Deep Learning based Detection of Hair Loss Levels from Facial Images

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Abstract— **Hair loss is a phenomenon known to affect people's morale and self-confidence. Often, the awareness of the phenomenon and the possibilities of treatment is late. This paper investigates deep learning methods for detecting hairs loss levels by men from face images. In this context, a specific training dataset has been prepared with face images having varied levels of baldness. Moreover, in spite of the low visibility of hairs in such images, a matching method is proposed for automatically classifying facial images with respect to pattern classification tables of male baldness from the medical area. Experimental results show the potential and the efficiency for medical, security and commercial applications.**

Keywords— **Patterned baldness classification, Hair loss diagnosis, Alopecia, Facial analysis, Deep learning.**

I. Introduction

Patterned Baldness (PB) refers to hair loss at the level of the head. The primary cause of PB is a hereditary excess of a male hormone known as androgenic alopecia. However, other factors may cause hair loss such as a permanent stress, an unbalanced diet or even a shampoo which is aggressive for the scalp. The PB generally starts in the front of the head and gradually evolves until reaching the vertex. The Hamilton-Norwood scale is one of the methods that is widely used to classify the severity of PB [1]. As illustrated in Figure 1, seven types of PB are represented for men from the least suffering to the very suffering. Each type is depicted by a lateral view of the face as well as a top view of the head. These types are as follows:

- Level 1: no problem of PB.
- Level 2: a PB starts to appear on the frontal part of the scalp.
- Level 3: temples are deepening.
- Level 4: the PB reaches the vertex.
- Level 5: the PB is clearly installed and there are more zones without hair than zones with hair.
- Level 6: the vertex is completely smooth and only the sides of the head have hairs.
- Level 7: the PB is definitely installed and there is almost no hair on the head except on the low crowns.

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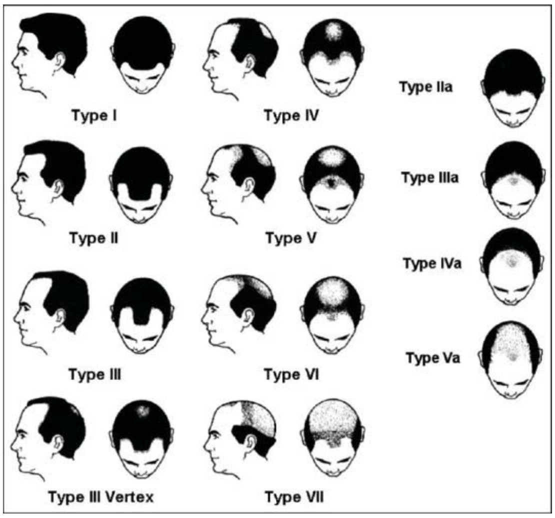

Fig. 1: Hamilton-Norwood scale for classifying patterned baldness. Image taken from [1].

It is worth mentioning that the treatment of the PB varies according to its level [2]. More specifically, it is suggested that level 2 corresponds to the one where it is possible to use medicines in order to stop the progression of the PB. Starting from level 5, two solutions are discussed; namely hair transplantation surgery which is an expensive operation or wearing a wig. In [3], a binary classification method is presented for early diagnosis of Alopecia (affected or not). Machine learning-based analysis were operated by considering a dataset of 4 physical attributes coming from 100 patients.

In this context, vision-based system for PB analysis could also be developed to raise men awareness on baldness treatments. Moreover, such a system can be useful for different types of applications. We hereafter summarize some of them and we classify them by category.

a) Medical applications: the system can be embedded into smart devices that are equipped with cameras such as a smartphone or a smart mirror at home [4]. In this case, the user can be alerted at the early stage of his PB and refereed to a specialist doctor. It can also be exploited by the specialist doctor as a medical measuring instrument for studying the efficiency of treatments on his patients and obtaining detailed statistics.

b) Security applications: in the state of the art many works have been developed to propose automatic tools for searching people (suspect or missing person) in video surveillance environments [5], [6], [7]. Proposed methods generally translate an eyewitness description into a set of attributes (clothes, glasses, size, etc.) to eventually localize the person in zones covered by cameras. In this context, a PB level recognition system can be exploited as an additional attribute to refine the search. It can also be exploited in tracking applications [8] where the goal is to trace the path of an individual in a multi-camera network system.

c) Commercial applications: the system can be exploited in shopping centers to propose to customers products that can be adapted to their PB (e.g. a wig, hat or medicines). It can also be used jointly with existing tools of counting people in crowd scenes [9] for collecting refined statistics such as the proportion of people that suffers of baldness.

In this paper, our goal is to show the feasibility for automatically recognizing levels of patterned baldness from frontal facial images using deep learning methods. In this work, hair loss of men is primary considered for various reasons; namely, i) the visibility on their baldness is often higher than for women, ii) the ratio of affected men is high, iii) the detection of hair loss levels from frontal face pictures seems perceptible for men but particularly difficult for women. Nevertheless, hair loss is also studied for women through computer aided imaging systems [10].

Another contribution of this paper is a dataset of facial images that we manually annotated into different levels of PB in accordance with Hamilton-Norwood patterns. Precisely, four dominant classification categories have been derived from the Hamilton-Norwood table in such a way to only keep classes that could be recognized from facial images. To the best of our knowledge, no such study on hair loss level detection has been addressed using deep learning methodology with facial images. The remaining of the paper is organized as follows. The next section gives an overview of related works. Section 3 presents some investigated deep learning architectures. Section 4 shows a set of experiments to evaluate the performance of the considered architectures and section 5 concludes the paper.

II. Related work

There exist very little work in the state of the art carrying out on the problem of patterned baldness analysis using vision-based methods. In fact, we have found only one work proposed by Lee and Yang [11] that deals with this problem. More specifically, authors proposed a semi automatic method of PB analysis from head images captured using a webcam. Because the webcam covers all the background of the scene, a user intervention is needed to crop the captured image in such a way to delimit the head zone. A clustering algorithm is then applied to quantify hair zones and none hair zones. Finally, the decision on the PB level is taken by calculating a distance between the output of the clustering step and a table of predefined synthesized head images representing the Hamilton-Norwood scale. The synthesized head image that gives the smallest distance corresponds to the identified PB level. The authors reported that the performance of the method is not high when considering only the first smallest distance. In our work, the method takes as an input facial images instead of top view of head images. Indeed, we consider that it is more comfortable for the user to capture his face than his head. Moreover, our method is fully automatic in the sense that there is no need of user intervention to delimit the face. This latter problem has been widely studied by the computer vision community and existing face detection algorithms are very efficient [12], [13]. In addition and contrary to the method proposed by Lee and Yang [11], our method exploits the power of deep learning to train a multi-class classifier.

While a very few work have been done on patterned baldness analysis problem, many works have already been conducted by the computer vision community on hair analysis [14], [15], [16]. Indeed, the hair is considered as a prominent attribute for characterizing a face and psychological studies [17] revealed the major role that hair plays in face perception and recognition. The state of the art works conducted on hair analysis using vision based systems can be declined in two main specific tasks: i) hairstyle and hair color recognition [18], [19], [20], and ii) evaluation of the quality/condition of the hair and/or scalp [21], [22], [23]. In what follows, we describe some of the most recent works proposed by the computer vision community on automatic hair analysis and associated applications.

Muhammad et al. [24] proposed an automatic method for hairstyle analysis from 2D head images. To this end, the authors proposed a workflow that goes through three main steps: global hair detection, precise hair segmentation and hairstyle classification in seven classes. They exploited for each step a machine learning method to train a classifier on texture-based features. The final choice of the machine learning methods together with the features has been done empirically. For the first and last steps they used a random forest classifier fed with CNN features while for the second step they used an SVM classifier fed with local binary pattern features. For testing the method, the authors created a public database of 1050 annotated images. They showed that the performance obtained by their analysis method notably the hairstyle classification outperforms those of existing methods.

Ileni et al. [25] proposed a method for hair color classification in facial images. As raised by the authors their work aims to facilitate the development of applications related to visagisme [1]. The authors method begins by segmenting the hair in the image then proceeds to its color classification. For the segmentation step, authors used a variant of the U-Net convolutional network architecture [26]. The architecture is exploited to detect hair pixels (binary classification problem on each pixel of the image) and the output is smoothed with a post-processing step based on flood-fill operation. For the hair color classification step, authors proposed to create a feature vector corresponding to a color histogram of pixels detected as hair in previous step and feed it to a neural network to classify the color of the hair into one of the five predefined classes. According to the authors, the proposed method gave an accuracy of 89.6%.

Kim et al. [27] proposed a system for hair and scalp condition analysis in order to prevent hair loss. To this end, authors proposed a method to extract automatically three key features from scalp microscopic images namely blotch area, thickness and hair count. To extract these characteristics, the scalp image undergoes a pre-processing pipeline including cropping to focus on the center of the image, stretching contrast to distinguish hair from scalp, morphological opening to attenuate the light reflection of the microscopy camera and finally the binarization to denote hair pixels as 0 and scalp pixels as 1. For blotch area detection the quantity of red is measured on the scalp regions. The regions where the red color exceeds a threshold are detected as blotch. For hair counting a Canny edge detector [28] is applied to detect contours. For hair thickness, a principal component analysis algorithm [29] is applied to calculate the hair direction. After that the thickness is determined from the distance between perpendicular lines to hair direction and hair boundaries. Authors proposed their own scalp image dataset to evaluate the performance of their method and reported an accuracy of more than 90% for the extraction of the three features.

III. Applied Methodology

Exploiting deep learning methods has become an obvious choice for a wide range of applications [30]. Moreover, in the field of imagery, CNNs have shown high performance in multiple fundamental tasks including object segmentation [31], classification [32] and retrieval [33]. A key strength of this type of methods is the ability of the convolutional neural network to efficiently learn, through multiple layers, convolution filters and adjustable weights the semantic representation of the image by identifying its most significant characteristics.

In this context, we have investigated three different convolutional neural networks namely Kaggle, DEX-IMDB-WIKI and DEX-ChaLearn Networks with facial images.

[1]Human appearance changing by choosing accessories that fit well with the face and its shape. This takes into consideration among other facial characteristics the texture of hair and its color.

A. Kaggle Network

This architecture is a variant of a kernel publicly proposed on the Kaggle platform [2]. More precisely, our variant is composed of nine convolution layers. For each convoloution layer we apply four successive operations namely batch normalization [34], ELU (Exponential Linear Unit function) activation [35], max-pooling and dropout [36]. We use the Adam optimization function. The numbers of feature map are $\{32, 32, 64, 64, 128, 128, 256, 256, 4\}$ with respect to the ascending order of considered convolution layers. The size of the used kernel filter is 3 except for the ninth layer where it is equal to 1. A global average pooling [37] is performed on the last convolution layer and fed into a softmax function to generate the belonging probabilities of each class. The size of the minibatches is in $\{16, 32, 64\}$.

B. DEX-IMDB-WIKI and DEX-ChaLearn Networks

We fine-tune the following two networks: DEX-IMDB-WIKI and DEX-ChaLearn-ICCV2015. For notation simplicity, we will refer to the second network by DEX-ChaLearn. The first one was trained on real age estimation using the cropped and aligned faces of the IMDB-WIKI dataset, while the second one is a fine-tuned version of the previous model, trained on apparent age using the challenge images. An ensemble of these models led to first place at the challenge (115 teams).

The Deep EXpectation (DEX) on apparent age method [38] uses the VGG-16 architecture for its networks, which are pre-trained on ImageNet for image classification. In addition, the authors explored the benefit of fine-tuning over crawled Internet face images with available age. In total, they collected more than 500,000 images of celebrities from IMDb and Wikipedia. The networks of DEX were fine-tuned on the crawled images and then on the provided images with apparent age annotations from the ChaLearn LAP 2015 challenge on apparent age estimation [39].

We fine-tune these two networks by adopting the following. We add a softmax layer for classifying the four classes. The fine-tuning was carried out using the classic softmax loss function with the Stochastic Gradient Descent paradigm. We fix the number of epochs to 10 or 20. The size of the mini-batches is in $\{8, 16, 32\}$.

IV. Experimental Study

In this section, we will first introduce the protocol we followed to build our dataset.

A. Dataset preparation

As previously mentioned, four dominant classification categories have been derived from the Hamilton-Norwood table in such a way to only keep classes that could be recognized from facial images. To this end, we exploited the Large-scale CelebFaces Attributes (CelebA) dataset [40] containing more

[2]Kaggle Network link

than 200K color images of faces with 40 attribute annotations notably a bald attribute.

Filtering stage — The dataset contains around 2% of these images that are labeled as bald and the remaining as not bald. By this way we did a preliminary filtering in order to extract these two classes. When analyzing the two classes we observed that they could be more refined by creating additional specific classes as follows:

- class 1 corresponding to type 1 from the Hamilton-Norwood table,
- class 2 corresponding to type 2, 3 and 4 from the Hamilton-Norwood table,
- class 3 corresponding to type 5, 6 and 7 from the Hamilton-Norwood table,
- class 4 corresponding to bald people which are not represented in the table.

This latter filtering has been done manually and led to the creation of our reference dataset with 225 images per class. An example of each class is depicted in Figure 2 (top row). Besides, we show in Figure 2 (bottom row) that face images of CelebA contain occlusions or deformities partially affecting the hair visibility. In the present study, no filtering of such images was done since our first objective is to evaluate the classification in the general case of facial acquisition (e.g., for crowd analysis).

(a) Class 1. (b) Class 2. (c) Class 3. (d) Class 4.

(e) Cap. (f) Arm. (g) Headphone. (h) Stretched.

Fig. 2: On the top row, sample images for classes derived from the Hamilton-Norwood table. On the bottom row, examples of image occlusions and deformities partially reducing hair visibility.

Dataset augmentation stage — To reduce overfitting during the training process we proceeded to an artificial enhancement of the dataset [41]. To this end, we applied on the images four label-preserving transformations: i) an horizontal reflection (flips), ii) a Gaussian noise, iii) a Gaussian blur and iv) the Contrast Limited Adaptive Histogram Equalization (CLAHE) [42]. An example of each applied transformation is depicted in Figure 3.

(a) Horizontal flip. (b) Gaussian noise. (c) Gaussian blur. (d) CLAHE [42].

Fig. 3: An example of image transformations applied on image of Figure (2a) for data augmentation.

B. *Performance evaluation*

To conduct our performance evaluation, we firstly prepared the training and test data. To this end, we split the reference dataset (225 images x 4 classes) into a test set composed of 50 images per class picked randomly from each class and a training set composed of the 175 remaining images for each class. This traning set is called basis. We then augmented the size and diversity of this set by applying the label-preserving transformations described above. This led to the creation of three augmented training sets as follows:

- Augmented1 using horizontal reflection + Gaussian noise resulting in 525 images per class,
- Augmented2 using Augmented1 + Gaussian blur resulting in 700 images per class,
- Augmented3 using Augmented2 + CLAHE [42] resulting in 875 images per class.

Table 1 presents a comparison for classification performance of baldness type by exploiting the three previously described CNN-based architectures. It shows the average accuracies obtained by these architectures on the test set using basis and augmented training sets. More precisely, the Kaggle-CNN, DEX-ChaLearn and DEX-IMDB-WIKI have reached **82.5%**, **84.5%** and **85.5%** of accuracy, respectively. For each architecture, we can observe that the best performances are obtained using the largest dataset, namely Augmented3. Also, we observe that the augmented data allows to increase the performance up to 6.5% in comparison with the Basis dataset. Moreover, the performance of DEX-IMDB-WIKI slightly overpasses the other ones. We emphasize that this latter architecture has firstly been pre-trained on the IMDB-WIKI dataset dedicated for age classification and then has been finely trained on our dataset. Since the IMDB-WIKI dataset was trained on a large dataset of facial images, it permitted to provide a good initialization of the architecture for further training with additional facial images from our dataset; although the targeted classification problem is different.

The histogram of Figure 4 shows in more details the accuracy values obtained by the architectures on the test set for each class using the Augmented3 training set. On the one hand, we can notice that class 1 is the easiest to predict by the architectures. Indeed, each architecture gave more than 90% of accuracy for this latter class. On the other hand, it

Data \ Network	Average accuracy (%) DEX-IMDB-WIKI	DEX-ChaLearn	Kaggle-CNN
Basis	79	79.5	82
Augmented1	82.5	83	78
Augmented2	82	84	74.5
Augmented3	**85.5**	**84.5**	**82.5**

Table 1: Comparison of average accuracies obtained on the test set classification using three CNN-based architectures over basis and augmented training sets.

seems that class 2 is the most difficult to predict since the best accuracy obtained for this class corresponds to the one of DEX-IMDB-WIKI which is equal to 76%. This performance decrease with respect to the other classes is probably due to the fact that class 2 corresponds to baldness of type 2, 3 and 4 from the Hamilton-Norwood scale representing the beginning of the hair loss phenomenon. The histogram also shows that no architecture succeeded to outperform the others over each class. Indeed, although the DEX-IMDB-WIKI reached the best average accuracy which is 85.5%, it still performs less than Kaggle-CNN and DEX-ChaLearn on class 3 and 4 respectively.

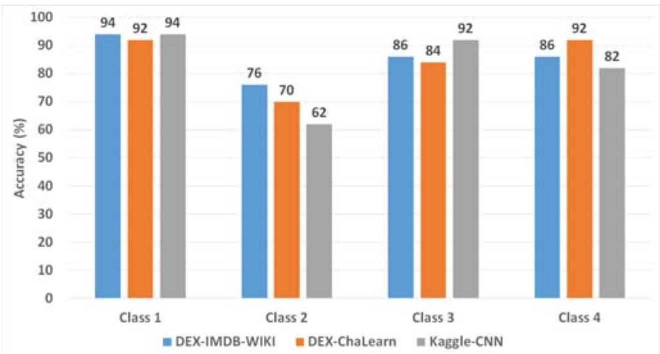

Fig. 4: Histogram of accuracies obtained on the test set for each class using the three CNN-based architectures trained from the augmented3 set.

Figure 5 presents the confusion matrix calculated from the prediction model of the DEX-IMDB-WIKI architecture together with associated recall and precision rates indicated on row 5 and column 5 respectively. In this matrix, we can observe that generally the images which are misclassified by the model are classified into adjacent classes. Only four images from the whole test set have been classified in extreme way (row 4 columns 1 and 2). The concerned images are depicted in Figure 6. They show special features in comparison with the other images from the same classes. In particular, these images show a low volume of hair with a color that is relatively close to that of the corresponding faces. This may be a reason for which the architecture classified them in class 4.

Fig. 5: Confusion matrix with recall and precision rates calculated from the prediction model of the DEX-IMDB-WIKI architecture.

(a) Class 1. (b) Class 2. (c) Class 2. (d) Class 2.

Fig. 6: An example of images classified by the DEX-IMDB-WIKI architecture in extreme way (all predicted in class 4).

V. Conclusion

The problem of hair loss classification is tackled by exploiting deep learning techniques with facial images. To this end, we stated an image-based hair loss classification according to the Hamilton-Norwood scale. In this sense a dataset has been prepared by manual annotation of facial images. To limit overfitting effects, this dataset has also been artificially augmented using different label-preserving transformations. Conducted experiments clearly show that the loss of hairs can be estimated from facial images by the way of deep learning architectures. Future works may investigate data augmentation by fined face-centered segmentation in the images (head cropping). Other investigations may be to combine the tested architectures while considering for each one of them the best predicted class.

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