Early Pancreatic Cancer Detection Using Deep Learning and Optical Neural Networks on Integrated Photonic Chips

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Abstract: Employing Integrated Photonic Chip-Based Optical Neural Networks (ONNs) for early pancreatic cancer detection, achieved an average Dice score of 0.58 for 2D and 0.6412 for 3D segmentation, matching or surpassing electronic models, demonstrating ONNs as efficient, high-speed alternatives to traditional electrical training systems.

1. Introduction

Pancreatic cancer has the lowest five-year survival rate and is projected to become the second leading cause of cancer-related deaths in the U.S. by 2030. Early detection is crucial, as prognosis worsens when tumors exceed 2 cm, and computed tomography (CT) often misses about 40% of small tumors [1]. Recent advances in deep learning (DL) show promise in medical image analysis, impacting areas like image recognition and medical diagnosis. As deep neural network (DNN) sizes and data volumes grow, the demand for efficient hardware accelerators increases; traditional electronic accelerators, such as GPUs and FPGAs, face challenges like latency and high energy consumption, while analog neuromorphic computing enhances DNN acceleration by improving both parallelism and energy efficiency. To address these challenges, we utilize Integrated Photonic Chip-Based ONNs in our deep learning model. ONNs are recognized for their low latency, high bandwidth, and light-based parallelism. Our earlier work developed an Optical Subspace Neural Network (OSNN) architecture using butterfly-style photonic meshes, focusing on minimizing optical component use and reducing area and energy consumption [2].

In this paper, we deploy our 4×4 butterfly-style photonic neural chip (BPNC) in both 2D and 3D U-Net models for pancreatic cancer segmentation using the NIH pancreas dataset, achieving a Dice score of 58% for 2D, outperforming electronic models, and 64.12% for 3D, comparable to electronic models.

2. Optical Subspace Neural Network Architecture

Figure 1 shows the layout of the OSNN architecture, illustrating the division of a weight matrix in a fully-connected layer into $(\frac{m \cdot m}{k}) \times k \times k$ (where 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 (P and B units) and a diagonal matrix unit with a column of modulators. Multiple units share each B/P unit, and only $\frac{n}{k} \times P$ units and $\frac{m}{k} \times B$ units are needed for an n-input, m-output layer, leading to a reduced chip size compared to previous models [3]. Notably, only the active $\frac{m \cdot n}{k}$ 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

The NIH Pancreas-CT dataset [5], collected by the National Institutes of Health Clinical Center, comprises 81 contrast-enhanced abdominal CT scans with a resolution of 512 x 512 pixels. Each scan has between 181 and 466 slices, with thicknesses of 0.5 to 1.0 mm, representing a diverse group of 53 men and 27 women aged 18 to 76, with an average age of 46.8 years. Detailed segmentation was performed by a medical student and verified by a radiologist, ensuring accurate labeling of anomalies, with annotated masks in NIfTI format indicating anomalies with a value of 1 and normal regions with 0. The dataset is utilized for both 2D and 3D medical image segmentation, where each slice is considered independently in the 2D approach. The dataset using a 70/10/20 split for training, validation, and testing. Augmentation techniques applied to enhance model generalization, including random affine transformations and elastic deformations.

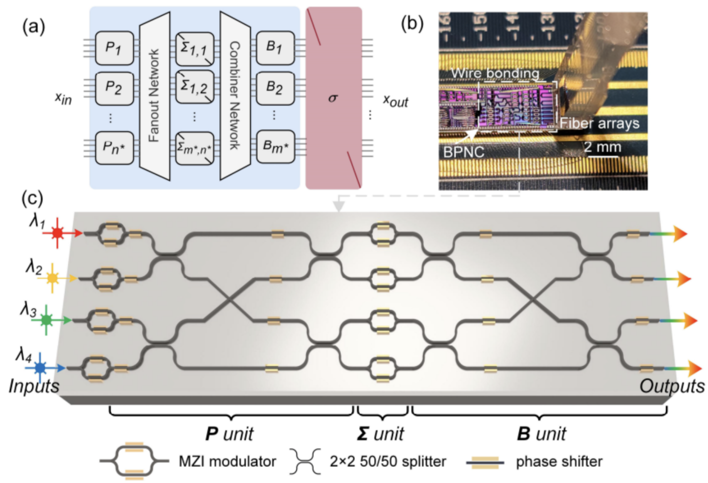

Fig. 1: The layout of the Optical Subspace Neural Network (OSNN) architecture. (a) Illustrates an n-input, m-output layer which consists of $n^* = \frac{n}{k}$ projection units (P units), $m^* = \frac{m}{k}$ butterfly-style transformation units (B units), $n^* \times n^*$ diagonal matrix units (Σ units), 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.

4. Model and Results

The segmentation tasks are performed using 2D and 3D-UNet [6] and integrated into our BPNC framework. Figure 5 visualizes patient predictions, demonstrating a strong alignment between ground truth masks and predicted outputs, effectively capturing tumor presence and size as the scans progress. For 2D segmentation, the OSNN achieves an average Dice score of 0.54, slightly outperforming the electronic model's 0.53. This is remarkable, as Integrated Photonic Chip-Based ONNs typically underperform compared to conventional electronic systems. In 3D segmentation, the OSNN scores 0.64, compared to 0.71 for the electronic model, demonstrating comparable performance. Additionally, the OSNN offers benefits such as enhanced processing speed, lower energy usage, and a more compact design. These advantages position our method as a promising, efficient alternative in medical imaging and analysis.

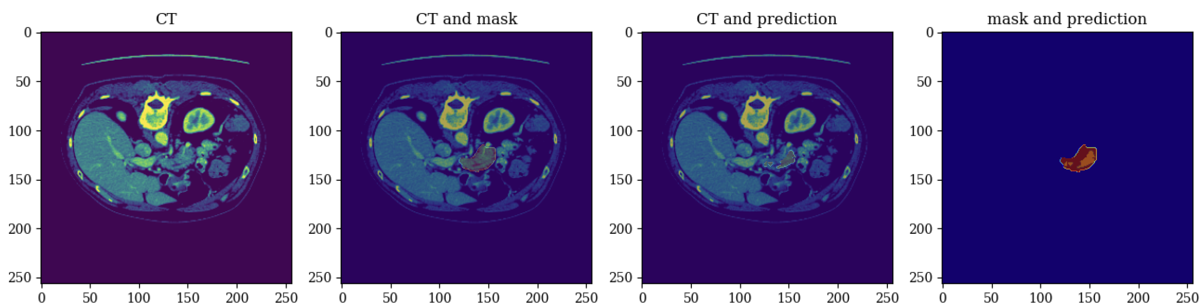

Fig. 2: Visualization of patient predictions with OSNN. From left to right: the original CT scan, the ground truth mask overlaid on the CT scan, the predicted mask, and a comparison of both the ground truth and predicted masks.

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