A Facial Affect Analysis System for Autism Spectrum Disorder Beibin Li, Sachin Mehta, Deepali Aneja, Claire Foster, Pamela Ventola, Frederick Shic, Linda Shapiro Contact: beibin@uw.edu



We introduce an end-to-end machine learning-based system for classifying autism spectrum disorder (ASD) using facial affect attributes such as expressions, action units, arousal, and valence. Our system classifies ASD using representations of different facial affect attributes from convolutional neural networks, which are trained on *images in* the wild. Our experimental results show that different facial affect attributes used in our system are statistically significant and improve sensitivity, specificity, and F1 score of ASD classification by a large margin.

Introduction

Along with two widely used categorical facial affect attributes (facial expressions and AUs) for natural images, our system also predicts two continuous facial affect attributes (arousal and valence) that have been found to be effective in autism related clinical studies [4]. For simplicity, we use facial affect attributes to represent facial expression, AUs, arousal, and valence. Since there are no publicly available datasets for autism with *all* of these different attributes, we learn representations for these attributes by leveraging two large-scale facial datasets of natural images that are collected in a wide variety of settings, including age, gender, race, pose, and lighting variations. The contributions of this work are:

- . Present an ASD classification system based on facial affect attributes
- 2. Show the importance of these attributes in improving the performance of our system through statistical analysis
- 3. Analysis of single vs. multi-task learning for facial affect attribute recognition

• Multi-task learning improves facial affect attributes recognition. • The addition of different affect attributes improves ASD/nonASD classification.

Overview of our end-to-end system for autism spectrum disorder (ASD) classification using facial affect attributes.

Training the Affect Recognition System

- We use public datasets collected in the wild to train our facial affect recognition system. We choose AffectNet and **EmotioNet** with 1.2 million images combined.
- MTL loss function: $\arg\min\sum_{t=1}^T \sum_{i=1}^N l(y_i^t, f(\boldsymbol{x}_i^t; \boldsymbol{w}^t))$



Figure 1: Single v.s. Multi-Task Learning **Expr = Expression, AU = Action Units,** Val = Valence, Aro = Arousal.

Data Collection from iPad Experiment

- We collect a video dataset of 105 children with one 720p 24 Hz video per participant using an iPad application; 88 of these children (ASD: 49; non-ASD: 39) finish the experiment and consent to use their data for our research.
- Each participant watches an expert-designed video stimulus on an iPad. While the participant watches a video, our application captures and records the participant's facial response using the iPad's front camera. The video recorded using the iPad application is about 6 minutes and 35 seconds (9,575 valid frames) per participant.

Inference Pipeline

Table 1: Results from Logistic Regression to
 classify ASD and nonASD with different combination of facial affect attributes

CNN Unit

Bottlenecl MobileNet EESP [3]

Bottlenecl MobileNet EESP [3] Performa

1. Use Multi-Task Learning (MTL) and Convolutional Neural Network (CNN) to extract facial affect attributes (expression, facial action unit, arousal, valence) for each frame of recorded videos.

2. Extract temporal features on each facial affect attribute for each participant.

3. Use temporal features on these affect attributes to classify children with and without autism.





Facial affect attributes				T 1	Songitivity	Specificity	
AU	Aro	Val	Expr		Sensitivity	specificity	
\checkmark				0.69	0.69	0.62	
\checkmark	\checkmark			0.72	0.71	0.67	
\checkmark	\checkmark	\checkmark		0.69	0.67	0.67	
\checkmark	\checkmark	\checkmark	\checkmark	0.76	0.76	0.69	

Limitation

Takeaway Message

- prediction.

References

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t	# Parama	FLOPs	Expr	AU	Val	Aro					
	π 1 at at 115		(F1)	(mF1Acc)	(CC)	(CC)					
Single-task											
k [1]	25.9 M	3.4 B	0.56	0.78	0.63	0.54					
t [2]	24.8 M	3.1 B	0.57	0.77	0.64	0.52					
	9.7 M	1.2 B	0.57	0.76	0.64	0.52					
		Multi-tc	ask								
k [1]	6.5 M	0.85 B	0.58	0.75	0.68	0.61					
t [2]	6.2 M	0.78 B	0.58	0.75	0.68	0.62					
	2.4 M	0.29 B	0.58	0.75	0.69	0.61					
nance of our Affect Analysis system on											
AffectNet and EmotioNet											

Anecinet and Emotionet.

• Expression \neq Emotion. Expression recognition is a hard task, and even human would not agree with each other.

• This is only a proof-of-concept study with only 88 valid participants. More clinical research are needed to fully study the facial behavior for children with autism.

• There are $2^4 = 64$ different combinations of these 4 facial affect attributes, and only analyzing 4 is not comprehensive. Using all 4 domains might overfit our dataset because n (the number of participants) is small.

• Interpretability and uncertainty are important in clinical application, but they are not fully studied in CNN.

• MTL can improve the performance for facial affective attribute recognition.

• Our system outperform SOTA in arousal and valence

• The affect attributes are statistically significant between children with and without ASD.

• Representations of different facial affect attributes improve the ASD classification performance by about 7% with F1 score of 76%.

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