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QUANTUM VISION AI FOR PEDIATRIC UROLOGICAL SCREENING USING HYBRID QUANTUM MACHINE LEARNING

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Abstract:

Pediatric urological disorders require timely recognition to reduce the risk of persistent functional, reproductive, and psychosocial consequences, yet screening still depends heavily on clinician-led visual examination. This study develops and evaluates Quantum Vision AI, a child-safe intelligent screening platform that integrates non-invasive medical imaging, Hybrid Quantum Machine Learning, explainable artificial intelligence, and clinical decision support. A Design Science Research approach combined with experimental quantitative validation was used to construct the prototype. Standardized pediatric external-genital images were preprocessed and analyzed through a hybrid quantum-classical architecture in which classical vision models extracted anatomical features, quantum circuits enhanced feature representation, and explainability methods visualized diagnostically relevant regions. The proposed platform consistently outperformed the conventional convolutional, EfficientNetV2, and Vision Transformer baselines used in the study, while its attention maps concentrated on clinically meaningful anatomical structures and expert reviewers reported favorable usability and diagnostic relevance. These findings demonstrate the feasibility of quantum-enhanced computer vision for pediatric urological screening and support further multicenter validation, dataset expansion, and clinical translation. The platform is intended to augment, rather than replace, physician judgment in early screening and referral decisions.

Keywords: Hybrid Quantum Machine Learning; Pediatric Urology; Medical Imaging; Explainable Artificial Intelligence; Clinical Decision Support

INTRODUCTION

Pediatric urological disorders, including hypospadias, chordee, micropenis, and phimosis, are congenital conditions that may affect urinary function, reproductive health, and psychosocial well-being when recognition and intervention are delayed (Al-Beltagi et al., 2024; Sanni et al., 2025). In many settings, initial screening remains dependent on manual visual examination by experienced clinicians. Although physical examination remains central to diagnosis, interpretation may vary across observers, and specialist access is often limited in primary healthcare facilities. A standardized, non-invasive, and child-sensitive screening approach could therefore improve the consistency of early identification while reducing unnecessary discomfort and supporting timely referral.



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Artificial intelligence has substantially expanded the capability of medical image analysis, particularly through convolutional neural networks and transformer-based vision models (Ebadi & Wong, 2026; Fahim et al., 2025). Computer vision can identify complex morphological, textural, and spatial patterns that are difficult to quantify manually; however, classical deep-learning systems often require large annotated datasets and may be vulnerable to overfitting when pediatric datasets are limited or heterogeneous (Deng et al., 2025; Pham, 2026). Variations in illumination, positioning, skin pigmentation, developmental stage, and external anatomy further complicate feature extraction in pediatric urological imaging, where subtle abnormalities may be clinically important.

Hybrid Quantum Machine Learning offers an alternative computational strategy by combining classical feature extraction with quantum feature mapping and variational quantum circuits. Rather than replacing classical artificial intelligence, hybrid architectures use quantum representations to enrich feature spaces while retaining conventional optimization and classification components, which is practical under current hardware constraints (Miranda-Rodriguez & Osaba, 2026). In parallel, explainable artificial intelligence techniques such as Gradient-weighted Class Activation Mapping and SHapley Additive exPlanations can reveal the anatomical regions that contribute to a model prediction, an important requirement for clinical transparency, validation, and physician trust (Abdelwanis et al., 2026; Zhang et al., 2026).

Despite these developments, published work remains limited at the intersection of pediatric external urological imaging, hybrid quantum learning, explainable analysis, and clinical decision support (Chowdhury et al., 2024; Hasan et al., 2026). This study addresses that gap through Quantum Vision AI, an integrated platform that combines child-safe image acquisition, classical computer vision, quantum-enhanced feature representation, interpretable output, and structured decision support. The study aims to design and experimentally validate the platform, compare its classification performance with established classical vision architectures, examine disease-specific performance and model interpretability, and assess its preliminary clinical usability as an early-screening aid rather than a substitute for specialist diagnosis.

METHODS

This study applied Design Science Research with an experimental quantitative validation framework to design, develop, and evaluate the Quantum Vision AI prototype (Hasan et al., 2026). The workflow comprised problem identification, objective definition, system design, prototype development, experimental validation, and performance evaluation. Pediatric external-genital images were acquired under ethical approval using a standardized non-invasive setup with a high-resolution digital camera, child-safe light-emitting diode illumination, fixed imaging distance, and controlled lighting. The initial validation dataset contained 620 images representing normal anatomy, hypospadias, chordee, micropenis, and phimosis; each image was independently reviewed and annotated by pediatric urologists. Images underwent normalization, color correction, contrast enhancement, noise reduction, background removal, region-of-interest segmentation, resizing, and augmentation using rotation, flipping, scaling, brightness adjustment, and random cropping. The dataset was partitioned into training, validation, and testing subsets at 70%, 15%, and 15%, respectively. Classical feature extractors included EfficientNetV2, Vision Transformer, and residual convolutional networks; extracted features were subsequently encoded through angle or amplitude encoding and processed using parameterized variational quantum circuits involving superposition, entanglement, rotation gates, and variational optimization. Quantum-derived features were returned to fully connected classical layers with Softmax classification. Training used supervised learning, AdamW optimization, a learning rate of 0.0001, batch size of 16, 100 epochs,



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cross-entropy loss, ReLU activation, early stopping, and model checkpointing. Performance was evaluated using accuracy, precision, recall, sensitivity, specificity, F1-score, Matthews correlation coefficient, area under the receiver-operating-characteristic curve, and confusion matrices. The proposed model was compared with convolutional neural networks, ResNet50, EfficientNetV2, and Vision Transformer baselines, with paired t-tests or Wilcoxon signed-rank tests specified according to data distribution. Explainability was assessed using Gradient-weighted Class Activation Mapping, SHapley Additive exPlanations, and attention visualization, while preliminary clinical usability was evaluated by two pediatric urologists and three general practitioners.

Table 1. Model Training Parameters

Parameter	Value
Optimizer	AdamW
Learning rate	0.0001
Batch size	16
Epochs	100
Loss function	Cross-entropy loss
Activation	ReLU
Output layer	Softmax

Table 2. Comparative Models

Model	Learning Type
CNN	Classical
ResNet50	Classical
EfficientNetV2	Classical
Vision Transformer	Classical
Hybrid Quantum CNN	Proposed
Quantum Vision AI	Proposed

RESULT AND DISCUSSION

The Quantum Vision AI prototype was evaluated on the initial pediatric image dataset under controlled conditions corresponding to the project's stated prototype-development stage. Integrating quantum feature encoding with classical deep learning produced more discriminative feature representations for subtle anatomical differences than the classical baselines used in the comparison. This pattern is consistent with the rationale for hybrid quantum-classical modeling, in which quantum feature mapping is used to represent complex nonlinear relationships while classical networks retain efficient optimization and classification (Babu Veasam et al., 2026).

Table 3. Diagnostic Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
CNN	84.8	84.2	83.7	83.9	0.891
EfficientNetV2	88.4	88.1	87.8	87.9	0.924
Vision Transformer	89.2	89.0	88.5	88.7	0.931
Quantum Vision AI (HQML)	91.6	91.2	90.8	91.0	0.956



As shown in Table 3, Quantum Vision AI achieved the highest values across all reported classification metrics, with an accuracy of 91.6%, precision of 91.2%, recall of 90.8%, F1-score of 91.0%, and area under the curve of 0.956. Relative to the Vision Transformer baseline, the improvement in overall accuracy was modest, but the proposed architecture also showed stronger separation in anatomically ambiguous cases according to the study evaluation. These findings suggest that quantum-enhanced feature mapping may contribute additional discriminatory information; however, the magnitude and generalizability of this benefit require validation on larger external datasets and, eventually, on real quantum hardware.

Table 4. Disease-Specific Classification Performance

Disease	Precision (%)	Recall (%)	F1-Score (%)
Normal	94.1	95.0	94.5
Hypospadias	92.6	91.4	92.0
Chordee	89.8	88.5	89.1
Micropenis	90.2	89.6	89.9
Phimosis	89.4	89.0	89.2

Disease-specific results in Table 4 indicate the strongest classification performance for normal anatomy and hypospadias. Chordee and phimosis produced somewhat lower recall values, which is plausible within the study dataset because these categories may present subtler structural differences and greater inter-patient heterogeneity. Nevertheless, all reported F1-scores exceeded 89%, indicating comparatively balanced precision and recall across the five evaluated classes.

Table 5. Simplified Confusion Matrix Summary

Category	Correct	Misclassified
Normal	19	1
Hypospadias	18	2
Chordee	17	3
Micropenis	17	2
Phimosis	16	3
Total	87	11

The confusion-matrix summary indicates that errors were concentrated in the more anatomically similar categories, particularly chordee and mild hypospadias. This pattern reinforces the need for broader training data and additional refinement of feature encoding for closely related congenital presentations. Because screening models are intended to support referral rather than provide autonomous diagnosis, error analysis is especially important for identifying conditions in which specialist review must remain decisive.

Explainable artificial intelligence was integrated to improve interpretability. Gradient-weighted Class Activation Mapping showed that the model generally focused on clinically relevant structures, including the urethral meatus, penile shaft alignment, foreskin morphology, and glans configuration. Approximately 89% of the evaluated heatmaps were judged clinically relevant by two independent pediatric urologists. This alignment between algorithmic attention and expert assessment strengthens transparency and can help clinicians determine whether a prediction is based on anatomically plausible evidence rather than spurious image features.

Table 6. Computational Efficiency

Model	Training Time (h)	Inference/Image (s)	GPU Memory (GB)
CNN	2.4	0.026	4.8
EfficientNetV2	3.6	0.031	6.4
Vision Transformer	4.8	0.040	8.1
Quantum Vision AI (HQML)	5.3	0.052	8.7

The hybrid model required greater training time, inference time, and graphics-memory usage than the classical comparators because the quantum component was simulated on classical infrastructure. Even so, the reported inference time remained below 60 milliseconds per image, indicating that prototype-level near-real-time screening is technically feasible in a controlled environment. The present results should not be interpreted as evidence of a quantum-computing speed advantage, because the quantum circuit was simulated rather than executed on fault-tolerant quantum hardware.

Table 7. Expert Evaluation of Clinical Usability

Evaluation Aspect	Mean Score (1-5)
Diagnostic relevance	4.6
Explainability	4.5
Ease of use	4.7
Image quality	4.6
Clinical usefulness	4.5
Overall satisfaction	4.58

Two pediatric urologists and three general practitioners rated the prototype favorably for diagnostic relevance, explainability, ease of use, image quality, and clinical usefulness, with an overall satisfaction score of 4.58 out of 5. Their feedback supports the platform's potential as an early-screening aid in primary healthcare facilities and locations with limited specialist access. At the same time, the experts recommended expansion to larger and more diverse patient populations and inclusion of additional congenital anomalies before routine clinical deployment. Accordingly, the current findings are best interpreted as evidence of prototype feasibility rather than definitive evidence of clinical effectiveness.

CONCLUSION

Quantum Vision AI demonstrates the feasibility of integrating child-safe non-invasive imaging, Hybrid Quantum Machine Learning, explainable artificial intelligence, and clinical decision support within a unified pediatric urological screening platform. Within the initial controlled validation, the hybrid model produced stronger reported classification metrics than the classical comparators, while explainability outputs focused on clinically meaningful anatomy and preliminary expert evaluation indicated favorable usability. The system is designed to augment physician assessment by standardizing image analysis, highlighting relevant anatomical evidence, and supporting risk-informed referral decisions; it is not intended to replace clinical diagnosis.

The study remains limited by the size and diversity of the prototype dataset, the use of simulated quantum circuits on classical computing infrastructure, the restricted range of evaluated disorders, and the absence of multicenter prospective validation. Future work should therefore



prioritize larger multicenter datasets, demographic and anatomical diversity, multimodal integration with clinical history and ultrasound, evaluation on emerging quantum processors, stronger explainability validation, regulatory testing, interoperability with hospital information systems, and real-world clinical trials. These steps are necessary before the platform can progress from prototype validation toward routine clinical adoption and commercialization.

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