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Quantum-Enhanced Sentiment Recognition using Natural Language Processing

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Abstract : Quantum computing provides powerful computational advantages, such as faster execution of complex calculations, parallel processing through quantum superposition, and efficient management of high-dimensional data. In parallel, natural language processing (NLP) has gained substantial attention as researchers seek to develop models capable of handling increasingly large and complex linguistic data. As a result, integrating quantum computing techniques into NLP applications—particularly sentiment analysis—presents a promising research direction. This study examines effective methods for representing sentiment-related sentences to enable their classification using a Quantum-Enhanced Support Vector Machine (QE-SVM). The investigation focuses on optimizing quantum circuit parameters and applying suitable data transformation techniques. The proposed framework includes converting sentences into quantum circuits, training circuit parameters, generating quantum state vectors, and conducting classification through training and testing stages. Experimental findings indicate that the combination of the Simultaneous Perturbation Stochastic Approximation (SPSA) optimizer with MPCA-based data transformation achieves the highest classification accuracy of 95.53%, outperforming the classical SVM baseline.

***IndexTerms* - Sentiment classification, SVM, quantum-enhanced, quantum representation**

I. INTRODUCTION

1.1 **Sentiment classification:** Sentiment classification is typically addressed using machine learning (ML) algorithms that rely on labeled training data to predict sentiment values. These learning algorithms enhance the prediction process by effectively handling opinionated sentences that are characteristic of natural human language. Quantum machine learning (QML) offers a novel approach to this problem by integrating quantum computing with artificial intelligence, particularly learning algorithms. Quantum computers provide the capability to tackle complex computational problems that are difficult or intractable for classical computing systems.

Sentiment analysis using machine learning is a method for identifying and categorizing opinions or emotions expressed in textual data as positive, negative, or neutral. It integrates natural language processing (NLP) techniques with machine learning algorithms to analyze large-scale text data, including product reviews, social media posts, and customer feedback. The typical workflow involves gathering labeled datasets, preprocessing text to eliminate noise, transforming textual information into numerical feature representations using techniques such as Bag of Words or Term Frequency–Inverse Document Frequency (TF-IDF), and training classification models such as Naive Bayes, Support Vector Machines, or Logistic Regression. These models learn underlying patterns from the training data and are subsequently used to predict the sentiment of previously unseen text. Due to its ability to automatically interpret public opinion, sentiment analysis is widely applied in domains such as market analysis, social media monitoring, and customer satisfaction assessment, supporting data-driven decision-making.

1.2. **Quantum Computing Vs. Classical Computing**

Quantum computers are expected to address certain classes of problems—particularly those involving a vast number of variables and possible outcomes—far more efficiently than classical computers. Such problems include applications like drug interaction simulations and supply chain optimization, where computational complexity grows rapidly with problem size.

One of the key distinctions between quantum and classical computers lies in how they process information. Classical computers rely on transistors that encode data as binary states, representing either a 0 or a 1 at any given time. In contrast, quantum computers utilize quantum bits, or qubits, which can exist in a superposition of states, allowing them to represent both 0 and 1 simultaneously. This fundamental difference enables quantum systems to perform certain computations more efficiently than their classical counterparts.

1.3. **Motivation**

The primary objective of this research is to identify the most effective data representation for quantum natural language processing (NLP) in sentiment classification, specifically for representing sentiment within sentences. In addition, various optimization techniques, including Simultaneous Perturbation Stochastic Approximation (SPSA) and Artificial Neural Network (ANN)–based optimizers, are investigated to enhance classification performance. These explorations aim to improve sentiment classification outcomes by transitioning from the classical Support Vector Machine (SVM) approach to the Quantum-Enhanced Support Vector Machine (QE-SVM) framework.

Previous studies have proposed quantum representations for sentiment classification by employing a state vector–based approach and incorporating negation handling through a NOT-box operation. While this method demonstrated feasibility, it resulted in high-dimensional vector representations and achieved limited predictive performance, with an accuracy of 81.67%. Therefore, a key challenge remains in developing an efficient and compact quantum representation of subjective sentences that enables fast and accurate computation within the QE-SVM learning paradigm.

II. LITERATURE REVIEW

Sentiment analysis is one of the most extensively studied areas in natural language processing (NLP) due to its wide range of practical applications. Recently, quantum machine learning (QML) has emerged as a promising approach for addressing sentiment analysis tasks. Several studies have explored quantum-inspired methods that mimic quantum mechanisms. For example, sentiment analysis on Twitter data has been investigated using a quantum-inspired representation model, in which semantic and sentiment information are modeled through a series of projectors in a probabilistic space. This approach was later extended into a Quantum-like Multimodal Network (QMN), which integrates quantum theory with Long Short-Term Memory (LSTM) networks to perform multimodal sentiment analysis in conversational settings.

Quantum algorithms have also been applied to sentiment analysis through Variational Quantum Classifiers (VQCs). In particular, some studies have implemented VQCs using EfficientSU2 and Real Amplitudes ansätze provided by the Qiskit quantum computing framework. Although conceptually similar to classical machine learning models, these quantum-based approaches have demonstrated improved classification performance over their classical counterparts.

A critical step in the Quantum NLP (QNLP) pipeline is the training of circuit parameters after textual data are encoded into quantum circuits. This optimization process is typically performed using gradient-based or gradient-free optimization algorithms, among which Simultaneous Perturbation Stochastic Approximation (SPSA) is widely adopted. SPSA is especially well suited for high-dimensional optimization problems, as it approximates gradients using only two evaluations of the objective function, regardless of the number of parameters. This property significantly reduces computational costs and makes SPSA particularly effective for variational quantum algorithms.

For classification tasks, kernel-based machine learning methods are commonly employed, with Support Vector Machines (SVMs) being among the most well-established techniques. By combining the strengths of SVMs with quantum computing, researchers have proposed quantum variational classifiers implemented using variational quantum circuits. Additionally, quantum kernel estimation methods have been introduced to enhance SVM performance by computing kernel functions within a quantum feature space. These developments form the foundation of the Quantum Support Vector Machine (QSVM) module available in the Qiskit framework, enabling broader adoption of quantum kernel methods.

The quantum kernel approach leverages a quantum feature space, where data are represented as quantum states in a Hilbert space. The inner product between two quantum states—representing encoded data points—can be computed directly on a quantum circuit by applying the inverse of one unitary transformation followed by the other and measuring the resulting state. Alternatively, the quantum states can be measured individually, and the inner product can be calculated classically. In both cases, the resulting kernel values are used in downstream machine learning tasks, such as identifying support vectors in SVM classification.

The motivation for employing quantum kernels lies in their potential to generate feature maps that are difficult to compute classically, while providing enhanced data separability in high-dimensional spaces. Building on this concept, the QSVM framework has been further developed for practical applications under the Noisy Intermediate-Scale Quantum (NISQ) paradigm. In these implementations, structured classical data are encoded into quantum states via quantum feature maps, and classification is subsequently performed using quantum kernel-based methods.

III METHODOLOGY

3.1. Quantum kernel and optimization

Kernel-based machine learning methods are widely used for classification tasks, with the Support Vector Machine (SVM) being one of the most well-known and effective traditional approaches. By integrating the strengths of SVMs with quantum computing, researchers have proposed the concept of a quantum variational classifier implemented using variational quantum circuits. In addition, a quantum kernel estimation approach has been introduced to enhance SVM performance by computing the kernel function within a quantum feature space. This quantum kernel method serves as the foundation for the Quantum Support Vector Machine (QSVM) module available in the Qiskit framework, enabling straightforward adoption of quantum-enhanced classification techniques by the research community.

The previously proposed QSVM concept was further extended to practical applications under the Noisy Intermediate-Scale Quantum (NISQ) paradigm. In this line of work, structured classical data are encoded into quantum states using quantum feature maps, after which classification is performed by evaluating a quantum kernel. The approach was validated using several benchmark datasets, including three standard datasets from the UCI Machine Learning Repository—Wine, Breast Cancer, and Handwritten Digits—as well as two artificially generated numerical datasets.

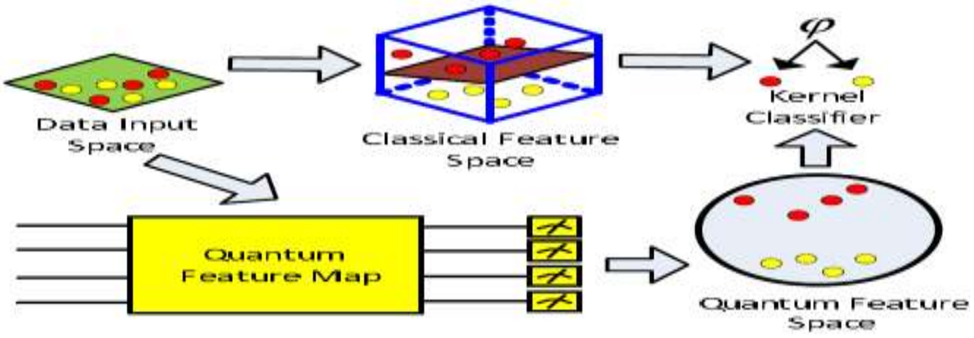

Figure 1: Illustration of comparison between quantum and classical kernel.

A crucial step prior to quantum kernel evaluation is data transformation, which generates suitable feature maps for quantum encoding. This transformation can be performed using predefined techniques or heuristic rules, such as Principal Component Analysis (PCA) or double-angle encoding, or it can be learned automatically through optimization algorithms. The latter approach has been explored using genetic algorithms to minimize the number of circuit parameters. This method has been evaluated on various structured datasets, including Parkinson's disease data, IoT-based irrigation data, and drug classification datasets.

3.2. Proposed method

The proposed pipeline converts sentences into quantum circuits, optimizes these circuits, and then uses them to perform sentiment classification with the QE-SVM method. In this study, we introduced modifications to the pipeline, particularly in the optimization stage, to enhance performance. The main stages of the pipeline are:

1. **Circuit Generation:** Converting sentences into corresponding quantum circuits.
2. **Circuit Parameter Training:** Optimizing the parameters of the generated circuits.
3. **State Vector Extraction:** Obtaining quantum state vectors from the circuits, which serve as sentence embeddings.
4. **QE-SVM Classification:** Using the extracted embeddings to train the QE-SVM classifier and predict the sentiment of each sentence.

This workflow is illustrated in Figure 2.

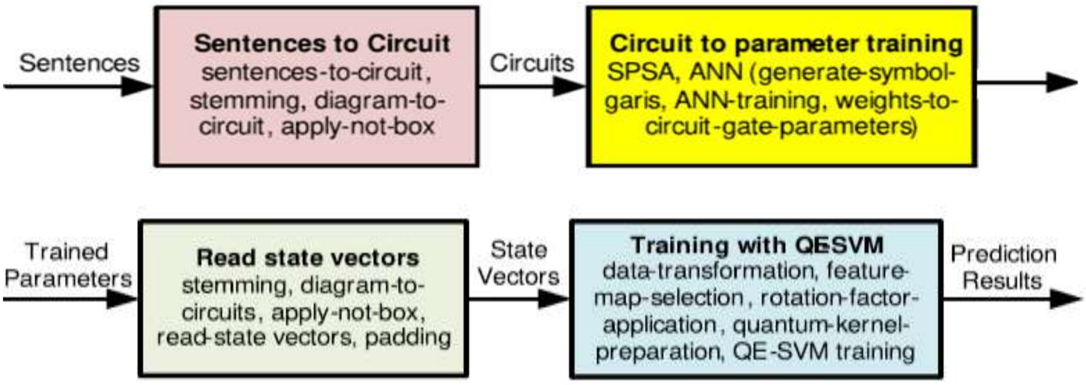

Figure 2: General pipeline in Quantum Natural Language Processing

3.2.1 Sentences to Circuits

1) Sentences to Circuits

1. The first step in the pipeline converts sentences into quantum circuits using the Quantum Pipeline with **Tket**, as described in the Lambeq 0.1.2 documentation. Sentences are initially transformed into **DisCoCat diagrams** via the DepCCG Parser, with negation words (e.g., "not") temporarily ignored. A DisCoCat diagram models the semantic interactions between words in a sentence.

2. The diagrams are then simplified using the **Lambeq Rewrite** package, which applies a set of transformation rules to modify the strings or boxes within the diagram. In our experiments, the **determiner, pre-adverb, and post-adverb rules** were consistently applied, while the use of **auxiliary rules** varied. Cups in the diagrams are removed using the **bigraph method** outlined in Lambeq 0.1.2. This process may require restructuring, such as moving all cups below the word boxes and ordering them so that cups on the right are positioned above those on the left.

2) Stemming

3. To reduce the complexity of words in the diagrams, stemming is performed after stop-word removal using **NLTK's Porter Stemmer**. This step standardizes word forms, reducing dimensionality in the subsequent quantum circuit representation.

3) Diagrams to Circuits

4. The simplified DisCoCat diagrams are then converted into quantum circuits using the **IQP Ansatz**, available in the Lambeq Ansatz package. This produces the initial circuit representation of each sentence.

4) Applying Not-Box Settings for Negative Sentences

5. To handle negation, **Not-Box settings** are applied to circuits by adding a **Pauli-X gate** to the output qubit. The output qubit represents the grammatical type 's' after type reduction. If the output qubit is located in the middle of the circuit, the Not-Box may

be applied there instead. This approach directly captures the semantic effect of negated words. The Pauli-X gate was chosen because it flips the probability of measurement for a single qubit, effectively reversing the sentence's sentiment when applied to the output qubit.

3.2.2 circuit-to-parameter training

The quantum circuits are converted into an **objective function** for **SPSA optimization**, where the output qubit of type 's' is compared against the corresponding sentiment label to evaluate the model's cost. During training, the free parameters of the circuits, which correspond to the gate rotation angles, are optimized to minimize this cost. Once the circuit parameters are trained, the optimized circuits are used to predict the sentiment of new sentences by measuring the output qubit, with its state indicating the classified sentiment.

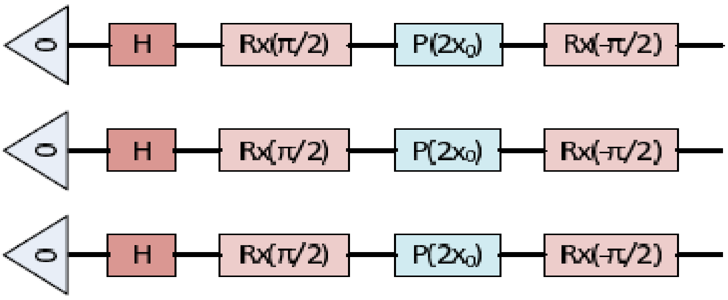

Figure 3.3: Feature map circuit.

3.2.3 **Reading state vectors**

1) Stemming and Diagrams to Circuits

6. The training process uses the **state vector representations** of each quantum circuit. These vectors are derived from the word boxes of a sentence, which are extracted from its string diagram. The sentence-level vector representation is obtained by taking the **tensor product** of the state vectors corresponding to each word box. To measure the quantum states, circuits are generated from diagrams in which the cups have not been removed.

2) Applying Not-Box Settings to Negative Sentences

7. For sentences containing negation (e.g., the word "not"), **Not-Box settings** are applied according to the chosen representation. This ensures that the semantic effect of negation is correctly encoded in the quantum circuit.

3) Reading State Vectors and Padding

8. Once the circuit parameters are initialized, the state vector values are read from the circuits. To maintain a **uniform feature size** across all input sentences, these state vectors are **padded with the |0⟩ state** to fill quantum registers to a consistent length, enabling proper input to the QE-SVM classifier.

3.2.4 Training with QE-SVM

Finally, the prepared inputs are used to train the **QE-SVM classifier** utilizing a quantum kernel. The state vector representations obtained from the previous stage are processed to be compatible with the QE-SVM framework. During training, each feature corresponds to a **state vector measurement** obtained after optimizing the quantum circuit parameters. In this study, circuit optimization is performed using either **Simultaneous Perturbation Stochastic Approximation (SPSA)** or an **Artificial Neural Network (ANN)**–based optimizer. The complete training pipeline is described in the following section.

IV IMPLEMENTATION

To implement multi-class brain tumor classification from MRI imaging data, machine learning techniques such as Support Vector Machine (SVM) and Random Forest Classifier (RFC) are employed. Required libraries include scikit-learn for model implementation, seaborn and matplotlib for visualization, and joblib for saving and loading trained models.

The workflow begins by checking for the existence of a pre-trained SVM model. If such a model is available, it is loaded; otherwise, a new SVM model is trained using the provided training dataset (x_train and y_train). Once trained, the SVM model is saved for future use. Predictions are then made on the test dataset, and performance metrics are calculated to evaluate the model's accuracy.

A similar procedure is followed for the RFC model. The code first checks for a pre-trained RFC; if none exists, a new RFC model is trained on the training data. The trained RFC model is saved, predictions are generated for the test data, and performance metrics are computed to assess the model's classification effectiveness.

Figure 4.1. Log in screen

Figure 4.2: Accuracy comparison

Enter Text: I am happy

Sentiment Result:
Positive Sentiment

Figure 4.3: Sentiment Analyzer Positive

Figure 4.5: Bar chart Sentiment Analyzer Negative

4.1. Opinion words

The In sentiment analysis, opinions are sometimes expressed explicitly, such as in statements like *"The video quality of this movie is marvelous."* Sentiment categorization generally focuses on identifying the overall emotion conveyed by an opinion, typically classifying it as positive or negative. The polarity of an opinion reflects whether it conveys a positive or negative sentiment. This can be analyzed at different levels, ranging from determining the overall polarity of a document to identifying the sentiment of individual subjective sentences within the text.

Conclusion:

This project presents a study on the application of Quantum-Enhanced Support Vector Machine (QE-SVM) for the NLP task of sentiment classification. Subjective sentences, which contain sentiment information, were transformed into quantum representations that serve as inputs to a quantum kernel. Experimental results demonstrated that the combination of the sentence-to-circuit conversion, SPSA optimization, and MPCA-based data transformation within the QE-SVM framework achieved the highest classification accuracy of 94.33%, representing a 16.6% improvement over the baseline classical SVM. This approach was effective for both positive and negative subjective sentences. The study highlights the potential of using quantum kernels in NLP tasks, paving the way for further exploration of quantum computing in natural language processing applications.

Future Enhancements:

For future research, it is recommended to extend this work by adopting **Variational Quantum Algorithms (VQAs)**, which provide a flexible framework for addressing complex optimization and learning tasks on near-term quantum devices. Implementing these algorithms on **actual quantum hardware** would enable the evaluation of their practical performance under realistic noise and device constraints. Such investigations could yield valuable insights into **scalability, convergence behavior, and robustness**, and allow for direct comparisons between classical simulations and real quantum executions. This line of research would help assess the feasibility and potential advantages of **quantum-enhanced approaches** in practical NLP and machine learning applications.

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