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Deep-learning based descriptors in application to aging problem in face recognition

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ABSTRACT

Nowadays, "aging" becomes a challenging problem for face recognition systems. The challenge is particularly due to age-related biological changes, which can lead to significant variations in facial characteristics between two images taken at different ages of the same person. As the face is the most heavily part affected by aging, there is a growing need to extracting robust face features for age-invariant face recognition, particularly, in the presence of large age differences of the same person face images. The aim of this paper is to examine effectiveness of deep-learning based methods as features extraction tool for age-invariant face recognition. In this study, we evaluate five popular pre-trained deep-convolutional neural network (CNN) models that are AlexNet, GoogleNet, Inception V3, ResNet50 and SqueezeNet, on a widely used face-aging database, namely FG-NET, using K-nearest neighbors (K-NN), discriminant analysis, and support vector machines (SVM) classifiers. Further, a statistical analysis test is performed to confirm the statistical significance of the obtained results. Experimental results on this database show the promise of using Convolutional Neural Networks(CNN) for face recognition across age progression. Also the AlexNet model appears to be most promising for age-invariant face recognition, as highest mean accuracy rate is always achieved with feature extraction using the AlexNet model. These results are more significant, according to a 95% confidence level hypothesis test.

1. Introduction

Recently, age-related face recognition has been a challenging question of extensive research for real-world applications of face recognition systems in which age consideration is very important (El Khiyari and Wechsler, 2016; Jain and Li, 2011). In such case, there may be a meaningful age difference between the query image and those stored in the database, and it may be impossible to update the database with the subject's recent face images.

The face is an important characteristic for biometric identification and verification systems, as it provides the necessary information about individual's identity. However, it is the characteristic most affected by aging process, which affects significantly the performance of face recognition algorithms.

Aging is constraining due to several reasons: first, the effects of aging cannot be controlled because it is not possible to eliminate aging variation during face image capture. Also, aging affects people differently; this may be due to ethnicity, lifestyle, environment, etc. Furthermore, aging is influenced by biological factors, like gender, ancestry, genetics, diseases which have been shown to contribute to facial aging effects (Lanitis, 2009). Even some external factors such as smoking, alcohol consumption, exposure to extreme climate, emotional stress, and dramatic changes in weight can speed up the aging process (Lanitis, 2009).

Therefore, elaborating age-invariant face recognition systems may help to accurately identify any person even in the presence of age differences, and avoids to update large facial databases with more recent images.

The methods that have been proposed in regards to the aging effects on face recognition can be categorized in two main classes (Ramanathan et al., 2009): "generative", and "discriminative" methods. Generative methods are based directly on age estimation and age transformation to convert the query image to the convenient age, then any standard recognition algorithm can be used to obtain the query identity. However, discriminative methods focus particularly on the choice of discriminatory features

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and metric learning that are invariant over time. Lately, another category can be added, it includes deep-learning based methods.

A recent survey on age-invariant face recognition systems, effects of aging on the performance of face recognition systems as well as some facial databases may be found in Sawant and Bhurchandi (2018).

In this paper, we are interested in the discriminative approaches, more specifically in feature extraction stage which is a very important step in face recognition, since it allows to extract from face images useful visual representations, that are discriminant, and fully describe aging face characteristics.

To extract features and obtain visual representations, traditional approaches are based on handcraft features that are computed from low level characteristics and statistical representations. However, with the development of deep-learning and convolutional neural networks (CNN), learning visual representations directly from pixels becomes the most used tool today.

Deep-learning based features extraction methods have been particularly successful in the area of face recognition, especially with regards to age progression (Wang et al., 2018; Sajid and Shafique, 2018).

Most of the deep-learning based approaches focus on new CNN architectures to extract features (Wang et al., 2018; Li et al., 2015), and generate better face representations that are aging invariant. Such an approach requires large amount of labeled databases for training which is mostly not practicable in real world applications, an alternative approach which may be of great importance is to reuse pretrained deep-CNN models.

In this paper, we investigate to gain insight into feature extraction using deep-learning approaches by evaluating the discriminatory power and the invariance of pre-trained deep-CNN models in the context of face recognition across age progression. We consider in this study five popular deep-CNN models,which are AlexNet (Krizhevsky et al., 2012), GoogleNet (Szegedy et al., 2015), Inception V3 (Szegedy et al., 2016), SqueezeNet (Iandola et al., 2016), and ResNet50 (He et al., 2016), to extract features from facial images. Our selection is based on the prominence of these pre-trained CNN-models in the research community.

On the other hand, in Mehdipour Ghazi and Kemal Ekenel (2016), it has been proved that it is very necessary to precede the CNN-based feature extraction stage with a pose and illumination normalization step, as it may provide better performance in the presence of different conditions, and enhance the accuracy rates (Grm et al., 2017). For this reason, we propose to perform an Active Appearance Model(AAM)-based pose normalization (Boussaad et al., 2016), prior to extracting features.

In the final stage, three of the most used classifiers for face recognition, that are K-nearest neighbor (K-nn), discriminant analysis (LDA), and support vector machines (SVM) are used for recognition. The study includes recognition accuracy rates and statistical significance of the rate differences.

The rest of the paper is organized as follows: in Section 2, we review some related works on existing methods for face recognition across age progression. In Section 3, we represent the evaluation methodology, the aging database, the pre-processing stage, the deep-learning models for feature extraction and the considered classifiers. Section 4 reports results and discussions and Section 5 concludes the paper.

2. Related works

This section outlines some earlier works that have been realized in regards to the aging impact on face recognition systems.

2.1. Generative methods

As we have already mentioned, the approaches in this category are mainly related on modeling or simulating the process of facial change due to age progression. Early carried-out study on face recognition across age progression has been reported by Ramanathan and Chellappa (2006, 2008), the first study focuses on modeling the process of facial growth during childhood, while the second simulates facial changes during adulthood. According to the authors, facial changes due to age progression in childhood are totally different from those in adulthood.

Also, Park et al. (2010, 2008) proposed a 3D model to simulate the changes in shape and texture of a face, which are caused by aging. The authors consider that the true craniofacial aging model (Pittenger and Shaw, 1975) can be only formulated correctly in the 3D domain, and the use of a 3D model offers a more powerful characterization than a 2D model since the changes in the appearance of the human face occur in 3D. In addition, the extension of the 2D domain shape model to the 3D domain can further compensate for the pose changes, and potentially the lighting problems. The authors showed that their approach can handle both the growth effects during childhood and the facial aging in adulthood.

Recently, in Duong et al. (2017), authors presented a generative probabilistic model, called Temporal Non-Volume Preserving (TNVP) transformation which can model the long-term aging process by separating it into various short-term stages. The model demonstrates its benefits both in capturing the non-linear age variations and in producing a smooth synthesis in age progression. The structure may be processed into a deep convolutional network while ensuring the benefits of probabilistic models with tractable log-likelihood density estimation.

2.2. Discriminative methods

Among the first studies in this category, we cite works of Ling et al. (2007, 2010). Based on previous works on the application of the gradient orientations for illumination-invariant face recognition (Chen et al., 2000), and on the cranio-facial growth model (Mark et al., 1981) and those of the color of the skin (Igarashi et al., 2005; Tsumura et al., 1999), the authors found that a pyramidal representation of the directions of the gradient (GOP: Gradient orientation pyramid) can be used to construct features that are insensitive to face aging changes. The authors proposed to combine the differences between image pairs calculated from the cosine between gradient orientations at all scales with a support vector machines (SVM) for a facial verification tasks through age progression.

Moreover, Meng et al. (2010) carried out a comparative study between the gradient orientation pyramids (GOP), the local binary patterns and the Gabor wavelets in the presence of age variations; the three representations are followed by a principal component analysis. According to the authors, Gabor wavelets using 5 scales and 8 orientations provided the best recognition rates among the three methods tested. Also, LBPs provide good performance in age ranges from 7 to 9 years and from 10 to 12 years.

Similarly, Gong et al. (2013) considered that the facial image of a person can be expressed as a combination of two components: an identity-specific component that is largely invariant over the aging process, and another component that reflects the aging effect which changes as the person grows, so they introduced a method called Hidden factor analysis to separate these two factors. They also developed a learning algorithm that jointly estimates the latent factors and the model parameters using an Expectation–Max imization procedure.

However, Li et al. (2017) consider that supposing identity and age components are independent is not the case in real life, they present a modified version of Hidden Factor Analysis (HFA) (Gong et al., 2013), which consider the correlation between the two components. The new model separates age-identity associated features and other facial variations from the independent identity features, also authors present a probabilistic matching framework to best identify the query face images, the method outperforms the HFA in recognition rate.

Recently, demographic estimation-based methods have been proposed (Sajid et al., 2016, 2018) to improve accuracy of age-invariant face recognition systems. These methods assumed that demographic estimation of human face images may lead to better understanding of the facial aging process and face recognition, since facial asymmetry is another crucial factor which varies with age progression (Sajid et al., 2018, 2016).

2.3. Convolutional neural networks (CNN) based methods

Recently, CNN have become a very popular technique used for face recognition applications, an example can be found in Wang et al. (2018), where authors proposed an orthogonal Embedding-CNN method which allows separating deep facial representation into two orthogonal components that correspond to features relative to age and identity and use the identity feature for age-invariant face recognition, even the proposed method was tested on LFW-database to verify its generalization capability to general face recognition.

In the same context, in Li et al. (2015), a deep convolutional neural network (CNN) is proposed for face verification across age progression to learn jointly features, distances and thresholds.

Furthermore, El Khiyari and Wechsler (2016) presented an age invariant face recognition using VGG-Face deep learning for feature extraction and ensembles of subspace discriminant classifiers for classification. In a second paper (El Khiyari and Wechsler, 2017), authors process all images for each subject as a single set, that is compared to sets of images for other subjects and features extraction is made using a convolutional neural network, results demonstrate that using set-based approach is better than using single-based one.

In the same context, in a recent paper, Sajid and Shafique (2018) presented a hybrid approach considering both the generative and the discriminative representations of age-invariant face recognition. In this method deep convolutional neural networks are used to separate features of age-sensitive and age-insensitive facial regions. Age-sensitive regions are described by pixel mean vector based on local binary patterns and the aging variations of age-sensitive regions are compensated using a demographic-aware generative model based on bridged denoising auto-encoders.

3. Methodology and experiments description

In this section, we present the entire algorithm used in this paper, the aging database, the pre-processing stage, the deep-learning methods for feature extraction and the considered classifiers.

After a main step of pre-processing using the method described in Section 3.2, images were transformed using five pre-trained convolutional neural networks, that are Alex-Net (Krizhevsky et al., 2012), GoogleNet (Szegedy et al., 2015), Inception V3 (Szegedy et al., 2016), ResNet50 (He et al., 2016), and SqueezeNet (Iandola et al., 2016) to obtain feature vectors, then classification is performed by three classifiers which are: K-nearest neighbor classifier, discriminant analysis and support vector machines. The entire process is given in Table 1.

Table 1
Selecting the greatest pre-trained deep-CNN models for age-invariant face description based on higher 10-folds cross validation (c.v.) average recognition accuracy rates.

Pretrained CNN	Classifiers		
	1-NN	LDA	SVM
AlexNet	C.V.	C.V.	C.V.
GoogleNet	C.V.	C.V.	C.V.
Inception V3	C.V.	C.V.	C.V.
ResNet50	C.V.	C.V.	C.V.
SqueezeNet	C.V.	C.V.	C.V.

3.1. Aging database

For this study, we used the well known FG-NET aging database (Face, 2000), it is a publicly available image database used to evaluate facial aging models. It contains 1002 face images showing 82 subjects at different ages ranging in age from newborns to 69, for which there were about 4 to 12 images per subject. Sample images from the database are shown in Fig. 1.

The coordinates of sixty-eight facial landmarks that were identified manually and the age of each facial image are also provided.

3.2. Image preprocessing

For normalization, we use the same AAM-based approach used in a previous work (Boussaad et al., 2016), a brief description is given bellow (for more details about the method see Boussaad et al. (2016)).

Starting with a set of 68 facial landmarks, which constitute the shape, and a set of pixels in a gray level inside this shape that form texture, the method is performed in four steps:

1. Align all shapes in the same referential by using a Procrustes analysis method (Cootes et al., 2004)
2. Warp image texture by using Delaunay triangulation and a piece-wise affine transformation, the aim is to get a free shape representation of texture (see Fig. 2).
3. Based on eye coordinates, Rotate images to obtain an horizontal inter-ocular segment.
4. Resize images to the size required by each CNN model and convert each gray-scale image to RGB image.

3.3. Feature extraction

In order to obtain the feature vector from a preprocessed image, we use five pre-trained deep-CNN models. In this context, it is worth noting that pre-trained CNN are already extensively applied in feature extraction as shown in multiple existing research (Moustafa et al., 2020; Anand et al., 2017).

The considered pre-trained deep-CNN models are among the largest applied in many research areas and they are seen among the most successful in use for recognition tasks.

The models present variations in different settings, such as number of parameters, depth, image input size and computational complexity. Table 2 summarizes their different characteristics. A

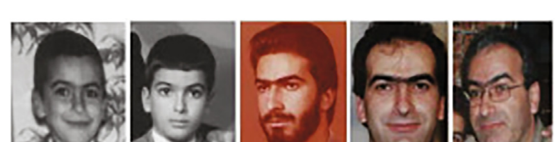

Fig. 1. Example images from the FG-NET aging database.

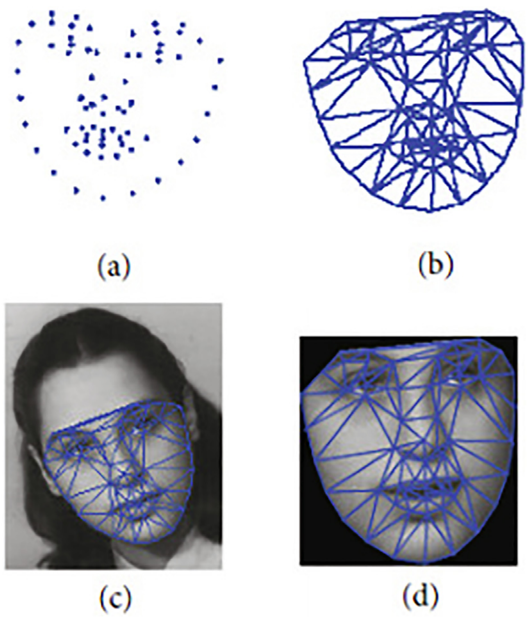

Fig. 2. Warping texture example. (a) The mean shape, (b) Delaunay triangulation of the mean shape, (c) original face image with its shape, and (d) warped texture (Boussaad et al., 2016).

Table 2
Summary of the properties of the used pre-trained deep-learning models.

Pre-trained CNN model	parameters (Millions)	Depth	Image input size
AlexNet (Krizhevsky et al., 2012)	61	8	227 by 227
GoogleNet (Szegedy et al., 2015)	7	22	224 by 224
Inception V3 (Szegedy et al., 2016)	23.9	48	299 by 299
SqueezeNet (Iandola et al., 2016)	1.23	18	227 by 227
ResNet50 (He et al., 2016)	25.6	50	224 by 224

brief outline of each pre-trained deep-CNN model used in this paper is presented in the following subsection.

3.4. Pretrained CNN models

1. AlexNet (Krizhevsky et al., 2012): It was the winner of LSVRC-2012. It is made up of eight trainable layers, five convolution layers and three fully connected layers. All of the trainable layers are followed by a ReLu activation function except for the last fully connected layer where a softmax function is used. The architecture also consists of non trainable layers: Three pooling layers, two normalization layers and one dropout layer.
2. GoogleNet (Szegedy et al., 2015): It was the winner of ILSVRC-2014, achieving a top-5 error rate of 6.67%, which is very close to human-level performance. It is constructed on a structure referred to as 'Inception architecture' containing nine parallel Inception modules. It is made up of a total of 22 layers, but with a number of parameters which is significantly lower than AlexNet.
3. Inception V3 (Szegedy et al., 2016): It is a deep-CNN that extend the googleNet Inception deep convolutional architecture by incorporating factorization ideas, in order to reduce the number of connections and parameters without decreasing the network efficiency. The network is a 48 layers deep.
4. SqueezeNet (Iandola et al., 2016): A small CNN architecture with equivalent accuracy of AlexNet. It can be 3 times faster and 500 times smaller than AlexNet. It is build on a specific architecture, called "Fire module", which contains a squeeze layer and an expand layer. Squeeze-Net stacks a bunch of fire modules and a few pooling layers. Squeeze layers are convolution layers that are made up of only 1×1 filters and Expand layers are convolution layers with a mix of 1×1 and 3×3 filters.
5. ResNet (He et al., 2016): It is short for Residual Network. ResNet was the winner of ILSVRC-2015. It features by the use of skip connections, providing incremental learning changes. ResNet50 is a 50 layers residual network.

4. Experimental results

The overall algorithm was implemented in Matlab (R 2018b), and all images of the FG-NET database are used for training and test. As we have already mentioned, all images are resized to the required size for each CNN model (see Table 2 for more details about the image input size). Any gray-scale image was converted to RGB by simple concatenation of three copies of the original image matrix along third dimension.

Results are reported in terms of average and standard deviation of the recognition accuracy rates following a 10-fold cross validation scheme. Recognition accuracy represents the percentage of samples that are correctly predicted.

Pre-trained CNN-models consist of multiple layers, however, they are not all good for extracting features. In the first experiment, feature extraction was conducted using the pre-trained CNN AlexNet model, descriptors are computed from fully-connected layers 'Fc6', 'Fc7' and 'Fc8' and classification was made by three classifiers; K-nn, Discriminant analysis and SVM.

Results are reported in Table 3. As it can be seen from this table, 'Fc7' based descriptor gives the highest recognition accuracy rates for the all classifiers, followed by the 'Fc6' descriptor. That clearly demonstrates the benefit of the 'Fc7' layer as age-invariant face descriptor. Combined with SVM classifier, the model achieved the higher accuracy rate of 98.21%.

The aim of the second experiment is to compare the five pre-trained CNN models that are AlexNet, GoogleNet, Inception V3, ResNet50 and SqueezeNet. For AlexNet model, we keep the obtained results using the 'Fc7' descriptor. For the other models, we apply activation of layer before the classification layer, named respectively, 'loss3-classifier', 'predictions', 'Fc1000' and 'Pool10'. Results in terms of average and standard deviation of recognition accuracy rates are reported in Table 4.

With regard to results showed in Table 4 and Fig. 3, it can be concluded the benefit of reusing pre-trained deep-CNN models as tools for face recognition across age progression, where good

Table 3
Recognition accuracy rates and standard deviations for AlexNet with descriptors from layers 'Fc6', 'Fc7', and 'Fc8'.

	1-nn		LDA		SVM	
Layers	Mean	STD	Mean	STD	Mean	STD
'fc6'	80.58%	1.63%	93.71%	1.21%	95.03%	1.15%
'fc7'	**86.28%**	2.53%	**97.37%**	1.05%	**98.21%**	0.89%
'fc8'	43.63%	1.6%	70.54%	1.38%	73.01%	1.74%

Bold value denotes the greatest accuracy rate.

Table 4
Recognition accuracy rates and standard deviations for deep-CNN models.

	1-nn		LDA		SVM	
Pretrained CNN	Mean	STD	Mean	STD	Mean	STD
AlexNet	**86.28%**	1.63%	**97.37%**	1.05%	**98.21%**	0.89%
GoogleNet	72.59%	0.85%	87.45%	1.42%	95.19%	0.76%
Inception V3	73.86%	2.06%	85.80%	1.05%	95.14%	0.88%
ResNet50	79.28%	1.26%	91.22%	1.14%	95.37%	1.33%
SqueezeNet	76.14%	0.99%	85.34%	1.7%	94.79%	1.07%

Bold value denotes the greatest accuracy rate.

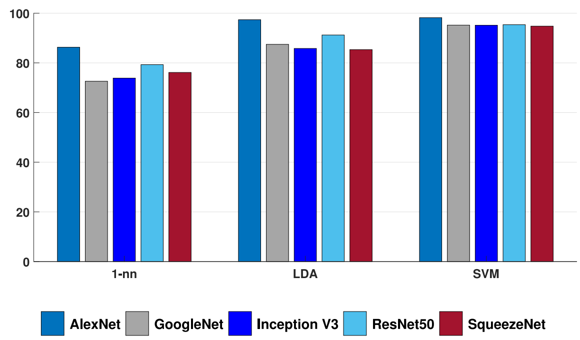

Fig. 3. Recognition accuracy rates for deep-CNN models.

results are reached with the five models, especially when they are combined with SVM classifier, where the lowest rate obtained is 72.59% when Google-Net model is combined with K-nn classifier, and this may be the result of the use of the K-nn classifier. Almost the same achievement when they are combined with Discriminant analysis, because LDA may have a good power to correctly separate the different classes in the features space.

Also, it is seen that AlexNet model seems to be an excellent tool for feature extraction, where the higher accuracy rate of 98.21% is obtained by the combination of AlexNet model and SVM classifier, and it is still the best in the case of the K-nn and LDA classifiers.

Once the results were obtained, we verify if these results are significant, according to a 95% confidence level hypothesis test. A confidence interval approach can be used (Ferreira and de Carvalho, 2017). It consists of calculating the confidence interval at 95% of the difference of the average accuracy rates of two different CNN-models:

- if this 95% confidence interval does not contain 0 as an element, then we will conclude that the two average accuracy rates are different,
- if this confidence interval contains 0, then we will conclude that there is no thing to confirm that the two means are different.

The confidence interval IC_{ij} of difference mean accuracy rates at 95% confidence level of two models i and j, is computed using the following equation:

$$IC_{ij} = (\mu_i - \mu_j) \pm 1.96\sqrt{(\delta_i^2 + \delta_j^2)} \quad (1)$$

Where μ_i and δ_i are, respectively, the mean accuracy rate and the standard deviation of the model i, and μ_j and δ_j are the mean accuracy rate and the standard deviation of the model j.

We compare five CNN models accuracy rates, Which represents ten confidence intervals (see Table 5).

From the hypothesis test results, presented by confidence intervals at 95% of the difference of mean accuracy rates of different models, computed by the Eq. (1), and showed in Figs. 4–6, It is clear that intervals 1, 2, 3 and 4 do not include the point zero, which means that the rates achieved by AlexNet model for FG-Net database still remain significantly better than the other models for the three classifiers.

However, in the case of the LDA classifier (Fig. 5), the interval 9 includes the point zero which shows that there is no difference between accuracy rates provided by Inception V3 and SqueezeNet models.

Also, in the case of SVM classifier (Fig. 6), the intervals 5, 6, 7, 8, 9 and 10 include the point zero which means that there is no dif-

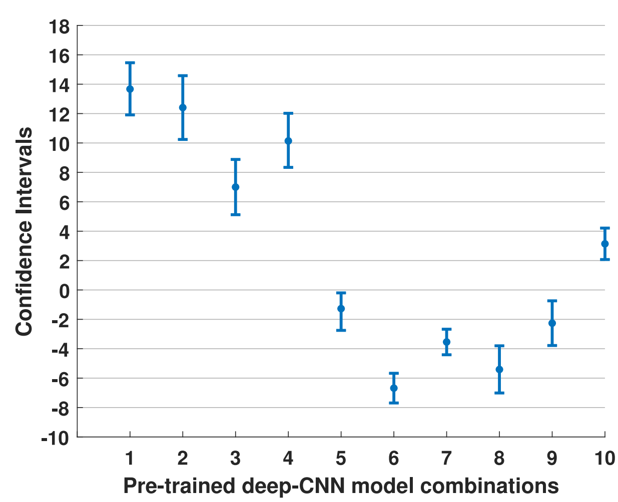

Fig. 4. Hypothesis test confidence intervals for the mean accuracy differences (K-nn classifier).

Table 5
Pre-trained deep-CNN models comparisons considered in the hypothesis test.

	AlexNet	GoogleNet	Inception V3	ResNet50	SqueezeNet
AlexNet	–	1	2	3	4
GoogleNet	–	–	5	6	7
Inception V3	–	–	–	8	9
ResNet50	–	–	–	–	10
SqueezeNet	–	–	–	–	–

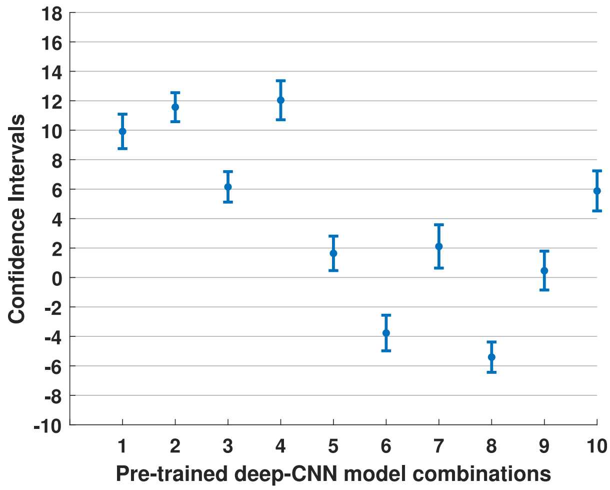

Fig. 5. Hypothesis test confidence intervals for the mean accuracy differences (LDA classifier).

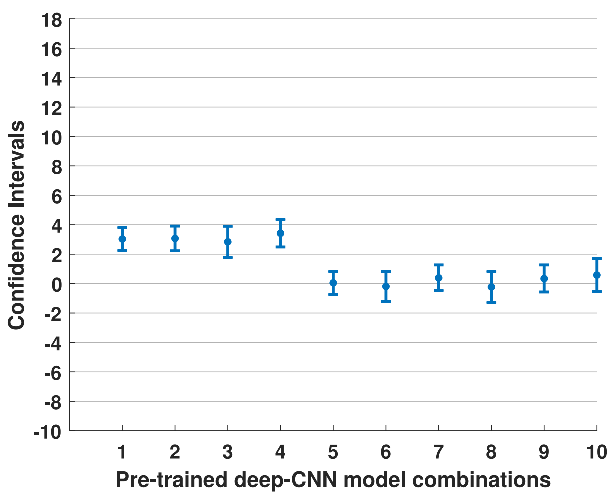

Fig. 6. Hypothesis test confidence intervals for the mean accuracy differences (SVM classifier).

ference between accuracy rates provided by GoogleNet, Inception V3, ResNet50 and SqueezeNet.

5. Conclusion

In this paper, we examined five popular deep-learning based-face characterization tools, namely AlexNet, GoogleNet, Inception V3, SqueezeNet, and ResNet50, combined with an important step of pose correction and three classifiers, in completely equal working conditions for temporal changes task. This experimental setup consists of fifteen different combinations to be compared.

From our results, we can draw the following conclusions:

- The reuse of pre-trained deep-CNN models for age-invariant face recognition can allow us to reach satisfactory performance without using large databases for training new architectures, which is totally impossible in real applications.
- AlexNet appears to be the best at handling variations in age and the most promising for age invariant face recognition.

In future, it is necessary to test these pre-trained models on other databases, study their performance over large time gaps, and combine them with other preprocessing approaches.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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