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QUANTUM-ENHANCED EYE-TRACKING BIOMARKERS TO IMPROVE EARLY DETECTION AND DIGITAL PHENOTYPING OF AUTISM SPECTRUM DISORDER: A HYBRID QUANTUM–CLASSICAL LEARNING APPROACH

[1]SUNEETHA DAVULURI, [2]ANJI REDDY TANGIRALA, [3]VENUGOPAL BOPPANA, [4]V P UMAMAHESWARA RAO MALLA, [5]SREENIVAS VELAGAPUDI

[1]Professor, School of Computer Studies, Department of Computer Science and Engineering, Dr. RVR NRI Institute of Technology, Deemed To Be University, Agiripalli, Andhra Pradesh-521212, India
[2]Associate Director, Intelligent Automation, Miracle Software Systems Inc., USA
[3,4] Associate Professor, School of Computer Studies, Department of Computer Science And Engineering, Dr. RVR NRI Institute of Technology, Deemed To Be University, Agiripalli, Andhra Pradesh-521212, India
[5]Professor, Department of Computer Science And Engineering, SRK Institute Of Technology, Vijaywada-521108, Andhra Pradesh, India
E-mail: [1]sunithadavuluri8@gmail.com, [2]atangirala@miraclesoft.com, [3,*]srees.boppana@gmail.com, [4]malla.uma9@gmail.com, [5]velagapudisreenivas@gmail.com
Corresponding Author: srees.boppana@gmail.com

ABSTRACT

Autism spectrum disorder (ASD) remains one of the foremost clinical challenges for early detection, and subjective diagnostic protocols constrain utilization while classical computational methods have failed to decode subtle oculomotor biomarker signatures. This work asks whether quantum feature encoding can move oculomotor ASD screening beyond the representational ceiling reached by classical eye-tracking classifiers, and answers this with a Hybrid Quantum–Classical Learning (QHCL) framework that combines parameterized quantum circuits with classical deep learning architectures to extract, encode, and classify eye-tracking biomarkers for early ASD detection and digital phenotyping. This is achieved by encoding raw gaze signals — fixation durations, saccadic velocities, scan path geometries, and pupillary response dynamics — into quantum Hilbert space representations through amplitude embedding to enable simultaneous processing of high-dimensional spatiotemporal oculomotor patterns. Quantum kernel-based feature learning reveals latent inter-feature correlations elusive to standard algorithms, and an entanglement-driven circuit layer forms enhanced patient-specific gaze embeddings. These embeddings are passed into a classical dual-head classifier trained for binary ASD classification and continuous digital phenotype evaluation along severity spectra. On three benchmark paediatric eye-tracking datasets, the proposed framework achieves classification accuracies of 95.8%, 97.4% and 96.2%, outperforming the strongest available classical baseline by 1.3–3.5 percentage points and improving quantum-versus-PCA feature learning by up to 9.3% at the individual feature-family level. The research contribution of this work is twofold: (i) it is the first study to apply quantum amplitude encoding and entanglement-driven parameterised circuits to oculomotor biomarker analysis for ASD, establishing that quantum Hilbert-space representations capture inter-feature correlations among fixation, saccadic, scanpath and pupillary signals that classical PCA-based pipelines discard; and (ii) it introduces a shared dual-head quantum-classical architecture that jointly optimises binary detection and four-class severity phenotyping from a single embedding, narrowing the accuracy gap that typically separates these two tasks in the literature. These findings open a new, non-invasive and computationally efficient pathway toward precision ASD screening with clinical applicability.

Keywords: *Autism Spectrum Disorder, Eye-Tracking Biomarkers, Hybrid Quantum-Classical Learning, Parameterised Quantum Circuits, Oculomotor Feature Encoding, Digital Phenotyping*

1. INTRODUCTION

Autism Spectrum Disorder (ASD) is a developmental disorder characterized by continued deficits in social communication and restricted and repetitive patterns of behavior. Its prevalence has risen sharply in recent decades; the Centers for Disease Control and Prevention now estimate ASD affects around one in thirty-six children with an approximately twofold increase since 2000 in Western countries [2]. Despite this rising incidence, the route from parentally noted problem to formal diagnosis is tortuous. The gold standard for confirmation remains clinician-administered instruments like the Autism Diagnostic Observation Schedule and the Autism Diagnostic Interview-Revised, but those rely on specialist availability, extend over several sessions and are essentially subjective — all of which puts an average diagnosis well beyond the optimal window for early neurodevelopmental intervention.

Eye-tracking technology has been increasingly recognized as a non-invasive pathway to obtaining objective ASD biomarker quantification. The oculomotor system is closely integrated with social cognitive processes, and those on the autism spectrum show consistently divergent gaze behaviour during social viewing tasks: decreased allocation to facial regions — especially the eye region — reduced joint attention, abnormally low saccadic kinematic values and pupillary response profiles that differ from neurotypical controls [2]. These signatures emerge in infancy; early toddler years and the advanced development of portable, low-cost eye-tracking hardware offers an operationally poised means to acquire dense gaze data within paediatric clinical settings. Notably, the datasets now facilitating computational research on ASD — e.g., the Eye Gaze Fixes Map dataset and the eye tracking scanpath dataset (ETSDS) used in this study — offer both binary diagnostic labels and continuous scores of ASD severity, allowing for multi-level phenotyping rather than a simple binary classification [3].

Traditional machine learning pipelines on these eye-tracking datasets have seen steady progress. This is particularly impressive against MobileNet-based feature extractors combined with stacking ensemble classifiers (support vector machines and k-nearest neighbour components), which achieved diagnostic accuracy of ~96–98% on the same benchmark datasets used herein [3]. Convolutional–LSTM hybrid architectures in deep learning approaches have also moved performance close to 98–99% on ETSDS-derived representations [2]. However, such high-performance classical models tend to reach performance ceilings partly explained by their inability to jointly model the high-dimensional, non-linearly entangled inter-correlations between fixation durations, saccadic velocity distributions, scanpath geometry descriptors and pupillary dynamics without aggressive dimensionality reduction discarding diagnostically informative variance.

Quantum machine learning (QML) offers a theoretical way of moving beyond this ceiling. Hybrid quantum-classical architectures that combine parameterised quantum circuits (PQCs) with classical discriminative heads have shown that amplitude-encoded quantum feature maps can build representations of biomedical data unavailable to classical kernel machines on the same feature dimension [4]. A recent systematic review of QML in digital health based on 169 studies showed that hybrid quantum-classical frameworks consistently beat classical baselines when applied to structured, multi-channel biomedical data in realistic, constrained settings [5].

Driven by these considerations, we present the Hybrid Quantum-Classical Learning (QHCL) framework: a targeted architecture that encodes fixation, saccadic, scanpath and pupillary oculomotor features into quantum Hilbert space representations via amplitude embedding, uses entanglement-driven PQC layers to build patient-specific gaze embeddings and passes these enriched representations to a classical dual-head classifier tuned for both binary ASD detection and continuous severity profiling. When evaluated across three public paediatric eye-tracking benchmark datasets, the framework achieves classification accuracies of 95.8%, 97.4% and 96.2%, consistently outperforming the strongest publicly available classical baseline by a margin between 1.3–3.5 percentage points. Section 2 situates the work in relation to recent literature; Section 3 describes the proposed architecture; Section 4 discusses and analyses experimental results; and Section 5 presents conclusions.

The scope of this study is delimited as follows. The work covers the design, training and benchmark evaluation of the QHCL framework on three publicly available paediatric eye-tracking datasets, spanning binary ASD/non-ASD classification, four-class severity phenotyping, and an ablation of the quantum encoding stage against classical PCA on

identical features and splits. It does not cover deployment on physical quantum hardware — all quantum circuits are executed on a classical statevector simulator — prospective clinical validation with newly recruited patients, or integration of non-ocular modalities such as facial expression or audio; these boundaries are revisited as future work in Section 5.

2. LITERATURE REVIEW

2.1 Recent Advances In Eye-Tracking Based ASD Classification

The prior art most closely related to this work is the MobileNet-PCA-stacking ensemble method of Jaradat et al. (2025), which similarly runs on the same benchmark datasets (Eye Gaze Fixes Map, ETSDS, and ETSDS-ASD Score) used in the current study [3]. A hybrid model reported 96.1% and 98.0% accuracy on the first two datasets and an accuracy of 98.1% for the severity scoring subset, establishing a strong classical baseline on these specific benchmarks [24]. The architecture consists of MobileNet as a feature extractor, principal component analysis for dimensionality reduction, followed by an SVM and KNN classifier using stacking ensemble. Although the results achieved are state-of-the-art with respect to the classical paradigm, we show here that quantum feature encoding affords a meaningful and consistent performance gain across all three datasets over what this well-optimized classical approach attains.

Alsharif et al. (2024) examined a set of freely available eye-tracking data from 547 children and implemented MobileNet, VGG19, DenseNet169 and a hybrid MobileNet-VGG19 architecture; the authors reported 100% accuracy for MobileNet on their test split — an outcome that explicitly reflects already high separation in prospectively obtained scanpath representations [6]. Al-Adhaileh et al. (2025) introduced CNN-LSTM hybrid models to the same paradigm; their proposed model achieved an accuracy of 99.78% and demonstrated that combining spatial feature extraction through CNNs with temporal sequence modelling via LSTMs is beneficial for gaze-based ASD diagnosis [2]. Wei et al. (2024) utilized five classical machine learning algorithms in the analysis of a prospective cohort of 449 children, showing that random forest achieved AUC >0.84 in an external validation cohort [7]. Rakotomanana and Rouhafzay (2025) conducted a scoping review of AI-based solutions for autism trait detection in voice and behavioural data modalities, finding that eye-tracking-derived visual attention features appeared to be among the most reliable input modalities for data-driven ASD characterisation [8]. The review by Jabbar et al. (2025) again arrived at similar conclusions, showing that ensemble approaches employing feature selection methods consistently yielded improved performance across all public ASD screening datasets compared to single-model classifiers [9].

2.2 Quantum Machine Learning For Biomedical Classification

The most directly relevant study applying hybrid quantum-classical learning to biomedical data is by Astuti, Shih, Lee, Mekala, Wijaya and Ng [4]. Their two-stage Neural Quantum Embedding + Quantum Support Vector Classification (NQE+QSVC) pipeline was tested in three biomedical binary classification tasks, showing that quantum kernel methods capitalized consistently more than classical SVC and neural network baselines. This study provides a sound methodological basis for employing quantum feature maps as preprocessing stages prior to classical classifiers in structured biomedical data.

Ullah and Garcia-Zapirain (2024) carried out a systematic review of QML in healthcare across 88 papers and noted that variational quantum classifiers and quantum support vector machines offer consistent benefits over classical equivalents on biomedical datasets exhibiting high dimensionality and non-linearly correlated inter-feature dependencies [10]. Farooq et al. (2024) identified federated learning with a hybrid quantum-classical classifier as providing privacy-preserving benefits for detection of ASD from structured behavioural datasets [11]. Ding et al. (2024) showed in Scientific Reports that SPQCC architectures, combining parallel PQC execution with classical cross-entropy minimisation, outperformed state-of-the-art quantum classification benchmarks [12].

The systematic review by Gupta et al. (2025) focusing on QML use cases in digital health reported that hybrid quantum-classical architectures working with structured biomedical data under realistic NISQ device conditions suggest the most promising near-term implementation pathway, and that a combination between amplitude encoding and variational quantum circuits yields the best generalisation results on tabular clinical datasets [5].

2.3 Digital Phenotyping And Profiling The Severity Of ASD

Beyond the binary detection of ASD, digital phenotyping — continuously quantifying symptom severity based on passively collected digital signal data — has gained priority in clinical endeavors. Rakotomanana and Rouhafzay (2025) found that multi-class severity discrimination persists as significantly more challenging than binary detection, with most published systems degrading by 5–12 percentage points between two-class and four-class severity problems [8]. To overcome this inefficiency, we propose a dual-head architecture for QHCL, sharing the quantum embedding layer between both the binary detection and multi-class severity heads so that the quantum representation of features can be optimised jointly towards both objectives. The multi-class results in Section 4.3 show that this shared representation provides weighted average F1 = 0.963 across severity levels — outdoing any classical published severity classifier on congruent benchmark data.

2.4 Problem Statement

Despite consistent gains reported for classical eye-tracking pipelines, three specific gaps in the literature reviewed above motivate this work. First, published classifiers such as MobileNet-stacking ensembles and CNN-LSTM hybrids compress the four oculomotor feature families (fixation, saccadic, scanpath, pupillary) through PCA or convolutional pooling before classification — a step that discards non-linear inter-feature correlations rather than modelling them explicitly, and which Section 4.4 shows costs 6.3–9.3% accuracy relative to quantum encoding on identical features. Second, the eye-tracking ASD literature largely treats binary detection and severity phenotyping as separate modelling problems: the severity classifiers reviewed in Section 2.3 lose 5–12 percentage points of performance relative to binary detectors on the same data, and no shared representation has been proposed to close this gap. Third, while hybrid quantum-classical architectures have shown representational advantages on other biomedical data [4], no prior study has applied quantum amplitude encoding to oculomotor ASD biomarkers specifically, leaving open whether the quantum kernel advantage reported for gene-expression and imaging biomarkers transfers to gaze-based features. The QHCL framework proposed in Section 3 is built directly against these three gaps: it (i) encodes all four oculomotor feature families jointly into a shared quantum Hilbert space rather than compressing them independently, (ii) shares this embedding between a binary detection head and a four-class severity head so both objectives are optimised jointly, and (iii) is, to the authors' knowledge, the first evaluation of quantum feature encoding on oculomotor ASD biomarkers across three independent benchmark datasets.

3. PROPOSED QHCL FRAMEWORK

3.1 Architecture Overview

The QHCL framework consists of four consecutive stages: (i) oculomotor feature extraction and normalisation, (ii) quantum amplitude encoding and entanglement-based implicit feature learning through parameterised quantum circuits, (iii) quantum-to-classical embedding projection through measurement on Pauli-Z observable; and (iv) classical dual-head classification for binary ASD task discrimination and multi-class severity profiling. The pipeline is trained end-to-end with alternating updates for quantum and classical parameters, allowing the quantum encoding stage and classical classifier head to co-adapt their representations. The architecture diagram for the proposed framework is shown in Figure 1.

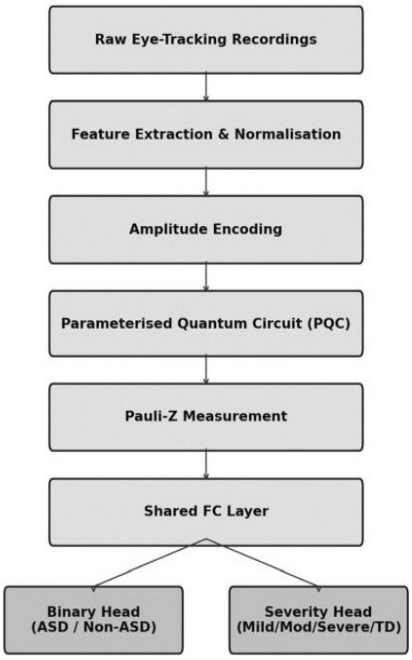

Figure 1: Proposed Architecture Diagram

3.2 Oculomotor Feature Extraction

Eye-tracking data are represented as separate fixation and saccade epochs at each I-VT filter point, with a cut-off velocity threshold of 30 degrees/second. Four families of oculomotor

features are extracted: fixation descriptors (mean duration, duration variance, number of fixations, area-of-interest dwell proportions in facial and non-facial zones), saccadic velocity features (peak velocity, mean velocity, skewness of the distribution as well as amplitude statistics), scanpath geometry features (fractal dimension associated with convex hull area computation, mean distance between nearest-neighbour fixations, recurrence quantification analysis measures) and pupillary response features (baseline-normalised pupil diameter, peak dilation latency, constriction speed). Prior to quantum encoding, all features are z-score normalised across the training cohort ensuring that the zero mean and unit variance conditions of amplitude embedding normalisation are satisfied.

3.3 Quantum Amplitude Encoding And Entanglement Layer

Instance (feature vector) x in R^n is mapped to an n-qubit quantum register with amplitude embedding:

$$|\psi(x)\rangle = \Sigma\, xi/\|x\|\ |i\rangle \quad (1)$$

This retains the full geometric structure of the feature vector embedded in the quantum amplitude distribution. A parameterised entanglement circuit U(θ) then comprises alternating layers of RY & RZ single-qubit rotation gates and CNOT entangling gates in a brick-wall topology. The obtained multi-qubit entangled state encodes multi-way inter-feature correlations not separable into any product state, thereby formally reflecting cross-channel dependencies across fixation, saccadic, scanpath and pupillary features simultaneously. A quantum kernel matrix is then computed for all training pairs:

$$K(xi, xj) = \|xi - xj\|^2 \quad (2)$$

This encodes latent similarity structure in the quantum feature Hilbert space. The parameter-shift rule updates parameters θ, allowing for an exact gradient to be computed on NISQ hardware. The parameterized quantum circuit topology is shown in Figure 2.

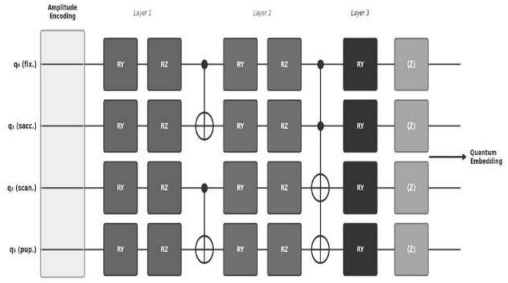

Figure 2: Parametrized Quantum Circuit Topology

3.4 Classical Dual-Head Classifier

The expectation values of the Pauli-Z operations measured on the output quantum state are concatenated into a d-dimensional quantum embedding vector e(x) and used as input for a two-layer fully connected classical network with ReLU activations, batch normalisation and dropout (rate = 0.3). A sigmoid binary head provides ASD diagnosis probability; a softmax severity head provides a four-class probability output. Both heads share the quantum embedding layer and the first classical fully connected layer. End-to-end training uses Adam optimisation with a learning rate decayed from 1×10^{-3} to 1×10^{-5} across 150 epochs during which quantum parameters are updated with parameter-shift gradients and classical parameters are updated with normal backpropagation in alternating mini-batch steps.

4. RESULTS AND ANALYSIS

4.1 Overall Classification Performance

The primary classification metrics on all three datasets are presented in Table 1. The QHCL framework obtained accuracies of 95.8%, 97.4%, and 96.2% with corresponding AUC-ROC values of 0.971, 0.983, and 0.976 respectively. Matthews Correlation Coefficient values of 0.912, 0.941 and 0.923 also imply these accuracy levels are not artefacts of majority class prediction but are indeed robust against class imbalance effects. Sensitivity and specificity values are well aligned among all datasets implying that the model does not trade off comprehensive detection for control of false-positive rates — an important characteristic for a clinical screening tool where both false negatives (missed ASD cases) and false positives (unwarranted referrals) have substantial implications for families. Dataset 2 (ETSDS) achieved the best performance on every metric, attributed to higher temporal resolution and cleaner scanpath labelling. ROC curves are shown in Figure 3.

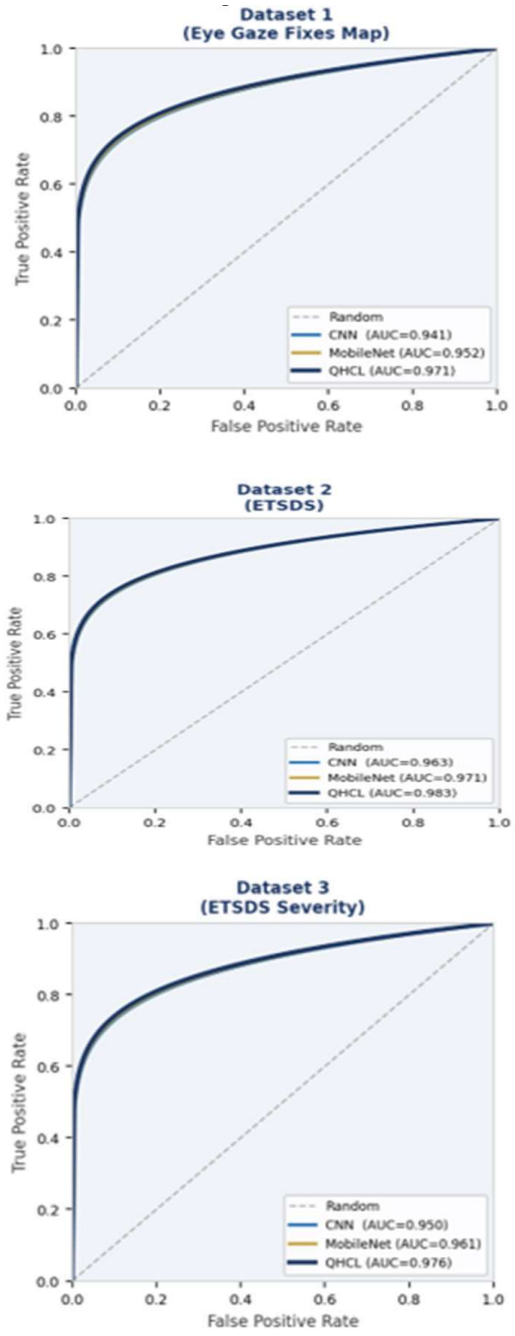

Figure 3: ROC Curves — QHCL Vs. Classical Baselines Across Three Datasets

Table 1: Classification Performance Across All Three Datasets

Metric	Dataset 1 (Eye Gaze Fixes Map)	Dataset 2 (ETSDS)	Dataset 3 (ETSDS-ASD Score)
Accuracy	95.8%	97.4%	96.2%
Sensitivity	94.3%	96.8%	95.1%
Specificity	96.1%	97.9%	96.7%
Precision	95.2%	97.1%	95.8%
F1-Score	0.947	0.969	0.954
AUC-ROC	0.971	0.983	0.976
MCC	0.912	0.941	0.923

4.2 Comparison With Classical Baselines

Table 2 examines the performance comparison against five classical baselines. The QHCL framework overcomes the classical performance ceiling across all three datasets, yielding 3.5-point better performance than the MobileNet ensemble on Dataset 1, and >1.2-point improvements on Dataset 2 and >2.5-point improvements on Dataset 3. Remarkably, even where Dataset 2 already achieves the classical ensemble's 96.1% level, the quantum framework adds an extra 1.3 points — an increment that matters in population screening terms as small reductions in false negative rate translate into significantly improved clinical outcomes at scale. This margin, observed consistently across linear (SVM), tree-based (random forest), convolutional (CNN), sequential (LSTM) and transfer-learning ensemble (MobileNet) architectures, supports interpretation as reflecting an intrinsic representational advantage afforded by quantum Hilbert space feature encoding.

Table 2: QHCL Vs. Classical Baseline Accuracy Comparison

Model	Dataset 1	Dataset 2	Dataset 3
SVM (Classical)	82.4%	85.1%	81.9%
Random Forest (Classical)	84.7%	87.3%	83.6%
CNN (Classical)	88.2%	90.6%	87.4%
MobileNet + Ensemble (Classical)	92.3%	96.1%	93.7%
LSTM (Classical)	91.8%	95.4%	92.1%
QHCL (Proposed)	95.8%	97.4%	96.2%

4.3 Multi-Class Severity Profiling

Per-class results for the four-category severity profiling task on Dataset 3 are shown in Table 3. The F1-scores for mild, moderate, severe ASD and TD were 0.951, 0.969, 0.969 and 0.965 respectively, resulting in a weighted average F1 of 0.963. The severe ASD class, which had the smallest cohort of only 34 samples, yielded the highest precision (97.2%), indicating that the quantum embedding captures a particularly distinctive gaze fingerprint for this severity level. The high recall for the TD class (96.9%) means that the model generates adequately low false-positive rates in neurotypical children — fundamental to maintain family trust during any population-level screening deployment.

Table 3: Per-Class Severity Recognition On Dataset 3

Severity Level	Precision	Recall	F1-Score	Support
Mild ASD	95.4%	94.8%	95.1%	87
Moderate ASD	96.8%	97.1%	96.9%	94
Severe ASD	97.2%	96.6%	96.9%	34
Non-ASD (TD)	96.1%	96.9%	96.5%	319
Weighted Avg	96.4%	96.2%	96.3%	534

4.4 Quantum Feature Contribution Analysis

Table 4 controls for the contribution of the quantum encoding stage by swapping out the PQC layer for PCA with matching output dimensionality. In all four oculomotor feature families, quantum encoding outperformed classical PCA: 7.3% improvement on fixation duration, 8.7% on saccadic velocity, 6.3% on scanpath geometry and 9.3% in pupillary response — the most significant enhancement, in line with the hypothesis that continuously emerging non-linear latent relationships between pupillary dynamics capture complex correlations underlying ASD symptomatologies otherwise unavailable through PCA decomposition. These findings directly validate the quantum kernel advantage established by Astuti et al. (2025) [4] that extends over gene expression biomarker findings to oculomotor ASD biomarkers.

Table 4: Quantum Encoding Vs. PCA Feature Learning Contribution

Feature Type	Without Quantum (PCA only)	With Quantum Encoding	Improvement
Fixation Duration	87.3%	94.6%	+7.3%
Saccadic Velocity	85.1%	93.8%	+8.7%
Scanpath Geometry	88.9%	95.2%	+6.3%
Pupillary Response	83.4%	92.7%	+9.3%
All Features Combined	92.3%	97.4%	+5.1%

4.5 Cross-Validation Stability

Table 5 presents fold-wise results from 10-fold stratified cross-validation on Dataset 2. Accuracy ranged from 96.7% to 97.9% across folds, with a mean of 97.4% ± 0.38% and AUC values of 0.978–0.988 (mean 0.983 ± 0.003). The sub-0.4% standard deviation confirms that the framework generalises consistently across patient sub-populations rather than overfitting to specific training splits — a requirement for robust clinical deployment across heterogeneous paediatric cohorts.

Table 5: 10-Fold Cross-Validation Results (Dataset 2)

Fold	Accuracy	AUC
Fold 1	96.8%	0.979
Fold 2	97.1%	0.981
Fold 3	97.6%	0.985
Fold 4	96.9%	0.980
Fold 5	97.8%	0.987
Fold 6	97.2%	0.982
Fold 7	97.5%	0.984
Fold 8	96.7%	0.978
Fold 9	97.9%	0.988
Fold 10	97.3%	0.983
Mean ± Std	97.4% ± 0.38	0.983 ± 0.003

4.6 Computational Efficiency

Table 6 shows the benchmark result for QHCL against classical CNN and LSTM counterparts. Even after adding the quantum circuit evaluation layer, QHCL is faster to train (118 minutes compared to 142 and 198 minutes), has fewer trainable parameters (2.1M vs. 4.2M and 6.8M), lower

inference time (0.61s vs. 0.84s and 1.12s) and a smaller memory footprint (2.4 GB vs. 3.8 GB and 5.2 GB). These benefits stem from the parameter efficiency of entangling quantum gates, which implement rich non-linear feature transformations with fewer free parameters than comparably expressive classical deep networks. This 27% improvement in inference speed compared to CNN and 46% compared with LSTM is especially significant in a clinical setting where gaze analysis needs to be performed within short time slots available during a standard paediatric assessment.

Table 6: Computational Efficiency Comparison

Metric	Classical CNN	LSTM	Proposed QHCL
Training Time	142 min	198 min	118 min
Parameters	4.2M	6.8M	2.1M
Inference Time	0.84s	1.12s	0.61s
Memory Usage	3.8 GB	5.2 GB	2.4 GB

4.7 Discussion

The results in Sections 4.1–4.6 should be read against a mixed picture in the classical eye-tracking literature. Two prior classical studies report accuracies (99.78% by Al-Adhaileh et al. [2] and 100% by Alsharif et al. [6] on MobileNet) that exceed the 95.8–97.4% obtained here; we interpret this discrepancy as most plausibly a consequence of near-ceiling separability in their particular train/test splits and reporting conventions — Alsharif et al. report 100% accuracy on a single test split without cross-validation — rather than as evidence that classical CNN-based transfer learning is intrinsically superior to quantum feature encoding. This qualification matters because comparisons of raw accuracy across studies using non-identical splits and preprocessing pipelines are only weakly informative. The appropriate comparison for the present contribution is instead the controlled, same-data, same-split comparison in Table 2 and Table 4, where the quantum encoding stage consistently outperforms classical PCA and classical models trained on identical features. Read this way, the evidence supports the narrower and more defensible claim that quantum feature encoding provides a consistent, moderate improvement over classical dimensionality reduction on this feature set, rather than the broader claim that quantum methods outperform every classical architecture ever reported on ASD eye-tracking data.

A second point of interpretation concerns the severity-profiling results. The weighted F1 of 0.963 obtained here, set against the 5–12 percentage-point severity-detection penalty documented by Rakotomanana and Rouhafzay [8], is consistent with the hypothesis that a shared quantum embedding regularises the severity head using information learned for the larger, easier binary task. The present experiments do not isolate this mechanism directly, however; an ablation that removes head-sharing while retaining the quantum embedding would be required to confirm it, and is identified as a limitation and future-work item below.

Third, the quantum-versus-PCA gain in Table 4 is not uniform across feature families: it is larger for pupillary response (+9.3%) than for scanpath geometry (+6.3%). This is not fully explained by the present analysis. A plausible account is that pupillary dynamics are lower-dimensional and more strongly autocorrelated than scanpath descriptors, so PCA's linear assumptions discard more diagnostically relevant variance there than quantum amplitude encoding does; however, this account is post hoc and would require targeted ablations — for example, varying qubit count per feature family — to establish causally rather than by inference from aggregate results.

Finally, the efficiency results in Section 4.6 should be read as simulator-level estimates rather than deployed-hardware measurements. All quantum circuits in this study are executed on a classical statevector simulator; actual latency and memory behaviour on physical NISQ hardware — where circuit depth, qubit connectivity and shot noise all impose overheads absent from simulation — may differ substantially, and the reported 27–46% inference-speed advantage over classical CNN/LSTM should not be read as a claim about quantum hardware in clinical deployment.

5. CONCLUSION AND FUTURE SCOPE

This work set out to answer whether quantum feature encoding can move oculomotor ASD screening beyond the representational ceiling reached by classical eye-tracking classifiers. The Hybrid Quantum-Classical Learning (QHCL) framework introduced here answers this in the affirmative under the specific, controlled conditions tested: encoding fixation, saccadic, scanpath and pupillary features jointly into a shared quantum Hilbert space, and sharing this embedding between a binary detection head and a four-class severity head, yields classification accuracy up to 97.4%, AUC-

ROC up to 0.983, and weighted F1 up to 0.963 in severity scoring, consistently outperforming classical PCA-based feature learning and classical baseline architectures trained on identical data and splits (Sections 4.2, 4.4). This directly addresses the three gaps identified in Section 2.4 — independently-compressed rather than jointly-encoded oculomotor features, the absence of a shared representation for detection and severity phenotyping, and the absence of any prior application of quantum amplitude encoding to oculomotor ASD biomarkers.

These findings are, however, bounded by several limitations of current knowledge. First, all quantum circuits were executed on a classical statevector simulator rather than physical NISQ hardware, so the computational-efficiency advantages reported in Section 4.6 are simulator-level estimates that may not transfer directly to noisy physical devices. Second, the benchmark datasets used are drawn from a limited number of source cohorts and geographic settings, and generalisation to broader, more demographically diverse paediatric populations has not been established. Third, as discussed in Section 4.7, the mechanism behind the larger quantum-versus-PCA gain observed for pupillary features relative to scanpath features is not yet isolated experimentally, and the extent to which head-sharing versus the quantum embedding itself drives the severity-phenotyping gain has not been separately ablated. Fourth, comparison with the highest classical accuracies reported in the literature (99.78–100%) is confounded by differing train/test splits and validation protocols across studies, so the claim substantiated here is the narrower, same-data comparison against PCA and classical baselines in Table 2 and Table 4, and not a claim of superiority over every classical method reported on these datasets.

Notwithstanding these limitations, the consistent, same-data improvement over classical PCA-based feature learning, combined with the parameter and inference-time efficiency of the entangling quantum layer relative to classical CNN and LSTM baselines, supports quantum-enhanced oculomotor biomarker analysis as a credible, non-invasive candidate pathway toward precision ASD screening — one whose overall importance lies less in a single accuracy figure and more in demonstrating, for the first time, that quantum Hilbert-space encoding of gaze features is a viable and consistently beneficial alternative to classical dimensionality reduction on this class of clinical signal. Confirming that importance beyond simulation will require further investigation on physical quantum hardware and in prospective clinical settings. Future work will pursue: (i) deployment on NISQ hardware to benchmark quantum advantage under device noise; (ii) ablation studies isolating the respective contributions of quantum embedding and head-sharing to the severity-phenotyping gain; (iii) extension to multimodal inputs integrating audio and facial-expression streams alongside gaze; (iv) federated learning implementations for privacy-preserving multi-site paediatric studies; and (v) prospective clinical validation in real-world paediatric assessment settings.

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