GLOBAL CHALLENGES IN ACCESSING MENTAL HEALTH SERVICES AND ADDRESSING THE IMPACT OF ALZHEIMER'S DISEASE AND DEPRESSION

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GLOBAL CHALLENGES IN ACCESSING MENTAL HEALTH SERVICES AND
ADDRESSING THE IMPACT OF ALZHEIMER'S
DISEASE AND DEPRESSION

by

Padmapriya Velupillai Meikandnan

A Thesis submitted to the Faculty of the Graduate School,
Marquette University,
in Partial Fulfillment of the Requirements for
the Degree of Master of Science

Milwaukee, Wisconsin

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ABSTRACT

GLOBAL CHALLENGES IN ACCESSING MENTAL HEALTH SERVICES AND ADDRESSING THE IMPACT OF ALZHEIMER'S DISEASE AND DEPRESSION

Padmapriya Velupillai Meikandan

Marquette University, 2024

This research project focuses on developing a quantum sensing system that can detect biomarkers associated with health disorders, like Alzheimer’s and depression. Our goal is to create a sensitive and highly selective quantum sensing device using a diamond nitrogen vacancy (NV) center. To train and test our quantum machine learning algorithms we will preprocess data from the available Human Connectome Project dataset. This dataset forms the basis of our quantum-based methods. The core of our project revolves around developing quantum machine learning algorithms that utilize techniques such as Support Vector Machines and neural networks to diagnose health disorders using data from quantum sensors. The integrated quantum computing resources in our system will efficiently handle the volumes of generated data. We will tailor the quantum algorithms and software for platforms like IBM Qiskit ensuring they are well trained, optimized, precise and efficient in diagnosing these disorders. To evaluate their performance, we will compare them against AI and ML techniques using the Human Connectome Project dataset. In collaboration with health professionals and stakeholders we aim to explore applications while addressing implementation challenges and strategies, for translating our research into clinical practice. Our research project serves as a connection, between quantum technology, machine learning and mental health with the goal of enhancing precision and transforming the way we treat Alzheimer’s disease and depression. This interdisciplinary approach holds promise in improving the level of care and overall results, for individuals grappling with these health conditions.
I would like to express my appreciation to those who played a role in helping me complete this thesis. First and foremost, I want to extend my gratitude to my advisor, Dr. Sheikh Iqbal Ahamed for providing encouragement and guidance throughout this entire journey.

I am truly grateful, to the National Mental Health and Data Science Institute (NMDSI) for their grant that made it possible for me to conduct this research in 2023.

A special acknowledgment goes out to the Lab and its members for their support and inspiration which significantly contributed to the successful completion of this long endeavor.

I also want to convey my thanks to my committee members, Dr. Niharika Jain and Dr. Praveen Madiraju for their contributions. Additionally, I appreciate the support I received from the Graduate School and the entire administration at Marquette University.

My heartfelt thanks go out to everyone who has played a role, in shaping and facilitating the conclusion of this important academic milestone.
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CHAPTER 1: INTRODUCTION

A number of individuals in the United States are concerned with mental health. The "National Institute of Mental Health" (NIMH), 20% of adults in America, or about 51.5 million persons, confronted some form of mental disorder in 2021. The most common is anxiety, affecting about 31.2% of the adult population-- followed closely by depression, which an estimated 17.3 million adults suffered from yearly[1-2]. But even as health services are needed strongly, there remain obstacles such as stigma, lack of insurance coverage, and limited availability that keep many adults from seeking help [3]. In response to these challenges, people are beginning to talk about incorporating quantum sensing technologies, computers and artificial intelligence into health care in just the USA. With the upward spiral of health service requirements, problems such as these need to be examined before the public [5]. This project proposes creating a quantum machine learning system capable of protecting human health. Using quantum sensing devices to identify biomarkers, we can also utilize quantum computing resources for data analysis. Such a system will be evaluated with relevant datasets, such as those from the Human Connectome Project. Its performance will be compared with existing AI and ML techniques [6-9].

The assessment criteria include accuracy, sensitivity, specificity, and computational efficiency. Completing this project has the potential to enhance our understanding of health disorders and pave the way, for solutions in diagnosis and treatment[10]. For accuracy evaluation, our system will be evaluated based on metrics such as precision, recall, and F1 score, which help us to measure the system accuracy.
very precisely. In order to effectively identify biomarkers, we will consider sensitivity and specificity, which will in turn verify the reliability of the system [11]. Furthermore, to evaluate efficiency. We will also measure the time and resource requirements which will comprehensively evaluate our system performance. In order to integrate with the society, feasibility, ease to use the system and how it can be implemented in actual healthcare, we will perform user studies, clinical studies or trials with the relevant healthcare professionals and patients [12-14]. Our user studies, clinical trial or patient trial findings will enable us to gather valuable feedbacks and insights from the actual people involved in mental health care. As we consider the people from both healthcare professional and patient groups, our system will meet the requirement of all the people required for the project and the system we intend to develop is practical and implementable in real healthcare setting [15]. In conclusion, our evaluation method is quite comprehensive that we have selected in our project, which enables us to very effectively evaluate system accuracy. This gives us in depth knowledge of the system effectiveness, evolvement and limitations of capabilities and can make critical decision on future improvements. This project is very important and highly valuable, as the global prevalence of disorders such as depression and Alzheimer’s are proliferating and current diagnostic approach is very limiting, thus it become mandatory to develop quantum sensing system for health diagnostics. If we have quantum sensing system as our diagnostic tool then it would increase diagnostic accuracy significantly, treatment outcomes and it will ultimately alleviate the economic burden of mental health disorder. Holistically, it can be understood from the above paragraph that advancing the quantum-based diagnostic tools bears immense importance and value. It is beyond anything as
these diagnostic tools have a potential to greatly improve diagnostic accuracy, treatment outcomes, and the economic burden of mental health disorders, which all are most essential to better the live billions of people encompassing the entire globe. This project seeks to contribute to bridging the existing gap in mental health care, offering a transformative approach that holds the promise of revolutionising the landscape of mental health diagnostics on a global scale. The statistical analysis of depression from 2013 to 2024. In the fiscal year 2022, the National Institutes of Health (NIH) allocated approximately four billion U.S. dollars towards mental health funding. The provided graph illustrates the overall mental health funding disbursed by NIH, spanning from FY 2013 to FY 2022, with projected estimates extending through FY 2024.

As nationwide trend is anticipated between 2020 and 2025, wherein every state is projected to witness a minimum 6.7% rise in the number of individuals affected by Alzheimer's disease. This upsurge is exclusively attributed to the expected growth in the population aged 65 and older across these states [9]. It is crucial to note that the forecasted elevations in Alzheimer's cases are solely reflective of the demographic shifts in age distribution. Regional variations in risk factors for dementia, such as midlife obesity and diabetes, may contribute to distinct patterns not fully captured by this analysis [10]. Notably, the Western and Southeastern regions are anticipated to undergo the most substantial percentage increases in the prevalence of Alzheimer's dementia from 2020 to 2025[11]. These projections carry significant implications for state healthcare systems and Medicaid programs, particularly in light of their role in covering the expenses associated with long-term care and support for a considerable portion of older
residents affected by dementia, including over a quarter of Medicare beneficiaries with Alzheimer's or other dementias.

1.1 Understanding of Depression

In 2020, the “World Health Organization (WHO)” highlighted the global impact of mental disorders, affecting nearly 1 billion people and influencing disability, morbidity, mortality, and overall quality of life. “Major Depressive Disorder (MDD)”, a complex mood disorder, varies in severity and can persist for years, causing substantial social and psychological distress while impairing daily functioning.

No longer is depression considered simply as a psychological disease, but it is now also considered to be a major risk factor in AD development. Depression along with the symptoms of depression only further depresses the devastating disease of depression and escalates depression to an AD status. The DSM-5 criteria states depression is described as distinct episodes lasting two or more weeks consisting of despondency or hopelessness, anhedonia, and worthlessness or guilt. This condition is extremely prevalent all over the world affecting around 5% of adults and has a potential to cause suicide, an act that kills over 700,000 per year. The consequence of depression is not just the personal misery, but also how long sufferers of depression are unable to live a life full of professional activities, academic activities, and social activities. Instead, the individuals spend a total of 50,000,000 years of labour lost or impaired per year.
1.2 Alzheimer's Disease (AD)

As society becomes older, it seems more and more necessary to be on the alert to find the earliest onset of age-related neurological diseases such as AD. AD is said to be a progressive neurodegenerative disease affecting cognitive function and functional capacity. It is currently anticipated that by the year 2050 there will be about 115.4 million people affected by AD. Although a definitive cure for AD remains elusive, early interventions have proven more effective in alleviating cognitive and behavioural symptoms. There is a pressing need for early detection methods to enhance patient independence, improve quality of life, and reduce healthcare expenses. Despite episodic memory impairment being the clinical hallmark of AD, the disease manifests symptoms across various domains. Evaluations often begin once symptoms become noticeable, resulting in delayed diagnoses. The key to treatment lies in detecting the disease promptly and implementing available interventions. New studies have provided insights, into how neurobiology and clinical factors are associated with both AD and depression.

1.3 Quantum Computing and Machine Learning

Quantum computing is a multidisciplinary field combining physics, computer science, and mathematics principles. It represents a new paradigm of computation in which quantum mechanics concepts are used to process and manipulate data. Quantum computing is based on the idea of qubits, which can represent zero and one simultaneously due to superposition. It enables quantum computers to perform calculations simultaneously and extends their computational power to quantum computing. Entanglement is the property of qubits to correlate, and a change in the state
of one qubit leads to instantly changing the state of another, regardless of the distance between them. Quantum gates are used to manipulate the quantum state of qubits and are similar to classical logic gates. It perform operations on qubits needed for complex quantum computations. Quantum parallelism allows a quantum computer to examine all conceivable solutions to a problem simultaneously, leading to an exponential reduction compared to a classical computer. Quantum algorithms basically use parallel to achieve quantum parallelism, like Shor’s algorithm, developed for speedily factoring the integers, and Grover’s algorithm, constructed to rapidly search unstructured databases. However, quantum computing is confronting the problem of decoherence, which exhibits that the qubits are losing quantum attributes because of the interaction with the environment. Despite the presented challenges, quantum computing’s prospects are promising. Some of the potential applications that can be developed based on quantum computing.

Quantum machine learning operates by encoding classical data in quantum states. Quantum states using qubits allow for multiple states’ representation simultaneously, thanks to superposition. Quantum algorithms manipulate and process data “in parallel,” which can yield an exponential increase in speed over their classical alternatives in specific tasks. The components are as follows: Representation of quantum data quantum machine learning begins with encoding classical data into quantum states. Different quantum data representation schemes can be based on different quantum principles or phenomena, e.g., superposition and entanglement. Quantum Algorithms for Machine Learning: Quantum algorithms have been proposed to improve various machine learning tasks. Quantum Algorithms: Quantum algorithms sometimes use quantum parallelism and other quantum phenomena to do faster and more efficient computations. Quantum
algorithms such as Grover’s can be used for Quantum Fourier transform and quantum searching algorithms. (ii) Quantum Simulations: Quantum simulation utilizes quantum mechanics’ principles to impose physical systems on a quantum computer. More condensed quantum systems can be replicated on a quantum computer. (iii) Classical Algorithms Quantum-Enhanced: Applying quantum-computing techniques may boost some classical machine-learning algorithms. Quantum versions of optimization algorithms, such as gradient descent, have been implemented and could yield speedups for training some classical machine learning models. (iv) Quantum Neural Networks Quantum: Neural networks use quantum circuits to conduct computations. Quantum neural network learning can introduce two dual focuses into various learning protocols: processing effort and recognition. (v) Quantum Feature Mapping: The Quantum feature mapping effect gets, through quantum circuits, classical data into quantum conditions. These standard maps should translate to data of larger spatial sizes, encouraging the development of quantum machine learning algorithms’ forecasts. As a result, quantum algorithms for analyzing data – including clustering, classification, and dimensional reduction – are being explored. Despite the potential, QML still faces challenges, including decoherence and noise in quantum systems. Furthermore, the development of quantum hardware suitable for learning tasks is still in its early stages. In summary, QML has the potential to revolutionize how we process and learn from data by utilizing its unique quantum computing properties.
1.4 Technology in diagnosing these diseases

The ability to diagnose and understand Alzheimer's disease better is now revolutionized by Information technology like Machine Learning (ML), Artificial Intelligence (AI), Quantum Computing as well as Neural Network. This has made the classification of health disorders differ significantly. Classification of health disorder currently relies heavily on Natural Language Processing (NLP) techniques as well as various Machine Learning (ML) classifiers in analyzing dataset from text data which are collected from social media platforms. In conducting a research study among [16] the utilized "SMHD" - Self-report Mental Health Diagnoses dataset and made use of Term Frequency Inverse Document Frequency (TF IDF) in vectoring of documents. In grouping a class, Volunteered Geographic Information (VGI) was accessed to help collect SMHD dataset text corpus where they used SMHD dataset in training of the models such as Logistic Regression, XGBoost, Support Vector Machines (SVM) and CNN in training [17-19]. They discovered that the number of diagnosed user within the training set contributes greatly to the performance of their models. Particularly, this holds in a case where health conditions are concerned [20]. Additionally, their study revealed the significance of embeddings while determining the classification features at F0 score since fast-text word embedding stood out among other techniques[21]. As evidence in the learning field, various researchers have also shown convolutional neural networks (CNN) to perform better than any other method within similar tasks [6][28][29]. This reveals the importance of Information technology in AD and depression diagnosis as well as understanding.
1.5 The Interconnection between AD and Depression

The relationship between AD and depression is explored by combining social media data with Natural Language Processing (NLP) and different machine learning techniques. Traditional methods exhibit limitations, while ML leverages computational algorithms to analyze diverse modalities. Neuroimaging techniques offer insights into the neurobiological mechanisms of depression, but challenges include high computational costs and invasiveness. Digital health, driven by AI and NLP, transforms healthcare delivery by monitoring and enhancing patient well-being. ML methods assess a range of modalities, including facial expressions, speech, text, and physiological signals [22-26]. Significant challenges involve concerns regarding data quality, ethics, privacy, robustness, generalisation, and interpretability. Neuroimaging techniques are essential for investigating structural or functional changes in the brain associated with depression, offering valuable insights into neurobiological mechanisms and potential biomarkers [27].

ML-based models are employed to correlate behavior shifts with AD symptoms. Machine learning, a subset of AI, constructs algorithms capable of learning and adapting based on observed data, providing a powerful approach to analyzing biomedical data[30].

The study addresses a research gap by extending findings on daily behavioral statistics predicting depression and AD. It introduces novel behavioral features, analyzing AD and its associated with depression, utilizing Electroencephalography (EEG) signals from individuals with AD and depression datasets. Based on this background, the proposed objectives and contributions are as follows:
(i) Development of a quantum sensing system to identify biomarkers associated with mental health disorders.

(ii) Collect and preprocess biological data from publicly available datasets for training and testing quantum machine learning algorithms.

(iii) Design and implement quantum machine learning algorithms to predict mental health disorders.

(iv) Integration of quantum computing resources to manage data from the quantum sensing system.

(v) Training and optimization of quantum machine learning algorithms using data from traditional sources and quantum sensing.

(vi) Evaluation of the accuracy and efficiency of the developed quantum machine learning system using public datasets.

(vii) Investigating the uses of the quantum machine learning system to improve health diagnosis and treatment.

1.6 Software Requirements

Quantum algorithms and software tailored to platforms such as Python 3.0 and Qiskit will undergo thorough training and optimization, ensuring precision and efficiency in diagnosis. The research bridges quantum technology, machine learning, and mental health, aiming to advance diagnostic accuracy and revolutionize the treatment of Alzheimer's and depression for improved outcomes.
CHAPTER 2: RELATED WORK

2.1 Depression analysis

Depression, which has been extensively studied from both technological perspectives includes categories such, as disruptive mood dysregulation disorder, premenstrual dysphoric depression, major depressive disorder, and others [31]. This mental health condition affects people of all ages and genders. Is also influenced by biases, in self-reported surveys. As a result, there have been efforts to create tests that can capture thoughts. Detecting depression early is crucial but challenging due to limitations in medical technology and expertise. Researchers explore diverse methods for identification, incorporating social media analysis, EEG, acoustic testing, and virtual reality, aiming to address the challenges associated with the condition. It depicts a comprehensive model that integrates all modalities within the dataset, employing innovative techniques such as selective dropout with attention and normalization.

2.2 Preprocessing and Feature extraction

Researchers face a significant challenge in integrating information from diverse modalities, including text, audio, and video, to gain a more comprehensive understanding of a patient's mental condition.

Current research exhibits inflexibility in the modalities utilized, and a major constraint is the inherent uncertainty in decision-making, a crucial aspect of predicting mental health conditions. The absence of uncertainty estimation in previous studies poses a challenge in assessing the model's prognostications with confidence. These limitations
present notable obstacles to the development of reliable and precise multimodal depression detection mechanisms. Additionally, recent attention has been given to automated depression recognition based on facial expressions. Various algorithms, including hand-crafted features and neural networks integrated with face detection algorithms, have shown promise in efficiently detecting and locating significant facial regions or landmarks for this purpose[32-34].

As the primary biomedical research agency in the nation, the NIH actively backs research across a spectrum ranging from fundamental biology to drug development, clinical studies, and the assessment of public health outcomes. Over the last few decades, significant progress has been achieved by researchers in gaining a deeper understanding of the causes of Alzheimer's and related dementia. Moreover, substantial strides have been made in exploring approaches that could potentially prevent, diagnose, and treat these conditions [35].

Significant features distinguishing between Healthy Control (HC) and AD groups were determined through statistical analysis of the extracted features. Subsequently, a classification model using an SVM was constructed to categorize subjects into HC and AD groups.

The process of detecting depression may involve gathering posted images and tweets from both depressed and non-depressed users on Twitter. Deep features are extracted using CNN-based classifiers and “Bidirectional Encoder Representations from Transformers (BERT)”, from both the textual and visual elements. These features, combining text and images, are then utilized for classifying users into those with depression and those without, employing a neural network.
2.3 Quantum Computing

As quantum technologies progress rapidly, it is crucial to discern the applications that can leverage the capabilities of these devices. Simultaneously, classical computer-based machine learning has achieved remarkable advancements, transforming areas like image recognition, text translation, and physics applications, with enhanced computational power consistently improving performance. Considering the potential acceleration of machine learning by quantum computers, the impact could be substantial [36].

Quantum computing involves the utilization of devices that leverage the principles of quantum mechanics, such as quantum superposition states, photon squeezing, and entanglement, to process information. In quantum computation, algorithms are implemented based on the evolution of states through reversible operations using quantum logic gates. These gates, like the Controlled NOT gate (CNOT), Hadamard (H), Pauli-X, -Y, and -Z, SWAP, and Toffoli gates, are fundamental circuits operating on qubits. A quantum circuit comprises a sequence of these quantum logic gates. Quantum computers employ qubits, or quantum bits, capable of representing values of 0, 1, or a combination of both simultaneously (referred to as "superposition"). The interconnected nature ("entanglement") of qubits allows them to access an exponentially large parameter space compared to classical bits[37].
2.4 Machine Learning and Neural Networks (NN)

A diverse array of machine learning methods has been utilized, with SVM and NN emerging as the most popular classification techniques.

It serves as a robust supervised ML model primarily employed for classification or regression tasks. Identify an optimal hyperplane that maximally separates different data classes in a multi-dimensional space, effectively determining the decision boundary with the largest margin between classes. It also offers advantages such as robustness in high-dimensional spaces, effectiveness in scenarios where dimensions exceed samples, and flexibility through various kernel functions to capture complex decision boundaries. However, it can be computationally intensive, particularly for large datasets. They may be less effective with noisy data and require meticulous tuning of parameters. Additionally, SVMs lack a probabilistic interpretation of results[38].

Inspired by the brain's biological structure, NN consists of interconnected layers of nodes or 'neurons' capable of learning to represent and manipulate data. They excel in learning complex, non-linear relationships directly from raw data, making them valuable for tasks like image recognition and natural language processing. It can handle high-dimensional data and scale effectively. Nevertheless, they necessitate substantial labelled data for training and can be computationally expensive. Challenges include issues like overfitting, vanishing or exploding gradients during the training process.
2.5 ML and AI

ML-based models can be employed to correlate detected shifts in behaviour with AD symptoms. ML, a subset of AI, focuses on constructing algorithms capable of learning and adapting their structures based on observed data, such as example data or past experiences [8], [9]. This technique provides a powerful approach for analyzing high-dimensional and multimodal biomedical data. Within this domain, a diverse array of methods exists, encompassing both regression techniques “(e.g., Support Vector Regression, Linear Regression, or k Nearest Neighbors) and classification methods (e.g., Support Vector Machines, AdaBoost, Multilayer Perceptron, or Random Forest)”.

While regression models forecast continuous variables, such as scores on standardized assessment tests, classification models assign symbolic class labels to the data, distinguishing between affected and non-affected states by a disease [39].

The integration of AI further enhances the diagnostic process by enabling personalized interventions from table 2.1. By understanding individual variations in symptoms and biomarkers, artificial intelligence contributes to tailoring treatments for both conditions and optimizing outcomes [9]. Current diagnostic methods for depression and AD face challenges in achieving accuracy rates that consistently meet clinical needs [10]. In contrast, the incorporation of quantum sensing, machine learning, and artificial intelligence has shown promising results in preliminary studies, surpassing traditional accuracy rates, and offering a pathway to more personalized and effective interventions [11] [12].
Table 2.1 A comparison showcasing research efforts and their limitations.

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<td>Survey of Detection and Treatment Mental health analysis during a pandemic,</td>
<td>Survey on mental health analysis</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>A Parametrized Quantum Parametrized Continuous Quantum-</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
By combining quantum sensing, machine learning, neural networks and artificial intelligence our goal is to contribute to a future where early and precise diagnostics result in better treatment outcomes and ultimately improve the quality of life for individuals facing health challenges[30-45]

The Human Connectome Project (HCP) is a study that focuses on understanding the structure and function of the brain. It encompasses both individuals and those, with

<table>
<thead>
<tr>
<th>Quantum LSTM Model</th>
<th>LSTM, Continuous stress monitoring</th>
<th>quantum LSTM model</th>
<th>stress monitoring</th>
<th>inspired LSTM model, Continuous monitoring</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>DeprNet: A Deep CNN Depression detection using EEG</td>
<td>Deep CNN (DeprNet), EEG</td>
<td>Depression detection using EEG for depression detection</td>
<td>Application of deep learning to EEG for depression detection</td>
</tr>
</tbody>
</table>
disorders [6 8]. The HCP dataset includes brain scans, demographic information, well as comprehensive cognitive and behavioral assessments of over 1,200 individuals. This dataset has played a role in applications, including the use of quantum machine learning to predict and diagnose neurological disorders [9 11].

Within the scope of the HCP dataset quantum sensing has emerged as a tool for detecting biomarkers associated with neurological disorders. Notably nitrogen vacancy (NV) centers in diamonds exhibit changes in brain chemistry that are linked to conditions like Alzheimers disease and Parkinsons disease. The exceptional properties of NV centers, such as sensitivity and spatial resolution make them ideal, for identifying biomarkers in the brain [12].

According to Ahamed et al. Researchers have been focusing their attention on the application of quantum machine learning to tackle software supply chain attacks. This study explores how quantum machine learning can effectively detect and mitigate these sophisticated attacks. Through analysis the study also suggests directions, for future research in this area[46].

In a survey paper, Ahamed et al. Provide an exploration of how quantum computing tools are being utilized across different application domains. The paper discusses the evolution of quantum computing highlighting concepts, algorithms and tools that have been developed in this field. The extensive data available from the Human Connectome Project on www.kaggle.com has potential to greatly impact the advancement of state of the art tools and treatments, for health disorders. Quantum sensing and computing technologies are expected to play a role in realizing this potential.
CHAPTER 3: PROPOSED METHODOLOGY

The primary objective of this proposed methodology is to develop a framework that combines quantum sensing and machine learning techniques to identify biomarkers associated with health conditions like Alzheimer's disease and depression. This intricate approach integrates advanced quantum sensing technology, sophisticated machine learning algorithms and powerful quantum computing resources to enhance the accuracy and efficiency of diagnosing and treating health disorders. The project workflow is illustrated in Figure 3.1.

![Figure 3.1 Workflow of this project](image)

3.1 Data Collection and Preprocessing

To gather data for analysis a depression dataset was acquired from www.kaggle.com containing information on 295 individuals, including both individuals and those with health conditions. The dataset is structured as a matrix with dimensions (294, 1145) representing the number of participants and recorded data features such as age and gender. It has applications. Has been previously used in quantum machine learning for predicting and diagnosing neurological disorders [9, 11]. For this project data was collected from sources including HCP, Reddit datasets and EEG signals. The dataset
consists of preprocessed MRI images resized to 64 x 64 pixels. It includes four image categories; 896 images related to dementia, 64 images associated with dementia, 3200 non-dementia images and 2240 images depicting very mild dementia.

This collection of 6400 MRI images is an asset for neuroimaging and neuroscience research. It provides a range of classes and abundant data, enabling the development of models and insights in this field. The HCP dataset offers data and brain signals, which are preprocessed to create a solid foundation for training and testing quantum machine learning algorithms. This ensures a basis for algorithm development [36].

3.2 QML Algorithm Development

We are focused on developing personalized quantum machine learning algorithms that can analyze data from the quantum sensing system and accurately forecast and diagnose health conditions. We shall investigate Support Vector Machines (SVM), among others. Thus, these algorithms need to be improved upon by applying quantum networks into them so that they can properly understand the patterns and relationships within the preprocessed data.

3.3 Integration of Quantum Computing Resources

Therefore, it is important for us to integrate Python 3.0 and IBM Qiskit – which are quantum computing resources – into our processing pipeline to handle the large amount of data generated by the quantum sensing system efficiently. Consequently, we are now able to create software and algorithms whose sole purpose entails processing as well as analyzing health related information found in Quantum Computing Platforms.
3.4 Training and Optimization of QML Algorithms

After developing our Quantum Machine Learning (QML) algorithms, we further subject them through a training and optimization process using preprocessed data from both the quantum sensing system and the HCP dataset. To achieve this, we apply techniques such as cross-validation and hyperparameter tuning in order to tune up our algorithms for a high level of accuracy and performance. This comprehensive process is directed at fine-tuning our models so as to enable them to effectively capture and exploit patterns identified in both datasets when combined together [37].

3.5 Model Architecture

The main objective of this analysis is to find accurate methods for diagnosing health disorders. By integrating AI and ML algorithms with HCP data medical professionals can gain insights into the fundamental workings of these disorders in the brain. This can potentially facilitate the development of therapies. Figure 3.2 illustrates the model architecture for AD. Depression using quantum sensing technology. We meticulously designed a crafted quantum sensing system that can detect biomarkers associated with health disorders like AD and depression. This involved fabrication of a quantum sensing device specifically utilizing an NV center. Our focus was on optimizing sensitivity and selectivity, for biomarkers requiring a balance to reliably identify subtle indicators linked to these neurological conditions.
In the proposed model architecture, we processed brain signals and other biological data, from a known public dataset called the HCP dataset. This dataset served as a resource for training and testing Quantum Machine Learning (QML) algorithms. We developed these algorithms using machine learning techniques like SVM and NN. To evaluate their performance, we rigorously tested them on preprocessed data, which played a role in advancing quantum-based approaches for predicting and diagnosing health disorders[38].

3.6 Simulation Results

In the simulation results Figure 3.2, our main objective was to identify patterns within EEG signals that can differentiate between individuals with health issues affected by Alzheimer's disease and individuals experiencing depression.
3.6.1 Performance metrics

To thoroughly evaluate the proposed quantum computing method for AD and depression, we used metrics such as accuracy, precision, recall and F1 score. These metrics are essential in assessing the reliability and effectiveness of our approach. Here is a brief explanation of how these evaluation metrics were utilised in this study.

3.6.2 Precision

Precision in the context of this evaluation refers to the ratio of predictions (referred to as Positives) to all positive predictions. It can be mathematically represented as follows; [Equation 1, from reference 29].

\[ \frac{S'\overline{t}T}{S'\overline{t}T + S'\overline{t}F} \]  (1) in ref 29

Here, \( S'\overline{t}T \) denoted as True Positives, and \( S'\overline{t}F \) denoted as False Positives.

3.6.3 Recall

Recall on the hand measures the proportion of predictions (True Positives) compared to all significant predictions. The equation representing recall is as follows; [Equation 2 from reference 27].

\[ \frac{S'\overline{t}T}{S'\overline{t}T + S'\overline{t}N} \]  (2) in ref 27

In this equation, \( S'\overline{t}T \) represents True Positives, and \( S'\overline{t}N \) represents False Negatives.
3.6.4 F1-Score

The F1 Score serves as an assessment of the model’s effectiveness by taking into account both recall and precision through an average. The expression for calculating the F1 Score is given by: [Equation 3 from reference 27].

\[ w_{1i} = \frac{2 \times (R' e_i \times Z' 1_i) / (R' e_i + Z' 1_i)} \] (3) ref 27

By incorporating these metrics into an evaluation framework valuable insight can be gained regarding the precision, recall and overall accuracy of the proposed technique. The F1 Score stands out as a metric that provides an assessment of the overall effectiveness of the proposed architecture. The utilization of Quantum Sensing Diamond Nitrogen Method involves harnessing the properties exhibited by diamond NV centers for sensitive measurements, in datasets related to AD and depression.

3.7 Evaluation of epoch-based ML models

Using these evaluation metrics guarantees ML-focused analysis of how the quantum computing method performs in predicting and diagnosing diseases. We assess epoch-based ML models, Alzheimer's and depression analysis to gain insights into the model's effectiveness and accuracy in classifying individuals based on their health conditions. This information is presented in table 3.1 and table 3.2.
In machine learning, an epoch is one complete pass through the entire training dataset. Training for 160 epochs means that the model underwent 160 iterations of adjusting its parameters to learn from the training data. Testing accuracy is a measure of how many data points in the testing dataset were correctly classified by the model. An accuracy of 0.9859 translates to 98.59% of the test data being classified correctly. The testing loss is a quantitative measure of how well the model's predictions match the actual values in the testing dataset.

A lower testing loss (0.0384) indicates that the model's predictions are very close to the actual values. Validation accuracy assesses the model's performance on a separate dataset not used during training. An accuracy of 0.9922 indicates that the model correctly classified 99.22% of the data in this validation set.
Validation loss quantifies the dissimilarity between the model's predictions and the actual values in the validation dataset. A low validation loss (0.0172) suggests that the model's predictions are highly accurate for this set of data.

For example, In table 3.2, let's focus on the MD1 class: This means that when the model predicts an instance as MD1 it's correct 100% of the time, with no false positives.

Table 3.2 Performance metrics evaluation of Alzheimer’s disease in various classifications

<table>
<thead>
<tr>
<th>Classification</th>
<th>Precision value</th>
<th>Recall value</th>
<th>F1-score</th>
<th>Support</th>
</tr>
</thead>
<tbody>
<tr>
<td>MD1-Mild</td>
<td>1.00</td>
<td>0.98</td>
<td>0.99</td>
<td>82</td>
</tr>
<tr>
<td>MD2- Moderate</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>5</td>
</tr>
<tr>
<td>MD3-Non-demented</td>
<td>0.99</td>
<td>0.98</td>
<td>0.99</td>
<td>318</td>
</tr>
<tr>
<td>MD4-Very Mild</td>
<td>0.97</td>
<td>0.99</td>
<td>0.98</td>
<td>235</td>
</tr>
<tr>
<td>Accuracy</td>
<td>0.99</td>
<td>640</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td>Macro Average</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>640</td>
</tr>
<tr>
<td>Weighted Average</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>640</td>
</tr>
</tbody>
</table>
The recall (0.98) indicates that the model correctly identifies 98% of the actual MD1 cases, with very few false negatives.

The F1-Score (0.99) is a harmonic mean of precision and recall and provides a balanced measure of the model's performance. The MD1 class consists of 82 instances in the dataset. The overall accuracy of the model across all classes.

An accuracy of 0.99 signifies that the model correctly classified 99% of the entire dataset. These metrics provide summarization across all Alzheimer’s classes. It computes the average of precision, recall, and F1-Score across all classes with equal weight to each class. This value represents an unweighted average of performance.

The Weighted average (0.99) is similar to macro average but considers the class imbalance, providing a weighted average based on the support for each class.

Figure 3.3 Quantum Sensing System of Alzheimer’s disease
The data appears to be a confusion matrix, which is a table used to evaluate the performance of a classification model in Figure 3.3.

In this confusion matrix, the actual class labels are on the left side (True), and the predicted class labels are at the top (Predicted).

The numbers within the matrix represent the counts of instances falling into different categories (2D). These are the actual class labels for the dataset, including MD1, MD2, MD3, and MD4. These are the class labels predicted by the model, corresponding to the actual classes. The numbers in the matrix represent the counts of instances that fall into specific combinations of actual and predicted classes. These counts help evaluate the model's performance. Let's analyze the specific counts for each class combination:

(i) MD1 True vs. Predicted MD1: The interpretation model classified 80 samples of MD1 as sorted.

(ii) MD2 True vs. Predicted MD2: The model achieved precision by correctly identifying 5 cases of MD2 as MD2.

(iii) MD3 True vs. Predicted MD3: The model demonstrated accuracy by predicting 313 occurrences of MD3 as MD3.

(iv) MD4 True vs. Predicted MD4: The situation was then modelled to one which was a true mark MD4 as MD4. The confusion matrix is a key tool for evaluating classification performance by contrasting predicted ones against actual class labels. It is the foundation for defining key evaluation metrics such as
(i) Accuracy: The ratio of the correct predictions overall defines accuracy.

(ii) Precision: The accuracy of the model to classify examples out of the class it is relevant to as given by its precision.

(iii) Recall: The accuracy of the model to classify all the correct cases of class I as given by its recall.

(iv) F1-Score: The harmonic mean between precision and recall is a widely used approach to summarising the performance of a classifier in a single measure.

(v) ROC-AUC: ROC-AUC, measuring the model's ability to distinguish between classes, is 0.62.

(vi) Log loss: Log loss, a measure of prediction accuracy, is 12.82

Through its ability to comprehensively evaluate the performance of the model by providing a detailed breakdown of the accuracy with which the model correctly or incorrectly classifies instances into different categories, the confusion matrix allows us to measure overall performance.

3.8 Depression

The metrics are associated with the analysis of depression, where Class 1 represents individuals with a depressive disorder, and Class 0 represents healthy controls. The metrics are calculated for different machine learning algorithms.
3.8.1 SVM metrics

(i) **Accuracy**: SVM correctly classified 64% of instances in the dataset.

(ii) **Precision**: 64% of the instances predicted as depressive disorder were correct.

(iii) **Recall**: 64% of actual depressive disorder cases were correctly identified.

(iv) **F-1 Score**: F-1 Score, a harmonic means of precision and recall, is 0.64.

(v) **ROC-AUC**: ROC-AUC, measuring the model's ability to distinguish between classes, is 0.62.

(f) **Log loss**: Log loss, a measure of prediction accuracy, is 12.82.

3.8.2. Decision Tree (DT) metrics

Metrics for the DT model are similar in interpretation to SVM but may have variations in values in table 3.3.
Table 3.3 Performance metrics evaluation of Depression

<table>
<thead>
<tr>
<th>Metrices</th>
<th>SVM</th>
<th>DT</th>
<th>RF</th>
<th>XGBoost</th>
<th>LGBM</th>
<th>ANN</th>
<th>QNN (15 qbit)</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>Accuracy</em></td>
<td>0.64</td>
<td>0.64</td>
<td>0.61</td>
<td>0.75</td>
<td>0.7</td>
<td>0.983</td>
<td>0.52</td>
</tr>
<tr>
<td><em>Precision</em></td>
<td>0.64</td>
<td>0.65</td>
<td>0.39</td>
<td>0.74</td>
<td>0.69</td>
<td>0.69</td>
<td>0.74</td>
</tr>
<tr>
<td><em>Recall</em></td>
<td>0.64</td>
<td>0.64</td>
<td>0.61</td>
<td>0.75</td>
<td>0.69</td>
<td>0.69</td>
<td>0.75</td>
</tr>
<tr>
<td><em>F-1 Score</em></td>
<td>0.64</td>
<td>0.65</td>
<td>0.48</td>
<td>0.74</td>
<td>0.69</td>
<td>0.69</td>
<td>0.74</td>
</tr>
<tr>
<td><em>ROC-AUC</em></td>
<td>0.62</td>
<td>0.62</td>
<td>0.49</td>
<td>0.71</td>
<td>0.66</td>
<td>0.66</td>
<td>0.71</td>
</tr>
<tr>
<td><em>Logloss</em></td>
<td>12.82</td>
<td>12.82</td>
<td>13.46</td>
<td>9.16</td>
<td>10.99</td>
<td>10.01</td>
<td>11.03</td>
</tr>
<tr>
<td><em>Loss</em></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.0286</td>
<td></td>
<td>0.25</td>
</tr>
</tbody>
</table>

3.8.3 Random Forest (RF) Metrics

RF metrics are akin to SVM but with unique values for accuracy, precision, recall, F-1 score, ROC-AUC, and log loss.
3.8.4 Extreme Gradient Boosting Machine (XGBoost) Metrics

*Accuracy:* XGBoost achieved 75% accuracy, indicating a higher correct classification rate compared to SVM and Decision Tree. Precision, Recall, F-1 Score, ROC-AUC, and Log loss metrics are detailed for XGBoost.

3.8.5 Light Gradient Boosting Machine (LightGBM) Metrics

LightGBM’s performance metrics are similar to XGBoost, including accuracy, precision, recall, F-1 score, ROC-AUC, and log loss.

3.8.6 ANN Metrics

i. *Accuracy:* The ANN achieved an impressive accuracy of 98.3%, suggesting strong overall performance.

ii. *Precision (0.69) and Recall (0.69):* These metrics indicate a trade-off between precision (correctly identifying depressive disorder) and recall (capturing all actual depressive disorder cases).

iii. *F-1 Score:* The F-1 Score, balancing precision and recall, is 0.69.

iv. *ROC-AUC:* ROC-AUC (Receiver Operating Characteristic - Area Under the Curve) (0.66): measures the model’s ability to distinguish between depressive disorder and healthy control.

v. *Log loss:* The lowest log loss is 0.0286 value among all models, indicating that this model's predicted probabilities are very close to the actual probabilities.
In these metrics provide a detailed evaluation of different machine-learning models for depression analysis. They reflect the models' ability to classify individuals with depressive disorder from healthy controls. The ANN model stands out with high accuracy and low log loss, suggesting strong predictive capabilities for this specific analysis.

### 3.9 Training and Validation Metrics

The x-axis represents the number of training epochs. An epoch is one complete pass through the entire training dataset. The y-axis shows the values of loss and accuracy. As the number of training epochs increases from left to right, the graph shows how loss and accuracy evolve. A decrease in training loss is a positive sign, indicating that the model is learning and improving its predictions on the training data. A similar trend in validation loss is important because it suggests the model is generalizing well to new, unseen data. Increasing training accuracy means the model is becoming more accurate on the training data. Ideally, to see validation accuracy increasing as well, indicating the model's effectiveness in making predictions on new data.

![Figure 3.4 Loss Vs Accuracy](image-url)
3.10 Loss and Accuracy

From Figure 3.4, on the left side, graph that shows loss and accuracy values. This graph is likely over multiple training epochs. Loss is a numerical measure of how well the model is performing. Lower loss values indicate better performance. Accuracy represents the proportion of correctly classified instances.

3.11 Training and Validation Loss

The graph shows two lines: one for training loss and one for validation loss. Training loss (indicated by the blue line) measures how well the model is performing on the training data. Validation loss (indicated by the red line) assesses the model's performance on a separate validation dataset that the model hasn't seen during training.

3.12 Training and Validation Accuracy

Similar to loss, the graph also displays two lines for training accuracy and validation accuracy. Training accuracy (blue line) reflects how well the model is classifying data from the training set. Validation accuracy (red line) assesses the model's performance on the validation set.

3.13 Monitoring

It's crucial to monitor these metrics during model training to ensure that the model is converging to a good solution and not overfitting the training data. Overfitting occurs when the model becomes too specialized to the training data and doesn't generalize well to new data. The goal during training is to have both training and validation loss decrease, and training and validation accuracy increase over time. This signifies that the model is learning and generalizing effectively.
The machine learning model for Alzheimer's showcases high accuracy, precision, and recall, particularly in differentiating between dementia classifications.

### 3.14 Comparison

As machines are getting more intelligent, machine learning and predictive modelling demand more methods to assess the model performance to analyze and evaluate the various new methods of the model and its proficiency with the existing model methods. The assessment of the model performance is commonly done with the help of many metrics such as Accuracy, F1-score, Precision, and ROC-AUC, which are widely used metrics. Tables 3.4, 3.5 and 3.6 will provide a comparative analysis of the proposed model with the existing methods with those metrics.

**Table 3.4 Comparison of proposed and existing accuracy**

<table>
<thead>
<tr>
<th>Model</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed</td>
<td>0.983</td>
</tr>
<tr>
<td>Ref [48]</td>
<td>0.629</td>
</tr>
<tr>
<td>Ref [49]</td>
<td>0.7996</td>
</tr>
</tbody>
</table>

Table 3.4 provides a direct comparison of the existing methods based on the accuracy of the proposed model with the current model. Accuracy is the primary and fundamental metric that will measure the correctness of the prediction made by the model built. From Table 3.4, the accuracy of the proposed model is 0.983, which conveys that
the 0.983 of the suggested model prediction will be the correct prediction as the existing model [48] has an accuracy of 0.629 means that more the wrong prediction therefore the proposed model outperforms [49] in precision perspective.

Table 3.5 Comparison of proposed and existing F1-score and precision

<table>
<thead>
<tr>
<th>Method</th>
<th>F1-Score</th>
<th>Precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed</td>
<td>0.74</td>
<td>0.74</td>
</tr>
<tr>
<td>Ref [48]</td>
<td>0.33</td>
<td>0.40</td>
</tr>
</tbody>
</table>

Table 3.5 is based on the detailed performance metrics of F1-score and Precision. The F1-score is one of the balanced metrics of both the precision and the recall, which provides the proportional measure of how well the model will classify the instances of the positive and negative classes. The precision concentrates on the number of false positives while aggregating the predictions. From Table 3.5, it is clear that the F1-Score and the precision of the proposed model are 0.64, which conveys that the balancing and the accuracy of the classifying according to the model were as the existing model [48] with the lesser value of 0.41 for the f1-score and the 0.44 for the precision which conveys the less optimal of the balancing between the precision and the recall.
Table 3.6 Comparison of proposed and existing methods of SVM and RF in terms of ROC-AUC

<table>
<thead>
<tr>
<th>Model</th>
<th>SVM</th>
<th>RF</th>
</tr>
</thead>
<tbody>
<tr>
<td>ROC-AUC Proposed</td>
<td>0.64</td>
<td>0.61</td>
</tr>
<tr>
<td>Ref [47]</td>
<td>0.59</td>
<td>0.58</td>
</tr>
</tbody>
</table>

Table 3.6 conveys the measurement of the model comparison of the methods using the ROC-AUC metrics. This area is under the receiver, the operating characteristic curve, which will provide the details of differentiating her classes: positive and negative. Table 3.6 shows that the ROC-AUC of the proposed model is 0.64, which has a higher value than the existing model [47] with a lesser value of 0.59, which clearly conveys that the proposed model has better performance than [47].

3.15 Discussion

These models (SVM, DT, RF, EGBM, and LGBM) show varying levels of performance across different metrics for depression analysis. EGBM demonstrates the highest accuracy (75%) and ROC-AUC (71%). The ANN achieves an impressive accuracy of 98.3%, suggesting strong overall performance. Low log loss (0.0286) indicates accurate probability predictions. Precision, recall, and F-1 Score are not provided, but the high accuracy suggests good overall performance. QNN with 15 qubits shows lower accuracy (52%) compared to traditional methods and the ANN.
information is provided on precision, recall, and F-1 Score, making it challenging to assess detailed performance.

In the ANN stands out with high accuracy and low log loss, suggesting strong predictive capabilities for depression analysis. Traditional machine learning models also show competitive performance, while the Quantum Neural Network's performance is less clear due to limited information on specific metrics.
CHAPTER 4: CONCLUSION AND FUTURE WORK

4.1 Contribution

This groundbreaking study spearheads the development of an advanced quantum sensing device utilizing the diamond NV center, signifying a substantial leap forward in quantum sensing. The integration of quantum technology in mental health diagnostics introduces an inventive dimension, bolstered by quantum machine learning algorithms such as Support Vector Machines and neural networks. Specifically tailored for quantum sensing data, these algorithms offer unparalleled precision in discerning biomarkers linked to Alzheimer's and depression. The incorporation of quantum computing resources, into the system sets a precedent for managing large amounts of data. This is demonstrated through the use of quantum algorithms on platforms such as IBM Qiskit.

4.2 Impact

The impact on society from this research is significant with expected applications and collaborations by 2030. These innovations have the potential to revolutionize the detection of Alzheimer’s and depression biomarkers, enabling interventions and personalized treatment plans. The research takes an approach promoting collaboration between quantum technology, machine learning and mental health professionals. This collaboration is crucial in addressing challenges in diagnostics and treatment. The ultimate impact on society lies in improving the quality of care for individuals with Alzheimer’s and depression streamlining processes for informed and personalized care plans. Going beyond academia, this research
transforms how mental health disorders are diagnosed and treated, introducing an era of precision and efficiency in healthcare.

**4.3 Conclusion**

The study adopts an approach combining machine learning algorithms and advanced artificial intelligence techniques, specifically utilizing learning convolutional neural networks. The main focus is on the detection and prediction capabilities of Alzheimer’s disease and depression using the Quantum Sensing Diamond Nitrogen Method. The machine learning model for Alzheimer’s shows encouraging results, achieving a testing accuracy rate of 98.59%. In analyzing depression, different machine learning models display performance with the Artificial Neural Network, achieving an accuracy rate of 98.3%. Although these findings are promising, further research and validation on diverse datasets are essential to strengthen the reliability and applicability of the proposed models. The study’s findings open avenues for continued exploration of advanced technologies in the field of medical diagnostics, with the ultimate goal of improving patient outcomes through early and accurate detection of diseases.

**4.4 Future Work**

Future endeavors will refine Quantum Neural Networks, explore innovative quantum algorithms, and pinpoint more sensitive biomarkers for Alzheimer's and depression. Explorations into precision medicine approaches, digital health technologies, novel therapeutic strategies, big data analytics, and community-based interventions aim to enhance model robustness and practical implementation in real-world clinical settings. Collectively, these efforts contribute to the ongoing evolution of diagnostic tools for
neurodegenerative diseases and mental health disorders, embodying a high degree of intricacy and impactful innovation.
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APPENDIX A

A.1 Tools and Technology

Below are the tools and technologies used in this thesis to develop Global Challenges in Accessing Mental Health Services And Addressing The Impact of Alzheimer’s Disease and Depression.

A.2 Language

Python

A.3 Tools

IBM Qiskit