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ORIGINAL RESEARCH

Enhanced QSVM with elitist non-dominated sorting genetic optimisation algorithm for breast cancer diagnosis

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Abstract

Machine learning has emerged as a promising method for predicting breast cancer using quantum computation techniques. Quantum machine learning algorithms, such as quantum support vector machines (QSVMs), are demonstrating superior efficiency and economy in tackling complex problems compared to traditional machine learning methods. When compared with classical support vector machine, the quantum machine produces remarkably accurate results. The suggested quantum SVM model in this study effectively resolved the binary classification problem for diagnosing malignant breast cancer. This work introduces an enhanced approach to breast cancer diagnosis by integrating QSVM with elitist non-dominated sorting genetic optimization (ENSGA), leveraging the strengths of both techniques to achieve more accurate and efficient classification results. ENSGA plays a crucial role in optimising QSVM parameters, ensuring that the model attains the best possible classification accuracy while considering multiple objectives simultaneously. Moreover, the quantum kernel estimation method demonstrated exceptional performance by achieving high accuracy within an impressive execution time of 0.14 in the IBM QSVM simulator. The seamless integration of quantum computation techniques with optimisation strategies such as ENSGA highlights the potential of quantum machine learning in revolutionising the field of healthcare, particularly in the domain of breast cancer diagnosis.

KEYWORDS

learning (artificial intelligence), quantum computing, quantum computing techniques

1 | INTRODUCTION

Quantum machine learning (QML) is a rapidly expanding and captivating domain that has the potential to revolutionise various realms of science and technology. With the advent of quantum computing, artificial intelligence, natural language processing, material science, and machine learning applications have become even more promising, as quantum algorithms hold the promise of delivering exponential enhancements compared to classical algorithms [1, 2]. Many proposals have been made to use variational quantum algorithms to handle important but computationally difficult intermediate-size quantum devices that are noisy. Variational quantum algorithms are used and present a numerical experiment. In addition, during classification, the algorithm's superiority over previous approaches is evident through the utilisation of very few qubits, shorter circuits, and very simple measurement requirements.

Numerous quantum-kernel-based machine learning methods will soon be appropriate for quantum applications. Some of the popular ones include quantum kernel estimators (QKE), quantum support vector regression (QSVR), and quantum neural network (QNN). These algorithms can be used in noisy intermediate scale quantum (NISQ) as they do not require expensive operations. Still, the training complexity of the time is even higher than that of classical SVM and

Quantum-boosted Support Vector Machine (SVM). The two prevailing and interconnected methods for addressing classification tasks using quantum computers are variational quantum classification (VQC).

The kernel function plays a pivotal role in support vector machines (SVMs), which are widely used for classification tasks. It functions as a metric to determine the degree of similarity between two data points in a high-dimensional feature space. The data is converted into a feature space where a linear classifier may successfully distinguish between several classes by using the kernel function. This method works with a range of kernel functions, such as the radial basis function (RBF) and the linear kernel. In the context of quantum computing, the quantum kernel is computed using a quantum circuit. The suggested strategy offers numerous benefits. Initially, it combines the benefits of both methods to enhance QSVM performance [3]. The proposed method for quantum SVM combines the angle-embedding kernel with the variational circuit to improve QSVM performance.

Due to quantum parallelism and entanglement, QSVMs can handle high-dimensional data more quickly and accurately, possibly providing greater computational speed and accuracy. This makes them especially useful for applications such as financial modelling and medical diagnostics that need intricate pattern detection and optimisation. In certain tasks, QSVMs can perform better than regular SVMs by utilising the special qualities of quantum mechanics, yielding faster and more accurate results.

Worldwide, the majority of women's cancer-related deaths occur from breast cancer; approximately one in eight women suffer from breast cancer. There are a lot of chances to address this issue at an early stage by analysing the report with QSVM. Quantum machines can enhance the computational performance of the support vector machine (SVM).Noisy intermediate-scale quantum computing (NISQ) have hardware limitations and some major error problems. As a result, this paper presents a quantum kernel estimation technique that mitigates measurement error and tests it on IBM quantum processors with the Wisconsin Breast Cancer database.

By utilising quantum parallelism, quantum machine learning (QML) offers several benefits over classical techniques, such as improved optimisation, faster processing, and superior handling of high-dimensional data. It enhances pattern recognition by utilising quantum concepts such as entanglement and interference. With potential applications in healthcare, finance, and cybersecurity, the developing discipline of QML investigates new quantum algorithms and hybrid quantum-classical techniques.

The remaining research is conducted as follows: The background of QSVM and multi-objective optimisation using genetic algorithms in the context of reviewed papers is covered in Section 2, the research methodology is described in Section 3, the computational result in cancer prediction and detection using the proposed methodology are covered in Section 4, the paper is concluded in Section 5, and potential directions for future research are highlighted in Section 6.

2 | RELATED WORKS

Support vector machines (SVMs) are remarkable and highly supervised learning algorithm used for clinical data classification and regression analysis. When SVMs were first created in the early 1960s, Vladimir Vapnik and associates took a fresh theoretical and applied approach to pattern identification. However, it was not until the 1990s that SVMs gained widespread recognition within the machine learning community. This was primarily made possible by Corinna Cortes' and Vladimir Vapnik's extremely hard and innovative research at AT&T Bell Laboratories, which produced the fascinating concept of maximum-margin hyperplanes. Through the maximising of the margin between those data points, these maximum-margin decision boundaries extremely successfully segregate data points belonging to binary classes [4].

The early works in QSVM proposed an algorithm for classification that offers an exponential acceleration compared to traditional algorithms [5]. Another crucial feature of QSVM is its resilience to noise QML handwriting algorithm on the quad-qubit test bench. The quantum speedup is immensely beneficial in addressing data challenges [6]. Supervised QML, such as QSVM [7, 8], can exhibit resilience to noise, thereby enhancing their applicability in real-world application and their consequences. Since then, numerous investigations have been carried out to enhance the efficiency of QSVM, with one such approach being the utilisation of kernel-based quantum feature maps approach [9]. An additional captivating study delves into the possible application of quantum state encoding as a nonlinear characteristic mapping, facilitating effective computations in a vast Hilbert space with utmost efficiency. It puts forward two methodologies for constructing a quantum-based model for classification, exemplified by many benchmark datasets [10].

Schuld et al. conducted a study to examine how different strategies for encoding quantum data affect the effectiveness of quantum circuits in approximating functions and their parameters [11]. The capacity of the quantum models describe all conceivable necessary sets of Fourier coefficients. Consequently, these models can work as universal function approximators provided that the accessible frequency has a suitable wide spectrum. This finding holds great significance in the development of QML algorithms for addressing intricate data challenges [12]. The link between the principles of quantum computing and kernel approaches helps to replace several fault-tolerant models with a general support vector machine (SVM), that makes use of a kernel for calculating separation between quantum states that encode data. This approach significantly improves the performance and potential to considerably simplify QML algorithms.

Quantum optimisation algorithm aiming to enhance the efficiency of QSVM on extensive real-world applications [13]. These scalability advancements associated with QSVM positioned it as an appropriate solution for tackling intricate use case utilised in domains, such as clinical informatics, e-commerce, face recognition, and material physics. These contribution [14] demonstrate that quantum machine learning models implemented on quantum computers outperform their classical counterparts. These findings demonstrate that quantum machine learning models implemented on quantum computers outperform their classical counterparts. The goal of QSVM is to surpass this constraint by utilising the fundamentals of quantum computing. The field of QSVM has undergone extensive research over time, delving into different theoretical and practical facets of the algorithm [15]. Numerous techniques have been devised by researchers to improve the efficiency of QSVM, such as the creation of several qubits, quantum kernels, measurement quantum feature mapping principles, quantum estimation circuits, and quantum optimisation techniques.

A class of evolutionary algorithms known as genetic sorting algorithms (GAs) was based on the theory of adaptive systems [16]. The emphasis on natural selection and evolution forms the foundation of these algorithms' operation. They are probability-based search techniques intended to operate in spaces where states are represented by strings [17]. Typically, they are employed to identify superior solutions for issues such as choosing crucial features or ideal parameters. The execution of genetic algorithms is commonly understood to involve five primary functions [18]: creating the initial population, assessing the population's "fitness," choosing the best solution, crossing over between the solutions, and potentially altering the population. The numerous recent advancements in genetic algorithms and potential future research directions were expounded [19, 20]. According to the research, GAs that used binary encoding had extraordinarily high computational complexity, but GAs that used real-world encodings frequently experienced premature convergence. To ensure that no fitness function can improve at the expense of the others, multi-objective GAs, or MOGAs, rely on several fitness functions, frequently through an optimal Pareto front [21, 22].

This work presents an enhanced quantum-inspired grey wolf optimization (QIGWO) algorithm-optimised support vector machine (SVM) breast cancer detection approach. When compared to conventional techniques, the optimised SVM model exhibits better accuracy, sensitivity, and specificity. The results demonstrate its potential for clinical use in the diagnosis of breast cancer [29]. In order to enhance quantum support vector machines (QSVM) using the combination of classical and quantum computing methods, this research study investigates hybrid quantum technologies. The hybrid approach uses both classical optimisation and quantum parallelism to improve computational accuracy and efficiency [30].

A quantum support vector machine (QSVM) for multi-class classification issues is presented in this study. The authors show that when compared to conventional techniques, QSVM offers considerable gains in classification accuracy and processing efficiency. This research study offers a theoretical framework and useful implementation tips for applying QSVM in challenging multi-class situations [31]. The NSGA-II-DL framework, which combines deep learning and the NSGA-II metaheuristic algorithm for optimal feature selection in HER2 breast cancer classification, is presented in this paper. The suggested approach chooses the most essential elements to increase classification efficiency and accuracy. The results show that the hybrid technique has tremendous potential in medical diagnostics, as evidenced by the large improvements in HER2 classification performance [32].

The improved fast non-dominated solution sorting genetic algorithm proposed in this research may effectively address multi-objective optimisation problems. The approach is appropriate for challenging optimisation jobs since it increases sorting speed and solution quality [33]. A refined NSGA-II-based feature selection technique designed for high-dimensional classification applications is presented in this work. By efficiently choosing pertinent features from huge datasets, the technique enhances classification performance [34]. In order to improve the accuracy of breast cancer detection, this work investigates multi-objective hyper parameter optimisation for gradient-boosting algorithms. The enhanced model has enhanced capability in detecting breast cancer, indicating the efficacy of this methodology [35].

3 | PROPOSED METHODOLOGY

To work with supervised learning, it is necessary to handle large volumes of labelled data. Subsequently, extensive memory resources are required to train our algorithms. To address this challenge, hardware capable of simultaneously managing multiple sets of information is required. The most promising solution to this issue appears to lie in quantum mechanical systems [23], as they exist in high-dimensional Hilbert spaces. Quantum computing and its advancements in contrast to classical computers shall commence by elucidating the core concepts of qubits, which serve as the foundational components of quantum computers. Figure 1 shows the proposed methodology framework.

3.1 | Objectives

1. The ZZ feature map, known for its flexibility and expressiveness, adeptly encodes complex relationships among clinical and genetic features into quantum states. Leveraging its capabilities within the quantum kernel method enhances the detection of subtle patterns crucial for accurate breast cancer classification.
2. PCA reduction can mitigate the curse of dimensionality, enhancing the efficiency of classification algorithms in analysing complex datasets.
3. Utilising quantum properties superposition and entanglement, the ZZ feature map represents breast cancer data in quantum states, enabling simultaneous exploration of multiple data representations. This quantum parallelism offers potential advantages over classical methods in specific classification tasks, harnessing the power of quantum computing for enhanced analysis.
4. Integration of enhanced QSVM-elitist non-dominated sorting genetic optimization algorithm enhances the quantum kernel method, potentially outperforming classical

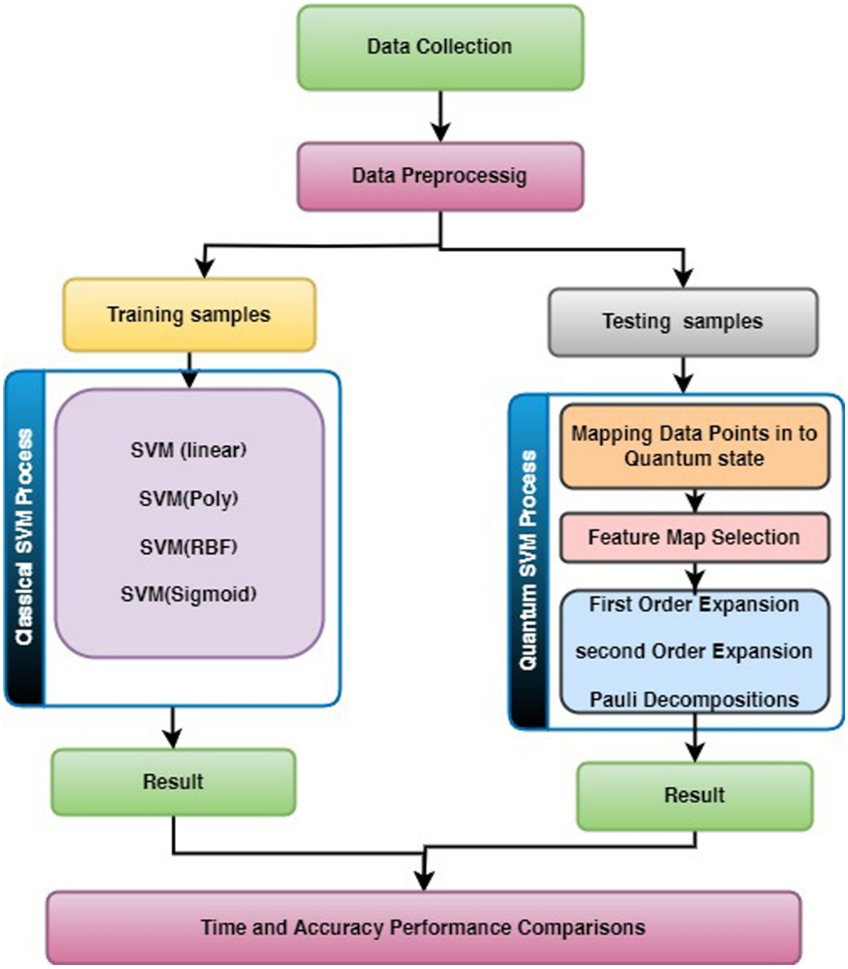

FIGURE 1 Proposed methodology framework.

methods in breast cancer classification accuracy. Quantum algorithms' capacity to unveil non-linear data patterns and correlations offers a promising avenue for achieving more precise classification outcomes compared to classical approaches.

Support vector machine (SVM) [27] is commonly used for data classification, dividing it into two distinct sets. By utilising a training set of data, it becomes possible to identify a line or hyperplane that effectively separates these data sets. The QVSM [24] algorithm revolves around two crucial components: feature map and kernel. Unitary transformation operations on input qubit sets and the encoding of classical quantum data in quantum space are common components of quantum algorithms and ultimately the measurement of the qubit(s) state to derive a classical output. Numerous researchers have showcased utilising qubits in both experimental and theoretical implementations to solve machine learning problems [36].

3.2 | Data collection

The Wisconsin Breast Cancer dataset, which was obtained from the UCI repository, was utilised for this project [28], which comprises measurements of breast tissue obtained through medical imaging techniques and includes various metrics. The main objective is to differentiate between benign (non-cancerous) and malignant (cancerous and hazardous) tumours by determining the nature of a tumour. The dataset from sci-kit-learn consists of 569 samples, with 30 real, positive features, including attributes related to cancer masses such as mean radius, mean texture, mean perimeter, and more shown in Figure 2. Out of these samples, 212 instances are labelled as “malignant,” while 357 instances are labelled as "benign”. Table 1 shows the breast cancer dataset characteristics.

3.3 | Data pre-processing

Before QSVM classification, the data undergoes pre-processing which includes scaling and normalisation principal component analysis (PCA). Numerous machine learning algorithms are highly influenced by the scale of the input features. By normalising the data, these algorithms can yield improved results. In this min-max method of data normalisation, the original data undergoes a linear transformation. The data is first analysed to determine the minimum and maximum values, and then each value is substituted using the formula provided.

$$v^1 = \frac{v - \min(A)}{\max\,(A) - \min(A)}\left(newmax(A) - newmin(A)\right) + newmin(A) \tag{1}$$

Where:

Attribute data –> A,

Min(A) Minimum absolute values of A.

Max(A) Maximum absolute values of A.

v ⇒ old data value

v' ⇒ new data value

newmax (A) and newmin (A) ⇒The maximum and minimum values of the range, or the boundary values.

It should be emphasised that the Wisconsin breast cancer dataset is quite complex, with more than 30 features, which poses a challenge for processing and analysis on a quantum computer with a limited number of qubits. To address this issue, will initially employ PCA to reduce the dataset's dimensionality to only four variables for the simulator and two for the quantum computer, making the task more feasible. To standardise features by removing the mean and scaling to unit variance, PCA can be utilised to decrease the dimensionality of features. Machine learning algorithms have evolved due to increased computational complexity yielding remarkable outcomes. Scaling, normalisation, and PCA in quantum computation are able to mathematically speedup QML.

Table 2 using several principal components 2, and 4, the classical SVM achieved an accuracy rate of approximately 92% and 95% respectively. Using 2, and 4 number of principal components, the QSVM achieved an accuracy rate of approximately 96% and 98% respectively.

Quantum computing allows parallel computations; parallelism can lead to faster QSVM classification. Especially handling high dimensional data with fewer principal components.

This will create a visually appealing curve chart comparing classical SVM and quantum SVM accuracy across different numbers of principal components in Figure 3.

3.4 | QSVM

The QSVM algorithm is suitable for classification problems that necessitate a feature map that cannot be efficiently computed using classical methods. Consequently, the computational resources required for such problems are anticipated to

TABLE 1 Breast cancer dataset description.

Number of instances	Number of attributes	Features	Class distribution
569	30	Radius	Benign-357 Malignant-212
		Texture	
		Perimeter area smoothness compactness concavity concave points symmetry fractal dimension	

TABLE 2 Accuracy comparison for PCA.

Number of principal components (PCA)	Classical SVM accuracy	Quantum SVM accuracy
2	92	96
4	95	98

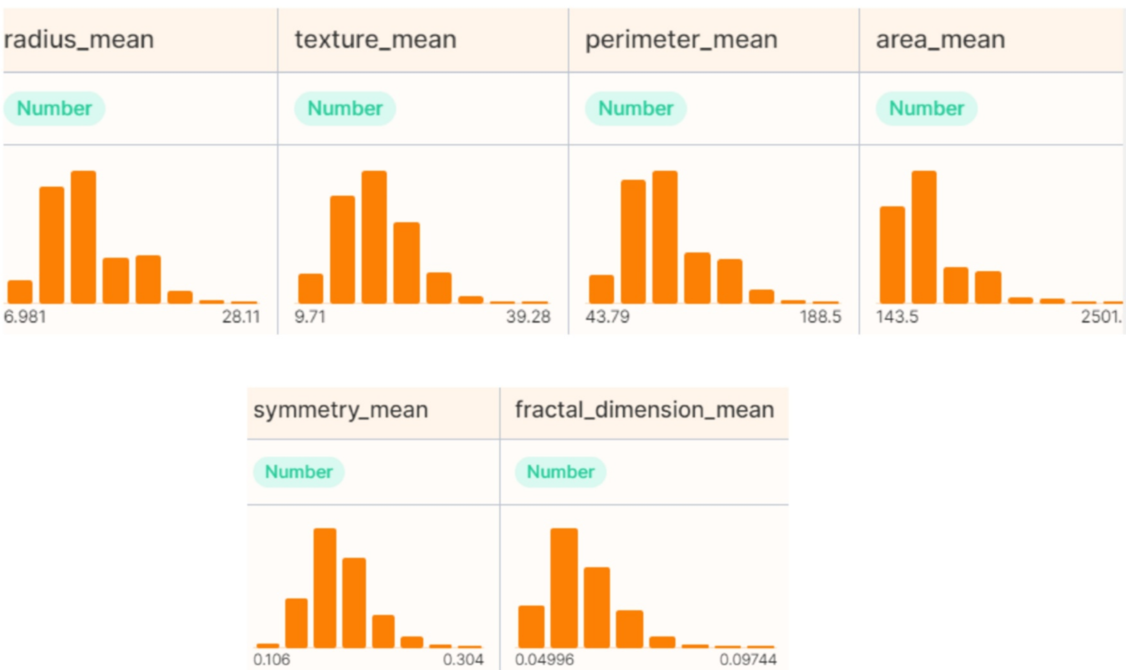

FIGURE 2 Breast Cancer Dataset mean values.

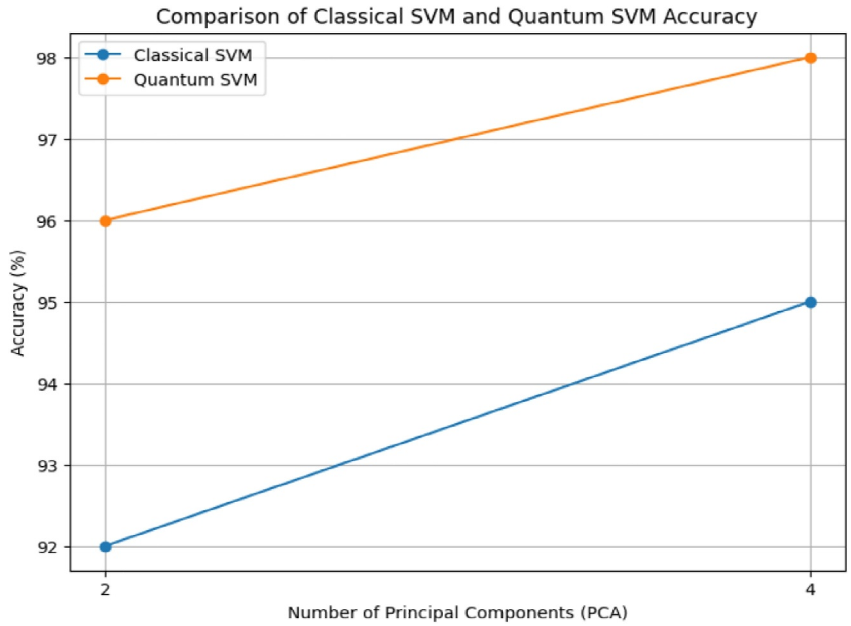

FIGURE 3 Comparison of classical SVM and quantum SVM accuracy.

exponentially increase with the problem size. QSVM addresses this challenge by utilising a quantum processor [25, 26]. This approach belongs to the supervised learning category, which involves following 2 phases:

1. Training phase: The computation of quantum kernel function.
2. Test or classification phase: To classify the correct label from unlabelled data.

The classical computation considers a bit 0 or 1 but in quantum computing quantum bit exist in a superposition state, this process effectively parallelising computations, quantum entanglement particles become exploits the correlations between qubits. This leads to a potentially exponential computational speedup. To improve the separability of data points through this mapping, which is usually non-linear and facilitates classification tasks.

Using this approach, support vectors and the kernel are computed during the training phase. The quantum computer handles kernel evaluation, the feature space is encoded using qubits quantum state, and the attribute mapping makes it possible to calculate the kernel matrix quickly.

3.5 | Feature mapping

It is important to note that linear hyperplane classification is only effective when the data is already linearly separable in its original space. However, not all data sets meet this requirement. In such cases, a feature map can be used to transform the location from a 2D plane into a higher dimension ‘K', allowing for the computation of an optimal hyperplane separating the two classes. This process involves calculating the distances between data points within the higher dimensional space. When data is mapped from its input dimension into the Hilbert space in a quantum computer, it is cast into a higher dimensional space. The linear classification data can be effectively achieved through the utilisation of a kernel-based quantum classifier. Variational quantum circuit finds the cost function for a given set of parameters; it is used as building blocks for quantum machine learning models.

- state preparation stage
- model circuit
- measurement stage
- designing parametric state

The input data has been encoded. A quantum-classical optimisation procedure outputs the eigen states of the specific Hamiltonian encoding the computational task. According to quantum mechanics, a vector in a complex vector space with an inner product called a Hilbert space represents the state of a physical system. A complete or closed infinite-dimensional inner product space is commonly referred to as a "Hilbert space." Finite-dimensional spaces, which by definition meet the completeness condition, are included in the term's current usage. Feature mapping to a high-dimensional quantum feature space, especially for quantum classifiers such as QSVM. It is intended to improve the separability of data points in the quantum feature space through this mapping, which is usually nonlinear and facilitates classification tasks.

The constraint is associated with the linear progression of traditional computing, which lacks the capability to execute simultaneous tasks. Given that quantum mechanical systems comprising N qubits exist within 2N dimensional Hilbert spaces and possess finite linear operators, the most intuitive approach to address this issue appears to be computing within this quantum space. In QSVM, the classical data is mapped into a Hilbert space using data-dependent parametric gates.

The classification result is produced by processing the input data onto a quantum state, which is then processed through a quantum circuit of QSVM. This circuit is made up of a series of quantum gates that manipulate the quantum data and execute the QSVM algorithm. By measuring the circuit's output, the classification model generated the output.

Feature Mapping Quantum function $\phi(x)$ based on, Input data $\overrightarrow{x} = (x_0, x_1 \ldots, x_{N-1})^T \in R^N$, dimensional input mapped to quantum states as follows:

$$\left|\Phi\left(\overrightarrow{x}\right)\right\rangle\left\langle\Phi\left(\overrightarrow{x}\right)\right| \tag{2}$$

$$\Phi : x \rightarrow \begin{cases} x_i & if\ S = \{i\} \\ (\pi - x_i)(\pi - x_j) & if\ S = \{i, j\} \end{cases} \tag{3}$$

$S \rightarrow$ Qubit pairs, set of k elements from 'n'.

Qubit data points $k = 1, 2\ldots\ n$, Zi.

The entanglement rotation operation was constructed based on:

$$\bigcup_{\varphi_{(x)}} = exp\left(i \sum_{s \subseteq C[n]} \varnothing S(x) \prod_{KES} z_i\right) \tag{4}$$

$R_Z \rightarrow$ Rotation operations.

The encoding qubits used Hadamard H; Unitary Operation produces the quantum circuit $U_{\Phi\left(\overrightarrow{x}\right)}$, resulting in feature mapping on:

$$\overrightarrow{x} = (x_0, x_1, \ldots, x_{N-1})^T$$

$$U_{\Phi\left(\overrightarrow{x}\right)} = \mathrm{U}_{\Phi\left(\overrightarrow{x}\right)} H^{\otimes n} \tag{5}$$

$$K\left(\overrightarrow{x}, \overrightarrow{y}\right) = \left|\left\langle\Phi\left(\overrightarrow{x}\right)\middle|\Phi\left(\overrightarrow{y}\right)\right\rangle\right|^2$$

$$= \left\langle 0^n \middle| U_{\Phi\left(\overrightarrow{x}\right)} U^{+}_{\Phi\left(\overrightarrow{y}\right)} \middle| 0^n \right\rangle \tag{6}$$

where U^{+}_{Φ} is the conjugate transpose of U, and n is the n x n identity matrix.

3.6 | Quantum kernel estimations for QSVM classification

Quantum kernel estimation techniques rely on feature mapping, with the primary concept being the creation of a kernel matrix through the mapping of classical data to quantum states. In this matrix, the entries represent the fidelity between various feature vectors. When dealing with finite data, the inner product of the feature vectors can be estimated by directly considering the leap amplitudes, as the states in the feature space are connected to the input data.

1. Encoding of classical data (dimensional data) to quantum state data (2-dimensional Hilbert space) using a transformation function based on the feature mapping circuit, can create the quantum kernel function circuit Kφ(x,y) []. By utilising two consecutive feature mapping circuits, to establish the kernel estimation of the quantum circuit for the quantum initial states |0n. []. Ultimately, to perform S measurements on the circuit and document the number of statistics Sx that yield all zeros in the obtained results.

$$\bigcup_{\Phi\left(\overrightarrow{x}\right)} = \exp\left(\mathrm{i} \sum_{s \subseteq [n]} \varnothing S\left(\overrightarrow{x}\right) \prod_{K \in S} \mathrm{P}_i\right), \mathrm{P}_i \in \{Z, XX\} \tag{7}$$

2. The ZZ feature map data encoding circuit from the Qiskit circuit library is utilised to define the feature map with feature dimension and the reps. Then, the feature map is fed into the quantum support vector machine along with the training data and the test data that require classification.

Figure 4 This circuit seems to consist of two qubits, q_0 and q_1, undergoing a series of quantum operations.

1. Hadamard gate (H) applied to both qubits:
   - o This puts both qubits into a superposition of |0⟩ and |1⟩ states.
2. U1 gate applied to q_0:
   - o This gate performs a phase rotation based on the parameter 2.0*x[0].
3. Controlled-X (CNOT) gate with q_0 as the control and q_1 as the target:
   - o This gate flips the state of q_1 if q_0 is in state |1⟩.
4. U1 gate applied to q_1:
   - o This gate performs a phase rotation based on the parameter 2.0*x[1].
5. Controlled-X (CNOT) gate with q_1 as the control and q_0 as the target:
   - o This gate flips the state of q_0 if q_1 is in state |1⟩.
6. U1 gate applied to q_0:
   - o This gate performs a phase rotation based on the parameter 2.0*(pi - x[0])*(pi - x[1]).
7. Controlled-X (CNOT) gate with q_0 as the control and q_1 as the target:

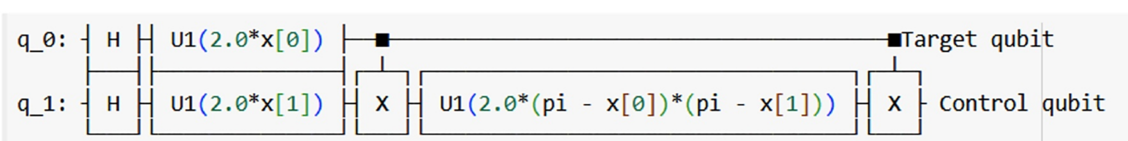

FIGURE 4 ZZ feature map circuit.

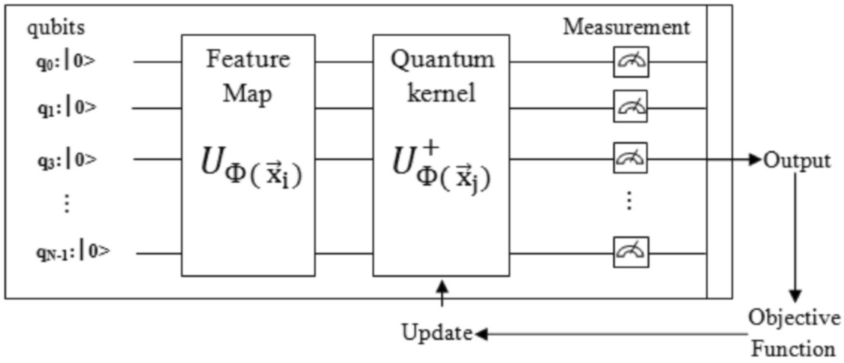

FIGURE 5 Schematic circuit of quantum kernel.

   o This gate flips the state of q_1 if q_0 is in state $|1\rangle$.
8. U1 gate applied to q_1:
   o This gate performs a phase rotation based on the parameter 2.0*x[1].
9. Controlled-X (CNOT) gate with q_1 as the control and q_0 as the target:
   o This gate flips the state of q_0 if q_1 is in state $|1\rangle$.
   o CNOT (Controlled-NOT) gate, is a fundamental two-qubit quantum gate in quantum computing. It's a controlled gate, that is, its action depends on the state of one qubit, called the control qubit, and it performs a specific operation on another qubit, called the target qubit, based on that control qubit's state

The sequence of operations entangles the qubits q_0 and q_1 and applies phase rotations based on the parameters x [0] and x [1]. The specific values of x [0] and x [1] would determine the precise effects of these gates on the quantum states.

- If the control qubit is in the state $|0\rangle$, the target qubit's state remains unchanged.
- If the control qubit is in the state $|1\rangle$, the target qubit's state is flipped (i.e., $|0\rangle$ becomes $|1\rangle$ and vice versa).

ZZ feature map is a feature map used to encode classical data into quantum states. It's parameterised by the feature dimension, which likely denotes the number of features in the dataset, and reps, which specifies the number of times the circuit should be repeated. In this case, the feature map is initialised with feature dimension and representations as 2, and used linear entanglement.

3. Assess the accuracy of our QSVM in predicting the input data for classification. Our test data contains known ground truth values for classifying as A or B, and our trained prediction from the training data has effectively determined the classification of our testing data. Next, the kernel matrix is produced and the kernel for a fresh batch of quantum data points (test data) for QSVM classification is estimated, it shown in Figure 5.

QSVMs have the advantage of faster training times compared to classical SVMs, to enhanced computational capabilities of quantum computers. This attribute proves particularly valuable when dealing with extensive machine learning tasks, where reducing training time is crucial, and it's tuned by Algorithm 1. Quantum machine learning algorithms can process large amounts of data much more efficiently than traditional machine learning algorithms by utilising the power of quantum computing; this leads to faster and more accurate results. Moreover, by recognising more subtle patterns in the data, quantum machine learning algorithms can improve the accuracy of health care tasks, potentially solving the medical image segmentation and classification to identify and predict cancers.

3.7 | Enhanced QSVM-elitist non-dominated sorting genetic optimisation algorithm (QSVM-NDSGOA)

To solve multi-objective optimisation problems, such as the dual problem in QSVM classification, the elitist non-dominated sorting genetic algorithm (NSGA-II) is an effective optimisation technique. By optimising kernel functions and fine-tuning parameters, NSGA-II can help improve the performance of QSVM classifiers by effectively exploring the solution space and capturing trade-offs between competing objectives.

Algorithm 1. QSVM-Elitist non-dominated sorting genetic optimisation algorithm

```
Input data: Breast cancer training, label
data points (Malignant, Benign), Qubits
The input data can be encoded as a quantum
state by utilising a quantum feature map.
Mapping the data into a distinct hyperspace
Apply a quantum gate to execute sentiment
classification on the provided input data.
Determine the quantum gate's output
measurement.
Computation of Quantum kernel estimation
using equation (a)
Optimisation of the dual problem
```

$$L_D(\alpha) = \sum_{i=1}^{t} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{t} y_i \, y_j \, \alpha_i \, \alpha_k \, K\left(\vec{x}_i \vec{x}_j\right)$$

kernel $K\left(\overrightarrow{x}_i \overrightarrow{x}_j\right)$ of QSVM is determined by allocating certain values to the parametric quantum programme and analysing the counts obtained after execution.
Computation of kernel Matrix of new data points concerning the support vectors
$\left(\overrightarrow{s}\right) = sign\left(\sum_{i=1}^{t} y_i\, \alpha_i^*\, K\left(\overrightarrow{x}_i \overrightarrow{s}\right) + b\right)$
$\overrightarrow{S} \Rightarrow$ Predicted label
kernel matrix contains the fidelities between various feature vectors.
Computation of multi-objective optimisation methodology
Elitist Non-Dominated sorting genetic algorithm
Merge parent Pt and offspring population Qt
$R_t = P_t \cup Q_t$
Pt = Parent
Qt = offspring Population
Rt = non-dominated shorting
Generate new population
$P_{t+1} = \emptyset andseti = 1$
Until $|P_{t+1}| + |F_i| < N$,
Compute non-dominated sorting, merge new parent population and fronts Fi
$P_{t+1} = P_{t+1} \cup F_i$ and increase i
Compute crowding distance sorting
$(N - |P_{t+1}|)$ of F_i in P_{t+1}
Generate offspring population
Q_{t+1} from P_{t+1}
Crowded distance selection, crossover, mutation operators
Find the maximum generation
Selection of suitable individuals to form a new parent
Optimal feature selection
Calculate the Accuracy of QSVM
Output the predicted Accuracy

a. Quantum Approach:

The input data can be encoded as a quantum state by utilising a quantum feature map.

- Mapping the data into a distinct hyperspace
- Apply a Hadamard gate to execute classification on the provided input data
- Determine the quantum gate's output measurement. Then Computation of Quantum kernel estimation using equation (8)

(b) Optimisation process across quantum
- Computation of kernel Matrix of new data points with respect to the support vectors
- kernel matrix contains the fidelities between various feature vectors.

(c) Elitist non-dominated sorting genetic algorithm
- Merge parent and offspring population
- Crowded distance selection, crossover, mutation operators
- Find the maximum generation Selection of suitable individuals to form new parent Optimal feature selection
- Calculate the Accuracy of QSVM Output the predicted Accuracy

Algorithm 1 is described as follows: encode input breast cancer training data and labels into a quantum state using a quantum feature map, enabling classification in a distinct hyperspace. Then apply a quantum gate for sentiment classification, measure its output, and compute the quantum kernel estimation using specified equations. Utilise elitist non-dominated sorting genetic algorithm for multi-objective optimisation, optimising the dual problem by analysing quantum gate outputs. Iteratively generate and evolve populations, merging parent and offspring populations, computing non-dominated sorting and crowding distance, selecting individuals, and optimising feature selection until reaching maximum generations. Finally, evaluate QSVM accuracy and output predicted accuracy.

4 | PERFORMANCE EVALUATION

Quantum support vector machines (QSVMs) have the potential to attain enhanced accuracy levels since they can employ quantum feature maps to map data into more expansive feature spaces. Classical SVM: Due to restrictions in classical feature space mapping, classical SVMs may not be as accurate as they could be, particularly when working with high-dimensional and complicated datasets.

Evaluation measures that have been previously defined, such as recall, F1 scores, classification accuracy, and precision, can be used to gauge how effective the proposed method is. True positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) are all included in the "confusion matrix" that forms the basis of these measures. Next, the kernel matrix is produced and the kernel for a fresh batch of quantum data points (test data) for QSVM classification is estimated.

Classification accuracy calculates the percentage of properly predicted examples in the dataset relative to all instances to assess the overall accuracy of a classification model.

Accuracy: It is a statistical measure used to assess a classification model's overall accuracy. The correctly predicted instances relative to the total number of instances in the dataset is quantified.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

Precision: It is a measure of how accurately a classification model produces positive forecasts. In comparison to the total number of instances projected as positive, it assesses the percentage of correctly predicted positive cases.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{9}$$

Recall: It calculates the percentage of accurately anticipated positive cases compared to the total number of positive cases that occurred.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{10}$$

F1 score: The F1 score is a measure that uses the harmonic mean to combine recall and precision. It provides a comprehensive assessment of a model's efficacy by accounting for both false positives and erroneous negatives.

$$\text{F1 Score} = 2* \frac{Precision*Recall}{Precision + Recall} \tag{11}$$

Use the IBM-quantum platform's quantum simulators and the sci-kit-learn library's classical models to set up our experiments in this study. In total, ten testing rounds were carried out using the breast cancer diagnosis dataset. 50 samples were chosen at random as the test set and 300 samples as the training set for each cycle. Quantum simulators and the IBM quantum processor were used in the trials, both with and without a noise suppression plan. On the same datasets, we also ran trials using a classical SVM model. Because QSVMs can forecast fresh data more precisely than standard SVMs, they perform better in generalisation. This is because QSVMs use higher-dimensional feature spaces to capture complex patterns in the data, made possible by the use of quantum kernel functions.

When it comes to handling non-linear data, QSVMs are more capable than standard SVMs. This is due to their use of quantum kernel functions, which allow data to be mapped onto a higher-dimensional space, making it linearly separable. On the other hand, the limitations of conventional support vector machines stem from their dependence on linear kernel functions, which prevents them from efficiently processing non-linear data.

To show how QC affects classification time and performance, the final step applies quantum computing to the breast cancer data classification approach and feature representation. This involves classifying data using a quantum method, which may lead to quicker classification times and better results than a conventional machine learning algorithm. To ascertain whether the method is more successful for accurate diagnosis of breast cancer dataset, the performance of both the SVM model and QSVM with optimization algorithm is evaluated. Table 3 describes the accuracy comparison of the prediction model with qubits 2,4,6,8, and10, which produces the result as 0.87, 0.94, 0.96, and 0.97, 0.97, respectively.

Figure 6 illustrates the performance of classical SVM and quantum SVM across varying numbers of qubits and SVM kernels. Classical SVM with linear, polynomial, and radial basis function (RBF) kernels shows steady accuracy improvements with increased qubits. Meanwhile, quantum SVM consistently outperforms classical SVM, achieving higher accuracy across all qubit configurations.

TABLE 3 Accuracy comparison of prediction model.

Prediction model	Qubits	2	4	6	8	10
Classical SVM	SVM (linear)	0.85	0.91	0.93	0.95	0.95
	SVM (Poly)	0.85	0.92	0.93	0.94	0.95
	SVM (RBF)	0.85	0.91	0.93	0.94	0.95
	SVM (Sigmoid)	0.80	0.84	0.87	0.88	0.90
Quantum SVM	SVM quantum kernel	0.87	0.94	0.96	0.97	0.97

With higher qubit counts, the accuracy of the traditional SVM with different kernels increases, as is especially clear with the RBF kernel. But in every qubit configuration, the quantum SVM with a quantum kernel performs better than the classical SVM, demonstrating greater predictive potential. This indicates that machine learning activities, particularly those involving complex data environments, may benefit from the application of quantum computing.

Table 4 optimisation significantly enhances performance in both classical and quantum SVM models, achieving perfect precision, recall, F1-score, and accuracy in the quantum model. The classical SVM, while achieving high metrics, still demonstrates some discrepancy between malignant and benign class performance without optimisation. Quantum SVM, especially with optimisation, showcases remarkable consistency and superiority across all evaluation metrics, suggesting its potential for robust and precise classification tasks.

Figure 7 shows, with optimisation, the classical SVM achieves slightly lower precision and recall for malignant cases but higher precision, recall, F1-score, and accuracy for benign cases. Optimisation significantly improves the overall performance of the Classical SVM, leading to higher accuracy and better balance between precision and recall for both classes.

4.1 | Classical SVM with optimisation

- **Precision**: The precision of the model in predicting malignant cases is 0.97, while for benign cases it's 0.89.
- **Recall**: The recall (sensitivity) of the model for malignant cases is 0.84, while for benign cases it's 0.97.
- **F1-Score**: The harmonic mean of precision and recall for malignant cases is 0.89, while for benign cases, it's 0.95.
- **Accuracy**: The overall accuracy of the model is 94%.

4.2 | Classical SVM with optimisation

o **Precision**: The precision of the model in predicting malignant cases is 0.90, while for begin cases it's 0.92.

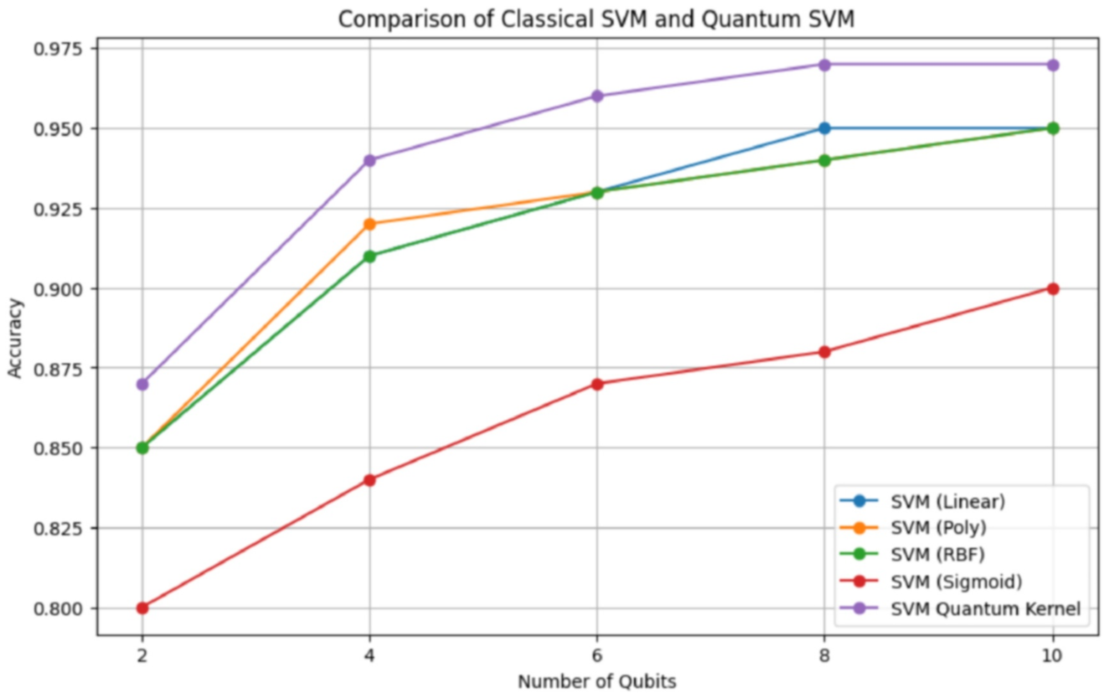

FIGURE 6 Comparison of classical SVM and quantum SVM accuracy.

TABLE 4 Performance evaluation comparison results.

SVM model	Optimisation strategy	Label	Precision	Recall	F1-score	Accuracy
Classical	Without optimisation	Malignant	0.97	0.84	0.89	0.94
		Benign	0.89	0.97	0.95	0.94
	With optimisation	Malignant	0.97	0.97	0.97	0.97
		Benign	0.97	0.97	0.97	0.97
Quantum	Without optimisation	Malignant	1.00	0.86	0.92	0.95
		Benign	0.93	1.00	0.96	0.95
	With optimisation	Malignant	1.00	1.00	1.00	1.00
		Benign	1.00	1.00	1.00	1.00

o **Recall:** The recall of the model for malignant cases is 0.92, while for benign cases it's 0.94.
o **F1-Score:** The F1-score for malignant cases is 0.94, while for benign cases it's 0.964.
o **Accuracy:** The overall accuracy of the model is 97%

4.3 | Quantum SVM with optimisation

- **Precision**: The precision of the model in predicting malignant cases is 1.00, while for benign cases it's 0.93.
- **Recall**: The recall of the model for malignant cases is 0.86, while for benign cases it's 1.00.
- **F1-Score**: The F1-score for malignant cases is 0.92, while for benign cases it's 0.96.
- **Accuracy**: The overall accuracy of the model is 95%.

4.4 | Quantum SVM with optimisation

o **Precision**: The precision of the model in predicting malignant cases is 1.00, while for benign cases, it's also 1.00.
o **Recall**: The recall of the model for both malignant and benign cases is 1.00.
o **F1-Score**: The F1-score for both malignant and benign cases is 1.00.
o **Accuracy**: The overall accuracy of the model is 100%.

Figure 8 shows, with optimisation, the quantum SVM achieves perfect precision, recall, F1-score, and accuracy for both malignant and benign cases. Without optimisation, the model still performs very well but has slightly lower precision and recall for malignant cases and slightly lower accuracy. Optimisation significantly improves the performance of the quantum SVM, leading to perfect classification results across all metrics.

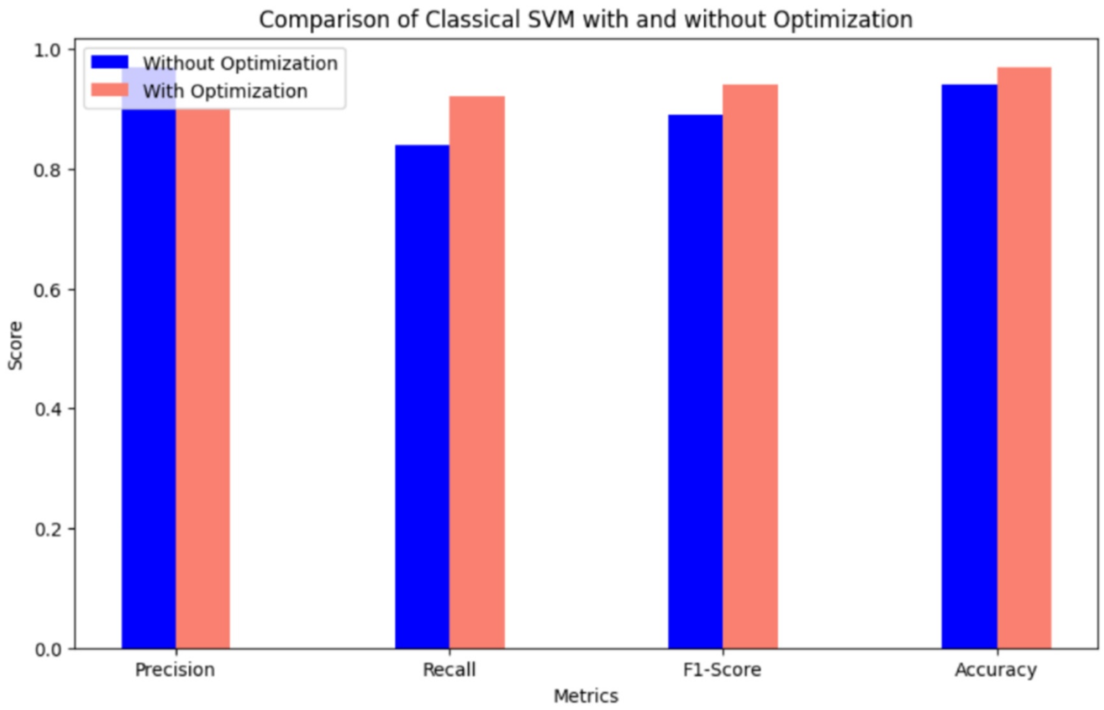

FIGURE 7 Classical SVM with and without optimisation.

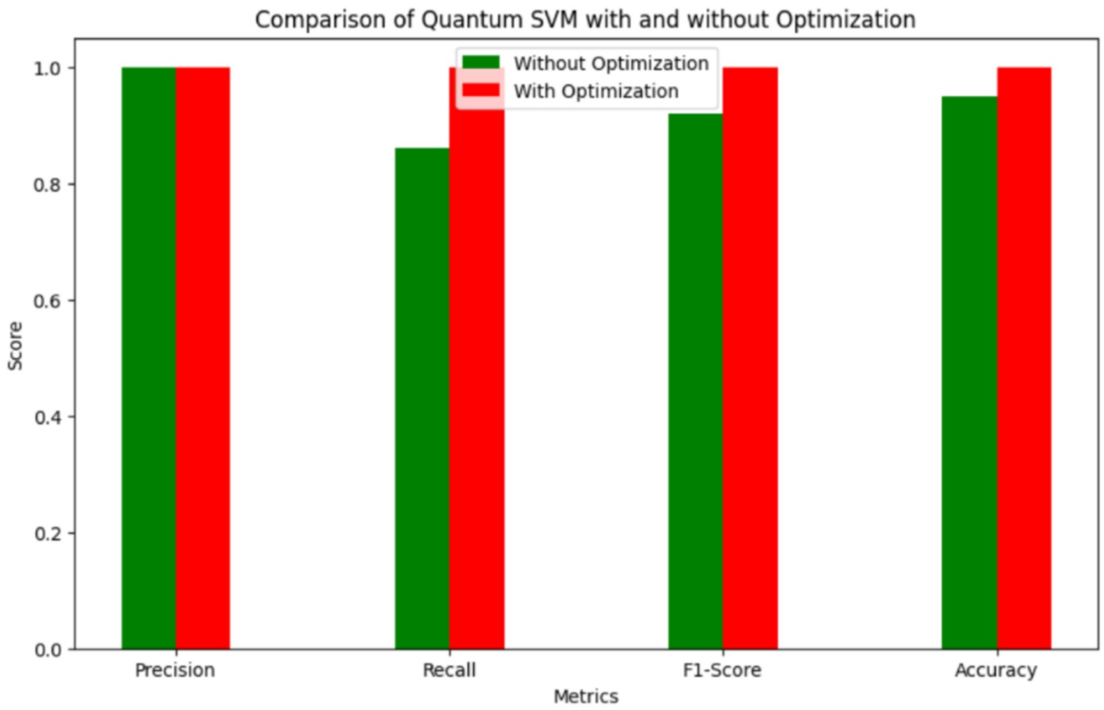

FIGURE 8 Quantum SVM with and without optimisation.

The classification result of the cancer dataset is described in Section 4. The performance evaluation comparison results describe the precision, Recall, F1-Score, accuracy of the classical SVM and quantum SVM training label Benign, Malignant. The quantum SVM, with optimization, obtained the maximum accuracy, that is, 100%. According to time complexity QSVM kernel IBMQX2, IBMQ_16_Melbourne, and IBM QASM simulator attained the accuracies 98.6%, 99.4%, and 100%, respectively. In this computational environment IBM QASM simulator execution time is 0.14. Compared to other simulator the execution time reduced drastically.

The proposed QSVM optimisation models are evaluated using metrics including precision, recall, F1 score, and accuracy with breast cancer labels "Malignant" and "Benign". The accuracy of QSVM with optimization performance results shows a higher accuracy value compared to classical SVM. Table 5 focused on the use of QSVM with various computational environments and the execution time of quantum simulators. IBM QASM simulator's execution time is 0.14 s, and it achieves 100% accuracy with an 8-vCore CPU and 32 GB of RAM. The Penny Lane Python library, which includes built-in techniques, was used to implement the Enhanced QSVM. Figure 9 shows the performance comparison of classical SVM versus QSVM kernel prediction accuracy over the execution time.

Mammography and other data from breast cancer screening can be analysed more precisely and effectively by integrating this cutting-edge diagnostic equipment into hospital diagnostic systems. This method can improve patient outcomes and survival rates by increasing diagnostic accuracy, decreasing false positives and negatives, and enabling earlier diagnosis and more individualised treatment strategies for patients. It is also possible to employ it in high-volume screening systems due to the faster processing times made possible by the increased computing efficiency.

5 | CONCLUSION AND FUTURE WORK

This work provides more details on a methodological approach that was performed to identify, assess, and analyse quantum machine learning algorithms in the field of healthcare; this suggested methodology concentrated on using QSVM for binary classification. Quantum support vector machines and support vector machines (Linear, Poly, RBF, Sigmoid) were compared and assessed. Additionally, a new strategy that results in the development of QSVM has been developed by integrating approaches, this suggests a feasible method for binary classification problems in the quantum machine learning domain of breast cancer diagnosis. The proposed QSVM-elitist non-dominated sorting genetic optimization algorithm performs admirably in terms of accuracy and computational efficiency. These results have enormous potential for developing quantum machine learning and all of its various applications. Quantum machine learning algorithms can process large amounts of data much more efficiently than traditional machine learning algorithms by utilising the power of quantum computing; this leads to faster and more accurate results. Moreover, by recognising more subtle patterns in the data, quantum machine learning algorithms can improve the accuracy of healthcare tasks, potentially solving the medical image segmentation and classification to identify and predict cancers.

Further research is needed to assess the suggested technique's efficacy in solving complex problems on a variety of datasets. By developing new quantum algorithms and applying cutting-edge optimisation techniques, the method can be made more scalable and efficient. By expanding the suggested approach to additional machine learning principles such as deep neural networks, transfer learning can be investigated. These initiatives have the potential to advance quantum machine learning research and provide new approaches to solving challenging real-world problems. This strategy has a huge potential impact, which calls for more academic research. Due to current limitations in quantum hardware, the QSVM algorithm

TABLE 5 Experiment setup and execution time comparison.

Algorithm	Computational environment	Time complexity	Execution time (seconds)	Accuracy (%)
Classical SVM	Local CPU	O (poly (NM)	228.60	97.0
QSVM kernel	IBMQX2	O (log (NM)	72.60	98.6
	IBMQ_16_Melbourne	-	37.50	99.4
	IBM QASM simulator	-	0.14	100.0

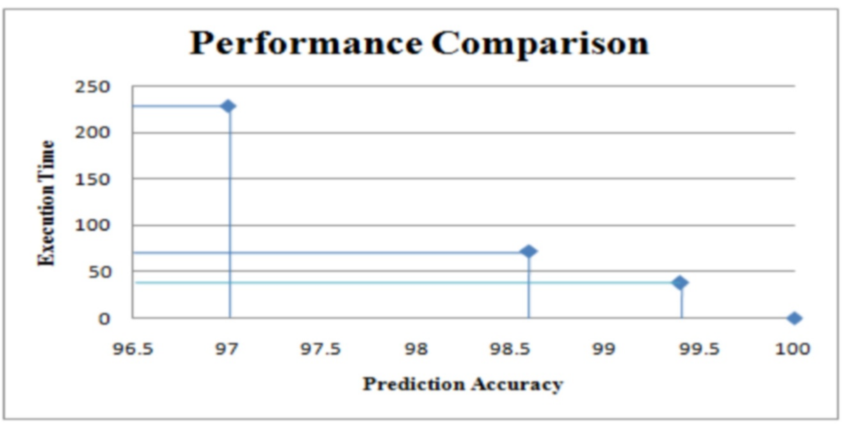

FIGURE 9 Prediction accuracy classical SVM versus QSVM kernel.

was designed for small-scale problems. There is limited comparative analysis and experimental validation.

Limitations of the NISQ device include a small qubit count, errors due to de-coherence, and limited qubit connectivity. Creating quantum circuits, converting classical data into quantum states, and combining classical and quantum components also result in training complexity overhead. Algorithmic constraints like circuit depth and expressivity also make practical implementations more difficult.

AUTHOR CONTRIBUTIONS

Jose P: Conceptualisation; Formal analysis; Writing - original draft. **Shanmugasundaram Hariharan**: Conceptualisation; Formal analysis; Methodology; Writing - original draft. **Vimaladevi Madhivanan**: Conceptualisation; Data curation; Formal analysis. **Sujaudeen N**: Conceptualisation; Data curation; Investigation; Methodology. **Murugaperumal Krisnamoorthy**: Data curation; Formal analysis; Investigation; Writing - original draft. **Aswani Kumar Cherukuri**: Conceptualisation; Formal analysis; Writing - original draft; Writing - review & editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest to report regarding the present study.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no datasets were generated or analysed during the current study.

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SUPPORTING INFORMATION

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