# A high performance fully tunable laser-based neural network

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**Summary.** We experimentally demonstrate a high-performance, stable, autonomous, fully tunable, and scalable neural network of 350+ discrete nodes based on a semiconductor laser. Using exclusively off the shelf components, our optical neural network achieves high performance and a high classification bandwidth of 15KHz for the MNIST dataset with potential scalability towards the MHz range.

Artificial Neural Networks (ANNs) have become a ubiquitous technology; indeed, their flexibility allows them to excel in a wide range of tasks, ranging from medical diagnosis to language models. Unlike classical algorithms, these networks process information in parallel. Photonics, in particular, shows great promise as a platform for implementing ANNs in terms of scalability, speed, energy efficiency and parallel information processing [1]. In [2], we physically implemented the first fully autonomous PNN (photonic neural network), using spatially multiplexed modes of an injection locked large area vertical cavity surface emitting laser (LA-VCSEL). All components of our PNN, including learning are fully realized in hardware using off-the-shelf, commercially available, low energy consumption components, while still achieving >98% accuracy in 6-bit header recognition tasks and promising initial results for the MNIST hand written digit recognition dataset, where we achieve 90% accuracy on average. Crucially, our system performs classification at a high bandwidth of 15 kHz, which is not limited by the LA-VCSEL (GHz bandwidth) and could potentially increase towards the MHz range.

The PNN presented here was first implemented in [2,3]. Whereas previously it followed the reservoir computing (RC) concept, where input and internal weights are fixed and only the output weights are trained, we now present an improved version of the setup where all connections in the PNN can be trained yielding therefore a highly tunable network. The experimental scheme is shown in Fig. 1. Input images $\mathbf{u}$ displayed on a digital micromirror device ($DMD_a$) are passed through a phase mask displayed on a spatial light modulator (SLM) which encodes the input weights $\mathbf{W}^{in}$. The phase modulated input is injected onto the LA-VCSEL through a multimode fiber (MMF) which passively implements a random linear mixing $\mathbf{W}^{rand}$. The VCSEL then transforms the injected information non-linearly yielding the perturbed mode profile $\mathbf{x}$. The final part of the PNN is its output layer. The VCSEL's surface is imaged onto $DMD_b$, whose pixels can flip between two positions, for one of which it reflects light onto the photodetector (DET), giving us Boolean output weights $\mathbf{W}^{out}$. 350+ nodes are implemented fully in parallel; the output of the PNN $\mathbf{y}$ is the optical power detected at DET. $\mathbf{W}^{out}$ and $\mathbf{W}^{in}$ are trained via iterative optimization based on evolutionary search algorithms or gradient descent using gradient estimation methods from reinforcement learning. Higher output weight resolutions can be achieved with higher imaging magnifications onto $DMD_b$. Additionally negative output weights can be achieved via recording the output of the PNN twice and implementing an electronic subtraction.
Fig. 2.(a) shows preliminary classification performance for the MNIST task using Boolean weights (BOOL), and trinary weights (3val -1,0, +1) reaching an average performance of 90% for trinary weights which have a significant positive impact on performance. In addition, we conducted a long-term stability analysis in Fig. 2.(b), over a period of 10 hours, showing little to no degradation in performance or drift. Moreover, the average cross correlation between different outputs over the 10 hours was 98%. We also studied the impact of different learning strategies and physical parameters of our PNN (injection power and wavelength, bias current, etc…) on its performance for classification tasks as well as how they impacted

other dynamical properties such as consistency and dimensionality, showing a promising consistency of 99%.

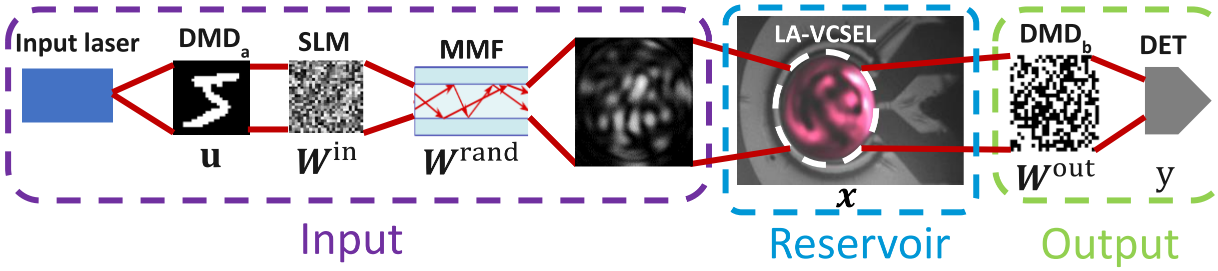


Figure 1. Working principle of our experimental photonic neural network

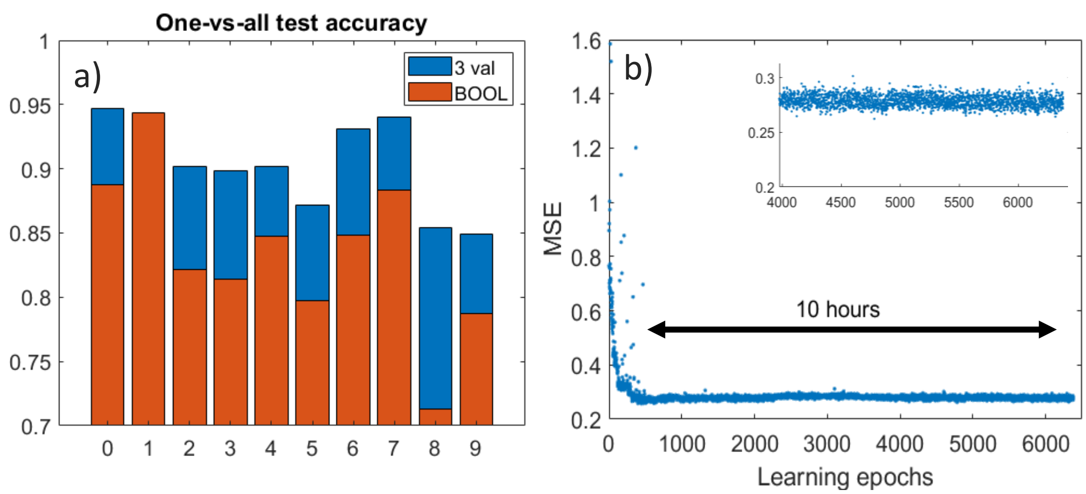


Figure 2. (a) One-vs-all test accuracy for the hand written MNIST dataset using Boolean (BOOL) and trinary (-1,0, +1) output weights. (b) Long term stability measurement showing minimal drift in performance over 10 hours showcasing the stability of our PNN.

In conclusion, we have demonstrated a fully parallel PNN consisting of 350+ neurons realized entirely in hardware. Our PNN shows long term stability and excellent performance in header recognition tasks as well as XOR and digital to analog conversion, and additionally, promising performance in the MNIST dataset while achieving classification at a bandwidth of 15kHz. Our approach is highly relevant, fully parallel and scalable both in terms network size and depth as we have a clear avenue for using VCSELs in a deep PNN configuration. Lastly the inference bandwidth is also highly scalable due to a fast VCSEL response time without any significant increase in power consumption.

## References


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