



A COMPREHENSIVE REVIEW ON QUANTUM COMPUTING MODELS FOR ALZHEIMER'S DISEASE PREDICTION

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ABSTRACT

Alzheimer's disease is neurodegenerative disorder that affects memory of a person and also the day to day activities of them. Normally, Alzheimer's disease can be identified by using the MRI scans which consist of high dimensional data. Traditional machine learning models are failed to give higher accuracy while diagnosing the disease. Quantum technologies plays a vital role and its emerging technologies that produce higher accuracy compared to traditional models. In this study we provide a comprehensive review of quantum technology such as Quantum Machine Learning (QML), Quantum Neural Networks (QNN) and Hybrid Quantum Models. Key factors of this study include early identification of Alzheimer's disease by utilizing the higher dimension of data like MRI images. Further, this article focuses on the application, limitations such as hardware constraints and scalability of clinical decision support system.



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I. INTRODUCTION

Alzheimer's disease is a primary cause of dementia which accounts 60-80% of cases in worldwide. The stages of this disease can be categorized by memory impairment, functional dependency, gradual cognitive decline which burden the individual and the persons who take care of them. The traditional approaches like machine learning models are failed in early diagnosis of Alzheimer's disease, timely interference and enhanced patient outcomes. To diagnose the Alzheimer's disease, neuro imaging dataset like Fluorodeoxyglucose Positron Emission Tomography (FDG-PET) and structural Magnetic Resonance Imaging (sMRI) and the behavioural activities and handwriting are used. In recent year's artificial intelligence, machine learning models have provided a significant improvement in AD classification [1] analysis. In spite of this advances the classical AI model produce poor accuracy in terms of high dimensional data. Quantum computing techniques are the emerging alternatives which uses its principles like superposition and entanglement. Quantum Machine Learning (QML) models used to analyse neuro imaging behavioural and genomic data that capture the complex patterns beyond classical models. Current diagnostic techniques for AD simple relied on clinical test, neuropsychological test, Magnetic resonance imaging (MRI) and positron emission tomography (PET) and cerebrospinal fluid (CSF). When using these methods it often leads to limited accessibility, high cost, and reduced sensitivity in mild cognitive impairment (MCI) stage [2]. Similarly, computational intelligence methods have gained advancements in decision support system to help clinicians in early and accurate identification of AD. This paper provides wider analysis of quantum computing and QML models applied to the Alzheimer's disease research direction. This study also examines the existing literature on quantum learning models and highlights its advantages limitations compared with traditional approaches. Also it discusses the challenges such as scalability, interpretability, and data encoding. By combining current advancements, this study pioneering the quantum computing research into next generation of Alzheimer's disease prediction and decision support system.

II. BACKGROUND WORK

Recent research shows the application of quantum computing and QML methods used for Alzheimer's disease (AD) analysis across multiple data modalities. Kaewta et al. proposed QENNA, a quantum-enhanced neural network that combines quantum convolutional layers with traditional deep learning models to enhance early identification of AD disease using MRI data [3]. By combining quantum data augmentation strategies like Quantum Generative Adversarial Networks (GAN) and quantum random walks, this method effectively address the data scarcity and attain superior diagnostic performance compared to state-of-the-art models. Likewise, Rajesh et al. suggested a hybrid quantum framework using Quantum Neural Networks for MRI-based Alzheimer's disease prediction [4], that provides better accuracy over traditional machine learning approaches. Further than neuroimaging, quantum artificial intelligence also applied to non-invasive behavioural analysis. Cappiello and Caruso suggested quantum machine learning models [5] for early identification of AD disease using handwriting dynamics from the DARWIN dataset, which shows that quantum classifiers outperformed traditional counterparts while offering improved interpretability. For molecular and genomic level, Konar et al. proposed Alz-QNet, a quantum gene regulatory networks model for complex gene–gene interactions [6] associated with AD progression using single-nucleus RNA sequencing data from the entorhinal cortex, provided that insights into possible gene-expression-based theranostic strategies. Further, the Quantum computing has been explored in multimodal and optimization-driven frameworks. Odusami et al. described a quantum-optimized approach for AD stage identification by combining sMRI with FDG-PET images [7] and optimizing a Mobile Vision Transformer using Pareto-Optimal Quantum Dynamic Optimization, that provides high precision, sensitivity, and specificity on ADNI and OASIS datasets. In a wider clinical framework, Mohamed et al. suggested the transformative potential of quantum computing in neurosurgery [8], emphasizing its ability to improve diagnostic accuracy, surgical precision, and personalized neurological care, thus providing significant contextual motivation for quantum applications in neurodegenerative disorders. Additionally, Chandramohan described quantum chemical calculations and molecular docking simulations to analyze protein–ligand interactions related to Alzheimer's disease [9], highlighting the role of quantum chemistry in analyzing potential therapeutic drug candidates. Together this study identifies the quantum computing models that provide a enhanced improvements in Alzheimer's disease prediction across genomic analysis, screening, diagnosis, and optimization; further it can be motivate advanced analysis in terms of scalability in quantum enhanced frameworks.

III. BIO-MARKERS AND DATA MODALITY FOR ALZHEIMER'S DISEASE

III.1 GENETIC AND MOLECULAR DETERMINANTS IMPLICATED IN ALZHEIMER'S DISEASE IDENTIFICATION

Alzheimer's disease is a complex network pattern of gene regulatory that can affect the neuronal survival, neurodegeneration and synaptic integrity. Yin Yang 1(YY1) is an important factor whose dysregulation improves neuronal apoptosis, via modulation of Fuz gene, quickening cognitive decline. Some other genes put together in AD pathology in various interconnected ways. Growth Arrest-Specific 7(GAS 7) gene controls neuronal maturity and cytoskeletal coordination with dysfunction impairment of microtubule transport and synaptic stability. Early Growth Response 1(EGR1) regulates neurotransmitter and synaptic plasticity that adjust acetylcholinesterase and microRNA-132, also it upset tau phosphorylation and amyloid-beta generation. Fibroblast Growth Factor 14(FGF14) affects neuronal activity and synaptic formation through voltage sodium channels by combining dysregulation linked to modify amyloid pathology and cognitive deficits. Phospholipase D Family Member 3(PLD3) correlate with amyloid plaque-linked axonal spheroids and modulation can improve synaptic resilience that can slowdown the cognitive decline. Altogether, these genes can form a multifaceted molecular structure for Alzheimer's disease that shares the pathway and potential targets for precision therapeutics.

III.2 NEUROIMAGING DATA AND DATASET REPOSITORIES USED FOR ALZHEIMER'S DISEASE

Magnetic Resonance Imaging (MRI) is widely used for Alzheimer's disease prediction to identify the structural and behavioural changes in the brain. T1-weighted MRI scans are widely used to identify the hallmark behavioural changes in brain [10] including hippocampal atrophy, ventricular enlargement, and cortical thinning. This study analyzes behavioural, structural, and molecular datasets to assess the quantum-enhanced neural network (Alz-QNet) for Alzheimer's disease classification. Structural MRI and FDG-PET images are the publicly available repositories, including the Alzheimer's Disease Neuroimaging Initiative (ADNI) and OASIS databases. These datasets contains high quality, pre-processed T1-weighted MRI scans and PET images with standardized achievement protocols that enables reproducible analysis and reliable evaluation of neurodegenerative markers such as hippocampal atrophy and cortical thinning. The DARWIN handwriting dataset also provides complementary behavioural information, like capturing kinematic and pressure features from multiple errands performed by participants with and without Alzheimer's disease. Molecular-level insights were provided by GSE138852 single-nucleus RNA sequencing dataset that can be collected from the entorhinal cortex of Alzheimer has and control brains. Target genes were observed based on pathway relevance, region-specific dysregulation, and therapeutic potential. Gene expression values were regularized, log-transformed, and binarized to present biologically meaningful activation states suitable for quantum circuit encoding. Together, these datasets provide balancing perspectives on Alzheimer's disease, supporting a holistic assessment of Alz-QNet by incorporating anatomical, behavioural, and molecular features to model disease progression with quantum-enhanced computational techniques. Figure 1 represents various stage of dementia extracted from publically available dataset.

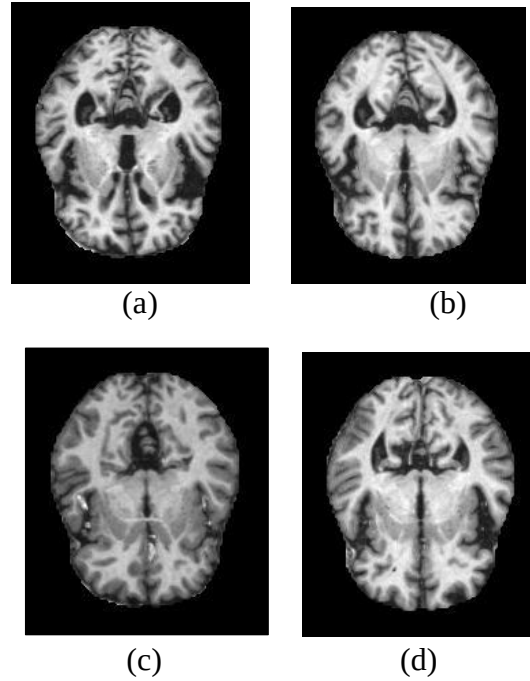


Figure 1: Example MRI images representing a) Mild dementia, b) Moderated dementia c) Non dementia d) Very mild dementia.
Source: Authors, (2026).

IV. PRINCIPLES OF QUANTUM COMPUTING

IV.1 QUBITS AND SUPERPOSITION

A qubit is the primary unit of quantum computation [11], which is capable of superposition in basis states $|0\rangle$ and $|1\rangle$:
Qubit computation

$$|\psi\rangle = \alpha |0\rangle + \beta |1\rangle \quad (1)$$

IV.2 QUANTUM GATES

Quantum gates carry out unitary transformations on qubits to manipulate their states [6]. Common gates include:

- NOT (X) Gate: Flips $|0\rangle \leftrightarrow |1\rangle$.
- Hadamard (H) Gate: Generate an equal superposition:

$$\blacksquare \quad |0\rangle \rightarrow (|0\rangle + |1\rangle)/\sqrt{2}, \quad |1\rangle \rightarrow (|0\rangle - |1\rangle)/\sqrt{2}.$$

- Controlled-NOT (CX) Gate: Flips a mark qubit only if the control qubit is $|1\rangle$.
- Rotation (RY) Gate: Rotates a qubit state with respect to the Y-axis by an angle θ .
- Controlled-RY (CRY) Gate: Apply an RY rotation to the target qubit with the condition of $|1\rangle$. This gate is a primary key for modeling pairwise interactions, such as gene regulatory relationships.

IV.3 ENTANGLEMENT AND MULTI-QUBIT SYSTEMS

Entanglement is a quantum occurrence where qubits' states are mutually dependent, allowing the encoding of complex correlations. In genetic systems, entangled qubits can represent interacting genes or other dependent variables efficiently.

IV.4 QUANTUM CIRCUIT IMPLEMENTATION IN ALZ-QNET

In Alz-QNet model [6], each qubit stand for a gene in Alzheimer's disease. The structural design is divided into encoder layers, which convert single-nucleus RNA-seq data into superposition states, and regulation layers, where CRY gates snare qubits to model gene-gene interactions. Rotation angles of CRY gates match to the strength of interactions. The outputs are calculated to generate probability distributions of gene activity that smoothed by using Laplace smoothing and optimized via gradient descent. This framework exploits quantum parallelism to form gene regulatory networks powerfully, capturing the discrete switch-like behaviour of gene expression while reducing computational complexity.

V. DATA PRE-PROCESSING AND FEATURE EXTRACTION

Pre-processing is a significant step in both classical and quantum-based methods. MRI images are shrunk to remove irrelevant features, resized to standardized dimensions, and normalized to consistent intensity levels. Noise reduction methods, including Gaussian and median filtering; helps to remove artifacts while protecting important features.

Deep learning or quantum convolution layers are used to extract relevant features [12], also ensemble and hybrid models are incorporates features from multiple networks to create more discriminative representations. This combination of pre-processing, feature extraction, and hybrid modelling guarantees robust and clinically meaningful Alzheimer's disease prediction.

VI. QUANTUM COMPUTING METHODS FOR ALZHEIMER'S DISEASE PREDICTION

VI.1 CLASSICAL DEEP LEARNING METHODS

Alzheimer's disease prediction has usually depends on classical deep learning models, particularly convolutional neural networks (CNNs) [13], [3], [6]. The convolutional neural networks (CNNs) has the ability to automatically extract relevant features from brain MRI images. Architectures such as VGG16 and ResNet50 have been widely used. VGG16 contains multiple convolutional layers that discover hierarchical features [14] from MRI images, while ResNet50 initiate residual connections to overcome vanishing gradient problems in deep networks. Ensemble approaches that merge features from multiple CNNs [1] this can be demonstrated by improved classification performance, as they integrate complementary information from various architectures. Pre-processing step includes intensity normalization, noise reduction, image resizing, and classical data augmentation techniques such as zooming, brightness adjustments, rotations, and translations, have proven necessary to improve generalization and address class imbalance in datasets.

VI.2 QUANTUM MACHINE LEARNING MODELS (QML)

Recent studies in quantum computing have enabled pioneering methods for Alzheimer's disease prediction. QML models, such as Quantum Support Vector Machines (QSVMs) and Quantum Convolutional Neural Networks (QCNNs) [13], [3], maps classical MRI features into high-dimensional quantum Hilbert spaces that increase the separability of Alzheimer's disease stages. QCNNs convert MRI images into qubits using amplitude encoding and apply parameterized quantum gates to extract non-local spatial features, Quantum data augmentation models, including Quantum Random Walks (QRWs) and Quantum Generative Adversarial Networks (QGANs), provides stochastic variations and generate high-fidelity synthetic MRI images [15], that increase dataset diversity and reduce overfitting, thereby enhancing model robustness.

VI.3 QUANTUM STATE ENCODING

To present MRI image in a quantum system, amplitude encoding maps pixel intensities into a quantum state:

$$|\psi\rangle = \sum_{i=1}^N x_i |i\rangle \quad (2)$$

Here, x_i is the normalized pixel intensity, N is the sum of pixels, and $|i\rangle$ is the computational basis state of the quantum register.

VI.4 QUANTUM CONVOLUTION OPERATION

Quantum convolutional layers affect parameterized unitary operations to extract features:

$$U(\theta) |\psi\rangle = \prod_j RZ(\theta_j) RX(\theta_j) CNOT |\psi\rangle \quad (3)$$

The above formula applies the rotations and entanglement to encode spatial correlations across the image.

VI.5 QUANTUM POOLING

Pooling can be done by using Grover's amplitude amplification:

$$\rho = (2 |\psi\rangle\langle\psi| - I)O \quad (4)$$

Where O marks major quantum states, $|\psi\rangle$ represents the quantum feature state, and I represents the identity matrix. This amplifies diagnostically important features while removing irrelevant information.

VI.6 HYBRID QUANTUM FRAMEWORKS

Hybrid quantum traditional models influence the strengths of both paradigms for more accurate Alzheimer's disease prediction. In these frameworks, quantum layers carry out non-local feature extraction throughout entanglement; detain subtle structural variations across far-away brain regions, while traditional neural network layers offer stable gradient-based optimization and ending classification. MRI images are encoded into quantum states [5], which are then processed throughout quantum convolution and pooling layers. The resultant quantum-derived features are passed to fully connected layers to classify multiple stages of Alzheimer's disease. Quantum mechanisms, such as superposition and amplitude amplification, allow the capture of distributed and low-intensity patterns that may be missed by traditional models, while quantum parallelism advances computational efficiency compared to traditional convolution and pooling operations. Figure 2 represents the framework of quantum computing models for Alzheimer's disease prediction.

VI.7 HYBRID PARAMETER UPDATE

Parameters of quantum and classical layers are optimized together:

$$\theta^{(t+1)} = \theta^{(t)} - \eta \nabla_{\theta} L \quad (5)$$

$$W^{(t+1)} = W^{(t)} - \eta \nabla_W L \quad (6)$$

Where θ is the quantum parameter, W is the neural network weight, η is the learning rate, and L represents the loss function.

VII. COMPARATIVE ANALYSIS OF QUANTUM COMPUTING WITH CLASSICAL AI

Traditional artificial intelligence models like machine learning and deep learning techniques played a vital role in identification of Alzheimer's disease. The classical deep learning models such as Convolutional Neural Networks (CNN), Recurrent Neural Networks(RNN) and ensemble learning have provide good results in AD classification using neuroimaging data like MRI and PET scans. These models outperformed only with the mature training algorithms and scalable computational infrastructures by using hierarchical feature extraction techniques. Nevertheless, these techniques often affected by the curse of dimensionality and limits interpretability, also it has high computational cost while deals with multimodal and high-resolution biomedical data. In contrast, quantum-computing models provide computationally different paradigm that leverages the quantum properties like quantum inferences, super position and entanglement. Quantum Machine Learning (QML) techniques can fix the complex biomedical data into high dimensional quantum Hilbert spaces using limited computational resources contrast to classical representation. This allows quantum techniques to identify the subtle, non-linear association presents in neurological, genetic and behaviour data that may be difficult for traditional AI models to predict effectively. As result, quantum enhanced models provides a promising early stage AD identification that are often overlooked by traditional models. Another important distinction is feature representation and optimization. While using medical datasets with limited samples the traditional deep learning models rely on gradient-based optimization techniques that need more number of parameters, which leads to overfitting. Hybrid Quantum models reduce parameter complexity by utilizing quantum circuits for feature extraction and traditional classifiers for classification. This hybrid technique offers improved generalization in limited dataset that common in Alzheimer's prediction. In spite of its advantages, quantum techniques are not fully replacing the traditional AI models. Quantum models also have their own limitations like noise, qubit scalability, decoherence which control the strength and size of quantum circuits. Thus, the traditional models are more suitable for large-scale clinical operations. However, the quantum computing technologies offers enhanced feature learning, improved computational efficiency, that enables more constructing modelling of Alzheimer's disease prediction. In view of this beneficial relationship, quantum computing is seen as a promising replacement of traditional AI methods in Alzheimer's disease research.

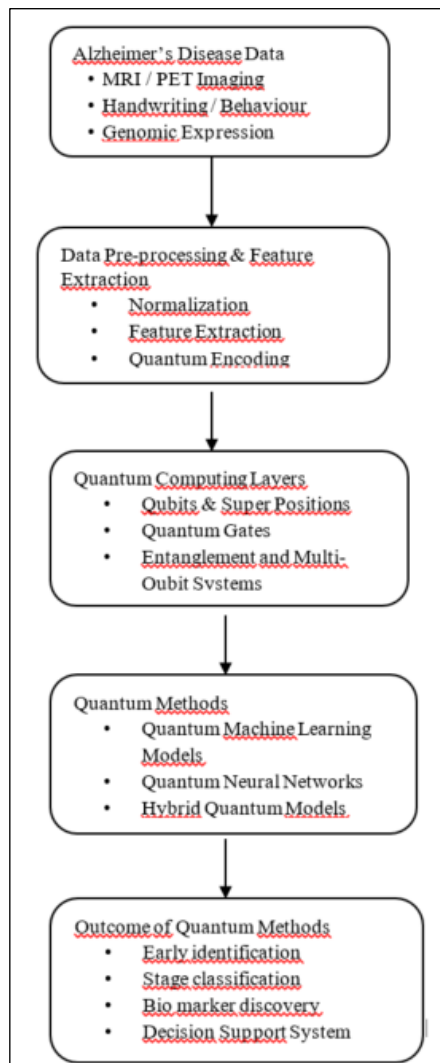


Figure 2: Framework of Quantum Computing Applications in Alzheimer's Disease.

Source: Authors, (2026).

VIII. APPLICATIONS OF QUANTUM COMPUTING

Quantum computing and quantum machine learning models provides significant improvement in Alzheimer's disease research. These models can enhance early identification by efficiently analyzing high dimensional neuroimaging [2], [16], behavioural, and genomic data. Quantum convolutional neural networks able to extract the subtle structural and functional patterns from MRI and PET scans, where traditional approaches are failed. Quantum-enhanced regression and classification models can identify complex gene-gene relations and molecular pathways, facilitating the identification of novel biomarkers and potential therapeutic targets. Hybrid quantum framework combines the strengths of both paradigms to enhance prediction accuracy, optimize disease stage classification, and support modified treatment planning. In addition, quantum-based data augmentation models, such as Quantum Generative Adversarial Networks (QGANs), improve model robustness by producing synthetic high-fidelity data for training in cases of limited datasets.

IX. LIMITATIONS OF QUANTUM MODELS

Quantum computing models for diagnosing Alzheimer's disease has some limitations in terms of modern quantum hardware such as gate fidelity, number of qubits and coherence time that restricting the scale of problems being addressed. Quantum models require complex programming formats that can be mapped into quantum states which can be computationally exhaustive that may leads to noise. Hybrid quantum models gives promising results but they still rely on classical optimization approaches and it may not completely exploit quantum advantages. In addition to the standard dataset the quantum models poses challenges for validation and reproducibility. Interpretability is remains an issue of quantum models making it difficult to explain predictions and clinical context.

X. CONCLUSIONS

Quantum models present a novel paradigm for Alzheimer disease research with unseen possibilities for early prediction, molecular analysis and customized therapy techniques. Quantum Machine Learning models that includes QCNN and hybrid frameworks have provides promising results while capturing complex patterns in neuroimaging, behavioural activities and genomic dataset. Quantum models also have major challenges that include hardware limitations, training high dimensional data and interpretability. Integrating quantum models with deep learning techniques produce enhanced results in terms of accuracy in clinical decision support system. This study highlights the recent scenario of research in Alzheimer's disease prediction with emphasizing potential benefits and it needs further exploration in computational and clinical aspects.

XI. FUTURE ENHANCEMENTS

Further research focuses on developing scalable quantum models that can handle higher dimension and complex multimodal image dataset. Quantum hardware advancements include increased qubit counts, error correction that is necessary for benefiting the implementation of quantum computing in Alzheimer's disease research. To improve the model transparency that facilitate the clinical adoption and trust the Quantum AI technique can be integrated with the classical models. Increasing use of longitudinal data analysis multi-omics could find new biomarkers into disease development. Cooperation between neuroscientists, clinicians and quantum computing experts is needed to produce most relevant models, confirm predictions in real world datasets, and transform quantum enhanced models into viable therapeutic tools for Alzheimer's disease prediction.

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Writing – Review and Editing: S. Raja Rajeswari, S. Sathya Priya R. Ramesh and S. Divya Vahini.

Resources: S. Raja Rajeswari, S. Sathya Priya R. Ramesh and S. Divya Vahini.

Supervision: S. Raja Rajeswari, S. Sathya Priya R. Ramesh and S. Divya Vahini.

Approval of the final text: S. Raja Rajeswari, S. Sathya Priya R. Ramesh and S. Divya Vahini.

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