Poster title:

Multi-Task Quantum Annealing for Rapid Multi-Class Classification

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Poster abstract:

Quantum computing offers new paradigms in machine learning, notably through Quantum Annealing (QA), which offers promising approaches to optimization problems. This study introduces an application of Multi-tasking Quantum Annealing (MTQA) to enhance multi-class Support Vector Machines (SVMs). Traditional QA methods require multiple cycles to classify multi-class datasets, significantly increasing computational demands. In contrast, MTQA embeds multiple SVM classifiers in parallel on a quantum annealer, thereby reducing the number of required annealing cycles to a single cycle. Utilizing the D-Wave Advantage 6.4 system, we evaluated our method across three benchmark datasets: a synthetic dataset (Blob), subsets of handwritten digits, and the Iris dataset with different feature focuses. Our findings demonstrate that MTQA achieves accuracy equivalent to that of classical Sequential Minimal Optimization (SMO), Simulated Annealing (SA), and standard QA methods while significantly improving computational efficiency. Despite the current limitations in quantum technology and the empirical selection of model parameters, these results highlight the emergent potential of quantum computing in machine learning. Further advancements in quantum algorithm optimization and parameter tuning are anticipated to enhance the efficacy of QA and MTQA, solidifying their practical application roles.

Poster relevance:

This research advances quantum computing by introducing Multi-tasking Quantum Annealing (MTQA) to enhance multi-class Support Vector Machines (SVMs), aligning with QCE24's focus on innovative quantum technologies. By embedding multiple SVM classifiers in parallel on a quantum annealer, our method significantly reduces the computational demands, demonstrating a practical application of quantum annealing in complex classification tasks. The findings not only push the boundaries of quantum hardware utilization but also signal broader implications for quantum computing in data-intensive fields. This study exemplifies the conference's aim of merging quantum theory with real-world applications, highlighting its potential impact on the evolution of quantum technologies.

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Abstract*—Quantum computing offers new paradigms in machine learning, notably through Quantum Annealing (QA), which offers promising approaches to optimization problems. This study introduces an application of Multi-tasking Quantum Annealing (MTQA) to enhance multi-class Support Vector Machines (SVMs). Traditional QA methods require multiple cycles to classify multi-class datasets, significantly increasing computational demands. In contrast, MTQA embeds multiple SVM classifiers in parallel on a quantum annealer, thereby reducing the number of required annealing cycles to a single cycle. Utilizing the D-Wave Advantage 6.4 system, we evaluated our method across three benchmark datasets: a synthetic dataset (Blob), subsets of handwritten digits, and the Iris dataset with different feature focuses. Our findings demonstrate that MTQA achieves accuracy equivalent to that of classical Sequential Minimal Optimization (SMO), Simulated Annealing (SA), and standard QA methods while significantly improving computational efficiency. Despite the current limitations in quantum technology and the empirical selection of model parameters, these results highlight the emergent potential of quantum computing in machine learning. Further advancements in quantum algorithm optimization and parameter tuning are anticipated to enhance the efficacy of QA and MTQA, solidifying their practical application roles.

Keywords*—*Quantum annealing, Multi-tasking Quantum Annealing (MTQA), Support Vector Machines (SVMs), Machine Learning Optimization, Quantum Computing Applications

I. INTRODUCTION

Quantum computing is a rapidly evolving field that uses quantum mechanics principles to perform calculations much faster than traditional computers. One of the key techniques in quantum computing is Quantum Annealing (QA), which is particularly effective at finding the best solution among many possible solutions to a problem [1-3]. This technique is particularly useful in areas such as machine learning, where computers are trained to recognize patterns and make decisions. This study focuses on a specific machine learning technique known as Support Vector Machines (SVMs) [4-5], which is commonly used for classification tasks, essentially teaching computers to categorize data into different groups. Traditionally, applying quantum annealing to SVMs to classify multiple groups of data requires running several cycles on the quantum computer[4], which can be time-consuming and resource-intensive[5]. Our research uses Multi-tasking Quantum Annealing (MTQA) to handle multiple classification tasks simultaneously, significantly speeding up the process by reducing the number of cycles needed to just one[2-3]. We use D-Wave Advantage 6.4 to test our approach on different types of data sets, including synthetic data (Blobs), handwritten digits, and the Iris flower dataset, which are standard benchmarks in machine learning. The goal of this study is to demonstrate that MTQA can classify data as accurately as traditional methods while using fewer resources, making quantum annealing a more practical option for solving real-world problems in machine learning. This could lead to faster and more efficient computing solutions that can be applied in various fields, from healthcare to finance.

II. METHODOLOGY

A. *Quantum formulation for Multi-Class SVMs*

Traditionally, SVMs identify a hyperplane that maximizes the margin between two classes. To adapt SVMs for multi-class classification using quantum annealing, the problem is reformulated into a Quadratic Unconstrained Binary Optimization (QUBO) format suitable for quantum processors.

Binary Encoding of Lagrange Multipliers: The SVM's dual problem includes Lagrange multipliers (α_n), which are used to determine the position of the hyperplane. In a quantum context, these multipliers are represented as binary sums to facilitate processing on quantum annealer:

$$\alpha_n = \sum_{k=0}^{K-1} 2^k a_{Kn+k} \tag{1}$$

where, a_{Kn+k} is binary variables, and K represents the number of binary variables used to encode α_n.

Objective Function: The objective function in SVM's dual form aims to maximize the margin between data points. For quantum processing, this is transformed into a minimization problem expressed in QUBO format:

$$E = \sum_{i=1}^{N} \alpha_i - \frac{1}{2}\sum_{i,j=1}^{N} y_i y_j \alpha_i \alpha_j k(x_i, x_j) + \left(\sum_{i=1}^{N} y_i \alpha_i\right)^2 \tag{2}$$

Here, $y_{i,j}$ is class label, $k(x_i, x_j)$ is the kernel function applied between feature vectors. In this study, we used rbf kernel. This expression combines the goal of maximizing the margin (first and second terms) and adhering to the class constraints (third term).

Multi-Class Classification: For multi-class classification, we employed OneVsRest strategy. In this strategy for multi-class classification, a separate binary SVM classifier is trained for each class to distinguish it from all others, using a quantum annealer to optimize each classifier within a QUBO framework. This strategy enhances efficiency by leveraging the parallel processing capabilities of quantum technology, allowing each classifier to operate independently. During prediction, the classifier with the highest decision function value determines the class assignment, effectively scaling SVMs to handle multiple classes while maximizing computational speed and accuracy.

TABLE I. ACCURACY COMPARISON ACROSS METHODS AND DATASETS

Data	Class	Train Points	Test Points	SMO Accuracy		SA Accuracy		QA		MTQA	
				Train Accuracy	Test Accuracy	Train Accuracy	Test Accuracy	Train Accuracy	Test Accuracy	Train Accuracy	Test Accuracy
Blob	3	30	90	100	100	100	100	100	100	100	100
Blob	4	28	92	100	100	100	100	100	100	100	100
Iris (Petal)	3	30	120	96.6	95.8	96.6	95.8	96.6	96.3 ± 0.9	96.6	96.4 ± 0.8
Iris (Sepal)	3	30	120	86.6	80	86.6	77.5	84.3 ± 3	77.8 ± 1.4	83.3 ± 2.8	75.3 ± 2.5
Digit 0,1,2	3	30	60	100	100	100	100	100	100	100	100
Digit 0,1,2,3	4	32	48	96.8	97.9	96.8	95.8	96.8	97.9	96.8	97.9
Digit 0,1,2,3,4	5	30	50	100	98	100	98	97,7 ± 1.3	96.8 ± 0.9	97.8 ± 1.3	96 ± 1.6

B. *Multi-tasking Quantum Annealing*

MTQA extends the capabilities of traditional quantum annealing by allowing simultaneous processing of multiple optimization tasks. This approach leverages the natural parallelism of quantum systems to perform concurrent computations, thereby enhancing the efficiency and throughput of quantum annealers [2-3]. In MTQA, different tasks, such as various binary classifiers in a multi class SVM setup, are embedded into the quantum hardware in parallel. This not only significantly speeds up the processing time by reducing the need for sequential runs but also optimizes the utilization of quantum resources such as qubits and couplers. The parallel execution of multiple tasks within the same quantum annealing cycle maximizes hardware usage and demonstrates a more effective approach to solving complex computational problems in a quantum computing framework.

C. *Datasets*

The efficacy of MTQA was tested using varied datasets. Synthetic data (Blob) from the sklearn package included configurations of three and four classes, specifically designed to test basic classification capabilities. The Iris dataset, divided into sepal and petal measurements, each with equal training and test samples, assessed feature-specific classification. The Digits dataset, encompassing different subsets of handwritten digits, examined the performance of MTQA in complex pattern recognition, proving its efficiency and accuracy enhancements in real-world applications.

III. RESULTS

The effectiveness of MTQA in handling complex classification tasks is illustrated in Table I, which compares performance metrics with SMO, SA, and QA.

Synthetic Blob Data: MTQA achieved perfect accuracy across configurations with three and four classes, matching the performance of SMO, SA, and QA, and demonstrating its robust capacity for straightforward classifications.

Iris Dataset: In petal measurements, MTQA matched the highest accuracies, achieving 96.6% in training and 96.4 ± 0.8% in testing, closely followed by its performance in sepal measurements, with 83.3 ± 2.8% training accuracy and 75.3 ± 2.5% testing accuracy. These results emphasize the importance of MTQA in noticing subtle feature variations.

Digits Dataset: For digit recognition, MTQA consistently outperformed or matched the other methods across various class configurations, maintaining high accuracy even as complexity increased, with the five-class setup achieving 97.8 ± 1.3% training accuracy and 96 ± 1.6% testing accuracy.

These results confirm that MTQA not only maintains high accuracy but also enhances computational efficiency by reducing the need for multiple annealing cycles. This efficiency is crucial for applications requiring rapid and accurate computational solutions, making MTQA a promising approach in fields that use complex machine learning tasks.

IV. DISCUSSION AND FUTURE WORK

The demonstrated capability of MTQA to efficiently handle SVM-based classification tasks is noteworthy, especially considering that MTQA can solve classification problems C (number of classes) times faster than traditional QA in Quantum Processing Unit (QPU) runtime. This improvement underscores the potential of MTQA to reduce computational time in multi-class scenarios. Future efforts will aim to further enhance the scalability and embedding techniques of MTQA for handling larger and more complex datasets. Moreover, exploring hybrid quantum-classical models could address the limitations of current quantum hardware, expanding practical applications of MTQA in fields that require rapid and accurate computational solutions, such as bioinformatics and financial modeling.

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Multi-Task Quantum Annealing for Rapid Multi-Class Classification

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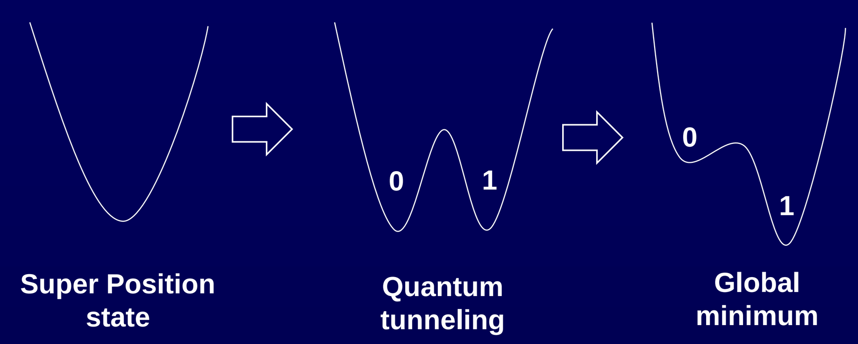
1. Introduction: Quantum annealing and Support Vector Machines

Quantum annealing

S. Boixo et al., Nature Phys. 10 (2014) 218.

D-Wave Systems:

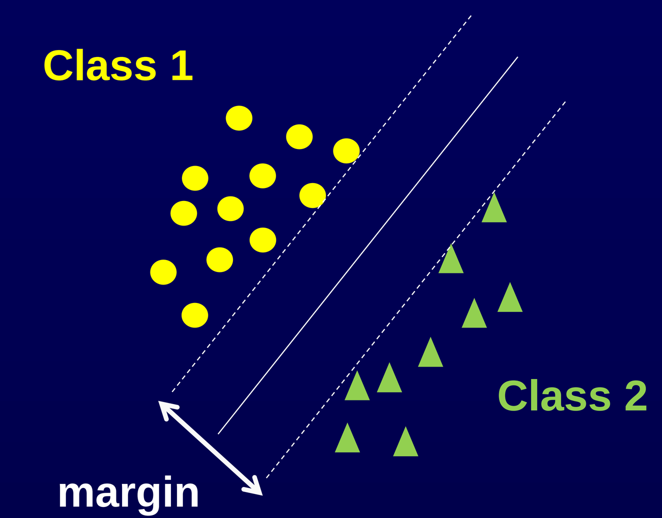
- Flux Quantum Bits
- Ultra Low Temperature
- More Than 5000 Qubits
- Quantum Annealing



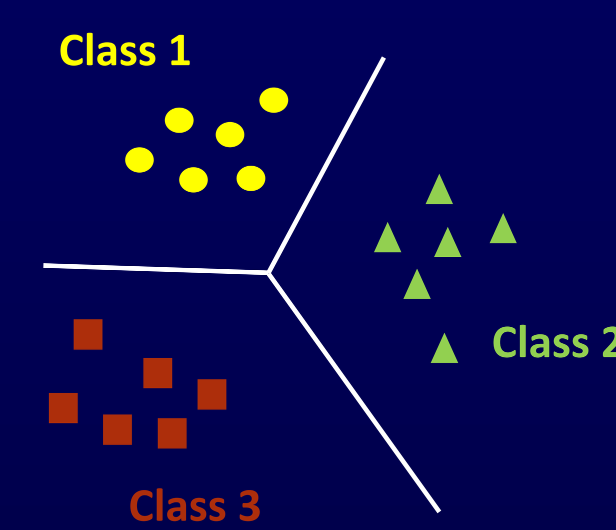
Real-World ⇨ Mathematical Modeling ⇨ Quantum Annealer ⇨ Real-World

Multi-Class Classification SVMs

Binary Classification



Multi-Class Classification



We employed OnevsRest strategy.

2. Rapid Multi-Class Classification Using D-Wave Quantum Annealer

SVM Quantum formulation

Real value to Binary encoder:

$$\alpha_n = \sum_{k=0}^{K-1} 2^k a_{Kn+k}$$

$a_{Kn+k} \in \{0,1\}$: Binary Variable

$y_{i,j}$ is class label, $k(x_i, x_j)$ is the kernel function

QUBO (Quadratic Unconstrained Binary Optimization):

$$\underbrace{\sum_{i=1}^{N} \alpha_i - \frac{1}{2}\sum_{i,j=1}^{N} y_i y_j \alpha_i \alpha_j k(x_i, x_j)}_{\text{maximizing the margin}} + \underbrace{\left(\sum_{i=1}^{N} y_i \alpha_i\right)^2}_{\text{class constraints}}$$

$y_{i,j}$ is class label

$k(x_i, x_j)$ is the kernel function, we used rbf kernel

N is class number

For each classifier in our study, a Quadratic Unconstrained Binary Optimization (QUBO) problem is formulated. This QUBO is then mapped directly onto a quantum annealer, allowing us to leverage the device's capabilities to optimize the solution. This process ensures that each classifier is efficiently tailored to maximize classification accuracy by finding the optimal hyperplane in the high-dimensional space.

Multi-tasking Quantum Annealing

OneVsRest strategy:

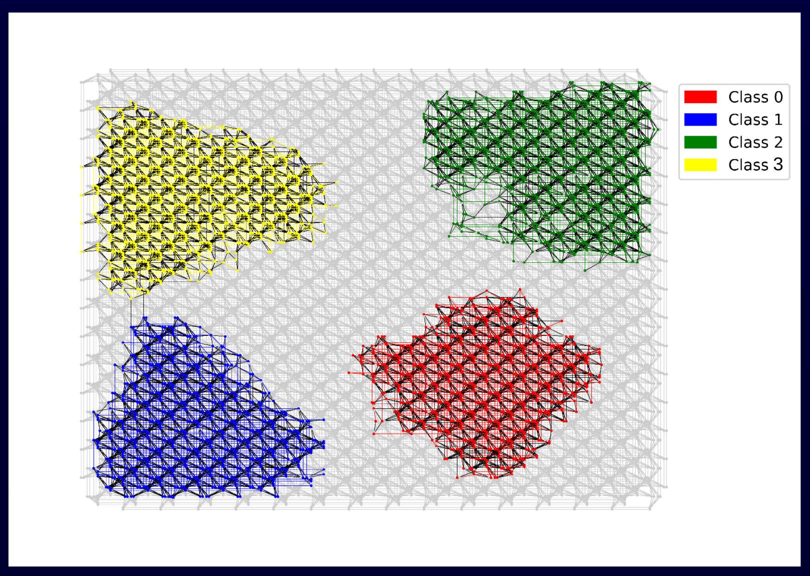
"Winner-takes-all"

Classifier	Output
C1 vs Rest	Not C1
C2 vs Rest	Not C2
C3 vs Rest	C3
Result	C3

Classifier	Output
C1 vs Rest	-120
C2 vs Rest	-100
C3 vs Rest	Not C3
Result	C1

Need to train N (number of classes) classifiers

Parallel Quantum Annealing



Hamiltonian combining into one:

$$H_{total} = \begin{bmatrix} H_1 & 0 & 0 & 0 \\ 0 & H_2 & 0 & 0 \\ 0 & 0 & H_3 & 0 \\ 0 & 0 & 0 & H_4 \end{bmatrix} \Longrightarrow [H_1, H_2, H_3, H_4]$$

Sequential Quantum Annealing

QA runs with the same embedding allocation for each classifier. In total, N run for training.

Example on left

Class 0 vs Rest
Class 1 vs Rest
Class 2 vs Rest
Class 3 vs Rest

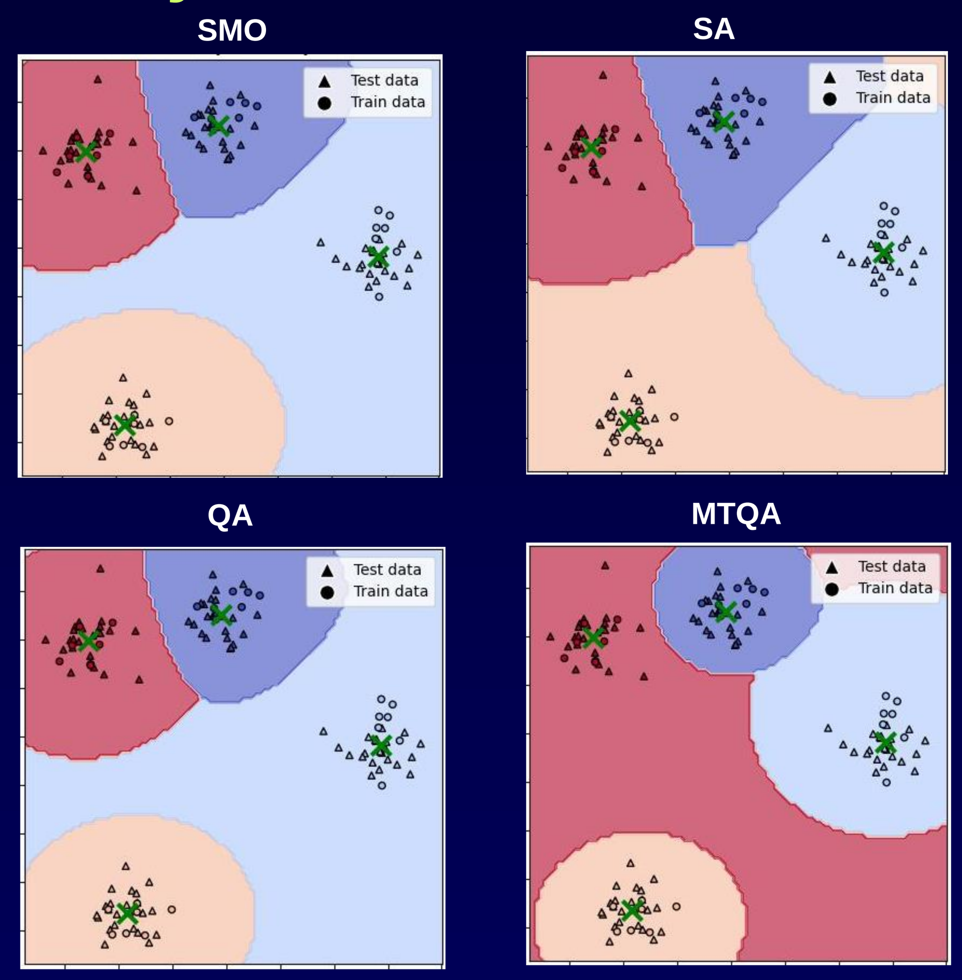
} **QA run 4 times**

Decoding into each classifier

The processes of combining and decoding are performed on the CPU for computation.

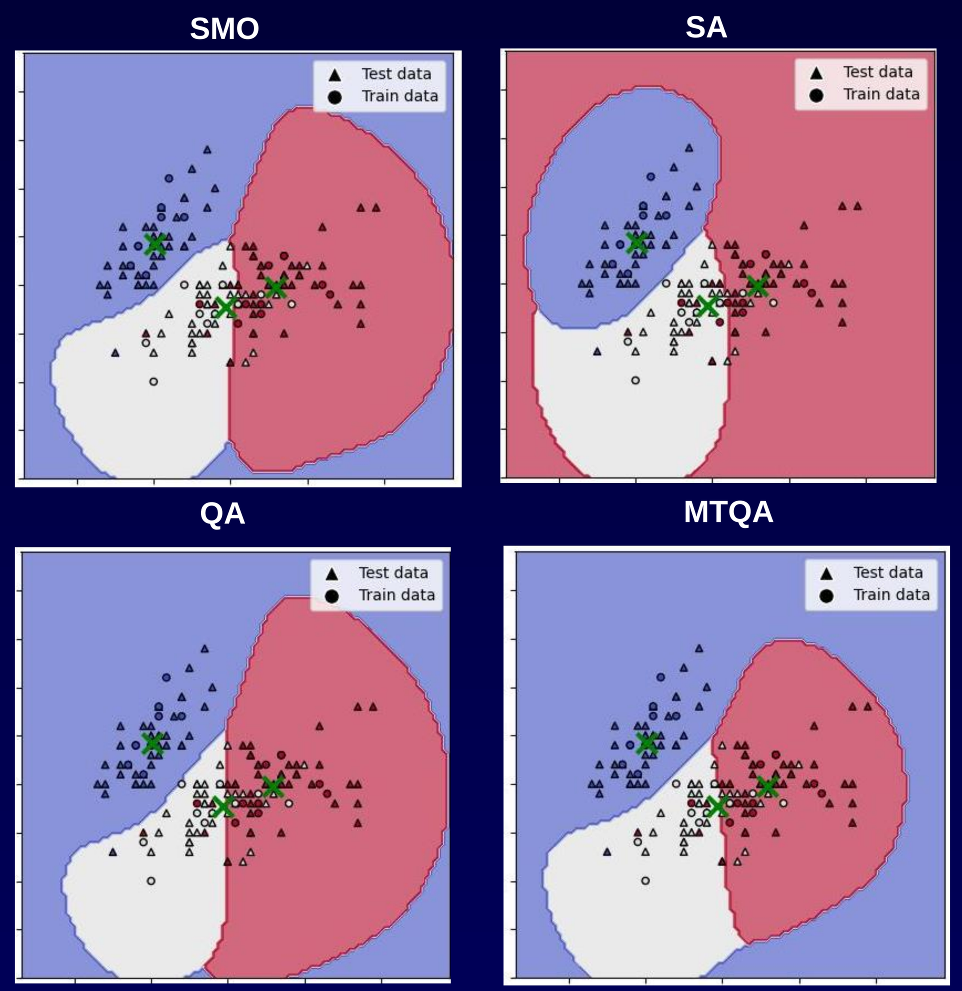
3. Experimental Results

Synthetic data: Blob



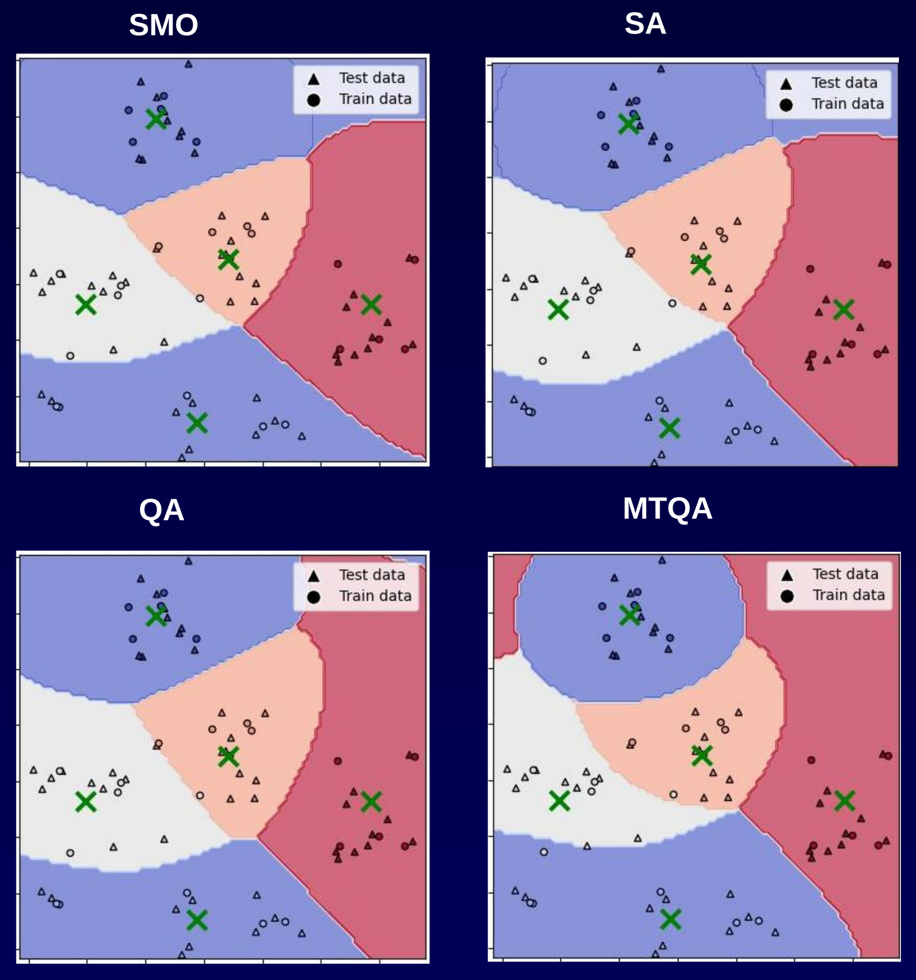
In the Blob dataset with four classes, MTQA matched the perfect 100% accuracy achieved by SMO, SA, and QA, confirming its capability to efficiently manage straightforward classification tasks without compromising on performance.

Iris



Despite the challenging nature of the Iris sepal dataset, MTQA closely approached the accuracy levels of SMO and SA, with slight reductions in testing accuracy suggesting areas for further optimization and robustness in feature-sensitive datasets.

Handwritten Digit



For the handwritten digits 0 to 4, MTQA showcased a strong performance, aligning closely with SMO and SA in accuracy while demonstrating its potential to efficiently handle more complex, multi-class recognition tasks in real-world applications.

4. Conclusions

- Efficiency Enhanced: Multi-tasking Quantum Annealing (MTQA) significantly reduces quantum processing cycles required for multi-class SVM classification, enhancing computational efficiency.
- Accuracy Maintained: MTQA maintains accuracy levels comparable to traditional methods, effectively handling multiple classification tasks simultaneously on quantum hardware.
- Future Potential: The success of MTQA in this study demonstrates its potential to transform machine learning applications, paving the way for advanced quantum computing solutions in complex data classification.