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Optimizing Quantum Support Vector Machines using ZX-Calculus

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Quantum Support Vector Machines (QSVMs) represent a promising approach for quantum-accelerated machine learning, but their implementation on Noisy Intermediate-Scale Quantum (NISQ) hardware is constrained by deep circuits and high gate counts, which intensify noise accumulation and decoherence [5]. To mitigate these limitations, ZX-Calculus is employed, a diagrammatic tool that applies mathematical transformations (such as spider fusion, identity removal, and local complementation) to reduce the number of operations without compromising circuit functionality [7]. This reduction in complexity makes QSVMs more viable for execution on noisy intermediate-scale quantum (NISQ) devices.

In Quantum Machine Learning (QML), QSVMs stand out for using quantum feature mapping, enabling a rich representation of data. Unlike classical SVMs, which explicitly define the kernel function, QSVMs utilize quantum circuits to implicitly compute kernel values, making it possible to represent complex feature spaces [6]. However, execution is still affected by circuit depth and entanglement overhead.

ZX-Calculus has emerged as a powerful technique for optimizing quantum circuits by representing them as tensor networks and enabling algebraic transformations that simplify their structure [1]. Although previous studies have used this approach to analyze barren plateaus and optimize circuit architectures [2, 4], few works apply it specifically to reduce feature mapping complexity in QSVMs. This study fills that gap by applying ZX-Calculus to optimize quantum kernels, reducing gate overhead without degrading classification accuracy.

The QSVM implementation used a ZZFeatureMap to encode classical data into quantum states [3]. Two entanglement schemes were analyzed: linear, where each qubit interacts only with its neighbor, and full, where all qubits interact. While full entanglement increases expressiveness, it also adds complexity. The study evaluated three parameters: entanglement (Ent.), repetitions (Reps.), which define how many times the feature map is applied, and features (Feat.), corresponding to the dimensionality of the mapped classical data. Their impact on circuit size (total operations) and depth (sequential layers) was analyzed, as shown in Table 1.

The extracted circuit was then converted into a ZX-diagram, where rewriting techniques were applied to eliminate redundant operations and optimize computational efficiency. Simulations using the Wine data set (100 samples) demonstrated that the application of ZX-Calculus reduced

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the number of gates by approximately 82% on average, with reductions ranging from 75% to 87% depending on the type of entanglement, the number of features and repetitions, as detailed in Table 1. Similarly, circuit depth was reduced by 91.3% on average, reaching a maximum reduction of 95%. Despite these simplifications, classification accuracy remained stable at 0.900 for most configurations, with a slight drop to 0.867 for three repetitions and three features, showing that ZX-Calculus preserves QSVM effectiveness while significantly reducing computational complexity.

Table 1: Optimized QSVM performance on Wine dataset (100 samples).

Ent.	Reps.	Feat.	Acc. (Orig. → Opt.)	Size (Orig. → Opt.)	Depth (Orig.→ Opt.)
FULL	2	2	0.900 → 0.900	24.00 → **5.91** (-75%)	18.00 → **2.97** (-84%)
	2	3	0.900 → 0.900	54.00 → **8.88** (-84%)	42.00 → **2.97** (-93%)
	2	4	0.900 → 0.900	96.00 → **11.85** (-88%)	60.00 → **2.97** (-95%)
	2	5	0.867 → 0.867	150.00 → **14.82** (-90%)	78.00 → **2.97** (-96%)
	3	2	0.900 → 0.900	34.00 → **5.91** (-83%)	26.00 → **2.97** (-89%)
	3	3	0.900 → 0.900	78.00 → **8.88** (-89%)	62.00 → **2.97** (-95%)
	3	4	0.900 → 0.900	140.00 → **11.85** (-92%)	86.00 → **2.97** (-97%)
	3	5	0.900 → 0.900	220.00 → **14.82** (-93%)	110.00 → **2.97** (-97%)
LINEAR	2	2	0.900 → 0.900	24.00 → **5.91** (-75%)	18.00 → **2.97** (-84%)
	2	3	0.900 → 0.900	42.00 → **8.88** (-79%)	30.00 → **2.97** (-90%)
	2	4	0.933 → 0.933	60.00 → **11.85** (-80%)	36.00 → **2.97** (-92%)
	2	5	0.900 → 0.900	78.00 → **14.82** (-81%)	42.00 → **2.97** (-93%)
	3	2	0.900 → 0.900	34.00 → **5.91** (-83%)	26.00 → **2.97** (-89%)
	3	3	0.867 → 0.867	60.00 → **8.88** (-85%)	44.00 → **2.97** (-93%)
	3	4	0.900 → 0.900	86.00 → **11.85** (-86%)	50.00 → **2.97** (-94%)
	3	5	0.900 → 0.900	112.00 → **14.82** (-87%)	56.00 → **2.97** (-95%)

Although the findings are promising, the study is limited by the small dataset size and the reduced number of qubits used in simulations. Future work should investigate the scalability of the method, expand circuit complexity, and test the approach on real quantum hardware and noisy simulators.

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