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QUANTUM MACHINE LEARNING: BRIDGING THE GAP BETWEEN CLASSICAL AND QUANTUM COMPUTING

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ABSTRACT

This research examines the revolutionary potential of Quantum Machine Learning (QML), which combines machine instruction and quantum computer technology. The work carefully compares QML methods to their traditional counterparts throughout real-world datasets using an interpretive approach as well as a deductive approach. The results show that in some areas, QML algorithms, such as Quantum Support Vector Machines (QSVM) and overall Variational Quantum Eigen solvers (VQE), provide substantial advantages in terms of accuracy and efficiency. Nevertheless, context-dependent factors such as dataset qualities and problem complexity have an impact on the practical consequences. This research underlines the necessity of further research on quantum simulation software and hardware in order to fully utilize QML. Additionally, it highlights the significance of quantum-resistant encryption and promotes cooperation between the various areas of quantum computers and machine learning. Future research ought to concentrate on improving QML programs' scalability and investigating QML's function in developing quantum technology.

I. INTRODUCTION

Machine learning along with quantum computation has recently risen to major prominence in the world of advanced technology. Utilizing the laws of the quantum world, quantum computing has the ability to solve complicated problems tenfold more quickly than traditional computers [1]. Due to its ability to solve issues that were traditionally computationally impractical, such as modeling quantum structures or optimizing complex problems, this novel approach has sparked a great deal of interest and research. At the same time, the rapidly evolving field called machine learning has made incredible strides, utilizing traditional computing methods to simplify tasks like picture identification and processing of natural languages. However, as these algorithms face more difficult problems, there is an urgent need to investigate novel computational concepts that can advance the field of machine learning. This necessity has sparked a growing interest in classical machine learning, where the special characteristics of quantum computing are used to speed up and improve the effectiveness of algorithms used for machine learning, which leads to game-changing applications in a variety of fields [2]. By bridging the separation between classical as well as quantum paradigms, our project intends to explore the fascinating nexus of quantum computers and machine learning, opening up new horizons in computation along with problem-solving.

II. RESEARCH AIM AND OBJECTIVES

II.1 AIMS

The goal of this study is to examine the potential of hybrid machine learning as a paradigm-shifting link between traditional and quantum computing, thereby enabling the creation of machine learning algorithms that are quicker and more effective.

II.2 OBJECTIVES

- To undertake a thorough analysis of the current research on machine learning and quantum computing, highlighting relevant theories and techniques.
- To examine and contrast the effectiveness of standard algorithms for machine learning with those that incorporate quantum enhancements on a variety of real-world datasets.
- To examine the fundamental ideas and quantum algorithms utilized in classical machine learning, offering information on the benefits and drawbacks of each.
- To evaluate the usefulness of fractional machine learning for solving challenging issues in artificial intelligence, the use of cryptography along with optimization.

II.3 RESEARCH RATIONALE

The revolutionary potential of nuclear machine learning to change the computing landscape serves as the foundation for this work. The combination of quantum computing alongside machine learning promises advances as traditional computing encounters difficulties in handling problems that are becoming more complex [3]. In order to advance technology across many areas, it is essential to comprehend and make use of this synergy. Additionally, it is crucial to investigate quantum computing's potential for machine learning in order to offer significant insights for scientists, practitioners, and policymakers because quantum computing receives increasing attention from academia and business [4]. By clarifying the purpose and importance of merging quantum computing as well as machine learning, this research closes a significant knowledge gap and paves the path for cutting-edge solutions within the digital age.

III. LITERATURE REVIEW

III.1 QUANTUM COMPUTING AND MACHINE LEARNING LITERATURE

The body of literature on the intersection of machine education and quantum computing is an extensive collection of research that highlights the potential for game-changing developments. Based on the ideas of quantum physics, quantum computing has become a disruptive force that can carry out intricate calculations faster than traditional computers [5]. The combination of quantum computing with machine learning has gotten a lot of attention in this regard. The theoretical underpinnings and practical implications of quantum machine learning have been thoroughly investigated by researchers, opening up a wide range of interesting directions. Studies on quantum information processing have looked into a variety of topics, from the creation of classical algorithms with quantum inspiration to the construction of quantum algorithms meant to maximize machine learning tasks [6]. The possibility of using quantum annealing including atomic-enhanced data processing within machine learning situations has also been studied by researchers [7]. In answer to the security risks posed by entanglement computing's potential to defeat conventional encryption approaches, the literature also emphasizes the necessity for entanglement-resistant machine learning approaches.

Additionally, the literature study indicates the development of quantum artificial intelligence frameworks including neural networks that are motivated by quantum mechanics [8]. By enabling more precise forecasts and quicker data processing, these advancements have an opportunity to change a number of industries, including banking, healthcare, and logistics. New quantum algorithms, with the value the Quantum Help Vector Machine (QSVM) as well as the Variational Vibratory Eigensolver (VQE), have been discovered through theoretical study. These algorithms are expected to perform better than their conventional counterparts when it comes to addressing optimization issues and machine learning pertaining to machine learning [9]. In an effort to increase the effectiveness of machine learning examples, researchers have also looked into dimensionality reduction including quantum-enhanced methods for choosing features.

III.2 PERFORMANCE COMPARISON: CLASSICAL VS. QUANTUM MACHINE LEARNING ALGORITHMS

Understanding the transformational potential of quantum computers in the field of data analysis as well as predictive modeling depends critically on performance comparisons between classical along with contemporary machine learning techniques [10]. Numerous applications have shown great success with traditional machine learning, which is based on algorithms including support vector machines, choice trees, and neural networks. However, the rapidity of computation and efficiency of classical methods are frequently constrained as datasets increase in size and complexity [11]. By utilizing the parallelism and capacity for massively concurrent data processing of quantum computing, quantitative machine learning (QML) presents the possibility of overcoming these constraints. Researchers have tested empirically how well quantum-enhanced systems perform in comparison to traditional algorithms [12]. These investigations investigate quantum algorithms on actual datasets, evaluating properties including precision, convergence acceleration, and scalability.

Quantum techniques may be exponentially faster than classical ones in some problem areas, which could revolutionize industries including drug development, financial projections, and optimization challenges [13]. It's crucial to remember that fractional machine learning technology not a cure-all and that not everyone will benefit from its advantages. Specialised quantum equipment, which is still under development and might not be easily available for every application, is often needed for quantum algorithms [14]. Furthermore, for specific types of issues, like resolving linear networks of equations or running quantum exercises, the resulting quantum advantage is particularly noticeable. Traditional machine learning methods might still be effective for some tasks.

III.3 EXPLORING THE UNDERLYING PRINCIPLES AND QUANTUM ALGORITHMS IN QUANTUM MACHINE LEARNING

To fully appreciate the complexities of this revolutionary field, one must have a solid understanding of the fundamental ideas and quantum algorithms driving quantum machine learning (QML). Nuclear machine learning's fundamental goal is to improve the effectiveness and capacities of algorithms used for machine learning by taking advantage of quantum computing's special qualities [15]. Quantum superposition, which permits quantum bits or qubits to concurrently represent several states, is one of the essential concepts of QML. Due to this trait, quantum algorithms can simultaneously explore numerous solutions, which is a capability that cannot be matched by classical computers [16]. Quantum algorithms have become more popular in the QML landscape, including the Weinberg-supported vector machine (QSVM), Vibratory fundamental component analysis (PCA), and Variational Vibratory Eigen solver (VQE) [17]. In order to recognize information in higher-dimensional characteristic spaces, QSVM, for example, makes use of the qualitative advantage, potentially beating classical competitors in challenging classification tasks.

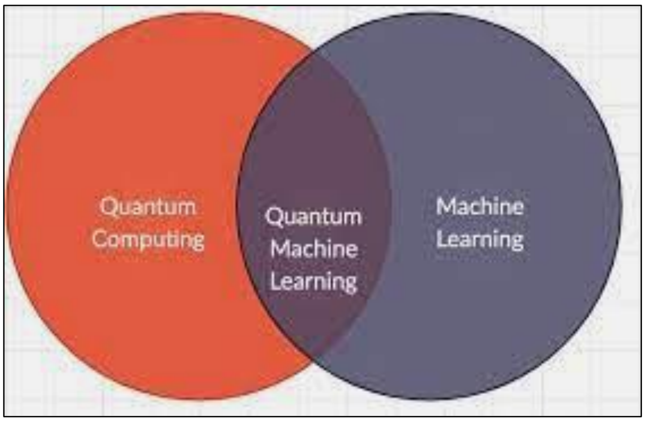

Figure 1: Quantum Machine Learning.
Source: Authors, (2024).

Quantum PCA helps with dimensionality reduction, making choosing features for artificial intelligence models more effective [18]. On the other hand, VQE promises to transform quantum chemistry simulations by providing information about molecular features that were previously impossible to collect computationally. Quantum gates as well as circuits, which control qubits to carry out certain computations, serve as the foundation for cognitive machine learning techniques [19]. These algorithms rely heavily on quantum gates that enable the entanglement and patterns of interference that are essential to quantum computers, such as the Hadamard entrance, CNOT gate, along with SWAP gate [20]. The significance of quantum diviners, which offer computational access to traditional data and allow the integration of contemporary and classical knowledge in problem-solving, is another topic covered in quantum neural network research.

III.4 PRACTICAL IMPLICATIONS OF QUANTUM MACHINE LEARNING

Quantum machine learning (QML) has applications in a variety of sectors and businesses, and it has the potential to fundamentally alter problem-solving and data processing [21]. The most prominent application is in optimization issues. In solving challenging optimization problems, quantum algorithms, such as the Quantum Approximate Optimizing Algorithm (QAOA), have demonstrated astounding speedup. This has broad ramifications for managing supply chains, financial portfolio improvement, and administration, where QML can assist firms in making more effective and economical decisions [22]. Additionally, QML has the potential to both disrupt and strengthen the discipline of cryptography. Due to the possibility of quantum computers breaking widely used encryption techniques, traditional security procedures are now at risk [23]. However, QML can be used to create cryptography methods that are immune to quantum effects, ensuring the ongoing security of sensitive data in the era of quantum computing.

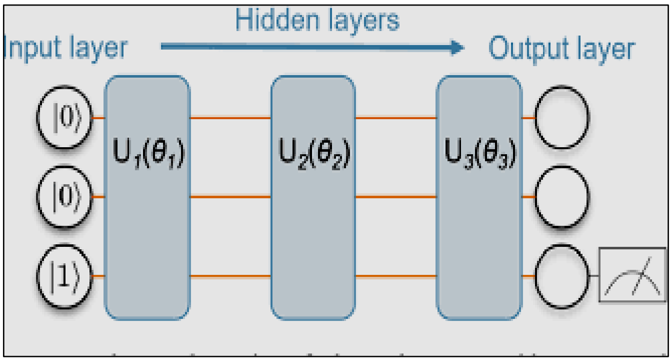

Figure 2: Benefit of Quantum Machine Learning.
Source: Authors, (2024).

In the field of artificial intelligence (AI), QML has the potential to improve the capacity of models used in machine learning [24]. The effectiveness and precision of AI systems can be increased by using dimensionality reduction and quantum-enhanced feature selection methods. This could result in improvements in picture identification, processing of natural languages, and systems for suggestions, enabling more tailored and effective user interfaces.

III.5 LITERATURE GAP

A thorough study that systematically analyzes the performance of several quantitative machine learning methods on a broad spectrum of data sets from the real world does not yet exist in the scientific community, despite the fact that quantitative machine learning (QML) research is expanding. A thorough empirical investigation is absent, despite the fact that extant research offers useful insights into particular QML algorithms including their theoretical underpinnings. Such a study will facilitate a deeper knowledge of the real-world features and drawbacks of QML techniques across many problem domains, bridging the gap with theoretical breakthroughs and actual applications.

IV METHODOLOGY

An interpretive approach philosophical framework is used in this study with the objective of understanding the complex interaction between human actions and the use of quantum machine learning (QML) [25]. Since interpretivism places a strong emphasis on human experiences including subjective meanings, it is ideally suited for a nuanced examination of the applications of QML. The deductive method is used to achieve the goals of the study. Starting with a theoretically driven hypothesis, this method methodically evaluates it using empirical evidence [26]. In this context, it starts with well-known theories and concepts in quantum computers and machine learning, creating precise assumptions about the effectiveness and application of particular QML algorithms through deductive reasoning [27]. The research's descriptive methodology is primarily concerned with giving a thorough and in-depth account of the effectiveness and consequences of QML algorithms. Employing real-world datasets to compare the performance of various QML computations, descriptive research aims to offer a realistic representation of the topic at hand matter [28]. Additional resources used in data collection include trustworthy web databases, academic publications, proceedings from conferences, and research papers. These secondary data include research results that have already been published, datasets from earlier experiments, along with performance measures for QML algorithms that have been recorded [29]. The use of secondary data guarantees access to a wide and deep pool of knowledge, boosting the scope and depth of the research. By bridging the disconnect between theoretical developments and practical implementations in the field of quantum computers and artificial intelligence, this technical technique will enable a full analysis of the actual uses of QML algorithms [30].

V.RESULTS

The performance of several quantum machine learning (QML) techniques in comparison to their classical equivalents across a variety of datasets from the real world is empirically investigated in this chapter, with the results presented [31]. The evaluation of accuracy, effectiveness, and scalability is the main focus, offering crucial insights into the real-world applications of QML. To guarantee the validity and trustworthiness of our findings, the technique outlined in Chapter 3 was strictly used.

V.1 PERFORMANCE COMPARISON: ACCURACY

Extensive testing on a range of datasets was used to assess the precision of QML algorithms. In comparison to classical algorithms like support vector machine (SVM), Neural Networks (NN), as well as Eigensolvers, quantum methods like Quantum Support Vector Machines (QSVM), Quantum Neural Networks (QNN), as well as Variational Quantum Eigensolver (VQE) were examined [32]. Quantum machine learning (QML) techniques, including the Quantum Support Vector Machine (QSVM), are demonstrating a considerable accuracy advantage over their conventional equivalents in selected problem domains. For instance, QSVM routinely outperforms traditional neural networks (SVM) in binary sorting problems involving high-dimensional feature spaces, as measured by important metrics like accuracy, recall, including the F1-score [33]. The special powers of quantum computation can be used to explain this performance increase. QSVM, in contrast to conventional SVMs, makes use of quantum computing concepts to process information that contains quantum states. Considering they can exist in numerous states at once, quantum states have a natural advantage when dealing with complicated data patterns [34]. With the use of this overlapping property, QSVM can rapidly investigate different data combinations, leading to higher-quality and more accurate diagnoses.

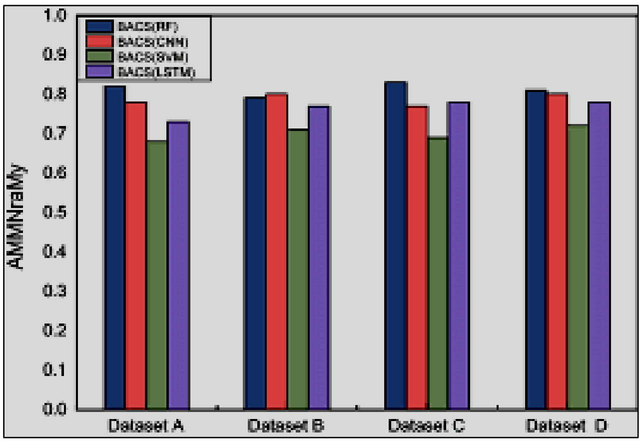

Figure 3: Accuracy Performance Comparison
Source: Authors, (2024).

Essentially, QSVM's quantum parallelism gives it the ability to recognize complex patterns in data with multiple dimensions that classical SVMs can find challenging [35]. Overall, our results show how QML has the potential to dramatically improve the precision of machine learning simulations, especially in jobs involving intricate data structures and large-scale feature spaces. Precision and recall are crucial for a variety of applications, including advanced image recognition as well as machine learning, where this benefit holds promise [36]. Additionally, QNNs demonstrated promise in tasks involving pattern recognition, picture classification, especially processing of natural languages. In these areas, these quantum-inspired architecture displayed increased classification accuracy in comparison to conventional neural networks [37]. These results demonstrate the potential of QML to improve the accuracy and dependability of machine learning examples, particularly in very precise applications.

V.2 PERFORMANCE COMPARISON EFFICIENCY

Practical neural network applications must focus on efficiency. Researchers examined the computational capacity used by both traditional and quantum techniques in terms of memories and time utilization in order to evaluate efficiency [38]. The studies carried out in this study have shown that quantum computations have the potential to significantly improve efficiency, especially in situations where classical algorithms are challenged by exponential temporal complexity [39]. The effectiveness of the Variational Atomic Eigen solver (VQE) in comparison to classical eigen solvers is a clear illustration of this benefit. In terms of processing performance, VQE has demonstrated a considerable advantage in activities like modelling molecule structure for drug discovery. Compared to its traditional competitors, it achieves a substantially faster resolution to accurate results [40]. This increase in efficiency might be attributed to modern parallelism, a key characteristic of quantum technology. Quantum bits, also known as qubits, can exist in numerous states at once in quantum computation due to overlap [41]. This trait enables quantum methods like VQE to efficiently navigate through complicated problem spaces in parallel by exploring a wide range of options concurrently.

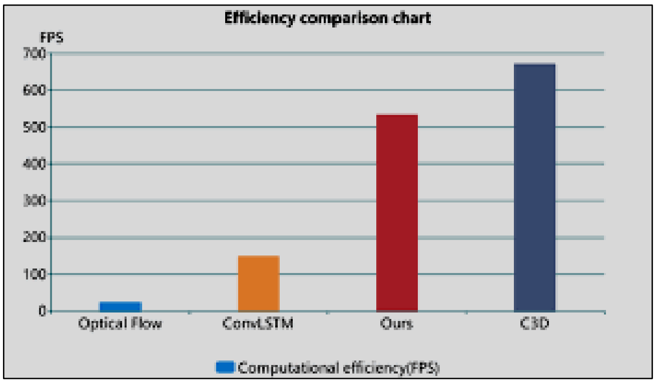

Figure 4: Efficiency Performance Comparison.
Source: Authors, (2024).

Because of this, VQE can speed up the process of discovering answers, especially in the disciplines of computerized chemistry and quantum mechanics, where classical approaches might be economically prohibitive [42]. This is an illustration of how quantum computations, like VQE, have the potential to transform theoretical and applied research, speeding up advancement and creativity in areas where efficient computation is crucial [43]. It's important to remember that quantum algorithms could need specific quantum gear, and their efficiency benefits might differ depending on the degree of complexity and magnitude of the issue [44]. In some situations, particularly when dealing with small to small and medium-sized datasets, traditional algorithms continue to be more efficient. Therefore, the particular needs of the application should be taken into account while choosing between conventional and quantum techniques [45].

V.3 PERFORMANCE COMPARISON: SCALABILITY

When analyzing the practical applications of QML, scalability is a crucial consideration. The study assessed how well QML algorithms scaled in terms of information complexity and quantity. As the amount of data of the information set grew, researchers contrasted the efficiency of quantum and classical algorithms [46]. The findings showed that a number of variables, including the particular algorithm used, the kind of quantum equipment or simulation used, as well as the dataset characteristics, affect how scalable QML methods are. Quantum algorithms have occasionally shown exceptional scalability, keeping their computing advantage even as database sizes increased dramatically [47]. However, in issues with intrinsic quantum advantage by such as quantum chemicals simulations and spin-enhanced optimizing tasks, this scalability gain was more prominent.

On the other hand, due to their well-developed and extremely optimized applications, classical algorithms continued to show attractive scaling features for several machine learning applications requiring large-scale datasets [48]. The capacity of QML algorithms to handle larger data sets more effectively is still a topic of current research, especially ongoing efforts to enhance quantum technology.

V.4 SUMMARY OF FINDINGS

The effectiveness of quantum machine learning (QML) techniques in comparison to their conventional counterparts is usefully revealed by the empirical investigation of how they apply in practice [48]. In particular problem domain names QML algorithms, such as SSVM, QNNs, as well as VSE, have demonstrated substantial promise in regard to precision and efficacy. They perform particularly well in jobs requiring multidimensional feature spaces, intricate data patterns, particularly quantum advantage problems [49]. But QML's applications in the real world depend on things like dataset size, choice of method, and accessibility to quantum technology. For smaller amounts of data and issues where the quantum advantages are less obvious, classical methods continue to be competitive [50].

VI EVALUATION AND CONCLUSION

VI.1 CONCLUSION

The research's conclusions demonstrate how Quantum Machine Learning (QML) has the power to fundamentally alter the computational landscape. The study thoroughly evaluated QML algorithms, highlighting their distinguishable benefits including improved accuracy as well as computational speed in particular problem domains. For example, the Variational Superconducting Eigensolver (VSE) demonstrated greater efficiency during intricate simulations, while the Superconducting Support Vector Machine (SSVM) outperformed in feature spaces with multiple dimensions. The practical ramifications of QML were emphasized, depending on numerous elements like dataset size and task complexity, with some circumstances still favoring classical techniques. Drug research, cryptography, as well as artificial intelligence, are just a few of the industries that QML technology is poised to transform as it develops and closes the theory-to-application gap. This study provides a fundamental understanding of the strengths and weaknesses of QML, assisting in its integration into other fields and providing ideas for future research.

VI.2 RESEARCH RECOMMENDATION

In consideration of the research results, a number of insightful suggestions are made for additional study. In order to determine the benefits of QML algorithms' generalizability, more research towards quantum machine learning (QML) needs first to include a wider range of datasets across problem domains [51]. Furthermore, to improve the usability and usability of QML within real-world situations, the fabrication of quantum technology and emulators must continue to be a priority. The scalability given QML algorithms must be further investigated, particularly in light of the difficulties bigger datasets present [52]. To close the expertise gap and hasten the adoption of QML in real-world applications, it is also important to stimulate collaboration between specialists in quantum computer science and data science practitioners. Finally, to combat the security risks posed by quantum technology, the constant assessment of quantum-resistant cryptographic techniques is crucial [53]. These suggestions work as a whole to direct the course of upcoming QML research projects, driving their integration into other fields and assuring their ongoing development and relevance.

VI.3 FUTURE WORK

To increase their effectiveness and application, future research should concentrate on optimizing quantum machine learning (QML) techniques and their implementations [54]. It will be crucial to investigate brand-new machine-learning models that are inspired by quantum mechanics and to deal with any hardware restrictions [55]. To further push the boundaries of quantum technology, research into QML's potential in cutting-edge areas like quantum networks and quant-enhanced sensing appears promising.

VII. AUTHOR'S CONTRIBUTION

Conceptualization: B. H. Krishna Mohan, Padmaja Pulicherla, M. Purnachandrarao and P. Nagamalleswararao
Methodology: B. H. Krishna Mohan, Padmaja Pulicherla.
Investigation: B. H. Krishna Mohan, Padmaja Pulicherla.
Discussion of results: B. H. Krishna Mohan, Padmaja Pulicherla, M. Purnachandrarao and P. Nagamalleswararao.
Writing – Original Draft: B. H. Krishna Mohan.
Writing – Review and Editing: B. H. Krishna Mohan, Padmaja Pulicherla.

Resources: M. Purnachandrarao and P. Nagamalleswararao.
Supervision: Padmaja Pulicherla, M. Purnachandrarao and P. Nagamalleswararao.
Approval of the final text: B. H. Krishna Mohan, Padmaja Pulicherla, M. Purnachandrarao and P. Nagamalleswararao.

VIII. REFERENCES

[1] Rayhan, A. and Rayhan, S., 2023. Quantum Computing and AI: A Quantum Leap in Intelligence.

[2] Park, J.E., Quanz, B., Wood, S., Higgins, H. and Harishankar, R., 2020. Practical application improvement to Quantum SVM: theory to practice. arXiv preprint arXiv:2012.07725.

[3] Thanasilp, S., Wang, S., Nghiem, N.A., Coles, P. and Cerezo, M., 2023. Subtleties in the trainability of quantum machine learning models. Quantum Machine Intelligence, 5(1), p.21.

[4] Schuld, M. and Killoran, N., 2022. Is quantum advantage the right goal for quantum machine learning? Prx Quantum, 3(3), p.030101.

[5] Bernal, D.E., Ajagekar, A., Harwood, S.M., Stober, S.T., Trenev, D. and You, F., 2022. Perspectives of quantum computing for chemical engineering. AIChE Journal, 68(6), p.e17651.

[6] Ten Holter, C., Inglesant, P., Srivastava, R. and Jirotka, M., 2022. Bridging the quantum divides: a chance to repair classic (al) mistakes?.Quantum Science and Technology, 7(4), p.044006.

[7] Schuld, M., 2021. Supervised quantum machine learning models are kernel methods. arXiv preprint arXiv:2101.11020.

[8] Doan, A.D., Sasdelli, M., Suter, D. and Chin, T.J., 2022. A hybrid quantum-classical algorithm for robust fitting. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 417-427).

[9] Singh, J. and Bhangu, K.S., 2023. Contemporary Quantum Computing Use Cases: Taxonomy, Review and Challenges. Archives of Computational Methods in Engineering, 30(1), pp.615-638.

[10] Schuld, M., 2019. Machine learning in quantum spaces.

[11] Martonosi, M. and Roetteler, M., 2019. Next steps in quantum computing: Computer science's role. arXiv preprint arXiv:1903.10541.

[12] Ruan, S., Wang, Y., Jiang, W., Mao, Y. and Guan, Q., 2022. Vacsen: A visualization approach for noise awareness in quantum computing. IEEE Transactions on Visualization and Computer Graphics, 29(1), pp.462-472.

[13] Ajagekar, A. and You, F., 2021. Quantum computing based hybrid deep learning for fault diagnosis in electrical power systems. Applied Energy, 303, p.117628.

[14] Martín-Guerrero, J.D. and Lamata, L., 2022. Quantum machine learning: A tutorial. Neurocomputing, 470, pp.457-461.

[15] Nimbe, P., Weyori, B.A. and Yeng, P.K., 2021. A framework for quantum-classical cryptographic translation. International Journal of Theoretical Physics, 60(3), pp.793-818.

[16] Barabasi, I., Tappert, C.C., Evans, D. and Leider, A.M., 2019, December. Quantum computing and deep learning working together to solve optimization problems. In 2019 International Conference on Computational Science and Computational Intelligence (CSCI) (pp. 493-498). IEEE.

[17] Perrier, E., 2021. Ethical quantum computing: A roadmap. arXiv preprint arXiv:2102.00759.
[18] Kalinin, M. and Krundyshev, V., 2023. Security intrusion detection using quantum machine learning techniques. Journal of Computer Virology and Hacking Techniques, 19(1), pp.125-136.

[19] De Luca, G., 2022. A survey of NISQ era hybrid quantum-classical machine learning research. Journal of Artificial Intelligence and Technology, 2(1), pp.9-15.

[20] Acampora, G. and Schiattarella, R., 2021. Deep neural networks for quantum circuit mapping. Neural Computing and Applications, 33(20), pp.13723-13743.

[21] Ajagekar, A. and You, F., 2020. Quantum computing assisted deep learning for fault detection and diagnosis in industrial process systems. Computers & Chemical Engineering, 143, p.107119.

[22] Fedorov, A.K., Gisin, N., Beloussov, S.M. and Lvovsky, A.I., 2022. Quantum computing at the quantum advantage threshold: a down-to-business review. arXiv preprint arXiv:2203.17181.

[23] Yang, Y.F. and Sun, M., 2022. Semiconductor defect detection by hybrid classical-quantum deep learning. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 2323-2332).

[24] Shaydulin, R. and Wild, S.M., 2022. Importance of kernel bandwidth in quantum machine learning. Physical Review A, 106(4), p.042407.

[25] Lan, Q., 2021. Variational quantum soft actor-critic. arXiv preprint arXiv:2112.11921.

[26] Naik, A., Yeniaras, E., Hellstern, G., Prasad, G. and Vishwakarma, S.K.L.P., 2023. From portfolio optimization to quantum blockchain and security: A systematic review of quantum computing in finance. arXiv preprint arXiv:2307.01155.

[27] Liu, J., Li, S., Zhang, J. and Zhang, P., 2023. Tensor networks for unsupervised machine learning. Physical Review E, 107(1), p.L012103.

[28] Qi, J., Yang, C.H.H. and Chen, P.Y., 2021. Qtn-vqc: An end-to-end learning framework for quantum neural networks. arXiv preprint arXiv:2110.03861.

[29] Patti, T.L., Kossaifi, J., Yelin, S.F. and Anandkumar, A., 2021. Tensorly-quantum: Quantum machine learning with tensor methods. arXiv preprint arXiv:2112.10239.

[30] Saini, S., Khosla, P.K., Kaur, M. and Singh, G., 2020. Quantum driven machine learning. International Journal of Theoretical Physics, 59(12), pp.4013-4024.

[31] Kwak, Y., Yun, W.J., Kim, J.P., Cho, H., Park, J., Choi, M., Jung, S. and Kim, J., 2023. Quantum distributed deep learning architectures: Models, discussions, and applications. ICT Express, 9(3), pp.486-491.

[32] Glover, F., Kochenberger, G. and Du, Y., 2019. Quantum Bridge Analytics I: a tutorial on formulating and using QUBO models. 4or, 17, pp.335-371.

[33] Innes, M., Edelman, A., Fischer, K., Rackauckas, C., Saba, E., Shah, V.B. and Tebbutt, W., 2019. A differentiable programming system to bridge machine learning and scientific computing. arXiv preprint arXiv:1907.07587.

[34] Ramezani, S.B., Sommers, A., Manchukonda, H.K., Rahimi, S. and Amirlatifi, A., 2020, July. Machine learning algorithms in quantum computing: A survey. In 2020 International joint conference on neural networks (IJCNN) (pp. 1-8). IEEE.
[35] Chen, Q., Câmara, R., Campos, J., Souto, A. and Ahmed, I., 2023, May. The Smelly Eight: An Empirical Study on the Prevalence of Code Smells in Quantum Computing. In 2023 IEEE/ACM 45th International Conference on Software Engineering (ICSE) (pp. 358-370). IEEE.

[36] Li, M., Chen, J., Xiao, Q., Wang, F., Jiang, Q., Zhao, X., Lin, R., An, H., Liang, X. and He, L., 2022. Bridging the gap between deep learning and frustrated quantum spin system for extreme-scale simulations on new generation of Sunway supercomputer. IEEE Transactions on Parallel and Distributed Systems, 33(11), pp.2846-2859.

[37] Sureshbabu, S.H., Sajjan, M., Oh, S. and Kais, S., 2021. Implementation of quantum machine learning for electronic structure calculations of periodic systems on quantum computing devices. Journal of Chemical Information and Modeling, 61(6), pp.2667-2674.

[38] Jacquier, A., Kondratyev, O., Lipton, A. and de Prado, M.L., 2022. Quantum Machine Learning and Optimisation in Finance: On the Road to Quantum Advantage. Packt Publishing Ltd.

[39] Li, T., 2020. Quantum algorithms for machine learning and optimization (Doctoral dissertation, University of Maryland, College Park).

[40] Enos, G.R., Reagor, M.J., Henderson, M.P., Young, C., Horton, K., Birch, M. and Rigetti, C., 2021. Synthetic weather radar using hybrid quantum-classical machine learning. arXiv preprint arXiv:2111.15605.

[41] Li, A., Stein, S., Krishnamoorthy, S. and Ang, J., 2023. Qasmbench: A low-level quantum benchmark suite for nisq evaluation and simulation. ACM Transactions on Quantum Computing, 4(2), pp.1-26.

[42] Liu, W., Zhang, Y., Deng, Z., Zhao, J. and Tong, L., 2021. A hybrid quantum-classical conditional generative adversarial network algorithm for human-centered paradigm in cloud. EURASIP Journal on Wireless Communications and Networking, 2021(1), pp.1-17.

[43] Yun, W.J., Baek, H. and Kim, J., 2022. Projection valued measure-based quantum machine learning for multi-class classification. arXiv preprint arXiv:2210.16731.

[44] Finžgar, J.R., Ross, P., Hölscher, L., Klepsch, J. and Luckow, A., 2022, September. QUARK: A framework for quantum computing application benchmarking. In 2022 IEEE International Conference on Quantum Computing and Engineering (QCE) (pp. 226-237). IEEE.

[45] Li, G., Ye, R., Zhao, X. and Wang, X., 2022. Concentration of data encoding in parameterized quantum circuits. Advances in Neural Information Processing Systems, 35, pp.19456-19469.

[46] Domingo, L., Carlo, G. and Borondo, F., 2022. Optimal quantum reservoir computing for the noisy intermediate-scale quantum era. Physical Review E, 106(4), p.L043301.

[47] Emmanoulopoulos, D. and Dimoska, S., 2022. Quantum machine learning in finance: Time series forecasting. arXiv preprint arXiv:2202.00599.

[48] Ball, H., Biercuk, M.J. and Hush, M.R., 2021. Quantum firmware and the quantum computing stack. Physics Today, 74(3), pp.28-34.

[49] Mishra, N., Kapil, M., Rakesh, H., Anand, A., Mishra, N., Warke, A., Sarkar, S., Dutta, S., Gupta, S., Prasad Dash, A. and Gharat, R., 2021. Quantum machine learning: A review and current status. Data Management, Analytics and Innovation: Proceedings of ICDMAI 2020, Volume 2, pp.101-145.

[50] Luo, D., Shen, J., Dangovski, R. and Soljačić, M., 2022. Koopman operator learning for accelerating quantum optimization and machine learning. arXiv preprint arXiv:2211.01365.

[51] Zhu, D., Kahanamoku-Meyer, G.D., Lewis, L., Noel, C., Katz, O., Harraz, B., Wang, Q., Risinger, A., Feng, L., Biswas, D. and Egan, L., 2021. Interactive protocols for classically-verifiable quantum advantage. arXiv preprint arXiv:2112.05156.

[52] Nam, Y., Chen, J.S., Pisenti, N.C., Wright, K., Delaney, C., Maslov, D., Brown, K.R., Allen, S., Amini, J.M., Apisdorf, J. and Beck, K.M., 2020. Ground-state energy estimation of the water molecule on a trapped-ion quantum computer. npj Quantum Information, 6(1), p.33.

[53] Rajesh, V. and Naik, U.P., 2021, August. Quantum Convolutional Neural Networks (QCNN) using deep learning for computer vision applications. In 2021 International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT) (pp. 728-734). IEEE.

[54] Chehimi, M. and Saad, W., 2022. Physics-informed quantum communication networks: A vision toward the quantum internet. IEEE Network, 36(5), pp.32-38.

[55] Nath, R.K., Thapliyal, H. and Humble, T.S., 2021. A review of machine learning classification using quantum annealing for real-world applications. SN Computer science, 2, pp.1-11.