Periorbital Hyperpigmentation and Puffiness Analysis on Social Media Selfies

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1 Abstract

Periorbital Hyperpigmentation(POH) and Puffiness(PP) become more and more popular among modern people, and these two symptoms are two direct reflections of stress, sleep deprivation, and some modern diseases. Therefore, the POH and PP distribution among age, gender, and race would be insightful for those who intend to analyze the sleep condition, stress degree, and etc. In this project, we have used computer vision and data mining techniques to run the POH/PP analysis on over 150,000 selfies on Twitter and Tumblr. The outcome, in a nutshell, is among 100,000 detected faces, the POH/PP population increments with age, male POH/PP population is larger than that of female, and among Asian, Black and White, the Black race has the highest POH/PP population percentage.

2 Introduction

Periorbital Hyperpigmentation can be commonly found among people nowadays. From medical perspective, the appearance of POH is related to many factors such as stress, sleep deprivation, and etc[3]. Similary, Periorbital Puffiness (PP), sometimes refers to Periorbital Oedema, also indicates health related issues. Thus, it is pragmatic to study POH and PP populations to acquire insights on the distributions of such symptoms in accordance with age, gender, and race, and apply these distributions for certain medical purposes.

To find those distributions, computer vision combined with data mining techniques were utilized. We first obtained the training faces from Color FERET databse, and applied dense sift as the feature extractor on the interest areas of each face. Then, SVM(support vector machine) was employed to classify the faces from with and without POH or PP.

Finally, over 150,000 selfie-tagged posts on Twitter and Tumblr have been analyzed, and the result will be presented in the results section.

3 Method

The primary phases of this project are illustrated below as a diagram, and the phase to phase details will be presented subsequently. Note that there are two major techniques were used to make detecting POH and PP feasible on human faces, they are dense sift feature extraction and binary SVM classification.

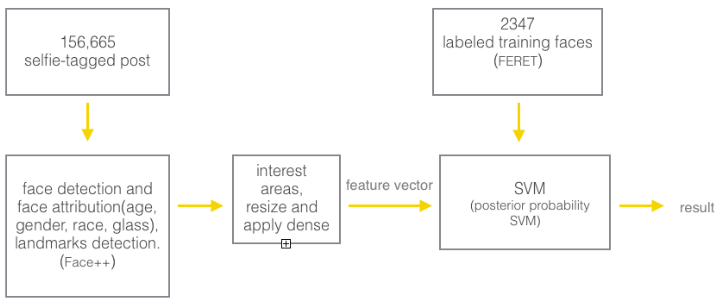


Figure 1: implementation diagram

In the phase of training data labeling, to keep the objectivity, each face is labeled by three individuals and the final label is determined via voting. The followings are several labeled samples, and positive sample indicates the face possesses either PHO or PP.

(a) positive sample

(b) negative sample

For the phase of feature extraction, with these labeled training images, we query Face++ API to obtain the facial landmarks and attributions. The landmarks are used to crop the interest areas under each eye while the attributions are used for later analysis. Note that the width of the interest area is the eye width, and the height of the interest area is set to be twice of the height of the eye. In order to keep the feature size the same for each observation, resizing is therefore applied to the interest area patches of each face. Subsequently, we run dense sift algorithm on each of those patches to form a feature vector that is a concatenation of sift features from the left and right interests area.

The diagram below illustrates this process more directly

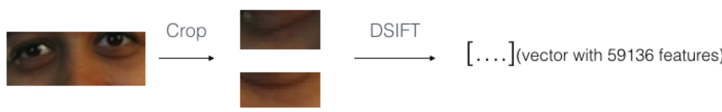
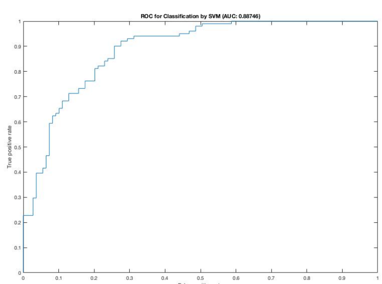
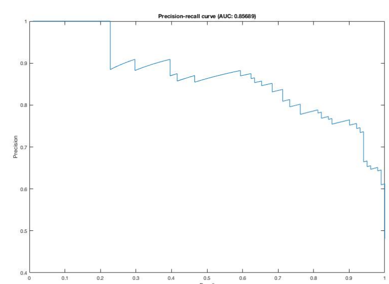


Figure 3: diagram for feature extraction

Next step is training the model, when the kernel is set to be Radial Basis Function and the misclassification penalty is set to be 10, the optimal performance was reached. The 10-fold cross validation was also carried out to test the quality of this model, the class loss(i.e the misclassification error rate) returned is 0.1802, which is fairly good. Below are the Receiver Operating Characteristic(ROC) and Precision Recall curves example of one fold from the cross-validation process. The accuracy for the ROC curve is around 89% and 86% for the PR curve.



(a) ROC



(b) PR

Moreover, in order to empower the SVM model with the capability of computing the prediction confidence(i.e posterior probability score), an optimal score-to-posterior-probability transformation function was added to the SVM model.

Then, for each selfie-tagged media image from Twitter and Tumblr with faces, we applied feature extraction on it and passed the resulting feature vector to the predictive model to obtain the classification decision and confidence.

Also, POH and PP samples are separated by a relatively simple mechanism. Besides cropping the interest areas, we also cropped a piece of normal skin with the same size. Then, both interest areas and the normal skin piece will be converted to Lab color space and their color difference is measured by the color distance(DeltaE). We set the threshold to be 8, it means if the DeltaE value between the interest area and the normal skin patch is higher than 8, the face will be categorized into POH set.

4 Results

Among 154,265 selfie-tagged media images, there are 71771(46.5%) have at least one human face, and we call them effective images. The total number of faces in the effective images that were detected is 99057. We have obtained the prediction results for all of these faces, and calculated the PHO and PP distributions in terms of gender, age, and race.

Few prediction examples are

(a) positive 95.9 (b) positive 96.4 (c) negative 99.9

There are 36262(36.6%) faces have been classified into positive set, and among male, 44.7% of them have POH or PP, and among female, the percentage is 33.11.

With respect to the distribution on age, the following chart suggests that with the growth of age, more and more people tend to carry either PHO or PP. Since total sleep time and sleep efficiency are consistently decreasing with age[2], we may conclude that POH or PP are highly associated with sleeping factors such as time and quality. Also, during the age from 30-50, the climbing percentage possibly can be related to the increasing working pressures.

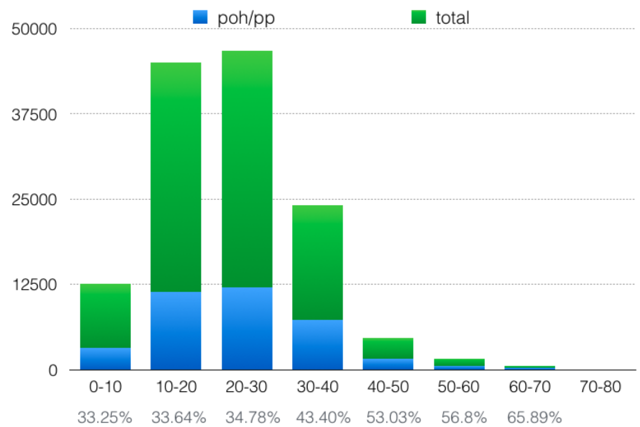


Figure 6: distribution in terms of age

Figure 7 is the distribution in terms of age and gender.

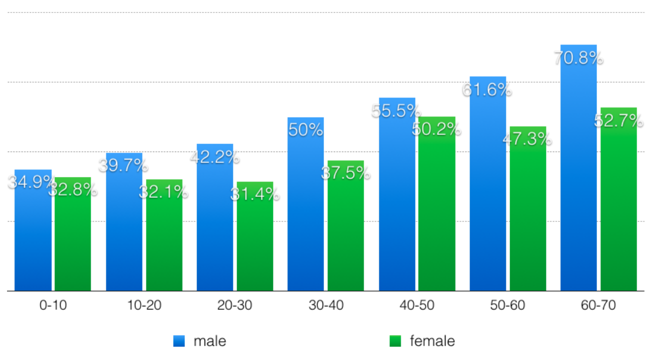


Figure 7: distribution in terms of age and gender

As shown, the above figure indicates that among all age intervals, the percentage of male with PHO or PP is always higher than that of female.

The POH and PP distribution in terms of races is also noteworthy.

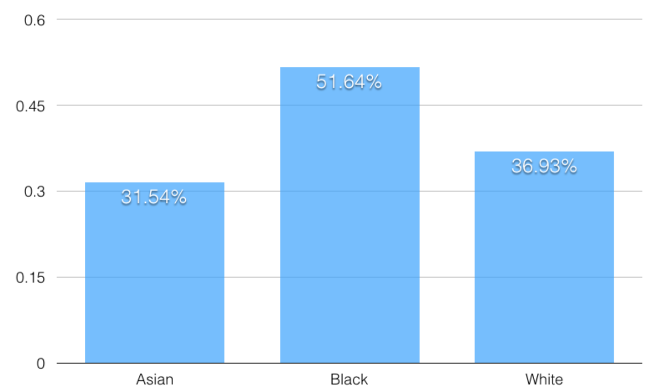


Figure 8: distribution in terms of race

The figure above suggests that Black race has the highest percentage of POH and PP population, this result is consistent with the claim made in Souza Daniela Morae's paper that POH is more prevalent in those who has darker skin[3]. Besides, the percentages of Asian and White are close.

It is also significant to look at POH and PP distribution separately. The following table shows the percentage of POH and PP among positive samples.

POH and PP distribution in terms of age		
Age	POH	PP
0-10	70.7%	29.3%
10-20	69.7%	30.3%
20-30	65.8%	34.2%
30-40	67.6%	32.4%
40-50	67.3%	32.7%
50-60	65.7%	34.3%
60-70	56.3%	43.7%

Below is the distribution table for POH in terms of age and gender, the corresponding PP rate can be calculated easily accordingly.

POH distribution in terms of age and gender		
Age	male POH	female POH
0-10	74.9%	69.7%
10-20	68.7%	70.1%
20-30	68.8%	68.3%
30-40	66.4%	69.0%
40-50	68.0%	66.3%
50-60	62.1%	75.6%
60-70	56.7%	54.2%

Then, we can take a look at the POH and PP distribution among race separately.

POH and PP distribution in terms of race		
Race	POH	PP
Asian	71.2%	29.8%
Black	60.0%	40.0%
White	69.3%	31.7%

5 Summary and Discussion

The POH and PP population increases with age, Maurice's paper[3] echos this by claiming the fact that with age grows, people's sleeping time as well as sleeping efficiency follows a decreasing tendency. Thus, it is fairly reasonable to conclude that POH and PP, to some extent, is related to the sleep. In terms of gender, it turns out that regardless of age interval, the POH/PP percentage for male is always higher than that of female. Besides, according to the POH/PP percentage for each race category, the Black ranked the most, which is around 51%. While 36.93%, the percentage of White POH/PP population, is 5.39% higher than that of Asian.

Among those positive samples, the POH population is always higher than that of PP. In terms of gender, in all age intervals, the gap between male and female POH and PP population is small.

There are two limitations. Some people naturally have slight eye bags under their eyes, and the degree of the puffiness may not reach the threshold to be classified as a medical symptom. One example is as below

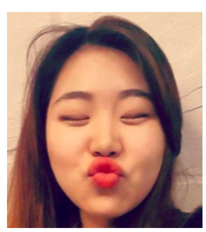


Figure 9: positive 99.8

In human perspective, the eye puffiness of the face in the figure above highly possible is natural born. However, our algorithm would classify it into positive set.

On the other hand, cosmetics may disguise POH and PP and therefore lower the total POH and PP population.

6 Related Work

A study[3] of POH and its causes has been done by researchers from Porto Alegre, the study provides an illustration of POH from anatomic perspective, and also suggests several possible factors of causing POH. This study provides us with a solid medical background of POH. Also, since one of the major focus of this project is finding the POH and PP distribution in terms of age, a study of meta-analysis of quantitative sleep parameters from childhood to old age is also referred[2]. The most important areas of determining if a face has POH or PP are the pair of area under left and right eyes, we will apply dense sift on this pair of area to obtain the features. Dense sift, namely the dense version of the Scale Invariant Feature Transform, is a fast, efficient and comprehensive feature extraction algorithm, and the most complete and up-to-date reference for the SIFT feature detector is introduced by David G. Lowe[1].

7 Future Work

This project is limited on exploring the POH and PP distributions of the faces on social medias. However, only knowing the distribution of POH and PP of the selfies on social media and the support from some medical papers does not suggest a strong correlation between POH/PP and sleep deprivation, efficiency and etc. In order to build a stronger relation between POH/PP and the health related issues, especially for sleeping issues, we can consider to combine tiredness level of a face with this face's POH/PP condition as a new predictor.

In order to achieve this combined predictor model, it is also necessary to train a regression model to suggest the degree of the sleepiness, and the prerequisite of achieving this is having specialists on medical filed to grade each training face's sleepy level. Besides, the amount of faces from social medias to predict in this project is around 100,000, thus, it is better to obtain more faces in order to get an even more accurate perception about the POH/PP distribution.

8 Acknowledgements

We first thank the Color FERET database for providing a very neat face data set. We also thank the service provided from Face++. Besides, a special thank to VLFeat, which offers a high quality Matlab tool box that implemented the Sift and Dense Sift algorithm.

Reference

[1] David G. Lowe. “Distinctive image features from scale-invariant keypoints.” In: *International Journal of Computer Vision* 60.2 (2004), pp. 91–110.

[2] et al Ohayon Maurice M. “Meta-Analysis of Quantitative Sleep Parameters From Childhood to Old Age in Healthy Individuals: Developing Normative Sleep Values Across the Human Lifespan.” In: *SLEEP-NEW YORK THEN WESTCHESTER* 27 (2004), pp. 1255–1274.

[3] et al Souza Daniela Moraes. “Periorbital hyperchromia.” In: *Surg Cosmet Dermatol* 3 (2011), pp. 233–239.