Unsupervised Autoencoder to Augment Fully Supervised Classification of Parkinson's Tremor

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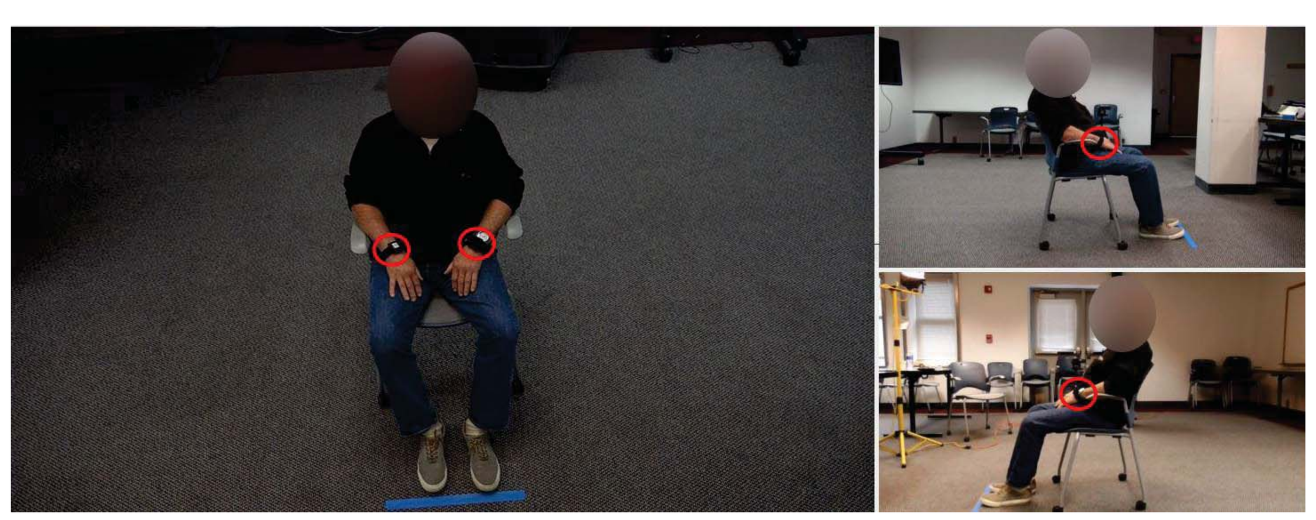
Motivation

Parkinson's disease affects 10 million people worldwide. Parkinson's Disease, while currently incurable, causes symptoms that can be combated by specific medication. Doctors need an accurate assessment of a patient's symptoms over time with which to base medication adjustments on. To monitor tremor caused by PD, researchers want to use wrist mounted accelerometers.

Using the wrist mounted sensors to detect tremor can actually be quite difficult. Many machine learning techniques struggle detecting these rhythmic vibrations when people are performing different actions. Some techniques perform extremely well detecting tremor when a patient's arm is resting on a table but many patients exclusively tremor while moving. To learn to detect multiple types of tremor we think a more complex machine learning technique is required.



Goal

The goal of our research is to train a single classifier that is invariant to different types of motion. Other approaches have trained as many as 8 different classifiers on different motion types which assumes all motion can be discretely broken up into 8 options.

Methodology

Data Set

	1	2	3	4	5	6
Lab Time	75 min	56 min	55 min	88 min	91 min	96 min
Home Time	411 hours		377 hours	456 hours		
% tremor	64%	73%	52%	39%	18%	14%

Network Structure

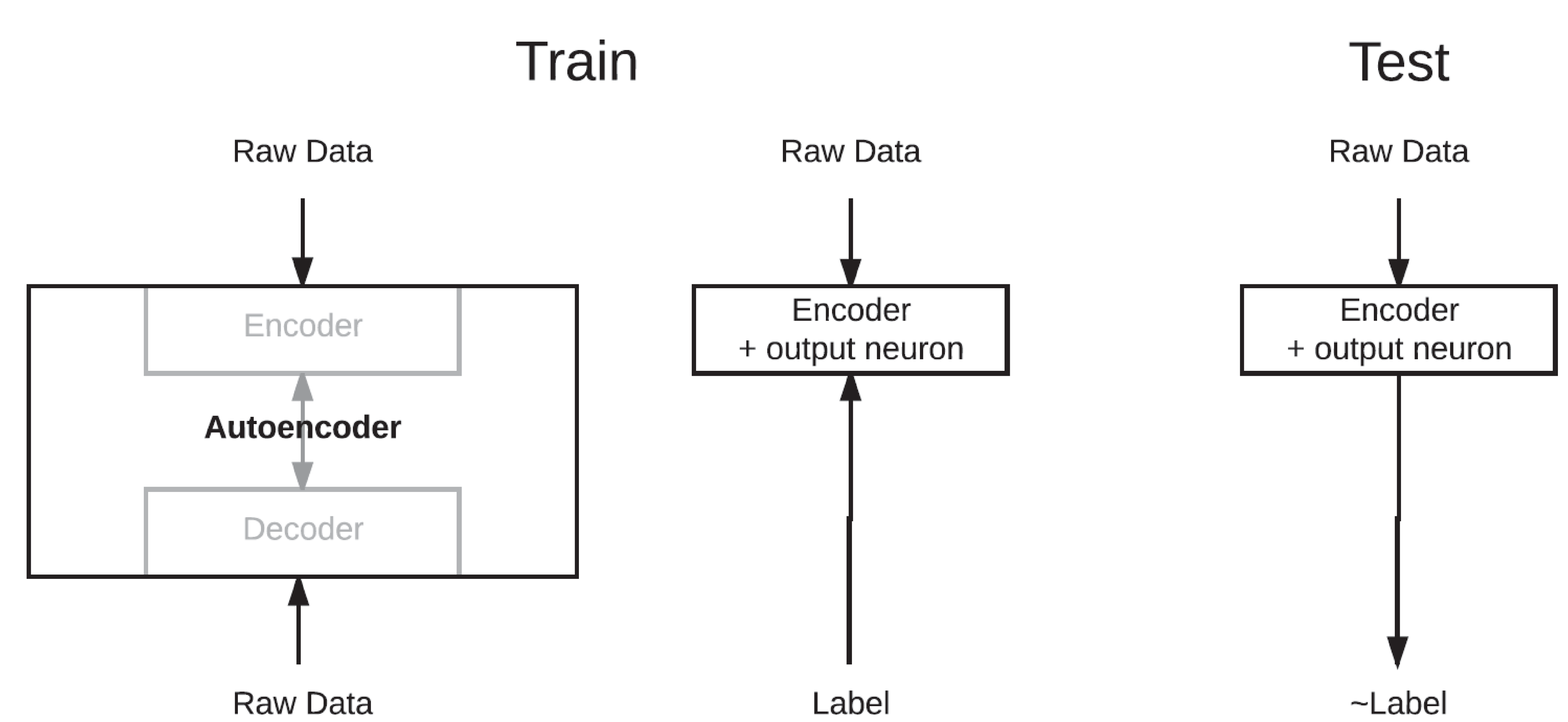
We designed a convolutional deep neural network to read through 3 second windows of time series data and classify if it was tremor or not. The network is layed out

- Convolutional layer- looks at 300 ms at a time (roughly the length of 1 period of tremor)
- Max pooling layer to condense the data and learn temporal invariance
- 3 Dense fully connected layers to lower the dimensionality to 32

Experiments

We made an autoencoer by taking the above structure and adding an identical inverted copy to bring the dimensionality back to the original signal. This autoencoder was trained on the 3 months of unlabeled home data. From there we ran 3 experiments with the labeled lab data

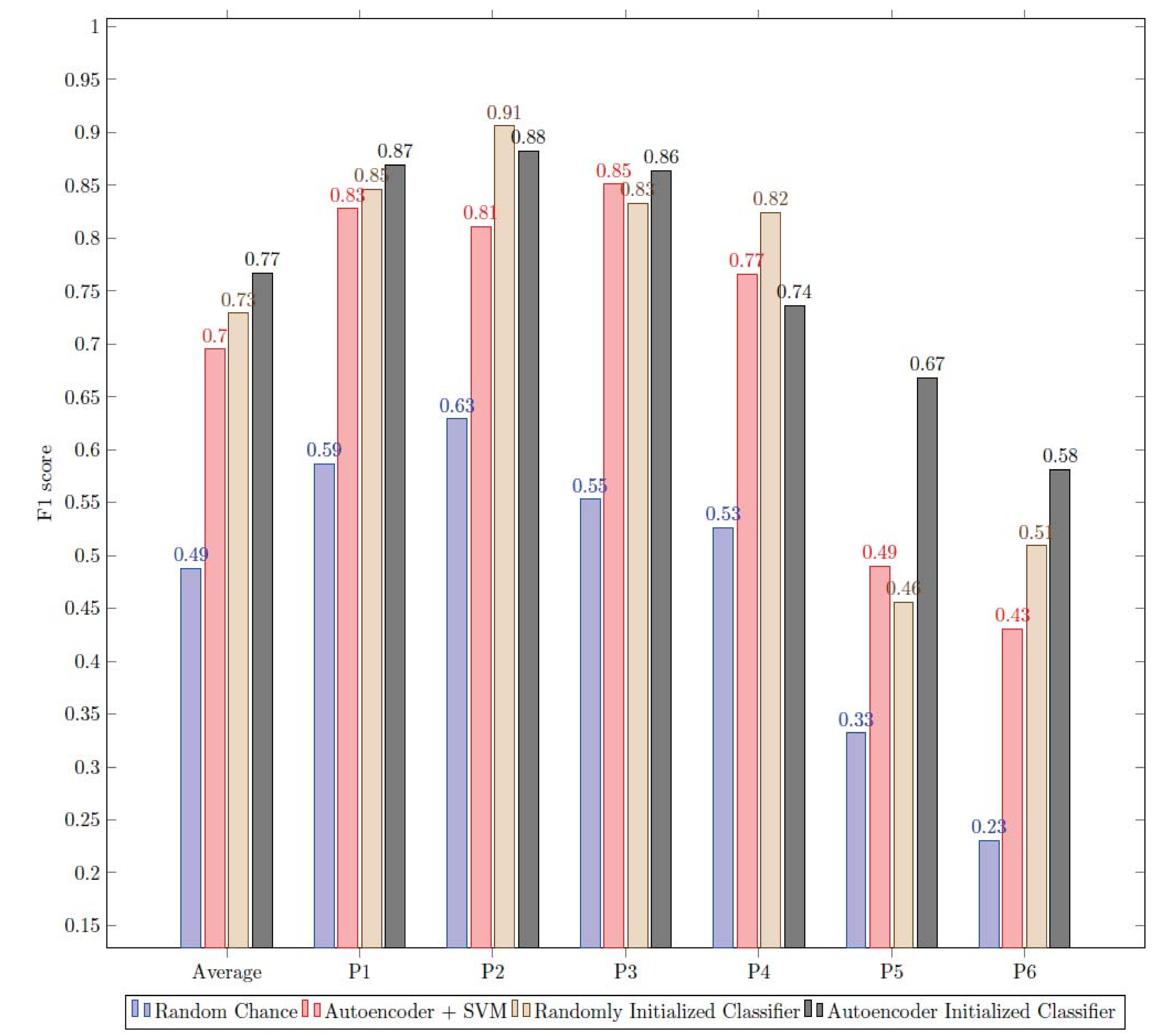
1. Train an SVM on the output of the middle condensed layer using 5 patients and predict on last patient.
2. Randomly initialize the original structured network and train it on the labeled lab data of 5 patients as a classifier
3. Take the original network after it has been trained as on autoencoder and use it to initialize the same classifier in experiment 2 (see figure below)



Results and Conclusion

The final results of the experiments can be seen in the figure below. We found that the autoencoder initialization outperformed the randomly initialized classifier by 3%. We also found that the classifier trained on the labels only outperformed the learned features from the autoencoder by 3%.

We believe that training on unlabeled data over an extended period of time makes it possible to train a general tremor classifier with little labeled data.



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