Deep Convolutional Network Based Age-Invariant Face Recognition(AIFR)

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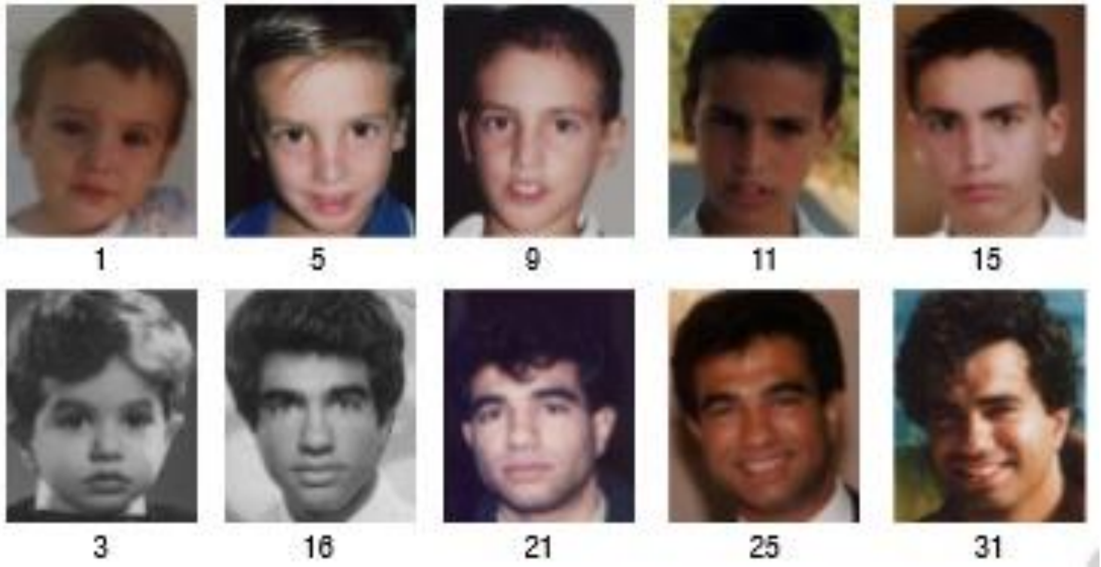
Problem Statement

Recognizing faces across ages



(a) Images from FGNET Dataset

(b) Images from CACD Dataset

Applications

- Biometrics
- Forensics, Surveillance and criminal investigations
- Finding Missing Children after years
- Verifying Passports
- Healthcare Industry

Face recognition(FR)

- Identifying or verifying the identity of an individual using their face.
- FR is of two types

  (i) Face Identification: is a classification problem that basically classifies a face image to class of face identities.

  (ii) Face Verification: is determining whether given two face images belong to the same identity or not.

Challenges

POSE

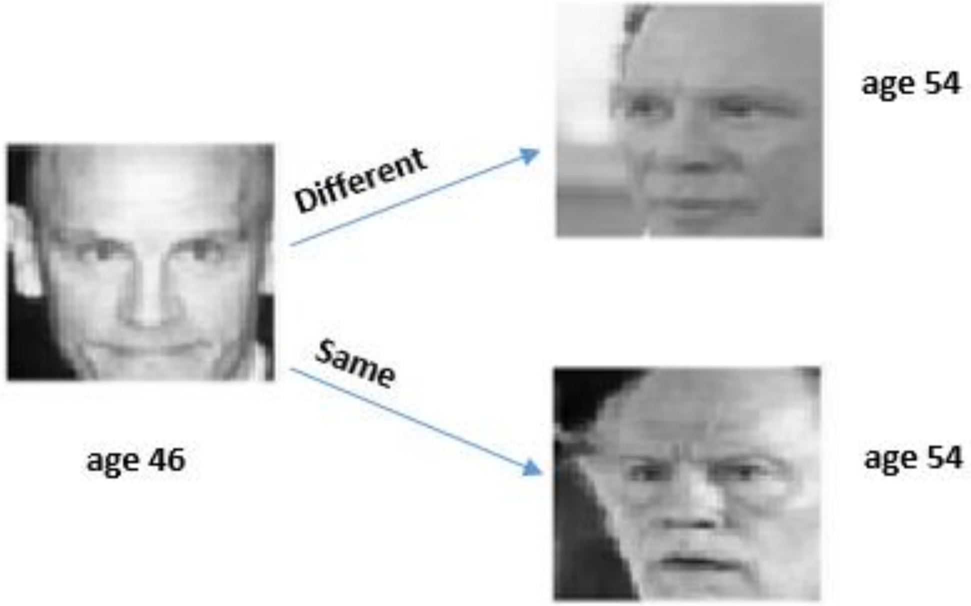
IMAGE QUALITY

LIGHTING

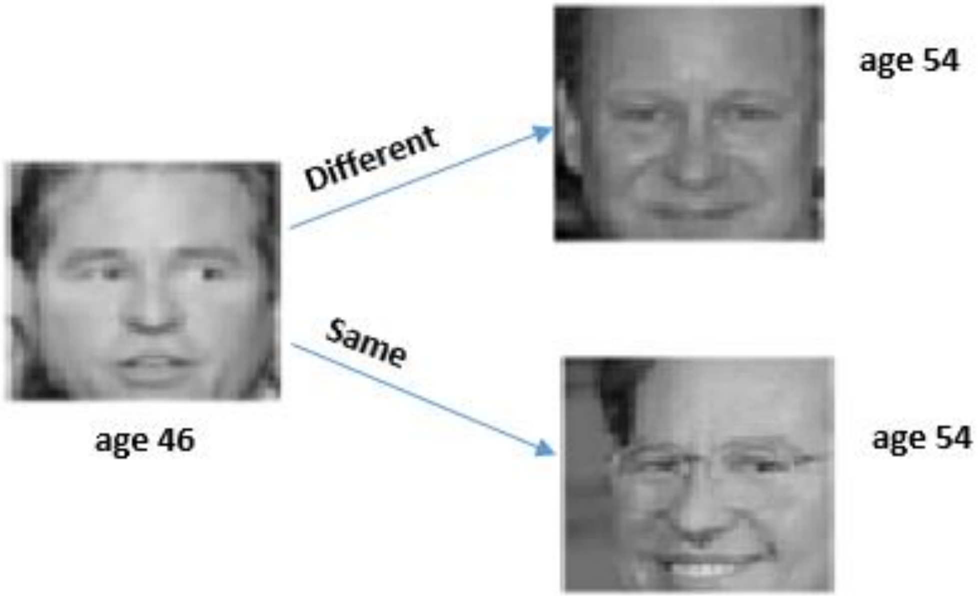
PARTIAL OCCLUSION

Contd..

- More Intra-class variation than Inter-class variation



(a)



(b)

3. Evolution

AIFR methods over the years…

GENERATIVE APPROACH → **DISCRIMINATIVE APPROACH** → **DEEP LEARNING APPROACH**

2010-2012

2010-2016

2017 onwards

Objectives

- Study of Deep Learning(DL) based methods for AIFR.

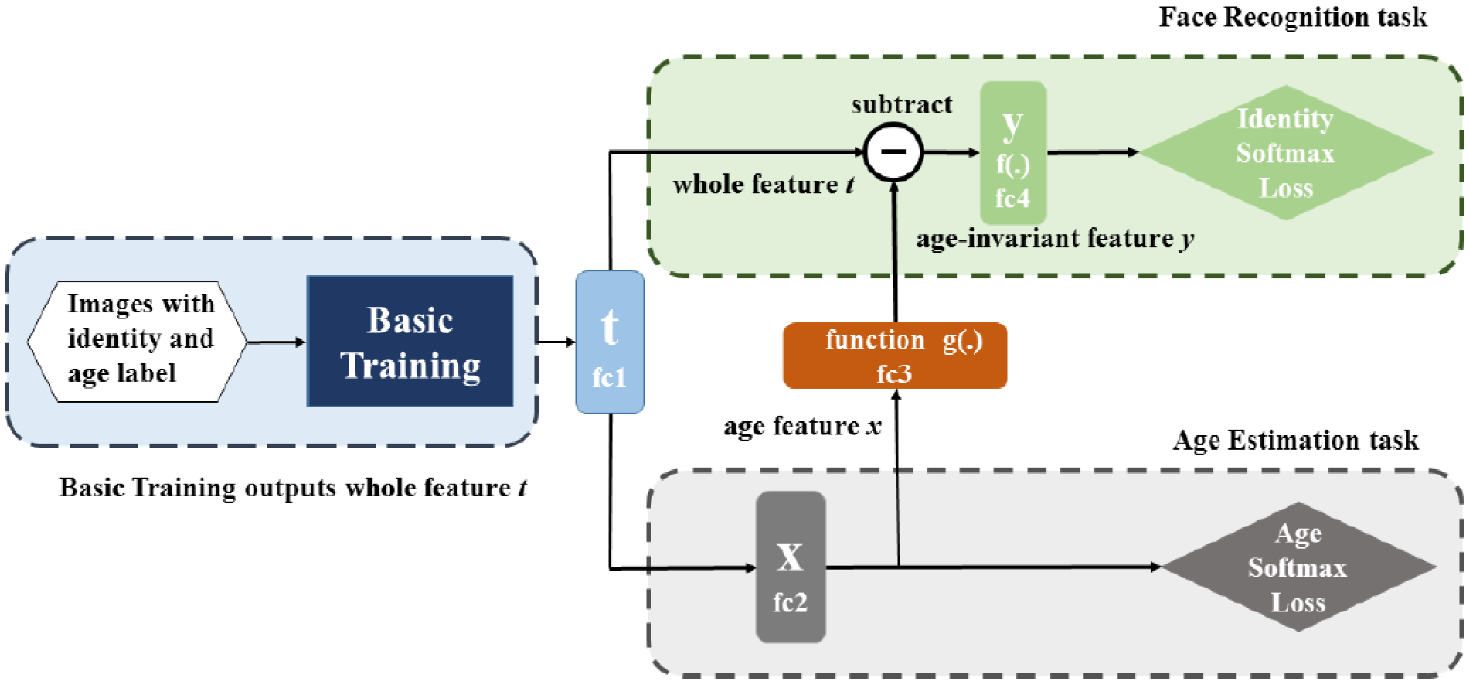
- To add value to this domain by contributing a new method for the AIFR.

Literature survey

1. **Age Estimation Guided Convolutional Neural Network for Age-Invariant Face Recognition,** *CVPR , Tianyue Zheng, Weihong Deng, Jiani Hu , 2017*
2. **Face Recognition with Contrastive Convolution,** *ECCV, Chunrui Han, Shiguang Shan, 2018*
3. **A Light CNN for Deep Face Representation with Noisy Labels,** *IEEE Transactions , Xiang Wu, Ran He, Zhenan Sun, Tieniu Tan,2017*
4. **Squeeze and Excitation Networks, Jie Hu, Li Shen, Samuel Albanie,** *CVPR, 2018*
5. **Cross-Age Reference Coding for Age-Invariant Face Recognition and Retrieval,** *IEEE Transactions, Bor-Chun Chen1, Chu-Song Chen1, Winston H. Hsu,2015*
6. **MORPH: A Longitudinal Image Database of Normal Adult Age-Progression,** *IEEE Transactions, Karl Ricanek Jr, Tamirat Tesafaye, 2006*
7. **Learning Face Representation from Scratch,** *Computing Research Repository(CoRR) Dong Yi, Zhen Lei, 2014*

Method 1

- Age Estimation guided convolution neural network (AE-CNN)



Age Estimation Guided Convolutional Neural Network for Age-Invariant Face Recognition, *CVPR , Tianyue Zheng, Weihong Deng, Jiani Hu , 2017*

Idea of the paper

- A new method to obtain age–invariant feature by subtracting age factor obtained by age estimation from the whole features which contain both identity and age features.

Datasets used

Datasets Info:	CACD (Cross-Age Celebrity Dataset)	MORPH Album2
No of Images	163,446	55,000
No of identity	2,000	13,000
Birth year	Yes	Yes
Rank of the celebrity	Yes	No
Age info	Yes	Yes
Range of age	16-62	16-77
Year when photo taken	Yes	No
Race/Gender	No	Yes
Illumination , poses	Yes	Yes

Results

Dataset – MORPH	No of identities	No of images	Recognition rate % Ours	Recognition rate % Authors
Training Set	10000	43102	--	--
Validation Set	2000	8100	93	--
Test Set	1000	4002	91	98

Dataset- CACD	No of identities	No of images	Mean average precision (MAP) Ours	Mean average precision (MAP) Authors
Training Set	1512	139118	--	--
Test Set (Query)	71	1211	--	--
Test Set (Gallery 1)	120	2377	0.91	0.70
Test Set (Gallery 2)	143	2715	0.92	0.75
Test Set (Gallery 3)	154	3444	0.93	0.78

Method 2

- AIFR with Contrastive Convolution

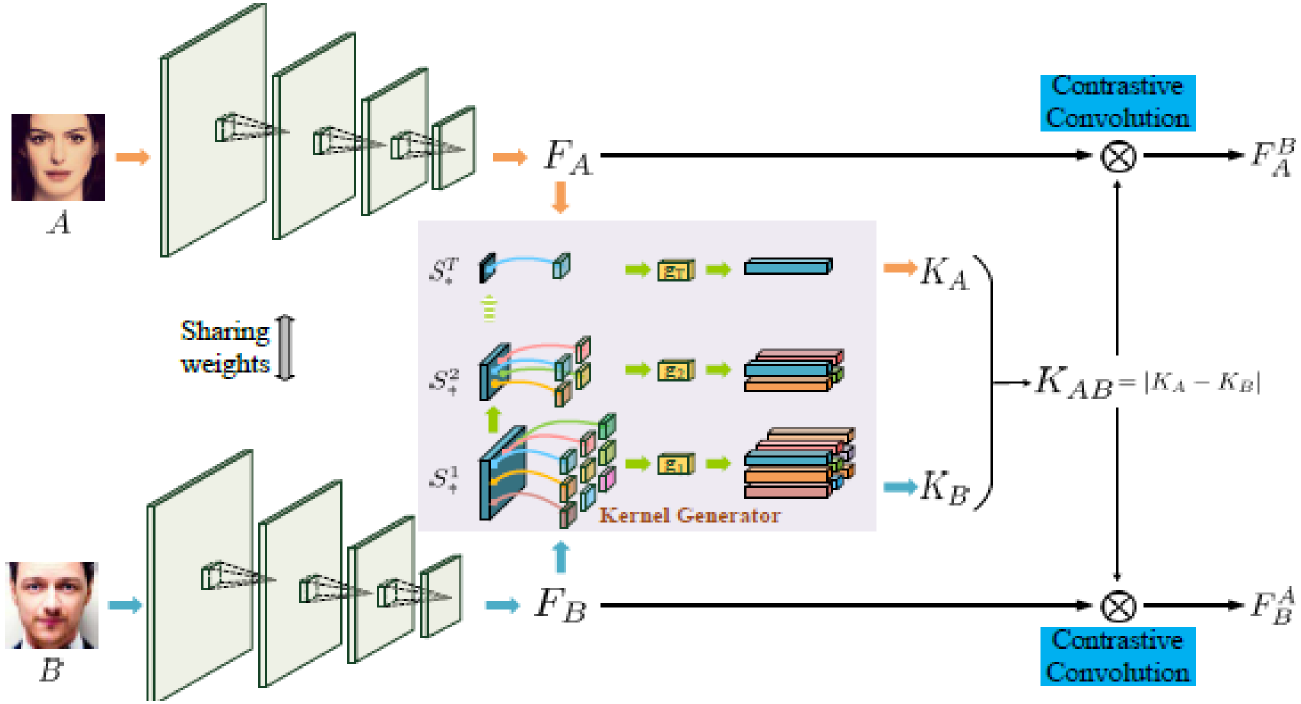
A vs. B_1

A vs. B_2

Face Recognition with Contrastive Convolution, *ECCV, Chunrui Han, Shiguang Shan, 2018*

Architecture

- The pipeline of Contrastive Convolutional Neural Network(CNN)



Face Recognition with Contrastive Convolution, *ECCV, Chunrui Han, Shiguang Shan, 2018*

Contrastive CNN

- Similarity between A and B is as follows:

$$S_{AB} = \frac{1}{2}(S_A^B + S_B^A)$$

where $S_A^B = \sigma(F_A^B \cdot W)$ and $S_B^A = \sigma(F_B^A \cdot W)$

- Objective function: $\min_{C,G,W,H} L_1 + \alpha L_2$

where $\min_{C,G,W} L_1 = -\frac{1}{N}\sum_{A,B}[L_{AB}\log(S_{AB}) + (1 - L_{AB})\log(1 - S_{AB})]$

and

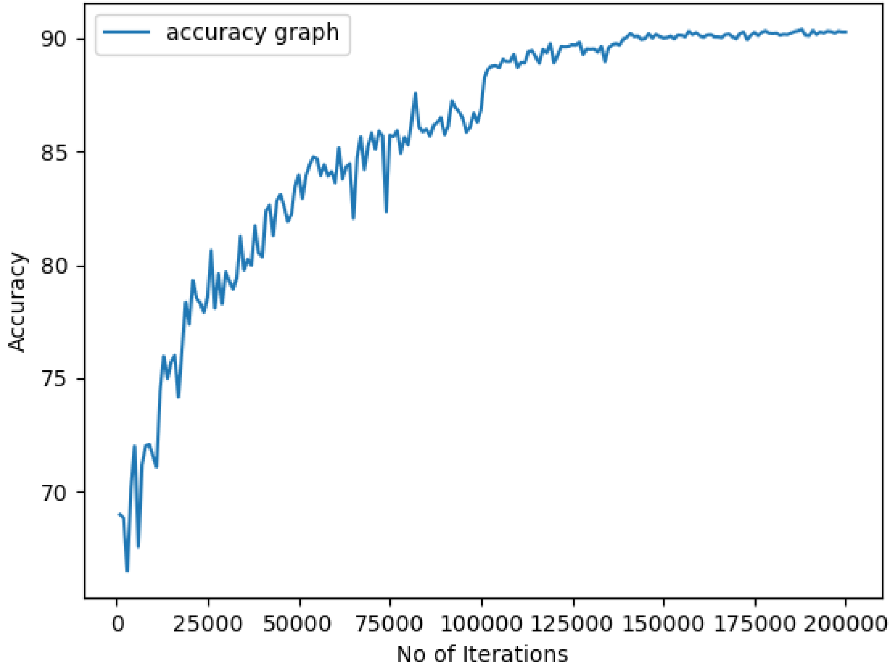
$$L_2 = -\frac{1}{2N}\left[\sum_A l_A \log(H(K_A)) + \sum_B l_B \log(H(K_B))\right]$$

Datasets used

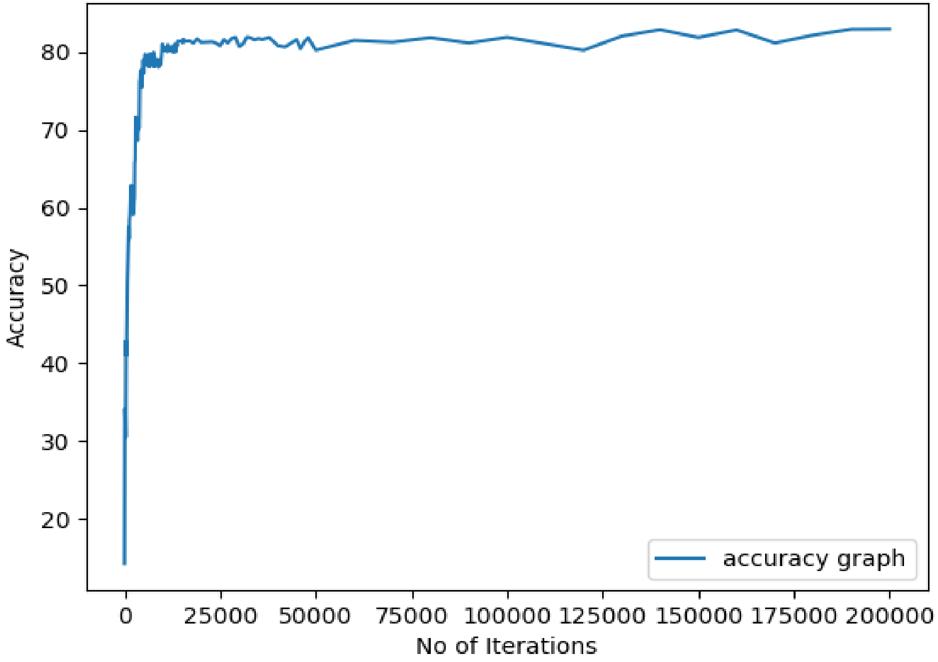
Datasets Info:	VGG2	CASIA	LFW
No of Images	3.31 million	500,000	13,233
No of identity	9,131	10,575	5,749
Age info	No	No	No
Illumination , poses	Yes	Yes	Yes

Training with CASIA

- Face Recognition with LFW and CACD-VS



(a)



(b)

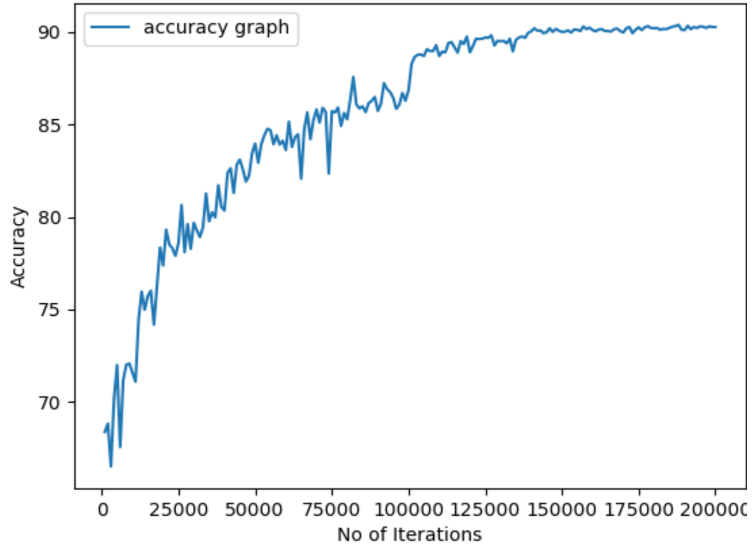
Recognition Rate (in %) for (a) LFW and (b) CACD-VS Dataset

Comparison

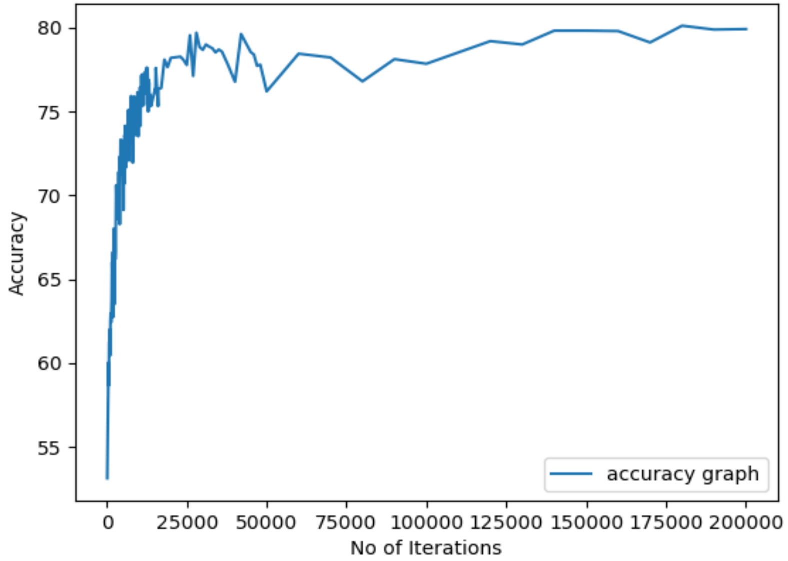
Architecture	mAcc on LFW(%) Result (authors)	mAcc on LFW(%) Result (Ours)
Contrastive CNN 4	98.20	93.12

Training with VGG2

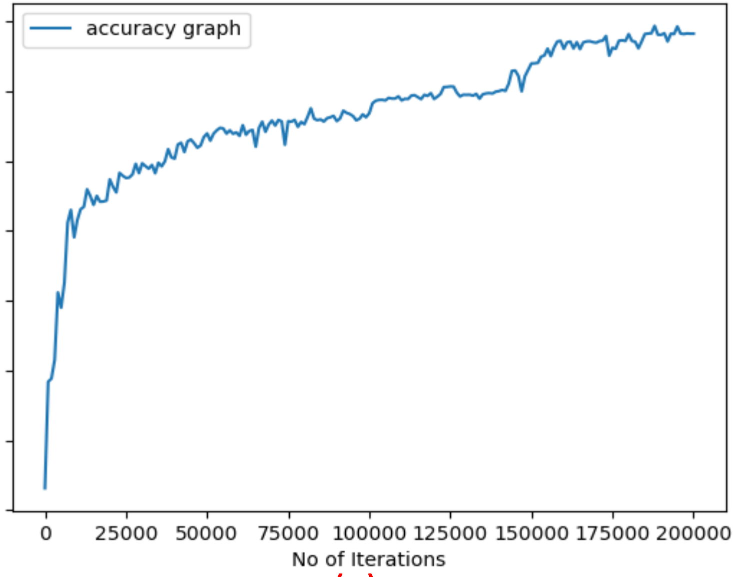
- Face Recognition with LFW, CACD-VS AND MORPH



(a)



(b)



(c)

Recognition Rate (in %) for (a) LFW, (b) CACD-VS and (c) MORPH Dataset

OUR CONTRIBUTIONS

Cleaning of CACD Dataset

- CACD Dataset contains wrong labelled and duplicate images

(a)

(b)

No of Duplicate images	No of wrong labelled images
Around 5,000 images	Around 8,000 images

(a) Figure showing images with wrong labels and (b) Figures showing images with duplicate images

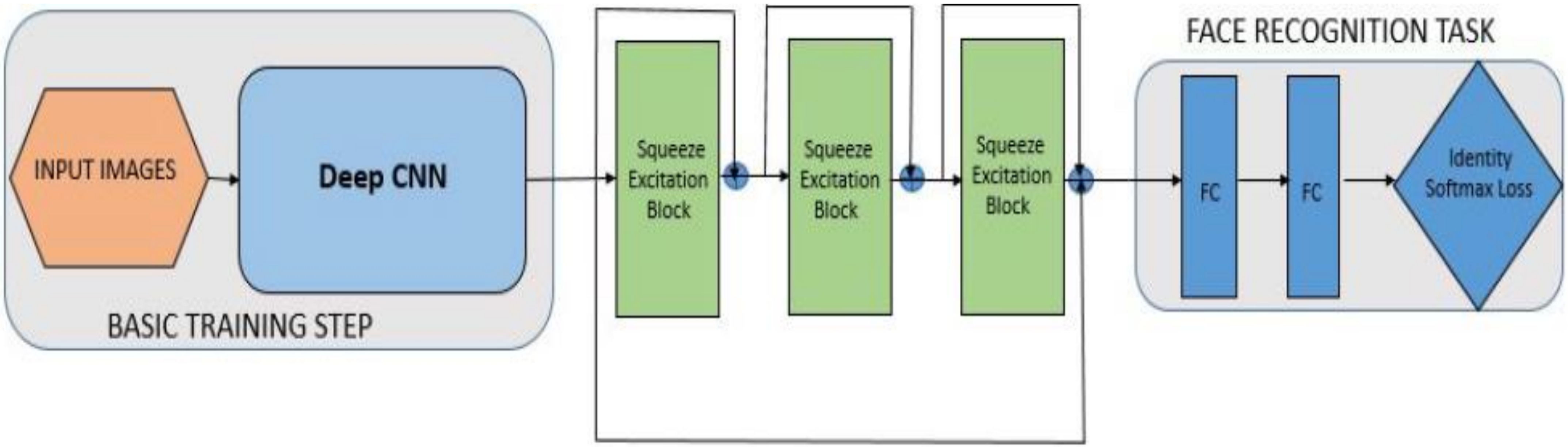
Motivation

- Output feature from Deep CNN may contain both informative and non-informative feature.

- AIFR require only informative feature.

- Aim is to generate a model which suppress the non-informative feature and give more weight to informative feature as much as possible.

Squeeze Excitation guided Convolution Neural Network for AIFR (SE-CNN)

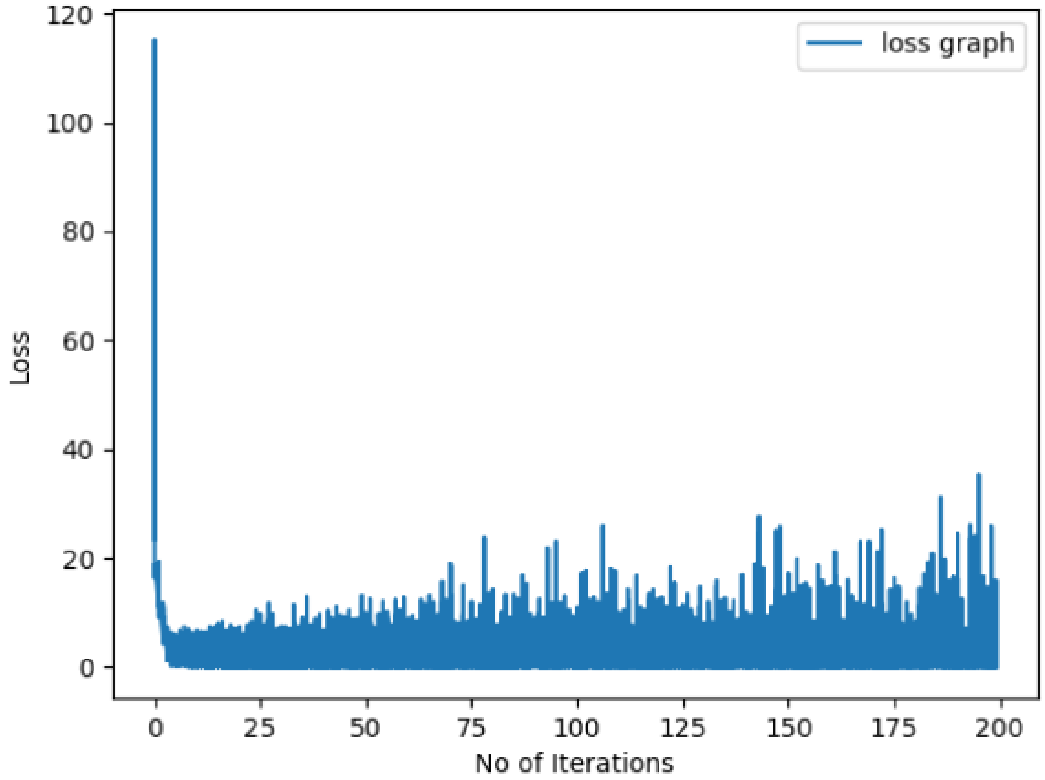


Results on Morph Dataset

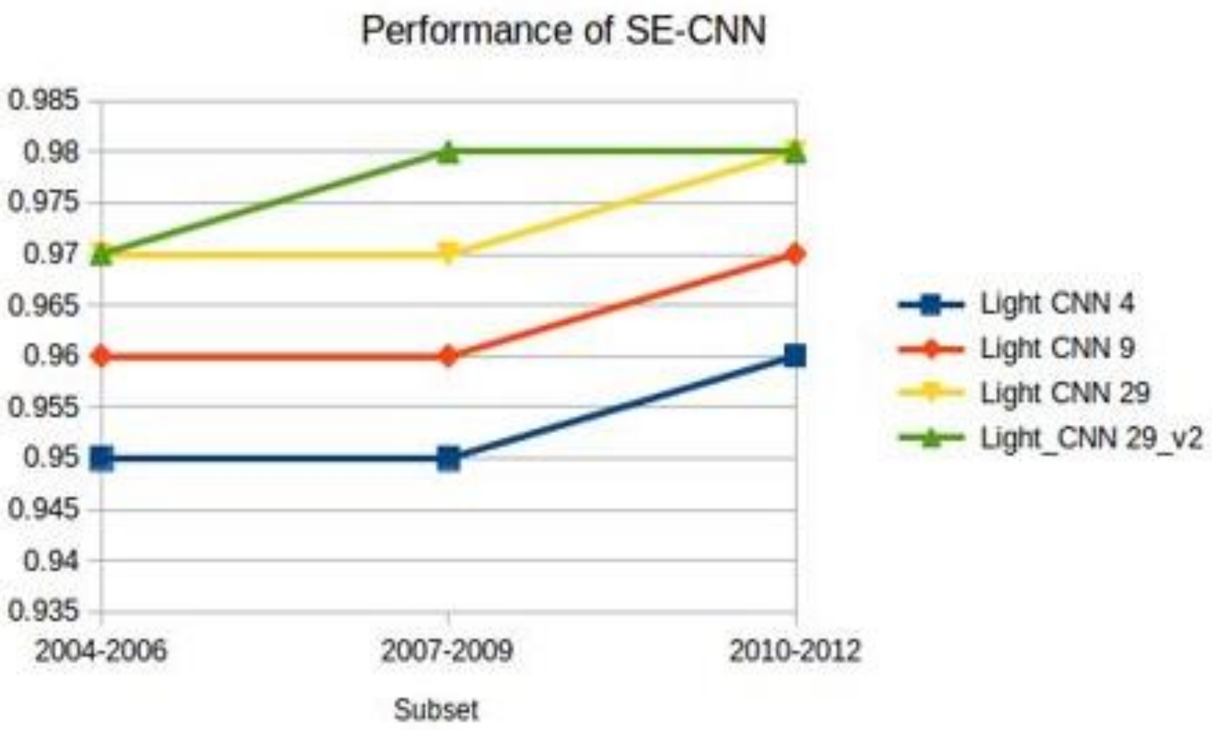
Sl.no	Pretrained Model	Test set accuracy
1	LightCNN-4	89.1
2	LightCNN-9	97.0
3	LightCNN-29	99.13
4	LightCNN-29v2	99.56

Rank 1 Identification rate of SE-CNN for MORPH Dataset

Results on CACD Dataset



(a)



(b)

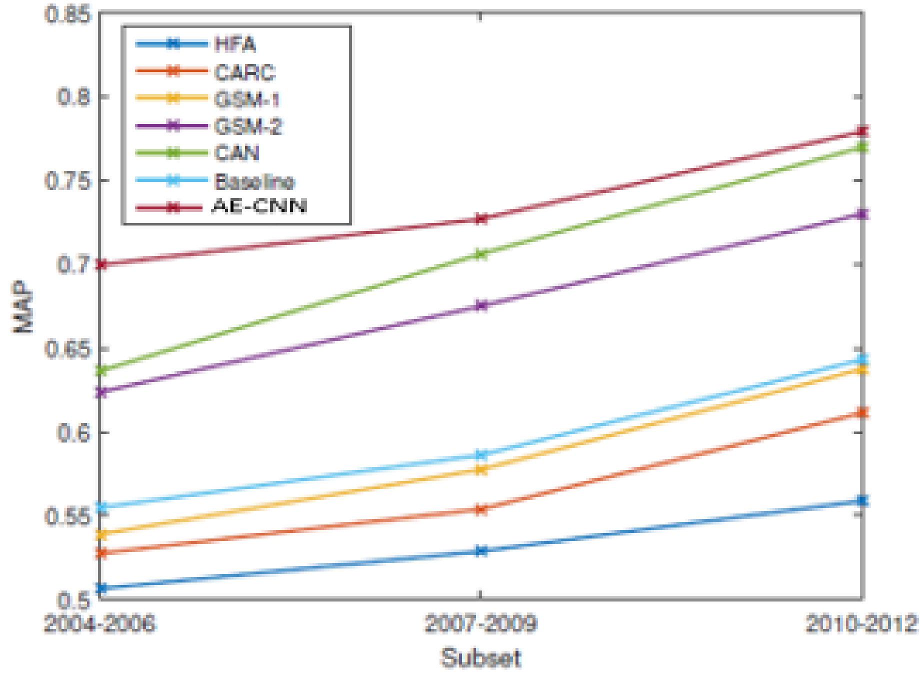
(a) Loss vs the no of Iterations and (b) MAP of SE-CNN with different versions of LightCNN

Recognition rates on MORPH

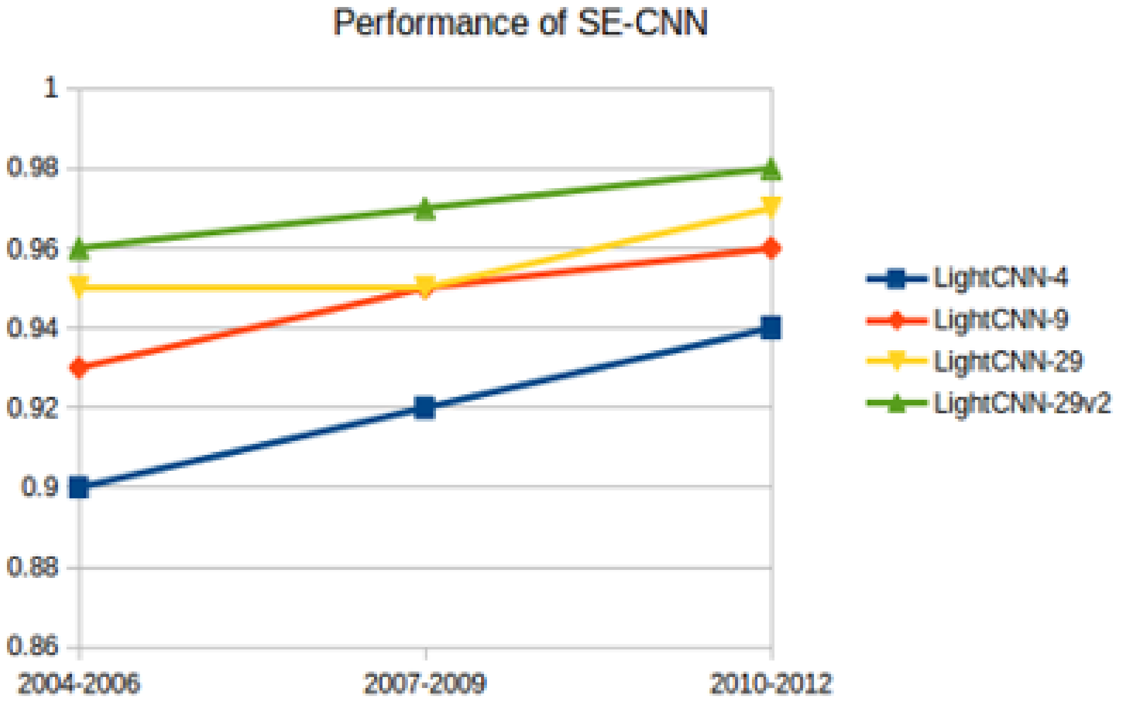
sl.no	Method	Year	Rank-1 Recognition Rate
1	HFA	2013	91.14%
2	CARC	2014	92.80%
3	MEFA	2015	93.80%
4	MEFA+SIFT+MLBP	2015	94.59%
5	GSM	2016	94.40%
6	LF-CNNs	2016	97.51%
7	AE-CNN	2017	98.13%
8	OE-CNNs	2018	98.67%
9	SE-CNN(LightCNN-4)	2019	89.1%
10	SE-CNN(LightCNN-9)	2019	97.0%
11	SE-CNN(LightCNN-29)	2019	99.13%
12	SE-CNN(LightCNN-29v2)	2019	99.56%

Age Estimation Guided Convolutional Neural Network for Age-Invariant Face Recognition, *CVPR , Tianyue Zheng,, 2017*

Comparison with different Methods:



(a)



(b)

(a) The performance of MAP of several state-of-the-art algorithms on CACD (reference: AE-CNN)
(b) compared with the proposed method SE-CNN(b)

Conclusion

- Preprocessing of several face datasets is done.
- A clean CACD dataset is contributed for better training of DL models.
- SE-CNN performs better than state-of-the-art methods for AIFR on MORPH and CACD datasets.

ANY QUESTIONS ?