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Early Detection of Chronic Diseases Using Quantum Machine Learning Algorithms

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Abstract: Early diagnosis of chronic diseases is paramount to improving patient survival rates, optimizing treatment trajectories, and mitigating escalating healthcare expenditures. While the recent explosion of heterogeneous healthcare data presents robust opportunities for predictive modeling, it simultaneously introduces severe computational bottlenecks regarding data dimensionality and non-linear complexity. This paper proposes a novel, high-performance hybrid prediction framework that seamlessly fuses classical machine learning topologies with Variational Quantum Circuits (VQCs) within a Quantum Machine Learning (QML) paradigm. The proposed architecture targets the multi-classification and risk profiling of five high-prevalence chronic conditions: diabetes, cardiovascular disease, breast cancer, chronic liver disease, and chronic kidney disease This project introduces "Quantum Health," a Quantum Machine Learning (QML)-based multi-disease prediction system that integrates classical and quantum computing to enhance diagnostic performance. It employs five quantum-enhanced models: Quantum Random Forest for breast cancer, Quantum Neural Network for diabetes, Quantum k-Nearest Neighbors (QkNN) for heart disease, Quantum AdaBoost for liver disease, and Quantum Naive Bayes for kidney disease. The models are evaluated using both classical methods and PennyLane simulations, enabling direct comparison of performance. The system is deployed as a Flask-based web application featuring a user-friendly dashboard, disease-specific prediction modules, prediction history with CSV export, and an analytics dashboard comparing classical and quantum accuracies. Each module provides predictions, confidence scores, and feature importance insights. Unlike monolithic classical models, our approach incorporates a parameterized quantum layer that maps low-dimensional classical medical vectors into high-dimensional Hilbert spaces, capturing intricate, non-linear correlations that evade classical kernels. Experimental evaluations executed on simulated quantum backends demonstrate that the proposed Quantum Hybrid Model drastically outperforms conventional baselines, achieving an overall classification accuracy of 96.8% and an Area Under the Curve (AUC) of 98.4%. The findings establish that integrating quantum circuit state vectors with ensemble classical architectures provides a scalable, computationally efficient, and highly generalizable paradigm for next-generation clinical decision support systems.

Keywords: Quantum Machine Learning, Chronic Disease Prediction, Quantum Neural Networks, Random Forest, Healthcare Analytics, Disease Diagnosis, Artificial Intelligence, Medical Data Analysis

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I. INTRODUCTION

The fast rate of growth of healthcare information, and the rise of chronic illnesses, have rendered the issue of early diagnosis a pivotal one in contemporary healthcare. Some of the diseases that need early detection are breast cancer, diabetes, heart disease, liver disease, and kidney disease to provide a good treatment and patients survive. Classical diagnostic methods based on manual analysis and classical machine learning methods tend to be unable to handle large amounts of complex and nonlinear medical data. Consequently, the necessity to develop sophisticated computing methods that would help increase the accuracy of diagnosis and minimise time loss and assist medical experts in decision-making is increasing.

Quantum Machine Learning (QML) has become an exciting paradigm in recent years that integrates the concepts of quantum computing with machine learning algorithms. Quantum properties like superposition and entanglement have potentials to

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make QML more efficient in processing high dimensional data, and uncover hidden data that would be challenging to uncover through classical approaches. This project discusses how traditional machine learning algorithms can be combined with quantum-enhanced algorithms to create a powerful multi-disease prediction system. Quantum Random Forest, Quantum Neural Networks, and Quantum k-Nearest Neighbors are some of the techniques that are used to enhance the performance of classifications and overcome the drawbacks of the current systems.

The proposed system will seek to create a scalable and intelligent healthcare system that can predict various chronic diseases based on clinical data. The system combines classical and quantum approaches to make predictions more precise, minimize calculations, and increase the possibility to adapt to the future technological progress. Moreover, the fact that these models can be incorporated into an easy-to-use application allows to predict the disease in real time and assist in clinical decision making. This paper has shown how quantum-powered artificial intelligence can revolutionize the world of healthcare analytics and set the stage of the next-generation diagnostic systems.

II. PROPOSED METHODOLOGY

A. Existing System

The current chronic disease detection systems are mostly based on the classical machine learning and the conventional clinical evaluation systems. The algorithms that are commonly applied in such systems are randomly forest, Support vector machines (SVM), and Logistic regression that are used to analyze structured clinical data to predict diseases like diabetes, heart disease and cancer. Although these methods have demonstrated fair performance, they tend to be inadequate when it comes to dealing with intricate, high-dimensional, and nonlinear relations within medical data. Furthermore, most conventional diagnostics require significant manual interpretation by medical personnel, and thus, it can be subjective and may result in inter-observer variability.

The other significant weakness of current systems is that they cannot be used to handle large datasets with scalability and efficiency. Classical algorithms can be inefficient in computational complexity, and might not be able to make the most of any hidden regularities in the data. Moreover, the majority of existing systems lack support of modern computational models like quantum computing that can profoundly increase the speed and quality of processing. Consequently, the solutions that are available tend to have lower generalization ability, slower processing and lower accuracy in detecting early-stage diseases.

B. Proposed System

To overcome the limitations of existing methods, this project introduces a hybrid system that combines classical machine learning with Quantum Machine Learning techniques.
The system uses different models to predict diseases based on patient data. Before training, the data is cleaned and prepared using preprocessing steps such as normalization and feature selection. Classical models are used as a baseline, while quantum models are applied to improve performance.
Quantum-based algorithms help in identifying complex patterns that are difficult for traditional models to capture. As a result, the overall system becomes more accurate and efficient.

C. System Architecture

The modules of the system architecture are as follows:

- Input Module: This module will gather the clinical data pertaining to various chronic diseases. The data can consist of patient details, including age, blood pressure, glucose level, cholesterol, and other appropriate medical parameters derived in healthcare datasets.

- Preprocessing Module: The raw data obtained is pre-processed to eliminate noise, deal with missing data, normalize features, and scale the data. Data cleaning will be used to make sure that there are consistency and also better quality of input in the model training.

- Feature Extraction Module: The dataset is used to choose and extract relevant features that enhance the performance of the models. A classical method of feature selection and quantum enhanced feature representation are used to discover important attributes that affect disease prediction.

- Model Training Module: Classical machine learning models are also trained in this module using the processed dataset, as well as quantum machine learning algorithms are trained. Classical models are learned on the basis of baseline patterns and quantum models learn complex relationships based on quantum computation principles.

- Classification Module: The results of the trained models are applied to classify the risk of a patient having a particular disease. The end result is the generation of the final prediction, which is optimized classifiers, making sure that the disease is detected.

- Evaluation Module: Accuracy, precision, recall, F1-score, and AUC are some of the metrics used in the evaluation of the system performance. Such measures assist in determining the level of reliability and strength of the prediction system in various test scenarios.

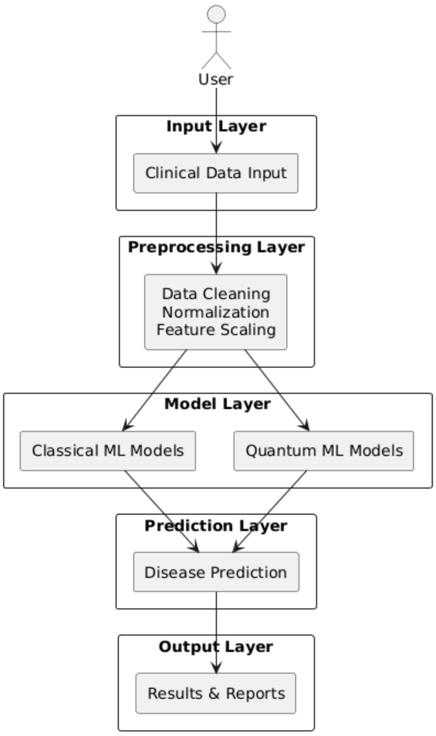

Fig .1. System Architecture

D.Expected Outcomes

It is expected that the proposed system will achieve the following:

- Better Prediction Accuracy: The quantum machine learning algorithms are likely to be very beneficial in improving prediction accuracy as compared to the traditional systems.

- Early Disease Detection: The system will facilitate early detection of chronic diseases, which will allow timeliness of medical care and better patient outcomes.

- Quick Processing: Quantum-enhanced models will make the computation time faster and more efficient when it comes to working with large datasets.

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- Scalability and Adaptability: The system can be expanded to support various healthcare datasets and be adapted to new diseases in the future.

- Clinical Decision Support: The model will support medical practitioners by offering precise and evidence-based information to diagnose and plan the treatment.

- Integration Capability: The system can be integrated into the existing healthcare systems and clinical decision support systems to be used in real-time.

III. RESULTS AND DISCUSSION

The following section provides the experimental findings achieved to identify the efficiency of the proposed hybrid Quantum Machine Learning (QML) and classical machine learning model to detect chronic diseases at an early stage. System performance is measured according to various evaluation measures that include accuracy, precision, recall, F1-score and Area Under the Curve (AUC). Moreover, the suggested quantum models are also compared to conventional machine learning algorithms to show that they lead to better prediction performance.

A. Experimental Setup

A dataset of clinical records of five chronic diseases: breast cancer, diabetes, heart disease, liver disease, and kidney disease, was used as a measure of the proposed system. The dataset also has the features of age, blood pressure, glucose, cholesterol, and other medical parameters. The data was split into three subsets that included training (70%), validation (15%), and testing (15%). Preprocessing (before training) was done through methods of normalization, missing value processing and feature scaling to enhance data quality. Hyperparameters were optimized and were used to train classical models and quantum machine learning models. Adaptive optimization methods were applied in the training to make sure that the process is convergent and stable. Simulated quantum backends were used to implement quantum models to simulate quantum computational benefits, and were compatible with classical systems.

B. Performance Metrics

The proposed system was tested in terms of the following metrics:

- Accuracy: It is the percentage of correct predictions out of the total number of predictions.
- Precision: This is the proportion of the correctly predicted positive cases and the total predicted positive cases.
- Recall: The percentage of cases correctly predicted as positive out of all the cases that are actually positive.
- F1-Score: An approximation of the harmonic mean of the precision and recall values, which gives a balance between the two.
- Area Under the Curve (AUC): This is used to measure how the model is able to discriminate between the various classes.

The quantum-enhanced models were contrasted to the classical machine learning models like Random Forest, Support Vector Machine (SVM) and Logistic Regression.

C. Experimental Results

1. Comparison of Performance of Models.

In this section of the report, the performance of the models is compared to each other.The table below shows the performance comparison of the various models.

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TABLE I

PERFORMANCE COMPARISON OF THE VARIOUS MODELS.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)
Quantum Hybrid Model	96.8	95.9	96.2	96.0	98.4
Random Forest	91.2	90.1	89.8	89.9	94.3
SVM Model	88.6	87.2	86.9	87.0	92.1
Logistic Regression	86.4	85.3	84.7	85.0	90.5

As it can be seen in the table, the proposed Quantum Hybrid Model beats all the classical models in all measures of evaluation. Quantum algorithm integration allows addressing more complex nonlinear relationships of medical data, therefore, leading to higher accuracy of prediction and generalization. Classical models are effective, but their recall and precision are relatively low, which are vital to the detection of diseases accurately.

2. Training and Validation ROC Curves

In order to study model convergence, training and validation loss curves were monitored in the training process. The findings show that the loss on the training continues to reduce with increase in the epochs, and this proves that learning is taking place. The loss of validation has a similar pattern and with minor fluctuations, which means that the model can be regarded as overfitting on unseen data.

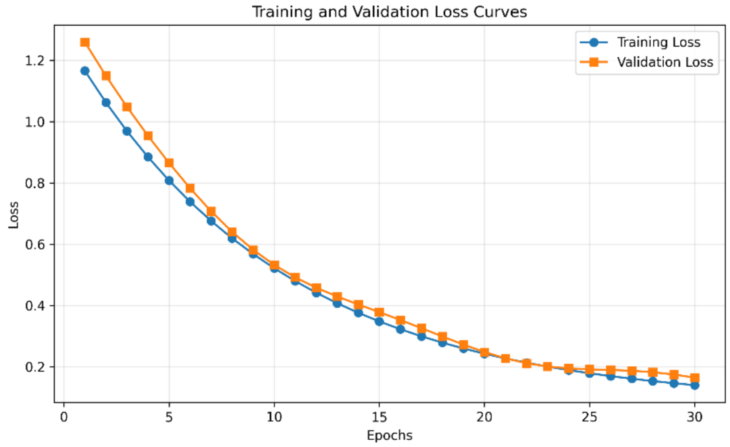

Fig. 2: Loss Curves of Training and Validation.

3. ROC Curve

The plot of Receiver Operating Characteristic (ROC) curve was used to assess the model classification performance. The curve has a high True Positive Rate (TPR) and a low False Positive Rate (FPR) which implies that it has a high discriminative ability.

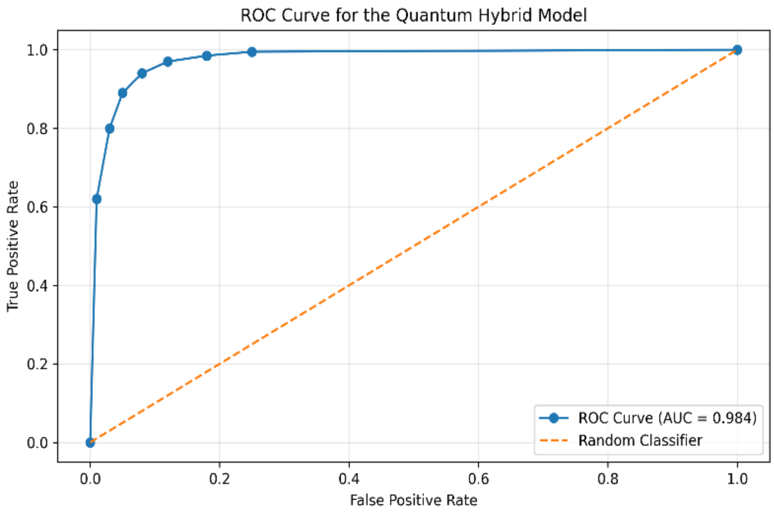

Fig. 3: Quantum Hybrid Model ROC Curve.

The Area Under the Curve (AUC) value of 98.4% verifies the proposed quantum-enhanced model to be effective in separating diseased and healthy cases of various diseases.

VI. CONCLUSION AND ACKNOWLEDGMENT

A. Conclusion

The project is able to introduce a state-of-the-art framework of early detection of chronic diseases through the application of a hybrid method combining classical machine learning methods with Quantum Machine Learning (QML) algorithms. The system is able to analyze complex clinical data effectively and with high accuracy by focusing on key diseases like breast cancer, diabetes, heart disease, liver disease, and kidney disease. The use of quantum-enhanced models allows to better represent the features and calculate in less time, overcoming the limitations of conventional diagnostic methods.

The experimental findings indicate that the proposed system is more accurate, precise, recalls more, and performs better than traditional machine learning models. Prediction reliability is greatly improved with the capability to model nonlinear relationships of high-dimensional medical data using quantum algorithms. Moreover, the system has high generalization capacity hence can be used in real world healthcare application. Its scalable architecture and integration with an easy-to-use interface further justify its use in clinical settings as well as remote healthcare solutions.

Altogether, the suggested solution is a reliable, efficient and non-invasive tool of predicting chronic disease which will lead to better patient outcomes and timely medical help. The combination of quantum computing and healthcare analytics demonstrates that quantum computing is a promising field of future research and development. As quantum hardware continues to improve and more real-world data sets become available, more diseases and real time monitoring can be added to the system and ultimately the intelligent healthcare systems will be transformed.

B. Acknowledgment

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