

Enhanced deep learning and quantum variational classifier for large-scale data analysis

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ARTICLE INFO

Keywords:

Quantum machine learning
Min-max normalization
Inception attentional-based VGG
Parameterized quantum circuits

ABSTRACT

Quantum machine learning (QML) is a method for analyzing vast volumes of health data, identifying possible higher-order interactions in medicine, and improving the accuracy of smart healthcare diagnosis and treatment. This paper presents a novel hybrid framework that integrates Inception-based Attentional VGG (IAV) with a Quantum Variational Classifier (QVC) and Parameterized Quantum Circuits (PQCs) for large-scale healthcare data analysis. Unlike existing models that face scalability, noise sensitivity, and high computational cost, the proposed approach combines deep learning feature extraction with quantum-enhanced classification to improve efficiency and accuracy. QML large-scale data are pre-processed with min-max normalization algorithms, which place feature values into a fixed range of uniformity and facilitate convergence learning. To extract features from pre-processed large-scale medical data analysis, Inception-based Attentional VGG is used. The quantum variational classifier is then utilized to categorize large-scale data in the classification method. Then, parameterized quantum circuits use a classical optimizer to get information about quantum measurements of parameters in tunable quantum functions. This model makes use of a dataset, namely the MIMIC-III clinical dataset, which is used to collect vast amounts of data for clinical health patients. The proposed model is then utilized to assess the performance of metrics like accuracy, precision, recall, and the F1 score. Experimental results show that the proposed approach achieves an accuracy of 98.76%, precision of 98.64%, recall of 98.12%, and F1-score of 98.86%, outperforming existing models such as SVM (89.23% accuracy), QSVM (90.13%), and QVK SVM (97.34%). These results demonstrate that the proposed hybrid QML-DL framework effectively handles high-dimensional clinical data, reduces computational overhead, and provides a strong foundation for next-generation healthcare analytics.

1. Introduction

QML is gaining popularity in computer science because it is connected to ML, which processes and analyzes data using a variety of decision-making models. Due to its ability to achieve quantum parallelism, quantum computing has been shown to be a viable solution to quantum computing's challenges and uncertainties. The term "quantum" denotes the smallest discrete unit of a "physical quantity". QML is a supervised approach for quantum support vector machines [1,2]. Quantum approaches have emerged as valuable tools in a variety of application domains, like chemistry, agriculture, NLP, and healthcare, as computational capacity has rapidly increased and ML algorithms have advanced [3–7]. Quantum computing has the ability to address

complicated problems that are currently intractable on traditional computers [8]. QML approaches are a new topic that utilizes quantum computing and ML to improve the effectiveness and accuracy of big data [9].

In medical applications, quantum machine learning was created as a continuation of quantum computing. QML employs quantum-based approaches to enhance the efficiency of ML problems involving non-linear data structures [10,11]. Classical bits are limited to binary states (0 or 1), whereas qubits make use of quantum processes like superposition and entanglement. Unlike classical bits, which occupy a single, finite value, qubits exist in overlapping states of 0 and 1 through the use of superposition. Quantum computing's potential to address computational problems that traditional machines cannot now manage

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makes it significant in medicine [12,13]. Big data is important when a large amount of information is gathered from several sources and then processed to identify linkages and trends for various objectives [14]. QML methods in healthcare can assist in speeding up and improving the computerization of current ML models [15–18], allowing various models to assess complicated illness patterns [19,20]. QML provides several advantages, including better runtime, learning efficiency, and learning ability [21].

Quantum algorithms, like QSVM and QNN, leverage quantum parallelism and resonance to outperform traditional approaches. Quantum support vector classifiers and QNN are two examples of quantum algorithms. This model improves the efficiency measures of conventional ML algorithms while also increasing computational economy by leveraging quantum mechanics concepts [22,23]. Quantum support vector machines offer significant speed and accuracy advantages, making them intriguing candidates for accelerating complicated ML challenges. QNNs are utilized to model quantum phenomena such as entanglement and superposition [24,25]. This approach is used to generate suitable data sets that are consistent with future actions of quantum algorithms, which use encryption techniques to turn classical information into quantum states [26].

A QML model is necessary for high-quality data sets in healthcare systems, and the quantum algorithm employed for medical field procedures contributed to effective results. Although there are still practical issues and technical procedures that need to be widely implemented in medical practices, QML algorithms are capable of diagnosing patients in emergency situations [27]. The XGBoost-quantum hybrid method addresses these challenges by combining quantum algorithms that can more efficiently explore the data space, revealing subtle correlations and patterns that may otherwise go unnoticed by classical algorithms alone [28,29]. The limitations of QML models include their reliance on quantum hardware, sensitivity to noise, scaling difficulties, and high processing needs [30]. This strategy tries to improve medical technology in terms of safety and accuracy. They are extremely sensitive, allowing for early detection and ongoing monitoring, hence facilitating timely and focused interventions [31]. The model improves on the existing system of quantum machine learning algorithms for large-scale data analysis by lowering computational costs, reducing scalability concerns, detecting disease early, and successfully protecting patient privacy.

1.1. Motivation and novelty

The rapid growth of healthcare data from electronic health records, medical imaging, and continuous patient monitoring has created an urgent demand for analytical models that can handle large-scale, high-dimensional, and noisy datasets. Traditional deep learning methods have achieved strong results in feature extraction and classification. Still, they struggle with scalability, computational overhead, and the risk of overfitting when applied to complex clinical data. On the other hand, quantum machine learning (QML) methods offer unique advantages such as quantum parallelism and the ability to represent non-linear data structures more efficiently, but existing QML models often face limitations related to noise sensitivity, limited hardware capacity, and high processing costs.

Therefore, there is a clear need for a hybrid framework that combines the robust feature extraction capability of deep learning with the enhanced computational efficiency and pattern recognition potential of QML. The motivation for this work is to address the shortcomings of purely classical or purely quantum approaches and to develop a model that can provide accurate, scalable, and resource-efficient solutions for large-scale healthcare data analysis. The originality of this work lies in designing a hybrid deep learning-quantum machine learning framework that combines Inception-based Attentional VGG for feature extraction with a Quantum Variational Classifier optimized through Parameterized Quantum Circuits. Unlike existing approaches that depend solely on classical deep learning or isolated quantum models, the

proposed method integrates the strengths of both paradigms to address challenges such as scalability, computational overhead, and noise sensitivity in large-scale healthcare data. This framework establishes a more robust and efficient pipeline for smart healthcare analytics, offering improved adaptability, interpretability, and reliability compared to prior models.

1.2. Objectives

- ü To apply the Inception-based Attentional VGG (IAV) network to extract discriminative features from large-scale healthcare data.
- ü To develop a Quantum Variational Classifier (QVC) to accurately categorize the extracted features effectively addresses scalability, noise sensitivity, and computational overhead in large-scale clinical data
- ü To employ Parameterized Quantum Circuits (PQCs) with classical optimizers to enhance model performance and scalability.

In this research, IAV network, which combines multi-scale convolution (Inception modules) with attention mechanisms, is used to capture both local and global discriminative features from high-dimensional clinical data while reducing redundancy. QVC leverages qubit superposition and entanglement to project classical features into higher-dimensional Hilbert spaces, enabling more effective separation of non-linear healthcare patterns compared to classical classifiers. Optimization through PQCs with classical gradient-based optimizers, treating variational parameters as trainable weights analogous to neural networks, to achieve efficient convergence, reduce noise sensitivity, and enhance scalability on near-term quantum devices.

In this paper, [Section 1](#) describes the quantum machine learning-based algorithms and related content, [Section 2](#) is related work on QML model algorithms, [Section 3](#) establishes the proposed method in this model to use various types of methods to be performed, [Section 4](#) discusses the result evaluation of suggested as well as current methods, and [Section 5](#) is future work with effective conclusions.

2. Related work

[Singh et al. \[32\]](#) suggested a quantum feature extraction method for large-scale data image categorization. The suggested large-scale data model classifies images using Hamming distance features. This large-scale data analysis model has an accuracy of 98%, respectively. These suggested models had computational costs in large-scale datasets, while data quality can lead to inaccurate predictions and interpretability.

[El Hmimdi et al. \[33\]](#) suggested a deep learning-based large-scale data analysis. Furthermore, the Hmimdi approaches were tested on real-world and experimental data that included real-life biases, including noise, eye tracking misalignment, and interchangeable diseases across non-academic difficulty classes. Furthermore, a time series classification problem-adaptive neural network architecture was employed to generalize a limited reference dataset while handling high-resolution signals. This model achieved a precision performance of 80.20%, and the system can handle missing data, hierarchical data, and structured and unstructured data. However, this system has various disadvantages, including high computational requirements, ethical concerns, and a time-consuming process.

[Chen et al. \[34\]](#) developed a system for Quantum-Enhanced SVM for Large-Scale Stellar Classification with GPU Acceleration. This model uses a quantum machine learning algorithm to analyze large amounts of data using conventional techniques like K-Nearest Neighbours (KNN) and Logistic Regression (LR). The accuracy and processing speed for star classification have significantly improved, highlighting the revolutionary potential of quantum ML in astronomical research. Machine learning technologies achieve 83% accuracy using effective quantum feature mapping. However, access to quantum hardware is expensive and

frequently limited to cloud platforms, which can cause latency and security issues.

Xue et al. [35] developed a DL model-based large-scale dataset to enhance the CT scan as well as X-ray image classification. This suggested large-scale data model is utilized to detect CT scans and analyze X-ray scan images. This model for large-scale data obtained 95% accuracy, respectively. However, the suggested models lacked interpretability, data quality, computational complexity, and ethical considerations.

Acharya et al. [36] created a DL CNN for large-scale handwritten character recognition. The suggested model uses a large-scale dataset for handwritten character recognition, which was split from handwritten documents. This model has an accuracy of 98.47%. However, the suggested model showed overfitting, a lack of interpretability, and a high computational cost. Table 1 illustrates existing research and analysis for quantum machine learning algorithms.

QML is gaining popularity in computer science because it is tied to ML, which processes and analyzes data utilizing a variety of decision-making algorithms. Quantum variational classifier, large-scale data analysis methods, and techniques are discussed in related work, including performance and limitations. Quantum feature extraction technique models provided a high accuracy of 98% while minimizing accuracy for low data quality and erroneous forecasts for large-scale data images [32]. A deep-learning-based large-scale data analysis model for real-life and experimental data, with a minimized accuracy of 80.20%, if needed, to account for computing costs and ethical considerations of the process [33]. Additionally, if the QSVM approach fails due to system latency and security issues, it was created to improve classification accuracy and processing speed [34]. The DL approach analyzes large-scale datasets for image classification in order to gain improved accuracy in image classification of large-scale data images, but it may have an impact on computational complexity and generalization issues due to dataset features [35,36]. A CNN framework that uses deep learning techniques to process and recognize large amounts of image data. However, it adds computational overhead, which may lead to overfitting and a lack of interpretability. In this view of limitations,

Table 1
Research analysis for quantum machine learning algorithms.

Author Name & References	Method	Performance	Disadvantages
Singh et al. [32]	Quantum feature extraction technique	This large-scale data analysis model achieves an accuracy of 98%, respectively.	These suggested models had computational costs in large-scale datasets, and data quality can lead to inaccurate predictions and interpretability.
El Hmimdi et al. [33]	Deep learning-based large-scale data analysis	The model achieved a precision performance of 80.20%, respectively.	This model had computational requirements and ethical considerations, as well as a time-consuming process.
Chen et al. [34]	QSVM	This model attained an accuracy of 83%, respectively.	However, access to quantum hardware is expensive and often restricted to cloud platforms, which can introduce latency and security issues.
Xue et al. [35]	DL	The large-scale data achieves an accuracy of 95%, respectively.	This model had a lack of interpretability, data quality, ethical concerns, computational complexity, and generalization issues.
Acharya et al. [36]	DL based CNN	The large-scale handwritten data achieves 98.47%, respectively.	However, this model had overfitting, a lack of interpretability, and a high computational cost.

the presented approach is intended to develop more consistent and efficient data for large-scale medical data analysis.

3. Proposed methodology

The proposed analysis discusses enhanced deep learning and quantum variational classifiers for large-scale data processing. Initially, the pre-processing method employed min-max normalization, which scales feature values within a given range of uniformity and improves convergence learning. The data for medical analysis is obtained following the IAV approach of feature extraction. Then, quantum variational circuits of data are QML algorithms that increase trainable circuit parameters by classifying the data. After classifying the data using the parameterized quantum circuit's optimization approach, this process employs classical optimizer parameter measurements. Finally, the healthcare data analysis process produces an output for clinical data. The workflow diagram of the suggested methodology is shown in Fig. 1.

3.1. Dataset description

In this suggested model, a clinical dataset for the PhysioNet profile was obtained from the MIMIC-III database. MIMIC-III is a huge, freely available database collecting de-identified health-related data from over 40,000 patients who were admitted to Beth Israel Deaconess Medical Center's intensive care units among 2001 and 2012. For example, in the US, the percentage of non-federal acute care hospitals with basic digital systems increased from 9.4 to 75.5% between 2008 and 2014. SUBJECT_ID represents an individual patient, HADM_ID denotes a hospitalization, and ICUSTAY_ID denotes an intensive care unit admission [43].

3.2. Pre-processing

Initially, large-scale data is pre-processed using min-max normalization. This min-max normalization helps scale feature values to a set range, ensuring uniformity and improved convergence during learning.

3.2.1. Min-max normalization

The normalization method improves the model's convergence speed, accuracy, and stability by changing the range and distribution of pixel values. The min-max normalization method aids in the application of min-max scaling values to a fixed range of convergence learning, hence improving model robustness and effectiveness [37].

The min-max normalization method is applied to each pixel according to its intensity. The Eq. (1) formula is given below:

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

here, y_j denotes the pixel intensity value of this normalization, $\max(y)$ and $\min(y)$ represents the maximum and minimum values of pixel intensity, respectively. y_{norm} denotes the normalized pixel intensity of value. The minimum value of intensity is 0, and the maximum value of intensity is 255.

This model uses the min-max normalizing method for pre-processing, which aids in min-max scaling values to feature values of a fixed range to uniformity and promotes learning convergence. The following step in the feature extraction process will be conducted.

3.3. Feature extraction for inception based attentional VGG

The inception module is a crucial part of the quantum-based classifiers. It is intended to capture properties from input frames at various sizes and resolutions. The convolutional layer extracts information from the input using filter sizes ($1 \times 1, 3 \times 3$ and 5×5). The output of each filter dimension is combined with the channel dimension to yield a

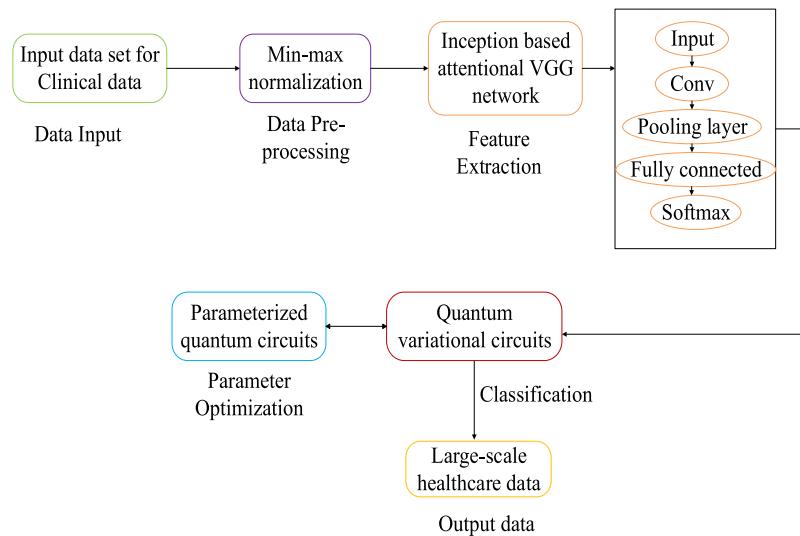


Fig. 1. Architecture diagram for enhanced deep learning and quantum variational classifier for large-scale data analysis.

single output tensor. The Inceptionv4 module improves network speed and performance with features such as block normalization and factorized compression. The initial blocks are piled on top of one another, and their output association values vary: as they go to higher levels, their spatial concentration is projected to diminish. The ratio of 3×3 and 5×5 coils should grow in the upper layers of the network. The inception blocks are used only in higher layers, with the initial layers maintaining a regular structure. The inception module diagram is exposed in Fig. 2.

In this proposed model, the inception module contains a filter size, a convolution, as well as a max pooling layer. The previous layer of the inception module is used for the 1×1 convolutional layer, and the 3×3 max pooling layer is processed by this quantum computing model. Then, the inception module comprises 1×1 , 3×3 as well as 5×5 convolutional layers that are connected to the max pooling layer of feature extraction of the data. After the concatenation function, the filter size is utilized to function in the convolutional layers and max pooling layers.

Attention module to perform both average as well as max pooling on the input tensor in the feature extraction model to extract data. After that, these two tensors, namely the maximum summed 2D tensor and the average summed 2D tensor, are concatenated together and perform a 7×7 filter size (g) compression utilizing the sigmoid function (σ). The concatenated resultant tensor ($U_t(G)$) is defined as,

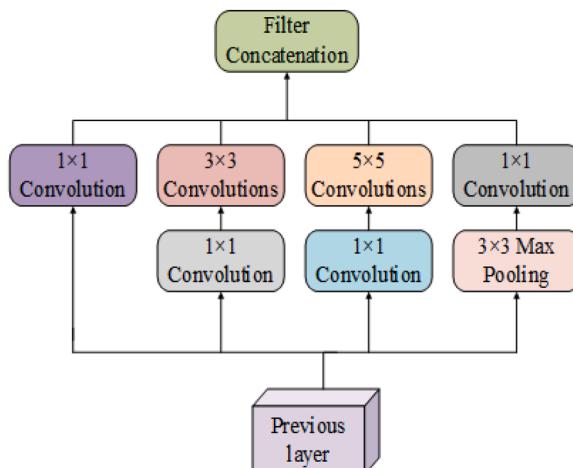


Fig. 2. Inception module architecture with multiple convolution layers.

$$U_t(G) = \sigma\left(g^{7 \times 7} \left[G_{avg}^t; G_{max}^t \right] \right) \quad (2)$$

here, $G_{avg}^t \in \mathbb{R}^{1 \times S \times T}$ and $G_{max}^t \in \mathbb{R}^{1 \times S \times T}$ denotes the 2D tensor attained by average as well as max pooling on the input tensor G , correspondingly. Sand T represents height and width tensor, respectively. The attention module diagram is shown in Fig. 3.

The proposed model's attention module diagram shows two pooling procedures that yield a 2D tensor input. There are two types of pooling: average as well as maximum pooling. The two poolings are then combined to form a 2D tensor that includes both the average summed 2D tensor and the maximum summed 2D tensor. The compressed 2D tensor is then incorporated into the model through a connection function. The attention module uses a 7×7 filter size to compress the sigmoid function of the effective module.

The proposed method builds the VGG network with very small convolutional filters. The VGG network is essentially a deep convolutional neural network designed to evaluate an appropriate later depth setting without increasing the network's complexity. To improve the network, a 3×3 small convolutional filter is added to extract more small

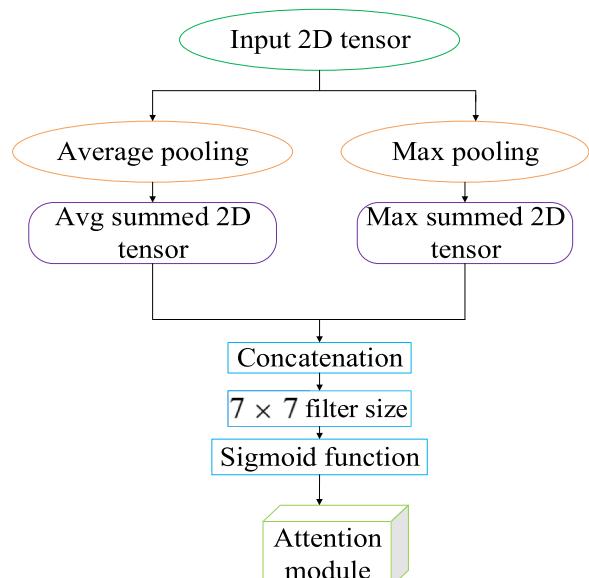


Fig. 3. Attention module with activation layers that coordinate the features.

data from the training data. Furthermore, by adding more layers, the VGG network decreased training loss while preserving more data for object detection. There are two types of VGG networks used in this model: VGG16 and VGG19. The VGG16 architecture has 13 convolutional as well as 3 fully connected layers, with 3×3 kernels and 2 \times 2 parameters for pooling. It has 16 convolutional layers and is quite similar to convolutional builders with 16 tightly connected layers. This model consists of 41 layers, including input, output, pooling, and execution. The VGG19 network is conceptually similar to the VGG16 model network. The VGG19 network model has three more convolutional layers [38]. The VGG network diagram is shown in Fig. 4.

The VGG network model was used for both the convolutional and maximum pooling layers. This network model makes use of 3 fully connected layers and one softmax layer. The feature extract model consists of 7 layers.

3.4. Classification

After feature extraction, the proposed model's classes are classified using the Quantum Variational Classifier.

3.4.1. Quantum variational classifier (QVC)

The QVC is a key QML technique for classifying physical phenomena of interest from background phenomena. The QVC model helps to achieve study results on NISQ devices without the need for additional error correcting approaches. QVC begins with the development of QML tasks, in which various feature mapping algorithms integrate classical data into quantum computing. The measured value is then used as feedback to improve the trainability of various circuits. The QVC algorithm consists of two stages: training and testing [39].

The fundamental idea underlying quantum bit mapping stems from the traditional ML kernel method, in which a dataset is nonlinearly

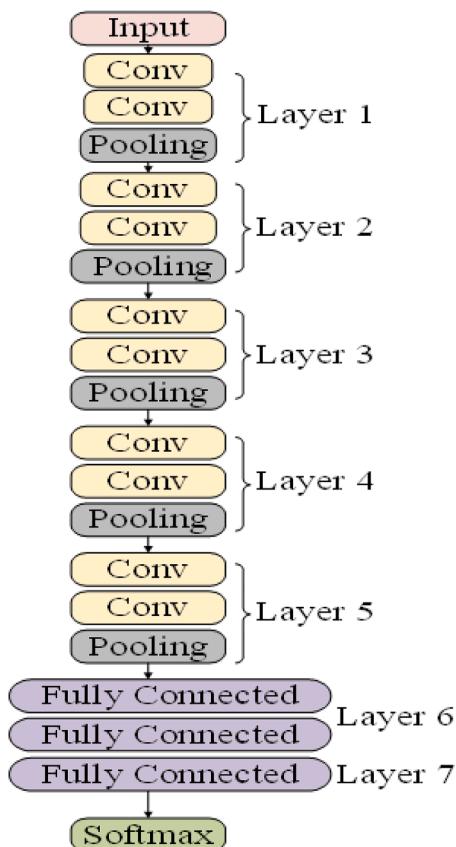


Fig. 4. VGG network layer wise architecture for feature extraction.

translated to a higher-dimensional space in order to find a hyperplane that characterizes the non-linear information.

$$V_{\Phi(y)} = \prod_c V_{\Phi(y)} G^{\otimes m} V_{\Phi(y)} G^{\otimes m} \quad (3)$$

here, G consist of a layer of Hadamard gates (G), which are inserted with complex blocks, encoding the classical data as well as the depth (c) of the circuits through the following equation,

$$V_{\Phi(y)} = \exp \left(i \sum_{R \subseteq [m]} \varphi_R(y) \prod_{t \in R} W_t \right) \quad (4)$$

where, $V_{\Phi(y)}$ is a unitary gate for varying angles to particular values. The Quantum variational classifier diagram is shown in Fig. 5.

The quantum variational classifier diagram illustrates the collection of datasets for the clinical database, followed by pre-processing techniques and circuit parameters that produce a feature map formulation, variational circuits within the parameter set of the process, and finally, optimizers.

3.5. Optimization for parameterized quantum circuits (PQC)

A classical optimizer is used iteratively to update the PQC parameter set(θ). The PQC is defined as the tunable unitary function $V(\vec{\theta})$ applied to a quantum state $|\psi_0\rangle$, often initialized to $|0\rangle^{\otimes m}$ or problem-affected initial state. The resulting value is obtained using a specific formula.

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

here, $\vec{\theta}$ is a vector of polynomial numbers of circuit parameters. These variables can reflect any variable aspect of a quantum function, but they often correspond to the degrees of the rotation gates. A PQC can be further decomposed into a product of P consecutively applied sub-units, which is typically denoted by the exponents.

$$V(\vec{\theta}) = V_P(\vec{\theta}_P) \dots V_2(\vec{\theta}_2) V_1(\vec{\theta}_1) \quad (6)$$

The modular nature of PQCs has recently been likened to classical computing, in which the PQC parameters correlate to the weights and biases of a traditional neural network. While PQC designs differ greatly in their goals and capabilities, they are similar to different neural network architectures. Hardware-efficient PQCs often seek to reduce both gate count as well as circuit depth. The parameterized quantum diagram is shown in Fig. 6.

The parameter optimization procedure is used to process the parameterized quantum circuit diagram. The PQC diagram is optimized using a conventional computer. The parameterized quantum circuits connect the classical computer to the optimization process. [Algorithm 1](#) shows the pseudo-code for the overall process of the proposed methodology.

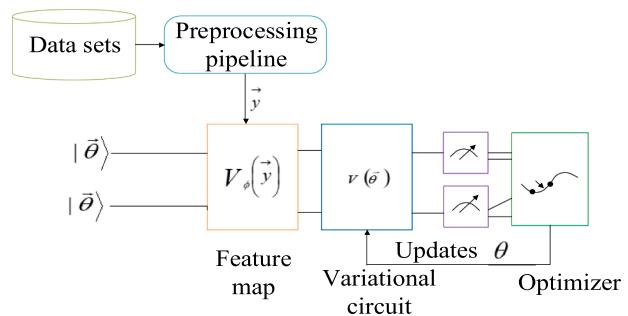


Fig. 5. Quantum variational classifier diagram.

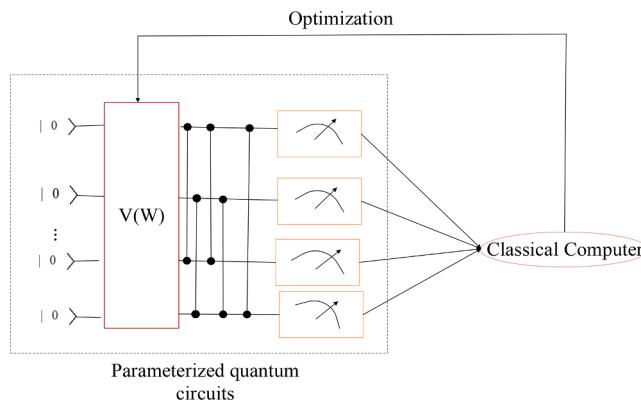


Fig. 6. Parameterized quantum circuits diagram.

4. Results and discussion

Python is the programming language used to implement the suggested paradigm. The resources are utilized to train and test ML models for large-scale data processing and advanced DL techniques. The average of each iteration's performance measures is then utilized to estimate the model's performance. The system configuration is labelled in Table 2.

For the IAV network Optimizer Adam with initial learning rate 0.001, Batch size 64, Number of epochs: 300, Dropout rate: 0.5 to prevent overfitting, and Activation functions ReLU (hidden layers), Softmax (output layer) are used. For the QVC, Quantum simulator Qiskit Aer backend (noisy simulator with up to 20 qubits), Feature encoding: Angle encoding with rotation gates (Rx, Rz), Variational ansatz: Hardware-efficient ansatz with depth = 3 layers, Classical optimize COBYLA and Adam (comparative runs). The number of shots per circuit execution is 1024 is used for analysis.

Algorithm 1

Overall proposed methodology.

```

Input: MIMIC-III clinical dataset images
Output: large-scale healthcare data images
Step1: Pre-processing
for all images in the dataset do
pre - process←Apply MMN
 $y_{norm} = \frac{y_j - \min(y)}{\max(y) - \min(y)}$ 
end for
Step 2: Feature extraction
for all images pre-processed do
extractfeatures←Inception based attentional VGG
end for
Step 3: Classification
for all extracted features do
classifier←Quantum variational classifier
 $V_{\Phi(y)} = \prod_c V_{\Phi(y)} G^{\otimes m} V_{\Phi(y)} G^{\otimes m}$ 
 $V_{\Phi(y)} = \exp(i \sum_{R \subseteq [m]} \varphi_R(y) \prod_{t \in R} W_t)$ 
end for
Step 4: Optimization
for all classify the classes do
optimizer←Parameterized quantum circuits
 $|\psi_0\rangle = V(\vec{\theta})|\psi_0\rangle$ 
 $V(\vec{\theta}) = V_P(\vec{\theta}_p) \dots V_2(\vec{\theta}_2) V_1(\vec{\theta}_1)$  #  $\vec{\theta}$  is a vector for a polynomial number of circuits
end for
Update Quantum machine learning ← large-scale data dependencies
    for large-scale medical data
        Retrieve medical data images for large-scale analysis
    end for
Return large-scale health care data
end

```

4.1. Performance metrics

This proposed approach is based on effective metrics like accuracy, precision, f1-score, and recall. These metrics are described as follows,

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (7)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (8)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (9)$$

$$F1 - Score = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (10)$$

here, TP - True Positives, TN - True Negatives, FP - False Positives, and FN - False Negatives.

4.2. Performance evaluation on MIMIC-III clinical dataset

The performance of this method is examined for a dataset using an existing model of an enhanced process. The presented performance evaluation approach for large-scale data analysis in the MIMIC-III clinical database. To assess the performance improvement of the suggested approach, five classic models were compared to clarify the research

Table 2
System configuration.

Components	Details
Edition	Windows 11 Pro
Processor	Intel(R) Core(TM) i5-9500 CPU @ 3.00 GHz 3.00 GHz
RAM	16.0 GB (15.8 GB usable)
System Type	64-bit operating system, × 64-based processor

value. There are five models: SVM, QSVM, QKSVM, QVSVM, and QVK SVM [40]. To perform the analysis for accuracy, precision, recall, as well as f1-score values. Fig. 7 shows the accuracy analysis results.

Fig. 7 and Table 3 show that the proposed framework significantly outperforms all baseline models in terms of accuracy. While traditional SVMs lag at under 90%, quantum-enhanced models such as QSVM and QVK SVM show progressive improvements, demonstrating the value of incorporating quantum principles. However, only the proposed hybrid model reaches close to 99% accuracy, which indicates that combining deep learning-based feature extraction with quantum variational classification is more effective than either approach alone. This performance advantage confirms that the integration of Inception-based Attentional VGG with QVC captures more discriminative features and ensures robust classification in high-dimensional healthcare data. The precision analysis result is exposed in Fig. 8.

The precision improves steadily across the baseline models, but the proposed method yields the highest precision. High precision reflects the ability of the model to minimize false positives, which is crucial in healthcare to prevent misdiagnosis. The consistent improvement from SVM to QSVM and further to QVK SVM highlights the effectiveness of quantum integration, while the proposed model surpasses them all, indicating that the hybrid pipeline is highly reliable in distinguishing relevant clinical patterns from noise. Fig. 9 illustrates the recall analysis of this proposed system.

Fig. 9 illustrates the recall performance, where the proposed model achieves the highest recall compared to baselines. High recall is particularly important in clinical settings because it minimizes false negatives, ensuring that patients with critical conditions are not overlooked. Although QVK SVM provides competitive recall values, the proposed framework's superior performance highlights its ability to detect subtle patterns in medical data that may be missed by existing approaches. The F1-score analysis of the proposed model is shown in Fig. 10.

This performance evaluation model compares F1-score analysis to the current model datasets. In the proposed model for analyzing these models, SVM attained an F1-score accuracy of 91.95%. The QSVM model attained an F1-score value of 92.54%. The QKSVM model performed with an F1-score of 93.21, respectively. The QVSVM model then attained an F1-score of 95.64 %. The QVK SVM model performed better, with an F1-score of 97.64%. The suggested method obtained an F1-score of 98.86%. The F1-score (Fig. 10 and Table 3) balances both precision and recall. The proposed model achieves the best F1-score, demonstrating that it provides both accurate and comprehensive detection. This balance is essential in healthcare analytics, where both avoiding false alarms and ensuring the correct detection of disease cases are equally important. The superiority of the proposed framework over QVK SVM confirms its robustness across different evaluation metrics.

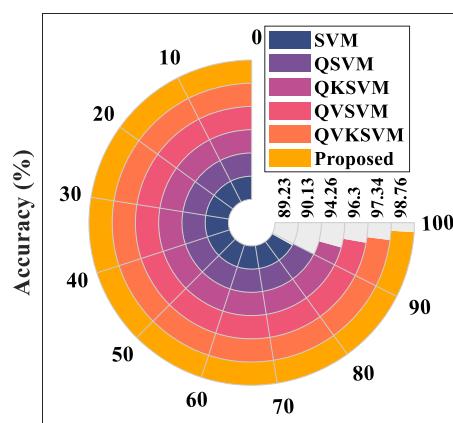


Fig. 7. Accuracy analysis of the proposed model compared to existing models.

Table 3
Performance evaluation of the effective approach in the clinical dataset.

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	96.3	96.26	95.02	95.64
QVK SVM	97.34	97.83	97.99	97.64
Proposed Model	98.76	98.64	98.12	98.86

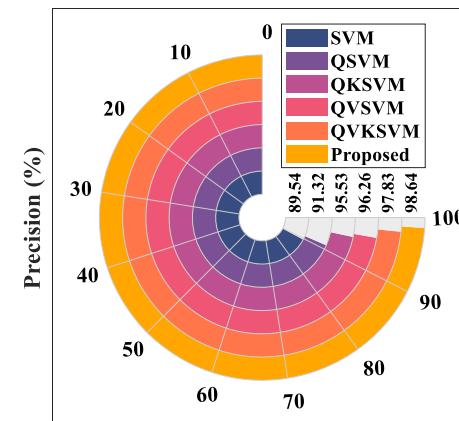


Fig. 8. Precision analysis of the proposed model compared to existing models.

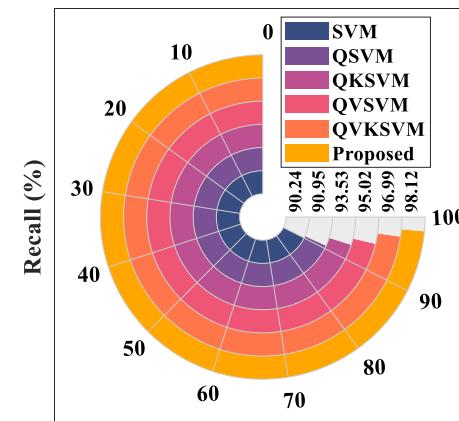


Fig. 9. Recall analysis of the proposed model compared to existing models.

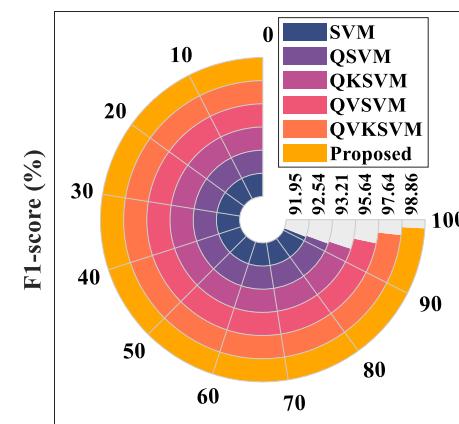


Fig. 10. F1-score analysis of the proposed model compared to existing models.

The training accuracy as well as the loss of analysis, are exposed in Fig. 11.

The analysis of the training accuracy and loss of the proposed model is conducted utilizing five different models. At different periods in the training process, each model performed differently in terms of accuracy and loss epoch. Furthermore, training and testing models are utilized to examine huge amounts of data in healthcare systems. This method uses a training model to process the dataset. Epoch-wise analytical models that explore variations in training accuracy and loss. The training accuracy value starts at 0 and ends at 1. The training loss value starts at 0 and ends at 0.4. Higher accuracy in training and testing results leads to improved performance. In this model, training loss leads to decreased performance. The testing accuracy and loss of analysis are exposed in Fig. 12.

The analysis of the training accuracy and loss of the proposed model is conducted using five different models. Furthermore, training and testing models are utilized to examine huge amounts of data in healthcare systems. This approach model employs a testing model to evaluate the dataset. Format-based analytical models are being tested for accuracy and loss epoch value. The testing accuracy value starts at 0 and ends at 1. The testing loss value starts at 0 and ends at 0.4. Higher accuracy in training and testing results leads to improved performance. Figs. 11 and 12 depict the training and testing accuracy and loss across epochs. The proposed model shows faster convergence and lower loss compared to baseline models, confirming its training efficiency. The stability of the loss curve suggests that the model generalizes well without overfitting. In comparison, traditional models exhibit slower convergence and higher variance, indicating less effective learning dynamics. In this

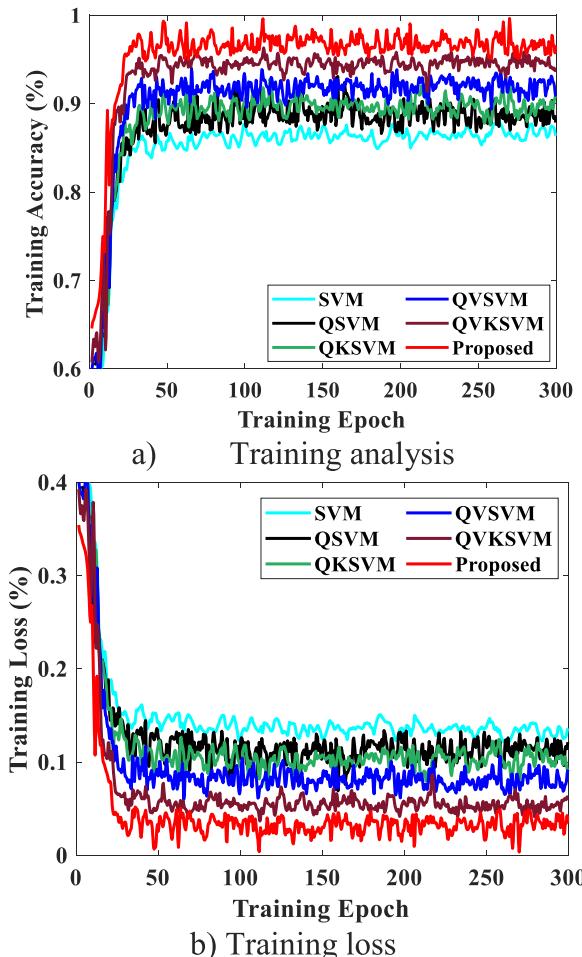


Fig. 11. (a-b) Training accuracy and loss of large-scale data analysis of the proposed model compared to existing models.

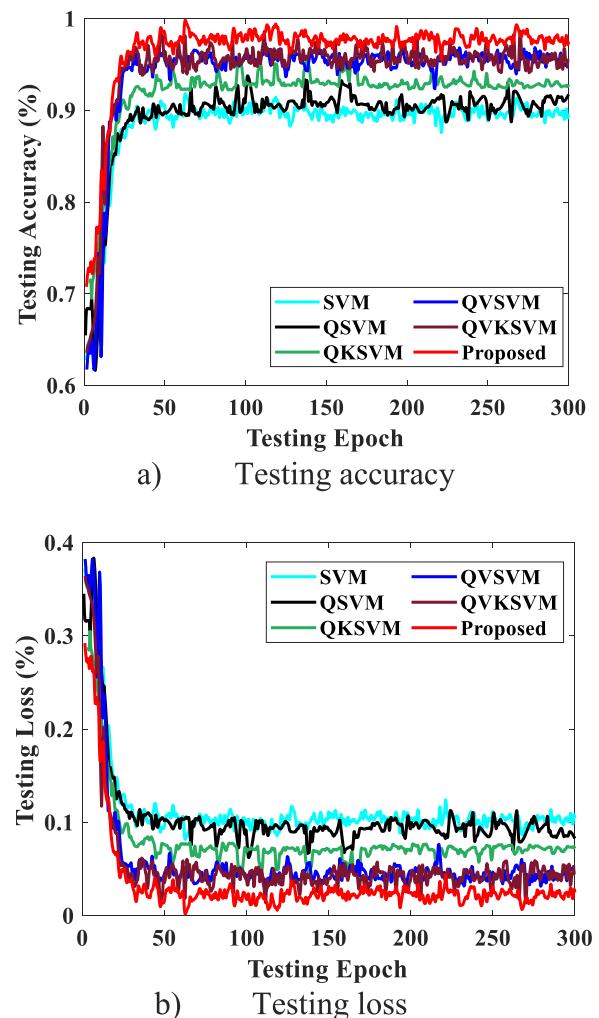


Fig. 12. (a-b) Testing accuracy and loss of large-scale data analysis of the proposed model compared to existing models.

model, testing results are lost, resulting in decreased performance. ROC curve large-scale data analysis is illustrated in Fig. 13.

The ROC curve representation is based on the true positive and false positive rates. The suggested ROC curve the upper left corner, indicating that it is extremely close to 1. The ROC curve positions the proposed method close to the upper-left corner, representing an excellent trade-off between sensitivity and specificity. This indicates that the hybrid framework can discriminate between positive and negative cases more

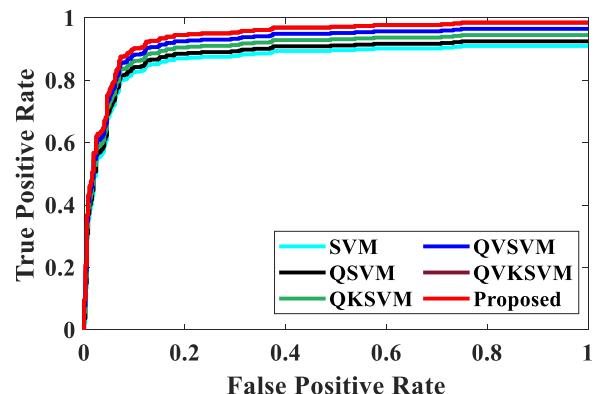


Fig. 13. ROC curve with large-scale data analysis of the proposed model compared to existing models.

effectively than baseline models, which is especially critical in medical decision support systems. Compared to current models, the proposed approach achieves higher accuracy on large-scale datasets. K-fold analysis is shown in Fig. 14.

This proposed model analyzes k-fold data for five models: SVM, QSVM, QKSVM, QVSVM, and QVK SVM. Accuracy points start at 85 and end at 100. K-fold data analysis starts at 5 and ends at 25. The values in Table 4 demonstrate the robustness of the proposed method under different folds of cross-validation. While SVM and QSVM show gradual improvements, their overall performance remains limited. By contrast, the proposed model maintains consistently high accuracy across all folds, confirming its stability and reliability in diverse data splits. This robustness suggests that the model can adapt well to unseen patient records in real-world healthcare scenarios. The effective metrics, like accuracy, precision, recall, as well as F1-score, are performed in a bar chart from K-fold data analysis. The confusion matrix is illustrated in Fig. 15.

In this proposed method, the confusion matrix data is analyzed in two dissimilar classes: the true class and the predicted class. The true class will start with 1 and end with 0. The predicted class will start with 0 and end with 1. Two classes achieved the highest value for better performances [42]. The confusion matrix highlights that the proposed model achieves very high true positive and true negative rates while keeping false predictions minimal. This reinforces the model's ability to correctly classify both diseased and non-diseased patients, ensuring balanced and dependable predictions. The proposed model of accuracy improvement is shown in Fig. 16.

The suggested method achieves the best performance among all evaluated models. The epoch values start at 0 and end at 300. Then, the accuracy improvement of the proposed model starts from 0 and ends with 100. The five models effectively analyze the results for the proposed model accuracy analysis. These models are efficiently analyzed in this proposed model to expect better performances [41]. The proposed model's accuracy improves rapidly during training and reaches higher final accuracy levels than other models. This demonstrates not only the efficiency of the optimization strategy via PQCs but also the benefit of the hybrid architecture in extracting richer features and achieving better classification boundaries. The performance evaluation approach is effective for the MIMIC-III clinical dataset utilizing five models, as indicated in Table 3.

The performance evaluation approach is based on large-scale data analysis of healthcare clinical datasets in order to improve and process complex clinical data more efficiently. The five models were assessed during the data analysis. The proposed model has a higher performance accuracy of 98.76%. The precision value was 98.64%, respectively. The recall value is 98.12%, with the highest F1-score of 98.86%. Table 4

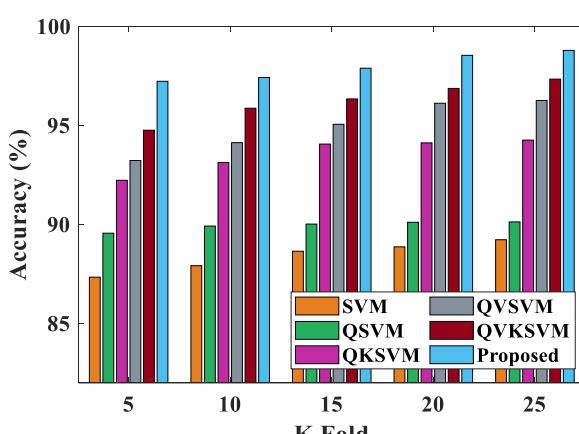


Fig. 14. K-fold analysis for the large-scale data of the proposed model compared to existing models.

Table 4
Performance evaluation approach is based on large-scale data analysis.

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

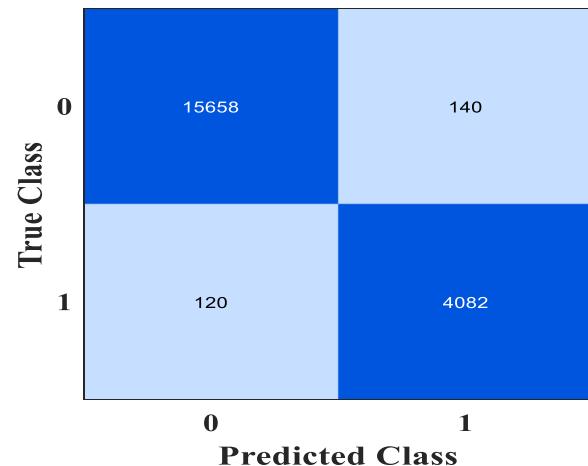


Fig. 15. Confusion matrix analysis of the proposed model.

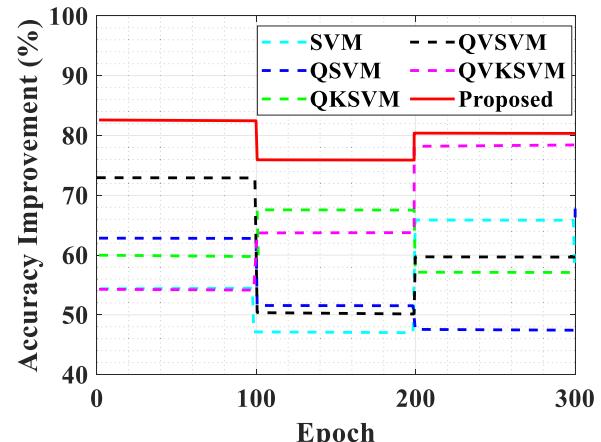


Fig. 16. Accuracy analysis in terms of epochs for the proposed model compared to existing models.

shows the proposed approach for evaluating the performance of large-scale data analysis for k-fold data.

The evaluation approach is based on the accuracy analysis of large-scale data utilizing a clinical dataset. There are several measures mentioned, such as accuracy and precision. The proposed method achieved accuracy results of 97.23%, 97.42%, 97.89%, 98.54%, and 98.79%, respectively. The outcome analysis is intended to improve performance in this evaluation. The proposed model is further compared with recent existing models [44] in Table 5.

4.3. Discussion

This novel technique proposes a study of quantum machine learning for a large-scale data analysis model. Singh et al. [24] suggested a quantum feature extraction approach that achieved high accuracy in

Table 5

Comparative analysis of the proposed model.

Metric	Proposed QML-DL	Quantum Neural Network (QNN)	Classical Neural Network (CNN)
Convergence Speed	Very Fast	Fast	Moderate
Training Loss (Final Iteration)	0.12	0.18	0.33
Processing Time (Average per Dataset)	170 ms	190 ms	250 ms
Computational Complexity	Lowest (Hybrid optimization)	Lower	Higher
Scalability	Very High (large-scale clinical data)	High	Moderate
Accuracy	98.76%	–	–
Precision	98.64%	–	–
Recall	98.12%	–	–
F1-score	98.86%	–	–

large-scale image classification, but their model incurred heavy computational costs and struggled with data quality issues that reduced interpretability. El Hmimdi et al. [25] introduced a deep learning-based framework capable of handling hierarchical and unstructured medical data; however, it faced challenges such as high computational requirements, ethical concerns, and slow processing time. Chen et al. [26] explored a quantum-enhanced support vector machine (QSVM) with GPU acceleration for stellar classification, which demonstrated promising accuracy but highlighted the limitations of costly and cloud-dependent quantum hardware. Similarly, Xue et al. [27] developed a deep learning framework for CT and X-ray image analysis, attaining strong classification performance but suffering from interpretability, computational complexity, and generalization issues. Acharya et al. [28] created a CNN-based model for handwritten character recognition, but it was prone to overfitting and lacked robustness when applied to diverse data sources. Taken together, these studies underscore both the potential and the limitations of existing deep learning and quantum models. By combining a Quantum Variational Classifier optimized through Parameterized Quantum Circuits with Inception-based Attentional VGG for efficient feature extraction, this work overcomes the drawbacks and improves robustness, scalability, and computational overhead for large-scale healthcare data analysis. Table 6 shows the types of datasets and their accuracy.

The performance evaluations validated in the MIMIC-III clinical dataset showed significant improvements to the existing model. The suggested method has a higher accuracy of 98.86, respectively.

5. Conclusions

The proposed model's conclusion indicated an accurately enhanced deep learning and a quantum variational classifier strategy for presenting large-scale QML data analysis. Small-scale data analysis leads to the development of multiple investigations. For this objective, QML employs large-scale data analysis. The large-scale data analysis is pre-processed using feature values into a predetermined range to facilitate convergence learning. The essential features are extracted using IAV, which aids in identifying quantum bits of functions. To present, this method effectively reduces errors by incorporating noisy data into QVC optimization calculations. Quantum variational classifiers are integrated with quantum probabilistic computations and quantum parallelism to show that the resulting hybrid model has higher scalability, performance, and accuracy. Then, PQCs work with classical optimizers to improve trainability by analyzing local cost functions. The proposed approach was created using a dataset, the MIMIC-III clinical dataset, to improve large-scale data analysis. This dataset was used with five models to test their performance in comparison to existing models. This model's performance was assessed utilizing a variety of effective

Table 6

Comparison of the proposed model with the existing model.

Author name	Methods	Accuracy
Singh et al. [24]	Quantum feature extraction technique	98%
El Hmimdi et al. [25]	Deep learning based large-scale data analysis	80.20%
Chen et al. [26]	QSVM	83%
Xue et al. [27]	DL	95%
Acharya et al. [28]	DL based CNN	98.47%
Proposed model	SVM, QSVM, QK SVM, QVSVM, and QVK SVM	98.86%

criteria, including accuracy, recall, F1-score, ROC curve, confusion matrix, and k-fold analysis for large-scale datasets. The suggested model had an accuracy of 98.86% and 98.79% on the large-scale clinical dataset. Despite these promising results, several limitations remain. First, the reliance on simulated or cloud-based quantum resources means that the framework's scalability on real quantum hardware is yet to be fully validated, particularly in the presence of noise and limited qubit counts. Second, while the MIMIC-III dataset provides a robust testbed, the generalizability of the model should be further assessed across diverse multimodal clinical datasets (e.g., combining genomics, imaging, and textual data). Third, interpretability remains an open challenge; although the hybrid model enhances accuracy, clinicians may require more transparent decision-making explanations to support adoption in real-world practice. Future research will address these limitations by testing the model on emerging quantum hardware with improved error correction, extending the framework to multimodal and cross-institutional healthcare datasets for broader applicability, and exploring integration with large language models to enable interactive, clinician-facing decision-support systems. By pursuing these directions, this work can evolve into a scalable, interpretable, and clinically viable solution for next-generation smart healthcare analytics.

Compliance with ethical standards

Funding: No funding is provided for the preparation of the manuscript.

Ethical Approval: This article does not contain any studies with human participants or animals performed by any of the authors.

Consent to participate: All the authors involved have agreed to participate in this submitted article.

Consent to Publish: All the authors involved in this manuscript give full consent for the publication of this submitted article.

Authors Contributions: All authors read and approved the final manuscript.

CRediT authorship contribution statement

Sudha D: Writing – original draft, Software, Resources, Project administration, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Anju A:** Writing – review & editing, Methodology, Investigation. **Ezhilarasi K:** Visualization, Validation, Supervision.

Declaration of competing interest

The Authors declare that they have no conflict of interest.

Data availability

No data was used for the research described in the article.

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