Implementation of Photonic Neural Network and Cross-talk Analysis

1 Abstract

Photonic Neural Networks (PNNs) offer unparalleled advantages in accelerating deep learning computations by harnessing the speed of light and low power consumption. However, challenges such as crosstalk noise and signal loss jeopardize their reliability, especially in very-large-scale systems. This report provides an in-depth analysis of these issues, focusing on their physical origins, impacts on system performance, and theoretical modeling. Additionally, a novel heterogeneous photonic-core architecture (Phoebe) is proposed as a solution to ensure reliability while maintaining computational efficiency.

2 Introduction

The field of deep learning has witnessed exponential growth in demand for computational power. Conventional electronic hardware often struggles to meet these requirements efficiently, leading to the exploration of alternative paradigms such as Photonic Neural Networks (PNNs). By leveraging the inherent advantages of photonic devices, PNNs achieve:

- Ultra-fast operations with speeds exceeding 10^{12} multiply-accumulate (MAC) operations per second.

- Energy-efficient computations with minimal power consumption per operation.

Despite these advantages, the analog nature of photonic systems introduces reliability concerns. Unlike digital systems, analog photonic systems are more susceptible to errors caused by physical imperfections such as:

- Signal loss during propagation through waveguides.

- Crosstalk due to coupling drift and thermal fluctuations.

- Finite precision in analog-to-digital (A/D) and digital-to-analog (D/A) conversions.

- Nonlinearities in optical amplifiers.

This report focuses on crosstalk, which becomes a dominant factor as circuit scales increase.

3 Crosstalk in Photonic Neural Networks

Crosstalk in PNNs refers to unwanted interference between adjacent optical paths within a photonic circuit. It arises from:

3.1 Physical Mechanisms

1. **Coherent Crosstalk:** Caused by phase errors due to fabrication imperfections or modulation bias. This type of crosstalk attenuates signal power, as represented by:
$$E_s \rightarrow (1 - K)E_s + KE_s e^{i\beta},$$

   where K is the crosstalk coefficient, and β is the phase shift.

2. **Incoherent Crosstalk:** Results from scattering on rough waveguide surfaces, leading to signal leakage into unintended paths. This noise accumulates along optical paths, especially in large-scale systems.

3.2 System-Level Impacts

As the number of modes in a PNN increases, crosstalk noise accumulates exponentially, degrading the signal-to-noise ratio (SNR). Theoretical analysis shows that when the number of modes exceeds 96, reliability drops to unacceptable levels under typical device parameters. This finding highlights the scalability challenge for Very-Large-Scale PNNs.

4 Impacts on Neural Network Performance

To understand the practical implications of crosstalk, experiments were conducted using various neural network architectures on PNN hardware:

4.1 Multi-Layer Perceptrons (MLPs)

MLPs demonstrated robust performance when only signal loss was considered. However, incorporating crosstalk noise caused significant accuracy degradation. For example:

- Without crosstalk, test accuracy remained above 95%.

- With crosstalk levels at -30 dB, accuracy dropped below 80%.

4.2 Convolutional Neural Networks (CNNs)

CNN architectures such as AlexNet, VGG-16, and ResNet-18 were tested under similar conditions. Results showed:

- AlexNet, with its larger convolutional kernel sizes, experienced the most significant degradation due to the cumulative effects of crosstalk.

- VGG-16 and ResNet-18, which use smaller kernels, were comparatively more robust, as their architectures minimized the propagation of crosstalk noise.

These experiments highlight the need for crosstalk-aware designs in photonic computing systems.

5 The Phoebe Architecture: A Proposed Solution

To address the challenges posed by crosstalk and loss, the Phoebe architecture introduces a heterogeneous approach:

5.1 Design Overview

Phoebe consists of:

- **Small-Scale Photonic Cores:** Multiple smaller photonic cores are used instead of a single monolithic core, reducing the accumulation of crosstalk.

- **Heterogeneous Integration:** Photonic and electronic chiplets are combined using inter-layer connections, enabling efficient task scheduling and data handling.

5.2   Benefits of Heterogeneous Cores

Phoebe's design offers:

- High reliability by limiting the number of modes per core.

- Flexibility for different neural network types, with dedicated cores for MLPs and CNNs.

- Cost-effectiveness by optimizing the trade-off between hardware resources and performance.

5.3   Performance Evaluation

Benchmarks comparing Phoebe with traditional monolithic designs show:

- Up to 15% improvement in test accuracy for mixed CNN tasks.

- Reduced hardware costs, with Phoebe requiring fewer detectors and amplifiers.

- Comparable computation time, ensuring minimal performance trade-offs.

6   Conclusion and Future Work

This report provided an in-depth analysis of crosstalk and loss in Photonic Neural Networks, emphasizing their impact on reliability and performance. The proposed Phoebe architecture offers a promising solution by combining heterogeneous cores to mitigate crosstalk while maintaining computational efficiency. Future work will focus on optimizing chiplet integration and exploring advanced error correction techniques to further enhance PNN scalability. Github link:
https://github.com/pratishtha-maker/Machine_Learning
All the results are uploaded on Github in Results folder inside Project.