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Photonic Quantum Neural Networks for AI Acceleration

A. Karthikeyan
UG Scholar, K Ramakrishnan College of Technology,Trichy ,India

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Abstract

AI is employed in practically every field, but the rapid growth of AI workloads is making it impossible to stay up with speed, energy utilisation, and the capacity to add more technologies. GPUs and TPUs are two examples of classic hardware accelerators that have gone beyond Moore's Law, although there are still certain basic physical limits. Quantum computers can speed up some operations a lot, but current systems are still constrained by their size and the fact that they lose coherence. But photonics might be a good platform because it can convey messages quickly, doesn't need a lot of power, and works at room temperature. This study looks at Photonic Quantum Neural Networks (PQNNs) as a new technique to speed up AI tasks by using quantum computing theory and photonic hardware together. We look into the theory underlying quantum neural networks (QNNs), photonic circuits for quantum operations, and how photonic devices might make matrix multiplications faster, introduce nonlinearities, and make quantum entanglement happen. We speak about how to test PQNNs in the real world, how they might help with computing, and challenges like noise, making mistakes, and fixing them. Finally, we talk about how PQNNs could make machine learning and complex AI models easier in the future.

Keywords

Quantum neural networks, photonic computing, AI acceleration, integrated photonics, quantum machine learning, optical circuits, and quantum photonics are some of the important terms.

Introduction

AI is making quick progress in areas including autonomous systems, computer vision, natural language processing, and drug development. This has made it necessary to have greater computational power than ever before. AI systems are becoming more complex and larger. Neural networks can drive cars without a driver, and deep learning models can write things that sound like they were written by a person. These systems have billions of parameters. For both training and inference, this increase needs a lot of computational power, which puts a lot of stress on the gear that is already there. The von Neumann barrier still slows down regular computers, even though dedicated accelerators like GPUs and TPUs have made a lot of progress in parallel processing. This makes memory and processing units less effective. Moore's Law also says that transistors can only get so big, require so much power, and give off so much heat. This makes it hard to keep getting higher performance with only regular electronics.

Researchers are exploring into strange ways of computing that use the underlying rules of quantum physics and the unique benefits of photonic systems to solve these difficulties. Quantum computing is an interesting area of study since it could, in theory, speed up several kinds of calculations, such discovering prime factors, optimising, and solving systems of linear equations. Superposition, entanglement, and quantum interference are all quantum effects that let you look at more than one processing stream at a moment. This is how these speedups are possible. But there are also a lot of drawbacks with modern quantum computers, such as noise, decoherence, and the fact that it's hard to add a lot of high-fidelity qubits. The hardware is still weak and expensive, and it needs to be kept very cold and go through a lot of error correction. This means that it can't do a lot of AI work.

At the same time, photonics gives us a new approach to speed up computers and consume less power. Light is used by photonic systems to send and process data. Some of their benefits are that they send messages quickly, don't become as hot, and have very low electrical resistance. Photonic integrated circuits are made from silicon photonics and other materials. These circuits can conduct linear algebra operations rather quickly, which is very significant for calculations in neural networks. Photonic processors can use light pulses instead of electrical ones to get far higher bandwidths and parallelism. This gives us new techniques to make AI work faster that regular electronic circuits can't.

Photonic Quantum Neural Networks (PQNNs) are a new way of thinking that brings together quantum computing and photonics. These gadgets use quantum information processing ideas and photonic technology to execute neural network calculations in ways that have never been done before. PQNNs use beam splitters, phase shifters, and interferometers in photonic circuits to encode and change information using the quantum states of light. These kinds of architectures might let neural networks work quicker and on a larger scale than ordinary electronic processors, while still being energy-efficient and maybe even finding new ways to use quantum physics in computing.

The purpose of this study is to collect together the most recent research on PQNNs and give a thorough description of how they work, how they are built, and how their algorithms are constructed. We discuss about how PQNNs can aid modern AI with the computing difficulties it has to solve. We discuss about the pros and cons, where further research is needed, and where they might go in the future. By linking quantum physics, photonics, and artificial intelligence, PQNNs could lead to new ways to execute high-performance computing. They might also find solutions that change how AI systems work in the future.

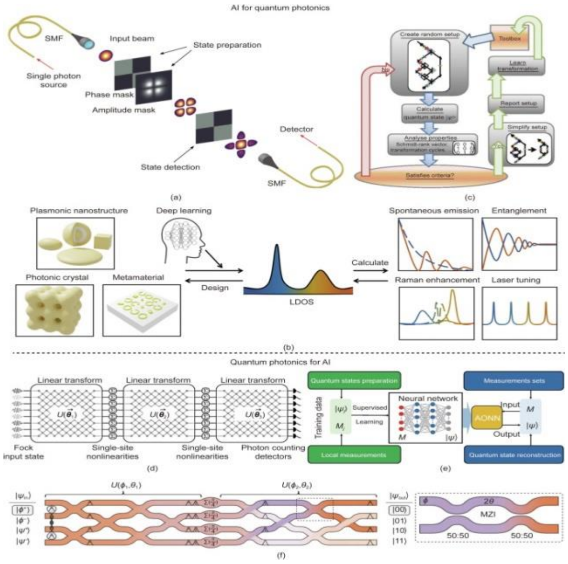

Figure 1: Photonic Quantum Neural Networks For Ai Acceleration

Background and Motivation

Classical neural networks (NNs) have done a lot of different things quite well. Some examples are convolutional neural networks (CNNs), which are great at finding spatial hierarchies in images; recurrent neural networks (RNNs), which are good at modelling sequential data like language and time series; transformers, which have changed the way we process natural language with self-attention mechanisms; and graph neural networks (GNNs), which work on data that is represented as graphs to find relational structures. As AI models develop bigger and more complex, though, these networks need a lot more processing power. The most recent models, such the GPT series or gigantic vision transformers, have hundreds of billions of parameters. This means they need a lot of resources to learn and make predictions quickly. This massive growth in size has led to an unprecedented amount of computer power being used, high operational costs, and greater concerns about the environment because giant data centres leave a big carbon imprint.

Quantum computing is a novel technique to conduct arithmetic that makes use of the notions of superposition, entanglement, and quantum interference. These quantum properties let you process data at the same time across a state space that is quite large. This might help computers do things that are really hard for them to do faster. For example, the Harrow-Hassidim-Lloyd (HHL) method could make it take a very lengthy time to solve systems of linear equations in some circumstances. This is highly useful for neural networks and machines that learn. Quantum algorithms for optimisation and sampling have also shown promise for making things better, including training neural networks or finding solutions in areas with a lot of dimensions. Even if it is possible, it is not easy to make quantum hardware that functions well. Scientists are still attempting to figure out how to make quantum systems work with a lot of qubits. The error rates are still high, and the coherence times of qubits are still short. Most quantum computers are in the noisy intermediate-scale quantum (NISQ) stage right now. This means that they can only be utilised to solve some problems and do some jobs.

Because of how light works, photonic systems have built-in advantages for processing information. Photons move at the speed of light and don't waste much energy. They don't have the same problems with losing heat or having high electrical resistance that electronic circuits do. Photonic integrated circuits (PICs) can swiftly execute a lot of different things at the same time. This is why they are perfect for the linear changes that neural networks need to make. Researchers have found that mesh designs that use Mach–Zehnder interferometers (MZIs) may quickly and easily do any unitary matrix multiplication. This indicates that photonics can solve hard math problems like matrix-vector products, which are needed for layers in neural networks. Unlike electrical circuits, photonic circuits don't have the same limits on how freely electrons can move. This means that they might have more bandwidth and use less energy for each task.

Quantum computers and photonics could work well together because they can both grow and work quickly. Photonic quantum computing stores quantum information in light waves. It builds quantum gates by dividing beams, changing their phase, and squeezing them. This platform uses quantum superposition and entanglement, as well as the natural benefits of photonic transmission and processing. Photonic Quantum Neural Networks (PQNNs) offer these kinds of properties, which make them great for speeding up AI tasks, especially the linear algebra calculations that neural networks do most of the time. PQNNs could make calculations, energy utilisation, and the complexity of hardware a lot less expensive. This gives them a good new way to get around the challenges that regular AI computing methods run into.

Principles of Quantum Neural Networks

Quantum neural networks (QNNs) are quantum circuits that use quantum effects to try to work like regular neural networks. You can use amplitude encoding, angle encoding, or qubit basis encoding to put data into quantum states in QNNs. In other words, quantum gates are like neural network weights because they have settings that modify how they perform. We use quantum measurements to find out what the network thinks will happen. These measures give us results that are probably correct.

QNNs are great at jobs that need them to do a lot of linear algebra and look for patterns that are hard to find. They should be able to make some functions go a lot faster. In classical networks, weight matrices can do unitary transformations. Quantum circuits can do the same thing. But it's hard to use nonlinear activation functions in purely quantum circuits since they have to be unitary.

Scientists have been investigating at hybrid quantum-classical models more recently. In these models, quantum circuits make changes that are straight lines, and classical electronics make changes that are not straight lines. On the other hand, quantum photonic systems can make things behave in a nonlinear way through nonlinear optical effects. This suggests that quantum mechanics can fully explain brain networks.

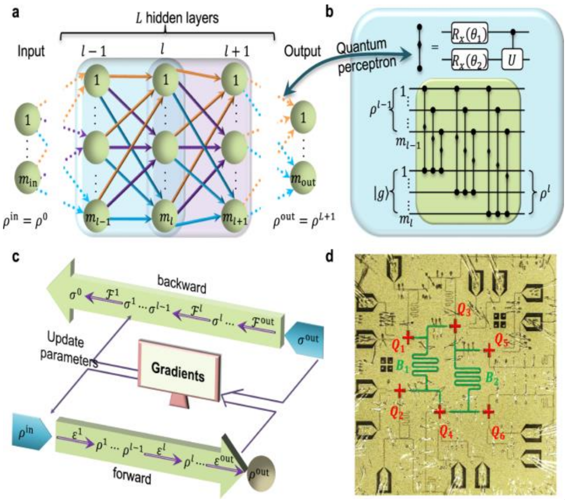

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Figure 2: Principles of Quantum Neural Networks

Photonic Implementations of Neural Networks

A. Photonic Circuits for Linear Operations

Photonic circuits are perfect for the linear algebra that neural networks use to do their calculations. The Mach-Zehnder interferometer (MZI) is one of the most significant pieces of photonic systems. It can execute custom unitary transformations by carefully changing the phase and interference patterns. Researchers have proved that they can build any unitary matrix by placing MZIs in mesh patterns. This helps the hardware quickly do huge matrix-vector multiplications. These linear transformations are highly critical for fully linked layers, convolutional filters, and even elements of more complex systems like transformers. These gadgets use light, which makes it easy for signals to move through the circuits swiftly. This is because light always travels in a straight line. It can do matrix multiplications in parallel and quickly, which is a huge benefit over regular electrical circuits. Normal circuits typically become stopped since they can only handle one thing at a time and have to wait for links to join.

B. Speed, Efficiency, and Integration

One of the best things about photonic devices is how fast they work. Photonic parts can work at frequencies in the terahertz range, which is far higher than the gigahertz clock speeds that most new electronic circuits employ. Because they have a lot of bandwidth, photonic systems can handle data streams faster than electrical devices. This affords us new techniques to speed up the process of making neural networks work and maybe even training them. Photonic devices also don't create as much heat when they work since photons don't have the same electrical resistance as electrons. This means that the energy efficiency gets up because there is less heat loss. This is really essential since AI models are getting bigger and need more processing power. Silicon photonics has helped photonic neural networks evolve by letting people construct tiny photonic integrated circuits (PICs). You can make these circuits using regular CMOS processes, which means you can put photonic elements on the same chip as electrical circuits. This combination makes it possible to construct a lot of affordable photonic accelerators that can be employed in data centres and edge computing devices.

C. Nonlinear Activation Mechanisms

Photonic neural networks are great at linear processes, but they have problems with the nonlinear activation functions that give neural networks their power. Nonlinearities help neural networks get close to hard functions and identify connections in data that aren't just simple linear transformations. In photonic systems, these nonlinearities generally emerge from optical nonlinear processes like the Kerr effect, which changes how much light a material bends based on how bright it is, or from saturable absorption, which makes absorption less at higher intensities. These processes can make behaviours that are similar to the activation functions employed in traditional neural networks, such as the ReLU (Rectified Linear Unit) and sigmoid functions. But it's still challenging for technology to get a lot of nonlinearity at low power levels. Many nonlinear optical processes need a lot of light to display changes. This might make photonic systems use more electricity. Researchers are still seeking for new materials, better device topologies, and hybrid photonic-electronic ways to add nonlinear activation functions to photonic neural networks without making them slower or more expensive.

Photonic Quantum Computing

Using the quantum properties of light, photonic quantum computing is a new technique to conduct arithmetic. It does this by using the physical properties of photons, such as their polarisation, phase, time-bin encoding, frequency modes, and number of photons, to show quantum information. Normal qubits are created in superconducting circuits or by trapping ions, however photonic qubits are not the same as normal qubits. Different optical parts can change the optical modes they are in. The main tools used to build quantum gates include beam splitters, phase shifters, mirrors, and waveguides. These gates make the interference patterns that quantum superposition and entanglement need. Photonic quantum circuits use interference to produce quantum logic gates and other things that make it easier to do arithmetic in the quantum state space.

One of the best things about photonic quantum computing is that it can use nonlinear optical processes like spontaneous parametric down-conversion (SPDC) to make and alter entangled states. In SPDC, a high-energy photon passes through a nonlinear crystal and divides into two lower-energy photons that are connected. These are called signal and idler photons. These photons are in quantum states that are connected to one other. Entanglement is a key part of quantum information protocols that use it, such as quantum teleportation, quantum cryptography, and quantum computing. You may also adjust quantum uncertainty by lowering the noise in one variable (like amplitude) while enhancing the uncertainty in its conjugate variable (like phase). This creates quantum states that classical light can't see.

Photonic quantum computing has a lot of benefits over other kinds of quantum computing. One huge plus is that photons work well at room temperature, so they don't need to be cooled down like a lot of other qubit technologies do. This makes the device easier and cheaper to use. Photons also don't interact with the stuff around them. This shows that quantum states can stay in sync over long distances for a long time. Photonic technologies are useful for quantum communication because they can readily send quantum information over optical fibres. This makes it possible to make designs for quantum internet and distributed quantum networks.

Linear Optical Quantum Computing, or LOQC, is a well-known concept in the field of quantum computing that uses light. LOQC does quantum computing utilising linear optical networks that have beam splitters and phase shifters, as well as observations and additional photons. Measurement-induced nonlinearities allow for the execution of some non-classical procedures in a probabilistic approach. This illustrates that in some circumstances, you can execute universal quantum computing with just linear elements. But LOQC needs to deal with a lot of difficulties that happen in real life. For big calculations, you need complicated optical circuits. This is a lot of extra work because they need a lot of optical elements and extra photons to be made and synced. As circuits develop more complex, accumulated optical losses and faults in the manufacturing process make it exceedingly tougher to scale up and maintain the calculations right.

Research in photonic quantum computing is moving swiftly, even though there are these challenges. Integrated photonic platforms have made photonic systems smaller and more stable. These platforms make exceedingly precise quantum circuits on a semiconductor. Quantum dots and defect centres in solid-state materials are two novel techniques to create single photons. These new technologies have made quantum light sources more reliable, which is good news for photonic devices that can be made bigger. Researchers are also looking at novel ways to remedy mistakes. For example, they are working on quantum error correction algorithms that are made just for photonic systems to deal with the noise and loss that happen when optical systems are employed.

Quantum computing and photonic hardware work well together to form a strong framework. This architecture is useful for quantum computing and lets people come up with new ideas, such Photonic Quantum Neural Networks (PQNNs). These systems could use both quantum mechanics and the good things about photonics at the same time. This might make computers much quicker, more parallel, and use less energy, all of which are vital for speeding up AI work and fixing problems that ordinary computers can't.

Photonic Quantum Computing

A. Encoding Quantum Information

Photonic quantum computing uses the strange properties of light to store and process information. There are many ways that photons can carry quantum bits (qubits), such as through polarisation, phase, time-bin, and frequency modes. It's easy to work with polarisation qubits when you use optical parts. Time-bin encoding lets you communicate quantum information over optical fibres without losing it. These diverse encodings allow you make quantum systems that are best for different kinds of processing and communication.

B. Quantum Operations and Entanglement

Optical tools like beam splitters, phase shifters, and interferometers let us regulate quantum states very precisely through phase and interference, which makes quantum gates possible in photonic systems. Entanglement is an important topic in the field of quantum information. One photon can often divide into two entangled photons, which is what happens in spontaneous parametric down-conversion (SPDC). Quantum protocols like quantum teleportation and secure communication work because of entangled states. They are also the building blocks of quantum logic operations.

C. Advantages and Challenges of LOQC

Photonic quantum computing has a lot of benefits over traditional ways of computing. For example, it can work at room temperature, has longer coherence periods, and might be able to process data quickly. Photons are useful for delivering quantum information via networks because they block out noise in the area. A well-known way to execute quantum calculations is Linear Optical Quantum Computing (LOQC). It uses linear optical circuits that have nonlinearities caused by measurements. But LOQC has some disadvantages, like high resource costs, optical losses, and the fact that it's hard to construct good single-photon sources. Photonic technology are advancing swiftly, and because of this, we can now build photonic circuits that are both reliable and can grow. These circuits might be useful for quantum computers in the future. Combining quantum computing with photonic technology could lead to some really cool new techniques to speed up AI and conduct maths that regular computers can't do.

Experimental Implementations And Prototypes

In the last few years, experimental research on Photonic Quantum Neural Networks (PQNNs) has made a lot of progress, and the framework has been established for systems that may be used in the real world. One of the most important things that have been done is to make photonic devices that can function with tiny quantum circuits. These devices can usually execute any kind of unitary transformation when they are set up in mesh patterns with networks of Mach–Zehnder interferometers (MZIs). By adjusting the phase shifters in these interferometers, scientists may very precisely change the patterns of interference. This lets you conduct complex linear changes that classical and quantum neural networks need. These integrated photonic circuits are exceedingly stable and take up less space, which makes them attractive candidates for scaling up quantum calculations in the future.

A lot of people want to know how to use quantum gates on photonic devices with a lot of accuracy. Silicon photonics and various ways to combine photonics have come a long way. You can now put quantum logic gates right into the gadget. Researchers have been able to exhibit basic operations like the controlled-NOT (CNOT) gate, which is important for entanglement and sophisticated quantum algorithms. Gates are more accurate and less noisy now that they use single-photon sources, efficient detectors, and waveguides that don't waste much light. While calculations are going on, these are particularly critical for keeping quantum information safe.

Researchers have discovered that Variational Quantum Algorithms (VQAs) are one of the best ways to learn about photonic quantum computing. In these methods, quantum circuits are put up and then improved again and again using classical feedback loops to lower certain cost functions. People have employed experimental photonic versions of VQAs for sorting jobs, where small-scale photonic quantum circuits learn to tell the difference between different types of input. These tests show that quantum machine learning works and that hybrid quantum-classical systems might be better than regular ones for particular tasks. They also illustrate how photonic hardware may be used to run quantum algorithms that function well on noisy intermediate-scale quantum (NISQ) devices.

The results are good, but there are still a lot of issues that need to be fixed before these prototypes can be made bigger and compete with regular deep learning systems. Most experimental setups only employ a few qubits or photonic modes right now because it's hard to line up a lot of optical parts, make them very accurately, and lose light. As time goes on, beam splitters, phase shifters, and waveguides all lose power, which makes photonic circuits grow. This makes the signal weaker and the calculations less accurate. Also, it's still very hard to create high-purity single photons on demand, make sure that they all arrive at the same moment, and make sure that all parts of big devices work the same way.

In the future, scientists will explore for new ways to deal with these issues. Researchers are now working on ways to improve optical properties, such as by using multiple photon sources, error-correcting technology, and novel materials. Another good way to construct PQNNs that can develop is to put photonic circuits and regular electronics on the same chip. As experimental methodologies and fabrication technology get better, photonic quantum neural networks will probably be able to speed up AI activities. We still have a lot of work to do, but the progress we've done in the lab so far is a strong start on the next generation of neural networks that employ quantum technology.

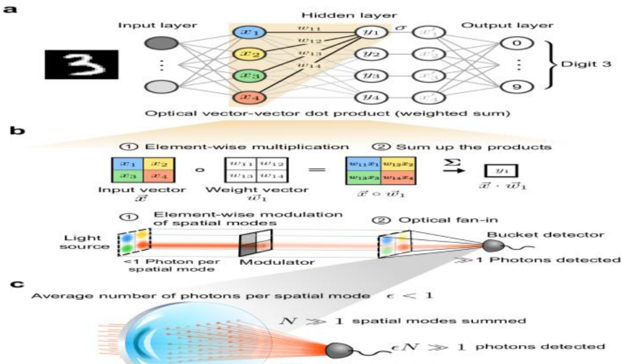

Figure 3: Experimental Implementations and Prototypes

Computational Advantages and Theoretical Speedups

Theoretical research reveals that PQNNs could speed up many AI activities. For example, quantum parallelism enables you examine at a lot of input configurations at once, which speeds up particular inference tasks. In the best cases, quantum linear algebra algorithms may solve linear systems ten times faster than regular methods.

Photonic circuitry speeds up calculations even further because it can work on more than one thing at once and sends signals incredibly quickly. Photonic circuits can do matrix multiplications, which are the most prevalent type of computation in neural networks, in constant time, no matter how big the matrix is. There are two factors that can slow things down: optical channel delays and device losses.

But you need to look at the situation closely to truly speed things up. Real quantum technology faces issues with noise, decoherence, and gate fidelity.

Challenges and Limitations

Despite their promise, PQNNs face numerous practical challenges:

- Scalability: Fabricating large-scale photonic quantum circuits with low losses and precise control over parameters is difficult. Device imperfections can accumulate, degrading computation fidelity.
- Noise and Decoherence: While photonic systems offer long coherence times, photon loss and imperfect quantum gates introduce noise that can disrupt computations.

- Nonlinear Activation Implementation: Optical nonlinearities often require high intensities, making low-power implementations challenging. Hybrid classical-quantum approaches introduce latency and diminish purely quantum advantages.
- Data Encoding: Transforming large classical datasets into quantum states involves significant overhead, which may outweigh computational benefits for certain applications.
- Error Correction: Quantum error correction for photonic systems remains an area of active research. Without robust error correction, large-scale PQNNs may be impractical.
- Algorithm Development: Many quantum algorithms remain in early development. Practical PQNN applications require new algorithms optimized for photonic hardware.

Future Directions

Advancing PQNNs requires innovations in both hardware and algorithms. Promising research directions include:

- Integrated Photonic Platforms: Developing silicon photonics and other integration technologies to fabricate dense photonic circuits with low loss.
- Novel Nonlinearities: Exploring new materials and mechanisms for low-power optical nonlinearities to enable native quantum activations.
- Hybrid Architectures: Combining quantum photonics with classical accelerators to leverage the strengths of each domain.
- Quantum Data Processing: Designing algorithms that operate on inherently quantum data, such as quantum states from physical systems or quantum sensors.
- Error-Tolerant PQNNs: Investigating methods for error mitigation and fault-tolerant architectures tailored to photonic hardware.
- Cross-Disciplinary Applications: Applying PQNNs to domains where quantum representations naturally align with the problem structure, including quantum chemistry, materials science, and cryptography.

PQNNs lie at the frontier of quantum technologies and AI, offering a pathway to overcome current computational barriers. While challenges remain substantial, continued interdisciplinary research may transform PQNNs from experimental prototypes into practical accelerators for the next generation of AI systems.

Conclusion

Photonic Quantum Neural Networks (PQNNs) represent an exciting convergence of quantum mechanics, photonics, and machine learning, embodying a vision to transcend the inherent limitations of classical computing architectures. As artificial intelligence continues to scale toward increasingly large and sophisticated models, the computational demands imposed by training and inference grow exponentially, straining conventional electronic hardware in terms of speed, energy efficiency, and scalability. PQNNs emerge as a compelling alternative, offering unique advantages derived from the principles of quantum parallelism and the ultrafast, low-loss nature of photonic systems. By encoding quantum information in the properties of light and leveraging optical circuits to perform essential computations, PQNNs provide a potential pathway to execute neural network operations with significantly improved speed and reduced power consumption.

Central to the promise of PQNNs is the ability to perform complex linear algebra operations, such as large-scale matrix multiplications, far more efficiently than traditional electronic processors. Photonic hardware, with its capability to execute operations at terahertz frequencies, coupled with quantum circuits' ability to exploit superposition and entanglement, opens the door to significant computational acceleration. Moreover, PQNNs hold the potential to revolutionize machine learning applications that depend on high-dimensional data processing, optimization, and pattern recognition. This synergy between quantum computational advantages and photonic hardware speed provides a foundation for transformative advances in AI acceleration.

Nevertheless, transforming the theoretical benefits of PQNNs into practical technology entails overcoming significant technical and scientific challenges. Fabrication of large-scale integrated photonic circuits with minimal optical losses and precise control over phase and interference remains a formidable engineering hurdle. As photonic circuits grow in complexity, cumulative losses and fabrication imperfections can degrade the fidelity of computations, limiting scalability. Additionally, generating high-quality, on-demand single-photon sources, synchronizing photon arrivals, and integrating reliable nonlinear components to implement activation functions are areas requiring substantial progress.

Algorithmic maturity also poses a critical challenge. While numerous theoretical proposals exist for quantum neural networks and hybrid quantum-classical learning schemes, the development of algorithms specifically optimized for photonic quantum hardware remains in its early stages. Ensuring that PQNN architectures can deliver practical speedups over classical systems for real-world machine learning tasks will require innovative algorithm design, careful benchmarking, and rigorous evaluation under realistic noise conditions. Furthermore, the need for explainable AI extends into the quantum domain, where understanding and interpreting the outputs of PQNNs will be essential for adoption in critical applications.

Despite these challenges, the progress achieved in experimental implementations and prototype demonstrations is highly encouraging. Researchers have successfully fabricated photonic chips capable of executing small-scale quantum circuits, implemented key quantum gates with high fidelity, and demonstrated proof-of-concept quantum machine learning algorithms such as variational quantum classifiers. The continued development of integrated photonics, advances in material science for low-loss components, and growing understanding of quantum algorithms all contribute to the momentum driving PQNN research forward.

Looking ahead, PQNNs may evolve from experimental prototypes into essential components of the AI computing ecosystem. As photonic integration technologies mature and quantum photonic devices become more reliable and scalable, PQNNs could enable breakthroughs not only in computational speed but also in energy efficiency and system miniaturization. Their potential applications extend beyond AI, encompassing quantum communication networks, cryptography, and complex simulations in physics, chemistry, and materials science.

In conclusion, the development of Photonic Quantum Neural Networks represents a bold and visionary step toward merging photonic engineering and quantum information science to shape the future of artificial intelligence. While significant research and engineering challenges remain, the unique advantages of PQNNs position them as a promising frontier capable of addressing the escalating demands of modern AI workloads. Continued interdisciplinary collaboration across physics, engineering, computer science, and AI will be essential to transform the vision of PQNNs into practical technologies that redefine the landscape of computational intelligence.

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