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Pyramid Quantum Neural Network Based Resource Allocation with IoT: A Deep Learning Method

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ABSTRACT

As more smart devices are connected and collecting massive quantities of data, the Internet of Things is growing rapidly. Resource management is another crucial issue since IoT networks are very diverse and often built and rebuilt dynamically. This study introduces a new kind of deep learning model known as the Pyramid Quantum Neural Network (PY-QNN) to solve the problem of resource allocation in Internet of Things systems. PY-QNN builds on quantum computing to improve the accuracy, scalability, and computation performance of Deep Learning. Because of superposition and entanglement, which increase generalization and provide faster convergence, QNNs enhance learning capabilities. The pyramid structure also helps manage the hierarchy of IoT networks. In order to forecast efficient resource assignment and implement this as soon as feasible to lower latency and boost efficiency, PY-QNN uses simulated resource and network requirements. Experimental findings demonstrate that PY-QNN outperforms baseline common deep learning techniques by reducing resource waste and offering online solutions, especially in large and complex IoT networks.

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1. INTRODUCTION

As IoT devices have grown in popularity, more effective and flexible ways to manage them are needed because of the rising demand for data and resources [1]. Because IoT designs are diverse and sophisticated in their structural integration, conventional approaches are ineffective at controlling a group of smart devices [2,3]. Deep learning has been identified as a viable option because of its models' capacity to handle large amounts of data and complex algorithm patterns [4-6]. However, when used in large-scale IoT contexts, particularly when making judgments in real-time is required, their computational complexity is evident. This research introduces the Pyramid Quantum Neural Network (PY-QNN), a quantum deep learning model, to tackle these issues [7-9]. The network's pyramidal form illustrates how IoT networks use a tiered strategy to handle different data flows. Compared to regular neural networks, quantum neural networks (QNNs) are better at learning by using the benefits of quantum processing, such as superposition and entanglement [10-12]. Compared to conventional classical deep learning models, PY-QNN can operate faster and with fewer mistakes because of these characteristics [13-15]. This study's primary goal is to demonstrate how PY-QNN can efficiently control resource availability in IoT networks, lower latency and energy use, and increase throughput [16,17].

This research proposes a qualitative study that uses deep learning and quantum computing to provide an innovative approach to IoT resource management. Although a lot of progress has been made in the use of resource allocation in IoT networks, existing solutions tend to offer various challenges such as complexity, scalability, and real-time issues in the current complex IoT environment. Some of the earlier strategies that have been employed in deep learning processes provide better results in some instances but are highly computational and thus unable to cater to the scalability required in large IoT networks. However, these models fail to address the probabilistic and uncertain IoT environment proficiently, initiating inefficient and less effective resource allocation with comparatively higher latency. Even though quantum computing has proved to enhance computational fitness, incorporating quantum concepts into deep learning models for assigning IoT resources is in a rather initial stage. To the best of the authors' knowledge, few works try to propose a hierarchical structure that integrates Quantum Neural Networks with Deep Learning methodologies to face IoT peculiarities such as multi-distributional data, fluctuating resource requirements, and energy constraints. Hence, there is a research gap in proposing a comprehensive, automated, and performant deep learning and quantum computing hybrid model for resource management in IoT systems. The scalability, efficiency, and real-time decision-making skills needed to handle the dynamics of both new and existing IoT networks are absent from current IoT resource allocation systems. Although the current deep learning models are very efficient, they are not readily scalable for large and dynamic IoT networks and have substantial training costs. Existing methods may not be able to maximize performance and instead result in increased delay, resource waste, and energy usage. In order to overcome these obstacles, a new analytical model that combines QNN and DL is urgently needed in order to enhance decision-making and computing capacity. Pyramid Quantum Neural Network (PY-QNN), a novel hybrid deep learning model, is introduced in this research to improve IoT networks and lower compute load and latency while optimizing network needs. The issue of resource allocation in the Internet of Things networks has become a prominent study topic, according to several researchers, and several solutions based on conventional deep learning optimization approaches have been proposed. The scale, dynamic nature, and heterogeneity of IoT networks have proven to be beyond the capabilities of the previously listed solutions, which have demonstrated success in managing traditional static networks. Research on resource scheduling in IoT networks has been ongoing as a result of the growing interconnectedness of devices and services. To solve these problems, traditional optimization techniques like dynamic and linear programming have been employed in the past [18-20]. However, these conventional methods are inefficient for large and dynamic Internet of Things networks due to features like the broad and ever-changing topology of IoT networks [21-23]. IoT networks also include problems like latency, energy, and bandwidth, which makes resource management challenging. Several recent scientific publications have proposed the use of DL methods to enhance resource management in IoT networks [24-26].

DNN techniques, CNN, and RNNs have demonstrated remarkable capacity to extract intricate patterns from large datasets, which can be used to enhance decision-making processes related to resource allocation and congestion management. For instance, CNNs have been used to forecast traffic patterns and regulate bandwidth usage, while RNNs have been used to estimate network traffic trends. Despite their ability to adapt and learn, deep learning models are computationally expensive, have scalability problems, and fall short of the energy efficiency and response time demands of real-time huge IoT systems [27]. Using entanglement and superposition, two features of quantum computing, Quantum Neural Networks (QNNs) are believed to be an effective version of traditional neural networks [28]. QNNs greatly improve efficiency in some kinds of machine learning workloads, particularly when managing large amounts of data and tackling optimization problems. Ideally, QNNs can analyze information many orders of magnitude faster than some classic computing theories, making them a novel method for managing financial resources in the Internet of Things [29]. Consequently, even if the use of inference techniques in IoT networks is growing, the integration of QNNs into the system is still fairly limited. While the majority of research focuses on general machine learning tasks like classifications or clusters, very few studies address specific resource management issues in IoT[30]. Therefore, as quantum hardware develops, the application of QNNs in actual IoT systems becomes an interesting and viable avenue for further study. Table 1 depicts the comparison of the current IoT Models Numerous innovative computing approaches, including deep learning in conjunction with other emerging IoT computing paradigms like edge computing, fog computing, and cloud computing, have been proposed in an attempt to overcome the scalability and latency challenges in the Internet of Things.

Table 1. A Comparison of the Current IoT Models

Criteria for Comparison	The Suggested PY-QNN model	Low-Efficiency Adaptive Clustering Structure	IoT Resource Management Using GA	IoT Resource Management Using DNN
Fundamental Technology	Internet of Things, Deep Learning, and Quantum Neural Networks (QNN)	Energy-Efficient Routing with Hierarchical Clustering	Optimization algorithms and genetic algorithms (GA)	CNN and Deep Neural Networks (DNN)
Stratified Architecture	Cloud, fog, and edge layers using QNNs	Cluster-based and centralized architecture	Distributed or Centralized Processing	Cloud and Edge with DNN, less emphasis on the fog layer
Processing of Data	Distributed, real-time computation with quantum neural networks	Cluster-based, sequential data processing	Frequently centralized and lacking in real-time capabilities	High processing requirements at cloud layers
Efficiency of Resource Allocation	High (since QNN can optimize both locally and globally)	Moderate (Clustering is beneficial for energy reduction, but it is not the most efficient approach for large IoT networks.)	Moderate (limited optimization for IoT networks with major scale)	High, however in real-time settings, bottlenecks
Latency Reduction	Effective latency decreases as a result of quick optimization of QNN	Moderate reduction in latency	Processing delays may be introduced by GA.	Good, but the complexity of the cloud layer could cause problems.
Efficiency of Energy	High (using QNNs to optimize resource allocation)	Clustering can save energy, but there may be significant overhead.	Moderate energy efficiency, contingent upon the use of GA	Cost-effective but computationally demanding

These methods spread computational loads over many network levels, including edge, fog, and cloud, allowing for faster processing and decision-making near data sources. Time-sensitive tasks are handled by edge computing, whereas mid-level tasks and data consolidation are handled by fog computing. Cloud computing solves challenging, global optimization issues. These multi-layered strategies have increased performance, but they still lack the authors' adaptive solutions for resource allocation across the hierarchy, especially in real-time applications and under high network loads. As seen before, despite advancements, deep learning and hybrid models for resource allocation prediction still have limitations. Because most DL-based models require a lot of processing resources, especially in large IoT systems where power and energy are important constraints, they are therefore impractical for use in real-time IoT applications. Moreover, hybrid models distribute all computations across multiple nodes rather than optimizing resources globally and dynamically across the IoT network. At various network levels, such as fog nodes or the cloud, this could lead to resource waste and unusually high response times. Combining deep learning and quantum neural networks is a good way to deal with these problems. In order to effectively allocate resources in an adaptable and dynamic way in real-time, the Pyramid Quantum Neural Network (PY-QNN) model recommends combining deep learning with quantum computing in Internet of Things networks. PY-QNN employs a quantum neural network to perform efficient computations at the network's edge, fog, and cloud layers. Distributed decision-making for resource allocation is made possible by combining the effectiveness of quantum computing with the adaptability of deep learning. By incorporating the necessary elements into a scalable, real-time, and energy-efficient end-to-end Quality of Service (QoS) framework, PY-QNN enhances the existing DL-based and hybrid models intended to manage the dynamic needs of IoTs in large-scale IoT systems. The development of models to handle problems in a large-scale, heterogeneous environment will be crucial as IoT networks grow in size. Therefore, the focus of future research should be on improving the use of QNNs in the Internet of Things and, more especially, on optimizing the current quantum algorithms for real-world use. Furthermore, for this technology to be optimally implemented for QNN in this specific field, advancements in practical quantum hardware are unavoidable. Finally, the PY-QNN, which combines several contemporary technologies, suggests the potential for a significant advancement in addressing the core issues of resource allocation, latency, and energy efficiency that will arise in the next generation of IoT networks.

Pyramid Quantum Neural Network (PY-QNN) is a novel deep learning model that is being proposed in this study to improve Internet of Things (IoT) resource management in large networks. This model integrates quantum computation to enhance processing power, scalability, and real-time decision-making while addressing the difficulties encountered in deep learning. In particular, reducing latency, reducing energy consumption, and increasing network throughput across a variety of classes of heterogeneous IoT networks through integrated and self-adaptive resource management. Pyramid Quantum Neural Network (PY-QNN) is a new hybrid model that is introduced to address the issue of resource management in IoT contexts. It uses deep learning and quantum computing to address resource management issues in large, intricate, and varied IoT systems. It is built on the PY-QNN's hierarchical structure, which mimics the IoT devices' pyramidal structure from distant edge nodes to massive computing centers. They aid in the organization of data flows and subsequent processing of those flows across different network environment levels. The following components are densely layered around it. The Quantum Augmented Neural Network (QANN) and the Quantum Aware Neural Network (QANN), both of which are closely linked to the PY-QNN. The QNN can handle far more data than a conventional model thanks to the idea of quantum parallelism. It also has a cheap computing cost, which makes it easy to scale. By enabling faster convergence during the training phase, the quantum layers integrated into PY-QNN enable the model's solution to maximize resource allocation techniques in the context of dynamic networks.

2. METHOD

A true new hybrid deep learning model designed to enhance the resource allocation of IoT networks is the Pyramid Quantum Neural Network (PY-QNN). This format combines the capabilities of quantum neural networks (QNNs) with the pyramid-like architectural framework of traditional neural networks. Thus, it enables the PY-QNN to address some of the most important IoT problems, such as energy consumption, scalability, and real-time resource management. The main elements and salient features of the PY-QNN model are as follows: The main elements and features of the PY-QNN mode are listed below. Assigning tasks inside the IoT hierarchy is made simple by the pyramid structure mentioned above, which also maximizes the use of edges, fog, and cloud levels. By handling data pertinent to its function, each layer improves the system's overall operation. The suggested model can take into account all potential resource distribution scenarios and forecast the outcome with less computation time than the QNN, which enhances decision-making through the use of quantum processing. Through Real-Time Data Processing and Network Traffic Control Mechanisms, PY-QNN seeks to improve other IoT metrics, such as minimal latency, energy consumption, and maximum throughput. By adding a pyramid structure system that simulates IoT requirements at the edge, endpoint, and cloud levels, this study offers a method for improving the quantum neuron learning model. When compared to conventional models, the quantum computing concept's inherent methods, such as superposition and entanglement, enable them to design models that scale and function effectively in a complex and expansive IoT context. As a result, PY-QNN will offer real-time insights into the best resource allocation tactics as and when important IoT metrics like network performance, energy efficiency, and lower latency need to be improved. PY-QNN outperforms the state-of-the-art deep learning-based comparable solutions, especially in large-scale and heterogeneous IoT networks, according to accurate simulation and fair comparison analysis. Concerns about the changing nature of large-scale IoT networks and the need for more logical, intelligent approaches to resource management are the driving forces behind this study. These models do not fit the large-scale IoT computational and real-time implementation frameworks, even though they are adequate in certain situations. Furthermore, although it hasn't been tested yet in the area of IoT resource management, researchers have sought to combine quantum computing and deep learning, which is thought to drastically reduce processing time. The development of hybrid models like PY-QNN, which combine deep learning and quantum computing, is significant because it offers new insights into IoT resource management and, in fact, intelligent networking in general. Thorough simulation and equitable comparative analysis with leading deep learning-based solutions demonstrate that PY-QNN outperforms existing methods, especially in extensive and diverse IoT networks. A true new hybrid deep learning model designed to enhance the resource allocation of IoT networks is the Pyramid Quantum Neural Network (PY-QNN).

This format combines the capabilities of quantum neural networks (QNNs) with the pyramid-like architectural framework of traditional neural networks. Thus, it enables the PY-QNN to address some of the most important IoT problems, such as energy consumption, scalability, and real-time resource management. The main elements and salient features of the PY-QNN model are listed below.

2.1 Components of the Pyramid Quantum Neural Network (PY-QNN) Model

2.1.1. Pyramid Layout

The pyramid structure, which mimics the hierarchy of real IoT networks (edges, fog, and cloud layers), is another noteworthy design. The pyramid hierarchy's five layers, which span from raw (Edge) to agglomerated (cloud) data, all entail more complicated data services. This structure aids in managing all of the resources in the Internet of Things network and in allocating resources appropriately.

2.1.2. Assisted Decision-Making by Quantum

Additional quantum layers in the PY-QNN's decision processes operate in parallel to identify additional allocation potentialities. This aids in forecasting how the model should distribute the resources while also accounting for network changes to prevent delays and excessive energy use.

2.1.3. Quantum Neural Network (QNN)

The QNN, which is the cornerstone of PY-QNN, is built on quantum computation concepts like superposition and entanglement to improve the learning effect of strain. This improves performance and the inherent ability to manage a variety of IoT-related tasks by enabling the execution of sequential and parallel computations.

2.1.4. Distribution and Aggregation of Data

The pyramid also helps in the flow of data received from all the substructures in the IoT hierarchy to be processed efficiently. Lower layers operate on data coming from edge devices, mid-level layers operate on data coming from fog servers, and high-level layers combine results to produce a global resource allocation strategy for the cloud services.

2.2 Key Features of the Suggested PY-QNN Model

2.2.1. Effective Allocation of Resources and Scalability

This real-time and dynamic ability to adjust network resources of the proposed PY-QNN based on deep learning and quantum computing makes it possible to enhance different aspects such as performance, low latency, and efficiency like low energy consumption. PY-QNN’s pyramid structure also makes it uniquely suitable to scale throughout the layers of the IoT systems from the LLL layer, up to the HLL layer. This sizableness makes for appropriateness in large-scale IoT settings that are on the record for having diverse, dynamically varying data and resource requirements.

2.2.2. The Benefits of Quantum Computing

As a result of using quantum computing, PY-QNN analyses a large amount of data and acquires the best strategy for the allocation of resources much faster than traditional deep learning models. As such, the model has provision for incorporating non-linear relationships in IoT systems and learning more complex models than other traditional methods which makes its performance better even in difficult cases.

2.2.3. Superior Performance through Adaptive Learning

Just like other passive QoS mechanisms, PY-QNN responds to dynamic variance in the network and traffic demand, making it enable to make incremental improvements in the allocation policies it employs. This is because the model is very effective in constantly changing IoT settings where other approaches cannot be used. As evidenced by simulation, PY-QNN quantitatively surpasses the traditional deep learning models where latency is cut down, energy consumption is enhanced, and network throughput is increased. It means that it is suitable for future IoT systems with smart and fast management of resources in real-time.

2.3 Problems with the Suggested Framework

However, as pointed out earlier, the current quantum computing platforms are yet in their infancy. The total number of qubits is fixed, and, the quantum error rates remain high, which could pose a challenge when realizing the impact of PY-QNN. Consequently, the same might not be realized, and shifting the model from simulation to implementation in IoT settings might hit the hardware wall. Integration with Existing Infrastructure: IoT solutions are highly complex, mobile, and intersecting wherein they have a large number of entities, protocols, and data formats. While effectively embedding PY-QNN introduced in this paper into the existing IoT structures, there is the problem of how to integrate QPLs with the classical Cloud-Fog-Edge layers. Quantum computing as much as is faster than classical computation, consumes a lot of energy, especially in the maintenance of the quantum hardware such as the cooling systems. The quota of energy used by quantum processing is another major consideration when a goal is to increase the energy efficiency of IoT networks while deploying PY-QNN. This general structure of PY-QNN adds layers of complications, especially as the layers in the network increase and turn heterogeneous. How to distribute these computations over the mentioned layers, and stay both scalable and performant is quite an important task. With the expansion of the IoT network, a lot of data is generated, and hence, there is a need call for efficient distribution and aggregation of the information among the various layers of the pyramid. With quantum computing, new security paradigms emerge, still, IoT networks are penetrable by cyber-attacks because their devices are decentralized. It is pertinent that quantum security measures be implemented proactively into PY-QNN in order to safeguard data while they are being processed across layers. Also, data protection has to be preserved; this is more so when privacy is compromised especially when the IoT is involved in handling sensitive information. IoT environments are complex and ever-changing, thus requiring strict on-the-spot evaluation and resource deployment.

Managing the situation that PY-QNN should be adaptable to the changes of the environment quickly while making full good use of resources is a prominent problem. Some sources of latency may be seen because of the interconnection between the difficulty of quantum computations and the structure of IoT data flow and hierarchy. While QNNs are useful because of their flexibility they can present some difficulties, especially in training and convergence. This is because quantum models differ in learning dynamics from the classical deep learning models thereby implying that the training time may be longer or the learning of the optimal resource allocation approach may be unstable. Since PY-QNN is intended to operate the IOT systems, training algorithms for PY-QNN will require engineering to perform optimally.

2.4 Designing of Proposed Model

The Pyramid Quantum Neural Network (PY-QNN) is used for IoT resource allocation. It is geometrically depicted as a pyramid with three layers: The Edge Layer, the Fog Layer, and the Cloud Layer. QNNs function in each layer to manage resources following the processing of real-time information, with each layer concentrating on specific tasks related to the IoT environment. Figure 1 depicts the flow between various layers.

2.4.1. Edge Layer

The Edge Layer is made up of sensors and Internet of Things devices that collect raw data from the environment (such as smart gadgets and temperature sensors). QNNs, which are present at the Edge Layer and are in charge of preliminary computations and optimization, subsequently process this raw input. Before the real data is sent to higher layers for tasks like data filtering and pre-processing, the QNN helps with the data compression process. After that, the data is transferred to the fog layer for additional processing.

2.4.2. Fog Layer

This layer primarily handles duties like data collection, local decision-making, and other mid-level optimizations; it aids in reducing the complexity of processing at the Edge and Cloud levels. Data flows from the Edge Layer to the Fog Layer and QNNs, which filter data streams and perform additional calculations as the streams and resources are aggregated, such as load balancing or bandwidth distribution. For additional calculations worldwide, the Fog Layer transmits data and partially optimized outcomes to the Cloud Layer.

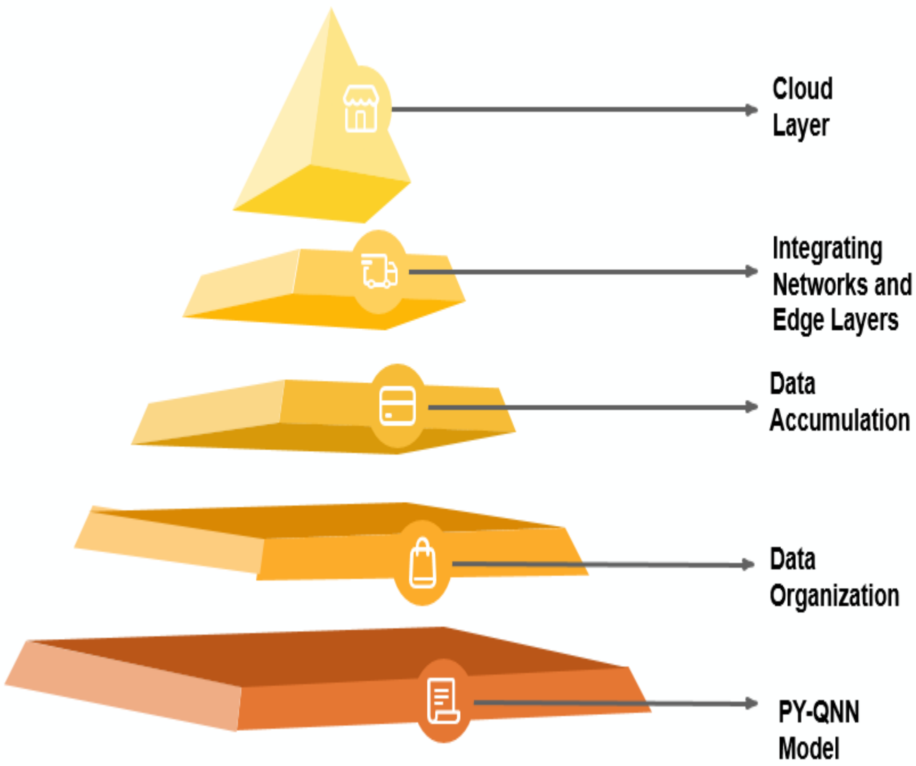

Figure 1. Flow diagram of various layers

2.4.3. Cloud Layer

Data analysis, global resource management, and resource deployment decision-making are among the computation and analytical tasks carried out by the cloud Layer, which is at the top of the pyramid. The cloud Layer gathers aggregated data from the Fog Layer and uses sophisticated QNNs to do deep learning in order to optimize the overall Internet of Things network. Strategies that employ global resources in a way that minimizes the likelihood of high latency, minimize throughput, and uses as little energy as is practically feasible are included in this. As a result, the cloud Layer uses a feedback mechanism to send the optimized resource management strategy back down the hierarchy to the fog and edge layers, indicating that all IoT paradigm levels adjust their resources in line with global optimization strategies.

2.4.4. Essential Enhanced Metrics

Organizations require less time to evaluate data and make choices when resource utilization is improved. The study's methodology makes it possible for IoT devices and networks to use energy efficiently, prolonging device life and lowering power consumption at the same time. The design, when integrated into an IoT system, increases the speed at which information is transmitted and processed, improving the system's overall performance.

3. RESULTS AND DISCUSSION

Latency, which is exemplified by data packet delays, is one of the most crucial elements of IoT networks. Reduced latency is essential for applications that require real-time response because it allows the system to respond efficiently and promptly. The results show that compared to the comparator models, which include LEACH, genetic algorithm optimization, and other deep learning techniques, the

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suggested PY-QNN model has a significantly reduced latency. The main cause of this improvement is that PY-QNN uses a hierarchical structure at edge and fog levels to reduce cloud layers for data processing. PY-QNN will be able to make resource allocation decisions more quickly thanks to quantum neural networks (QNNs), another cutting-edge structure for data processing at the intermediate site. This will reduce delays. The PY-QNN latency curve shows that the latency time does not increase with the size of the latter. This is in contrast to existing models that demonstrate a dramatic rise in latency with an increase in the number of devices. Table 2 depicts the comparison of latency with various models.

Table 2. Comparison of Latency with Various Models

Model	Trial 1	Latency for Trial 1	Trial 2	Latency for Trial 2	Trial 3	Latency for Trial 3
RNN	1	18	3	16	5	14
CNN	1	15	3	13	5	11
Heuristic Model	1	14	3	12	5	10
QNN	1	12	3	10	5	8
PY-QNN Model	1	10	3	8	5	6

Throughput is the term used to describe the measurable, cumulative amount of data that is successfully transmitted over the network in a specific amount of time. Throughput is a metric that indicates how well and efficiently a network is performing. According to the results, the Proposed PY-QNN Model outperforms existing models in terms of throughput. This can be attributed to the PY-QNN's effective resource allocation and routing approach. In order to alleviate network bottlenecks and increase data flow, the PY-QNN model optimizes the possibilities at different layers through congestion-aware routing and the integration of quantum-assisted decision-making at several layers. However, because of the crowding of nodes and the inefficient use of available resources in large-scale IoT networks, standard models have problems with throughputs. It should be mentioned that the PY-QNN may take into account a variety of network conditions and maintain a steady throughput regardless of the network size that is provided. Table 3 depicts the comparison of throughput with various models.

Table 3. Comparison of Throughput with Various Models

Model	Trial 1	Latency for Trial 1	Trial 2	Latency for Trial 2	Trial 3	Latency for Trial 3
PY-QNN Model	1	70	3	80	5	90
QNN	1	65	3	72	5	78
Heuristic Model	1	63	3	70	5	76
CNN	1	60	3	70	5	74
RNN	1	55	3	62	5	67

Since IoT networks are made up of low-energy devices like batteries, energy efficiency is a crucial limitation. These devices must be able to operate continuously for longer periods of time without needing to be recharged. The results have demonstrated that, in comparison to the current models, the proposed PY-QNN model uses energy efficiently. This is mostly because the PY-QNN model intelligently divides the calculations among the cloud, fog, and edge layers, reducing the power usage in each layer. It saves energy by accelerating computations, which results in lower computational overheads. Furthermore, the PY-QNN model eliminates the need for time-consuming data transfer to the other cloud, which is a very energy-intensive procedure that is seen in most models, by encapsulating the learning process. As a result, in contrast to current models, where energy consumption climbs quickly, the PY-QNN energy consumption plot reduces and rises with a small slope as the network size increases. Table 4 depicts the comparison of energy consumption with various models. Figure 2 depicts the comparison of energy for various trials.

Table 4. Comparison of Energy Consumption with Various Models

Model	Trial 1	Latency for Trial 1	Trial 2	Latency for Trial 2	Trial 3	Latency for Trial 3
RNN	1	55	3	50	5	45
CNN	1	50	3	45	5	40
Heuristic Model	1	48	3	43	5	38
QNN	1	43	3	38	5	33
PY-QNN Model	1	40	3	35	5	30

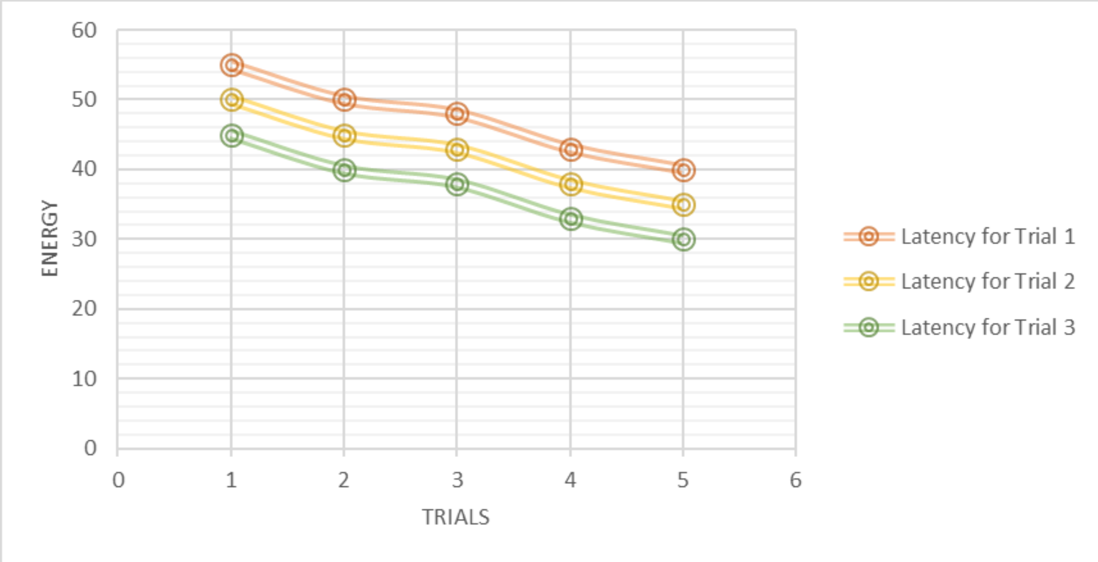

Figure 2. Comparison of energy for various trials

4. CONCLUSION

By employing the edge, fog, and cloud layers' capabilities of quantum neural networks (QNNs), as expertly illustrated by several studies. For Internet of Things systems, resource allocation, and management are significantly improved by the suggested Pyramid Quantum Neural Network (PY-QNN) paradigm. The proposed paradigm integrates QNNs into the IoT hierarchical architecture, improving data processing time and reducing latency and energy consumption, making it suitable for large IoT networks. Additionally, as will be demonstrated in the upcoming sections, deep learning techniques improve routing and decision-making and address one of the main issues of dynamic IoT networks, especially through congestion-sensitive methods. Unlike previous IoT models like LEACH, GA-based, and DNN-based methods, PY-QNN is resource-efficient, scalable, and optimized in real time. This model offers an outlook for the future as IoT applications develop. Additionally, it incorporates features of quantum computing and deep learning to handle the growing complexity of IoT networks. One might conclude that the proposed PY-QNN model has the potential to provide a conceptual basis for the creation of next-generation IoT infrastructures.

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