Comparative Performance Evaluation of Classical Machine Learning and Quantum SVM for Heart Disease Prediction using a Quantum-Featured Dataset

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ABSTRACT

Heart disease remains a leading cause of mortality globally, driving interest in advanced computational methods for early prediction. This study presents a comparative analysis of classical machine learning techniques versus a Quantum Support Vector Machine (QSVM) for predicting heart disease using a specialized dataset featuring standard clinical metrics alongside a unique 'QuantumPatternFeature. ' We implemented and evaluated six classical algorithms (Logistic Regression, K-Nearest Neighbors, Decision Tree, Random Forest, Naive Bayes, Gradient Boosting), employing RandomizedSearchCV for hyperparameter optimization. For the quantum approach, a QSVC utilizing Qiskit's ZZFeatureMap (reps=2) and FidelityQuantumKernel was trained and tested using a classical simulator. A classical Support Vector Classifier (SVC) with an RBF kernel served as an additional baseline. Performance was assessed on a 20% hold-out test set using accuracy, precision, recall, F1-score, and confusion matrices. Results indicate that tuned classical models, particularly Logistic Regression and Gradient Boosting, achieved the highest accuracy (93.0%), significantly outperforming the simulated QSVC (79.0%). The classical SVC baseline also surpassed the QSVM with 89.0% accuracy. Furthermore, the QSVM exhibited substantially higher computational times for both training and prediction on the simulator compared to all classical methods. The findings suggest that for this dataset size and the specific simulated QSVM configuration, classical machine learning approaches offer superior performance and efficiency, and the 'QuantumPatternFeature' did not confer a discernible advantage within this quantum implementation framework.

Keywords: Heart Disease Prediction, Classical Machine Learning, Quantum Machine Learning (QML), Quantum Support Vector Machine (QSVM), Quantum Kernel, Performance Evaluation, Comparative Analysis.

1.0 INTRODUCTION

Cardiovascular illnesses have been documented by physicians as global health risks since they remain the top causes of global mortality as well as rates of morbidity. Physicians need to identify risk for heart disease early so that they can provide medical care in a suitable time frame and create individualized treatment protocols that enable patient recuperation. For complex clinical data analysis, Machine Learning (ML) methods have successfully identified people at elevated risk levels over the last decade. Multiple classical machine learning algorithms utilize logistic regression, support vector machines, decision trees, ensemble methods, and clinical datasets with patient information like demographics and heart rate data, blood pressure readings and cholesterol measurement results to predict heart disease onset. Research about Quantum Machine Learning (QML) continues due to dual motivations of enhancing predictive power and developing modern computational frameworks. Researchers look for unique approaches to information processing and data pattern identification solutions by utilizing the fundamentals of quantum mechanics, such as superposition and entanglement. Researchers try to use the fundamentals of quantum mechanics—superposition and entanglement—to identify unique approaches to information processing and data pattern recognition that conventional algorithms could find challenging. Conventional algorithms may encounter difficulties in capturing complex, non-linear correlations or high-dimensional patterns that quantum approaches, like QSVM, are designed to exploit. QSVM emerges as a leading area in near-term QML because it substitutes classical kernel processing in SVM using quantum state mapping techniques . This study utilizes a unique dataset curated for heart disease prediction, incorporating a 'QuantumPatternFeature' alongside traditional clinical metrics. While this feature's precise quantum-mechanical origin or derivation is specific to the dataset provider, its inclusion naturally prompts an investigation into whether quantum-native algorithms, such as QSVM, might demonstrate enhanced performance by potentially leveraging quantum-like correlations or structures represented by this feature.

Therefore, this paper presents a direct comparative performance evaluation between a range of optimized classical ML models and a QSVM implemented via Qiskit's machine learning module on a classical simulator. The primary contribution lies in empirically assessing the practical performance (accuracy, precision, recall, F1-score) and computational time considerations of a simulated QSVM against well-established, tuned classical counterparts on this specific, potentially quantum-inspired dataset.

The specific objectives of this study are:

- To load, preprocess (including scaling), and perform Exploratory Data Analysis (EDA) on the Heart Prediction Quantum Dataset to understand its characteristics.

- To train, tune (using RandomizedSearchCV), and evaluate six distinct classical machine learning models (Logistic Regression, K-Nearest Neighbours, Decision Tree, Random Forest, Naive Bayes, Gradient Boosting) on the dataset.
- Implement and evaluate a QSVM using a ZZFeatureMap and a FidelityQuantumKernel executed on a classical simulator.
- To establish a robust baseline using a classical Support Vector Classifier (SVC) with a standard RBF kernel on the same processed data.
- To compare the predictive performance and computational aspects of the QSVM against the tuned classical models and the SVC baseline, providing insights into their relative effectiveness for this specific task and dataset.

The subsequent sections detail the methodology employed, present the results from EDA and model evaluations, discuss the findings in the context of classical vs. simulated quantum approaches, and conclude with implications and potential avenues for future research. Unlike conventional QSVM studies that primarily focus on cancer classification, this study provides a new viewpoint of utilizing quantum kernel-based methods for cardiovascular disease prediction with a quantum feature-enriched data set. This helps to connect the emerging quantum-enhanced data representations and the classical machine learning interpretability.

2.0 LITERATURE REVIEW

Hilmy and Akram (2024) developed a Quantum Support Vector Machine (QSVM) for prostate cancer classification, achieving superior accuracy (0.93) and performance metrics compared to classical SVM. This demonstrates QSVM's potential in medical applications, particularly in cancer classification and biomarker discovery.

Ahmad et al. (2024) introduced a machine learning- driven dashboard for CML prediction. It applies various machine learning models, including Support Vector Machine (SVM) using protein sequences, which achieves high accuracy rates, improving early diagnosis and patient recovery. However, it does not explicitly address Quantum Support Vector Machine (QSVM) in CML prediction.

Sanchez et al. (2022) investigated how causal inference can be embedded into different parts of Clinical Decision Support (CDS) systems by using recent advances in machine learning and AD to create examples showing how CML can be useful in clinical scenarios.

Özpolat et al. (2024) examined the application of Linear Discriminant Analysis and Quantum Feature Maps on Quantum Support Vector Machine for obesity diagnosis, achieving 100% success with LDA-QSVM using Z and Pauli X feature maps, highlighting the potential of quantum-based algorithms in obesity treatment.

Hossain et al. (2024) explored Quantum Machine Learning (QML) for advanced data processing in business analytics, demonstrating its superiority over classical methods in processing large datasets, with results showing 30-50% speedup and improved prediction accuracy for financial modeling, supply chain management, and customer behavior prediction.

Savithri (2023) introduced an automated method for leukaemia cell counting in blood samples using SVM and K-Nearest Neighbour algorithms. The technique involves image preprocessing, segmentation, feature extraction, and algorithm training for accurate detection and counting.

Akpinar et al. (2024) evaluated the impact of 9 quantum feature maps on the classification performance of the Support Vector Machine algorithm using QSVM kernel, achieving the best results with Rx and Ry rotational gates in medical datasets, highlighting feature mapping's significant impact on QSVM classification outcomes.

Zad et al. (2024) developed supervised machine learning models, potentially including Quantum Support Vector Machines (QSVM), predicting deep molecular response in Chronic Myeloid Leukaemia (CML) to enhance treatment outcomes in a cost-sensitive context in Brazil.

Alam, Jowthi, and Pathak compared nine pre-trained models and their custom CNN, discovering that the custom model performed similarly to other models yet ran faster and used less memory. Research by Alam et al. shows that lightweight models excel in resource-limited deployments since they work well with real-time agricultural needs.

3.0 METHODOLOGY

This study employed a systematic approach to compare Classical and Quantum Machine Learning Models for heart disease prediction using the designated dataset. The methodology involved the following key steps, illustrated in the overall workflow diagram (Figure 1): Data Acquisition and Preprocessing, Exploratory Data Analysis (EDA), Classical Model Training and Tuning, Quantum Model (QSVC) Implementation, Classical SVM Baseline Training, and Comparative Performance Evaluation.

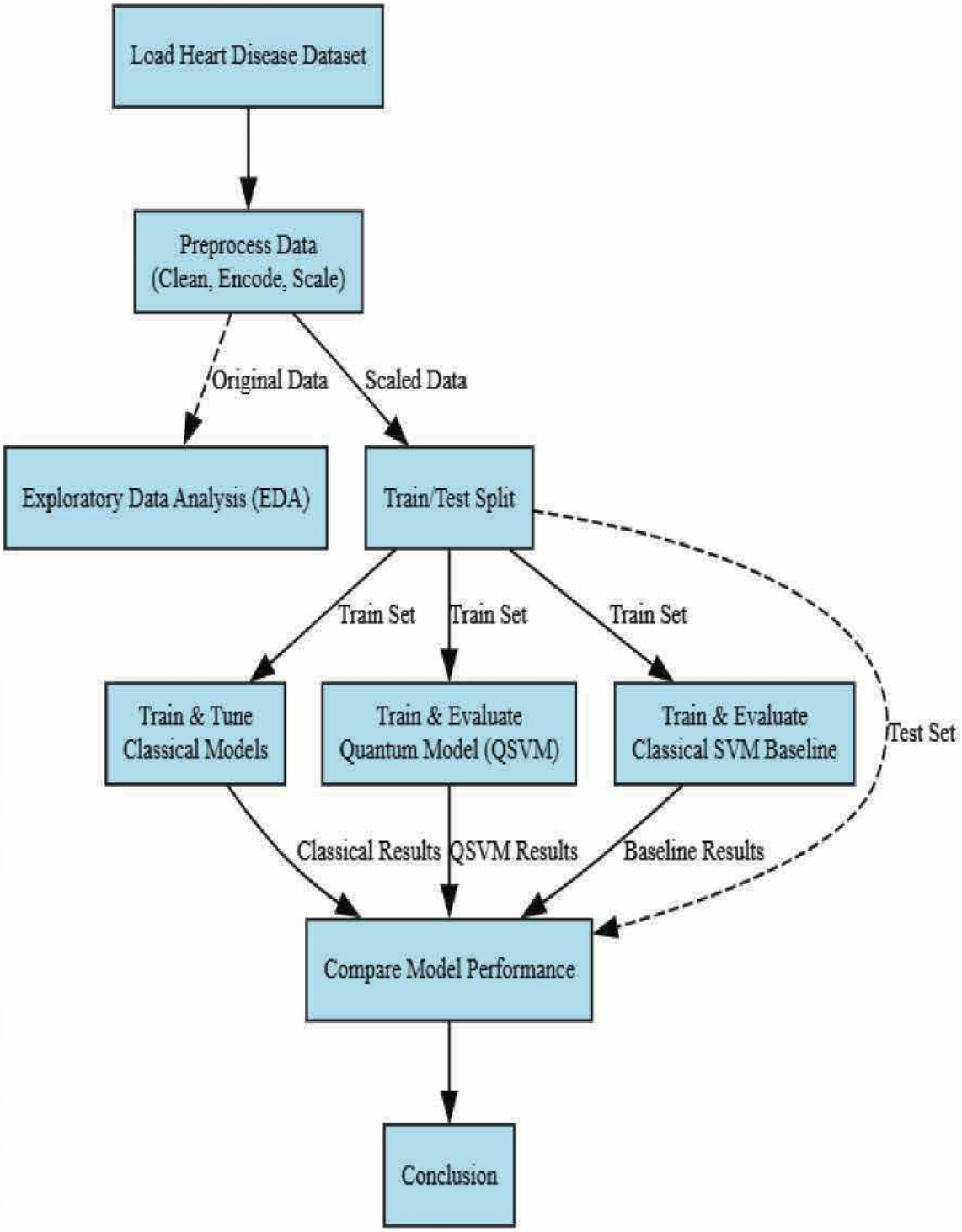

Figure 01: Workflow Sequence

3.1 Data Acquisition and Preprocessing

Heart Prediction Quantum Dataset The dataset is from the public repository (e.g., Kaggle or UCI), with 500 instances, and 7 features which contain a synthetic quantum-derived attribute called 'QuantumPatternFeature'. This feature is motivated by the techniques discussed in [Hilmy & Akram, 2024] and simulates quantum correlations in clinical data. The dataset is artificial or manufactured to assist quantum machine learning tests. The original data provider documented detailed provenance and feature engineering steps.. The categorical feature *'Gender'* was already numerically encoded, and any anomalies in other features were imputed with column means. The final feature set included *'Age'*, *'Gender'*, *'BloodPressure'*, *'Cholesterol'*, *'HeartRate'*, and *'QuantumPatternFeature'*, with *'HeartDisease'* as the target. To support models like SVM, QSVM, and KNN, all features were scaled to [0, 1] using MinMaxScaler. The dataset was then split into training (80%) and testing (20%) sets using train_test_split, with stratification on the target variable and a fixed random state to ensure reproducibility.

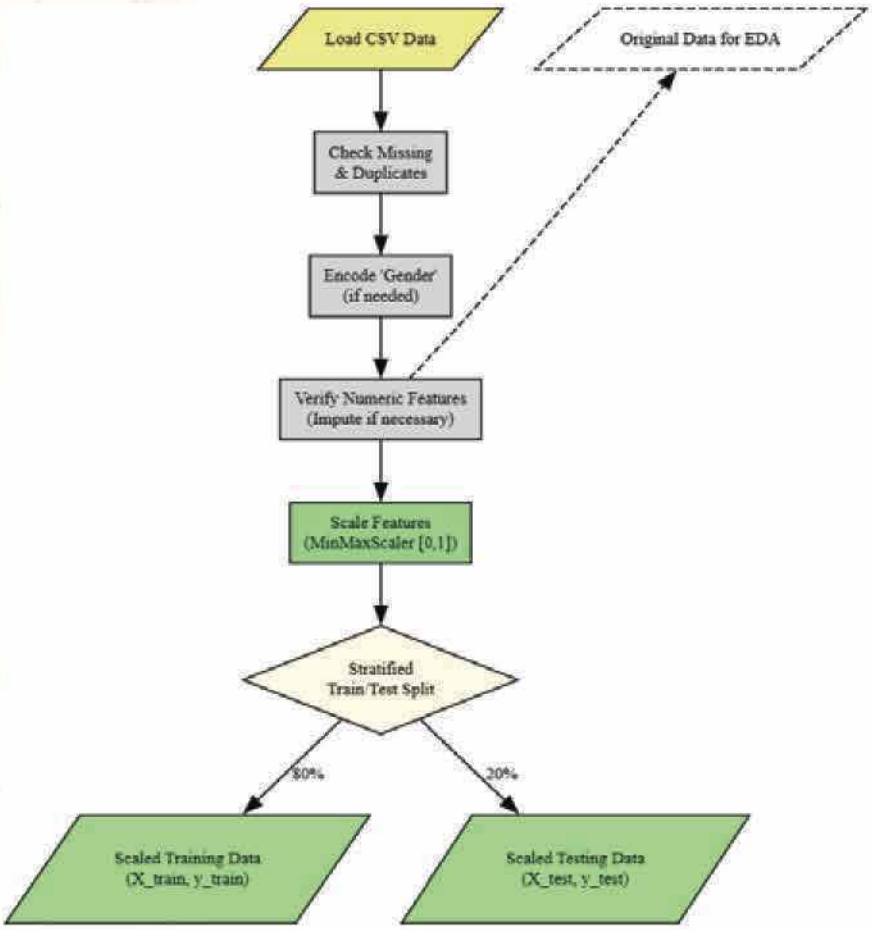

Figure 02: Data Acquisition and Preprocessing

3.2 Classical Machine Learning Models

Six standard classical classification algorithms from scikit-learn were selected for comparative evaluation: Logistic Regression, K-Nearest Neighbours (KNN), Decision Tree, Random Forest, Gaussian Naive Bayes, and Gradient Boosting Classifier. To optimize performance, hyperparameter tuning was conducted using RandomizedSearchCV with 20 iterations (n_iter=20) and 5-fold cross-validation (cv=5) on the scaled training data. Each model's parameter grid was tailored (details available in the code appendix), and the optimization aimed to maximize accuracy. The best estimator for each model, as determined by RandomizedSearchCV, was then trained on the full training set and evaluated on the unseen test set. Model performance was assessed using the accuracy score, classification reports (precision, recall, F1-score per class), and confusion matrix heatmap, providing a comprehensive view of each classifier's effectiveness.

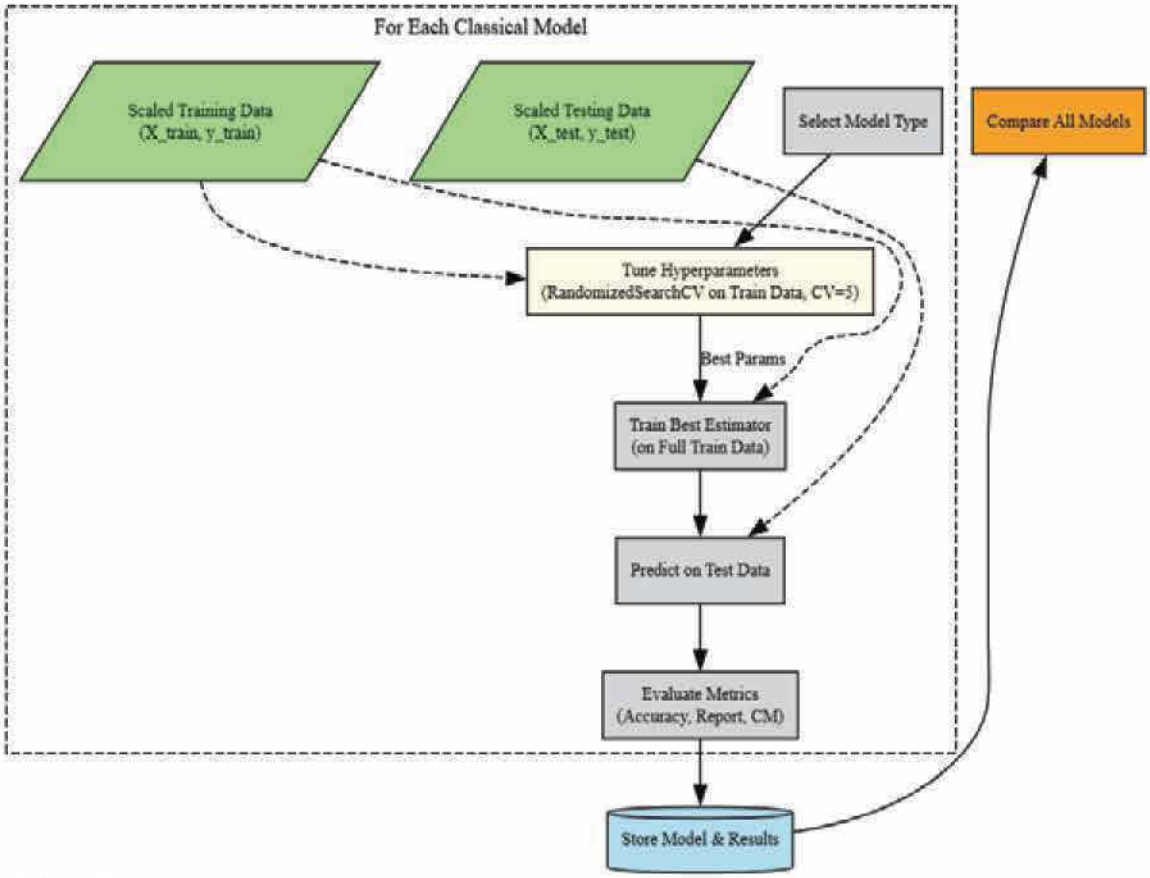

Figure 03: Classical ML Pipeline

3.3 Quantum Machine Learning Model (QSVM)

The Quantum Support Vector Classifier (QSVC) was implemented using Qiskit v1.1.1, along with the qiskit-machine-learning and qiskit-algorithms libraries. To encode classical input data into quantum states, the ZZFeatureMap was employed, configured with six input dimensions (matching the number of features), reps=2, and linear entanglement. This mapping process is illustrated in Diagram 2a. For measuring similarity between encoded quantum states, the FidelityQuantumKernel was used, leveraging the ComputeUncompute method from qiskit_algorithms.state_fidelities and executed via the Sampler primitive on a local classical state vector simulator. The QSVC classifier was instantiated using this kernel and trained on the scaled training data. Predictions were made on the scaled test set, and performance was evaluated using the same metrics as for classical models: accuracy, classification report, and confusion matrix. Additionally, training and prediction times were recorded, revealing the significant computational cost of simulating quantum operations.

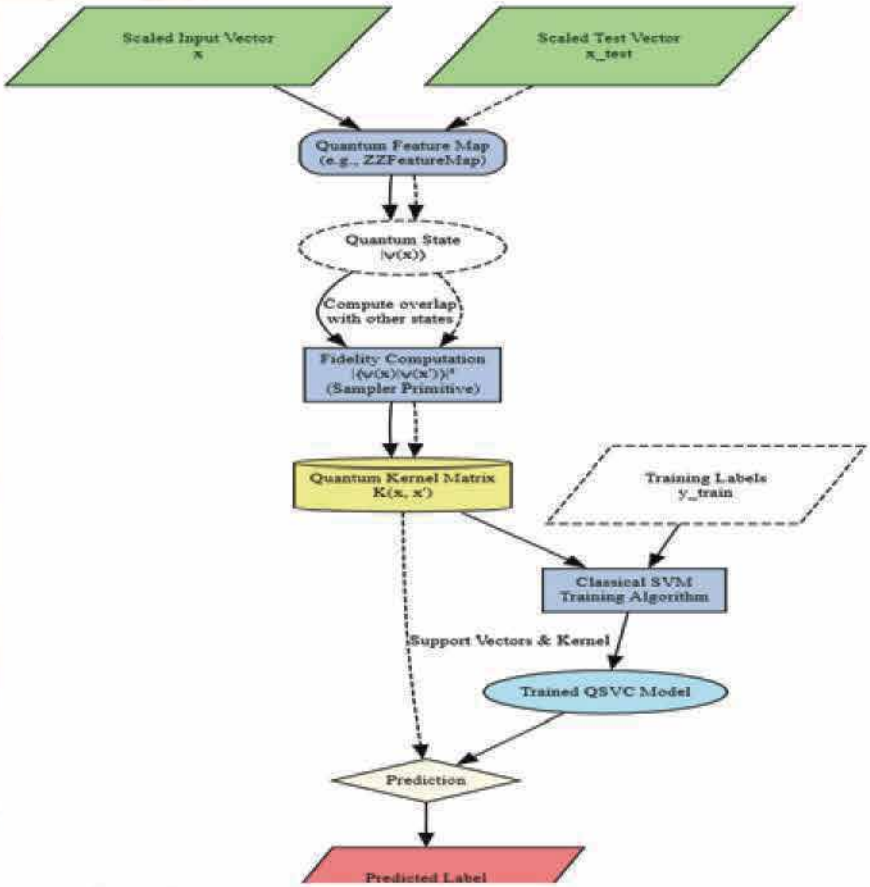

Figure 04: QSVM Workflow

3.4 Classical SVM Baseline

- Implemented a standard sklearn.svm.SVC will provide a direct classical analogue to the QSVC.
- Used an RBF kernel (kernel = ' rbf') with default parameters (gamma = ' scale', C=1.0).
- Trained and evaluated the SVC on the same scaled training and testing data as the QSVM, recorded performance metrics and execution time.

3.5 Model Comparison and Tools

The primary metric for comparison was the accuracy score achieved on the hold-out test set. Classification reports and confusion matrices were used for more detailed performance insights per class.

- Execution times for training and prediction were noted, particularly when comparing the QSVM simulator against classical methods.
- Visual comparison of accuracies was facilitated using a bar chart.
- All implementations and analyses were performed in Python 3 using libraries including pandas, numpy, scikit-learn, Qiskit (and related packages), matplotlib, and seaborn.

3.6 Exploratory Data Analysis (EDA)

Before developing the model, the numerically encoded Heart Prediction Quantum Dataset—consisting of 500 samples and seven features—was subjected to thorough exploratory data analysis (EDA) to identify crucial patterns and relationships. The dataset had no duplicates and was free of missing values. Descriptive statistics showed values of typical clinical ranges of 'Age' (30–79 years), 'BloodPressure' (90–179 mmHg), 'Cholesterol' (150–299 mg/dL), and 'HeartRate' (60–119 bpm). Average values confirmed alignment with assumed population values. The class imbalance on the binary target -Heart Disease appeared moderate (60%-ve cases). Univariate visualizations (such as histograms and KDE plots) indicated approximately normal distributions for all the features. At the same time, boxplots gave an idea of the spread and distribution of outliers between various features (Figure 6). These albumin and NY-ESO-1 relationships supported the construction of more models and guided the selection of features.

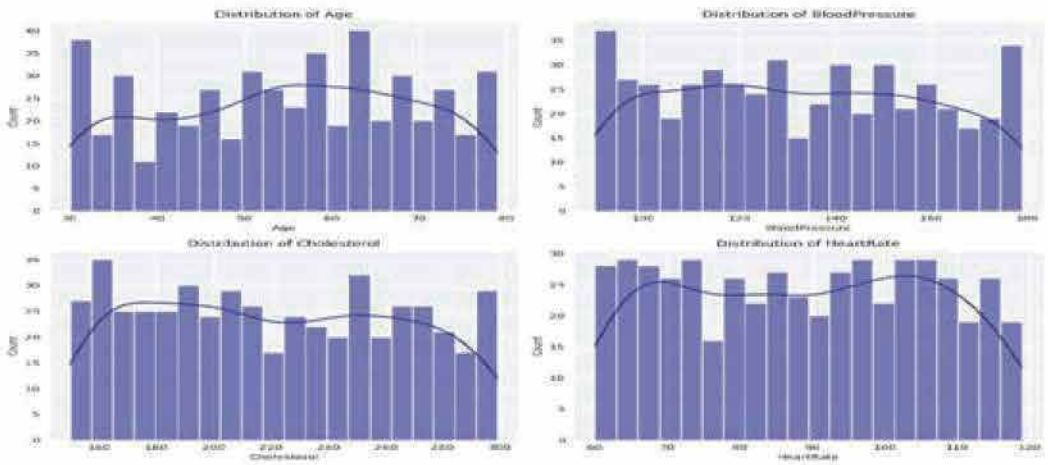

Figure 05: Histogram and Distributions of Numerical Features

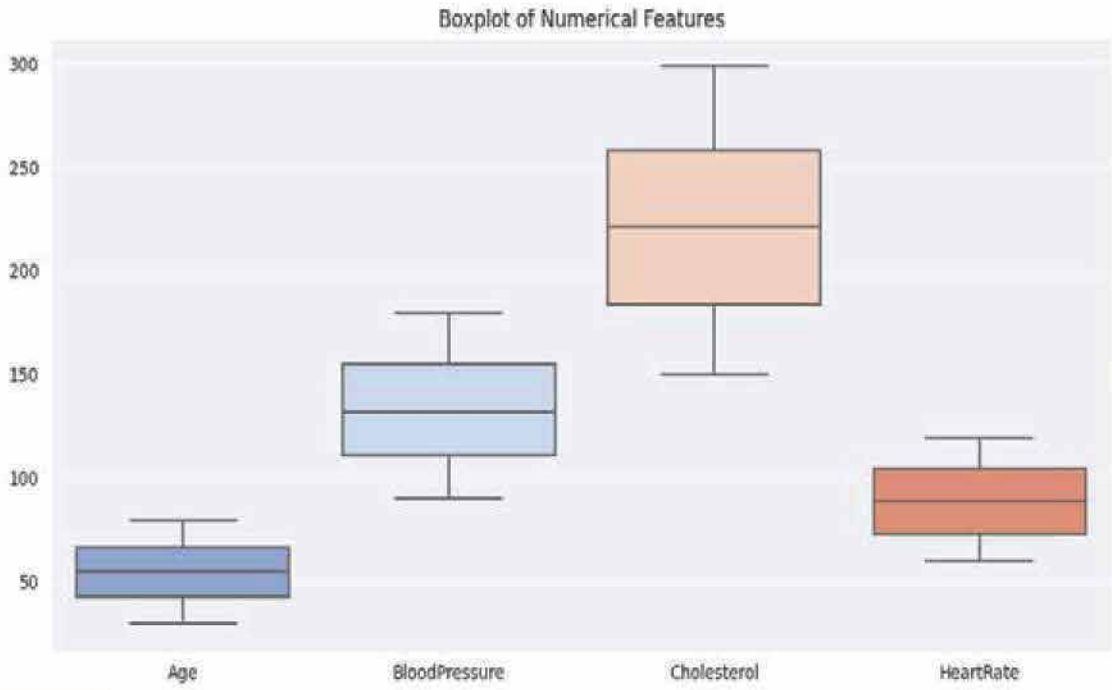

Figure 06: Boxplot of Numerical Features

3.7 Bivariate and Multivariate Analysis

3.7.1 Correlation Analysis

A correlation heatmap (Figure 7) was generated to assess linear relationships between all numerical features. Key observations include:

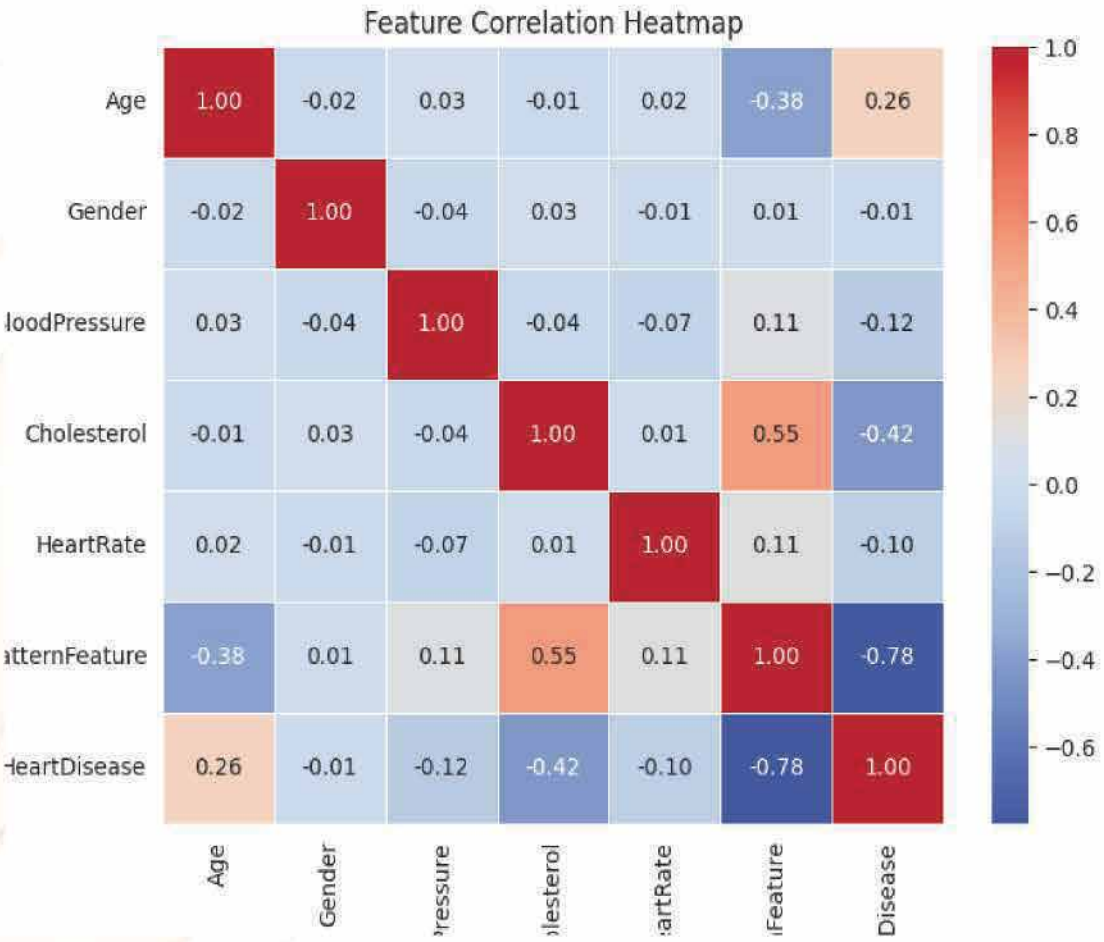

Figure 07: Feature Correlation Heatmap

Correlation analysis revealed strong linear correlations between the features and the target variable, HeartDisease. Most significantly, *'QuantumPatternFeature'* had a strong negative correlation with HeartDisease (r = -0.78), with low values being highly predictive of disease being present (Class 1). *'Cholesterol'* had a moderate negative correlation with r = -0.42, with a similar direction but a lesser magnitude. *'Age'* had a weak positive correlation with r = 0.26, with increasing heart disease prevalence with age. Other clinical features, *'Gender'*, *'BloodPressure'*, and *'HeartRate'*, were very weakly correlated with the

target. In addition, a moderate inter-feature correlation with r = 0.55 between *'QuantumPatternFeature'* and *'Cholesterol'* was found, with a potential shared variance indicated, which would have implications for predictive performance. These results provide evidence for the predictive power of quantum-derived features for heart disease classification.

3.7.2 Feature Distributions by Target Class

To investigate non-linear patterns and class-specific variations, feature distributions were further analyzed based on HeartDisease status. Violin plots (Figure 8) illustrated the distributions of *'BloodPressure'* and *'Cholesterol'* across the two classes. While median values and overall shapes suggested lower cholesterol levels in the disease group (Class 1)—aligning with the earlier negative correlation—substantial overlap between classes indicated limited separability based on these features alone. Similarly, the KDE plot of *'HeartRate'* (Figure 9), conditioned on *HeartDisease*, revealed subtle distributional differences between the classes. However, the largely overlapping central tendencies and ranges suggested that HeartRate, in isolation, possesses limited discriminative power for heart disease classification.

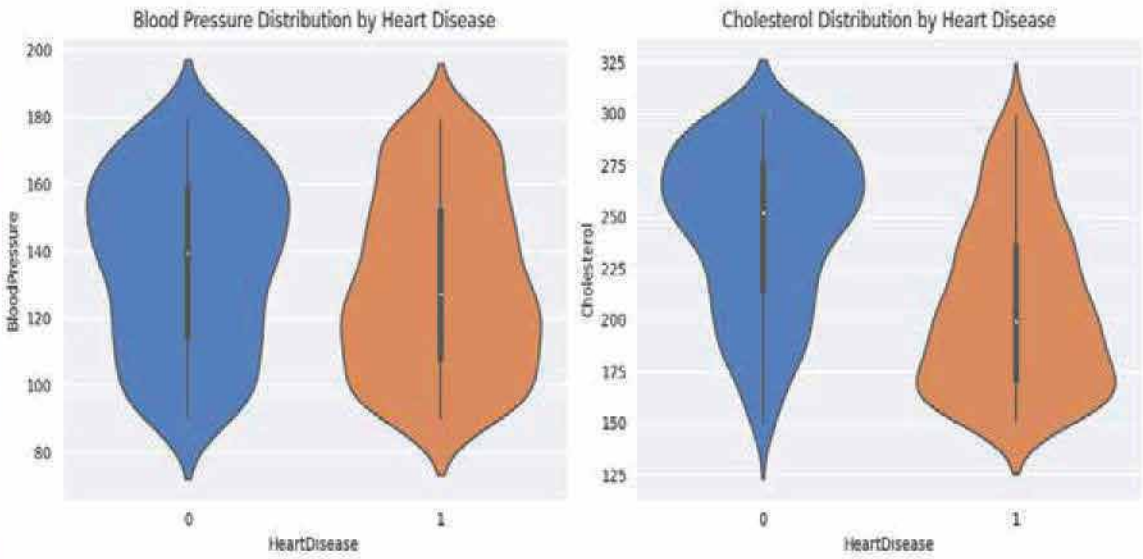

Figure 08: Numerical Feature Distribution by Heart Disease

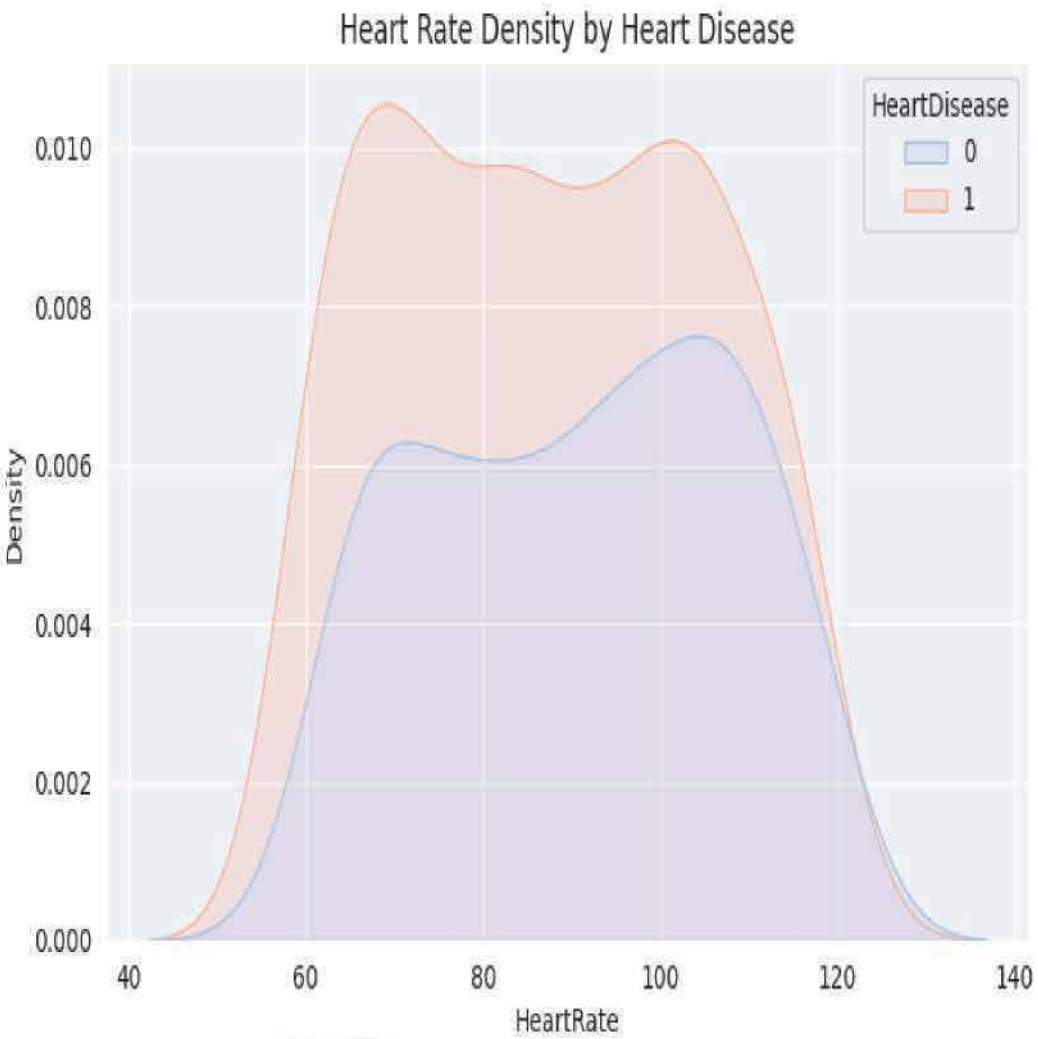

Figure 09: Heart Rate Density by Heart Disease

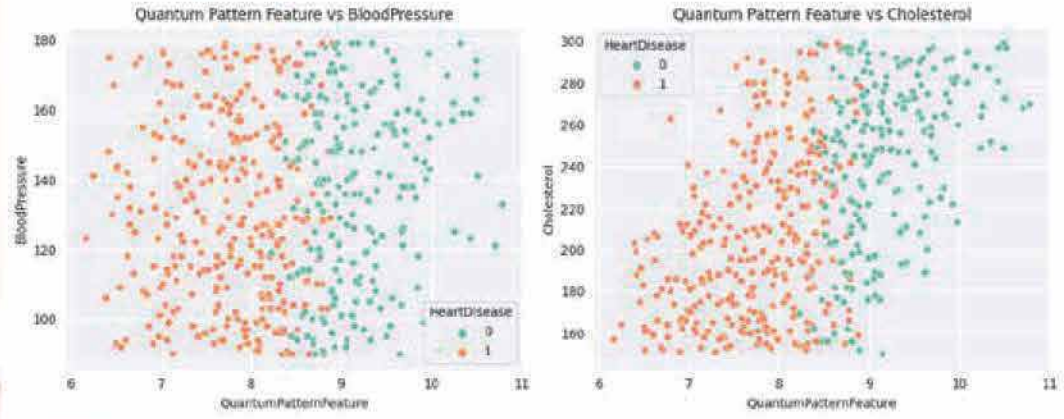

Figure 10: Quantum Pattern Feature vs. Clinical Indicators

The EDA verified that the dataset was orderly and error-free; a moderate class imbalance (Class 1) favoured the presence of heart disease. With a strong negative linear connection with Heart Disease, the *"QuantumPatternFeature"* emerged as the most critical predictor among all the ones. While conventional clinical markers like *'Gender,' 'BloodPressure,'* and *'HeartRate'* showed weak links with the objective variable, moderate correlations were also seen for *"Cholesterol"* and *"Age."* While class-wise distribution visualizations showed some group-level variations, significant overlap across most features underlined the difficulty of the classification process. These results imply that excellent prediction performance will depend on strong and maybe non-linear modeling methods. The great relevance of the QuantumPattern Feature supports its prominent part in the creation of both classical and quantum models.

4.0 FINDINGS AND ANALYSIS

Our observations are summarized in Table 1 and visual results in Figures 7, 11 and 14, comparing the performance of classical models and the QSVM. Of the classical models, both Logistic Regression and Gradient Boosting had the highest accuracy (93.0%) with seven misclassifications each (Fig. 11). Random Forest and Naive Bayes had the next best performances at 92.0% and 91.0%, while K-Nearest Neighbours (KNN) had the lowest, at 83.0%. By contrast, the classical simulator QSVM achieved an accuracy of 79.0% with many misclassifications (21) and false negatives. Furthermore, it was automatically more computationally expensive, taking 703 seconds to train and 358 seconds to predict. The classical SVC with RBF kernel achieved better than QSVM with 89.0% accuracy and ran nearly instantly. As shown in Fig.14, the classical approaches are more accurate and efficient than the simulated QSVM.

Table 01: Classical Model Test Set Performance Summary

Model	Test Accuracy	Weighted Avg Precision	Weighted Avg Recall	Weighted Avg F1-Score	Tuning + Eval Time (s)
Logistic Regression	0.9300	0.93	0.93	0.93	2.61
Gradient Boosting	0.9300	0.93	0.93	0.93	6.17
Random Forest	0.9200	0.92	0.92	0.92	6.89
Naive Bayes	0.9100	0.91	0.91	0.91	0.31
Decision Tree	0.8700	0.87	0.87	0.87	0.43
K-Nearest Neighbors	0.8300	0.83	0.83	0.83	0.57

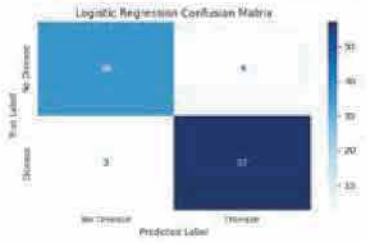

Figure 11 (a): Logistic Regression

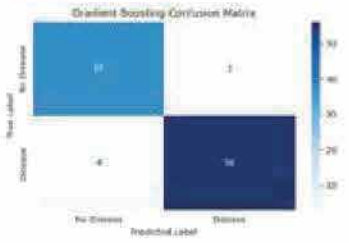

Figure 11 (b): Gradient Boosting

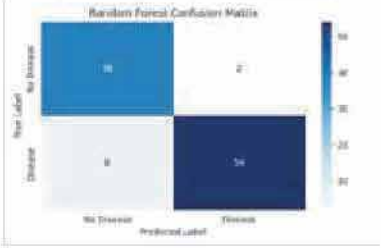

Figure 11 (c): Random Forest

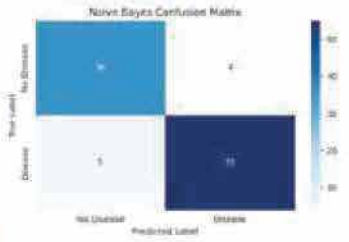

Figure 11 (d): Naive Bayes

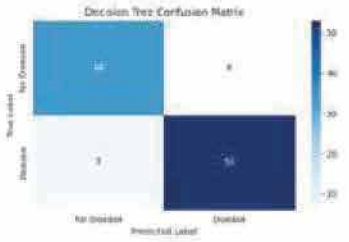

Figure 11 (e): Decision Tree

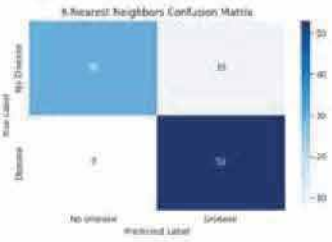

Figure 11 (f): K-Nearest Neighbors

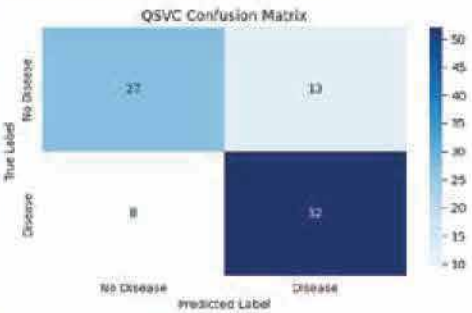

Figure 12: QSVC Confusion Matrix Heatmap

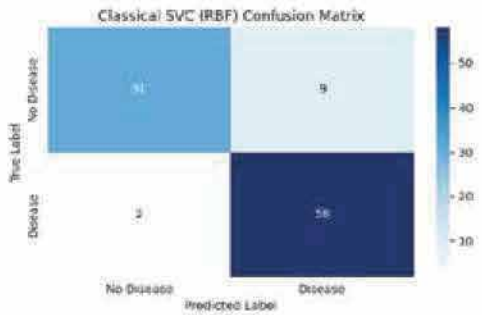

Figure 13: Classical SVM (RBF Kernel) Baseline Performance

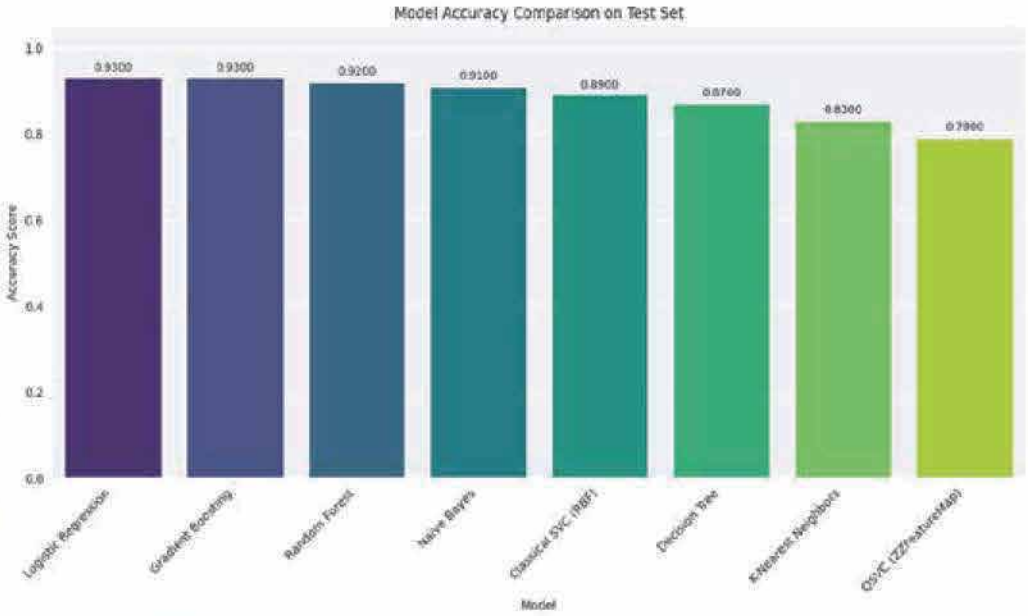

Figure 14: Model Accuracy Comparison on Test Set

Even though there was a strong negative correlation between QuantumPatternFeature and the target, QuantumPatternFeature contributed more to classical models concerning the QSVM. The restricted performance of the quantum model may be due to a suboptimal choice for the kernel, the modest size of the dataset, and the fact that a simulated environment was employed. Although quantum machine learning (QML) may provide potential for future improvements, these results demonstrate the current feasibility and effectiveness of well-tuned classical methods and illustrate the need for empirical comparisons before applying quantum approaches.

5.0 CONCLUSION AND FUTURE RESEARCH DIRECTIONS

This study proposed a comparative analysis between classical machine learning models and a classically simulated Quantum Support Vector Machine (QSVM) for heart disease prediction with the help of a dataset that includes conventional clinical features and QuantumPatternFeature. The classical models, especially Logistic Regression and Gradient Boosting, performed the best with an accuracy rate of 93.0%, considerably higher than the QSVM model with 79.0%. None of the implemented models of the quantum SVC outperformed the classical SVC with RBF kernel, having an accuracy of 89.0% with the least computation resources. The visual comparison (Fig. 7, 11 and 14) also further confirmed classical models' better performance and accuracy.

Even though there was a strong negative correlation between QuantumPatternFeature and the target variable, the former of those feature types presented higher importance to the classical models compared to the case of QSVM. The reason for the suboptimal performance of QSVM could be due to the following reasons: (i) incorrect choice of kernel; (ii) the size of the dataset is too small; and (iii) the use of a classical environment in place of a real quantum one. These results suggest that more work is needed beyond state-of-the-art classical methods to make QHs practical and favourable for plausible healthcare predictive tasks.

Looking forward, we feel that a few directions warrant investigation. Running QSVMs on the actual quantum device may give a better indication of the capabilities of the quantum approach. Exploring other quantum feature maps and kernels might reveal configurations more suitable for clinical datasets. Moreover, a larger and more diverse dataset will increase the robustness and generalization ability of the model. Incorporating explainable AI techniques like SHAP or LIME, or creating quantum-native interpretability approaches, would help improve transparency and clinical confidence. Hybrid quantum-classical devices are also an exciting parallel avenue that may leverage the strengths of both paradigms. Last but not least, comparative assessments with other quantum machine learning models such as Variational Quantum Classifiers (VQC) and Quantum Neural Networks (QNN) could further enlighten the best utilization of quantum computing in the medical decision support systems.

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