

## Machine Learning Models to Aid Autism Diagnoses

Using AI for interpretable diagnoses on sparse data

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## Who am I?

#### Thanks for asking!

- Rising Junior at Lynbrook High School, San Jose, CA
- Professional <del>copy and paster</del> coder
- r/ProgrammerHumor Junkie
- Researcher at Wall Lab, Stanford University









## Agenda

#### Where we are headed

- ML Workflow
  - Introduction
  - Mission
  - Data Processing
  - Model Training
  - Results
- Demo
- Q&A Session

## Introduction

Let's get started

- Worked at the Wall Lab ('21-'22)
- Developed a novel ML model(s) for classifying a key indicator of autism in videos for a faster diagnosis
- Demonstrates that ML is feasible for *explainable* diagnoses in healthcare
- Paper is published in JMIR Biomedical Engineering
- Preprint here: <a href="https://arxiv.org/abs/2108.07917">https://arxiv.org/abs/2108.07917</a>

Create an ML model to detect hand flapping from crowdsourced videos to aid in an autism diagnosis.



## **Building a model**

The bare necessities of creating an ML model

- Needed to collect relevant data
- Design a model to train
- Train that model
- Design a fair evaluation technique
- Evaluate that model
- Reiterate

## **Data Collection**

#### Finally, we're talking data at a data conference!

- Needed videos of hand flapping (and without hand flapping)
- Self Stimulatory Behavior Dataset (SSBD) is the only publicly available dataset with this information
- ≈25 YouTube videos depicting hand flapping stored in XML Files

	Used For POSITIVE Videos	Used For CONTROL	Videos	Used For POSITIVE Videos				
$\langle -$	Hand Flapping	$\rightarrow$	$\langle -$	Hand Flapping	$\rightarrow$			
	Video							
			Time		$ \rightarrow $			

## **Data Cleaning**

"Bad Data, Bad Data Everywhere"

- Shakiness + Excessive Motion in SSBD
- The application would be on a phone, so videos will be shaky
- Manually cleaned it up



# Designing The Model



## Long-Short Term Memory Primer

Sorry, it's not a transformer...



$$z_t = \sigma \left( W_z \cdot [h_{t-1}, x_t] \right)$$

$$r_t = \sigma \left( W_r \cdot [h_{t-1}, x_t] \right)$$

$$\tilde{h}_t = \tanh \left( W \cdot [r_t * h_{t-1}, x_t] \right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Who even cares about this when TensorFlow exists

## Images are Huge

And machines don't "see" them

- Usually are around 10^6 floats
- Cannot squish images into vectors and feed them in
- Need to reduce dimensionality



## Approach 1: MediaPipe

#### Gotta start somewhere

- Made by Google for Pose Estimation and Landmark Detection
- Landmarks = Key Points
- Used Hand Detection => returns the (x, y, z) coordinates for 21 landmarks





## **Quick Sketch**





## Variants of Approach One

Just different takes on the same idea

- All Landmarks: Use all 21 Landmarks on Each Hand
- Six Landmarks: Only use finger tips
- Mean Landmark: Take the mean location
- Single Landmark: Only use 1 landmark



## Approach 2: MobileNet V2 Pretraining

#### Just use

- Used MobileNet V2's Convolutional Layers Pretrained on ImageNet
- Fed the extracted vector from these conv layers into the LSTM



# Evaluation Technique



## Fair Evaluation: 5-fold Cross Validation 100x

#### No cherry-picking!

- Created 100 different datasets of 5 folds, and ran 5-fold cross validation on each of them
  - For all approaches (all, six, one, mean landmarks + mobile net)
- Needed for an objective measurement



## **Metrics**

#### Can't manage what you can't measure

- ROC Curve (receiver operating characteristics)
- Accuracy, precision, recall, and F1
- Tracked both training + testing



## Results

#### What I've been stalling all along

#### Approach 1: MediaPipe

- Got in the high 69-70%
- Could not overfit to 100% accuracy
- More Fluctuations between variant approaches
- Overall:
  - 1) Six Landmarks
  - 2) All Landmarks
  - 3) Mean Landmark
  - 4) One Landmark

#### Approach 2: MobileNet V2 Pretrained

- Hovered in the 85% accuracy range
- Had capacity to overfit to 100% accuracy
- Overall a much more accurate model

## **More Comparisons**



Run Type	Accuracy (%)	Precision (%)	Recall (%)	F1 (%)
Training	76.8 ± 1.95	78.7 ± 2.9	74.7 ± 3.5	76.2 ± 2.1
Testing	69.55 ± 2.7	71.7 ± 3.5	67.5 ± 5.5	68.3 ± 3.6



Run Type	Accuracy (%)	Precision (%)	Recall (%)	F1 (%)
Training	97.7 ± 1.0	99.5 ± 0.0	95.9 ± 1.7	97.6 ± 1.0
Testing	85.0 ± 3.14	89.6 ± 4.3	80.4 ± 6.0	84.0 ± 3.7

## Code Demo

<u>https://github.com/anish-</u> <u>lakkapragada/Hand-</u> <u>Classification-For-Autism-</u> <u>Diagnosis</u>



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# Q&A Session!



## DATA+AI SUMMIT 2022

# Thank you!

Anish Lakkapragada Wall Lab @ Stanford University