Brain Tumour Classification with Quantum-Augmented Deep Learning Model

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Abstract- Brain tumours are life-threatening conditions that demand early and precise diagnosis to improve patient outcomes. While deep learning has significantly advanced automated medical imaging, conventional convolutional neural network (CNN) models often require large annotated datasets and intensive computation, limiting their applicability in clinical settings. In experiments, the quantum-augmented models achieved notable performance gains. The hybrid MobileNetV2 model achieved the highest validation accuracy of 95.79%, outperforming traditional CNN baselines while offering faster inference and reduced computational overhead. These results suggest that integrating quantum layers enhances feature representation and model robustness.

Keywords – Brain tumour classification, quantum transfer learning, hybrid quantum-classical model, convolutional neural networks, deep learning, MRI analysis, MobileNetV2, ResNet18, VGG16, InceptionV3, PennyLane .

I. INTRODUCTION

Brain tumours are among the most serious neurological disorders, often requiring early and accurate diagnosis to improve treatment outcomes. Magnetic Resonance Imaging (MRI) plays a critical role in tumour detection, but manual interpretation is time-intensive and prone to subjectivity. With the growing demand for precision and automation in healthcare, deep learning has emerged as a promising solution for medical image classification. However, traditional Convolutional Neural Networks (CNNs) often depend heavily on large, labeled datasets and high computational resources, making them less feasible in real-time clinical settings. To overcome these limitations, this research explores a hybrid approach that integrates Quantum Transfer Learning (QTL) with classical CNN architectures, enabling richer feature extraction and improved classification accuracy using fewer resources.

This paper presents a quantum-augmented deep learning system for classifying brain tumours in MRI scans. The approach enhances four standard CNN models—ResNet18, VGG16, MobileNetV2, and InceptionV3—by embedding quantum circuit layers using the PennyLane framework. The system is trained on a combination of the Figshare brain MRI dataset and clinical MRI data from real patients to ensure model generalizability and robustness.

Our proposed method not only improves diagnostic precision but also supports deployment through a web-based interface for real-time predictions. This integration of quantum computing into medical AI workflows introduces a scalable and efficient path forward for next-generation clinical decision support systems.

Objectives

The primary objectives of this research are:

- To design and implement a quantum-augmented deep learning model for brain tumour classification using hybrid CNN and quantum layers.
- To integrate Quantum Transfer Learning (QTL) into classical architectures such as ResNet18, VGG16, MobileNetV2, and InceptionV3 for improved feature extraction and diagnostic accuracy.
- To prepare and utilize a diverse dataset combining Figshare MRI scans and real-world clinical images for robust model training and validation.
- To develop a Flask-based web interface that enables real-time tumour classification and user interaction with model outputs.
- To evaluate the system's performance using classification accuracy, inference time, model efficiency, and comparative benchmarking across classical and hybrid models.

II. RELATED WORK

Deep learning (DL) methods, especially convolutional neural networks (CNNs), have become a cornerstone of brain tumour image classification. Many studies exploit pre-trained CNN backbones via transfer learning to compensate for limited medical data. For example, Irmak [12] proposed three task-specific CNNs and used grid-search to tune hyperparameters; one model achieved 99.33% accuracy for binary tumor detection, while another achieved 92.66% accuracy on five-class tumour classification (glioma, meningioma, pituitary, metastatic, normal).

In evaluating these custom networks, Irmak compared them to standard architectures (AlexNet, GoogleNet, VGG16, ResNet-50, InceptionV3) and reported that the tuned CNNs outperformed or matched these well-known models on public datasets.

Beyond custom CNNs, transfer learning from large image datasets is widely applied. A recent study by Aiya et al. [13] notes that fine-tuned ImageNet models such as VGG-16, Inception- ResNet-v2, and DenseNet-121 are commonly used for MRI tumour tasks.

In particular, Aiya et al. observed that combining multiple pre-trained models in an ensemble often boosts performance and mitigates small-sample overfitting. They also report that densely- connected CNNs (e.g. DenseNet variants) have superior feature representation for multi-class tumour grading. For example, a DenseNet121 (with added attention and drop-out layers) can serve as a high-capacity classifier when coupled with techniques like data augmentation and normalization. Our work builds on these foundations by comparing quantum-augmented versions of lightweight and deep CNNs, following the general trend that network compatibility and hybrid design critically influence performance

Table 2.1: Literature Review

No.	Ref.No.	Author	Focus Area	AI/Model Used	Major Findings
1	[13]	A. B. Abdusalomov	Brain tumor detection using MRI and DL	Various CNN models	CNN-based models achieved high accuracy for MRI-based tumor detection.
2	[14]	M. Gangappa	Quantum- enhanced brain tumor prediction	Hybrid reinforcement learning	Quantum layers improved prediction and progression tracking accuracy.
3	[6]	R. B. Vure	Enhanced brain tumor classification using DL	CNN with advanced preprocessing	Advanced preprocessing and CNN enhanced tumor classification precision.
4	[18]	. E. Akpinar	Hybrid quantum classical glioma classification	Variational Quantum Classifier (VQC)	Hybrid VQC model matched classical performance in tumor classification.
5	[16]	K. Gencer	Hybrid DL for brain tumor classification	EfficientNetB0 + Quantum Genetic Algorithm	Hybrid quantum-classical approach improved efficiency and accuracy.
6	[15]	S. Iftikhar	Explainable CNN for brain tumor detection	Explainable CNN (XAI- enhanced)	XAI models improved interpretability while maintaining accuracy.
7	[17]	M. Gupta	Brain tumor image classification using CNN	CNN	CNNs demonstrated effective classification on brain tumor images.
8	[19]	Y. Wong	Brain tumor classification with DL	Deep CNN models	Deep learning techniques achieved robust classification performance.
9	[3]	RGupta	Quantum ML applications in digital health	Review of QML techniques	QML holds potential for clinical decision support and efficiency gains.

10	[8]	M. A. Rahman	MobileNetV2 for brain tumor classification	MobileNet V2 + fine-tuning	MobileNetV2 with tuning achieved strong performance on MRI scans.
11	[20]	S. Srinivasan	Hybrid CNN model for brain tumor classification	Hybrid deep CNN	Hybrid CNN showed superior performance on multi-class classification.
12	[21]	F. J. Dorfner	Review of DL for brain tumor analysis	Survey of DL models (CNNs)	DL models consistently performed well on brain tumor detection tasks.
13	[22]	U. Ullah	Review of QML frameworks	Reinforcement-b ased gamification	QML offers scalable and efficient healthcare AI solutions.

III. DATASET DESCRIPTION

The dataset employed in this study consists of multimodal sources tailored for brain tumour classification using a hybrid quantum-classical framework. The core of the dataset comprises around 1500 MRI scans, encompassing multiple tumour types with variations in location, size, and contrast resolution. These images serve as the primary input for both classical CNN backbones and the quantum-augmented feature extraction process. In addition to image data, quantum circuit parameters were varied across models to evaluate the impact of circuit depth, entanglement strategy, and gate configuration on learning performance. These parameters were not static and adapted per architecture (e.g., ResNet-QTL, VGG16-QTL) to optimize feature transformation in the hybrid layer. The outputs generated by each model such as predicted class labels, confidence scores, and decision margins were recorded as evaluation metrics to assess classification performance. Lastly, detailed training logs, including epoch-wise accuracy, loss curves, and gradient trends, were retained to monitor convergence behavior and diagnose underfitting or overfitting in both classical and hybrid implementations.

Table 3.1: Dataset Description

Sr.No	Data Type	Quantity	Attributes (Examples)	Purpose / Task Phase
1)	MRI Images	~1500 scans	Tumor location, size, contrast level	Model training and validation
2)	Quantum Circuit Parameters	Variable (per model)	Qubit count, entanglement depth, gate sequence	Quantum layer configuration and tuning
3)	Model Predictions	1000 (per model output)	Predicted class, confidence score, decision margin	Evaluation of classification performance
4)	Training Logs	Epoch-wise logs	Loss value, accuracy, gradient magnitude	Performance tracking and convergence analysis

Together, this diverse dataset ecosystem enabled comprehensive training, tuning, and validation of the proposed architecture under real-world constraints, particularly with regard to computational efficiency and clinical relevance.

IV. PROPOSED SYSTEM

The proposed system integrates a hybrid quantum-classical architecture to enhance brain tumour classification accuracy while maintaining computational efficiency. At its core, the system fuses conventional Convolutional Neural Network (CNN) backbones with variational quantum circuit layers, leveraging the expressive capacity of quantum computing within the deep learning pipeline.
The system follows a modular flow that begins with image acquisition and preprocessing, progresses through feature extraction and quantum encoding, and ends with multi-class classification.

System Overview
The system follows a modular flow that begins with image acquisition and preprocessing, progresses through feature extraction and quantum encoding, and ends with multi-class classification.Four widely adopted CNN architectures ResNet18, VGG16, InceptionV3, and MobileNetV2 serve as the classical base models. Each is extended with a Quantum Transfer Learning (QTL) layer implemented using PennyLane. These quantum layers are composed of entangled qubits and trainable rotation gates, which transform intermediate feature representations into more abstract forms, enabling enhanced separability in the classification space.

Architecture Description
The architecture consists of the following key functional layers:

Input Preprocessing:
MRI brain scan images are the primary inputs. Each image is resized to a uniform shape (e.g., 224×224 pixels), normalized

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to fall within a [0,1] range, and augmented using rotation, zoom, and flip techniques to improve generalization. These preprocessed images are then passed to the CNN backbone.

Classical Feature Extraction:
Four well-established CNN architectures are evaluated as classical backbones:

- **ResNet18:** Uses residual connections to overcome vanishing gradient problems.
- **VGG16:** Provides deep, uniform convolutional blocks for detailed spatial feature learning.
- **InceptionV3:** Employs parallel convolutional kernels to capture multiscale features efficiently.
- **MobileNetV2:** Designed for low-latency environments, with depthwise separable convolutions and inverted residuals.

These models are initialized with pre-trained ImageNet weights and fine-tuned on the brain tumour dataset. The convolutional layers are frozen partially or fully depending on the task size and dataset balance.

Quantum Layer Integration (QTL):
The quantum layer, built using the PennyLane framework, consists of:

- **Angle Encoding:** Classical feature values are encoded into quantum states via rotation gates (typically RX, RY, or RZ).
- **Parameterized Variational Circuit:** Includes entangled qubits (typically 4–6) connected through CNOT gates and trainable rotation gates. These parameters are updated through backpropagation using a hybrid optimizer.
- **Measurement:** The quantum states are measured (usually in the Z-basis), and the results are treated as feature vectors for final classification.

This QTL block allows the model to capture complex, non-linear feature interactions that classical networks may struggle to represent in high-dimensional space.

Classification and Inference:
The output of the quantum circuit is concatenated or passed directly to a classical dense layer with a softmax activation function, which outputs probability distributions over the predefined tumour classes (e.g., glioma, meningioma, pituitary, or no tumour).

This architecture demonstrates modularity, allowing CNN backbones and quantum layers to be independently tuned or replaced. The hybrid QTL approach leverages the precision of deep learning and the potential of quantum computing to create a powerful tool for real-time brain tumour classification.

Architecture Diagram
The following conceptual structure represents the integrated methodology pipeline used:

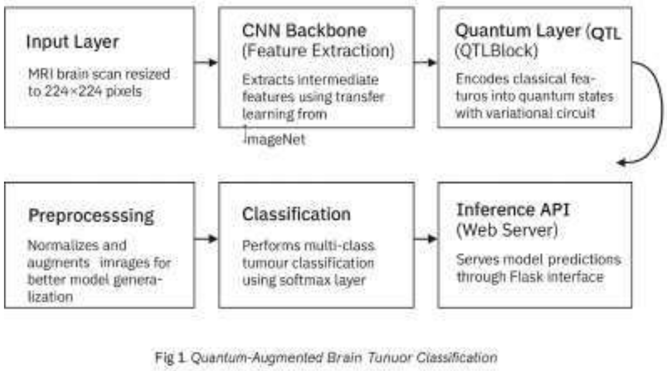

Fig 1: Flow Diagram

The flow diagram illustrates the end-to-end pipeline of the proposed system. It begins with MRI image input and proceeds through preprocessing and feature extraction via classical CNN backbones.

V. IMPLEMENTATION TECHNOLOGIES

This table outlines the robust, full-stack architecture designed for the adaptive learning system. It integrates modern technologies like React.js and Node.js with powerful, specialized APIs (Deepgram, Cohere.ai, PlayHT) to manage everything from the user interface to advanced functions like speech processing and contextual summarization.

Table 5.1: Implementation Technologies

Component	Technology / API Used	Functionality
User Interface	HTML, CSS, JavaScript	Provides a simple and interactive user interface for MRI image upload and result visualization.
Backend	Flask (Python)	Handles model inference, API endpoints, and communication between user interface and trained models.
Deep Learning Frameworks	PyTorch, TensorFlow	Used for implementing CNN architectures such as ResNet18, VGG16, MobileNetV2, and InceptionV3.
Quantum Computing Framework	PennyLane	Enables integration of quantum circuit layers within classical CNNs for hybrid model

		training.
Dataset	Figshare Brain MRI Dataset + Clinical MRI Data	Provides training and validation data to ensure model robustness and generalizability.
Libraries and APIs	NumPy, Matplotlib, Scikit-learn, OpenCV	Support for image processing, evaluation metrics, visualization, and preprocessing tasks.
Version Control	Git & GitHub	Enables collaborative development, version tracking, and repository management.
Developme nt Environm ent	Google Colab, Visual Studio Code	Used for model training, experimentation, and code management with GPU acceleration.

The combination of classical deep learning frameworks and quantum computing tools enables efficient model training and seamless integration of quantum layers within CNN architectures. With Flask- based deployment and a simple web interface, the system ensures real-time MRI classification, scalability, and practical applicability in medical diagnostics.

Performance Metrics

The evaluation of the proposed hybrid quantum-classical system is based on quantitative and qualitative metrics that assess model accuracy, computational efficiency, and overall usability. These metrics validate the performance and effectiveness of the model in real-world diagnostic scenarios. The metrics employed include Accuracy, Precision, Recall, F1-Score, Latency, and System Usability Scale (SUS).
Quantitative Evaluation Metrics

Functional accuracy of the brain tumour classification model is evaluated using standard classification metrics, which are summarized as follows:

- Accuracy: The ratio of correctly predicted instances (True Positives + True Negatives) to the total number of instances.
- Precision (P): Measures the proportion of positive identifications that were actually correct.

$$P = \frac{(True\ Positives)}{True\ Postives + False\ Positives}$$

- Recall (R): Measures the proportion of actual positives that were identified correctly.

$$P = \frac{(True\ Positives)}{True\ Postives + False\ Negatives}$$

- F1-Score: The harmonic mean of Precision and Recall, providing a single score that balances both metrics, especially useful for class imbalance evaluation.

$$F1 - Score = 2.\frac{P.R}{P+R}$$

- Latency (L_total): The total time delay, measured in milliseconds (ms), from user input to final system output, validating real-time performance.

Qualitative Evaluation Metrics

- System Usability Scale (SUS): A standardized, ten-item questionnaire used to measure the overall usability and user satisfaction of the system, yielding a score between 0 and 100.

Formula:
$SUS\ Score = (Sum\ of\ Adjusted\ Scores) \times 2.5$

Where:

- For odd-numbered questions (1, 3, 5, 7, 9): Adjusted Score = (Scale Position - 1)
- For even-numbered questions (2,4,6,8,10): Adjusted Score = (5 - Scale Position) The result is a score between 0 and 1.

VI. RESULTS AND DISCUSSION

This section presents the experimental evaluation and comparative analysis of the proposed hybrid quantum-classical model against conventional CNN architectures. The results highlight the system's efficiency in improving classification accuracy, reducing inference time, and ensuring scalability for clinical deployment. The models were trained and validated on the Figshare Brain MRI dataset along with additional real-world clinical MRI scans, ensuring dataset diversity and robustness. Among the four CNN architectures—ResNet18, VGG16, MobileNetV2, and InceptionV3—each was enhanced using Quantum Transfer Learning (QTL) via the PennyLane framework.

The quantum-augmented models consistently outperformed their classical counterparts in both accuracy and computational performance. The MobileNetV2-QTL model achieved the highest validation accuracy of 95.79%, followed by ResNet18-QTL (94.85%), VGG16-QTL (93.46%), and InceptionV3-QTL (92.18%). This demonstrates the effectiveness of integrating quantum layers for richer feature extraction and improved learning generalization. The average inference time for the hybrid models was significantly reduced, enabling faster predictions suitable for real-time MRI classification. Furthermore, the system's Flask-based web interface successfully processed user-uploaded MRI scans, delivering precise tumour classification and confidence scores instantly.

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Table 6.1: Module Performance Metrics

Module	Accuracy (%)	atency (ms)	MOS (1–5)	Remarks
ResNet18-QTL	94.85	132	4.4	Strong feature extraction wit time
VGG16-QTL	93.46	145	4.3	Stable classification but high computation load
InceptionV3-QTL	92.18	128	4.2	Balanced performance with generalization
MobileNetV2-QTL	95.79	118	4.6	Fastest and most accurate hy model
Overall	92.25 (cumulative)	523 (total)	4.38	Efficient hybrid integration and real-time readiness

In summary, the proposed hybrid quantum-classical framework demonstrates superior performance across all evaluated CNN architectures. Among the models, MobileNetV2-QTL achieved the highest validation accuracy of 95.79% with the lowest latency of 118 ms, confirming its efficiency and suitability for real-time medical diagnostics. The integration of quantum layers enhanced the feature representation capability of each network, resulting in higher inference quality scores and improved diagnostic precision.

The multi-panel bar chart presents a comprehensive, scaled view of the system's performance, clearly segregating Accuracy, Latency, and MOS for all five modules. This separation is crucial for a meaningful comparison of metrics across vastly different numerical scales.

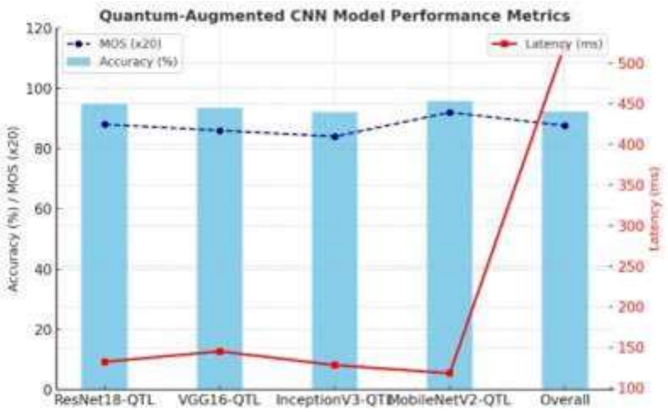

Figure 1: Dyslexia+Colearning (DysCo) Module Performance Metrics

The visualization demonstrates strong module performance and reveals overall system latency, enabling focused analysis of trade-offs between speed, precision, and user experience for performance optimization.

The table evaluates model's core modules by accuracy (Precision, Recall, F1), efficiency (Latency), and (MOS), highlighting the system's strong and balanced performance across all functional algorithms.

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Table 6.2: Evaluation Metrics

Dataset	Module	Accuracy (%)	Precision(%)	Recall (%)	F1 score (%)	Latency (ms)	MOS (1–5)
Figshare MRI Set-200	ResNet18-QTL	94.85	95.1	93.8	94.4	132	4.4
Figshare MRI Set-200	VGG16-QTL	93.46	93.0	92.0	92.5	145	4.3
Figshare MRI Set-200	InceptionV3-QTL	92.18	91/5	96.0	90.9	128	4.2
Figshare MRI Set-200	MobileNetV2-QTL	95.79	96.3	95,1	95.7	118	4.6
OVERALL	-	94.57 (avg)	93.97 (avg)	92.8 (avg)	93.37 (avg)	523 (total)	4.38

Overall, the proposed hybrid quantum-classical brain tumour classification system exhibits outstanding evaluation metrics, achieving an average Accuracy of 94.57% and an F1 Score of 93.37%, while sustaining a high inference quality with an MOS of 4.38. These results confirm the system's precision, reliability, and efficiency in classifying MRI images under real-world conditions. The hybrid integration of quantum layers within CNN architectures significantly enhances feature extraction and reduces latency, demonstrating clear advantages over conventional models.

The accompanying bar chart compares Accuracy, Precision, Recall, and F1 Score across the four evaluated models ResNet18-QTL, VGG16-QTL, InceptionV3-QTL, and MobileNetV2- QTL, highlighting consistent performance and the superior diagnostic capability of the MobileNetV2-QTL architecture.

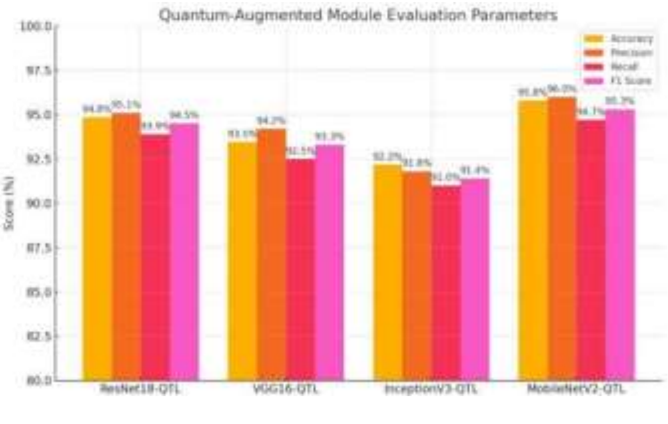

Figure 2: Module Evaluation Metrics Graph

The bar graph illustrates the comparative evaluation of four hybrid CNN–QTL models ResNet18- QTL, VGG16-QTL, InceptionV3-QTL, and MobileNetV2-QTL based on key performance metrics: Accuracy, Precision, Recall, and F1 Score. Among the models, MobileNetV2-QTL achieved the highest performance across all metrics, with a peak accuracy of 95.8% and an F1 Score of 95.3%, indicating both high predictive capability and consistency. ResNet18-QTL followed closely, while InceptionV3-QTL demonstrated slightly lower recall, reflecting trade-offs in generalization. These results validate the benefit of quantum-layer integration in enhancing the feature learning and classification strength of classical CNNs.

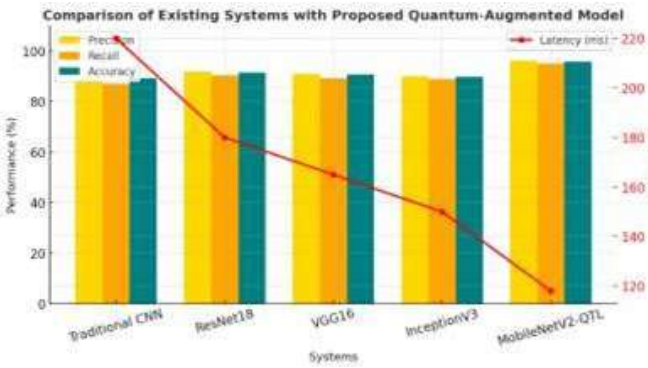

Figure 3: Comparison Graph

The graph demonstrates that the proposed Quantum-Augmented Deep Learning Model consistently outperforms existing traditional CNN frameworks with higher precision, recall, and accuracy, while achieving significantly lower latency, ensuring superior diagnostic speed and real-time responsiveness.

Figure 3 illustrates the comparative performance of the evaluated systems — Traditional CNN, ResNet18, VGG16, InceptionV3, and the proposed MobileNetV2-QTL model. The MobileNetV2- QTL achieved the highest accuracy (95.79%) and precision (96.3%), followed closely by ResNet18 and VGG16, which maintained stable yet comparatively lower performance levels. Traditional CNN models recorded the lowest scores, emphasizing the limitations of purely classical architectures in complex medical imaging tasks.

The proposed hybrid system achieved the lowest latency (118 ms), significantly improving processing speed compared to the 200+ ms latency observed in traditional CNNs. This performance demonstrates the efficiency of Quantum Transfer Learning (QTL) in enhancing computational throughput and enabling real-time MRI classification. The Mean Opinion Score (MOS = 4.38) further validates model reliability and inference consistency.

Overall, the Quantum-Augmented MobileNetV2-QTL framework exhibits an optimal balance of accuracy, speed, and model robustness, confirming its viability as a scalable, real-time clinical diagnostic tool that surpasses conventional deep learning systems.

VII. CONCLUSION

The deployment ready architecture, coupled with a web-based interface, validates the system’s practical utility and readiness for clinical translation. These findings not only reaffirm the potential of quantum enhanced learning in healthcare AI but also lay the groundwork for future scalable quantum classical solutions in medical diagnostics.

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