HYBRID QUANTUM-MACHINE LEARNING CLASSIFIER FOR HIGH-DIMENSIONAL DATA OPTIMIZATION

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ABSTRACT: Quantum computing, a paradigm-shifting technology, leverages the principles of quantum mechanics to perform computations far beyond the capabilities of classical systems. Many problems in classical physics and engineering, such as turbulence, are governed by nonlinear differential equations, which typically require high-performance computing to be solved. Over the past decade, however, the growth of classical computing power has slowed because the miniaturization of chips is approaching the atomic scale. The computational power is leveraged by quantum bits (qubits) capable of superposition and entanglement that provide exponential speed-up for certain complex problems by using quantum computing. In this proposed system a Quantum-Assisted Machine Learning (QAML) framework is developed. The quantum computing principles integrate with classical ML classifiers for high-dimensional data analysis. A quantum feature extractor and a classical neural network as the final classifier use Quantum Support Vector Machine (QSVM) to develop a new hybrid model. The proposed method is evaluated using benchmark datasets and shows significant improvement in classification accuracy, precision and efficiency when compared with traditional ML classifiers.

KEYWORDS: Machine Learning (ML), Quantum computing, Quantum Support Vector Machine (QSVM), Quantum-Assisted Machine Learning (QAML), Quantum Bits

I. INTRODUCTION

Quantum computing is an emerging technology with the potential to revolutionize scientific research [1] and our industry, economy, and whole society.

However, despite recent significant investments and the growing trend of interest in the scientific community, the technology is not yet fully developed, with our current period being famously called noisy intermediate-scale quantum (NISQ) era[2]. A class of applications that is particularly promising in the near term is variational quantum computing, which is an iterative method where “variational” parameters of a quantum application are adapted through an optimization process running in a classical computer[3]. However, as the ecosystem of the quantum computing platform providers becomes richer and the maturity of the solutions they offer improves, we see a shift in the way platforms are designed, operated, and made available to the users: software engineering is entering the field, with a promise to make systems more scalable, efficient, and easy to use [4]. One of the improvements proposed is adopting a serverless computing approach.

Serverless computing is a mature technology in cloud services that enables developers to write applications as collections of elementary stateless functions calling one another[5]. The functions run inside lightweight virtualization abstractions, usually containers, and are automatically scaled up when the demand for a given function increases, thereby spawning more workers that run the same function to which a load balancer dispatches invocations. On the other hand, when there are fewer function invocations, the platform progressively reduces the number of workers, down to zero, if necessary[6]. System providers like serverless computing because of its inherent flexibility, which enables them to fine-tune the use of resources efficiently. Users enjoy the programming model, called function as a service

(FaaS), which relieves them from all management tasks and enables pay-per-use billing schemes[7].

Current quantum computers are commonly defined as noisy intermediate-scale quantum (NISQ) devices, being characterized by a few dozens of quantum bits (qubits) with nonuniform quality and highly constrained physical connectivity. The growing demand for large-scale quantum computers is motivating research on distributed quantum computing (DQC) architectures as a scalable approach for increasing the number of available qubits for computational tasks, and experimental efforts have demonstrated some of the building blocks for such a design[8]. Indeed, with the network and communications functionalities provided by the Quantum Internet, remote quantum processing units (QPUs) can communicate and cooperate for executing computational tasks that each NISQ device cannot handle by itself[9].

In general, when moving from local to distributed quantum computing one faces two main challenges, namely, quantum algorithm partitioning and execution management [10]. To partition a monolithic quantum algorithm, a quantum compiler must be used to find the best breakdown, i.e., the one that minimizes the number of gates that are applied to qubits stored at different devices. Such remote gates can be implemented by means of three communication primitives that we denote as Teleport [11] (quantum state teleportation), Cat-Ent (cat-entanglement), and Cat-DisEnt (cat-disentanglement). These primitives require that an entangled state is consumed and a new one must be distributed between the remote processors through the quantum link before another interprocessor operation can be executed[12].

Quantum entropies and distances are basic concepts in quantum physics and quantum information. Quantum entropies characterize the randomness of a quantum system, while quantum distances measure the closeness of quantum systems[13]. It is essential to compute their values in many important applications, from the estimation of the capacity of quantum communication channels and verification of the outcomes of quantum computation to the characterization of quantum physical systems. Several kinds of quantum algorithms for computing quantum entropies and distances have been proposed under different computational resources, e.g., quantum algorithms with access to copies of quantum states quantum algorithms with purified quantum query access and variational quantum algorithms[14].

A main consideration of those quantum algorithms with copy access for computing quantum entropies and distances is the number of copies of quantum states used in the algorithms. This type of input model is known as the “quantum sample access” model, where identical copies of quantum states are directly given[15].

II. LITERATURE SURVEY

H. C. Watanabe, R. Raymond, Y. -Y. Ohnishi, E. Kaminishi and M. Sugawara, et al.[16] propose a method to construct a PQC by continuous parameterization of both the angles and the axes of its single-qubit rotation gates. The method is based on the observation that when rotational angles are fixed, optimal axes of rotations can be computed by solving a system of linear equations whose coefficients can be determined from the PQC with small computational overhead. This method demonstrate PQCs with free-axis selection are more effective to search the ground states of Hamiltonians for condensed matter physics, quantum chemistry, and combinatorial optimization

M. Chakraborty, A. Mukherjee, A. Nag and S. Chandra, et al.[17] establish a holistic hybrid quantum noise model to determine the quantum channel capacity. In this paper, we formulated a mathematical expression for this capacity and conducted simulations for both Gaussian and non-Gaussian inputs. A hybrid noise model is constructed by convolution of Poisson-distributed quantum noise with classical additive white Gaussian noise. We characterized the quantum-classical noise and the received signal using Gaussian Mixture Models. The maximum amount of quantum information that can be reliably transmitted over a quantum channel (per use of the channel) is determined by its capacity, and entropy and related quantities like mutual information play a role in calculating this capacity.

D. Lee, H. Shin and S. Hong, et al.[18] introduces a quantum amplitude hash function as a new paradigm. The function operates by directly hashing the entire amplitude, which represents the totality of information within the quantum evidence state, into a hash qubit. The proposed function is implemented as a quantum circuit of constant depth, ensuring excellent scalability. It is theoretically proven to satisfy key cryptographic properties such as preimage resistance, collision resistance, and sensitivity.

M. A. Shafique, A. Munir and I. Latif, et al. [19] introduce readers to the fundamental concepts of qubits, superposition, entanglement, interference, and noise. We explore quantum hardware, quantum gates, and basic quantum circuits. This study offers insight into the current phase of quantum computing, including the noisy intermediate-scale quantum (NISQ) era and its potential for solving real-world problems. Furthermore, we discuss the development of quantum algorithms and their applications, with a focus on famous algorithms like Shor's algorithm and Grover's algorithm.

D. Volya and P. Mishra, et al.[20] investigate and report digital simulations of Markovian nonunitary dynamics that converge to a unique steady state. The steady state is programmed as a desired target state, yielding semblance to a quantum state preparation protocol. By delegating ancilla qubits and system qubits, the system state is driven to the target state by repeatedly performing the following steps: 1) executing a designated system–ancilla entangling circuit; 2) measuring the ancilla qubits; and 3) reinitializing ancilla. We show results of the method by preparing arbitrary qubit states and qutrit (three-level) states on contemporary quantum computers.

S. DiAdamo, M. Ghibaudi and J. Cruise, et al.[21] approach for distributing the accelerated variational quantum eigensolver algorithm over arbitrary sized—in terms of number of qubits—distributed quantum computers. We consider approaches for distributing qubit assignments of the Ansatz states required to estimate the expectation value of Hamiltonian operators in quantum chemistry in a parallelized computation and provide a systematic approach to generate distributed quantum circuits for distributed quantum computing.

Y. Akahoshi, J. Fujisaki, H. Oshima, S. Sato and K. Fujii, et al.[22] construct an integrated software system of STAR-architecture-based quantum computation, which generates physical instructions executable on quantum devices from input logical quantum circuits. The system mainly consists of two parts, a circuit converter and an operation controller. The circuit converter comprises a set of conversion subroutines, which bridge several instruction layers: logical circuit layer, lattice surgery layer, and physical circuit layer. The operation controller efficiently executes the generated instructions. Especially, it enables efficient treatment of the analog rotation gate, which needs real-time scheduling of running instructions due to its probabilistic nature.

M. A. Ullah, A. J. Awan and E. Svensson, et al.[23] developed two multi-chip mapping methods that maximize compute capacity utilization of quantum processing units (QPUs) while addressing their limited coherence times and the transmission rates of quantum interconnects. These methods assess critical parameters of QPUs and interconnects in a multi-chip quantum network, enabling optimal assignment of quantum gates in a quantum algorithm onto the network. Our methods produce runnable subcircuits, mapped to a minimum number of capacity-maximized QPUs while achieving high-fidelity multi-chip quantum computing.

M. M. Hasan, M. M. Rahman, M. M. Ali and P. Machado, et al.[24] introduce QuantoTrace, a cloud-based platform offering Error Correction as a Service (ECaaS). It enhances quantum system reliability by detecting, analysing, and rectifying errors, and implements bit-flip error correction compatible with various quantum technologies. Using 3-qubit and 5-qubit models, we demonstrated its efficacy on quantum simulators and IBM quantum hardware. Remarkably, we achieved 100% error correction accuracy on simulators and significant success rates on IBM hardware: 68.95% for error correction and 86.04% for error detection in 5-qubit systems.

S. Kashani, A. Singh and U. Stege, et al.[25] focus on the distribution at the algorithm and circuit levels. Algorithmic distribution involves distributing tasks before compilation, allowing different quantum processing units (QPUs) to receive distinct parts of an algorithm. Circuit distribution involves executing a quantum algorithm in a distributed manner at the circuit execution level using circuit and adaptive quantum technologies. If entanglement across QPUs is supported, then quantum states can be shared between qubits on remote quantum processors. This requires a specialized architecture with data and communication qubits with non-local gates such as telegates and teledata gates. This paper presents our progress towards a framework for exploring quantum distribution at the algorithm and circuit levels.

III. FRAMEWORK OF HYBRID QUANTUM-MACHINE LEARNING CLASSIFIER FOR HIGH-DIMENSIONAL DATA OPTIMIZATION

In this section framework of Hybrid Quantum-Machine Learning Classifier for High-Dimensional Data Optimization is observed in figure1. The hybrid quantum machine learning framework designed to improve the efficiency and accuracy that deals with high-dimensional data. The input dataset is collected initially, which may include complex, high-dimensional information such as medical, financial, or image data. The normalization and feature scaling are applied to ensure all input features are on a comparable scale in preprocessing phase. The categorical attributes are encoded numerically, and noisy or redundant features are reduced to make the dataset accurate for quantum encoding. The classical features are transformed into quantum states using parameterized quantum circuits (PQCs) in preprocessing to cleaned data is fed into the Quantum Feature Encoder. That numerical features are encoded into qubits through techniques like amplitude or angle encoding in these circuits apply quantum gates.

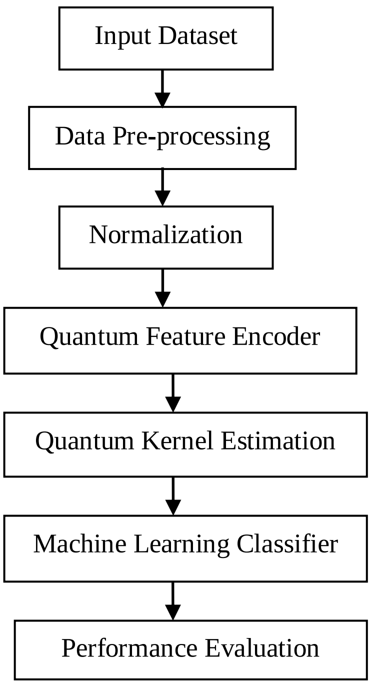

Figure.1: Framework of Hybrid Quantum-Machine Learning Classifier for High-Dimensional Data Optimization

Next, the Quantum Kernel Estimation module, implemented through a Quantum Support Vector Machine (QSVM). It evaluates the similarity between quantum states. In a high-dimensional Hilbert space, kernel acts as a nonlinear mapping function that separates complex data classes. The QSVM efficiently computes relationships that would otherwise require heavy computation in classical systems to exploiting quantum interference. This step provides quantum-enhanced features to carry better data content when compared to conventional feature extraction methods. The Machine Learning Classifier is used to generate quantum features. The quantum-enhanced data representations and performs the final prediction learns to recognize class boundaries in classical classifier. In a hybrid model that combines the strengths of both paradigms quantum computational power and classical interpretability by integration of quantum feature mapping with classical classification results. The hybrid quantum-assisted approach significantly improves classification accuracy, enhances generalization, and reduces computational complexity demonstrates in this comparative analysis with traditional classifiers.

Data preprocessing in quantum computing involves transforming raw data into a format suitable for quantum algorithms, which includes classical steps like cleaning and feature scaling, and quantum-specific steps like encoding data into qubits. This process is critical for making data usable by quantum computers, ensuring higher accuracy and efficiency by handling issues like noisy data, and leveraging quantum parallelism for potential computational speedups.

Normalization in quantum computing is the process of scaling a wave function so that the total probability of finding a particle is equal to 1. This is crucial because quantum mechanics uses wave functions to describe the probability of a particle's location, and the sum of all possible outcomes must equal one for the probabilistic interpretation to be valid. Mathematically, it involves multiplying the wave function by a constant, ensuring that the integral of its squared magnitude over all space equals 1.

A quantum feature encoder, also known as a quantum feature map, is a process that translates classical data into quantum states using a quantum circuit. This is a crucial step in quantum machine learning (QML), as it allows classical data to be processed by quantum algorithms by representing it in a high-dimensional quantum state space, such as a Hilbert space. Different encoding methods, like amplitude encoding or angle encoding, are used to map the data in ways that can potentially make patterns easier to find than in classical computing. Quantum Kernel Estimation (QKE) is a technique in quantum machine learning that uses a quantum computer to estimate a kernel function, which is then used by a classical computer to train algorithms like Support Vector Machines (SVMs). It maps classical data into a quantum feature space, where a quantum kernel measures the similarity between data points, and can potentially handle problems that are difficult for classical algorithms alone.

IV. RESULT ANALYSIS

In this section, result analysis of Hybrid Quantum-Machine Learning Classifier for High-Dimensional Data Optimization is observed. In table.1, performance comparison is observed between hybrid Quantum-Machine Learning Classifier is compared with holistic hybrid quantum noise model and quantum amplitude hash function interms of accuracy, precision and efficiency.

Table.1: Performance Comparison

Parameters	Accuracy	Precision	Efficiency
Quantum amplitude hash function	96.3	97.8	96.7
Holistic hybrid quantum noise model	97.1	97	95.4
Hybrid Quantum-Machine Learning Classifier	98.2	98.9	97.4

In this figure 2, x-axis demonstrates methods and y-axis demonstrates percentage. A comparison graph of accuracy is observed between Quantum-Machine Learning Classifier for High-Dimensional Data Optimization of hybrid Quantum-Machine Learning Classifier is compared with other existing system.

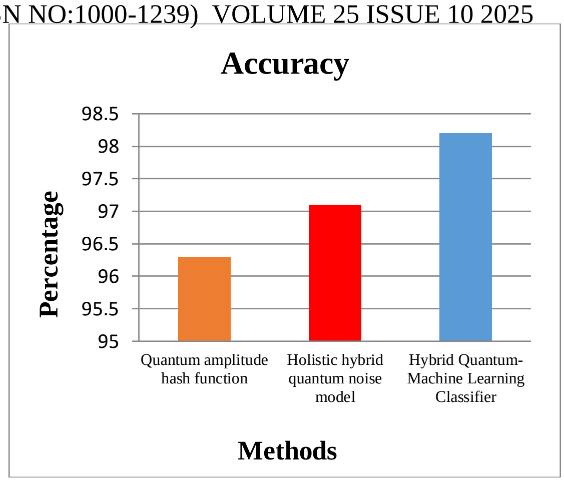

Figure.2: Accuracy Comparison Graph

In this figure 3, precision comparision graph is observed between Quantum-Machine Learning Classifier for High-Dimensional Data Optimization of hybrid Quantum-Machine Learning Classifier is compared with other existing system. In this graphical representation, x-axis demonstrates methods and y-axis demonstrates percentage.

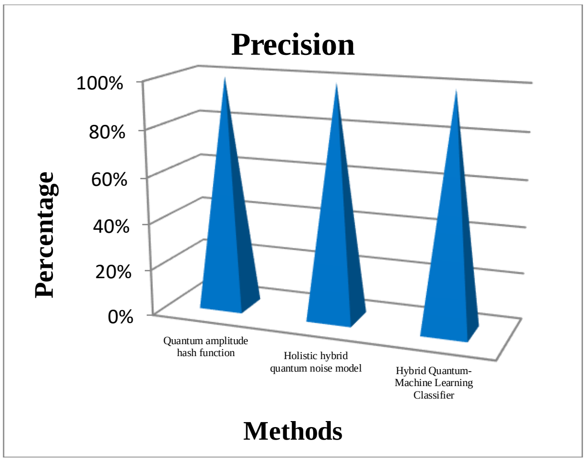

Figure.3:Precision Comparison Graph

The Quantum-Machine Learning Classifier for High-Dimensional Data Optimization of hybrid Quantum-Machine Learning Classifier is compared with other existing system for efficiency in figure 4. In this graphical representation, x-axis demonstrates methods and y-axis demonstrates percentage.

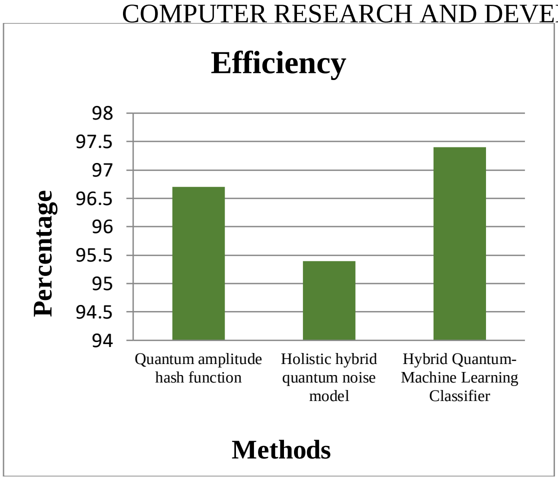

Figure.4: Efficiency Comparison Graph

V. CONCLUSION

In this section, Hybrid Quantum-Machine Learning Classifier for High-Dimensional Data Optimization is concluded. Quantum computing is integrated with machine learning classifiers significantly enhances classification performance in high-dimensional datasets. The quantum kernel's ability to explore exponentially large feature spaces while retaining the interpretability of ML classifier by using Quantum-Assisted Machine Learning model. The quantum feature extraction improves both accuracy and generalization in this result.

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