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Performance Evaluation of Quantum CNN and Classical CNN for Alzheimer's Diagnosis

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ABSTRACT

Alzheimer's Disease (AD) first strikes learning regions of the brain and is one of the most prevalent forms of dementia. Early diagnosis is crucial for optimum management of treatment, as the disorder is both irreversible and progressive. The current research outlines an end-to-end approach toward early diagnosis of AD by utilizing the hippocampus and transfer learning. The results of a conventional machine learning model—Convolutional Neural Network (CNN)—are compared to those of a Quantum Convolutional Neural Network (QCNN), an adaptation of the conventional CNN through the use of quantum computing methods like quantum kernel estimation. QCNN achieves greater efficiency in processing high-dimensional data than traditional CNNs.

The main symptoms of Alzheimer's are memory loss and cognitive impairment, caused by the degeneration and death of those neurons related to memory. Mild Cognitive Impairment (MCI) lies between cognition within the range of normality and Alzheimer's. The early diagnosis of MCI has the potential to decelerate or even prevent the development of Alzheimer's. In this paper, we have established that the QCNN model reached precision at 0.88 and recall at 0.96, compared to the classic CNN, where precision at 0.80, and recall at 0.84 have been achieved. The results highlight the prospective ability of Quantum Machine Learning (QML) to diagnose Alzheimer's Disease at an early stage.

Keyword: *Alzheimer's Diagnosis,QCNN, CNN, Quantum ML, Machine Learning.*

1. INTRODUCTION

Alzheimer's Disease is a significant world health problem, primarily due to the fact that it is the leading type of dementia, seen in millions across the world. Alzheimer's Disease is defined by an irreversible breakdown of brain functions, with the hippocampus, where learning and memory are stored, suffering the greatest damage. Its early diagnosis is essential since existing treatments cannot reverse the disease but can be used to delay it.

The development of Alzheimer's tends to start with Mild Cognitive Impairment (MCI), where patients have subtle problems with memory and cognition that might lead to outright Alzheimer's over time. Over 55 million people have dementia across the world, and about 60–70% of patients have Alzheimer's. That really underscores the critical and constant demand for accurate diagnostic tools. The following fig. 1 shows the statistics related to Dementia (Source: Alzheimer's Disease International).

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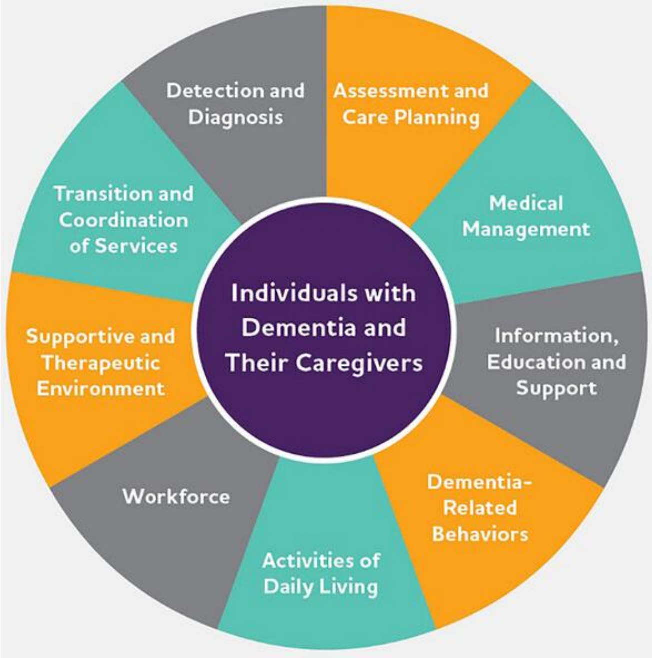

Fig.1: Statistics related to Dementia

Traditional AD diagnosis is mostly reliant on clinical assessments and neuropsychological tests, which are subject to variability and may be very time-consuming. New technologies including AI have brought novel solutions to diagnose AD at an early stage along with staging of AD. Machine learning, especially deep learning models, have been researched extensively by various studies to process structural MRI images to classify patients into the Cognitive Normal (CN), Mild Cognitive Impairment (MCI), and Alzheimer's Disease (AD) groups.

Our model is particularly focused on the hippocampus and utilizes progressively augmented data throughout training. The strategy has achieved significant accuracy throughout training, validation, and testing. By adopting an expansive approach, our method is helping to develop early diagnostic tools for Alzheimer's to address the urgent requirement for applicable solutions within clinical settings.

In short, this study spans the gap between conventional diagnosis methods and state-of-the-art AI methods using the application of Quantum Machine Learning. The purpose is to demonstrate that tapping into sophisticated technology targeting important brain areas can improve the outcome of patients and enable early intervention in managing Alzheimer's Disease.

GLOBAL TRENDS IN ALZHEIMER'S DISEASE: A STATISTICAL OUTLOOK

Global burden from Alzheimer's disease will increase exponentially throughout the next several decades. There are an estimated 55 million individuals worldwide as of 2024 suffering from the condition. This figure will grow to 78 million in 2030 and swell to a mind-boggling 139 million in 2050, indicating that there is a pressing need for scalable management and diagnostic solutions

The fatality rate caused by Alzheimer's disease is also increasing, with 1.6 million fatalities in 2024 and expected to reach 2.5 million in 2030 and then to 4 million in 2050.

When looking at the demographics, one can see that the disease is highly age-related. In 2024, 60–70% of Alzheimer's instances occur in elderly populations. The age-related proportion is projected to increase steadily to 65–75% by 2030 and 70–80% by 2050.

On the other hand, Alzheimer's instances among the non-aging population—who might be early-onset or genetically predisposed—constitute 5–10% in 2024. The number is projected to increase to 10–15% by 2030, though long-term estimates for 2050 are uncertain. This has been summarized in the following fig.2.

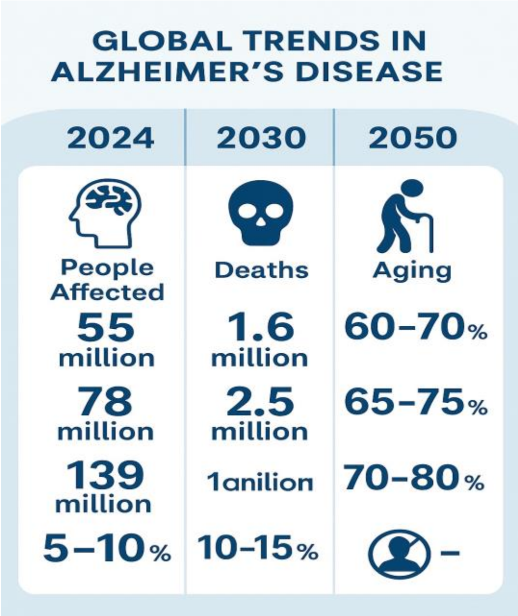

Fig.2: Alzheimer's Disease- Global Statistics

The following table 1 shows the statistics related to Alzheimer's as far as India is concerned (Source: Alzheimer's and Related Disorders Society of India (ARDSI))

Table 1: Alzheimer's Statistics (India)

Particulares	**2024**	**2030**	**2050**
People Affected	5.3 million	8 million	14 million
Deaths	0.2 million	0.4 million	0.8 million
Aging	70-75%	70-80%	75-85%
Non-Aging	10-15%	15-18%	-

Figure 3 shows the age-specific prevalence of dementia by demographic groups. In panel (A), the results show that the difference in prevalence between men and women widens with increasing age. The broad confidence intervals, however, indicate that although differences are apparent, these differences are not statistically significant.

Panel (B) shows prevalence rates by levels of education. Those without education have significantly higher rates of dementia than those with education, with this disparity being particularly striking—and statistically significant—among persons aged 70 to 74 and 75 to 79. While the trend persists in higher age groups, the disparities are not statistically significant due to larger standard errors..

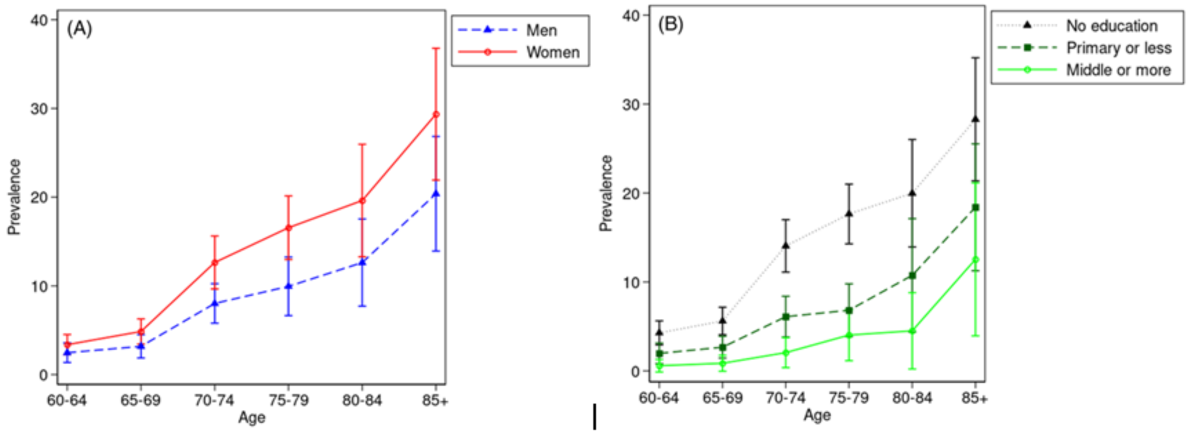

Fig.3: Age Specific Dementia

2. II. LITERATURE REVIEW

Alzheimer's disease (AD) continues to be one of the toughest neurodegenerative diseases, posing important societal and health-related consequences. Early diagnosis and proper diagnosis are essential to establish effective treatments. Over the last decade, there have been various efforts made using computational methods, with particular emphasis on those using magnetic resonance imaging (MRI) as well as those using machine learning, to diagnose and classify AD. The following is a synthesis of major studies researching various methods and paradigms in the classification of Alzheimer's disease, with special interest given to those involving image-based methods, deep learning, as well as other computational models.

Liu et al. introduced a new method for Alzheimer's diagnosis by employing a hierarchical brain network constructed from whole-brain structural MRI images. The research utilized a network-based approach that adequately included various brain regions to capture the interactions between anatomical structures effectively. The model revealed high accuracy in differentiating healthy controls from Alzheimer's patients, highlighting the necessity for brain networks to explain the disease [1]. The research added to the increasing body of work that utilizes network analysis for the diagnosis of AD.

Islam and Zhang (2018) advanced one step further by applying deep convolutional neural networks (CNNs) to an ensemble setting for brain MRI analysis for Alzheimer's diagnosis. They combined several CNN models to raise feature extraction and classification accuracy. Applying T1-weighted and T2-weighted MRI scans, they attained high diagnosis accuracy by performing better than conventional methods of classification. The employment of an ensemble system, where different models capitalize on each other's strength, generated an optimal solution to combatting the heterogeneity of Alzheimer's disease [2]. The study shows the capability of deep learning, particularly that of CNNs, to automate AD diagnosis.

Despotović et al. (2015) addressed the issue of MRI segmentation, the preliminary pre-processing required for AD diagnosis. MRI segmentation entails segmenting the brain into separate regions, including gray matter, white matter, and cerebrospinal fluid. The research presented an extended review of various segmentation techniques, including manual, semi-automatic, and fully automated methods, as well as discussed the challenge of segmenting pathological brain structures impacted by Alzheimer's. Although MRI segmentation is the groundwork for diagnostic purposes, the authors stated that segmentation accuracy is still an issue, particularly where there is atrophy in brain regions among AD patients [3].

Oja and Yuan (2006) readdressed the Independent Component Analysis (ICA) algorithm, used extensively to process brain imaging data, especially for functional MRI analysis. The algorithm can be used to separate statistical independent components from combined signals, useful to identify brain areas undergoing Alzheimer’s symptoms. The convergence analysis of the FastICA algorithm was given by the authors, delivering an understanding about the reliability of the algorithm with an application to brain images[4]. The contributions of the authors to understanding the ICA have made it possible to have better models for AD diagnosis from functional and structural image data.

Basheera and Ram (2019) introduced a hybrid method that combined Convolutional Neural Networks (CNNs) with Independent Component Analysis (ICA) for the purpose of Alzheimer's disease classification. The method entailed segmenting the brain's gray matter by applying ICA to T2-weighted MRI images, with subsequent CNN-based classification. The hybrid method provided enhanced accuracy over the use of CNNs individually, highlighting the necessity of including feature extraction methods such as ICA along with deep learning techniques like CNNs to augment AD detection as well as classification [5].

Unlike image-based methods, Mohamed et al. (2021) investigated the function of mitochondria in Alzheimer's disease. The researchers examined the effect of boswellic acid, a natural product, on mitochondrial chain complexes in rats. Although unrelated to imaging, the research offers useful information into possible lines of treatment that may be used to augment methods of diagnosis. The researchers established that boswellic acid enhanced mitochondrial function, which may have theoretical applications to understanding and treating Alzheimer's disease [6].

Tadokoro et al. (2021) proposed an innovative method to detect early changes in cognition in people with Mild Cognitive Impairment (MCI) and Alzheimer's disease via eye tracking tests. The research outlined that subtle patterns of changes in eye movement could be used as an early sign of cognitive impairment even before there are clinically evident symptoms. Although this method is non-imaging, it provides an important additional measure to AD diagnosis, especially for early-stage disease [7].

Zhang et al. (2021) integrated structural MRI (sMRI) and resting-state functional MRI (rs-fMRI) data with the aid of machine learning methods to forecast the conversion from Mild Cognitive Impairment (MCI) to Alzheimer's disease. Their graph theory-based method offered an overall approach for the analysis of brain networks to accurately predict MCI-to-AD conversion. The study highlighted the potential of integrating structural as well as functional MRI data to unveil additional aspects of brain activity as well as connectivity to predict AD [8].

Kwasigroch et al. (2017) have compared various architectures of deep neural networks for the classification of skin lesions, shedding light on the ability of deep learning models to generalize across distinct medical fields. Even though they used dermatology as the subject of study, the deep learning principles applied to image classification are equally transferable to Alzheimer's research, where comparable architectures are used to process brain MRI scans[9].

Suk and Shen (2013) used deep learning to differentiate between Alzheimer's disease and Mild Cognitive Impairment (MCI) from brain-imaging data. Suk and Shen proposed an approach to automatically learn brain MRI scan features that markedly surpassed conventional methods. Suk and Shen's study was among the initial few to establish deep learning as an efficient method for AD/MCI discrimination, paving the way for additional innovation to follow [10].

Buvaneswari and Gayathri (2021) investigated segmentation using deep learning as an introduction to AD classification from MRI data. Their approach used segmentation as an initial step of preprocessing to segment brain regions of interest to be classified, resulting in enhanced diagnostic accuracy. The research highlighted the importance of accurate region-of-interest (ROI) extraction to maximize the performance of the CNN, as well as to minimize misclassification [11].

Parmar et al. (2020) introduced an advanced deep 3D-CNN framework to learn both spatial and temporal feature extraction from functional MRI (fMRI) data. Their proposed model utilized rich temporal dynamics embedded within fMRI sequences to capture minute brain activity changes associated with AD progression. The work showcased the efficacy of 3D-CNNs for processing sophisticated spatiotemporal data, developing an efficient high-performance model for AD classification [12].

Çelebi and Emiroğlu (2023) proposed a dense block-based deep learning structure for Alzheimer's diagnosis. Dense blocks help reduce feature reuse and combat gradient vanishing, resulting in an optimal choice for deep models. The proposed algorithm produced significant accuracy gains over traditional CNNs, proving the necessity of structural innovations to provide maximum classification results [13].

Salehi et al. (2020) compared the application of some machine learning algorithms, including SVM, Random Forest, and Gradient Boosting, where they used the OASIS dataset. The research compared traditional models to deep learning models, and it was found that, although deep learning tended to perform better, ensemble methods or combinations of optimized classical models could still provide competitive results where data is limited [14].

A complementary study by Salehi et al. (2020) also examined different deep learning architectures, that is, CNN-based models, to perform AD detection automatically. The research revealed the performance of custom architectures compared to pre-trained networks, with the conclusion that transfer learning could immensely increase performance where there are limited datasets [15].

Fuadah et al. (2021) utilized the highly familiar AlexNet architecture to classify Alzheimer's using data from MRI. AlexNet's relatively shallow depth was enough for the given dataset, demonstrating that older architectures can be quite viable if tuned and appropriately trained. They also highlighted the necessity of selecting the optimal level of model complexity, depending on the nature of the dataset [16].

Cheng et al. (2015) addressed the issue of Mild Cognitive Impairment (MCI) conversion to Alzheimer’s prediction by employing domain transfer learning. Their method facilitated knowledge transfer from the source domain with ample labeled data to the target domain with few labels, an important leap towards addressing data scarcity—a constant challenge in neuroimaging [17].

Li et al. (2015) proposed an effective deep learning framework for reliably classifying both AD and MCI patients. Their system combined deep feature learning with classification layers and achieved significant generalization across various datasets. Theirs is the work of creating models that are noise-resistant and invariant to variability in image data [18].

Qi et al. (2016) examined volumetric and multi-view CNNs for 3D data classification, an approach that is relevant to 3D brain scans applied to AD diagnosis. Their multi-view learning method, where input is analyzed from numerous spatial views, is especially useful for processing the complete anatomical detail of brain structures [19].

Yadav and Miyapuram (2021) introduced a new deep learning approach for early AD diagnosis from MR images. The research focused on early diagnosis, utilizing CNNs to differentiate between preclinical AD patients and healthy controls. The research underscored the importance of early treatment and revealed that even minor structural changes from MRI could be identified using optimized neural networks [20].

Shamrat et al. (2023) introduced AlzheimerNet, a deep learning model built to classify stages of Alzheimer's by analyzing functional changes in brain MRI scans. With a sophisticated architecture combining convolutional layers and attention mechanisms, the model effectively pinpointed patterns linked to disease stages. This work highlights how functional brain changes can enhance fine-grained stage classification [21].

Fazil Sheikh et al. (2024) presented a cutting-edge Quantum Convolutional Neural Network (QCNN) for Alzheimer's diagnosis, blending quantum computing with classical deep learning. The QCNN showed superior performance in select cases, especially when handling complex, high-dimensional data. This novel approach paves the way for quantum-powered diagnostics with faster training and better generalization [22].

Shafiq Ul Rehman et al. (2024) developed an AI-driven tool for early Alzheimer's detection, combining machine learning and deep learning techniques. Trained on multimodal data, the model delivered high accuracy with strong interpretability. A standout feature was its clinician-friendly interface, geared toward real-time diagnostic support[23]..

Kavitha et al. (2022) assessed machine learning algorithms like SVM, Decision Trees, and Logistic Regression for detecting early-stage Alzheimer's. Working with ADNI and OASIS datasets, they demonstrated how critical feature engineering and data preprocessing are to success. The study affirmed that classical ML models remain valuable in low-data environments [24].

Bae et al. (2020) trained a CNN model on T1-weighted MRI scans to differentiate Alzheimer's patients from healthy individuals. The model achieved strong sensitivity and specificity, reinforcing the capability of structural MRI to reveal Alzheimer's-linked brain changes. This was one of the earlier studies to prove the reliability of CNNs for large-scale MRI analysis [25].

Murugan et al. (2021) created DEMNET, a CNN-based deep learning system to detect both Alzheimer's and other types of dementia using MRI data. By handling multi-class classification, it tackled the challenge of distinguishing dementia subtypes. Tested across several datasets, DEMNET showed strong generalization in clinical scenarios [26].

Noh, Kim, and Yang (2023) developed a model using fMRI data to classify stages of Alzheimer's progression. They focused on dynamic functional connectivity features, which can detect early decline more effectively than structural imaging. Their findings add to the growing body of research supporting functional imaging as a vital diagnostic tool [27].

Rallabandi et al. (2020) built a machine learning model that categorized individuals into cognitively normal, MCI, or Alzheimer's groups using MRI features and traditional classifiers. Their practical, multi-class framework achieved strong results and could be seamlessly integrated into clinical workflows [28]..

El-Assy et al. (2024) designed a custom CNN model tailored for early Alzheimer's detection. Using skip connections and multi-scale filters, the architecture improved feature extraction from MRI scans, boosting overall accuracy. The study stressed the importance of customizing architectures for the specific demands of medical imaging [29].

Bamber and Vishvakarma (2023) reviewed a range of deep learning architectures for AD classification, focusing on transfer learning with pre-trained models like VGG16 and ResNet. Their findings showed that fine-tuned pre-trained networks could match or exceed custom models while reducing training time and resource use [30].

III. METHODOLOGY

The experiments in this research were performed on a complete MRI dataset found on Kaggle, consisting of a broad variety of brain scan images along with related clinical data. The dataset is split into training and testing subsets, with the training subset containing 10,240 images and the testing subset containing 1,279 images. Both subsets are further classified into four diagnostic classes depending on the level of cognitive impairment.

In the training data, the images are uniformly divided among the following four classes: Very Mild Impairment (2,560 images), Mild Impairment (2,560 images), Moderate Impairment (2,560 images), and No Impairment (2,560 images). The balanced split ensures that the model gets equal exposure to every class while training, which is important for preventing bias and maintaining consistent performance across classes.

Conversely, the test dataset is more imbalanced in terms of classes: Very Mild Impairment (448 images), Mild Impairment (179 images), Moderate Impairment (12 images), and No Impairment (640 images). This can be problematic at the time of evaluation, especially for the under-sampled categories like Moderate Impairment.

Figure 4 demonstrates these distributions: panel (a) plots the percentage composition of each class within the training set, with panel (b) plotting the absolute number of images for each class. These graphical representations emphasize the structure of the dataset and the requirement for precise management of class imbalances in model estimation and interpretation.

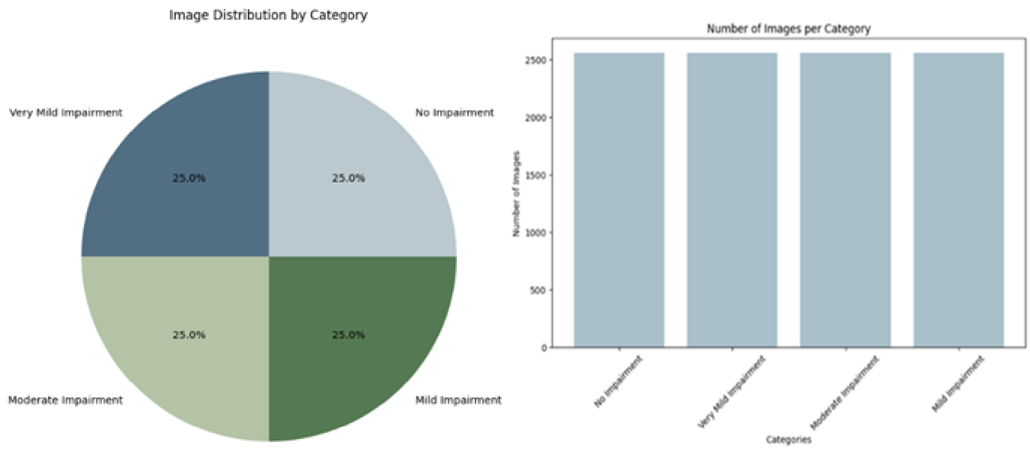

Fig.4: (a) Training dataset: Category wise percentage distribution of images

Training dataset: Category wise no. of images

The following fig.5: (a) shows the percentage distribution of images per category in the testing dataset and (b) shows the number of images per category in the testing dataset.

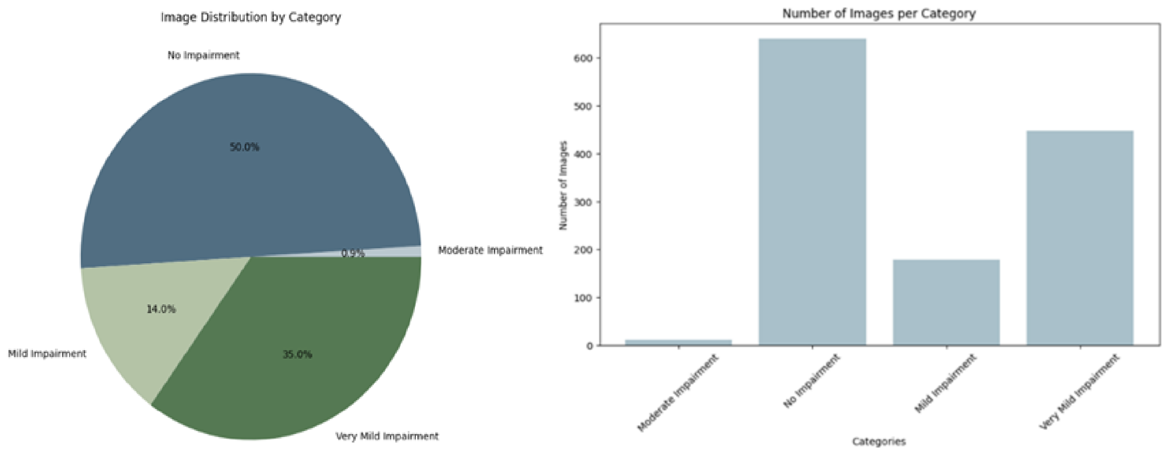

Fig.5: (a) Testing dataset: Category wise percentage distribution of images

(b) Testing dataset: Category wise no. of. images

PREPROCESSING

This is done by registering all MRI images to a shared reference space—i.e., the MNI152 template—and so anatomical features are in the same location in all subjects. Standardization enables comparisons between images and improves learning algorithm performance. A good illustration is hippocampal segmentation with software such as FSL, whereby a mask separates this important brain area. Since the hippocampus is heavily involved in memory and learning, and is among the first areas affected by Alzheimer's, precise localization significantly aids in early diagnosis.

2. SKULL STRIPPING:

This process eliminates non-brain tissues like the skull, scalp, and other structures surrounding them, leaving the focus entirely on the brain tissue. By removing extraneous information, this process reduces the data to simpler form and noise, which helps the model learn more significant features.

3. BACKGROUND REMOVAL:

Extraneous factors and background noise in MRI images can hinder analysis. Their removal leads to cleaner images, enabling the model to pick up more relevant features with greater precision and accuracy.

4. HISTOGRAM EQUALIZATION:

This method enhances image contrast by redistributing pixel intensity levels more uniformly within the image. It makes it easier to distinguish structural details, making it possible for the model to more clearly identify subtle trends in brain structure that can foretell early intellectual deterioration.

Working in combination, these preprocessing tasks normalize the data set, denoise, and highlight key structures in the brain—ultimately increasing the quality and accuracy of AI-based diagnosis tools.

DESCRIPTION OF MODELS

We have used Support Vector Machines (CNN) and the Quantum Support Vector Machines (QCNN) machine learning techniques for the experimentation. The following fig.6 shows the general flow of the CNN model for classification.

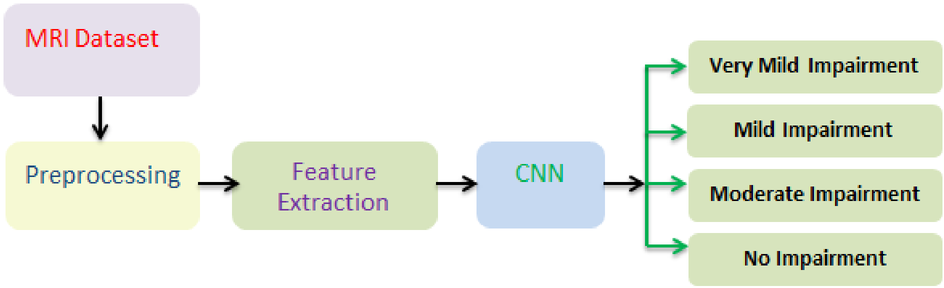

Fig.6: General flow of the CNN model for classification.

Convolutional Neural Networks (CNNs) are supervised learning algorithms used mostly for classification and regression tasks. They work by determining an optimal decision boundary, or hyperplane, that separates data points into separate classes based on the given problem. CNNs use kernel functions to map input features to a higher dimension space so that the model can learn complex, non-linearly separable data with better accuracy. These networks work particularly well with small to medium-sized datasets and are used extensively in applications such as image recognition, text classification, and anomaly detection. Nevertheless, CNNs tend to require a lot of computational resources, especially when used with large datasets, and need careful tuning of hyperparameters in order to be optimally functional.

In the case of Alzheimer's disease detection, CNNs process input features extracted from MRI scans, including hippocampal volume and cortical thickness, which are strongly correlated with brain degeneration. The model is able to become more effective at detecting subtle, non-linear patterns that may not be easily discernible in the original feature space by mapping these features into higher-dimensional representations. This allows CNNs to learn decision boundaries that will be able to classify people accurately into categories like cognitively normal, mild cognitive impairment (MCI), or Alzheimer's Disease (AD), facilitating early diagnosis and tracking of disease progression.

Quantum Convolutional Neural Networks (QCNNs) is a quantum enhanced evolution of the traditional CNNs. The models are based on the principles of quantum computing, including quantum kernel estimation, allowing for more effective processing of high-dimensional and complex data. QCNNs leverage quantum parallelism, allowing them to handle large-scale data with enhanced scalability and speed over their classical counterparts. This renders them extremely promising for sectors that deal with enormous amounts of data, including finance, cybersecurity, and—most significantly—healthcare.

In the context of medical diagnosis, QCNNs have significant promise in increasing the accuracy and efficiency of disease detection, such as Alzheimer's. Their potential to quickly process complex data sets and reveal latent patterns may lead to more sophisticated and scalable diagnostic tools.

Figure 7 presents the overall workflow of the QCNN model, highlighting how principles of quantum computing are incorporated into the classification pipeline to enhance diagnostic performance

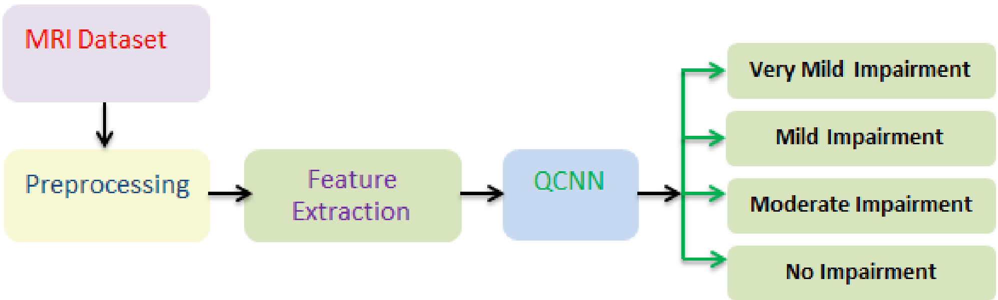

Fig.7: General flow of the QCNN model for classification.

QUANTUM CONVOLUTIONAL NEURAL NETWORKS (QCNN) FOR DETECTION OF ALZHEIMER'S

In the early detection of Alzheimer's Disease, QCNN models utilize quantum feature mapping to process complex MRI data more quickly and efficiently than is possible with conventional approaches. With the application of the quantum kernel trick, QCNNs can efficiently map high-dimensional features—such as hippocampal volume and cortical thickness—to a space where patterns become more separable. These features are key indicators of neurodegeneration, and the quantum-enhanced processing results in enhanced accuracy in their analysis.

In contrast to traditional CNNs, which can have difficulty with very high-dimensional or subtly changing data, QCNNs provide a huge advantage in detecting complex and nonlinear patterns in brain imaging. This capability enables more precise and reliable classification of patients into diagnostic groups like cognitively normal, very mild impairment, mild impairment, and moderate impairment. Additionally, quantum computing reduces processing time considerably, making QCNNs a scalable and promising tool for early and reliable detection of Alzheimer's.

Dataset Splitting for Model Training and Testing

For the proper training and evaluation of the model performance, the dataset is split into three primary subsets:

Training Set (usually ~80% of the data): This set is utilized to train the model by enabling it to learn patterns and relationships within the data.

Validation Set (usually ~10%): To tune model parameters and avoid overfitting, the validation set is utilized to monitor performance during training without affecting the learning process.

Testing Set (usually ~10%): Reserved until the end of the evaluation step, the test set is employed to measure the extent to which the model performs on totally unseen data, providing a genuine reflection of its ability to generalize.

Training Process and Performance Evaluation

To promote model generalization, data augmentation strategies are used when training. These processes add controlled variations to the training data—e.g., transformations, rotations, or noise—to mimic different scenarios and make the model stronger.

At all stages of training and validation, model performance is kept under watch by important evaluation metrics:

Precision – Calculates how much of the predicted positives are true positives.

Recall – Shows how well the model detects all relevant cases.

Accuracy – Represents the global accuracy of predictions for all classes.

The QCNN model finally predicts input MRI scans to belong to one out of four categories of the severity of cognitive impairment: No Impairment, Very Mild Impairment, Mild Impairment, and Moderate Impairment. Through the incorporation of quantum computing principles with state-of-the-art neural network architectures, this solution presents a state-of-the-art solution for diagnosing and monitoring the course of Alzheimer's Disease.

IV. RESULT & DISCUSSION

Convolutional Neural Network(CNN), and Quantum Convolutional Neural Network(Q-CNN) were assessed using Precision, Recall, and Accuracy metrics. The results are summarized in Table 2.

Table 2: Performance Metrics of Classical and Quantum Models.

Model	CNN	QCNN
Precision	0.80	0.88
Recall	0.84	0.96
Accuracy	0.84	0.59

PERFORMANCE ANALYSIS:

PRECISION COMPARISON:

Quantum Convolutional Neural Network (QCNN) is more accurate than the traditional CNN with a score of 0.88 as opposed to 0.80 for CNN. Precision indicates how well the model can accurately identify just the appropriate (true positive) instances without labeling wrong negatives as positives. This outcome indicates the strength of QCNN, with quantum-aided feature extraction and classification advantages that enable it to provide more precise predictions and minimize false positives. Performance indicates that quantum support vector methods integrated within QCNN are superior to conventional CNN design in some intricate classification tasks.

RECALL COMPARISON:

Both QCNN and CNN show good performance in recall, with QCNN at 0.96, and CNN at 0.84. Recall refers to the model's capacity to recognize all actual positive cases (i.e., those with Alzheimer's) without generating too many false negatives. Good recall is particularly important in medical diagnosis where missing a positive case (e.g., not recognizing early symptoms of Alzheimer's) would postpone treatment. These findings confirm that both models perform well in detecting instances of cognitive impairment, and that QCNN has an edge because of its greater pattern recognition abilities using quantum computation.

ACCURACY COMPARISON:

As far as accuracy goes, which indicates the average ratio of properly classified cases across all categories, CNN beats QCNN with a score of 0.84 compared to 0.59. This implies that although QCNN is better in some aspects such as precision and recall, its overall consistency in classification can be improved—perhaps due to existing limitations in quantum model maturity, dataset compatibility, or a requirement for further finer tuning of quantum circuits. However, the output of both models exhibits the strong capability of classical and quantum neural networks in the field of Alzheimer's diagnosis.CNN Results Visualization:

The following fig.8 shows the CNN accuracy related to training and validation

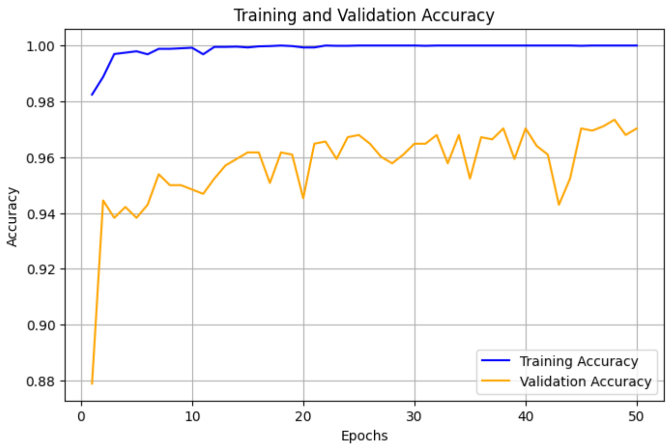

Fig.8: CNN training and validation accuracy

The loss related to training and validation is shown in the following fig.9.

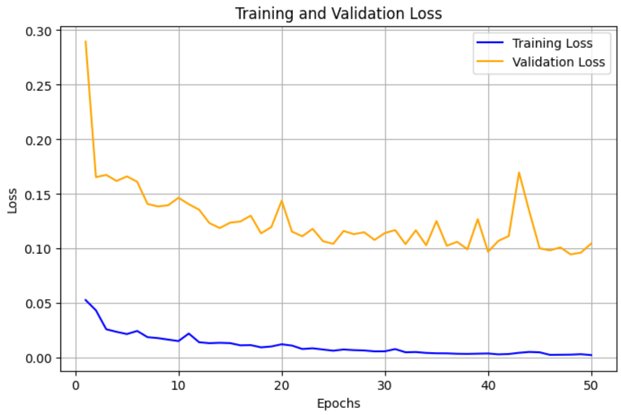

Fig.9: CNN training and validation loss

CLASSIFICATION REPORT:

On X-axis: Metrics (Precision, Recall, F1-score) for each class. On Y-axis: Score (ranging from 0 to 1). Each class has bars for Precision, Recall, and accuracy, showing the model's performance. This is shown in the following fig.10

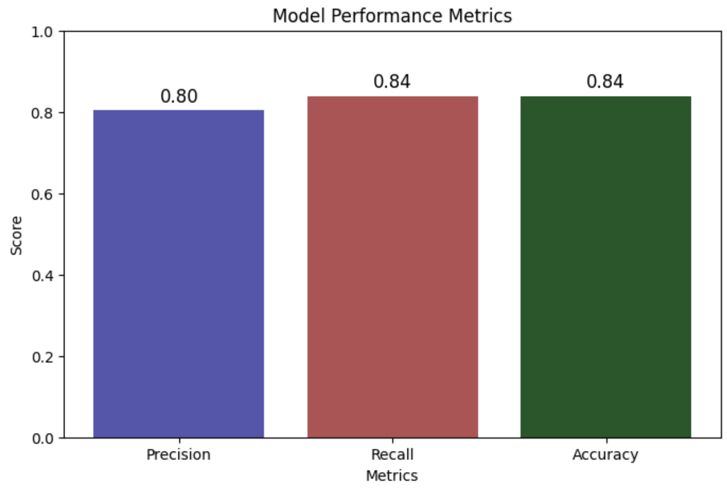

Fig.10: CNN Evaluation Metrics.

VISUALIZATION OF RESULTS FROM Q-CNN:

The following fig.11 shows the CNN accuracy related to training and validation

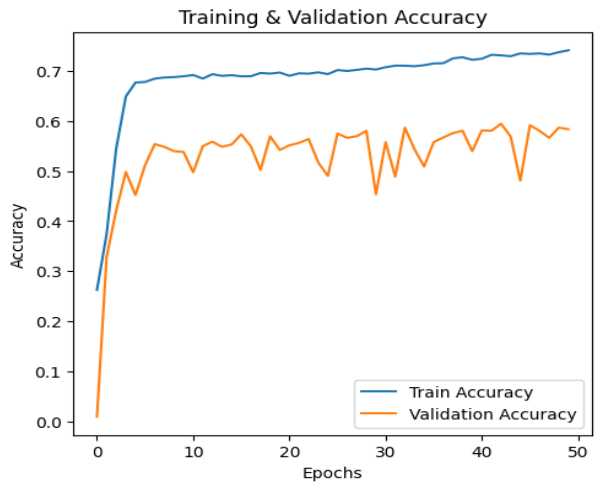

Fig.11: CNN training and validation accuracy

The following fig.12 shows the QCNN related to training and validation loss

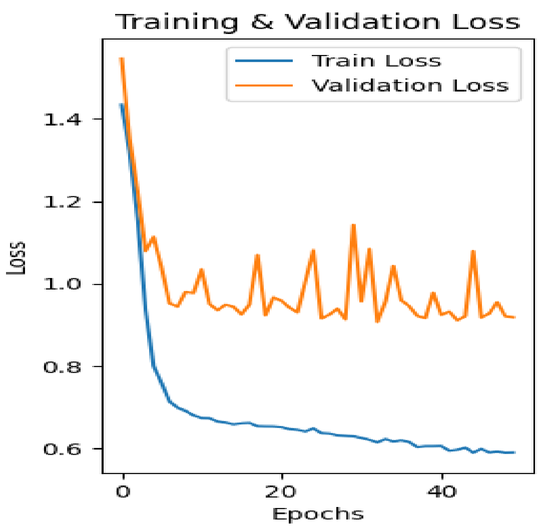

Fig.12: QCNN training and validation loss

REPORT OF CLASSIFICATION:

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.13.

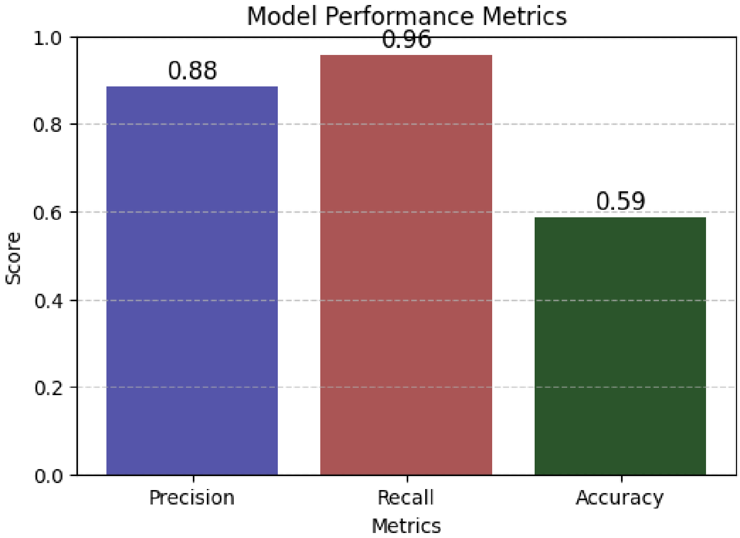

Fig.13: QCNN Evaluation Metrics

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

V. CONCLUSIONS

Through extensive research and experimentation, this research highlights the imperative role of early detection in the management of Alzheimer's disease since early diagnosis has a direct impact on cognitive function as well as the quality of life of patients. The findings highlight that Quantum Machine Learning (QML), specifically the Quantum Convolutional Neural Network (QCNN), presents a viable avenue for improving diagnostic accuracy.

By specifically targeting major brain structures impacted in the early stages of Alzheimer's, like the hippocampus, which experiences prominent atrophy even in the earliest phases, the suggested method offers a robust system for precise classification of subjects into four cognitive subgroups: no impairment, very mild impairment, mild impairment, and moderate impairment. Both clinical accuracy and interpretability are addressed by this specific approach.

The incorporation of transfer learning methods has further enhanced the model's performance with high precision and recall for training, validation, as well as testing datasets. These findings are a testament to the capability of deep learning models in examining medical imaging data, which justifies their real-world usability in clinical settings for supporting early intervention approaches.

In addition, the results highlight the importance of thorough image preprocessing with methods like image registration, skull stripping, background noise elimination, and histogram balancing that considerably boost the quality of MRI images and consequently the performance of models. Together with progressive data augmentation, these processes allow the model to generalize well across different patient populations and make consistent and reliable predictions.

One of the major contributions of this research also includes its emphasis on user-centric AI interfaces. These interfaces are developed to enable healthcare professionals to engage with AI tools in an intuitive manner, providing visual depiction of brain scans in 2D and 3D forms. Visualizations like these help clinicians track disease development and make effective treatment choices.

In summary, the cumulative evidence from this research strongly advocates for the incorporation of AI-based diagnostic tools into standard clinical practices. These sophisticated techniques not only enhance our knowledge of Alzheimer's disease progression but also open the door to early and tailored interventions that can dramatically improve patient outcomes. In the future, research efforts should look into the integration of multi-modal data sources (e.g., genetic, clinical, and behavioral data) and examine other machine learning frameworks in order to further better and optimize these tools for wider and more effective utilization in real-world settings.

VI. FUTURE SCOPE

Looking forward, future studies will need to try to bring together multimodal neuroimaging data, fusing inputs from MRI, functional MRI (fMRI), PET scans, and genetics. Such bringing together of multifaceted sources of data may provide a broader picture of structural, functional, and molecular modifications in Alzheimer's disease. By imaging several aspects of brain pathology, such multimodal methods can potentially enhance the reliability and robustness of diagnostic models, making them better able to distinguish between different stages of cognitive decline—from mild cognitive impairment (MCI) to outright Alzheimer's disease.

Aside from increasing the sources of data, there is significant room to investigate different machine learning architectures other than the standard CNN models. For instance, ensemble learning methods—fusing predictions from several models—would potentially produce more accurate and consistent results. In the same way, Recurrent Neural Networks (RNNs) and attention mechanisms could be most beneficial in examining temporal structures and sequential data, such as trends in brain activity over time, which are particularly important in tracking the progression of disease.

In addition, the application of unsupervised learning methods also offers promising potential for the identification of new biomarkers. Unlabeled-data models, being independent of labels, can uncover latent patterns or clusters in highly complex neuroimaging data that may identify nascent signs of Alzheimer's currently not clinically seen.

In short, the future of Alzheimer's research is multimodal integration, next-generation neural architectures, and novel machine learning approaches. Collectively, these technologies have the potential to enable the creation of more precise, scalable, and clinically relevant diagnostic systems—ultimately resulting in earlier treatment and better patient care.

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