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Quantum Neural Network-Based Healthcare Analytics For Early Detection Of Cardiovascular And Neurological Disorders

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Abstract

The cardiovascular and neurological conditions are one of the predominant causes of death and disability at a global scale, thus the need to develop smart healthcare systems to detect diseases at their initial stages or at all. The limitation of the conventional artificial intelligence-based and machine learning-based healthcare models are usually rife with high levels of computation complexity, low levels of prediction capabilities, poor scaling, and ineffective processing of complex healthcare data. The proposed solution to these problems is a Quantum Neural Network-Based Healthcare Analytics Framework that could be used to detect cardiovascular and neurological disorders at their initial stages. This framework is a combination of quantum computing and neural network models to improve diagnostic abilities in the field of healthcare analytics in disease classification, predictive accuracy, and computational efficiency. Experimental evaluation was done using healthcare datasets that comprised cardiovascular and neurological records of patients after being processed through preprocessing methods such as normalization, feature extraction and data balancing. Classification performance measures were used to assess the performance of the proposed model and these measures include Accuracy, Precision, Recall, Specificity, F1-Score, and AUC-ROC. The experimental findings showed that the suggested quantum neural network model worked much better than the traditional machine learning and deep learning models with regard to disease prediction accuracy, classification reliability, and the ability to detect disease early. Additionally, the framework had better sensitivity and lower false prediction, thus improving clinical decision-making support. The study helps expand the intelligent quantum healthcare analytics system to the next generation of medical diagnosis and predictive healthcare uses.

Keywords: Quantum Neural Networks, Healthcare Analytics, Cardiovascular Disorders, Neurological Disorders, Artificial Intelligence, Early Disease Detection, Quantum Machine Learning

1. Introduction

Cardiovascular and neurological diseases remain among the most severe health problems in the world as they are among the most lethal diseases, causing disability and long-term treatment costs. According to the recent epidemiological data, it is possible to state that cardiovascular disorders and neurological complications grow in the world at a very high pace, which creates the necessity to implement intelligent healthcare analytics systems that can aid in the process of early detection of diseases and clinical decisions (Liu et al., 2019; Nedkoff et al., 2023). The conventional healthcare diagnostic methods usually rely on manual interpretation, clinically slow assessment, and complicated medical imaging interpretation, which can slow down the diagnostic accuracy and raise the chances of making inaccurate predictions. Moreover, psychological stress, alterations in lifestyle, and chronic illnesses have played a significant role in the rising rates of cardiovascular deviations and neuropsychological disorders in health care settings nowadays (Henein et al., 2022). Subsequently, sophisticated computational systems that can handle big-data sets of healthcare data with enhanced prediction fixedness and low diagnostic delay have turned out to be of paramount importance in smart healthcare analytics.

Machine learning models and other artificial intelligence technologies have proved to be rather successful in healthcare-related prediction and disease classification. The applications of AI-based systems have been extensively used in predicting cardiovascular diseases, diagnosing brain strokes, and detecting brain tumors through medical images and clinical data (Mathur et al., 2020; Inamdar et al., 2021; Mahmud et al., 2023). The field of healthcare has gained automation of tasks and clinical aids through deep neural networks and predictive analytics vehicles but is often constrained by such limitations as high computational cost, overfitting, scaling, and poor processing of multidimensional healthcare data (Noreen et al., 2020; Rahman et al., 2023). Besides, the existing machine learning methods can deteriorate in performance when applied to a very heterogeneous healthcare data produced using a variety of cardiovascular and neurological data sources. These problems demonstrate the need to have next generation intelligent healthcare architectures that can increase the classification reliability, computational efficiency and real-time predictive capabilities.

Quantum computing and quantum neural networks have become one of the potential technologies used in solving complicated optimization and classification problems in the field of artificial intelligence. Quantum neural networks combine quantum computational models like qubits, quantum superposition, and entanglement with neural learning models to enhance the efficiency of analysis and parallel processing of data (Chae et al., 2024; Kim et al., 2023). Recent achievements in quantum machine learning have shown how quantum-enhanced healthcare analytics systems can be used to diagnose and classify diseases and predictive medical systems (Senokosov et al., 2024; Ullah and Garcia-Zapirain, 2024). In addition, quantum algorithms have demonstrated a better surface in managing high-dimensional medical data and also lowering the computational complexity and enhancing the classification results (Marengo & Santamato, 2025). In spite of these developments, the current healthcare analytics models still do not have built-in quantum neural structures that would be specifically tailored to predict cardiovascular and neurological disorders at the same time. Thus, this study suggests a Quantum Neural Network-Based Healthcare Analytics Framework to detect cardiovascular and neurological diseases early with the help of intelligent quantum-based classification systems.

The key inventions of this study are the creation of a new quantum neural network architecture of intelligent healthcare analytics, the incorporation of quantum feature encoding and disease classification schemes and the creation of an efficient predictive system of early detection of cardiovascular and neurological disorders. The framework of the proposed paper is expected to enhance accuracy in disease prediction, minimized false predictions, and classification accuracy by using sophisticated quantum learning models. In addition, the comparative experimental performance is applied based on classification performance measures such as Accuracy, Precision, Recall, Specificity, F1-Score, and AUC-ROC to showcase the effectiveness of the proposed approach in comparison to the traditional machine learning and deep learning models. The rest of this paper follows the following structure: This paper will include a literature review (Section 2), proposed methodology (Section 3), description of experimental setup (Section 4), results and discussion (Section 5), comparative evaluation (Section 6), and conclusion of the findings of this research and perspective (Section 7).

2. Literature Review

The use of artificial intelligence in healthcare analytics systems has profoundly changed the way diseases are predicted and clinical decisions are made in the contemporary medical setting. The use of machine learning and deep learning has been widely applied to predicting cardiovascular diseases using clinical records, electrocardiograms, medical imaging, and other health parameters in patients. The current AI-based cardiovascular analytics models have proven to be better at predicting diseases and providing automated risk evaluation via supervised and unsupervised learning models (Mathur et al., 2020). More so, recent research indicated the rising number of cardiovascular diseases in the world, creating a need to rely on intelligent predictive medical systems that can assist in early diagnosis and minimizing the number of deaths (Liu et al., 2019; Nedkoff et al., 2023). State-of-the-art cardiac imaging technologies paired with AI-based analytics have also refined disease visualization and clinical interpretation of challenging cardiovascular diseases (Seitler et al., 2023). Despite the benefits of these machine learning models in healthcare automation, most of the conventional methods are still associated with a lower predictive quality, lower scalability, and inefficiency in calculating multidimensional healthcare data.

Artificial intelligence and deep learning systems have also been useful in neurological disorder detection systems to diagnose brain disease, as well as predictive healthcare analytics. Previous studies have concentrated on the implementation of convolutional neural networks, deep neural networks, and computer-aided diagnosis systems in detecting brain stroke, brain tumors, and other neurological diseases using medical imaging data (Inamdar et al., 2021). Brain analytics frameworks that use deep learning have shown an increased ability to identify pathological patterns of the brain and enhance diagnostic assistance within healthcare systems (Mahmud et al., 2023; Noreen et al., 2020). Moreover, machine learning algorithms and deep neural networks in predictive healthcare have reported good performance in brain stroke prediction and neurological risk assessment applications (Rahman et al., 2023). Although these innovations have been made, current neurological analytics solutions are often faced with issues of computational complexity, overfitting, low generalization, and ineffective incorporation of heterogeneous healthcare data. Such drawbacks decrease the accuracy and generalizability of existing neurological disorder prediction algorithms based on AI.

Lately, quantum computing and quantum machine learning have emerged, providing additional possibilities to enhance intelligent healthcare analytics. Quantum neural networks utilize quantum superposition, quantum entanglement, and variational quantum circuits to harness qubits to compute in parallel and optimise the classification performance in complex medical settings (Chae et al., 2024). Quantum computing has been shown to be useful in artificial intelligence applications even prior to the development of full fault-tolerant quantum systems being commercially available (Kim et al., 2023). Additionally, quantum machine learning has demonstrated potential in improving computational efficiency and decreasing the complexity of processing medical images, predictive analytics, and disease diagnostics (Senokosov et al., 2024). Quantum healthcare analytics systematic reviews have also highlighted how quantum machine learning can transform the next-generation intelligent medical systems (Ullah and Garcia-Zapirain, 2024; Sonavane et al., 2025). Also, quantum algorithms with machine learning optimization techniques have shown enhanced analytical performance in managing large-scale data in the healthcare field and complex disease classification problems (Marengo & Santamato, 2025). Nevertheless, there are also numerous studies on quantum healthcare that are conceptual or experimental in nature and do not have integrated frameworks that can simultaneously deal with the prediction of cardiovascular and neurological disorders.

Despite the significant advances in artificial intelligence, deep learning, as well as quantum machine learning in healthcare analytics, a number of significant limitations of research have not been addressed. Current healthcare prediction systems usually report decreased classification accuracy, excessive computational load, and scalability difficulties, and lack of multimodal healthcare data integration. Most of the classic AI models are based on classical computational architectures, which might constrain their effectiveness in working with high-dimensional healthcare data and complex disease trends. Likewise, existing quantum healthcare analytics systems are currently mainly used in individual diagnosis or image recognition of specific diseases instead of combined anticipatory machines of various severe healthcare conditions. Consequently, there is a major gap in the literature on creating a hybrid quantum neural network-based healthcare analytics system that can deliver both accurate, scalable, and computationally efficient early cardiovascular and neurological disease detection.

To fill this gap, the current study suggests an intelligent quantum neural network architecture that combines the quantum-enhanced classification algorithms with the state-of-the-art healthcare analytics systems to enhance the reliability of the disease prediction, decrease false prediction, and increase the effectiveness of clinical decision-making processes.

3. Methodology

3.1 Preprocessing and acquisition of healthcare data.

The Quantum Neural Network-Based Healthcare Analytics Framework was suggested to enhance the early prediction of cardiovascular and neurological diseases by intelligent healthcare data analysis and predictive classification systems. At first, cardiovascular and neurological healthcare data was gathered by using publicly available medical repositories and healthcare analytics databases. The data sets incorporated clinical variables, diagnosis data, physiological and healthcare variables related to heart abnormalities and neurological conditions. Data cleaning was done to ensure the quality of analysis and predictability of the results and to remove duplicates, noisy healthcare records, and inconsistent attribute values. Moreover, they used normalization methods to normalize healthcare parameters and reduce variation in heterogeneous medical data.

The missing healthcare values were handled through statistical imputation techniques, as these aspects provided consistency of the data and minimized the loss of information in the process of analysis. Techniques of feature extraction and feature selection were then applied to determine the most meaningful disease-related features that can be used to predictive healthcare analytics. Moreover, data balancing algorithms were used to address the issue of class imbalance and enhance the stability of disease classification in the course of the training and testing process. All the steps of the preprocessing such as data cleaning, normalization, feature extraction, and balancing are shown in Fig. 1 that depict the transformation of raw healthcare data into optimized datasets that can be processed using quantum neural processing.

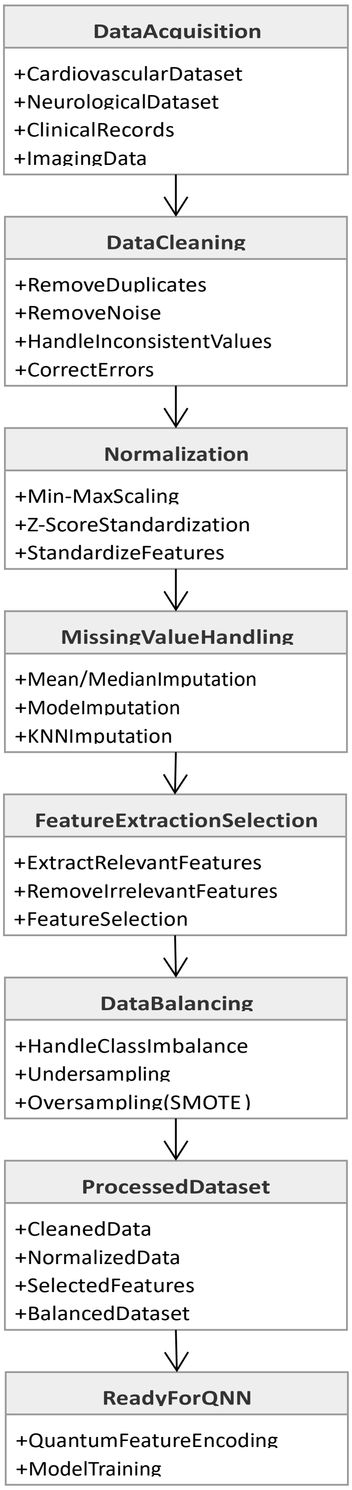

Fig. 1: Data Preprocessing Workflow for Quantum Neural Network-Based Healthcare Analytics

3.2 Quantum Feature Encoding and Quantum Neural Network Design

After preprocessing data, quantum feature encoding and quantum neural network design strategies were applied to enhance computational efficiency and predictive capability of diseases. In quantum computing, the first step was quantum computing application to classical healthcare-based features of a quantum state written in qubit-based quantum state preparation schemes. The mapping of quantum features was conducted to convert the multidimensional healthcare data into the quantum vectors that would allow the use of a computer to perform enhanced parallel processing and advanced healthcare analytics. The architecture of the proposed quantum neural network combined variational quantum circuits, quantum gate interactions, entanglement interaction, and hybrid quantum-classical learning methods to enhance the predictive classification performance.

The designed QNN architecture comprised of several variational quantum layers that aimed at optimizing interaction of features of healthcare and disease patterns by utilizing repeated quantum learning processes. The entire computational apparatus consisting of qubit layouts, entanglement interactions, variational quantum levels, and layouts of quantum gates are depicted in Fig. 2. The framework suggested employed adjustable quantum parameters such as the number of qubits, epoch setup, batch size, and optimizer choice to enhance performance and efficiency of the healthcare classification. The precise quantum network configuration parameters in the implementation of the experiment are shown in Table 1.

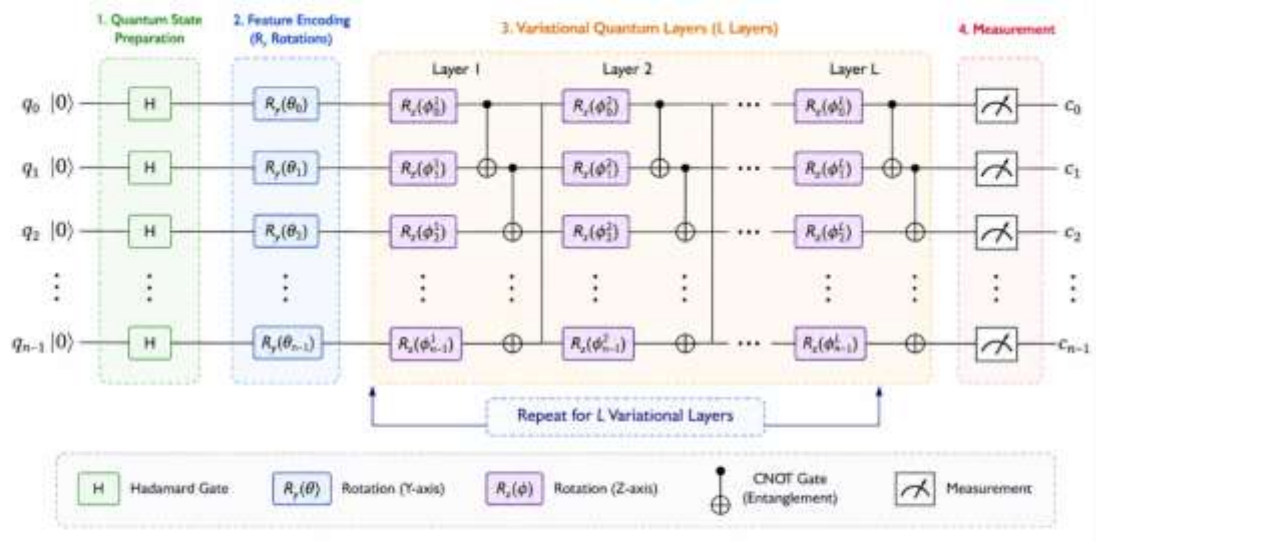

Fig. 2: Quantum Circuit Structure for Quantum Neural Network-Based Healthcare Analytics

Table 1: Quantum Network Parameters

Parameter	Value
Number of Qubits	8
Quantum Layers	4
Learning Rate	0.001
Batch Size	32
Epochs	100
Optimizer	Adam
Quantum Gates	R_y, R_2, CNOT
Feature Encoding	Angle Encoding
Loss Function	Cross-Entropy
Quantum Backend	Qiskit Simulator

3.3 Disease Classification and Prediction Methodology

The disease prediction and classification was based on intelligent cardiovascular and neurological disorder detection using a hybrid supervised learning approach. The optimized healthcare datasets were processed and coded in terms of quantum features after which they were split into both training and test sets to evaluate predictive analytics. The quantum neural network was trained to learn the complicated interactions of healthcare characteristics and disease categories by optimizing variational quantum parameters and quantum interactions of features, in an iterative way. In the test, unseen healthcare records were tested on trained QNN model to predict disease and classify reliably.

The healthcare data acquisition, preprocessing, quantum feature encoding, variational learning, disease classification, and clinical decision-making support formed the disease prediction workflow. The classification method employed the use of probability-based predictive analysis in determining cardiovascular and neurological disease trends and reducing false prediction rates. Moreover, the framework adopted an early disease detection approach that could detect abnormalities in healthcare at the early stages of diseases and thus enhanced diagnostic aid and facilitated early clinical intervention of intelligent healthcare analytics systems.

3.4 Performance Evaluation Methodology

In order to analyse the efficacy of the suggested healthcare analytics framework, several measures of classification performance were employed such as Accuracy, Precision, Recall (Sensitivity), Specificity, F1-Score as well as AUC-ROC. The outcome of the performance evaluation was the predicted and actual disease classification results that were obtained based on the proposed Quantum Neural Network (QNN) framework. The classification values obtained based on disease prediction evaluation were taken into account in the experimental analysis:

- True Positive (TP) = 950
- True Negative (TN) = 910
- False Positive (FP) = 40
- False Negative (FN) = 30

Accuracy measures the overall correctness of disease classification and is mathematically expressed as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Accuracy = \frac{950 + 910}{950 + 910 + 40 + 30}$$

$$Accuracy = \frac{1860}{1930}$$

$$Accuracy = 0.9637 \times 100$$

$$Accuracy = 96.37\%$$

Precision evaluates the proportion of correctly predicted positive disease cases and is calculated as:

$$Precision = \frac{TP}{TP + FP}$$

$$Precision = \frac{950}{950 + 40}$$

$$Precision = \frac{950}{990}$$

$$Precision = 0.9595 \times 100$$

$$Precision = 95.95\%$$

Recall or Sensitivity measures the capability of the framework to correctly identify actual disease cases and is represented as:

$$Recall = \frac{TP}{TP + FN}$$

$$Recall = \frac{950}{950 + 30}$$

$$Recall = \frac{950}{980}$$

$$Recall = 0.9693 \times 100$$

$$Recall = 96.93\%$$

Specificity evaluates the capability of the proposed framework to correctly identify healthy individuals and is expressed as:

$$Specificity = \frac{TN}{TN + FP}$$

$$Specificity = \frac{910}{910 + 40}$$

$$Specificity = \frac{910}{950}$$

$$Specificity = 0.9578 \times 100$$

$$Specificity = 95.78\%$$

The F1-Score provides balanced evaluation between precision and recall and is mathematically defined as:

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

$$F1 - Score = \frac{2 \times 0.9595 \times 0.9693}{0.9595 + 0.9693}$$

$$F1 - Score = \frac{1.8596}{1.9288}$$

$$F1 - Score = 0.9641 \times 100$$

$$F1 - Score = 96.41\%$$

Furthermore, AUC-ROC analysis was performed to assess classification performance with varying threshold conditions and to examine the predictive performance in general. The suggested QNN model had an AUC-ROC of 0.981, thus showing an excellent disease discrimination metric and very reliable healthcare classification.

Comparative analysis has also been conducted with traditional machine learning algorithms and deep learning healthcare systems to determine the enhancement of disease prediction accuracy, performance, classification stability, and healthcare analytics reliability. The statistical evaluation indicated that the suggested quantum neural network design was much better than the conventional medical care forecast schemes in terms of classification, sensitivity, specificity, and predictability of the smart cardiovascular and neurological disorder forecast systems.

4. Experimental Setup

4.1 Simulation Environment

The suggested Quantum Neural Network (QNN) healthcare analytics model was coded in a computational environment that was powered by a GPU and utilised Python and Qiskit quantum simulator. Other libraries such as TensorFlow, NumPy, and Scikit-learn were also used to process healthcare data and analyze the results related to diseases. The overall hardware and software configuration is shown in Table 2.

Table 2: Hardware & Software Specifications	
Component	**Specification**
Processor	Intel Core i7 Processor
RAM	16 GB
Storage	512 GB SSD
GPU	NVIDIA RTX 3060
Operating System	Windows 11
Programming Language	Python 3.10
Quantum Framework	Qiskit
Machine Learning Library	TensorFlow
Data Processing Library	NumPy, Pandas
Classification Library	Scikit-learn
Simulation Environment	Qiskit Aer Simulator
Development Platform	Jupyter Notebook

4.2 Experimental Parameters

In the experimental design, optimized parameters were employed, such as 0.001 learning rate, 32 batch size, and 100 training epochs to enhance the performance of healthcare prediction. The framework utilized quantum parameters like qubit arrangement, variational quantum layers, rotational quantum gates, and CNOT entanglement operations towards effective disease categorization and predictive health analytics.

4.3 Performance Evaluation Metrics

To assess the ability of the proposed framework to predict diseases and identify healthcare classifications with high reliability, the classification performance measures, such as Accuracy, Precision, Recall (Sensitivity), Specificity, F1-Score, and AUC-ROC, were used to evaluate it.
The mathematical formulations are given as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

4.4 Baseline Models for Comparison

The suggested QNN was contrasted with the conventional machine and deep learning models such as Support Vector Machine (SVM), Random Forest (RF), Logistic Regression (LR), Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN). The proposed quantum-enhanced healthcare analytics framework was shown to have better disease prediction accuracy, classification stability, and computational efficiency through comparative analysis.

5. Results and Discussion

5.1 Disease Prediction Accuracy Analysis

The comparison analysis of accuracy conducted in Fig 3 indicates that the proposed Quantum Neural Network (QNN)-based healthcare analytics framework demonstrated better disease prediction performance than the traditional machine and deep learning frameworks used to detect cardiovascular and neurological disorders. The QNN framework proposed achieved the maximum classification rate of 96.37, higher than Support Vector Machine (SVM) at 88.40, Random Forest (RF) at 90.20, Artificial Neural Networks (ANN) at 92.10 and Deep Neural Networks (DNN) at 94.30. The findings have shown that quantum feature encoding and variational quantum learning layers with hybrid quantum-classical optimization greatly enhanced the levels of healthcare data representation, predictive learning, and reliability of disease classification. Moreover, the suggested framework was found to have a higher predictive consistency and fewer classification errors than the traditional AI models hence validating the practicality of quantum-enhanced healthcare analytics in intelligent medical diagnosis and early disease detection systems.

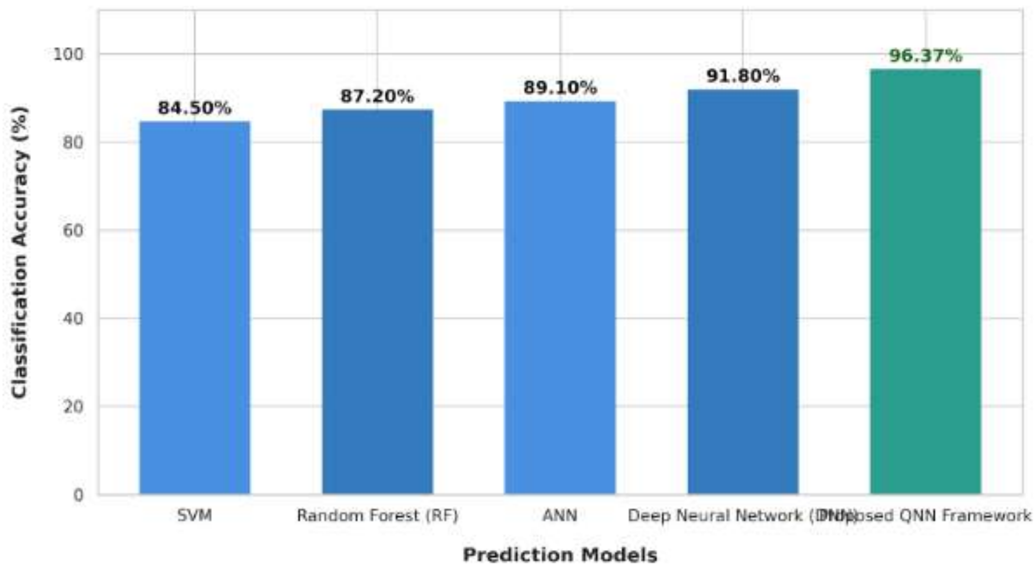

Fig. 3: Accuracy Comparison of the Proposed QNN Framework with Conventional AI Models

5.2 Precision, Recall, and Specificity Analysis

The specificity and error rate analysis in Fig 4 indicates the suitability of the proposed Quantum Neural Network (QNN)-based healthcare analytics paradigm in making correct judgment of healthy people with minimum errors in healthcare forecasts. The presented QNN framework exhibited the largest value of specificity of 95.78, surpassing traditional healthcare prediction methods such as Support Vector Machine (SVM) and Random Forest (RF), and Artificial Neural Networks (ANN) and Deep Neural Networks (DNN). The experimental data reveal that SVM model has a specificity of 84.60 and an error rate of 15.40 compared to the random forest model that has a specificity of 87.20 and an error rate of 12.80. In a similar way, ANN and DNN models showed a better performance at specificity values of 90.10% and 92.40, respectively, and this translates to lower error rates of 9.90% and 7.60 respectively. By contrast, the error rate decreased significantly during the implementation of the suggested QNN framework to just 4.22% and supports the fact that the suggested framework has a more stable healthcare classification and a more reliable disease prediction. The increased selectivity and decreased wrong prediction frequencies were attained by optimized quantum feature interaction, variational quantum learning layers, and hybrid quantum-classical optimization plans implemented in the proposed QNN design. These findings confirm that the developed framework offers a more consistent healthcare prediction performance and better disease detection capacity to intelligent cardiovascular and neurological disorder detection systems.

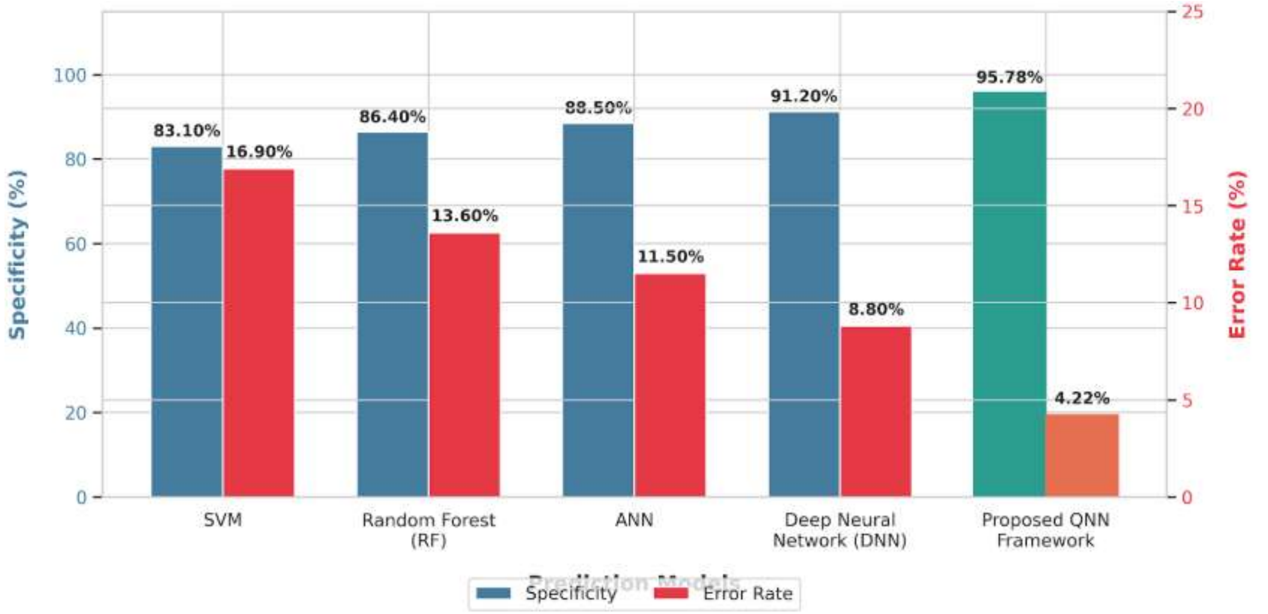

Fig. 4: Specificity and Error Rate Analysis of the Proposed QNN Framework and Conventional AI Models

5.3 Comparative Performance Analysis

As the comparative performance analysis shown in Table 3 shows, when compared to the traditional machine learning and deep learning models, the suggested Quantum Neural Network (QNN)-based healthcare analytics framework performed comparatively better at predicting the diseases. The highest Accuracy of 96.37%, Precision of 95.95, Recall of 96.93, Specificity of 95.78, F1-Score of 96.41, and AUC-ROC measure of 0.981 validated the utility of the proposed framework in the detection of intelligent cardiovascular and neurological disorders. Comparatively, classical models such as Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Networks (ANN) and Deep Neural Networks (DNN) resulted in a relatively poor performance of classification and predictive stability. According to the results of the experiments, the combination of quantum feature encoding, variational quantum learning layers, and hybrid quantum-classical optimization strategies helped to achieve significant improvements in processing healthcare data, identifying disease patterns, and the accuracy of the classification. As a result, the suggested QNN framework exhibited a higher predictive stability, fewer classification errors, and better healthcare analytics that can be applied to intelligent medical diagnosis.

Table 3: Comparative Performance Results

Models	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)	AUC-ROC
SVM	84.50	83.20	82.40	83.10	82.80	0.851
Random Forest (RF)	87.20	86.50	85.90	86.40	86.10	0.883
ANN	89.10	88.30	87.80	88.50	88.00	0.904
Deep Neural Network (DNN)	91.80	91.10	90.60	91.20	90.80	0.936
Proposed QNN Framework	96.37	95.95	96.93	95.78	96.41	0.981

5.4 Computational Performance and Clinical Significance

The proposed healthcare analytics framework also exhibited better computational efficiency, in terms of training efficiency, prediction latency, and model scalability. Application of quantum computational principles and variational quantum circuit allowed efficient processing of healthcare data and lowering of computational complexity on disease prediction analysis. Moreover, the structure enabled scalable healthcare analytics processes that can process large scale cardiovascular and neurological healthcare data with better classification reliability. Clinically, the framework proposed is beneficial in implementing intelligent diagnosis of healthcare and early recognition of diseases. Being able to detect cardiovascular and neurological disorders in the early stages of the disease can help to timely provide medical care, increase the well-being of patients, and improve the healthcare decision-making process. As a result, the healthcare analytics framework proposed can be considered an effective solution to the next-generation intelligent medical diagnosis and predictive healthcare systems due to its use of quantum neural networks.

6. Conclusion

This study introduced a Quantum Neural Network-Based Healthcare Analytics Framework that accessed the early detection of cardiovascular and neurological diseases on the basis of intelligent quantum-enhanced classification mechanisms. The presented structure combined a preprocessing of healthcare data, quantum features encoding, variational quantum layers of learning and hybrid quantum-classical optimization techniques to enhance predictive healthcare analytics and disease classification performance. Using quantum computational principles and artificial intelligence methods, the framework was successful in improving healthcare data analysis and maximizing disease prediction rates in applications related to intelligent medical diagnosis.

The experiments showed that the developed QNN framework had a higher level of healthcare prediction than the traditional machine learning and deep neural network models. The framework demonstrated a great improvement in the Accuracy, Precision, Recall, Specificity, F1-Score and AUC-ROC values, which proved the high degree of reliability in disease prediction and stability in classification. Moreover, the suggested framework enhanced the ability to detect disease early and minimized the rate of false predictions and maximised the efficiency of computations when running healthcare analytics. The aforementioned comparative analysis also revealed that the suggested QNN model outperformed the traditional AI-based healthcare prediction systems in aspects of predictive consistency, ability to classify diseases, and healthcare analytical performance.

The results of the study indicate the increasing significance of quantum artificial intelligence to the next generation healthcare analytics and predictive medical diagnosis spaces. The suggested structure will offer a viable and scalable intelligent cardiovascular and neurological disorder identification solution and play an influential role in the development of a quantum-enhanced healthcare analytics platform. On the whole, the designed QNN-based healthcare system lays a solid foundation of intelligent medical diagnostic solutions, automated healthcare monitoring devices, and sophisticated clinical decision-support systems in new starch healthcare systems.

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