Classification of Neural Interferometric Imaging: Machine Learning for Non-invasive Neurosensing

Stanford ENGINEERING

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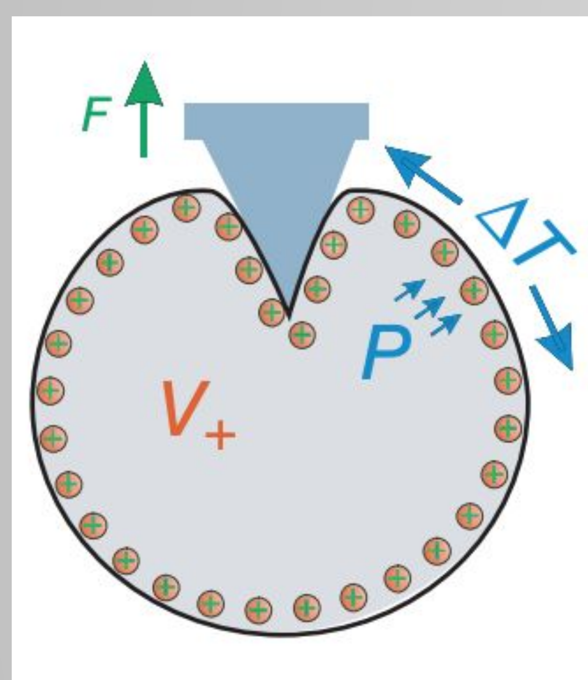
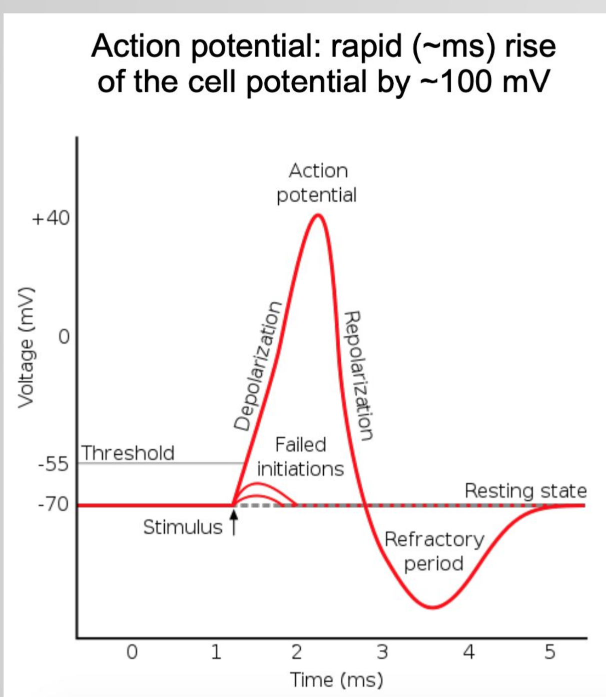
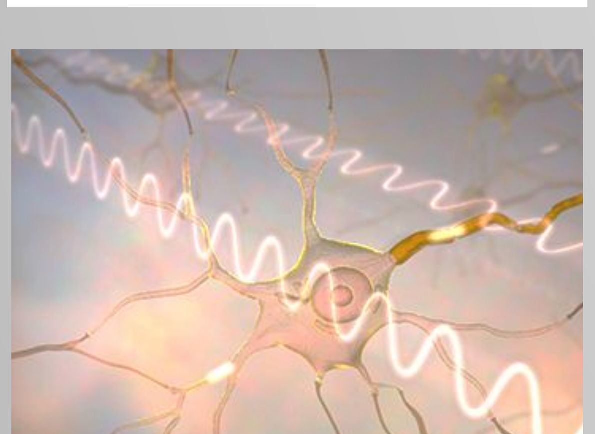
Motivation

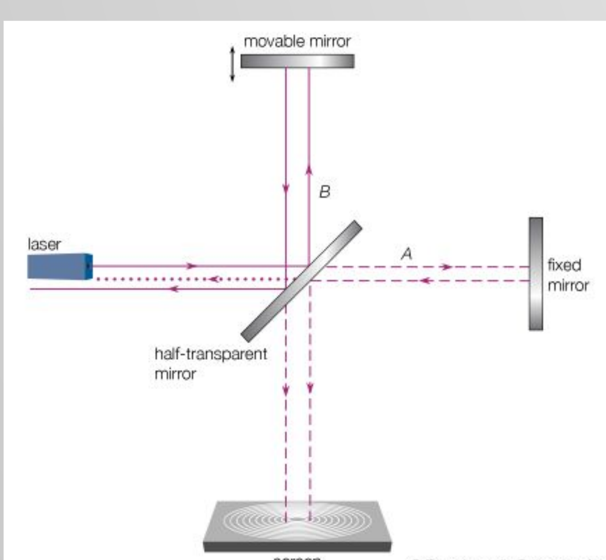
- Interferometric imaging of neurons has recently been tested and proven as a non-invasive optical means for the detection of neural signals.
- This method, or optophysiology, measures the deformation of a cell during an action potential through the optical phase shift of an interferometer--sensitive to changes with a sub-nanometer precision.
- Due to large amounts of noise in the data as well as the small deformation signal of an neuron's action potential classification of single interferograms (even with binning, frame averaging, and signal processing) remains a difficult task for a single action potential event.



Displacement: Lateral repulsion of charges changes surface tension. The equivalent change in pressure (P) to a positive potential (V+) produces a force



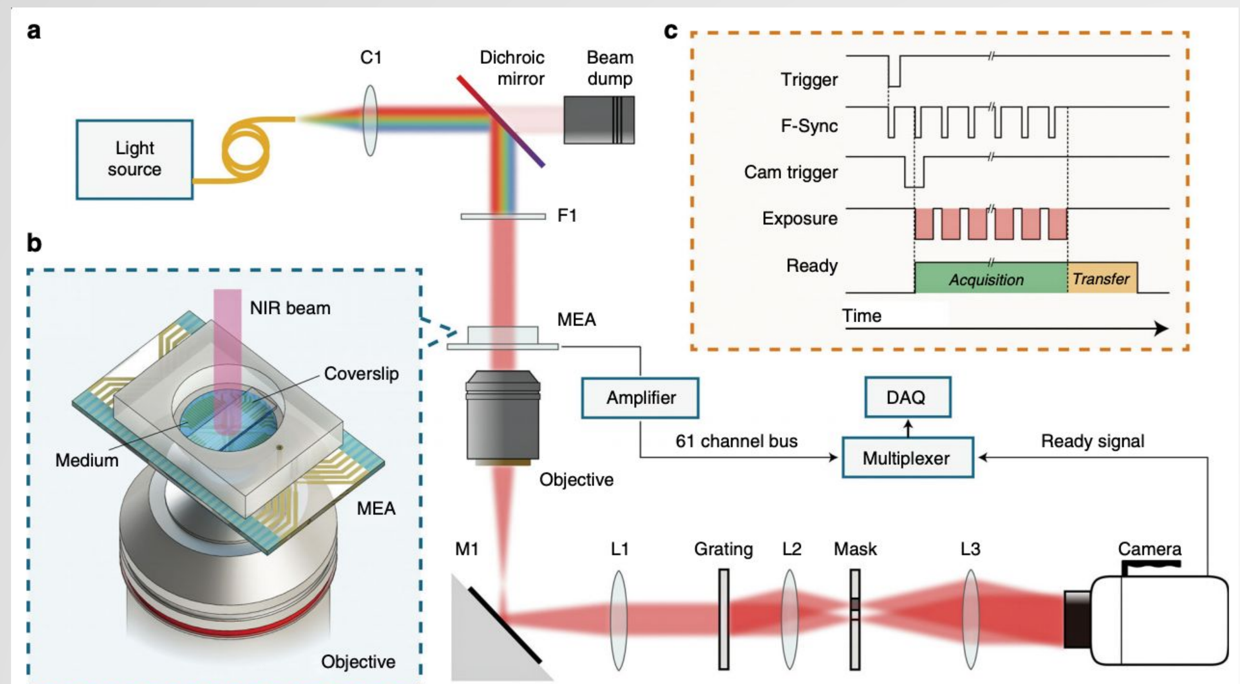


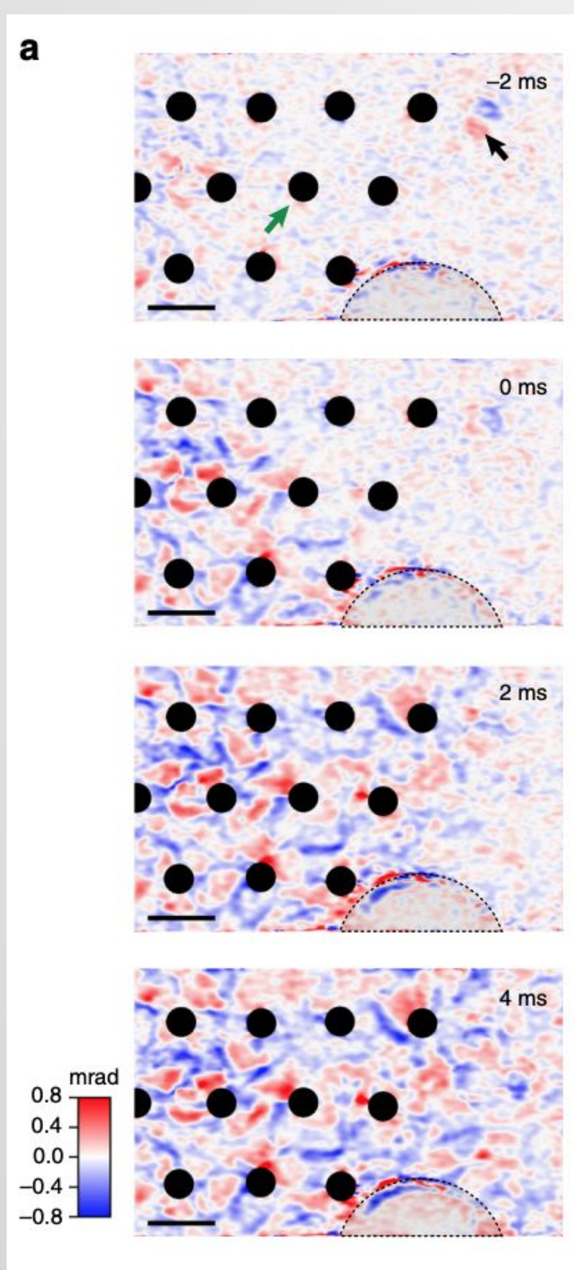


Objective

- The input to the machine learning algorithms tested for this research was a set of 40 by 40 interferometric frames with values of the optical phase shift of one cell, and the output was a prediction for whether or not an action potential was firing in a given frame.
- The goal of this research involved determining the best possible ML algorithm to for this classification task

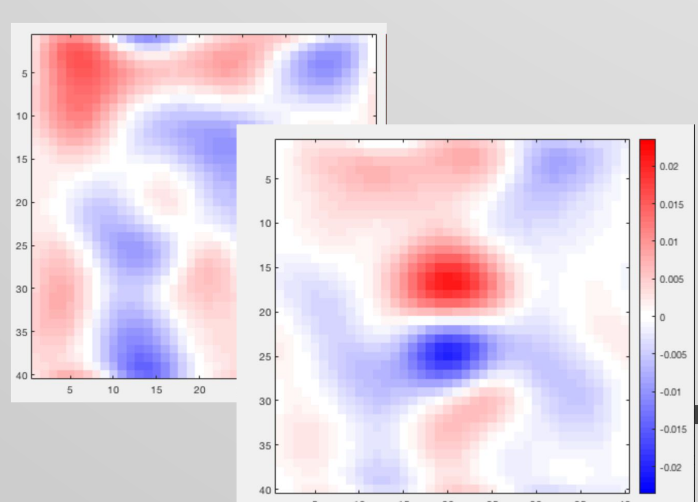
Data





- Dataset of 100,000 frames of computer simulated action potential interferograms modeled to match the Palanker Lab's experimental setup (above)
- All examples were labeled with ground truth--with binary values classifying the presence of an action potential event
- Data was verified to be well-balanced, with exactly 47.98% action potential labeled frames (allowing for testing accuracy as a justifiable
- Each simulated frame contained the activity of one model cell for action potential events set at a 100nm deformation

Features

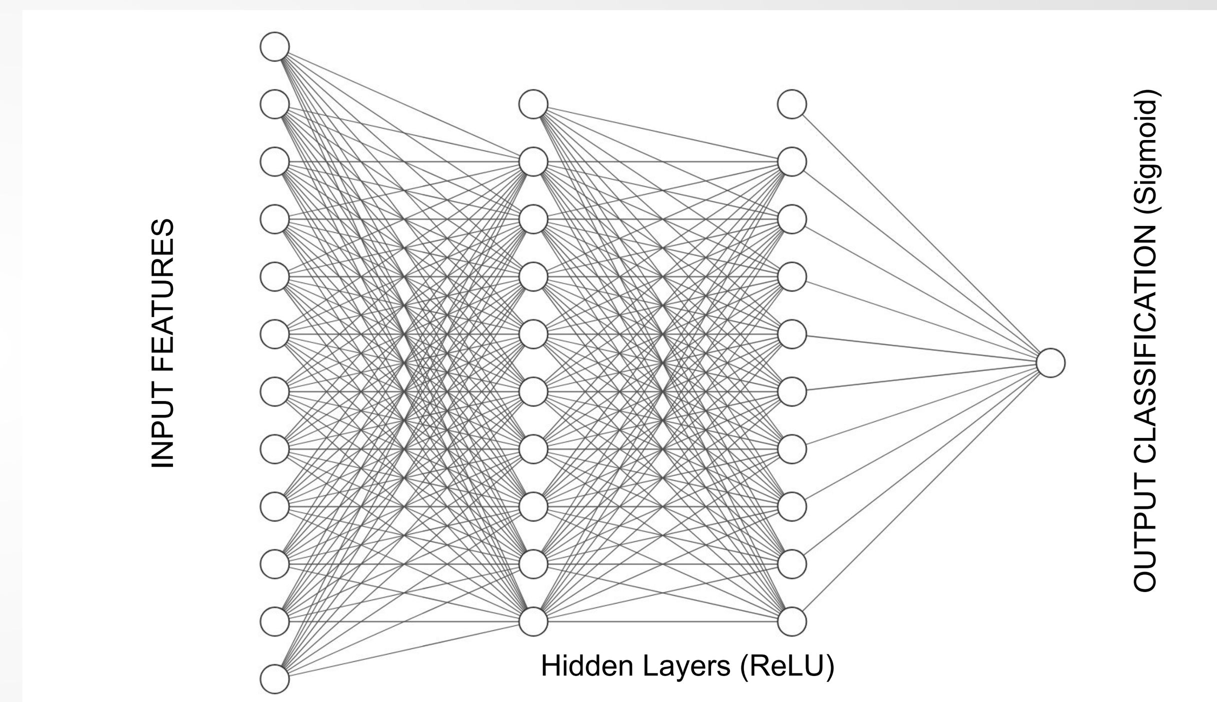


Features consisted of the unrolled 40x40 frames containing "pixels" of optical phase shift values

$$x^{(m)} \in \mathbb{R}^{1600}$$

Models

- **Logistic Regression**
  - Unregularized
  - Regularized: parametric sweep computed to yield most accurate C value on cross validation dataset
- **Neural Networks** (visualized below, 1/10x layer size)
  - ReLU hidden layers & sigmoid output non-linearities
  - Number of layers: varied between 2, 3, and 6
  - Default hidden layer size of 100 neurons
- **Convolutional Neural Network** (CNN)



Results

Model trained for 25 epochs	Training Accuracy	Test Set Accuracy	Test Set Precision	Test Set Recall	Test Set F-Score
Logistic Regression	0.739	0.731	0.748	0.645	0.693
Regularized Logistic Reg. (C = 2.5)	0.750	0.744	0.761	0.663	0.708
Neural Net (2 layers)	0.787	0.783	0.823	0.682	0.746
Neural Net (3 layers)	0.792	0.790	0.824	0.699	0.748
Neural Net (9 layers)	0.826	0.821	0.840	0.717	0.766
CNN *(*Iterated for 1 epoch)*	0.743	0.710	0.724	0.633	0.675

Discussion

- The best model for our 100nm cellular deformation data remained the 9 hidden-layer neural network, with 100 neurons in each layer activated by ReLU functions. This exceeded all other models tested on every evaluation metrics. Perhaps deeper neural nets can yield greater success for this classification task in the future.
- NNs performed significantly better than Unregularized Logistic Regression which delivered our baseline performance of a testing accuracy of 73.1%.
- Although only partially trained, the CNN looks to be the most promising of all the models thus far, yielding a higher accuracy than other models after only one epoch of training.

Future

- **Data Variation** - more tests can be run on cellular setups of different types, numbers, deformations and shapes, boosting the generalizability of the model
- **Parameter Tuning** - number of layers, number of hidden units, activation functions, regularization, and other parameters of the NNs and CNNs should be further validated and tuned.
- **Additional Feature Resolution** - increasing the resolution of our input interferograms can allow for training on more features to achieve greater accuracy

Acknowledgements

This research would not be possible without the assistance of Kevin Boyle and Prof. Daniel Palanker of The Palanker Lab in the Hansen Experimental Physics Laboratory at Stanford.

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References

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