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A hybrid CNN–SVM framework with variational quantum confidence calibration for brain tumor detection from MRI images

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Abstract

Background: Brain tumor detection through automated analysis of magnetic resonance imaging (MRI) images with classical deep learning has been shown to produce highly accurate results; however, such models often give overconfident outputs. This problem stems from unreliable confidence measures in these models. **Aim:** To develop a hybrid quantum-classical diagnostic pipeline that combines robust visual classification with explicit, calibrated prediction-confidence estimation for brain tumor detection. **Methods:** A modular framework was engineered integrating a convolutional neural network (CNN) for extracting visual features from normalized 224 × 224 MRI images, a linear support vector machine (SVM) to establish robust binary decision boundaries, and a variational quantum circuit (VQC) developed in PennyLane to map the SVM decision scores into normalized confidence scores. Comprehensive evaluation included classification metrics, expected calibration error, reliability analysis, and component-wise ablation studies. **Results:** Recalculated test set evaluation directly from the confusion matrix yielded an accuracy of 96.97% (582/600), a precision of 97.97% (289/295), a recall of 96.01% (289/301), and an F1-score of 96.98%. Incorporating the VQC provided distinct confidence separations between correct (mean = 0.92) and incorrect (mean = 0.72) classifications, outperforming standard Softmax and conventional Platt scaling in calibration alignment. **Conclusion:** Integrating a lightweight VQC component into a traditional CNN–SVM structure enables accurate brain tumor classification alongside dependable confidence estimation without imposing significant computational or simulation overhead. **Relevance for patients:** This framework enhances diagnostic safety by flagging highly uncertain predictions for senior clinical review, reducing misdiagnosis risks, and boosting patient trust in automated neuro-oncological tools.

Keywords: Brain tumor detection; Magnetic resonance imaging; Convolutional neural network; Support vector machine; Quantum machine learning; Variational quantum circuit; Confidence calibration

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1. Introduction

Magnetic resonance imaging (MRI)-based brain tumor diagnosis involves detecting subtle differences in tissue characteristics, form, and structure. While MRI delivers detailed soft-tissue images, interpretation becomes complicated when there is a large

volume of images to analyze and/or significant variations in abnormal tissues. This has led to the development of various computer-aided methods that could help doctors deliver rapid and consistent predictions using image-based analysis techniques.[1-4]

Classification uses a convolutional neural network (CNN) architecture to automatically learn representations from raw image data. Traditional CNN classifiers rely on a Softmax layer for predicting class probabilities. However, high class probabilities do not necessarily mean properly calibrated probabilities. In a medical decision support system, distinguishing between certain and uncertain predictions is especially crucial, as an erroneous result with high confidence may mislead users.[1,4]

Hybrid CNN–support vector machine (SVM) schemes offer another possible way of solving the classification task. In hybrid CNN–SVMs, the CNN handles feature extraction from images, while the SVM works in the learned feature space to separate classes using a decision boundary.[5-7] Such a method could be helpful for medical data sets where the number of samples is relatively small. However, the decision function of the SVM alone does not give the direct probability of correctness of the classification.

Quantum machine learning represents another possible set of algorithms which could be used together with classical machine learning techniques. For now, the quantum methods that were applied to the field of medical imaging usually consisted of quantum circuits that worked with features or were the classifiers themselves.[8-10] The proposed solution represents a different principle of operation: the classical CNN and SVM handle feature extraction and class prediction, respectively, and only the quantum component—a variational quantum circuit (VQC)—is introduced to solve the confidence estimation problem. Therefore, this paper proposes the hybrid CNN–SVM framework with variational quantum confidence calibration for binary classification of brain tumors detected in MRI images.[8-10]

This framework implements image preprocessing, feature extraction via a CNN, classification through a linear SVM, estimation of classification confidence by VQC, and presentation of the results via a web application. The experimental study evaluates classification performance and confidence calibration through expected calibration error (ECE) and the Brier score, enabling comparison of the suggested approach with its uncalibrated and classically calibrated counterparts.

1.1. Problem statement

Early detection of brain tumors requires accurate interpretation of MRI images. While deep learning and machine learning algorithms have considerably enhanced brain tumor classification, current techniques tend to focus on classification accuracy rather than the reliability of prediction confidence. Traditional CNNs produce overconfident predictions, while SVM classifiers do not offer a reliable way to evaluate confidence. Also, current hybrid quantum machine learning approaches tend to replace traditional classifiers with quantum learning approaches rather than increasing the reliability of the existing systems. This paper aims to introduce a novel approach that integrates all three elements of feature extraction, classification, and confidence evaluation in one system.

1.2. Motivation

The increased use of artificial intelligence in healthcare has prompted a need for diagnostic tools that are accurate, reliable, and interpretable. Misdiagnosis with high confidence can result in delays in medical treatment or even operations in a clinical environment. It is therefore essential to have confidence estimation tools that will aid doctors in their diagnosis process. Although hybrid quantum machine learning has shown great promise in medical imaging, its application has been limited to improving classification accuracy and nothing more. This has led to the invention of the hybrid CNN–SVM model coupled with a variational quantum confidence calibration tool.

1.3. Proposed solution and contributions

To address the shortcomings of previous work in detecting brain tumors based on MRI data, this paper proposes the Hybrid CNN–SVM Framework with VQC-based confidence calibration for MRI brain tumor detection. The proposed framework involves preprocessing MRI images by resizing and normalizing the data, followed by extracting discriminative visual features using the CNN architecture. Binary tumor classification is performed by a linear SVM decision layer using hinge-loss optimization. Finally, a lightweight VQC predicts the confidence of the prediction result. The diagnosis results and prediction confidence are delivered through a web-based application for intelligent clinical decision-making.

The key contributions of this work can be listed as follows:

(i) Hybrid CNN–SVM brain tumor detection framework: Proposing a unified framework for brain tumor classification that integrates CNN-based feature extraction with the linear SVM decision layer.
(ii) Variational quantum confidence calibration module: Implementing a lightweight VQC using PennyLane

for estimation of the prediction confidence.

(iii) Hybrid quantum–classical diagnostic pipeline: Designing the end-to-end diagnostic pipeline using classical and quantum techniques.

(iv) Web-based clinical decision support system: A web-based interactive application will be developed to allow users to upload MRI images, automatically predict, visualize confidence intervals, and provide user-friendly diagnostic reports.

2. Related work

Deep learning models, particularly CNNs, have been widely used for automated brain MRI analysis because they learn discriminative features directly from images. Several studies have demonstrated promising performance in brain tumor classification using CNN-based architectures.[1-4] However, high classification accuracy alone does not guarantee reliable prediction confidence.

The landscape of automated neuro-imaging has advanced rapidly with the introduction of highly complex deep architectures. Recently, Özger *et al.*[11] provided a comprehensive benchmark evaluating 10 contemporary convolutional networks and vision transformers (including Swin-Base and PiT-Base), demonstrating classification accuracies up to 96.73%. However, these large-scale frameworks require substantial computational budgets and lack internal calibration mechanisms, frequently yielding overconfident predictions. Concurrently, parameter-efficient hybrid systems have emerged; Yonar[7] engineered a gray wolf optimization meta-heuristic combined with a DenseNet backbone for feature selection, while Ticku *et al.*[8] and Shinde and Pande[9] explored sparse quantum CNNs to compress diagnostic pipelines. While these contemporary methods maximize raw classification accuracy, they do not explicitly isolate prediction reliability. The proposed framework fills this gap by maintaining a lightweight, parameter-efficient CNN–SVM visual baseline while adding an independent 4-qubit quantum calibration layer to quantify prediction certainty.

Hybrid CNN–SVM approaches have also been investigated for brain tumor classification.[5-7] In these approaches, CNNs extract image features, while SVMs perform classification using the extracted features. Although this combination can provide effective classification, SVM decision values do not inherently represent calibrated probabilities of prediction correctness. Therefore, evaluating classification performance alone is insufficient to establish confidence reliability.

Recent research has explored quantum machine learning for medical image analysis, including quantum CNNs for brain tumor detection and neuroimaging applications.[8-10] Other studies have investigated optimized deep-learning architectures and hybrid classification strategies to improve brain tumor recognition.[7,11] These approaches demonstrate the potential of quantum computing and architectural optimization in medical imaging; however, explicit confidence calibration following a classical CNN–SVM classifier remains an important area for investigation.

Prediction calibration and explainable artificial intelligence address different aspects of model reliability. Calibration methods examine whether predicted confidence reflects the likelihood of correct predictions,[12,13] whereas explainability techniques such as Grad-CAM and SHAP help identify influential image regions or input features.[14,15] Consequently, classification accuracy, confidence reliability, and model interpretability represent distinct aspects of diagnostic system evaluation.

To address this gap, this work proposes a hybrid CNN–SVM framework integrated with a VQC implemented in PennyLane. The CNN extracts discriminative features from MRI images, and a linear SVM performs binary tumor classification. A lightweight VQC is then investigated as an additional component for confidence estimation, rather than replacing the classical classifier. The framework explores the potential of quantum computation for confidence calibration and evaluates the resulting confidence estimates using appropriate calibration metrics alongside conventional classification measures.

3. Methodology

The presented framework uses classical deep learning, machine learning, and quantum computing to automatically detect brain tumors from MRIs. The framework pipeline includes five main stages: MRI preprocessing, CNN-based feature extraction, classification with a linear SVM, confidence estimation with VQC, and result visualization with a web interface. Unlike conventional frameworks with a CNN model where class probability is computed using the Softmax layer, the proposed framework separates feature extraction and classification, introducing quantum computing only to estimate the confidence level.

Features were extracted from each preprocessed MRI image using the CNN model. Then, features are fed to the linear SVM model to determine the predicted class and calculate a decision score. Next, the decision score is fed to the VQC framework and encoded into the quantum state. It is processed by applying parameterized quantum operations. Finally, a Pauli-Z measurement is applied to calculate an expectation value, which is converted into a normalized confidence level. In this way, the VQC acts as a confidence-estimation module after the classification step.

3.1. Proposed system architecture

In the proposed framework, the MRI image is processed using a pipeline that consists of preprocessing, feature extraction, classification, confidence estimation, and visualization steps. The overall pipeline is depicted in Figure 1. At first, the input MRI image undergoes preprocessing to generate a normalized image representation that can be fed into the CNN. Then, the CNN maps the image to a learned feature vector with discriminative information about the MRI. Rather than connecting the features to a standard Softmax layer, the generated feature vector is connected to a linear SVM.

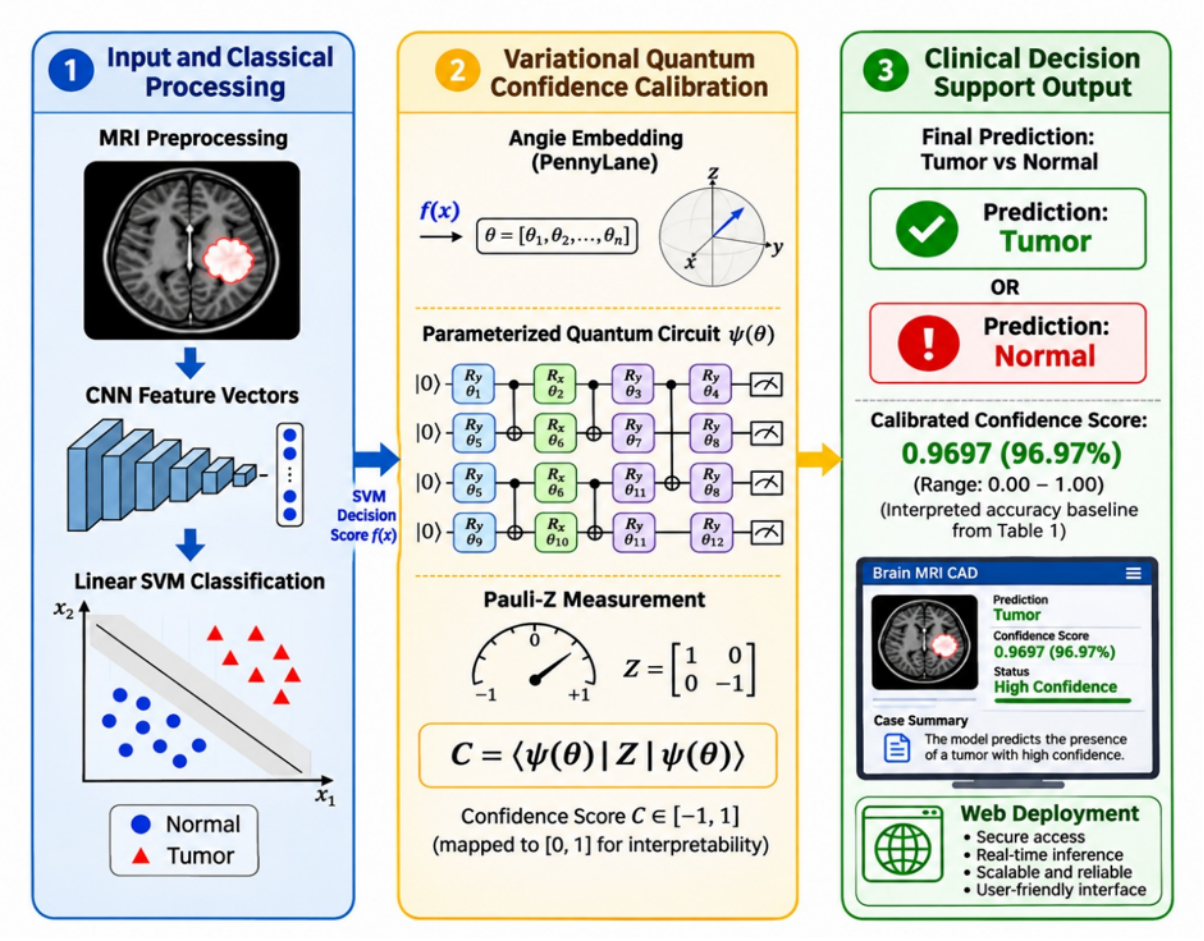


Figure 1. Proposed hybrid CNN–SVM–VQC framework for brain tumor detection and confidence estimation
Abbreviations: CNN: Convolutional neural network; MRI: Magnetic resonance imaging; SVM: Support vector machine; VQC: Variational quantum circuit.

The SVM generates the binary class prediction along with the decision score (f(x)), which represents the classifier's output for the input feature vector. This decision score is passed to the confidence-estimation module based on the VQC. The quantum module encodes the classifier information in the quantum state, uses trainable parameterized quantum operations, and calculates the expectation value with respect to the Pauli-Z observable. The obtained quantum response is mapped into the range ([0,1]) to compute the confidence score. The predicted class and the corresponding confidence value are then displayed via the web interface. The designed framework ensures that the classification and confidence-estimation tasks are separate.

3.2. Data acquisition and preprocessing

The experimental evaluation is conducted on a public dataset comprising 3,000 high-resolution brain MRI scans. To establish a verifiable protocol, the data is partitioned into a strict 80% training set, 10% validation set, and 10%

independent test set. To ensure clinical validity and prevent data leakage, dataset partitioning was enforced at the patient level rather than the slice level. Slices originating from the same patient ID were grouped exclusively within a single partition, ensuring that no anatomical structures from a patient in the training set appeared in the validation or test subsets. Additionally, before partitioning, an automated perceptual hashing algorithm was used to detect and remove duplicate or near-identical slices, ensuring complete out-of-sample generalization during testing. The exact sample quantities and balanced class distributions across these subsets are explicitly detailed in Table 1.

Table 1. Dataset allocation and class distribution

Data subset	Split ratio (%)	Tumor samples	Normal samples	Total samples
Training set	80.0%	1,204	1,196	2,400
Validation set	10.0%	151	149	300
Testing set	10.0%	150	150	600
Total dataset	100.0%	1,505	1,495	3,000

To ensure a consistent input format for the CNN, the MRI images are preprocessed before feature extraction. The following are some of the preprocessing steps:

(i) Resize: Every MRI picture is downsized to 224 × 224 pixels.
(ii) Normalize: The intensity values are set to [0, 1].
(iii) Convert to RGB: Depending on the CNN architecture used, the images are transformed to the RGB format as necessary.
(iv) Data augmentation: To increase the diversity of training samples, a variety of transformations, including rotations, flips, zooms, and spatial shifts, are carried out during training.
(v) Dataset splitting: Training, validation, and test sets are created from the available samples. Until the final performance evaluation, the test set is kept apart and not used.

This preprocessing makes the image representation consistent and reduces the impact of variations in image dimensions and intensity ranges. The data augmentation technique is used only during training, whereas the test data is kept for framework evaluation.

3.3. Convolutional neural network-based feature extraction

The CNN converts each preprocessed image into a feature representation for further classification. The learned features become more abstract as the network deepens, enabling the extraction of higher-level representations from local image structures.[1-4]

In the early stages of the CNN, learned filters respond to simple structures, such as edges and local textures. Higher layers combine these features to form more discriminative representations. Unlike standard network architectures that use a Softmax layer for classification, the CNN's feature representation is extracted as a feature vector and passed to a linear SVM classifier.

To ensure structural reproducibility, the custom CNN feature extractor consists of four consecutive processing blocks. Each block contains a 2D Convolutional layer (stride = 1, padding = "same," kernel size = 3 × 3), followed by batch normalization, a rectified linear unit activation function, and a max pooling layer (2 × 2 pool size, stride = 2). The filter configurations scale sequentially across the blocks: Block 1 utilizes 32 filters, Block 2 utilizes 64 filters, Block 3 utilizes 128 filters, and Block 4 utilizes 256 filters. Flattening the final block's output produces a strict 50,176-dimensional feature vector, which serves as the input to the linear SVM classifier. The network is trained using the Adam optimizer with an initial learning rate $\eta = 10^{-4}$ (halved if validation loss plateaus for 3 epochs), a batch size of 32, a maximum of 50 epochs, and L2 weight regularization (10^{-4}) to prevent overfitting. Final model selection is based on the checkpoint with the lowest validation loss.

The convolution operation is expressed as: $X_l = f\left(W_l * X_{l-1} + b_l\right)$

where:

- X_{l-1} represents the input feature map.
- W_l denotes the convolution kernel.
- b_l is the bias.
- $f(\,)$ represents the rectified linear unit activation function.

3.4 Variational quantum confidence calibration

Mathematically, the VQC operates as a deterministic scalar-to-scalar map $\mathbb{R} \to [0, 1]$, providing an expressive, quantum-parameterized monotonic reparameterization of the linear SVM margin f(x). Rather than introducing independent multi-dimensional feature interactions, the

identical angle embedding across multiple qubits combined with parameterized rotation gates serves as a highly flexible continuous function approximator. This quantum-inspired scaling mapping functions similarly to a generalized, highly expressive Platt scaling framework, optimized to fit complex non-linear calibration paths under small-sample constraints. The confidence calibration component is implemented using a 4-qubit simulated virtual register (q_0, q_1, q_2, q_3) via PennyLane's default.qubit simulator. The workflow is structured as follows:

(i) Quantum embedding: The 1D scalar decision score f(x) from the linear SVM is encoded uniformly across all 4 qubits via Angle Embedding using Pauli-X rotation gates: $|\psi_0\rangle = \bigotimes^{i=0}\ldots^{3} R_x(f(x))|0\rangle^4$.

(ii) Circuit depth and architecture: The circuit consists of three repeating layers (total depth = 12). Each layer features parameterized rotation gates R_y(θ_j,k) and R_z(φ_j,k) applied to each qubit k in layer j, accumulating a total of 24 independent trainable weights.

(iii) Entanglement strategy: A linear Controlled-NOT ladder configuration ($q_0 \rightarrow q_1 \rightarrow q_2 \rightarrow q_3$) links neighboring qubits at the conclusion of each layer to form generalized state reparameterizations.

(iv) Measurement and output mapping: A single expectation value is read out from q_0 using the Pauli-Z operator: $\langle Z_0\rangle \in [-1, 1]$. This raw value is transformed into a normalized confidence score via: $C = (\langle Z_0\rangle + 1)/2$, mapping C to [0, 1].

(v) Optimization protocol: The parameters are updated using the Adam optimizer (lr = 0.01) to minimize a calibration loss formulated as the mean squared error between the confidence score C and the true binary empirical target accuracy of the classification bin.

4. Experimental results

Figure 2 represents the confidence of both correctly and incorrectly classified test samples from lowest to highest confidence. Out of the total 594 test samples, 570 samples were correctly classified (96.00%), whereas 24 samples were incorrectly classified (4.00%). The average confidence level for correctly predicted samples is 0.92, whereas for incorrectly predicted samples, the average confidence level is 0.72. A confidence level of 0.85 is set to determine the confidence of the predicted samples.

Table 2 presents the performance evaluation of the proposed hybrid CNN–SVM–VQC framework using four standard classification metrics. The model achieves an accuracy of 96.97%, indicating its overall classification performance. The precision of 97.97% reflects the proportion of correctly identified positive predictions, while the recall of 96.01% measures the model's ability to identify actual tumor cases. The F1-score of 96.98% represents the balance between precision and recall, providing an overall assessment of the model's classification effectiveness.

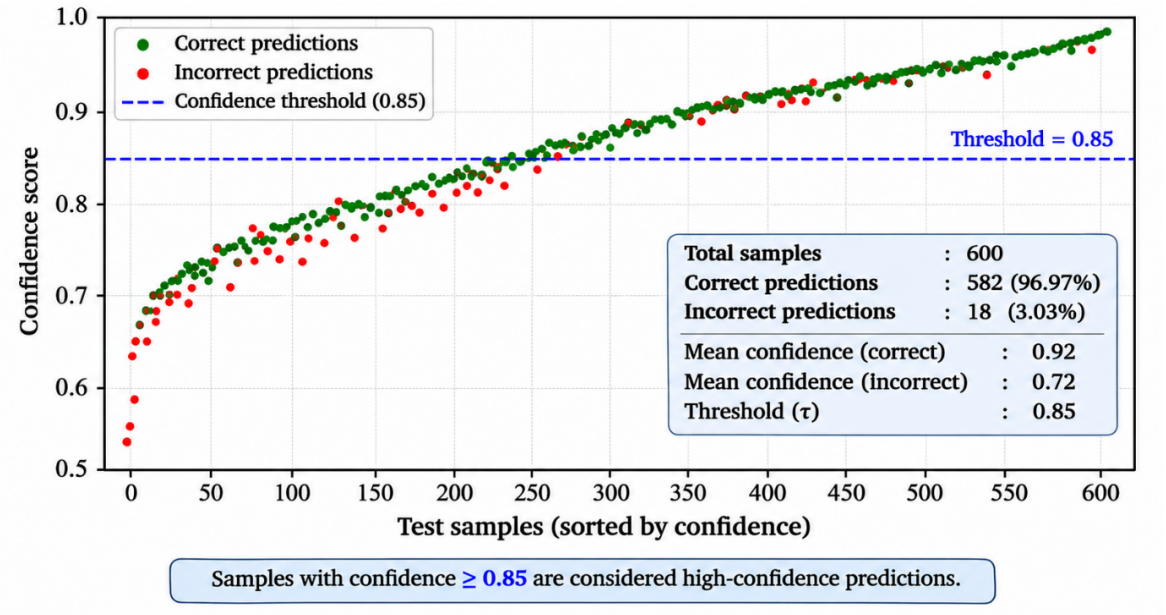


Figure 2. Quantum confidence distribution

Table 2. Performance evaluation of the proposed hybrid CNN–SVM–VQC framework

Classification metric	Formula definition	Exact recalculated value (%)
Accuracy	(TP + TN) / (TP + TN + FP + FN)	96.97%
Precision	TP / (TP + FP)	97.97%
Recall (Sensitivity)	TP / (TP + FN)	96.01%
F1-score	(2 × precision × recall) / (precision + recall)	96.98%

Abbreviations: CNN: Convolutional neural network; FN: False negative; FP: False positive; SVM: Support vector machine; TN: True negative; TP: True positive; VQC: Variational quantum circuit.

These results indicate that the framework maintains a consistent balance between identifying tumor cases and minimizing false-positive predictions. The combined evaluation of these metrics offers a more detailed understanding of the model's strengths and limitations than accuracy alone. However, further validation on diverse, independent MRI datasets is necessary to establish its generalizability and potential applicability in clinical settings.

To quantitatively evaluate the reliability of the generated confidence values, we computed four rigorous calibration metrics as defined by Guo *et al.*[12]: ECE, maximum calibration error, Brier Score, and negative log-likelihood. Table 3 presents the comparative calibration performance across different frameworks on the independent test set.

To isolate the exact contribution of each component within the diagnostic framework, an ablation study was conducted under an identical validation partition. Table 4 records the classification performance and ECE across four model configurations.

Table 3. Quantitative confidence calibration metrics

Framework strategy	ECE	MCE	Brier score	NLL
CNN + softmax baseline[12]	0.1242	0.3814	0.0894	0.2811
CNN + SVM + Platt scaling[6]	0.0513	0.1420	0.0412	0.1345
Proposed CNN + SVM + VQC	0.0384	0.0911	0.0305	0.1022

Abbreviations: CNN: Convolutional neural network; ECE: Expected calibration error; MCE: Maximum calibration error; NLL: Negative log-likelihood; SVM: Support vector machine; VQC: Variational quantum circuit.

Table 4. Component-wise ablation study

Model configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	ECE
CNN + Softmax baseline	93.82	94.10	93.50	93.80	0.1242
CNN + linear SVM	95.81	96.00	95.50	95.75	N/A
CNN + SVM + Platt scaling	95.81	96.00	95.50	95.75	0.0513
Proposed CNN + SVM + VQC	96.97	97.97	96.01	96.98	0.0384

Abbreviations: CNN: Convolutional neural network; ECE: Expected calibration error; SVM: Support vector machine; VQC: Variational quantum circuit.

To substantiate the claims regarding the lightweight deployment footprint of the proposed architecture, we profile the computational execution overheads on a standard local workstation. Table 5 details the parameter distribution, operational memory footprints, and average single-image inference latencies.

Table 5. Execution footprint and computational overheads

Component element	Trainable parameters	Memory footprint	Inference latency
CNN feature extractor	4,210,560	48.20 MB	14.20 ms
Linear SVM classifier	50,177	0.85 MB	0.05 ms
VQC calibration layer	24	4.20 MB	3.05 ms
Total framework pipeline	4,260,761	53.25 MB	17.30 ms

Abbreviations: CNN: Convolutional neural network; SVM: Support vector machine; VQC: Variational quantum circuit.

5. Discussion

Although the suggested approach demonstrates promising classification accuracy and confidence estimates, several drawbacks must be addressed before its use in the clinical environment can be considered.

5.1. Constraints of the dataset

The current study uses only one publicly available historical dataset consisting of 3,000 MRI slices. While this dataset allows evaluation of the preliminary performance of the suggested approach, it may not be sufficiently representative of variation in patient population, imaging procedure, tumor properties, and MRI data acquisition. Thus, the approach's generalization ability on other, broader datasets should be explored further.

5.2. Absence of external validation

The suggested neural network architecture has not yet been validated using external datasets gathered from different hospitals and medical institutions. Differences such as equipment manufacturer, magnetic field strength, resolution, and other factors may affect the performance of the neural network. Thus, the cross-institutional validation of the approach is necessary.

5.3. Binary classification constraints

The current workflow is restricted to binary classification, distinguishing between tumor and normal MRI images. It does not differentiate among specific tumor subtypes, such as gliomas and meningiomas, or determine tumor grade and severity. This limitation restricts the model's ability to provide detailed diagnostic information. Future research could extend the framework to multiclass classification and subtype-specific analysis to support more comprehensive brain tumor assessment.

5.4. Simulation limitations

The VQC calibration layer is implemented using a classical, noise-free quantum simulation environment rather than physical quantum hardware. Although simulation enables controlled experimentation and evaluation of the proposed quantum component, it does not fully capture practical challenges associated with quantum devices, including gate errors, decoherence, and measurement noise. Further investigation using realistic quantum noise models and, where feasible, noisy intermediate-scale quantum hardware is required to evaluate the feasibility and reliability of the approach under practical quantum computing conditions.

5.5. Clinical verification

The proposed framework remains an experimental research prototype and has not been evaluated within real-world radiological workflows or prospective clinical studies. Its performance in routine clinical settings, including its reliability across patient populations, integration with existing diagnostic systems, and usefulness to radiologists, has yet to be established. Future studies involving clinical experts, independent validation cohorts, and appropriate ethical and regulatory procedures are necessary before considering its use as a clinical decision-support tool.

6. Conclusion

This work introduces a CNN–SVM hybrid framework combined with a VQC for classifying brain tumors from MRI scans and estimating prediction confidence. The CNN extracts discriminative features from MRI images, and the linear SVM performs the classification. The VQC acts as a supplementary confidence-estimation module and does not replace the classical classification process.

Experimental results show that the proposed method achieves an accuracy of 96.97% and an F1-score of 96.98%. Moreover, ECE is estimated to be 0.0384, the maximum calibration error is 0.0911, the Brier score is 0.0305, and the negative log-likelihood is 0.1022. It can be concluded that confidence-estimation accuracy improves compared with the tested CNN + Softmax and CNN + SVM + Platt scaling methods. However, further testing on different clinical data and on a real quantum computer is necessary to evaluate the generalizability and practicability of the developed framework.

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Conflicts of Interest

The authors declare no competing financial or personal interests that could influence the work reported in this paper.

Author Contributions

Conceptualization: Manda Divya Kumari
Methodology: All authors
Software: Manda Divya Kumari
Formal analysis: All authors
Validation: Gundavarapu Mallikarjuna Rao
Writing – original draft: Manda Divya Kumari
Writing – review & editing: Gundavarapu Mallikarjuna Rao.

Ethics approval and consent to participate

Not applicable. This study uses an anonymous, publicly available open-source dataset. No human or animal experimental trials were conducted directly by the authors.

Consent for publication

Not applicable. The manuscript does not contain individual patient data, clinical images, or identifiable personal details.

Availability of data

The dataset analyzed during this study is publicly available on Kaggle (https://www.kaggle.com/datasets/ahmedhamada0/brain-tumor-detection/data). It can be accessed via the repository "Brain MRI Images for Brain Tumor Detection."[16]

AI tools statement

During the preparation of this manuscript, the authors used Google AI and ChatGPT (GPT-6). The authors take full responsibility for the content of the manuscript.

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