



Attractiveness Predictions

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The background features several decorative elements consisting of white dotted lines that meander across the frame. Interspersed along these lines are glowing cyan circles of varying sizes. Some circles are simple, while others have a double-ring effect, creating a sense of depth and movement. The overall aesthetic is modern and tech-oriented.

Model

Predict attractiveness score of males and females based on their features

- Images
- Facial Measurements
- Race
- Facial Expressions

Data Collection

- Our goal was to web-scrape and collect profile photos from Tinder's web app. We would then train a model on the binary decision to swipe left or right depending on the image





You Have Been Banned From Tinder

It's important to us that Tinder is a welcoming and safe space for everyone. Unfortunately, we found that you violated our [Terms of Use](#) and so we've made the decision to remove you from the Tinder Platform.

You will no longer be able to access your Tinder account or create new accounts in the future.

Please note that if you are subscribed to any premium services through the App Store or Google Play, you will need to cancel your subscription with the appropriate provider.

Dataset Sample

AutoSave OFF

CFD 3.0 Norming Data and Codebook

Home Insert Draw Page Layout Formulas Data Review View Automate Developer XLSTAT Cloud StatPlus Acrobat Tell me

Calibri (Body) 11 A A

General Conditional Formatting Insert Delete Format as Table Cell Styles

Open recovered workbooks? Your recent changes were saved. Do you want to continue working where you left off? Yes No

A1

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1		CHICAGO FACE DATABASE																	
2		Version 3.0																	
3		CFD Main Image Set																	
4		U.S. Norming Data																	
5																			
6																			
7		S001	S002	S003	R002		R003	R004	R005	R005A	R005B	R005C	R005D	R005E	R006	R007	R008	R009	R010
8	Model	EthnicitySelf	GenderSelf	AgeSelf	AgeRated		FemaleProb	MaleProb	AsianProb	ChineseAsianPr	JapaneseAsianP	IndianAsianProt	OtherAsianProb	MiddleEasternP	BlackProb	LatinoProb	MultiProb	OtherProb	WhiteProb
9					R002_mean	R002_sd													
10	AF-200	A	F		32.57142857		1	0	1						0	0	0	0	
11	AF-201	A	F		23.66666667		1	0	0.962962963						0	0	0.037037037	0	
12	AF-202	A	F		24.44827586		0.827586207	0.172413793	0.310344828						0.068965517	0.137931034	0.448275862	0.034482759	
13	AF-203	A	F		22.75862069		1	0	0.75862069						0	0.068965517	0.172413793	0	
14	AF-204	A	F		30.13793103		0	0.827586207							0	0.068965517	0.103448276	0	
15	AF-205	A	F		26.59259259		1	0	0.846153846						0	0	0.153846154	0	
16	AF-206	A	F		26.52380952		0.857142857	0.142857143	1						0	0	0	0	
17	AF-207	A	F		28.4137931		1	0	0.035714286						0.428571429	0.035714286	0.357142857	0.107142857	0.035714286
18	AF-208	A	F		28.53846154		1	0	0.230769231						0.115384615	0.384615385	0.230769231	0.038461538	
19	AF-209	A	F		22.56		1	0	0.08						0.08	0.4	0.32	0.12	
20	AF-210	A	F		23.53846154		1	0	0.384615385						0	0.192307692	0.230769231	0.192307692	
21	AF-211	A	F		22.5		0.923076923	0.076923077	1						0	0	0	0	
22	AF-212	A	F		23.85714286		1	0	0.928571429						0	0	0.035714286	0.035714286	
23	AF-213	A	F		40.18181818		1	0	0.956521739						0	0	0.043478261	0	
24	AF-214	A	F		26.84615385		1	0	1						0	0	0	0	
25	AF-215	A	F		30.44444444		1	0	1						0	0	0	0	
26	AF-216	A	F		25.93333333		1	0	0.933333333						0	0.033333333	0.033333333	0	
27	AF-217	A	F		19.70833333		1	0	0.208333333						0	0.208333333	0.375	0	0.208333333
28	AF-218	A	F		24.03571429		1	0	0.857142857						0	0.035714286	0.107142857	0	
29	AF-219	A	F		25.10714286		1	0	0.821428571						0	0	0.178571429	0	
30	AF-220	A	F		25.26086957		1	0	0.739130435						0	0.086956522	0.130434783	0.043478261	
31	AF-221	A	F		25.62962963		1	0	0.666666667						0	0.222222222	0.111111111	0	
32	AF-222	A	F		24.86206897		1	0	0.827586207						0.034482759	0.034482759	0.068965517	0.034482759	
33	AF-223	A	F		44.80769231		1	0	0.814814815						0	0	0.148148148	0.037037037	

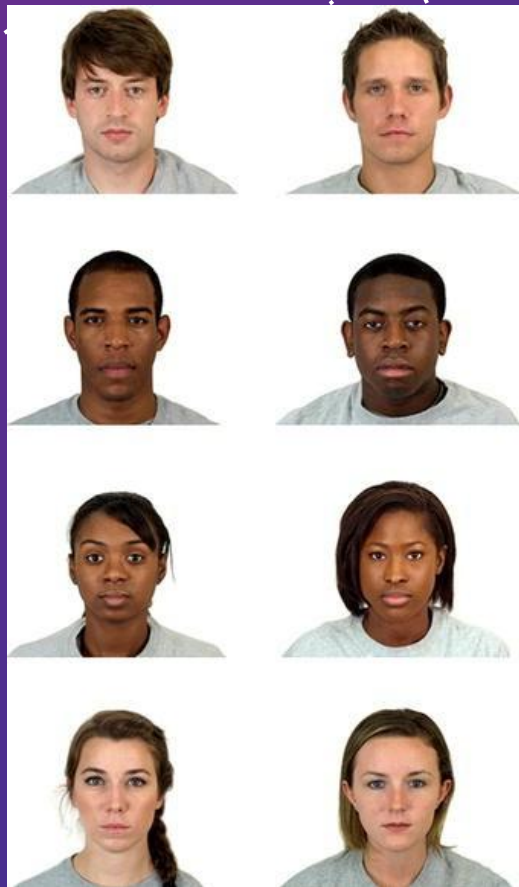
CFD 3.0 Codebook CFD U.S. Norming Data CFD-MR U.S. Norming Data CFD-I U.S. Norming Data CFD-I INDIA Norming Data

Ready Accessibility: Good to go

100%

About the Data

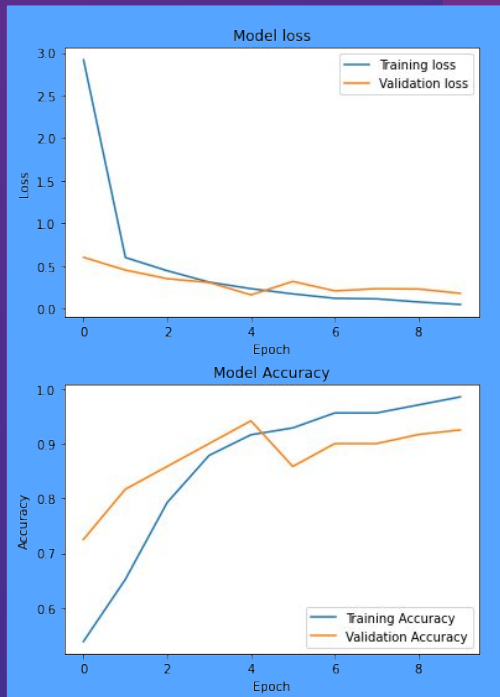
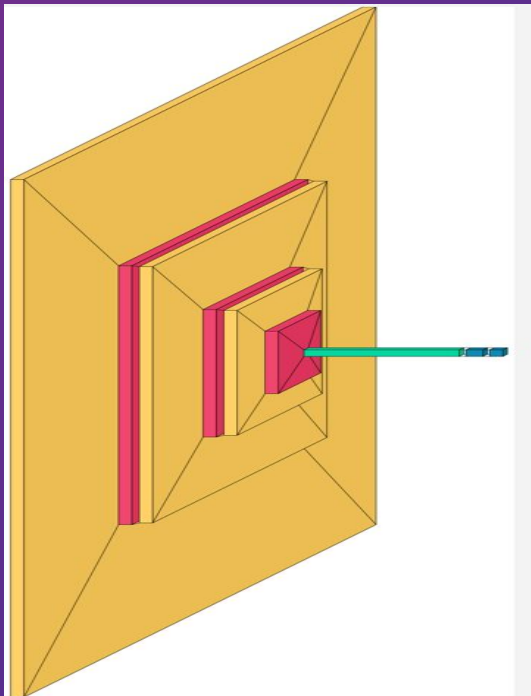
- We care primarily about Attractiveness, Gender, and Age, since those are key considerations on dating apps
- Each face was labeled by humans and the perception of features were averaged
- For men:
 - Average attractiveness rating of 3.0
 - Average age of 29.1
- For women:
 - Average attractiveness rating of 3.4
 - Average age of 28.6



Gender Identification Model

Model: "sequential_7"

Layer (type)	Output Shape	Param #
conv2d_42 (Conv2D)	(None, 398, 398, 32)	896
max_pooling2d_21 (MaxPooling2D)	(None, 199, 199, 32)	0
conv2d_43 (Conv2D)	(None, 197, 197, 64)	18496
max_pooling2d_22 (MaxPooling2D)	(None, 98, 98, 64)	0
conv2d_44 (Conv2D)	(None, 96, 96, 128)	73856
max_pooling2d_23 (MaxPooling2D)	(None, 48, 48, 128)	0
flatten_7 (Flatten)	(None, 294912)	0
dense_21 (Dense)	(None, 256)	75497728
dense_22 (Dense)	(None, 1)	257
...		
Total params: 75,591,233		
Trainable params: 75,591,233		
Non-trainable params: 0		

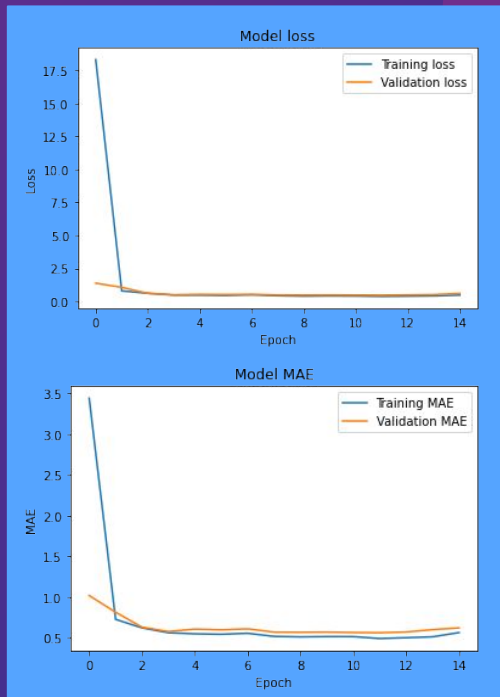
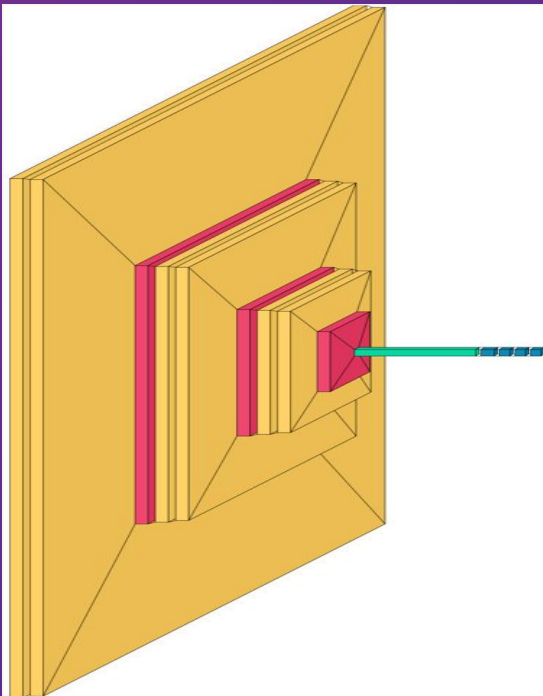


loss: 0.0472 - accuracy: 0.9853 - val_loss: 0.1779 - val_accuracy: 0.9250

Male Attractiveness Model

Model: "sequential_13"

Layer (type)	Output Shape	Param #
conv2d_75 (Conv2D)	(None, 398, 398, 32)	896
conv2d_76 (Conv2D)	(None, 396, 396, 32)	9248
max_pooling2d_39 (MaxPooling2D)	(None, 198, 198, 32)	0
conv2d_77 (Conv2D)	(None, 196, 196, 64)	18496
conv2d_78 (Conv2D)	(None, 194, 194, 64)	36928
max_pooling2d_40 (MaxPooling2D)	(None, 97, 97, 64)	0
conv2d_79 (Conv2D)	(None, 95, 95, 128)	73856
conv2d_80 (Conv2D)	(None, 93, 93, 128)	147584
max_pooling2d_41 (MaxPooling2D)	(None, 46, 46, 128)	0
...		
Total params: 69,665,569		
Trainable params: 69,665,569		
Non-trainable params: 0		

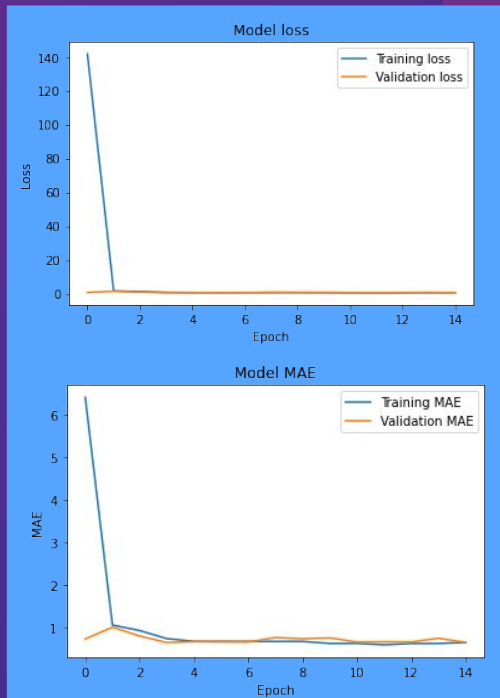
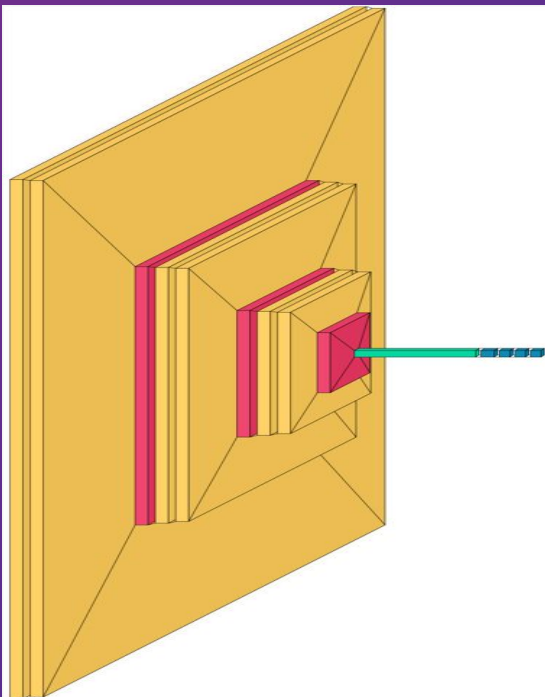


loss: 0.4779 - mae: 0.5629 - val_loss: 0.6079 - val_mae: 0.6205

Female Attractiveness Model

Model: "sequential_15"

Layer (type)	Output Shape	Param #
conv2d_87 (Conv2D)	(None, 398, 398, 32)	896
conv2d_88 (Conv2D)	(None, 396, 396, 32)	9248
max_pooling2d_45 (MaxPooling2D)	(None, 198, 198, 32)	0
conv2d_89 (Conv2D)	(None, 196, 196, 64)	18496
conv2d_90 (Conv2D)	(None, 194, 194, 64)	36928
max_pooling2d_46 (MaxPooling2D)	(None, 97, 97, 64)	0
conv2d_91 (Conv2D)	(None, 95, 95, 128)	73856
conv2d_92 (Conv2D)	(None, 93, 93, 128)	147584
max_pooling2d_47 (MaxPooling2D)	(None, 46, 46, 128)	0
...		
Total params: 69,665,569		
Trainable params: 69,665,569		
Non-trainable params: 0		



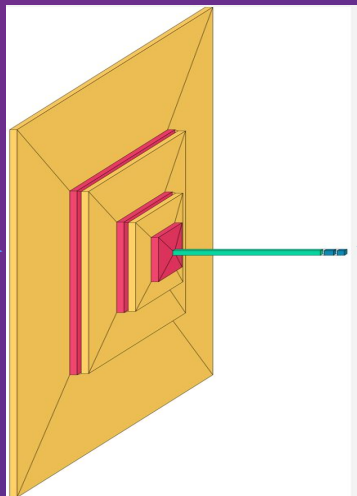
loss: 0.5973 - mae: 0.6365 - val_loss: 0.5979 - val_mae: 0.6364

Model Application

Unseen Image

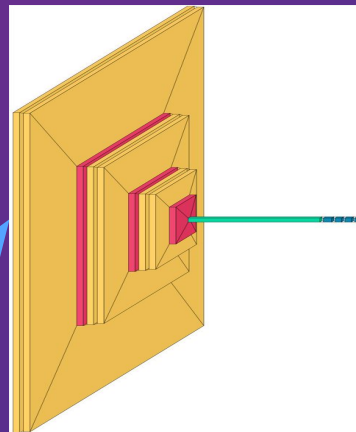


Gender Prediction

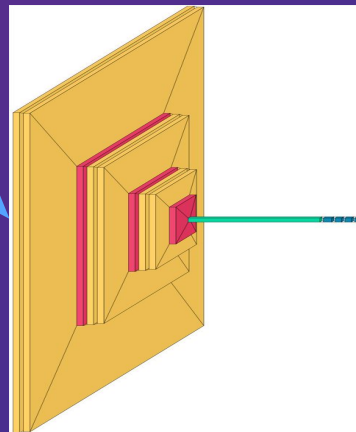


Probability Male: 1.0

Male Model



Female Model



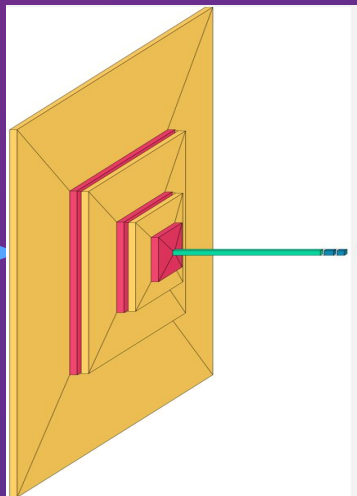
Attractiveness
Prediction: 2.099

Model Application

Unseen Image

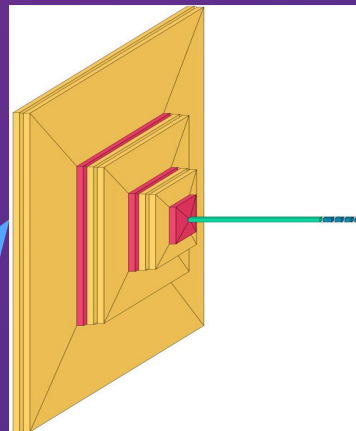


Gender Prediction

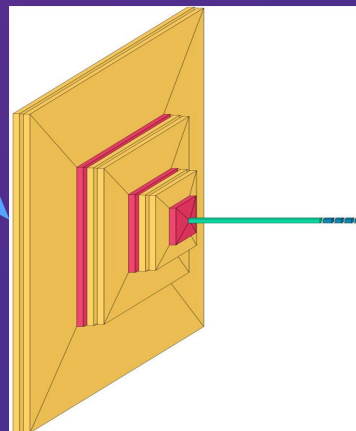


Probability Male: 0.0

Male Model



Female Model



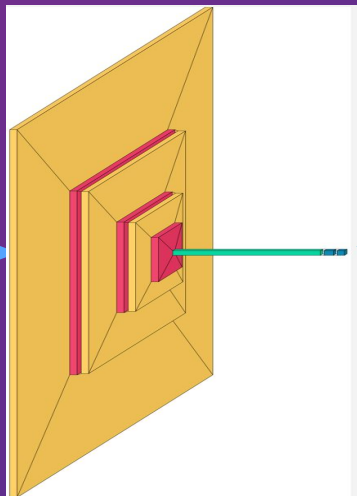
Attractiveness
Prediction: 2.163

Model Application

Unseen Image

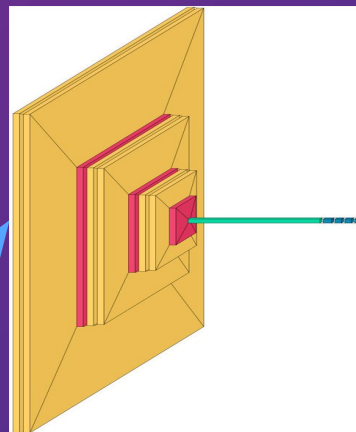


Gender Prediction

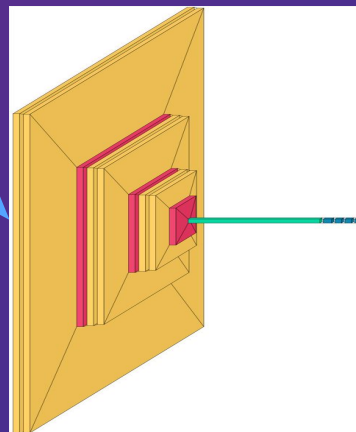


Probability Male: 0.07

Male Model



Female Model



Attractiveness
Prediction: 2.468



Next Steps

- Fine tuning the model on the preferences of an individual
 - Implement Grad-CAM to interpret model's feature detection
 - Add more regularization layers to the model to decrease the over fitting of the model
- 