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Analyzing Quantum CNN and Quantum SVM for Alzheimer's Diagnosis

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ABSTRACT

Alzheimer's disease affects our thinking and behavior. It is one of the types of dementia. It initially affects the brain's learning regions. Since the disease is both progressive and irreversible, early diagnosis is vital for effective treatment management. This research presents a comprehensive, end-to-end approach for early detection of Alzheimer's by focusing on the hippocampus and leveraging transfer learning. The study compares the performance of a Quantum Convolutional Neural Network (QCNN) with that of a Quantum Support Vector Machine (QSVM). Findings suggest that QCNN is more efficient at handling high-dimensional data compared to QSVM. Alzheimer's disease is mainly defined by the deterioration of memory and cognitive abilities, which results from the degeneration and death of neurons that play a crucial role in memory function. Mild Cognitive Impairment (MCI), which sits between normal cognitive function and Alzheimer's, offers a critical window for early intervention. Diagnosing MCI early may help delay or even prevent the onset of Alzheimer's. The results of our experiment show that the QCNN model achieved a precision of 0.88, recall of 0.96, and an accuracy of 0.59. In contrast, the QSVM model recorded a precision of 0.85, recall of 1.00, and an accuracy of 0.85. These findings indicate that both quantum machine learning models demonstrate strong potential and complement each other in performance.

Keywords: Alzheimer's Diagnosis, QCNN, QSVM, Quantum ML, Machine Learning.

I. INTRODUCTION

Alzheimer's Disease (AD) is a major global health concern, recognized as the most common form of dementia and affecting millions worldwide. Due to it, there is a progressive and irreversible decline in brain function, with the hippocampus—responsible for learning and memory—experiencing the most severe damage. Because current treatments cannot reverse the disease, early diagnosis is critical to help delay its progression.

Alzheimer's often begins with Mild Cognitive Impairment (MCI), a condition involving subtle memory and cognitive issues that may eventually develop into full-blown Alzheimer's. Currently, more than 55 million individuals worldwide are affected by dementia, with 60–70% of these cases being Alzheimer's disease, highlighting an urgent demand for precise and effective diagnostic instruments. Figure 1 illustrates the global statistics on the top 10 causes of death, emphasizing the scale of the issue.

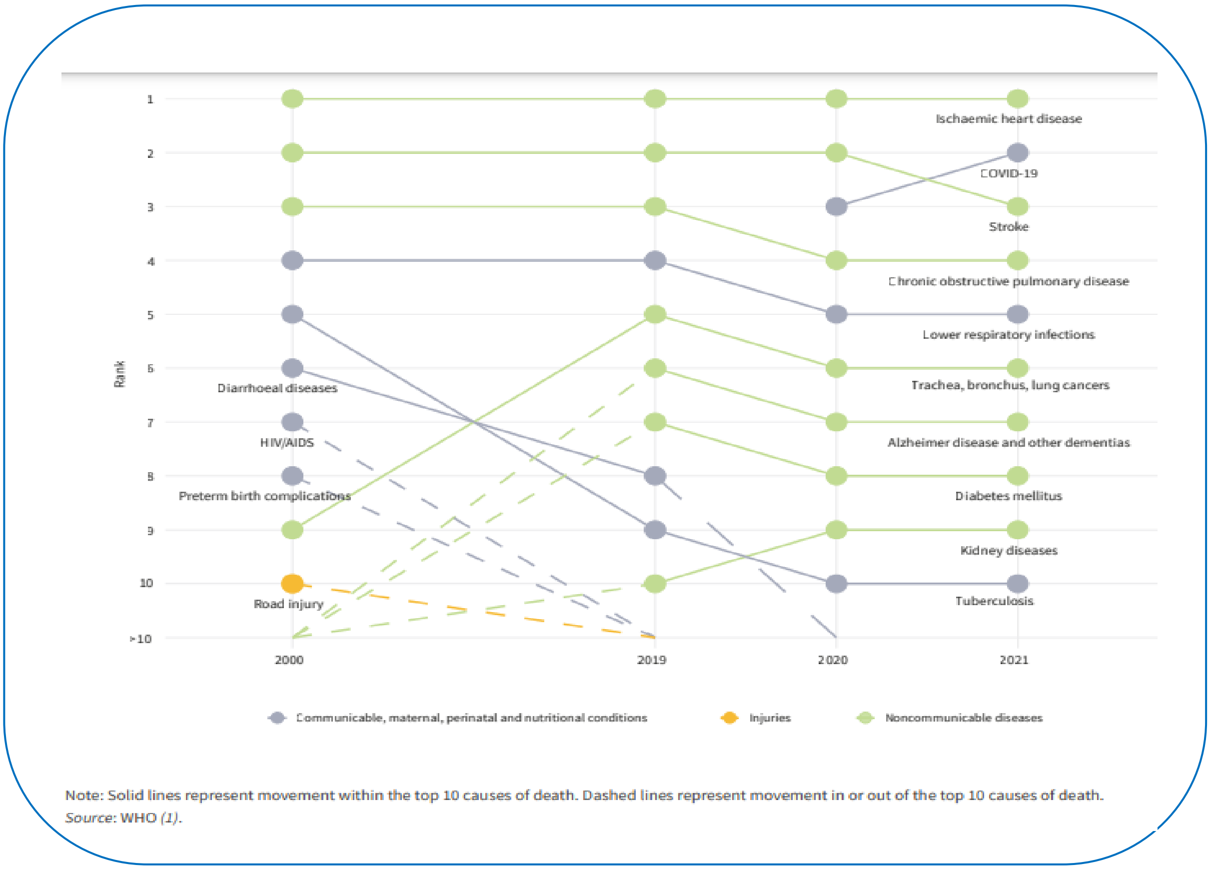

Fig.1: Top 10 causes of Death

(Source: https://www.who.org)

Conventional methods for diagnosing AD primarily rely on clinical evaluations and neuropsychological testing, which can be time-consuming and subjective. However, advancements in artificial intelligence (AI) have introduced innovative approaches to early diagnosis and staging of the disease. Recent advancements in machine learning, especially deep learning models, have demonstrated potential in the analysis of structural MRI scans for the classification of individuals into Cognitive Normal (CN), Mild Cognitive Impairment (MCI), and Alzheimer's Disease (AD) categories.

Global Trends in AD

Globally, the burden of Alzheimer's is projected to grow dramatically over the coming decades. In 2024, approximately 55 million people are living with the disease. This number is expected to rise to 78 million by 2030 and an estimated 139 million by 2050, highlighting the urgent need for scalable diagnostic and management solutions.

The number of deaths from Alzheimer's is also rising, with 1.6 million fatalities expected in 2024, increasing to 2.5 million in 2030 and reaching 4 million by 2050. Figure 2 illustrates the timeline of AD progression.

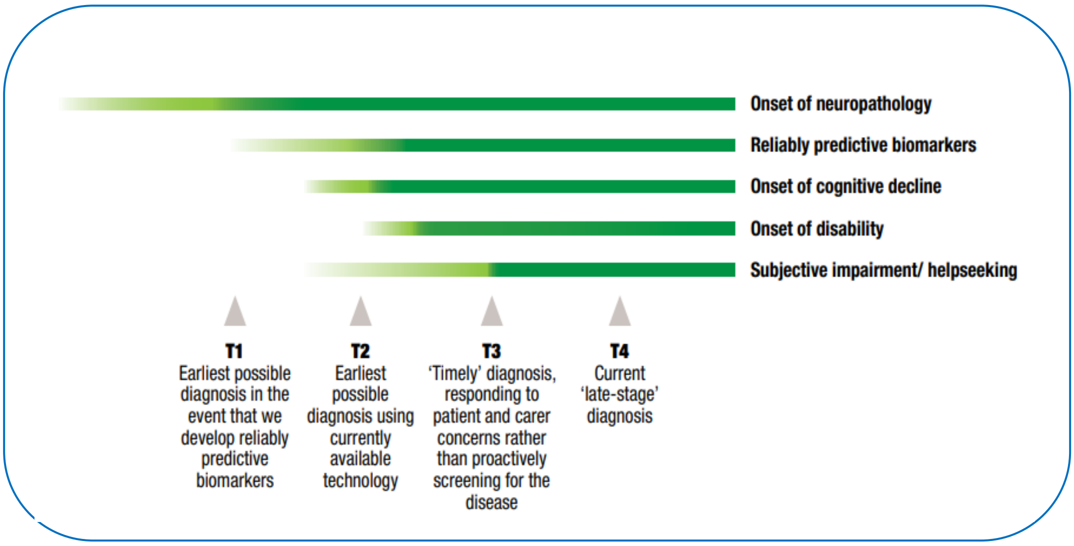

Fig.2: Timeline of Alzheimer's Disease Progression
(Source: https://www.who.org)

Demographic trends show that Alzheimer's is strongly age-related. In 2024, 60–70% of cases occur in the elderly population. This percentage is projected to grow to 65–75% by 2030 and 70–80% by 2050. Conversely, early-onset and genetically predisposed cases, currently 5–10% in 2024,are expected to rise to 10–15% by 2030, although projections for 2050 remain uncertain. The following fig. 3 shows the statistics related to Alzheimer's in India. (Source: ARDSI).

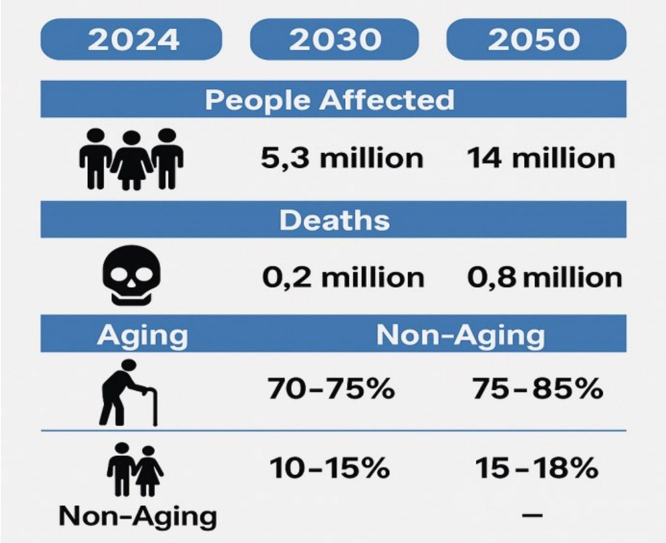

Fig 3: Alzheimer's Statistics (India)

India has a significant number of people living with dementia, with estimates suggesting over 4 million individuals affected. According to the available data, India's prevalent case rate for Alzheimer's disease and other dementias was approximately 295 cases per 100,000 people in 2021. This number might seem relatively low compared to other countries, but it's essential to consider India's large population and the potential for underreporting due to limited awareness and resources.

There are several challenges in India like:

- Low awareness and stigma surrounding dementia lead to delayed diagnosis and treatment.
- Limited access to healthcare services, especially in rural areas, exacerbates the issue.
- There's a significant shortage of specialists trained to diagnose and treat dementia.
- Long-term care services are scarce, and families often bear the burden of caregiving.

Stages of Alzheimer's Disease

Alzheimer's disease progresses through a series of stages, each marked by increasing cognitive and functional decline. While the disease affects individuals differently, most medical sources recognize either a three-stage or a more detailed seven-stage model to describe its progression.

Three Main Stages

1. Early Stage (Mild Alzheimer's Disease)

Individuals may function independently but start to experience memory lapses, such as forgetting familiar words, names, or the location of everyday objects. Other symptoms include difficulty performing tasks in social or work settings, losing or misplacing valuable objects, and trouble with planning or organizing. These symptoms are often more noticeable to family and close friends than to the individual themselves.

2. Middle Stage (Moderate Alzheimer's Disease)

Memory loss and confusion worsen; individuals may have trouble recalling personal history, recognizing friends and family, or performing complex tasks such as managing finances. Changes in mood and behaviour, such as increased confusion, suspicion, or agitation, are common. Assistance with daily activities becomes necessary as independence declines.

3. Late Stage (Severe Alzheimer's Disease)

Individuals lose the ability to respond to their environment, carry on a conversation, or control movement. They may require help with all activities of daily living, including eating and personal care. Physical abilities, such as walking, sitting, and swallowing, deteriorate, and individuals become vulnerable to infections.

Seven-Stage Model (Global Deterioration Scale)

For a more detailed breakdown, the seven-stage model is often used by clinicians:

Stage	Description
1.	No impairment: No symptoms, but brain changes may be occurring.
2.	Very mild decline: Subtle memory lapses, not evident to others.
3.	Mild cognitive decline: Noticeable memory or concentration problems, trouble with complex tasks.
4.	Moderate cognitive decline: Clear-cut deficits in performing complex tasks, such as handling finances or planning meals; diagnosis often made at this stage.
5.	Moderately severe decline: Need help with daily activities, such as choosing appropriate clothing; memory gaps become more pronounced.
6.	Severe cognitive decline: Require help with dressing, bathing, and toileting; may forget names of close family, experience personality changes, and lose awareness of surroundings.

7. Very severe decline: Loss of ability to speak, walk, or control movement; require full-time

care; may lose ability to smile or hold up head.

Preclinical Stage: Brain changes associated with Alzheimer's can begin years before symptoms appear. This is sometimes called the preclinical or "no impairment" stage.

Progression: The duration of each stage varies; the disease can last more than a decade from onset to late-stage symptoms.

Diagnosis and Care: Staging helps guide care planning and support, but not all individuals progress in the same way or at the same pace.

Understanding these stages helps caregivers, families, and healthcare providers anticipate needs and provide appropriate support throughout the course of Alzheimer's disease. The following fig.4 shows the Nerve Growth Factor (NGF).

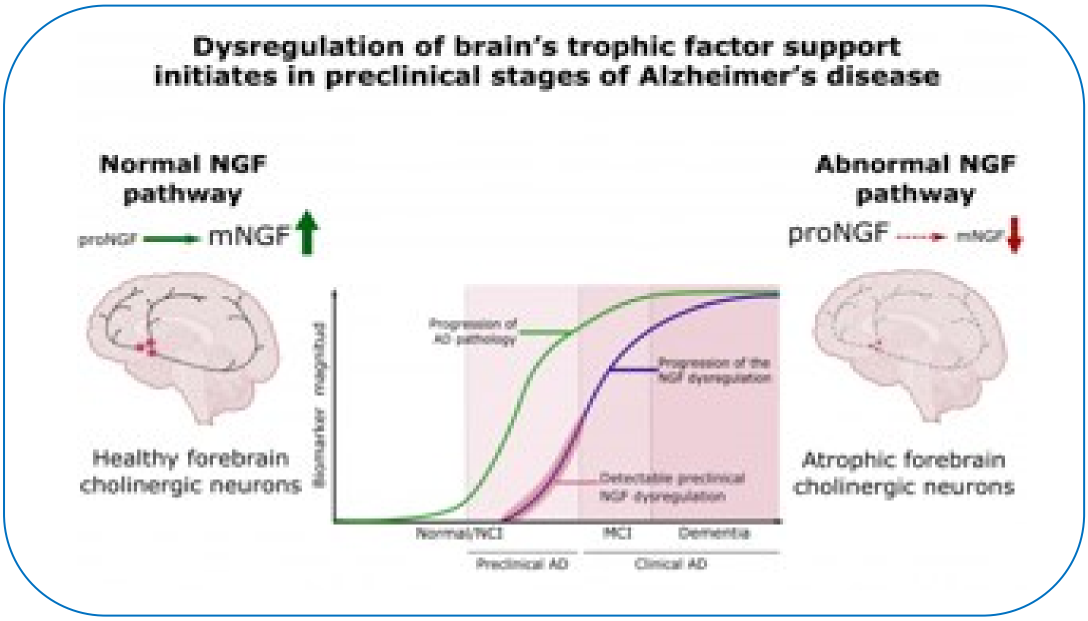

Fig 4: Nerve Growth Factor

(Src:https://l1nq.com/sxG8T)

The image illustrates how dysregulation of the brain's trophic factor support, specifically involving nerve growth factor (NGF), initiates in the preclinical stages of Alzheimer's disease.

Left Side: Normal NGF Pathway

Shows a brain with healthy forebrain cholinergic neurons. It indicates a normal NGF pathway where proNGF is converted to mature NGF (mNGF), supporting neuron health. It is associated with normal cognitive function.

Right Side: Abnormal NGF Pathway

Shows a brain with atrophic (degenerated) forebrain cholinergic neurons. It indicates an abnormal NGF pathway where proNGF accumulates and mNGF levels decrease, leading to neuronal atrophy. It is linked to Alzheimer's pathology.

Center: Progression Graph

The central graph plots "Biomarker magnitude" (y-axis) against disease progression from Normal/NC (normal cognition), MCI (mild cognitive impairment), to Dementia (x-axis). The green line represents the progression of AD pathology, which rises early in the preclinical stage. The purple line shows the progression of clinical symptoms, which lags behind the pathology.

The shaded area highlights the preclinical Alzheimer's disease (AD) phase, where biochemical changes occur before clinical symptoms appear. This image emphasizes that disruption in NGF signaling (decreased mNGF, increased proNGF) begins before clinical symptoms of Alzheimer's disease, leading to neuronal degeneration and cognitive decline.

Our models focus on the hippocampus and leverages progressively augmented data during training. This strategy has yielded high accuracy across training, validation, and testing phases. By employing a comprehensive AI-driven approach, our work contributes to the development of early diagnostic tools that can be practically implemented in clinical settings.

In short, we can say that this work bridges the gap between traditional diagnostic practices and cutting-edge AI solutions, specifically through the use of Quantum Machine Learning. The goal is to harness advanced technology to target critical brain regions and enable early intervention, ultimately improving patient outcomes in Alzheimer's care.

Quantum Machine Learning

Quantum Machine Learning (QML) is an interdisciplinary field that combines principles from quantum computing and machine learning to develop new algorithms and models that can solve complex problems more efficiently. QML leverages the power of quantum computing to improve machine learning models. Quantum computers use quantum bits or qubits, which can exist in multiple states simultaneously, allowing for parallel processing of vast amounts of data. Following are some of the key terms in QML.

1. Quantum Circuits: Quantum circuits are the building blocks of QML models. They consist of

quantum gates that manipulate qubits to perform computations.

2. Quantum Algorithms: Quantum algorithms are designed to take advantage of quantum computing's
unique properties. Examples include Quantum Support Vector Machines (QSVM) and Quantum
Circuit Learning (QCL).
3. Hybrid Quantum-Classical Approach: Many QML models use a hybrid approach, combining quantum and classical computing to leverage the strengths of both paradigms.

QML offers several benefits like:

Speedup: QML can provide a speedup over classical machine learning algorithms for certain tasks.

Improved Accuracy: QML can improve the accuracy of machine learning models by leveraging quantum computing's unique properties.

New Insights: QML can provide new insights into complex systems and phenomena.

There are many applications of QML viz.:

Image Recognition: QML can be used for image recognition tasks, such as classifying images or detecting objects.

Natural Language Processing: QML can be applied to natural language processing tasks, such as text classification or sentiment analysis.

Materials Science: QML can be used to simulate the behaviour of materials and molecules, leading to breakthroughs in materials science.

Healthcare: QML can be applied to medical imaging analysis, disease diagnosis, and personalized medicine. etc.

QML is a fast growing field, with new breakthroughs and advancements being made regularly. As quantum computing technology improves, we can expect to see more applications of QML in various industries. Quantum Machine Learning is being explored for disease diagnosis, particularly in analyzing large medical datasets to identify patterns and predict disease occurrence or progression. Some prominent QML algorithms and techniques include:

Quantum Support Vector Machines (QSVM): Used for classification tasks, such as disease diagnosis, by analyzing complex patterns in medical data.

Quantum Circuit Learning (QCL): Applied to disease diagnosis and prediction by learning from medical data.

Quantum Deep Learning: Facilitates different mining procedures by incorporating precise advancements in quantum computing, used in predicting diseases like Parkinson's.
Quantum-Enhanced Machine Learning Algorithms: Techniques like Quantum Particle Swarm Optimization (QPSO) are being used to enhance machine learning models for heart disease prediction.

As research continues to advance, we can expect to see more applications of QML in various industries. Quantum computing and machine learning are transforming healthcare in various ways, particularly in:

- Disease Diagnosis: Analyzing chest X-rays to diagnose pneumonia using machine learning algorithms like support vector machines, which can be more accurate and efficient than traditional methods.
- Personalized Medicine: Enabling fast DNA sequencing, which opens possibilities for tailored treatments based on individual genetic profiles.
- Drug Discovery: Simulating molecular interactions to develop new therapies and medicines through detailed modelling, potentially accelerating the discovery process.
- Medical Imaging: Creating efficient imaging systems that provide clinicians with enhanced fine-grained clarity in real-time, aiding diagnosis and treatment.
- Operational Optimization: Solving complex optimization problems involved in devising optimal radiation plans for cancer treatment, minimizing damage to healthy tissues.

QML seems to have the potential to fundamentally transform approaches to early disease diagnosis.
It can identify subtle patterns in medical data, potentially leading to more accurate diagnoses.

II. LITERATURE REVIEW

Islam and Zhang [1] proposed an ensemble of deep CNNs to process brain MRI data to achieve greater diagnostic precision using multiple CNN models. Basheera and Ram [4] also used a model fusing improved ICA -Independent component analysis and CNNs to diagnose AD using 'segmented gray matter' of T2-weighted MRIs.Suk & Shen [8] presented an auto-encoder architecture to derive high-level features from multimodal data to enhance AD and mild cognitive impairment (MCI) classification. SegNet-based segmentation was used by Buvaneswari and Gayathri [9] to segment AD-relevant regions from the brain and attained high-classification accuracy. A deep dense block-based model was proposed by Çelebi and Emiroğlu [11] and was found to achieve 95.81% accuracy on the dataset - ADNI.

Despotović et al. [2] discussed MRI segmentation methods and identified challenges in demarcating the structures of the brain because of anatomical variability and imaging distortions. Parmar et al. [10] used a 3D-CNN on 'resting-state' fMRI data to facilitate spatiotemporal feature derivation and AD diagnosis. Zhang et al. [6] integrated structural MRI and resting-state fMRI through graph theory & ML to predict the MCI to AD transition. Oja and Yuan [3] returned to the FastICA algorithm with a convergence analysis important to blind source separation in neuroimaging data. A domain transfer learning technique was proposed by Cheng et al. [13], using data from normal controls and AD to enhance MCI conversion prediction.

Tadokoro et al. [5] proposed an eye-tracking test to differentiate cognitive functions between normal controls, MCI, and AD subjects and to provide a non-invasive screening tool. Deep neural networks were compared by Kwasigroch et al. [7] to classify skin lesions and illustrate the flexibility of CNN architectures. Salehi et al. [12] presented a review on DL methods in AD diagnosis with a highlight on the leading role played by CNNs in medical image assessment.

Different studies investigated CNNs to diagnose AD from MRI data. Bae et al. [18] proposed a CNN-based classifier using T1-weighted MRI scans in heterogeneous populations & found high accuracy in differentiating normal controls and AD patients. Murugan et al. [19] presented 'DEMNET', DL model to produce high-resolution probability maps of diseases by evaluating local structures of the brain to facilitate early diagnosis of AD and dementia. El-Assy et al. [20] presented a new CNN design using the ADNI dataset to improve early diagnosis and AD classification.

New research has explored the utility of quantum computing in AD diagnosis. Fazil Sheikh et al. [16] proposed a Quantum Convolutional Neural Network (QCNN) model and discussed potential advancements in AD diagnosis. Fazil Sheikh and Amdani [24] further analyzed and compared QCNN against traditional CNN models and identified the benefits of using quantum methods in analyzing complicated neuroimaging data.

Combining different imaging methods and transfer learning has been found to possess promise in the detection of AD. Yadav and Miyapuram [15] used deep learning on MRI images, highlighting the ability of sophisticated models in differentiating neurodegenerative diseases.

Shafiq Ul Rehman et al. [17] proposed an AI tool using the VGG16 model with transfer learning to analyze the hippocampus in the early detection of AD.

Functional MRI (fMRI) data has played a key role in elucidating the progress of AD. Noh et al. [21] presented a CNN-LSTM-based model classifying the different stages of AD through examination of the 4D fMRI data with good accuracy. Rallabandi et al. [23] constructed an automatic machine learning technique to classify cognitively normal individuals, early mild cognitive impairment, late mild cognitive impairment, and AD using structural MRI analysis.

Advances in the classification of 3D data have also supported better object identification in medical images. Volumetric and multi-view CNN structures were proposed by Qi et al. [14] as object classifiers on 3D data and highlighted insights which were extendable to neuroimaging research.

Mushir Akhtar et. al. [25] introduce the Flexi-Fuzz-LSSVM framework to robustly handle noisy, outlier-filled, and imbalanced datasets, including ADNI data. They proposed: A novel membership weighting scheme incorporating proximity to class centers, class probability, and imbalance ratio. Two variants using mean vs. median for class-center determination. Evaluation on UCI, KEEL, and ADNI datasets, showing improved diagnostic accuracy over standard LSSVM baselines.

J. Wen et.al. [26]This study employs a regularized multikernel SVM fed by: Joint embeddings from MRI and PET images.Cognitive and demographic features (e.g., ApoE4, cognitive scores).Uses ensemble low-rank feature reduction for dimensionality compression. AlMansoori et al. [27] leverage blood gene-expression, SNP, and clinical data from 623 ADNI participants, using MI-based feature selection with an SVM classifier: Combined model (gene+SNP+clinical) yielded 95% accuracy, AUC 0.94.Biomarker-only models (gene or SNP) performed moderately (AUC ~0.63–0.65).SHAP analysis revealed key biomarkers tied to neural processes (axon myelination, synaptic vesicle).

D. Zhang et al. [28] integrates MRI voxel-based morphometry with top AD-associated SNP features using: Feature construction from top 24 SNPs. A genetic algorithm to optimize multi-kernel SVM parameters. Zhang et al. [29] proposed an end-to-end ResNet-based 3D CNN augmented with attention mechanisms. It combines multi-layer MRI/PET features to highlight subtle brain changes.

Hoang, Lee & Kim [30] introduced 3D-DAM, a reproducible 3D CNN enriched by dual attention mechanisms. Training on ADNI and testing on AIBL/OASIS1. Altwijri et al.[31] presented a transfer-learning enhanced CNN for MRI-based AD severity classification using limited data sets. By enhancing preprocessing and tuning pretrained models. Khatun et al. [32] proposed a hybrid model combining VGG16-derived CNN features with LSTM for temporal context on MRI scans from ADNI.

Majee et al. [33] introduced a 3D HCCT, a hybrid model combining CNNs and lightweight transformers trained on MRI. Evaluations show it exceeds state-of-the-art CNNs in both accuracy and interpretability. L. Li [34] model uses 3D CNNs to extract features from MRI and PET, feeds them into an improved Transformer for cross-modal fusion. J. Song [35] reports a study using 3D CNNs to predict individual ADAS-Cog13 sub-scores from MRI and FDG-PET. They mapped cognitive subdomains to specific brain regions, demonstrating the CNN's capability for explainable regression-based diagnosis.

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III. METHODOLOGY

The experiments conducted in this study utilized a comprehensive MRI dataset available on Kaggle, which includes a wide range of brain scan images along with corresponding clinical data. This dataset was divided into training and testing subsets, with 10,240 images allocated for training and 1,279 for testing. Both subsets are categorized into four diagnostic classes based on the degree of cognitive impairment.

In the training dataset, the distribution of images is balanced across the following four categories: Very Mild Impairment (2,560 images), Mild Impairment (2,560 images), Moderate Impairment (2,560 images), and No Impairment (2,560 images). This equal representation ensures that the model is trained on a uniform sample from each class, which is crucial for minimizing bias and achieving consistent classification accuracy across all categories.

In contrast, the test dataset exhibits a notable class imbalance: Very Mild Impairment (448 images), Mild Impairment (179 images), Moderate Impairment (12 images), and No Impairment (640 images). This uneven distribution can pose challenges during evaluation, particularly for underrepresented classes like Moderate Impairment, where the limited number of samples may impact performance assessment.

Figure 5 visualizes these distributions: Panel (a) displays the percentage breakdown of each class in the training set, while Panel (b) presents the absolute image counts per class. These visualizations underscore the dataset's composition and highlight the importance of addressing class imbalances during model evaluation and interpretation.

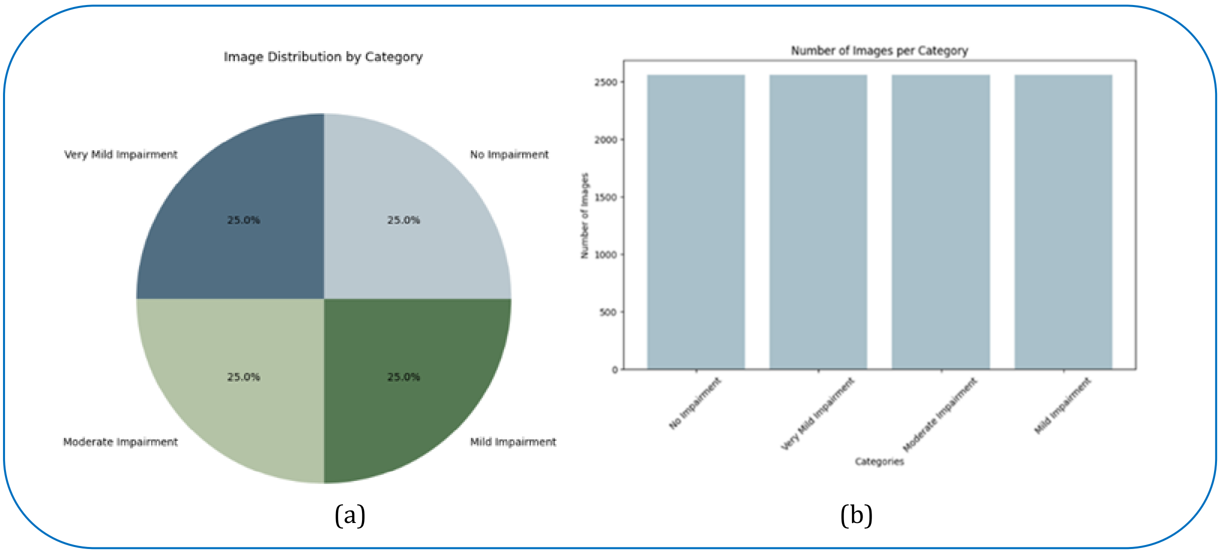

Fig.5: (a) Training dataset: Category wise percentage distribution of images
(b) Training dataset: Category wise no. of images

DESCRIPTION OF MODELS

For this work, we employed two quantum machine learning techniques: Quantum Convolutional Neural Networks (QCNN) and Quantum Support Vector Machines (QSVM).

QCNN represents a quantum-enhanced evolution of traditional Convolutional Neural Networks (CNNs). These models are built on the foundations of quantum computing—most notably, quantum kernel estimation—which enables them to process high-dimensional and complex data more efficiently. By utilizing quantum parallelism, QCNNs offer improved scalability and speed, making them particularly well-suited for analyzing large datasets.

This capability positions QCNNs as a powerful tool across various data-intensive domains such as finance, cybersecurity, and—most critically in this context—healthcare. Their ability to manage and interpret extensive medical imaging data presents promising potential for early and accurate diagnosis.

Figure 6 illustrates the overall architecture and workflow of the QCNN model, detailing how quantum computing principles are integrated into the classification pipeline to enhance diagnostic accuracy and performance.

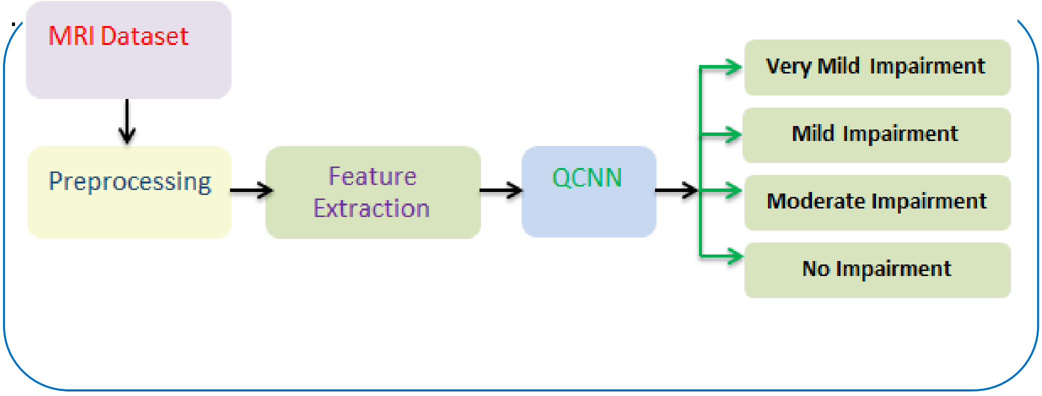

Fig.6: General flow of the QCNN model for classification.

QCNN:

In the context of early Alzheimer's Disease detection, Quantum Convolutional Neural Networks (QCNNs) leverage quantum feature mapping to process complex MRI data more efficiently than traditional methods. By applying the quantum kernel trick, QCNNs can project high-dimensional features—such as hippocampal volume and cortical thickness—into a space where they become more easily distinguishable. These features are critical biomarkers of neurodegeneration, and quantum-enhanced processing allows for more accurate interpretation.

Moreover, the inherent efficiency of quantum computing significantly reduces processing time, making QCNNs a scalable and highly promising solution for the early and reliable diagnosis of Alzheimer's Disease. The following fig. 7 shows a QCNN architecture.

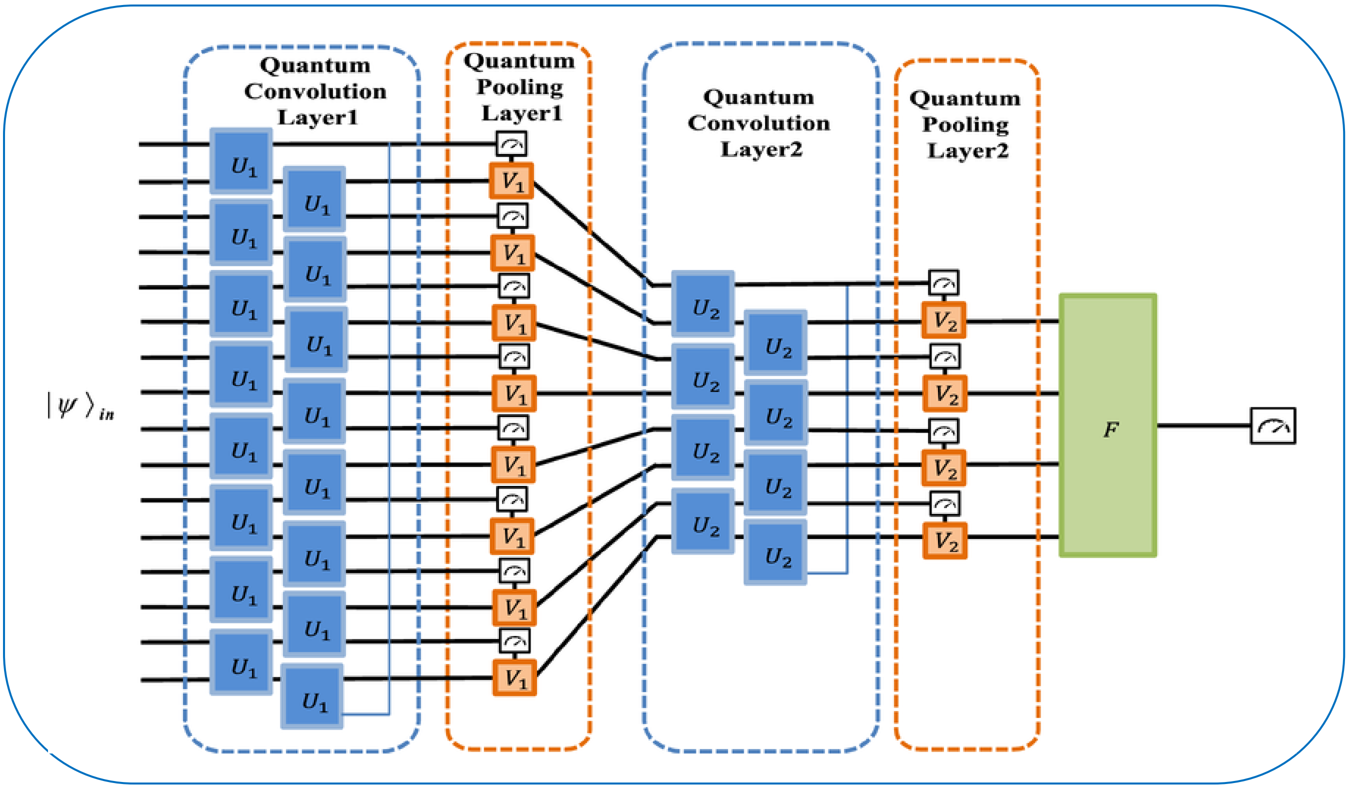

Fig 7: QCNN Architecture
(src : https://images.app.goo.gl/T6cwscmvk31KZQ9j8)

Quantum Convolutional Neural Network (Q-CNN) combines classic conventions with Quantum Computing principles. While the pairing layers remain equal to classic CNN, the quantum section introduces quantum gates and quantum layers that can process data in a high dimensional room using quantum mechanics.

Convolutional layers work by sweeping across the input array and applying different filters (often 2x2 or 3x3 matrices) block by block. These are used to detect specific features of the image wherever they might appear. Pooling layers are then used to down sample the results of these convolutions to extract the most relevant features and reduce the size of the data, making it easier to process in subsequent layers. Common pooling methods involve replacing blocks of the data with their maximum or average values.

Here, convolutions are operations performed on neighbouring pairs of qubits — they are parameterized unitary rotations, just like a regular variational circuit! These convolutions are followed by pooling layers, which are affected by measuring a subset of the qubits, and using the measurement results to control subsequent operations. The analogue of a fully-connected layer is a multi-qubit operation on the remaining qubits before the final measurement. Parameters of all these operations are learned during training.

Quantum ports in conversion: Quantum ports change the traditional convention filter. These quantum gates work on quantum pieces (quotes), which can be present in many states together (superpts), possibly so that Q-CNN can process data more efficiently.

Quantum calculation: The use of quantum circuits allows Q-CNNS to handle data that will otherwise be very complex for classic networks, especially in tasks such as high-dimensional computer classification, where quantum mechanics can provide a calculation benefit.

We can have its advantages like:

Efficiency: Quantum calculation can dramatically reduce the calculation costs for high - dimensional data analysis.

High-dimensional data processing: Q-CNN can capture more complex patterns due to quantum-sensed functional representation.

Application in Alzheimer's Diagnosis:

Q-CNNs are especially useful when working with large and complex brain images. By using quantum gates, Q-CNN can potentially identify complex patterns in brain tissue that can miss traditional CNN. This is especially important for detecting the initial phase or subtle changes in the brain structure associated with dementia.

QSVM:

Quantum Support Vector Machines (QSVMs) represent a quantum adaptation of the classical SVM algorithm. They also utilize quantum kernel estimation to process high-dimensional data more efficiently than traditional SVMs. Like QCNNs, QSVMs benefit from quantum parallelism, offering improved scalability and faster classification performance. These characteristics make QSVMs a valuable tool for data-heavy fields such as finance, cybersecurity, and healthcare. In particular, they hold considerable potential for advancing disease diagnosis through more efficient data handling.

Figure 8 illustrates the general classification workflow of the QSVM model, showcasing its integration of quantum computing techniques to enhance performance.

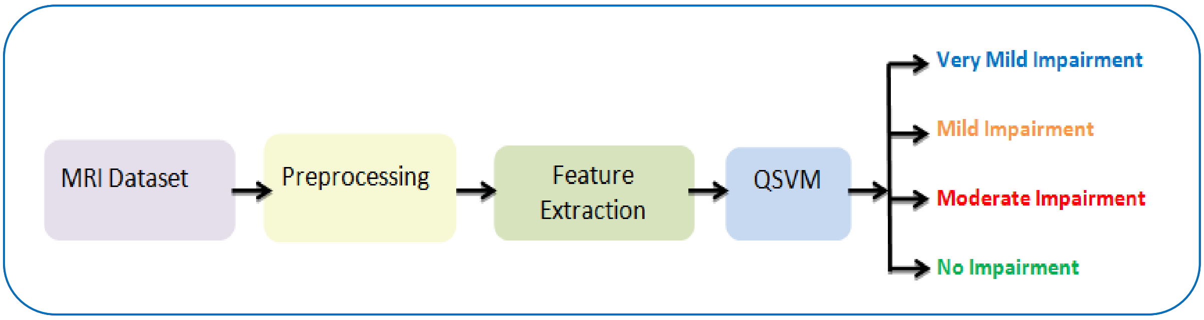

Fig.8: General flow of the QSVM model for classification.

The Quantum Support Vector Machine (QSVM) applies quantum feature mapping to accelerate the processing of complex MRI data, offering a significant advantage in Alzheimer's Disease detection. By leveraging the quantum kernel trick, QSVM efficiently handles high-dimensional features such as hippocampal volume and cortical thickness—key indicators of neurodegeneration—with greater precision than classical SVMs. This quantum-enhanced framework enables more accurate identification of patterns within brain scans, facilitating improved classification of patients across diagnostic categories. The computational speed provided by quantum computing further enhances QSVM's viability as a scalable and reliable tool for early diagnosis of Alzheimer's. The following fig. 9 shows a general circuit for QSVM [22].

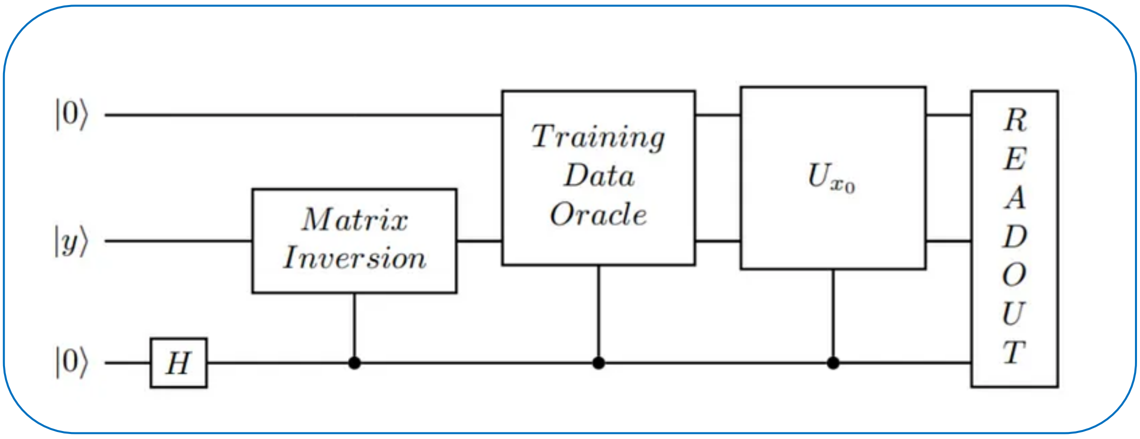

Fig. 9: QSVM General Circuit

This quantum circuit represents a quantum algorithm for supervised machine learning, specifically for quantum linear system solving, which is central to quantum machine learning methods such as quantum support vector machines and quantum least squares regression.
This circuit prepares quantum states that represent the input data and labels. It performs matrix inversion to solve a linear system, which is a core step in many machine learning algorithms.It Uses oracles to access training data and apply the test input. It measures the output to obtain the result, such as a predicted label or regression value.

The top line is initialized to |0⟩, likely representing the data or solution register. The middle line is labeled |y⟩, representing the input vector. The bottom line is initialized to |0⟩ and passes through a Hadamard gate (H), creating a superposition. The first operation after initialization is "Matrix Inversion," which is a quantum subroutine for inverting a matrix (such as the HHL algorithm or Quantum Singular Value Transformation (QSVT) based inversion).

This block is controlled by the bottom qubit, indicating a conditional operation. The next block is the "Training Data Oracle," which encodes access to the training data in quantum memory (quantum RAM or qRAM). This oracle allows the quantum computer to efficiently query training data for further computation. The unitary operation likely encodes the test input x0x0 for which a prediction or classification is being made.The final step is "READOUT," where measurement occurs to extract the computational result, such as the classification or regression output.

The following fig. 10 shows a circuit for Quantum Kernel [22].

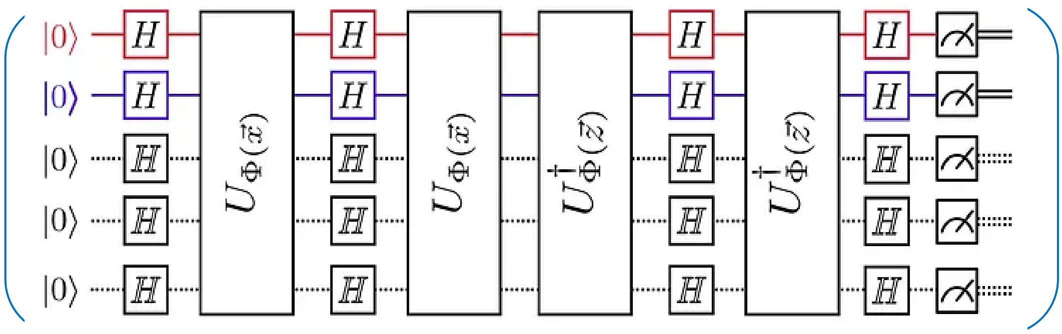

Fig. 10: Quantum Kernel

"Quantum Kernel" refers to a **kernel function used in Quantum Machine Learning** that allows classical machine learning algorithms—like **Support Vector Machines (SVMs)**—to leverage **quantum computing** to potentially improve performance, especially in high-dimensional or complex feature spaces. In classical SVMs, a **kernel function** K(x,x′) computes the similarity between two input vectors x and x′x. It allows mapping data into higher-dimensional spaces without explicitly computing the transformation—a concept known as the **kernel trick**.

A **Quantum Kernel** uses a **quantum computer** to compute this kernel function in a **Hilbert space** defined by a **quantum feature map**.

A **Quantum Kernel** is defined as:

$$K(x, x') = |\langle \phi(x) | \phi(x') \rangle|^2$$

Where:

- $\phi(x)$ is the **quantum feature map** that encodes classical data into a quantum state.
- $|\phi(x)\rangle$ is a quantum state representing the input x.
- The inner product $\langle \phi(x) | \phi(x') \rangle$ is calculated using a quantum circuit.

It's Workflow is as follows:

Classical Input: Start with classical data (e.g., features from an MRI).

Feature Map: Encode each input vector into a quantum state using a parameterized quantum circuit (e.g., using rotation gates).

State Overlap: For each pair (x,x′), compute the overlap (inner product) of the quantum states.

Kernel Matrix: Use the inner products to create a Gram (kernel) matrix.

Classical SVM: Use the kernel matrix in a classical SVM for classification or regression.

In the above fig.10, 'U' is a unitary gate. It takes the feature vector as a parameter that represents the following:

$$U_{\Phi(\vec{x})} = \exp\left(i \sum_{S\subseteq[n]} \phi_S(\vec{x}) \prod_{i\in S} Z_i\right)$$

Here, 'S' is the test dataset. For a classical feature function ϕ, it represents a Unitary gate. The concept of quantum kernels involves leveraging quantum mechanics to enhance outcomes when transforming the feature vector. The basic principles for this transformation include encoding classical information into qubits, executing operations (like superposition and rotations within the Bloch sphere), and then calculating the dot product of the resulting states. While it can be intricate, quantum kernels must execute operations that classical machines cannot in order to surpass them. In the example provided, the circuit incorporates Hadamard gates and Z Pauli matrices to gain an edge over classical machines.

Qiskit offers kernels that enables users to design circuits for encoding classical data.

The following table 1 shows a comparision between Classical and Quantum Kernel.

Table 1: Classical and Quantum Kernel

Feature	**Classical Kernel**	**Quantum Kernel**
Feature Space	Predefined (linear, RBF)	Implicit high-dimensional Hilbert space
Efficiency	Efficient on small data	Advantage on complex patterns
Hardware	Classical CPU/GPU	Requires quantum computer (or simulator)

For every dimension in the feature set, a qubit is assigned that will pass through a Hadamard gate and a unitary gate Uϕ. As illustrated, the circuit is designed to be linear, meaning it doesn't 'crossover' information between the qubits (there are no CNOT gates involved), which helps to keep it free from entanglement apart from the H gates.

As shown in the above fig.9, five qubits are initialized to the $|0\rangle$ state.Hadamard gates (H) are applied to the first four qubits to create superposition states.The bottom qubit is in the $|0\rangle$ state initially. The circuit contains a series of controlled unitary operations labeled U_θ_0, U_θ_1, U_θ_2, U_θ_3, and U_θ_4.Each U_θ_i represents a parameterized quantum gate where θ_i is a trainable parameter.These gates are arranged in a structured pattern across multiple layers. The parameterized gates are the controlled operations, where certain qubits act as control qubits for the unitary transformations.This circuit shows a layered architecture with multiple rounds of parameterized operations. The final stage shows measurement operations on all qubits.These measurements extract the classical output from the quantum computation.

The repeated pattern of parameterized gates forms what's called a quantum ansatz or trial wavefunction. The θ parameters can be optimized classically to minimize a cost function.The controlled operations create entanglement between qubits, which is essential for quantum advantage. This circuit represents a typical structure used in near-term quantum algorithms where classical optimization is combined with quantum computation to solve complex problems.

The following fig. 11 shows a circuit for ZfeatureMap [22].

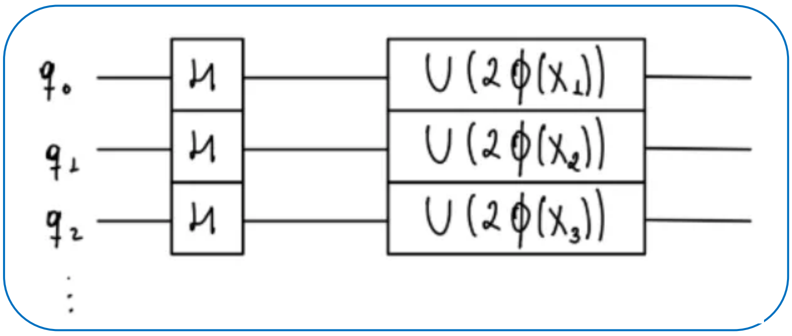

Fig.11: Circuit for ZFeatureMap

It is used for quantum feature encoding. It is a key step in many quantum machine learning algorithms. The circuit has three qubits labelled q0, q1, and q2. Each qubit first passes through a Hadamard gate. The Hadamard gate creates a superposition, placing each qubit in an equal probability of being measured as 0 or 1. After the Hadamard gates, each qubit undergoes a unitary operation parameterized by the input data. Specifically, each qubit qi receives a gate U(2ϕ(xi)), where ϕ(xi) is a function that encodes the classical input feature xi into a quantum rotation or phase. The factor of 2 in the argument is common in quantum feature maps to amplify the effect of the input data.

The following fig. 12 shows how an entanglement is added to the quantum system by ZZFeatureMap [22].

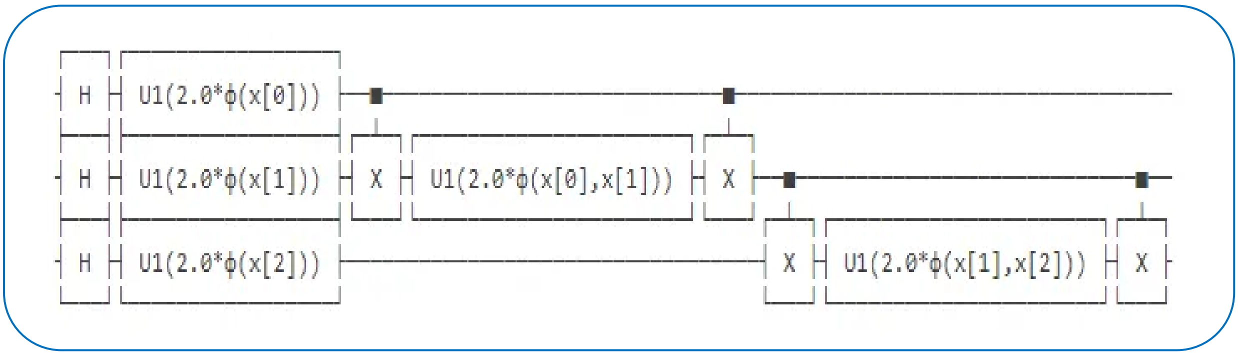

Fig.12: Circuit for ZZFeatureMap

This figure depicts a quantum circuit designed for three qubits, often used in quantum machine learning. There are three horizontal lines, each representing a qubit (q0, q1, q2).Each qubit is initialized with a Hadamard gate, creating a superposition state. After the Hadamard gates, each qubit receives a U1 gate (a general single-qubit phase gate), parameterized by $2.0*\phi(x[i])$, where x[i]is a component of the input feature vector. This encodes classical data into the quantum state. The vertical lines with a filled square and a connecting line represent controlled operations (CZ or CNOT gates), introducing entanglement between pairs of qubits.

After entanglement, each pair of qubits receives a block of gates:

•Hadamard (H)

•X (Pauli-X)

•U1 gate parameterized by $2.0*\phi(x[i],x[j])$, encoding pairwise interactions between features.

•X and Hadamard gates to complete the entangling operation.

PauliMatricesMap adds Pauli matrices – X, Y, or Z – to the system to rotate a certain amount in the Bloch Sphere. The following fig. 13 shows a circuit for PauliMatrices (Z, Y and ZZ matrices) [22]

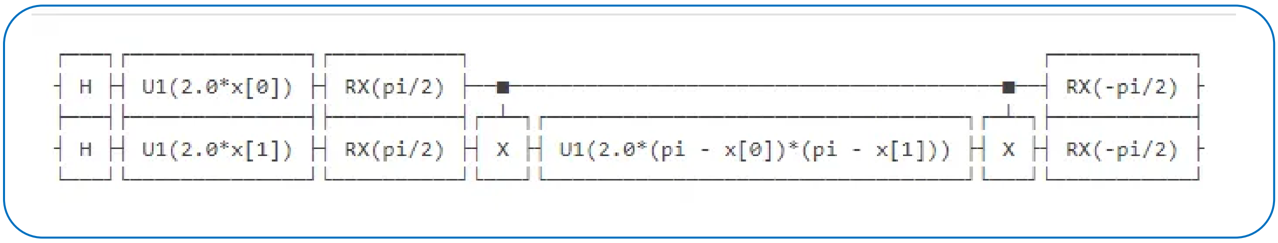

Fig.13: Circuit for PauliMatrices (Z, Y and ZZ matrices)

There are two horizontal lines, each representing a qubit (q0 and q1).

Each qubit is acted on by a Hadamard gate (H), placing them into an equal superposition of $|0\rangle$ and $|1\rangle$.Each qubit receives a U1 gate (a phase rotation), parameterized by $2.0\times x2.0\times x$ for the first qubit and $2.0\times x[1]$for the second, where xx and x[1] are classical input features.Both qubits undergo another Hadamard (H) followed by an RX rotation by $\pi/2$, preparing them for entanglement.

A controlled operation is applied (depicted by a control dot and a connecting line), likely a CNOT or CZ gate, entangling the two qubits.The second qubit receives a sequence of gates: H, X, a U1 gate parameterized by $2.0\times(\pi-x)\times(\pi-x[1])$ (encoding pairwise interaction between features), X, and H.Both qubits undergo RX rotations by $-\pi/2$ and a final Hadamard, returning them to the computational basis.

Model performance was evaluated using standard metrics:

- **Precision** – Measures the proportion of predicted positive cases that are true positives.
- **Recall** – Indicates the model's ability to identify all relevant instances.
- **Accuracy** – Reflects overall correctness across all classification categories.

Both the QCNN and QSVM models classify MRI inputs into one of four diagnostic categories based on cognitive impairment severity: No Impairment, Very Mild Impairment, Mild Impairment, and Moderate Impairment. By integrating quantum computing principles with advanced neural network architectures, this study introduces a next-generation diagnostic approach for tracking and managing the progression of Alzheimer's Disease.

IV. Result & Discussion

Quantum Convolutional Neural Network (QCNN), and Quantum Support Vector Machine (QSVM) were assessed using Precision, Recall, and Accuracy metrics. The results are summarized in Table 2.

Table 2: Performance Metrics of QCNN and QSVM Models

Model	QCNN	QSVM
Precision	0.88	0.85
Recall	0.96	1.00
Accuracy	0.59	0.85

Performance Analysis:

The **Quantum Convolutional Neural Network (QCNN)** achieved a **precision of 0.88**, while the **Quantum Support Vector Machine (QSVM)** attained a slightly lower precision of **0.85**. Precision measures the model's ability to correctly identify only true positive instances—those that genuinely belong to a particular class—without incorrectly labeling negative cases as positive. This metric is critical in minimizing false positives, and the results suggest that QCNN slightly outperforms QSVM in this regard.

In terms of **recall**, QCNN scored **0.96**, whereas QSVM achieved a perfect **1.00**. Recall reflects a model's ability to correctly identify all true positive cases, which, in medical diagnostics, is vital. A high recall ensures that fewer cases of Alzheimer's are missed, which is crucial for early intervention and treatment planning. Thus, although both models perform strongly, QSVM shows a slight advantage in recognizing all relevant Alzheimer's cases without omission.

Regarding **accuracy**, which represents the overall proportion of correctly classified cases across all classes, **QSVM significantly outperforms QCNN** with a score of **0.85** compared to **0.59**. This suggests that QSVM provides more consistent classification across the four diagnostic categories.

Figure 14 provides a visual comparison of these metrics. The X-axis represents different evaluation metrics—**Precision**, **Recall**, and **Accuracy**—for each class (**Alzheimer** and **Non-Alzheimer**), while the Y-axis shows the corresponding metric scores (ranging from 0 to 1). Each bar reflects the score for a specific class under a given metric, offering a clear illustration of the comparative performance of both models.

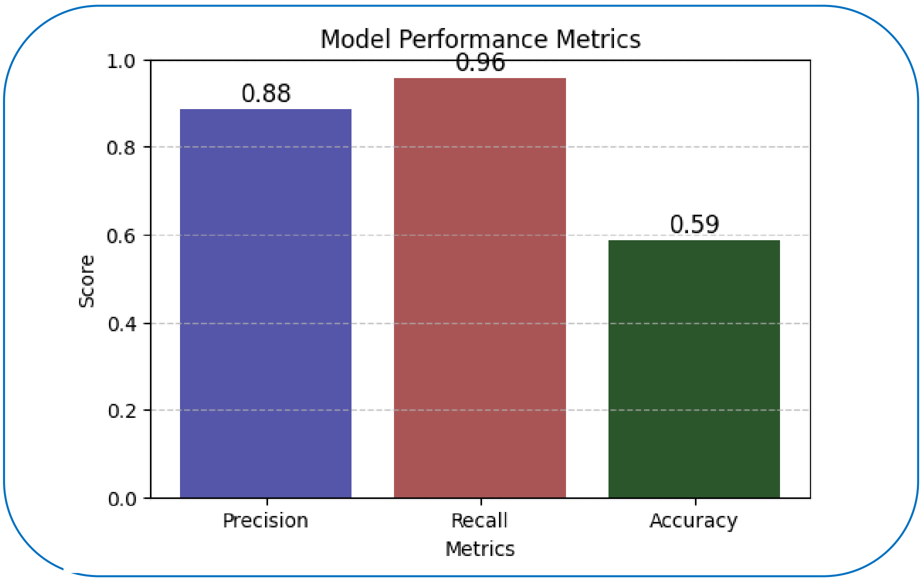

Fig.14: QCNN Evaluation Metrics

The **drop in QCNN accuracy** suggests a need for further refinement, possibly in quantum circuit depth, feature encoding, or optimization strategies.

Visualization of Results from QSVM

On X-axis: Different metrics (Precision, Recall, accuracy) for each class (Non-Alzheimer & Alzheimer). On Y-axis: The corresponding metric score (ranging from 0 to 1). And the bars

Represent scores for each class (Alzheimer & Non-Alzheimer) under different metrics. This is shown in the following fig.15.

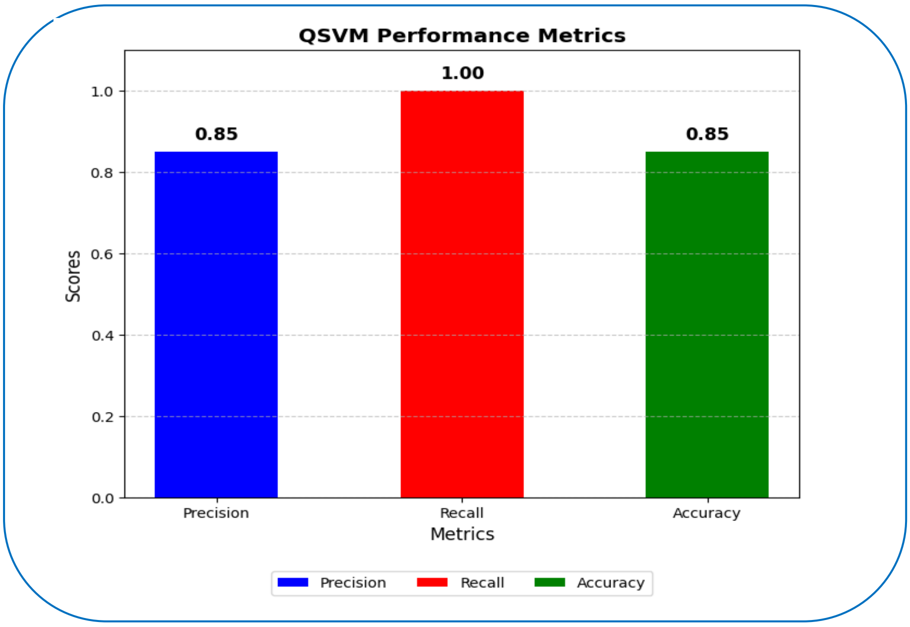

Fig.15: QSVM Evaluation Metrics

V. Conclusions

Through comprehensive research and experimentation, this study underscores the critical importance of early detection in the management of Alzheimer's Disease. Early diagnosis not only helps preserve cognitive function but also significantly enhances patients' quality of life. The findings demonstrate that both Quantum Machine Learning (QML) techniques—Quantum Convolutional Neural Networks (QCNN) and Quantum Support Vector Machines (QSVM)—exhibit competitive performance in classifying cognitive impairment.

By focusing on the hippocampus, a region notably affected in the earliest stages of Alzheimer's, the proposed methodology facilitates accurate classification across four cognitive categories: No Impairment, Very Mild Impairment, Mild Impairment, and Moderate Impairment. This approach not only improves diagnostic precision but also maintains a balance between model performance and clinical interpretability.

In summary, the results strongly support the integration of AI-driven diagnostic tools into routine clinical workflows. These advanced models enhance our understanding of Alzheimer's progression and pave the way for earlier, more personalized interventions that could substantially improve patient outcomes. Future developments should focus on expanding the scope and scalability of these tools to meet the needs of diverse clinical environments.

VI. Future Scope

Looking ahead, future research should prioritize the integration of multimodal neuroimaging and non-imaging data, combining inputs from structural MRI, functional MRI (fMRI), PET scans, and genomic profiles. Such a comprehensive data fusion approach could offer a richer understanding of structural, functional, and molecular alterations associated with Alzheimer's Disease.

By simultaneously mapping multiple aspects of brain pathology, these multimodal frameworks have the potential to significantly boost the accuracy and reliability of diagnostic models. This could lead to more robust classification across the spectrum of cognitive decline—from Mild Cognitive Impairment (MCI) to full-blown Alzheimer's Disease—thereby enhancing early detection and disease staging in real-world clinical applications.

References

[1] Islam, J., Zhang, Y., 'Brain MRI analysis for Alzheimer's disease diagnosis using an ensemble system of deep convolutional neural networks', Brain informatics, Vol. 5, No. 2, pp. 1–14.2018.

[2] Despotović, I., Goossens, B., Philips, W. 'MRI segmentation of the human brain: challenges, methods, and applications', Computational and Mathematical Methods in Medicine.Vol. 2015.

[3] Oja, E., Yuan, Z. The FastICA algorithm revisited: Convergence analysis. IEEE Transactions on Neural Networks, Vol. 17, No. 6, pp.1370–1381,2006.

[4] Basheera, S., Ram, M. S. S. (2019). Convolution neural network–based Alzheimer's disease classification using hybrid enhanced independent component analysis based segmented gray matter of T2 weighted magnetic resonance imaging with clinical valuation. Alzheimer's & Dementia: Translational Research & Clinical Interventions, Vol. 5, pp. 974–986,2019.

[5] Tadokoro, K. et al. Early detection of cognitive decline in mild cognitive impairment and Alzheimer's disease with a novel eye tracking test. J. Neurol. Sci. 427, 117529, 2021.

[6] Zhang, T. et al. Predicting MCI to AD conversation using integrated sMRI and rs-fMRI: Machine learning and graph theory approach. Front. Aging Neurosci. 2021.

[7] Kwasigroch, A., Mikołajczyk, A., Grochowski, M. (2017). Deep neural networks approach to skin lesions classification—a comparative analysis. 22nd International Conference on Methods and Models in Automation and Robotics, pp. 1069–1074. DOI: 10.1109/MMAR.2017.8046978.

[8] Suk, H. I., Shen, D. (2013). Deep learning-based feature representation for AD/MCI classification. In International conference on medical image computing and computer-assisted intervention Springer, Berlin, Heidelberg. pp. 583–590. DOI: 10.1007/978-3-642-40763-5_72.

[9] Buvaneswari, P. & Gayathri, R. Deep learning-based segmentation in classification of Alzheimer's disease. Arab. J. Sci. Eng. 46, 5373–5383, 2021.

[10] Parmar, H. et al. Spatiotemporal feature extraction and classification of Alzheimer's disease using deep learning 3D-CNN for fMRI data. J. Med. Imaging 2020.

[11] Çelebi, S. B. & Emiroğlu, B. G. A novel deep dense block-based model for detecting Alzheimer's Disease. Appl. Sci. 13(15), 8686.2023.

[12] Salehi, A. W., Baglat, P. & Gupta, G. Alzheimer's disease diagnosis using deep learning techniques. Int. J. Eng. Adv. Technol 9(3), 874–880 ,2020.

[13] Cheng, B. et al. Domain transfer learning for MCI conversion prediction. IEEE Trans. Biomed. Eng. 62(7), 1805–1817,,2015.

[14] Qi, C. R. et al. Volumetric and multi-view CNN for object classification on 3d data. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition,2016.

[15] Yadav, K. S. & Miyapuram, K. P. A novel approach towards early detection of Alzheimer's disease using deep learning on magnetic resonance images. In Brain Informatics: 14th International Conference, BI 2021, Virtual Event, September 17–19, 2021, Proceedings 14 (Springer, 2021).

[16] Fazil Sheikh, S. Y. Amdani, Shaini Suraj, 'Quantum convolutional neural network for Alzheimer's disease diagnosis', AIP Conf. Proc. 3188, 040009, 2024.

[17] Shafiq Ul Rehman, Noha Tarek, Caroline Magdy, Mohammed Kamel, Mohammed Abdelhalim, Alaa Melek, Lamees N. Mahmoud, Ibrahim Sadek, AI-based tool for early detection of Alzheimer's disease, Heliyon, Volume 10, Issue 8, 2024, e29375, ISSN 2405-8440.

[18] Bae, J.B., Lee, S., Jung, W. *et al.* Identification of Alzheimer's disease using a convolutional neural network model based on T1-weighted magnetic resonance imaging. *Sci Rep* 10, 22252 (2020).

[19] Murugan, S. et al. DEMNET: A deep learning model for early diagnosis of Alzheimer diseases and dementia from MR images. IEEE Access 9, 90319–90329, 2021.

[20] El-Assy, A.M., Amer, H.M., Ibrahim, H.M. *et al.* A novel CNN architecture for accurate early detection and classification of Alzheimer's disease using MRI data. *Sci Rep* 14, 3463 (2024).

[21] Noh, J.-H., Kim, J.-H. & Yang, H.-D. Classification of Alzheimer's progression using fMRI data. Sensors 23(14), 6330,2023.

[22]https://medium.com/mit-6-s089-intro-to-quantum-computing/quantum-support-vector-machine-qsvm-134eff6c9d3b.

[23] Rallabandi, S., Tulpule, K. & Gattu, M. Automatic classification of cognitively normal, mild cognitive impairment and Alzheimer's disease using structural MRI analysis. Inf. Med. Unlock. 18, 100305, 2020.

[24] Fazil A. Sheikh, Dr. S.Y.Amdani,(2025). Performance Evaluation of Quantum CNN and Classical CNN for Alzheimer's Diagnosis. Journal of Neonatalsurg., 14 (21s), 276-290.

[25] M. Akhtar, M. Rizwanullah, S. Sharma, A. Khan, and A. Abraham, "Flexi-Fuzz-LSSVM: A robust and flexible fuzzy least squares support vector machine," Applied Intelligence, vol. 54, no. 13, pp. 15351–15369, Oct. 2024.

[26] J. Wen, Y. Qiu, M. Lyu, B. Zhang, Y. He, and D. Shen, "Ensemble feature reduction with multiclass SVM for Alzheimer's diagnosis using multimodal imaging," Medical Image Analysis, vol. 89, p. 102748, 2024.

[27] A. Al Mansoori, A. ElSawy, and H. Mathkour, "Explainable machine learning model for Alzheimer's disease prediction using gene-expression and SNP data," Scientific Reports, vol. 14, no. 1, p. 3351, Feb. 2024.

[28] D. Zhang, Y. Wang, L. Zhou, H. Yuan, and D. Shen, "Multimodal classification of Alzheimer's disease and mild cognitive impairment," NeuroImage, vol. 55, no. 3, pp. 856–867, 2023.

[29] Z. Zhang, W. Li, Y. Chen, and D. Shen,"Attention-based deep learning with multi-level features for Alzheimer's disease diagnosis using MRI and PET," Neurocomputing, vol. 538, pp. 126365, Aug. 2023.

[30] M. Hoang, J. Lee, and M. Kim,"3D-DAM: A 3D deep learning model with dual-attention module for Alzheimer's disease classification,"Computers in Biology and Medicine, vol. 169, pp. 107553, Oct. 2023.

[31] A. Altwijri, A. M. Al-Turaiki, and F. Alharbi,"Deep learning approach for early-stage Alzheimer's disease classification using structural MRI,"Scientific Reports, vol. 13, no. 1, p. 20948, Dec. 2023.

[32] S. Khatun, A. M. Reza, and T. Islam,"CNN-LSTM model for Alzheimer's disease classification from MRI,"Heliyon, vol. 10, no. 3, p. e22485, Mar. 2024.

[33] A. Majee, P. Biswas, and S. Mitra,"3D HCCT: A hybrid compact convolutional transformer for Alzheimer's disease diagnosis from MRI,"Biomedical Signal Processing and Control, vol. 89, p. 105147, Mar. 2024.

[34] L. Li, Q. Wang, and H. Zhang,"Multimodal Alzheimer's disease diagnosis with 3D CNN and transformer-based fusion,"BioMedical Engineering OnLine, vol. 23, no. 1, p. 11, Jan. 2024.

[35] J. Song, Y. Wang, H. Wu, and D. Shen,"Predicting ADAS-Cog13 sub-scores from brain imaging via 3D convolutional neural networks,"Brain Informatics, vol. 11, no. 1, p. 22, Feb. 2024.