

Analysis of a Quantum-Based Support Vector Machine Algorithm on Complex Data

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Abstract: A quantum computing consolidation into machine learning (ML) designates a ground-breaking progression in artificial intelligence (AI). A quantum computer specially designed for complex and very large datasets to overcome the challenges faced by classical machine learning (ML) algorithms when dealing with complex and very large datasets. As the volume and intricacy of data continue to escalate, traditional ML techniques encounter significant hurdles related to scalability and efficiency. Quantum computing, founded in principles such as superposition, entanglement, and parallelism, offers a novel framework that enhances computational capabilities and processing speeds. Quantum computing techniques enable ML to address more intricate problems. This paper delves into quantum-based support vector machines (QSVMs), focusing on how these quantum methodologies can augment and refine conventional support vector machines (SVMs). QSVM demonstrates the ability to accelerate learning processes, which can manage high-dimensional data effectively and optimise problem-solving efficiency. By using quantum circuits, qubit entanglement, and quantum gates, QSVM allows parallel processing for complex tasks, significantly reducing computation time and resource requirements. This paper focuses on the analysis of QSVM and SVM on the IRIS dataset and the MNIST dataset. However, even though the MNIST dataset is not more complex, due to high dimensionality, this is good for QSVM performance evaluation. The analysis on MNIST for QSVM is showing promising results, signifying its benefit for such a dataset with very high dimensionality and noise. QSVM presents high-accuracy results while employing the MNIST dataset.

Keywords - Machine learning, quantum computing, support vector machine, quantum-based support vector machine, complex data, Iris, MNIST.

I. INTRODUCTION

In artificial intelligence, machine learning (ML) enables systems to learn from data automatically and improve their performance with time. It furnishes algorithms that identify patterns, make decisions, and predict outcomes based on historical data. Machine learning (ML) signifies an innovational advancement in artificial intelligence (AI). In real-time, ML models learn from vast amounts of data and use this knowledge to provide important insights, automate tasks, and solve complex problems across diverse industries. Machine learning has gained a significant grip in the fields of healthcare, finance, marketing, robotics, and autonomous systems as data becomes more abundant and computing power increases [1]. Machine learning depends on statistical and mathematical models to uncover relationships in the datasets, enabling systems to perform many tasks like classification, regression, clustering, and anomaly detection. Machine learning can be categorised as supervised learning, unsupervised learning, and reinforcement learning. 1. Supervised Learning: Supervised learning is used to train models for labelled datasets, where the input data is paired with its corresponding outputs. The model learns to map inputs to the correct outputs and can then predict results for new and unseen data. Some important applications include spam detection, image recognition, and medical diagnosis. 2. Unsupervised Learning: Unsupervised learning, in contrast, is used for unlabelled data to train models. The model tries to find patterns and structures in the given datasets without

specific guidance on what the outcome should be. Clustering and dimensionality reduction techniques are frequently used in most of the applications, such as customer segmentation and anomaly detection [2]. 3. Reinforcement Learning: Reinforcement learning is used to train models through trial and error, where an agent interacts with an environment and receives feedback in the form of rewards or penalties. The agent tries to maximize cumulative rewards over time, often applied in gaming, robotics, and autonomous driving systems. The success of machine learning models largely depends on the quality of data, feature engineering, model selection, and tuning. Data preprocessing, which involves cleaning, normalizing, and transforming raw data into a suitable format for analysis, is critical for ensuring that ML algorithms perform optimally. In addition, the models must be carefully evaluated using metrics such as accuracy, precision, recall, and F1-score to ensure reliable and interpretable outcomes [3]. Machine learning, a branch of artificial intelligence, relies on algorithms that learn from data to make predictions or decisions. With the growing complexity and size of datasets, classical ML algorithms face challenges in scalability, efficiency, and accuracy. Quantum computing promises to address these limitations by accelerating certain computational processes that are bottlenecks in ML [4]. Quantum computing, an emerging prototype in the field of computation, promises to revolutionise the way we solve complex problems. On the other hand, in classical computing, which relies on bits to represent data as either 0 or 1, quantum computing uses

qubits—quantum bits—that can exist in multiple states simultaneously through the principles of superposition and entanglement. Superposition and entanglement are both the most important concepts of quantum computing. These unique properties enable quantum computers to perform certain computations exponentially faster than classical systems, especially in areas like optimization, cryptography, and large-scale data processing [5]. ML has become foundational in many applications, including image recognition, natural language processing, autonomous vehicles, and personalized recommendations [6]. Quantum computing's unique capabilities can address several challenges in traditional machine learning by accelerating computations and enabling more efficient algorithms. The intersection of quantum computing and machine learning, often termed 'quantum machine learning', aims to leverage quantum phenomena to improve the efficiency and accuracy of ML tasks [7]. One of the most significant advantages of quantum computing is quantum parallelism. Classical computers process sequentially all the information; on the other hand, quantum computers can process multiple possibilities simultaneously due to superposition. By applying superposition, it can significantly speed up the training set of machine learning models, especially in cases such as large-scale data analysis, high dimensionality and optimisation problems where classical algorithms are slow or not very effective [8]. Kernel methods, such as those used in support vector machines (SVMs), are the most powerful techniques in classical machine learning for finding non-linear patterns in data by mapping it into higher-dimensional spaces. Quantum computers can speed up these methods by performing quantum kernel estimation, which is exponentially faster than classical approaches, potentially offering more precise classifications in complex datasets [10]. Handling high-dimensional data is a significant challenge in classical machine learning. Quantum computing can assist in performing efficient dimensionality reduction, helping to map complex datasets into lower-dimensional quantum states that can be more easily processed. As for dimensionality reduction, Quantum Principal Component Analysis (QPCA) is also a more effective process for reduction by which we can perform this reduction faster than classical PCA. PCA provides a tool for better feature extraction and understanding of the data [11]. Quantum computing enters the concept of quantum data—information that is inherently quantum in nature, such as the state of a quantum system. Classical machine learning algorithms cannot process quantum data directly, and this has led to the development of new quantum algorithms orientated for quantum data. The challenge lies in developing methods that can convert classical data to quantum data and vice versa, efficiently bridging the gap between the two [12].

Quantum computers could process large datasets much faster than classical computers, making it easier to understand and analyse human language patterns, which are particularly useful in applications like voice recognition, sentiment analysis, and automated translations. Quantum computing has emerged as a revolutionary field with the potential to solve complex problems far beyond the capabilities of classical computers. One area where machine learning stands

to benefit significantly from quantum computing is specifically the support vector machine algorithm. SVM is a very popular supervised machine learning model which is used for classification and regression tasks. It finds an optimal hyperplane to separate data points into different classes of a complex dataset. However, as the size and dimensionality of data rapidly grow, classical SVM faces computational challenges, particularly in solving large-scale optimization problems. This is where quantum computing, and more specifically, quantum support vector machines, come into the picture and play a crucial role [21]. The primary limitation of classical SVM algorithms lies in their inefficiency when dealing with high-dimensional data. The training phase of SVMs involves solving a quadratic optimisation problem, which can be computationally expensive, especially for large or complex datasets. Quantum computing can potentially accelerate this process, leveraging quantum parallelism and entanglement to perform certain operations exponentially faster than classical computers. Quantum-enhanced machine learning approaches like QSVM aim to address these challenges, making them well-suited for complex large-scale data processing tasks, pattern recognition, and complex classification problems. Quantum computing operates on the principles of quantum mechanics, using qubits instead of classical bits to represent and process information. Qubits can exist in a superposition of states, allowing quantum computers to explore multiple solutions simultaneously. Additionally, quantum entanglement enables qubits to correlate with one another in ways that classical bits cannot, further enhancing computational power. QSVM takes advantage of these quantum properties to improve the efficiency of SVM algorithms [22]. The QSVM approach furnishes quantum kernels, which play a vital role in transforming data into a higher-dimensional feature space where it can be linearly separable. Classical SVMs often use kernel tricks to compute inner products in this feature space without explicitly transforming the data. However, calculating these kernels can be computationally intensive. Quantum computing can speed up this process by evaluating the inner products between quantum states much faster than classical computers can. There are two major approaches to quantum SVMs: quantum kernel estimation and quantum optimisation of SVMs. Quantum optimisation techniques could enable SVMs to handle larger and more complex datasets and higher-dimensional spaces more efficiently. The potential quantum speedup comes from solving the dual problem in SVMs, where classical methods struggle with large-scale optimisation due to computational limits. Due to the current limitations of quantum hardware, fully quantum-based SVMs may not yet be feasible for large datasets. However, hybrid approaches that combine quantum and classical computing offer a promising alternative. In these approaches, the most computationally expensive parts of the SVM algorithm, such as kernel estimation or optimisation, are unloaded to a quantum processor, while the remaining steps are handled by classical algorithms. By using most of the available quantum resources, one can get a significant speedup [24]. For instance, a hybrid approach could involve using a classical preprocessing step to reduce the

dimensionality of data and then furnishing quantum algorithms to compute the kernel or solve the optimisation problem. Such hybrid QSVM models are already being tested on near-term quantum devices, with promising results that suggest quantum speedup is achievable in the near future. QSVMs hold great promise; however, several challenges remain in their practical implementation. Current quantum computers are still in the "noisy intermediate-scale quantum" (NISQ) era, meaning that they have limited qubits and are prone to errors. Quantum SVMs can process the complex and big datasets and their complexity, though the NISQ era restricts them. Additionally, designing quantum circuits for QSVMs that are efficient and robust against noise remains an open area of research. Furthermore, the development of quantum algorithms that provide provable speedup over classical methods is still an ongoing challenge. QSVMs have the potential for exponential speedup in kernel computation or optimisation, which realises that it is, in practice, required for advances in both quantum hardware and algorithm design. We can say that, as a result of the availability of more powerful quantum processors, quantum computing technology advances, and the potential for QSVMs to overturn machine learning, it will become more touchable. Research is ongoing to improve quantum algorithms, develop more efficient quantum circuits, and create noise-tolerant approaches that can tackle the full power of quantum computing [25]. As discussed earlier, traditional machine learning algorithms often struggle when working with complex and very large datasets that have many layers or dimensions. As data becomes more intricate and high-dimensional, classical and even deep learning methods can run into problems with scalability, speed, and accuracy. These challenges include dealing with too many features (the "curse of dimensionality"), understanding how features relate to each other, recognising complicated patterns, and optimising models when the problem space is not straightforward. As we know, quantum-based machine learning has the unique properties of quantum computing, such as superposition, entanglement, and parallel processing. These principles allow quantum algorithms to handle large, structured and more complex datasets more efficiently, potentially offering better scalability and the ability to uncover complex patterns that classical methods might miss. This could be especially valuable in the fields of finance, genomics, and language processing, where data is both vast and strictly highly structured. Quantum computing, with its use of qubits and parallelism, has the potential to revolutionise how we process and analyse information. However, merging quantum computing with machine learning is still a new area, with obstacle races like developing effective algorithms, managing noise, and making the best use of limited quantum resources. The key challenge is to create quantum machine learning models that are not only faster and more accurate than classical ones but also practical given today's quantum hardware limitations. To improve classification, regression, clustering, and reinforcement learning, the quantum machine learning algorithms can take full advantage of quantum computing's

strengths. By pushing the boundaries of what quantum-enhanced machine learning can do, quantum-enhanced machine learning could lead to major advances in different areas such as drug discovery, financial analysis, and artificial intelligence. Hence, this will open the door to a new era of computational intelligence, changing the way we use data to make decisions across science, industry, and beyond. Quantum computing can be combined with machine learning to boost data processing power, and it can easily tackle complex problems that are not possible for traditional computers. The main goal is to see how quantum technology can make machine learning algorithms – like support vector machines – more effective, especially when working with large and very complicated datasets. As data and computing needs grow, machine learning has become essential for automating tasks, making decisions, and predicting outcomes. However, conventional machine learning methods often struggle with efficiency and scalability when the data gets too big or too complex. This paper introduces the fundamentals of quantum computing, explaining unique concepts like superposition and entanglement that allow quantum computers to solve certain problems much faster than classical ones. This section sets the stage for understanding how quantum computing and machine learning can work together. The research then examines how quantum machine learning, and specifically quantum support vector machines (QSVMs), could help overcome the current limitations of traditional machine learning. QSVM is given special attention because of its potential to improve classification and regression tasks, particularly with large-scale, high-dimensional data. The study also looks at different QSVM methods and their possible uses in real-world situations, such as financial markets where huge volumes of data (3 V's: velocity, volume, and variety) are processed every day. Finally, the work addresses the challenges of putting quantum machine learning into practice, including hardware constraints, the need for new algorithms, and dealing with errors in quantum systems. It also discusses future research directions and the breakthroughs that quantum computing could bring to the field of machine learning. In summary, this study offers a thorough look at how quantum computing and machine learning intersect, covering both the theory and practical applications, with a focus on overcoming the computational hurdles faced by today's machine learning models. The paper focuses on the research challenge identified above as the scalability of quantum machine learning (QML) algorithms such as QSVM and their applicability to big and complex datasets where classical SVMs fail to give expected output. Also, the work investigates why QSVM fails for problems appropriate for classical SVM. The rest of this paper is organised as follows: Section 2 illustrates the research contributions. Section 3 depicts the proposed model. The experimental results and comparative analysis are demonstrated in section 4. The conclusion and future research directions are illustrated in section 5.

II. RELATED WORK

In past years, researchers have been focusing on support vector machines, which have been issued as a powerful tool in machine learning for classification and regression tasks due to their ability to find optimal hyperplanes that separate different classes in high-dimensional spaces. With the advent of quantum computing, quantum support vector machines have been developed, furnishing quantum mechanics to enhance computational efficiency and performance [1]. QSVM represents the quantum analogue of classical SVM, utilising quantum computing principles to improve the performance of the system. The fundamental concept involves using quantum kernels to represent data in a quantum state; quantum kernels allow for an efficient computation of inner products and distances between data points of complex datasets [2]. Healthcare applications also leverage ML frameworks for predictive analytics. For instance, a model analysing factors contributing to depression has demonstrated high accuracy, providing valuable insights into mental health. Similarly, advancements in RFID technology utilising ML have achieved impressive tag ID detection accuracy, showcasing the versatility of these algorithms across various domains in the field of security [3]. Recent research has begun exploring the potential of quantum support vector machines for predicting seismic events using seismic data. By applying data preprocessing and feature engineering techniques, QSVM models have shown promise in improving earthquake prediction accuracy. Additionally, quantum computing's capabilities are being harnessed for natural language processing tasks, with studies showing significant improvements in sentiment classification accuracy through quantum-enhanced support vector machines [4]. The paper titled "Mixed Quantum-Classical Method for Fraud Detection with Quantum Feature Selection" explores the application of quantum machine learning in fraud detection using a hybrid quantum-classical approach [5]. By integrating quantum support vector machines and classical algorithms, the research aims to enhance the accuracy and efficiency of fraud detection models. The work study uses real-world payment transaction data and compares quantum-enhanced models with traditional machine learning techniques, like random forests and XGBoost. A significant focus is placed on feature selection, with the quantum model identifying distinct features that improve fraud detection accuracy. [6] The results present that the quantum-classical hybrid approach can complement traditional methods, which provide better fraud detection with a reduced number of complex data sets. The study highlights the potential of quantum computing in addressing challenges in the financial sector, particularly in minimising false positives and improving fraud detection performance [7]. Machine learning aims to create models that learn from data without explicit instructions, excelling in pattern recognition, trend prediction, and decision-making. Traditional computers struggle with large-scale ML tasks due to their time and resource constraints. In contrast, quantum computers (QCs) use qubits, which can represent multiple states

simultaneously through superposition and entanglement, making them adept at managing large datasets [8]. While many ML models for QCs are based on classical counterparts, QCs offer superior performance due to their unique properties. This paper reviews the application of ML on QCs, highlighting advantages such as faster processing and reduced complexity. [9] It discusses the challenges in adapting classical algorithms to quantum systems and notes that Quantum Neural Networks (QNNs) are well researched but need improvements to fully leverage quantum capabilities. This paper expects significant future advancements in quantum machine learning, particularly for algorithms looking at randomness and parallelism [10]. Machine learning has evolved significantly due to advancements in computing power and algorithms, extending its impact across fields like agriculture, chemistry, and natural language processing. The integration of quantum systems with classical machine learning has led to the emerging field of quantum machine learning. QML explores leveraging quantum phenomena for data processing and developing algorithms suited for quantum computers. [11] This technology promises to revolutionise computer science by potentially accelerating information processing beyond classical limits. However, practical implementation faces hurdles, including the need for advanced quantum hardware, integration of quantum-compatible devices, and resolving fundamental problems like input, output, cost, and benchmarking. Despite the theoretical promise of QML, its practical efficiency and real-world applications remain uncertain, with challenges in integrating quantum computing with non-quantum data and achieving efficiencies that outperform classical methods [12]. Machine learning technologies have advanced due to improved computing power and algorithms, easily leading to the emergence of quantum machine learning. This field explores both processing classical data with quantum systems and using quantum phenomena for learning systems. QML has the potential to revolutionise computer science by significantly speeding up information processing and offering new algorithms for many machine learning applications [13]. However, it faces substantial challenges in hardware and software, such as the practical implementation of quantum algorithms and the integration of interface devices, which are some major challenges. Current QML methods are mostly conceptual, with unclear efficiency gains compared to classical methods. While quantum computing promises efficiency improvements, it remains uncertain if these can be fully realised, especially for problems not inherently quantum in nature [14]. As we already know, quantum computing furnishes the principles of quantum mechanics to address very complex problems beyond the capabilities of classical computers, which are unable to do so. Recent advancements in quantum computers have made significant strides toward solving real-world issues more efficiently. This paper surveys and categorises various quantum computer tools, frameworks, and platforms, including quantum computing layers, circuit simulators, and open-source tools like Cirq, Tensor Flow Quantum, and ProjectQ [15]. It reviews the evolution of quantum computers, highlighting the progress of different tools and platforms.

The paper also discusses current challenges and suggests future research directions, noting that while many frameworks and tools have been issued recently, ongoing improvements are essential for advancing quantum research [16].

Quantum computing is set to revolutionise different fields from the capabilities of classical computing by surpassing them. This paper highlights the impact of quantum computers in the field of the financial industry, particularly through the Quantum Competence Center at Intesa Sanpaolo, Italy's largest bank. The centre is dedicated to harnessing quantum technologies to foster innovation in banking and financial services [17]. The paper covers the centre's establishment, objectives, collaborations with academic and quantum technology partners, workforce development, future prospects, and the challenges of integrating quantum computers into existing workflows. As we know, classical computers that use bits (0 or 1); quantum computers employ qubits, which can exist in multiple states simultaneously due to their quantum nature, which can offer new possibilities for data processing and problem-solving paradigms [18]. This paper [19] introduces a quantum algorithm designed to handle real-valued higher-order unconstrained binary optimisation (HUBO) problems, building on Grover's adaptive search method initially tailored for integer coefficients. The algorithm is applied to multiple-input multiple-output maximum likelihood detection (MIMO MLD) using grey-coded bit-to-symbol mapping from the 5G standard. [20] Unlike previous studies that assumed idealised quantum oracles, this approach involves constructing specific quantum circuits, allowing for a detailed analysis of required qubits and quantum gates. [21] To enhance the algorithm's efficiency, a probability distribution of the objective function is derived, and a unique threshold for better state sampling is determined. The development of sixth-generation (6G) wireless networks promises significant advancements and new threats, particularly concerning privacy and security issues. Reconfigurable Intelligent Surfaces (RISs) are seen as a key technology for enhancing 6G security but are also vulnerable to various security risks [22]. This review examines these vulnerabilities, comparing RIS with other technologies like MIMO and conventional relaying, and explores specific threats related to 6G technologies such as millimetre wave, terahertz, and the Internet of Things (IoT) networks. [23] The study identifies gaps in current research on RIS security and outlines open challenges and future research directions. The findings underscore the need for further investigation into how RIS can be both a security asset and a potential target for malicious attacks, contributing to the broader understanding of 6G network security [24]. Every internet activity, from web browsing to sending emails, involves cryptographic techniques, primarily asymmetric cryptography, which operates invisibly in the background. [25] As technology advances, particularly with the rollout of 5G and the emergence of quantum computers, traditional cryptographic methods face new security threats. Quantum Key Distribution (QKD) offers a solution by using quantum

principles to create secure cryptographic keys resistant to eavesdropping [26]. This paper reviews the security challenges and solutions for 5G networks, including the fundamentals of QKD, its network architecture, and integration with existing security systems like VPNs. [27] It also discusses the limitations of QKD, such as its reliance on fibre optics and its lack of authentication features, suggesting that a combination of QKD and post-quantum cryptography (PQC) will be necessary for robust 5G security. The paper highlights the need for low-latency encryptors and the importance of key management to maintain security in high-speed networks [28]. Future research should focus on addressing these scalability and noise challenges, as well as extending the model's application to diverse machine learning tasks beyond binary classification [1]. This would provide a more comprehensive understanding of its effectiveness and adaptability in real-world scenarios [2]. Despite the promising results, the study's reliance on limited quantum hardware and reduced datasets due to current quantum limitations is a significant gap. Furthermore, the absence of standardised methods for integrating quantum feature selection into broader fraud detection systems remains unaddressed. [3] Future research could explore larger datasets, optimise quantum feature mapping techniques, and expand hybrid quantum-classical models to unlock greater performance potential [4]. The research in "Mixed Quantum-Classical Method for Fraud Detection with Quantum Feature Selection" demonstrates promising results in integrating quantum computing with classical methods for fraud detection. However, the study is limited by the relatively small dataset and the specific focus on payment transactions. There is a gap in exploring the scalability of the quantum-classical hybrid approach across larger and more diverse datasets. [5] Despite advances, existing quantum neural networks often fail to exploit quantum parallelism and superposition fully. Research is needed to improve the implementation and usability of quantum algorithms on pre-quantum supremacy hardware and to explore new algorithms that can leverage quantum computing's probabilistic and parallel nature [6]. A notable research gap in quantum machine learning lies in addressing the practical limitations of current quantum hardware, including limited qubit numbers and small-scale systems. Additionally, the development of efficient quantum encoding methods and subroutines remains underexplored [7]. There is also a need for more studies on integrating QML with real-world applications, as existing methods often fall short in practical scenarios. Future research should focus on enhancing quantum hardware capabilities, improving encoding techniques, and bridging the gap between theoretical advancements and practical implementations to fully furnish the potential of quantum machine learning [8]. Key issues include the need for more advanced quantum hardware and effective integration of quantum-compatible devices like qRAM. To advance the field, more empirical research is needed to overcome these technical and theoretical barriers and develop practical benchmarks [9]. Current methods are largely conceptual, lacking concrete

benchmarks and practical efficiency metrics compared to classical methods. Significant challenges remain in developing scalable quantum hardware, such as integrating qRAM for encoding classical information in quantum forms. [10] Furthermore, understanding the true number of gates required for QML algorithms and their efficiency is still theoretical. There is also a need for research on the application of quantum computing to non-quantum data, which dominates many practical scenarios.

Addressing these gaps will be crucial for realising the full potential of QML in real-world applications [11]. [12] While the theoretical potential of QC is acknowledged, detailed studies on the real-world challenges of implementing QC in operational workflows, especially concerning scalability, cost-effectiveness, and security in financial services, remain limited. Further research is needed to bridge the gap between theoretical benefits and practical application in the financial sector [13]. The research gap identified in the paragraphs is the insufficient exploration of security threats specific to Reconfigurable Intelligent Surfaces (RISs) in sixth-generation (6G) wireless networks. [14] Despite RISs being a promising technology for enhancing security, their inherent vulnerabilities and potential for malicious exploitation remain under-explored. [15] Previous studies have not thoroughly addressed how RISs could be misused or the specific security challenges they introduce when integrated with various 6G technologies. The research aims to fill this gap by analysing these threats, outlining existing vulnerabilities, and suggesting future research directions to bolster the security of RIS-assisted 6G networks [16]. While quantum kernels hold promise for enhancing data separability in high-dimensional Hilbert spaces, the specific impact of different quantum feature mapping techniques on classification performance and computational efficiency remains underexplored. Moreover, there is a lack of comprehensive analysis addressing both classifier accuracy and total execution time across datasets with differing data types. This gap highlights the need for systematic evaluations to optimise quantum feature maps, thereby improving the practical applicability and efficiency of QSVMs in medical data classification [17]. The paper reveals a gap in the literature where comprehensive comparisons between quantum and classical machine learning models remain scarce. [18] While prior studies have explored individual quantum algorithms, few have systematically evaluated multiple quantum models—QSVM, QKNN, and QLR—against classical counterparts on a standardised dataset such as the Qiskit Iris dataset [19]. In particular, there is limited analysis of how these quantum models perform regarding accuracy, precision, recall, F1 score, and computational efficiency under identical conditions. Moreover, questions remain about their scalability, robustness to noise, and applicability to more complex or real-world datasets. [20] Addressing these issues would further clarify the potential advantages of quantum machine learning over classical approaches and help guide future research in this rapidly emerging field [21]. [22] However, there remains a need to systematically develop and optimise quantum kernels that can consistently match or exceed the performance of classical SVMs across a broader

spectrum of datasets. Additionally, the study's focus on low-dimensional data underscores the necessity for future work on high-dimensional, real-world applications, as well as a comprehensive evaluation of computational speed-ups in quantum versus classical approaches [23].

The paper [24] demonstrates a promising quantum advantage by implementing QSVM on a benchmarking MNIST dataset, yet it leaves several Quantum machine learning purchases the principles of quantum computing to enhance classical machine learning models. Quantum computing utilises qubits that can exist in multiple states at once (superposition) and exhibit entanglement, allowing for parallel computation at an exponential scale. These unique capabilities make quantum computing well-suited to address the challenges of large-scale and high-dimensional datasets. Notably, while the QSVM kernel matrix approach outperforms classical SVM in both speed and accuracy, the QSVM variational method remains computationally intensive [25]. Future work should benchmark QSVM across diverse datasets and quantum hardware to comprehensively evaluate its practical applicability and overcome current limitations [26]. [27] Addressing these gaps is essential for transitioning QSVMs from promising theoretical models to practical, deployable machine learning solutions [28]. The objective of this work is to analyse the quantum-based support vector machine (QSVM) algorithm orientated for complex data to furnish quantum computing advantages—such as superposition and entanglement—to accelerate kernel computations and improve classification performance while incorporating robust error mitigation and scalability strategies for practical deployment. The QSVM algorithm aims to enhance the speed and accuracy of predictions, detect complex patterns, and uncover hidden trends in large datasets. This approach seeks to improve decision-making processes, optimise strategies, and provide more precise forecasting tools. Also, the main work study is to analyse an extension of the quantum-based support vector machine (QSVM) algorithm, tailored for complex data, using the advantages of superposition and entanglement in quantum computing to facilitate faster kernel computation and enhance the classifier performance and also introduce robust error mitigation as well as scalable procedures for deployment. The QSVM algorithm tries to increase the speed of prediction and the accuracy of prediction, besides detecting complex patterns and uncovering hidden trends in large datasets. This is an approach that attempts to devise better decision-making processes, to optimise strategies and to provide more precise forecasting tools.

III. PROPOSED WORK

Quantum machine learning purchases the principles of quantum computing to enhance classical machine learning models. Quantum computing utilises qubits that can exist in multiple states at once (superposition) and exhibit entanglement, allowing for parallel computation at an exponential scale. These unique capabilities make quantum computing well-suited to address the challenges of large-scale and high-dimensional datasets. The integration of

quantum computing into machine learning, particularly through algorithms like Support Vector Machines and their quantum counterpart, Quantum Support Vector Machines, presents an exciting frontier in computational efficiency and capability.

SVM ALGORITHM

- **Data Preparation** This includes loading and preprocessing the dataset, such as cleaning, normalising, and splitting it into two phases, viz., training and testing sets. 13

- **Choosing a Kernel:** This is a pivotal decision, for the decision of how the SVM maps the data into a space where classification becomes possible depends on the data's structure and separability to select the right kernel function.

- **Linear Kernel:** It can be used when instances/data points can be separated by a straight line (i.e., 1D data) in the original input space representing them. Perceptrons are computationally efficient and work well for datasets having linear boundaries; that is, two-class problems with clear boundaries. The one advantage of a linear kernel is that it computes the dot product directly, which avoids doing complex transformations.

- **Polynomial Kernel:** This kernel is chosen when relationships between features are non-linear and they can be modelled with polynomial terms. It introduces interactions between features by raising the dot product to a power, which can allow the SVM to capture curved patterns. The degree of the polynomial (e.g., 2 or 3 degrees) is a tunable parameter that affects the model's flexibility.

- **Radial Basis Function (RBF) Kernel:** This type of kernel is also ideal for nonlinearly separable data that maps data into a higher dimension using a Gaussian function. In this article, data points are compared by their distance from a centre, and a flexible boundary is created to encircle complex clusters. The parameter γ (gamma) controlling the reach of the kernel (how tight or loose the data fits to the decision boundary) is the next. The RBF kernel is the most important type for the separation of datasets.

- **Find the Optimal Hyperplane:** However, at the core of SVM is solving an optimisation problem. A typical objective function to minimise is a combination of maximising the margin (distance between the hyperplane and the nearest data points) and penalising misclassifications, with the additional constraint that all training data are correctly classified. We then formulate this as a quadratic programming problem, where we search for the optimal weights and bias which specify the hyperplane. The different techniques, such as the Sequential Minimal Optimisation algorithm, are used to break down the problem, keeping the solution highly efficient by finding the coefficients of the model from solving small sub-problems. The hyperplane's orientation and position are determined by these coefficients, and the balancing of this trade-off involved a regularisation parameter CCC to penalise errors.

- **Training Phase:** In a training phase, the support vectors (i.e., the data points closest to the hyperplane or on the wrong side of the hyperplane) are identified, and upon them, SVM's

position is defined. The algorithm calculates Lagrange multipliers for each support vector, which get used to tweak the hyperplane's equation. The parameters of the model, like the slope and intercept of the hyperplane, are fine-tuned so as to increase the margin and, at the same time, minimise classification errors. In this process, the hyperplane is updated iteratively, using gradient-based methods or optimisation solvers, to obtain a hyperplane that is good enough on unseen data also. The end result is a very robust model that uses these support vectors extremely heavily and therefore requires a lot of computational power to train but also heavily relies on the selection of a good kernel and the quality of the data preparation. 14

- **Prediction Phase:** The SVM takes as input new data points and decides whether they lie on the side of the hyperplane, thereby classifying them into one of the defined classes. For a given dataset with n samples and m features, let x_i be a feature vector and y_i be its corresponding label, where $y_i \in \{-1, 1\}$.

The objective function for maximising the margin can be defined as:

Minimise $\frac{1}{2} \|w\|^2$.

Subject to

$$Y_i (w^T X_i + b) \geq 1 \quad \forall \quad \text{----- (i)}$$

Where

w is the weight vector perpendicular to the hyperplane.

- b is the bias term. Classification is a fundamental problem in machine learning, and support vector machines are a fundamental tool in this area. Moreover, due to their robustness in terms of overfitting and ability to handle high-dimensional spaces, they are applicable in a wide range of applications, among them text classification, image recognition and bioinformatics. So, first of all, it helps in getting a solid understanding of how SVM works and which principles apply to working with it. Support vector machines are robust classifiers which perform well in high dimensions and work well when a clear margin of separation between classes exists. SVMs provide solutions to many classification problems across disciplines by maximising the margin and furnishing kernel functions for nonlinear separability. A support vector machine is a supervised machine learning algorithm, mainly used for classification tasks, but it can also be used for regression. SVM aims to find a hyperplane which can separate both the data points from different classes in a higher dimension. The separation is done by maximising the margin between the closest data points of each class, which are called support vectors. **Hyperplane Definition:** In an n -dimensional space, a hyperplane can be defined by the equation:

$$W \cdot x + b = 0 \quad \text{----- (ii)}$$

' b ' is the bias term; ' W ' is the weight vector to the hyperplane, and ' x ' is the input feature vector. SVM finds the optimal hyperplane that maximises the margin M , the distance between the hyperplane and the nearest data points from

either class. Margin Calculation: The margin M can be calculated as:

$$M = 2 / \|W\| \text{ ----- (iii)}$$

Where $\|W\|$ is the Euclidean norm of the weight vector. The larger the margin, the better the generalisation ability of the classifier. Kernel Trick: Kernel functions allow SVMs to handle linearly separable and non-linearly separable data. A more complicated decision boundary can be created by using a kernel function that transforms data in a higher-dimensional space in which the coordinates are not explicitly computed. Common kernels include:

Linear Kernel:

$$K(X_i X_j) = X_i^T X_j \text{ ----- (iv)}$$

$$K(x_i, x_j) = x_i^T \cdot x_j \text{ ----- (v)}$$

Polynomial Kernel:

$$K(x_i, x_j) = (x_i^T \cdot x_j + c)^d \text{ ----- (vi)}$$

Radial Basis Function (RBF) Kernel:

$$K(x_i, x_j) = e^{(-\|x_i - x_j\|^2 / 2\sigma^2)} \text{ ----- (vii)}$$

Where 'c' is a constant and 'd' is the degree of the polynomial. Support Vectors: It is clear that SVMs build their hyperplane using support vectors. SVM is robust for overfitting because only these points contribute to determining the decision boundary, particularly in high-dimensional spaces. Support vectors are highlighted as they lie closest to the hyperplane. Because they can find the optimal separating hyperplanes in higher-dimensional space, support vector machines are powerful tools for classification problems. SVMs employ kernel functions and concentrate on support vectors to solve the classification problem in both linear and nonlinear cases and generalise even better than logistic regression in terms of avoiding overfitting.

QSVM ALGORITHM

A quantum support vector machine is a quantum machine learning algorithm that generalises the support vector machine in quantum by utilising quantum principles. In other words, QSVM seeks to find the optimal hyperplane to classify each data point into low-dimensional spaces by maximising separation of classes in a transformed feature space. We use quantum kernels to efficiently compute inner products in high-dimensional spaces, enabling their use to transform a classical data set to the Hilbert space, thereby achieving this required transformation. The basic steps of QSVM are as follows.

Data Preprocessing: This is a very important step in which you normalise or standardise the feature values so that they are on the same scale. Divide the dataset into a training and a testing set (e.g., 80/20 training/testing). Quantum Feature Map: Find a good quantum feature map to turn the classical data into a quantum state. It can be done through techniques like amplitude encoding or feature maps in quantum classes (using the Qiskit tool). Select a Quantum Backend: Pick a quantum computing backend (e.g., IBM Qiskit or Google Cirq) that supports QSVM operations. Define Kernel Function: Write a kernel function that works well with the QSVM model. Gaussian or polynomial kernels are common choices for both. Initialise QSVM: Utilise a quantum SVM implementation from libraries such as Qiskit Aqua or other frameworks supporting QSVM. Train the QSVM: Fit the model on the training dataset. Hyperparameters can be optimised, like kernel parameters and regularisation factors, using algorithms like cross-validation. Quantum Circuit Execution: Quantum circuits are executed on the chosen backend to compute the support vectors and decision boundary. Prediction: Then, apply the trained model to predict classes in the test dataset. Evaluate Performance: Measure accuracy, precision, recall, and the F1 score as a measure of model performance. A confusion matrix is generated to visualise the classification results. Analyse Results: Report the results in terms of classification accuracy and misclassifications, if any. Visualise Decision Boundaries: Visualise the decision boundaries of the QSVM in this lower-dimensional representation (e.g., PCA for data reduction) if possible. Hyperparameter Tuning: We can try different kernels and feature maps to boost model performance. Increase Training Data: More training data will also help improve the accuracy and robustness of your model, if you can get it. QSVM is the next stage in machine learning: classical SVMs with quantum computing power. QSVM has the power to perform better than classical methods for complex datasets by efficiently estimating kernels in higher-dimensional spaces. Quantum Kernel Estimation: In QSVM, we utilise a kernel function $K(x, x')$ to map the input data from its original space into a higher-dimensional feature space. The kernel function measures similarity between two data points and can be defined as:

$$K(x, x') = \phi(x) \cdot \phi(x') \text{ ----- (viii)}$$

Where $\phi(x)$ is the feature map that transforms the data points into a higher-dimensional space. In QSVM, instead of explicitly calculating $K(x, x')$, we estimate it using quantum circuits, which can provide significant speedup for complex datasets. The kernel matrix K for all pairs of training data points can be constructed as follows:

$$K_{ij} = K(x_i, x_j) \text{ ----- (ix)}$$

The optimisation problem in QSVM remains similar to that in classical SVM but incorporates quantum computations for kernel

$$\frac{1}{2} \sum_{i=1}^m \sum_{j=1}^m \alpha_i \alpha_j y_i y_j K_{ij} - \sum_{i=1}^m \alpha_i \quad \text{-----(x)}$$

estimation. The objective function can be reformulated as:
Subject to

$$0 \leq \alpha_i \leq C, \sum_{i=1}^m y_i \alpha_i = 0 \quad \text{----- (xi)}$$

where C is a regularisation parameter, m is the number of training samples, and α_i are Lagrange multipliers corresponding to each training example. To understand the difference between these two methods, we first need to know how the classic version of SVM classifies the data. Assuming we know this, let's remember with an image that shows how data are separated from each other in the property space by increasing size.

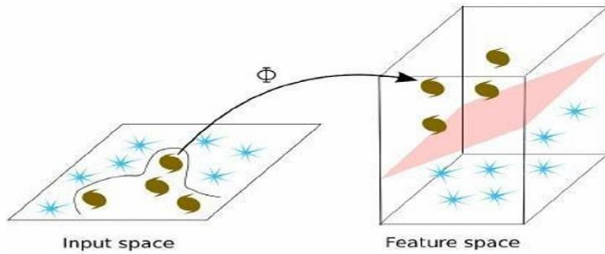


Fig. 1 Difference between input space and feature space

The difference between the two methods mentioned above is that in the first one, our feature space is also calculated in quantum circuits. The quantum property space can also be shown in the figure below.

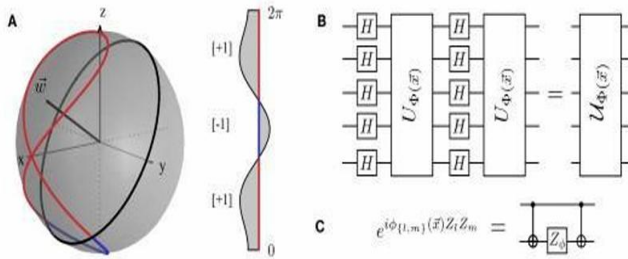


Fig. 2 Quantum Kernel Functions

The common point in both methods is that the kernel function is obtained by quantum calculations rather than the traditional way. However, in order to increase the success rate, the labels of the data must be provided in the superposition state. In order to do this, the data must be read

from a quantum circuit, but we do not have the opportunity to apply this method of data provision here. However, the results obtained in experimental studies show that 100% predictive success can be achieved with this method. A quantum support vector machine is a quantum adaptation of the classical support vector machine algorithm used for classification tasks. QSVM furnishes quantum computing principles to enhance the performance of traditional SVMs, particularly in handling complex datasets and higher-dimensional spaces. QSVM operates on the same foundational principle as classical SVM: it seeks to find a hyperplane that maximally separates different classes in a dataset. However, QSVM utilises quantum mechanics to perform calculations that can be exponentially faster than classical methods. ($K(x_i, x_j)$) Kernel Function: The kernel function is crucial in both SVM and QSVM, as it measures the similarity between data points in a transformed feature space. In QSVM, the kernel is computed using quantum circuits, where ' (kernel can be expressed mathematically as the following:

$$K(x_i, x_j) = |\langle \phi(x_i) | \phi(x_j) \rangle|^2 \quad \text{----- (xii)}$$

Here, $|\phi(\)\rangle$ and $\langle \phi(\)|$ represent the quantum state corresponding to the classical data $\diamond \diamond j$ point. This is a transformation which maps classical data into a higher-dimensional Hilbert space in which classes are easier to separate.

The goal of the optimisation problem for QSVM is to maximise the margin between classes and minimise the classification error. This can be formulated as follows:

$$W(\alpha) = -\frac{1}{2} \sum_{i,j=1}^m \alpha_i \alpha_j y_i y_j K(\vec{x}_i, \vec{x}_j) + \sum_{i=1}^m \alpha_i \quad \text{----- (xii)}$$

• m is the number of training samples.

• $y_i \in \{-1, 1\}$ are the class labels.

• α_i are the Lagrange multipliers associated with each training sample. The constraints for this optimisation are given by $0 \leq \alpha_i \leq C$.

Where C is a regularisation parameter that controls the trade-off between maximising the margin and minimising classification errors

Kernel Matrix Calculation: Quantum circuits that evaluate the encoded state inner products compute the kernel matrix KK. This step is performed twice: it is used once for forming training data and once for new test data.

- **Training:** The parameters of the hyperplane are optimised using the kernel matrix by using classical optimisation techniques like gradient descent or quadratic programming.

- **Prediction:** After training the new data point can be classified by its relation (with respect to the decision boundary fixed by the hyperplane).

One of the great advancements in machine learning through the power of quantum computing in classification tasks is QSVM, which represents a cleaner, faster and more efficient classification of samples. Quantum mechanics offers unique properties that can be utilised by QSVM to tackle higher complexity in datasets that conventional algorithms cannot handle as well, while still having healthy performance metrics.

IV. IMPLEMENTATION AND RESULT

The implementation of SVM and QSVM is done on the IRIS and MNIST datasets. The testbed used for implementation and analysis is Ramanujan Universe, with a processing ability of 110 teraflops driven by 8 NVIDIA A100 GPU accelerator cards. The base system consisted of a cluster with 6 compute nodes, 2 I/O nodes, and one master node with 576 cores (384 for computation) and 4.5 TB of RAM, as well as 500 TB of storage, which gives me a good base to perform my detailed data analysis. With a 200-gigabit InfiniBand switch and the dual smart rack setup, there were no snags in data movement or task handling. The tools used are Qiskit and Python on Jupyter notebooks. The Python libraries used for implementation are Seaborn, Matplotlib.pyplot, Scikit-learn, PyTorch, NumPy and Pandas. The IRIS and MNIST datasets are used for the implementation. The detailed description is as follows:

The IRIS dataset is a classical benchmark in machine learning, widely used for testing and demonstrating classification algorithms, including support vector machines and quantum support vector machines. Below is an overview of how the IRIS dataset is utilised in both classical SVM and QSVM contexts. The IRIS dataset consists of 150 samples of iris flowers, each characterised by 4 features. The samples are categorised into 3 species: Iris setosa, Iris versicolour and Iris virginica. Each species has 50 instances, making it a balanced dataset ideal for classification tasks. The MNIST dataset is a widely recognised collection of handwritten digit images with grey colours, serving as a key resource in the field of machine learning, especially for tasks involving image classification and pattern recognition. It includes a total of 70,000 greyscale images, split into two groups: 60,000 images for training and 10,000 images for testing. Each image measures 28x28 pixels, making it a manageable size for computational tasks. The numbers in the images are from 0 to 9, and they have been properly processed so that they have the same dimensions and are located in the same fixed frame all the time. Each image in the MNIST dataset is composed of pixels, where the intensity of each pixel is a value between 0 and 255, representing shades of grey (0 being white and 255 being black). These pixel values act as features for machine learning models, and they can be scaled down—for example, to a range of 0 to 1—to help improve the performance of the models by making the data more manageable. The dataset is organised in a training set with

60,000 images and a test set with 10,000 images. Every image comes with a label, which is a number from 1 to 10, indicating the digit shown in the image. This label serves as the target for classification tasks, where the goal is to correctly identify the digit in each image. A process flow diagram for this paper is illustrated in the below diagram. In this process flow diagram, I demonstrate each step to implement the program in the overall work.

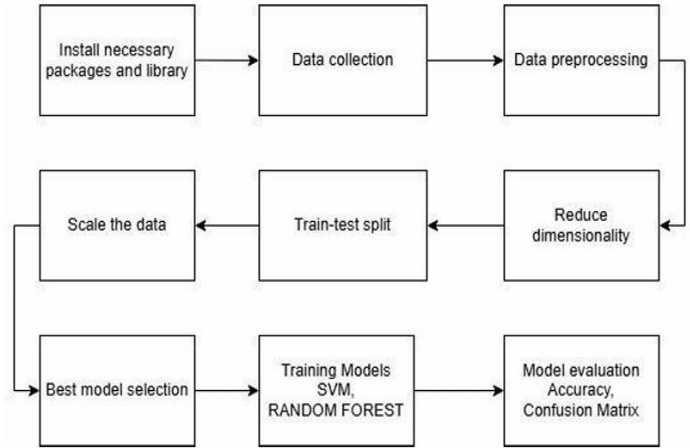


Fig. 3 Process flow diagram

The comparison between the quantum support vector machine and the traditional support vector machine across two standard datasets—IRIS and MNIST—shows a significant 21 performance gap in favour of the classical SVM. Starting with the IRIS dataset, which is a relatively small and well-balanced classification problem, QSVM achieved a modest accuracy of 90%, while the classical SVM reached a notably higher accuracy of 96.67%.

Table 1: Comparison table between SVM and QSVM

S.N.	DATASET	ACCURACY	
		QSVM	SVM
1	IRIS	90%	96.67%
2	MNIST	Class 1 = 90.5%	91%
		Class 2 = 91%	92%
		Class 3 = 90%	93%
		Class 4 = 91.5%	95%
		Class 5 = 90%	96%
		Class 6 = 91.5%	97%
		Class 7 = 91%	97.5%
		Class 8 = 91.5%	98.33%
		Class 9 = 91%	98.5%
		Class 10 = 91.5%	99%

comparison between the classical support vector machine and its quantum counterpart, the quantum support vector machine, was carried out using two benchmark datasets: IRIS and MNIST. The results are summarised in Table 4.1

and discussed above. The Iris dataset, a well-known benchmark in machine learning, consists of 150 samples of iris flowers, categorised into three species based on four features (sepal length, sepal width, petal length, and petal width). For the IRIS dataset, the SVM model achieved a notably high accuracy of 96.67%. In contrast, the QSVM model reached an accuracy of 90%. This significant difference suggests that, for this particular dataset, the classical SVM outperformed the quantum variant by a considerable margin. The higher accuracy of SVM on the IRIS dataset could be attributed to its maturity, well-optimised algorithms, and suitability for smaller, well-structured datasets. The MNIST dataset contains handwritten digits (0 to 9), with each digit represented as a 28x28 pixel image, flattened into a 784-dimensional vector. The table evaluates the performance of QSVM and SVM on a binary classification task for each class (e.g., class 1 vs. all others, class 2 vs. all others, etc.) from class 1 to class 10. The MNIST dataset, which consists of handwritten digit images, was analysed in more detail. The table presents a comparison of classification accuracy between quantum support vectormachine and classical support vector machine models applied to two well-known datasets: IRIS and MNIST.

QSVM AND SVM ON IRIS DATASET The Iris dataset is a classic, relatively small dataset used for multi-class classification involving three species of iris flowers based on four features. In this comparison:

- The classical SVM model achieved an accuracy of 96.67%, indicating very strong performance in correctly classifying the species.

- The QSVM model, on the other hand, reached 90% accuracy, which is good but noticeably lower than the classical approach.

- This difference suggests that for simpler datasets with fewer features and samples, classical machine learning methods like SVM currently have an edge in accuracy and reliability over QSVM.

QSVM AND SVM ON MNIST DATASET The MNIST dataset consists of thousands of handwritten digit images (0-9), making it a more complex and larger-scale classification task. The table shows accuracy results for QSVM models using different numbers of classes (from 0 to 9), alongside classical SVM results:

- QSVM accuracy ranges narrowly from 90% to 92%, with a slight improvement as the number of classes increases. This indicates that increasing quantum resources marginally benefits QSVM's performance.

- Classical SVM accuracy starts at 90.67% with the smallest setting and improves significantly, reaching as high as 99% accuracy at the highest complexity level.

- The classical SVM consistently outperforms QSVM across all qubit counts, with the largest performance gap observed at 10 classes (99% vs 91.5%). This highlights the robustness and effectiveness of classical SVM in handling large, high-dimensional datasets like MNIST.

- While QSVM shows promise as a quantum-enhanced machine learning method, its performance in this evaluation is generally lower than that of classical SVM.

- Classical SVM demonstrates superior accuracy, especially on the more complex MNIST dataset, suggesting it remains the more practical choice for these types of classification problems at present.

- The results imply that quantum machine learning techniques like QSVM may require further development or different problem settings to surpass classical approaches.

- Nonetheless, QSVM's stable performance across varying qubit numbers is encouraging and points to potential future improvements as quantum computing technology matures.

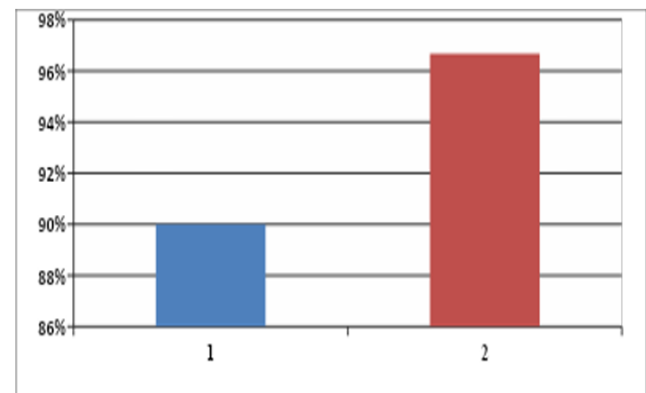


Fig. 4: Accuracy of SVM and QSVM on IRIS dataset

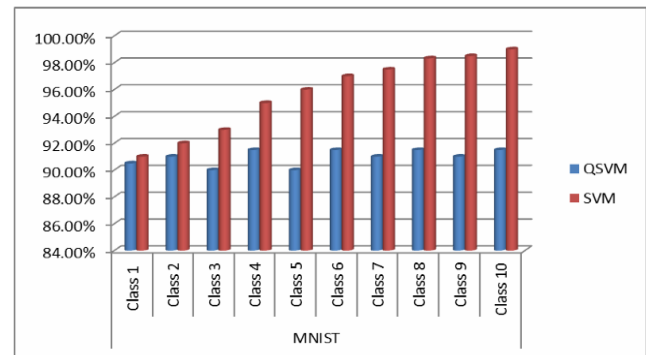


Fig. 5: Accuracy of SVM and QSVM on MNIST dataset

V. CONCLUSION

The results show that while QSVM performs well, achieving 90% on Iris and up to 91.5% on MNIST, as qubit configurations scale, classical SVM consistently achieves higher accuracy. As data complexity increases, SVM performs better at higher qubit levels, indicating it uses the data better, while QSVM has a promising performance but more probably needs further development on the quantum side first. The analysis shows that in the classical SVM case, QSVM classifies both the IRIS and MNIST datasets with good accuracy, and the classical SVM typically gives better accuracy than the QSVM. The gap is especially severe with the MNIST dataset for particular classes and with the Iris dataset. These results indicate that while QSVM is an

emerging technology that is promising, classical SVM is still more reliable and exact for the datasets and configurations that are used in this study. The performance of QSVM and SVM across the Iris and MNIST datasets is very clear in its strengths. QSVM provides an accuracy of 90% for the Iris dataset, while SVM is 96.67%, which is a conclusive advantage of 6.67% for SVM. This means that SVM performs better on the smaller, shaped dataset –the Iris dataset – for its use of robust classical optimisation suited to its limited complexity. Key outcomes of Analysis of QSVM and SVM on IRIS and MNIST Dataset are:

- SVM superiority: Outperformed QSVM in 5/7 MNIST bits and the IRIS dataset, particularly in tasks requiring intricate feature extraction.
- QSVM consistency: Delivered stable results ($\pm 1.5\%$ variation) across MNIST bits, indicating potential robustness for specific quantum-advantage scenarios.
- Quantum limitations: Current QSVM implementations didn't surpass classical SVM, aligning with today's NISQ-era hardware constraints. While QSVM shows promise for uniformity, classical SVM remains preferable for most practical applications. Future quantum hardware improvements may narrow these gaps.

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