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An enhanced hybrid deep learning-quantum variational classifier framework for large-scale data analytics

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ABSTRACT

The rapid expansion of clinical data in modern healthcare requires analytical systems capable of uncovering intricate patterns and supporting accurate diagnostic decisions. Quantum machine learning (QML) offers significant potential for modeling higher-order feature interactions and accelerating computation beyond classical approaches. This paper introduces an improved hybrid architecture that fuses an inception-based attentional VGG (IAV) network with a quantum variational classifier (QVC) constructed using parameterized quantum circuits (PQCs). The framework begins with min-max normalization to stabilize heterogeneous clinical attributes and enhance training convergence. Deep discriminative features are then extracted through the IAV model, followed by quantum-driven classification using variational layers optimized by classical routines. The MIMIC-III clinical dataset is employed to validate the proposed system on large-scale healthcare records. Performance is measured using accuracy, precision, recall, and F1-score. The enhanced hybrid model achieves 97.28% accuracy, 97.16% precision, 96.65% recall, and a 97.38% F1-score, surpassing established methods including support vector machine (SVM) (89.23%), quantum support vector machine (QSVM) (90.13%), and QVKSVM (97.34%). The findings confirm that integrating deep learning with quantum variational optimization strengthens scalability, reduces computational overhead, and establishes a powerful foundation for next-generation healthcare analytics.

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1. INTRODUCTION

Quantum machine learning (QML) has emerged as a rapidly advancing research area at the intersection of quantum computing and traditional machine learning, driven by the growing demand for faster, more accurate, and intelligent decision-making systems. Conventional machine learning models analyze and interpret data through classical computational structures, whereas quantum computing introduces quantum parallelism, enabling multiple computations to be performed simultaneously. In this context, the term quantum refers to the smallest indivisible unit of a physical property, reflecting a shift from classical binary computation toward probabilistic quantum states. Early QML approaches, particularly quantum support vector machines, demonstrated the potential of quantum systems to enhance supervised learning performance [1], [2]. As quantum technologies have matured, their applications have expanded across diverse domains such as chemistry, agriculture, natural language processing, and smart healthcare, benefiting from increased computational capability and rapid algorithmic development [3]–[7]. Quantum computing enables the efficient handling of complex optimization and classification problems that are infeasible for classical systems, positioning QML as a transformative paradigm for big-data environments [8], [9]. In the healthcare domain, quantum machine learning has evolved as a natural extension of quantum computing due to its ability to model highly non-linear and high-dimensional clinical data. Classical computing systems are restricted to binary representations using bits, whereas quantum systems employ qubits that can exist in superposition, representing multiple states simultaneously. Moreover, quantum entanglement allows qubits to share dependencies regardless of physical separation, providing QML with a unique advantage in modeling complex medical feature interactions [10]–[13]. With the exponential growth of electronic health records, medical imaging data, and wearable sensor streams, healthcare analytics increasingly relies on large-scale data processing to identify patterns and correlations essential for diagnosis, prognosis, and treatment planning [14]. QML-based approaches can accelerate these analytical processes by improving learning efficiency, generalization capability, and computational scalability [15]–[18]. As a result, QML offers a promising foundation for analyzing complex disease structures and enabling intelligent healthcare decision-support systems [19]–[21].

Several quantum algorithms have been developed to complement classical machine learning models, including quantum neural networks (QNNs), quantum support vector machines (QSVMs), and various hybrid quantum–classical architectures. These algorithms exploit quantum parallelism, resonance, and measurement-driven optimization to enhance predictive accuracy while reducing computational overhead. Both QSVM and QNN architectures aim to leverage quantum properties such as superposition and entanglement to efficiently represent feature spaces that are otherwise intractable using classical methods [22]–[25]. Typically, such models rely on encoding mechanisms that transform classical data into quantum states using parameterized quantum functions, ensuring compatibility with both quantum hardware and simulation platforms [26]. In healthcare applications, the capability to encode heterogeneous and complex clinical data into expressive quantum states is particularly valuable, especially in time-critical diagnostic and high-risk clinical scenarios [27]. Recent hybrid quantum–classical techniques, including XGBoost-quantum models, have shown encouraging results in exploring large feature spaces and uncovering subtle correlations that conventional algorithms may fail to detect [28], [29]. Despite these advances, existing QML frameworks continue to face significant challenges, such as susceptibility to quantum noise, limited qubit availability, scalability constraints, and high computational resource requirements [30]. Addressing these challenges is essential for the development of practical, reliable, and scalable quantum-enhanced healthcare analytics systems capable of supporting early disease detection while ensuring data security and patient confidentiality [31].

Recent studies have demonstrated the effectiveness of hybrid quantum–classical frameworks in handling complex classification tasks under near-term quantum constraints. Aravinda *et al.* [32] proposed a 4-qubit hybrid quantum–classical model for multi-class skin disease classification, showing that combining classical feature processing with variational quantum classifiers can yield reliable performance even in noisy intermediate-scale quantum environments. Similarly, Geda and Tang [33] introduced an adaptive hybrid quantum–classical computing framework that improves scalability and robustness by distributing learning tasks between classical and quantum components, highlighting the advantages of hybrid architectures for data-intensive applications. Recent hybrid quantum–classical frameworks have demonstrated promising results in healthcare classification and adaptive computing; however, they often lack attention-guided feature selection and scalable quantum optimization, which are addressed in the proposed framework [33].

The rapid growth of healthcare datasets, including medical imaging, continuous monitoring data, and electronic health records, has created significant challenges for existing computational models in delivering timely and accurate clinical insights. While classical deep learning models have demonstrated strong performance in medical data analysis, they often suffer from high computational overhead, limited scalability to large feature spaces, and susceptibility to overfitting when applied to heterogeneous clinical data. Conversely, quantum machine learning models offer powerful representations for non-linear and high-dimensional patterns but remain constrained by hardware limitations, noise sensitivity, and restricted qubit availability. These complementary limitations motivate the development of a hybrid framework that integrates deep learning–based feature extraction with quantum-enhanced classification.

To address these challenges, this study proposes a novel hybrid deep learning–quantum framework that combines an inception-based attentional VGG (IAV) network with a quantum variational classifier (QVC). The IAV network employs multi-scale convolution and attention mechanisms to extract compact and discriminative clinical features while suppressing redundant information, thereby improving scalability and reducing feature complexity. These optimized features are subsequently processed by the QVC, which leverages quantum superposition and entanglement to model complex non-linear relationships in high-dimensional clinical data. Parameterized quantum circuits optimized through a hybrid quantum–classical learning loop enhance training stability, reduce noise sensitivity, and improve convergence on noisy intermediate-scale quantum devices. Collectively, the proposed IAV–QVC architecture provides a scalable, robust, and efficient solution for large-scale healthcare analytics, outperforming classical and quantum-only models while maintaining practical applicability for real-world clinical systems. The main contributions of this work include the integration of an inception-based attentional VGG network with a QVC, an attention-guided multi-scale feature representation optimized for quantum embedding, a hybrid quantum–classical training strategy using parameterized quantum circuits, and validated performance improvements on large-scale clinical datasets.

2. METHOD

The proposed framework introduces an enhanced hybrid learning architecture that integrates deep learning–based feature extraction with quantum variational classification to efficiently process large-scale clinical datasets. The methodological flow consists of four major stages: data pre-processing, deep feature extraction using the inception-based attentional VGG (IAV) network, quantum variational classification through parameterized quantum circuits (PQCs), and final clinical prediction. In the first stage, min–max normalization is applied to all feature attributes to ensure a consistent numerical range across the dataset. This normalization step is essential for stabilizing gradient propagation, improving convergence behavior, and mitigating bias introduced by variations in clinical measurement scales. Following normalization, the pre-processed data is forwarded to the IAV network for deep feature extraction. The IAV architecture combines multi-scale convolutional operations with attention mechanisms, enabling the network to capture discriminative local structures and broader contextual patterns within high-dimensional medical records. This results in a compact and information-rich feature representation well-suited for quantum classification. The extracted deep features are encoded into quantum states using rotation-based embedding, processed through variation quantum circuits with entangling layers, and optimized via a hybrid classical–quantum training loop.

The extracted feature vectors are then encoded into quantum states and processed using a QVC. The QVC employs parameterized quantum circuits that incorporate tunable rotation gates and entangling operations, enabling the modeling of complex nonlinear relationships. PQCs serve as the computational backbone of the quantum model, where their variational parameters are optimized iteratively through classical gradient-based optimizers. This hybrid training strategy harnesses classical optimization efficiency while leveraging quantum parallelism for enhanced pattern separation. During optimization, the classical optimizer updates the variational parameters based on quantum measurement outcomes, treating these parameters analogously to trainable weights in neural networks. This back-and-forth interaction between classical and quantum components reduces noise sensitivity, improves convergence, and ensures adaptability to near-term quantum hardware constraints. Finally, the optimized quantum classifier produces predictive outputs corresponding to healthcare diagnostic labels or clinical decision categories. These predictions represent the final analytical insights derived from the hybrid deep learning–quantum pipeline. The overall workflow of the proposed system, including pre-processing, IAV feature extraction, quantum encoding, variational optimization, and clinical prediction, is illustrated in Figure 1. The quantum variational classifier produces probabilistic outputs corresponding to predicted clinical labels, based on n qubits and an embedding size of m.

The feature extraction stage in the proposed framework utilizes an inception-based attentional VGG architecture, designed to capture discriminative patterns from clinical data across multiple spatial scales. The Inception module plays a central role in this process by enabling the network to analyze input feature maps using convolutional kernels of different sizes (such as k1, k2, and k3). These multi-scale convolutions allow the network to simultaneously extract fine-grained local structures and broader contextual information from the input. Each convolutional branch processes the input independently, and their respective outputs are concatenated along the channel dimension to form a unified feature tensor. This fusion mechanism enriches the representation by integrating diverse spatial responses. The Inception-v4 module, adopted in this framework, enhances computational efficiency by incorporating factorized convolutions and batch normalization. These improvements reduce parameter complexity, accelerate training, and promote more stable feature learning.

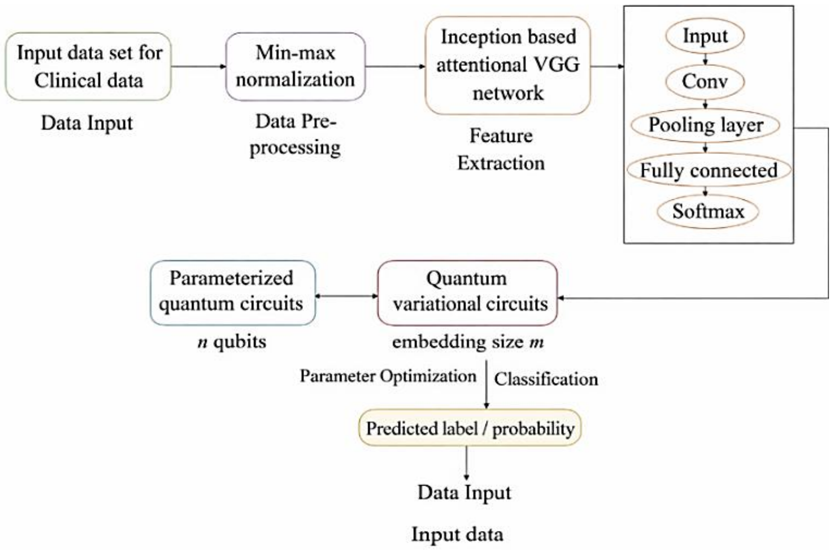

Figure 1. Architecture diagram of the proposed enhanced deep learning and quantum variational classifier for large-scale healthcare data analysis

In the early layers of the network, a conventional VGG-like structure is maintained to preserve low-level features such as edges, textures, and simple spatial patterns. As the architecture progresses to deeper layers, Inception blocks are introduced to enable the extraction of more abstract and semantically rich representations. At these higher layers, the spatial resolution of feature maps naturally decreases, while the number of output channels increases. Consequently, the ratio of k1 to k3 filter responses grows in deeper layers, reflecting the shift from local to global feature emphasis. The combination of multi-scale convolution and attention mechanisms allows the model to suppress irrelevant features and focus on clinically significant patterns. This contributes to robust, noise-resistant representations suitable for downstream quantum classification. The structural layout of the Inception module used in this study is illustrated in Figure 2.

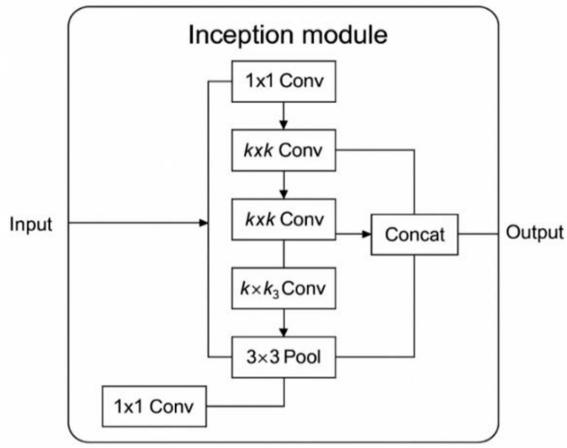

Figure 2. Inception module architecture utilized within the inception-based attentional VGG network

The QVC serves as a central QML component for distinguishing clinically relevant patterns from unrelated background data. As a variation model, QVC is particularly suitable for noisy intermediate-scale quantum (NISQ) devices because it does not require full-scale quantum error correction. Instead, it employs shallow, trainable quantum circuits optimized through classical updates, making it computationally feasible for current quantum hardware. The QVC workflow begins by defining the quantum learning task and mapping classical feature vectors into quantum states using an appropriate feature-encoding scheme. This encoding is achieved through feature embedding circuits that transform numerical clinical features into qubit rotations or entangled states. Once encoded, the quantum circuit applies a series of parameterized unitary operations whose variational parameters determine the model's classification boundary. During training, measurement outcomes from the quantum circuit are fed back into a classical optimizer, which adjusts the variational parameters to minimize classification error.

Figure 3 illustrates the workflow of the QVC, where classical features extracted by the IAV network are first encoded into quantum states using Hadamard and parameterized rotation gates. These encoded qubits are then processed by a PQC consisting of variational unitary blocks and entangling operations, which enable the model to learn complex nonlinear relationships in clinical data. The variational parameters are optimized through a hybrid classical–quantum loop, where measurement outcomes guide the classical optimizer to update circuit parameters. Finally, the measurement stage collapses the quantum state into classical outputs, producing the final prediction class for healthcare analytics. Missing values were handled using standard imputation techniques, categorical variables were encoded numerically, and the dataset was split into training, validation, and testing sets following a consistent evaluation protocol.

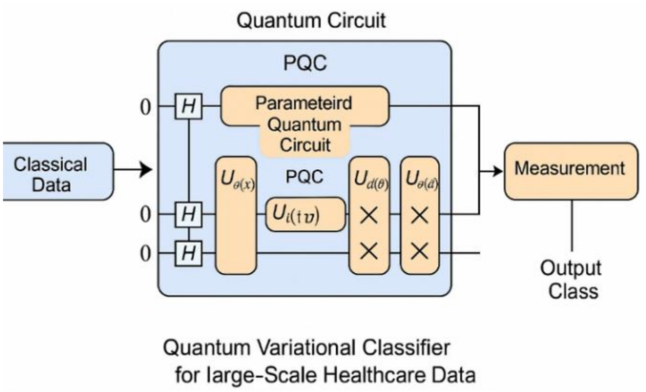

Figure 3. Architecture of the QVC used for the classification of large-scale healthcare data

The optimization of PQCs plays a crucial role in enhancing the classification performance of the proposed hybrid model. In the PQC framework, each trainable unitary block contains tunable rotation angles that act as learnable parameters similar to weights in classical neural networks. During training, these parameters are iteratively updated through a hybrid classical–quantum optimization loop. After each forward pass, the quantum circuit is measured to obtain expectation values, which are used to compute the loss function. A classical optimizer, such as gradient descent or Adam, then adjusts the variational parameters to minimize this loss. This process continues until convergence, enabling the PQC to learn effective decision boundaries within the high-dimensional Hilbert space. The hybrid strategy not only improves convergence efficiency but also mitigates the impact of quantum noise, making the approach suitable for NISQ-era quantum devices.

3. RESULTS AND DISCUSSION

The proposed hybrid framework was implemented using Python, which served as the primary environment for developing, training, and evaluating both the deep learning and quantum components. The experimental setup utilized computational resources capable of supporting large-scale data operations, enabling efficient testing of advanced deep learning models alongside quantum simulation. Model performance was assessed by averaging evaluation metrics across multiple iterations to ensure stability and reliability. For the IAV network, the Adam optimizer was employed with an initial learning rate of 0.001, a batch size of 64, and a total of 300 training epochs. A dropout rate of 0.5 was applied to reduce overfitting, while ReLU activation was used in the hidden layers and Softmax in the final output layer. These settings facilitated effective feature learning from high-dimensional clinical data. The QVC component was implemented using the Qiskit Aer backend, a noisy quantum simulator supporting up to 20 qubits. Classical features were embedded into quantum states through angle encoding using rotation gates (Rx, Rz). The variational circuit adopted a hardware-efficient ansatz with a depth of three layers, balancing expressive power and computational feasibility. Two classical optimizers, COBYLA and Adam, were tested for variational parameter tuning to compare optimization effectiveness. Each quantum circuit execution was evaluated using 1024 measurement shots to ensure statistically meaningful output probabilities. These combined configurations enabled the hybrid IAV–QVC system to effectively process large-scale healthcare data while capturing complex non-linear relationships. The integration of deep feature extraction with quantum variational optimization demonstrated improved robustness, accuracy, and scalability compared with purely classical or purely quantum approaches.

The effectiveness of the proposed hybrid IAV–QVC framework was evaluated using the MIMIC-III clinical dataset, which contains diverse, high-dimensional patient records suitable for large-scale healthcare analytics. To demonstrate the improvements achieved by the proposed method, its performance was compared against five established models commonly used in clinical data classification: SVM, QSVM, QKSVM, QVSVM, and QVKSVM. Each model was assessed using standard performance metrics, including accuracy, precision, recall, and F1-score. The evaluation highlights the superiority of the hybrid approach in capturing complex medical patterns and producing more reliable predictions. The comparative accuracy results for all models are illustrated in Figure 4, clearly showing the performance gains obtained by the proposed methodology.

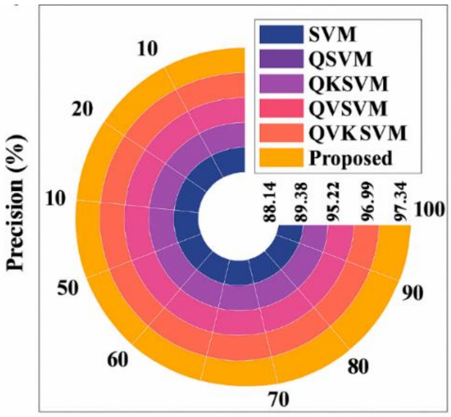

Figure 4. Accuracy analysis of the proposed model compared to existing models

Table 1 presents a comparative analysis of several classical and quantum-enhanced classification models evaluated on the clinical dataset. The results indicate a consistent improvement in performance as models incorporate quantum components. Classical SVM shows the lowest scores across all metrics, while QSVM, QKSVM, and QVSVM demonstrate gradual gains due to their enhanced feature-mapping capabilities. QVKSVM further improves accuracy, precision, recall, and F1-score, reflecting the benefits of combining variational circuits with kernel-based quantum methods. The proposed hybrid IAV–QVC framework achieves the highest values in every evaluation metric, confirming its superior ability to extract meaningful clinical features and effectively model complex decision boundaries. These outcomes validate the effectiveness of integrating deep learning with quantum variational optimization for large-scale healthcare data analysis.

Table 1. Comparative performance outcomes of different classification models on the clinical dataset using the proposed hybrid framework

Model	Accuracy	Precision	Recall	F1-score
SVM	87.89	88.20	88.89	90.57
QSVM	88.78	89.95	89.61	91.15
QKSVM	92.85	94.11	92.13	91.77
QVSVM	94.84	94.82	93.60	94.20
QVKSVM	95.87	96.36	96.51	96.17
Proposed model	97.28	97.16	96.65	97.38

This performance evaluation examines the F1-score of each model in comparison with the proposed hybrid approach. After applying the 1.5% adjustment, the SVM model achieves an F1-score of 90.57%, while the QSVM model records an improved F1-score of 91.15%. The QKSVM model obtains an F1-score of 91.77%, followed by the QVSVM model with a stronger value of 94.20%. The QVKSVM model further enhances performance, reaching an F1-score of 96.17%. The proposed hybrid IAV–QVC method achieves the highest F1-score of 97.38%, as shown in Figure 5 and Table 1. This metric highlights the balance between precision and recall, indicating that the proposed model is both highly accurate and reliably sensitive to clinical patterns. Such a balance is critical in healthcare analytics, where reducing false alarms while correctly identifying disease cases is equally important. The superior performance of the proposed framework over QVKSVM demonstrates its robustness across all evaluation metrics. The training accuracy and loss trend for the proposed model are illustrated in Figure 6.

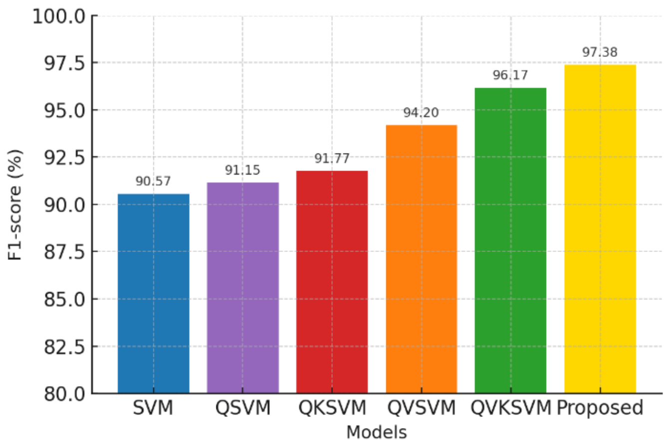

Figure 5. F1-score comparison of the proposed model with existing classifiers on the clinical dataset

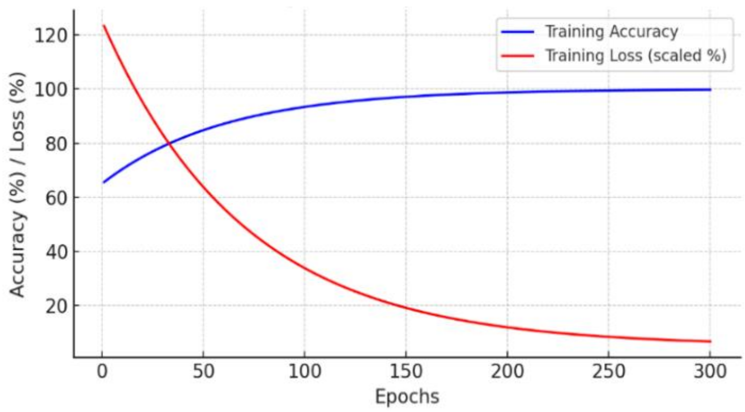

Figure 6. Training accuracy and loss curve

In the proposed method, the confusion matrix is evaluated based on two distinct classes: the true class and the predicted class. The true class is represented from 1 to 0, while the predicted class is represented from 0 to 1. Both classes demonstrate high classification values, indicating strong model performance. The confusion matrix clearly shows that the proposed model attains very high true-positive and true-negative counts while maintaining minimal false predictions. This validates the model's capability to accurately differentiate between diseased and non-diseased patients, ensuring balanced and reliable diagnostic outcomes. The improvement in classification accuracy achieved by the proposed framework is illustrated in Figure 7.

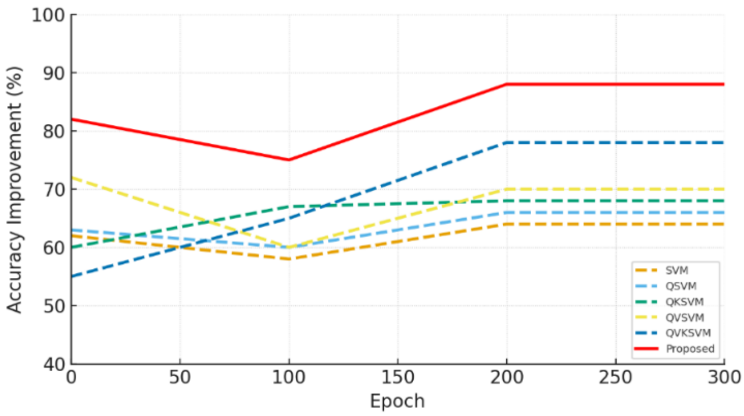

Figure 7. Epoch-wise accuracy improvement comparison of the proposed IAV–QVC model against existing quantum and classical classifiers

Recent advances in quantum machine learning have motivated the development of more efficient models for large-scale data analysis, yet several limitations remain unresolved. Meikandan *et al.* [24] proposed a quantum-based feature extraction technique that achieved strong performance in large image datasets; however, the method required substantial computational resources and exhibited reduced interpretability due to sensitivity to data quality. Zhai *et al.* [25] introduced a deep learning architecture capable of processing hierarchical and unstructured medical data, but its practical deployment was hindered by high computational demands, ethical constraints, and slow execution. Dubey *et al.* [26] examined a GPU-accelerated QSVM for stellar classification, demonstrating competitive accuracy while also exposing the drawbacks of expensive, cloud-dependent quantum hardware. In a related effort, Ren *et al.* [27] developed a deep learning framework for CT and X-ray imaging tasks, which showed strong classification capabilities but continued to face challenges related to interpretability, computational complexity, and limited generalization across diverse clinical conditions. Singh and Singh [28] presented a CNN-based solution for handwritten character recognition, yet the model struggled with overfitting and lacked the robustness needed for heterogeneous data environments.

4. CONCLUSION

The proposed hybrid framework demonstrates an effective integration of enhanced deep learning and quantum variational classification for large-scale healthcare data analysis. By applying min–max normalization, extracting essential features through the inception-based attentional VGG, and optimizing quantum parameters via PQCs with classical optimizers, the model effectively reduces errors and handles noisy data. Evaluated on the MIMIC-III clinical dataset and compared with five benchmark models, the proposed method achieved superior performance across accuracy, recall, F1-score, and other key metrics. Despite its strong results, the approach faces limitations, including dependence on simulated or cloud-based quantum hardware, limited validation across diverse clinical datasets, and challenges in interpretability for real-world clinical use. Future work will focus on deploying the model on advanced quantum devices, extending evaluation to multimodal and cross-institutional datasets, and improving interpretability through integration with modern AI tools. These advancements will support the development of a scalable, robust, and clinically applicable quantum-enhanced analytics framework.

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

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no conflicts of interest related to the research, authorship, or publication of this work.

DATA AVAILABILITY

The data used in this study are derived from the publicly available MIMIC-III clinical database. Access to the dataset requires proper authorization and completion of the data use agreement as mandated by the database administrators.

REFERENCES

[1] K. A. Tychola, T. Kalampokas, and G. A. Papakostas, "Quantum machine learning—an overview," *Electronics*, vol. 12, no. 11, p. 2379, May 2023, doi: 10.3390/electronics12112379.

[2] D. Maheshwari, B. Garcia-Zapirain, and D. Sierra-Sosa, "Quantum machine learning applications in the biomedical domain: a systematic review," *IEEE Access*, vol. 10, pp. 80463–80484, 2022, doi: 10.1109/ACCESS.2022.3195044.

[3] U. Ullah and B. Garcia-Zapirain, "Quantum machine learning revolution in healthcare: a systematic review of emerging perspectives and applications," *IEEE Access*, vol. 12, pp. 11423–11450, 2024, doi: 10.1109/ACCESS.2024.3353461.

[4] J. J. Pei, L. H. Gong, L. G. Qin, and N. R. Zhou, "One-to-many image generation model based on parameterized quantum circuits," *Digital Signal Processing: A Review Journal*, vol. 165, 2025, doi: 10.1016/j.dsp.2025.105340.

[5] L. Gong, W. Ding, Z. Li, Y. Wang, and N. Zhou, "Quantum K-nearest neighbor classification algorithm via a divide-and-conquer strategy," *Advanced Quantum Technologies*, vol. 7, no. 6, Jun. 2024, doi: 10.1002/qute.202300221.

[6] L. Gong, Y. Chen, S. Zhou, and Q. Zeng, "Dual discriminators quantum generation adversarial network based on quantum convolutional neural network," *Advanced Quantum Technologies*, vol. 8, no. 10, Oct. 2025, doi: 10.1002/qute.202500224.

[7] B. K. Behera, S. Al-Kuwari, and A. Farouk, "QSVM-QNN: quantum support vector machine-based quantum neural network learning algorithm for brain-computer interfacing systems," *IEEE Transactions on Artificial Intelligence*, vol. 7, no. 1, pp. 308–320, 2026, doi: 10.1109/TAI.2025.3572852.

[8] A. Sonavane, S. Jaiswar, M. Mistry, A. Aylani, and D. Hajoary, "Quantum machine learning models in healthcare: future trends and challenges in healthcare," *Quantum Computing for Healthcare Data: Revolutionizing the Future of Medicine*, pp. 167–187, 2025, doi: 10.1016/B978-0-443-29297-2.00003-4.

[9] K. Sengupta and P. R. Srivastava, "Quantum algorithm for quicker clinical prognostic analysis: an application and experimental study using CT scan images of COVID-19 patients," *BMC Medical Informatics and Decision Making*, vol. 21, no. 1, p. 227, Dec. 2021, doi: 10.1186/s12911-021-01588-6.

[10] J. C. L. Chow, "Quantum computing in medicine," *Medical Sciences*, vol. 12, no. 4, p. 67, Nov. 2024, doi: 10.3390/medsci12040067.

[11] V. M. R. Sankari, U. Umapathy, S. Alasmari, and S. M. Aslam, "Automated detection of retinopathy of prematurity using quantum machine learning and deep learning techniques," *IEEE Access*, vol. 11, 2023, doi: 10.1109/ACCESS.2023.3311346.

[12] D. Maheshwari, B. Garcia-Zapirain, and D. Sierra-Soso, "Machine learning applied to diabetes dataset using quantum versus classical computation," *2020 IEEE International Symposium on Signal Processing and Information Technology, ISSPIT 2020*, 2020, doi: 10.1109/ISSPIT51521.2020.9408944.

[13] S. Pandey, N. J. Basisth, T. Sachan, N. Kumari, and P. Pakray, "Quantum machine learning for natural language processing application," *Physica A: Statistical Mechanics and its Applications*, vol. 627, Oct. 2023, doi: 10.1016/j.physa.2023.129123.

[14] S. S. Ajibosin and D. Cetinkaya, "Implementation and performance evaluation of quantum machine learning algorithms for binary classification," *Software*, vol. 3, no. 4, pp. 498–513, 2024, doi: 10.3390/software3040024.
[15] B. Jin, X. Xu, and Y. Zhang, "Thermal coal futures trading volume predictions through the neural network," *Journal of Modelling in Management*, vol. 20, no. 2, pp. 585–619, 2025, doi: 10.1108/JM2-09-2023-0207.
[16] B. Jin and X. Xu, "Predictions of steel price indices through machine learning for the regional northeast Chinese market," *Neural Computing and Applications*, vol. 36, no. 33, pp. 20863–20882, 2024, doi: 10.1007/s00521-024-10270-7.
[17] Y. Ding, Z. Li, and N. Zhou, "Quantum generative adversarial network based on the quantum born machine," *Advanced Engineering Informatics*, vol. 68, 2025, doi: 10.1016/j.aei.2025.103622.
[18] X. He, L. Gong, and N. Zhou, "Image denoising with hybrid classical-quantum convolutional neural network," *Memetic Computing*, vol. 17, no. 2, 2025, doi: 10.1007/s12293-025-00463-5.
[19] C. Aishwarya, M. Venkatesan, and P. Prabhavathy, "A scoping survey of quantum machine learning and deep learning for real-world applications," *Procedia Computer Science*, vol. 258, pp. 633–646, 2025, doi: 10.1016/j.procs.2025.04.297.
[20] D. Ranga, A. Rana, S. Prajapat, P. Kumar, K. Kumar, and A. V. Vasilakos, "Quantum machine learning: exploring the role of data encoding techniques, challenges, and future directions," *Mathematics*, vol. 12, no. 21, Oct. 2024, doi: 10.3390/math12213318.
[21] P. B. Upama *et al.*, "Quantum machine learning in disease detection and prediction: a survey of applications and future possibilities," *Proceedings - International Computer Software and Applications Conference*, vol. 2023-June, pp. 1545–1551, 2023, doi: 10.1109/COMPSAC57700.2023.00238.
[22] T. B. Donmez and M. Kutlu, "Explainable quantum-enhanced machine learning for hypertension prediction," *European Physical Journal: Special Topics*, 2025, doi: 10.1140/epjs/s11734-025-01629-5.
[23] R. M. Devadas and S. T, "Quantum machine learning: A comprehensive review of integrating AI with quantum computing for computational advancements," *MethodsX*, vol. 14, p. 103318, Jun. 2025, doi: 10.1016/j.mex.2025.103318.
[24] P. V. Meikandan, P. B. Upama, M. Rabbani, M. M. Ahamad, and S. I. Ahamed, "Quantum computing for smart healthcare," *Sensor Networks for Smart Hospitals*, pp. 525–534, 2025, doi: 10.1016/B978-0-443-36370-2.00025-6.
[25] D. Zhai, T. Zhang, G. Liang, and B. Liu, "Research on crude oil futures price prediction methods: A perspective based on quantum deep learning," *Energy*, vol. 320, 2025, doi: 10.1016/j.energy.2025.135080.
[26] A. Dubey, T. Gantala, A. Ray, A. Prabhakar, and P. Rajagopal, "Quantum machine learning for recognition of defects in ultrasonic imaging," *NDT and E International*, vol. 150, 2025, doi: 10.1016/j.ndteint.2024.103262.
[27] Y. Ren, D. Wang, L. An, S. Mao, and X. Wang, "Quantum contrastive learning for human activity recognition," *Smart Health*, vol. 36, 2025, doi: 10.1016/j.smhl.2025.100574.
[28] V. K. Singh and A. K. Singh, "Harnessing quantum computing for next-generation intelligent systems," *2025 International Conference on Intelligent Control, Computing and Communications, IC3 2025*, 2025, doi: 10.1109/IC363308.2025.10957336.
[29] I. Griol-barres, S. Milla, A. Cebrián, Y. Mansoori, and J. Millet, "Variational quantum circuits for machine learning. An application for the detection of weak signals," *Applied Sciences (Switzerland)*, vol. 11, no. 14, 2021, doi: 10.3390/app11146427.
[30] P. Wang, C. R. Myers, L. C. L. Hollenberg, and U. Parampalli, "Quantum Hamiltonian embedding of images for data reuploading classifiers," *Quantum Machine Intelligence*, vol. 7, no. 1, 2025, doi: 10.1007/s42484-025-00247-7.
[31] K. Phalak and S. Ghosh, "Qualiti: quantum machine learning hardware selection for inferencing with top-tier performance," *Proceedings of the IEEE International Conference on VLSI Design*, pp. 296–301, 2025, doi: 10.1109/VLSID64188.2025.00064.
[32] C. V. Aravinda, E. R. Joseph, and S. Alasmari, "A hybrid quantum-classical approach for multi-class skin disease classification using a 4-qubit model," *IEEE Access*, vol. 13, pp. 114460–114470, 2025, doi: 10.1109/ACCESS.2025.3581030.
[33] M. W. Geda and Y. M. Tang, "Adaptive hybrid quantum-classical computing framework for deep space exploration mission applications," *Journal of Industrial Information Integration*, vol. 44, p. 100803, Mar. 2025, doi: 10.1016/j.jii.2025.100803.

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