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Performance Evaluation of Quantum Machine Learning and Classical Machine Learning Techniques for Alzheimer's Disease Diagnosis

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Abstract: Alzheimer's Disease (AD) first affects the brain parts that are associated with learning. It is one of the most prevalent forms of Dementia. Its early diagnosis is crucial for properly managing the disease treatment because it is chronic and irreversible. This paper introduces a holistic approach to achieve early detection of AD using the hippocampus and transfer learning. Here we have compared the results from the classical machine learning model – Support Vector Machine (SVM)and the Quantum Support Vector Machine (QSVM) model. QSVM - a quantum variant of standard SVM algorithm. It is developed using techniques such as quantum kernel estimation in quantum computing for more efficient processing of high-dimensional data than standard SVMs.. The most common symptoms of Alzheimer's are loss of memory and cognitive impairment. This stems from the destruction and death of nerve cells in the brain related to memory. Mild Cognitive Impairment (MCI) is a condition between normal brain function and Alzheimer's. From the prodromal MCI stage, it progresses gradually to dementia. Several studies show that Alzheimer's develops at a rate of 10–15% per year from MCI. The early identification of patients with MCI may halt/delay the progression from MCI stage to Alzheimer's. The results with the precision of 0.85 with the QSVM compared to the precision of 0.78 and recall of 1.00 compared to the 0.89 with the traditional SVM shows that our technique of Quantum Machine Learning (QML) is very useful in Alzheimer's early diagnosis.

***Keywords**: Alzheimer's Disease, Quantum ML, Machine Learning, SVM, QSVM, Disease Diagnosis, Hippocampus.*

I. Introduction

Alzheimer's Disease represents a significant global health challenge, primarily due to its status as the most prevalent type of dementia, impacting millions of individuals worldwide. Alzheimer's disease (AD) is marked by a permanent deterioration in cognitive abilities, predominantly impacting the hippocampus, the brain region linked to memory and learning processes. Early identification of AD is essential, as existing treatments do not reverse the condition but instead aim to slow its advancement. The disease typically starts at Mild Cognitive Impairment (MCI) level, which is where patients begin to have minor memory and thinking problems, which can lead to full Alzheimer's disease. Over 55 million people have dementia worldwide, of whom 60-70% are diagnosed with AD, thereby making it a high-need diagnostic test both in the present and the future.

The following fig. 1 shows the statistics related to Dementia (Source: Alzheimer's Disease International).

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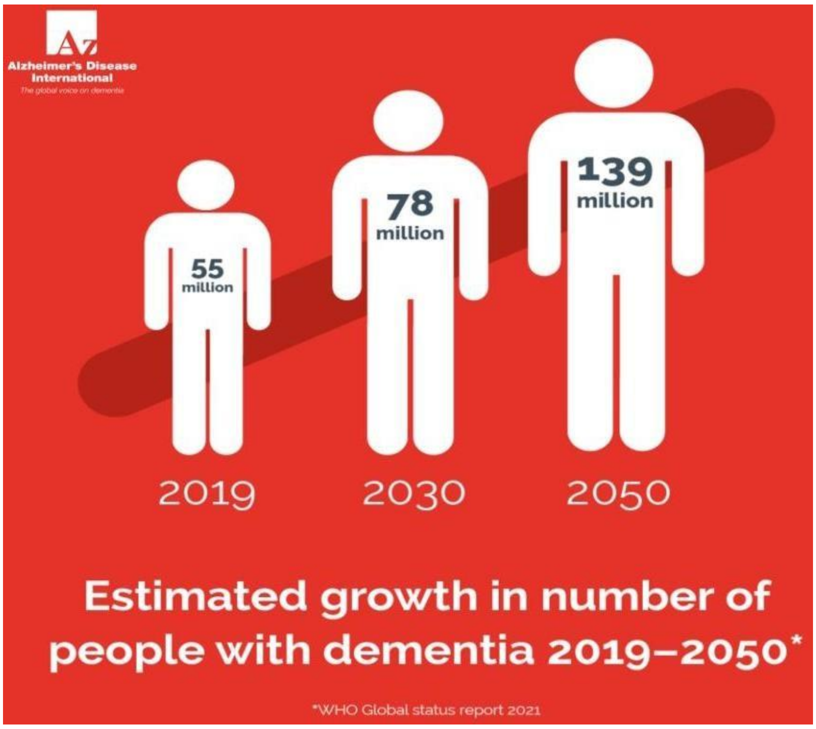

Fig.1: Statistics of Dementia

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

The traditional methods are often relied on clinical examination and neuropsychological tests, which are subjective and time-consuming. The recent advent of Neuroimaging and Artificial Intelligence (AI) has led to the development of new ways to make early detections and classify AD stages. There are a number of works that focus on the machine learning techniques, in particular deep learning models in analyzing structural Magnetic Resonance Imaging (MRI) data to classify patients into CN(Cognitive Normal), MCI, and AD groups.

The emphasis of our model is on the hippocampus using a progressive data augmentation approach throughout the training process. This has resulted in an impressive accuracy for the testing, validation, and even training sets. This holistic Approach is a step towards advanced early detection techniques of Alzheimer's disease and answers the urgent call for such diagnostic tools for the clinical practice scenario.

In conclusion, this work bridges the gap between traditional diagnosis and modern AI-driven approaches towards a comprehensive early detection of Alzheimer's disease using the Quantum Machine Learning technique. Hope this work will provide a compressive view of how an enhanced patient outcome can be promoted and timely intervention adopted in managing this debilitating condition with cutting-edge technology with a focus on critical brain structures.

The following table 1 shows the worldwide statistics related to Alzheimer’s (Source: WHO).

Table1: Alzheimer’s Statistics (Worldwide)

Particulars	**2024**	**2030**	**2050**
People Affected	55 million	78 million	139million
Deaths	1.6million	2.5million	4million
Aging	60-70%	65-75%	70-80%
Non-Aging	5-10%	10-15%	-

The following table2 shows the statistics related to Alzheimer's as far as India is concerned (Source: Alzheimer's and Related Disorders Society of India (ARDSI)).

Table2: Alzheimer's Statistics (India)

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

The following fig.2 shows the cost associated with Dementia (Source: WHO).

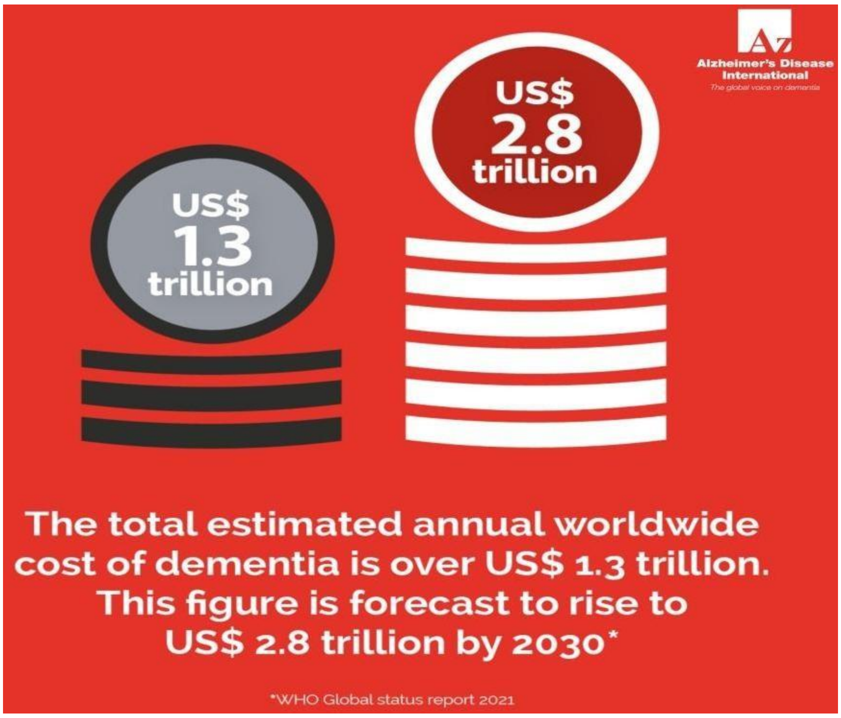

Fig.2: Cost of Dementia

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

Following is a description of the various terminologies used in this work.

Alzheimer'sDisease

A long-term, advancing neurodegenerative condition marked by a decline in cognitive abilities, memory impairment, and alterations in behavior. This disorder represents the most prevalent type of dementia, influencing millions of individuals globally and profoundly affecting the quality of life for both patients and their caregivers.

Hippocampus

The major brain structure important in memory processing and navigation through a space. These areas of the brain are primarily targeted during early stages of Alzheimer's, leading to emphasis upon these for earliest detection and identification.

Transfer Learning

A method within machine learning that allows a model created for one task to serve as a foundational starting point for a model addressing a different task is known as transfer learning. By utilizing transfer learning, researchers specializing in medical imaging can leverage pre-trained models, such as VGG16, to enhance performance in particular tasks, including disease classification.

Cognitively Normal (CN)

A classification used in Alzheimer's research to describe individuals who show no signs of cognitive impairment. This group is a control in studies comparing cognitive function across different stages of Alzheimer's disease.

Mild Cognitive Impairment (MCI)

Cognitive decline that is noticeable but more than what would be expected in a person's age and does not reach a level that severely interferes with daily life. MCI is often considered the precursor to Alzheimer's disease.

ADNI

This is the biggest research project on developing biomarkers to enable early identification and monitoring of Alzheimer's disease. The neuroimaging, clinical, genetic, and biospecimen data available in the ADNI dataset comes from participants over time.

Image registration

This involves aligning a number of images into a common coordinate system. It is a procedure that guarantees the neuroimaging data will be compared and analyzed objectively, irrespective of whether the images are at different times or with different modalities.

Skull Stripping

a pre-treatment, and in this procedure, one removes the non-brain tissues from the

brain images such as skull and scalp. This increases the focus on the brain structures and increases accuracy in subsequent analysis.

The major brain structure important in memory processing and navigation through a space. These areas of the brain are primarily targeted during early stages of Alzheimer's, leading to emphasis upon these for earliest detection and identification.

II. Literature Review

Feature selection enhances model accuracy, particularly when dealing with extensive datasets. To surpass conventional feature selection techniques such as filter methods, wrapper methods, and embedded methods, deep learning strategies have been developed to achieve improved accuracy using large healthcare datasets. The essence of feature extraction lies in the selection of a subset of input variables from the complete set utilized by the learning algorithm, represented as follows: $\{f1,f2,f3,...,fm\}\rightarrow\{fij,\dots,fuv,\dots,fun\}$, where $uv\in\{1,\dots,m\}$ and $v=1,\dots,n$. The manual methods employed by radiologists are often more intricate, complicating the process of feature degeneration for enhanced detection.

A large amount of unlabeled data is used to learn the features in unsupervised learning approaches. Convolutional Neural Network (CNN) has been creating good research on text analysis, image detection, speech recognition, etc. in the field of deep learning. Numerous studies have demonstrated that Convolutional Neural Networks (CNNs) out perform traditional methods such as Support Vector Machines (SVMs) in feature extraction, particularly in the classification of skin concerns using deep neural networks. Unsupervised techniques represent a significant area of research, particularly in the application of Stacked Autoencoders (SAEs) for classifying Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI).

The classification of AD through a comprehensive whole-brain hierarchical network has been thoroughly articulated in the literature. Furthermore, the use of deep convolutional neural networks to classify AD based on MRI and fMRI data marks a significant advancement in feature analysis. Despotovic et al.[8] provided an extensive review of various segmentation techniques, all of which utilize evolutionary algorithms. A range of strategies has been proposed to enhance performance by considering the diverse anatomy and functions inherent in medical imaging. The

FastICA algorithm has been detailed in the literature, and Basheera et al. [10] achieved a 90.4% accuracy in analyzing MRI grey matter images through a hybrid enhanced independent component analysis approach.

Fu'adah et al. [11] introduced a CNN classification model based on AlexNet, which attained an impressive 95% accuracy using a dataset of MRI images associated with Alzheimer's Disease. In their work, the authors developed a model based on domain transfer learning to predict MCI conversion, utilizing various modalities and both target and auxiliary domain data samples. Their experimental approach led to a prediction accuracy of 79.40%.

Additionally, a robust deep learning methodology incorporating MRI and PET modalities was presented, which utilized a dropout strategy to improve classification performance. The implementation of multi-task learning within the deep learning framework allowed for an assessment of performance variations with and without dropout, resulting in a notable 5.9% improvement. Lastly, two CNN-based models were evaluated, focusing on volumetric and multi-view CNNs in classification tests, with the integration of multi-resolution filtering having a direct impact on classification outcomes.

In order to categorize brain slices into four groups—NC, MCI, and AD—the authors of [15] suggested a2DCNN techniquebasedonResNet50 that incorporates many batch normalization and activation methods. The accuracy rate of the suggested model was 99.82%. Another study [16] used a SegNet-based deep learning strategy to identify particular local brain morphological features necessary for AD diagnosis, and discovered that using a deep learning technique and a pre-trained model considerably improved classifier performance. Using resting-state fMRI data, a 3D CNN was created in [17] to differentiate between AD and CN.

Meanwhile, Çelebi et al. [18] preprocessed MRI data using morphometric images from Tensor-Based Morphometry (TBM). In order to diagnose Alzheimer's disease at an early stage with great accuracy, their study used the deep, dense block-based Xception architecture-based DL approach. Issues including dataset heterogeneity, overfitting, and difficulties with TBM image feature extraction were not addressed in this study, though.

Baglat et al. [19] suggested hybrid machine learning-based models that used logistic regression, SVM, and Random Forest to identify Alzheimer's disease. The OASIS dataset's MRI patient scans were used in their models. Using a deep learning approach would improve early-stage Alzheimer's disease predicting, according to Salehi et al.'s [20] analysis. They each made use of the ADNI and OASIS datasets. A CNN model was introduced by Murugan et al. [21] for the identification of Alzheimer's disease. Using the ADNI MRI image dataset, their suggested model—which included four dementia network blocks, one max-pooling layer, and two convolutional layers—achieved an accuracy of 95.23%.

In a separate study, Salehi et al. [19] used MRI scans and a CNN to identify Alzheimer's disease, with an average accuracy of 84.83%. At the same time, Noh et al. [22] presented a 3D-CNN-LSTM model that achieved high accuracy values of 96.43%, 95.71%, and 91.43% by using extractors for spatial and temporal features. Using the ADNI database, Rallabandi et al. [23] proposed a method for early identification and classification of AD and MCI in older cognitively normal people. Their model's accuracy across a range of machine learning techniques was 75%. Additionally, Odusami et al.[24] presented a pre-trained CNN hybrid model that uses gradient-weighted class activation mapping, weight randomization, and deep feature concatenation to improve Alzheimer's disease identification and stage classification from brain MRIs, outperforming conventional techniques with a test accuracy of 98.67%. [27-30] described the use of Quantum CNN for the diagnosis of Alzheimer's disease.

III. Methodology

Acquisition of the Datasets

The experiments were done on the Kaggle dataset that has an exhaustive set of MRI images with its corresponding clinical data. This dataset contains Training Data (10240) and Testing Data(1279) each having four subclasses. In the training data the division is as follows: Very Mild Impairment (2560), Mild Impairment (2560), Moderate Impairment (2560) and No Impairment (2560).

Whereas in the testing data set the division is as follows: Very Mild Impairment (448), Mild Impairment (179), Moderate Impairment (12), No Impairment (640).The following fig.3 shows the number of images per category in the training dataset.

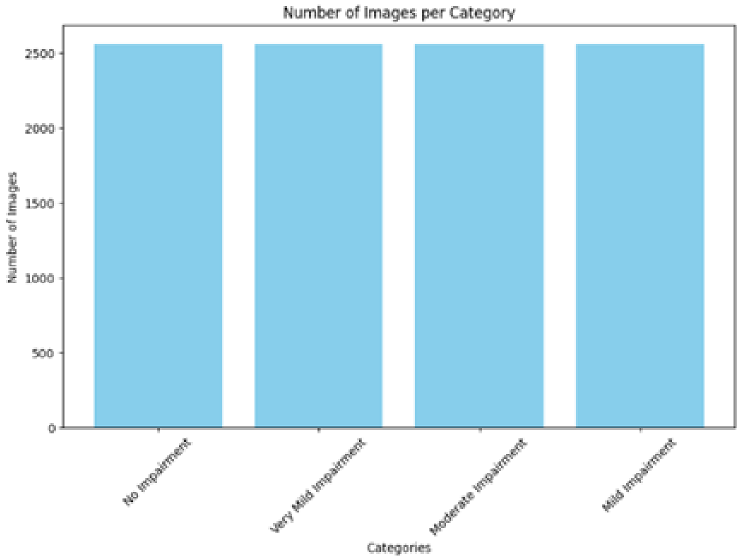

Fig.3:Number of images per category in the training dataset

The following fig.4 shows the percentage distribution of images per category in the training dataset.

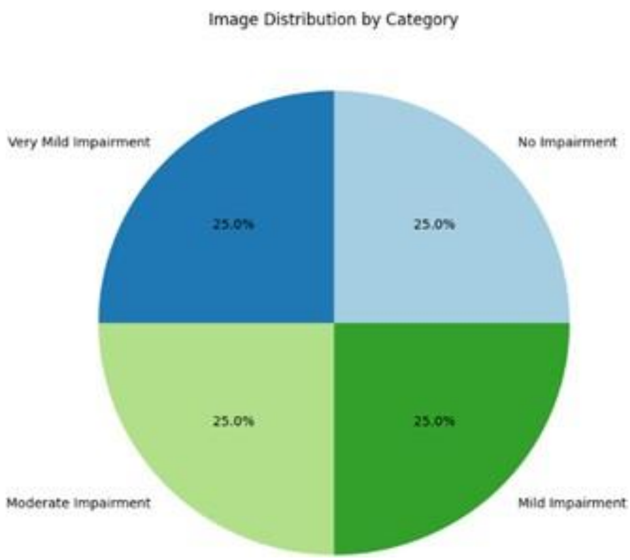

Fig.4: Percentage distribution of images per category in the training dataset.

The following fig.5 shows the number of images per category in the testing dataset.

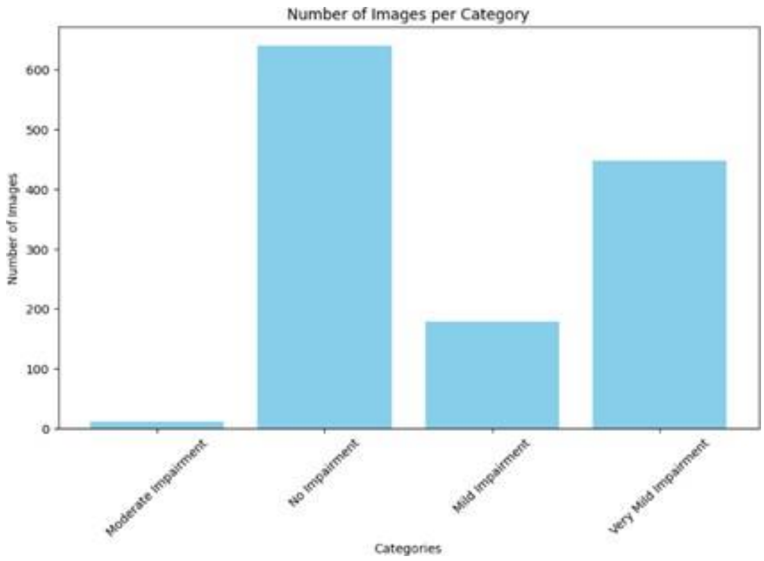

Fig.5:Number of images per category in the testing dataset.

The following fig.6 shows the percentage distribution of images per category in the testing dataset.

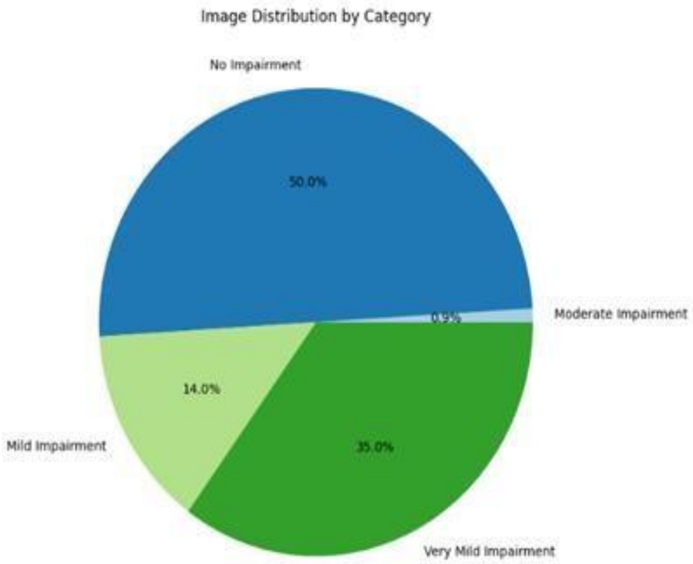

Fig.6: Percentage distribution of images per category in the testing dataset.

Pre processing of data

The preprocessing of the MRI images (dataset) improves the quality before it is feeded into the ML models. Usually the preprocessing steps are:

Image Registration: Images are aligned to a standard orientation using templates, such as MNI152, to achieve consistency in the datasets. For instance, the hippocampal segmentation, which has been done using for example FSL, creating a mask isolating this region, turns out to play a very huge role in early detection of Alzheimer's disease and its involvement.

Skull stripping: Removing these non-brain tissues from scans and focusing much on the image of the human brain.

Background removal: Simply removing extraneous noise in these images to bring about greater accuracy and precision with their models.

Histogram Equalization: Contrast images by making equal the distribution of pixel intensities to emphasize structural details.

Models Used

We have used Support Vector Machines (SVM) and the Quantum Support Vector Machines (QSVM) machine learning techniques for the experimentation. The following fig.7 shows the general flow of the SVM model for classification.

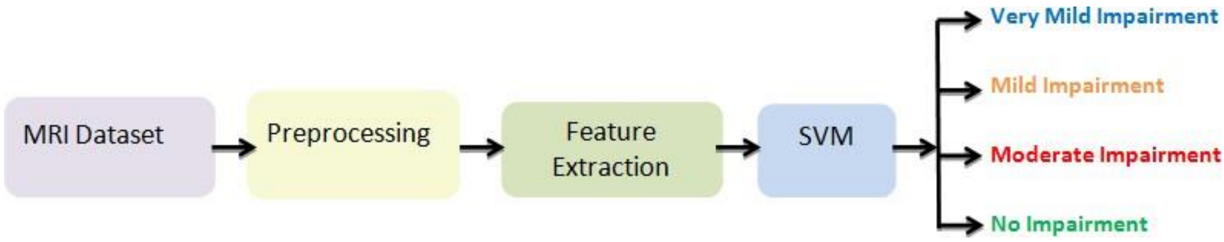

Fig.7 General flow of the SVM model for classification.

The Support Vector Machine is a supervised algorithm typically used for classification and regression tasks. It uses an optimal hyper plane that separates the data points into separate categories based on the classification needed. SVM uses kernel functions to transform the features from the input into higher-dimensional space; hence, it handles non-linearly separable data more efficiently. SVMs are best used for small-to-medium sized datasets and have applications like text classification, image recognition, and anomaly detection. However, SVMs require careful tuning of hyper parameters and can be computationally expensive for very large datasets.

In Alzheimer's detection, the SVM model works by processing the input features, such as the size of the hippocampus and cortical thickness extracted from MRI scans, which are indicative of degeneration in the brain. Using kernel functions, SVM maps these features into higher dimensional spaces, which means it is easier to find the subtle patterns that are not linearly separable in the original space.

Then, the model makes use of determining the optimal decision boundary that effectively separates the classes, including the healthy individuals and patients with mild cognitive impairment as well as those with Alzheimer's disease. This approach thus allows for precise classification for early diagnosis and analysis of disease progression.

Quantum Support Vector Machine is a quantum variant of the standard SVM algorithm. It is developed using techniques such as quantum kernel estimation in quantum computing for more efficient processing of high-dimensional data than standard SVMs. QSVMs make use of quantum parallelism for better scalability and speed of classification.

These could be very important in industries dealing with vast data, including finance, cyber security, and health. However, QSVMs seem to have potential to improve the process of disease diagnosis. The following fig.8 shows the general flow of the QSVM model for classification.

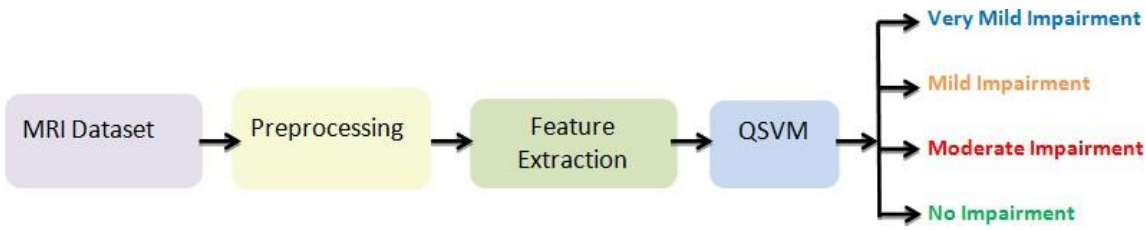

Fig.8: General flow of the QSVM model for classification.

QSVM in Alzheimer's detection uses quantum feature mapping that processes complex MRI data at a faster rate. By using the quantum kernel trick, QSVM can process high dimensional features like hippocampal volume and cortical thickness, which is very precise compared to a classical SVM. This quantum-enhanced approach enables the improved recognition of patterns in brain scans, allowing for more accurate classification of patients into the specified categories. Quantum computing accelerates computations, making QSVM a promising tool for early and reliable Alzheimer's diagnosis.

Splitting of data set as Training and Testing

The given datasets are split into training, validation, and testing datasets to benchmark the performance of the model:

Training Set: Data used for training the model, for example 80% of the data.

- Validation Set: The set used in fine-tuning model parameters (for example, 10% of the data).

- Testing Set: The set on which the last judgment of the model's performance is done, for example, 10% of the data.

Training and Evaluation of the Model

Techniques like data augmentation are employed in order to help the model generalize better through presenting variations in training data.

Performance is monitored using metrics such as Precision, Recall and Accuracy for both the training and validation phases.

The output is classified into very mild impairment, mild impairment, moderate impairment, no impairment.

IV. Result & Discussion

Support Vector Machine (SVM), and Quantum Support Vector Machine (Q-SVM) were assessed using Precision, Recall, and Accuracy metrics. The results are summarized in Table 3.

Table3: Performance Metrics of Classical and Quantum Models.

Model	SVM	Q-SVM
Precision	0.78	0.85
Recall	0.89	1.00
Accuracy	0.89	0.85

Performance Analysis

- QSVM achieves the highest precision (0.85), followed by SVM(0.78), showing the betterness of quantum support vector machines over the classical SVM.
- SVM has a recall of 0.89 and Q-SVM achieves the highest recall of 1.00, indicating that it correctly classifies all positive cases without false negatives.
- SVM achieves the highest accuracy (0.89), followed by Q-SVM (0.85), showing the robustness of both classical and quantum support vector machines.

Visualization of Results from classical SVM

Confusion Matrix:

On X-axis: Predicted Labels (What the SVM model predicted) On Y-axis: True Labels (Actual Ground truth). The heatmap shows how many times each class was predicted correctly or incorrectly. This is shown in the following fig.9.

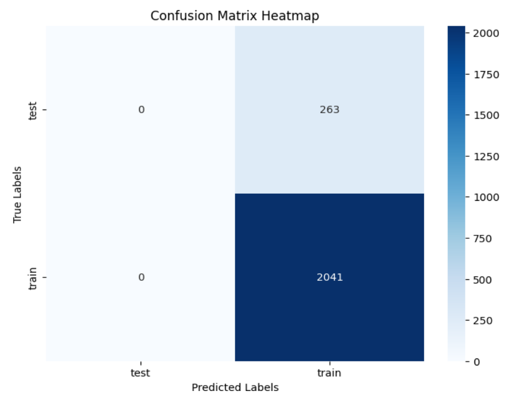

Fig.9: SVM Confusion Matrix

Classification Report:

On X-axis: Metrics (Precision, Recall, Accuracy) 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.

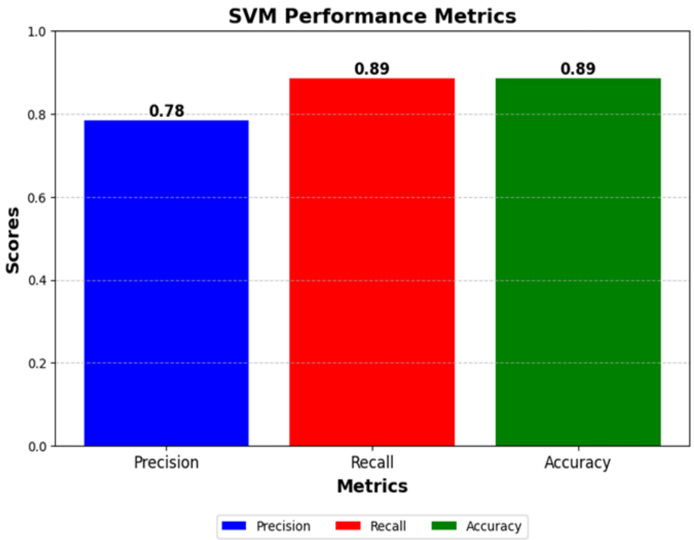

Fig.10: SVM Evaluation Metrics.

ROC Curve:

On X-axis: False Positive Rate (FPR) i.e (Ratio of incorrectly classified negative samples)

On Y-axis: True Positive Rate (TPR) i.e (Ratio of correctly classified positive samples)

The curve shows how well the model distinguishes between classes. A perfect classifier would have a curve that hugs the top-left corner. This is shown in the following fig. 11.

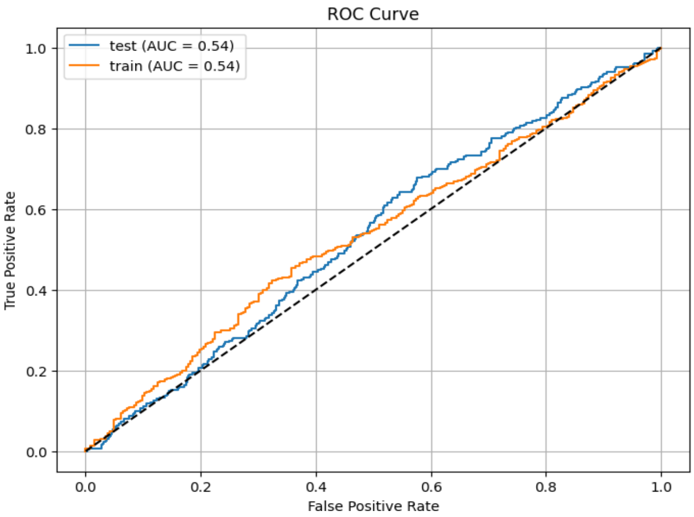

Fig.11: ROC Curve

Visualization of Results from Q-SVM

Confusion Matrix :

On X-axis (Predicted Labels): What the QSVM model predicted (Non-Alzheimer, Alzheimer). On Y-axis (True Labels): The actual ground truth labels (Non-Alzheimer, Alzheimer) and cells presents the number of instances classified into each category:

- Top-left: True Negatives (TN)→Non-Alzheimer correctly predicted.
- Top-right: False Positives (FP)→Non-Alzheimer misclassified as Alzheimer.
- Bottom-left: False Negatives (FN)→Alzheimer misclassified as Non-Alzheimer.
- Bottom-right: True Positives (TP)→Alzheimer correctly predicted.

This is shown in the following fig.12.

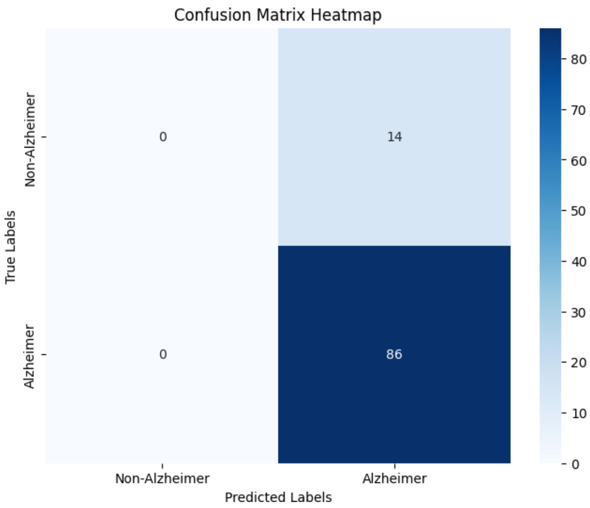

Fig.12: QSVM Confusion Matrix

Classification Report:

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). The bars represent scores for each class (Alzheimer & Non-Alzheimer) under different metrics. This is shown in the following fig.11.

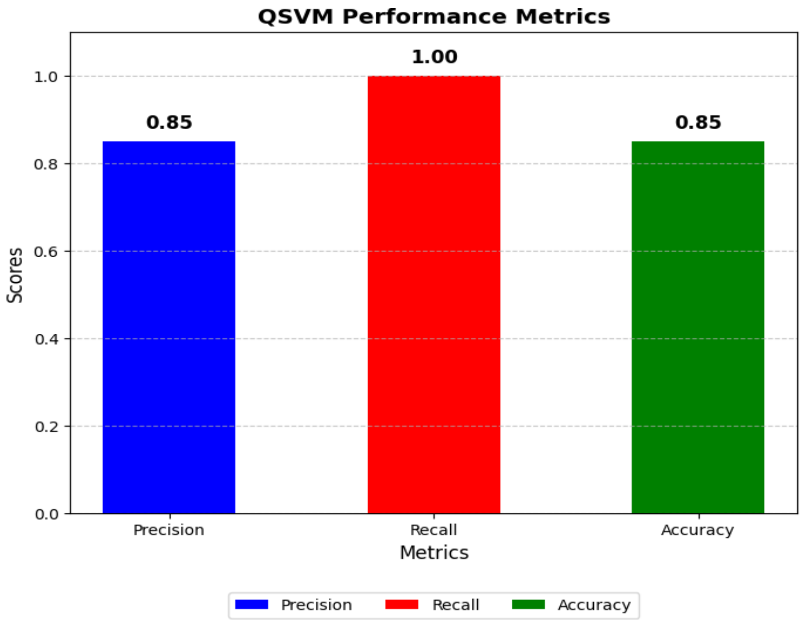

Fig.11: QSVM Evaluation Metrics

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

Data Augmentation and Preprocessing

To enhance model generalization and robustness, data augmentation techniques were employed, including image rotation, flipping, noise addition, and contrast enhancement. These techniques improve the model's ability to learn diverse patterns and prevent over fitting.

Additionally, preprocessing techniques such as normalization, feature extraction, and dimensionality reduction were applied to improve model stability and training efficiency. These preprocessing steps are particularly crucial in quantum models, where data encoding plays a vital role in overall performance.

Clinical Implications

They collectively focus on the earlier diagnosis and proper staging among the AD stages of the individual (very mild impairment, mild impairment, moderate impairment, no impairment). Methods generally improve the diagnosis for it to be more reliable in terms of accuracy, but earlier interventions are made that may help stop or at least delay the degenerative process.

V. Conclusions

This work, through various investigations and experimentation, suggests that the management of Alzheimer's disease needs early detection in relation to significant impacts on cognitive functions and the quality of life. Investigations point out that application of Quantum Machine Learning, for instance, QSVM can make diagnosis very precise. Based on methodologies centered upon some of the key structures targeted early inthe pathology of Alzheimer's disease - particularly the hippocampus, with notable atrophy within it very early in Alzheimer's disease itself-it presents a rigorous basis for differentiating patients clearly into one of three categories: very mild impairment, mild impairment, moderate impairment, no impairment.

High precision and recall has been achieved in all the datasets based on integration of transfer learning. Results thus validate that deep learning models can be efficiently applied to medical images and emphasize its real-world application in clinical setups.

Apart from that, the studies show the need for proper preprocessing techniques such as image registration, skull stripping, and histogram equalization, which improve the quality of images and, hence, the performance of models. Progressive data augmentation strategies also enhance generalization models with predictions remaining reliable across different patient populations.

Such basic contributions of these studies are thus user interfaces, making healthcare professionals use AI-driven tools effectively. The platforms provide the users with a visual presentation of their images in both 2D and 3D formats, allowing them to analyze and monitor disease progress intuitively.

In summary, collective findings from the studies strongly justify the application of AI-based diagnostic tools in clinics. The methods that have been mentioned not only facilitate the understanding of Alzheimer's disease but also help initiate timely interventions with the prospect of improving the prognosis of the patient. Further studies should include multi-modal data incorporation and also test other machine learning methods to better polish these techniques so that they become more useful for real-life application.

VI. Future Scope

Multimodal Integration of Data

The future work should integrate multimodal neuroimaging data that consist of MRI, fMRI, PET scans, and genetic information. Multimodality might enhance the robustness of the diagnostic models better through offering a larger-scale vision of the biological changes linked to the disease Alzheimer's. Potentially, it might increase the accuracy for distinguishing different stages between cognitive impairment and AD.

Advanced machine learning techniques

Plenty of scope is left out and in practice for further techniques other than the ones the CNN architectures portray these days. Long term studies on how ensemble techniques and recurrent neural network techniques and also the attention mechanism can be utilized even more to create an even better model with increased accuracy or maybe unsupervised learning for potential identification of biomarkers.

Studies with longitudinal basis in respect to the progress of the disease

Longitudinal studies will help track patients over time and give a good insight into the progression of Alzheimer's disease. Changes in neuroimaging data analyzed with clinical assessments will allow researchers to develop predictive models that classify current stages but also predict future cognitive decline.

User-Centric Tools for Clinical Application

Translation of these research findings into clinical practice will demand such interfaces to be designed in tool sets that are easy to use for clinicians. Future work will then be toward building such tools for enhancing the real-time analysis and visualization of patient data that will guide the rapid decisions that clinicians make.

Approaches to Personalized Medicine

Research should be targeted at the formulation of customized approaches in diagnostic and therapeutic strategies based on individual patient profiles. The approach can be made more effective for the management of Alzheimer's disease by incorporating machine learning algorithms with genetic, environmental, and lifestyle factors.

Collaboration with Clinical Practices

Real-life validation of AI-based diagnosis will depend upon collaborations formed between researchers and clinical practitioners to work on studies and come up with data collections on different populations for improved generalization of results.

Early Interventions Strategies

The upcoming research studies should instead target early interventions by means of AI-based strategies. The findings from the diagnostic procedures based on AI-based methodologies can then detect and treat MCI and even early AD cases more timely. This would probably give better patient outcomes because interventions at an earlier therapeutic stage could potentially be much improved.

Ethical concerns and data protection

The development of frameworks should be ethical but, at the same time, maximize the benefits of AI in diagnosing Alzheimer's disease. Patient's data privacy and algorithmic bias are two common

Issues that come up when integrating AI into healthcare.

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