Deep Learning Enhanced Early Detection of Pancreatic Cancer Using Integrated Photonic Chip Based Optical Neural Networks

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Abstract: Employing Integrated Photonic Chip-Based ONNs for early pancreatic cancer detection, achieved an 80% Dice score, demonstrating efficient, high-speed alternatives to traditional electrical training systems for medical imaging.

1. Introduction

Pancreatic cancer is the fourth leading root of cancer-related death in the USA. There had been minimal progress with regard to cancer-specific outcomes in recent decades. It is known for its poor prognosis and low five-year survival rates [1]. Deep neural networks (DNNs) demonstrated superior performance in measuring tumor size and detecting location for planning effective treatments [2]. However, electronic digital hardware accelerators are inevitably limited by millisecond-level latency, high energy consumption, excessive heat, and high interconnect cost. We tackled these issues by using Integrated Photonic Chip Based Optical Neural Networks (ONNs) to train our deep learning model. Using ONNs in this situation continues to show great promise. ONNs are notable for their low latency, wide bandwidth, and high parallelism of light [3]. Using ONNs boosted the power of DNNs by offering a solid platform for fast and efficient processing of complex data. Previous studies have introduced high-efficiency integrated Optical Neural Networks (ONNs) for performing General Matrix Multiplications (GEMMs) in DNN models [4]. Yet, these GEMM-based ONNs often involve high area costs and complex control mechanisms. In our previous research [5], we developed an Optical Subspace Neural Network (OSNN) (Fig. 1(a)) architecture utilizing butterfly-style photonic meshes. This design prioritizes reduced optical component use, lower area and energy consumption over the universal adaptability of weight representation.

In this paper, we deploy our 4×4 butterfly-style photonic neural chip (BPNC) (shown in Fig. 1(b)) in a hierarchical 3D feature learning based model for pancreas cancer segmentation with the NIH pancreas dataset, obtaining an average Dice score of about 80%.

2. Optical subspace neural network architecture

Figure 1 shows the layout of the OSNN architecture. It illustrates the division of a weight matrix in a fully-connected layer into $\frac{m*m}{k}$ $k \times k$ (k is 4 or 8) submatrix units. As shown in Fig. 1(c), each submatrix unit consists of two $k \times k$ butterfly-style photonic meshes ($\boldsymbol{P}$ and $\boldsymbol{B}$ units) and a diagonal matrix unit (Σ unit) with a column of modulators. Multiple units share each ***B/P*** unit, and only $\frac{n}{k}P$ units and $\frac{m}{k}B$ units are needed for an n-input, m-output layer, leading to a reduced chip size compared to previous models [6]. Notably, only the active $\frac{mn}{k}$ photonic devices in the Σ units need to be trained, making the total number of trainable elements $k-1$ times fewer than those in ONNs for GEMMs [4], greatly lowering weight loading and computation complexity.

3. Dataset

We trained with the NIH pancreas dataset [7], a large and well-known dataset in this field, which includes 82 CT scans of the abdomen. Each scan's resolution is $512 \times 512 \times L$, where 'L' varied between 181 and 466, indicating the number of slices in each scan. The dataset has a total of 19,327 slices from 82 people, with the thickness of each slice ranging from 0.5 to 1.0 mm. We only used the slices that showed the pancreas. To test our model, we employed standard four-fold cross-validation. We divided the dataset into four parts, each with images from 20 people. We trained our model on three parts and tested it on the fourth.

4. Model and Results

We applied transfer learning based on a 3D fully-convolutional network [8], focusing on a multi-scale features approach to generate intermediate segmentation masks for a coarse-to-fine segmentation process. The intermediate masks, capturing fine details, are derived from decoders processing deeper features, while coarse segmentation details come from decoders of initial features. Our results demonstrate a Dice score of around 80%, showcasing a performance comparable to electrical hardware-based systems, but with the added advantages of Integrated Photonic Chip-Based ONNs. These benefits include increased processing speed, reduced energy consumption, and a smaller hardware footprint, positioning our approach as a promising alternative in medical imaging and analysis.

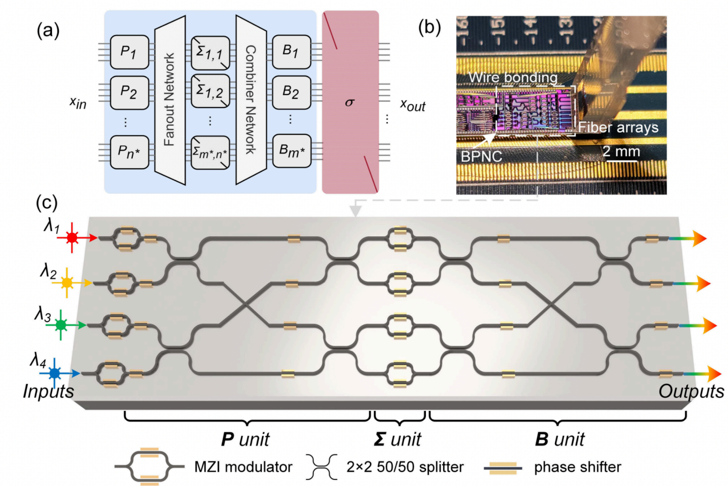

Fig. 1 **The layout of the Optical Subspace Neural Network (OSNN) architecture.** (a) illustrates a n-input, m-output layer which consists of $n^* = \frac{n}{k}$ projection units (***P*** units), $m^* = \frac{m}{k}$ butterfly-style transformation units (***B*** units), $n^* \times n^*$ diagonal matrix units (Σ units), and an electrical σ unit for activation functions. (b) shows a photo of our 4 × 4 butterfly-style photonic-electronic neural chip (BPNC). (c) shows the design of the 4 × 4 BPNC under the multi-wavelength-input mode, where different photonic circuit units (***P***/***B***/Σ) are shown.

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