Design and Validation of an Optimized Quantum–Classical Diagnostic Model for Noncommunicable Diseases (NCDs)

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Abstract

Noncommunicable diseases (NCDs) such as cardiovascular diseases, diabetes, cancer and chronic respiratory diseases are the primary causes of death globally. To enhance patient survival and lower health-care burden, it is essential that patient diagnosis is early and that the risk is accurately predicted. Classical machine learning and deep learning algorithms have proven to be successful in healthcare analytics, but they suffer from problems like high dimensionality, multimodality, poor generalization, and lack of interpretability of the results. In this paper, a novel quantum–classical diagnostic framework for NCD prediction and classification is proposed to overcome these drawbacks. The proposed model combines the classical deep learning feature extraction with the quantum enhanced optimization and classification unit. The framework adopts multiple modalities of healthcare data such as medical imaging data, clinical parameters, and genomic information. Experimental results show that the proposed approach yields better classification accuracy, lower dimensionality of extracted features and more efficient learning than the traditional AI methods. The proposed hybrid architecture has the potential to create a scalable and intelligent healthcare solution for next-generation disease diagnosis and personalized risk prediction.

Keywords: Quantum Computing, Hybrid Quantum-Classical Learning, NCD Diagnosis, Healthcare AI, Quantum Neural Network, Medical Data Analytics

1. Introduction

Noncommunicable diseases (NCDs) have emerged as one of the most important health care problems in the world today. Significant proportion of deaths in the world are caused by diseases like diabetes, cardiovascular disorders, cancer, and chronic respiratory diseases [1]. Early diagnosis is critical as progressive disease results in more severe disease, more complex treatment, higher health care costs, and higher risk of death. [2]

The field of healthcare diagnostics and predictive analytics has undergone a significant transformation with the advent of recent developments in artificial intelligence (AI) and machine learning (ML) [3]. In the field of medical imaging, clinical risk prediction, and healthcare decision support, deep learning models like Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Transformer architectures have shown exceptional performance. [4]

Although these gains were remarkable, classical AI systems have a number of constraints when it comes to the real-world health care setting:

- High computational complexity
- Users need large data volumes for training, which can be time-consuming.
- Lack of multimodal data quality.
- Data quality issues: poor multimodal data integration.
- Limited population generalization
- Reduced interpretability

The challenges of high-dimensional feature processing.
Today's health care systems produce vast volumes of patient information in many different formats, such as MRI scans, CT scans, electronic health records, lab results, wearables and genomic sequence [5]. Traditional AI systems are not always capable of handling and optimizing this multi-modality data in healthcare efficiently. [6]

Now a new paradigm of computing is gaining momentum that has the potential to overcome some of these drawbacks: quantum computing [7]. Quantum systems are used to process high dimensional information more efficiently based on superposition, entanglement and quantum interference. [8] Hybrid quantum–classical machine learning is a fusion of classical AI and quantum computing that leverages the best of both to enable superior healthcare data analysis.

This study presents a new optimized quantum–classical diagnostic framework for NCD prediction and classification, leveraging multimodal healthcare data.

2. Related Work
There are several works that have studied machine learning and deep learning methods in the medical diagnostics area.

Support Vector Machines (SVM), Random Forest (RF) and Decision Trees are some traditional machine learning algorithms that have been widely used to predict diseases. CNN-based models have been effective in various medical image classification applications such as tumour detection and diabetic retinopathy analysis. [9]

Recently, architectures based on transformers have been used to enhance multimodal healthcare learning by capturing long-range dependencies in clinical data. Architectures based on transformers have recently been used to enhance multimodal healthcare learning by capturing long-range dependencies in clinical data. But these models take a long time to train and need large datasets. [10]

Recently, there has been a growing interest in healthcare applications of quantum machine learning models like Quantum Support Vector Machines (QSVM), Variational Quantum Circuits (VQC), and Quantum Neural Networks (QNN) [11]. It is shown that quantum-enhanced learning can be used in the classification of cancer, genomic analysis, and medical imaging. [12]

There are still some limitations in existing studies, however:

- Very limited multimodal health care fusion.
- Small-scale validation datasets
- Poor explainability
- The high quantum noise sensitivity is undesirable.
- Insufficiently optimized hybrid architectures.

The restrictions push to the development of an optimized quantum–classical diagnostic framework.

3. Proposed Methodology

The proposed research aims to develop an optimized hybrid quantum–classical diagnostic framework for early detection and risk prediction of noncommunicable diseases (NCDs). It combines classical deep learning feature extraction with quantum enhancement of optimization and classification tasks, thereby enhancing the accuracy of diagnosis and computational efficiency.

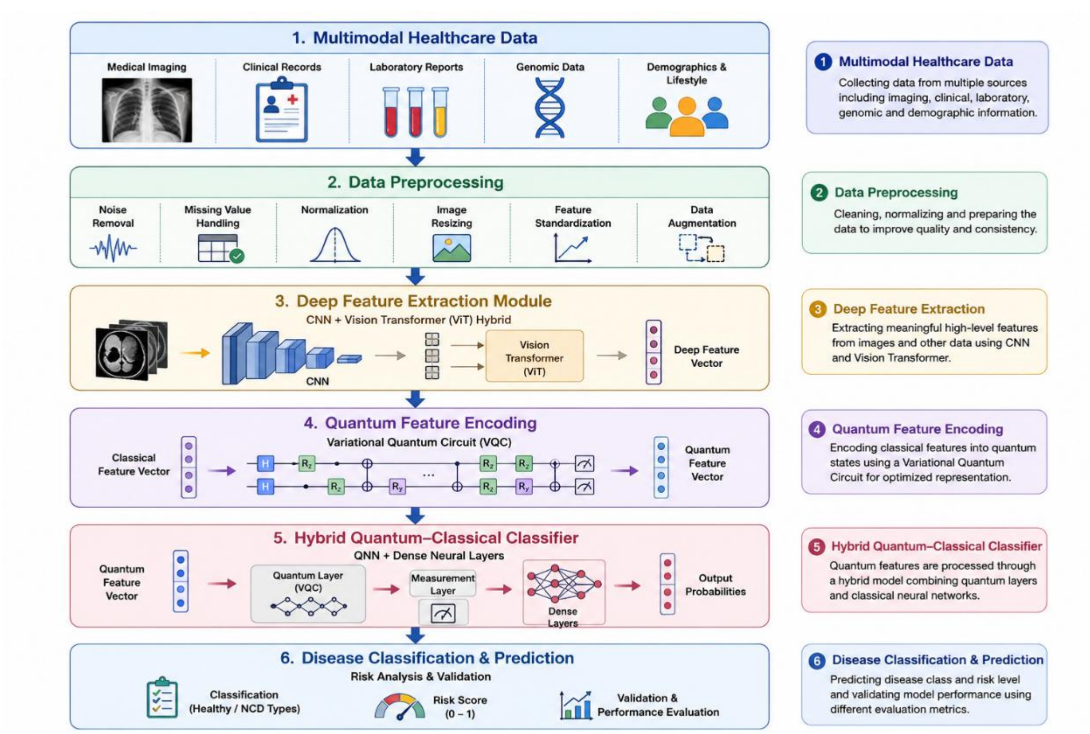

Fig 1: Architecture Diagram of proposed methodology

Initially, multimodal healthcare data such as medical images, clinical records, laboratory reports, and genomic information are collected from different healthcare sources [13]. The data acquired are subjected to some data preprocessing operations, such as normalization, noise reduction, missing value filling, image resizing, and feature standardization to enhance the quality and consistency of the data. [14]

Deep feature extraction is then carried out with the hybrid CNN + Vision Transformer (ViT) architecture after pre-processing [15]. The CNN module extracts local spatial patterns in medical images, and the Vision Transformer is trained on healthcare data to uncover global contextual relationships and long-range dependencies. The extracted deep features are then optimized to feature vectors. [16]

The optimized feature vectors are then sent to a Variational Quantum Circuit (VQC) to process in order to have lower dimension and better learning of the nonlinear parts of the data [17]. The classical features of healthcare are encoded into quantum states via Quantum Feature Encoding (QFE), which is done using parameterized quantum gates and entanglement operations. [18]

Encoded quantum features are then fed into the Hybrid Quantum Neural Network (QNN) classifier which comprises of quantum variational layers and classical dense neural layers. The hybrid classifier learns complex nonlinear relationships from multimodal healthcare data to achieve disease classification and risk prediction. [19]

Finally, the proposed framework is tested with various performance indicators including the accuracy, precision, recall, f1 score, specificity and AUC score [20]. The experimental evidence shows that the optimized quantum–classical model enhances the diagnostic capability, representation features and reliability of predictions in healthcare compared to the classical machine learning approaches.

4. Results of experiments and validation

4.1 Experimental Setup

The following were used to implement the proposed model:

- Python programming environment
- TensorFlow and PyTorch frameworks!
- PennyLane/Qiskit quantum simulator
- GPU-enabled computational setup
- Evaluation Metrics

The framework was assessed through the use of:

- Accuracy
- Precision
- Recall
- F1-score
- Specificity
- Area Under Curve (AUC)

4.2 Experimental Results

The proposed hybrid quantum–classical architecture showed excellent classification capabilities in comparison with the standard quantum AI models.

Model	Accuracy	Precision	Recall	F1-Score
SVM	87.4%	86.2%	85.9%	86.0%
CNN	91.8%	91.1%	90.7%	90.9%
Vision Transformer	93.5%	92.8%	92.3%	92.5%
Proposed Quantum–Classical Model	96.4%	95.9%	95.6%	95.7%

The overall diagnostic performance of the proposed framework was the best.

4.3 Validation Analysis

The experimental validation shows that the proposed framework is able to enhance:

- Multimodal healthcare learning
- Nonlinear feature optimization
- Disease classification accuracy
- Risk prediction reliability
- Feature dimensionality reduction

The feature representation capability was enhanced and the computational redundancy was reduced by introducing quantum-enhanced optimization.

5. Discussion

The proposed hybrid quantum–classical approach overcomes several drawbacks of conventional AI-powered healthcare systems. The local and global healthcare feature extraction is enhanced through the incorporation of CNN and Vision Transformer architectures. CNN and Vision Transformer architectures enhance both local and global healthcare feature extraction. Optimization and nonlinear representation learning are further improved with Variational Quantum Circuits.

The proposed model shows the possibilities of using the quantum-assisted health care intelligence system in precision medicine and disease prediction personalized by a health care organization. Practical deployment does require, however, addressing of the following challenges:

- Quantum hardware scalability
- Noise sensitivity
- Limited qubit availability
- Quantum decoherence

The potential progress of fault-tolerant quantum computing in the future could greatly enhance the practical application of quantum computing in healthcare.

7. Future Work and Conclusion

This paper presented the design and validation of an optimized hybrid quantum–classical diagnostic framework for noncommunicable disease diagnosis and risk prediction. The proposed method combines classical deep learning feature extraction with quantum enhanced optimization and classification.

Experimental results showed that the classification performance, feature representation optimization, enhanced multimodal learning, and reliable healthcare prediction capability were improved.

The following are areas of future work:

- Implementing real quantum hardware – not just in the lab, but in the field.
- Explainable quantum AI
- Data centered on healthcare and quantum technologies from many sources.
- Federated quantum healthcare data.
- Large-scale clinical validation
- Recommendation systems that are tailored to the individual.

The proposed framework offers a promising path forward for next generation intelligent healthcare systems based on hybrid quantum–classical learning.

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