A Review on transformative impact of Quantum Computing by Machine Learning

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***Abstract*—This review examines the integration of quantum computing and machine learning, highlighting the transformative potential of quantum machine learning (QML) for advanced data processing beyond classical computational limits. Based on a systematic analysis of 32 key studies, the paper reviews recent advancements in QML algorithms and their emerging applications, with particular emphasis on cybersecurity. The literature survey, conducted primarily using the ScienceDirect database, categorizes existing research according to algorithms, applications, challenges, and future research directions. The findings indicate a growing trend toward the practical implementation of quantum-enhanced machine learning techniques. Key challenges, including hardware limitations, ethical considerations, and data security concerns, are also discussed. Overall, this review provides a structured overview of the current state of QML and identifies critical research gaps that must be addressed to enable wider real-world adoption.**

***Index Terms*—Quantum computing, Machine learning algorithms, Quantum machine learning, Cybersecurity, Data security, Pattern recognition, Emerging technologies.**

I. INTRODUCTION

Machine learning (ML), a core subfield of artificial intelligence (AI), focuses on developing systems capable of learning from data and improving performance without explicit programming. Quantum computing (QC), grounded in the principles of quantum mechanics, introduces fundamentally new computational paradigms that enable novel approaches to information processing. The convergence of ML and QC has the potential to drive transformative advances in computer science. As noted by Martín-Guerrero and Lamata (18), the synergy among machine learning, quantum computing, and quantum information (QI) has led to the emergence of Quantum Machine Learning (QML) as a rapidly evolving research area.

Recent progress highlights the growing maturity of the field. For example, Giuntini et al. (6a) proposed quantum-inspired algorithms for classification tasks, while Ning et al. (9) explored quantum-based approaches for handling large-scale datasets, demonstrating the feasibility of quantum-enhanced learning models. Among the promising application domains, cybersecurity has received significant attention. Studies such as Shi et al. (28), which investigated quantum cryptography using continuous variable quantum neural networks (CVQNNs), illustrate the potential of QML to provide robust defenses against emerging cyber threats. Despite these advances, challenges related to hardware limitations, algorithmic complexity, and scalability continue to impede widespread adoption.

While quantum computing presents a compelling pathway for revolutionizing machine learning, several open research gaps must be addressed to fully realize its potential across diverse application domains. These observations motivate the following research questions:

RQ1: How do quantum computing principles enhance machine learning algorithms?

This question examines the role of quantum mechanics in improving the performance and capability of machine learning models.

RQ2: What are the implications of quantum computing for application domains such as cybersecurity?

This question explores how quantum technologies may provide advantages over classical approaches in securing communication and protecting sensitive data.

RQ3: How do quantum algorithms compare with classical algorithms in terms of efficiency and applicability?

This question investigates the relative strengths and limitations of quantum and classical algorithms for various machine learning tasks.

This review presents the research methodology in Section 2, followed by a comprehensive literature review of recent advances in quantum machine learning in Section 3. Section 4 discusses key insights and implications derived from the analysis, addressing the proposed research questions (RQ1 RQ3). Finally, Section 5 concludes the paper by summarizing the main findings and outlining directions for future research. This structured approach aims to provide a clear and systematic overview of the role of quantum computing in advancing machine learning, highlighting both its potential and the challenges that remain.

II. METHODOLOGY

his review, conducted as part of a broader research initiative on quantum computing applications, examined existing literature on the role of quantum computing in machine learning. Established literature review methodologies were followed (Levac et al.,6; Arksey and O'Malley, 2). An initial broad search using the keyword phrase "quantum computing application" was performed to capture a wide range of relevant studies. A total of 300 recent publications (2024 2025) were retrieved from the Science Direct database.

A detailed content analysis was subsequently carried out to identify studies related to artificial intelligence, machine learning, and application-oriented research. This screening process reduced the dataset to 257 articles addressing quantum computing applications. Further refinement was applied based on publication relevance, regency, and explicit discussion of artificial intelligence and machine learning, resulting in a final selection of 22 articles for in-depth analysis. This systematic and methodical approach provides a comprehensive overview of current trends, practical implementations, and future research directions in quantum machine learning.

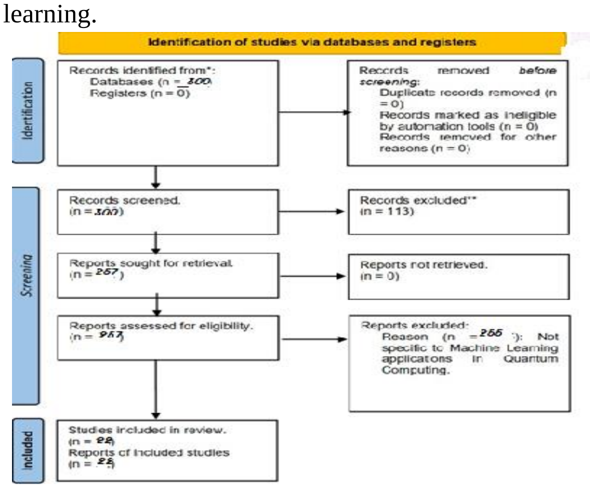

Figure 1: PRISMA flow chart diagram showing the systematic selection process of literature from an initial dataset of 300 studies to 22 key papers on machine learning in quantum computing.

The methodological approach and detailed stages of the literature review are described, followed by the inclusion of a PRISMA flowchart to visually summarise the process. This diagram (see Figure 1) effectively illustrates the progression from the initial set of 300 documents to the final selection of 22 relevant papers. It highlights the screening, eligibility, and inclusion stages, providing a clear and concise visual representation of the systematic review process, thereby ensuring a thorough selection of the most relevant literature (Page and Moher, 19).

III. LITERATURE REVIEW

Impact of Quantum Computing on Machine Learning: Key Advances and Algorithm Improvements

The intersection of machine learning (ML) and quantum computing has emerged as a rapidly expanding research area with the potential to fundamentally transform data processing and analytical methodologies. This review synthesizes key studies that demonstrate advances in quantum-enhanced computational efficiency and the development of quantum-inspired and quantum-native machine learning approaches. In particular, the superiority of quantum algorithms in specific tasks especially pattern recognition and data classification is highlighted by the works of Rana et al. (21) and Houssein et al. (8).

The emergence of quantum neural networks (QNNs) and quantum support vector machines (QSVMs) represents a shift toward more sophisticated quantum computational paradigms. Notably, Ning, Yang, and Du (28) introduced Quantum Kernel Logistic Regression (QKLR), illustrating an early yet practical application of quantum techniques in machine learning and demonstrating their transformative potential. Building on this foundation, QSVMs studied by Zhang et al. (23) and Rana et al. (24) leverage quantum computing to efficiently process complex, high-dimensional datasets, showing measurable improvements over classical approaches in data-intensive tasks.

Several studies have explored hybrid quantum classical frameworks to bridge theoretical advances and real-world applications. Suryotrisongko and Musashi (26) proposed a hybrid deep learning model for botnet

detection, achieving competitive performance with classical models and marginal accuracy improvements (up to 94.7%) in specific scenarios. However, their findings also revealed sensitivity to random initialization and circuit design, underscoring the need for further optimization to ensure robustness and scalability in cybersecurity applications.
Beyond cybersecurity, quantum machine learning has demonstrated promise across diverse domains. Tiwari et al. (27) investigated Quantum Fuzzy Neural Networks (QFNNs) for advanced text analysis tasks such as sarcasm detection, while Wei et al. (2023) applied quantum techniques to medical image analysis. Additional contributions by Houssein et al. (8) on quantum-inspired binary classifiers and Villalba-Diez et al. (2022) on quantum deep learning further illustrate the integration and refinement of quantum concepts within established ML frameworks. Martín-Guerrero and Lamata (11) provided a comprehensive tutorial, offering valuable theoretical grounding and methodological guidance for the field.
Progress toward practical implementation is evident in studies such as Yulianti et al. (2023), who enhanced ensemble classifiers using hybrid quantum annealing, and Li et al. (2023), who proposed a quantum-based approach to k-fold cross-validation to simplify classification workflows. These contributions highlight the potential of quantum computing to augment and optimize traditional machine learning techniques.
Addressing hardware-related constraints, Acampora et al. (1) introduced a novel training strategy for variational quantum classifiers designed for Noisy Intermediate-Scale Quantum (NISQ) devices. Complementing this work, Kim et al. (10) examined quantum convolutional neural networks (QCNNs), demonstrating effective integration of quantum and classical computing paradigms. Further extending hybrid approaches, Vadyala and Betgeri (3) proposed Quantum Physics-Informed Neural Networks (PINNs), which incorporate quantum mechanical principles to enhance neural network reliability and computational power when solving complex problems.
Theoretical advancements also continue to play a critical role in shaping the field. Perkowski (21) advanced quantum-enhanced machine learning through contributions in inverse problems, constraint satisfaction, reversible logic, and Grover-based quantum oracles, strengthening the theoretical foundations necessary for scalable quantum ML algorithms. Additionally, Dong et al. (4) identified negational symmetry in quantum neural networks during binary pattern classification, revealing algorithmic behaviours absent in classical neural networks and highlighting the influence of quantum properties on learning dynamics.
Collectively, these studies demonstrate the substantial potential of quantum computing to enhance traditional machine learning algorithms. They point toward a future in which quantum principles fundamentally reshape ML methodologies, enabling more efficient computation, improved handling of complex data, and innovative algorithmic designs beyond the capabilities of classical approaches.
Quantum computing applications in machine learning exhibit a wide spectrum of approaches, ranging from purely quantum algorithms to hybrid quantum–classical models. This methodological diversity, observed across domains such as image processing and natural language processing, reflects the rapidly evolving landscape of quantum machine learning. Hybrid quantum–classical architectures, as explored by Villalba-Diez et al. (29) and Sharma et al. (23), integrate the strengths of classical learning frameworks with quantum computational capabilities. Their results demonstrate improved performance in image analysis and classification tasks, often surpassing purely classical methods, particularly in applications demanding high accuracy and computational efficiency, such as medical image analysis.
Complementing these hybrid approaches, studies focused on fully quantum algorithms (7,12 &32) advance the development of Quantum Neural Networks (QNNs) and Quantum Support Vector Machines (QSVMs). These methods exploit fundamental quantum properties, such as superposition and entanglement, to enable efficient processing of complex, high-dimensional data. Such capabilities are especially relevant in application areas like natural language processing and reinforcement learning, where quantum algorithms show promise in managing large datasets and complex decision-making processes more effectively than classical counterparts.
Further empirical evidence is provided by Rana et al. (22) and Sharma et al. (24), who demonstrated the advantages of quantum algorithms in tasks including handwriting recognition and text classification. Their findings reinforce the applicability of quantum approaches across diverse machine learning problems. In the cybersecurity domain, quantum-enhanced models

exhibit distinct advantages in efficiency, accuracy, and scalability. For example, Suryotrisongko and Musashi (2022) showed that quantum-based methods can process complex security-related datasets more effectively, offering robust solutions for threat detection and mitigation.

Comparative Analyzes

Study	Quantum Technique / Model	Application Domain	Key Contribution	Comparison with Classical Methods
Raza et al. (2022)	Quantum Support Vector Machine (QSVM)	Handwriting recognition	Demonstrated improved classification accuracy and processing speed using QSVMs	Outperformed classical SVMs in multiple recognition tasks
Sharma et al. (2023)	Quantum kernel methods	Text classification	Shown that quantum kernel-based feature space enhances text pattern separation	Achieved better performance than classical kernels
Kumar et al. (2023)	Hybrid classical–quantum Spiking Neural Network (QSNN) with Variational Quantum Circuits (VQC)	Noise robust audio analysis	Improved robustness and stability of audio signal classification in noisy environments	Outperformed classical deep neural networks in noisy audio tasks
Servetomazade and Mrozski (2021/2022)	Hybrid quantum–classical model	Cybersecurity	Demonstrated enhanced threat detection capability	Marginal accuracy improvement over classical models, better performance on large-scale problems
Villalba-Diez et al. (2021)	Quantum Deep Learning (QDL)	Industrial quality control	Achieved faster pattern learning for defect prevention	Showed promising gains compared to classical CNN-based approaches
Jimenez et al. (2022)	Quantum and hybrid ML models	Mobile communications	Provided a conceptual framework for quantum-aided resource allocation and channel prediction	Indicated potential performance gains over traditional optimization techniques
Singh et al. (2022)	Quantum-enhanced image processing algorithms	Image processing	Enhanced edge detection and denoising quality	Outperformed several classical image processing formulations
Wei et al. (2023)	Quantum algorithms for ML	Medical image analysis	Improved diagnosis/classification of high-dimensional medical data	Demonstrated better scalability and efficiency than classical methods

Table I-Comparative Summary of Quantum-Enhanced Machine Learning Studies

Study Quantum Technique / Model Application Domain Key Contribution Comparison with Classical Methods. Rana et al. (2022) Quantum Support Vector Machine (QSVM) Handwriting recognition Demonstrated improved classification accuracy and processing speed

using QSVMs Outperformed classical SVMs in specific recognition tasks
Sharma et al. (2023) Quantum kernel methods Text classification Showed that quantum entanglement enhances kernel expressiveness Achieved better performance than classical kernels.Konar et al. (2023) Hybrid classical quantum Spiking Neural Network (SQNN) with Variational Quantum Circuits (VQC) Noise-robust image classification Improved robustness and accuracy
on noisy datasets through hybrid architecture Outperformed classical spiking neural networks in noisy conditions. Suryotrisongko and Musashi (2022) Hybrid quantum–classical deep learning model Cybersecurity (botnet detection) Demonstrated enhanced threat detection capability Marginal accuracy improvement over classical models; sensitivity to circuit design noted. Villalba-Diez et al. (29) Quantum Deep Learning (QDL) Industrial quality control Achieved faster image processing for defect detection Faster processing than classical CNN based approaches. Houssein et al. (8)Quantum and hybrid ML models (survey) Multiple domains Provided a comprehensive overview of quantum and hybrid ML techniques Identified advantages and limitations relative to classical ML.Singh et al. (25).Quantum-enhanced image processing methods Image processing Offered theoretical insights into quantum advantages in image analysis Highlighted potential improvements over classical formulations.(30).Quantum algorithms for MLMedical image analysis Demonstrated efficient handling of high-dimensional medical data, Showed advantages over classical methods in scalability and efficiency.

V. CASE STUDIES AND APPLICATIONS

The integration of quantum computing with machine learning is driving innovation in a variety fields. In cybersecurity, the work of Suryotrisongko and Musashi (2022) stands out. They have applied hybrid quantum-classical models to improve botnet DGA detection. This case study is a prime example of how quantum computing can address complex cybersecurity challenges, improving detection accuracy and response times.

Continuing their pioneering efforts, Giuntini et al. (2023a) have introduced quantum- inspired classifiers and hybrid quantum-classical frameworks, respectively, to advance machine learning classification and generative models. Their work illustrates the synergy between quantum and classical computing paradigms in reshaping the practical landscape of quantum computing. Further illustrating this trend, (6) have applied Quantum Deep Learning (QDL) to industrial quality control, particularly to precision-critical sectors such as the steel industry. Their work demonstrates the practical utility of quantum algorithms in real-world applications. Complementing this, (20) have shown how Quantum Machine Learning (QML) can tackle complex natural language processing tasks, such as parts-of-speech tagging in code-mixed datasets, highlighting the versatility of quantum methods for linguistic challenges. In addition, Ovalle-Magallanes et al. (18) have innovated in quantum convolutional neural networks (QCNNs) by implementing quantum angular encoding with learnable rotation, improving computational performance in image processing tasks and overcoming qubit and circuit depth limitations.

The contributions of Rana et al. (22) and Wei et al. (30) also stand out. Rana et al. focus on Quantum Support Vector Machines (QSVM) for image recognition, promoting the superiority of quantum computing in pattern recognition over classical methods. Wei et al. extend this to medical data analysis with Quantum Neural Networks (QNNs), demonstrating their ability to handle high-dimensional medical data.

Exploring quantum-classical hybrid models, Ovalle-Magallanes et al. (18) introduce an innovative approach to QCNNs that improves their efficiency. Their research, tested on datasets such as MNIST and Fashion- MNIST, shows improved performance and adaptability of these models in image processing, broadening the application scope of quantum computing in machine learning.

Taken together, these case studies not only showcase the practical and theoretical applications of quantum computing in machine learning but also highlight the evolving and diverse nature of the field. They illustrate how quantum computing is able to enhance traditional methods and open up new possibilities in data processing and analysis, thereby underlining its potential to deliver significant advances across a range of industries.

VI. FUTURE TRENDS AND RESEARCH DIRECTIONS

Implications for RQ1: Quantum Enhancement of Machine Learning Algorithms

The reviewed studies demonstrate that quantum computing principles such as superposition, entanglement, and quantum kernel methods can enhance machine learning algorithms by improving computational efficiency and representational capacity. Hybrid quantum classical models and variational quantum circuits emerge as practical approaches for near-term implementation, particularly under NISQ constraints. Continued optimization of these models is essential to fully leverage quantum advantages in real-world scenarios.

Implications for RQ2: Application Domains and Practical Impact

Case studies in cybersecurity, industrial quality control, medical image analysis, and natural language processing indicate that quantum machine learning can outperform classical methods in domain-specific tasks requiring high efficiency and accuracy. Quantum-enhanced cybersecurity solutions, in particular, show strong potential for improved threat detection and data protection. Expanding application-driven research will be crucial for validating the transformative impact of QML across industries.

Implications for RQ3: Quantum vs. Classical Performance Comparison

Comparative analyses reveal that quantum and hybrid models can surpass classical algorithms in certain tasks, especially those involving high-dimensional or complex data. However, performance gains are often task-dependent and influenced by hardware limitations. Establishing standardized benchmarking protocols and evaluation metrics is necessary to rigorously assess the advantages and limitations of quantum machine learning relative to classical approaches.

Future Research Directions in Quantum Machine Learning

Algorithmic Optimization (RQ1):

Further research is required to optimize quantum and hybrid quantum classical algorithms, particularly to improve stability, scalability, and robustness on Noisy Intermediate-Scale Quantum (NISQ) hardware.

Hybrid Quantum Classical Architectures (RQ1):

Developing efficient hybrid models that balance classical learning frameworks with quantum computational advantages remains a key research priority, especially for high-dimensional and data-intensive tasks.

Cybersecurity Applications (RQ2):

Expanding quantum-enhanced cybersecurity solutions, including intrusion detection, malware analysis, and cryptographic protocols, is critical to address increasingly sophisticated cyber threats.

Domain-Specific Applications (RQ2):

Future studies should explore industry-specific implementations of QML in healthcare, manufacturing, natural language processing, and image analysis to validate practical benefits.

Quantum vs. Classical Benchmarking (RQ3):

Systematic benchmarking frameworks are needed to quantitatively compare quantum and classical machine learning algorithms across performance, efficiency, and scalability metrics.

Hardware and Scalability Challenges (RQ3):

Advancements in quantum hardware, error mitigation techniques, and qubit-efficient circuit design are essential to support large-scale deployment of QML models.

Accessibility and Tooling (RQ1 RQ3):

The development of user-friendly platforms and low-code frameworks can accelerate adoption and foster collaboration between quantum computing researchers and machine learning practitioners.

VII. LIMITATIONS AND CHALLENGES

Despite significant progress, the application of quantum computing in machine learning particularly in cybersecurity continues to face several critical challenges. As highlighted by Suryotrisongko and Musashi (26), data privacy concerns and the inherent complexity of quantum algorithms pose major obstacles to secure and reliable deployment. These challenges are further compounded by the limitations of current quantum hardware, including restricted qubit counts, noise susceptibility, and scalability constraints. Studies by Tiwari et al. (27) and Zeng et al. (32) also emphasize the difficulty of integrating complex quantum algorithms into practical machine learning pipelines. Addressing these limitations is essential for enabling the effective and widespread adoption of quantum machine learning techniques across cybersecurity and other application domains.

VIII. DISCUSSION

This review of Quantum Machine Learning (QML) highlights a rapidly evolving field in which advances in quantum computing are increasingly leveraged to enhance machine learning capabilities. As summarized in Table II, algorithmic innovations such as Quantum Kernel Logistic Regression (QKLR) proposed by Ning et al. (17) aim to overcome the limitations of classical logistic regression when handling complex and high-dimensional data, offering improved pattern recognition and classification performance. Similarly, Quantum Support Vector Machines (QSVMs) demonstrate potential efficiency gains in processing complex datasets, as reported by Rana et al. (22) and Zhang et al. (2023), although further empirical validation and scalability studies remain necessary.

Hybrid quantum–classical learning models also represent a promising direction. As illustrated by Suryotrisongko and Musashi (22), hybrid deep learning architectures can achieve accuracy comparable to, or exceeding, that of purely classical models in cybersecurity applications such as botnet detection. However, these models often exhibit sensitivity to initialization parameters and circuit design, underscoring the need for further optimisation and robustness analysis.

The practical relevance of these algorithmic advances is demonstrated in Table III, which presents real-world application case studies. Notably, the hybrid quantum–classical model developed by Suryotrisongko and Musashi (26) achieved substantial improvements in botnet detection accuracy. Beyond cybersecurity, quantum-based techniques applied by Wei et al. (30) show strong performance in medical image analysis, particularly for high-dimensional data, while Villalba-Diez et al. (29) demonstrated the effectiveness of Quantum Deep Learning (QDL) for enhanced image processing in industrial quality control. These examples illustrate the broad and transformative potential of QML across multiple sectors.

Nevertheless, significant barriers remain, as summarized in Table IV. Current quantum hardware is constrained by limited qubit availability, high error rates, and restricted circuit depth, which collectively limit the complexity and scalability of quantum machine learning applications. Furthermore, as quantum computing capabilities continue to advance, the protection of sensitive data becomes increasingly critical. Ensuring data privacy and security in a quantum-enabled environment necessitates the development of quantum-resistant encryption methods and secure learning frameworks. Addressing these technical and security challenges will be crucial for translating the theoretical promise of QML into robust, large-scale, real-world solutions.

Despite significant progress, the application of quantum computing in machine learning, and cybersecurity in particular, faces notable challenges. As highlighted by Suryotrisongko and Musashi (2022), data privacy concerns and the complexity of quantum algorithms are significant hurdles in security applications. These issues are compounded by the limitations of current quantum hardware and scalability challenges. Studies such as those by Tiwari et al. (27) and Zeng et al. (32) also highlight the difficulties of integrating complex quantum algorithms. Overcoming these challenges will be critical to the practical application and effectiveness of quantum ML techniques in cybersecurity and other domains.

8.1 Limitations and Open Issues

Despite notable progress in Quantum Machine Learning (QML), several limitations continue to hinder its widespread adoption and practical deployment, particularly in security-critical domains such as cybersecurity. One of the primary challenges lies in the inherent complexity of quantum algorithms, which complicates their integration into existing machine learning pipelines and increases the difficulty of model design, training, and interpretation. As noted by Suryotrisongko and Musashi (22), these complexities are further exacerbated by data privacy concerns when quantum-enhanced models are applied to sensitive cybersecurity datasets.

Hardware constraints represent another significant limitation. Current Noisy Intermediate-Scale Quantum (NISQ) devices are characterized by limited qubit counts, short coherence times, and high error rates, which restrict the depth and scalability of quantum circuits. These limitations directly affect the performance and reliability of QML algorithms, as highlighted in studies by Tiwari et al. (27) and Zeng et al. (32). As a result, many proposed quantum learning models remain confined to small-scale or simulated environments.

Scalability and robustness also remain open issues. Hybrid quantum classical models, while promising, often exhibit sensitivity to parameter initialization, circuit architecture, and noise, leading to inconsistent performance across datasets and applications. Ensuring stable convergence and reproducibility under realistic operating conditions remains an unresolved challenge.

From a security perspective, the advancement of quantum computing introduces new risks related to data protection and cryptographic resilience. As quantum hardware matures, existing encryption and privacy-preserving mechanisms may become vulnerable, necessitating the development of quantum-resistant encryption techniques and secure quantum-aware learning frameworks. Addressing these limitations is essential to bridge the gap between theoretical advancements and real-world applications of quantum machine learning.

Advancement	Authors	Impact	Challenges
Quantum-based Logistic Regression (QXLR)	Yang et al. (17)	Enhances pattern recognition and data classification	Limited to linear problems; logistic regression limitations in high-dim data
Quantum Support Vector Machines (QSVMs)	Raza et al. (2), Zhang et al. (32)	Improves efficiency in processing complex data	Requires further exploration for broader applications
Hybrid Quantum–Classical Deep Learning	Suryotongko & Musaibi (26)	Increases accuracy in cybersecurity applications	Selective use requires careful security optimization

Application Domain	Study	Model / Technique	Key Findings
Cybersecurity	Suryotongko & Musaibi (26)	Hybrid Quantum–Classical approach	Achieved up to 91.7% accuracy in threat detection
Medical Image Analysis	Wei et al. (30)	Quantum Techniques	Demonstrated effectiveness in advanced image analysis
Industrial Quality Control	Villalba-Diez et al. (29)	Quantum Deep Learning (QDL)	Enhanced inline inspection capabilities for production tasks

Challenge	Description	Implications for QML
Limited Hardware Capabilities	Current quantum hardware offers a constrained number of qubits and stability	Constrains the complexity and scalability of QML applications
Data Privacy Concerns	Quantum computing could disrupt existing encryption models, risking sensitive data	Necessitates the development of quantum-resilient security frameworks

Advancement Authors Impact Challenges

Quantum Kernel Logistic Regression (QKLR) Ning et al. (17) Enhances pattern recognition and data classification Limited to linear problems; logistic regression limitations addressed by QKLR. Quantum Support Vector Machines (QSVMs) Rana et al. (21), Zhang et al. (32) Improves efficiency in processing complex data Requires further exploration for broader applications. Hybrid Quantum Classical Deep Learning Models Suryotrisongko & Musashi (22) Comparable or superior accuracy in cybersecurity applications Sensitive to initial conditions; requires optimization

Application Domain Study Model / Technique Key Findings.

Cybersecurity Suryotrisongko & Musashi (26) Hybrid Quantum Classical Model Achieved up to 94.7%

accuracy in botnet detection, Medical Image Analysis Wei et al. (30) Quantum Techniques Demonstrated effectiveness in advanced image analysis. Industrial Quality Control Villalba-Diez et al. (29) Quantum Deep Learning (QDL) Enhanced image processing capabilities for precision tasks

Challenge Description Implications for QML

Limited Hardware Capabilities Current quantum hardware offers a limited number of qubits and is prone to errors Constrains complexity and scalability of QML applications

Data Privacy Concerns Quantum computing could disrupt existing encryption practices, raising security concerns Necessitates the development of quantum-resistant encryption and secure frameworks.

IX. CONCLUSION

This review investigated the current state of Quantum Machine Learning (QML), with emphasis on recent algorithmic developments such as Quantum Kernel Logistic Regression and Quantum Support Vector Machines, as well as their potential applications in areas including cybersecurity, medical image analysis, and industrial quality control. The identified algorithmic advances, addressing Research Question 1 (RQ1), indicate strong potential for enhanced pattern recognition and efficient processing of complex and high-dimensional data. The application domains discussed in relation to Research Question 2 (RQ2) further demonstrate the transformative capabilities of QML across scientific and industrial sectors. However, the challenges associated with Research Question 3 (RQ3) particularly hardware limitations and data privacy concerns remain significant obstacles to large-scale deployment. While this review provides a quantitative overview of the field, it highlights the need for more practice-oriented and experimentally validated studies to bridge the gap between theoretical developments and real-world implementations. Addressing these challenges is essential for enabling QML to achieve practical maturity and to contribute meaningfully to the future evolution of machine learning.

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