A Comparative Study of Classical and Quantum SVMs

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1. Introduction

The convergence of Quantum Computing, High Performance Computing (HPC), and Artificial Intelligence (AI) is opening unprecedented avenues in computational science and data analysis. This project explores how the synergy of these three technological pillars can lead to breakthroughs in solving complex problems that are intractable using classical computing methods alone. The report provides foundational insights into quantum computing concepts, investigates performance benchmarks using HPC environments, and evaluates AI integration methods to optimize computations and model accuracy.

2. Quantum Computing Overview

Quantum computing leverages the principles of quantum mechanics—specifically superposition and entanglement—to perform computations in fundamentally different ways than classical computers. A quantum bit or qubit, unlike a binary bit, can represent both 0 and 1 simultaneously, thereby enabling parallel processing at an exponential scale. The report illustrates how quantum gates manipulate qubit states, paving the way for faster search and factorization operations. Additionally, the role of quantum circuits and simulators (like Qiskit) is discussed for running experiments on currently available quantum hardware.

3. Dataset Overview

The experiment uses the Banknote Authentication dataset from the UCI Machine Learning Repository. It consists of 1,372 instances with four real-valued features extracted using wavelet transformations. The target variable is binary, where class '0' indicates a forged banknote and class '1' represents a genuine one. This dataset is particularly suitable for this task due to its numerical nature and well-separated classes, which are ideal for both classical and quantum kernel methods.

4. Preprocessing Steps

1. Load dataset from UCI repository
2. Normalize features using `StandardScaler`
3. Reduce dimensions from 4 to 2 using `PCA` for quantum circuit compatibility
4. Train-test split: 70% training, 30% testing

5. Quantum SVM (QSVM) Setup

Quantum Support Vector Machines represent a quantum analogue of classical SVMs. QSVMs use quantum feature maps to encode classical data into high-dimensional Hilbert spaces. In this project, QSVM is implemented using Qiskit's `machine_learning` module. The process includes:

- Encoding features using quantum circuits via `ZZFeatureMap`
- Using quantum kernels to compute pairwise distances between data points
- Training a quantum-enhanced SVM model using `QuantumKernel` and `QSVM` from Qiskit

Due to limitations in current quantum devices, a quantum simulator backend is used to run these experiments. The project compares QSVM against classical SVM on the same dataset to evaluate advantages in data representation and classification accuracy.

6. Results

Extensive benchmarking is carried out between classical SVM and QSVM, including metrics like training time, prediction accuracy, and scalability:

Classical SVM Performance

```
Classical SVM Accuracy: 0.7
Best C: 100
Classification Report (Classical):
              precision    recall  f1-score   support

           0       0.71      0.83      0.77        12
           1       0.67      0.50      0.57         8

    accuracy                           0.70        20
   macro avg       0.69      0.67      0.67        20
weighted avg       0.70      0.70      0.69        20

Time of execution: 0.1959 seconds
```

Quantum SVM Performance

```
Best C: 10
Accuracy: 0.6
Classification Report:
              precision    recall  f1-score   support

           0       0.62      0.83      0.71        12
           1       0.50      0.25      0.33         8

    accuracy                           0.60        20
   macro avg       0.56      0.54      0.52        20
weighted avg       0.57      0.60      0.56        20

Time of execution: 0.0446 seconds
```

- **Analysis**

❖ The Classical SVM performs better in terms of overall accuracy and class-wise balance, particularly for the minority class (Class 1), where QSVM struggles.

❖ Despite being more experimental, the QSVM demonstrated faster execution on the quantum simulator. This could be attributed to a smaller kernel complexity or efficient simulation under simplified feature mappings.

❖ QSVM underperformed significantly on Class 1 recall (0.25), indicating potential issues in capturing class boundaries with the current quantum kernel.

❖ While Classical SVM is more reliable for small, structured datasets, QSVM offers a novel advantage when quantum feature spaces are better suited for data complexity. However, more robust performance may require optimized quantum kernel construction or noise-resilient circuits.

Conclusion

This project demonstrates the practical integration of Quantum Computing, High Performance Computing (HPC), and Artificial Intelligence (AI) through a comparative study of Classical and Quantum Support Vector Machines. While the Classical SVM outperforms in accuracy and stability, the Quantum SVM shows promising speed and potential for handling complex, high-dimensional data when scaled. The findings highlight that quantum-enhanced models, although currently limited by hardware and simulation constraints, hold significant promise for the future of intelligent computing.

Repository Link - https://github.com/yashraj9922/Q-HPC