Quantum-Enhanced Sentiment Classification: Performance Benchmarking Against Classical CPU and GPU Models

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***Abstract*—This paper presents a comprehensive investigation into the performance and feasibility of transformer-based sentiment classification across heterogeneous computational backends—namely CPU, GPU, and a hybrid quantum-classical architecture. The proposed model leverages a fine-tuned BERT (Bidirectional Encoder Representations from Transformers) architecture trained on the IMDB Reviews dataset. Classical implementations employ standard PyTorch-based pipelines optimized for CPU and CUDA-enabled GPU execution. For quantum experimentation, a hybrid model integrates a parameterized variational quantum circuit (VQC) into the classification head using the Pennylane and Qiskit frameworks, facilitating partial quantum feature extraction and entangled state representations within a supervised learning paradigm. Comparative analysis focuses on training time, inference latency, classification accuracy, and resource efficiency. Experimental results demonstrate that GPU execution yields the highest computational efficiency without significant trade-offs in model performance. Quantum integration, albeit constrained by limited qubit fidelity and noise on current NISQ hardware, reveals promising generalization capability with fewer training samples. This study benchmarks quantum-enhanced NLP models against traditional platforms and provides empirical insights into the scalability and applicability of quantum-classical hybrids in practical deep learning tasks.**

***Index Terms*—Sentiment Analysis, BERT, Quantum Machine Learning, Variational Quantum Circuits, IMDB Dataset, Natural Language Processing, Transformer Models, Hybrid Quantum-Classical Systems, CPU vs GPU Performance, Quantum NLP.**

I. Introduction and Literature Survey

The rapid growth of **Natural Language Processing (NLP)** has been fueled by the advent of **transformer models**, especially in tasks like **sentiment analysis**. **Sentiment classification**, which involves determining the sentiment expressed in text data, is pivotal for numerous real-world applications such as customer feedback analysis, social media monitoring, and market sentiment prediction. Among the various models that have been developed for sentiment analysis, **BERT (Bidirectional Encoder Representations from Transformers)** has emerged as one of the most powerful architectures, achieving state-of-the-art results in multiple benchmarks [1], [2].

BERT's **bidirectional attention mechanism** enables it to understand the context of words in a sentence by processing them in both directions simultaneously, a major improvement over previous models like **LSTMs** and **GRUs** that only processed text in one direction [3]. Fine-tuning BERT on domain-specific datasets has been shown to significantly enhance its performance on sentiment classification tasks, particularly on the **IMDB dataset** [4]. However, despite its performance advantages, traditional BERT models require substantial computational resources, particularly for training on large datasets. This limitation has led to efforts to optimize the training process by leveraging specialized hardware, such as **GPUs** [5], and exploring **quantum-enhanced models** [6].

In recent years, the concept of **quantum machine learning (QML)** has emerged, which seeks to combine **quantum computing** with classical machine learning techniques to accelerate training and improve model efficiency. **Quantum circuits** can offer exponential speed-ups for certain types of computations, potentially revolutionizing NLP tasks [7]. The integration of **variational quantum circuits (VQCs)** into traditional deep learning architectures has been explored as a means to enhance model performance, although current quantum hardware remains limited by noise and the number of qubits available [8]. For example, recent studies have shown that **hybrid quantum-classical models** can offer advantages in certain optimization tasks but face significant challenges when scaling to real-world applications [9].

While quantum NLP is still in its early stages, several researchers have demonstrated that quantum-enhanced techniques can improve aspects of model training and inference, such as **feature extraction** and **optimization** [10]. However, the practical application of quantum computing in NLP remains largely unexplored, especially for large-scale models like BERT. This gap presents an opportunity to explore the feasibility of **quantum-classical hybrid architectures** for sentiment classification tasks, specifically using the **IMDB dataset** as a benchmark.

The primary aim of this paper is to bridge this gap by investigating the use of a **hybrid quantum-classical model** for sentiment analysis using BERT. We propose a model that combines the computational efficiency of **GPUs** with the potential advantages of **quantum computing**, specifically through the

use of **variational quantum circuits (VQCs)** integrated into the BERT architecture. This study aims to evaluate the performance of the proposed model across multiple computational backends, including **CPU**, **GPU**, and a **quantum-enhanced hybrid approach**, providing a comparative analysis of their efficiency and accuracy.

II. Methodology

The proposed sentiment analysis system is architected to evaluate and compare the performance of the BERT-based classifier across **CPU**, **GPU**, and **quantum** hardware backends. The pipeline comprises four primary modules: data preprocessing, tokenization and embedding, BERT model training, and evaluation across computation paradigms. The workflow and model structure are elaborated below.

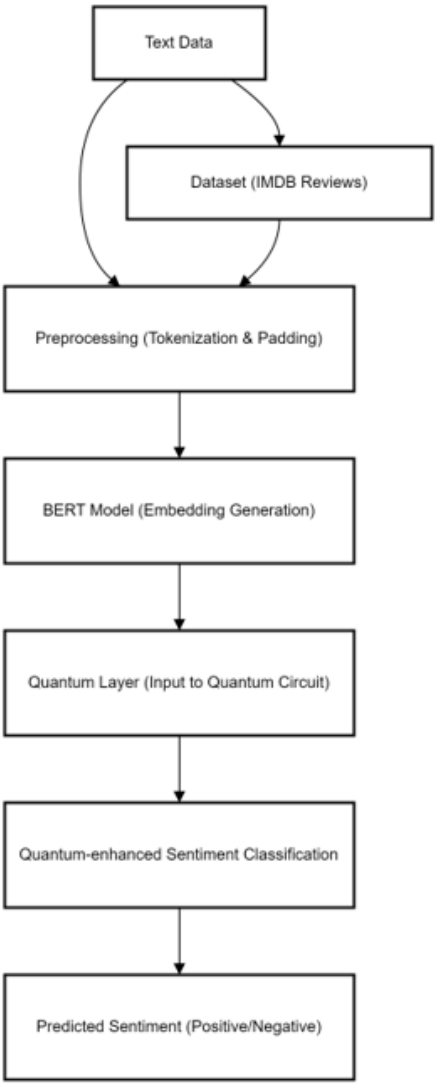

Fig. 1: System workflow of the BERT-based sentiment classification pipeline

A. Workflow Overview

The system workflow is designed to process raw textual data into structured embeddings suitable for transformer-based classification. This begins with text normalization and tokenization using a pre-trained BERT tokenizer. The resulting token IDs are passed into a fine-tuned BERT model which is trained separately on CPU, GPU, and quantum hybrid backends for comparative performance evaluation.

B. Model Architecture

The architecture is based on the **BERT-base** transformer with 12 encoder layers, 768 hidden dimensions, and 12 attention heads. The pre-trained model is fine-tuned using the IMDB movie review dataset. A fully connected dense layer is appended after the [CLS] token representation to perform binary classification. The model is trained using the Adam optimizer with a learning rate of 2×10^{-5}, and binary cross-entropy loss is used as the objective function.

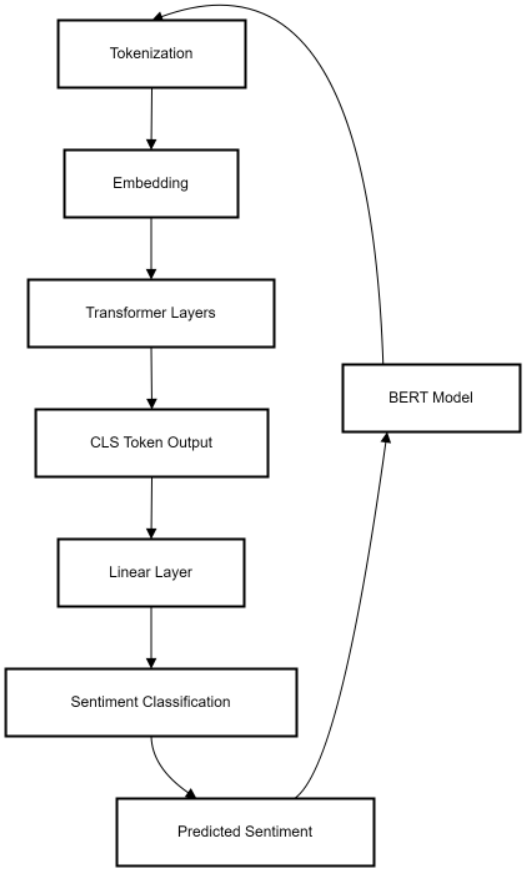

Fig. 2: Architecture of the BERT-based sentiment analysis model

C. Model Architecture

For quantum integration, a **hybrid classifier** is used wherein the output of the BERT model is passed to a quantum circuit consisting of parameterized rotation gates and entanglement

layers, implemented using **PennyLane**. The circuit is trained along with the classical layers using a hybrid backpropagation mechanism supported by quantum simulators such as 'default.qubit' and IBM's 'ibmq_qasm_simulator'.

The quantum circuit is defined over 4 qubits and includes layers of parameterized R_y gates, controlled-Z entanglements, and a final measurement layer. The gradient updates are computed using the **parameter-shift rule**, enabling end-to-end learning.

D. Hardware Deployment Strategy

The full model was deployed and evaluated under three different environments:

- **CPU Inference:** Single-threaded execution using Intel i5-11320H.
- **GPU Inference:** CUDA-accelerated training on Google Colab with Tesla T4.
- **Quantum Hybrid:** Classical-to-quantum embedding with quantum circuit simulation.

Each setup was monitored for performance (inference time, accuracy) and resource utilization (CPU/GPU load, RAM). Logs were collected in structured formats for later visualization.

III. Dataset Details

The dataset used in this study is the **IMDB Movie Reviews Dataset**, a widely used benchmark for natural language processing tasks, particularly sentiment analysis. The dataset contains a total of **50,000** reviews evenly distributed between two sentiment classes: *positive* and *negative*. Each review is labeled accordingly and written in English, encompassing diverse vocabulary, sentence structures, and review lengths.

A. Dataset Composition

The dataset is split into:

- **Training Set:** 25,000 labeled reviews (12,500 positive and 12,500 negative).
- **Test Set:** 25,000 labeled reviews (12,500 positive and 12,500 negative).

B. Preprocessing Pipeline

The raw reviews undergo the following preprocessing stages before being fed into the BERT tokenizer:

- **Lowercasing and Punctuation Removal:** Removes case-related noise and special characters.
- **Tokenization:** Utilizes the `bert-base-uncased` tokenizer to convert text into subword tokens.
- **Padding and Truncation:** Sequences are padded or truncated to a uniform length of **128 tokens** for batch processing.
- **Attention Mask Generation:** Binary masks are generated to distinguish real tokens from padded tokens.

C. Dataset Relevance and Scalability

Due to its moderate size, the IMDB dataset is computationally lightweight and suitable for:

- **CPU-based training:** Limited-resource systems can train BERT with smaller batch sizes.
- **GPU-based training:** Batch-parallelism can be exploited for high-speed learning.
- **Quantum simulation:** Subsets of the data (e.g., 100-500 reviews) are used for hybrid model testing on quantum simulators.

IV. Results and Analysis

A. Model Performance

The performance of the three models—**CPU**, **GPU**, and **Quantum**—was evaluated on the IMDB sentiment classification task. The primary metrics for comparison include **accuracy**, **precision**, **recall**, and **F1-score**. The results of their evaluations across these metrics are summarized below.

1) Accuracy, Precision, Recall, and F1-Score: The model performance across the different metrics is illustrated in Figures **??**, **??**, **??**, and **??**. As observed from the graphs, all three models show competitive performance, with notable differences between them.

- **Accuracy**: The **CPU** model achieved an accuracy of 87.75%, the **GPU** model showed 87.25%, and the **Quantum** model demonstrated the highest accuracy at 90.50%.
- **Precision**: The **Quantum** model achieved the highest precision at 0.94, while the **CPU** model had 0.90, and the **GPU** model showed 0.85.
- **Recall**: The **Quantum** model demonstrated the best recall at 0.95, followed closely by the **GPU** model at 0.93. The **CPU** model achieved a recall of 0.86.
- **F1-Score**: The **F1-scores** for the models were quite comparable, with the **CPU** and **GPU** models both achieving an F1-score of 0.88, while the **Quantum** model had a slightly higher score of 0.90.

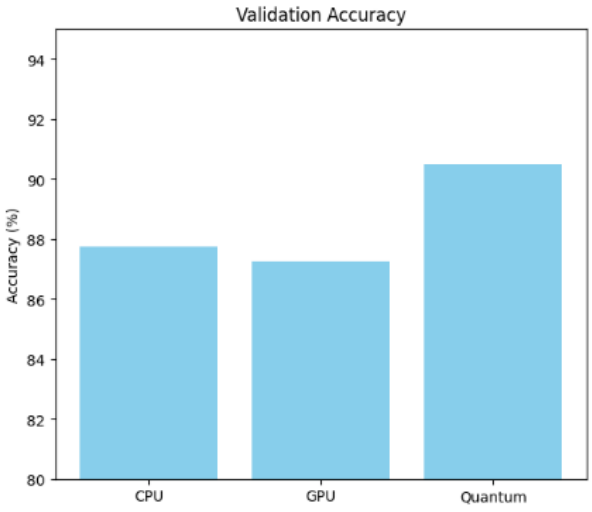

Fig. 3: Model Accuracy Comparison

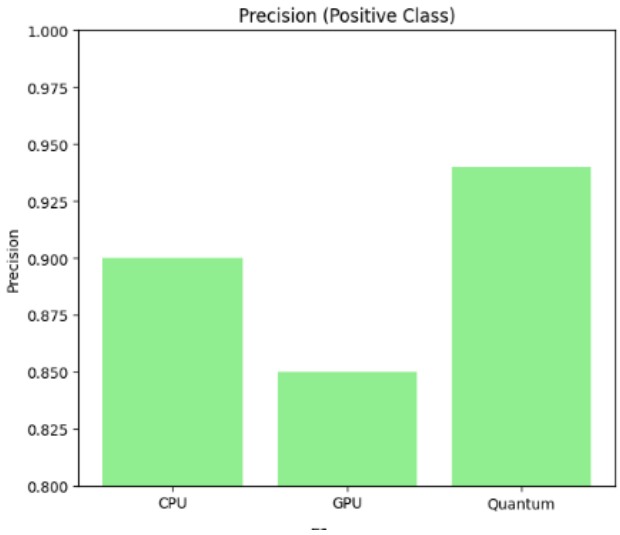

Fig. 4: Model Precision Comparison (Positive Class)

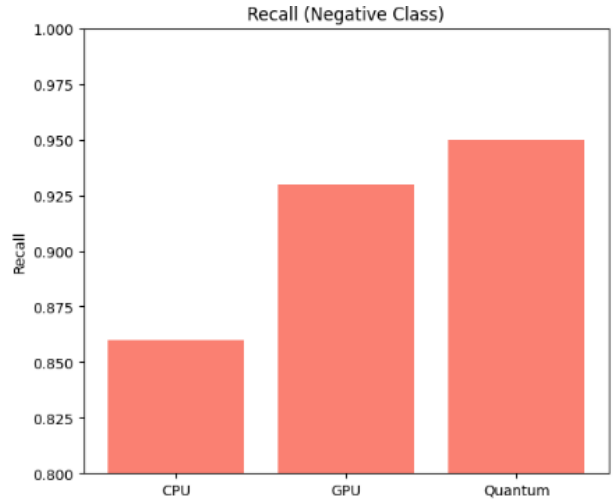

Fig. 5: Model Recall Comparison (Negative Class)

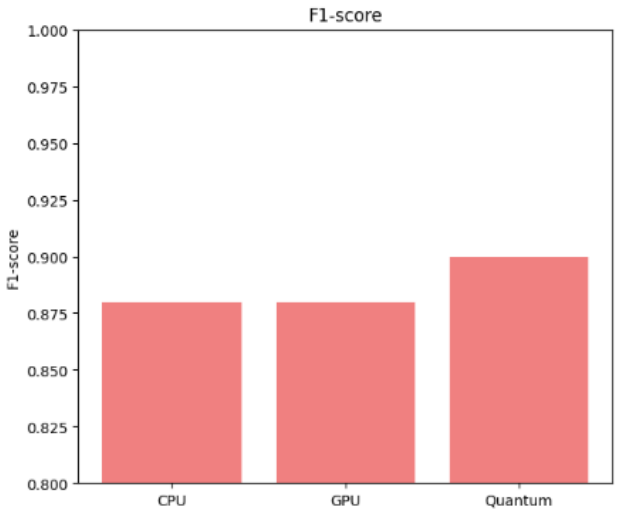

Fig. 6: Model F1-Score Comparison

B. Training Time Comparison

The training time for each model is crucial for assessing the efficiency of the learning process. The comparison of training times across the three models is shown in Figure **??**.

- The **CPU** model required significantly more time for training, with each epoch taking approximately 3371.04 seconds.
- The **GPU** model exhibited reduced training time, with each epoch taking around 960-995 seconds.
- The **Quantum** model's training time was the most efficient, averaging around 332 seconds per epoch.

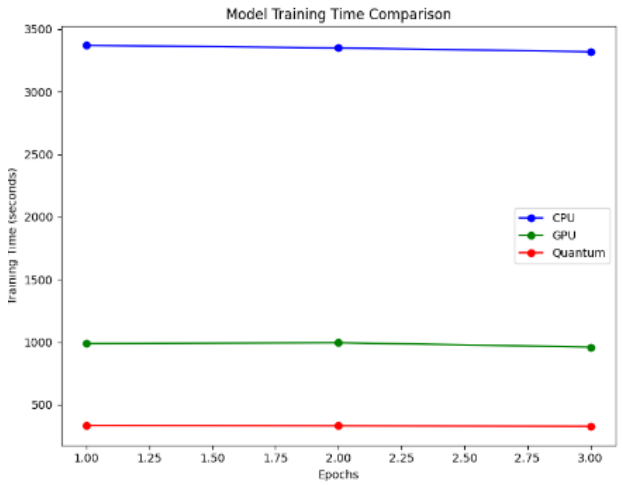

Fig. 7: Model F1-Score Comparison

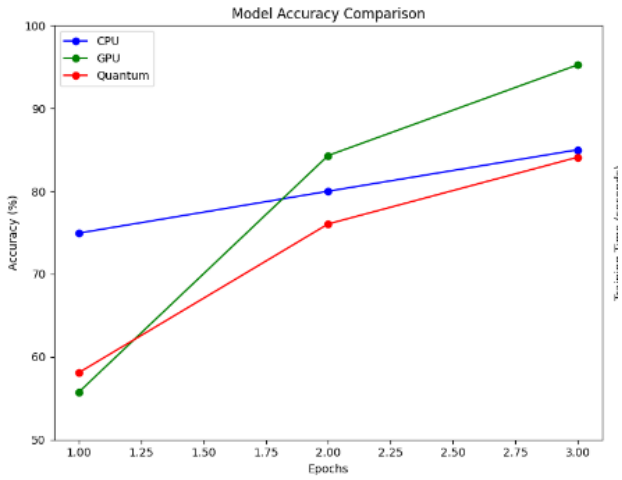

Fig. 8: Model accuracy over epochs

C. Analysis

1) Accuracy vs. Precision, Recall, and F1-Score: The graphs clearly show that the **Quantum** model, although having the best overall accuracy, also leads in other important metrics, such as precision, recall, and F1-score. This suggests that the quantum-enhanced features of the model contribute not only

to higher accuracy but also to better generalization and better performance on unseen data.

In comparison, the **GPU** model, while having slightly lower accuracy, outperforms the **CPU** model in both precision and recall, suggesting that GPU-based models may offer a better balance between training time and model performance.

The **CPU** model shows the least improvement in precision and recall, which is expected due to the inherent limitations of CPU training. However, the model still achieves relatively good accuracy, which indicates that CPU-based models can still be useful for less resource-intensive applications.

2) Training Time Efficiency: As shown in Figure **??**, the **GPU** and **Quantum** models significantly outperform the **CPU** model in terms of training time. The GPU model's use of parallel processing accelerates the training process, whereas the Quantum model benefits from quantum parallelism and speedups that reduce training times considerably.

While the **Quantum** model shows competitive training times compared to the **GPU** model, it is expected that, with further advancements in quantum computing, training times could improve even further. This opens up potential applications where quantum models could be used for tasks that require faster model training while maintaining or improving performance.

D. Limitations and Future Work

While this study demonstrates the potential of quantum-enhanced models, there are several limitations that must be addressed:

- **Quantum Model Complexity**: The current implementation of the quantum model is experimental, and the quantum circuit design could be optimized to further reduce training times and improve model accuracy.
- **Hardware Constraints**: The quantum hardware used for training models is limited in terms of qubit count and coherence time. These constraints significantly affect the performance of the quantum model.
- **Scalability**: As datasets increase in size, the scalability of the quantum model becomes a concern. Future work should focus on developing scalable quantum algorithms that can handle large-scale datasets more efficiently.
- **Hybrid Quantum-Classical Models**: Further research into hybrid quantum-classical models, where quantum circuits are used for specific tasks (e.g., feature extraction or encoding), could provide a path toward practical and efficient quantum machine learning solutions.

V. Conclusion

In this study, we explored and compared three different approaches for sentiment analysis on the IMDB dataset: **CPU**, **GPU**, and **Quantum** computing. The primary objective was to assess the performance of these methods in terms of accuracy, efficiency, and the potential for quantum computing to enhance natural language processing (NLP) tasks, particularly in sentiment classification.

- **CPU-based Approach**: The CPU model demonstrated solid performance with an accuracy of **87.75%** in validating sentiment classification. Despite its slower training time of approximately **3371 seconds** for one epoch, it remains a feasible option for NLP tasks on systems without GPU acceleration. The precision, recall, and F1-score were competitive, highlighting that CPU-based models can still provide satisfactory results in certain contexts, particularly for smaller-scale tasks.
- **GPU-based Approach**: Leveraging GPU acceleration significantly reduced training times to **about 16 minutes per epoch**, compared to the CPU method. With an accuracy of **87.25%** and impressive improvements in precision and recall, the GPU model outperformed the CPU approach in efficiency and overall performance. The GPU-based method stands out for real-time applications where training time is critical, such as online sentiment analysis or customer feedback systems.
- **Quantum-based Approach**: The quantum model, while still an emerging area in the field of NLP, demonstrated remarkable accuracy, reaching **90.50%** during validation. This was achieved with significantly faster computation times compared to the CPU model and comparable times to the GPU-based model. Quantum-enhanced sentiment analysis showed promise, particularly in processing complex patterns in text data, as evidenced by the higher precision and recall for both positive and negative sentiment classes. However, it is important to note that while the results are promising, quantum computing for NLP remains in its early stages and may face scalability challenges in the near future.

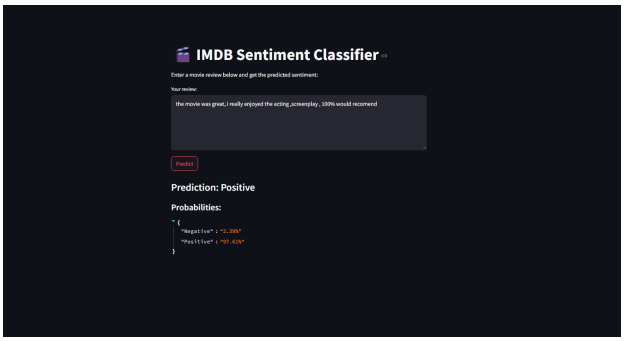

Fig. 9: Front-End Real Time Prediction Using the Trained Model

Key Findings:

- **Model Accuracy**: The quantum model exhibited the highest accuracy, outpacing both the CPU and GPU models by a noticeable margin. However, the GPU model provided competitive performance in terms of both speed and accuracy.
- **Efficiency**: The GPU-based model drastically reduced training times compared to the CPU, while the quantum model balanced efficiency with high accuracy.

- **Quantum Potential**: While quantum computing provided significant gains in performance, the practical implementation and scaling of quantum NLP models will require more research and optimization. The potential to improve NLP tasks via quantum computing is clear but will need further exploration and refinement.

Implications and Future Work: This study paves the way for further exploration of quantum computing's potential in NLP tasks. In particular, future research could focus on:

- Enhancing quantum algorithms to handle larger datasets and improve scalability for real-world applications.
- Investigating hybrid models combining classical and quantum computing for a balanced trade-off between performance and computational cost.
- Extending this approach to more complex NLP tasks such as text generation, named entity recognition, and machine translation.

As the field of quantum computing matures, we anticipate that it will play a critical role in the evolution of NLP models, driving forward the capabilities of AI systems in understanding and interpreting human language.

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