Classifying Central and Peripheral Vision Loss from Gaze Data

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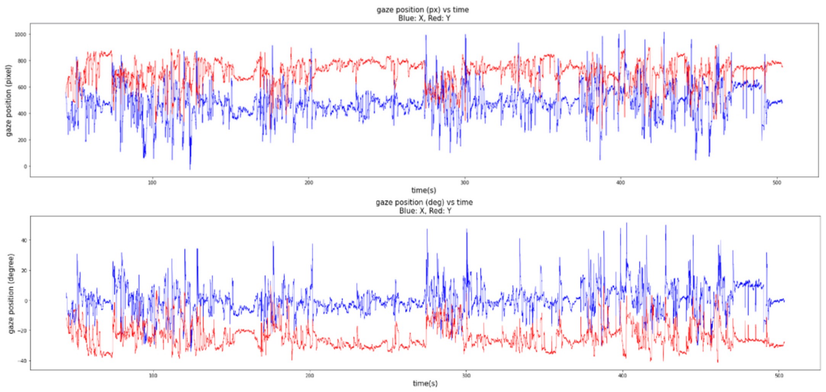
Introduction

Eye movements provide us a wealth of information and can tell us about a person's mental state, awareness, action, etc. Uncovering such features have traditionally begun with classifying types of eye movements such as saccades, fixations, smooth pursuits, and blinks. However, such classification has proved difficult given noisy data. To bypass this step and get right to feature extraction, I run a neural network on gaze data. Given participants with various types of visual impairment, my goal is to classify between central vision loss (CVL) and peripheral vision loss (PVL).



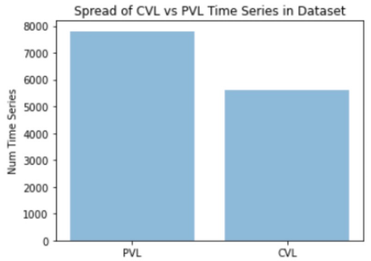
Data-sets

Data was collected in summer 2021. Twenty-five participants completed three tasks (making a sandwich, eating cereal, and walking down a hall) while wearing Pupil Invisible glasses. The output gaze data includes pixel position (combined across both eyes) and timestamp at a sample rate of 66 Hz. Some of the datasets, however, are not usable. In total there are 25 useable datasets of varying lengths across 10 participants (5 with CVL and 5 with PVL) .

I use just the datasets of the participants making a sandwich to obtain uniformity across task, bringing the total number of datasets to 10.

Input features

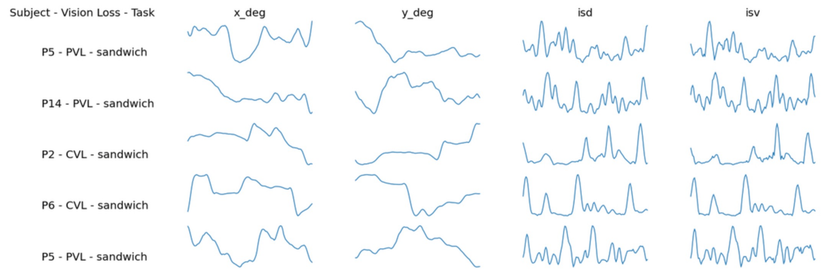
- **x_deg** : x-position (deg)
- **y_deg** : y-position (deg)
- **isd** : intersample displacemet
- **isv** : intersample velocity



Pre-processing

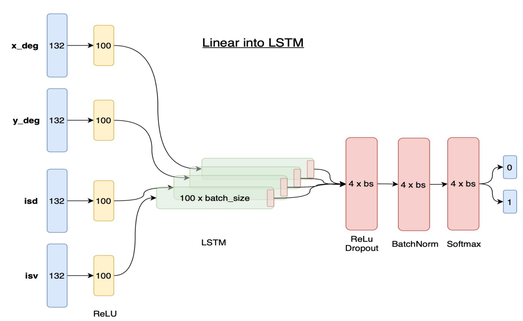
The original gaze data is very noisy and uncalibrated. Using the valid calibrated data, I calculate two more features (isd, isv) and drop samples where isv > 1000 deg/s, which is physiologically impossible. I run a savgol signal filter across the data to lightly smooth it while trying not to lose nuances. I standardize each feature across all datasets to increase model robustness using Z-score normalization: $z_i = \frac{x_i - \mu}{\sigma}$.

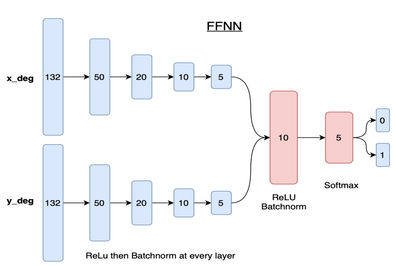
Lastly, I increase the number of datasets by running a sliding window of 2 seconds (132 samples) across each dataset which moves forward in time by 20% (or 0.4 sec). The result is 20262 datasets, each of four features of length 132.



Models

Two distinct architectures: LSTM vs FFNN





	LSTM	FFNN
Batch Size	128	128
Hidden Size	100	-
Learning Rate	3e-4	3e-4
Loss Criterion	CE*	CE*
Optimizer	Adam	Adam

Parameters

I found that when I increased batch size, the training accuracy would be higher, but there was generally not a significant improvement in the test results.

*CrossEntropyLoss: $\mathrm{L}(y,t) = -\sum_i \log(t_i * y_i)$

Results

Overall, CVL is more difficult to classify than PVL, perhaps because the data skews PVL. Test accuracy is higher when the training and test sets are split from the same shuffled data, as shown here. When we exclude the participants used in the test set from the training set, test accuracy is about 15% lower across the board.

I was surprised to find that the simple FFNN outperforms the LSTM.

Future work

Additional features to gaze data have been extracted from the experiment, including patients' motor and process AMPS score (an observational measurement of performance of daily tasks) and the amount of time and number of steps taken to reach the kitchen. Adding these features into the model produce very promising preliminary results. However, for the purpose of this report I wanted to focus solely on building a model given gaze data.

LSTM

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Overall accuracy of test: 60.98 %
CVL classified correctly 20.4% of the time with an average accuracy of 76.4%.
PVL classified correctly 91.0% of the time with an average accuracy of 75.8%.
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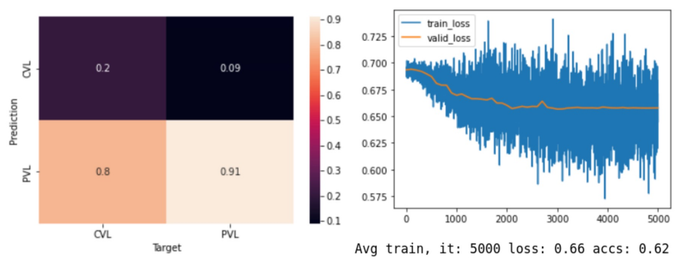


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Avg train, it: 5000 loss: 0.66 accs: 0.62
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FFNN

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Overall accuracy of test: 65.35 %
CVL classified correctly 61.1% of the time with an average accuracy of 76.8%.
PVL classified correctly 68.5% of the time with an average accuracy of 87.6%.
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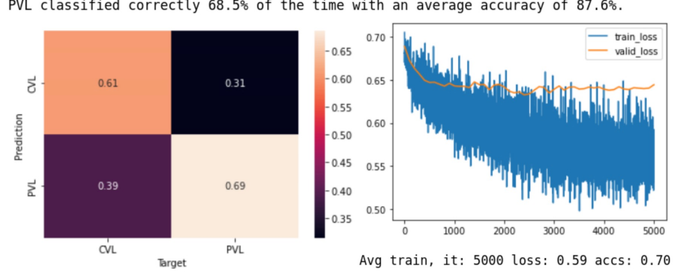


```
Avg train, it: 5000 loss: 0.59 accs: 0.70
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