Efficient Facial Representations for Age, Gender and Identity Recognition in Organizing Photo Albums using Multi-output CNN

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Abstract. This paper is focused on the automatic extraction of persons and their attributes (gender, year of born) from album of photos and videos. We propose the two-stage approach, in which, firstly, the convolutional neural network simultaneously predicts age/gender from all photos and additionally extracts facial representations suitable for face identification. We modified the MobileNet, which is preliminarily trained to perform face recognition, in order to additionally recognize age and gender. In the second stage of our approach, extracted faces are grouped using hierarchical agglomerative clustering techniques. The born year and gender of a person in each cluster are estimated using aggregation of predictions for individual photos. We experimentally demonstrated that our facial clustering quality is competitive with the state-of-the-art neural networks, though our implementation is much computationally cheaper. Moreover, our approach is characterized by more accurate video-based age/gender recognition when compared to the publicly available models.

Keywords: Face identification, age and gender recognition, face clustering, convolutional neural network (CNN)

1 Introduction

Nowadays, due to the extreme increase in multimedia resources there is an urgent need to develop intelligent methods to process and organize them [1]. For example, the task of automatic organizing photo and video albums is attracting increasing attention [2,3]. The various photo organizing systems allow users to group and tag photos and videos in order to retrieve large number of images in the media library [4]. The most typical processing of a gallery includes the face grouping, and each group can be automatically tagged with the facial attributes, i.e., age (born year) and gender [5]. Hence, the task of this paper is formulated as follows: given a large number of unlabeled facial images, cluster the images into individual persons (identities) [4] and predict age and gender of each person [6].
This problem is usually solved using deep convolutional neural networks (CNNs) [7]. At first, the clustering of photos and videos that contains the same person is performed using the known face verification [8,9] and identification [10] methods. The age and gender of extracted faces can be recognized by other CNNs [5,6]. Though such approach works rather well, it requires at least three different CNNs, which increases the processing time, especially if the gallery should be organized on mobile platforms in offline mode. Moreover, every CNN learns its own face representation, which quality can be limited by the small size of the training set or the noise in the training data. The latter issue is especially crucial for age prediction, which contains incorrect ground truth values of age.

It is rather obvious that the closeness among the facial processing tasks can be exploited in order to learn efficient face representations which boosts up their individual performances. For instance, simultaneous face detection, landmark localization, pose estimation, and gender recognition is implemented in the paper [11] by a single CNN.

Therefore the goal of our research is to improve the efficiency in facial clustering and age and gender prediction by learning face representation using preliminarily training on domain of unconstrained face identification from very large database. In this paper we specially developed a multi-output extension of the MobileNet [12], which is pre-trained to perform face recognition using the VGGFace2 dataset [13]. Additional layers of our network are fine-tuned for age and gender recognition on Adience [5] and IMDB-Wiki [6] datasets. Finally, we propose a novel approach to face grouping, which deals with several challenges of processing of real-world photo and video albums.

The rest of the paper is organized as follows: in Section 2, we formulate the proposed approach of organizing facial photos with simultaneous prediction of age and gender of obtained persons. In Section 3, we present the experimental results in face clustering for the LFW, Gallagher and GFW datasets and the video-based age/gender recognition for video clips from Eurecom Kinect, Indian Movie, EmotiW and IJB-A. Finally, concluding comments are given in Section 4.

2 Materials and Methods

2.1 Multi-output CNN for Simultaneous Age, Gender and Identity Recognition

In this paper we consider several different facial analytic tasks. We assume that the facial regions are obtained in each image using any appropriate face detector, e.g., either traditional multi-view cascade Viola-Jones classifier or more accurate CNN-based methods [14]. The gender recognition task is a binary classification problem, in which the obtained facial image is assigned to one of two classes (male and female). The age prediction is the special case of regression problem, though sometimes it is considered as a multi-class classification with, e.g., \(N = 100\) different classes, so that it is required to predict in an observed person is 1,2,... or 100 years old [6]. In such case these two tasks become very similar and can be
solved by traditional deep learning techniques. Namely, the large facial dataset of persons with known age and/or gender is gathered, e.g. the IMDB-Wiki from the paper [6]. After that the deep CNN is learned to solve the classification task. The resulted networks can be applied to predict age and gender given a new facial image.

The last task examined in this paper, namely, unconstrained face identification significantly differs from age and gender recognition. We consider the unsupervised learning case, in which facial images a gallery set should be assigned to one of \( C \geq 1 \) subjects (identities). The number of subjects \( C \) is generally unknown. The training sample is usually rather small (we can assume that \( C \approx R \)) to train complex classifier (e.g. deep CNN). Hence, the domain adaptation can be applied [7]: each image is described with the off-the-shelf feature vector using the deep CNN, which has been preliminarily trained for the supervised face identification from large dataset, e.g., CASIA-WebFace, VGGFace/VGGFace2 or MS-Celeb-1M. The \( L_2 \)-normalized outputs at the one of last layers of this CNN for each \( r \)-th gallery image are used as the \( D \)-dimensional feature vectors \( x_r = [x_{r;1}, \ldots, x_{r;D}] \). Finally, any appropriate clustering method, i.e., hierarchical agglomerative clustering [15], can be used to make a final decision for these feature vectors.

In most research studies all these tasks are solved by independent CNNs even though it is necessary to solve all of them. As a result, the processing of each facial image becomes time-consuming, especially for offline mobile applications. In this paper we propose to solve all these tasks by the same CNN. In particular, we assume that the features extracted during face identification can be rather rich for any facial analysis. For example, it was shown the the VGGFace features [16] can be used to increase the accuracy of visual emotion recognition [17,18]. As our main requirement is the possibility to use the CNN on mobile platforms, we decided to use straightforward modification of the MobileNet [12] (Fig. 1). The bottom of our network (conventional MobileNet v1 pre-trained on ImageNet) extracts the representations suitable for face identification. It was experimentally noticed that one new hidden layer with dropout regularization after extraction of identity features slightly improves the power of age and gender recognition performed by two independent fully connected layers with softmax and sigmoid outputs, respectively.

The learning of our model is performed incrementally, At first, we train the base MobileNet for face identification using very large dataset, e.g., VGGFace2 with 3M photos of 10K subjects [13]. Next, the last classification layer is removed, and the weights of the MobileNet base are freezed. Finally, the remaining layers in the head are learned for age and gender recognition. In our study we populate the training dataset by 300K frontal cropped facial images from the IMDB-Wiki dataset [6]. Unfortunately, the age groups in this dataset are very imbalanced, so the trained models work incorrectly for faces of very young or old people. Hence, we decided to add all (15K) images from the Adience [5] dataset. As the latter contains only age intervals, e.g., “(0-2)”, “(60-100)”, we put all images from this interval to the middle age, e.g., “1” or “80”.
It is necessary to emphasize that not all images in the IMDB-Wiki contains information about both age and gender. Moreover, the gender is sometimes unknown in the Adience data. As a result, the number of faces with both age and gender information is several times smaller when compared to the whole number of facial images. Finally, the gender data for different ages is also very imbalanced. Thus, we decided to train both heads of the CNN (Fig. 1) independently using different training data for age and gender classification. In particular, we alternate the mini-batches with age and gender info, and train only the part of our network, i.e., the weights of the fully connected layer in the age head of our model are not updated for the mini-batch with the gender info.

This CNN has the following advantages. First of all, it is obviously very efficient due to either usage of the MobileNet base or the possibility to simultaneously solve all three tasks (age, gender and identity recognition) without need to implement an inference in three different networks. Secondly, in contrast to the publicly available datasets for age and gender prediction, which are rather small and dirty, our model exploit the potential of very large and clean face identification datasets to learn very good face representation. Moreover, the hidden layer between the identity features and two outputs further combines the knowledge necessary to predict age and gender. As a result, our model makes it possible to increase the accuracy of age/gender recognition when compared to the models trained only on specific datasets, e.g. IMDB-Wiki or Adience. Subsection 3.2 will experimentally support this claim.

2.2 Proposed Pipeline for Organizing Photo and Video Albums

The complete data flow of the usage of the CNN (Fig. 1) for organizing albums with photos and videos the is presented in Fig. 2.
Here we detect faces in each photo using the MTCNN. Next, an inference in our CNN is performed for all detected faces $X_r$ in order to extract $D$ identity features and predict age and gender. After that, all facial identity feature vectors are clustered. As the number of subjects in the photo albums is usually unknown, we used a hierarchical agglomerative clustering \[15\]. Only rather large clusters with a minimal number of faces are retained during the cluster refinement. The gender and the born year of a person in each cluster are estimated by appropriate fusion techniques, e.g., simple voting or maximizing the average posterior probabilities at the output of the CNN (Fig. 1). For example, the product rule \[19\] can be applied if we naively assume the independence of all facial images $X_r, r \in \{r_1, ..., r_M\}$ in a cluster:

$$\max_{n \in \{1, ..., N\}} \prod_{m=1}^{M} p_n(X_{r_m}) = \max_{n \in \{1, ..., N\}} \sum_{m=1}^{M} \log p_n(X_{r_m}),$$

(1)

where $N$ is the total number of classes (in our study $N = 2$ and $N = 100$ for gender and age recognition, respectively) and $p_n(X_{r_m})$ is the $n$-th output of the CNN for the input image $X_{r_m}$.

The same procedure is repeated for all video files. We select only each of, e.g., 3 or 5 frames, in each video clip, extract identity features of all detected faces and initially cluster only the faces found in this clip. After that we compute the normalized average of identity features of all clusters \[2\], and add them to the dataset $\{X_r\}$ so that the “Facial clustering” module handles both features of all photos and average feature vectors of subjects found in all videos.
Let us summarize the main novel parts of this pipeline despite the usage of our multi-output neural network (Fig. 1).

Firstly, the simple age prediction by maximizing the output of the corresponding head of our CNN is not accurate due to the imbalance of our training set. Addition of the Adience data leads to the decision in favour of one of the majority class. Hence, we decided to aggregate the outputs \( \{ p_a(X_r) \} \) of the age head. However, we experimentally found that the fusion of all outputs is again inaccurate, because the majority of subjects in our training set are 20-40 years old. Thus, we propose to choose only \( L \in \{ 1, 2, ..., 100 \} \) indices \( \{ a_1, ..., a_L \} \) of the maximal outputs and compute the expected mean \( \bar{a}(X_r) \) for each gallery facial image \( X_r \) using normalized top outputs as follows:

\[
\bar{a}(X_r) = \frac{\sum_{l=1}^{L} a_l \cdot p_{a_l}(X_r)}{\sum_{l=1}^{L} p_{a_l}(X_r)}.
\]

Secondly, we estimate the born year of each face subtracting the predicted age from the image file creation date. In such case it will be possible to organize the very large albums gathered over the years. In addition, we use the predicted born year as an additional feature with special weight during the cluster analysis in order to partially overcome the known similarity of young babies in a family.

Finally, we implement several tricks in the cluster refinement module (Fig. 2). At first, we specially mark the different faces appeared on the same photo. As such faces must be stored in different groups, we additionally perform complete linkage clustering of every facial cluster. The distance matrix specially designed so that the distances between the faces at the same photo are set to the maximum value, which is much larger than the threshold applied when forming flat clusters. Moreover, we assume that the most important clusters should not contain photos/videos made in one day. Hence, we set a certain threshold for a number of days between the earliest and the eldest photo in a cluster in order to disambiguate large quantity of non-interested faces.

3 Experimental Results

The described approach (Fig. 2) is implemented in a special software\(^1\) using Python language with the Tensorflow and Keras frameworks and the scikit-learn/scipy/numpy libraries.

3.1 Facial Clustering

In this subsection we provide experimental study of the proposed system (Fig. 2) in facial clustering task for images gathered in unconstrained environments. The identity features extracted by base MobileNet (Fig. 1) are compared to the publicly available CNNs suitable for face recognition, namely, the VGGFace

\(^1\) [https://github.com/HSE-asavchenko/HSE_FaceRec_tf](https://github.com/HSE-asavchenko/HSE_FaceRec_tf)
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(VGGNet-16) [16] and the VGGFace2 (ResNet-50) [13]. The VGGFace, VGGFace2 and MobileNet extract $D = 4096$, $D = 2048$ and $D = 1024$ non-negative features in the output of “fc7”, “pool5_7x7_s1” and “reshape_1/Mean” layers from 224x224 RGB images, respectively.

All hierarchical clustering methods from SciPy library are used with the Euclidean ($L_2$) distance between feature vectors. As the centroid and the Ward’s linkage showed very poor performance in all cases, we report only results for single, average, complete, weighted and median linkage methods. In addition, we implemented rank-order clustering [20], which was specially developed for organizing faces in photo albums. The parameters of all clustering methods were tuned using 10% of each dataset. We estimate the following clustering metrics with the scikit-learn library: ARI (Adjusted Rand Index), AMI (Adjusted Mutual Information), homogeneity and completeness. In addition, we estimate the average number of extracted clusters $K$ relative to the number of subjects $C$ and the BCubed F-measure. The latter metric is widely applied in various tasks of grouping faces [4,21].

In our experiments we used the following testing data.

– Subset of LFW (Labeled Faces in the Wild) dataset [22], which was involved into the face identification protocol [23]. $C = 596$ subjects who have at least two images in the LFW database and at least one video in the YTF (YouTube Faces) database (subjects in YTF are a subset of those in LFW) are used in all clustering methods.

– Gallagher Collection Person Dataset [24], which contains 931 labeled faces with $C = 32$ identities in each of the 589 images. As only eyes positions are available in this dataset, we preliminarily detect faces using MTCNN [14] and choice the subject with the largest intersection of facial region with given eyes region. If the face is not detected we extract a square region with the size chosen as a 1.5-times distance between eyes.

– Grouping Faces in the Wild (GFW) [4] with preliminarily detected facial images from 60 real users albums from a Chinese social network portal. The size of an album varies from 120 to 3600 faces, with a maximum number of identities of $C = 321$.

The average values of clustering performance metrics are presented in Table 1, Table 2 and Table 3 for LFW, Gallagher and GFW datasets, respectively.

The average linkage is the best method according to most of the metrics of cluster analysis. The usage of the rank-order distance [20] is not appropriate due to rather low performance. Moreover, this distance requires an additional threshold parameter for the cluster-level rank-order distance. Finally, the computational complexity of such clustering is 3-4-times lower when compared to other hierarchical agglomerative clustering methods. One of the most important conclusion here is that the trained MobileNet (Fig. 1) is in most cases more accurate than the widely-used VGGFace. As expected, the quality of our model is slightly lower when compared to the deep ResNet-50 CNN trained on the same VGGFace2 dataset. Surprisingly, the highest BCubed F-measure for the
### Table 1. Clustering Results, LFW subset \((C = 596\text{ subjects})\)

|                      | \(K/C\) | ARI  | AMI  | Homogeneity | Completeness | F-measure |
|----------------------|---------|------|------|-------------|--------------|-----------|
| **Single**           |         |      |      |             |              |           |
| VGGFace              | 1.85    | 0.884| 0.862| 0.966       | 0.939        | 0.860     |
| VGGFace2             | 1.22    | 0.993| 0.969| 0.995       | 0.986        | 0.967     |
| Ours                 | 2.00    | 0.983| 0.851| 0.998       | 0.935        | 0.880     |
| **Average**          |         |      |      |             |              |           |
| VGGFace              | 1.17    | 0.980| 0.937| 0.985       | 0.971        | 0.950     |
| VGGFace2             | 1.06    | 0.997| 0.987| 0.998       | **0.994**    | **0.987** |
| Ours                 | 1.11    | 0.995| 0.971| 0.993       | 0.987        | 0.966     |
| **Complete**         |         |      |      |             |              |           |
| VGGFace              | 0.88    | 0.616| 0.848| 0.962       | 0.929        | 0.823     |
| VGGFace2             | 0.91    | 0.760| 0.952| 0.986       | 0.978        | 0.932     |
| Ours                 | 0.81    | 0.987| 0.929| 0.966       | 0.986        | 0.916     |
| **Weighted**         |         |      |      |             |              |           |
| VGGFace              | 1.08    | 0.938| 0.928| 0.979       | 0.967        | 0.915     |
| VGGFace2             | 1.08    | 0.997| 0.982| 0.998       | 0.992        | 0.983     |
| Ours                 | 1.08    | 0.969| 0.959| 0.990       | 0.981        | 0.986     |
| **Median**           |         |      |      |             |              |           |
| VGGFace              | 2.84    | 0.827| 0.674| 0.987       | 0.864        | 0.751     |
| VGGFace2             | 1.42    | 0.988| 0.938| 0.997       | 0.972        | 0.947     |
| Ours                 | 2.73    | 0.932| 0.724| **0.999**   | 0.884        | 0.791     |
| **Rank-Order**       |         |      |      |             |              |           |
| VGGFace              | 0.84    | 0.786| 0.812| 0.955       | 0.915        | 0.842     |
| VGGFace2             | **0.98**| 0.712| 0.791| 0.989       | 0.907        | 0.888     |
| Ours                 | 0.86    | 0.766| 0.810| 0.962       | 0.915        | 0.863     |

### Table 2. Clustering Results, Gallagher dataset \((C = 32\text{ subjects})\)

|                      | \(K/C\) | ARI  | AMI  | Homogeneity | Completeness | F-measure |
|----------------------|---------|------|------|-------------|--------------|-----------|
| **Single**           |         |      |      |             |              |           |
| VGGFace              | 9.13    | 0.601| 0.435| 0.966       | 0.555        | 0.662     |
| VGGFace2             | 2.75    | 0.270| 0.488| 0.554       | 0.778        | 0.637     |
| Ours                 | 12.84   | 0.398| 0.298| **1.000**   | 0.463        | 0.482     |
| **Average**          |         |      |      |             |              |           |
| VGGFace              | 1.84    | 0.858| 0.792| 0.916       | 0.817        | 0.874     |
| VGGFace2             | 2.94    | 0.845| 0.742| 0.969       | 0.778        | 0.869     |
| Ours                 | 2.03    | **0.890**| **0.809**| 0.962 | 0.832 | **0.897** |
| **Complete**         |         |      |      |             |              |           |
| VGGFace              | 1.31    | 0.571| 0.624| 0.886       | 0.663        | 0.706     |
| VGGFace2             | 0.94    | 0.816| 0.855| 0.890       | **0.869**    | 0.868     |
| Ours                 | 1.47    | 0.644| 0.649| 0.921       | 0.687        | 0.719     |
| **Weighted**         |         |      |      |             |              |           |
| VGGFace              | **0.97**| 0.782| 0.775| 0.795       | 0.839        | 0.838     |
| VGGFace2             | 1.63    | 0.607| 0.730| 0.876       | 0.760        | 0.763     |
| Ours                 | 1.88    | 0.676| 0.701| 0.952       | 0.735        | 0.774     |
| **Median**           |         |      |      |             |              |           |
| VGGFace              | 9.16    | 0.613| 0.433| 0.942       | 0.555        | 0.663     |
| VGGFace2             | 4.41    | 0.844| 0.715| 0.948       | 0.761        | 0.860     |
| Ours                 | 12.38   | 0.439| 0.324| 0.960       | 0.482        | 0.531     |
| **Rank-Order**       |         |      |      |             |              |           |
| VGGFace              | 1.59    | 0.616| 0.488| 0.902       | 0.582        | 0.702     |
| VGGFace2             | 1.94    | 0.605| 0.463| 0.961       | 0.566        | 0.682     |
| Ours                 | 3.06    | 0.249| 0.251| 0.986       | 0.424        | 0.398     |
### Table 3. Clustering Results, GFW dataset (in average, $C = 46$ subjects)

|                | $K/C$ | ARI  | AMI  | Homogeneity | Completeness | F-measure |
|----------------|-------|------|------|-------------|--------------|-----------|
| Single         | VGGFace    | 4.10 | 0.440 | 0.419       | 0.912        | 0.647     | 0.616     |
|                | VGGFace2   | 3.21 | 0.580 | 0.544       | 0.942        | 0.709     | 0.707     |
|                | Ours       | 4.19 | 0.492 | 0.441       | 0.961        | 0.655     | 0.636     |
| Average        | VGGFace    | 1.42 | 0.565 | 0.632       | 0.860        | 0.751     | 0.713     |
|                | VGGFace2   | 1.59 | 0.603 | 0.663       | 0.934        | 0.761     | 0.746     |
|                | Ours       | 1.59 | 0.492 | 0.441       | 0.961        | 0.751     | 0.746     |
| VGGFace        | 0.95 | 0.376 | 0.553 | 0.811       | 0.690        | 0.595     |
| Complete       | VGGFace2   | 1.44 | 0.392 | 0.570       | 0.916        | 0.696     | 0.641     |
|                | Ours       | 1.28 | 0.381 | 0.564       | 0.886        | 0.693     | 0.626     |
| Weighted       | VGGFace    | 1.20 | 0.464 | 0.597       | 0.839        | 0.726     | 0.662     |
|                | VGGFace2   | 1.05 | 0.536 | 0.656       | 0.867        | 0.697     | 0.710     |
|                | Ours       | 1.57 | 0.487 | 0.612       | 0.915        | 0.727     | 0.697     |
| Median         | VGGFace    | 5.30 | 0.309 | 0.307       | 0.929        | 0.587     | 0.516     |
|                | VGGFace2   | 4.20 | 0.412 | 0.422       | 0.929        | 0.639     | 0.742     |
|                | Ours       | 6.86 | 0.220 | 0.222       | 0.994        | 0.552     | 0.411     |
| Rank-Order     | VGGFace    | 0.82 | 0.319 | 0.430       | 0.650        | 0.694     | 0.630     |
|                | VGGFace2   | 1.53 | 0.367 | 0.471       | 0.937        | 0.649     | 0.641     |
|                | Ours       | 1.26 | 0.379 | 0.483       | 0.914        | 0.658     | 0.652     |

most complex GFW dataset (0.751) is achieved by our model. This value is slightly higher than the best BCubed F-measure (0.745) reported in the original paper [4]. However, the most important advantages of our model from the practical point of view are excellent run-time/space complexity. For example, the inference in our model is 5-10-times faster when compared to the VGGFace and VGGFace2. Moreover, the dimensionality of the feature vector is 2-4-times lower leading to the faster computation of a distance matrix in a clustering method. In addition, our model makes it possible to simultaneously predict age and gender of observed facial image. The next subsection will support this claim.

### 3.2 Video-Based Age and Gender Recognition

In this subsection we compare our model with publicly available CNNs for age/gender prediction:

1. Age\_net/gender\_net [25] trained on the Adience dataset [5]
2. Deep expectation (DEX) VGG16 network trained on rather large IMDB-Wiki dataset [6]

In addition, we examined two special cases of the MobileNet-based model (Fig. 1). Firstly, we compressed our model by using standard Tensorflow quantization graph transforms. Secondly, we fine-tuned all layers in our model for age and gender predictions. Though such tuning obviously reduce the accuracy
of face identification with identity features at the output of the base MobileNet, it caused an increase of validation accuracy on 1% and 2% for gender and age classification, respectively. We run the experiments on the MacBook 2016 Pro laptop (CPU: 4xCore i7 2.2 GHz, RAM: 16 GB) and two mobile phones, namely: 1) Honor 6C Pro (CPU: MT6750 4x1 GHz and 4x2.5 GHz, RAM: 3 GB); and 3) Samsung S9+ (CPU: 4x2.7 GHz Mongoose M3 and 4x1.8 GHz Cortex-A55, RAM: 6 GB). The size of the model file and average inference time for one facial image are presented in Table 4.

| CNN                      | Model size, Average CPU inference time, s. | Laptop | Mobile phone 1 | Mobile phone 2 |
|--------------------------|---------------------------------------------|--------|----------------|----------------|
| age_net/gender_net       | 43.75                                       | 0.091  | 1.082          | 0.224          |
| DEX                      | 513.82                                      | 0.21   | 2.730          | 0.745          |
| Our MobileNet            | 13.48                                       | 0.021  | 0.354          | 0.069          |
| Our MobileNet, quantized | 3.41                                        | 0.019  | 0.388          | 0.061          |

As expected, the MobileNets are several times faster than the deeper convolutional networks and require less memory to store their weights. Though the quantization reduces the model size in 4 times, it does not decrease the inference time. Finally, though the computing time for the laptop is significantly lower when compared to the inference on mobile phones, their modern models (“Mobile phone 2”) became all the more suitable for offline image recognition. In fact, our model requires only 60 ms to extract facial identity features and predict both age and gender, which makes it possible to run complex analytics of facial albums on device.

In the next experiments we compare the accuracy of our models in gender recognition and age prediction. The following video datasets have been used:

- Eurecom Kinect [26], which contains 9 photos for each of 52 subjects (14 women and 38 men).
- Indian Movie Face database (IMFDB) [27] with 332 video clips of 63 males and 33 females. Only four age categories are available: “Child” (0-15 years old), “Young” (16-35), “Middle: (36-60) and “Old” (60+).
- Acted Facial Expressions in the Wild (AFEW) from the EmotiW 2018 (Emotions recognition in the wild) audio-video emotional sub-challenge [28]. It contains 1165 video files. We detected the facial regions with the MTCNN [14].
- IARPA Janus Benchmark A (IJB-A) [29] with more than 13000 total frames of 1165 video tracks. Only gender information is available in this dataset.

In video-based gender recognition we firstly classify gender of each video frame. After that we utilize two simple fusion strategies, namely, simple voting and the product rule (1). The obtained accuracies are shown in Table 5.
Firstly, our models are much more accurate than the publicly available CNNs. It can be explained by the pretraining of the base MobileNet on face identification task with very large dataset, which helps to learn rather good facial representations. Secondly, the usage of product rule generally leads to 1-2% decrease of the error rate when compared to the simple voting. Thirdly, the fine-tuned version of our model achieves the lowest error rate only for the Kinect dataset and is 1-3% less accurate in other cases. Finally, though the compression of the CNN makes it possible to drastically reduce the model size (Table 4), it is characterized by up to 7% decrease of the recognition rate.

In the last experiment we present our results for age predictions (Table 6).

### Table 5. Gender Recognition Accuracy

| CNN          | Aggregation     | Eurecom | Kinect | IMFDB | AFEW | IJB-A |
|--------------|-----------------|---------|--------|-------|------|-------|
| gender_net   | Simple Voting   | 0.73    | 0.71   | 0.75  | 0.60 |
|              | Product rule    | 0.77    | 0.75   | 0.75  | 0.59 |
| DEX          | Simple Voting   | 0.84    | 0.81   | 0.80  | 0.81 |
|              | Product rule    | 0.84    | 0.88   | 0.81  | 0.82 |
| Our MobileNet| Simple Voting   | 0.94    | 0.98   | 0.93  | 0.95 |
|              | Product rule    | 0.93    | 0.99   | 0.93  | 0.96 |
| Our MobileNet| Simple Voting   | 0.88    | 0.96   | 0.92  | 0.93 |
| quantized    | Product rule    | 0.86    | 0.96   | 0.93  | 0.94 |
| Our MobileNet| Simple Voting   | 0.93    | 0.95   | 0.91  | 0.94 |
| fine-tuned   | Product rule    | 0.95    | 0.97   | 0.92  | 0.95 |

### Table 6. Age Prediction Accuracy

| CNN            | Aggregation     | Eurecom | Kinect | IMFDB | AFEW |
|----------------|-----------------|---------|--------|-------|------|
| age_net        | Simple Voting   | 0.41    | 0.68   | 0.27  |
|                | Product Rule    | 0.45    | 0.48   | 0.27  |
|                | Expected Value  | 0.69    | 0.32   | 0.30  |
| DEX            | Simple Voting   | 0.60    | 0.29   | 0.47  |
|                | Product Rule    | 0.71    | 0.29   | 0.48  |
|                | Expected Value  | 0.71    | 0.54   | 0.52  |
| Our MobileNet  | Simple Voting   | 0.92    | 0.32   | 0.46  |
|                | Product Rule    | 0.94    | 0.36   | 0.46  |
|                | Expected Value  | 0.94    | 0.77   | 0.54  |
| Our MobileNet, | Simple Voting   | 0.86    | 0.34   | 0.44  |
| quantized      | Product Rule    | 0.88    | 0.36   | 0.46  |
|                | Expected Value  | 0.85    | 0.58   | 0.50  |
| Our MobileNet, | Simple Voting   | 0.74    | 0.33   | 0.45  |
| fine-tuned     | Product Rule    | 0.77    | 0.35   | 0.45  |
|                | Expected Value  | 0.92    | 0.72   | 0.51  |
Here we assumed that age is recognized correctly for the Kinect and AFEW datasets (with known age) if the difference between real and predicted age is not greater than 5 years. The fusion of age predictions of individual video frames is implemented by: 1) simple voting, 2) maximizing the product of age posterior probabilities \((1)\), and 3) averaging the expected value \((3)\) with choice of \(L = 3\) top predictions in each frame.

One can notice that our models are again the most accurate in practically all cases. The DEX models are comparable with our CNNs only for the AFEW dataset. The lowest error rates are obtained for the computation of the expected value of age predictions. For example, it is 2% and 8% more accurate than the simple voting for the Kinect and AFEW data. The effect is especially clear for the IMFDB images, in which the expected value leads to up to 45% higher recognition rate.

4 Conclusions

In this paper we proposed an approach to organizing photo and video albums (Fig. 2) based on a simple extension of MobileNet (Fig. 1), in which we extract facial representations suitable for face identification, age and gender recognition problems. The main advantage of our model is the possibility to solve all three tasks simultaneously without need for additional CNNs. As a result, we implemented a very fast facial analytic system, which can be installed even on mobile devices (Table 4). It was shown that our approach extracts facial clusters rather accurately when compared to the known models (Table 1 and Table 2). Moreover, we slightly improved the known state-of-the-art BCubed F-measure for very complex GFW data (Table 3). What is more important, the accuracy of age recognition and gender predictions using extracted facial representations significantly outperforms the results of the publicly available neural networks (Table 5 and Table 6).

In future works it is necessary to deal with the aging problem. In fact, the average linkage clustering usually produces several groups for the same person (especially, a child). The single linkage clustering can resolve this issue if there exist photos of the same subject made over the years. Unfortunately, the performance of the single linkage is rather poor when compared to another agglomerative clustering methods (Table 1, Table 2 and Table 3). An additional research direction is a thorough analysis of distance measures in the facial clustering [20], i.e., the usage of distance learning [30] or special regularizers [10]. Finally, it is necessary to examine more complex aggregation techniques, i.e., learnable pooling [31] or special implementation of attention mechanism [32] in order to improve the quality of decision-making based on all facial images in a cluster.

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