Face Recognition In Children: A Longitudinal Study

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Objective and Motivation:

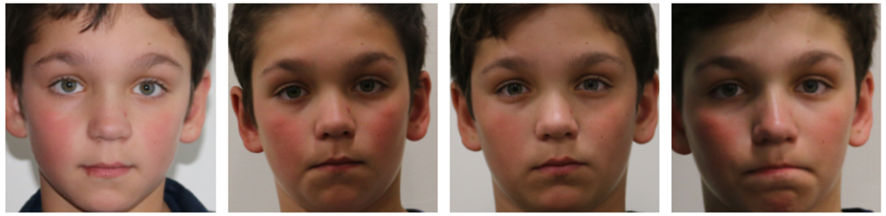
- Currently several longitudinal datasets such as CACD-VS, AgeDB, MORPH-II, and LAG are publicly available to facilitate the development of cross-age **face recognition systems in adults**.

- Aging in children involves **a non-linear cranial growth, i.e changes in the bone structure of the skull that changes the appearance of the face.** As a result, face recognition in children requires special considerations, and models developed on adults may not always be applicable to children.

- The lack of high fidelity and publicly available longitudinal children face datasets is one of the main limiting factors in the evaluation and development of children face recognition.

- In this work we introduce, **Young Face Aging (YFA), longitudinal high-quality dataset for children face recognition and a comprehensive analysis of the biometric performance of the state-of-the-art face recognition models.**

Image Acquisition Process of YFA



(a) (b) (c) (d)

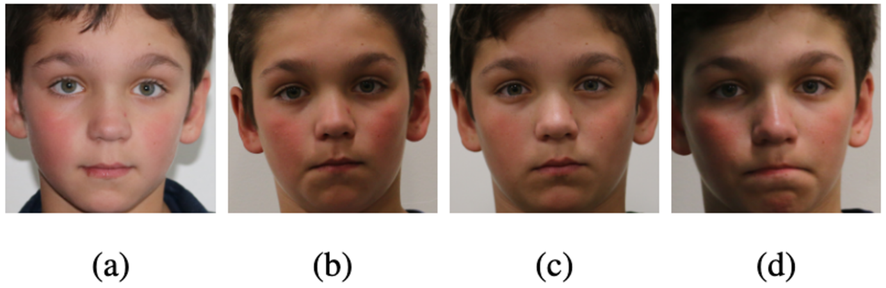
Fig. 1. Age progression of a subject in YFA: a) template b) 12 months, c) 24 months, d) 36 months. **Best viewed in color**

Objective and Motivation:

- Prior work using **In-the-wild and uncontrolled longitudinal datasets** suggest degradation of performance over short-age gap in children [12]–[15].

- Limited prior work using single COTS matcher with **Operational, high quality and controlled dataset** (93.1% TAR at 0.7% FAR using a fixed threshold based on 0.1% FMR in Adults). [18]

- Given the varying degrees of factors such as pose, illumination, expression and **quality** observed in the uncontrolled in-the-wild datasets[12]–[15], **it is difficult to disentangle the effects of aging from other within-identity factors affecting the performance of face matchers.**



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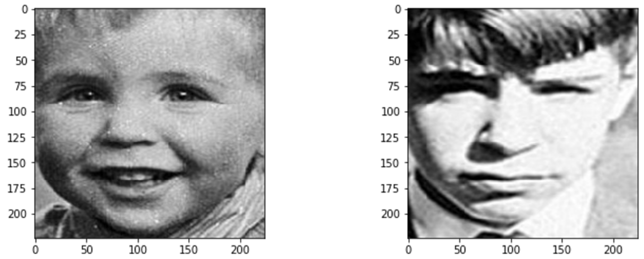


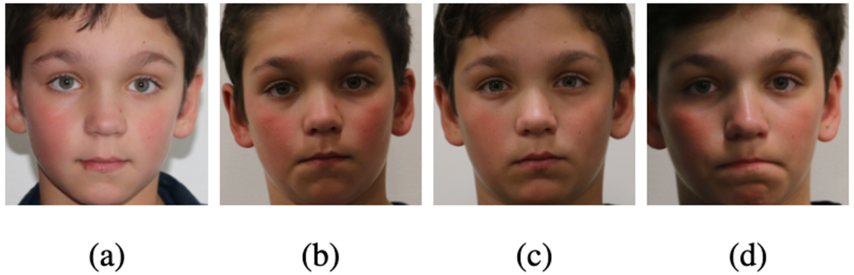
AgeDB: Dr. Stephen Hawking at 3 and 15 years old

Young Face Aging (YFA):

- In this work, we present the **Young Face Aging (YFA) dataset.** YFA samples are captured under consistent indoor lighting, expression, and pose (**controlled environment) from 231 subjects collected at a higher frequency of 6 months over a period of 3 years.**

- We evaluated the verification performance of the following matchers using YFA in conjunction with CACD-VS, AgeDB, MORPH-II, and LAG longitudinal adult datasets.
  - Facenet
  - VGGFace
  - VGGFace2
  - ArcFace
  - ArcFace-Focal
  - MagFace

- Finally, we evaluated the impact of **age-gap, enrolment age, and gender** using Linear Mixed Effect (LME) modeling.



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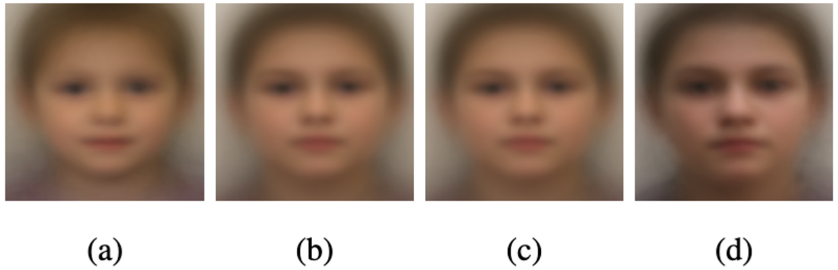
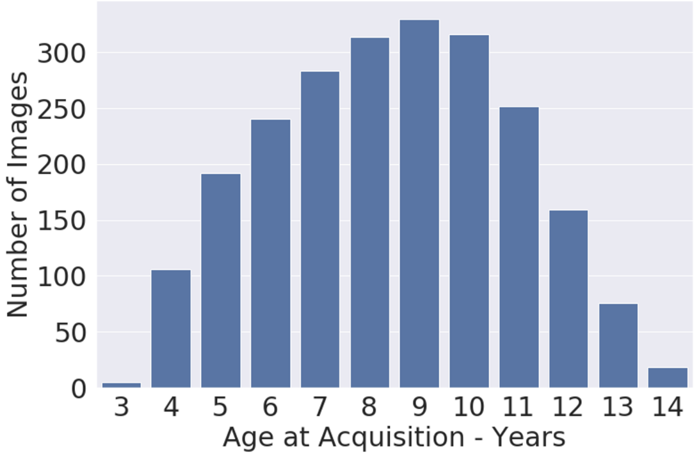


Fig. 2. Age progression in the average of YFA samples: a) Avg. of samples younger than 6 years old b) Avg. of 6 to 8 years old samples , c) Avg. of 9 to 11 years old samples d) Avg. of 12 to 14 years old samples. **Best viewed in color**

Young Face Aging (YFA):

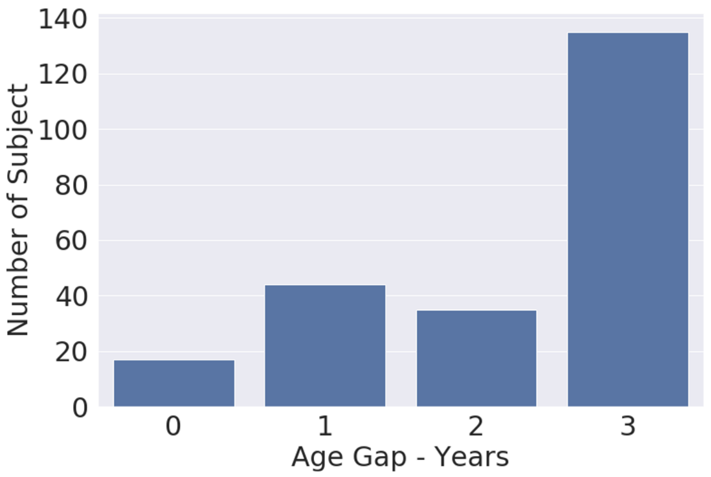
- Young Face Aging (YFA) dataset contains **2293 samples from 231 subjects collected in a controlled environment**
- **Samples are captured from 3-14 years old children with a time-lapse of 6 months over the period of 3 years.**
- Images are captured using a DSLR camera at the resolution of 3648 by 5472 pixels
- **The image acquisition is carried out with consistent indoor lighting, natural expression, and minimal variation in the subject's pose.**

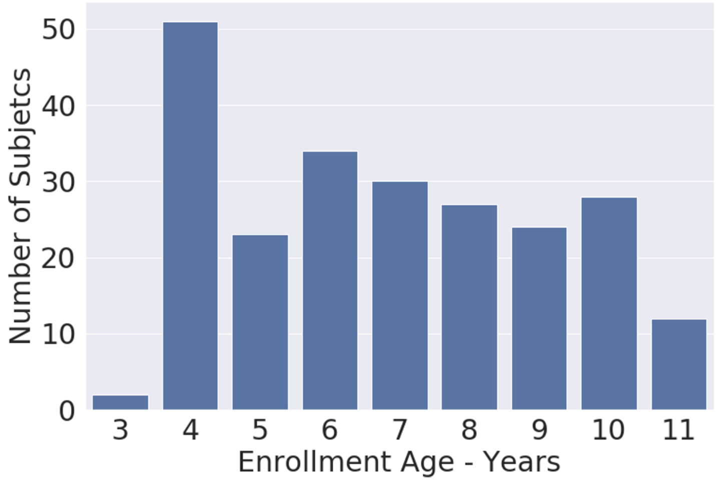
A sample from Young Face Aging (YFA) dataset



Young Face Aging (YFA):

- Each subject is captured at least twice during each session.
- YFA has a **maximum age-gap of 3 years** with 135 out of 231 subjects **(58%) reaching the maximum age gap** in the dataset.
- The Year of birth (or grade if the year is unavailable) for each subject is recorded during the enrolment process and has been used to record the age at subsequent acquisitions. The enrollment age of the subjects are between 3 to 11 years old.
- Most subjects are of **Caucasian background**. **YFA is balanced in terms of gender** (117 Female, 114 Male).
- We utilize the BEAT platform in order to provide the research community with the ability to utilize the YFA while preserving the privacy of the subjects.





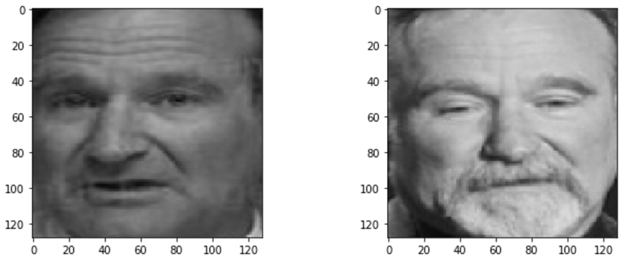
Cross-Age Datasets:

- **CACD-VS:** The Verification Section of the Cross-Age Celebrity Dataset (CACD-VS) contains 2000 mated, 2000 non-mated pairs for 2000 celebrities. **CACD VS is annotated by human annotators to confirm the correct identity.**

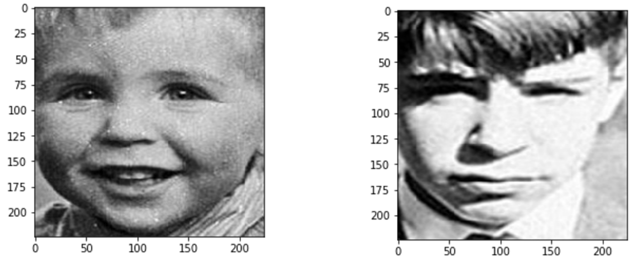
- **MORPH-II:** The academic MORPH dataset is **longitudinal and controlled dataset**. This dataset is used to evaluate the performance of **short age-gap (up to 5 years) in adults**.

- **AgeDB:** AgeDB is in-the-wild cross-age dataset with large maximum age gap of 90 years. **This dataset provides 183 samples from 109 children under 16**.

- **Large Age Gap (LAG)**: This dataset does not provide accurate age labels. However, each subject has at least one sample denoted by authors as **"child/young"** and multiple samples denoted as **adults**.



CACD-VS: Robin Williams at 53 and 61 years old



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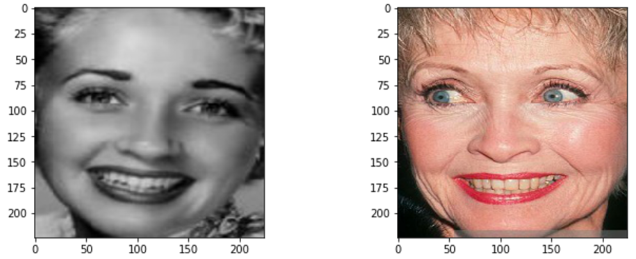

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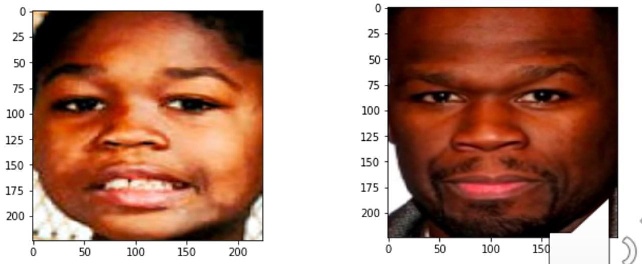

LAG: 50-Cents at Young and Adult

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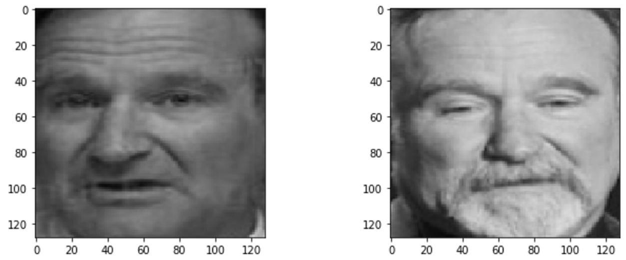

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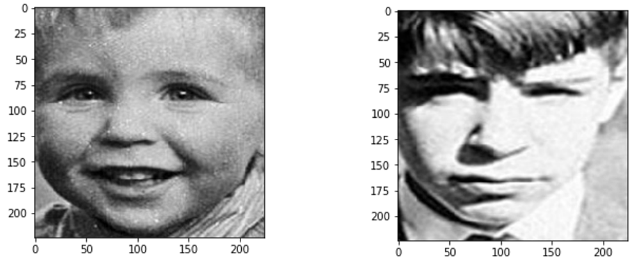

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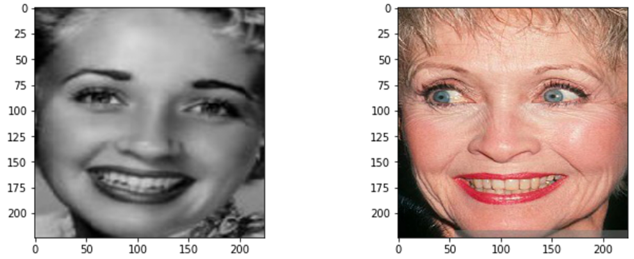

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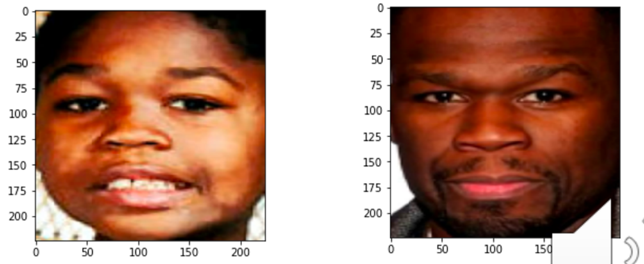

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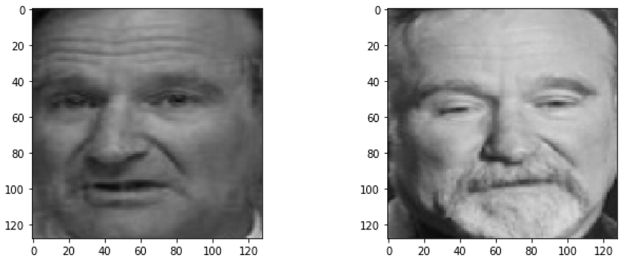

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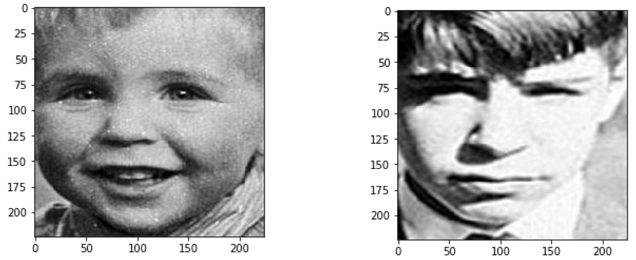

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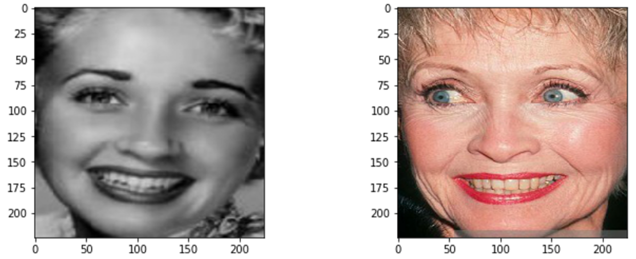

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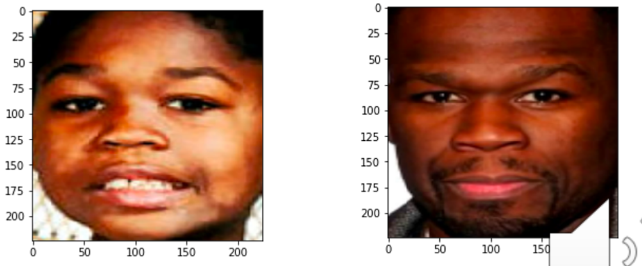

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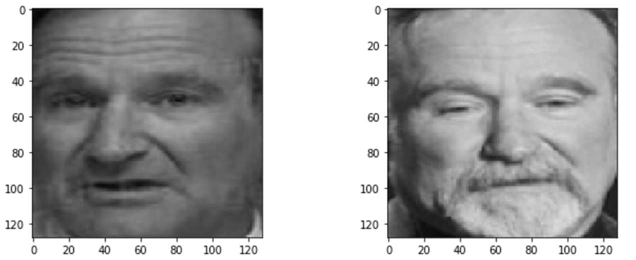

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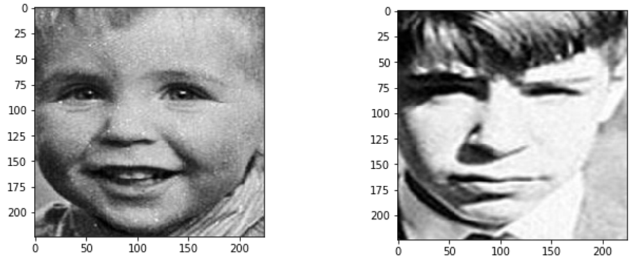

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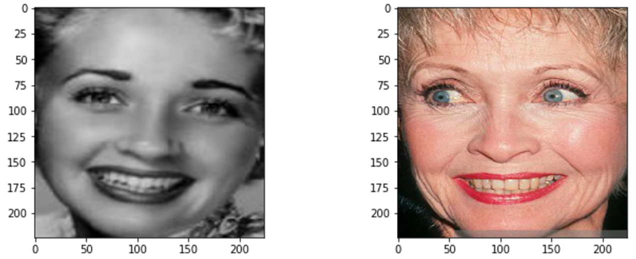

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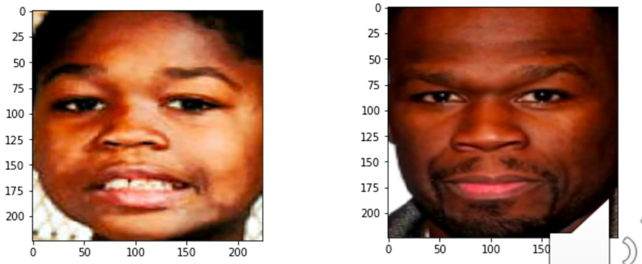

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Cross-Age Datasets:

- Our result indicates a lower performance in the four top performing matchers in YFA (short age-gap, children) with respect to that of Morph-II (short age-gap, adults) confirming the challenging nature of the child face recognition.
- Facenet-V1 achieves **80.1% and 43.4% TAR at 0.01% FPR** at 1 and 3 years age-gap (YFA) vs **67.9% and 34.7% TAR** with 1 and 3 years of age-gap on the **publicly unavailable CLF dataset** [15].
- **Magface only suffers from 3.5% reduction in TAR at 0.01% FAR and achieves 93.3% TAR at 0.01% FAR.**

Face Matchers				Datasets				
Matcher	Training Dataset	Input size	#Features	CACD-VS	MORPH-II	AgeDB	LAG*	**YFA**
Facenet-V1 [16]	MS-Celeb [17]	160 × 160	128	0.944	0.970	0.484	0.105	0.708
Facenet-V2 [16]	VGG-Face2 [23]	160 × 160	512	0.586	0.708	—	—	0.293
VGGFace [22]	LFW [5]	224 × 224	4096	0.396	0.215	—	—	0.312
VGGFace2 [23]	VGG-Face2 [23]	224 × 224	512	0.549	0.526	0.195	0.081	0.331
ArcFace [19]	MS1MV2 [19]	112 × 112	512	0.770	0.968	0.379	0.231	0.772
ArcFace-Focal [20]	MS1MV2 [19]	112 × 112	512	**0.964**	**0.989**	**0.681**	**0.297**	0.854
MagFace [21]	MS1MV2 [19]	112 × 112	512	0.832	0.968	0.402	0.242	**0.933**

TABLE II

FACE MATCHER DESCRIPTION INCLUDING TRAINING DATASET, INPUT SIZE, AND # FEATURES (LEFT FOUR COLUMNS). VERIFICATION PERFORMANCE (TAR AT 0.01% FAR) (RIGHT FIVE COLUMNS). "—" INDICATES THAT THE MATCHER DID NOT ACHIEVE 0.01% FAR. "*" THE VERIFICATION OF PERFORMANCE FOR THE LAG DATASET IS CALCULATED USING ONLY YOUNG TO ADULT GENUINE COMPARISONS.

Young Face Aging (YFA):

- Our result confirms the previously identified downward trend in the TAR of Facenet-V1 matcher [15].
- We observed a noticeable degradation in the **TAR even at age-gap of 6 months** for Facenet-V1, ArcFace and ArcFace-Focal.
- **Contrary to previous work, we observe that this reduction is not substantial in MagFace.**

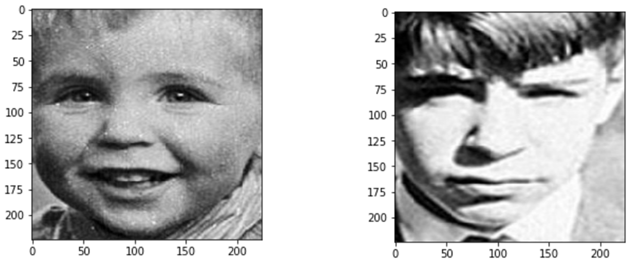
Model	FAR	Threshold	ΔT = 6M	ΔT = 12M	ΔT = 18M	ΔT = 24M	ΔT = 30M	ΔT = 36M
Facenet-V1	0.1%	0.630	95.8	94.8	92.5	84.3	82.7	76.0
Facenet-V1	0.01%	0.826	85.6	80.1	74.5	64.8	57.0	43.4
ArcFace	0.1%	0.474	87.6	88.1	85.3	84.8	86.3	81.1
ArcFace	0.01%	0.556	81.0	78.8	78.1	74.8	75.6	69.9
ArcFace-Focal	0.1%	0.532	97.6	98.3	95.4	92.7	93.1	91.6
ArcFace-Focal	0.01%	0.630	92.8	91.5	87.9	79.5	78.5	72.8
MagFace	0.1%	0.453	**98.2**	**98.3**	**98.0**	**97.2**	**97.3**	**94.9**
MagFace	0.01%	0.549	**96.9**	**95.2**	**93.2**	**91.6**	**92.9**	**84.7**

TABLE III

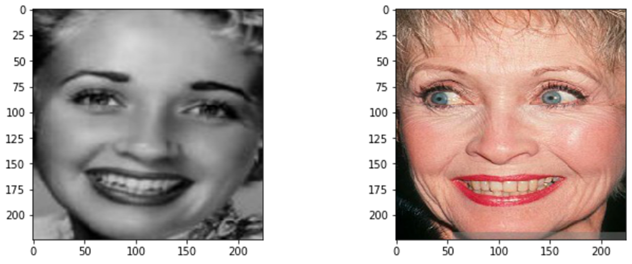
VERIFICATION PERFORMANCE (TAR AT 0.01% AND 0.1% FAR) OF FACENET-V1, ARCFACE, ARCFACE-FOCAL, AND MAGFACE MODELS FOR INCREASING AGE-GAP (6-36 MONTHS) BETWEEN ENROLLMENT AND QUERY SAMPLES IN YFA DATASET.

Linear Mixed Effect (LME) modeling:

- We utilized LME models to investigate the influence of factors affecting the Match Score (MS) of FR systems in children.
- We define two mutually exclusive subsets (**Young and Adult**) to independently analyze younger and older cohorts of AgeDB.
- Our **Young section** includes mated pairs with enrolment age **younger than 15 years old and query images up to 20 years old.**



Young - AgeDB: Dr. Stephen Hawking at 3 and 15 years old



Adult - AgeDB: Jane powell at 23 and 64 years old

Linear Mixed Effect (LME) modeling:

- We extend the previous work by investigating the significant and matcher independent factors affecting the MS.

- We present our model to predict the MS of the children FR systems. Where,

$$1.\quad MS \sim \beta_0 + \beta_1 \Delta T + \beta_2 EA + \beta_3 G + b_{0i} + b_{1i}\Delta T + b_{2i} G$$

  - $\beta_0 + b_{0i}$ is the sum of fixed and subject specific random intercept corresponding to the initial state.
  - $\beta_k + b_{ki}$ is the sum of fixed and subject specific random intercept corresponding parameter, k.
  - ΔT denotes the age-gap between enrollment and query samples in years.
  - EA denotes Enrolment Age (Years).
  - G denotes the gender of the subject, encoded as 0 for Male and 1 for Female subjects. G is considered for both fixed and random effect.

Linear Mixed Effect (LME) modeling:

- **Effect of Age-Gap**:
  - We reject the null hypothesis with p < 0.001 across the evaluated matchers, **confirming a significant decaying relationship between age-gap and MS in both adults and children.**
  - We observe **a much higher estimated decrease in the MS, due to age-gap in Children vs Adults.**

Variable	Parameter	MagFace $(Est \pm SE)$	ArcFace-Focal $(Est \pm SE)$	Facenet-V1 $(Est \pm SE)$
Morph-II				
Intercept	β_0	$0.700 \pm 0.002^{***}$	$0.796 \pm 0.002^{***}$	$0.862 \pm 0.001^{***}$
ΔT	β_1	$-0.11 \pm 0.000^{***}$	$-0.010 \pm 0.000^{***}$	$-0.008 \pm 0.000^{***}$
EA	β_2	$0.000 \pm 0.000^{***}$	$0.000 \pm 0.000 NS$	$-0.000 \pm -0.000*$
G	β_3	$-0.010 \pm 0.002^{***}$	$-0.038 \pm 0.002^{***}$	$-0.025 \pm 0.002^{***}$
AgeDB - Adults				
Intercept	β_0	$0.374 \pm 0.004^{***}$	$0.512 \pm 0.006^{***}$	$0.649 \pm 0.002^{***}$
ΔT	β_1	$-0.004 \pm 0.000^{***}$	$-0.004 \pm 0.000^{***}$	$-0.005 \pm 0.001^{***}$
EA	β_2	$0.001 \pm 0.000^{***}$	$0.001 \pm 0.000^{***}$	$0.001 \pm 0.000^{***}$
G	β_3	$-0.007 \pm 0.004 NS$	$-0.005 \pm 0.003 NS$	$-0.004 \pm 0.007 NS$
AgeDB - Young				
Intercept	β_0	$0.439 \pm 0.045^{***}$	$0.412 \pm 0.053^{***}$	$0.698 \pm 0.042^{***}$
ΔT	β_1	$-0.022 \pm 0.004^{***}$	$-0.024 \pm 0.005^{***}$	$-0.026 \pm 0.004^{***}$
EA	β_2	$-0.000 \pm 0.002 NS$	$0.008 \pm 0.002^{**}$	$0.001 \pm 0.002 NS$
G	β_3	$-0.055 \pm 0.029 NS$	$-0.077 \pm 0.037^{*}$	$-0.075 \pm 0.031^{*}$
Young Face Aging (YFA)				
Intercept	β_0	$0.745 \pm 0.018^{***}$	$0.757 \pm 0.018^{***}$	$0.897 \pm 0.012^{***}$
ΔT	β_1	$-0.033 \pm 0.003^{***}$	$-0.042 \pm 0.003^{***}$	$-0.028 \pm 0.002^{***}$
EA	β_2	$0.000 \pm 0.002 NS$	$0.006 \pm 0.002^{**}$	$-0.001 \pm 0.000 NS$
G	β_3	$0.003 \pm 0.010 NS$	$-0.010 \pm 0.011 NS$	$-0.002 \pm 0.007 NS$

TABLE IV

FIXED EFFECTS OF THE FACENET-V1, ARCFACE-FOCAL, AND MAGFACE MODELS EVALUATED ON THE MORPH-II, AGE-DB, AND YFA DATASETS. SIGNIFICANCE CODE: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 ; *** INDICATES P-VALUE BETWEEN 0 AND 0.001 WITH SIGNIFICANCE LEVEL 0.001 AND SO ON. EST.: ESTIMATE, SE: STANDARD ERROR, NS: NOT SIGNIFICANT

Linear Mixed Effect (LME) modeling:

- **Effect of Enrolment Age:**
  - We can not observe a consistent and matcher independent pattern across the estimated effects of enrolment age (β2) on the match scores of either adults or children

Variable	Parameter	MagFace $(Est \pm SE)$	ArcFace-Focal $(Est \pm SE)$	Facenet-V1 $(Est \pm SE)$
Morph-II				
Intercept	β_0	$0.700 \pm 0.002^{***}$	$0.796 \pm 0.002^{***}$	$0.862 \pm 0.001^{***}$
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G	β_3	$-0.010 \pm 0.002^{***}$	$-0.038 \pm 0.002^{***}$	$-0.025 \pm 0.002^{***}$
AgeDB - Adults				
Intercept	β_0	$0.374 \pm 0.004^{***}$	$0.512 \pm 0.006^{***}$	$0.649 \pm 0.002^{***}$
ΔT	β_1	$-0.004 \pm 0.000^{***}$	$-0.004 \pm 0.000^{***}$	$-0.005 \pm 0.001^{***}$
EA	β_2	$0.001 \pm 0.000^{***}$	$0.001 \pm 0.000^{***}$	$0.001 \pm 0.000^{***}$
G	β_3	$-0.007 \pm 0.004 NS$	$-0.005 \pm 0.003 NS$	$-0.004 \pm 0.007 NS$
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G	β_3	$-0.055 \pm 0.029 NS$	$-0.077 \pm 0.037^{*}$	$-0.075 \pm 0.031^{*}$
Young Face Aging (YFA)				
Intercept	β_0	$0.745 \pm 0.018^{***}$	$0.757 \pm 0.018^{***}$	$0.897 \pm 0.012^{***}$
ΔT	β_1	$-0.033 \pm 0.003^{***}$	$-0.042 \pm 0.003^{***}$	$-0.028 \pm 0.002^{***}$
EA	β_2	$0.000 \pm 0.002 NS$	$0.006 \pm 0.002^{**}$	$-0.001 \pm 0.000 NS$
G	β_3	$0.003 \pm 0.010 NS$	$-0.010 \pm 0.011 NS$	$-0.002 \pm 0.007 NS$

TABLE IV
FIXED EFFECTS OF THE FACENET-V1, ARCFACE-FOCAL, AND MAGFACE MODELS EVALUATED ON THE MORPH-II, AGE-DB, AND YFA DATASETS. SIGNIFICANCE CODE: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 ; *** INDICATES P-VALUE BETWEEN 0 AND 0.001 WITH SIGNIFICANCE LEVEL 0.001 AND SO ON. EST.: ESTIMATE, SE: STANDARD ERROR, NS: NOT SIGNIFICANT

Linear Mixed Effect (LME) modeling:

- **Effect of Gender:**
  - We reject the null hypothesis with $p < 0.001$ across all matchers in the Morph-II dataset (short age-gap, adult), suggesting a significant decaying relationship between gender and MS only in this dataset.
  - Our analysis confirms the findings of [15], as as we do not observe a significant relationship between gender and MS either in AgeDB or YFA.

Variable	Parameter	MagFace ($Est \pm SE$)	ArcFace-Focal ($Est \pm SE$)	Facenet-V1 ($Est \pm SE$)
Morph-II				
Intercept	β_0	$0.700 \pm 0.002^{***}$	$0.796 \pm 0.002^{***}$	$0.862 \pm 0.001^{***}$
ΔT	β_1	$-0.11 \pm 0.000^{***}$	$-0.010 \pm 0.000^{***}$	$-0.008 \pm 0.000^{***}$
EA	β_2	$0.000 \pm 0.000^{***}$	$0.000 \pm 0.000 NS$	$-0.000 \pm -0.000*$
G	β_3	$-0.010 \pm 0.002^{***}$	$-0.038 \pm 0.002^{***}$	$-0.025 \pm 0.002^{***}$
AgeDB - Adults				
Intercept	β_0	$0.374 \pm 0.004^{***}$	$0.512 \pm 0.006^{***}$	$0.649 \pm 0.002^{***}$
ΔT	β_1	$-0.004 \pm 0.000^{***}$	$-0.004 \pm 0.000^{***}$	$-0.005 \pm 0.001^{***}$
EA	β_2	$0.001 \pm 0.000^{***}$	$0.001 \pm 0.000^{***}$	$0.001 \pm 0.000^{***}$
G	β_3	$-0.007 \pm 0.004 NS$	$-0.005 \pm 0.003 NS$	$-0.004 \pm 0.007 NS$
AgeDB - Young				
Intercept	β_0	$0.439 \pm 0.045^{***}$	$0.412 \pm 0.053^{***}$	$0.698 \pm 0.042^{***}$
ΔT	β_1	$-0.022 \pm 0.004^{***}$	$-0.024 \pm 0.005^{***}$	$-0.026 \pm 0.004^{***}$
EA	β_2	$-0.000 \pm 0.002 NS$	$0.008 \pm 0.002^{**}$	$0.001 \pm 0.002 NS$
G	β_3	$-0.055 \pm 0.029 NS$	$-0.077 \pm 0.037^{*}$	$-0.075 \pm 0.031^{*}$
Young Face Aging (YFA)				
Intercept	β_0	$0.745 \pm 0.018^{***}$	$0.757 \pm 0.018^{***}$	$0.897 \pm 0.012^{***}$
ΔT	β_1	$-0.033 \pm 0.003^{***}$	$-0.042 \pm 0.003^{***}$	$-0.028 \pm 0.002^{***}$
EA	β_2	$0.000 \pm 0.002 NS$	$0.006 \pm 0.002^{**}$	$-0.001 \pm 0.000 NS$
G	β_3	$0.003 \pm 0.010 NS$	$-0.010 \pm 0.011 NS$	$-0.002 \pm 0.007 NS$

TABLE IV

FIXED EFFECTS OF THE FACENET-V1, ARCFACE-FOCAL, AND MAGFACE MODELS EVALUATED ON THE MORPH-II, AGE-DB, AND YFA DATASETS. SIGNIFICANCE CODE: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 ; *** INDICATES P-VALUE BETWEEN 0 AND 0.001 WITH SIGNIFICANCE LEVEL 0.001 AND SO ON. EST.: ESTIMATE, SE: STANDARD ERROR, NS: NOT SIGNIFICANT

Conclusion and Future work:

- **Our analysis confirms statistically significant and matcher independent decaying relationship between the match scores of the MagFace, ArcFace-Focal and Facenet-V1 matchers and the age-gap in children.**

- **Contrary to previous work using uncontrolled datasets, our verification performance analysis (Table-II) indicates that a combination of high-quality samples and state-of-the-art quality-aware deep face matchers could be a viable solution for children face recognition with age-gaps of up to 3 years.**

- **Future work can further investigate the within-identity structure of these matchers for linear and non-linear feature projection methods to possibly even further increase the performance.**

Questions?:

The Match Scores and LME analysis will be available at:

https://github.com/keivanB/Young_Face_Aging_YFA