A Comparison of Neuromorphic Classification Tasks

John J. M. Reynolds[1], James S. Plank[1], Catherine D. Schuman[2], Grant R. Bruer[1], Adam W. Disney[1], Mark E. Dean[1], Garrett S. Rose[1]

TENN LAB
NEUROMORPHIC
ARCHITECTURES. LEARNING. APPLICATIONS.

University of Tennessee, Knoxville

Oak Ridge National Labs

07/24/2018

What's the premise?

- Neural networks are reaching dizzying levels of success
- Researchers often compelled to try a "neuromorphic approach"
- How can the appropriate model be chosen?

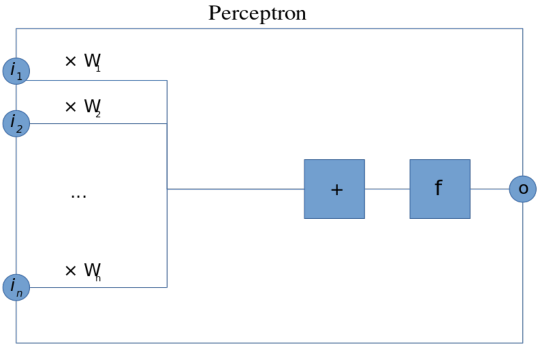
Premise

- We compared different approaches from the viewpoint of a layperson, as it can often be unclear as to which model is most appropriate.

Models

Name	Software	Neural Network	Training
Perceptron	TENN-Lab	Feed Forward	Back-propagation
MLP	Keras / TensorFlow	Feed Forward	Back-propagation
Conv	Keras / TensorFlow	Feed Forward	Back-propagation
LSTM	Keras / TensorFlow	Nodes with recurrency	Back-propagation
EONS	TENN-Lab / NIDA	Spiking, Recurrent	Evolutionary Optimization
Reservoir	TENN-Lab / NIDA	Spiking, Recurrent + Perceptron	Random + Back-propagation

Models - Perceptron



$$o = f\left(\sum_{k=1}^{n} i_k \cdot W_k\right)$$

- *By Mat the w at English Wikipedia, CC BY-SA 3.0, https://commons.wikimedia.org/w/index.php?curid=23766733*

Models - Multilayer perceptron

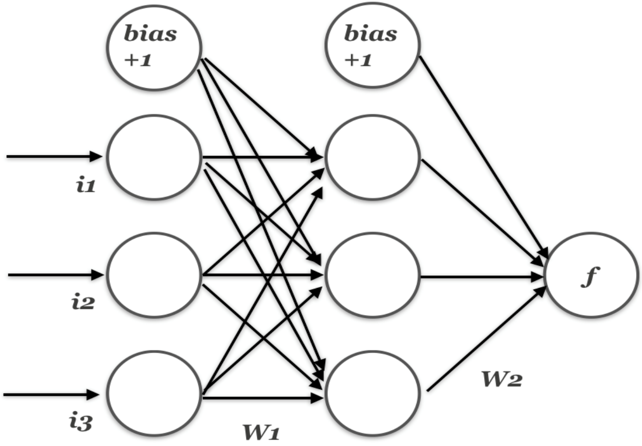


Figure 1: This is an example multilayer perceptron.

Models - Convolutional net

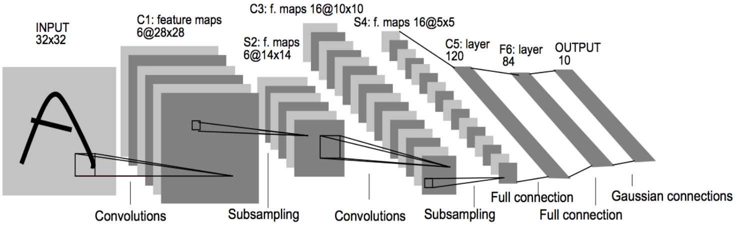


Figure 2: This is a diagram of LeNet-5; the canonical example of a simple convolutional deep learning model.

- *Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, Gradient-based learning applied to document recognition, Proc. IEEE 86(11): 2278–2324, 1998.*

Models - Long short-term memory

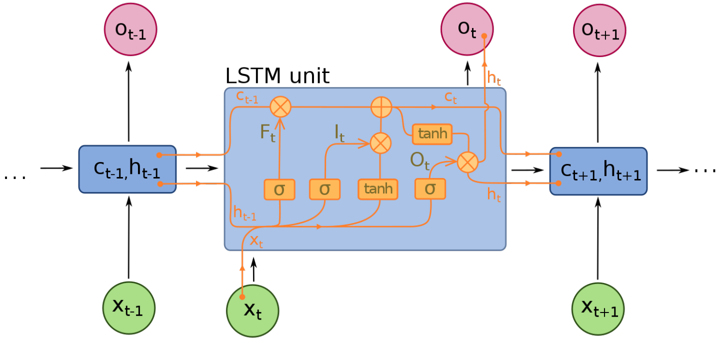


Figure 3: This is an example diagram of the long short-term memory model. It's a recurrent artificial neural network.

Models - EONS

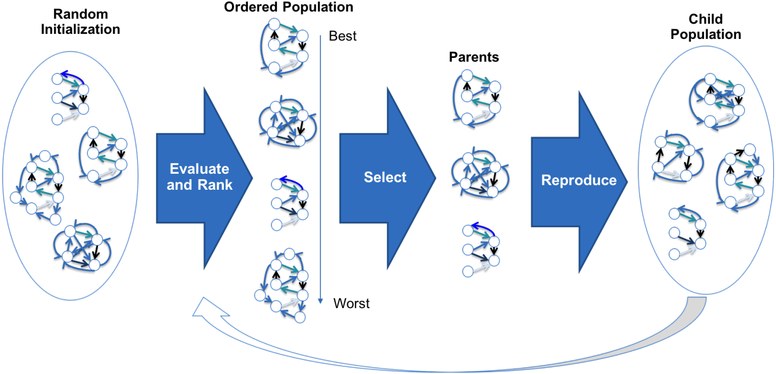


Figure 4: This diagram demonstrates the work flow of the Evolutionary Optimization of Neuromorphic Systems (EONS) model.

Models - Reservoir

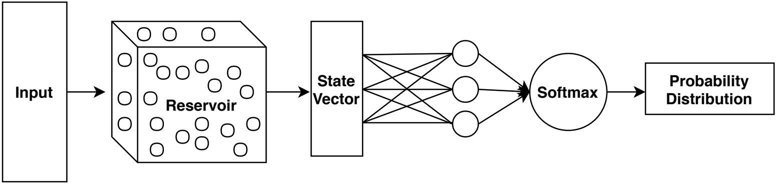


Figure 5: Depicted above is the reservoir computing paradigm outlined in our paper. In this work, the reservoir is spiking, thus following the liquid state machine theoretical framework.

Datasets Intro

- Datasets with different characteristics were chosen
- Some are static classification
- Others are spatio-temporal

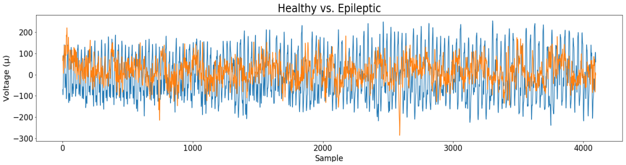
Takeaway

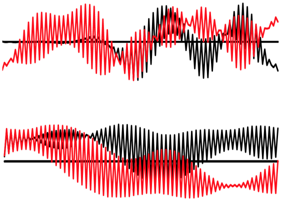
- The datasets were chosen to highlight different aspects of the models being compared.

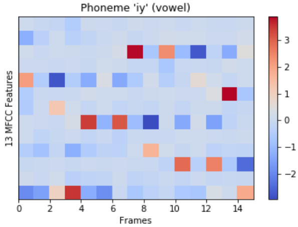
Datasets

Name	r	c	Classes	Training Data Points	Testing Data Points	N (Time Steps)	M (Output Window)
Iris	4	1	3	75	75	440	330
WBC	9	1	2	560	139	440	330
Pima	8	1	2	615	153	440	330
Radio	2	128	2	667	166	1400	1200
EEG	1	4097	2	160	40	4100	4000
TIMIT	13	48	2	2000	200	500	450

Example Samples







- The top figure is an example EEG. The bottom right is of MFCC vectors composing an 'iy' phoneme. The bottom left plots 8PSK vs. GPSK from the radio dataset.

Results Intro

- We can draw some conclusions from the empirical data
- The models aren't optimized, so results could be improved

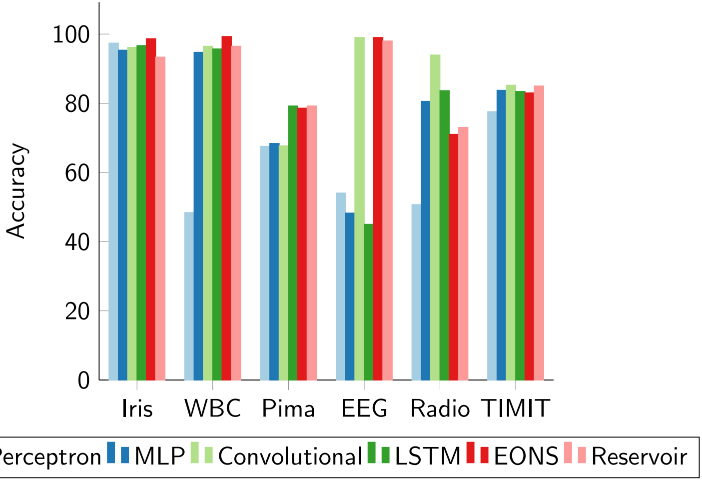
Results Table

Model / Data	Iris	WBC	Pima	Radio	EEG	TIMIT
Perceptron	97.38	48.40	67.54	50.70	54.05	77.57
MLP	95.33	94.71	68.37	80.53	48.25	83.73
Conv	96.13	96.45	67.70	93.95	99.00	85.20
LSTM	96.67	95.71	79.22	83.64	45.00	83.40
EONS	98.66	99.28	78.57	71.00	99.00	83.00
Reservoir	93.33	96.47	79.22	73.00	98.00	85.00

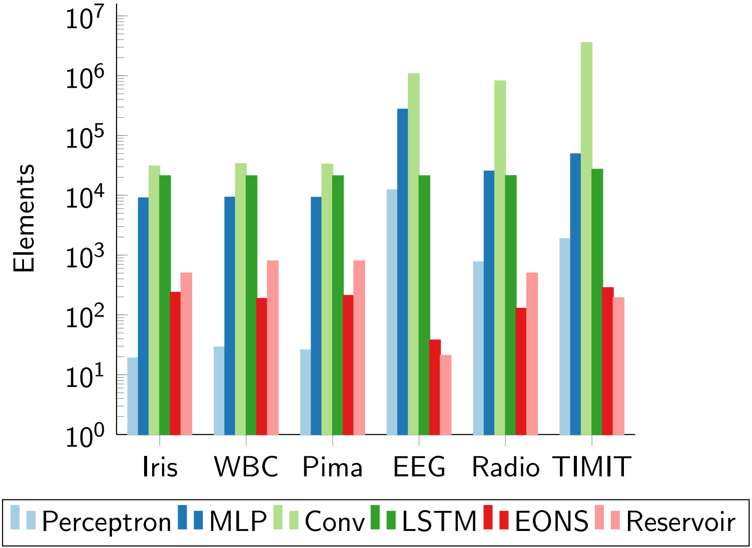
Sizes Table

Model / Data	Iris N	Iris S	WBC N	WBC S	Pima N	Pima S	Radio N	Radio S	EEG N	EEG S	TIMIT N	TIMIT S
Perceptron	7	12	11	18	10	16	258	512	4099	8194	626	1248
MLP	199	8835	203	9090	202	9026	450	24898	4291	270722	818	48450
Conv	775	30019	2678	31042	2314	30786	12278	805652	876547	202562	28006	3530652
LSTM	99	21091	98	21058	98	21058	98	21186	98	21058	98	27074
EONS	74	164	22	166	38	173	26	103	8	30	39	246
Reservoir	200	300	200	600	200	600	200	300	200 (7)	900 (14)	200 (53)	1000 (140)

Accuracy


Accuracy
100
80
60
40
20
0
Iris
WBC
Pima
EEG
Radio
TIMIT
Perceptron
MLP
Convolutional
LSTM
EONS
Reservoir

Network Sizes



Conclusions

Accuracy

- No clear winner across all tasks in terms of **accuracy**

Size Weight and Power (SWaP)

- Spiking approaches seemingly produce orders of magnitude smaller networks.

Future Work

Datasets

- Larger datasets
- More classes
- Control Applications

Timings

- Training and testing times need to be recorded and compared in both qualitative and quantitative manners.

References

- John J. M. Reynolds, James S. Plank, Catherine D. Schuman, and Grant R. Bruer, Adam W. Disney, Mark E. Dean, Garrett S. Rose. 2018. A Comparison of Neuromorphic Classification Tasks. In ICONS 2018: International Conference on Neuromorphic Systems, July 23-26, 2018, Knoxville, TN, USA. ACM, New York, NY, USA, 8 pages. - in press

- Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, Gradient-based learning applied to document recognition, Proc. IEEE 86(11): 2278–2324, 1998.