Missing Persons
Age-Invariant Face Recognition

Supervisor
Lecturer, PhD. Diana-Laura Borza

Author
Rusu Raluca-Maria

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Introduction

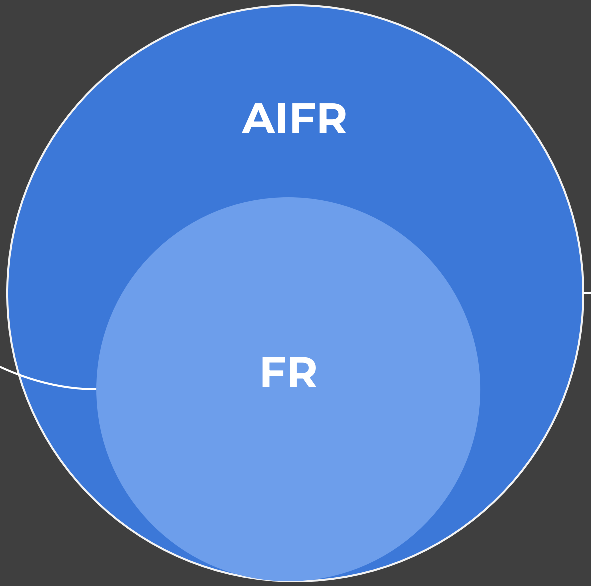
Context

Face Recognition

positively identifying a face in a media file
by comparing it to a database of faces
that already exist and are considered correct

Age-Invariant Face Recognition

performing **face recognition**
that remains **consistent**
despite age-related facial changes

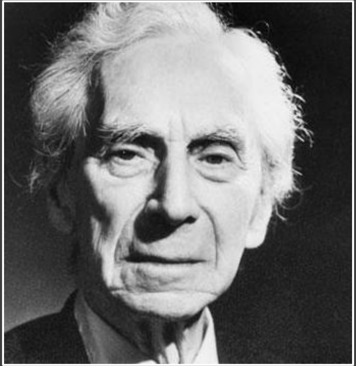


Same person?

01

02

03



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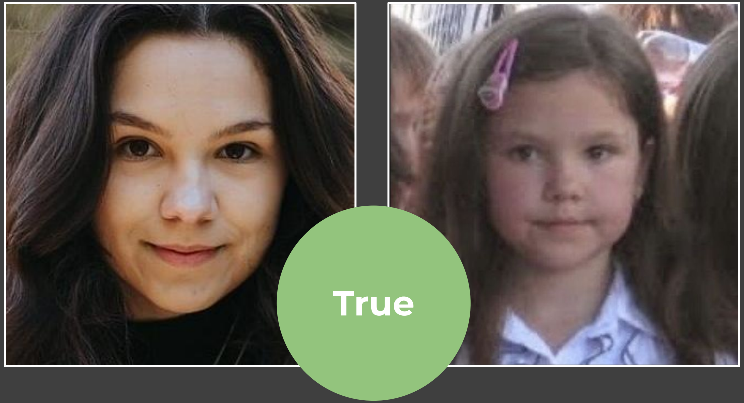
Same person?

01



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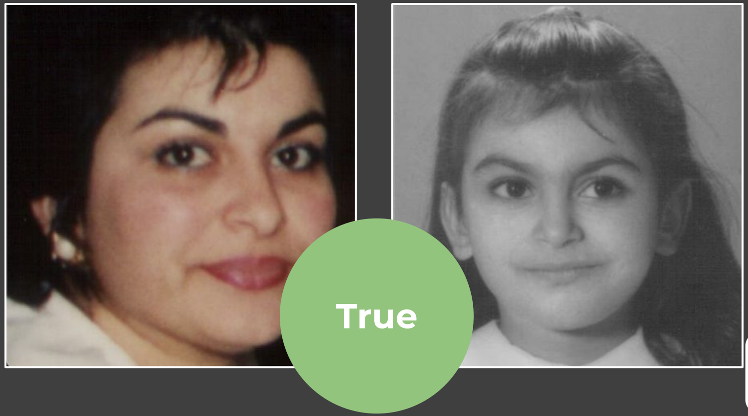


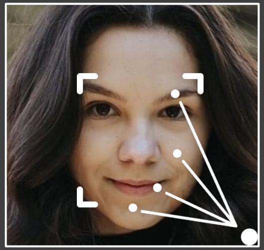
Motivation

face recognition has become **increasingly common in our daily life**,
yet algorithms struggle to recognize faces with an age gap larger than 8.5 years [20]
as significant facial aging differences can overpower identity features [1]

Biometric authentication [2] for banks, phones etc.

Airport Passport Identity Verification

Access Control



Identifying Long-Missing Persons

Time & Attendance Monitoring

Protecting Problem Gamblers

Video Surveillance [3]

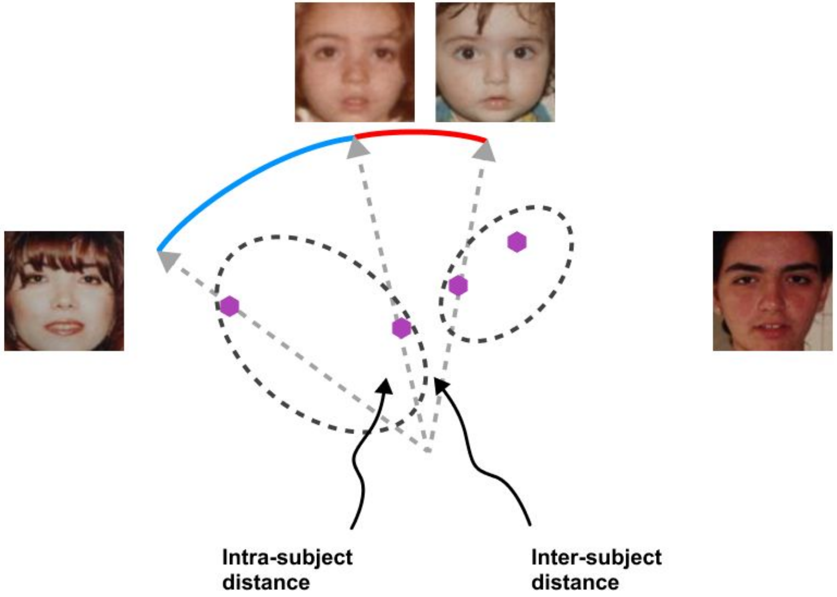
Difficulties

Intra-subject variations

alterations in the same person's images as they age

Inter-subject variations

resemblance between the images of different people



significant age differences, causing the intra-subject distance to be larger than the inter-subject distance

Related works

- typically **segregated facial attributes without considering their potential interdependencies**
- have **shown limitations in addressing the underlying connections between facial features [7]**

Latent Factor guided CNN [4]

2017

reduce the age variations in features

Age Estimation guided CNN [5]

2018

learning guided by the age estimation of the image

Orthogonal Deep Features Decomposition CNN [6]

2018

decomposition encoding identity information in the angular space and age information in the radial direction

Decorrelated Adversarial Learning for AIFR [7]

2019

considered interdependencies only on aging facial attributes

02

Research Objectives

Proposed solution

Develop a capable AIFR model

Factors the **facial features into 3 similar** yet **unique attributes for each individual (age group, gender, identity)** and learns to classify and adversarially maximize and minimize their correlation **to account for inter and intra-subject variances**.

Integrate it into a REST API

Ti be **easily used into various applications and services by developers,** promoting its **usability** and **scalability**.

Missing Persons Web Application

Designed to **identify** missing persons **through image analysis,** offers a **practical and impactful real-world use case** for our model.

03

Age-Invariant Face Recognition Model

Available Datasets

Dataset	No. Images	No. Subjects	Age Labels	Age Range	Gender Labels
FG-NET [8]	1002	82	yes	0 to 69	no
AgeDB[9]	16.488	568	yes	1 to 101	yes
MORPH[10]	55.125	13,617	yes	16 to 77	yes
CACD[11]	163.446	2000	yes	16 to 62	yes
VGGFace[12]	~3.310.000	9,131	yes	-	yes

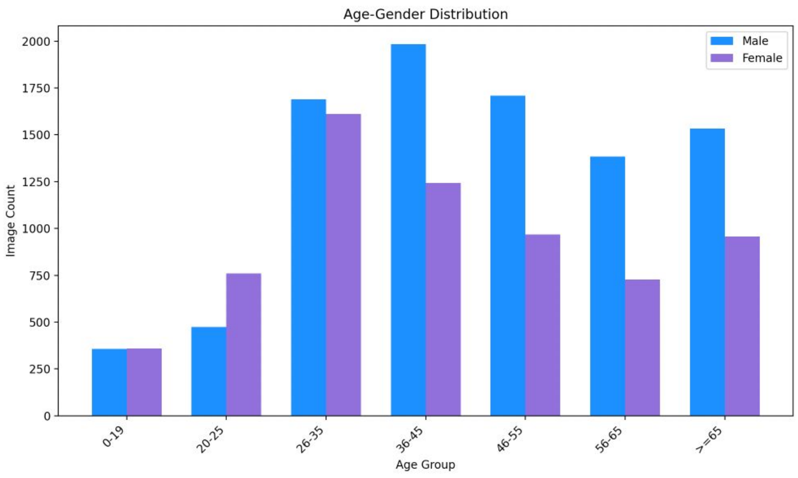
Training Datasets (gathered from Age-DB & CACD)

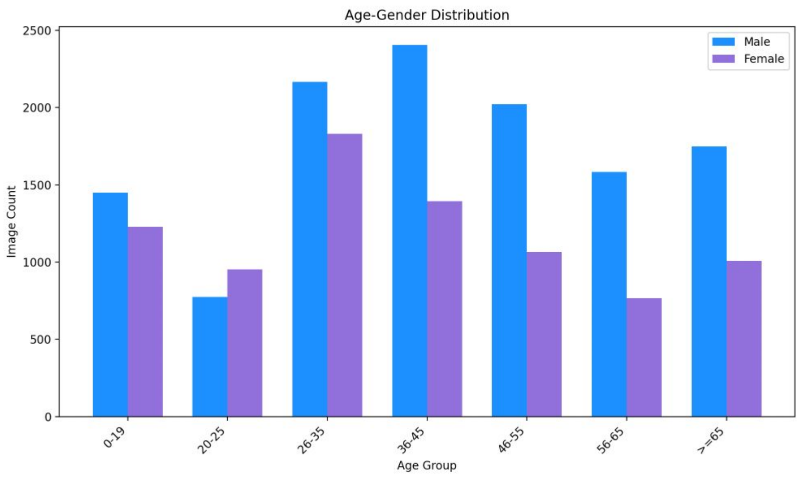
Small

- **500** unique **identities**, each with **over 20 images**, spanning ages 0 to 101
- **15, 752** images

Large

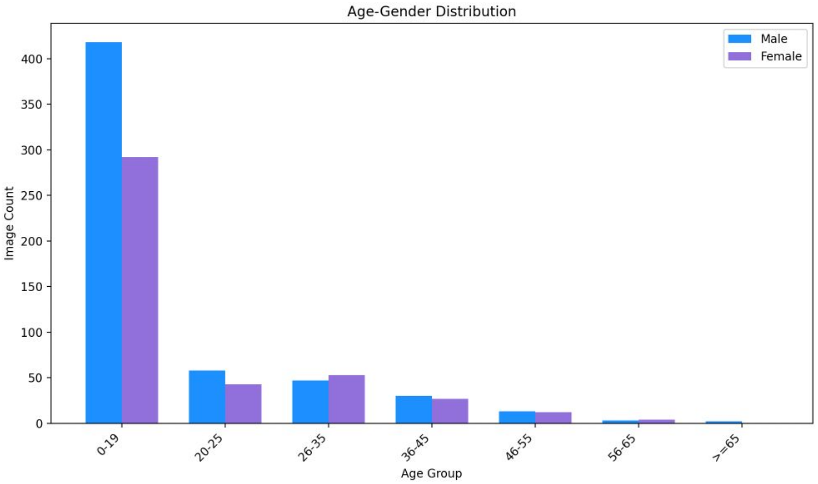
- **1035** unique **identities**, each with **over 5 images**, spanning ages 0 to 101
- **20, 387** images





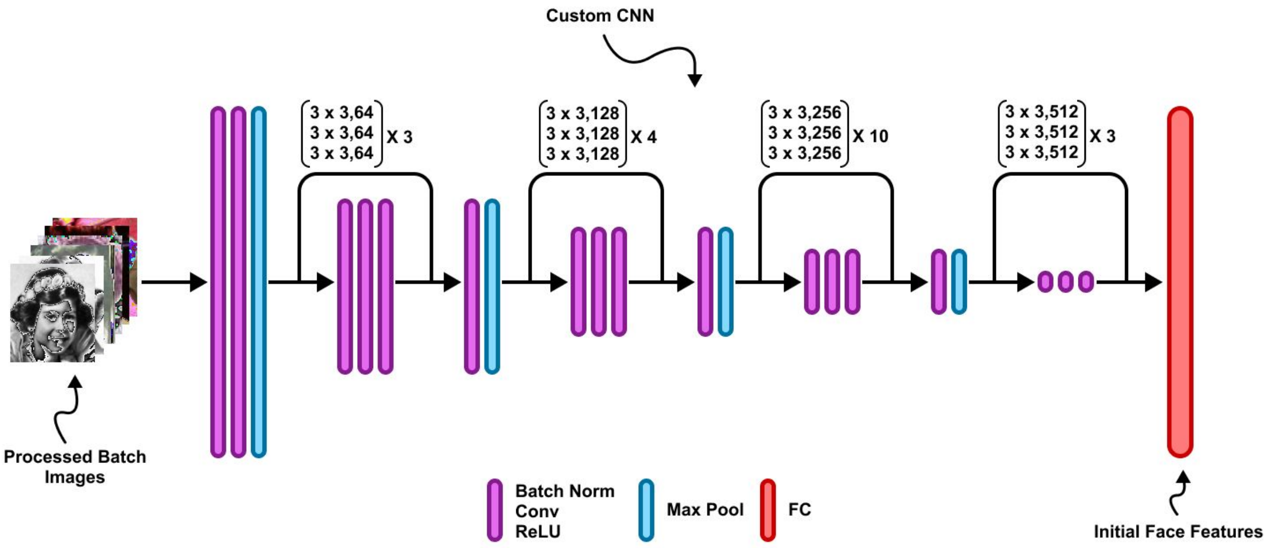
FG-NET Dataset (used in evaluations)

- **82** unique **identities**, each with **over 10 images**, spanning ages 0 to 69
- **1002** images



Custom Backbone CNN

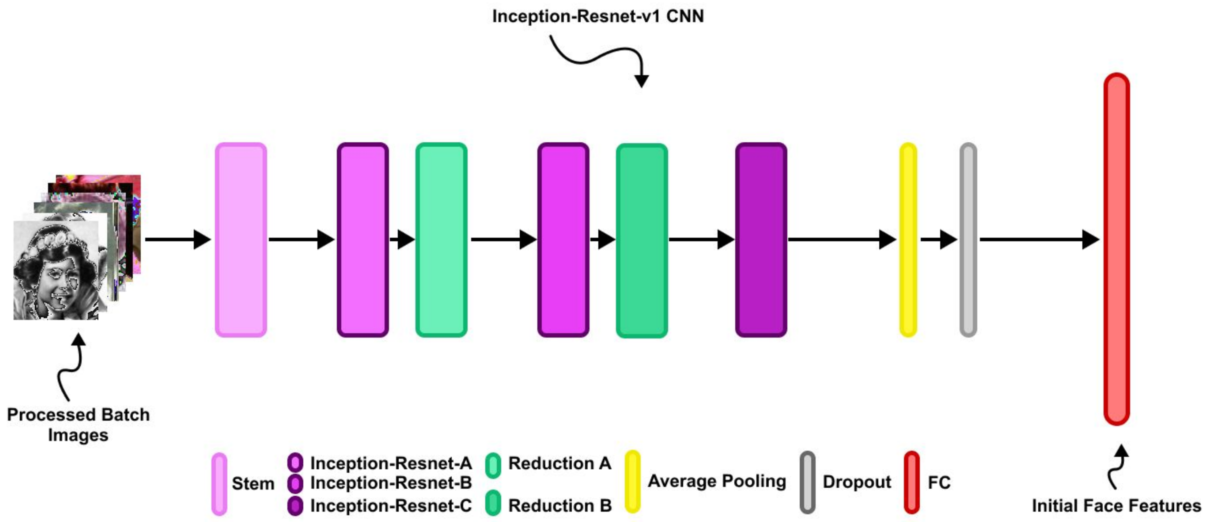
inspired by ResNet, following [7] and [6]'s Orthogonal with added Batch Normalization



got insignificant results, as the dataset's size and diversity were limited and the learning task was immensely dependent on these resources

Transfer Learning Backbone CNN

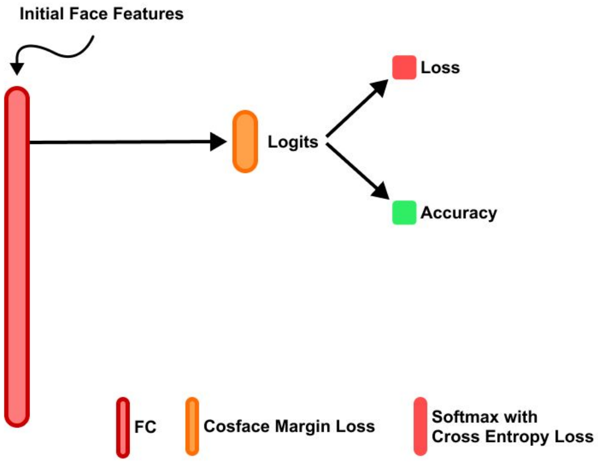
conducted research and concluded that the best suited for our task is
the **Inception-Resnet-v1** from [13], **pre-trained** on the **VGGFace** [12] dataset



serves as our **feature extractor**
converting input images into embeddings or initial face features

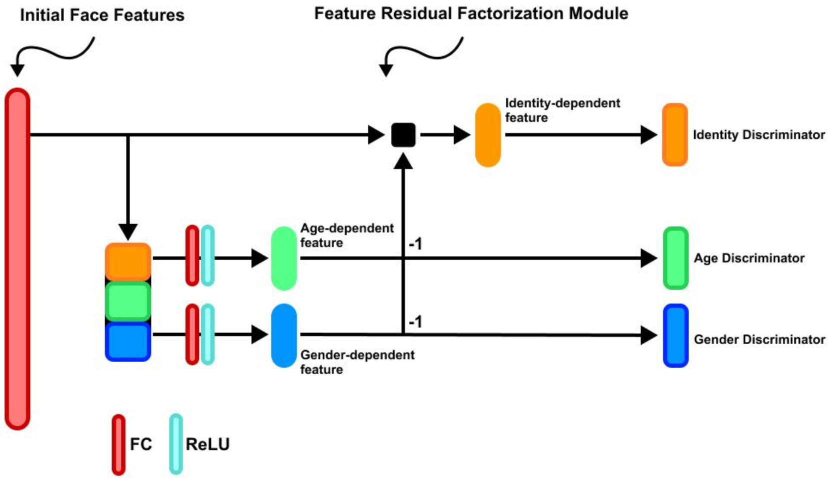
Single-Task Model

baseline model that **only classifies** the **identity** from facial images, using directly the embeddings from the Backbone

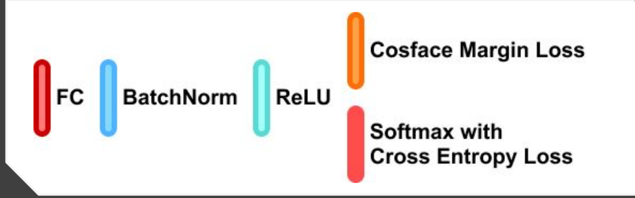


Multi-Task Model

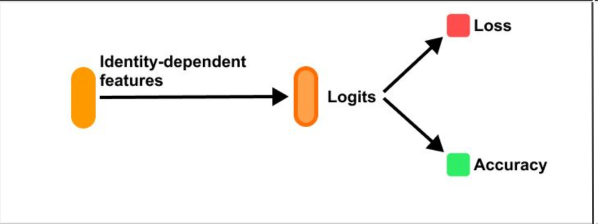
simultaneously classifies identity, age group, and gender from facial images, using the decomposed embeddings returned by the **Feature Residual Factorization Module (FRFM)**



Discriminators



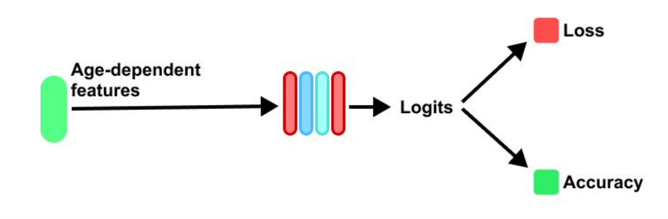
Identity



- similar to the Single-Task model, but **uses only the identity features**
- **Cosface Margin Loss** that increases inter-class separability and intra-class compactness

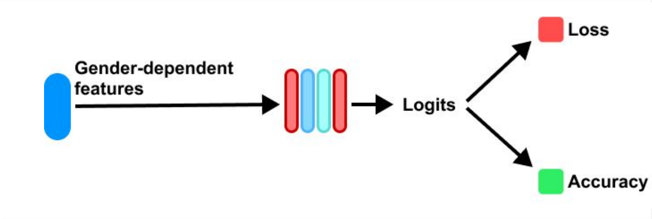
$$\mathcal{L}_{ID} = -\frac{1}{N}\sum_{i=1}^{N}\log\frac{e^{s(\cos(\theta_{y_i,i})-m)}}{e^{s(\cos(\theta_{y_i,i})-m)}+\sum_{j\neq y_i}e^{s\cos(\theta_{j,i})}}$$

Age group



- **classification for 3 age groups:**
  0 – 25 (**young**)
  25 – 55 (**adults**)
  and 56+ (**elderly**)

Gender

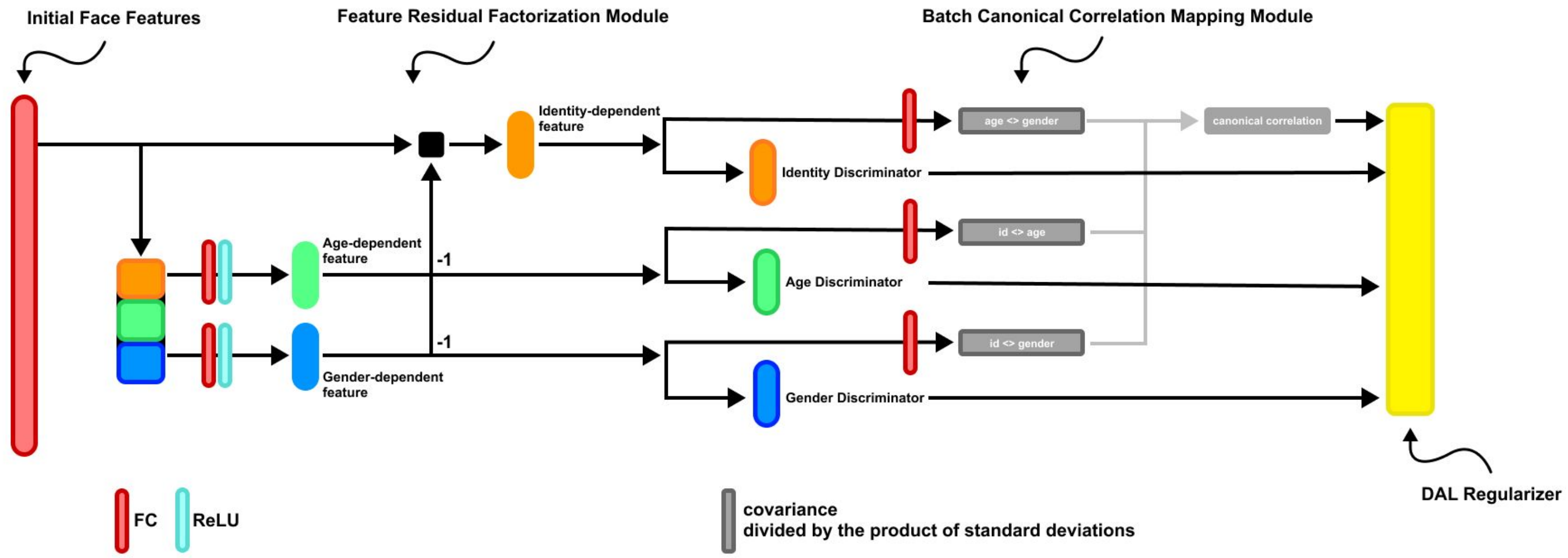


- **gender classification:**
  0 (**male**)
  1 (**female**)

- **Cross-Entropy Loss** from **PyTorch** combines the log softmax and negative log-likelihood loss into a single function
  converts raw model outputs (logits) into probabilities
  measures the difference between the predicted probabilities and the true labels, penalizing incorrect predictions

Multi-Task + DAL model

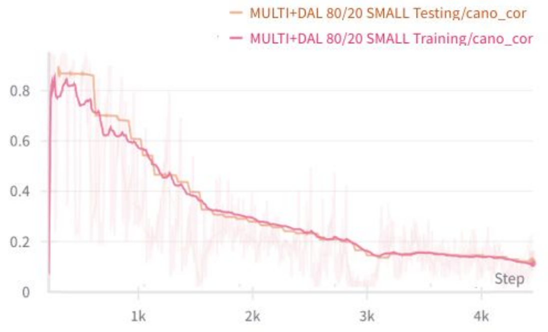
decomposes features and performs **multitask classification** using the **FRFM module**
calculates the identity, age group, and gender **correlation** using the **BCCM module**, and
adversarially learns to maximize and minimize it using the **DAL Regularizer**

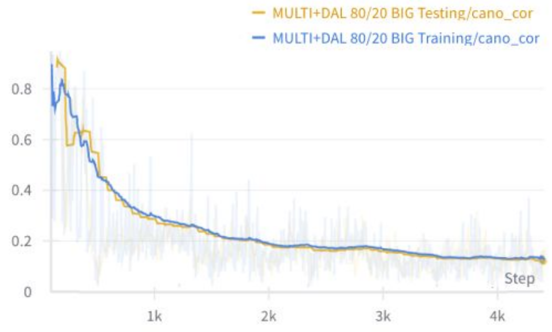


Decorrelated Adversarial Learning (DAL)

strategically manipulate gradients and **optimize different parameters during training**

- for **40 iterations minimization process**:
  - train only the Backbone and FRFM parameters
  - freeze the BCCM parameters
- for **30 iterations maximization process**:
  - freeze the Backbone and FRFM
  - train only the BCCM parameters and flipping its gradients for adversarial training





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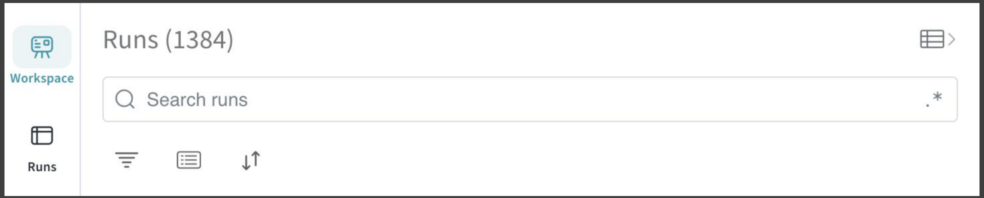
Experiments & Evaluations

Trial and error was key



Embedding Size
512

Learning Rate
0.01

Batch Size
64

No. Epochs
40

Loss Computation

Single-Task:
- only identity discriminator loss

Multi-Task:
- combined identity, age, and gender discriminator losses, weighted by lambdas: 1, 0.9, 0.9

Multi-Task + DAL:
- combined identity, age, gender, and DAL discriminator losses, weighted by lambdas: 1, 0.9, 0.9, 0.9

Optimizer

SGD optimizer with momentum 0.9

Single-Task:
- optimize Backbone

Multi-Task:
- optimize Backbone and FRFM

Multi-Task + DAL:
- DAL strategy

Evaluations

80/20 Split

Model	Trained on	80/20 Split
Single-Task	large	85.65%
Multi-Task	large	85.92%
Multi-Task + DAL	large	**86.24%**
Single-Task	small	93.02%
Multi-Task	small	93.12%
Multi-Task + DAL	small	**93.89%**

- **on 20% of our curated datasets** (excluded from training)

Two-Pairs

Model	Trained on	Evaluation two-pairs
Single-Task	large	79.31%
Multi-Task	large	79.83%
Multi-Task + DAL	large	**80.00%**
Single-Task	small	78.85%
Multi-Task	small	79.42%
Multi-Task + DAL	small	**82.21%**

- **FG-NET dataset**
- 1000 positive and negative pairs
- **minimum 15 years age difference**
- **equal gender distribution**
- **threshold of 0.5** to determine if two images likely depict the same person

Leave-One-Out

Method	Rank-1
Park et al. (2010) [14]	37.40%
Li et al. (2011) [15]	47.50%
HFA (2013) [16]	69.00%
MEFA (2015) [17]	76.20%
CAN (2017)[18]	86.50%
LFCNNs (2017) [4]	88.10%
AIM (2018) [19]	93.20%
Age + DAL (2019) [7]	94.50%
Multi-Task + DAL	**94.61%**

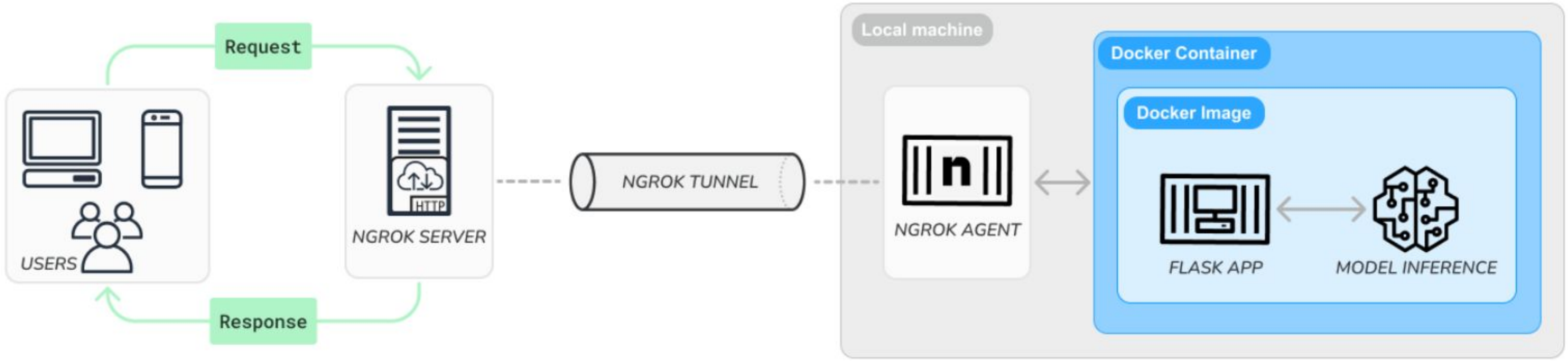
- **FG-NET dataset**
- rigorous testing protocol
- **each image** in the dataset used **once as a test image**, **while the rest** formed **the training set**

05
REST API

Requests

REQUEST	TYPE	PARAMS			RESPONSE
/images_similarity	POST	KEY	VALUE		{ "similarity": -0.70 } can throw **invalid_request_error** or **request_error**
		image1	File	img1.jpg	
		image2	File	img1neg.jpg	
/batch_images_similarity	POST	KEY	VALUE		{ "similarity": 0.89 } can throw **invalid_request_error** or **request_error**
		imageList1	File	4 files	
		imageList2	File	4 files	

Architecture

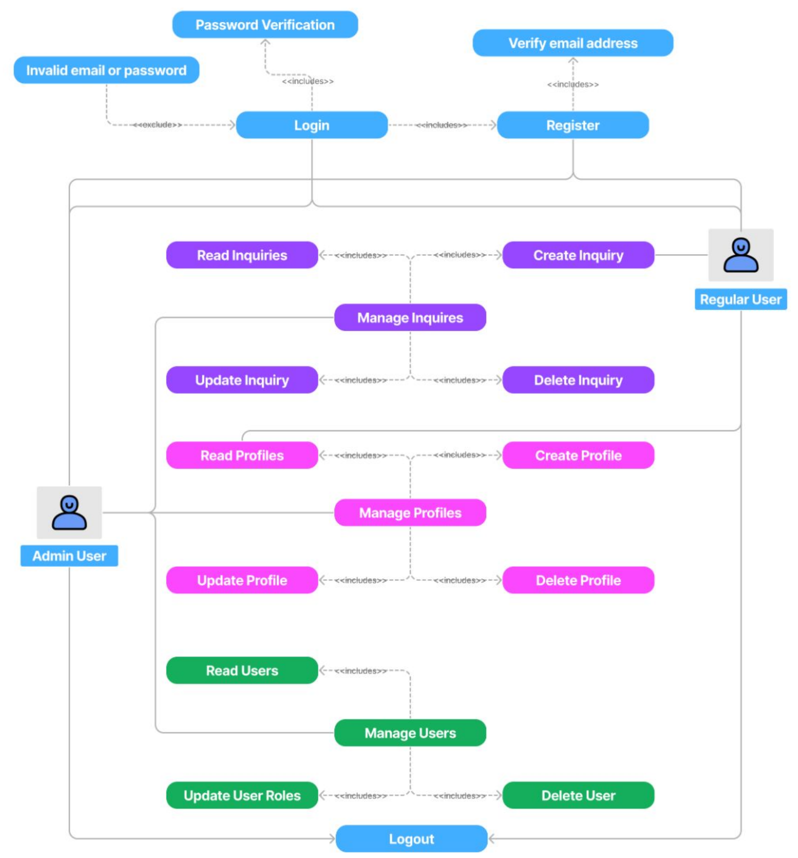


demo

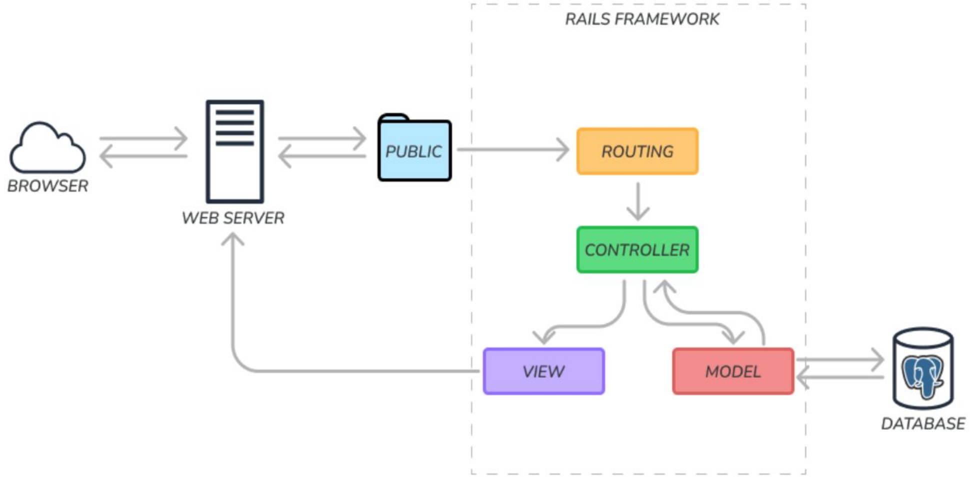
06

Missing Persons Web Application

Functionalities



Architecture



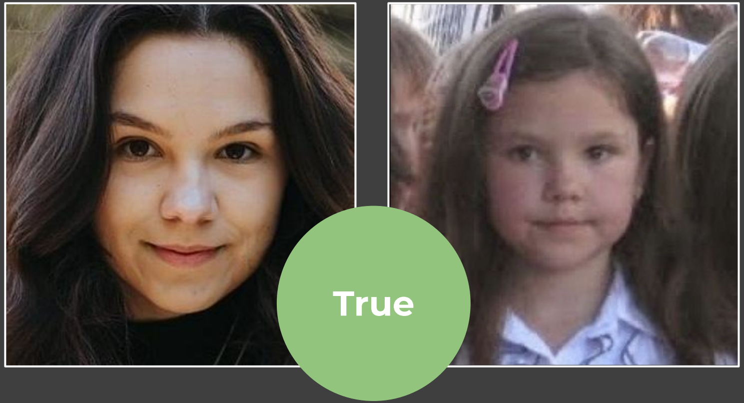
demo

07

Conclusions & Future Improvements

Same person?

01



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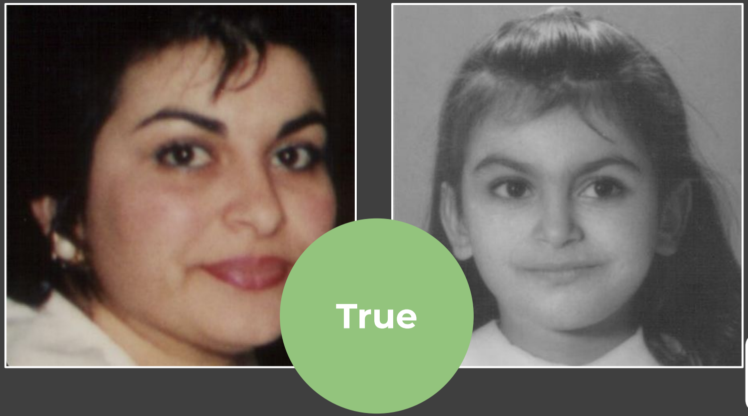
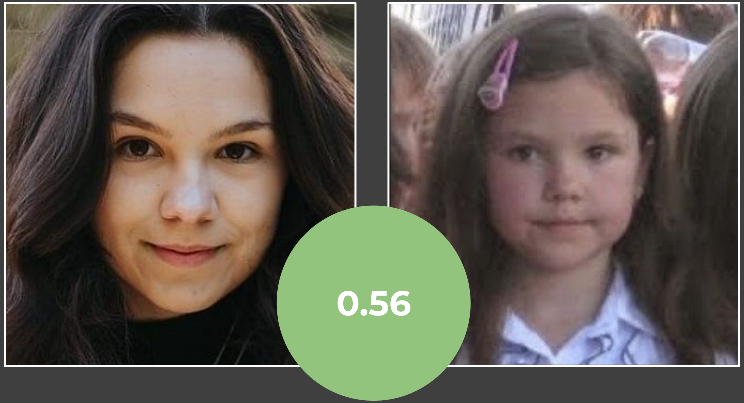


Same person?

01



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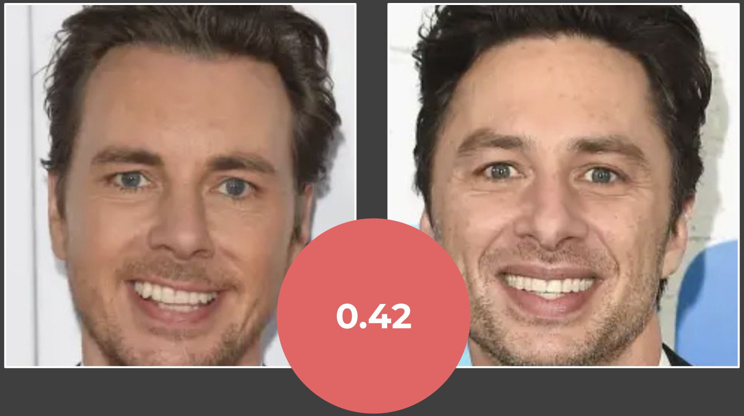
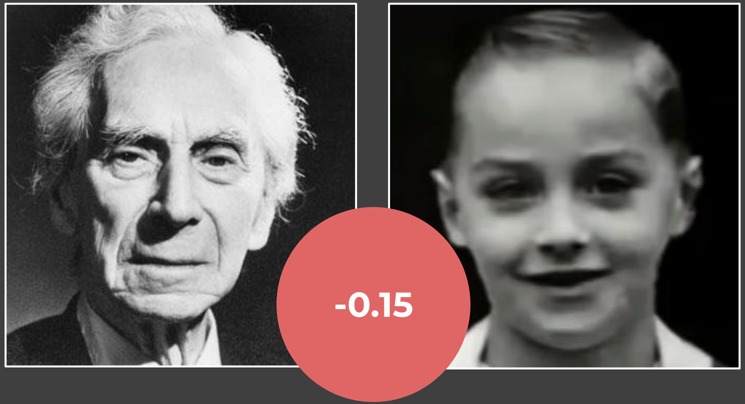


03



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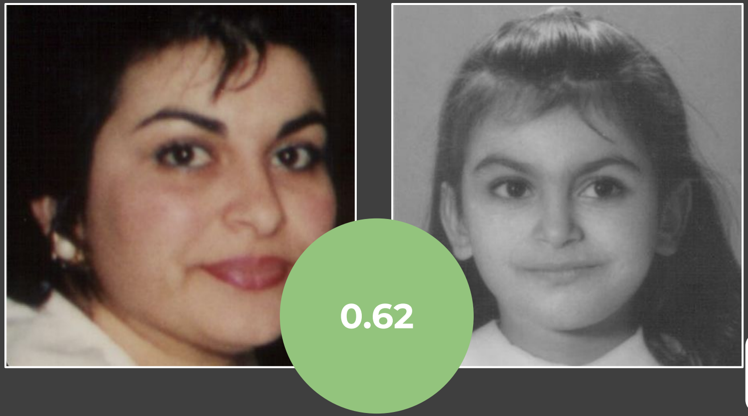


Future Improvements

integrating
other biometric characteristics

optimizing
hyperparameters

experimenting with
different loss functions

fine-tuning on
more diverse datasets

08

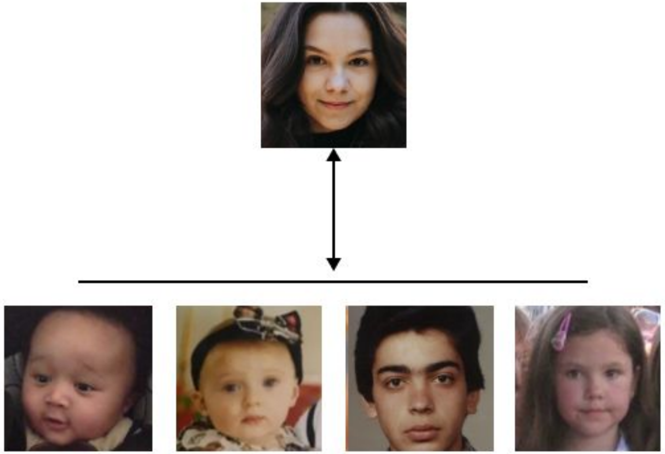
References

References

[1] - Zhang Junping Shan Hongming Huang, Zhizhong. When age-invariant face recognition meets face age synthesis: A multi-task learning framework and a new benchmark. IEEE Transactions on Pattern Analysis and Machine Intelligence, 45:7917–7932, 2023.
[2] - M. M. Sawant, K. M. Bhurchandi.Age Invariant Face Recognition: a Survey on Facial Aging Databases, Techniques and Effect of Aging. Artificial Intelligence Review. 10.1007/s10462-018-9661-z, 2019, 52, 1-28.
[3] - G. Guo and N. Zhang. A survey on deep learning based face recognition. Computer Vision and Image Understanding, 189:102805, 2019
[4] - Y. Wen, Z. Li, and Y. Qiao. Latent factor guided convolutional neural networks for age-invariant face recognition. In IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016. 2, 4, 5, 7
[5] - T. Zheng, W. Deng, and J. Hu. Age Estimation Guided Convolutional Neural Network for Age-Invariant Face Recognition. In IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2017. 2, 7
[6] - Y. Wang, D. Gong, Z. Zhou, X. Ji, H. Wang, Z. Li, W. Liu, and T. Zhang. Orthogonal Deep Features Decomposition for Age- Invariant Face Recognition. In European Conference on Computer Vision (ECCV), 2018. 2, 5, 7, 8
[7] - Zhifeng Li Wei Liu Hao Wang, Dihong Gong. Decorrelated adversarial learning for age-invariant face recognition, 2019.
[8] - Lanitis, A., Taylor, C.J., Cootes, T.F. Toward automatic simulation of aging effects on face images. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2002.
[9] - Papaioannou Athanasios Sagonas Christos Deng Jiankang Kotsia Irene Zafeiriou Stefanos Moschoglou, Stylianos. Agedb: The first manually collected, in-the-wild age database. pages 1997–2005, 2017.
[10] - Tesafaye T. Ricanek, Karl. Morph: A longitudinal image database of normal adult age-progression. pages 341 – 345, 2006.
[11] - Chen Chu-Song Hsu Winston Chen, Bor-Chun. Face recognition and retrieval using cross-age reference coding with crossage celebrity dataset. IEEE Transactions on Multimedia, page 804–815, 2015.
[12] - W. Xie O. M. Parkhi A. Zisserman Q. Cao, L. Shen. Vggface2: A dataset for recognising faces across pose and age. In International Conference on Automatic Face and Gesture Recognition, 2018.
[13] - V. Vanhoucke A. Alemi C. Szegedy, S. Ioffe. Inception-v4, inception- resnet and the impact of residual connections on learning, 2016.
[14] - A. K. Jain U. Park, Y. Tong. Age-invariant face recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), 2010.
[15] - A. K. Jain Z. Li, U. Park. A discriminative model for age invariant face recognition. IEEE transactions on Information Forensics and Security (TIFS), 2011.
[16] - D. Lin J. Liu X. Tang D. Gong, Z. Li. Hidden factor analysis for age invariant face recognition. International Conference on Computer Vision (ICCV), 2013.
[17] - D. Tao J. Liu X. Li. D. Gong, Z. Li. A maximum entropy feature descriptor for age invariant face recognition. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), page 5289–5297, 2015.
[18] - M. Ye C. Xu, Q. Liu. Age invariant face recognition and retrieval by coupled auto-encoder networks. Neurocomputing, 2017.
[19] - J. Zhao, Yu Cheng, Yi Cheng, Y. Yang, H. Lan, F. Zhao, L. Xiong, Y. Xu, J. Li, S. Pranata, S. Shen, J. Xing, H. Liu, S. Yan, J. Feng. Look Across Elapse: Disentangled Representation Learning and Photoreal- istic Cross-Age Face Synthesis for Age-Invariant Face Recognition, 2018.
[20] Ling, H., Soatto, S., Ramanathan, N., & Jacobs, D. (2010). Face Verification Across Age Progression Using Discriminative Methods. IEEE Transactions on Information Forensics and Security, 5, 82-91.

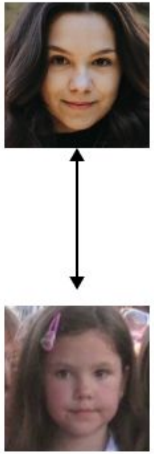
THANK YOU!

Context



Age-Invariant Face **Recognition** **(1:n matching)**

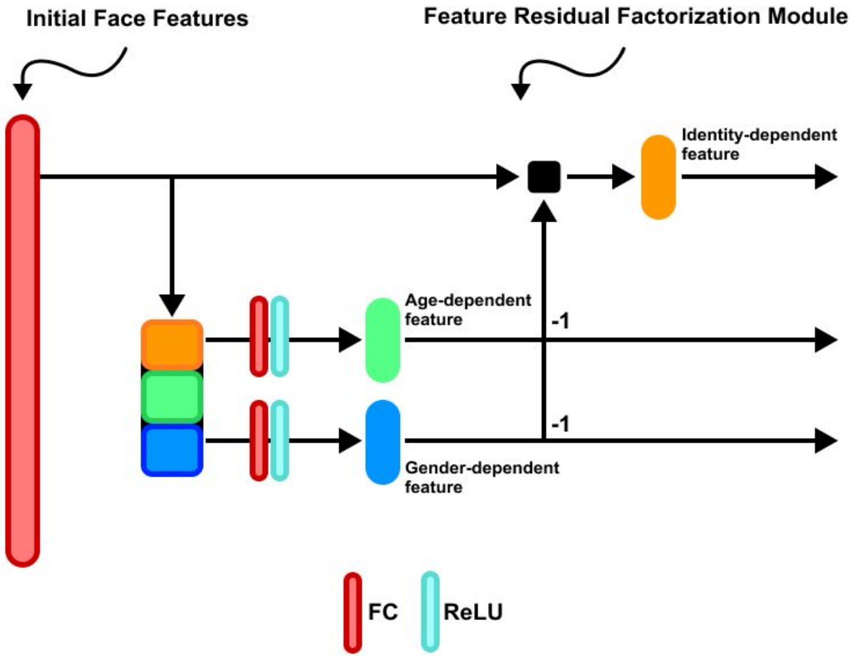
matching a given image of an individual
with other images of the individual at different ages
that are present in a collection with multiple identities



Age-Invariant Face **Verification** **(1:1 matching)**

determine if two or more provided photos
reveal the same or different identities
by calculating the cosine similarity between
the features extracted from the images

Feature Residual Factorization Module (FRFM)



Batch Canonical Correlation Mapping Module (BCCM)

measures the linear relationship between features

each feature set (identity, age, gender) is reduced to one dimension using a linear predictor

predictions are used to calculate means and variances

pairwise correlations are then computed using covariance divided by the product of standard deviations

$$\text{id\_age\_corr} = \frac{(\text{age\_pred} - \text{age\_mean}) * (\text{id\_pred} - \text{id\_mean})}{\sqrt{\text{age\_var} * \text{id\_var}}}$$

$$\text{id\_gender\_corr} = \frac{(\text{gender\_pred} - \text{gender\_mean}) * (\text{id\_pred} - \text{id\_mean})}{\sqrt{\text{gender\_var} * \text{id\_var}}}$$

$$\text{age\_gender\_corr} = \frac{(\text{age\_pred} - \text{age\_mean}) * (\text{gender\_pred} - \text{gender\_mean})}{\sqrt{\text{age\_var} * \text{gender\_var}}}$$

overall correlation coefficient is obtained by averaging these three pairwise correlations

Decorrelated Adversarial Learning (DAL)

strategically manipulate gradients and **optimizing different parameters during training**

- for **40 iterations minimization process**:
    - train only the Backbone and FRFM parameters
    - freeze the BCCM parameters

- for **30 iterations maximization process**:
    - freeze the Backbone and FRFM
    - train only the BCCM parameters and flipping its gradients for adversarial training

training governed by a **multi-task loss function:**

$$TL = L_{CE}(x_{\text{id}}) + \lambda_1 L_{CE}(x_{\text{age}}) + \lambda_2 L_{CE}(x_{\text{gender}}) + \lambda_3 L_{DALR}(\text{id}, x_{\text{age}}, x_{\text{gender}})$$

Objectives

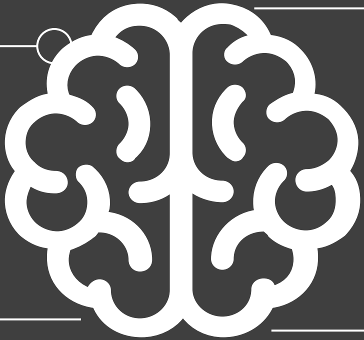
Age-Invariant Face Recognition model available for use

AIFR model

decompose mixed facial features
into three components:
identity, age, and gender

Canonical Correlation Mapping

calculate the **correlation** between
the three components



Decorrelated Adversarial Learning

adversarially maximize and
minimize the **correlation**
between the components
to account for both
inter and intra-subject variances

Multi-Task Learning

age group, gender, and **identity**
classification tasks

03

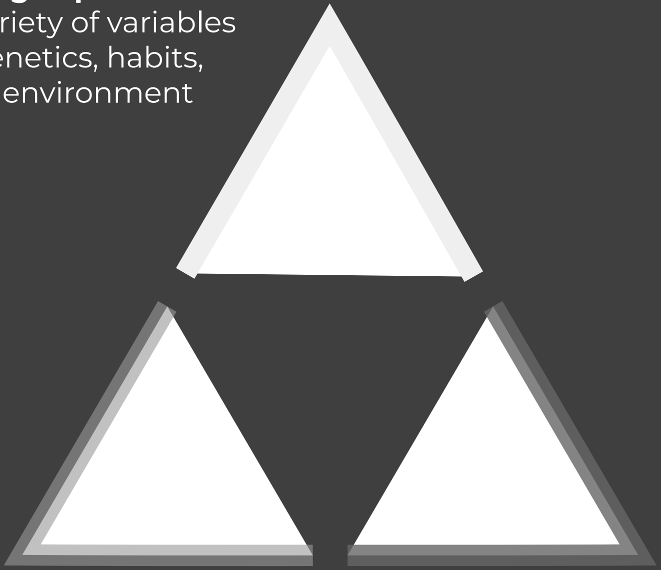
Approach and Difficulties

02

Motivation

Shallow Face Recognition

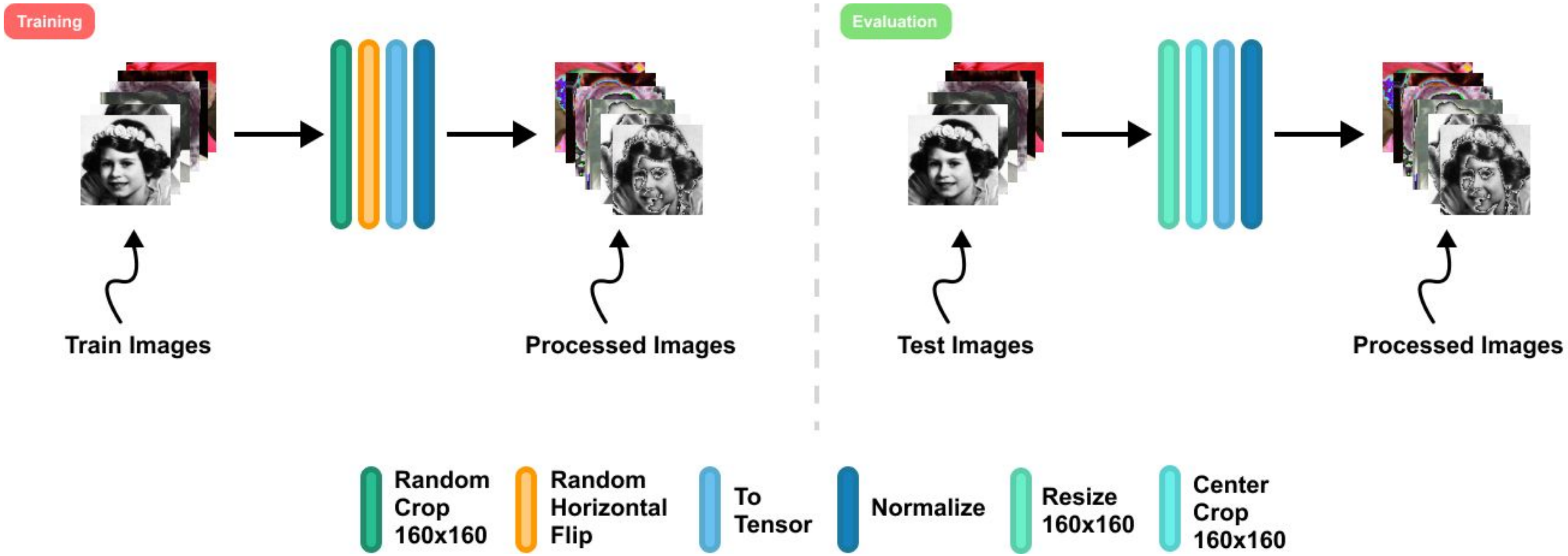
different aging experiences
subject to a variety of variables
including genetics, habits,
health, and environment



large age gaps
between dataset images

illumination, **pose**, **clarity**,
or **facial expressions variations**
in dataset images

Data Preprocessing



Same person?

01

False

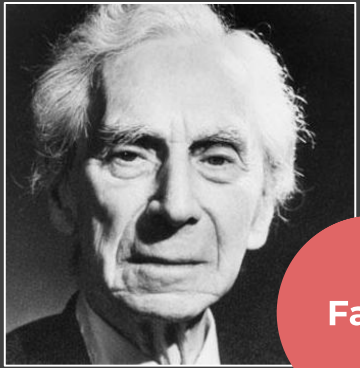
02

True

03

False

04



False

Same person?

01

False

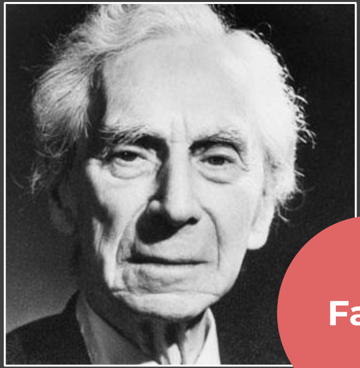
02

True

03

False

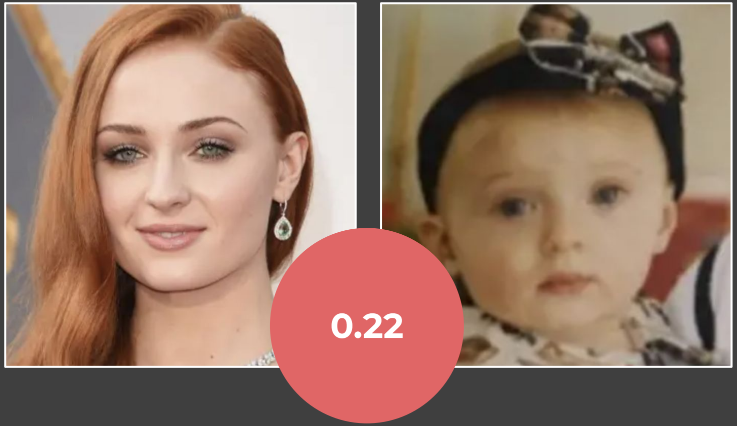
04



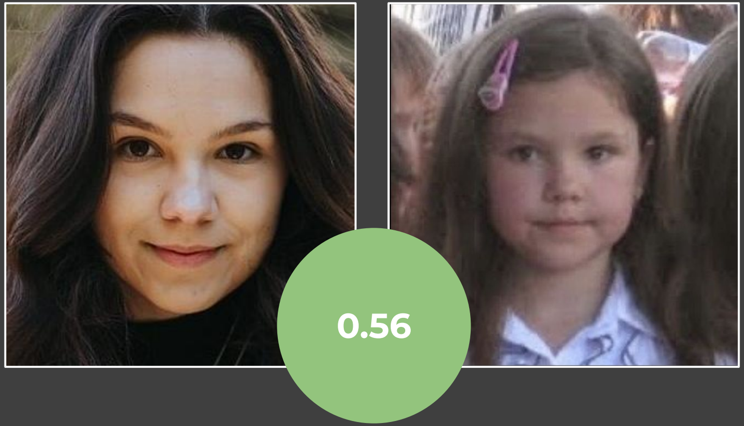
False

Same person?

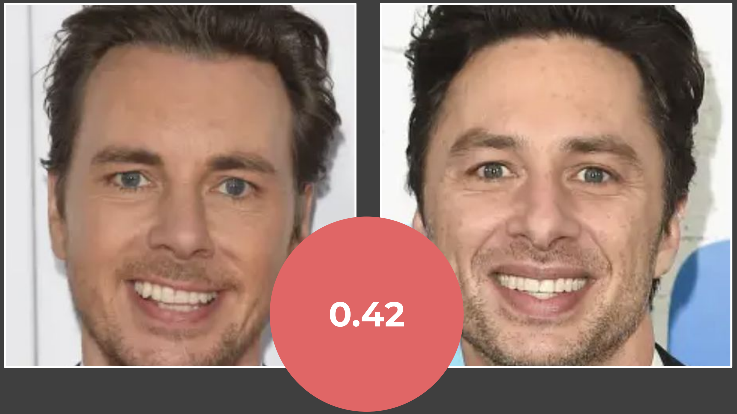
01



02



03



04