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Quantum Machine Learning for Cybersecurity: Applications and Challenges in the NISQ Era

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Abstract

The rapid advancement of quantum computing presents both unprecedented opportunities and significant challenges for cybersecurity. Classical machine learning methods increasingly struggle with high-dimensional network traffic, evolving attack vectors, and real-time response requirements. Quantum machine learning (QML), which leverages quantum mechanical phenomena such as superposition and entanglement, has emerged as a promising paradigm for enhancing threat detection, anomaly analysis, and secure communication. This paper provides a comprehensive overview of QML applications in cybersecurity, examining key techniques including Quantum Support Vector Machines (QSVMs), Variational Quantum Circuits (VQCs), and hybrid quantum-classical approaches. The analysis evaluates recent implementations in intrusion detection, malware classification, and encrypted-traffic analytics, drawing on empirical evidence from benchmark datasets. Results indicate that QML models can achieve up to 94.6% accuracy in intrusion detection tasks, with quantum-enhanced frameworks demonstrating significant improvements in detection accuracy and threat response latency compared to conventional baselines. However, significant challenges persist, including hardware limitations of noisy intermediate-scale quantum (NISQ) devices, scalability constraints, and the vulnerability of quantum models to adversarial attacks. The paper concludes by outlining future research directions for noise-resilient QML architectures and the integration of quantum computing with agentic AI for proactive cybersecurity defense.

Keywords: quantum machine learning; cybersecurity; intrusion detection; quantum support vector machine; NISQ; adversarial robustness

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1. Introduction

The growing complexity and frequency of cyber attacks have increasingly challenged the effectiveness of conventional rule-based and signature-driven cybersecurity approaches [1]. Classical machine learning methods, while widely adopted for intrusion detection, malware analysis, and anomaly identification, often struggle with the exponential growth of network data, the curse of high-dimensional feature spaces, and the constantly evolving tactics of adversaries [2]. The emergence of quantum computing introduces both a threat—as quantum algorithms like Shor's algorithm threaten classical cryptographic infrastructure—and an opportunity for enhancing defensive capabilities [3].

Quantum machine learning (QML) represents a paradigm that combines quantum computing capabilities with learning algorithms, harnessing quantum phenomena including superposition, entanglement, and interference to achieve potential computational advantages over classical approaches for certain problem classes [4]. Key QML techniques applicable to cybersecurity include Quantum Support Vector Machines (QSVMs), Variational Quantum Circuits (VQCs), Quantum Neural Networks (QNNs), and hybrid quantum–classical approaches [5]. These methods have been mapped across supervised, unsupervised, and generative learning paradigms to address core cybersecurity tasks including intrusion and anomaly detection, malware and botnet classification, and encrypted-traffic analytics [6].

The present era of noisy intermediate-scale quantum (NISQ) hardware simultaneously imposes constraints on QML deployment in cybersecurity while opening new avenues for innovation [7].

Recent research has demonstrated the feasibility of QML-based intrusion detection systems on near-term quantum hardware, with promising results in both binary and multiclass classification tasks [8]. However, significant challenges remain, including quantum noise, limited qubit coherence, scalability constraints, and the vulnerability of quantum models to adversarial attacks [9].

This paper provides a comprehensive analysis of QML applications in cybersecurity, examining key techniques, empirical performance, and persistent challenges in the NISQ era. The specific objectives are: (1) to identify and characterise QML algorithms applicable to cybersecurity tasks; (2) to evaluate empirical performance on benchmark datasets; (3) to analyse the unique security challenges posed by quantum computing; and (4) to propose future research directions for quantum-enhanced cybersecurity.

2. Materials and Methods

2.1 Systematic Review Methodology

This study adopts a systematic review approach to examine QML techniques for cybersecurity applications. The analysis is organised around three dimensions: (1) QML algorithms and their theoretical foundations; (2) empirical performance on benchmark cybersecurity datasets; and (3) implementation challenges on NISQ hardware and adversarial robustness considerations [10].

2.2 Quantum Machine Learning Techniques for Cybersecurity Tasks

QML algorithms applicable to cybersecurity tasks include Quantum Support Vector Machines (QSVMs), which exploit quantum feature maps to achieve high-dimensional classification with fewer parameters [11]. Variational Quantum Circuits (VQCs) leverage parameterised quantum gates optimised by classical optimisers, making them suitable for NISQ devices [12]. Quantum Neural Networks (QNNs) extend classical neural architectures to quantum circuits, enabling representation of complex functions [13]. Hybrid quantum–classical approaches combine classical pre-processing with quantum classification, offering practical near-term solutions [14]. Table 1 summarises key QML algorithms and their cybersecurity applications.

Table 1. QML algorithms for cybersecurity applications.

Algorithm	Core principle	Cybersecurity Application	Qubit Requirements	Maturity
QSVM	Quantum feature maps	Intrusion detection, malware classification	4-8	High
VQC	Parameterised circuits	Anomaly detection, pattern recognition	4-12	Medium
QNN	Quantum neurons	Network traffic analysis	6-20	Low
QGAN	Quantum generation	Adversarial training, synthetic data	8-16	Low
Hybrid QML	Classical + quantum	Real-time threat detection	4-10	High

2.3 Benchmark Datasets and Performance Metrics

Performance is evaluated using standard metrics including accuracy, precision, recall, F1-score, and area under the ROC curve (AUC). Benchmark datasets for cybersecurity QML research include NSL-KDD, CIC-IDS2017, UNSW-NB15, and ToN_IoT [15]. These datasets provide diverse attack scenarios including denial-of-service, probing, remote-to-local, user-to-root, and botnet attacks [16]. Table 2 summarises the key characteristics of these datasets.

Table 2. Benchmark cybersecurity datasets for QML evaluation.

Dataset	Instances	Features	Classes	Attack types
NSL-KDD	148,517	41	5	DoS, Probe, R2L, U2R
CIC-IDS2017	2,830,743	80	15	Brute force, DoS, DDoS, Port scan
UNSW-NB15	2,540,044	49	10	Fuzzers, Analysis, Backdoors, Shellcode
ToN_IoT	15,000,000	46	15	DDoS, Ransomware, XSS, Injection

3. Results

3.1 Intrusion Detection Performance with QSVM

Quantum Support Vector Machines have demonstrated competitive performance on intrusion detection tasks. A hybrid classical-quantum approach using Pegasos-QSVC achieved 94.6% accuracy on binary classification of network traffic, outperforming classical SVM (89.7%) and Random Forest (91.2%) [8]. The quantum advantage was most pronounced for high-dimensional feature spaces (>100 dimensions), where quantum feature maps enabled better class separation [11]. Table 3 compares the performance of QSVM with classical baselines across multiple datasets.

Table 3. Performance comparison of QSVM versus classical baselines.

Dataset	Classical SVM	Random Forest	QSVM (4 qubits)	QSVM (8 qubits)
NSL-KDD	89.7%	91.2%	92.8%	94.6%
CIC-IDS2017	87.3%	89.5%	90.1%	93.2%
UNSW-NB15	85.1%	87.8%	88.6%	91.5%

3.2 Anomaly Detection Using Variational Quantum Circuits

Variational Quantum Circuits have been evaluated for anomaly detection in network traffic. VQC-based models achieved F1-scores of 89.3% on the ToN_IoT dataset, with reduced false-positive rates compared to classical autoencoders [12]. The parameter efficiency of VQCs—requiring only 12-20 trainable parameters—enables deployment on resource-constrained

edge devices.

3.3 Assessment of Quantum Advantage in Cybersecurity

The quantum advantage in cybersecurity applications arises from three mechanisms: (1) quantum feature maps enable classification in exponentially expanded Hilbert spaces; (2) quantum parallelism allows simultaneous evaluation of multiple hypotheses; and (3) quantum entanglement captures complex correlations in network traffic data [10]. However, quantum advantage is dataset-dependent, with most pronounced benefits for high-dimensional, non-linear, and highly imbalanced datasets [14].

3.4 NISQ Hardware Limitations and Error Mitigation

Noise simulations reveal that current NISQ devices degrade QML accuracy by 8-15% due to gate errors and decoherence [7]. Error mitigation techniques—including readout error mitigation (REM), zero-noise extrapolation (ZNE), and probabilistic error cancellation (PEC)—recover 4-7% of lost accuracy [9]. Table 4 summarises the impact of noise on QML performance and the effectiveness of mitigation strategies.

Table 4. Impact of noise on QML performance and mitigation effectiveness.

Noise level	Baseline Accuracy	REM	ZNE	PEC
No noise	94.6%	-	-	-
Low (0.0005)	91.8%	93.2%	93.5%	94.0%
Medium (0.001)	87.5%	90.1%	90.8%	91.8%
High (0.005)	79.3%	84.6%	85.2%	87.1%

4. Discussion

4.1 Key Findings and Their Implications

The results demonstrate that QML offers promising enhancements for cybersecurity applications, particularly in intrusion detection and anomaly analysis. The 94.6% accuracy achieved

by 8-qubit QSVM on NSL-KDD represents a significant improvement over classical baselines, suggesting that quantum feature maps provide genuine expressive advantages for network traffic classification [11].

The parameter efficiency of VQCs is particularly noteworthy for edge deployment in cybersecurity contexts, where computational resources are constrained. However, the noise sensitivity observed in NISQ simulations indicates that error mitigation remains essential for real-world deployment, especially for high-stakes security applications where false negatives carry significant consequences [9].

4.2 Positioning Within the Current Research Landscape

The findings align with prior research demonstrating QML advantages for classification tasks [4,6]. The NSL-KDD results (94.6%) are consistent with recent work on hybrid classical-quantum intrusion detection [8], while the VQC performance on ToN_IoT (F1=89.3%) extends prior results to more complex, real-world datasets [12].

The quantum advantage analysis confirms that the benefits of QML are most pronounced for datasets with complex, non-linear feature interactions—consistent with theoretical predictions on quantum kernel methods [11]. The hardware constraints identified mirror those reported in broader QML literature [7], underscoring the need for continued advances in quantum hardware and error mitigation.

4.3 Open Challenges and Practical Constraints

Several challenges persist. Hardware limitations remain the primary barrier: current NISQ devices support only 4-12 qubits with limited coherence times, restricting the complexity of QML models that can be deployed [7]. Scalability to real-world cybersecurity datasets, which often contain millions of instances, remains an open challenge. The vulnerability of quantum models to adversarial attacks—where small perturbations to input data cause misclassification—has been documented in both classical and quantum contexts [13]. Additionally, the gap between simulation and hardware performance persists, requiring careful validation on physical quantum devices [9].

4.4 Emerging Research Directions

Future research should prioritise noise-resilient QML architectures, including quantum error correction and noise-adaptive circuit design [9]. Quantum federated learning offers a promising direction for privacy-preserving cybersecurity, enabling collaborative model training without sharing

sensitive network data [17]. The integration of quantum computing with agentic AI could enable proactive, self-adaptive cybersecurity systems capable of anticipating and responding to threats in real time [18].

5. Conclusion

Quantum machine learning offers a promising paradigm for enhancing cybersecurity in the NISQ era. QSVM-based intrusion detection achieves 94.6% accuracy on NSL-KDD, significantly outperforming classical approaches for high-dimensional, non-linear classification tasks. VQCs offer parameter-efficient solutions suitable for edge deployment, while quantum feature maps enable classification in exponentially expanded Hilbert spaces. However, hardware limitations, scalability constraints, and adversarial vulnerabilities remain significant challenges. Future research should prioritise noise-resilient architectures, quantum federated learning, and the integration of quantum computing with agentic AI for proactive cybersecurity defense.

Author Contributions

Conceptualization, E.F.; methodology, E.F. and W.Z.; software, T.O.O.; validation, A.H.K.; formal analysis, E.F.; investigation, T.O.O.; writing—original draft preparation, E.F.; writing—review and editing, all authors. All authors have read and agreed to the published version of the manuscript.

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Ethics Approval

Not applicable

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Conflicts of Interest

The authors declare no conflicts of interest to report regarding the present study.

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