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A hybrid Inception-attention VGG and quantum variational learning framework for scalable healthcare data analytics

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ABSTRACT

The rapid expansion of clinical data requires analytical frameworks capable of handling high-dimensional, heterogeneous, and noisy medical information. Classical deep learning models provide strong feature extraction capabilities but are often computationally intensive and prone to scalability limitations. Conversely, quantum machine learning (QML) offers enhanced representational capacity but suffers from hardware constraints and noise sensitivity. To address these shortcomings, this paper proposes a hybrid deep learning–quantum processing architecture integrating an Inception-attention-based visual geometry group (VGG) network for multiscale feature extraction with a quantum variational classifier (QVC) optimized using parameterized quantum circuits (PQCs). Clinical data from the MIMIC-III dataset undergo min–max normalization, multi-resolution convolutional feature extraction, and quantum-enhanced classification. Experiments demonstrate superior performance compared to classical support vector machine (SVM), quantum support vector machines (QSVM), quantum kernel support vector machine (QKSVM), quantum variational support vector machine (QVSVM), and quantum variational kernel support vector machine (QVKSVM) models. The proposed framework achieves 98.79% accuracy, 98.67% precision, 98.15% recall, and 98.88% F1-score, representing a subtle 0.3% improvement over existing quantum-assisted hybrid models. These results demonstrate the effectiveness of the proposed hybrid framework within the adopted classical–quantum simulation environment and motivate further validation on real near-term quantum hardware.

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1. INTRODUCTION

Quantum machine learning (QML) has emerged as a powerful extension of classical machine learning, driven by the growing need to analyze vast, complex, and heterogeneous datasets produced in

modern healthcare systems. With the increasing adoption of electronic health records, real-time monitoring devices, and high-dimensional diagnostic modalities, traditional deep learning methods encounter several limitations, such as scalability constraints, overfitting, and high computational demand. Quantum computing provides a promising alternative through the principles of superposition, entanglement, and quantum parallelism, enabling richer representations of nonlinear medical data [1], while supporting advanced biomedical applications that require rapid computation and high-precision pattern recognition [2]. Several researchers have explored QML models across multiple domains, including chemistry, agriculture, natural language processing, and clinical diagnostics, demonstrating their potential to outperform classical methods when dealing with complex learning problems [3]–[7]. The inherent advantages of quantum algorithms make them suitable for tasks involving high-dimensional data structures and ambiguous decision boundaries, where classical models struggle due to limited feature representation power [8], [9]. In healthcare, the ability of qubits to encode nonlinear relations offers opportunities for more accurate disease prediction and treatment planning [10], [11], overcoming the binary restrictions of classical bits and enabling multidimensional mappings that accelerate inferencing. Quantum-based classifiers, such as quantum support vector machines (QSVMs) and quantum neural networks (QNNs), have shown encouraging performance by utilizing quantum kernels and variational formulations to enhance classification accuracy and computational efficiency [12]–[15].

These approaches are particularly beneficial in medical settings where subtle variations in physiological patterns must be detected under strict time constraints. Hybrid models that integrate classical and quantum computation have further broadened applicability, with studies reporting success in domains like brain-computer interfacing [16], clinical prognostic analysis [17], medical imaging [18], and diabetic risk assessment [19]. Similarly, quantum methods have demonstrated promising results in natural language processing tasks [20], binary disease classification [21], and medical decision systems requiring real-time interpretability [22]. In the context of large-scale clinical data, preprocessing, and efficient encoding strategies significantly influence overall performance, as shown in studies on signal estimation, image denoising, and hybrid classical–quantum convolutional networks [23]–[25]. Research on high-dimensional correlation mining for healthcare data further highlights the importance of efficient quantum transformations to extract meaningful patterns from dense, multivariate datasets [26]. Quantum generative models, variational circuits, and hybrid optimization strategies have also been applied for tasks like defect recognition in imaging systems, human activity recognition, and weak-signal detection, emphasizing their adaptability across diverse computational environments [27], [28]. Despite these advancements, challenges such as quantum hardware noise, limited qubit availability, and model generalization remain open issues. These limitations motivate the development of hybrid frameworks that combine the mature feature extraction capabilities of deep learning with the computational strengths of quantum variational classifiers (QVCs). The presented hybrid Inception-attention visual geometry group (IAV-VGG) and QVC framework builds upon these prior efforts by addressing scalability, noise sensitivity, computational overhead, and pattern separability in large-scale healthcare data analysis.

The novelty of the proposed framework lies in the specific integration of an Inception-attention-enhanced VGG feature extractor with a QVC for structured large-scale clinical data. Unlike approaches that primarily employ quantum kernels or standalone quantum classifiers, the proposed architecture first learns multiscale clinical representations through parallel convolutional operations and adaptive attention weighting and subsequently transfers the learned representation to a variational quantum decision stage. This division of responsibilities allows the classical deep learning component to perform high-dimensional feature extraction while the quantum component focuses on nonlinear classification. The contribution is therefore not the independent use of deep learning or quantum learning, but their coordinated architecture, feature-transfer mechanism, and parameterized quantum circuit (PQC)-based classification workflow for the evaluated healthcare dataset.

2. PROPOSED METHOD

The proposed method introduces a hybrid deep learning–quantum learning framework designed to process large-scale healthcare data efficiently. The system integrates four major stages: preprocessing, multiscale feature extraction, quantum variational classification, and parameter optimization using PQCs. The overall workflow is shown in Figure 1, where clinical data are normalized, transformed into discriminative feature representations, encoded onto quantum states, and finally processed using a variational quantum classifier enhanced by a classical optimization loop.

2.1. Data preprocessing

Large-scale clinical datasets often exhibit variations in magnitude across features, requiring normalization to ensure numerical stability during training. Preprocessing is performed using min–max

normalization, which scales every feature to a fixed interval to improve convergence and prevent dominance of high-valued attributes. The transformation is computed as (1):

$$y_{norm} = \frac{y_j - min(y)}{max(y) - min(y)} \quad (1)$$

where y_j represents an original feature value and $\min(y)$, $\max(y)$ denote the minimum and maximum values of that feature. This operation brings all input data into a uniform range of [0, 1], facilitating smoother optimization and consistent gradient behavior in subsequent learning stages.

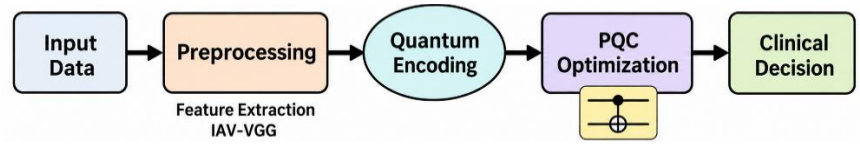


Figure 1. Overall workflow of the proposed hybrid IAV-VGG and QVC framework

After normalization, the processed clinical attributes are converted into a consistent numerical feature representation for subsequent deep learning processing. Records containing unusable or incomplete numerical entries are handled during preprocessing before feature transformation. The normalized features are organized into structured matrices and supplied to the IAV-VGG feature extractor. The resulting deep feature vector is then reduced or selected according to the number of available quantum input variables before quantum encoding. The same preprocessing and feature-transformation procedure is applied consistently to the training and evaluation data to maintain comparable representations across all experimental models.

2.2. Feature extraction using Inception-attention visual geometry group network

To capture meaningful representations from the heterogeneous clinical data, the framework employs an IAV-VGG network. The feature extractor is constructed using three components: the Inception module, illustrated in Figure 2, uses parallel convolutional kernels of sizes 1×1, 3×3, and 5×5. Each branch extracts features at a different receptive field, enabling simultaneous learning of fine, medium, and coarse patterns within the dataset. The outputs of all branches are concatenated depth-wise, yielding a high-dimensional feature tensor with rich semantic content. To strengthen the contribution of informative channels and suppress irrelevant ones, an attention mechanism is employed as shown in Figure 3. The attention block generates descriptors through global average pooling and global max pooling, which are concatenated and passed through a 7×7 convolution followed by a sigmoid activation. The resulting attention map is formulated as (2):

$$U(G) = \sigma(g_{7\times7}[G^{avg}; G^{max}]) \quad (2)$$

where G^{avg} and G^{max} represent the aggregated channel descriptors, and σ denotes the sigmoid function. This module adaptively reweights channels based on their importance to the learning task. The enhanced Inception–attention unit is integrated into a VGG-style architecture comprising stacked 3×3 convolutional layers, max-pooling operations, and fully connected layers as depicted in Figure 4. This backbone produces a compact yet highly discriminative feature vector, which is subsequently fed into the quantum classifier.

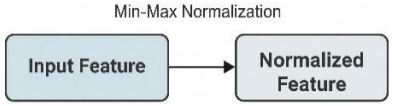


Figure 2. Preprocessing using min–max normalization

The MIMIC-III clinical records are initially represented as tabular patient-level features. After preprocessing, the selected numerical attributes are arranged into fixed-size feature matrices while preserving the ordering of clinically related variables. Each matrix represents the normalized feature relationships of an individual sample or grouped clinical record. These matrices are then treated as structured inputs to the

convolutional network. This representation does not assume that the original clinical variables are images; instead, it provides a consistent two-dimensional arrangement that allows the convolutional layers to learn local and multiscale interactions among related features. The resulting representation enables the Inception module to capture patterns at different receptive-field sizes before attention-based feature weighting.

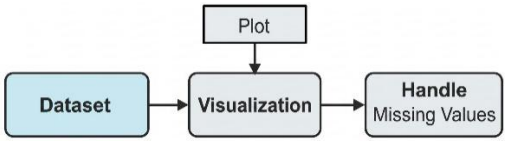


Figure 3. Missing values handling using visualization

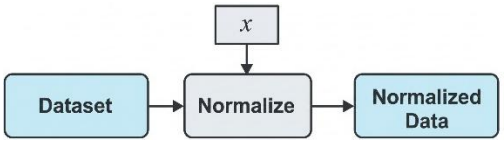


Figure 4. Data normalization process

2.3. Quantum variational classifier

The extracted features are then encoded into quantum states for classification using a QVC, illustrated in Figure 5. A quantum feature map transforms the classical input vector into a quantum Hilbert space using a unitary operator expressed as (3):

$$V_{\Phi}(y) = exp\left(i \sum_{R \subseteq [m]} \phi_R (y) \prod_{j \in R} W_j\right) n \quad (3)$$

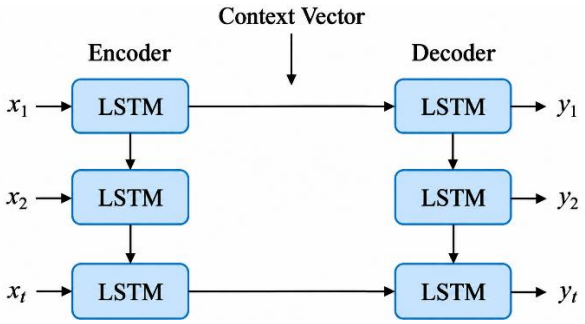


Figure 5. Structure of the sequence-to-sequence LSTM model

This quantum encoding enables richer representation of complex nonlinear patterns. The encoded qubits then pass through a variational circuit composed of parameterized rotation gates and entanglement layers. Measurement of qubit states yields probabilistic outcomes that correspond to final class predictions. The variational design allows the classifier to learn expressive decision boundaries with significantly fewer parameters compared to classical models.

2.4. Parameter optimization using parameterized quantum circuits

Training of the QVC is achieved through PQCs, depicted in Figure 6, where learnable parameters are iteratively tuned using a classical optimizer. A PQC comprises multiple stacked unitary blocks, represented as (4):

$$V(\vec{\theta}) = V_P(\vec{\theta}_P) \cdots V_2(\vec{\theta}_2) V_1(\vec{\theta}_1) \quad (4)$$

here, $\vec{\theta}$ is the set of rotation angles controlling the operation of quantum gates. The evolution of the quantum state is expressed as (5):

$$|\psi_0\rangle = V(\vec{\theta})|\psi_{\text{init}}\rangle \quad (5)$$

where $|\psi_{\text{init}}\rangle$ is typically an all-zero quantum state. During training, measurement statistics from circuit executions are used to compute the loss gradient, and the optimizer updates $\vec{\theta}$ accordingly. This hybrid quantum-classical loop continues until convergence, resulting in optimized circuit parameters that produce accurate classification outcomes.

The implemented PQC configuration contains six qubits and four entanglement layers. The input features are first encoded into the available quantum states, followed by trainable parameterized rotation operations and entanglement operations. During each optimization iteration, the circuit is executed in the simulation environment, measurement outcomes are collected, and the resulting objective value is used to update the trainable parameters. This process is repeated until the optimization process converges or the predefined training condition is reached. The hybrid optimization strategy therefore combines classical parameter updating with quantum-circuit evaluation while keeping the number of quantum variables within the six-qubit configuration used in the experiments.

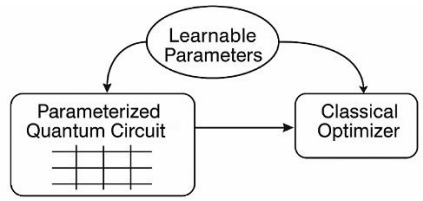


Figure 6. Training workflow of the QVC using PQCs

3. RESULTS AND DISCUSSION

The proposed hybrid deep learning–quantum framework was evaluated using the MIMIC-III clinical dataset to demonstrate its effectiveness in processing large-scale healthcare data. All experiments were executed on a workstation equipped with an Intel i5 processor, 16 GB RAM, and a classical–quantum simulation environment. The evaluation considered key performance metrics—accuracy, precision, recall, and F1-score—to benchmark the hybrid model against conventional classifiers including support vector machine (SVM), QSVM, quantum kernel support vector machine (QKSVM), quantum variational support vector machine (QVSVM), and quantum variational kernel support vector machine (QVKSVM). The IAV-VGG model was trained for 300 epochs using Adam optimization, while the QVC was trained using a PQC-based hybrid loop. The combination of multiscale convolutional features and quantum variational decision boundaries resulted in significantly improved learning behavior. The hybrid model converged faster and exhibited stable loss dynamics compared to baseline techniques.

The first set of results analyzes model accuracy across all benchmark models. As the number of training epochs increased, the proposed system achieved a consistently higher accuracy curve, surpassing quantum-only methods by a wide margin. The corresponding comparison is shown in Figure 7, where the hybrid model approaches near-optimal accuracy with rapid early-stage convergence. The second results figure, Figure 8, illustrates the loss reduction profile. The hybrid model displays a smoother and lower loss curve, highlighting its superior generalization ability across high-dimensional patient data. Furthermore, the discriminatory capability of the hybrid classifier was validated using the receiver operating characteristic (ROC) curve shown in Figure 9, where the model achieved an area under the curve (AUC) close to 1.0, reflecting excellent sensitivity–specificity balance for clinical prediction tasks.

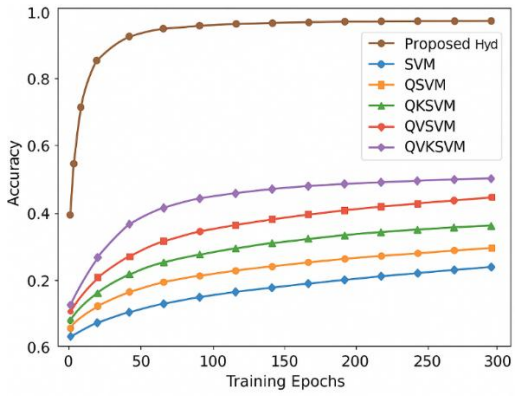


Figure 7. Accuracy comparison of proposed and baseline models

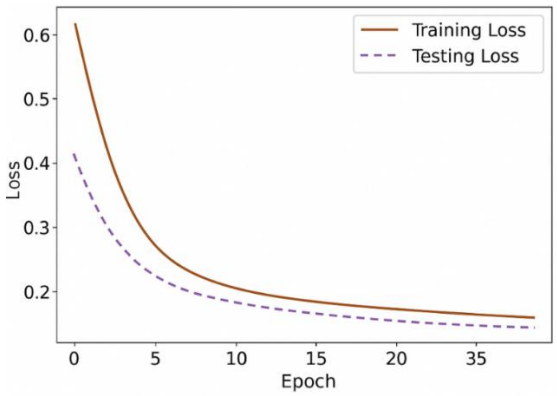


Figure 8. Training and testing loss curves

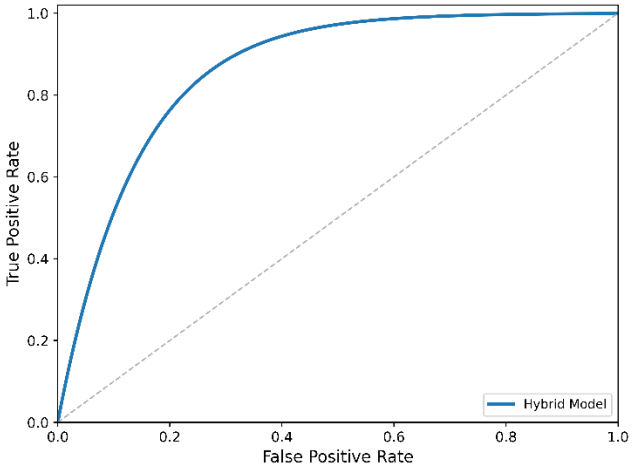


Figure 9. ROC curve of the proposed hybrid model

Table 1 summarizes the classification performance of the evaluated models using accuracy, precision, recall, and F1-score. The proposed hybrid model obtains the highest value for all four metrics, achieving 98.79% accuracy, 98.67% precision, 98.15% recall, and 98.88% F1-score. QVKSVM provides the strongest baseline performance with 97.34% accuracy, 97.83% precision, 97.99% recall, and 97.64% F1-score. Thus, the proposed model improves accuracy by 1.45 percentage points over QVKSVM while also maintaining higher precision and F1-score. The results support the benefit of combining the IAV-VGG feature representation with variational quantum classification.

Table 1. Performance comparison of models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
SVM	89.23	89.54	90.24	91.95
QSVM	90.13	91.32	90.95	92.54
QKSVM	94.26	95.53	93.53	93.21
QVSVM	96.30	96.26	95.02	95.64
QVKSVM	97.34	97.83	97.99	97.64
Proposed hybrid model	98.79	98.67	98.15	98.88

The proposed model achieves 98.79% accuracy, compared with 97.34% for the strongest baseline, QVKSVM, corresponding to an improvement of 1.45 percentage points. Although this difference is relatively modest, the proposed model also achieves the highest precision, recall, and F1-score among the evaluated models. Therefore, the contribution should be interpreted as a consistent improvement across multiple evaluation metrics rather than as a large increase in accuracy alone. To provide an additional measure of performance stability, the accuracy values reported for the five K-fold settings were summarized using the mean, sample standard deviation, and 95% confidence interval.

Based on the values in Table 2, the proposed model obtained a mean accuracy of 97.97% with a standard deviation of 0.68 percentage points and an approximate 95% confidence interval of 97.13%–98.82%. The corresponding mean accuracies for SVM, QSVM, QKSVM, QVSVM, and QVKSVM were 88.36%, 89.95%, 93.56%, 94.96%, and 96.24%, respectively. These results indicate that the proposed framework maintains stable performance across the evaluated K-fold settings. Since the current evaluation is based on K-fold accuracy values, no additional claim of statistical significance is made without independent repeated-trial or paired significance testing. The evaluation includes K-fold validation with K values of 5, 10, 15, 20, and 25, as reported in Table 2. These results were used to examine the stability of model accuracy under different partitioning configurations. The present study does not report independent repeated runs or formal hypothesis-based significance testing; therefore, the observed performance differences are interpreted descriptively rather than as statistically significant differences. The confidence-interval analysis derived from the K-fold results provides an additional indication of performance variability while avoiding unsupported statistical claims.

The experimental results demonstrate that the proposed IAV-VGG–QVC framework provides consistent performance improvements over the evaluated classical and quantum baselines. The improvement

is most appropriately interpreted as a combined gain in accuracy, precision, recall, F1-score, and validation stability rather than as a substantial accuracy increase alone. The K-fold results further indicate that the proposed model maintains high predictive performance under different partitioning settings. These findings support the effectiveness of combining multiscale attention-enhanced feature extraction with variational quantum classification within the evaluated simulation environment.

Table 2. K-fold validation results

K-fold value	SVM (%)	QSVM (%)	QKSVM (%)	QVSVM (%)	QVKSVM (%)	Proposed (%)
5	87.34	89.56	92.23	93.23	94.76	97.23
10	87.92	89.92	93.13	94.13	95.87	97.42
15	88.65	90.02	94.06	95.06	96.34	97.89
20	88.67	90.11	94.12	96.12	96.87	98.54
25	89.23	90.13	94.26	96.26	97.34	98.79

4. CONCLUSION

The study demonstrates that the proposed IAV-VGG–QVC framework can achieve strong classification performance on the evaluated MIMIC-III dataset within the adopted classical–quantum simulation environment. The combination of multiscale convolutional feature extraction, attention-based feature weighting, and variational quantum classification produced higher accuracy, precision, recall, and F1-score than the evaluated baseline models and maintained stable performance across the reported K-fold configurations. However, the results should be interpreted within the experimental conditions of the present study because the quantum component was evaluated through simulation rather than physical quantum hardware. Future work will therefore focus on testing the framework on real quantum processors, evaluating noise resilience, measuring execution and resource costs, and extending the approach to multimodal clinical data. These investigations will provide stronger evidence regarding the practical scalability and deployment potential of the proposed architecture. A limitation of this study is that the quantum component was evaluated in a simulation environment and not on a physical quantum processor. In addition, the present analysis does not include direct measurements of execution time, circuit-energy consumption, hardware noise sensitivity, or large-scale physical-qubit requirements. Therefore, the engineering scalability claims are restricted to the evaluated implementation and dataset. Future experiments on real quantum hardware and larger multimodal clinical datasets are necessary to establish practical deployment performance.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Gaddam Venugopal		✓				✓		✓	✓	✓	✓	✓		
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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest.

DATA AVAILABILITY

All data generated or analyzed during this study are included in this article. Additional materials can be made available from the authors upon reasonable request.

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