Cancer Cell Detection Using a Hybrid Quantum and Classical Machine Learning Model

Kalluru Hitesh and Pushpa P.V. *Senior Member* , *IEEE*
Department of Electronics and Communication Engineering
Dayananda Sagar University
Bangalore, India , 560068
Email: hiteshkalluru@gmail.com , alladpushpa@gmail.com

Abstract— The early diagnosis of cancer using MRI is vital in medical diagnostics. Traditional machine learning approaches struggle with the high dimensionality and complexity of medical image data. As quantum computing technology progresses, such hybrid approaches are expected to become increasingly practical, leading to significant advancements in the early detection and diagnosis of cancer. This research investigates quantum machine learning for the classification task, utilizing a Support Vector Machine (SVM) with a quantum kernel to detect cancer cells from MRI scans with improved accuracy and efficiency. The quantum feature space is created through quantum feature mapping of classical data, enhancing the SVM's ability to classify cancerous and non-cancerous cells. The proposed solution consists of a quantum machine learning model, that utilizes the classical algorithm with quantum kernel, showing a significant potential to revolutionize medical diagnostics. By integrating the strengths of quantum computing with classical machine learning techniques, this approach provides a powerful and efficient tool for medical image analysis. The proposed quantum machine learning model gives the accurate analysis of cancer cells detection present in MRI scans of the brain.

Index Terms— Quantum computing, Quantum Machine Learning, Feature Mapping, Support Vector Machine, Quantum Kernel, Optimization

I. Introduction

Detecting cancer is crucial in medical diagnosis, with MRI and other imaging techniques playing a key role. Traditional image analysis methods, though effective, require significant computational power and miss small but critical details that distinguish cancerous cells from healthy ones [3]. Quantum Machine Learning (QML) offers a promising solution to improve medical image analysis. By leveraging quantum phenomena like superposition and entanglement, QML algorithms can process complex datasets and identify subtle patterns that conventional methods overlook [1]. The proposed optimized solution combines Classical Machine Learning and Quantum Computing, utilizing a classical Support Vector Machine (SVM) model with a quantum kernel [2]. This hybrid approach aims to enhance the accuracy and reliability of cancer cell detection from MRI scans of brain. The quantum kernel maps the input datasets into a high-dimensional quantum feature space, making data points more separable [4]. This integration of classical and quantum techniques can significantly improve detection performance.

The core of this approach is the quantum feature map, which transforms classical input data into quantum states. This mapping enables the SVM model to operate within a quantum-enhanced framework. The quantum kernel computes the inner product of these quantum states, providing a similarity measure that feeds into the SVM. By reformulating the problem in this manner, the SVM provides a better and more expressive feature space, improving its ability to distinguish between cancerous and non-cancerous cells. QML's potential advantages over traditional methods are numerous. The higher dimensionality of the quantum feature space can reveal intricate structures in the data, enhancing pattern recognition capabilities. Additionally, the inherent parallelism of quantum computing allows for the simultaneous processing of multiple states, potentially speeding up computations and improving efficiency [5].

These benefits are particularly valuable in medical imaging, where accurate and timely diagnosis is critical. Implementing this hybrid quantum-classical approach involves several key steps. Initially, classical MRI data is pre-processed and converted into a format suitable for quantum processing. The quantum feature map then transforms this data into quantum states. This research work is expected to yield higher accuracy in cancer detection compared to traditional machine learning methods.

In this paper, we discuss the related work in section II. The section III describes about the process of the detection of cancer cells using the quantum machine learning model. Simulation results and discussions are presented in section IV, followed by the conclusion in section V.

II. Related work

The following is related work performed in various papers, journals and books in the field of quantum machine learning and medical image analysis. In the work [1], the author introduced the concept of quantum-enhanced feature spaces, demonstrating how quantum kernels can be used to improve the performance of classical machine learning algorithms like support vector machines (SVM). The authors in [2] highlighted applications of quantum computing in chemistry, with implications for medical imaging. The work in [3] provided an overview of quantum machine learning algorithms and their applications, including medical imaging. The authors in [4] investigated the use of quantum neural networks for classification tasks. A detailed review of advancements in QML and its potential applications, including healthcare is presented in [5]. The work in [6] discusses quantum information processing techniques relevant to QML. The authors in [7] introduced foundational quantum algorithms for machine learning, emphasizing the potential speed-ups for data processing. The work in [8] provides a comprehensive review of QML algorithms and their potential for various applications, including medical diagnostics. In the paper [9], application of Quantum Support Vector Machine (QVSM) is applied to the prostate cancer. A high-dimensional QSVM framework and its application to image classification is reviewed in [10]. The paper [11] demonstrates quantum neural networks on a quantum computer by detecting breast cancer.

III. Quantum Machine Learning Algorithm for the Cancer Cells Detection

Quantum Machine Learning is the integration of machine learning programs with quantum algorithms. In this research work, we developed a quantum machine learning model for detecting the cancer cells from the MRI scans of images.

The datasets are obtained from Kaggle. There are two types of datasets taken for this work, testing and training. Each dataset consists of cancer and non-cancer MRI scans of brain. Fig. 1 shows one of the training MRI scans of the cancer cells belonging to the tumor called glioma.

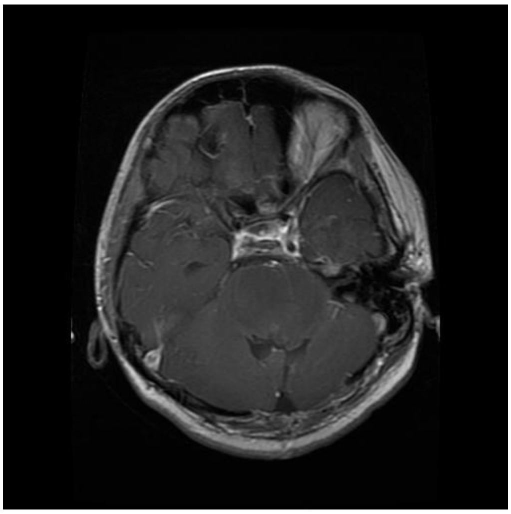

Fig.1. MRI scan of brain consisting glioma

The Fig. 2 shows one of the training MRI scans of benign cells (non-cancer cells).

Fig.2. MRI scan of benign cells

These datasets are then incorporated into the quantum states. The study of Support Vector Machine and Quantum Kernel is performed using the following steps:

A. *Data Encoding*

A collection of 24 datasets comprising MRI scans of both glioma (cancer) and benign (non-cancer) cells, distinguishing between cancerous and non-cancerous cell samples are considered in this work, each described by D features. Each feature is encoded into quantum states using qubits. Let $|x_i\rangle$ represent the quantum state corresponding to the i^{th} data point. This encoding transforms classical data into quantum states, which can then be processed using quantum feature maps.

B. *Feature Mapping*

Quantum feature mapping is a step that allows classical data to be encoded in quantum states so as to leverage some intrinsic properties of quantum mechanics in capturing the intricate patterns existing in the data. By applying a feature map Φ, input data points are mapped into a higher-dimensional quantum feature space, enhancing the ability to detect complex relationships within the data.

$$|x_i\rangle \rightarrow |\boldsymbol{\Phi}(x_i)\rangle$$

C. *Quantum Kernel*

A quantum kernel K(x, y) measures the similarity between two quantum states $|\varphi(x)\rangle$ and $|\varphi(y)\rangle$. This quantum kernel is fundamental in the Support Vector Classifier (SVC) optimization process. It helps find the optimal hyperplane that separates data points into various classes. The quantum kernel enables the SVC to operate in a higher-dimensional space, thus improving its ability to distinguish between cancerous and non-cancerous cells. Following equation establishes the relation between the quantum kernel and the quantum states.

$$\mathrm{K}(x_i, x_j) = \langle \boldsymbol{\Phi}(x_i) | \, \boldsymbol{\Phi}(\, x_j) \rangle$$

D. *Optimization*

The Support Vector Classifier (SVC) optimization using quantum kernel is used to find the optimal hyperplane, which separates the data points into various classes. High accuracy obtained proves the effectiveness of the quantum-enhanced approach in identifying cancerous cells from MRI scans of brain. Consider α_i, α_j to be the Lagrange multipliers, then

$$\dot{min}_{\alpha} \, (\Sigma_{i,j} \alpha_i \alpha_j y_i y_j \mathrm{K}(x_i, x_j)) - \Sigma_i \alpha_i \; ; 0 \le \alpha_i \le \mathrm{C} \;\&\; \Sigma_i \alpha_i y_i = 0$$

In traditional Support Vector Machines (SVMs), an optimal hyperplane is identified to distinguish between different data classes. However, by applying a quantum feature map like ZZFeatureMap, classical image data can be elevated to a high-dimensional Hilbert space. Our approach leverages the FidelityQuantumKernel, which measures the similarity between data point pairs by assessing the fidelity of their corresponding quantum state representations. This quantum kernel is then seamlessly integrated into a classical SVM, enabling the creation of a robust classifier. This classifier excels at identifying complex, non-linear decision boundaries within the quantum feature space, enhancing its ability to accurately categorize data.

E. Execution

The implementation of the SVM algorithm utilizing a quantum kernel involves a series of steps. First, MRI scans of brain images are retrieved from the datasets and resized to a uniform scale. The input data is then categorized into testing and training sets, with each set containing both cancerous and non-cancerous images. To prevent feature imbalance, standard scaling is applied to normalize the MRI scan features. Following scaling, the data is divided into training and testing sets to assess the model's performance.

A quantum circuit comprising 8 qubits is developed using the PauliFeatureMap, mirroring the feature dimension. Subsequently, a quantum kernel fidelity object is created using the feature map and quantum simulator backend. The backend operation is performed using QASM Simulator. With the precomputed kernel, an SVC classifier is initialized using the quantum kernel. The SVM model is then trained using the quantum kernel matrix computed on the training data. The model's performance is evaluated on the testing data by calculating accuracy and fine-tuning parameters such as the C value and number of repetitions. This iterative process enables optimization of the model's performance.

Throughout this process, the quantum kernel facilitates the exploration of complex relationships within the data, enhancing the model's ability to accurately distinguish between cancerous and non-cancerous images. By leveraging quantum computing's capabilities, this approach offers a promising avenue for improving medical diagnosis and treatment.

The pseudo code for the implementation of support vector machine using quantum kernel for the cancer cells detection is given below.

Table I: Pseudo Code

```
LOAD & PREPROCESS MRI scans (resize, normalize, flatten)
SPLIT DATA into training and test sets
SCALE FEATURES using StandardScaler
INITIALIZE ZZFeatureMap with input feature dimension
CREATE FidelityQuantumKernel using the feature map
SETUP SVC with precomputed kernel
PIPELINE with scaler and SVC
COMPUTE training kernel matrix with quantum kernel on training data
TRAIN SVM model with training kernel matrix
        K_train = [K (x_i, x_j)] ∀ x_i, x_j ∈ X_train
COMPUTE test kernel matrix with quantum kernel on test data
PREDICT with SVM model on test kernel matrix
        K_test = [K (x_i, x_j)] ∀ x_i ∈ X_test, x_j ∈ X_train
CALCULATE & DISPLAY accuracy with test labels and predictions
```

IV. SIMULATION RESULTS AND DISCUSSIONS

The simulation is performed using qiskit. Fig.3 illustrates the quantum circuit architecture, accompanied by a cross-validation accuracy of 0.88 ± 0.24. The model's accuracy reaches 1.00 when rounded-off to two digits. The specific values inside the PauliFeatureMap define the transformations applied to each qubit within the feature map. These parameters are essential as they determine the encoding of classical data into quantum states, directly impacting the effectiveness of the quantum machine learning model.

The maximum accuracy is achieved by altering C-Value, randomness, repetitions of the circuit's execution. In quantum machine learning, the concepts of the `C value`, randomness, and repetition are pivotal. The `C value`, used in Support Vector Machines (SVM), balances model complexity and training accuracy, with higher values focusing on minimizing training errors and lower values promoting generalization. Randomness in machine learning and quantum computing appears in random initialization of model parameters, data sampling, and the inherent probabilistic nature of quantum states and measurements. Repetition is essential for obtaining reliable results, whether through averaging outcomes of multiple quantum measurements or cross-validation in classical machine learning to ensure stability and generalization of models. These elements interplay in quantum kernels and SVMs, where the quantum instance executes numerous trials to average out the inherent randomness and stabilize the model's predictions, all while carefully tuning the `C value` to achieve an optimal balance between overfitting and underfitting.

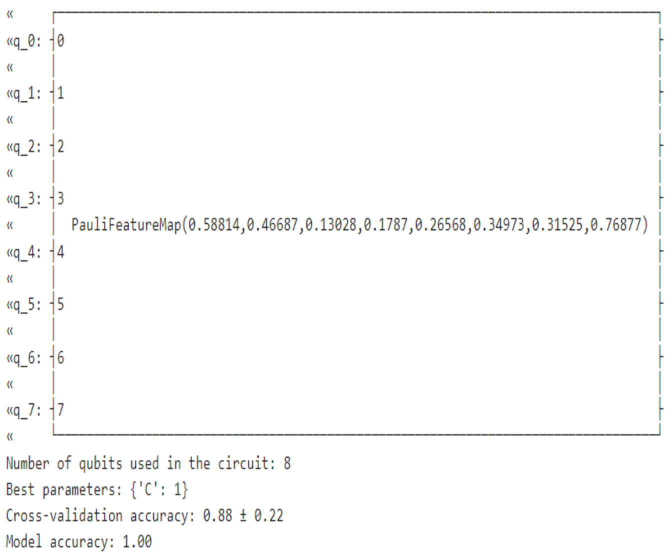

Fig.3. Output of the SVM model using Quantum Kernel

The graph in Fig.4 represents support vector machine using quantum kernel. The contour lines of red and blue colours indicate the probability of finding cancer and non-cancer cells respectively. The black-coloured contour lines indicate the difficulty in classification of cancer and non-cancer cells, due to the similarities within the training and testing datasets.

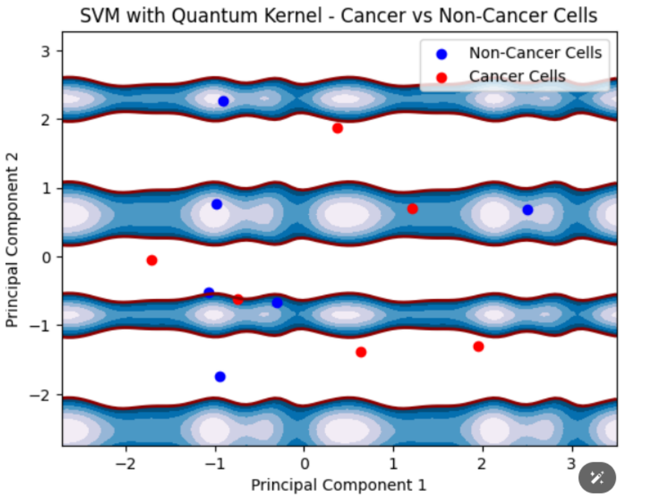

Fig.4. Graph of Support Vector Machine using Quantum Kernel

Fig.5 shows the graph of number of Repetitions vs C Value vs Accuracy, keeping Randomness constant. The accuracy increases as the number of repetitions and the C value increases.

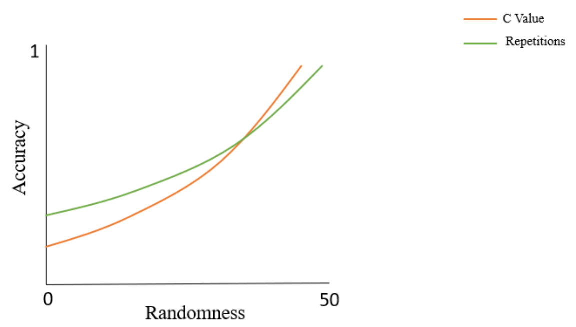

Fig 5: Graph of Repetitions vs C Value vs Accuracy

V. Conclusion

The proposed work illustrates the potential of Quantum Machine Learning in the medical field. By using Support Vector Machine (SVM) with Quantum Kernel, cancer detection from MRI scans is achieved with a higher accuracy. The pre-processing of classical MRI data using quantum feature mapping, and with the quantum kernel to calculate similarity measures, the hybrid model accurately classifies cancerous and non-cancerous cells. This model combines the strengths of both quantum and classical computing, providing a powerful and efficient tool for medical image analysis. As quantum computing technology progresses, such hybrid approaches are expected to become more feasible, leading to significant advancements in early cancer detection and diagnosis. The proposed model gives accurate detection of cancer cells using quantum machine learning, thereby enhancing the analysis of medical image diagnostics.

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