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INVESTIGATING THE POTENTIAL OF QUANTUM INSPIRED MACHINE LEARNING APPROACHES FOR MENTAL HEALTH DETECTION OF YOUNG ADULTS

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ABSTRACT

Medical Health Informatics has envisaged quantum computing as flurry of promising solutions to deal with mental health related issues of young adults in recent times. Even though traditional machine algorithms try to find an amicable solution to healthcare service providers, still the efficient detection and classification of the highly complex patterns that emerges from the healthcare datasets needs further investigations. Quantum machine learning, inspired from the principle from Quantum computing is found to be a transformative alternative in redefining the healthcare applications. In this article, Quantum inspired Support Vector Machines (QISVMs) and Quantum inspired Neural Networks (QINN) as two efficient quantum machine learning approaches are proposed by combining the traditional yet very popular and powerful machine learning algorithms such as Support Vector Machine (SVM) and Artificial Neural Network (ANN) with the power of quantum computing principles. The proposed Quantum inspired machine learning approaches are evaluated with several figure of merit and then, compared with the performance of the traditional algorithms counterpart for analyzing the most complex nature of the healthcare data with proper identification of minute wise data patterns and biomarkers in order to detect the early-stage healthcare issues pertained to a patient. Experimental study shows the efficacy of these quantum machine learning methods in comparison to the existing literature with threats to validity, some hidden challenges, and ethical issues associated with these technological advancements.

I. INTRODUCTION

Due to the present life style changes in the society, there are several critical healthcare issues predominating in health of young adults in particular. These healthcare issues pose challenges before the healthcare activists to develop innovative and sustainable artificial intelligence solutions for a better diagnosis, suggest best possible treatment and effective patients' data management with highest precision levels [1]. The existing machine learning approaches find difficulty in dealing with such a high dimensional and complex healthcare datasets, and hence demand for a quantum computing based machine learning approach to solve the issues.

Quantum machine learning with its unique characteristics from quantum mechanics proves to be beneficial in handling such challenging situations in a very short span of time, so that early disease detection, personalized medicine, and efficient drug discovery can be possible as a part of future healthcare system [2]. For instance, recently Accenture Labs , India in collaboration with 1Qbit has started their R&D initiatives with Biogen to apply quantum computing to accelerate drug discovery and QpiAI India Pvt Limited, a Bangalore, India based company developed its first commercial quantum computer that might be used by the Physicians globally as a perfect match for the development of new drugs to save millions of lives that are lost due to drug-resistant bacteria every year.

With the rapid growth of deep learning and quantum computing taking the shape, the limitations of the machine learning model due to vanishing gradient problems, trapped into a local minimum, learning inefficiencies in hyperparameter tuning along with extraction and detection of critical information are successfully redressed to a great extent [3],[4]. Looking into the recent developments of the quantum machine learning approaches, this section introduces some fundamental concepts of quantum computing, quantum machine learning with their challenges is discussed.

I.1 QUANTUM COMPUTING

Quantum computing is considered to be a paradigm shift from classical computation by taking the advantages of quantum mechanics principles including superposition, entanglement, and quantum interference. While classical computation uses any one of the possible states (0 or 1) as classical bits (or cbits), quantum computing uses quantum bits (qubits) as a superposition of both the states simultaneously [5]. This way, quantum computing through its intrinsic parallel qubit operations on a state space of bigger magnitude offers advantages over the classical ones and found suitable in solving the complex intractable problems [6]. Initially, quantum computation is coined through the Hilbert transforms, where the qubits are represented as vectors and their operations are carried out by using unitary transformations [7].

Quantum gates are then used to operate on these states logically, so that Grover's search algorithm and Shor's integer factorization algorithm can be efficiently implemented on them to provide quantum speedup over their counterparts [8]. In quantum computation, a single qubit can be represented in either mathematically, geometrically, vector form and/or physically, the definitions are as given below. Mathematically, a single qubit is a two-level quantum system, and considered to be a superposition of two basis states: $|0\rangle$ and $|1\rangle$. However, generally a qubit state $|\psi\rangle$can be written as a linear combination (superposition) of these above two basis states [9], as shown in eq. (1):

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle \tag{1}$$

where:

- $\alpha$and $\beta$are complex probabilities of observing $|0\rangle$ and $|1\rangle$ from the qubit,
- $|\alpha|^2$= probability of measuring the qubit in state $|0\rangle$
- $|\beta|^2$= probability of measuring it in state $|1\rangle$
- The normalization condition ensures total probability equals to 1: $|\alpha|^2 + |\beta|^2 = 1$
- Thus, the qubit's state is a unit vector in a 2-dimensional Hilbert space $\mathbb{C}^2$.

Secondly, a single qubit can also be represented geometrically using polar coordinates through Bloch Sphere Representation [10]. Since global phase (a common multiplier$e^{i\gamma}$) has no effect on measurement outcomes, a single qubit can also be represented using two real parameters, $\theta$and ϕ, as per eq. (2):

$$|\psi\rangle = \cos(\tfrac{\theta}{2})|0\rangle + e^{i\phi}\sin(\tfrac{\theta}{2})|1\rangle \tag{2}$$

where:

- $\theta \in [0, \pi] \rightarrow$ polar angle
- $\phi \in [0, 2\pi) \rightarrow$ azimuthal angle

These representations map a single qubit on the surface of a 3-D unit sphere, called as Bloch sphere, a unit sphere in 3D space for a geometric visualization of qubit states. This can also be visualized through a labelled diagram of the Bloch sphere showing how a single qubit is represented (with |0⟩, |1⟩, |+⟩, |–⟩ states, and angles θ, φ), as shown in Figure 1.

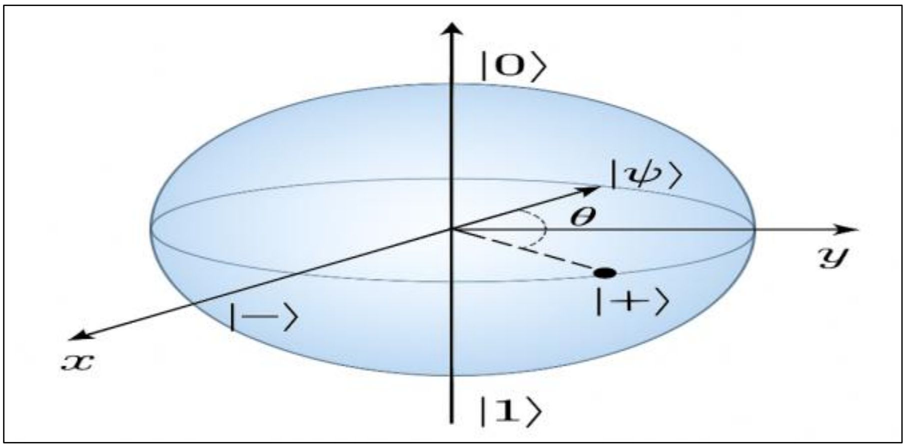

Figure 1: A labelled diagram of the Bloch sphere showing the representation of a single qubit.
Source: Authors, (2026).

Next, a single qubit can further be represented in matrix and vector form [11] as shown in eq. (3) and eq. (4) below:

$$\text{In matrix (column vector) notation: } |0\rangle = \begin{bmatrix}1\\0\end{bmatrix}, \quad |1\rangle = \begin{bmatrix}0\\1\end{bmatrix} \tag{3}$$

$$\text{Hence, in general, } |\psi\rangle = \begin{bmatrix}\alpha \\ \beta\end{bmatrix}, \text{with } |\alpha|^2 + |\beta|^2 = 1 \quad (4)$$

Finally, a single qubit can physically be encoded with the following details: (i) For Photon polarization → horizontal = |0⟩, vertical = |1⟩; (ii) In case of Electron spin → spin-up = |0⟩, spin-down = |1⟩; (iii) Superconducting circuits' → current circulating clockwise vs. counterclockwise; and (iv) Ion traps or quantum dots → ground and excited energy states. Through physical realization of a single qubit, one can find pathways to implement a quantum two-level system applied in a real-world physical device with highest storage reliability, can effectively manipulate, and obtain the quantum information associated with it. At the same time, a multi-qubit quantum system comprises of two or more qubits, is represented as the tensor product (or Kronecker product) of n single qubits. For n=2, the multi-qubit quantum system is referred to as a two- qubit quantum system. In this, Quantum entanglement [12] is one of the non-classical features of quantum mechanics, where a correlation between different qubits in this system is described even though the qubits are far away from each other. Further, entanglement violates Bell's inequalities by finding non-local correlations between two-qubits the explanations of which is difficult in case of classical probability computing [12]. In quantum entanglement, observation of the first qubit directly determines that of the second qubit which are then controlled by quantum gates in a quantum circuit to perform a quantum computation.

In quantum computing, quantum gates are unitary operators that manipulate the state of qubits according to the principles of quantum physics and unlike classical computing, they are reversible that allow to act on superpositions and can create entanglement with $U^\dagger U = I$, where U is a unary operator. Further, a quantum gate that acts on m-qubits or a register, is usually represented by 2^mx2^m unitary matrix and a set of all such quantum gates with the group matrix multiplication is called as a unitary quantum group with U(2^m). It is to be noted that in gate-based quantum computing, even though a sequence of unitary operators with either a single- and two-qubit are applied on a set of qubits, but sometimes there may not have any direct interaction between qubits while applying on a two-qubit gate [13]. Next, a one-qubit quantum gate is defined to transform a Bloch vector to another by rotating the Bloch vector. So, any one-qubit quantum gate is represented as rotation or a combination of rotations. These rotations may be further expressed as a combination of RX Gate, RY Gate and RZ Gate, which are necessary enough to perform every quantum computation [14]. However, parameter free gates along with three rotation gates are not only necessary but also considered to be sufficient, for efficient implementations of all possible quantum gates. Following are the representations of the three quantum gates that are more commonly used [9]. The RX Gate is a single-qubit rotation through angle θ (radians) around the x-axis and the angle of rotation must be specified in radians which can either be positive or negative, which is represented in eq. (5).

$$R_x(\theta) = \begin{bmatrix} \cos(\frac{\theta}{2}) & -i\sin(\frac{\theta}{2}) \\ -i\sin(\frac{\theta}{2}) & \cos(\frac{\theta}{2}) \end{bmatrix} \quad (5)$$

Similarly, The RY Gate is a single-qubit rotation through angle θ (radians) around the y-axis and can be represented as shown in eq. (6) below.

$$R_y(\theta) = \begin{bmatrix} \cos(\frac{\theta}{2}) & -\sin(\frac{\theta}{2}) \\ \sin(\frac{\theta}{2}) & \cos(\frac{\theta}{2}) \end{bmatrix} \quad (6)$$

Finally, RZ Gate is a single-qubit rotation through angle θ (radians) around the z-axis and can be represented as shown in eq. (7).

$$R_z(\theta) = \begin{bmatrix} e^{-i\frac{\theta}{2}} & 0 \\ 0 & e^{i\frac{\theta}{2}} \end{bmatrix} \quad (7)$$

In addition to these basic quantum gates, CX (Controlled-X) or CNOT gates are also considered to be one of the most essential gates for quantum computation. It is observed that any controlled gate can be realized by a combination of CX gates and one-qubit gates including X. The circuit symbol for CX gate is shown in Figure 2.

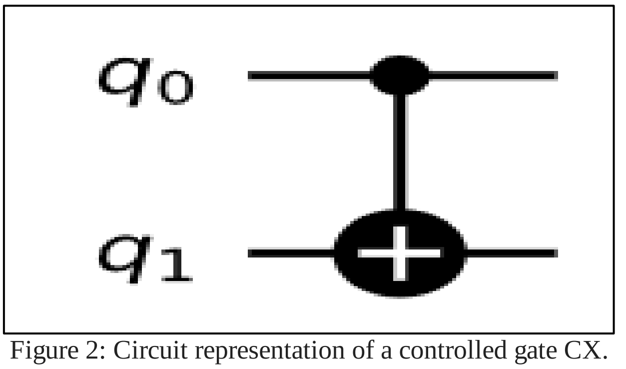

Figure 2: Circuit representation of a controlled gate CX.
Source: Authors, (2026).

Here, CX gate or CNOT gate performs the NOT operation (equivalent to applying an X gate) on the second qubit only when the first qubit is |1⟩ and otherwise leaves it unchanged. Also, while applying the CNOT gate on the state |00⟩, we get output state as |00⟩ as CNOT does the inversion of the input state applied to it.

Similarly, CNOT|00⟩=|00⟩, CNOT|01⟩=|01⟩, CNOT|10⟩=|11⟩, CNOT|11⟩=|10⟩, where {|0⟩= (10), |1⟩ = (01)} denotes the computational representations. In this, first qubit is considered as the controlled qubit, whereas the second qubit is the target qubit. As can be seen from Figure 2, if the first (Controlled) qubit is in the state |1⟩, then apply the X (NOT) gate to obtain the second (Target) qubit, otherwise to leave it as unchanged [15].

I.2 QUANTUM MACHINE LEARNING

Machine learning and artificial intelligence has become a household term now-a-days for its usefulness in transforming our lives in this ever-growing digital world. The tech giants including Amazon, Google, Netflix, Facebook, Apple, OpenAI, etc. to name a few, use machine learning and Generative AI techniques as the core idea with an aim to benefit heavily from the wide range of applications with a shortest possible time. However, due to global digitization, the size of the datasets has increased in order of zettabytes (of the order of 10^{21}) [16], which creates a bottleneck situation for the classical computers with the traditional machine learning algorithms for efficient processing, hence the whole world is now looking at the quantum computers and quantum computing methodologies to provide an amicable solution in near future. This requirement has motivated researchers to explore further possibilities in terms of quantum machine learning to deal with such huge and complex datasets in ease through quantum random access memory [17] and quantum artificial intelligence. Future quantum computers and a quantum internet need these quantum memories (or random-access quantum memories) to store and retrieve qubits. Despite several approaches existing to encode qubits and to implement quantum memories, no single "gold standard" has yet emerged till date [18].

I.3 COMPUTATIONAL COMPLEXITY IN CLASSICAL AND QUANTUM MACHINE LEARNING

The following presents a bird eye view on the complexities of both classical machine learning (CML) and quantum machine learning is provided, to further enhance our intentions why to go for quantum computing for recent applications of machine learning.
As our proposed research is based on how to deal with large datasets based on quantum machine learning (QML), it is imperative to understand how these algorithms perform in terms of scalability and practical feasibility. To achieve this, computational complexity (both in time and space) comparison among these machine learning algorithms whether classical or quantum based, considered as a primary tool for evaluating their potential advantages or pit falls. The quantum advantage with reference to a popular classical Grover's algorithm, in which the classical machine learning algorithm has time complexities of O(n) for n-inputs whereas the same algorithm can be executed through quantum machine learning with O(sqrt(n)), presents a significantly faster algorithm which is very interesting. It is also coined by the researchers that quantum machine learning can achieve faster solution to solve the linear algebra problems in comparison its classical counterpart, which are later popularly known as HHH (Harrow–Hassidim–Lloyd) algorithm [19]. A comparison between CML and QML is presented in Table 1.

Table 1: Comparison of Complexity in Classical and Quantum Machine Learning.

Criteria	**CML**	**QML**
Parallelism	limited	Inherent due to superposition
Processing speed	Largely depends upon available resources	Exponential for linear systems through HHH algorithms
Scalability	Challenging for extensive computations	Highly scalable
Complexity Classes	4 types: P (Polynomial Time); NP (Non-deterministic Polynomial Time); NP-hard and NP-Complete	BQP (Bounded-error Quantum Polynomial time), where
Algorithms	Conventional ML algorithms like: Neural Network, Support Vector Machines, Decision trees	Quantum SVM, Quantum NN, Quantum Deep Neural Network
Complexity	1. for SVM- Complexity range from $O(n^2d)$ to $O(n^3d)$ depending on the implementation and support vector kernel, where n is the number of data points and d is the dimensions of the data. 2. for Artificial Neural Networks- Complexity varies depending on the network architecture. For dense networks, one iteration might scale up to O (n·∣Weights∣). Hence, computational complexity largely depends on ANN architecture, dataset size, and number of iterations.	1. For QSVM- the complexity is O(log(nd), which achieve near-logarithmic complexity with respect to both the dimensionality of feature vectors 'n' (qubit number) and 'd'' the size of the training dataset (dataset size). 2. For QNN- Computational complexity is expensive due to long training times and can range from $O(n^2)$ to O(log(n)), where n represents the number of elements (e.g., neurons, data points, or parameters)

Source: Authors, (2026).

Apart from all the above, Time and Space Complexity in QML are affected by Qubit count (width), Gate depth (circuit time), Measurement repetitions (shots), and Deep circuits which when applied on a large dataset may lead to exponential scaling. Further, QML complexity may be understood from the type of quantum circuits used. For example, in case of swallow quantum circuits, it is easier to execute, but has limited expressivity and on the other hand, for deeper ones, it has more expressive power but prone to noise. Hence, a trade-off is suggested in this case. The complexity analysis of QML and CML provides us a understanding for future development in algorithms, circuits, and hardware that may be customized for a practicable and yet a powerful quantum machine learning system. The remainder of the paper is organized as follows.

To efficiently perform the mental health prediction of young adults using quantum machine approaches, related work that are presently available in literature is presented in Section 2, followed by the technical knowhow of the proposed quantum machine learning such as QSVM and QNN are discussed in Section 3. Next, understandings of the mental health dataset with its descriptive analytics are presented in Section 4. In Section 5, investigation on the effectiveness of the proposed quantum machine approaches is performed through an experimental setup, and then, the obtained simulations result with discussions are reported in Section 6 with threats to validity. Finally, we summarize the proposed work in Section 7.

II. THEORETICAL REFERENCE

According to [20] presented some quantum machine learning algorithms for classification tasks by applying on several biomedical datasets and then compare their performances with conventional ones in terms of different performance matrix. They concluded that Pegasos Quantum Support Vector Classifier is best among the quantum classifiers but upto 10% lesser accuracy than that of conventional classifiers, needs more research for further explorations. In [21] proposes an Quantum neural network model with incremental qubit numbers after the dataset undergone pre-processing through z-score normalization and features extraction by using information gain method. They compared the performance of Quantum neural network model in terms of accuracy and computational time with several deep learning and quantum machine learning models including Bi-LSTM, QCNN, DNN and RNN etc. with a learning rate of 0.7 and reported their effectiveness.

According to [22] provided an intial study of Quantum inspired quantum orthogonal neural network technique for medical image classification and showed its effectiveness through software simulations and hardware demonstartions in terms of scalability and computational time. They observed that their approach has several limitations in terms currently available hardware and at the same time opines that using future quantum computers with GPU capabilities along with potential Hilbert spaces can solve these limitations. However, the practicability of such a parametrized quantum circuits with large Hilbert spaces is still considered to be an open challenge in this area of research and envisaged to be solved in near future as the newer version of specialized hardware evolves.

According to [23] developed a quantum machine learning model by combining the strengths of contrastive and transfer learning with quantum mechanics and applied to mental health monitoring and diagnosis. Considering the challenging charactristics of the large scale mental health dataset and limitations in computing environment, they used QASM simulator with 8 qubits for their experiments and suggested to use more qubits and a real quantum device in future to further increase the performance if practically possible. According to [24] used both classical neural network model and quantum machine learning model on EEG signals to detect human drowsiness after performing pre-processing tasks. They explored the performance of the three layers quantum based classifier by using different quantum circuit architectures with rotation and entanglement Gates and suggests for improvements.

Iin [25] introduces a hybrid quantum support vector machine by combining the power of quantum computing with Support vector machine for stress detection in older adults. They used wearable sensor and stressed sensor to obtain the normal and anomaly data respectively, from 40 old adults. Kernel based pre-processing is used to extract the complex features from the above collected data and used TSST protocol for understanding the usefulness of the approach in terms of high accuracy and recall values, which helps in early diagnostic or treatment of the high stress of the old adults on time and saves life. According to [26] initially presented a summary of powerful features of quantum machine learning and then discusses how the technology revolutionizes today's healthcare sector in achieving better personalized treatment and precision healthcare.

While implementing the quantum machine learning algorithms in genomic data analysis, they suggested developing more formal optimization methods with low resource usage in terms of number rotations Gates and size of the qubits, to practically make it feasible to develop an efficient precision medicine approach in days to come. In [27] pointed the drawbacks of the classical machine learning approaches in dealing with large psychiatric dataset for early detection and prediction of schizophrenia disease. They provided an insightful discussion on the suitability of these quantum machine learning methods with proper selection of performance measures and their validation, for disease detection and diagnosis at an early stage.

For [28] presented a review on basic concepts of quantum computing and its integration with traditional machine learning methods, its potential application areas and drawbacks, for a clear understanding. They concludes by outlining the future of quantum-inspired machine learning in solving clinical diagnostics and personalized treatments. According to [29] advocates for quantum computing for its capability to process the big data in terms of both speed and time, when applied to identify the disease specific bio-markers, especially for neurodegenerative and psychiatric diseases. It further explore its possibilities in clinical research, hospital management , resource allocation and most importantly patient's health monitoring with potential ethical issues being addressed. According to [30] surveyed five quantum enhanced machine learning algorithm by hybridizing the traditional support vector machine, neural network, *k*-nearest neighbour, principal component analysis and *k*-Means clustering algorithm with quantum mechanics.

They presented a discussion on how these methods can be successfully applied on drug discovery, image processing and cyber security applications with inherent limitations in design hardware circuits, data encoding, and noise. In [31] discusses about the challenges prevailing in Parkinson's disease, the fastest-growing neurodegenerative disorder globally and the need for a sustainable method for early detection to save the patients' life. They used mPower dataset with four key bio-markers, used random forest method as a feature selection algorithm and then quantum support vector machine for classification and prediction of the disease efficiently. With an overall accuracy of 90%, they concluded that a practically achievable and simulation based quantum machine learning model on a standard hardware configuration is better than resource intensive quantum computers, which needs further research.

For [32] carried out a 10 years of extensive research starting from 2015 to 2024, by including published studies available several databases including PubMed, Embase, IEEE, Scopus and Preprint servers related to application of quantum machine learning in digital health care. Their studies reveal that there are no clear-cut trends to differentiate or support empirical quantum utility in digital medicine and health service delivery. This encourages further research in this area, to unveil the full potential of quantum machine learning models.

In this paper, the main objectives are to use two Quantum Inspired Machine Learning approaches including QNN (Quantum inspired Neural network) and QSVM (Quantum inspired Support Vector Machine) models considering their possible implementation on real quantum circuits, with an aim to address the challenges that are being faced while implementing through traditional approached in mental health application in young adults in todays scenario.

The key contributions of our work include: (1) An approach to quantum embedded encoding (angle embedding and encoding) is proposed which can transform the classical features to qubits and then generate shallow quantum circuits. The motivation of using this is to reduce the complexity of the quantum encoding block compared to the existing methods; and (2) An efficient and faster quantum inspired machine learning algorithm model is developed by hybridizing quantum processing with the classical neural network and SVM model. The proposed QINN and QISVM models are realized based on the fundamental quantum gates on a quantum circuit and effectiveness are validated with several figure of merit metrics.

The remainder of this paper is organized as follows: Section 3 introduces the preliminaries with materials and methods used. The Experimental design using QNN and QSVM algorithms along with the analysis of obtained results are presented in Section 4. Finally, Section 5 concludes this paper.

III. MATERIALS AND METHODS

In this section, we introduce the details about the mental health dataset used for our experiments followed by some preliminary knowledge of quantum computing and quantum machine learning models.

III.1. MENTAL HEALTH DISORDER DATASET

The mental health disorder dataset collected freely from openml (Scikit-Learn) database, comprises electronic health records from 10,000 patients diagnosed over the past ten years with either an affective disorder (encoded as 0) or schizophrenia (encoded as 1). It includes demographic variables such as sex and race, psychosocial characteristics, and clinical assessment data related to psychiatric symptoms. A binary classification model has been developed to predict diagnostic outcomes based on patient intake information. This predictive model is intended to support clinical triage by assigning patients to the appropriate treatment pathway either for affective disorders or schizophrenia based on the predicted diagnosis. The objective is to assess the reliability and effectiveness of this model in informing triage decisions within a clinical setting.

III.1.1 Description Of The Dataset:

This case study explores the use of a machine learning (ML) model in a mental health care setting to predict patient diagnoses based on intake data. The aim is to examine how algorithmic bias may emerge, particularly when structural inequities are embedded in training data. Although the scenario is based on a simulated and simplified dataset, it is designed to highlight key concerns related to fairness, bias, and diagnostic equity in healthcare ML applications.

III.1.2 Background And Relevance:

Research has shown that Black patients particularly Black men are diagnosed with schizophrenia at disproportionately higher rates compared to other demographic groups, including white patients [30]. Schizophrenia is a severe psychiatric disorder with a chronic course, characterized by both positive symptoms (e.g., hallucinations, delusions) and negative symptoms (e.g., lack of motivation, flat affect). Misdiagnosis of schizophrenia instead of affective disorders such as depression may result in significant clinical and ethical concerns, including delayed or inappropriate treatment, greater stigma, more severe side effects from antipsychotic medications, and reduced trust in the healthcare system. This disparity in diagnosis [31] is likely multifactorial, involving both biological and social determinants. However, diagnostic bias where clinicians may overemphasize psychotic features in Black patients and under-recognize depressive symptoms has been identified as a key contributor. These issues reflect the broader concept of labelling bias, where outcome labels in clinical datasets may themselves encode structural inequities, inadvertently perpetuating disparities when used to train ML models [32].

III.1.3 Reference Case: Algorithmic Fairness In Healthcare

To contextualize the potential risks of biased ML deployment in healthcare, the study by [33] is referenced. In their evaluation of a risk stratification algorithm used by insurance providers for approximately 50,000 patients, the algorithm systematically underestimated the disease severity of Black patients. This occurred primarily because the algorithm used total healthcare expenditure as a proxy for illness severity a flawed assumption given the socioeconomic disparities that affect healthcare access and spending. The study in [34] illustrates how proxy variables and a lack of intersectional analysis can result in substantial fairness harms.

III.1.4 Hypothetical Scenario

A simulated dataset has been constructed to replicate the type of bias highlighted above. This dataset contains electronic health records for 10,000 patients diagnosed at Health System A over the past ten years with either an affective disorder (labelled as 0) or schizophrenia (labelled as 1). Features include demographic variables (sex and race), psychosocial factors, and symptom-related data from clinical assessments.A binary classification model has been developed using this data. Its purpose is to assign a diagnosis to new patients based on intake information, thereby directing them to the appropriate treatment pathway without further clinical evaluation. The hospital administration, motivated by cost-reduction strategies, intends to rely solely on this automated system for triage and treatment decisions. To support the model’s deployment, executives have commissioned a performance evaluation using a test dataset of 1,000 patients. They report high sensitivity and specificity, suggesting the classifier performs well overall.

However, external stakeholders have raised concerns about potential bias and disproportionate harms, particularly toward subpopulations defined by intersecting axes of race and gender. To address these concerns, an independent audit of the classifiers performance and fairness implications has been requested. The evaluation must consider not only aggregate metrics but also subgroup level performance disparities, with attention to potential intersectional bias. This analysis is essential before any deployment of the model in clinical practice, especially given the risks of misdiagnosis and its downstream effects.

III.2. QUANTUM INSPIRED MACHINE LEARNING (QIML)

Quantum inspired machine learning (QIML) can be developed either when both data and methods are in quantum form or else only model is quantum but the dataset is in traditional form. When the data is in traditional format, then it is first transformed into its corresponding quantum format by using a parameterised circuit called quantum feature map. Here, Z feature map is used as a quantum feature for data encoding through a series of operations for this data transformation.

In this case, entanglement is absent, as there are no interaction amongst the features' of the dataset present while using Z feature map. In the next step, dimensionality reduction is performed in order to reduce the number of quantum features for efficient implementation, hence reduces the computational complexity, presents clarity on feature importance and produces a faster implementation. A quantum kernel may be used as a pre-processing algorithm in case of quantum inspired support vector machine model (QISVM). While using a quantum inspired neural network (QINN), parameterized operation includes entanglement along with parameter optimization method (per say ADAM optimiser) for significantly improvement in the overall performance and effectiveness of the model.

III.2.1. Quantum Inspired Support Vector Machines (QISVMS)

The pseudo code of the Quantum Inspired Support Vector Machines (QISVMs) is presented in Figure 3.

<u>Pseudo Code for QISVM</u>

Input: Training dataset $D = \{(x_1, y_1), ..., (x_i, y_i)\}$, where $x_i \in R^d$ and $y_i \in \{+1, -1\}$

Output: Quantum Inspired SVM model

1. Encode classical data into quantum states:

For each x_i in D:

$|\psi_i\rangle$ = Quantum_Feature_Map(x_i)   # Pauli Feature Maps used

2. Compute quantum kernel matrix K: #Quantum kernel using angle embedding fidelity

For all pairs (i, j):

$K[i][j] = |\langle\psi_i|\psi_j\rangle|^2$

3. Solve the dual optimization problem:

Maximize: $L(\alpha) = \Sigma_i \alpha_i - ½ \Sigma_{ij} \alpha_i \alpha_j y_i y_j K[i][j]$

Subject to: $\Sigma_i \alpha_i y_i = 0$ and $0 \leq \alpha_i \leq C$

4. Construct decision function:

$f(x) = \Sigma_i \alpha_i y_i \langle\psi_i|\psi\rangle$, where $|\psi\rangle$ = Quantum_Feature_Map(x)

5. Predict label:

y_pred = sign(f(x))

Figure 3: Pseudo Code of QISVM.
Source: Authors, (2026).

III.2.2 Detailed Explanation

- **Quantum_Feature_Map(x)**: Encodes classical data into quantum states using parameterized quantum circuits. Pauli Feature Map is used in this research using PennyLane.
- Kernel Matrix: Measures similarity between quantum states. Quantum computers can estimate this efficiently using interference patterns. In this, we used Angle Embedding Fidelity kernel to obtain the complex data relationships that classical kernels might miss.
- **Optimization**: Solved classically using quadratic programming, but the kernel is computed via quantum means.
- **Prediction**: Uses the trained support vectors and quantum kernel to classify test data.

Based on the pseudo-code, the workflow of QISVM is presented in Figure 4.

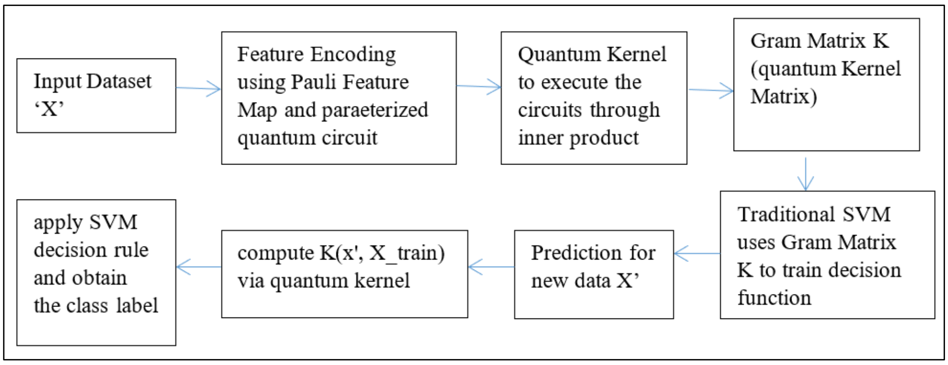

Figure 4: Workflow of quantum Inspired SVM.
Source: Authors, (2026).

III.2.3 Computational Complexity

A comparison between QISVM and Traditional SVM is presented for better understanding.

- **Quantum Kernel Estimation**: Scales as $O(D^{4.67}/err^2)$, where D is the number of training samples and err is the error tolerance.
- **Classical SVM**: Typically scales as $O(D^2)$ to $O(D^3)$ depending on the SVM types.
- **Quantum Limitations**: As shot noise is introduced during Quantum measurements, repeated sampling are needed, which may induce more computational complexity.

Even though QISVM is one of the most efficient and stable algorithm, it is best suited for low-dimensional circuits having less number of features or qubits. For high dimensional datasets, some kind of feature reduction techniques might be handy to deal the situation effectively.

III.2.4. Quantum Inspired Neural Network (Qinn)

The pseudo code for Quantum Inspired Neural network (QINN) is presented in Figure 5. Following the Pseudo-code, Figure 6 demonstrates how a basic quantum inspired neural network (QINN) works.

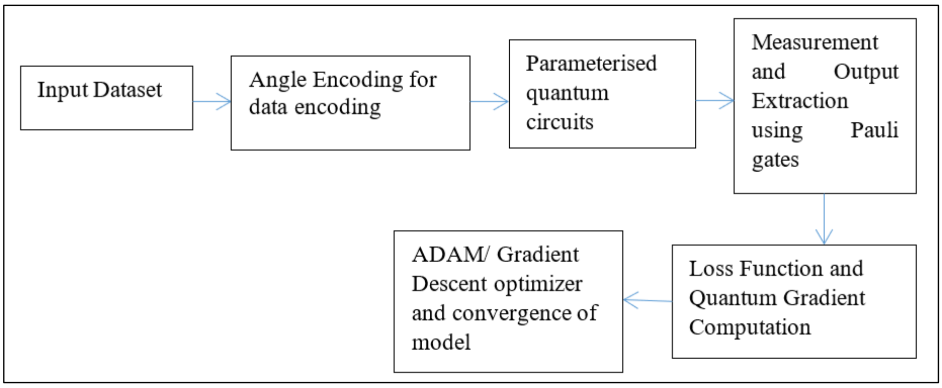

Figure 5: Operational Workflow of QINN.
Source: Authors, (2026).

Initially, the input dataset having classical feature vector is applied for angle encoding where the feature vector x_i is encoded into a quantum state (or qubit state) with an appropriate number of qubits and then the features in the raw data are mapped through the parameterized rotation gates and entangling gates for a given number of layers (i.e. $RY(x_i)$). The entire network highly resemblance to that of a classical neural network layer, where θ are defined as weights. The mapped qubit state is then applied through Pauli gates to measure the qubit state. The output of the Pauli gate provides the model's prediction, analogous to a neuron's activation value in case of traditional Neural Network. Then the obtained measurements of qubit states are decoded back into the appropriate output data which are finally optimized by using ADAM optimiser. The loop continues till the termination criteria is satisfied. In this case, mean square error (MSE) is used as a loss function and parameter shift is performed by gradient calculation. In quantum inspired neural network, parameter shift through error backpropagation is not possible, hence gradient descent/ADAM optimizer is used to update the parameters. The final trained parameters θ'define the optimized QINN capable of generalizing to new inputs.

III.2.5 Advantages of Quantum Neural Networks

The advantage of using QINN lies its ability (i) to apply successfully in large dimensional feature spaces, (ii) models non-linear dependencies through entanglement (CNOT gates), (iii) its faster convergence due to quantum expressiveness and most importantly less computational overhead in comparison to its traditional counterpart. In spite of its several advantages, it is not away from limitations in terms of (i) quantum gradient vanishing due to its incapability to perform backpropagation and not using any activation function and (ii) near-term device compatibility with a large error rate and a complicated error correction process.

Algorithm: Quantum Inspired Neural Network for Binary Classification

Input:

- *Training dataset* $D = \{(x_i, y_i)\}$, *where* $x_i \in \mathbb{R}^n$ *and* $y_i \in \{0,1\}$
- *Number of qubits* q *and Quantum circuit depth* L
- *Learning rate* η *and Number of training epochs* E

Output:

- *Trained quantum parameters* θ^*

```
1.  Initialize Quantum Neural Network parameters θ randomly
2.  For each epoch in range(1, E + 1):
3.      For each training example (xᵢ, yᵢ) in dataset D:
4.          # Step 1: Encode classical input into quantum state
5.          |ψ_input⟩ = QuantumEncode(x_i)          # (e.g., using angle encoding,)
6.          # Step 2: Apply parameterized quantum circuit (variational layer)
7.          |ψ_output⟩ = U(θ) |ψ_input⟩
# U(θ) is a sequence of quantum gates parameterized by θ
# Example: U(θ) = RY(θ1) * RZ(θ2) * CNOT * RY(θ3) * ...
8.          # Step 3: Measure qubits to obtain classical output
9.          zᵢ = Measure(|ψ_output⟩)
# Measurement collapses the quantum state and gives an expectation value
# Example: zᵢ = ⟨ψ_output| Z |ψ_output⟩
10.         # Step 4: Compute loss
11.         L(θ) = (zᵢ - yᵢ)^2          # Mean squared error (MSE) is used
12.         # Step 5: Compute gradient using parameter-shift rule
13.         ∇θ L = ParameterShift(U(θ), L)  # Quantum gradient computed by evaluating
circuit at θ+Δ and θ−Δ
14.         # Step 6: Update parameters using gradient descent /ADAM
15.         θ = θ - η * ∇θ L
16.     End for
17. End for
18. Return optimized parameters θ'
```

Figure 6: Pseudo Code for operational procedure of QINN.
Source: Authors, (2026).

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

IV.1. EXPERIMENTAL SETUP

All the experiments carried out in this paper is performed on an Intel Core i7 machine with 1TB HDD, 8GB RAM, 2.67GHz CPU using Kaggle Notebook in Python environment. PeenyLane is used for developing the quantum machine learning model using Neural network and SVM. The Architectural Flow of Quantum inspired Machine Leaning models for Mental Health Detection is presented in Figure 7. The parameter setting used in this paper is provided in Table 2.

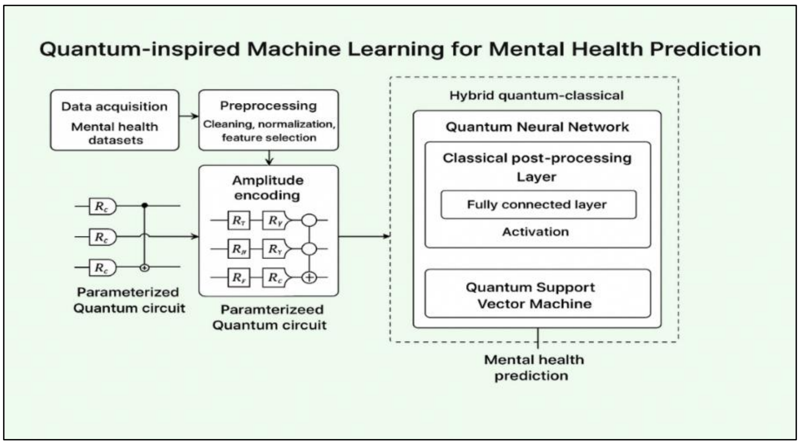

Figure 7: Experimental Flow for Quantum Inspired Machine Learning in mental health prediction.
Source: Authors, (2026).

Table 2: Parameter Setting for the Quantum Machine Learning Approaches.

Feature / Parameter	Quantum Neural Network (QNN)	Quantum Kernel SVM (QK-SVM)
Qubits Used	8	8
Layers	4 (3 × Strongly Entangling Layers + 1 final rotation layer)	1 (Angle Encoding only)
Trainable Parameters	96 total = (n_layers + 1) × n_qubits × 3	0
Single-Qubit Gates	80	8
Two-Qubit (Entangling) Gates	24	14
Circuit Depth	≈ 13	≈ 22
Training Required	Yes (gradient descent on variational parameters)	No (only classical SVM training)
Inference Speed	Medium	Slow (due to kernel matrix evaluation)
Expressivity	High	Medium
Preprocessing Used	Angle Encoding — RY rotations with inputs scaled to [0, π]	Angle Encoding — RY rotations with inputs scaled to [0, π]
Output Type	Learned Quantum State (trainable feature map)	Quantum Feature Kernel (fixed feature map)

Source: Authors, (2026).

In Figure 7, the mental health dataset from OpenAI is collected in data acquisition block which may either be the survey data, clinical assessments, wearable device readings and/or patient-reported outcomes. The attributes of the mental health dataset include the patients' symptoms, behavioural patterns, demographic information and Psychological/ mental disorder signals etc. with class label depicting the patient's mental health condition which may be categorized as depression, Schizophrenia, or healthy. In the second step, data pre-processing is carried out where missing values, outliers and noise if any are cleaned, followed by data normalization to convert the attributes values to fall in to a comparable range (we use Min-Max normalization here) for efficient data encoding and then, feature selection/ dimensionality reduction is done to reduce the data complexity and make the data a quality one before quantum embedding process. Further, scaling is performed to address the issue of class imbalance, if any and remove biasness.

In third step, we create a parameterized quantum circuit to transform the classical data into their corresponding quantum states either by using amplitude or Angle encoding, so that it is ready for quantum processing. We use angle encoding here, where the it maps the features to rotation angles of qubits by using Ry or Rz quantum gates. In this process, number of qubits denotes the feature dimensions after angle encoding. In quantum processing block, we develop a hybrid model by combining quantum processing using classical Neural network and Support Vector Machine Classifier. Multiple layers of parameterized quantum gates such as Rx, Ry, Rz, CNOT are used to serve as a core of quantum machine learning approaches. Entanglement is also introduced in this step, to obtain the cross correlation between qubits to explore inherent relationships in mental health datasets and then quantum measurements are performed by extracting expectation values from qubits to serve as intermediate initial attributes.

In quantum inspired neural network, layer depth may affect the neural network learning capacity which sometimes considered as a trade-off between noise and data de-coherence. The output of the QINN needs normalization by using either softmax function or sigmoid function depending whether the mental health datasets contains binary class or multi-class disease prediction. This way, the raw output of the quantum circuits can be transformed in terms of class probabilities and hence, ensures efficient model building with accurate and interpretable mental health prediction and classifications. On the other hand, QISVM uses the angle encoding circuit followed by number of adjoint encoding circuits to implement the quantum kernel function and obtain the correlation between quantum states in a high dimensional Hilbert space by using quantum Gram Matrix. In this paper, Pauli feature map criteria is used to convert the classical attributes to quantum states using rotations gates and Pauli operators, then crates entanglement between qubits to find out the non-linear relationships among features. This way, QISVM could effectively develop a computationally efficient quantum classifier with acceptable accuracy in mental health conditions classification.

V. RESULTS AND DISCUSSIONS

In this section, the results obtained after performing the experiments as per the architectural overflow shown in Figure 7 are presented with comparisons with related work for validation of the proposed research in this paper. In this, figure of merit is considered as one of the approach to understand the performance of the QINN and QISVM considering the high dimensional and highly imbalanced mental health dataset. Here, accuracy, Precision, Recall and ROC are used as figure of merit metrics for evaluations, where one could able to take steps to accurately detecting the true positives while minimizing false positives. Here the full data set is converted into train, validation and test dataset 80%, 10% and 10% respectively. The results obtained are presented in Figures 8 to Figure 16. Figure 8 shows the quantum kernel with entangling circuit and the adjoint circuits to obtain the correlations between quantum states.

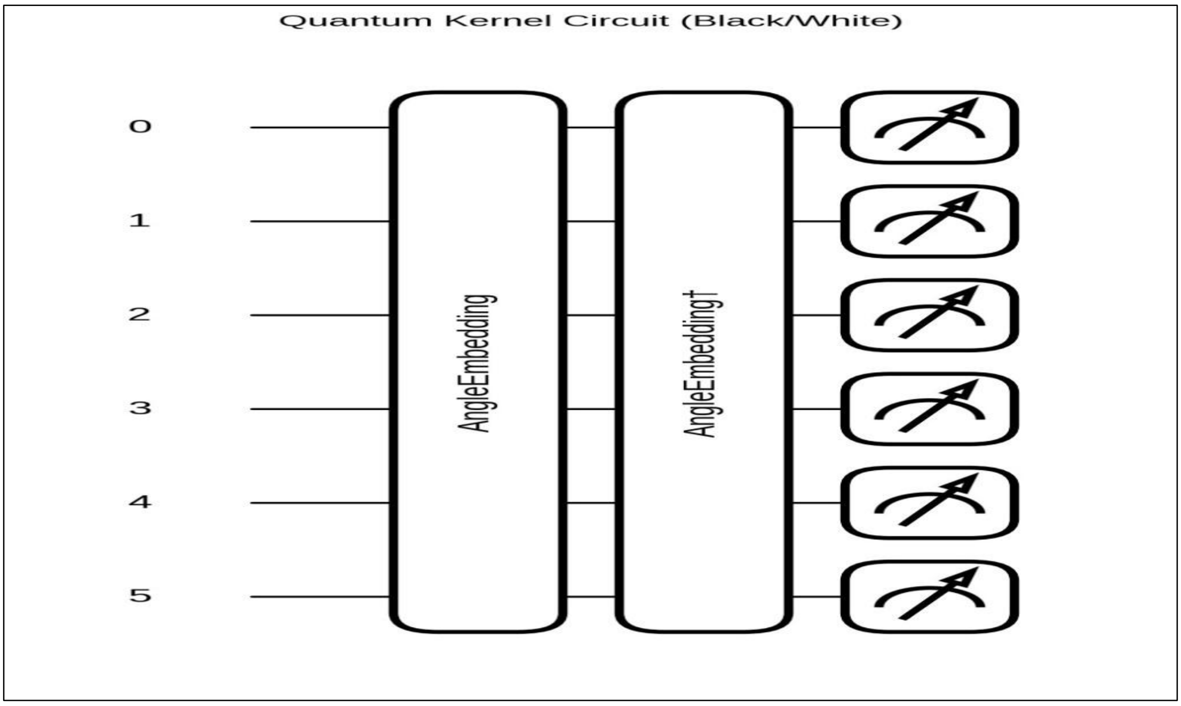

Figure 8: Quantum Kernel for Correlation between quantum states.
Source: Authors, (2026).

Figure 9 and Figure 10 provides the quantum generated circuits for quantum machine learning using classical neural Network and SVM. Figure 11 and Figure 12 highlights a ROC comparison (True Positive Rate Vs. False Positive Rate) of classical and quantum _inspired NN and SVM approaches on test set. From Figure 11, it is observed that AUC (area under the curve) for QISVM with 0.968 is better than its neural network counterpart having AUC of 0.904. Further, from Figure 12, it can be seen that classical machine algorithms (SVM and NN) outperform their quantum inspired ones by achieving more AUC of 0.979 and 0.962 respectively.

V.1 FIGURE OF MERIT

Further, several figures of merit metrics are used to evaluate the performance of the classical and quantum inspired neural network and SVM models which are presented in Figure 13 and Figure 14 respectively. Further, accuracy and loss comparison with respect to number of epochs are presented in Figures 15 and Figure 16 respectively, to understand the efficacy of the approach.

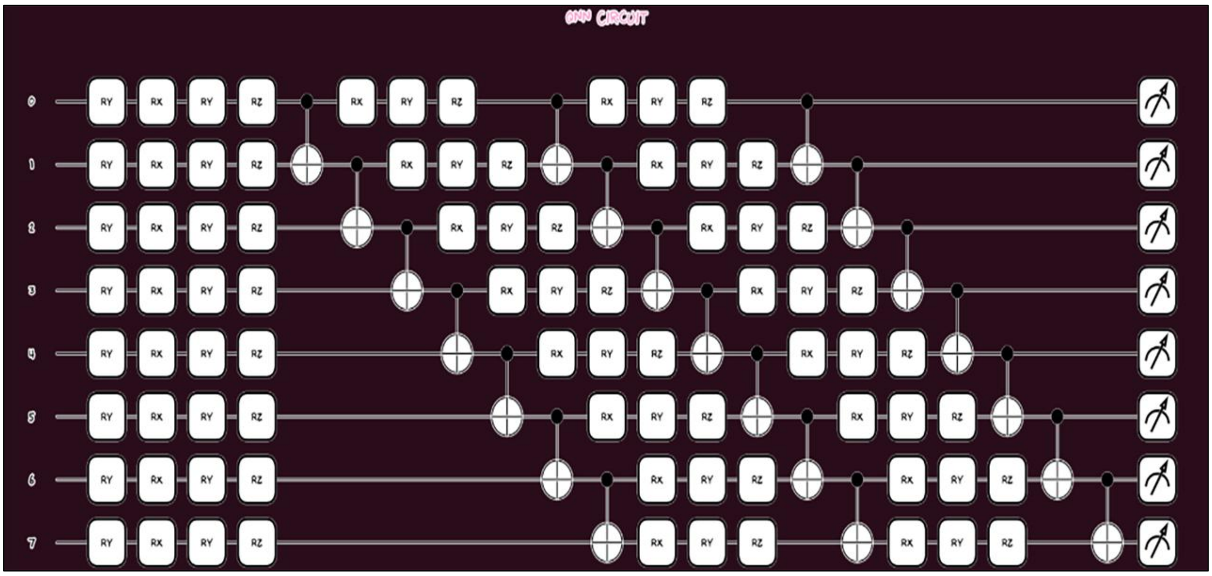

Figure 9: Quantum circuit for QINN.
Source: Authors, (2026).

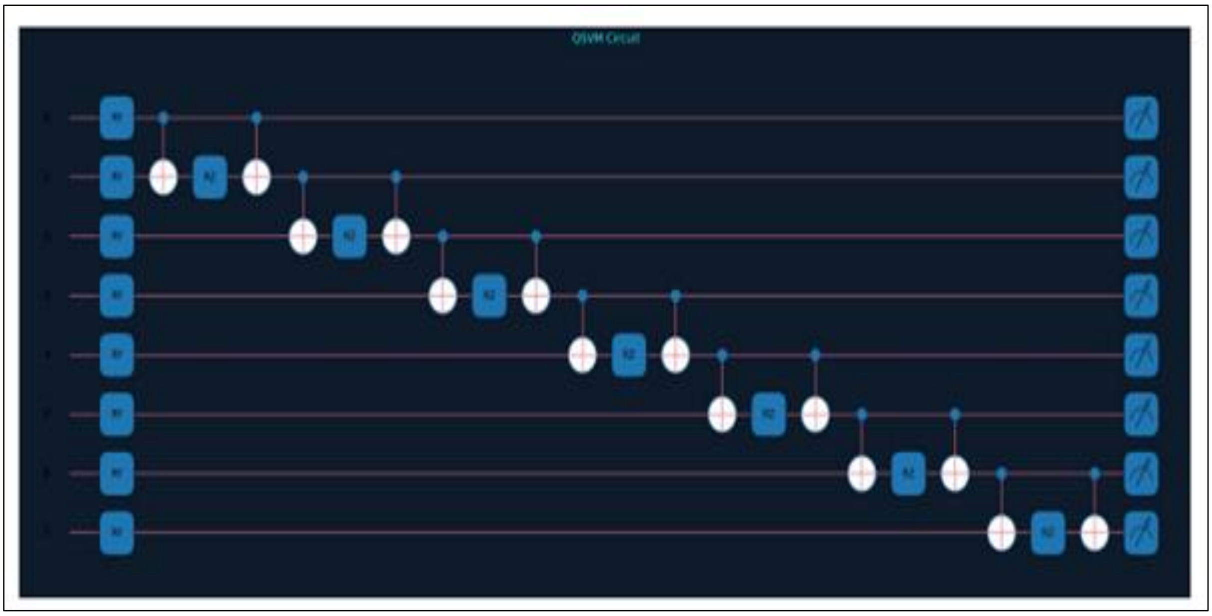

Figure 10: Quantum circuit for QISVM.
Source: Authors, (2026).

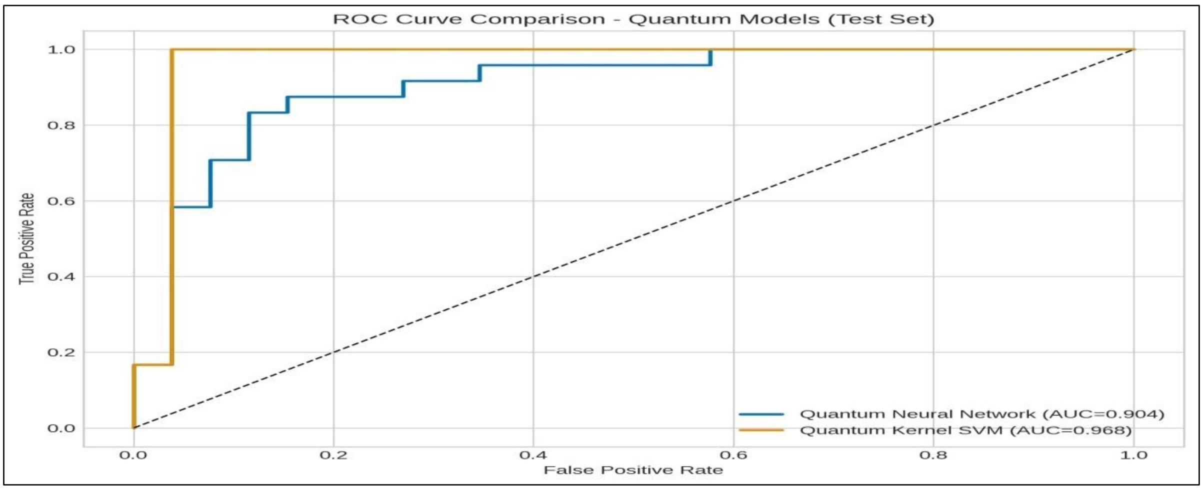

Figure 11: FPR Vs. TPR Comparison between QINN and QISVM.
Source: Authors, (2026).

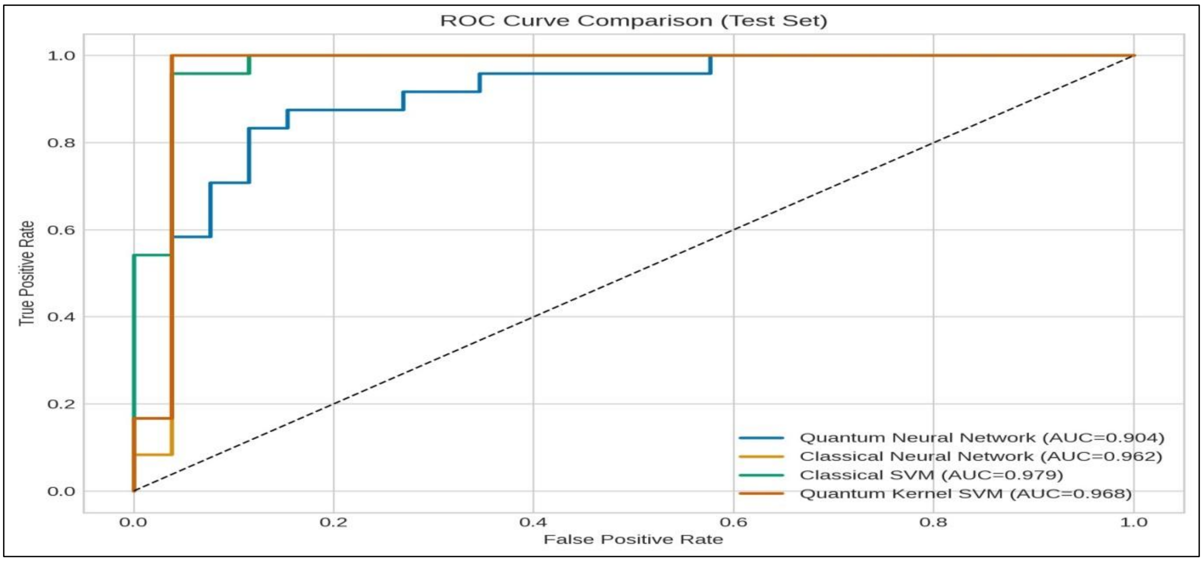

Figure 12: AUC comparison amongst classical and Quantum inspired NN and SVM.
Source: Authors, (2026).

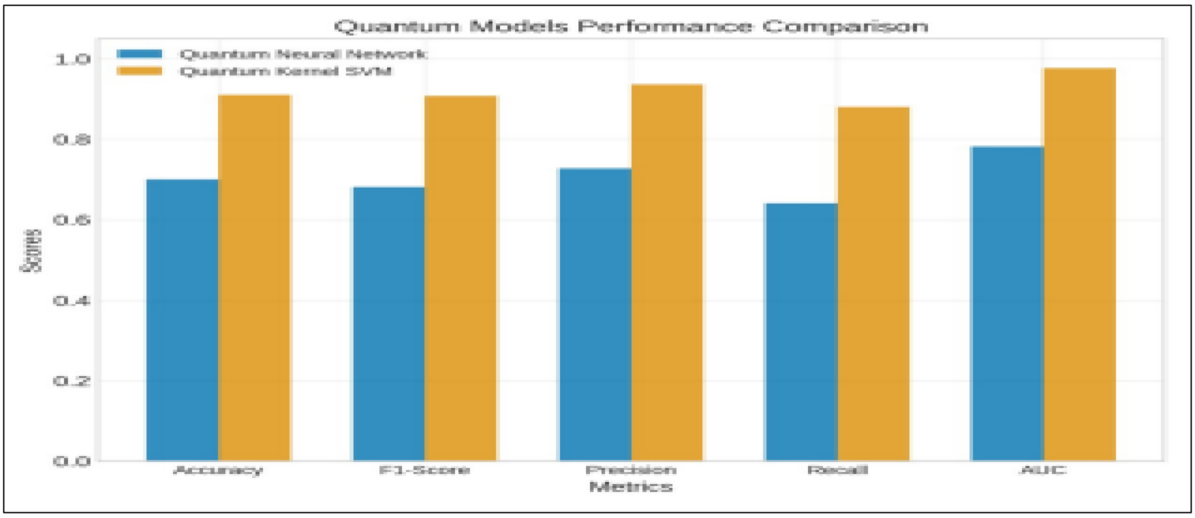

Figure 13: QINN Vs QISVM comparison.
Source: Authors, (2026).

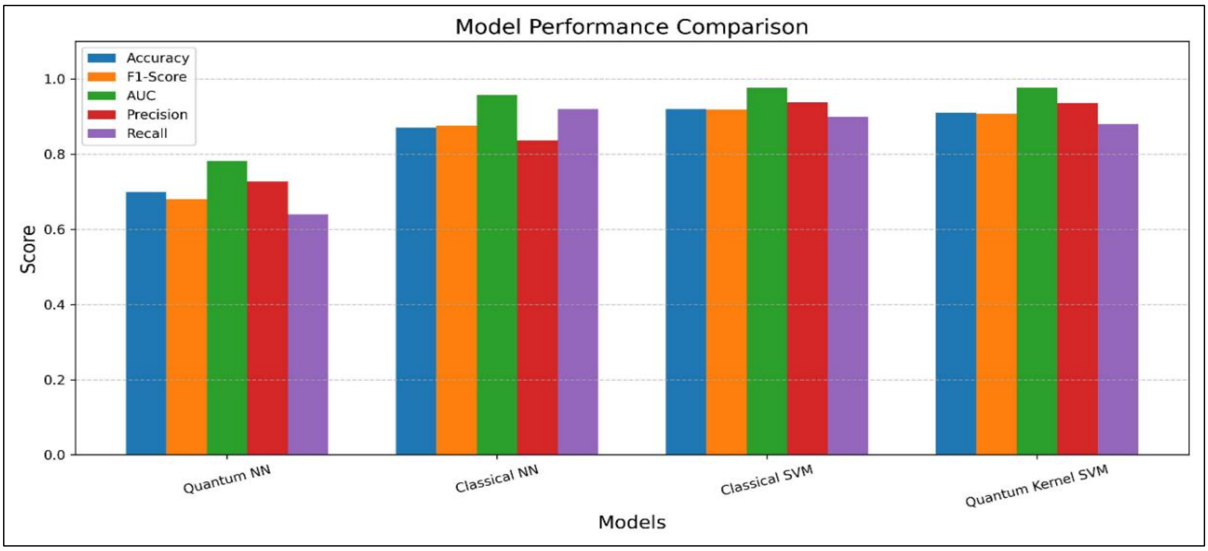

Figure 14: Classical Vs Quantum machine learning comparison (QINN-CNN-CSVM-QISVM).
Source: Authors, (2026).

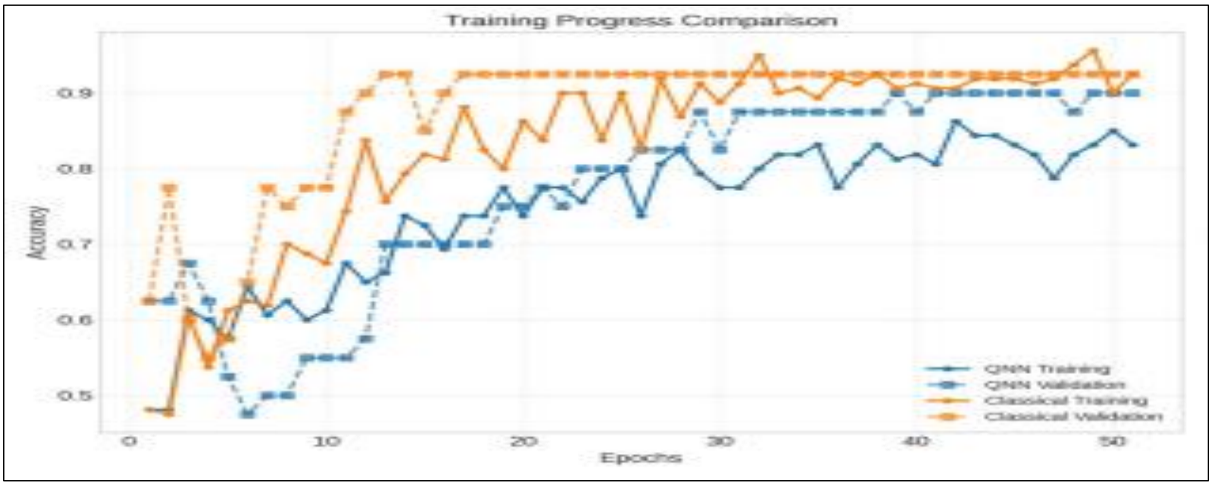

Figure 15: Number of epoch Vs Accuracy Comparison.
Source: Authors, (2026).

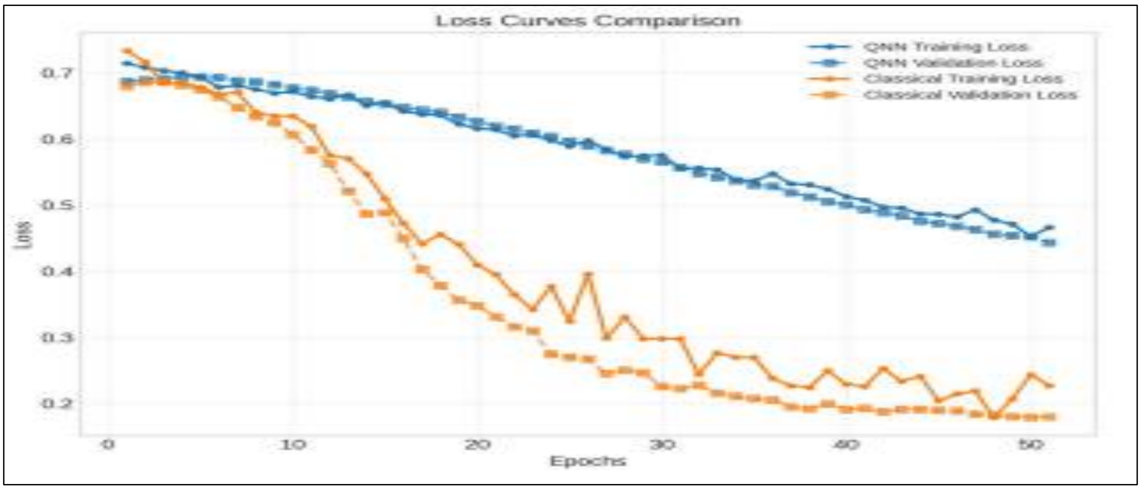

Figure 16: Loss comparison between classical and quantum inspired Neural network classifier.
Source: Authors, (2026).

Further, it is observed that QISVM performs better than QINN with high accuracy. Low loss, high Precision, high Recall, High f1 score and high AUC, makes it QISVM is a better choice in comparison to QINN. It is also observed that for the mental health dataset, the baseline classical algorithms performs better than their counterparts, might be due to overfitting but their effectiveness in dealing with highly imbalanced dataset with high dimensionality is a major concern, where QINN and QISVM wins the race. Hence, there are several threats to validity are identified which may be addressed for further research.

V.2 THREATS TO VALIDITY:

At first, there is possibly an internal threat to validity where small dataset sizes in mental health research may lead to overfitting, and the quantum simulator might not be able to emulate the behaviour of real quantum circuits perfectly at the present scenario. Secondly, external threats to validity pertains to generalizing the observations from a small available dataset attributing demographic variables such as sex and race, psychosocial characteristics, and clinical assessment data related to psychiatric symptoms to diverse adult populations. These challenges depending on the fidelity of feature representation may affect the prediction accuracy, may attributed to construct validity. Finally, technological threats to validity lie in initial NISQ phase of quantum hardware as of today, with restricting qubit count and circuit depth, where quantum inspired simulated results are envisaged of not fully extrapolate to real devices.

VI. CONCLUSIONS

In this paper, potential applications of quantum inspired neural network and SVM in efficient and fast detection of mental health illness of young adults re studied in detail. This research evaluates the performance of the QINN and QISVM models with their baseline classical models and observed that the performance of this quantum inspired models are limited by overfitting. While comparing between the two quantum inspired models, QISVM wins the race by having highest figure of merit in comparison to QINN. There are several threats to validity discussed in this research which encourages the interested researchers to explore further possibilities to apply this quantum inspired machine algorithms on several other large datasets and by developing some more potential algorithms in future.

VII. AUTHOR'S CONTRIBUTION

Conceptualization: M. Panda, S. R. Mahanta.
Methodology: M. Panda, S. R. Mahanta.
Investigation: M. Panda, S. R. Mahanta.
Discussion of results: M. Panda, S. R. Mahanta.
Writing – Original Draft: M. Panda.
Writing – Review and Editing: M. Panda.
Resources: M. Panda, S. R. Mahanta.
Supervision: M. Panda.
Approval of the final text: M. Panda, S. R. Mahanta.

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