Future of Privacy Forum

Performance Considerations for Automated Age Verification

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If age is just a number, what is that number measuring?

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Overview

- Age Verification
- Types of Age Measures
- Modalities of Age Verification
- Early Age Verification: pre–Deep Learning
- Performance Comparison of Commercial Age Verification Solutions

Why Automatic Age Verification?

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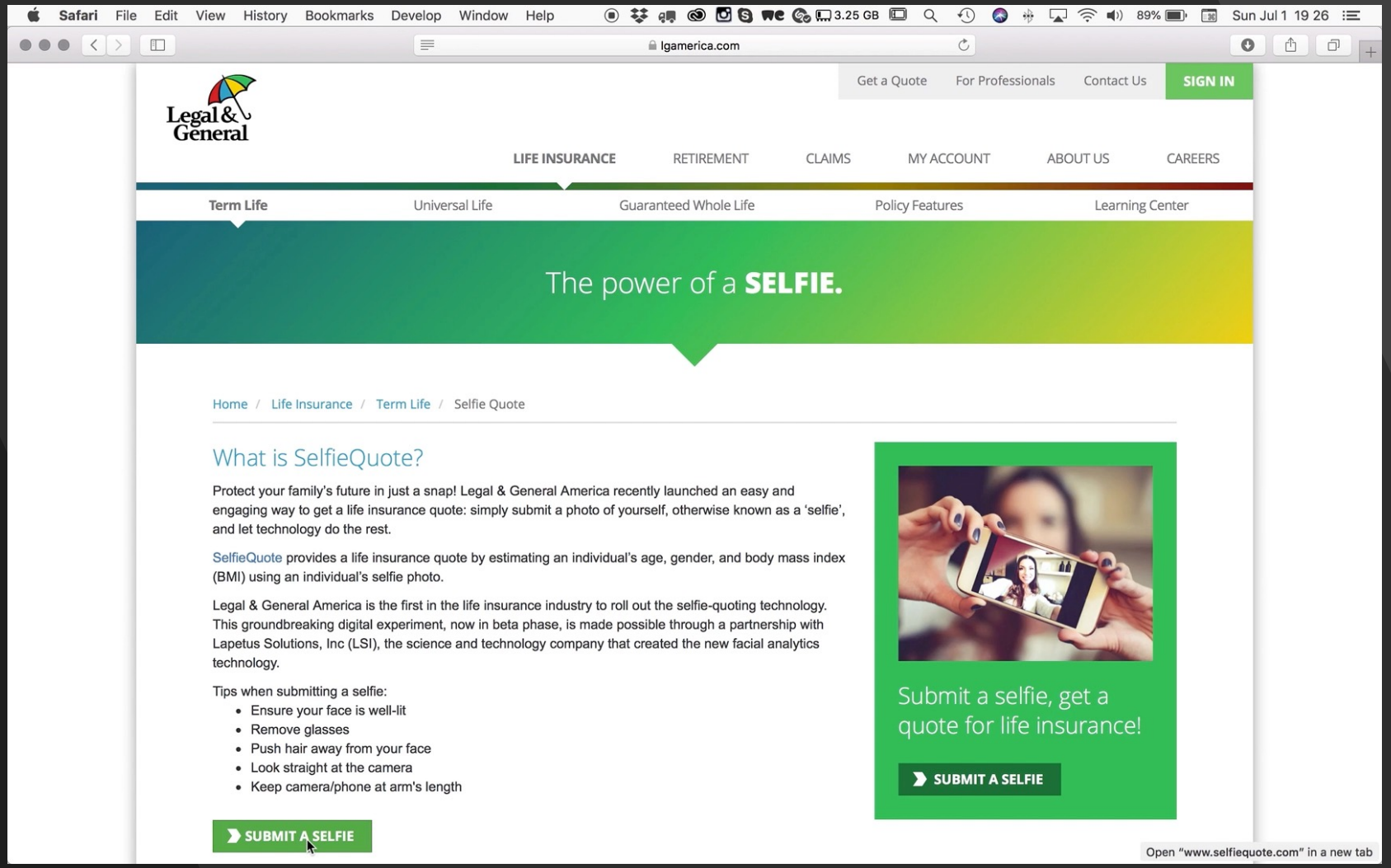
Access Control

Digital Signage & eCommerce

Source: Minority Report Movie (2002)

Digital Signage & eCommerce

Source: Legal & General UK (Lapetus Solutions, Inc)



Types of Age Measures

- **Chronological Age**
  - the amount of time elapsed since an individual's birth, typically expressed in terms of months and years. Also called **calendar age**.
    (Source: https://dictionary.apa.org/chronological-age)

- **Perceived Age**
  - Qualitative measure of chronological age based on a set of observers. Observers can be humans or machines.

- **Biological Age**
  - Qualitative measure of the senescing rate as a function of chronological age. Is the person aging faster, slower, or the same as some one their chronological age.

Age Measures

- Perceived Age: Man on right is older
- Chronologically these men are equal at 70 years old.
- Biologically these men are vastly different. The man on the left can expect to much longer than the man on the right

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Age Measures Identical Twins

- Perceived Age: Different
- Chronological Age: Same
- Biological Age: Severely Different

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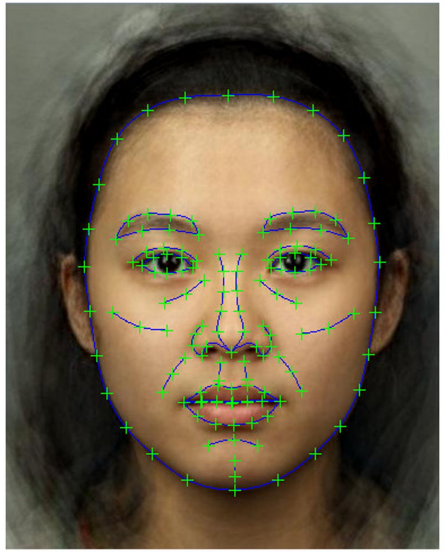
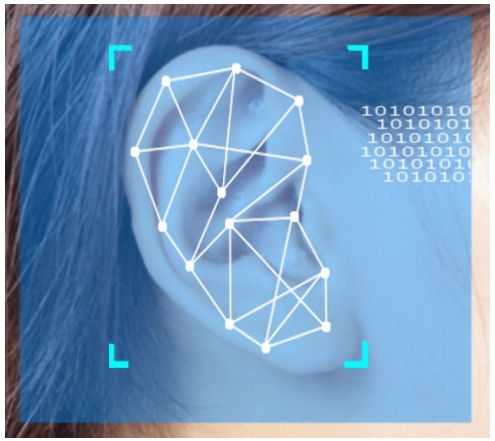
Automatic Age Verification Modalities





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Age and Gender Classification from Ear Images

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Abstract—In this paper, we present a detailed analysis on extracting soft biometric traits, age and gender, from ear images. Although there have been a few previous work on gender classification using ear images, to the best of our knowledge, this study is the first work on age classification from ear images. In the study, we have utilized both geometric features and appearance-based features for ear representation. The utilized geometric features are based on eight anthropometric landmarks and consist of 14 distance measurements and two area calculations. The appearance-based methods employ deep convolutional neural networks for representation and classification. The well-known convolutional neural network models, namely, AlexNet, VGG-16, GoogLeNet, and SqueezeNet have been adopted for the study. They have been fine-tuned on a large-scale ear dataset that has been built from the profile and close-to-profile face images in the Multi-PIE face dataset. This way, we have performed a domain adaptation. The updated models have been fine-tuned once more time on the small-scale target ear dataset, which contains only around 270 ear images for training. According to the experimental results, appearance-based methods have been found to be superior to the methods based on

Gait-based age estimation using multi-stage convolutional neural network

Atsuya Sakata, Noriko Takemura & Yasushi Yagi

IPSJ Transactions on Computer Vision and Applications **11**, Article number: 4 (2019) | Cite this article

Abstract

Gait-based age estimation has been extensively studied for various applications because of its high practicality. In this paper, we propose a gait-based age estimation method using convolutional neural networks (CNNs). Because gait features vary depending on a subject's attributes, i.e., gender and generation, we propose the following three CNN stages: (1) a CNN for gender estimation, (2) a CNN for age-group estimation, and (3) a CNN for age regression. We conducted experiments using a large population gait database and confirm that the proposed method outperforms state-of-the-art benchmarks.

Hand Image-Based Human Age Estimation using a Time Distributed CNN-GRU

October 2020

DOI: 10.1109/ICDABI51230.2020.9325667

Conference: 2020 International Conference on Data Analytics for Business and Industry: Way Towards a Sustainable Economy (ICDABI)

Project: Biometrics

Mohamed Ait Abderrahmane · Ibrahim Guelzim · Abdelkaher Ait Abdelouahad

Age Prediction from Iris Biometrics

December 2013

DOI: 10.1049/ic.2013.0258

Conference: 5th International Conference on Imaging for Crime Detection and Prevention

Meryem Erbilek · M. Fairhurst · Márjory Da Costa-Abreu

Soft-Biometrics for Age Verification

- Soft biometrics uses the biometric signals to determine automatic age.
- Often uses age ranges instead of point estimates
- 2011 face-based soft-biometrics was formalized into facial analytics

Early Approaches to Chronological Age Verification (2008 to 2012)

Multi-factor Statistical Learning via Active Appearance Models

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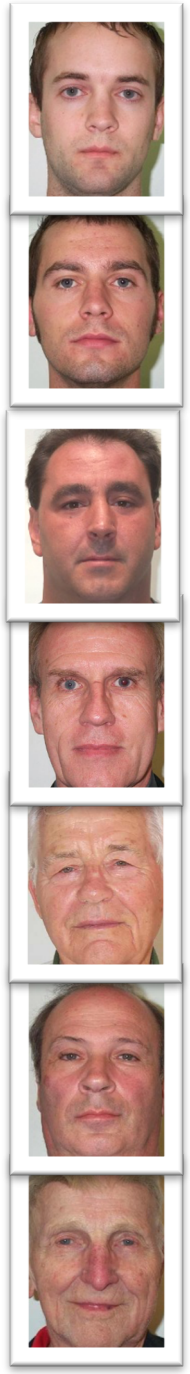
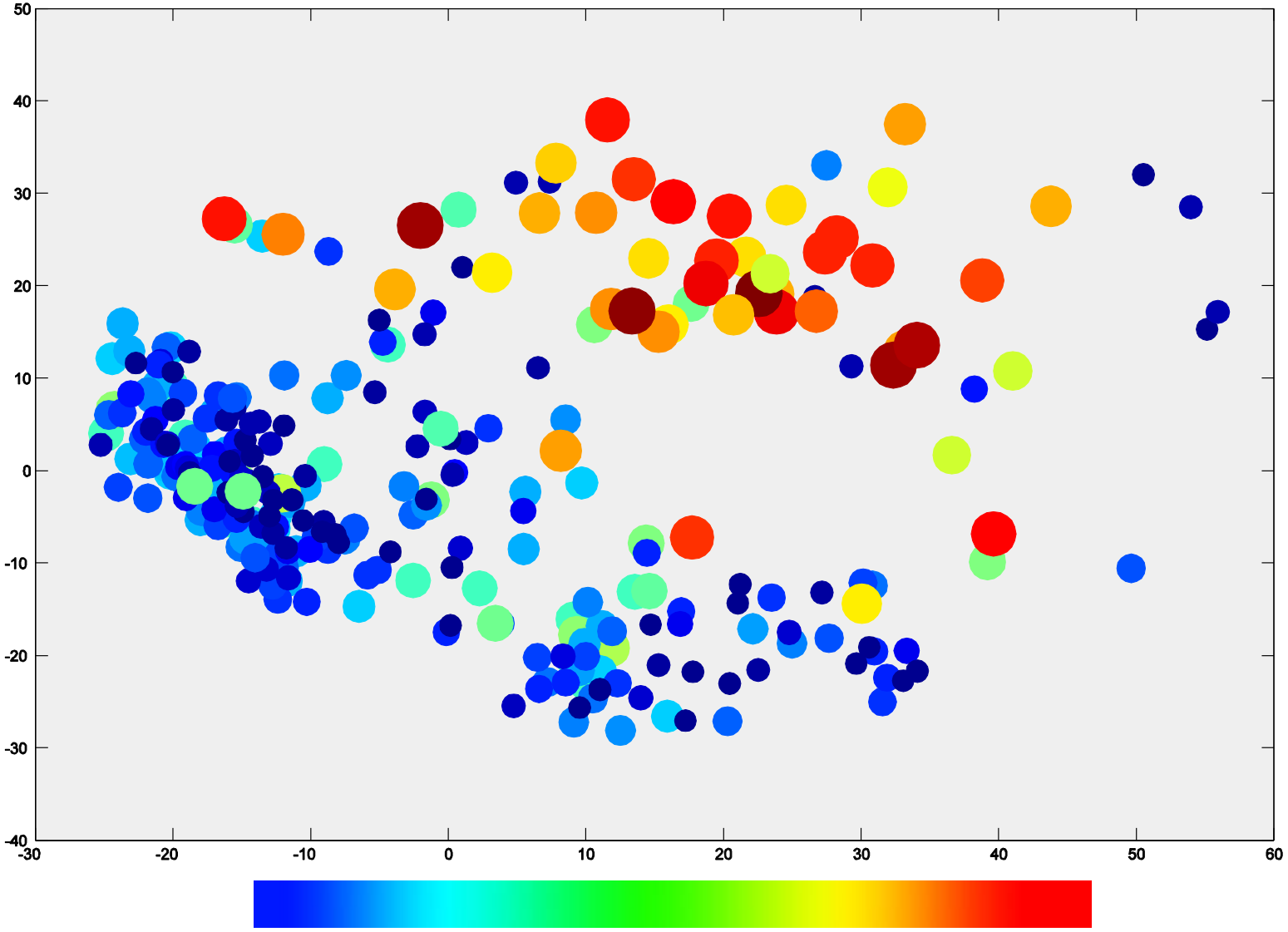
High Fidelity Synthetic Age Progression

Active Appearance Models in Age Space





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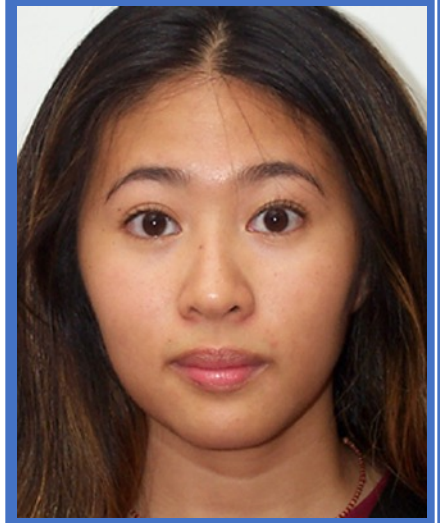
Est: **MAE 3.4 yrs**

Cor: **MAE 2.1 yrs**

Chronological Age Estimation
Example of Results (age 18-29)



True age: 19

Est. age: 18.88

Abs Error: 0.12

True age: 20

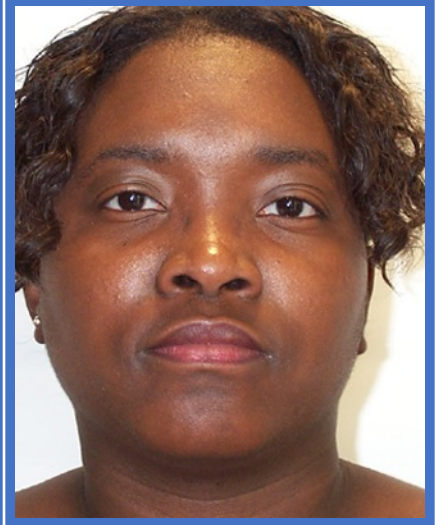
Est. age: 20.02

Abs Error: 0.02

True age: 22

Est. age: 22.09

Abs Error: 0.09



True age: 29

Est. age: 29.43

Abs Error: 0.43

Chronological Age Estimation
Example of Results (age 30-59)

True age: 34	True age: 45	True age: 47	True age: 54
Est. age: 33.74	Est. age: 45.76	Est. age: 47.20	Est. age: 53.86
Abs Error: 0.76	***Abs Error: 0.76***	***Abs Error: 0.20***	***Abs Error: 0.14***

Chronological Age Estimation
Example of Results (age 60-93)

True age: 63	True age: 72	True age: 83	True age: 93
Est. age: 63.10	Est. age: 71.99	Est. age: 83.14	Est. age: 92.48
Abs Error: 0.10	***Abs Error: 0.00***	***Abs Error: 0.14***	***Abs Error: 0.52***

Summary

- Pros
  - Data requirements are dramatically less than Deep Learning
  - Robust to gender and ethnicity
  - Model captures aging factors

- Cons
  - Trail and error to identify parameters in the larger face space
  - Performance impacted by:
    - pose variations
    - illumination
    - expression

Deep Machine Learning Age Performance

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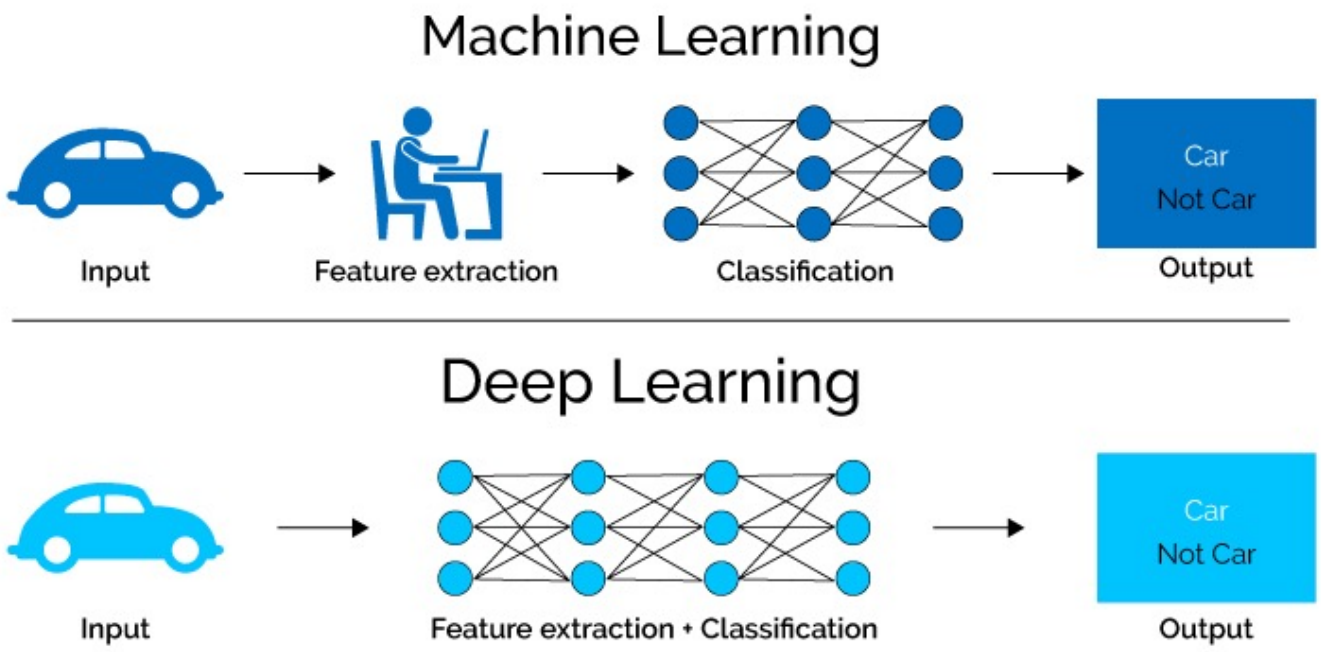
Deep Machine Learning

- Deep learning attempts to mimic the human brain—albeit far from matching its ability—enabling systems to cluster data and make predictions with incredible accuracy.

Source: https://www.ibm.com/cloud/learn/deep-learning



Deep Machine Learning

- Pros
  - incredible ability to extract meaning, patterns, from data
  - feature generation
  - feature abstraction
  - performance

- Cons
  - volumes of data required (100,000 to 1,000,000 data points)
  - can easily be biased
  - modes of sensitivity are not well understood; requires extensive sensitivity testing prior to deployment

Large Scale Comparison of three Commercial Age Verification Solutions

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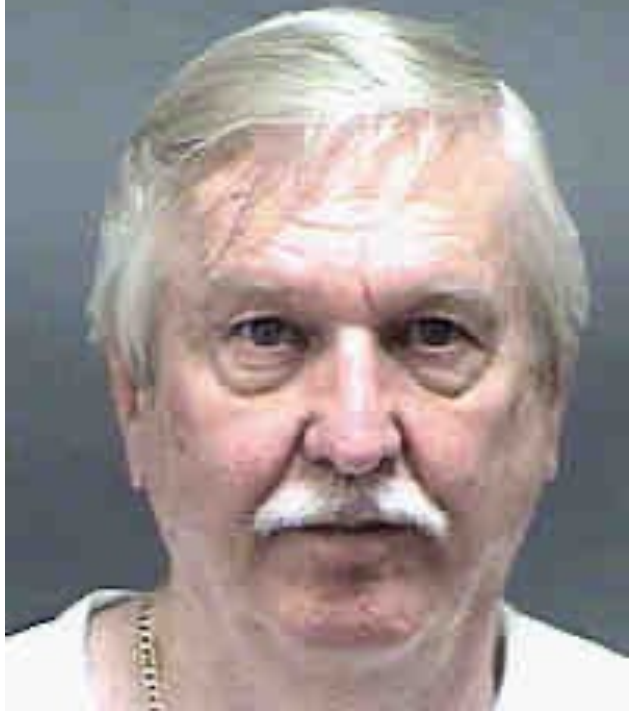



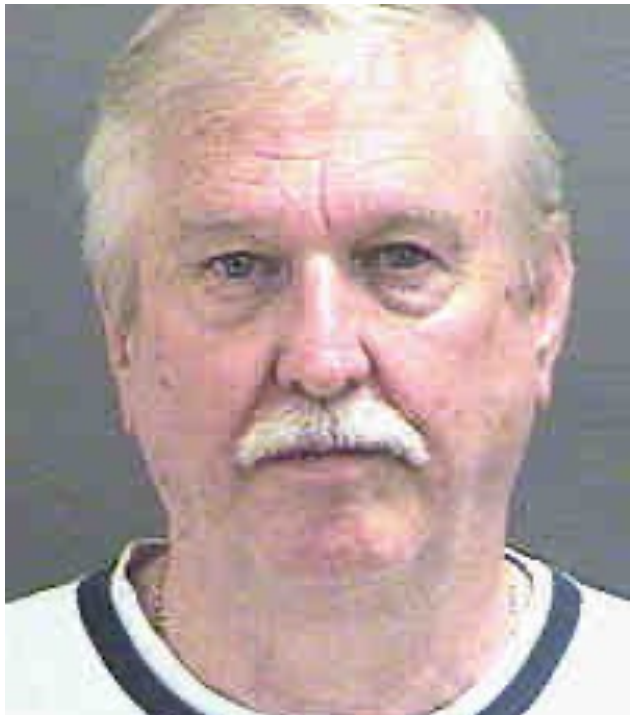

Evaluation Dataset

- MORPH is a large-scale data corpus comprised of images with metadata for gender and age. The dataset contains multiple images of a person across time.
- MORPH: https://uncw.edu/oic/tech/morph.html

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Chronological Age Verfication

n = 138,839

Row Labels	Microsoft (MAE)	Lapetus (MAE)	Sighthound (MAE)	Count
<20	4.170152307	3.414740018	7.909638554	8798
20-29	3.496826562	3.297766729	5.799274643	46322
30-39	4.193529521	4.188204963	6.986920807	37617
40-49	6.193381304	4.412858936	8.117486508	32242
50-59	6.150498713	3.772531215	10.46806628	12432
60-69	5.569196429	3.915738061	11.13095238	1344
70-79	10.55952381	5.429652269	7.25	84
Grand Total	**4.616419018**	**3.85517101**	**7.263679514**	**138839**

Sightcorp is formerly Sighthound

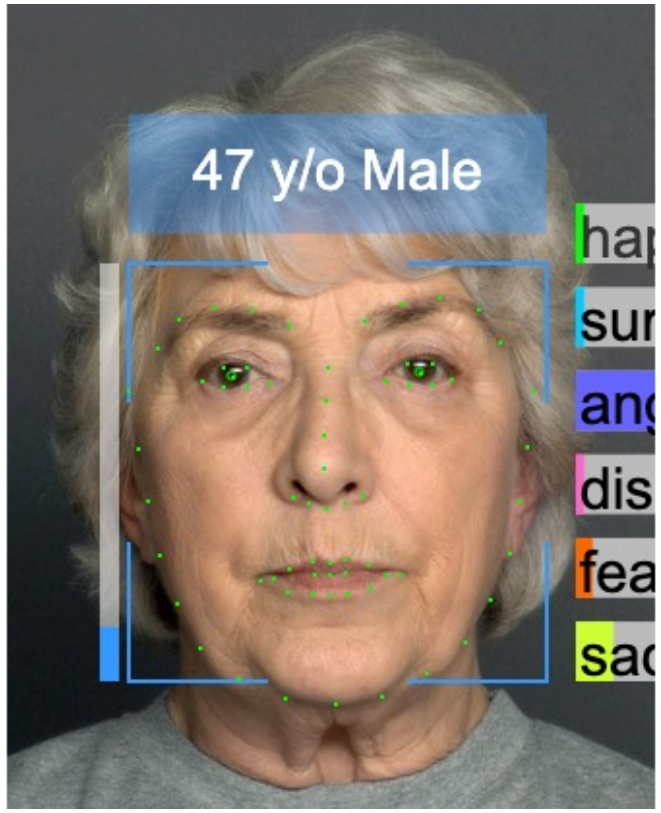
Age Verfication by Race

GT_gender	(All)			
GT_race	European/White			
Row Labels	**Microsoft (MAE)**	**Lapetus (MAE)**	**Sighthound (MAE)**	**Count**
<20	5.364222401	2.846522437	7.775181305	1241
20-29	4.587845734	3.581140032	6.907804181	7701
30-39	3.786919315	3.764435822	7.529217604	8180
40-49	4.965258216	3.961672431	9.222803488	7455
50-59	6.338821205	4.120600534	12.30852815	3037
60-69	4.632275132	3.834055567	11.37301587	378
70-79	8.375	5.386317745	9.375	24
Grand Total	**4.682467162**	**3.766813792**	**8.391490577**	**28016**

Age Verfication by Race

GT_gender	(All)			
GT_race	Black/African			
Row Labels	**Microsoft (MAE)**	**Lapetus (MAE)**	**Sighthound (MAE)**	**Count**
<20	3.920051304	3.505222312	7.900669802	7017
20-29	3.219734293	3.217100132	5.505148076	36130
30-39	4.332788632	4.297234802	6.772149201	28150
40-49	6.607241195	4.546191936	7.770065343	24333
50-59	6.112091222	3.660681159	9.870159208	9296
60-69	5.986170213	3.92202747	11.06276596	940
70-79	11.61016949	5.426429415	6.271186441	59
Grand Total	**4.623157895**	**3.874969818**	**6.953665329**	**105925**

Example: Female 80 years old

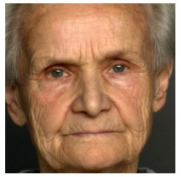


Gender: Female

BMI: Normal (21.3)

Age: 72.5

Results



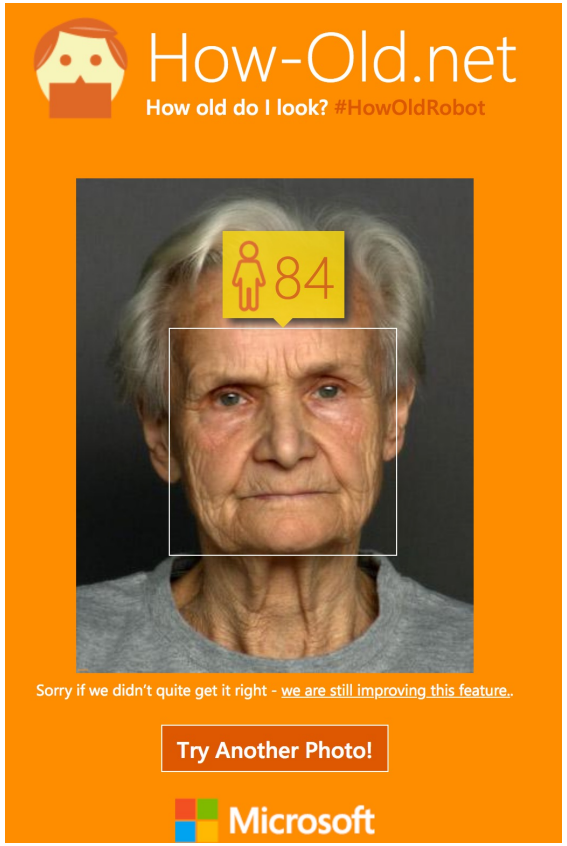
looks like a face	99.9 %
appears to be male	99.4 %
age range	60 - 90 years old
not smiling	70.8 %
not wearing glasses	99.9 %
not wearing sunglasses	99.9 %

Gender: Female

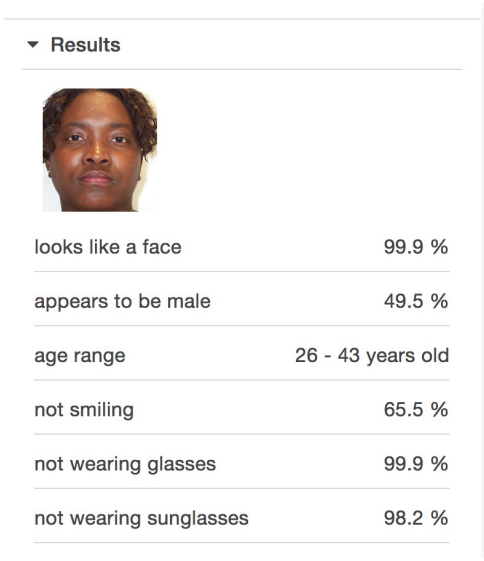
BMI: Normal (19.9)

Age: 77.6

Smoker: Yes



Example: Female 80 years old

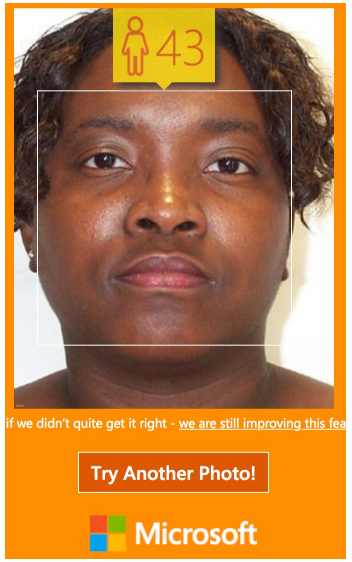


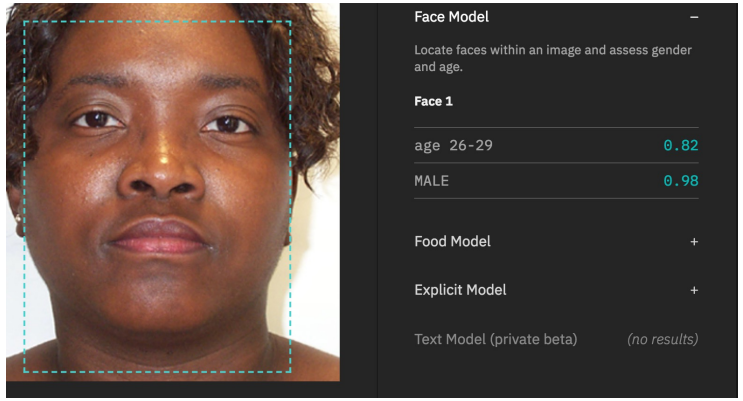
Gender: Female

BMI: Obese (36)

Age: 39.8

Smoker: No





Example: Female 40 years old

Questions

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