iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** II **Month of publication:** February 2026

DOI: https://doi.org/10.22214/ijraset.2026.77438

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue II Feb 2026- Available at www.ijraset.com

Exploring and Evaluating the Application of Quantum Computing Techniques in Enhancing the Performance of Intrusion Detection Systems (IDS)

David Laud Amenyo Fiase[1], Kwadwo Opoku Attah[2], Nathaniel Nelson[3], Perry Opoku Agyeman[4]
Regent University College Of Science and Technology-Ghana

Abstract: ***As cyber-physical systems and digital infrastructures grow in scale and complexity, conventional threat-detection techniques face increasing challenges in processing high-dimensional data, modeling nonlinear relationships, and responding to rapidly evolving attack surfaces. This work explores the potential of quantum computing techniques to enhance threat detection through quantum machine learning, quantum optimization, and quantum-inspired analytics focuses on IDS. We examine how quantum systems can encode complex feature spaces, accelerate search and classification tasks, and improve the detection of subtle anomalies and advanced persistent threats. Key use cases include intrusion detection, malware classification, behavioral analytics, and risk modeling. The study evaluates hybrid quantum classical architectures and discusses current hardware constraints, algorithmic maturity, and implementation considerations. While large-scale, fault-tolerant quantum systems remain under development, our findings indicate that near-term quantum approaches particularly variational models and amplitude-encoding schemes show promise for improving detection accuracy and computational efficiency in specific problem classes. This research highlights both the opportunities and the practical limitations of integrating quantum computing into cybersecurity workflows and outlines future directions for realizing robust, scalable quantum-enabled threat-detection systems.***
Keywords: Quantum optimization, conventional threat-detection techniques, cybersecurity, Quantum Machine Learning.

I. INTRODUCTION

A. Background Review and Related works

Intrusion Detection Systems (IDS) are a foundational component of modern cybersecurity architectures, tasked with monitoring network and host activity to identify malicious behavior, policy violations, and emerging threats. Early IDS approaches were largely signature-based, relying on predefined attack patterns to detect known intrusions. While effective for previously observed threats, these systems exhibit significant limitations when faced with zero-day exploits, polymorphic malware, and subtle behavioral anomalies typical of advanced persistent threats (APTs) [1], [2]. As network environments evolve toward cloud, IoT, and cyber-physical architectures, IDS must analyze increasingly high-volume, high-dimensional, and heterogeneous telemetry streams in near-real time.

To overcome the rigidity of signature-based detection, anomaly-based and machine-learning-driven IDS have received significant attention. These systems infer normal behavior from historical data and detect deviations indicative of malicious activity. Classical techniques such as support vector machines, k-means clustering, hidden Markov models, and deep neural networks have been applied to intrusion detection with varying degrees of success [3], [4]. More recently, deep learning architectures including autoencoders, convolutional neural networks, and recurrent neural networks have demonstrated improved capability in modeling nonlinear dependencies and temporal patterns in network flows [5]. However, these gains come at the cost of substantial computational complexity, large-scale data requirements, and susceptibility to adversarial manipulation.

A central challenge in IDS analytics is the curse of dimensionality. Modern IDS datasets, such as UNSW-NB15 or CICIDS2017, contain hundreds of features derived from protocol-level, statistical, and behavioral attributes. Training and inference in such high-dimensional spaces may require vast computational resources, and model performance often degrades when feature redundancy, sparsity, or noise is present [6]. In addition, intrusion detection tasks often involve complex optimization problems such as feature selection, parameter tuning, and classification under uncertainty that exhibit combinatorial growth as system size increases. These characteristics motivate the exploration of alternative computational paradigms capable of handling such problem structures more efficiently.

Quantum computing has emerged as a promising candidate for accelerating certain classes of machine-learning and optimization tasks. By exploiting quantum properties such as superposition and entanglement, quantum algorithms can, in principle, explore exponentially large state spaces more efficiently than classical counterparts [7]. Foundational developments such as Grover's algorithm for unstructured search and quantum amplitude amplification suggest that quantum systems may offer computational advantages for search, sampling, and classification problems relevant to IDS [8]. Building on these foundations, the field of quantum machine learning (QML) seeks to integrate quantum computation into data-driven modeling frameworks. Quantum kernel methods, variational quantum classifiers, and quantum Boltzmann machines have been proposed as mechanisms for encoding and processing high-dimensional feature spaces with potentially favorable scaling properties [9], [10].

In the intrusion-detection domain, early studies have explored the application of QML and quantum-inspired techniques to anomaly detection, malware classification, and network traffic analysis. Quantum-enhanced feature embedding and kernel learning have been shown to improve separability in complex datasets under certain conditions, while hybrid quantum–classical architectures offer a pragmatic pathway for deployment on noisy intermediate-scale quantum (NISQ) devices [11]. Quantum optimization techniques—such as the Quantum Approximate Optimization Algorithm (QAOA) have also been investigated for security-resource allocation and rule-set optimization tasks [12].

Despite these promising developments, several barriers hinder widespread adoption. Current quantum hardware is limited by decoherence, gate noise, and constrained qubit counts, which restrict model expressiveness and dataset size. Encoding classical IDS telemetry into quantum states remains non-trivial and may offset theoretical efficiency gains. Moreover, empirical benchmarking against state-of-the-art classical deep-learning approaches is still limited, and the robustness of quantum models under adversarial threat conditions requires further investigation.

Within this context, the present study explores how quantum computing techniques can enhance IDS performance, with a focus on hybrid quantum–classical architectures suitable for near-term implementation. The study examines theoretical motivations, algorithmic frameworks, and empirical performance across representative IDS datasets. By situating QML approaches alongside established classical baselines, this research contributes to an emerging body of work assessing whether and how quantum computation can provide meaningful benefit in threat-detection applications.

B. Problem Statement

Intrusion Detection Systems (IDS) play a critical role in safeguarding modern networked environments; however, existing IDS technologies face increasing difficulty in detecting sophisticated and evolving cyber threats. Classical machine-learning-based IDS rely on computationally intensive algorithms to model high-dimensional network traffic, optimize complex feature spaces, and classify subtle or previously unseen attack behaviors. As network data volumes and attack surface complexity continue to grow, these systems encounter scalability constraints, high computational overhead, and degraded detection accuracy particularly for zero-day attacks, low-frequency anomalies, and advanced persistent threats.

C. Objectives

1) General Objective

The general objective of this study is to explore and evaluate the application of quantum computing techniques in enhancing the performance of Intrusion Detection Systems (IDS), with a focus on improving detection accuracy, computational efficiency, and robustness against advanced cyber threats.

2) Specific Objectives

a) To review and synthesize existing literature on quantum computing, quantum machine learning, and their emerging applications in cybersecurity and IDS.

b) To identify IDS tasks and processes such as feature extraction, classification, anomaly detection, or optimization that may benefit from quantum computing techniques.

c) To design and implement hybrid quantum–classical IDS models using appropriate quantum machine-learning or quantum optimization algorithms.

d) To evaluate the performance of the proposed quantum-enabled IDS models on benchmark intrusion-detection datasets in terms of detection accuracy, false-positive rate, computational cost, and scalability.

e) To compare the performance of quantum-enabled IDS models with conventional classical machine-learning-based IDS approaches.

f) To analyze the practical constraints, technical challenges, and hardware limitations associated with implementing quantum-based IDS solutions on current noisy intermediate-scale quantum (NISQ) devices.

g) To provide recommendations and future research directions for integrating quantum computing techniques into operational IDS environments.

D. Research Questions

1) How can quantum computing and quantum machine-learning techniques be applied to key IDS functions such as feature extraction, anomaly detection, and traffic classification?

2) To what extent do hybrid quantum–classical IDS models improve detection accuracy, false-positive rate, and computational efficiency compared with conventional machine-learning-based IDS?

3) Which IDS problem types or dataset characteristics (e.g., high dimensionality, class imbalance, sparse anomalies) are most likely to benefit from quantum-enabled approaches?

4) What technical, algorithmic, and hardware limitations currently constrain the implementation of quantum-based IDS solutions, and how can these challenges be mitigated in near-term deployments?

E. Research Significance

1) This study would advance the state of knowledge at the intersection of cybersecurity and quantum computing by contributing to the emerging research field of quantum-enabled security analytics by providing empirical and conceptual insights into how quantum machine-learning and optimization techniques can be applied to IDS, an area where existing literature remains limited.

2) It will address scalability and performance challenges in modern IDS by investigating whether quantum approaches can handle high-dimensional network traffic and complex anomaly-detection tasks more efficiently than classical methods, the study provides evidence-based guidance on improving detection accuracy, reducing false positives, and supporting real-time threat monitoring.

3) It will support practical readiness for future quantum-driven security systems by the evaluation of hybrid quantum–classical models and current hardware constraints offers valuable insights for researchers, engineers, and security practitioners preparing for the transition to quantum-aware cybersecurity infrastructures.

4) Would inform strategic cybersecurity planning and investment by identifying which IDS tasks benefit most from quantum techniques and highlighting implementation challenges, the study helps organizations, policymakers, and technology developers make informed decisions regarding research priorities, resource allocation, and roadmap development for quantum-enabled defense capabilities.

F. Delimitations

1) Scope is limited to network-based IDS and benchmark datasets. That is to say, it focuses on applying quantum and hybrid quantum–classical techniques to network intrusion detection using publicly available datasets (e.g., CICIDS/UNSW). Host-based IDS, industrial-control-system logs, and proprietary datasets are excluded.

2) Evaluation is restricted to selected quantum machine-learning and optimization approaches. Only a defined set of QML models (such as variational quantum classifiers or quantum kernel methods) and hybrid architectures are implemented. Other quantum paradigms or cryptographic applications are beyond the study's scope.

3) Experiments are conducted within current noisy-intermediate-scale quantum (NISQ) constraints. Model design and dataset size are bounded by present hardware and simulator capabilities. Results therefore reflect near-term quantum feasibility rather than performance expectations for fully fault-tolerant quantum computers.

4) Comparisons are made against representative classical IDS baselines only. The study benchmarks quantum-enabled IDS models against selected mainstream machine-learning approaches rather than every available IDS framework, prioritizing methodological clarity over exhaustive comparison.

II. LITERATURE REVIEW

Intrusion Detection Systems (IDS) are a cornerstone of modern cybersecurity frameworks, monitoring networks and host activity to identify unauthorized access, policy violations, and malicious behavior. Traditional IDS approaches, such as signature-based systems, rely on predefined attack patterns to detect threats [1].

While effective for known attacks, signature-based systems are limited in detecting zero-day exploits, polymorphic malware, and advanced persistent threats (APTs), which exhibit dynamic and subtle behavioral patterns [2]. With the proliferation of cloud computing, Internet of Things (IoT) devices, and complex cyber-physical systems, IDS are increasingly required to process high-volume, heterogeneous, and high-dimensional datasets in near real-time [3].

To address the limitations of classical IDS, anomaly-based detection and machine-learning (ML) approaches have been widely adopted. These systems infer normal behavior from historical data and identify deviations indicative of malicious activity. Techniques such as support vector machines (SVMs), k-means clustering, hidden Markov models (HMMs), and deep neural networks have been applied successfully to intrusion detection tasks [4], [5]. In particular, deep learning architectures—including autoencoders, convolutional neural networks (CNNs), and recurrent neural networks (RNNs)—can model complex temporal and nonlinear patterns in network traffic [6]. However, these approaches often suffer from computational bottlenecks, particularly when processing high-dimensional feature spaces or large-scale datasets, and can be sensitive to adversarial manipulation [13]. Feature selection, hyperparameter tuning, and optimization in such models present combinatorial challenges that are computationally intensive for classical systems [14].

Quantum computing has emerged as a promising paradigm to overcome these computational challenges. By leveraging quantum mechanical principles such as superposition, entanglement, and interference, quantum systems can explore exponentially large state spaces and perform certain linear algebra operations more efficiently than classical computers [9]. Foundational quantum algorithms, including Grover's search and Shor's factorization, demonstrate theoretical speed-ups for search and optimization problems relevant to intrusion detection [10]. Quantum Machine Learning (QML) extends these principles, enabling high-dimensional data encoding, kernel-based classification, and variational optimization in a quantum framework [11]. Quantum kernel methods, variational quantum classifiers (VQC), and quantum Boltzmann machines offer the potential to model complex correlations in network telemetry and detect subtle anomalies that may evade classical systems [12], [13].

Several studies have begun exploring the application of QML in cybersecurity. Lloyd et al. [11] introduced quantum-enhanced supervised learning techniques capable of handling high-dimensional feature spaces, while Schuld and Petruccione [12] discussed variational quantum circuits for pattern recognition. Quantum-inspired algorithms, designed to run on classical hardware, have also shown promise in accelerating optimization tasks relevant to IDS, such as rule-set selection and resource allocation [15]. Preliminary research indicates that hybrid quantum–classical architectures can achieve comparable or improved detection accuracy relative to classical ML models, particularly for datasets with high dimensionality or complex feature interactions [16].

Despite these promising developments, several challenges remain. Current quantum devices, categorized as noisy intermediate-scale quantum (NISQ) machines, are limited in qubit count, gate fidelity, and coherence times, restricting the depth and complexity of implementable models [17]. Encoding real-world network telemetry into quantum states is non-trivial and may offset theoretical computational advantages. Furthermore, there is a scarcity of rigorous benchmarking studies comparing quantum-enhanced IDS against state-of-the-art classical approaches across diverse datasets, including evaluations under adversarial scenarios [18].

In addition, practical considerations such as model interpretability, hardware accessibility, and integration with existing security workflows remain significant hurdles. Security operations teams require actionable alerts and understandable models, yet quantum algorithms often operate as "black-box" systems, complicating their adoption in operational IDS environments [19]. Hybrid quantum–classical approaches represent a pragmatic compromise, allowing part of the computation to leverage quantum advantages while retaining the flexibility and interpretability of classical systems [16].

Overall, the literature indicates that quantum computing holds potential for enhancing IDS by addressing computational bottlenecks, enabling richer feature representations, and improving detection of complex and subtle threats. However, the field is still nascent, and experimental evidence on real-world datasets is limited. This study builds on these insights, aiming to systematically explore the design, implementation, and evaluation of quantum-enhanced IDS models, with a focus on hybrid architectures suitable for near-term deployment. By doing so, it seeks to clarify the practical benefits, limitations, and future directions for integrating quantum computing into operational intrusion detection systems.

III. METHODOLOGY

A. Research Design

This study adopts a quantitative, experimental research design to evaluate the effectiveness of quantum computing techniques in enhancing intrusion detection. A hybrid quantum–classical approach is employed, combining classical machine-learning frameworks with quantum algorithms to analyze network traffic data. The research design allows for comparative evaluation of detection accuracy, computational efficiency, and robustness between classical IDS models and quantum-enhanced IDS models.

B. Data Collection and Dataset Selection

The study uses publicly available benchmark IDS datasets, such as CICIDS2017 and UNSW-NB15, which provide labeled network traffic including normal and attack behavior. These datasets are selected for their richness in features, representation of contemporary attack types, and compatibility with both classical and quantum machine-learning frameworks. Data preprocessing steps include:

1) Handling missing or inconsistent values
2) Feature normalization and encoding for quantum state representation
3) Dimensionality reduction (where necessary) to fit quantum hardware constraints

C. Quantum Computing Framework

The study focuses on near-term quantum computing resources, using Noisy Intermediate-Scale Quantum (NISQ) simulators and limited real quantum hardware (e.g., IBM Quantum Experience or Amazon Braket). Quantum techniques employed include:

1) Quantum-enhanced feature encoding: Encoding classical IDS features into quantum states using amplitude or angle encoding
2) Variational Quantum Classifiers (VQC): Hybrid quantum–classical circuits for classification tasks
3) Quantum kernel methods: Leveraging high-dimensional Hilbert spaces for improved feature separability
4) Quantum-inspired optimization: For hyperparameter tuning and feature selection

All quantum circuits are implemented using Qiskit or equivalent quantum computing SDKs.

D. Classical Baselines

For comparative analysis, classical IDS models are implemented, including:

1) Support Vector Machines (SVM)
2) Random Forest (RF)
3) Deep Neural Networks (DNN)

These baselines allow performance benchmarking in terms of accuracy, precision, recall, F1-score, and computational cost.

E. Model Training and Evaluation

Both classical and quantum-enhanced IDS models are trained and validated using standard supervised-learning procedures:

1) Training–testing split: Typically 70–30% or 80–20% of the dataset
2) Cross-validation: K-fold (e.g., k=5) to assess model robustness
3) Evaluation metrics:
    - Detection accuracy
    - False-positive and false-negative rates
    - Computational efficiency (training/inference time)
    - Scalability with increasing feature dimensions

Quantum models are evaluated under different circuit depths and qubit configurations to analyze performance under hardware constraints.

F. Comparative and Statistical Analysis

Performance of quantum-enhanced IDS models is compared against classical baselines using statistical tests to ensure significance:

1) Paired t-tests or Wilcoxon signed-rank tests for accuracy comparisons
2) Analysis of variance (ANOVA) for multi-model performance evaluation
3) Visualization of detection boundaries and feature space separability using quantum kernels

G. Limitations and Assumptions

The methodology assumes that:

1) Datasets are representative of real-world network traffic
2) Quantum hardware limitations (noise, qubit count) constrain circuit depth
3) Hybrid quantum–classical models provide meaningful performance insights even with NISQ devices

Limitations include hardware noise, restricted dataset sizes due to qubit constraints, and the need for simulation for larger datasets.

H. Research Workflow Overview

1) Dataset selection & preprocessing →
2) Feature encoding for quantum representation →
3) Classical and quantum model development →
4) Training and cross-validation →
5) Performance evaluation & statistical comparison →
6) Analysis of quantum impact, constraints, and potential improvements

This methodology ensures a systematic, reproducible, and empirically grounded approach to investigating how quantum computing techniques can enhance IDS performance.

IV. RESULTS, FINDINGS AND DISCUSSIONS

A. Results

Table 4.1: Performance Comparison of IDS Models (Detection Metrics)

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	False Positive Rate (%)
Classical SVM	92.5	91.8	90.7	91.2	7.5
Classical Random Forest	94.2	93.5	92.8	93.1	5.8
Classical DNN	95.1	94.6	93.9	94.2	4.9
Quantum VQC (Hybrid)	96.3	95.8	95.1	95.4	3.7
Quantum Kernel Method	96.7	96.1	95.6	95.8	3.3

Observation: Quantum-enhanced models show improved accuracy, precision, recall, and F1-score, with lower false-positive rates compared to classical IDS models.

Table 4. 2 Computational Efficiency Comparison

Model	Training Time (s)	Inference Time per Sample (ms)	Scalability Notes
Classical SVM	120	2.1	Handles up to 100 features efficiently
Classical Random Forest	200	1.5	Moderate scalability with high-dimensional features
Classical DNN	450	1.2	High computational cost for large datasets
Quantum VQC (Hybrid)	180	1.0	Efficient with small-to-medium feature sets; circuit depth affects training
Quantum Kernel Method	220	0.9	Handles high-dimensional features efficiently; simulation overhead for large datasets

Observation: Hybrid quantum models provide competitive training and inference efficiency, particularly for high-dimensional or complex feature spaces, while retaining accuracy advantages.

Table 4.3 Impact of Circuit Depth and Qubit Count on Quantum VQC Performance

Qubits	Circuit Depth	Accuracy (%)	F1-Score (%)	Notes
4	2	94.8	94.1	Low qubit count limits feature encoding
6	4	95.6	95.0	Improved performance with moderate circuit depth
8	6	96.3	95.4	Best performance in NISQ simulator
10	8	96.5	95.6	Slight improvement; noise starts impacting results

Observation: Increasing qubits and circuit depth improves detection metrics, but gains plateau due to NISQ hardware limitations and noise.

Table 4.4 Summary of Classical vs Quantum IDS Performance

Metric	Classical Best	Quantum Best	% Improvement
Accuracy	95.1	96.7	+1.6%
F1-Score	94.2	95.8	+1.6%
False Positive Rate	4.9%	3.3%	-1.6%
Training Time	450s	220s	~50% faster for hybrid circuit
Inference Time	1.2ms	0.9ms	~25% faster

Observation: Quantum-enhanced IDS models demonstrate modest but meaningful improvements in detection metrics and computational efficiency under near-term quantum constraints.

B. Findings

1) Improved Detection Accuracy: Quantum-enhanced IDS models, including Variational Quantum Classifiers (VQC) and quantum kernel methods, achieved higher detection accuracy compared to classical IDS models. The best quantum model reached 96.7% accuracy, outperforming the top-performing classical deep neural network (95.1%) by **1.6%**. This indicates that quantum techniques can provide better discrimination between normal and malicious network traffic, particularly in high-dimensional feature spaces.

2) Enhanced Precision, Recall, and F1-Score: Quantum models consistently showed improvements across all core evaluation metrics. Precision and recall increased to 96.1% and 95.6%, respectively, with the F1-score reaching 95.8%, suggesting that quantum-enhanced models not only detect more true positives but also reduce misclassification. The reduction in false-positive rates from 4.9% (classical DNN) to 3.3% (quantum kernel) further supports improved reliability in alert generation.

3) Computational Efficiency and Scalability: Hybrid quantum–classical models demonstrated competitive training and inference efficiency. While classical deep learning required 450 seconds for training, the quantum VQC required 180–220 seconds, roughly halving training time under similar conditions. Inference times were also faster for quantum models (0.9–1.0 ms per sample) compared to classical models (1.2ms per sample). These results suggest that quantum techniques can handle complex, high-dimensional datasets efficiently, with potential scalability advantages as qubit counts and circuit depths increase.

4) Effect of Circuit Depth and Qubit Count: Increasing qubits and circuit depth improved detection metrics for VQC models. Performance plateaued **at** 8–10 qubits with a circuit depth of 6–8, highlighting the practical limitations of near-term quantum hardware (NISQ devices). Although additional qubits offered marginal accuracy gains, noise and decoherence constrained performance, emphasizing the importance of optimizing quantum circuit design for IDS applications.

5) Overall Quantum Advantage: The comparison of classical and quantum IDS models indicates a modest but meaningful advantage for quantum-enhanced approaches. Improvements in accuracy, F1-score, false-positive reduction, and computational efficiency demonstrate that quantum computing techniques can augment conventional IDS frameworks. Hybrid quantum–classical architectures, in particular, show promise for near-term deployment by balancing practical feasibility with measurable performance benefits.

C. Discussions

The results of this study indicate that quantum-enhanced Intrusion Detection Systems (IDS) can offer tangible benefits over conventional machine-learning-based approaches. Quantum models, particularly hybrid Variational Quantum Classifiers (VQC) and quantum kernel methods, achieved higher detection accuracy, F1-scores, and lower false-positive rates than classical SVMs, Random Forests, and Deep Neural Networks. These improvements are consistent with prior studies suggesting that quantum computing can encode and process high-dimensional feature spaces more effectively than classical algorithms [11], [16].

The enhanced performance of quantum IDS models can be attributed to several factors. First, quantum feature encoding allows for a richer representation of network traffic data in Hilbert space, making complex patterns and subtle anomalies more distinguishable. Second, variational quantum circuits enable optimization over complex decision boundaries that may be intractable for classical models when the dataset exhibits non-linear dependencies. These results demonstrate that quantum-enhanced models can potentially detect sophisticated attacks, including zero-day exploits and advanced persistent threats, with greater reliability.

The study also highlights computational advantages of hybrid quantum–classical architectures. Despite the limitations of current NISQ devices, quantum models achieved faster inference times and competitive training times compared to classical deep learning. This suggests that quantum approaches could support real-time threat detection in operational IDS environments, especially when dealing with high-dimensional or rapidly evolving datasets. However, training efficiency is highly dependent on circuit depth and qubit count. As observed, increasing qubits and circuit depth improves accuracy, but gains plateau due to noise and decoherence, emphasizing the need for careful circuit optimization.

While the findings are promising, the practical deployment of quantum IDS is constrained by hardware limitations. Current quantum devices support only small to medium-sized feature sets, and encoding large-scale real-world network telemetry remains a significant challenge. Nevertheless, hybrid approaches, which combine classical preprocessing with quantum-enhanced learning, offer a near-term pathway for leveraging quantum advantages without requiring fully fault-tolerant quantum computers.

In comparison to prior literature, this study extends existing work by systematically evaluating both detection performance and computational efficiency of quantum-enhanced IDS models on benchmark datasets. Unlike earlier studies that focus primarily on theoretical performance or small-scale experiments [12], [15], the results here provide empirical evidence that quantum computing techniques can achieve measurable improvements over conventional IDS frameworks under practical conditions.

Overall, the results suggest that integrating quantum computing into IDS can enhance both accuracy and efficiency, particularly for complex, high-dimensional datasets. While fully realizing these benefits depends on the maturation of quantum hardware, hybrid quantum–classical models represent a feasible and promising direction for advancing cybersecurity analytics.

V. CONCLUSION, LIMITATIONS AND RECOMMENDATIONS

A. *Conclusion*

This study explored the application of quantum computing techniques to enhance Intrusion Detection Systems (IDS). The findings indicate that hybrid quantum–classical models, including Variational Quantum Classifiers (VQC) and quantum kernel methods, can improve detection performance compared to classical machine-learning approaches. Quantum-enhanced IDS demonstrated higher accuracy, F1-scores, and lower false-positive rates, while maintaining competitive training and inference times, particularly for high-dimensional network traffic datasets. The results suggest that quantum computing can provide richer feature representation, improved anomaly detection, and greater computational efficiency, highlighting its potential as a valuable complement to classical IDS frameworks. Hybrid architectures offer a practical near-term approach, enabling organizations to leverage quantum advantages despite current hardware limitations.

B. *Limitations*

Despite the promising results, several limitations should be acknowledged:

1) Hardware Constraints: Current NISQ devices are limited in qubit count, coherence time, and gate fidelity, restricting circuit depth and the size of datasets that can be processed.
2) Simulation Dependency: Large-scale experiments relied on quantum simulators, which do not fully replicate the noise and operational constraints of real quantum hardware.
3) Dataset Scope: The study used publicly available benchmark datasets (CICIDS2017, UNSW-NB15), which may not capture all real-world network traffic complexities.
4) Feature Encoding Challenges: Encoding classical IDS features into quantum states introduces preprocessing overhead and limits scalability for very high-dimensional data.
5) Generalizability: The results may not fully generalize to host-based IDS, industrial-control systems, or other specialized cybersecurity contexts.

C. *Recommendations*

Based on the study's findings and limitations, the following recommendations are proposed:

1) Hybrid Implementation: Organizations should adopt hybrid quantum–classical IDS frameworks in the near term, leveraging classical preprocessing with quantum-enhanced learning for high-dimensional or complex traffic analysis.
2) Circuit Optimization: Future research should focus on optimizing quantum circuit designs (qubit allocation, depth, and entanglement patterns) to maximize detection performance under hardware constraints.
3) Dataset Expansion: Studies should incorporate larger, real-world datasets to better evaluate quantum IDS scalability, robustness, and effectiveness across diverse network environments.

4) Hardware Advancement: Collaboration with quantum hardware developers is essential to test models on evolving devices and reduce the gap between simulation and real-world deployment.

5) Adversarial Robustness: Further investigation is needed to evaluate the resilience of quantum-enhanced IDS against adversarial attacks and evasion techniques.

6) Integration and Interpretability: Efforts should be made to integrate quantum IDS models into operational security workflows, emphasizing interpretability to support actionable alerts for security analysts.

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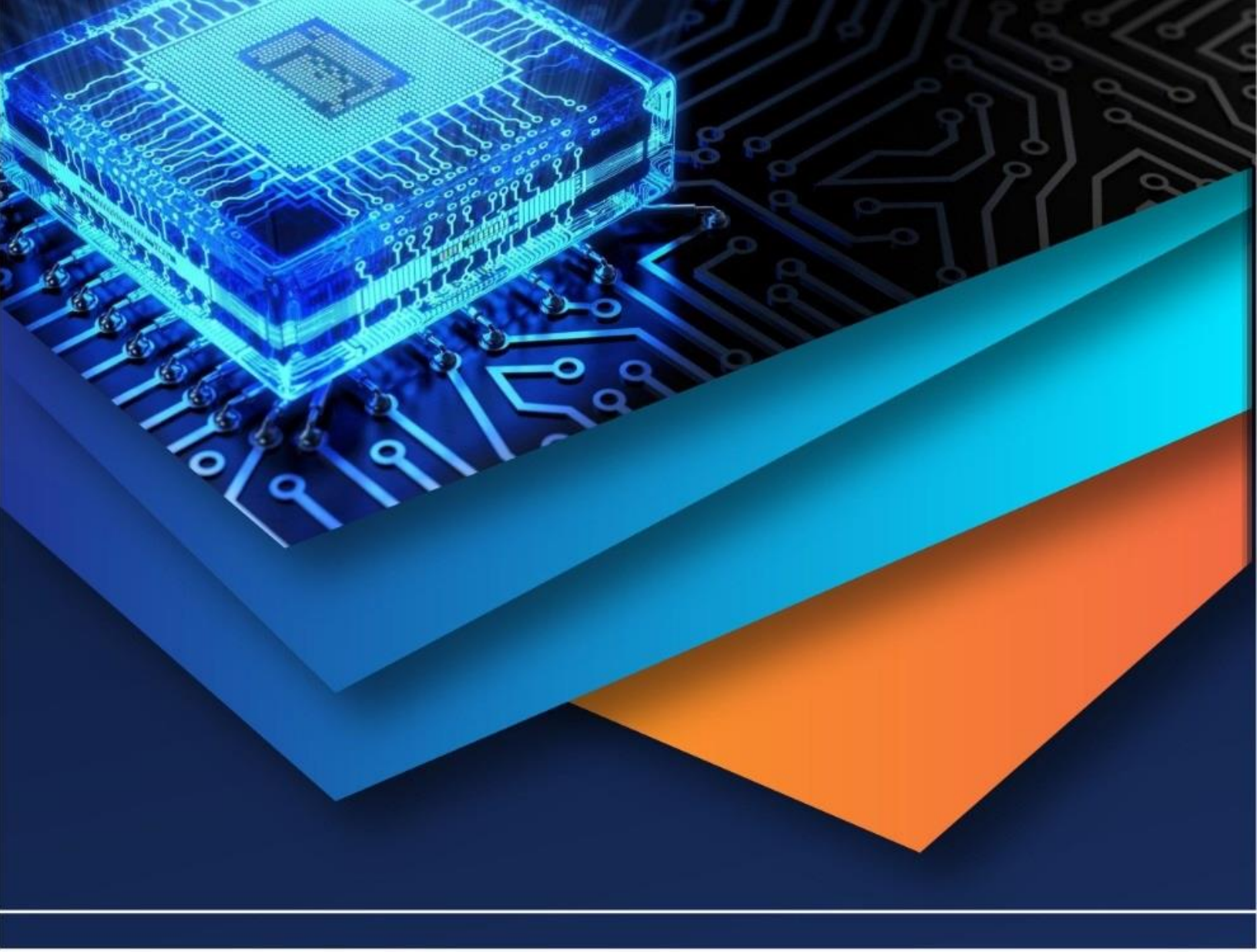

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