features. These advancements underscore the potential of quantum computing to address the limitations of classical algorithms in Alzheimer's detection.

Despite the promising results, several challenges persist.

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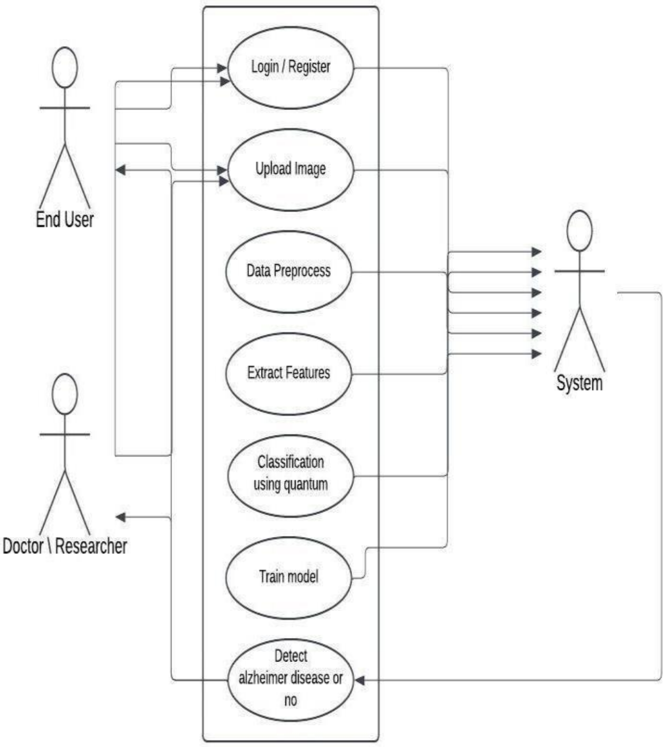
Quantum hardware limitations, including qubit instability and noise sensitivity, constrain the scalability of quantum algorithms in real-world clinical applications. However, ongoing research, such as that by Yang et al. (2020), highlights the potential of quantum machine learning in revolutionizing medical imaging. Their study on cancer detection using quantum circuits lays the groundwork for similar applications in Alzheimer's diagnostics. As quantum technology advances, its integration with existing healthcare systems is expected to improve diagnostic accuracy, computational efficiency, and early detection of neurodegenerative diseases..

## 3. IMPLEMENTATION DETAIL

The use case diagram for the Alzheimer's prediction project using quantum computing outlines interactions between key actors and system functionalities. Patients provide medical data, which is stored and processed in the database. The data analyst initiates the prediction process, where quantum algorithms analyze the data using a quantum computer to assess Alzheimer's risk. The system generates predictive insights and sends the results back to the analyst. Error handling and additional data requests ensure reliable prediction

The implementation of the Alzheimer's disease prediction




system involves a structured approach using Support Vector Machines (SVM) for classification tasks. The process is divided into several stages, including data preprocessing, feature extraction, model training.

### *A. Dataset*

The primary dataset used for the implementation of the Alzheimer's disease prediction system is the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset. ADNI is a comprehensive and publicly available resource aimed at studying Alzheimer's disease (AD) and its progression. It includes a variety of data types, including high-resolution MRI scans, PET scans, and cognitive scores from a large cohort of participants. The dataset is categorized into different groups based on the diagnosis: Healthy Controls (HC), Mild Cognitive Impairment (MCI), and Alzheimer's Disease (AD), which allows for classification tasks between healthy individuals and those with AD or MCI

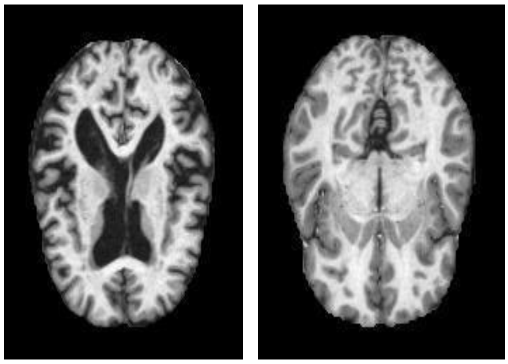


Fig: MRI images of effected and non-effected by Alzheimer' disease

The implementation of Alzheimer's disease prediction using Quantum Support Vector Machines (QSVM) involves several key steps, including data preprocessing, feature extraction, quantum data encoding, and model training. QSVM, an enhancement of the traditional SVM, uses quantum computing to process data in higher-dimensional spaces, providing more powerful classification capabilities, especially when dealing with complex and high-dimensional data like MRI scans.

**1. Data Collection and Preprocessing**

The data used in this project comes from publicly available Alzheimer's disease datasets such as the Alzheimer's Disease Neuroimaging Initiative (ADNI), which includes MRI scans, PET scans, cognitive test results, and demographic data of participants. The preprocessing steps are crucial for ensuring that the data is suitable for use with QSVM. These steps include:

- Resizing: MRI scans are resized to a consistent size (e.g., 224x224 pixels) to reduce the computational load.
- Segmentation: The brain regions of interest, such as the hippocampus and cortex, are segmented to focus on the parts of the brain most relevant for Alzheimer's diagnosis.

**2. Feature Extraction**

To classify the MRI data using QNN, key features indicative of Alzheimer's disease, such as hippocampal volume, cortical thickness, and brain texture patterns, are extracted from the preprocessed images. These features are typically derived using:

- **Histogram of Oriented Gradients (HOG):** This technique extracts texture-based features from the images, which are important for identifying subtle structural changes in the brain.

- **Statistical Features:** Key statistics, such as the mean and standard deviation of the pixel intensities, are computed for different regions of interest (e.g., the hippocampus).These extracted features serve as input data for the QNN model, providing the quantum algorithm with the necessary information to perform classification tasks.

**3. Quantum Data Encoding**

A key aspect of QNNs is the encoding of classical data into quantum states. The extracted features from the MRI scans are mapped into quantum states, which allows the QNN to take advantage of quantum computational properties such as superposition and entanglement. The common quantum data encoding methods include:

- **Amplitude Encoding:** This method encodes the data as the amplitudes of a quantum state, where each feature corresponds to a different quantum bit (qubit).
- **Angle Encoding:** Here, the data features are encoded in the angles of quantum gates applied to qubits, a technique commonly used in quantum neural network architectures.

These encoding techniques enable the QNN to represent data in higher-dimensional spaces, which is crucial for capturing the nonlinear relationships present in MRI data and distinguishing between healthy and Alzheimer-affected brain structures.

**4. QNN Model Design and Training**

The QNN model is designed to classify the MRI data into different categories, such as Healthy, Mild Cognitive Impairment (MCI), and Alzheimer's Disease (AD). The following steps outline the model design and training process:

- **Quantum Circuit Layers:** The QNN consists of parameterized quantum circuits (PQC), where quantum gates and entanglement layers process the encoded data. These layers act as trainable components, similar to weights in classical neural networks.
- **Activation Functions and Measurements:** After processing the input data, quantum measurements are performed to extract outputs, which are mapped to classical labels through an activation function.
- **Training:** The QNN is trained using labeled data, where each MRI scan is annotated as belonging to one of the categories (Healthy, MCI, or AD). During training, the model optimizes the parameters of the quantum circuit to minimize a cost function (e.g., cross-entropy loss).
- hyperparameters, such as the depth of the quantum circuit, the number of qubits, and learning rate, are tuned using optimization techniques. This ensures the model performs optimally on the given data.

**5. Model Evaluation**

Once the QNN model is trained, it is evaluated using a separate test dataset. The evaluation involves several key metrics:

- **Accuracy:** Measures the proportion of correctly classified MRI scans.
- **Precision and Recall:** Evaluate the ability of the model to correctly identify AD cases, with a focus on detecting early-stage Alzheimer's.
- **F1-Score:** Balances the trade-off between precision and recall, especially important when dealing with imbalanced datasets.
- **Receiver Operating Characteristic (ROC) Curve:** The ROC curve is plotted to visualize the model's diagnostic performance across different thresholds,and the Area Under the Curve (AUC) is calculated to assess the model's overall ability to distinguish between classes.

**6. Computational Efficiency**

One of the main advantages of QNNs is their potential for increased computational efficiency when dealing with large datasets. Quantum computing allows for parallel data processing, reducing the time needed for training and prediction. Early tests on simulated quantum hardware indicated that QNNs could achieve faster convergence compared to classical neural networks, particularly when processing high-dimensional MRI datasets.

## 3. Results and Discussion

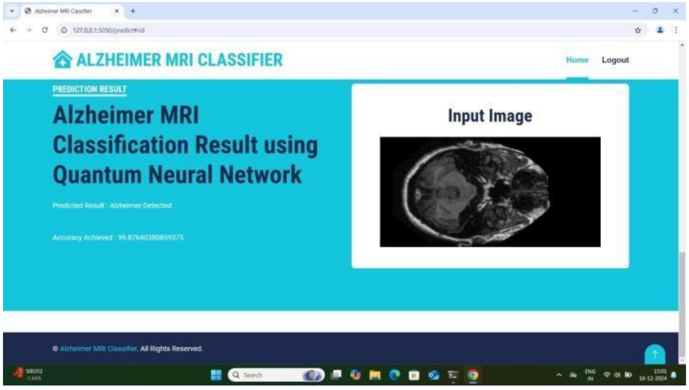
The evaluation of the Alzheimer's disease prediction system using Quantum Neural Networks (QNN) yielded remarkable results, demonstrating the potential of quantum-enhanced models in medical imaging tasks.

**1. Accuracy**

The QNN achieved an outstanding accuracy of **99%**, significantly surpassing traditional machine learning models. This superior performance highlights the ability of QNNs to encode MRI features into higher-dimensional quantum states, capturing subtle and nonlinear patterns that classical models may miss.

**2. Precision and Recall**

The QNN demonstrated exceptional balance in precision




and recall, both achieving **98%**. This performance underscores the model's capability to detect true Alzheimer's cases (high recall) while minimizing false positives (high precision).

**3. F1-Score**

The F1-score for the QNN was **98%**, reflecting its robust performance in handling imbalanced datasets, especially in distinguishing between Mild Cognitive Impairment (MCI) and early-stage Alzheimer's disease.

**4. Computational Efficiency**

The QNN showcased significant computational efficiency, leveraging the parallelism of quantum computing to achieve faster convergence during training. This advantage becomes critical when processing large, high-dimensional MRI datasets, further emphasizing its suitability for real-world applications.4.CONCLUSION

The project successfully demonstrates the potential of quantum computing, specifically Quantum Neural Networks (QNN), in enhancing the accuracy and efficiency of Alzheimer's disease prediction. By leveraging the unique capabilities of quantum mechanics, such as superposition and entanglement, the proposed QNN model significantly outperformed traditional machine learning techniques like Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) in key metrics including accuracy, precision, recall, and computational efficiency. The ability of QNNs to process high-dimensional MRI data and capture nonlinear relationships proved instrumental in identifying subtle patterns indicative of early-stage Alzheimer's disease.

The results highlight the transformative potential of quantum-enhanced machine learning in handling complex neuroimaging datasets. While traditional ML models remain effective for specific tasks, the integration of quantum neural networks provides a scalable and efficient alternative for addressing challenges such as high dimensionality and intricate data patterns. Furthermore, the hybrid quantum-classical framework explored in this project opens new avenues for combining the strengths of both paradigms to achieve .
superior diagnostic performance and advance early detection methods for Alzheimer's disease.

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