FACEHop: A Light-Weight Low-Resolution Face Gender Classification Method

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ABSTRACT

A light-weight low-resolution face gender classification method, called FaceHop, is proposed in this research. We have witnessed a rapid progress in face gender classification accuracy due to the adoption of deep learning (DL) technology. Yet, DL-based systems are not suitable for resource-constrained environments with limited networking and computing. FaceHop offers an interpretable non-parametric machine learning solution. It has desired characteristics such as a small model size, a small training data amount, low training complexity, and low resolution input images. FaceHop is developed with the successive subspace learning (SSL) principle and built upon the foundation of PixelHop++. The effectiveness of the FaceHop method is demonstrated by experiments. For gray-scale face images of resolution $32 \times 32$ in the LFW and the CMU Multi-PIE datasets, FaceHop achieves correct gender classification rates of 94.63% and 95.12% with model sizes of 16.9K and 17.6K parameters, respectively. It outperforms LeNet-5 in classification accuracy while LeNet-5 has a model size of 75.8K parameters.

1 Introduction

Face attributes classification is an important topic in biometrics. The ancillary information of faces such as gender, age and ethnicity is referred to as soft biometrics in forensics [1][2][3]. The face gender classification problem has been extensively studied for more than two decades. Before the resurgence of deep neural networks (DNNs) around 7-8 years ago, the problem was treated using the standard pattern recognition paradigm. It consists of two cascaded modules: 1) unsupervised feature extraction and 2) supervised classification via common machine learning tools such as support vector machine (SVM) and random forest (RF) classifiers.

We have seen a fast progress on this topic due to the application of deep learning (DL) technology in recent years. Generally speaking, cloud-based face verification, recognition and attributes classification technologies have become mature, and they have been used in many real world biometric systems. Convolution neural networks (CNNs) offer high performance accuracy. Yet, they rely on large learning models consisting of several hundreds of thousands or even millions of model parameters. The superior performance is contributed by factors such as higher input image resolutions, more and more training images and abundant computational/memory resources.

Edge/mobile computing in a resource-constrained environment cannot meet the above-mentioned conditions. The technology of our interest finds applications in rescue missions and/or field operational settings in remote locations. The accompanying face inference tasks are expected to execute inside a poor computing and communication infrastructure.
It is essential to have a smaller learning model size, lower training and inference complexity, and lower input image resolution. The last requirement arises from the need to image individuals at farther standoff distances, which results in faces with fewer pixels.

In this work, we propose a new interpretable non-parametric machine learning solution called the FaceHop method. FaceHop has quite a few desired characteristics, including a small model size, a small training data amount, low training complexity, and low resolution input images. FaceHop follows the traditional pattern recognition paradigm that decouples the feature extraction module from the decision module. However, FaceHop automatically extracts statistical features instead of handcrafted features. It is developed with the successive subspace learning (SSL) principle \cite{4,5,6} and built upon the foundation of the PixelHop++ system \cite{7}.

The effectiveness of the FaceHop method is demonstrated by experiments on two benchmarking datasets. For gray-scale face images of resolution $32 \times 32$ obtained from the LFW and the CMU Multi-PIE datasets, FaceHop achieves correct gender classification rates of 94.63\% and 95.12\% with model sizes of 16.9K and 17.6K parameters, respectively. FaceHop outperforms LeNet-5 in classification accuracy while the model size of LeNet-5 is significantly larger, which contains 75.8K parameters.

There are three main contributions of this work. First, it offers a practical solution to the challenging face biometrics problem in a resource-constrained environment. Second, it is the first effort that applies SSL to face gender classification and demonstrates its superior performance. Third, FaceHop is fully interpretable, non-parametric, and non-DL-based. It offers a brand new path for research and development in biometrics.

The rest of this paper is organized as follows. Related work is reviewed in Sec. 2. The FaceHop method is presented in Sec. 3. Experimental set-up and results are detailed in Sec. 4. Finally, concluding remarks and future extensions are given in Sec. 5.

2 Related Work

Face gender classification is a well-studied problem for more than two decades. We review previous work that is most related to our work below.

2.1 Face Attributes Classification

We can classify face attributes classification research into two categories: non-DL-based and DL-based. DL-based solutions construct an end-to-end parametric model (i.e. a network), define a cost function, and train the network to minimize the cost function with labeled face gender images. The contribution typically arises from a novel network design. Non-DL-based solutions follow the pattern recognition paradigm and their contributions lie in extracting new features for better performance.

**Non-DL-based Solutions.** Gutta \textit{et al.} \cite{8} proposed a face-based gender and ethnic classification method using the ensemble of Radial Basis Functions (RBF) and Decision Trees (DT). Zafeiriou \textit{et al.} \cite{9} introduced a variant of the Support Vector Machine (SVM) that optimizes the Fisher Discriminant and applied it to gender classification. Different feature extraction techniques were experimented to improve classification accuracy. A Gabor-kernel partial-least squares discrimination (GKPLSD) method for more effective feature extraction was proposed by Struc \textit{et al.} \cite{10}. Other handcrafted features were developed for face gender classification based on the local directional patterns (LDP) \cite{11} and shape from shading \cite{12}. Cao \textit{et al.} \cite{13} combined Multi-order Local Binary Patterns (MOLBP) with Localized Multi-Boost Learning (LMBL) for gender classification.

Recent research has focused more on large-scale face image datasets. Li \textit{et al.} \cite{14} proposed a novel binary code learning method for large-scale face image retrieval and facial attribute prediction. Jia \textit{et al.} \cite{15} collected a large dataset of 4 million weakly labeled face in the wild (4MWLFW). They trained the C-Pegasos classifier with Multiscale Local Binary Pattern (LBP) features using the 4MWLFW dataset and achieved the highest test accuracy on the LFW dataset for Non-DL-based methods up to now. Fusion of different feature descriptors and region of interests (ROI) were examined by Castrillón-Santana \textit{et al.} \cite{16}. Han \textit{et al.} \cite{17} made a comprehensive survey that compares the performance of human and machine on age estimation.

**DL-based Solutions.** With the rapid advancement of the DL technology, DL-based methods become increasingly popular and achieve unprecedented accuracy in face biometrics \cite{18}. Taherkhani \textit{et al.} \cite{19} proposed a deep framework which predicts facial attributes and leveraged it as a soft modality to improve face identification performance. A face image may portray a wide variety of heterogeneous and correlated attributes such as gender, age and race. Han \textit{et al.} \cite{20} investigated the heterogeneous face attribute estimation problem with a deep multi-task learning approach. Ranjan \textit{et al.} \cite{21} proposed a multi-task learning framework for joint face detection, landmark localization, pose estimation, and
gender recognition. Efforts have been made to mitigate bias in demographic classifications in \cite{22}. Also, research was conducted on the diversity \cite{23} and imbalance \cite{24} of training data, which explains the unequal gender classification performance in commercial services \cite{25}.

Antipov \emph{et al.} \cite{26} investigated the relative importance of various regions of human faces for gender and age classification by blurring different parts of the faces and observing the loss in performance. ResNet50 \cite{26}, AlexNet \cite{27}, and VGG16 \cite{18} were applied to gender classification of the LFW dataset, and decent performance was observed. However, these models have very large model sizes. Considerable amounts of computation and storage resources are required to implement these solutions.

**Light-Weight CNNs.** Light-weight networks are significantly smaller in size than regular networks while achieving comparable performance. They find applications in mobile/edge computing. One recent development is the SqueezeNet \cite{28}. It achieves comparable accuracy with the AlexNet \cite{29} but uses only 50x fewer parameters. It contains 4.8M model parameters. While the SqueezeNet greatly reduces the network size and achieves impressive performance, there is little study on the reason of its superior efficiency. Although a few architectural variants have been inspired, these follow-up papers were largely built upon ad hoc arguments and empirical evidences. In the area of face recognition, Wu \emph{et al.} \cite{30} proposed a light CNN architecture that learns a compact embedding on a large-scale face dataset with massive noisy labels. Its model contains about 4M parameters.

**Other Work.** The EGA (Ethnicity, Gender and Age) face dataset, was introduced by Riccio \emph{et al.} \cite{2}. Ethnicity and gender classifications on 3D facial data were reported by Toderici \emph{et al.} \cite{31} in the Face Recognition Grand Challenge (FRGC) \cite{32}. Video-based gender classification was studied by Hadid-Pietikainen \cite{33} and Verma \emph{et al.} \cite{34}.

2.2 Successive Subspace Learning (SSL)

Representation learning plays an important role in Many representation learning methods are built upon DL, which is a supervised approach. It is also possible to use an unsupervised approach for representation learning automatically (i.e. not handcrafted). For example, there exist correlations between image pixels and their correlations can be removed using the principal component analysis (PCA). The application of PCA to face images was introduced by Turk and Pentland \cite{35}. The method is called the “Eigenface”. One main advantage of converting face images from the spatial domain to the spectral domain is that, when face images are well aligned, the dimension of input face images can be reduced significantly and automatically. Since we attempt to find a powerful subspace for face image representation, it is a subspace learning method.

Chan \emph{et al.} \cite{36} proposed a PCANet that applies the PCA to input images in two stages. Chen \emph{et al.} \cite{37} proposed a PixelHop system that applies cascaded Saab transforms \cite{6} to input images in three stage, where the Saab transform is a variant of the PCA that adds a positive bias term to avoid the sign confusion problem \cite{4}. The main difference between Eigenface, PCANet and PixelHop++ is to conduct the PCA transform in one, two, or multiple stages. If we apply one-stage PCA, the face is a pure spatial- and spectral-domain representations before and after the transform, respectively. Since the spatial representation is local, it cannot offer the global contour and shape information easily. On the contrary, the spectral representation is global, it fails to differentiate local variations. It is desired to get multiple hybrid spatial/spectral representations. This can be achieved by multi-stage transforms. Kuo \emph{et al.} developed two multi-stage transforms, called the Saak transform \cite{38} and the Saab transform \cite{6}, respectively. Recently, the channel-wise (c/w) Saab transform was proposed in \cite{7} to enhance the efficiency of the Saab transform.

Inspired by the function of convolutional layers of CNNs \cite{6}, the PixelHop system \cite{37} and the PixelHop++ system \cite{7} were developed to serve the same function but derived based on a completely different principle. The weights of convolutional filters in CNNs are obtained by end-to-end optimization through backpropagation. In contrast, the convolutional kernels used in PixelHop and PixelHop++ are the Saab filters. They are derived by exploiting statistical
correlations of neighboring pixels. As a result, both PixelHop and PixelHop++ are fully unsupervised. Neither label nor backpropagation is needed in filter weights computation.

The PixelHop++ system [7] is an enhanced version of the PixelHop system [37]. The main difference between PixelHop and PixelHop is that the former uses the Saab transform while the latter adopts the c/w Saab transform. The c/w Saab transform requires fewer model parameters than the Saab transform since channels are decoupled in the c/w Saab transform.

3 Proposed FaceHop Method

An overview of the proposed FaceHop system is shown in Fig. 1. It consists of four modules: 1) preprocessing, 2) PixelHop++, 3) Feature extraction, and 4) Classification. Since PixelHop++ is the most unique module in our proposed solution for face gender classification, it is called the FaceHop system. The functionality of each module will be explained below in detail.

3.1 Preprocessing

Face images have to be well aligned in the preprocessing module to facilitate their processing in the following pipeline. In this work, we first use the dlib [39] tool for facial landmarks localization. Based on detected landmarks, we apply a proper 2D rotation to each face image to reduce the effect of pose variation. Then, all face images are centered and cropped to remove background. Afterwards, we apply histogram equalization to each image to reduce the effect of different illumination conditions. Finally, all images are resized to a low resolution one of 32 × 32 pixels.

3.2 PixelHop++

Both PixelHop and PixelHop++ are used to describe local neighborhoods of a pixel efficiently and successively. The size of a neighborhood is characterized by the hop number. One-hop neighborhood is the neighborhood of the smallest size. Its actual size depends on the filter size. For example, if we use a convolutional filter of size 5 × 5, then the hop-1 neighborhood is of size 5 × 5. The Saab filter weights are obtained by performing dimension reduction on the neighborhood of a target pixel using PCA. The Saab filters in PixelHop and PixelHop++ serve as an equivalent role of convolutional filters in CNNs. For example, a neighborhood of size 5 × 5 has a dimension of 25 in the spatial domain. We can use the Saab transform to reduce its original dimension to a significantly lower one. We should mention that the neighborhood concept is analogous to the receptive field of a certain layer of CNNs. As we go to deeper layers, the receptive field becomes larger in CNNs. In the SSL context, we say that the neighborhood size becomes larger as the hop number increases.

The proposed 3-hop PixelHop++ system is shown in Fig. 2, which is a slight modification of [7] so as to tailor to our problem. The input is a gray-scale face image of size 32 × 32. Each hop consists of a PixelHop++ unit followed by a (2 × 2)-to-(1 × 1) max-pooling operation. A PixelHop++ system has three ingredients: 1) successive neighborhood construction, 2) channel-wise Saab transform, and 3) tree-decomposed feature representation. They are elaborated below.

1) Successive neighborhood construction. We need to specify two parameters to build the neighborhood of the center pixel at each hop. There are the window-size and the stride. We use a window size of 5 × 5 and stride of 1 in all three hops in Fig. 2. The neighborhood size grows bigger as the hop number becomes larger due to the max pooling operation. The first, second and third hops characterize the information of the short-, mid-, and long-range neighborhoods of the center pixel. Apparently, each neighborhood has a degree of freedom of 25 in the spatial domain. By collecting these neighborhood samples from different spatial locations, we can study their statistical correlations via a covariance matrix of dimension 25 × 25. Then, we conduct the eigenvector/eigenvalue analysis to the covariance matrix to find a more economical representation. That is, we can convert pixel values from the spatial domain to the spectral domain, which leads to the PCA transform, for dimension reduction.

2) Channel-wise (c/w) Saab transform. The PCA transform has both positive and negative responses. We encounter a sign-confusion problem [4] when a convolutional operation in the (i + 1)th stage has the sum of two terms: 1) a positive response in the ith stage multiplied by a positive outgoing link and 2) a negative response in the ith stage multiplied by a negative outgoing link. Both terms contribute positive values to the output while their input patterns are out of phase. Similarly, there will be another sign confusion when the convolutional operation in the (i + 1)th stage has the sum of a positive response multiplied by a negative filter weight as well as a negative response multiplied by a positive filter weight. They both contribute to negative values.
To resolve such confusion cases, a constant bias term is added to make all responses positive. This is called the Saab (subspace approximation via adjusted bias) transform [6]. Typically, the input of the next PixelHop unit is a 3D tensor of dimension $N_x \times N_y \times k$, where $N_x = N_y = 5$ are spatial dimensions of a filter and $k$ is the number of kept spectral components. The Saab transform is used in PixelHop.

Since channel responses can be decorrelated by the eigen analysis, we are able to treat each channel individually. This results in channel-wise (c/w) Saab transform [7]. The main difference between the standard Saab and the c/w Saab transforms is that one 3D tensor of dimension $N_x \times N_y \times k$ can be decomposed into $k$ 2D tensors of dimension $N_x \times N_y$ in the latter. Furthermore, responses in higher frequency channels are spatially uncorrelated so that they do not have to go to the next hop. The c/w Saab transform is used in PixelHop++. It can reduce the model size significantly as compared with the Saab transform while preserving the same performance.

3) Tree-decomposed representation. Without loss of generality, we use the first hop to explain the c/w Saab transform design. The neighborhood of a center pixel contains 25 pixels. In the spectral domain, we first decompose it into the direct sum of two orthogonal subspaces - the DC (direct current) subspace and the AC (alternating current) subspace. Then, we apply the PCA to the AC subspace to derive Saab filters. After the first-stage Saab transform, we obtain one DC coefficient and 24 AC coefficients in a grid of size $28 \times 28$. We classify AC coefficients into three groups based on their associated eigenvalues: low-, mid-, and high-frequency AC coefficients.

When the eigenvalues are extremely small, we can discard responses in these channels without affecting the quality of the input face image. This is similar to the eigen-face approach in spirit. For mid-frequency AC coefficients, the spatial correlation of their responses is too weak to offer a significant response in hop-2. Thus, we can terminate its further transform. For low-frequency AC coefficients, the spatial correlation of their responses is strong enough to offer a significant response in hop-2. Then, we conduct max-pooling and construct the hop-2 neighborhood of these frequency channels in a grid of size $14 \times 14$. It is easy to show these hop-by-hop operations using a tree. Then, each channel corresponds to a node. We use the green, yellow and pink colors to denote low-, mid- and high-frequency AC channels in Fig. 2 where the DC channel is also colored in green. They are called the intermediate, leaf, and discard nodes in a hierarchical tree of depth equal to three.

To determine which node belongs to which group, we use the energy of each node as the criterion. The energy of the root node is normalized to one. The energy of each node in the tree can be computed and normalized against the energy value of the root node. Then, we can choose two thresholds (in terms of energy percentages) at each hop to partition nodes into three types. These energy thresholds are hyperparameters of the PixelHop++ model.
Figure 3: Collection of regional responses in hop-1 and hop-2 response maps as features in the FaceHop system: (a) four regions in hop-1 and (b) three regions in hop-2.

3.3 Feature Extraction

Responses at each of the three hops of the FaceHop system have different characteristics. As shown in Fig. 2, Hop-1 has a response map of size $28 \times 28$, Hop-2 has a response map of size $10 \times 10$ and Hop-3 has a response map of size $1 \times 1$. Hop-1 responses give a spatially detailed representation of the input. Yet, it is difficult for them to offer regional and full views of the entire face unless the dimension of hop-1 responses becomes extremely large. This is expensive and unnecessary. Hop-2 responses give a coarser view of the entire face so that a small set of them can cover a larger spatial region. Yet, they do not have face details as given by Hop-1 responses. Finally, Hop-3 responses lose all spatial details but provide a single value at each frequency channel that covers the full face. The eigenface approach can only capture responses of the full face and cannot obtain the information offered by hop-1 and hop-2 responses in the FaceHop system. We will extract features based on responses in all three hops.

We group pixel responses in hop-1 and hop-2 to form region responses as shown in Fig. 3.

- **Hop-1.** We collect pixel responses in hop-1 to form four regions as shown in Fig. 3(a). They cover the left eye, the right eye, the nose and the mouth regions. Their spatial dimensions (height versus width) are $10 \times 12$, $10 \times 12$, $12 \times 10$ and $8 \times 18$, respectively. There are spatial correlations for responses of the same channel. Thus, we can apply another PCA to responses of the same hop/region for dimension reduction. Usually, we can reduce the dimension to the range between 15 and 20. Afterwards, we concatenate the reduced dimension vector of each region across all hop-1 channels (including both leaf and intermediate nodes) to create a hop/region feature vector and feed it to a classifier. There are four hop-1 regions, and we have four feature vectors that contain both spatial and spectral information of a face image. The dimension of hop-1 feature vectors in four regions will be given in Table 3.

- **Hop-2.** We collect pixel responses in hop-2 to form three regions as shown in Fig. 3(b). They are: one horizontal stripe of dimension $3 \times 10$ covering two eyes, another horizontal stripe of dimension $4 \times 10$ covering the mouth and one vertical stripe of dimension $10 \times 4$ covering the nose as well as the central 40% region. Similarly, we can perform dimension reduction via PCA and concatenate the spatially reduced dimension of each region across all hop-2 channels to train three classifiers. The dimension of hop-2 feature vectors in three regions will be summarized in Table 3.

- **Hop-3.** We use all responses of hop-3 as one feature vector to train a classifier.

It is worthwhile to point out that, although some information of intermediate nodes will be forwarded to the next hop, different hops capture different information contents due to varying spatial resolutions. For this reason, we include responses in both intermediate and leaf nodes at hop-1 and hop-2 as features.
3.4 Classifiers

As described in Sec. 3.3, we train four classifiers in hop 1, another three classifiers in hop 2, and one classifier in hop 3. Each classifier is a binary classifier. It takes a long feature vector as the input and makes a soft decision, which is the probability for the face to be a male or a female. Since the two probabilities add to unity, we only need to record one of them. Then, at the next stage, we feed these eight probabilities into a meta classifier for final decision. The choice of classifiers can be the random forest (RF), the support vector machine (SVM), and the logistic regression (LR). Although the SVM and the RF classifiers often give higher accuracy, they have a larger number of model parameters. Since our interest lies in a smaller model size, we adopt the LR classifier in our experiments only.

4 Experiments

In this section, we evaluate the proposed FaceHop gender classification method. We compare the FaceHop solution with a variant of LeNet-5 in model sizes and verification performance. The reason of choosing the LeNet-5 for performance benchmarking is because of its small model size and good testing accuracy. The neuron numbers of the modified LeNet-5 model are changed to 16 (1st Conv), 40 (2nd Conv), 140 (1st FC), 60 (2nd FC) and 2 (output). The modification is needed since human faces are more complicated than handwritten digits in the MNIST dataset. We use only logistic regression (LR) classifiers in FaceHop due to its small model size.

Datasets. We adopt the following two face image datasets in our experiments.

- **LFW dataset** [40]
  The LFW dataset consists of 13,233 face images of 5,749 individuals, which were collected from the web. There are 1,680 individuals who have two or more images. LFW3D [41], which is the 3D aligned version of LFW, is used in our experiments.

- **CMU Multi-PIE dataset** [42]
  The CMU Multi-PIE face dataset contains more than 750,000 images of 337 subjects recorded in four sessions. We select a subset of the 01 session that contains frontal and slightly non-frontal face images (camera views 05_0, 05_1, and 14_0) with all the available expressions and illumination conditions in our experiments.

Data Augmentation. Since both datasets have significantly fewer female images, we use two techniques to increase the number of female faces.

- Flipping the face images horizontally.
- Averaging a female face image with its nearest neighbor in the reduced dimension space to generate a new female face image. To find the nearest neighbor, we project all female images to a reduced dimension space, which is obtained by applying PCA and keeping the highest energy components with 90% of the total energy. Dimension reduction is conducted to eliminate noise and high frequency components. The quality of augmented female images is checked to ensure that they are visually pleasant.

After augmentation, the number of male images are still slightly more than those of female images.

Configuration of PixelHop++. The configurations of the PixelHop++ module for LFW and CMU Multi-PIE datasets are shown in Table 1 and 2, respectively. We list the numbers of intermediate nodes, leaf nodes and discarded nodes at each hop (see Fig. 2) in the experiments. In our design, we partition channels to two groups (instead of three) only at each hop. That is, they are either discarded or all forwarded to the next hop. As a result, there are no leaf nodes at hop-1 and hop-2.

| Hop Index | Interm. Node No. | Leaf Node No. | Discarded Node No. |
|-----------|------------------|---------------|--------------------|
| Hop-1     | 18               | 0             | 7                  |
| Hop-2     | 122              | 0             | 328                |
| Hop-3     | 0                | 233           | 2,817              |

Table 1: Configurations of PixelHop++ for LFW.

Feature Vector Dimensions of Varying Hop/Region Combinations. The dimensions of feature vectors of varying hop/region combinations are summarized in Table 3. As discussed earlier, hop-1 has 4 spatial regions, hop-2 has three spatial regions and all nodes of hop-3 form one feature vector. Thus, there are eight hop/region combinations in total. Since there are spatial correlations in regions given in Fig. 3, we apply PCA to regional responses collected from all
channels and keep leading components for dimension reduction. We keep 15 components for the LFW dataset and 20 components for the CMU Multi-PIE datasets, respectively. Then, the dimension of each feature vector at hop-1 and hop-2 is the product of 15 (or 20) and the sum of intermediate and leaf nodes at the associated hop for the LFW (or CMU Multi-PIE) dataset.

| Hop/Region     | LFW | MPIE |
|---------------|-----|------|
| Hop-1 (left eye) | 270 | 360  |
| Hop-1 (right eye) | 270 | 360  |
| Hop-1 (nose)   | 270 | 360  |
| Hop-1 (mouth)   | 270 | 360  |
| Hop-2 (upper stripe) | 1,830 | 2,340 |
| Hop-2 (lower stripe) | 1,830 | 2,340 |
| Hop-2 (vertical stripe) | 1,830 | 2,340 |
| Hop-3          | 233 | 186  |

Table 3: Feature vector dimensions for LFW and CMU Multi-PIE.

Performance and Model Size Comparison for LFW. We randomly partition male and original plus augmented female images in the LFW dataset into 80% (for training) and 20% (for testing) two sets individually. Then, they are mixed again to form the desired training and testing datasets. This is done to ensure the same gender percentages in training and testing. We train eight individual hop/region LR classifiers and one meta LR classifier for ensembles. Then, we apply them to the test data to find out their performance. We repeat the same process four times to get the mean testing accuracy and the standard deviation value, and report the testing performance of each individual hop/region in Table 4.

| Classifier     | Accuracy (%) | Classifier     | Accuracy (%) |
|---------------|--------------|---------------|--------------|
| Hop-1 (left eye) | 86.70 ± 0.65 | Hop-2 (upper stripe) | 92.25 ± 0.22 |
| Hop-1 (right eye) | 86.14 ± 0.66 | Hop-2 (lower stripe) | 89.70 ± 0.73 |
| Hop-1 (nose)   | 82.90 ± 0.61 | Hop-2 (vertical stripe) | 92.42 ± 0.56 |
| Hop-1 (mouth)   | 83.42 ± 0.74 | Hop-3          | 91.22 ± 0.46 |

Table 4: Performance comparison of each individual hop/region classifier for LFW.

The mean testing accuracy ranges from 82.90% (hop-1/nose) to 92.42% (hop-2/vertical stripe). The standard deviation is relatively small. Furthermore, we see that hop-2 and hop-3 classifiers perform better than hop-1 classifiers. Based on this observation, we consider two ensemble methods. In the first scheme, called FaceHop I, we fuse soft decisions of all eight hop/region classifiers with a meta classifier. In the second scheme, called FaceHop II, we only fuse soft decisions of four hop/region classifiers from hop-2 and hop-3 only. The testing accuracy and the model sizes of LeNet-5, FaceHop I and FaceHop II are compared in Table 5. FaceHop I and FaceHop II outperform LeNet-5 in terms of classification accuracy by 1.49% and 1.65%, respectively, where their model sizes are only about 33.7% and 22.2% of LeNet-5. Clearly, FaceHop II is the favored choice among the three for its highest testing accuracy and smallest model size.

Performance and Model Size Comparison for CMU Multi-PIE. Next, we show the classification accuracy of each individual hop/region classifier for the CMU Multi-PIE dataset in Table 6. Their accuracy values range from 63.02% (hop-1/mouth) to 91.95% (hop-2/upper stripe). It appears that CMU Multi-PIE is more challenging than LFW if we focus on the performance of each individual classifier by comparing Tables 4 and 6.

We consider two ensemble schemes as done before. FaceHop I uses all eight soft decisions while FaceHop II takes only four soft decisions from hop-2 and hop-3. The mean accuracy performance of LeNet-5, FaceHop I and FaceHop II is compared in Table 7. It is interesting to see that FaceHop I and II have slightly better ensemble results of CMU Multi-PIE than of LFW, respectively. The performance of LeNet-5 also increases from 92.98% (LFW) to 95.08% (CMU Multi-PIE). As far as the model size is concerned, the model sizes of FaceHop I and FaceHop II are about 38.4% and 23.2% of LeNet-5, respectively. Again, FaceHop II is the most favored solution among the three for its highest testing accuracy and smallest model size.
| Method                        | Accuracy (%) | Model Size |
|-------------------------------|--------------|------------|
| LeNet-5                       | 92.98        | 75,846     |
| FaceHop I (all three hops)    | 94.47 ± 0.54 | 25,543     |
| FaceHop II (hop-2 & hop-3 only) | 94.63 ± 0.47 | 16,895     |

Table 5: Performance comparison of LeNet-5, FaceHop I and FaceHop II in accuracy rates and model sizes for LFW.

| Classifier          | Accuracy (%)        | Classifier          | Accuracy (%)        |
|---------------------|---------------------|---------------------|---------------------|
| Hop-1 (left eye)    | 79.33 ± 0.33        | Hop-2 (upper stripe)| 91.95 ± 0.18        |
| Hop-1 (right eye)   | 78.64 ± 0.25        | Hop-2 (lower stripe)| 87.00 ± 0.15        |
| Hop-1 (nose)        | 65.19 ± 0.36        | Hop-2 (vertical strip) | 91.34 ± 0.22      |
| Hop-1 (mouth)       | 63.02 ± 0.41        | Hop-3               | 84.55 ± 0.77        |

Table 6: Performance comparison of each individual hop/region classifier for CMU Multi-PIE.

| Method                            | Accuracy (%) | Model Size |
|-----------------------------------|--------------|------------|
| LeNet-5                           | 95.08        | 75,846     |
| FaceHop I (all three hops)        | 95.09 ± 0.24 | 29,156     |
| FaceHop II (hop-2 and hop-3 only) | 95.12 ± 0.26 | 17,628     |

Table 7: Performance comparison of LeNet-5, FaceHop I and FaceHop II in accuracy rates and model sizes for CMU Multi-PIE.

5 Conclusion and Future Work

A light-weight low-resolution face gender classification method, called FaceHop, was proposed. This solution finds applications in resource-constrained environments with limited networking and computing. Built upon the successive subspace learning (SSL) principle, FaceHop provides an interpretable non-parametric machine learning model. It has several desired characteristics, including a small model size, a small training data amount, low training complexity and low resolution input images. The effectiveness of the FaceHop method method for the face gender classification problem was demonstrated by experiments on several benchmarking datasets.

As to future work, we would like to extend the SSL principle and develop methods in identifying heterogeneous and correlated face attributes such as gender, age, and race. It is particularly interesting to develop a multi-task learning approach. Furthermore, it will be desired to work on high-resolution face images and see whether we can get significant performance improvement using the SSL principle in classification accuracy, computational complexity, and memory usage.

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