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Overview of Quantum Computing in Quantum Neural Network and Artificial Intelligence

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ABSTRACT

In recent years, quantum computing has emerged as a potentially game-changing technology, with applications across various disciplines, including AI and machine learning. In recent years, the combination of quantum computing and neural networks has led to the development of quantum neural networks (QNNs). This paper explores the potential of QNNs and their applications in solving complex problems that are challenging for classical neural networks. This paper explores the fundamental principles of quantum computing, the architecture of QNNs, and their advantages over classical neural networks. Furthermore, this will highlight key research areas and challenges in the development and utilization of QNNs. Through an in-depth analysis, it demonstrates the QNNs hold significant promise for addressing complex computational problems and advancing the field of artificial intelligence.

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1.0 INTRODUCTION

Quantum neural networks (QNNs) represent an exciting intersection of two cutting-edge fields: quantum computing and artificial neural networks. These networks hold immense potential for revolutionizing various domains, from machine learning and optimization to drug discovery and complex data analysis (Schuld *et al.*, 2014; Schuld *et al.*, 2020). By harnessing the power of quantum

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mechanics, QNNs offer the possibility of solving complex problems more efficiently than classical neural networks. Traditional neural networks, which draw inspiration from the structure of the human brain, are composed of interconnected layers of artificial neurons that analyse and transmit data (Adcock and Nowotny, 2015). They have proven to be highly successful in diverse applications such as image identification, natural language understanding, and speech processing. However, as problems become more intricate, the computational demands increase exponentially, posing significant challenges for classical computers (Biamonte et al., 2017; Wang et al., 2019; Dunjko et al., 2020).

1.1 Background

1.1.1 Quantum Computing

Quantum computing explores a quantum mechanics, a branch of physics that describes the behaviour of matter and energy at the smallest scales.

1.1.2 Artificial Neural Networks

ANNs consist of interconnected artificial neurons organized in layers. Each neuron receives inputs, applies a mathematical operation to them, and produces an output. By stacking multiple layers of neurons, ANNs can learn complex patterns and make predictions or classifications based on input data. ANNs have proven highly successful in various domains, including computer vision, natural language processing, and speech recognition. However, as problems become more complex, traditional ANNs face challenges due to computational limitations, such as the curse of dimensionality and the need for extensive training data.

1.1.3 Quantum Neural Networks

They aim to leverage the unique properties of qubits, such as superposition and entanglement, to enhance the capabilities of classical neural networks. By incorporating quantum algorithms and quantum circuits into the structure and operations of neural networks, QNNs have the potential to solve certain problems more efficiently and accurately. The potential applications of QNNs span across various domains.

1.2 Motivation

- *Computational Power:* Quantum computing offers the potential for exponentially faster computation compared to classical computers for certain problems. By integrating quantum computing principles into neural networks, QNNs can potentially overcome the computational limitations of classical neural networks and enable more efficient solutions to complex problems.
- *Complex Data Analysis:* Many real-world problems, such as optimization, pattern recognition, and data analysis, involve high-dimensional and intricate datasets. Classical neural networks face challenges in processing and extracting meaningful insights from such complex data.
- *Quantum Advantage:* Quantum algorithms, such as Grover's algorithm and quantum support vector machines, have shown that certain computational tasks can be performed more efficiently on quantum computers compared to classical algorithms.

- *Quantum Simulation:* Quantum systems, such as molecules and materials, are difficult to simulate using classical computers due to their exponential complexity. QNNs offer a pathway to simulate and understand quantum systems more accurately by leveraging the principles of quantum computing.
- *Future-proofing Machine Learning:* As machine learning and artificial intelligence continue to advance, the demand for more powerful computational tools increases. Exploring the potential of QNNs is driven by the need to develop future-proof machine learning techniques that can tackle ever-growing data volumes and complex problem domains.

1.3 Objective

This survey explores the potential applications of artificial neural networks in various domains, including technical, organizational, and economic fields. It presents a practical approach for incorporating artificial neural networks into different applications and discusses the prospects of utilizing them in product development. It emphasizes that artificial neural networks are not magical solutions, but rather designs grounded in robust mathematical principles.

Neural networks better than computer for processing of sensorial data such as “signal processing, image processing, pattern recognition, robot control, non-linear modelling and prediction.”

2.0 QUANTUM COMPUTING AND NEURAL NETWORKS

2.1 Quantum Computing Fundamentals

Quantum computing goes beyond the conventional use of bits in classical computers to represent and process information. Instead, quantum computers utilize qubits, which have the unique property of existing in multiple states simultaneously.

Key principles and fundamentals of quantum computing include:

- *Superposition:* This means that a qubit can be in a state that represents both 0 and 1 at the same time, allowing for parallel processing of information.
- *Entanglement:* Entanglement is a phenomenon in which two or more qubits become interconnected in a manner where the state of one qubit is linked to the state of the other(s). Through entanglement, quantum computers can perform computations on a large number of qubits simultaneously, leading to potentially exponential speedup for certain types of problems.
- *Quantum Gates:* These gates operate on qubits, manipulating their states in various ways to perform computational operations. Examples of quantum gates include the “Hadamard gate, CNOT gate, and the Pauli gates (X, Y, Z).”
- *Quantum Algorithms:* Quantum algorithms are designed specifically to harness the power of quantum computing. Notable examples include Shor’s algorithm, which can factor large numbers exponentially faster than the others.

2.2 Neural Networks - Classical vs. Quantum

Neural networks, both classical and quantum, are computational models inspired by the structure and functionality of the human brain. They are used for various tasks such as pattern recognition, classification, regression, and optimization.

2.2.1 Classical Neural Networks

Classical neural networks, also known as artificial neural networks (ANNs), are based on classical computing principles and are the foundation of modern deep learning. They consist of interconnected layers of artificial neurons, where each neuron performs a simple computation on its input and passes the result to the next layer. The connections between neurons are characterized by weights, and during training, these weights are adjusted to optimize the network's performance.

The most common type of classical neural network is the feedforward neural network, where data flows in one direction, from input to output layers.

2.2.2 Quantum Neural Networks

Quantum neural networks are a more recent development that leverages the principles of quantum mechanics to perform certain computations more efficiently than their classical counterparts. The foundation of quantum neural networks is quantum computing, a new paradigm that uses quantum bits (qubits) to represent data and perform computations.

Quantum neural networks attempt to harness quantum entanglement and superposition to process information in a fundamentally different way. They have the potential to perform certain tasks exponentially faster than classical neural networks, especially for problems that require large-scale parallelism or complex quantum interactions.

2.3 Quantum Machine Learning

This fusion aims to leverage the unique properties of quantum systems to enhance the capabilities of traditional machine learning algorithms. By harnessing the power of quantum mechanics, quantum machine learning holds the potential to revolutionize various aspects of data analysis, pattern recognition, and decision-making.

Quantum machine learning holds immense potential for advancing the field of machine learning and enabling more powerful and efficient data analysis. By harnessing the principles of quantum mechanics, researchers aim to develop algorithms and techniques that can leverage the unique capabilities of quantum systems.

3.0 QUANTUM NEURAL NETWORKS - ARCHITECTURE AND MODELS

3.1 Basics of Quantum Neural Networks

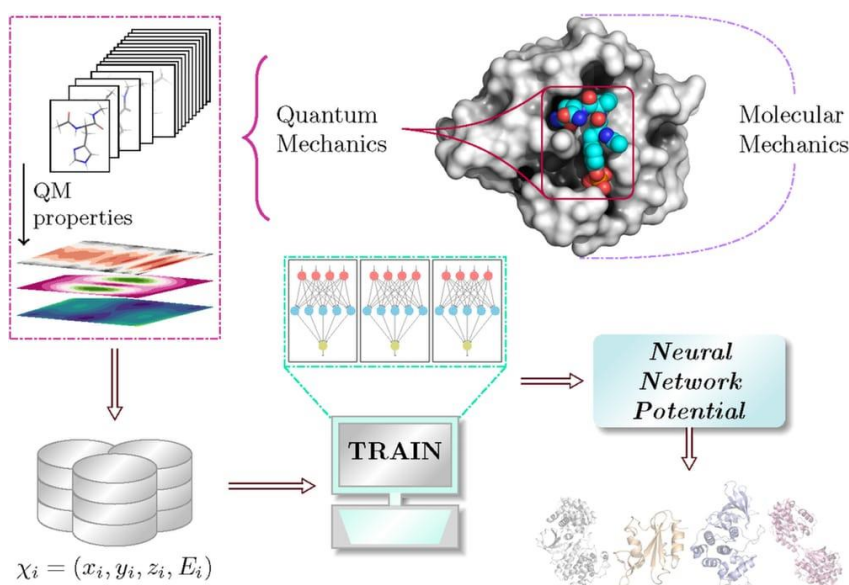
- *Quantum Bits (Qubits)*: In classical computing, information is encoded using bits that have discrete values of either 0 or 1. In contrast, quantum computing utilizes qubits as the fundamental unit of information, which can exist in a superposition of both 0 and 1 states simultaneously. This means that qubits can simultaneously represent multiple values.
- *Quantum Gates*: Similar to classical logic gates (e.g., AND, OR, NOT gates), quantum gates manipulate qubits to perform specific operations. Examples of quantum gates include the Hadamard gate (creates superposition), the Pauli-X gate (bit-flip), and the controlled-NOT gate (entangles two qubits).
- *Quantum Circuits*: Quantum neural networks use quantum circuits, which are composed of quantum gates, to process and transform quantum information. These circuits can be designed to perform various computational operations, such as encoding input data, applying quantum operations, and extracting output information.

- *Quantum Neurons:* In quantum neural networks, quantum neurons serve a similar purpose. They receive quantum inputs (qubits) and apply quantum operations, such as quantum gates, to process the information.
- *Quantum Layer and Architecture:* Quantum neural networks consist of multiple layers of quantum neurons, forming a quantum layer. Each quantum layer can apply different quantum operations to the inputs, similar to the activation functions in classical neural networks. The arrangement and connectivity of quantum layers define the network's architecture.
- *Quantum Training:* Training a quantum neural network involves optimizing its parameters to minimize a cost function. Quantum algorithms, such as variational quantum eigen solvers (VQE) or quantum gradient descent, can be used for this purpose. During training, the quantum circuit parameters are adjusted iteratively to improve the network's performance.
- *Hybrid Approaches:* Due to the limitations of current quantum technologies, practical quantum neural networks often utilize a hybrid approach. This means that the network incorporates both classical and quantum components. The classical part handles pre- and post-processing tasks, while the quantum part focuses on the quantum information processing.
- *Applications:* Quantum neural networks have the potential to enhance various domains, including quantum chemistry simulations, optimization problems, pattern recognition, and machine learning tasks. They can offer improved computational power and enable the exploration of quantum advantages in solving specific problems.

3.2 Quantum Neurons and Quantum Gates

In contrast, quantum computing makes use of quantum bits, known as qubits, which can simultaneously exist in a superposition of 0 and 1 states. This unique property of superposition enables quantum computers to execute certain computations with greater efficiency compared to classical computers.

Quantum gates play a crucial role in quantum circuits, which are sequences of quantum gates applied to qubits to perform specific computations. By combining different quantum gates in a circuit, quantum algorithms can be implemented to solve complex problems, such as factorization, optimization, and simulation, with potential advantages over classical algorithms.



3.3 Quantum Circuit Architectures for QNNs

Quantum circuit architectures are essential components in the development and deployment of quantum neural networks (QNNs), which are machine learning models that harness the principles of quantum mechanics for specific purposes. The architecture of a quantum circuit determines how qubits are interconnected and the specific operations performed on them. Here are a few commonly used quantum circuit architectures for QNNs:

- *Variational Quantum Circuit (VQC)*: VQC is a popular architecture for QNNs. It consists of parameterized quantum gates followed by measurements. The parameters of the gates are trained using classical optimization algorithms to minimize a cost function. VQC architectures are often used for tasks such as quantum classification or regression.
- *Quantum Convolutional Neural Network (QCNN)*: Inspired by classical convolutional neural networks (CNNs), QCNNs utilize convolutional layers to process quantum data. These layers consist of quantum gates that operate on qubits and their neighbours. QCNN architectures are suitable for tasks involving quantum image or pattern recognition.
- *Quantum Recurrent Neural Network (QRNN)*: QRNNs are designed to process sequential quantum data and have a memory-like capability similar to classical recurrent neural networks (RNNs). They incorporate quantum gates and operations that can handle time-dependent quantum information. QRNN architectures are useful for tasks such as quantum time series analysis or quantum language processing.
- *Quantum Boltzmann Machine (QBM)*: QBM is a generative model architecture that uses a network of interacting qubits to represent probabilistic distributions. It consists of interconnected quantum units that perform computations based on energy functions. QBM architectures are employed in tasks such as quantum generative modelling or unsupervised learning.
- *Quantum Autoencoder (QAE)*: QAEs are quantum versions of classical autoencoders, which are neural networks used for dimensionality reduction and data compression. QAEs utilize quantum gates to encode data into a quantum state and decode it back to its original form. QAE architectures are applicable to quantum data compression and analysis.

3.4 Variations of QNN Models

Quantum neural networks (QNNs) combine concepts from quantum computing and neural networks to explore the potential advantages of quantum computation in machine learning tasks. There are several variations of QNN models that have been proposed and studied.

The *QBM* is a quantum analogue of the classical Boltzmann machine, a type of stochastic recurrent neural network. In a QBM, qubits are used to represent binary states, and quantum gates are employed to perform computations. The learning process involves optimizing the parameters of the quantum gates to model the data distribution.

The *QHN* is inspired by classical Hopfield networks, which are recurrent neural networks used for associative memory and pattern recognition tasks. In a QHN, qubits are used to represent binary states, and quantum gates are employed to perform computations. The network is trained to store and retrieve patterns using quantum algorithms.

The *QCNN* is an extension of classical convolutional neural networks (CNNs) to the quantum domain. It utilizes quantum circuits to perform convolutional operations on quantum states. The trainable parameters in the quantum circuits are optimized using techniques such as gradient descent or variational methods.

The *QRBM* is a quantum version of the classical restricted Boltzmann machine, a type of generative model used for unsupervised learning tasks such as dimensionality reduction and feature learning. In a QRBM, qubits are employed to represent visible and hidden units, and quantum gates are used for computations and training.

The *QRNN* is a quantum analogue of classical recurrent neural networks (RNNs). It leverages quantum circuits to perform computations on quantum states, enabling the modelling of sequential data and capturing temporal dependencies. The parameters of the quantum gates are optimized through training processes.

4.0 ADVANTAGES AND POTENTIAL APPLICATIONS

4.1 Advantages of Quantum Neural Networks

- *Quantum parallelism:* Quantum computers can perform computations in parallel across multiple quantum states, known as superposition.
- *Improved memory capacity:* Quantum systems have the ability to store and manipulate vast amounts of information in quantum states.
- *Quantum feature mapping:* QNNs can utilize quantum algorithms, such as quantum feature maps, to efficiently map classical data into quantum states.
- *Quantum resilience:* Quantum neural networks can be designed to be more resilient to noise and errors inherent in quantum computing systems.

4.2 Quantum Neural Networks for Classification

- *Encoding data:* In a QNN, input data is encoded into quantum states, typically using qubits (quantum bits). For example, a binary classification problem with N features can be represented using N qubits.
- *Quantum gates:* Quantum gates serve as the foundational elements of quantum circuits, enabling the manipulation and transformation of qubits. These gates can perform operations such as superposition, entanglement, and phase shifts. They allow the QNN to process information in parallel and explore multiple possibilities simultaneously.
- *Measurement and inference:* After training, the QNN can be used for classification. The final step involves measuring the quantum state of the output qubits, which yields classical information representing the predicted class labels.

4.3 Quantum Neural Networks for Regression

Regression tasks involve predicting a continuous value output based on a set of input features. QNNs can be used for regression problems by adapting the architecture and training methods of traditional neural networks to the quantum domain. Here's a general overview of how QNNs can be applied to regression:

Similar to classical neural networks, the first step is to encode the input data into a suitable quantum representation. This can be done using techniques like amplitude encoding or quantum feature maps, which transform classical data into quantum states. QNNs consist of quantum gates and layers of qubits that process the quantum-encoded data.

The performance of the QNN regression model can be evaluated using standard metrics.

4.4 Quantum Neural Networks for Optimization

QNNs are typically designed to address optimization problems that involve a large number of variables and complex search spaces. These problems often require finding the best solution from a vast set of possibilities, which can be computationally challenging for classical computers.

QNNs can be trained using various optimization algorithms specifically tailored for quantum systems. For example, quantum gradient descent algorithms can be used to optimize the parameters of a QNN by minimizing a cost function.

To fully unlock the potential of QNNs, it is essential to have quantum computers that possess an adequate number of stable qubits and exhibit low error rates.

5.0 CHALLENGES AND FUTURE DIRECTIONS

5.1 Training and Learning in QNNs

This encoding process maps classical data to quantum superposition states using techniques such as quantum circuit preparation or quantum embeddings. Quantum gates analogous to classical neural network layers are used to process the quantum data.

At the end of the quantum computation, a measurement is performed to obtain classical results. The quantum state collapses to a classical state, and the measurement outcomes are used for further processing or analysis.

One popular approach in training QNNs is through variational quantum circuits. These are parameterized quantum circuits where the parameters are optimized through iterative techniques like gradient descent.

5.2 Scalability and Quantum Error Correction

5.2.1 Scalability in Quantum Computing

Scalability refers to the ability of a system to handle an increasing workload or to expand its capabilities as more resources are added.

Quantum systems are highly sensitive to various sources of noise, such as interactions with the environment, imperfect control operations, and inherent quantum decoherence.

- *Improving qubit coherence:* Increasing the coherence time of qubits, which refers to the duration when the quantum state of a qubit remains unaffected, can contribute to error reduction.
- *Developing fault-tolerant quantum error correction codes:* Quantum error correction (QEC) is a crucial method used to safeguard quantum information against errors.
- *Building larger qubit arrays:* Researchers are working on increasing the number of qubits and building larger quantum systems.

5.2.2 Quantum Error Correction

Quantum error correction is a fundamental technique in quantum computing that enables the protection of quantum information from errors and noise. It involves encoding the logical quantum state into a larger number of physical qubits and implementing error-detection and error-correction procedures.

The basic idea behind quantum error correction is to redundantly encode the logical qubits into multiple physical qubits. By measuring these physical qubits and comparing their states to an expected outcome, errors can be detected. If an error is detected, appropriate operations are applied to correct it. Quantum error correction codes are designed to be fault-tolerant, meaning they can effectively handle errors even in the presence of noise and imperfections.

5.3 Integration of QNNs with Classical Computing

- *Hybrid models:* One common approach is to develop hybrid models that incorporate both classical and quantum components. In this setup, the classical computer handles tasks suitable for classical processing, while the QNN performs quantum-specific computations.
- *Quantum-enhanced classical algorithms:* Another approach is to use QNNs as a quantum-enhanced version of classical machine learning algorithms.
- *Quantum-inspired neural networks:* Quantum-inspired neural networks, also known as quantum-inspired models or quantum machine learning models, are classical neural network architectures that incorporate ideas or techniques inspired by quantum computing.
- *Error correction and noise mitigation:* QNNs are susceptible to noise and errors due to the inherent fragility of quantum systems.
- *Training and optimization:* Classical computers can be used to train and optimize QNN models. Techniques like classical gradient descent can be employed to update the parameters of the QNN based on classical feedback, improving the performance and convergence of the quantum model.

5.4 Hybrid Quantum-Classical Approaches

In hybrid quantum-classical approach, classical computing is used to control and optimize quantum computations. Quantum computers are powerful but are currently limited in terms of the number of qubits, their coherence times, and the reliability of quantum operations.

The results obtained from the quantum subproblem are combined with classical data and processed using classical optimization algorithms. These classical algorithms help in refining the solution, finding optimal parameters, or making decisions based on the quantum results.

Refining the solution by adjusting the parameters and re-running the quantum subproblem using updated classical information. This feedback loop allows for the exploitation of classical and quantum resources to iteratively improve the overall solution.

5.5 Quantum Neural Networks in Real-World Applications

- *Quantum Pattern Recognition:* Quantum computers have the potential to process and analyse large amounts of data in parallel, which can improve the efficiency of pattern recognition algorithms.

- *Quantum Optimization:* QNNs can be applied to optimization problems, which are prevalent in various fields such as logistics, finance, and manufacturing. Quantum computers can utilize quantum phenomena, such as quantum superposition and entanglement, to enhance their computational capabilities and efficiently navigate the solution space to find optimal or nearly optimal solutions.
- *Quantum Chemistry:* Quantum neural networks can assist in simulating and understanding complex quantum systems, such as chemical reactions and molecular structures.
- *Quantum Generative Models:* Generative models are used to create new data samples that resemble the training data. QNNs can be utilized in generative modelling tasks to generate quantum states that exhibit desired properties.
- *Quantum Financial Modelling:* QNNs have the potential to assist in financial modelling and prediction tasks. Quantum computers can efficiently process large datasets and complex financial models, which can be useful for tasks such as portfolio optimization, risk analysis, and algorithmic trading.

The practical implementation of QNNs in real-world applications will require further advancements in quantum hardware, quantum algorithms, and optimization techniques.

6.0 CONCLUSION

The potential of quantum neural networks in various applications holds great promise for the future of machine learning. The combination of quantum computing principles with neural network architectures opens up new possibilities for solving complex problems and improving computational efficiency.

6.1 Summary of Findings

Quantum neural networks (QNNs) are a type of neural network that leverage quantum computing principles and quantum information processing to perform certain computational tasks. While I don't have access to the latest research findings beyond my September 2021 knowledge cutoff, I can provide you with a general summary of findings related to QNNs up to that point.

- *Quantum Advantage:* QNNs have the potential to outperform classical neural networks in specific applications. Quantum computing offers exponential parallelism and the ability to process and manipulate quantum states, which can provide advantages for certain computational tasks such as optimization, machine learning, and data analysis.
- *Quantum Circuit-Based Models:* One common approach in QNNs is to represent the neural network as a quantum circuit, where quantum gates are applied to qubits to perform computations. Various architectures, such as quantum variational circuits and quantum convolutional neural networks, have been explored to design and train QNNs.
- *Quantum Data Encoding:* QNNs require input data to be encoded into quantum states. Different encoding schemes have been proposed, including amplitude encoding, angle encoding, and quantum embedding techniques, to map classical data to quantum states that can be processed by the network.

- *Quantum Hardware Constraints:* The implementation of QNNs faces challenges due to the limitations of current quantum.
- *Applications:* QNNs have shown promise in various domains, including quantum chemistry, optimization problems, quantum image and pattern recognition, and generative modelling.

6.2 Potential Impact and Future Outlook

Enhanced Computational Power: QNNs leverage the principles of quantum mechanics, such as superposition and entanglement, to perform computations in parallel and explore multiple solutions simultaneously. This parallelism allows QNNs to handle exponentially larger datasets and compute complex functions more efficiently than classical neural networks.

- *Quantum Advantage:* Quantum computers, including those used for QNNs, offer the potential for quantum advantage. This refers to the ability of quantum systems to solve certain problems exponentially faster than classical computers.
- *Improved Learning and Generalization:* QNNs have the potential to improve the learning and generalization capabilities of neural networks. Quantum computers can explore high-dimensional feature spaces more effectively, enabling QNNs to learn complex patterns and relationships in data.
- *Quantum Machine Learning Algorithms:* QNNs can drive the development of new machine learning algorithms tailored for quantum computing architectures.
- *Quantum-Safe Machine Learning:* As quantum computers become more powerful, they pose a potential threat to classical cryptographic systems. Quantum-resistant or quantum-safe machine learning techniques are being developed to mitigate this risk. QNNs can contribute to the development of secure and privacy-preserving machine learning models that can withstand attacks from quantum computers.
- *Overcoming Challenges:* There are several challenges that need to be addressed to fully realize the potential of QNNs. Overcoming these challenges will require advances in both quantum hardware and software.

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