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# Comparative Evaluation Of Classical And Quantum Machine Learning Models For Breast Cancer Diagnosis And Sustainable Healthcare

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***Abstract:***

*Breast cancer is rated as one of the top leading diagnosed and deadliest cancers affecting women worldwide and causing high mortality rate among cancers. With the data-driven applications, hybrid quantum-classical machine learning models have evolved as significant alternatives for handling complex feature spaces with the growing interest in quantum computing. This paper presents a systematic comparative study of classical and quantum machine learning approaches for breast cancer classification using the Wisconsin Breast Cancer Dataset.*

*In this architecture we have preprocessed classical feature vectors using standard normalized techniques and parallelly quantum states are mapped through data embedding techniques which relies on parameterized rotational gates. In this work we have implemented all quantum models using the Pennylane library, resulting in hybrid quantum–classical optimization on near-term quantum simulators.*

*The comparison results in multiple classical and quantum models. In classical we have Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and Convolutional Neural Networks (CNN), which are compared with the quantum-based models such as the Variational Quantum Classifier (VQC), Quantum Support Vector Machine (QSVM) and Quantum Convolutional Neural Network (QCNN). In QSVM, we have performed dimensionality reduction using Principal Component Analysis (PCA) before to quantum embedding, and quantum-generated features are used to train a classical linear SVM. The evaluation metrics results in accuracy, precision, recall, F1-score, ROC curves and confusion matrices.*

*The classical models achieves the accuracy in the range of 94%-96%, whereas competitive performance of quantum models demonstrate depending on the embedding strategy and circuit configuration. In the implemented quantum models, the variational quantum classifier achieved the highest classification accuracy of 96.06%, surpassing other evaluated models. These results demonstrate quantum embedding combined with variational quantum circuits can effectively capture discriminative patterns in medical datasets, indicating the implementation of quantum machine learning models for breast cancer diagnosis with the present quantum simulating platforms.*

***Keywords:*** *Machine Learning, Variational Quantum Classifier, Sustainable Health Care, Quantum Machine Learning, Quantum Embedding*.

## 1. INTRODUCTION

Breast cancer is among the most commonly diagnosed and deadliest cancers affecting women worldwide, with an incidence rate of one in every eight women, leading to the highest mortality rate among cancers [1]. As per the project records in 2022, 2.3 million women suffered from the breast cancer and out of which, 6,70,000 mortalities are reported. This hipe in the score is increasing based on the new developments of human civilization. To support, the statement, it is observed that countries with high Human Development Index (HDI), for every 12 women atleast 01 is suffering from breast cancer and the mortality rate is also reported high in these countries. Whereas, countries with low HDI, this recording is slight low, but still alarming because of low reporting of diagnosis. Breast cells, usually in the ducts or lobules of the breast, are where this cancer matures. Early signs in affected individuals may include edema, skin irritation, breast lumps, and retractions of the nipples, redness, lymph node alterations, and more.

Further, there have been steady improvements in the last few decades in the development of reliable methods that are highly effective in both diagnosing and treating this type of cancer. Moreover, studying the potential uses of quantum computing-based methods has gained attention in recent years [2].
Its application include in the fields of healthcare, financial risk analysis, Optimization, and many real world problems. In the recent era Quantum computers have gained significant importance. Nevertheless, they still face challenges such as noise, hardware deficiency and decoherence [1].
Classical machines basically uses bi-state representing as '0' and '1' or 'YES' or 'NO' [3]. Whereas, quantum computing uses a qubit or quantum bit, which is represented by the basis state |0> and |1>, not only exists in a single state but multiple states simultaneously, hence enabling parallel computations. Furthermore, quantum computers (QC) have enormous power to handle and manipulate several quantum states at once because of the concepts of superposition and entanglement. The idea of QC began in the year 1981 by Richard Feynman. Recently, the authors Donovan et al. developed quantum kernel-assisted support vector machines (QSVM)s and quantum convolutional neural networks (QCNN)s methods for the application of binary classification of pulsars [4]. When working with high-dimensional and complicated datasets, quantum machine learning (QML) is said to conduct computations more efficiently than conventional methods since it applies quantum mechanics to the process [5]. In fields like machine learning, encryption, chemistry, and other fields where computational problems are traditionally unsolvable, quantum computing is showing promise as a paradigm [1]. New approaches with regards to pattern identification and data classifications are made feasable by algorithms such as QSVM, QCNN, and Variational Quantum Classifier (VQC).
Quantum computing back up theoretical possibilities, finding practical applications beyond proven examples have been a challenge. It is a complex task to design an effective quantum algorithm, then expect to surpass classical algorithms in speed and complexity. Therefore, the latest enhancements advocate machine learning as a capable area for quantum computing applications, primarily in multivariate optimization situations associated with quantum strengthening and adiabatic quantum computing [6]. Nevertheless, scalability remains a considerable impairment [7].
The research paper work is organized as follows. Section 1 entails introduction to the topic and offers related background information. Section 2 summarizes related research, outlining prior work related to this domain. Section 3 presents the implemented work. Section 4 analyses and concludes the experimental findings. Finally, Section 5 concludes the study by discussing our results and suggesting avenues for future research.

## 2. RELATED WORK

In breast cancer screening, QSVM has shown promised results. According to the study by Shan et al. [1], the QSVM surpasses classical SVM in terms of classification accuracy; the QSVM reaches 100% accuracy in classification, whereas latter ones only reach 95%. The authors Shubham Vashisth et al. [2] enhanced breast cancer diagnosis efficiency and accuracy with the use of quantum SVMs. SVM approaches and quantum computing concepts have been integrated to develop QSVMs, which have demonstrated greater performance in identifying benign and malignant tumors. Using Wisconsin data sets related to breast cancer to actually illustrate the application of a QML model based on the QSVM technique to solve a classification issue. The results presented in this study demonstrate how quantum-driven machine learning might be able to handle many challenging problems with quantum rapidity. It was noticed that the QML problem solved on a local machine using the quantum simulator was 234 times faster than the solution for the classical version. That is 51.6% less than the classical SVM model run with kernel-based SVM model for breast cancer classification on a 14-qubit real-time superconducting processor. In contrast, accuracy resulted in a quantum model that was 5% less than the classical model [3].
Furthermore, the techniques, such as QSVM, CNN, SVM, and Logistic Regression, demonstrated accurately in classifying normal and cancerous binary classes, with accuracy ranging from 93% to 98.6%. These outcomes elucidate the possible of QML for improving diagnostic accuracy [8]. Based on astute studies done by Bisarya et al. [9] the breast cancer diagnosis has significantly accentuated or improved with the adoption of deep learning models such as CNNs and Quantum Neural Networks (QNN)s. Conversely, CNNs depicted accuracy rates of up to 99% in segmentation and classification applications. In addition, QNNs rated excellent accuracy levels of 96.67% and 100% in classifying instances of breast cancer, thus describing the potential of quantum computing in improving diagnostic capacities. The researchers Deshmukh et al. [10] have developed certain simulations pertain to hybrid models that could cluster, quite accurately, medical statistical information such as breast cancer images and knee MRI

records using classical and quantum computing techniques combined, using the quantum k-means algorithm. These models deliver understandability and transparency to medical specialists by using explainable artificial intelligence (XAI) techniques such as Local Interpretable Model-Agnostic Explanations (LIME), these techniques generate succinct explanations of the output from the predictions acquired through clustering algorithms. Further, it has been highlighted the research in [11] the predominant use of XAI models like LIME and SHAP enhances diagnostic accuracy, besides these diagnostic accuracy has demonstrated the potential benefits of integration approaches such as XAI in recognizing breast cancer. Quantum Neural Networks were also reviewed to establish their possible application in the classification of breast cancer, thereby returning accuracy rates of 96.67% and 100% at different magnification levels.

According to Vanda Azevedo et al. [12], a normal residual neural network with no Transfer learning (TL) resources achieved an accuracy of 67%; however, tests with TL resources produced an accuracy of 84%. When classical ResNet with and without the TL approach was evaluated, the task execution time was found to have been decreased by half. Further, the study in [13] discusses the Molecular Classification of Breast Cancer as Luminal-A, Luminal-B, Normal-like, HER2-enriched, and Basal-like with Breast Cancer Diagnostic Techniques. It opens a door for further optimization through quantum gates that offers an innovative approach for improving the breast cancer diagnosis. The authors Musaddiq Al et al. [14] worked on early breast cancer detection. Numerous postulate studies have described how leading-edge technologies like quantum neural networks and neural networks can augment the diagnostic process. By leveraging QNNs models in medical diagnosis, one can achieve significant advancements with absolute accuracy and efficiencies, resulting in better early detection of the disease and timely intervention for breast cancer patients. On the other hand, Aswiga R V et al. [15] established a QML pipeline with a Quantum Kernel Support Vector Machine (QKSVM) framework for diagnosing breast cancer from Digital Breast Tomosynthesis (DBT) images. The primary objective of the developed approach of DBT images are to categorize the highly complex breast cancer samples utilizing applicable feature extraction and dimensionality minimization techniques [16].

## 3. METHODOLOGY

This segment projects the techniques used for data collection and preprocessing. Further, it explains various classical and quantum-based machine learning models and their architectures, along with the evaluation metrics.

### 3.1. Data Collection and Preprocessing

The proposed approach used the Wisconsin Breast Cancer dataset [17]. The dataset contains features extracted from breast cancer biopsies, including texture, area, and smoothness, and consists of 569 instances. For model training and testing, the train test split ratio is 70-30%. Further, the data is preprocessed by normalizing the feature values and encoding the target labels as binary values (malignant and benign).

### 3.2. Classical Machine Learning Models

Numerous studies gives the implementation of breast cancer diagnosis and prediction using multiple computational methods. Computers can now learn from data and make predictions using Machine learning (ML) techniques, which replace traditional explicit programming with data-driven indirect programming that let computers improve actions or predictions based on data [18].

#### 3.2.1. SVM

A supervised learning algorithm largely known for labeling tasks [1]. Its objectives is to analyze hyperplane that exploits the brim between classes by leveraging a small subset of support vectors to construct a decision boundary for separating data into distinct categories. SVMs are adaptable for an extensive variety of applications which include text categorization of text, recognition of images, filtering of spam, handwriting recognition, gene expression analysis etc.

For the breast cancer dataset, the proposed approach standardized feature values using a standard scalar to ensure equal contribution of each feature. Fig.1 depicts the SVM base model with Dimensionality reduction with a PCA to hold the majority of the dataset's discrepancy. The SVM model was trained and evaluated utilizing the Receiver Operating Characteristic (ROC) curve in which area under the curve measures the discriminative power. Additional performance of metrics are computed to provide an inclusive estimation.

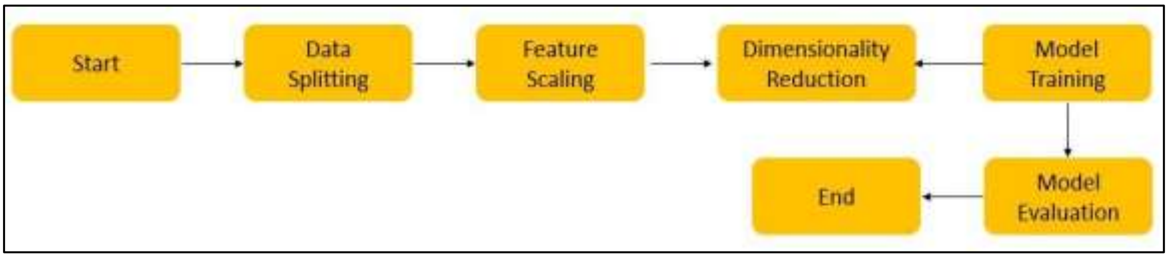


Figure.1 Workflow of SVM-based model

### 3.2.2. KNN

It is a simple and effective algorithm in ML. It is a nonparametric method that categorizes data points founded on their contiguity to the K adjacent neighbors [19] using distance metrics such as Euclidean distance. KNN is applicable to both numerical and categorical data and is less profound to outliers associated to other similar algorithms. Fig.2, depicts the KNN-based model.

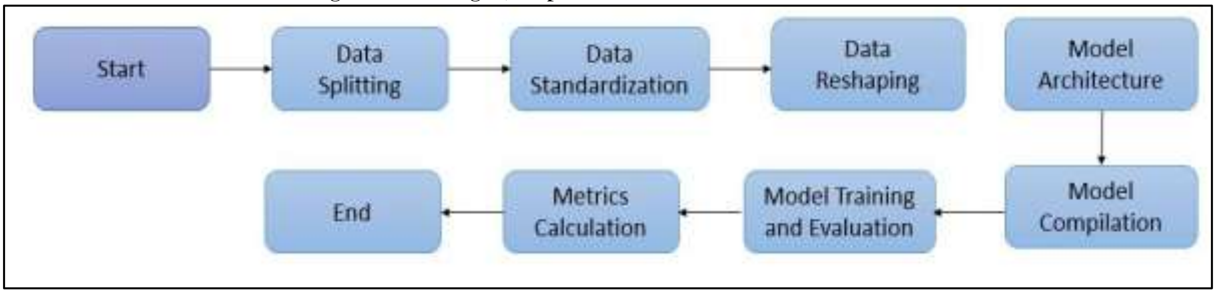


Figure. 2 Workflow of KNN-based model

### 3.2.3. CNN

CNNs are designed for grid-structured inputs with significant spatial connections in local regions, such as images. CNNs maintain spatial correlations through layers by applying convolutional filters, pooling, and activation functions like ReLU. The network's layers preserve the spatial hierarchy from one layer to the next, making CNNs particularly effective for image data [9].

The CNN-based model was a proposed approach to develop and evaluated for classifying binary using the breast cancer dataset. The model splits the dataset into testing and training sets for proper training.
The data was remodeled to fit the ID CNN input requirements. The CNN model consists of
Dense layers with ReLU and sigmoid activations. The Adam optimizer model used for training categorical cross-entropy as a loss function, with 20% validation data performed with 10 epochs. The model is depicted in Fig.3.

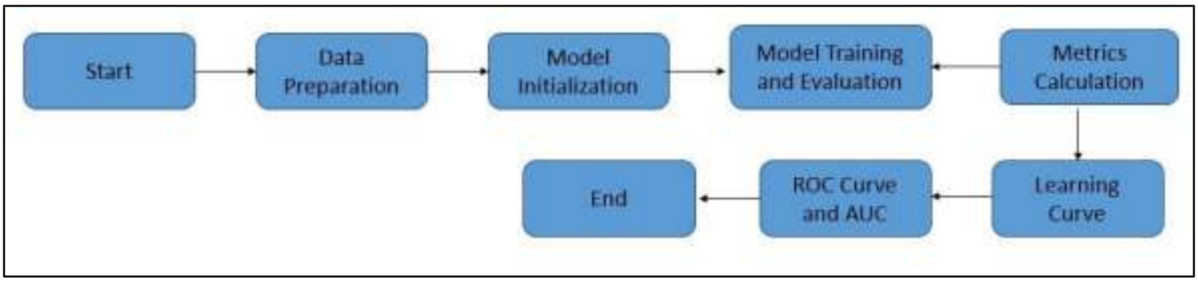


Figure. 3 Workflow of CNN-based model

### 3.3. Quantum Computing Foundations

The basic essentials of quantum computing is discussed here to explain the quantum models implemented in this framework.
In QC we store the information in the form of qubits also called as quantum bit and is represented as $|0>$ and $|1>$ which are the orthogonal basis state and can be mathematically expressed with $|\varphi>= a|0> +b|1>$ wherea, $b \in C, |a|^2 + |b|^2 = 1$ and the ket notation $|\varphi>$ denotes the quantum state in a two-dimensional Hilbert space $C^2$. The two- dimensional Hilbert space is also called as the complex vector space.

Quantum gates can be used to alter the system state. Consequently, a quantum circuit $(U)$ functions as $U = U_{m-1}U_{m-2} \ldots . U_2U_1$ with $|\psi' >=U| \psi >$. Notice that one needs to define a fixed initial state and a measurement step in a quantum circuit. The initial state preparation is often a key stage in designing quantum circuits. Using a quantum feature map $\mu$ we can map the classical input data $y \in IR^n$ into a Hilbert space $H$ during the state initialization. This is often referred to as quantum embedding and we can define it formally $\mu: y \rightarrow H$. There are many embedding techniques to convert the classical data into quantum state. The common embedding techniques used are angle embedding, amplitude embedding, tensor product embedding etc.
Using quantum gates quantum information can be processed. We have single qubit and multi qubit gates. Table 1. Explains the most commonly used quantum gates and their operation on qubits.

Table 1. Quantum gates and their operation on qubits

| Quantum Gate | Symbol | Matrix Notation | Quantum Operation |
|---|---|---|---|
| Pauli-X | X | $\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$ | Bit-flip |
| Pauli-Y | Y | $\begin{bmatrix} 0 & -i \\ i & 0 \end{bmatrix}$ | Bit-flip and Phase-flip |
| Pauli-Z | Z | $\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$ | Phase-flip |
| Hadamard | H | $\frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$ | Creates Superposition |
| R-X | RX | $\begin{bmatrix} \cos\left(\frac{\theta}{2}\right) & -i\sin\left(\frac{\theta}{2}\right) \\ -i\sin\left(\frac{\theta}{2}\right) & \cos\left(\frac{\theta}{2}\right) \end{bmatrix}$ | Rotates the qubit state of angle $\theta$ around $x-$ axis |
| R-Y | RY | $\begin{bmatrix} \cos\left(\frac{\theta}{2}\right) & -\sin\left(\frac{\theta}{2}\right) \\ \sin\left(\frac{\theta}{2}\right) & \cos\left(\frac{\theta}{2}\right) \end{bmatrix}$ | Rotates the qubit state of angle $\theta$ around $y-$ axis |
| R-Z | RZ | $\begin{bmatrix} e^{-i}\frac{\theta}{2} & 0 \\ 0 & e^{i}\frac{\theta}{2} \end{bmatrix}$ | Rotates the qubit state of angle $\theta$ around $z-$ axis |

In this work we have implemented rotational gates to change the quantum states. In quantum machine learning these gates represent nonlinear feature transformation operators. The implementation of QML models in this framework is because of their potential advantages comprising of superposition, Entanglement and affluent feature representations.

### 3.4. QML Models

QC leverages QML to handle complicated problems that are challenging for classical machine learning. With quantum features like superposition and entanglement, QML offers diverse benefits over outmoded approaches. The utilization will be productive to numerous domains, encompassing quantum clustering, pattern recognition, image classification, feature extraction, and data supervision.
In this study, the following QML models are implemented for breast cancer classification:

- QSVM
- VQC
- QCNN

Using angle encoding Classical input features are mapped to quantum states, where normalized feature values are encoded as qubit rotation angles prior to processing by parameterized quantum circuits.

#### 3.4.1. QSVM Model

It assimilates quantum computing practices to perform classification tasks. Unlike classical SVMs, QSVMs employ quantum kernels to accomplish classification without mapping data to high-dimensional spaces. In the proposed model, the Breast Cancer dataset is reduced via Principal Component Analysis (PCA) to accommodate the four qubits available on the quantum device. Using angle encoding, and a parameterized quantum circuit the reduced features are encoded into quantum states. Using a linear kernel the circuit outputs are subsequently fed to a classical SVM. The performance of the QSVM is evaluated using accuracy, precision, recall, and F1-score, highlighting its applicability for quantum-enhanced biomedical classification [17]. The process of the proposed QSVM-based model is depicted in Fig.4.

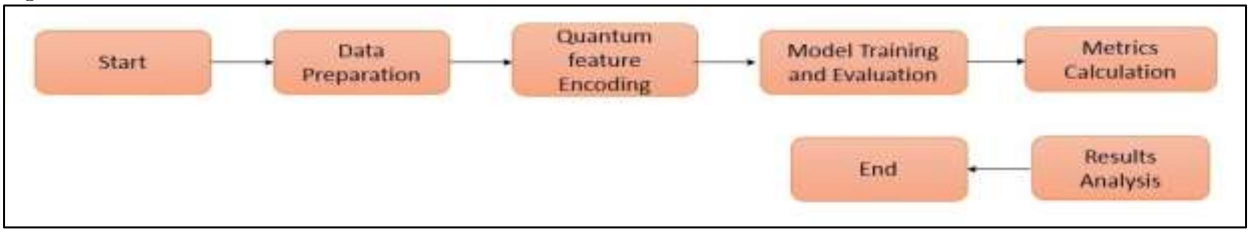


Figure. 4 Workflow of proposed QSVM-based model

### 3.4.2. VQC model

It is a semi-supervised QML technique personalized for noisy intermediate-scale quantum (NISQ) devices which helps in analyzing the outcomes without extensive error correction and parameter optimization on conventional processors. Analogous to traditional neural networks, they combine quantum circuits with standardized optimization to achieve approximate continuous functions [4].

The projected VQC-based model utilizes Breast Cancer dataset to categorize tumors. The developed four qubit quantum circuit with two variation layers encrypts the input data with the help of CNOT and rotational gates. It utilizes gradient descent and binary cross-entropy loss over mini-batches for 10 epochs. The accurate and high precision results on the test set depict the VQC capability to identify the patterns in their data set. The below figure represents the proposed VQC-based workflow..
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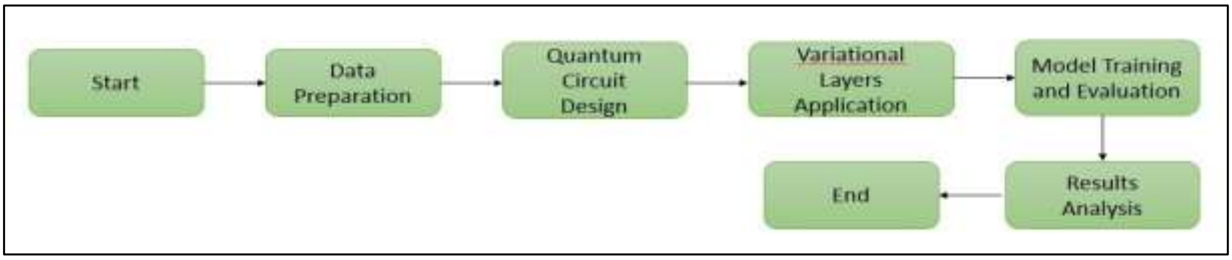


Figure. 5 Workflow of proposed VQC-based model architecture

### 3.4.3. QCNN Model

Quantum Convolutional Neural Networks (QCNNs) are the quantum analog of classical CNNs, where convolution and pooling operations are implemented via parameterized quantum circuits. The model designed on a four-qubit device and included rotation gates for feature encoding [1] [2]. The proposed model generates the training and test sets from the preprocessed Breast cancer dataset after standardization. Further, the QCNN model, trained for 50 epochs with a batch size of 32, achieved a test accuracy of 95.00%. The Fig.6 depicts the QCNN model....
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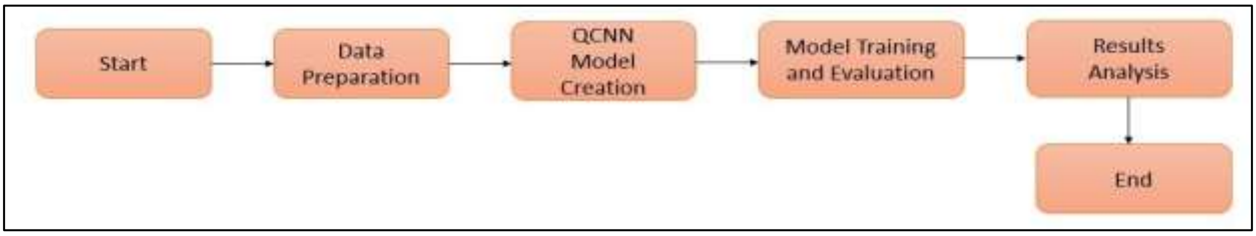


Figure. 6 Workflow of QCNN-based model

### 3.5. Model Evaluation Metrics

Although model assessment is vital for analyzing the performance of machine learning models, several metrics are frequently used to evaluate the efficiency of models, such as accuracy, precision, recall, F1-score, confusion matrix, and AUC-ROC curve [13].

• **Confusion Matrix:** It is a matrix with N x N dimension of target classes, which explains real and expected outputs. It relates the counts of actual versus predicted outputs. Table 2 depicts the confusion matrix. And the table project the following metrics:
TP: Accurate positive estimation
TN: Accurate negative estimation
FP: Inaccurate positive estimation (Type I Error)
FN: Inaccurate negative estimation (Type II Error)

Table 2. Confusion matrix structure

| | **Estimated Positive** | **Estimated Negative** |
|---|---|---|
| **Real Positive** | True Positive (TP) | False Negative (FN) |
| **Real Negative** | False Positive (FP) | True Negative (TN) |

• **Accuracy:** It is ratio of accurate estimates to the total number of estimates.
Accuracy = (TP + TN) / (TP + TN + FP + FN)
• **Precision:** It gives the accurate positives to the sum of accurate and inaccurate positives.
Precision = TP / (TP + FP)
It define the accuracy of positive estimates.
• **Recall:** It Measures the ratio of accurate positives to the sum of accurate and inaccurate negatives.
Recall = TP / (TP + FN)
Recall assesses the ability to correctly identify positive samples.
• **F1 Score:** It is defined as the harmonic mean of Precision and Recall and is calculated as
F1 Score = (2 × Precision × Recall) / (Precision + Recall)
• **AUC-ROC Curve:** It is called as Area under the Curve (AUC) of the Receiver Operating Characteristic (ROC) Curve. This metric assesses and plots across different thresholds:
• **True Positive Rate (TPR):** It specifies the rate of real positive values recognized. It is similar to the Recall.
• **False Positive Rate (FPR):** The ratio of inaccurate Positives to the sum of inaccurate Positives and accurate Negatives.

## 4. RESULTS AND ANALYSIS

In this segment we describe the experimental study of classical and quantum-based models like SVM, KNN, CNN, QSVM, QCNN, and VQC models using performance metrics like accuracy, precision, recall, and F1-score. All the evaluations are carried on the breast cancer dataset.

### 4.1. Classical ML Models

Table 3 summarizes the performance of classical machine learning models using accuracy, precision, recall, and F1-score. Further, in classical SVM for dimensionality reduction, PCA was applied. The PCA-reduced pair plot and ROC curve for SVM model are visualized in Fig. 7 and Fig. 8. Respectively. Furthermore, learning curve for KNN and ROC curve for KNN classifier are visualized in Fig. 9 and 10. Moreover, for CNN-based models, the training- validation accuracy, and training-validation loss are displayed in Fig. 11 and Fig. 12, respectively.

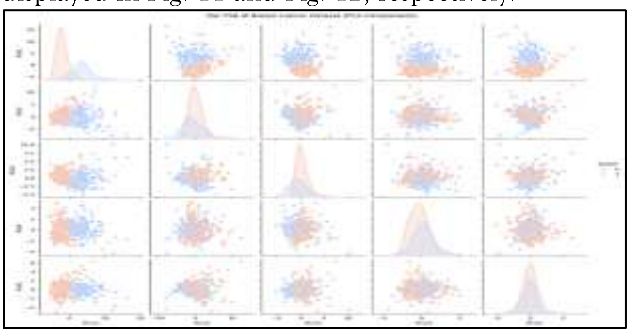

Figure. 7 Pair Plot of PCA-reduced Breast Cancer Dataset

Table 3. Comparison of classical machine learning models

| Model | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| SVM | 95.61% | 94.90% | 96.10% | 95.50% |
| KNN | 94.74% | 93.70% | 96.30% | 94.98% |
| CNN | 95.61% | 94.80% | 96.20% | 96.00% |

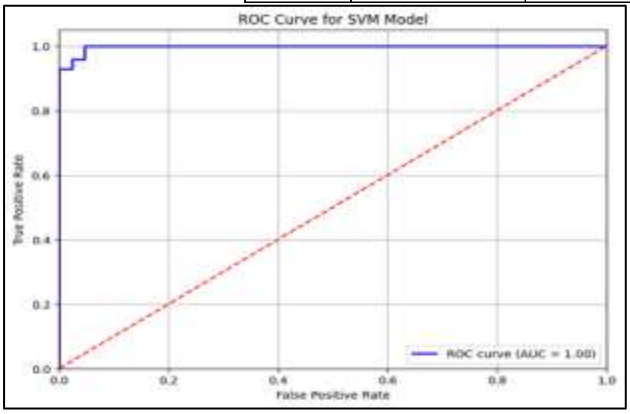


Figure. 8 ROC Curve for SVM Model

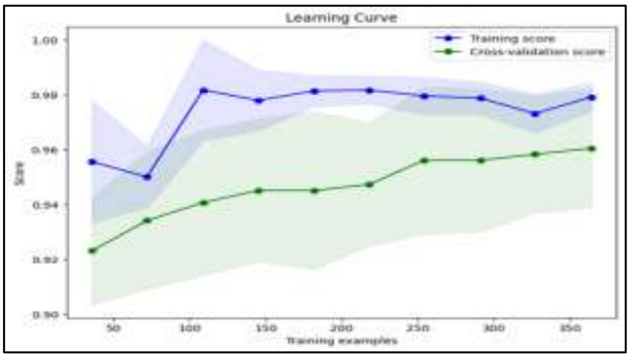


Figure. 9 Learning Curve for KNN

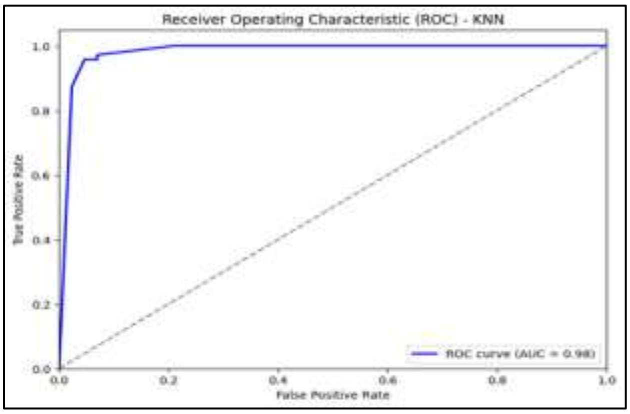


Figure. 10 ROC Curve for KNN

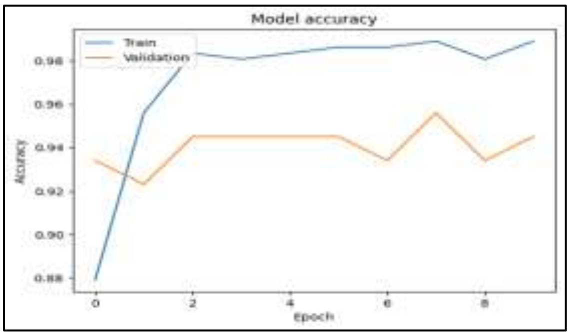


Figure. 11 Training and Validation Accuracy for CNN-based model

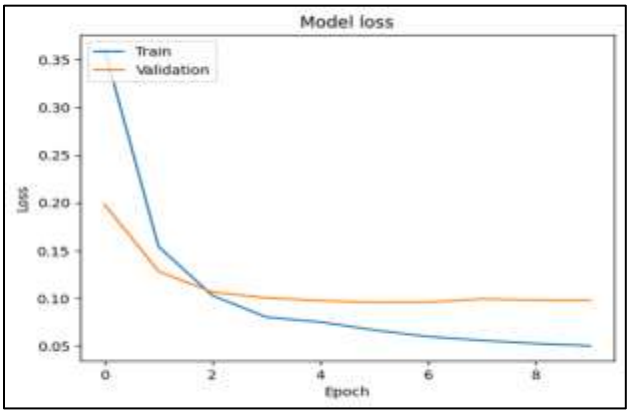

Figure. 12 Training and Validation Loss for CNN-based model

**4.2. QML Classifiers**

In this section we present the performance evaluation of QML models—QSVM, VQC, and QCNN—using accuracy, precision, recall, and F1-score. Table 4. Summarizes the comparative results.

Further, in QSVM for dimensionality reduction, PCA was applied. The PCA-reduced pair plot, confusion matrix, and ROC curve for QSVM model are visualized in Fig. 13, Fig. 14, and Fig. 15, respectively.

Furthermore, the circuit diagram of VQC, confusion matrix, and ROC curve for the VQC classifier are visualized in Fig. 16, Fig. 17, and Fig. 18, respectively.

Finally, for QCNN-based models, the ROC curve is displayed in Fig. 19.

Table 4. QML Classifier's performance comparison

| Algorithm | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| QSVM | 67.25% | 70.63% | 82.41% | 76.07% |
| VQC | 96.06% | 88.24% | 97.22% | 92.51% |
| QCNN | 95.91% | 97.51% | 96.30% | 96.74% |
| QSVC [8] | 93% | - | - | - |
| VQC [8] | 78% | - | - | - |
| DenseNet [12] | 84% | 98% | 75% | 81% |
| ResNet [12] | 83% | 99% | 91% | 81% |
| ResNeXt [12] | 83% | 99% | 69% | 80% |

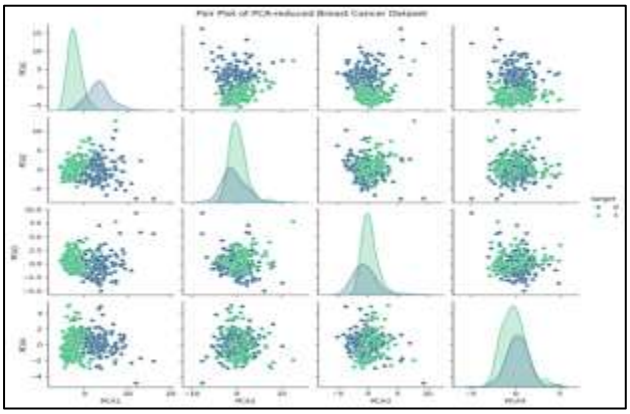
Figure. 13 Pair Plot of PCA-reduced Breast Cancer Dataset

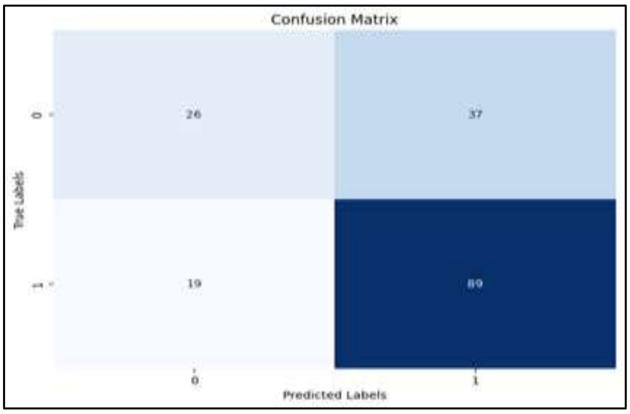

Figure. 14 Confusion Matrix for QSVM Model

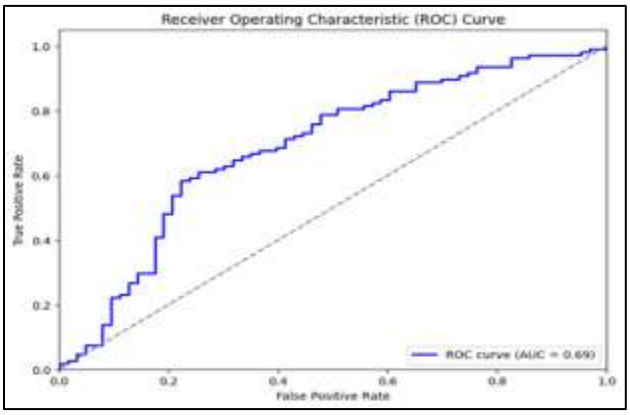

Figure. 15 ROC Curve for QSVM Model

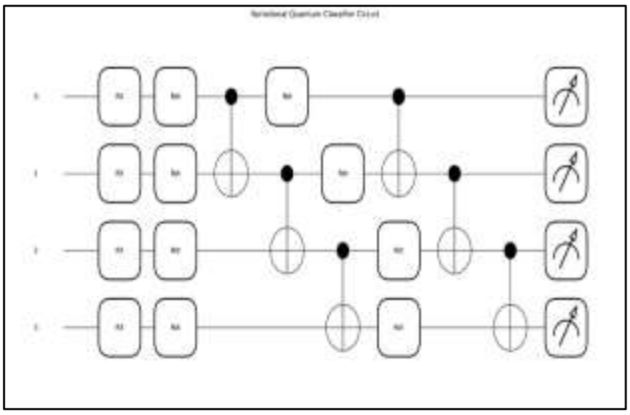
Figure. 16 Variational Quantum Classifier Circuit Diagram

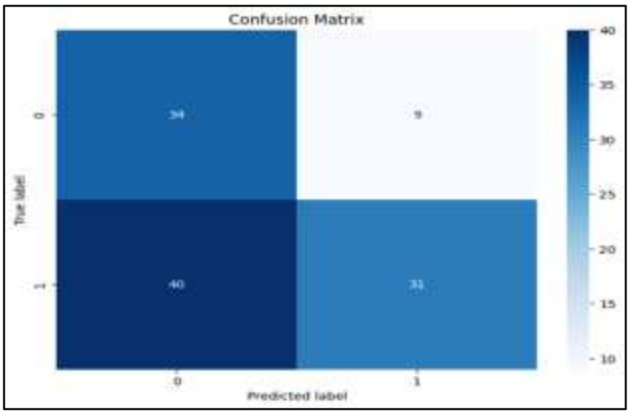

Figure. 17 Confusion Matrix for VQC Model

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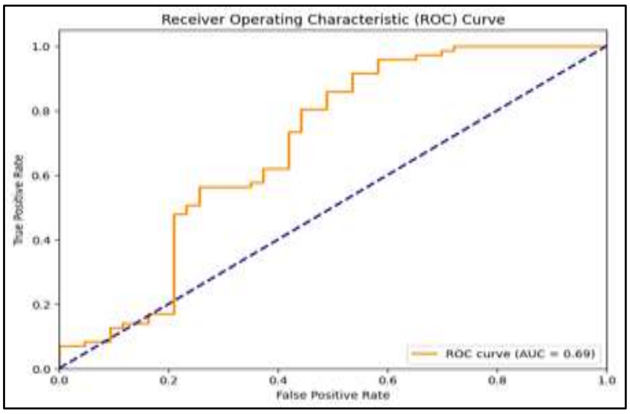


Figure. 18 ROC Curve for VQC Model

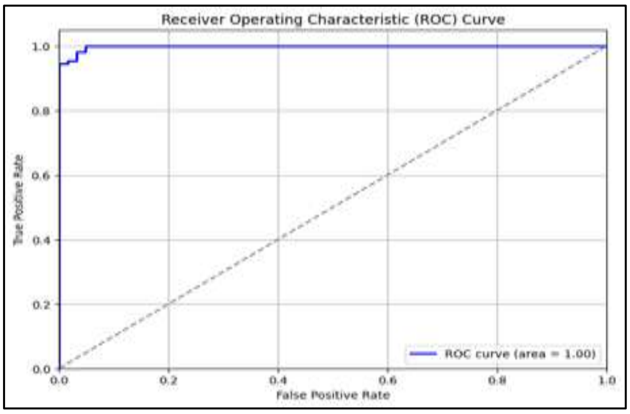


Figure. 19 ROC Curve for QCNN Model

## 5. CONCLUSION AND FUTURE IMPROVEMENTS

In this paper we have explored classical and quantum-enhanced algorithms for breast cancer tumor classification, including SVM, KNN, CNN, QSVM, VQC, and QCNN. Among the classical models, CNN achieved the highest accuracy of 96.49%, outperforming SVM (95.61%) and KNN (94.74%). The CNN is a promising technology with an ability to extract and automatically learn to update from the dataset. The proposed simulation results demonstrate the pros and cons of the classical and quantum techniques in medical screening.

Among the quantum developed models, the proposed VQC model demonstrated the highest accuracy of 96.06% performance matching close to the QCNN model with an accuracy 95.91%. The above work demonstrates QML capacity in early detection and prediction of medical diagnosis and also enhance the performance of machine learning for complex tasks. Also, the QSVM based algorithm performance is degraded to 67.25% due to the scarce representation of quantum featured map, these challenges are alleged to the optimizations of quantum circuits.

These results demonstrate that quantum circuits can enhance machine learning performance for complex classification tasks. In contrast, the QSVM performance was lower (67.25%) due to limited representation in the quantum feature map, reflecting the challenges in quantum circuit optimization.

In conclusion improved quantum featured map and kernel functions can further increase the accuracy of quantum based QSVM and other latest models. Using advanced optimization techniques we can improve the performance of the quantum algorithms drastically. Hybrid Classical and quantum approaches can achieve even better performance due to integrated features of both technologies. With the fast growing technical advancements, the gap between classical and quantum algorithms are reducing paving the way for broader applications of quantum machine learning in public health and sustainable healthcare.

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