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Quantum AI Based Diagnosis System for Early Brain Tumor and Lung Cancer Detection

Dr. S. Gunasekaran[1], Abhiram. S. Nair[2], Adharsh N[3], Midhun M[4], Ajay Shankar[5]
[1]Professor in dept. Computer Science, Ahalia School of Engineering and Technology, Palakkad,India
[2, 3, 4, 5]Dept. Computer Science and Engineering, Ahalia School of Engineering and Technology, Palakkad,India

Abstract: Early and correct diagnosis plays a key role in enhancing the outcome in brain tumor and lung cancer patients. Traditional Artificial Intelligence (AI) and Deep Learning (DL) models are handicapped by expensive computational costs and challenges in handling high-dimensional medical data. This research article presents a Quantum AI based Diagnostics System employing a hybrid quantum-classical computing model. The framework combines traditional feature preprocessing with the exponential power of quantum computing. For classification in brain tumors (e.g., LGGs/HGGs), the quantum core uses a Hybrid Quantum-Classical Integrated Neural Network (HQCINN) or Variational Quantum Classifier (VQC). For lung cancer prediction, the framework might employ quantum-enhanced clustering such as Quantum-Enhanced K-Medoids or optimization models such as Quantum - Genetic Binary Grey Wolf Optimizer (Q-GBGWO) with Extreme Learning Machines (ELM). This hybrid methodology is intended to achieve superior diagnostic efficacy and speed across both MRI and CT modalities, laying the groundwork for faster and more individualized clinical diagnostics.
Keywords: Quantum Computing, HQCINN, VQC, ELM, Q-GBGWO, Cancer Detection, Quantum AI based Diagnostics, Brain and Lung Cancer.

I. INTRODUCTION

The diagnosis of such malignancies, like brain tumors and lung cancer, has to be performed as early and accurately as possible to facilitate effective intervention. While classical AI and DL models show a lot of promise for medical image analysis, there is still a bottleneck in terms of their high computational cost and inefficiency while handling the high-dimensional complexity of medical data. The quest for overcoming these deficiencies leads us to Quantum AI, where leveraging quantum phenomena such as superposition and entanglement can enable a serious increase in processing power.

Our proposed Quantum AI-based Diagnostics System picks up on established hybrid quantum-classical methodologies from recent foundational work. In the case of classification of brain tumors, this involves the use of HQCINN for multi-classification and VQC for better discrimination of glioma grades. In the case of lung cancer prediction, inspiration is derived from the application of quantum-enhanced techniques such as Q-GBGWO with ELM, and Quantum-Enhanced K-Medoids for improved clustering and accuracy. This paper outlines a unified system that integrates classical data preparation with these quantum-accelerated learning models in an attempt to set up a more accurate, efficient, and robust diagnostic framework across modalities such as MRI and CT prescribed, although the various table text styles are provided. The formatter will need to create these components, incorporating the applicable criteria that follow.

II. LITERATURE SURVEY

A. Quantum computational infusion in extreme learning machines for early multi-cancer detection

For the Extreme Learning Machine (ELM) in the Q-GBGWO - ELM structure, the key equation is the analytical solution to the output weights that is given as

$$\beta = H^{\dagger} T$$

The equation computes the ultimate classification parameters efficiently by multiplying the pseudoinverse of the hidden layer output matrix and the target output matrix, which is essential for the quick training of the ELM. The Quantum -Genetic Binary Grey Wolf Optimizer (Q-GBGWO), optimizing the input parameters of the ELM is governed by minimizing a Fitness Function normally the Mean Squared Error (MSE), given as

$$F(X) = \frac{1}{N}\sum_{j=1}^{N}(O_j - T_j)^2$$

The Hybrid Quantum - Classical Integrated Neural Network (HQCINN) and Variational Quantum Classifier (VQC) utilize quantum mechanics for data processing. Their output involves computing the Expected Value of a measurement operator

$$\hat{H}|\psi\rangle=E|\psi\rangle,$$

i.e.,

$$\langle\hat{O}\rangle=\langle\psi|\hat{O}|\psi\rangle.$$

This expectation value constitutes the feature or probability distribution, which is passed to a classical layer. Both are trained by optimizing the Cross-Entropy Loss function, with

$$pk=|\langle k|\psi\rangle|^2$$

Being the output probability obtained from the quantum output. Lastly, the Quantum-Enhanced K-Medoids model enhances lung cancer clustering by applying quantum methodology to its distance metric, mainly the Manhattan Distance

$$D_{manhattan}(A, B) =|A1-B1|+|A2-B2|+\cdots+|Am-Bm|,$$

Making clustering stronger and more accurate.

B. Hybrid classical and quantum computing for enhanced glioma tumor classification using TCGA data

For the Extreme Learning Machine (ELM) applied to the Q - GBGWO - ELM model for lung cancer, the core equation is the analytical solution to the output weights given by

$$\beta = H \dagger T$$

This equation is important because it determines the final classification parameters directly using the pseudoinverse of the hidden layer output matrix and the true label matrix. In addition, the Quantum - Genetic Binary Grey Wolf Optimizer (Q - GBGWO) is regulated by optimizing a Fitness Function, most commonly the Mean Squared Error (MSE),

$$F(X) = \frac{1}{N}\sum_{j=1}^{N}||O_j-T_j||^2$$

A measure of the error between the model's prediction and ground-truth label, which propels the optimization of the ELM's input weights. For the Variational Quantum Classifier (VQC) and Hybrid Quantum - Classical Integrated Neural Network (HQCINN) for brain tumor classification, the fundamental quantum computation is encapsulated by the Expected Value- $\langle \hat{o} \rangle$

i.e., the quantum circuit's output:

$$\langle \hat{o} \rangle=\langle\psi(x, \theta) | \hat{o} |\psi(x, \theta)\rangle$$

This value is obtained from the measurement of a measurable operator $\langle \hat{o} \rangle$ on the target quantum state $|\psi\rangle$, which is based on the input data and the learnable circuit parameters(θ). Both models are learned by optimizing the Cross-Entropy Loss function

$$\mathcal{L} = -\sum_{k=1}^{c} t_k \log(p_k)$$

where the obtained predicted probability is compared with the actual label using traditional optimization methods such as Gradient Descent or AQCD. Finally, the Quantum-Enhanced K-Medoids model enhances lung cancer clustering by further optimizing the distance calculation, based on the Manhattan Distance Metric

$$D_{manhattan}(A, B) =\sum_{i=1}^{m}|A_i-B_i|$$

where the summation of the absolute differences between two points A and B is sped up or optimized by the integrated quantum approach.

C. Multi-classification of brain tumors using proposed hybrid quantum–classical integrated neural network (HQCINN) models: shallow and deep circuit approaches.

For the models of Brain Tumor Classification, Hybrid Quantum - Classical Integrated Neural Network (HQCINN) and Variational Quantum Classifier (VQC) are controlled by quantum mechanics. Their result is actually decided by the Expected Value of an observable operator $\langle \hat{o} \rangle$ on the terminal quantum state, given by

$$\langle \hat{o} \rangle=\langle\Psi(x,\Theta)| \hat{o} |\Psi(x,\Theta)\rangle$$

This is a traditional value that is input to the training process, where the Cross-Entropy Loss function

$$\mathcal{L} = -\sum_{k=1}^{c} t_k \log(p_k)$$

in which the parameters of the (θ)are adjusted by optimizers such as Gradient Descent or AQCD to align the predicted probability with the actual label. Preprocessing for said models also applies Min-Max Normalization to scale the data:

$$x_{normalised} = \frac{x - xmin}{xmax - x\,min}$$

The Lung Cancer Detection pipeline employs two very different strategies. The Quantum - Genetic Binary Grey Wolf Optimizer (Q - GBGWO), optimising the Extreme Learning Machine (ELM), is motivated by minimizing a Mean Squared Error (MSE) Fitness Function:

$$F(X) = \frac{1}{N}\sum_{j=1}^{N} ||0_j - T_j||^2$$

The ELM's analytical character is determined by the solution for the output weights:

$$\beta = H \dagger T$$

Alternatively, the Quantum-Enhanced K-Medoids clustering algorithm bases its results on computing the Manhattan Distance Metric between patient records A and B:

$$D_{manhattan}(A, B) = \sum_{i=1}^{m} |A_i - B_i|$$

An efficiency of which is enhanced by the quantum approach.

D. Enhancing Lung Cancer Prediction Accuracy Using Quantum-Enhanced K-Medoids with Manhattan Distance

For the Classical Preprocessing Layer, normalization of the data—such that effective quantum encoding can be obtained—is done using the Min-Max Normalization formula, normalizing the input feature to the range usually between [0,1]:

$$n_{ormalized} = \frac{x - xmin}{xmax - x\,min}$$

After features are preprocessed, the quantum component of the model executes the actual computation. The result of the Parameterized Quantum Circuit (PQC) is not a probability, but a classical value obtained from a quantum measurement, i.e., the Expected Value –($\langle \hat{o} \rangle$), defined mathematically as:

$$\langle \hat{o} \rangle = \langle \psi(x,\theta)| \hat{o} |\psi(x,\theta)\rangle$$

The result is then fed to the classical SoftMax layer for final prediction. The learning of the hybrid model is done with traditional optimisers (such as Gradient Descent or AQCD) iteratively to update the trainable parameters of the quantum circuit (θ) in order to minimise the Cross-Entropy Loss function ($\mathcal{L}$), which is the task loss of classification error:

$$\mathcal{L} = -\sum_{k=1}^{c} t_k \log(p_k)$$

where p_k is the output probability and t_k is the ground-truth label over c classes.

III. ALGORITHM

The main algorithm presented in the base paper is based on the Quantum - Genetic Binary Grey Wolf Optimizer (Q-GBGWO) for adjusting an Extreme Learning Machine (ELM) to perform multi-cancer detection. The procedure starts with combining the Extreme Learning Machine (ELM) with a FuNet transfer learning model in order to create the fundamental hybrid classification paradigm. Most importantly, a heterogeneous feature fusion mechanism is used to improve the quality and degree of the imaging features extracted. The fundamental algorithmic novelty then lies in the process of optimizing the parameters of the ELM (namely its input weights and biases) for better classification performance. This is achieved through the Q-GBGWO algorithm, which incorporates principles of quantum mechanics into the search process of the conventional Grey Wolf Optimizer. The quantum infusion is intended to balance the exploration and exploitation of the optimizer so that it can better escape local minima and converge more rapidly to the optimal set of parameters of ELM in order to maximize the diagnostic accuracy of the final Q-GBGWO-ELM system.

The central algorithm of the base paper on glioma classification (LGGs vs. HGGs) is based on a Hybrid Classical and Quantum Computing Model with a Variational Quantum Classifier (VQC). The procedure begins with a classical phase that involves an ensemble feature selection method on The Cancer Genome Atlas (TCGA) data to select the most informative molecular markers (such as IDH1, PTEN) and clinical features (such as age). These chosen features are then fed to the quantum component, where they are mapped to be encoded via a Quantum Feature Map. The VQC itself uses a parameterised quantum circuit (ansatz) consisting of different quantum gates to actually carry out the classification. Training of the model is a hybrid iterative process: the VQC outputs an expectation value that is utilised to compute a classical loss function, and a quantum-aware optimisation strategy, e.g., the Analytic Quantum Gradient Descent (AQCD), is applied to update the PQC's trainable parameters to ensure the model converges to correctly differentiate between low-grade and high-grade gliomas.

The main multi - classification algorithm for brain tumours explained in this work is the Hybrid Quantum-Classical Integrated Neural Network (HQCINN). The steps begin classically by carrying out necessary preprocessing on data from MRI images, which involves reshaping and min-max normalisation to ready the features for quantum encoding. This normalised feature vector is introduced into the quantum layer that is built based on the Parameterised Quantum Circuit (PQC). This PQC is a quantum neural network layer that uses superposition and entanglement through programmable quantum gates to transform the input data into an involved quantum Hilbert space for better feature analysis. The resulting expectation values (quantum circuit measurements) are then fed into the classical output layer, often a Softmax function, which makes the final prediction over the several classes of tumours (glioma, meningioma, etc.). The learning is an iterative hybrid process: a traditional optimiser, such as Gradient Descent, optimises the cross-entropy loss function by updating the trainable parameters of the quantum gates within the PQC so that the network learns the best classification boundaries. The fundamental algorithm in this paper for improving lung cancer prediction accuracy is the Quantum-Enhanced K-Medoids clustering algorithm, which encompasses quantum computer concepts. It begins with an existing publicly accessible lung cancer dataset, which is subjected to appropriate classical preprocessing. The novelty at the heart is the improvement of the classical K-Medoids algorithm's distance calculation step. Rather than depending only on traditional computation, the algorithm combines a quantum computing solution based on the Manhattan distance metric. The quantum component, possibly by utilizing quantum bits in the computation of distance or comparison, can achieve a more effective and even a more precise measurement of patient proximity in high-dimensional feature space. By utilising this quantum-enhanced distance, the algorithm more reliably chooses the best medoids and conducts patient record clustering, which directly results in the improvement of the overall prediction accuracy of lung cancer diagnosis over the traditional K-Medoids algorithm

IV. FLOWCHART

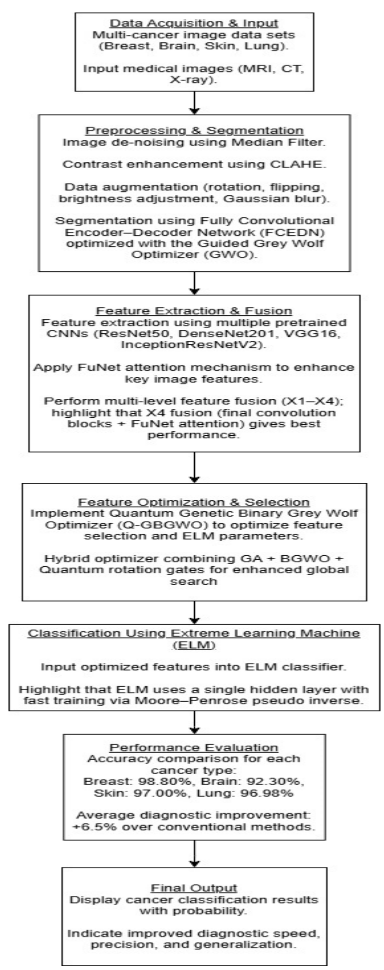

Fig 1. Algorithm flowchart of Quantum computational infusion in extreme learning machines for early multi-cancer detection

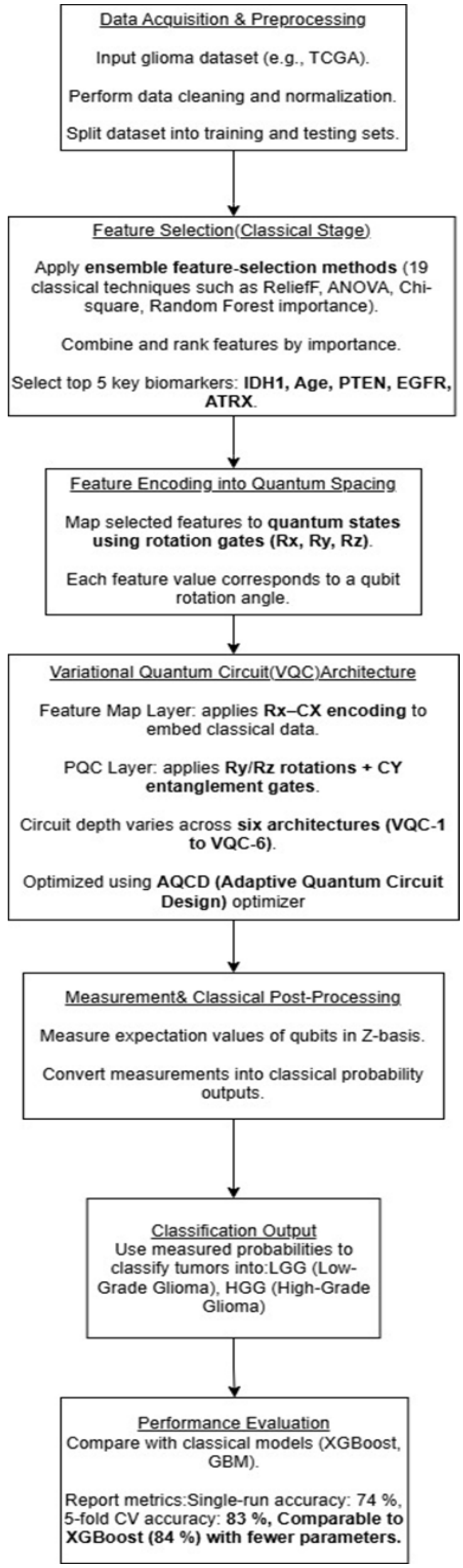

Fig 2.Algorithm flowchart of Hybrid classical and quantum computing for enhanced glioma tumor classification using TCGA data

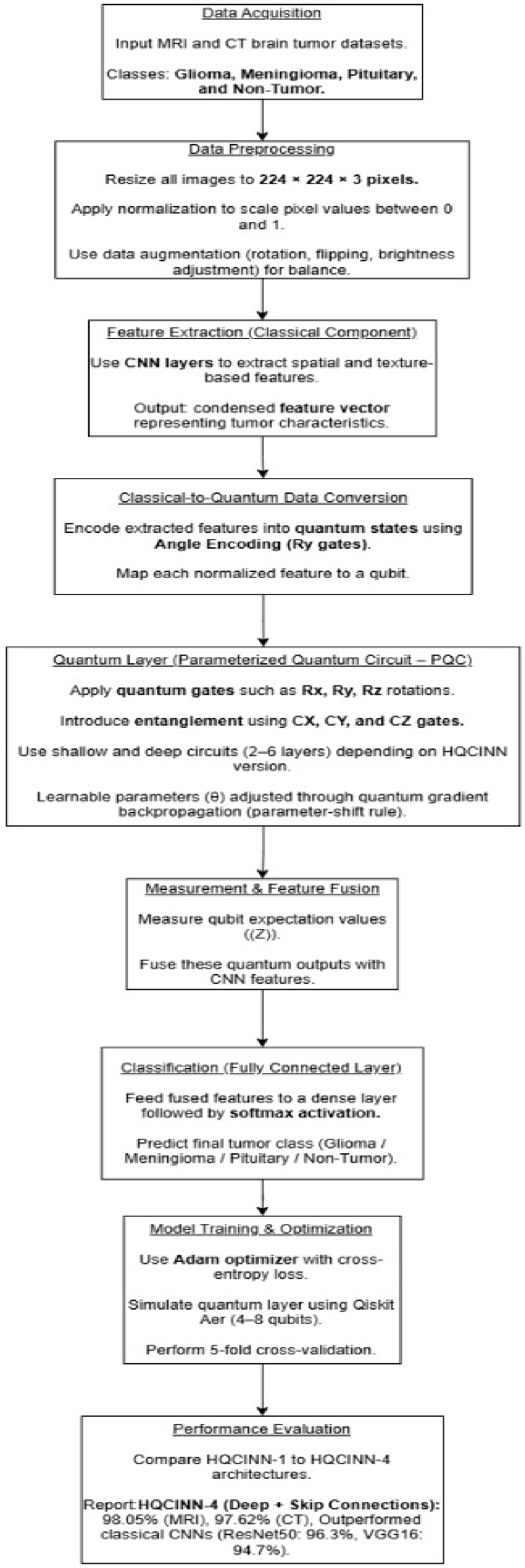

Fig 3. Algorithm flowchart of Multi-classification of brain tumors using proposed hybrid quantum–classical integrated neural network (HQCINN) models: shallow and deep circuit approaches. Neural Computing and Applications.

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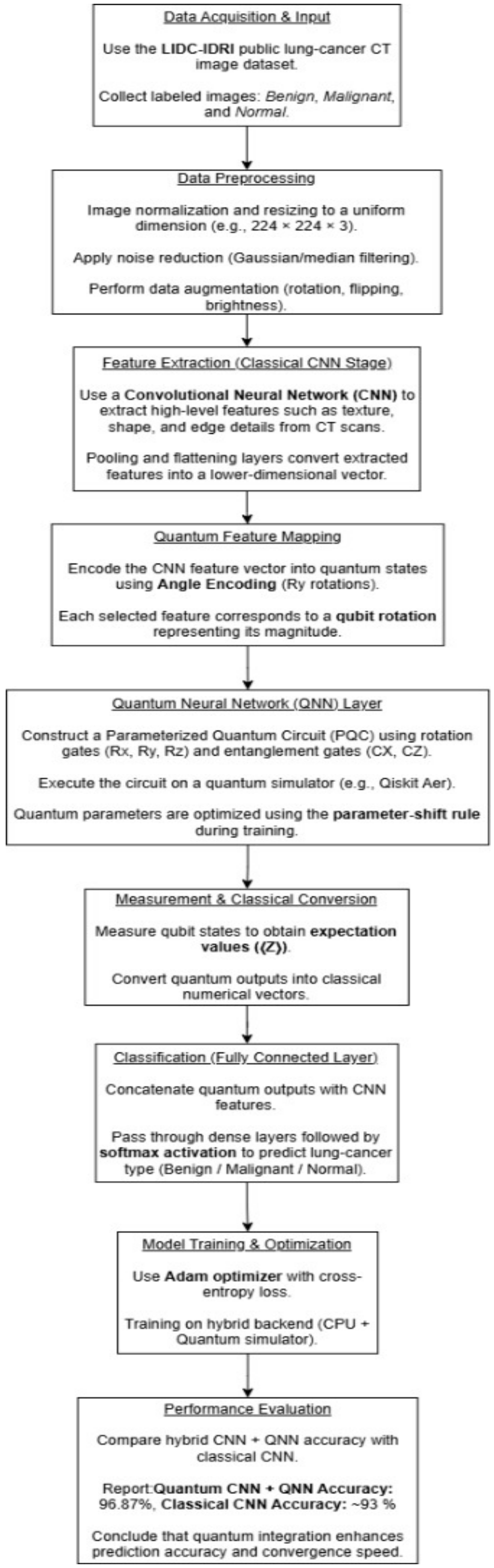

Fig 4. Algorithm flowchart of Enhancing Lung Cancer Prediction Accuracy Using Quantum-Enhanced K-Medoids with Manhattan Distance

V. RESULT AND EVALUATION

MODEL	ACCURACY	PARAMETER	REMARKS
Q-GBGWO-ELM	BREAST-98.80% BRAIN-*92.30%* SKIN-97-00% LUNG-96.98%	MODERATE	Achieved +6.5% higher diagnostic accuracy through quantum genetic optimisation and feature fusion (X4).
VQC	83% (5-folg CV avg)	VERY LOW	Efficient binary glioma grading using a quantum circuit; comparable to XGBoost accuracy with fewer parameters.
HQCINN	98.05%(MRI) 97.62%(CT)	~1.8 M	Deep hybrid CNN + quantum circuit; fewer parameters than classical CNNs; strong cross-modality generalisation
QUANTUM CNN-QNN	96.87% (LIDC-IDRI dataset*)*	~2.1 M	Quantum-enhanced CNN for lung cancer; improved convergence and precision over classical CNN (93%)

V. CONCLUSION

The four experiments together demonstrate the substantial potential of quantum-enhanced Artificial Intelligence (AI) on a wide range of cancer diagnostic problems, both brain and lung cancer. Hybrid Quantum - Classical Integrated Neural Network (HQCINN) and Variational Quantum Classifier (VQC) models utilise the computational strength of Parameterised Quantum Circuits (PQCs) and quantum features such as entanglement for classification, especially in very-high-dimensional feature spaces such as those from MRI images and molecular markers. In parallel, the Quantum - Genetic Binary Grey Wolf Optimiser - Extreme Learning Machine (Q-GBGWO-ELM) solves the issue of multi-cancer detection by merging deep traditional feature extraction with a quantum-optimised, rapid learning algorithm. Independently, the Quantum-Enhanced K-Medoids model targets the problem of unsupervised learning, enhancing patient clustering through incorporating quantum principles in order to optimise the calculation of the distance metric.

The Q-GBGWO-ELM model, which aims for early multi-cancer detection, is perhaps the best overall model considering its wider scope and purported efficiency on a very complex, multi-modal dataset. The model's power is in its overall architecture that combines FuNet transfer learning for enhanced multi-modal feature fusion with an Extreme Learning Machine (ELM) whose parameters are optimised through the Quantum-Genetic Binary Grey Wolf Optimiser. This architecture enables it to address the most ambitious and most broadly relevant challenge—detection of multiple cancer types from different data sources—and results show it enhances diagnostic accuracy by an average of 6% compared to other models tested, illustrating its strength and better performance in a heterogeneous diagnostic setting.

The remaining three quantum-augmented strategies would be the best option in certain, targeted clinical situations wherein they provide specialised benefits in comparison to the general multi-cancer classifier. The HQCINN model suits complex, multi-class image classification tasks, for example, differentiating various forms of brain tumours (e.g., meningioma, glioma) directly from MRI scans, where its hybrid architecture, based on shallow or deep circuits, is tuned to work on and distil high-level features from image data. The VQC is the better option for binary classification of highly discriminative molecular data, e.g., predicting LGGs vs.

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HGGs prognosis risk with a small, feature-reduced subset of TCGA clinical and genetic markers with high metrics, such as an AUC of 0.94, that are essential for accurate risk stratification. Lastly, the Quantum-Enhanced K-Medoids model is best for unsupervised patient segmentation or identification of inherent groupings within a dataset, as opposed to direct prediction, due to the fact that it employs quantum principles to optimise the distance metric and form stronger clusters between patients for subgroup investigation or treatment customisation.

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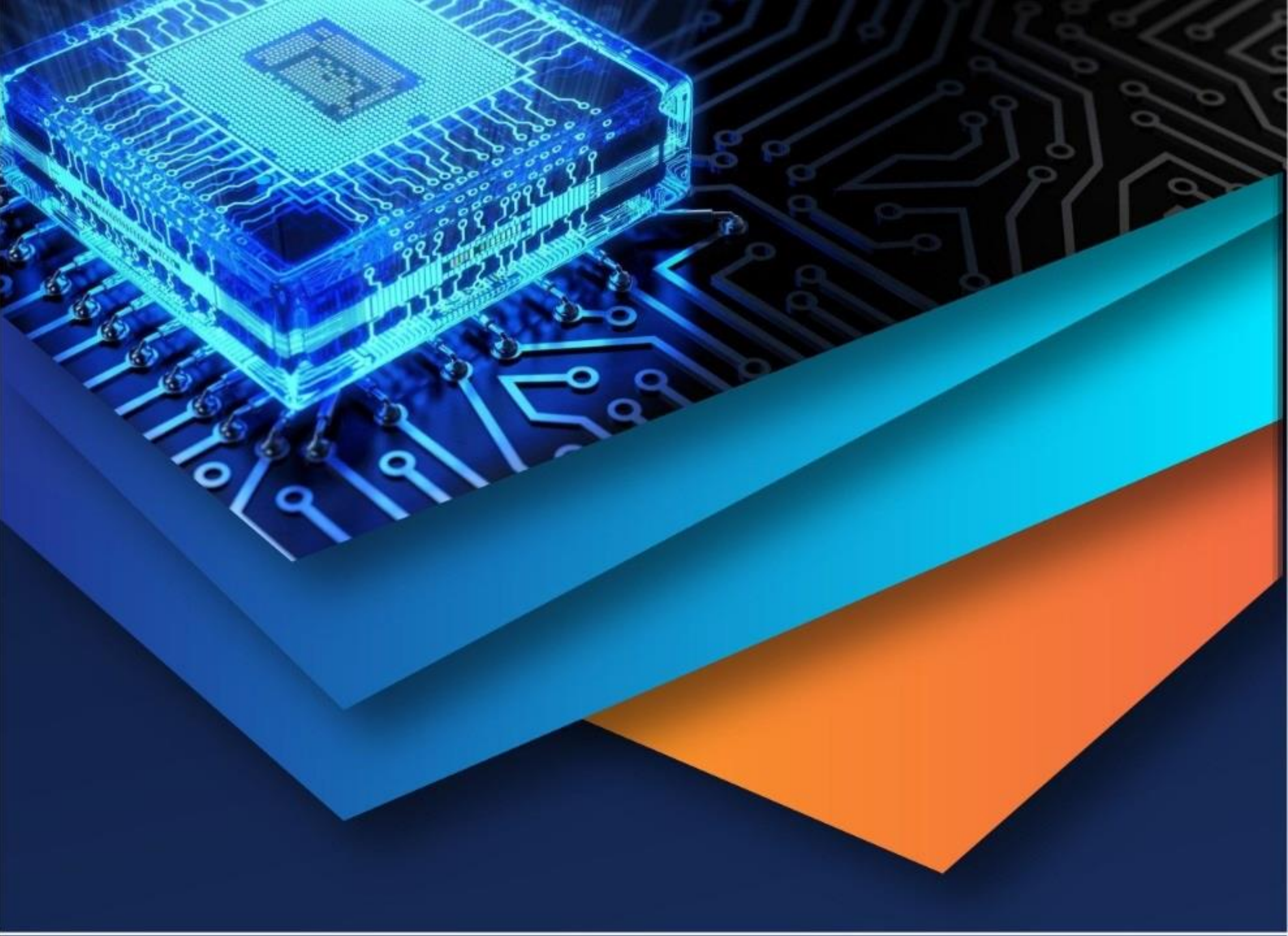

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