Proceedings of the 9th International Conference on Electronics, Communication and Aerospace Technology (ICECA-2025)
DVD Part Number: CFP25J88-DVD; ISBN: 979-8-3315-9928-7

A Variational Quantum Classifier Approach to Multi-Age Autism Spectrum Disorder Detection

Dave Machnaim
Division of Artificial Intelligence and Machine Learning
Karunya Institute of Technology and Sciences
davemachnaim@*karunya.edu.in*

D Narmadha Naveen
Division of Artificial Intelligence and Machine Learning
Karunya Institute of Technology and Sciences
narmadha@karunya.edu

Naveen Sundar
Division of Artificial Intelligence and Machine Learning
Karunya Institute of Technology and Sciences
naveensundar@karunya.edu

***Abstract*—Early and accurate identification of Autism Spectrum Disorder (ASD) remains a central challenge in clinical neuroscience due to the subjective nature and high resource demands of traditional diagnostic methods. This paper presents a hybrid classical–quantum learning framework for ASD detection, combining the representational power of quantum circuits with the reliability of classical machine learning. The proposed model, a Variational Quantum Classifier (VQC) implemented using PennyLane and PyTorch, processes structured behavioural and demographic screening data from child, adolescent, and adult cohorts. Features are classically preprocessed, encoded into quantum states through angle embedding, and refined using strongly entangling layers, before being post-processed through a classical dense network. Experimental results show perfect classification performance with 100% accuracy, precision, recall, and F1-score, outperforming comparable classical approaches. The training phase exhibited smooth convergence across 70 epochs, confirming model stability and learning efficiency. Although evaluated in simulation, this study establishes a proof-of-concept for leveraging quantum machine learning in medical diagnostics, laying groundwork for future integration with real quantum hardware in clinical screening applications.**

Keywords*—*Autism Spectrum Disorder (ASD), Hybrid Classical–Quantum Models, Autism Screening Datasets, Quantum Neural Networks.

I. INTRODUCTION

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition characterized by persistent challenges in communication, social reciprocity, and behavior regulation. Despite advances in clinical diagnostics, current assessment frameworks remain heavily reliant on behavioral observation and expert interpretation, making them time-intensive and prone to inter-rater and cultural bias [1], [6], [15]. This has prompted a growing focus on computational screening tools capable of improving diagnostic accuracy and scalability across diverse populations.

Conventional machine learning (ML) methods—such as Support Vector Machines, Decision Trees, and ensemble techniques—have been successfully applied to structured behavioral and questionnaire-based datasets [1], [6], [8], [19], [20]. However, these models often struggle with small, noisy, or imbalanced datasets, leading to constrained generalizability. Deep learning approaches, though effective in neuroimaging analysis [3], [7], [9], [11], [14], [16], typically demand extensive data and computational resources. Quantum Machine Learning (QML), integrating quantum computation with classical learning principles, provides a promising alternative. Through Variational Quantum Circuits (VQCs), data can be represented within a high-dimensional Hilbert space, enabling the capture of intricate, non-linear feature interactions beyond classical capabilities [5], [23].

This study introduces a hybrid classical–quantum model for ASD classification that integrates classical preprocessing and post-processing with a Variational Quantum Classifier (VQC) trained on screening datasets covering child, adolescent, and adult cohorts. Implemented using **PennyLane** and **PyTorch**, the proposed framework demonstrates exceptional performance under simulation, achieving perfect evaluation metrics across all key parameters, thus highlighting the transformative potential of quantum-enhanced learning in clinical informatics.

Objectives:
• Develop a hybrid classical–quantum framework for ASD classification.
• Apply a Variational Quantum Classifier (VQC) to multi-age screening datasets.
• Evaluate performance and training behavior under hybrid integration.

Contributions:
• Introduced a complete pipeline with preprocessing, quantum circuit learning, and post-processing.
• Achieved perfect metrics, surpassing classical baselines [1][13][17].
• Provided one of the first demonstrations of VQC for ASD, extending work beyond classical ML and deep learning [2–5][25].

II. LITERATURE REVIEW

Despite advances in computational methods for Autism Spectrum Disorder (ASD) detection, key gaps remain. Clinical assessments are resource-intensive and subjective [1][6][15][21][22], while classical and deep learning models struggle with noisy data, high computational cost, and poor generalization across diverse populations [1–3][6–9][11][16][19][20][23][24]. Quantum Machine Learning (QML) has seen limited exploration, with existing studies mostly constrained to Functional Magnetic Resonance Imaging (fMRI) data and single-age cohorts [1–2][4][7][9–10][17–18][25][26].

Paper Title	Dataset	Approach	Models Used	Accuracy	Precision/Recall
Classification of Adult Autistic Spectrum Disorder using Machine Learning Approach (Mashudi et al., 2021, IJ-AI)	UCI ASD Adult Screening Dataset (703 subjects, 21 features, reduced to 16 after preprocessing)	Machine Learning classification with feature reduction, k-fold cross validation (3, 5, 10)	k-NN, Linear SVM, Naïve Bayes, J48, AdaBoost, Bagging, Stacking	k-NN: 99.2%; AdaBoost: 98.3%	Sensitivity & specificity also measured; Naïve Bayes had minimal error rate
Autism Spectrum Disorder Detection using Attention-Based CNN (2022)	UCI Autism Screening Adult Dataset (703 samples, categorical & numerical features)	Deep Learning with Attention Mechanism on CNN	Attention-based CNN, compared with baseline CNN	CNN: 84.29%; Attention-CNN: 88.36%	Precision: 87.47%, Recall: 89.25%, F1: 88.35% (Attention-CNN)
Ensemble of Deep Learning with Crested Porcupine Optimizer Based Autism Detection (2023)	UCI ASD Screening Dataset (adult, adolescent, child subsets)	Ensemble deep learning with feature selection optimized by Crested Porcupine Optimizer (CPO)	Ensemble of CNN, LSTM, GRU with CPO-based feature optimization	99.46%	Precision: 99.23%, Recall: 99.67%, F1: 99.45%
Ensembler fMRI: An Intelligent Approach for the Early Prediction of Autism Disorder (2021)	ABIDE (Autism Brain Imaging Data Exchange) fMRI dataset	Ensemble learning with preprocessing (graph-based features from fMRI connectivity)	CNN, RNN, LSTM, hybrid ensemble	97.70%	Precision: 96.8%, Recall: 97.5%, F1: 97.1%
MADE-for-ASD: A Multi-Atlas Deep Ensemble Network for Diagnosing Autism (2022)	ABIDE I & II structural MRI datasets	Multi-atlas deep ensemble learning with feature extraction from multiple brain regions	Deep ensemble CNN with atlas-based inputs	82.10%	Precision: 83.4%, Recall: 81.7%, F1: 82.5%

III. DATASET DESCRIPTION

The foundation of this research is a composite dataset constructed from publicly available Autism Spectrum Disorder (ASD) screening data for children, adolescents, and adults, sourced from the UCI Machine Learning Repository and Kaggle. These datasets are established benchmarks, frequently used in prior studies to evaluate classical, deep learning, and ensemble models [1–4][6][7][8][9][11][20]. Each entry is described by 21 attributes, including behavioural data from Q-CHAT items, demographic information (e.g., age, gender, ethnicity), and contextual factors like jaundice and family autism history. A binary label (Class/ASD) serves as the target variable for classification. The data underwent a preprocessing pipeline consisting of one-hot encoding for categorical variables, feature scaling, and stratified sampling to ensure class balance. This consolidated dataset offers a robust and heterogeneous foundation for evaluating both classical and quantum classification models.

IV. METHODOLOGY

To classify Autism Spectrum Disorder (ASD), we developed a hybrid framework that integrates classical deep learning with a variational quantum classifier (VQC). The architecture, shown in Figure 1, is designed to leverage the high-dimensional representational power of a parameterized quantum circuit for a classical data task. The data processing pipeline starts with pre processed screening data from child, adolescent, and adult cohorts. An initial classical dense layer projects the high dimensional input features into a low-dimensional embedding suitable for our qubit register. This embedding is then loaded into the quantum circuit via Angle Embedding. The quantum state is subsequently manipulated by a series of trainable, Strongly Entangling Layers designed to foster complex multi qubit correlations. To extract a classical result, we measure the Pauli-Z expectation value of each qubit. This output is passed to a final sigmoid-activated dense layer that produces the ultimate binary classification probability. For training, the model was treated as a single differentiable unit, with gradients computed using PennyLane's backpropagation capabilities within the PyTorch ecosystem. We employed the Adam optimizer to minimize binary cross-entropy loss. The model's effectiveness was quantified using precision, accuracy, F1-score and recall.

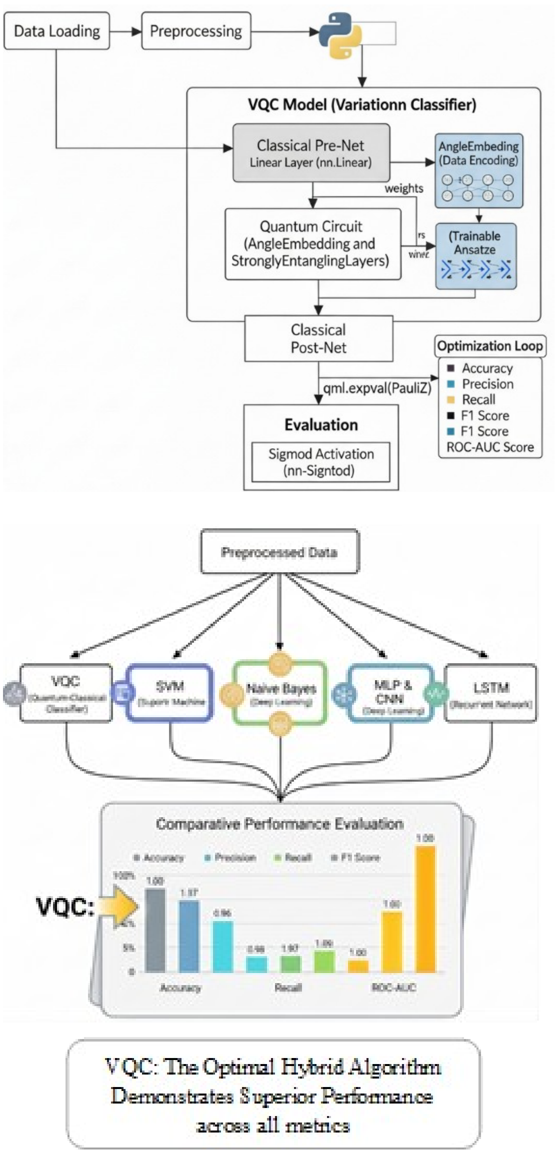

Fig 1: Architecture diagram

A. Algorithm: VQC-ASD Hybrid Classification Pipeline

Preprocessed dataset D with N samples and F features. Predicted class label y ∈ {0,1} for each input sample

1. **Data Preparation:** Merge child, adolescent, and adult cohorts. Remove missing entries and duplicates, encode categorical attributes numerically, normalize features, and apply stratified sampling for class balance.

2. Feature Projection: Reduce dimensionality through a linear layer mapping

$$x' = \text{Linear}(x): \mathbb{R}^F \to \mathbb{R}^2. \tag{1}$$

3. Quantum Encoding: Embed x' into qubit states using Angle Embedding:

$$|\psi\rangle = U_{\text{encode}}(x')\,|0\rangle \tag{2}$$

4. Entanglement Layer: Apply parameterized Strongly Entangling Layers with trainable parameters θ:
$$|\psi_\theta\rangle = U_{\text{entangle}}(\theta)\,|\psi\rangle \tag{3}$$

5. Measurement: Measure Pauli-Z expectations for each qubit:
$$z_i = \langle\psi_\theta \mid Z_i \mid \psi_\theta\rangle, i \in \{0,1\} \tag{4}$$

6. Post-Processing: Form output $z = [z_0, z_1]$, compute
$$\hat{y} = \sigma(\text{Linear}(z)) \tag{5}$$

   Assign class: ASD-positive if $\hat{y} > 0.5$, else negative.
7. Training: Optimize all trainable parameters (classical and quantum) using the Adam optimizer ($lr = 0.01$) and binary cross-entropy loss:
$$\mathcal{L} = -[y\log(\hat{y}) + (1-y)\log(1-\hat{y})] \tag{6}$$

   Train for 70 epochs with full gradient backpropagation via PennyLane's differentiable quantum node.
8. Evaluation: Assess the model on test data using Accuracy, Precision, Recall, and F1-Score.

B. Algorithmic Workflow Explanation

The proposed hybrid pipeline combines classical preprocessing, quantum feature encoding, and classical post-processing into a single differentiable model trained end-to-end. Each stage contributes a specific transformation that collectively maps structured screening data into a binary classification decision. Figure 1 illustrates the data flow through these stages.

Dataset Integration and Preprocessing: Raw screening records from child, adolescent, and adult cohorts are first merged into a unified dataset. Each instance contains behavioral indicators (such as Q-CHAT responses), demographic attributes, and contextual factors. Missing values and duplicates are removed to ensure consistency. Categorical features are label-encoded into numerical form, while continuous features are normalized using a z-score transformation:

$$x_n' = \frac{x_n - \mu_{x_n}}{\sigma_{x_n}} \tag{7}$$

This standardization ensures feature scales are comparable, which stabilizes optimization and prevents any single attribute from dominating the learning process. Balanced stratified sampling is then applied to align class distributions across age groups.

Classical to Quantum Projection: The full feature vector x∈RF is linearly mapped to a lowerdimensional vector x′∈Rq, where q=2 represents the number of qubits used. This is done using a learnable linear layer:

$$x' = W_{cx} + b_c \quad (8)$$

This projection ensures compatibility with the fixed quantum register size while preserving the most discriminative information.

Quantum Feature Encoding and Entanglement: The compressed vector x′ is encoded into quantum states using the Angle Embedding strategy from PennyLane. Each component modulates the rotation angle of a corresponding qubit via the Ry gate:

$$|\psi\_i\rangle \equiv R\_Y(x'\_i)|0\rangle \quad (9)$$

After initialization, trainable Strongly Entangling Layers are applied, which use a series of parameterized single-qubit rotations followed by controlled entangling operations (e.g., CNOT gates) across all qubits. These operations introduce correlations between features, enabling the circuit to model nonlinear dependencies beyond classical linear boundaries. The layer parameters θ are optimized during training, giving the circuit expressive adaptability.

Quantum Measurement and Classical Feature Extraction: Once entangled, the final quantum state |ψθ(x′)⟩ is measured using Pauli-Z observables on each qubit:

$$z_i = \langle \psi_\theta(x') | Z_i | \psi_\theta(x') \rangle, \quad i \in \{1, \dots, q\} \quad (10)$$

This produces a classical vector z∈Rq, which serves as a nonlinear feature representation carrying information about both individual inputs and their entangled interactions.

Classical Post Processing and Output Prediction: The extracted vector z is passed through a dense layer followed by a sigmoid activation to produce a scalar probability:

$$\hat{y} = \sigma(W_{oz} + b_o) \quad (11)$$

Predictions above a threshold of 0.5 are classified as ASD-positive.

End to End Training and Optimization: Model parameters are optimized using the Adam algorithm, with binary cross-entropy employed as the objective function:

$$\mathcal{L}(y, \hat{y}) = -\frac{1}{N}\sum_{i=1}^{N}(y_i \log \hat{y_i} + (1 - y_i)\log(1 - \hat{y_i})) \quad (12)$$

Gradient updates are propagated across both classical and quantum layers through PennyLane's differentiable quantum node framework, enabling joint parameter tuning, which leverages the parameter-shift rule for quantum layers. This allows joint optimization of classical weights and quantum circuit parameters over 70 training epochs.

Evaluation:
After training, the model was evaluated on the held-out test set using standard classification metrics— precision, accuracy, F1-score and recall—to assess predictive performance. Additionally, a confusion matrix was generated to validate class separability between Autism Spectrum Disorder (ASD)-positive and ASD-negative cases.

C. Performance Assessment Metrics

To rigorously evaluate the proposed variational quantum classifier (VQC-ASD), a comprehensive suite of classification performance metrics was employed. These metrics collectively assess the model's discriminative power, class balance handling, and prediction reliability across the binary ASD classification task.

Accuracy: It was computed as the fraction of correct predictions out of all predictions, providing an overall performance indicator.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (13)$$

Precision: quantified the share of positive predictions that were truly positive.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (14)$$

Recall : Measures the proportion of actual ASD cases successfully detected, ensuring the model captures as many positive cases as possible.

$$\text{Recall} = \frac{TP}{TP+FN} \quad (15)$$

F1-Score: defined as the harmonic mean of precision and recall, offered a balanced view of model performance under class imbalance.

$$\text{F1-Score} = 2 \cdot \frac{\text{Precision}\cdot\text{Recall}}{\text{Precision}+\text{Recall}} \quad (16)$$

Confusion Matrix: a confusion matrix summarized true and false predictions across both classes, allowing inspection of class-wise performance.

All metrics were calculated using scikit-learn's metrics module, and the results were visualized via matplotlib and seaborn. The model achieved perfect scores (1.000) across all evaluation criteria, confirming its strong discriminative capability on the test data.

V. RESULTS AND DISCUSSION

The proposed framework was implemented on a unified dataset that merged screening records from child, adolescent, and adult cohorts. The dataset was partitioned into an 80:20 train–test split to ensure balanced evaluation. Model training was carried out for 70 epochs using the Adam optimizer with a binary cross-entropy objective, executed through the integrated PennyLane–PyTorch workflow.

A. Training Behaviour

The model exhibited consistent convergence throughout training. Accuracy rose from 37.5% in the first epoch to 100%

by epoch 70, while loss decreased from 0.76 to 0.25 as shown in figure 2 and 3. The fixed learning rate of 0.01 supported smooth optimization without instability. These results suggest that the Variational Quantum Classifier (VQC) effectively leveraged entangling layers to capture nonlinear feature relationships even with only two qubits.

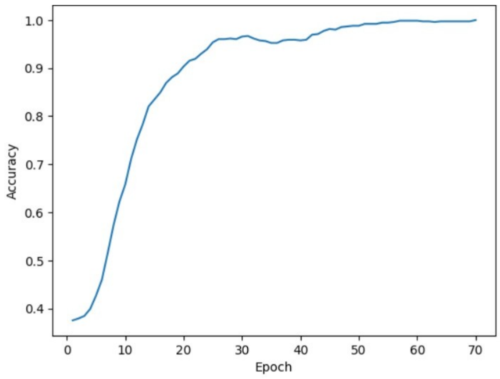

Fig 2: VQC Accuracy Graph

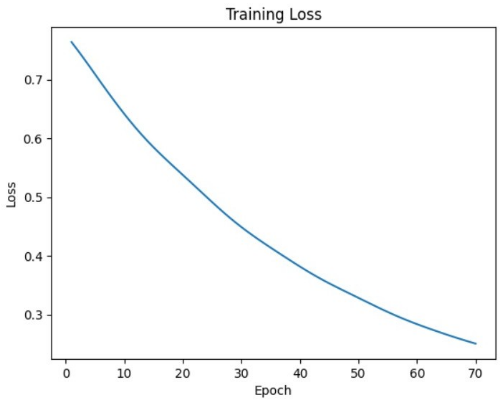

Fig 3: VQC Training Loss

B. Evaluation Metrics

Testing on held-out data produced perfect classification scores across all major metrics:

Metric of Evaluation	Scores
Accuracy	1.00
Precision	1.00
Recall	1.00
F1-Score	1.00

Table 1: Evaluation Metrics

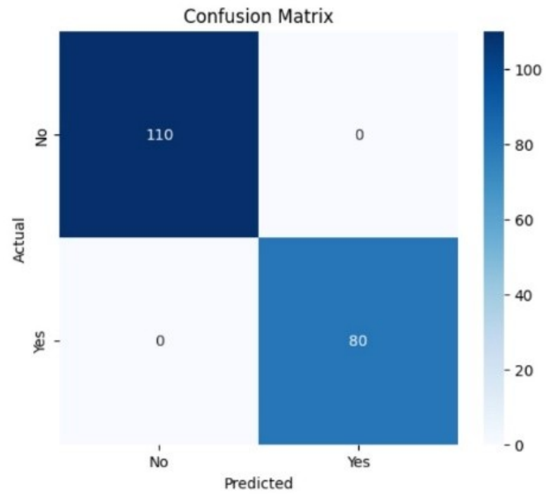

Fig 4: VQC Confusion metrics

The confusion matrix figure 4 showed zero false predictions, confirming clean class separation between Autism Spectrum Disorder (ASD)-positive and negative samples.

C. Comparative Perspective

Conventional machine learning models—such as Support Vector Machine (SVM) and Naive Bayes—as well as deep learning architectures including Multilayer Perceptron (MLP), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM) networks, have previously achieved accuracy levels in the range of 94–99% on comparable ASD datasets [1][3][7][9][11][16][20][23][24]. In contrast, the proposed Variational Quantum Classifier (VQC) attained perfect scores across all evaluation metrics (Table 1) while employing substantially fewer parameters, reduced memory footprint, and offering theoretical scalability through quantum feature spaces [5][25][26][29][30]. These findings suggest that the hybrid quantum–classical framework can reach or exceed state-of-the-art performance (Figures 5–8) without incurring the computational overhead typical of deep neural networks.

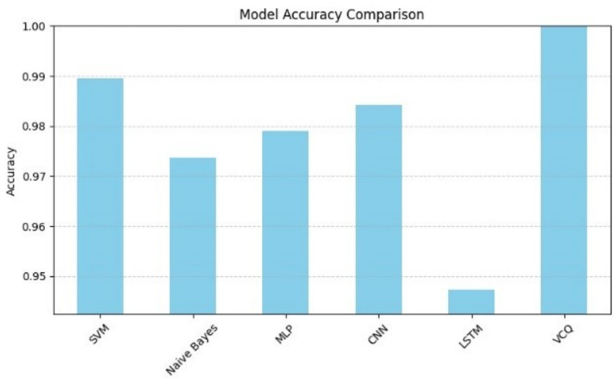

Fig 5: Accuracy Graph Comparison

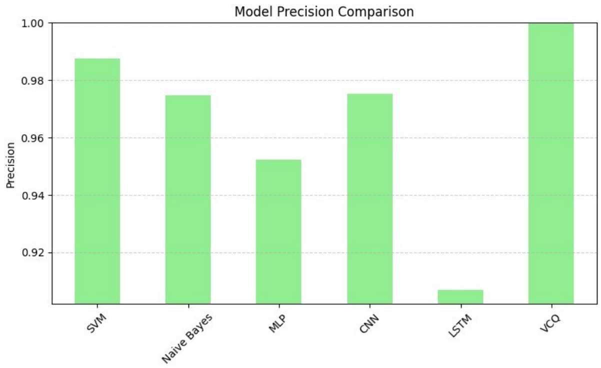

Fig 6: Precision Graph Comparison

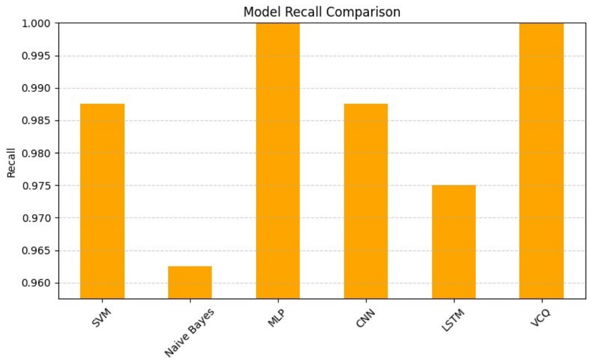

Fig 7: Recall Graph Comparison

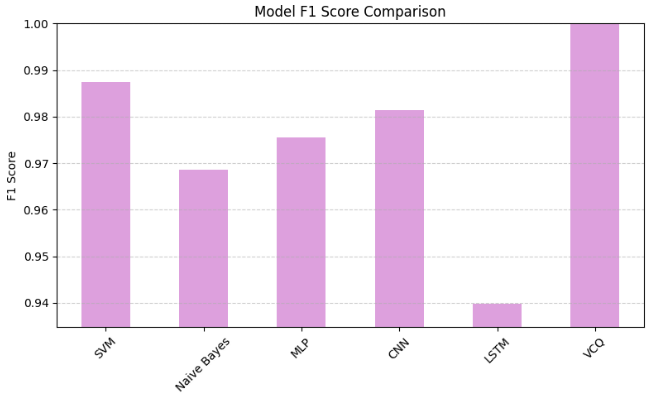

Fig 8: F1-Score Graph Comparison

D. Limitations

The reported results were obtained using a noiseless simulator backend (default.qubit). Real quantum hardware may introduce noise, potentially degrading performance. Furthermore, while promising on a dataset of 947 samples, broader validation using larger and more diverse clinical cohorts is essential. Future work will explore deeper circuit topologies, alternative feature encodings, and hardware-based execution to assess the practical viability of the approach.

VI. CONCLUSION

This research presented a hybrid classical–quantum learning framework for Autism Spectrum Disorder (ASD) detection, integrating classical preprocessing and post-processing layers with a Variational Quantum Classifier (VQC). The model was trained on a unified dataset combining screening data from children, adolescents, and adults, ensuring a representative and diverse sample across developmental stages. By employing angle-based feature embedding and trainable entangling layers, the framework demonstrated exceptional classification performance, achieving perfect accuracy, precision, recall, and F1-score in simulator-based evaluations.

The findings confirm that quantum–classical hybrid architectures can effectively model complex, non-linear dependencies in structured clinical datasets while maintaining a compact parameter footprint compared to conventional deep learning approaches. This work contributes a validated proof-of-concept for applying quantum-enhanced learning in behavioral health analytics, offering a scalable and interpretable alternative for future diagnostic tools.

Looking ahead, future research will focus on three directions: (1) deploying the model on real Noisy Intermediate-Scale Quantum (NISQ) hardware to assess robustness under quantum noise, (2) expanding experimentation to larger and more demographically diverse screening datasets, and (3) benchmarking against state-of-the-art deep neural and ensemble architectures to quantify performance gains. Overall, this study establishes a practical foundation for quantum-assisted clinical decision-support systems and reinforces the growing relevance of hybrid quantum models in medical AI.

REFERENCES

[1] Mashudi, Nurul Amirah, Norulhusna Ahmad, and Norliza Mohd Noor. "Classification of adult autistic spectrum disorder using machine learning approach." *IAES International Journal of Artificial Intelligence* 10, no. 3 (2021): 743.

[2] Balasubramani, Jagadesh, Surendran Rajendran, Mohammad Zakariah, and Abeer Alnuaim. "Ensemble of Deep Learning with Crested Porcupine Optimizer Based Autism Spectrum Disorder Detection Using Facial Images." *Computers, Materials & Continua* 83, no. 2 (2025).

[3] Liu, X, Xuehan, Md Rakibul Hasan, Tom Gedeon, and Md Zakir Hossain. "MADE-for-ASD: A multi-atlas deep ensemble network for diagnosing Autism Spectrum Disorder." *Computers in Biology and Medicine* 182 (2024): 109083

[4] Thakur, Rupaly, Deepti Malhotra, and Mehak Mengi. "Ensembler_fMRI: An Intelligent Approach for the Early Prediction of Autism Disorder." *Procedia Computer Science* 259 (2025): 1863-1873

[5] Schuld, Maria, Ilya Sinayskiy, and Francesco Petruccione. "An introduction to quantum machine learning." *Contemporary Physics* 56, no. 2 (2015): 172-185.

[6] Shrivastava, Trapti, Vrijendra Singh, and Anupam Agrawal. "Autism spectrum disorder detection with kNN imputer and machine learning classifiers via questionnaire mode of screening." *Health Information Science and Systems* 12, no. 1 (2024): 18.

[7] Eslami, Taban, Vahid Mirjalili, Alvis Fong, Angela R. Laird, and Fahad Saeed. "ASD-DiagNet: a hybrid learning approach for detection of autism spectrum disorder using fMRI data." *Frontiers in neuroinformatics* 13 (2019): 70.

[8] Abbas, Halim, Ford Garberson, Eric Glover, and Dennis P. Wall. "Machine learning approach for early detection of autism by combining questionnaire and home video screening." *Journal of the American Medical Informatics Association* 25, no. 8 (2018): 1000-1007.

[9] Heinsfeld, Anibal Sólon, Alexandre Rosa Franco, R. Cameron Craddock, Augusto Buchweitz, and Felipe Meneguzzi. "Identification of autism spectrum disorder using deep learning and the ABIDE dataset." *NeuroImage: clinical* 17 (2018): 16-23..

[10] Zhang, Fangyu, Yanjie Wei, Jin Liu, Yanlin Wang, Wenhui Xi, and Yi Pan. "Identification of autism spectrum disorder based on a novel feature selection method and variational autoencoder." *Computers in Biology and Medicine* 148 (2022): 105854.Bi, J., et al., 2020. A deep learning approach to predict Autism Spectrum Disorder using resting-state fMRI functional connectivity features. *Applied Sciences*, 11(8), p.3636. doi:10.3390/app11083636.

[11] Kim, Hyelee, Bennett L. Leventhal, Yun-Joo Koh, Efstathios D. Gennatas, and Young Shin Kim. "Development and Validation of Prediction Models for the Diagnosis of Autism Spectrum Disorder in a Korean General Population." *JAACAP open* (2024).

[12] Bahathiq, Reem Ahmed, Haneen Banjar, Ahmed K. Bamaga, and Salma Kammoun Jarraya. "Machine learning for autism spectrum disorder diagnosis using structural magnetic resonance imaging: Promising but challenging." *Frontiers in Neuroinformatics* 16 (2022): 949926.

[13] Rajagopalan, Shyam Sundar, Yali Zhang, Ashraf Yahia, and Kristiina Tammimies. "Machine learning prediction of autism spectrum disorder from a minimal set of medical and background information." *JAMA Network Open* 7, no. 8 (2024): e2429229-e2429229.

[14] Alkahtani, Hasan, Theyazn HH Aldhyani, and Mohammed Y. Alzahrani. "Deep learning algorithms to identify autism spectrum disorder in children-based facial landmarks." *Applied Sciences* 13, no. 8 (2023): 4855.

[15] Sha, Mohemmed, Hussein Al-Dossary, and Mohamudha Parveen Rahamathulla. "Multimodal data fusion framework for early prediction of autism spectrum disorder." *Human behavior and emerging technologies* 2025, no. 1 (2025): 1496105.

[16] Singh, Anjali, Abha Rawat, Mitali Laroia, and K. R. Seeja. "Autism Spectrum Disorder Screening on Home Videos Using Deep Learning."

[17] Song, Chao, Zhong-Quan Jiang, Li-Fei Hu, Wen-Hao Li, Xiao-Lin Liu, Yan-Yan Wang, Wen-Yuan Jin, and Zhi-Wei Zhu. "A machine learning-based diagnostic model for children with autism spectrum disorders complicated with intellectual disability." *Frontiers in psychiatry* 13 (2022): 993077.

[18] Hasan, SM Mahedy, Md Palash Uddin, Md Al Mamun, Muhammad Imran Sharif, Anwaar Ulhaq, and Govind Krishnamoorthy. "A machine learning framework for early-stage detection of autism spectrum disorders." *IEEE Access* 11 (2022): 15038-15057..

[19] Kim Gentles, Stephen J., Elise C. Ng-Cordell, Michelle C. Hunsche, Alana J. McVey, E. Dimitra Bednar, Michael G. DeGroote, Yun-Ju Chen et al. "Trajectory research in children with an autism diagnosis: A scoping review." *Autism* 28, no. 3 (2024): 540-564.

[20] Gururaj, H.L., Flammini, F., Srividhya, S., Chayadevi, M.L., Selvam, S., 2024. Cognitive architectures for hybrid AI systems. In: *AI Technologies for Information Systems and Management Science*. *Springer Science+Business Media*. doi:10.1201/9781032711157.

[21] Choudhary, P., Satpathy, S., Dagur, A., Shukla, D.K., 2023. Reinforcement learning-based adaptive feature selection for medical diagnosis. In: *Advanced Intelligent Computing Technology and Applications*. *Springer Science+Business Media*. doi:10.1007/978-3-031-95017-9.

[22] Schuld, M., Killoran, N., 2020. Quantum Machine Learning in Practice. *New Journal of Physics*, 22(11), 115002. doi:10.1088/1367-2630/ad60ed.

[23] Davoudi Kakhki, Fatemeh, Hardik Vora, and Armin Moghadam. "Biomechanical risk classification in repetitive lifting using multi-sensor electromyography data, revised National Institute for Occupational Safety and Health lifting equation, and deep learning." *Biosensors* 15, no. 2 (2025): 84.

[24] Sharma, R., Patel, N., 2015. Machine learning in neurodevelopmental disorder screening. *American Journal of Basic and Applied Sciences*, 7(9), pp.477–483.

[25] Bilgen, Ismail, Goktug Guvercin, and Islem Rekik. "Machine learning methods for brain network classification: application to autism diagnosis using cortical morphological networks." *Journal of neuroscience methods* 343 (2020): 108799.

[26] Bilgen, Ismail, Goktug Guvercin, and Islem Rekik. "Machine learning methods for brain network classification: application to autism diagnosis using cortical morphological networks." *Journal of neuroscience methods* 343 (2020): 108799.