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# Biologically Plausible Deep Learning by Dendritic Gating of Plasticity

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## Introduction

- Artificial Neural Networks (ANNs)** are good at recognizing patterns, but they follow rules that are not biologically plausible.
- A standard learning rule used in machine learning is **backpropagation**, which uses gradient descent. It follows the weight update rule:

$$\Delta W \sim \frac{\partial \text{Error}}{\partial W} \sim \frac{\partial \text{Error}}{\partial A_{\text{post}}} \times A_{\text{pre}}$$

- This is not biologically plausible since it uses **nonlocal error**.
- We hypothesize that separate **soma** and **dendrite** compartments can be used to compute local error<sup>1,2,3</sup>. Learning rules based on this were then compared to backprop as a benchmark on a non-linear classification task.
- We first tested this idea in our “**dendritic temporal contrast**”<sup>4</sup> model:

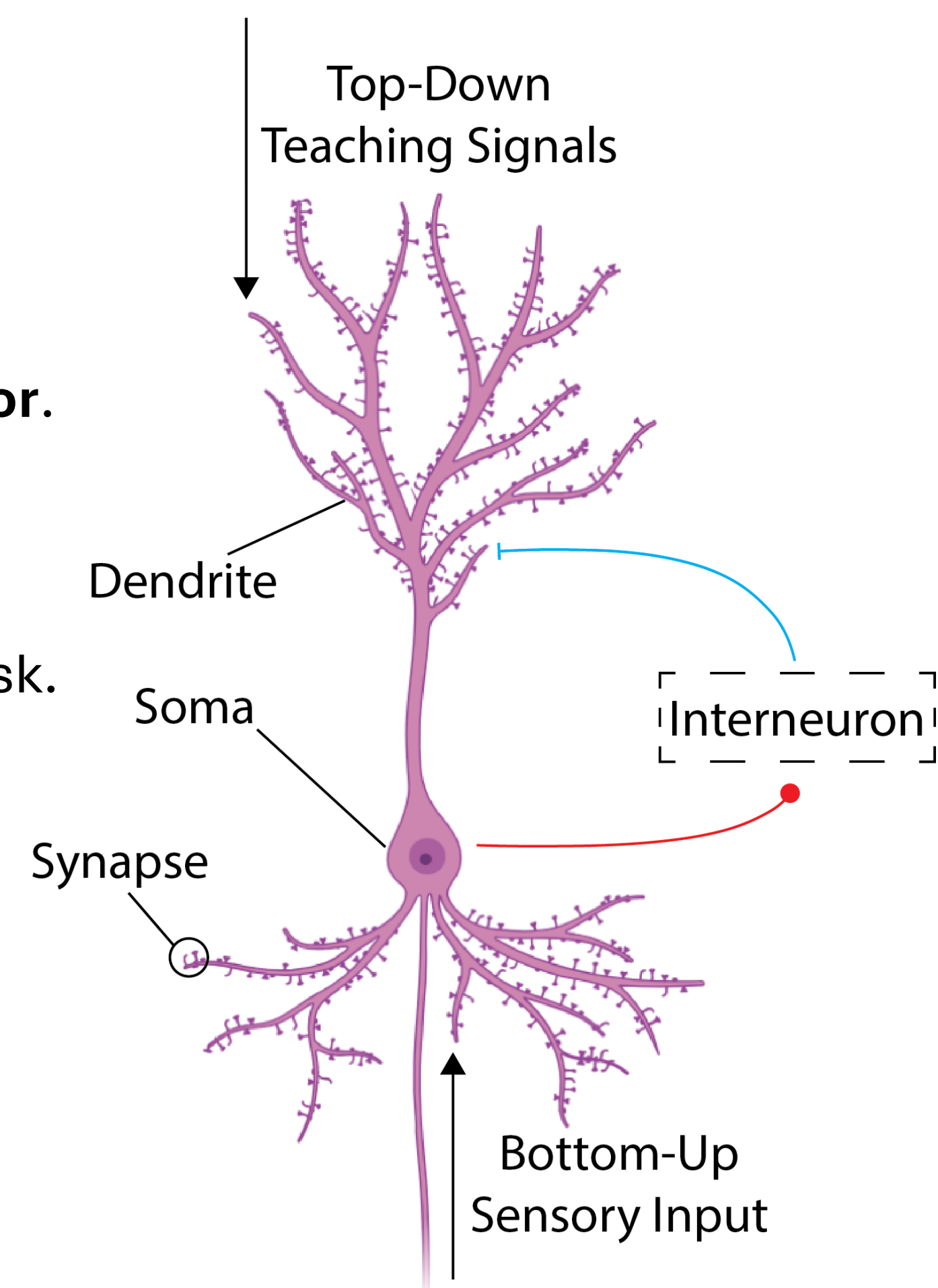
$$N \sim D_B - D_F; \Delta W \sim N \times A_{\text{pre}} \\ A_{\text{post}} \leftarrow A_{\text{post}} + N$$

- This model compares top-down input before and after a teaching signal (nudge) is applied.
- We extended this further by using **interneurons**. Here, a comparison is made between top-down input and lateral current input to dendrites:

$$N \sim D_B = I_{TD} - I_{Int}; \Delta W \sim N \times A_{\text{pre}}$$

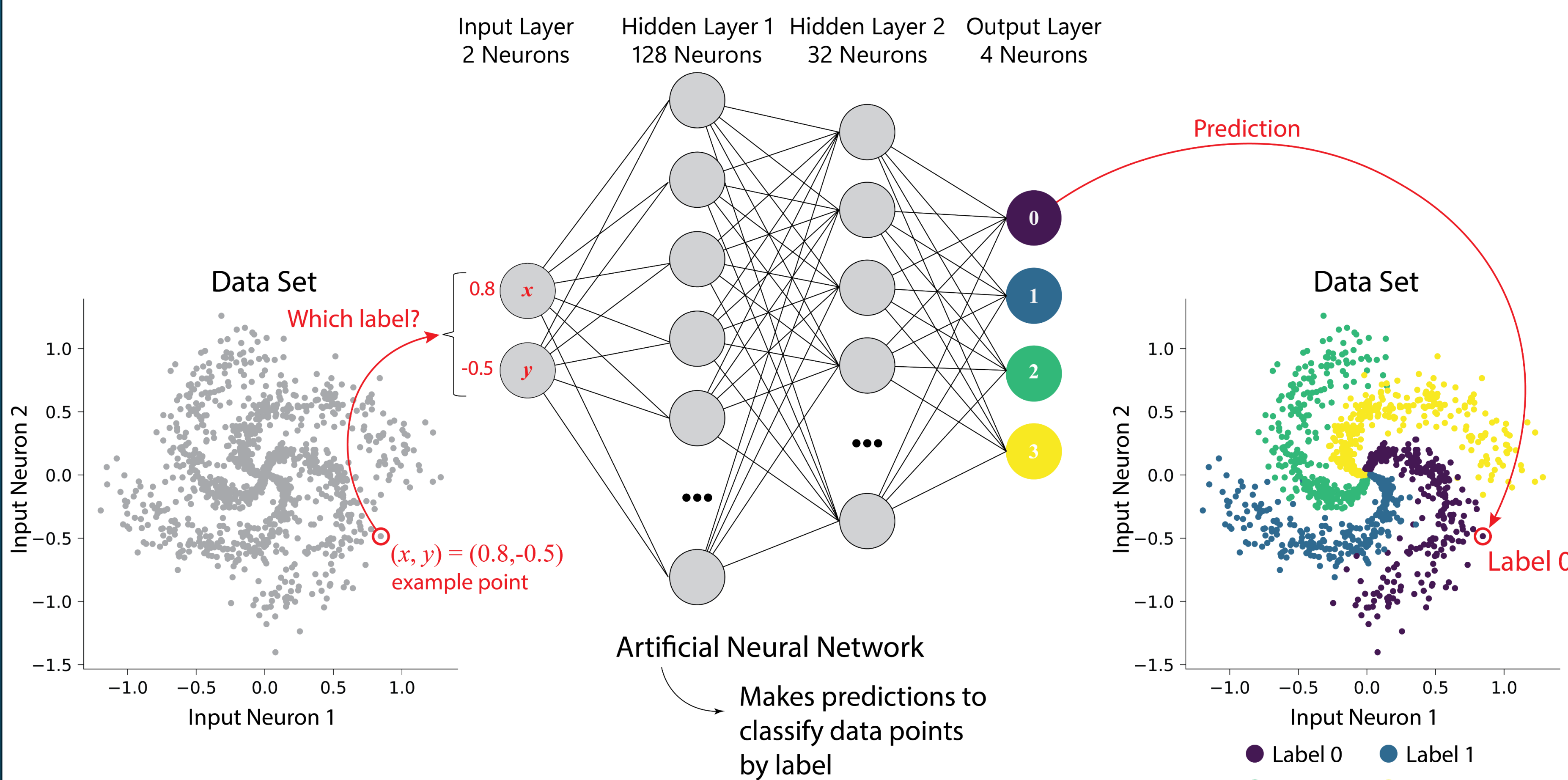
### Legend:

W: Weights (synaptic strength) D: Dendritic state  $I_{TD}$ : Top-Down Input  
A: Activity (firing rate of neuron) B: Backward pass  $I_{Int}$ : Interneuron Input  
N: Nudge (teaching signal) F: Forward pass



**Fig 1:** Neuron compartmentalized into soma and dendrite, with lateral interneuron connection. Example neuron in one layer of ANN.

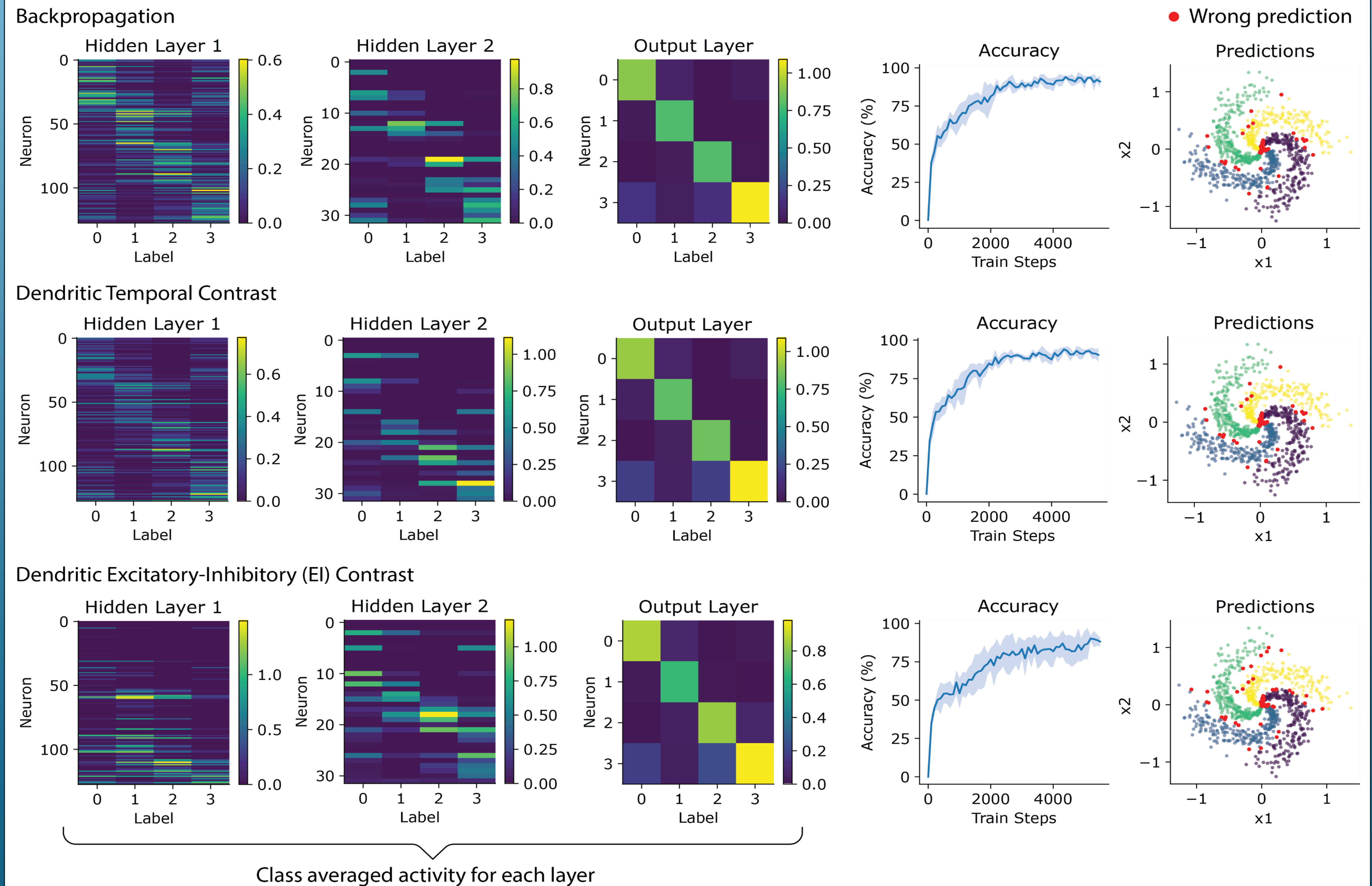
## Methods



**Fig 2:** ANN Architecture and spiral dataset used

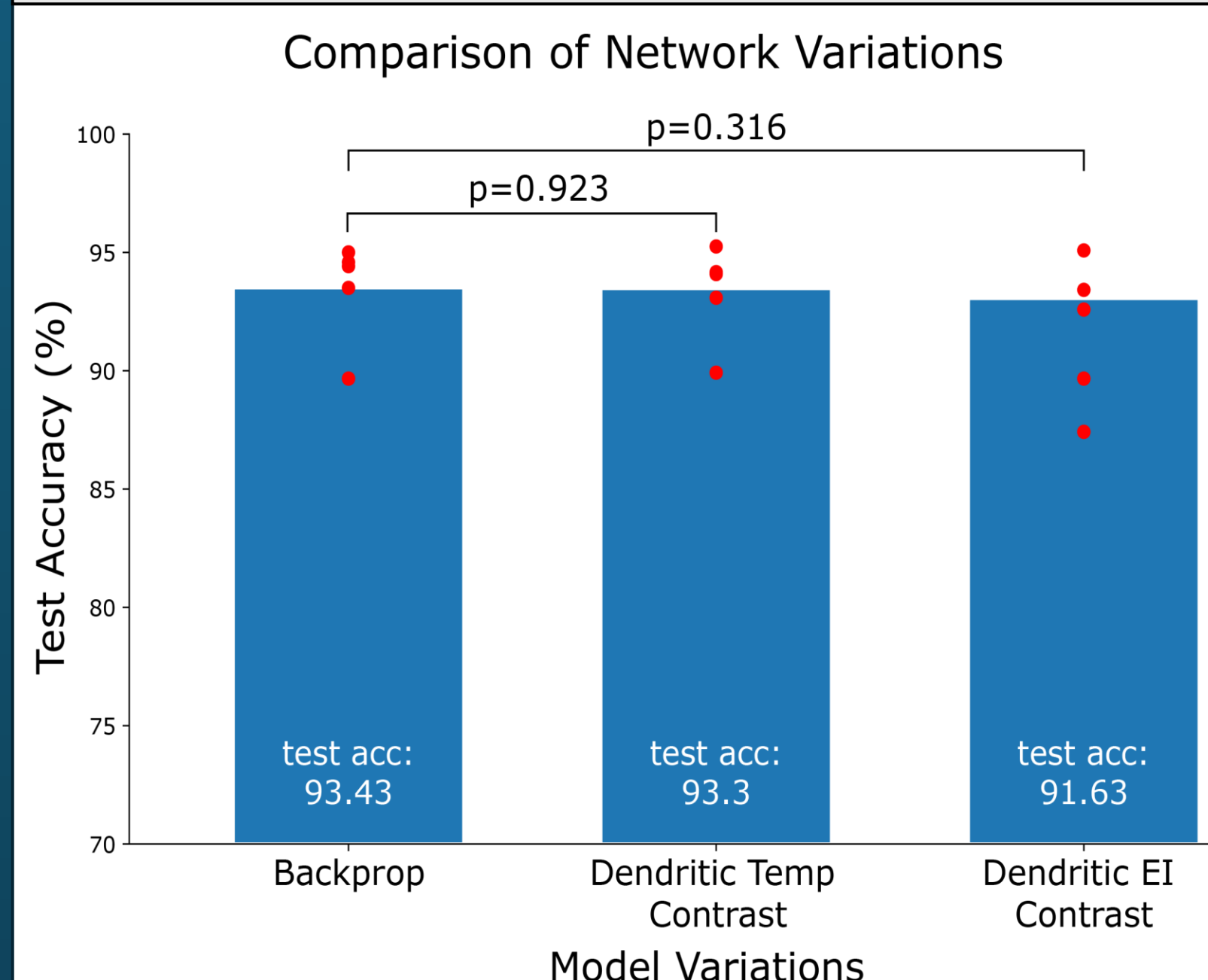
- Developed neural network with PyTorch in Python 3.
- Trained network with data points from data set.
- Optimized hyperparameters with Optuna.

## Results



**Fig 3:** Summary plots for all 3 ANN configurations

## Conclusions



**Fig 4:** Comparison of validation accuracies for 3 ANNs, with p-values in comparison to Backprop

- Compartmentalizing neurons into dendrites and somas to pass error signals can be used to approximate backprop in a biologically plausible way.
- Dendrite-targeting interneurons effectively separate self-generated signals from true error signals, to accurately approximate the gradient.

### Future Directions

- Learn top-down weights on the backward pass instead of using the transpose matrix.
- Use separate excitatory and inhibitory neurons to make network more biologically plausible.

## Acknowledgements

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## References

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  - <sup>2</sup>Milstein, A., Li, Y. et al. *eLife*, 2021. doi: 10.7554/eLife.73046
  - <sup>3</sup>Galloni, A., Yuan, Y., et al. *PNAS*, 2024. doi: 10.1073/pnas.2318362121
  - <sup>4</sup>Xie, X., Seung, H. S. *Neural Computation*, 2003. doi: 10.1162/089976603762552988
- Figures created with Python, Adobe Illustrator, and BioRender.