Image classification with a fully connected opto-electronic neural network

Alexander Song¹,²,*†, Sai Nikhilesh Murty Kottapalli¹,²,**†, and Peer Fischer¹,²,∗∗∗

¹Max Planck Institute for Medical Research, Jahnstraße 29, 69120 Heidelberg
²Institute for Molecular Systems Engineering and Advanced Materials, Universität Heidelberg, Neuenheimer Feld 225, 69120 Heidelberg
† Equal Contribution

Abstract. Optical approaches have made great strides enabling high-speed, scalable computing necessary for modern deep learning and AI applications. In this study, we introduce a multilayer optoelectronic computing framework that alternates between optical and optoelectronic layers to implement matrix-vector multiplications and rectified linear functions, respectively. The system is designed to be real-time and parallelized, utilizing arrays of light emitters and detectors connected with independent analog electronics. We experimentally demonstrate the operation of our system and compare its performance to a single-layer analog through simulations.

1 Introduction

Deep learning is widely used to solve a variety of problems, such as image and speech recognition, drug discovery, and protein folding [1]. Optical approaches for implementing deep learning architectures are a promising solutions for energy efficient, high-speed computation [2–5]. However, these approaches face some challenges such as scalability, stability/accuracy, and external interfacing [6]. Existing systems typically perform only one set of linear operations for each set of data read-in/read-out, leading to high energy consumption. We address this problem by designing and experimentally demonstrating an optical computing framework that is able to perform multiple layers of computation for each set of data read-in/read-out.

2 Design of the opto-electronic neural network

Our computing paradigm uses a series of paired optoelectronic devices and optical interconnects (shown in Figure 1) to implement a fully connected multilayer perceptron. Each opto-electronic device corresponds to either input layer (Input), hidden layer, or output layer (Output). The opto-electronic devices encode the neuronal activations and apply the rectified linear function (ReLU) while the optical interconnects implement a matrix vector multiplication.

For the hidden layers, we use a printed circuit board (PCB) that contains a 2D array of photodiodes and LEDs, along with amplification electronics. An independent circuit consists of two photodiodes, subtraction and amplification circuits and an LED to output the resulting intensity.

This circuit acts as a Rectified Linear Unit (ReLU) applied on the difference in current between the two photodiodes (shown in Figure 2, top). In each optical interconnect, light from a 2D array of LEDs propagates in free space through a mask (Optical Weights) to this 2D array of photodiodes in the subsequent layer. We design the optical propagation using geometric optics to ensure there is a region on the mask that encodes the weight between a given LED and photodiode without optical crosstalk.
3 Training and testing of network

Prior to training, we carefully calibrate and fit the electronic response functions of the optoelectronic layers and the optical transfer functions of the LEDs. We use the MNIST dataset [7] to train our four-layer network, which consists of an input layer of size 49, two hidden layers of size 50, and an output layer of size 10. The MNIST dataset is averaged in 4x4 blocks, generating a set of 7x7 images of handwritten digits. We designed a four layer network, with an input layer of size 49, two hidden layers of size 50, and an output layer of size 10. The network is trained using two different methods. In the first method, linear layers and ReLUs are implemented with standard functions, and the generated weights are normalized by the calibration matrix for the optical transfer function and the measured gains of the photodiodes. This method allows the weights to be directly incorporated into any optoelectronic neural network. In the second method, we constrain the linear layers to be nonnegative and explicitly include the measured gains of the photodiodes within the ReLU model.

![Network diagram](image)

**Figure 2.** Schematized depiction (top) of the positive (black) and (red) negative encoded contributions for each neuron activation and example activations (bottom; simulation in blue, experimental in green) of a reduced MNIST classifier network.

We use data acquisition hardware (DAQ) to read-in and read-out sets of digits to and from the input and output layers. To demonstrate how the signal evolves through our multilayer optoelectronic neural network, we provide example neuronal activations for a network trained on the MNIST dataset (shown in Figure 2, bottom). The simulated results are displayed in blue, while the experimental results are shown in green. First, an image of a digit is read-in to the Input and emitted from the LEDs. The inputs then propagate through the optical interconnect and are mapped to the photodiodes of Hidden Layer 1. There, pairs are differenced and a ReLU is applied. This process repeats in Hidden Layer 2, and the output is read-out in the Output layer.

4 Network Performance

The multilayer optoelectronic neural network has more demanding experimental requirements compared to a single-layer network. While the correlation of neuronal activations in a hidden layer showed an overall Pearson’s correlation of 0.955 compared to simulated values, the overall correlation at the output decreased with additional layers.

To evaluate the performance of the multilayer neural network, we simulated its performance on the reduced MNIST dataset and compared it to a linear network (Figure 3). We calculated the confusion matrix on the test set to show the fraction of correctly labeled digits of each type on the diagonal. The test accuracy of the multilayer network was 0.960, compared to 0.862 for the linear network. However, higher precision parts and calibration will be necessary for large-scale integration of this approach.

![Confusion matrices](image)

**Figure 3.** Simulated confusion matrices of MNIST digits for a multilayer opto-electronic neural network (top) and a linear network (bottom).

References