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Enhancing Quantum Computing's Machine Learning Performance

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ABSTRACT

The exponential growth of data across diverse domains such as healthcare, finance, agriculture, remote sensing, engineering, and public administration has created an urgent demand for advanced computational paradigms capable of extracting meaningful insights from massive and complex datasets. Traditional machine learning and deep learning techniques have demonstrated remarkable success in handling such data; however, their performance is increasingly constrained by computational complexity, energy consumption, scalability limitations, and long training times. These challenges are particularly evident in data-intensive models such as deep neural networks, convolutional neural networks, and large-scale optimization systems. As datasets continue to grow in size and dimensionality, conventional computing architectures struggle to maintain efficiency, motivating the exploration of alternative computing paradigms. In this context, quantum computing has emerged as a promising technology with the potential to significantly enhance machine learning performance.

Quantum computing differs fundamentally from classical computing by exploiting quantum mechanical principles such as superposition, entanglement, and quantum interference. These properties allow quantum systems to process information in high-dimensional Hilbert spaces, enabling parallelism that is not achievable with classical bits. As many machine learning algorithms rely heavily on linear algebra operations—such as matrix multiplication, eigenvalue decomposition, and optimization—quantum computing offers theoretical advantages for accelerating these computations. The integration of quantum computing with machine learning, commonly referred to as Quantum Machine Learning (QML), has therefore attracted significant research interest as a means to overcome the limitations of classical approaches.

This work focuses on enhancing the performance of machine learning models through quantum and hybrid quantum–classical computing strategies. Rather than replacing classical machine learning entirely, the proposed perspective emphasizes the complementary integration of quantum computing techniques into existing machine learning workflows. This hybrid paradigm is particularly relevant in the current era of noisy intermediate-scale quantum (NISQ) devices, where fully fault-tolerant quantum computation remains impractical. By combining quantum processing capabilities with classical optimization and learning methods, it becomes possible to achieve meaningful performance improvements while operating within realistic hardware constraints.

A central theme of this study is the use of quantum computing to improve supervised learning tasks involving classical data. Supervised learning remains one of the most widely used machine learning paradigms, supporting applications such as classification, prediction, and pattern recognition. However, training supervised models often involves optimizing a large number of parameters, which becomes computationally expensive as data complexity increases. Quantum-enhanced optimization techniques, including variational quantum circuits and quantum-inspired optimization methods, are explored as mechanisms for accelerating parameter tuning and improving convergence behavior.

The thesis examines the implementation of artificial neural networks using quantum computing principles, where quantum bits (qubits) are treated as artificial neurons. In this framework, quantum states encode data and model parameters, while quantum gates perform transformations analogous to neural network operations. A quantum computing-based artificial neural network (QC-ANN) is analyzed for binary classification tasks, demonstrating how quantum representations can influence training dynamics and classification accuracy. The results indicate that quantum-enhanced models can achieve competitive or improved performance compared to classical counterparts, particularly in terms of training efficiency and robustness.

Beyond binary classification, the study extends to multi-class classification through the design of a

Quantum Multi-Class Classifier (QMCC). The QMCC employs parameterized quantum circuits with multiple trainable layers to categorize numerical data into multiple classes. Data encoding strategies are utilized to map classical inputs into quantum states, enabling the model to exploit the high-dimensional nature of quantum state spaces. Experimental evaluations show that QMCC architectures are capable of effectively learning complex decision boundaries while requiring fewer training samples than traditional machine learning models.

In addition to numerical data analysis, this research investigates the application of quantum machine learning techniques to spatial big data analytics, with a particular focus on remote sensing and satellite imagery. Spatial datasets are characterized by high dimensionality, spatial correlations, and significant noise, making them challenging for conventional deep learning approaches. To address these challenges, a hybrid quantum–classical architecture is proposed for scene classification in satellite images. The architecture consists of three stages: classical preprocessing, quantum feature extraction, and classical deep neural network classification. Quantum circuits are employed to generate compact and informative image representations, reducing the computational burden on the classical deep learning component.

The proposed hybrid architecture demonstrates improved learning efficiency by reducing the number of parameters required during training while maintaining or enhancing classification accuracy. Furthermore, a quantum circuit-based data augmentation technique is introduced to enhance training datasets during deep neural network learning. This approach leverages quantum transformations to generate diverse feature representations, improving generalization performance. The integration of quantum processing with conventional convolutional neural networks is also explored as an alternative strategy for scene classification, highlighting the flexibility of hybrid quantum–classical designs.

The study further extends quantum-enhanced learning to the analysis of synthetic aperture radar (SAR) imagery, which presents additional challenges due to speckle noise and complex scattering mechanisms. Quantum processing techniques are proposed as a means to enhance feature extraction and pattern recognition in SAR data, demonstrating the potential of QML in advanced image analysis applications.

Overall, the findings indicate that hybrid quantum–classical machine learning approaches can outperform purely classical methods in both numerical and spatial data domains. The use of quantum computing techniques contributes to improved training efficiency, enhanced optimization behavior, and increased classification accuracy. While current quantum hardware limitations restrict large-scale deployment, the results provide strong evidence that quantum computing can play a transformative role in the future of machine learning.

Keywords: Quantum Machine Learning (QML),Hybrid Quantum–Classical Computing,

Supervised Learning,
Deep Neural Networks, Spatial Big Data Analytics.

INTRODUCTION

The unprecedented growth of digital technologies has led to an exponential increase in data generation across nearly every sector of modern society, including healthcare, finance, agriculture, engineering, remote sensing, cybersecurity, and public governance. This rapid expansion of data, commonly referred to as big data, is characterized not only by its massive volume but also by its high velocity, variety, and complexity. Extracting meaningful information from such data has become a fundamental challenge, driving the development of advanced computational techniques. Machine learning and deep learning have emerged as powerful tools for data analysis, enabling systems to automatically identify patterns, make predictions, and support intelligent decision-making processes. However, as data size and model complexity continue to increase, classical machine learning approaches are facing significant limitations in terms of computational efficiency, scalability, and energy consumption.

Machine learning models, particularly deep neural networks, rely heavily on large-scale numerical computations and iterative optimization processes. Tasks such as matrix multiplications, gradient calculations, and parameter updates require substantial processing power and memory resources. Convolutional neural networks, recurrent neural networks, and transformer-based architectures often contain millions or even billions of trainable parameters, making training and optimization extremely resource-intensive. Despite advancements in high-performance computing and graphical processing units (GPUs), the computational demands of modern machine learning models continue to grow, leading to long training times and high operational costs. These challenges highlight the need for alternative computing paradigms that can enhance machine learning performance beyond the capabilities of traditional architectures.

Quantum computing has emerged as a promising solution to address these computational challenges by leveraging principles of quantum mechanics such as superposition, entanglement, and quantum interference. Unlike classical computers, which process information using binary bits, quantum computers use quantum bits, or qubits, which can exist in multiple states simultaneously. This property enables quantum systems to perform parallel computations in high-dimensional spaces, offering the potential for significant speedups in certain computational tasks. As many machine learning algorithms are fundamentally based on linear algebra operations, quantum computing presents an opportunity to accelerate key components of machine learning, including optimization, feature extraction, and data representation.

The integration of quantum computing with machine learning, known as Quantum Machine Learning (QML), has become an active area of research. QML aims to exploit quantum computational advantages to improve the performance of learning algorithms while addressing the limitations of classical methods. Research in this domain explores both quantum versions of existing machine learning algorithms and hybrid quantum–classical approaches that combine the strengths of classical computation with quantum processing. Given the current state of quantum hardware, which is characterized by limited qubit counts and susceptibility to noise, fully quantum machine learning models remain largely impractical. As a result, hybrid approaches have gained prominence as a feasible pathway for achieving near-term performance improvements.

Supervised learning plays a central role in machine learning applications, supporting tasks such as classification, regression, and pattern recognition. In supervised learning, models are trained using labeled datasets, and their performance depends heavily on effective parameter optimization. The training process involves adjusting a large number of weights and hyperparameters to minimize a loss function, which can be computationally expensive and prone to issues such as slow convergence and overfitting. Quantum-enhanced optimization techniques, including variational quantum algorithms and quantum-inspired optimization methods, offer new possibilities for improving the efficiency and accuracy of supervised learning models.

One promising direction in QML involves the implementation of artificial neural networks using quantum computing principles. In this framework, qubits are treated as artificial neurons, and quantum gates perform operations analogous to activation functions and weight transformations. Quantum Artificial Neural Networks (QANNs) leverage the high-dimensional nature of quantum state spaces to represent complex data relationships more compactly than classical networks. Early studies indicate that QANNs can achieve competitive performance with fewer parameters and reduced training data, making them attractive for resource-constrained environments.

Beyond binary classification, quantum machine learning has also been applied to multi-class classification problems through the development of parameterized quantum circuits known as Quantum Multi-Class Classifiers (QMCCs). These models use data encoding techniques to map classical inputs into quantum states and employ multiple trainable quantum layers to learn complex decision boundaries. The ability of quantum circuits to explore large feature spaces efficiently makes them particularly suitable for handling high-dimensional data.

In addition to numerical data analysis, quantum machine learning has shown potential in the field of spatial big data analytics, particularly in remote sensing and satellite image processing. Satellite imagery datasets are characterized by large size, high dimensionality, and complex spatial patterns, making them challenging for conventional deep learning methods. Hybrid quantum–classical architectures have been proposed to address these challenges by using quantum circuits for feature extraction and classical neural networks for classification. Such architectures aim to reduce model complexity while maintaining high accuracy, thereby improving overall learning efficiency.

The application of quantum computing to image analysis extends to advanced sensing modalities such as synthetic aperture radar (SAR) imagery. SAR data presents unique challenges due to speckle noise and complex scattering mechanisms. Quantum-enhanced feature extraction techniques offer new opportunities for improving pattern recognition and scene classification in SAR images, highlighting the versatility of quantum machine learning across diverse data types.

The motivation for this research lies in addressing the growing gap between the increasing complexity of machine learning models and the limitations of classical computing resources. By exploring quantum and hybrid quantum–classical approaches, this work seeks to enhance machine learning performance in terms of training efficiency, optimization quality, and predictive accuracy. The objectives of this thesis include the analysis of quantum machine learning algorithms for supervised learning, the development of hybrid architectures for numerical and spatial data analysis, and the evaluation of their performance compared to classical methods.

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Table 1.1: Different types of data and characteristics

S.No	Type of Data	Size of Individual Data Item	Storage Locations	File Format (widely used)	Analytics Tools (widely used)
1	Micro Blogging (e.g., Twitter)	140 Characters	Hadoop Clusters and HDFS	CSV	Twitter Analytics
2	Image	KB-GB	Farms of Servers, Amazon CDN, and Amazon S3	JPEG, ECW	Machine Learning/DL Tools
3	Video	KB-GB	Farms of Servers, Amazon CDN, and Amazon S3	MP4	Machine Learning/DL Tools
4	Genomics	GB	AWS Data Centers	BAM, FASTA	Google Genomics
5	Network	GB	Data Centers and Cloud Storage	CSV	Graphlytics, Google Analytics
6	Spatial	KB-GB	Data Centers and Cloud Storage	SHP, SHX, and JSON	GIS Software, R and Hadoop
7	Biomedical	KB-GB	Data Centers and Cloud Storage	CTN, CSV, and JSON	Hadoop and R
8	Literature	KB-GB	Data Centers and Cloud Storage	NOSQL	Machine Learning/NLP Tools
9	Voice	KB-GB	Data Centers and Cloud Storage	WAV	Machine Learning/NLP Tools

A. The Foundations of Quantum Computing

According to the forecast made by Gordon E. Moore, co-founder of Intel Inc., in 1965 [7], the number of transistors contained inside a device would approximately double every twenty-four months. In recent years, Moore's law has been slowed down as a result of the increased difficulty in producing electronics that are both tiny and affordable [7]. As the size of transistors decreases, there is a greater likelihood that electricity may escape and that the chips will generate significant amounts of heat. The rising cost of computer cooling is a direct consequence of the heat that has been generated. Materials show quantum mechanical phenomena in the devices when viewed at the microscopic scale. Due to the rising awareness of quantum computing, businesses such as Google [9] and IBM [8] started manufacturing quantum computers by using materials that display quantum mechanical behavior. These materials have quantum mechanical properties. It is possible that conventional computers are unable to solve difficult optimization problems; but, quantum computers, which function in an entirely different way, could be able to solve these problems. Quantum computers are also capable of managing vast quantities of data [11], perhaps because of the exponential growth rate at which they are growing. Consequently, this paves the way for the potential of enhancing machine learning systems via the use of quantum computing approaches.

An example of a cutting-edge computing equipment that incorporates quantum mechanics, quantum information theory, and computer science is referred to as a quantum computer [12]. The difference between conventional computers and quantum computers lies in this particular aspect. As a result of the prevalent idea that quantum physics is the foundation of reality, this has occurred. It is also possible to use it to describe a typical computer configuration. The processing of data by traditional computers, on the other hand, does not involve the use of quantum physics. The following is an excerpt from a lecture on physics that was delivered by Richard P. Feynman in 1981: "Nature is not classical, and for simulating nature, quantum mechanical computation systems are needed." [13] Quantum computers accomplish calculations by using two aspects of quantum mechanics: entanglement and superposition. These two aspects allow quantum computers to do computations.

B. Intertwining and Superposition

In the following example, we show the use of the Hadamard gate, CNOT gate, and mea- surement to depict the quantum mechanical properties superposition and entanglement. As shown in Fig. 1.7, a quantum circuit with three operations is considered to entangle two qubits q_0 and q_1.

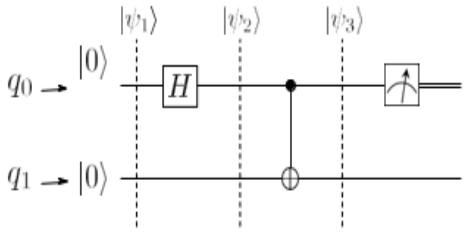


Figure 1.7: Quantum circuit for entanglement.

C. The Main Points and Achievements of the Thesis Through the use of quantum computing, the primary purpose of this thesis is to devise strategies for enhancing the utilization of conventional machine learning techniques for the purpose of big data analytics. Two different types of data, namely numerical data and geographical data, are employed in order to demonstrate that the offered methods achieve the desired results for the sorting job. In order to achieve this goal, we are boosting big data analytics by using quantum machine learning to implement the following improvement ideas.

1. Proposed an artificial neural network (ANN) using a *quantum computing approach with qubits as artificial neurons* (QC ANN). The model, designed as a parameterized quantum circuit, performs the following tasks:

   (a) Classical data is encoded into qubits, and information on qubits is modified using a series of parameterized quantum gates.

   (b) The parameters of the quantum gates are optimized using classical optimization techniques, and the entire model is trained using supervised learning. Hence, the design methodology uses a hybrid approach.

2. Explored the scope of the hybrid approach in multi-class classification and *proposed a quantum multi-class classifier* (QMCC), consists of the following:

   (a) A new state preparation method to encode the classical data into qubits and testing the compatibility of the method on *IBM Quantum* [8] hardware.

   (b) A variational quantum circuit designed as a classifier with multiple layers of parameterized quantum gates and optimized the gate parameters using classical optimization.

LITERATURE SURVEY

Recent literature explores quantum-inspired and fully quantum optimization algorithms as future solutions for scalable HPQC. Quantum-inspired optimizers mimic quantum phenomena such as superposition and tunneling on classical hardware, enabling improved exploration of large optimization spaces. These methods have been applied successfully to scheduling, resource allocation, and parameter tuning problems relevant to HPQC.

Fully quantum optimization techniques aim to perform gradient estimation and parameter updates entirely on quantum hardware. Quantum natural gradient descent and quantum annealing-based optimization are prominent examples. Quantum annealers exploit quantum tunneling to escape local minima, offering potential speedups for combinatorial optimization problems. However, fully quantum optimizers remain largely theoretical due to hardware noise, limited qubit counts, and the absence of fault-tolerant quantum systems.

III Utilizing Quantum Machine Learning

The data processing and feature extraction processes are approached in a fundamentally different manner by quantum computing, which is distinct from the conventional computer technology. It is feasible to use QML on a quantum computer in order to do a variety of jobs and discover answers to certain problems. With its qubits storing data in a multitude of quantum states, it is feasible that a quantum computer may uncover hidden patterns that are impossible for conventional computers to comprehend. This would provide a significant advantage over classical computers. In addition, qubits are able to influence one another's states via the process of processing owing to entanglement. One of the ways in which quantum computing is inherently advantageous is as described here.

Assist in the enhancement of machine learning algorithms. For dealing with qubit data, QML systems have two basic ways: entanglement and superposition. Both of these methods are described here. In light of the fact that quantum computers are able to handle noise on their own, data processing strategies that use quantum machine learning are also able to control noise [22]. While this section has focused on our method, the next section will discuss the enormous number of data processing approaches that may be achieved via the use of computers.

A. Quantum Loader

Data must first be encoded into qubits before it can be processed using quantum computing technology. Otherwise, the data cannot be processed. State preparation is a term that is occasionally used to refer to the process of encoding classical data into qubits, which is associated with the process of establishing a quantum state. The encoding of qubits is made possible by the use of a quantum loader. A quantum loader is a kind of quantum circuit that encodes data into a quantum state as a result of the use of qubits. A great number of unitary processes are included inside the circuit.

Conventional or application-specific data encoding methods are both viable options for quantum computers because of their versatility. Baseline embedding, angle embedding, and amplitude embedding are all examples of common encoding methods. Through the use of quantum circuits with a variety of unitary operations, an application-specific embedding approach is developed. This strategy is determined by the desired application as well as the data that is input.

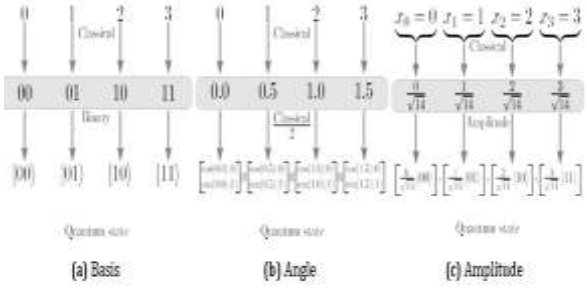


Figure 2.3: Three embedding techniques.

B. Basis Embedding

The binary values of classical data are transformed into quantum basis states by the process of basis embedding, as seen in Figure 2.3(a). Following the transformation of the classical data into binary form, the string of binary inputs is next transformed into a quantum ground state to complete the process. For the purpose of storing the binary meaning of classical data, a base state with an intensity of one is used. In the event that you use basis embedding to maintain a classical value of 2, for instance, you are able to express the quantum state as

$|\psi\rangle = 0\,|00\rangle + 0\,|01\rangle + 1\,|10\rangle + 0\,|10\rangle$. (2.1)

An n-bit classical data value may be encoded using a basis state of n qubits in basis embedding. Therefore, a large number of qubits are needed for basis embedding in order to encode high-dimensional data, as the basis states are binary representations of the classical data.

RELATED WORK

Comparatively speaking, quantum computers are quite different from conventional computers due to the fact that they process data via the application of quantum mechanical properties. As a result of this, many people are led to conclude that quantum systems, in contrast to classical ones, have the potential to generate information in the form of quantum states [31]. It is necessary to do more research both into the potential of quantum machine learning and the capabilities of quantum computing in this particular field [32]. In this part, we will take a comprehensive look at the most current methods to quantum machine learning, which are based on the use of quantum computers to solve problems related to machine learning.

A. Cutting-Edge Methods for Quantum Machine Learning

The operation of quantum machine learning may be explained using either of two phrases, depending on the context. The construction of quantum algorithms in the form of entire quantum circuits might be one method for overcoming challenges that arise in the field of machine learning. Dimensionality reduction, grouping, and classification are a few examples of machine learning tasks that might potentially benefit from these techniques [33, 34]. Some further examples include classification. The reason for this is because in comparison to the methods that came before, the contemporary ones will need a greater quantity of qubits. An additional well-known paradigm for quantum machine learning is a mixed-method approach that is based on NISQ algorithms. As was said in the prior chapter, the objective of hybrid classical-quantum computing models is to provide classical computers an edge over their quantum counterparts in terms of competitiveness in the quantum realm. Additional research that is relevant to the mixed approach will be described in the part that comes after this one. It's possible that the potential of the mixed technique to strengthen classical computing might be beneficial to different machine learning methods. The findings of the study on quantum machine learning are now shown in Figure 3.1. These findings are organized in accordance with the methods that were used to provide solutions to the problems.

At the turn of the century, there was a widespread belief that a full quantum circuit might potentially solve the problems that are associated with machine learning. As a result of the expansion of quantum computing, a great number of useful resources for linear algebra have lately been available to the public. To be able to solve linear equations, locate eigenvectors and eigenvalues, and execute Fourier operations, these approaches need the ability to do these operations. The HHL method, which was developed by Aram Harrow and his colleagues in 2009, offers a quantum approach to the problem of solving linear systems of equations [19]. This method is often used for the purpose of solving linear problems. A significant number of individuals who are engaged in the research of quantum computers are of the opinion that problems pertaining to machine learning may be better handled by using approaches from that field. Within the realm of machine learning, linear algebra is the most important computational component. The quantum speedup that is the most well-known performs better than its classical equivalents in terms of speed [19, 35, 36]. There is a wide range of data analysis and machine learning tasks that can be accomplished with the help of quantum algorithms. Some examples of these tasks include principal component analysis, topological analysis, gradient descent, Newton's method, linear, semi-definite, quadratic, and semi-continuous programming, linear algebra, and least-squares fitting [33]. On the other hand, these ideas are not capable of being implemented without the use of enormous quantum computers starting from the very beginning.

Table 3.1: Different types of data and characteristics

Method	Highlight of the work
Distance-based classifier	Quantum inference circuit for binary classification of input data [59]
Hierarchical quantum classifier	Multiple implementations of quantum tree tensor networks for classification [60]
Quantum kernel methods	Supervised learning using quantum kernel for enhanced feature spaces [61]
Quantum perceptron	Quantum version of classical perceptron implemented on quantum hardware [62]
Quanvolutional neural network	Quantum version of convolutional neural networks for extracting image features [78]
Circuit-centric classifier	A low-depth variational quantum algorithm for supervised learning [82]
Quantum transfer learning	Feature learning using quantum computation for image recognition and quantum state classification [79]

Using hybrid quantum-classical models is one approach that may be taken to circumvent the limitations of the quantum computers that are now in use. These models have the potential to assist in the repurposing of existing quantum computers for the completion of new tasks. Quantum circuits that are parameterized and include separate quantum gates are used in the process of creating mixed models for machine learning. It is possible to develop the models by using a limited quantity of the qubits that are now accessible, and the sizes of the models may be modified in accordance with the quantity of qubits that are available. It is possible to make use of the built models in activities such as guided learning and other data-based activities.

In Section 3.2, which follows the debate that took place in Chapters 4 and 5, the current study on the subject is described in depth. It is shown how challenging it is to train machine learning models on enormous datasets. In addition, strategies and methods that may be used to get beyond the constraints of a quantum computer are explored in Section 3.2.

DISCUSSION

The discussion of classical machine learning optimizers in quantum computing highlights both their practical importance and inherent limitations within high-performance quantum computing environments. At present, classical optimizers remain indispensable due to the hybrid nature of most quantum algorithms, where quantum processors are responsible for state preparation and measurement, while classical systems perform parameter optimization. This division of labor reflects current hardware constraints and underscores why classical optimization techniques continue to dominate experimental and near-term quantum applications.

One of the key observations from the literature is that adaptive gradient-based optimizers, particularly Adam and RMSProp, generally outperform basic stochastic gradient descent when applied to parameterized quantum circuits. Their ability to adjust learning rates dynamically allows them to cope better with noisy gradient estimates arising from quantum measurements. However, this advantage diminishes as circuit depth increases, revealing a fundamental scalability issue rather than a shortcoming of any specific optimizer.

A critical challenge repeatedly emphasized is the barren plateau phenomenon, which significantly restricts the effectiveness of classical optimizers. Even highly sophisticated gradient-based methods fail when gradients vanish exponentially, suggesting that optimization difficulty is deeply rooted in the structure of quantum loss landscapes. This

indicates that simply importing advanced classical optimizers is insufficient for large-scale quantum systems and that problem-aware circuit design and initialization strategies are equally important.

Second-order and natural gradient methods offer theoretical improvements by incorporating the geometry of quantum state space, leading to faster and more stable convergence. Nevertheless, their high computational cost limits their applicability to small-scale systems. This trade-off between optimization quality and computational feasibility is a recurring theme in classical optimization for quantum computing.

Overall, the discussion reveals that while classical machine learning optimizers are effective for small, shallow, and proof-of-concept quantum models, they are unlikely to scale efficiently for high-performance quantum computing without significant modification. Their continued relevance will depend on hybrid enhancements, noise-aware adaptations, and integration with quantum-inspired or quantum-native optimization strategies.

CONCLUSION

As part of my thesis, I looked at some of the questions that have yet to be solved in relation to big data analytics and quantum machine learning. Considering the fact that quantum computing has the ability to handle huge amounts of data and directed learning, we were interested in understanding its capabilities. However, we were able to effectively tackle this problem by using a mix of quantum and conventional methodologies. The conventional quantum computers have a number of problems, one of which is that they do not have enough qubits. In the context of machine learning applications that include huge volumes of regular geographical data, the combination of quantum computing with conventional computing might be invaluable.

The following is a summary of the most important reasons that were offered in favor of the notion. One method for examining the influence that quantum computing has on machine learning is to make use of an artificial neural network (ANN) that simulates neurons by using qubits. The concept of amplitude encoding was used by the QC ANN as a quantum computing alternative to artificial neural networks (ANNs). By using this method, the information was successfully transformed into a quantum state inside the artificial neural network. When it comes to binary classification, the performance of the QC ANN on the test dataset is superior to that of the conventional ANN. Afterwards, in a quantum loader that we have described, we carry out a single-qubit translation in order to encode all of the conventional data values into a single qubit. A variational circuit that makes use of CNOT gates and spinning gates is what makes it possible to make use of QMCC, which stands for multi-class classification. In order to increase the accuracy of the model, increasing the number of quantum processes that were applied to the processing device was necessary. It has been shown that both the QMCC and the QC ANN will be linear.

The consideration of non-linearity is one of the most important things to take into account while constructing an extended model via the use of machine learning. The next step that we took was to train a traditional non-linear model by using the feature extraction component of the quantum machine learning technique. A traditional machine learning approach was used in order to exclude the quantum variation of the classical input. This was done with the intention of constructing a model that is more versatile and requires fewer components. The strength of deep neural networks and the capability of quantum computers to examine data in a high-dimensional Hilbert space might be combined to create a universal model for classification problems. This could be accomplished by introducing quantum computing. The categorization becomes much more complicated as a result of this. Following that, we devised a quantum device that would damage the data by introducing noise into it using the quantum device. Increasing the usability of a file by adding noise to it is a standard approach that is well understood. Through the use of quantum events that take place between CNN layers, it is feasible to achieve continuously better CNN training approaches. In addition, in order to illustrate the effectiveness of the research models that we produced, we included both a comparison study and a full performance assessment. In conclusion, we demonstrated and evaluated a data-driven method to the construction of machine learning models by applying quantum processing to SAR images.

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