Age estimation by facial analysis based on applications available for smartphones

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ABSTRACT

Background: Forensic Dentistry has an important role in the human identification cases and, among the analyses that can be performed, age estimation has an important value in establishing an anthropological profile. Modern technology invests for new mechanisms of age estimation: software apps, based on special algorithms, because there is not interference based on personal knowledge, cultural and personal experiences for facial recognition.

Materials and methods: This research evaluated the use of two different apps: "How Old Do I Look? – Age Camera" and "How Old Am I? – Age Camera, Do You Look Like in Selfie Face Pic?", for age estimation analysis in a sample of 100 people (50 females and 50 males). Univariate and multivariate statistical methods were used to evaluate data.

Results: A great reliability was seen when used for the male volunteers. However, for females, no equivalence was found between the real age and the estimated age.

Conclusion: These applications presented satisfactory results as an auxiliary method, in male images.

INTRODUCTION

Forensic Dentistry has great applicability in the forensic field, through the study of specific characteristics that can differentiate people. Through their knowledge and methods for sex determination, age and ancestry,[1,2] we can highlight the age estimation of an individual, which presents an important expert function.

Anthropological examinations of the skull are used to estimate age, getting safe results (92% certainty) when compared to other bones of the skeleton, however, it is necessary ample knowledge of head anatomy and Forensic Anthropology, being the Odontologist the most qualified professional to carry out these studies, being able to even use techniques that go beyond the estimation of age by anthropometrics methods, such as facial recognition, dental elements or overlapping of images with scanned *ante-mortem* photographs with skull images in proportional scale. Besides that, in Brazil, Forensic Odontologists can act in different fields in Forensic Sciences and perform age estimation by facial images for in criminal cases.[3-7]

New research has pointed to a new method for the age estimation of an individual - facial analysis, since it is the main part of the visual examination of an individual and age as a crucial factor.[8]

Although the human visual system devotes specialized neural resources to face perception, age estimation through facial aesthetics can be affected by individual, cultural and social experiences, however, through the interpretation of software applications there is no interference based on personal knowledge, since only special algorithms are needed.[9,10] Also, due to rapid advances in computer graphics, facial age estimation, based on computer apps has become a particularly prevalent theme, because of the recent growth and development of technology, therefore, an essential goal of researchers in the field is to create automated facial recognition systems, which can be equal or even surpass human performance.[10]

It's possible to find apps on smartphones and tablets, since they are commercially available, so the present study aims to verify the use of two different apps "How Old Do I Look? - Age Camera" (Lucky Studio Games, USA) and "How Old Am I? - Age Camera, Do You Look Like in Self Face Pic?" (Liu Wang, China) in age estimation analysis.

MATERIALS AND METHODS

The research was approved by the Ethics Committee (CAAE 53719216.6.0000.5419), according to the requirements of Resolution 466/2012 (Brazilian National Health Council, 2012). The sample consisted of 100 individuals, between 18 and 60 years old, divided equally between female and male. Individuals who had the following characteristics in the region of face: inflammation, trauma, malformation, deformity, surgical scars, and who were not turns 18 at the time of data collection were not selected.

For photographing, a white background panel was used to standardize all portraits, and the same camera was used (Nikon Coolpix L810, Tokyo, Japan). Six front images of each participant were taken. The photos were taken with the height of the individual's eyes at the same height of the camera, perpendicular to the photographic beam, with a distance of 1,5m.[11] The background was always well illuminated (natural light of the day), avoiding shade projected at the white background panel, turning off the flash. The participant was instructed to remove caps, glasses or other loose items of clothing, keep their posture straight and arms closed to the body. From these photographs, three images presented a natural facial expression, and the others three, a smiling facial expression, so that a comparison was made between the ages estimated by both apps.

The age based on the photograph was estimated and recorded using two different apps: "How Old Do I Look? - Age Camera" – App A (Lucky Studio Games, USA) (Version 1.6, 2015, DeBuguer, USA), using Samsung Note 2 (Model GT-N7100, Andoid 4.3) and "How Old Am I?" – App B (Version 1.5, 2015, lemon Inc., China), using iPhone (Version 5, iOS9, Apple, Cupertino, CA, USA).

In this research we used univariate and multivariate methods to evaluate data. We performed the data analysis through two different statistical approaches. The idea was to verify how data behaves according each one. When we use univariate methods to handle data, average values are took into account and maybe they can hide important information. In the case of multivariate data, we are able to verify the values individually. Each age estimated by the photos (replicated three times for each person) was evaluated as a variable; this procedure provides more information about the system, allowing to observe the variation in data collecting regarding to the studied apps. Multivariate Analysis was executed by the Pirouette® package.[12-15]

The goal was to check how samples behave according to each situation:

Set 1: to verify results according to sex; training group was the entire set of results for women and men, using all replicates for the two applications in the studied features. Each sex was evaluated to verify how they behave individually.

Set 2: classification intended to check the possibility of separating the samples according to each software for each sex. Regression was used to check the coefficients by sex in each software.

Set 3: classification was used to check the possibility of separating the samples in relation to the feature for each sex. Regression intended to check the coefficients by sex in each feature.

For classification, the unsupervised learning was performed by means of PCA- Principal Component Analysis, which is a technique used to reduce the system dimension when there are many variables. A linear combination of the original variables is performed to generate a new axes system: the principal components (also called factors or latent variables). The purpose is to evaluate the natural similarities and the way the samples behave in clusters. Another way to verify classification is by supervised learning. In this case, we used SIMCA - Soft Independent Modeling of Class Analogies method.[18] The goal is to evaluate if each sample is correctly foresee in a class previously assigned. SIMCA is a technique that uses previous information to the analysis and it is recommended when there is more than ten samples for each class.[17,18] Classes are modelled by PCA and they give the information about how likely a sample is foresee into each class.

Partial least square (PLS) regression is commonly used to verify how a system with many independent variables are related to a specific property or observation, which corresponds to the dependent variable.[19-21] In the case of this work, the goal was to verify how ages collected by the apps fit to the dependent variable (real ages). Some indicators are important to verify the quality of results. In the PLS regression, there are two principal steps: validation and calibration. The method used in the first one was leave one out (LOO) cross validation, which consists of removing one of the samples from the set before perform the regression for the remaining ones. This procedure is repeated for all samples and provide the value of Q^2, which is correlation coefficient model cross validation. For calibration, values of the coefficient of the determination, related as R^2, must be evaluated. R^2 is used to give information about the linear correlation between the dependent and independent variables. This correlation is better as the value of R^2 increases. R^2 must be higher than Q^2.[18] The Root Mean Square Error of validation (RMSEV) and validation (RMSEC) must be compared as well, and RMSEC must be lower than RMSEV.

RESULTS

Set 1

The results for PCA (Figure 1) and SIMCA (Table 1) show that samples were well classified according to sex. In regression results for set 1 (Table 2) we observe the amount of information according to the number of optimal principal components for each regression (second column) and the statistical correspondences were obeyed, value of 0.68 for R^2 is achieved (Line 1). However, individual sex repression showed a poor correlation for women (R^2 0.12) whereas a good one was found for men (R^2 0.77). The same tendency was found for univariate regression (Table 3), which was performed over average values. The best correlation was found for men (R^2 0.72 for men, R^2 0.12 for women and R^2 0.65 for general).

Figure 1: PCA 3D-scores for Set 1.
W is the abbreviation used for female samples, here coloured as black. M is the abbreviation for male samples, here they are represented by red colour. PC1, PC2 and PC3 are the latent variables, which corresponds to the linear combination of the original ones.

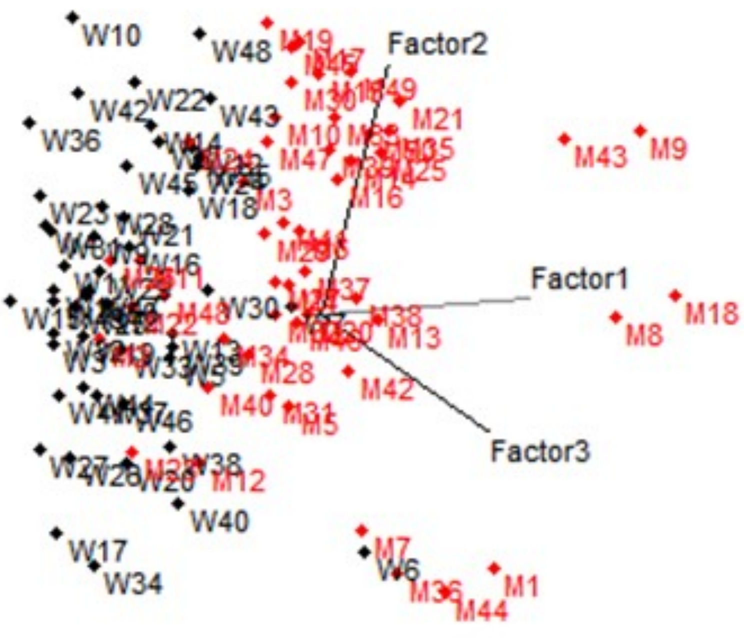


Table 1: SIMCA results for set 1: classification errors for each gender.

	Preview in women's class	Preview in men's class
Women	43	7
Men	5	45

Table 2: PLS results for set 1

	# PCs	% cumulated variance	RMSEV	Q^2	RMSEC	R^2
General	2	99.12	5.59	0.66	5.48	0.68
Women	1	97.89	4.88	0.11	4.83	0.12
Men	2	99.44	5.97	0.74	5.72	0.77

#PCs = Principal Components; % cumulated variance = amount of information according to the number of optimal principal components; RMSEV = Root Mean Square Error of Validation; Q^2 = internal correlation coefficient model cross validation; RMSEC = Root Mean Square Error of Calibration; R^2 = correlation coefficient for calibration.

Table 3: Univariate Regression results for set 1

	Equation	R^2
General	$y = 0.76x + 5.73$	0.65
Men	$y = 0.37x + 12.78$	0.12
Women	$y = 0.70x + 9.77$	0.72

x = raw matrix; y = dependent variable

Set 2

In this case, each software was evaluated according to the sex. Red samples are regarding App B where as black ones belong to App A. Figure 2 A and B show the PCA results for women and men, respectively.

In SIMCA analysis, we observed that there is no good classification, indicating the absence of pattern for each software (Table 4).

The PLS analysis shows a slightly better result for App B since the errors are smaller for both sex and we observe poor values of correlation for women (R^2 0.14 for App B and R^2 0.10 for App A) whereas better values are observed for men (R^2 0.78 for App B and R^2 0.75 for App A) (Table 5).

However, univariate regression made over medium values showed a better correlation (Table 6) for women (R^2 0.71 for App B and R^2 0.60 for App A) instead multivariate values. For men, all results were similar (Univariate Regression: R^2 0.71 for App B and R^2 0,72 for App A) (Tables 5 and 6).

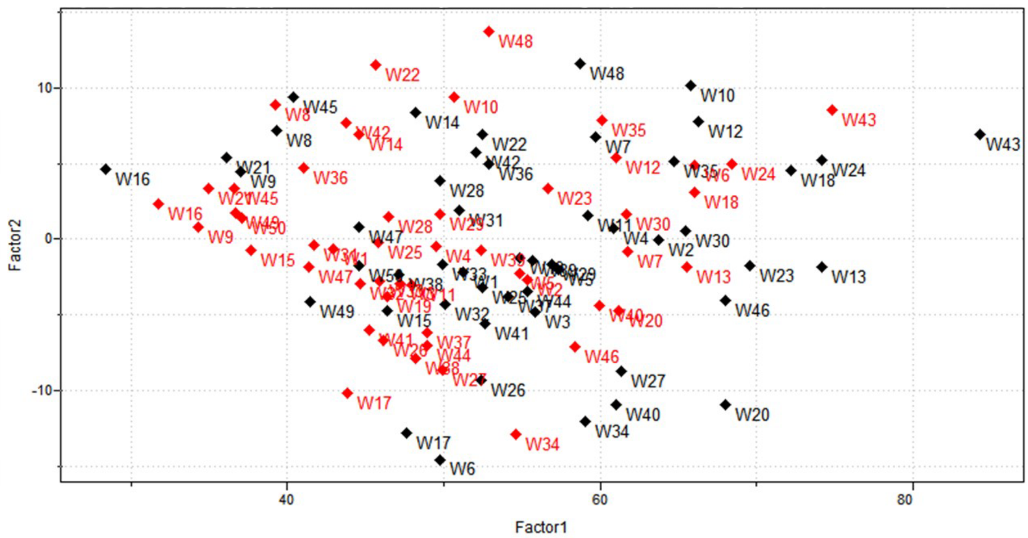
Set 3

Data in set 3 were organized to evaluate both software methods according to different features: natural and smiling. Data were evaluated according to sex. PCA analysis (Figure 3) presents results for women in natural (red samples) and smiling (black samples) for both software (a) and the results for men (b).

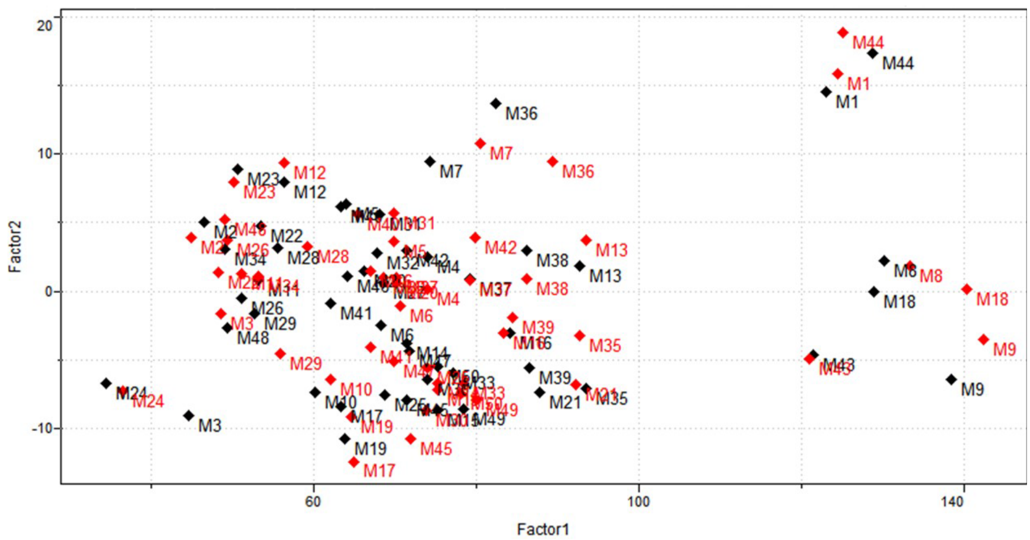
In both cases of SIMCA classification (Table 7), no pattern was found and is not possible to separate samples according to each feature.
PLS and univariate regression are presented in Tables 8 and 9 respectively. The results showed that both applications failed to determine age for women in both natural and smiling (R^2 0.07 for natural and R^2 0.09 for smiling) (Table 8). However, for the men the result was satisfactory (R^2 0.76 for natural and R^2 0.62 for Smiling) (Table 8), being the natural one that presented less errors.

Figure 2: PCA results for set 2.

W is the abbreviation used for female samples and M is the abbreviation for male samples. App A is represented by the black colour and App B by the red colour



A Females



B Males

Table 4: SIMCA results for set 2

	App A	**App B**	**Misclassified**
Women			
App A	27	22	1
App B	22	28	0
Men			
App A	27	22	1
App B	17	32	1

App A = “How Old Do I Look? – Age Camera”; App B = “How Old Am I? – Age Camera, Do You Look Like in Selfie Face Pic?”

Table 5: PLS results for set 2

	# PCs	**% cumulated variance**	**RMSEV**	**Q^2**	**RMSEC**	**R^2**
Women						
App A	1	97.89	5.09	0.09	5.03	0.10
App B	1	98.21	4.88	0.13	4.83	0.14
Men						
App A	2	99.56	6.17	0.73	5.98	0.75
App B	2	99.49	5.89	0.75	5.61	0.78

#PCs = Principal Component; % cumulated variance = amount of information according to the number of optimal principal components; RMSEV = Root Mean Square Error of Validation; Q^2 = internal correlation coefficient model cross validation; RMSEC = Root Mean Square Error of Calibration; R^2 = correlation coefficient for calibration; App A = “How Old Do I Look? – Age Camera”; App B = “How Old Am I? – Age Camera, Do You Look Like in Selfie Face Pic?”

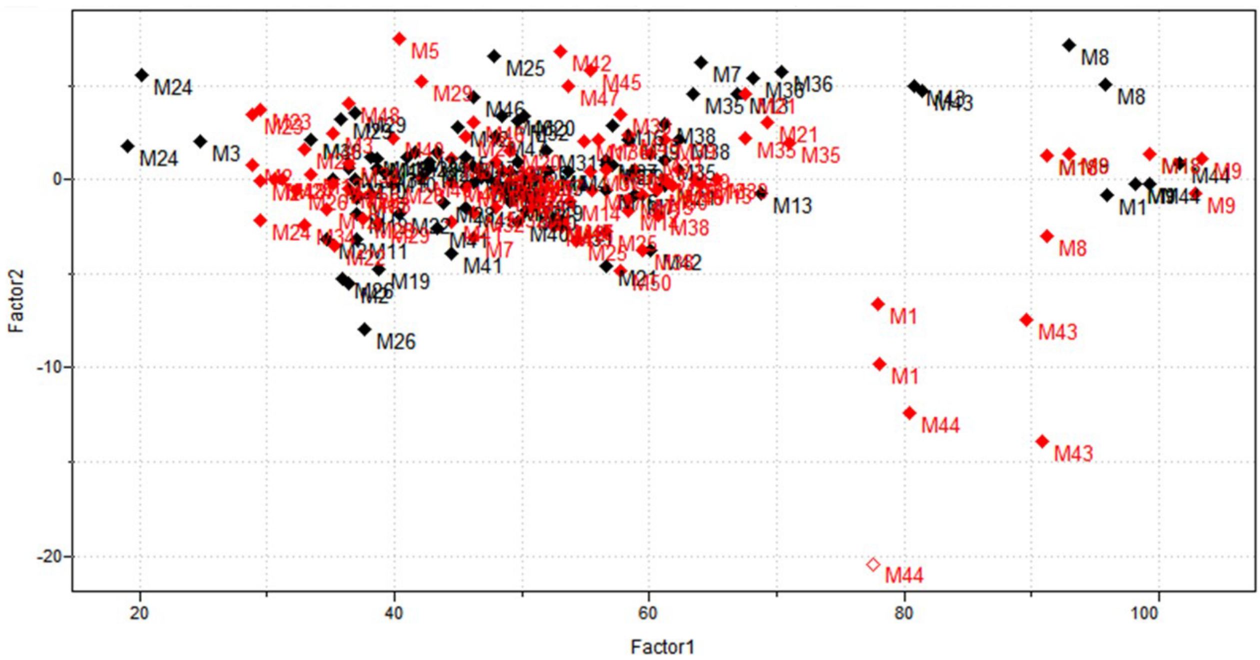
Table 6: Univariate Regression results for set 2

	Equation	**R^2**
App A	$y = 0.58x + 10.02$	0.60
App B	$y = 0.67x + 7.37$	0.71
App A	$y = 0.70x + 9.61$	0.72
App B	$y = 0.71x + 9.94$	0.71

App A = “How Old Do I Look? – Age Camera”; App B = “How Old Am I? – Age Camera, Do You Look Like in Selfie Face Pic?”; x = raw matrix; y = dependent variable

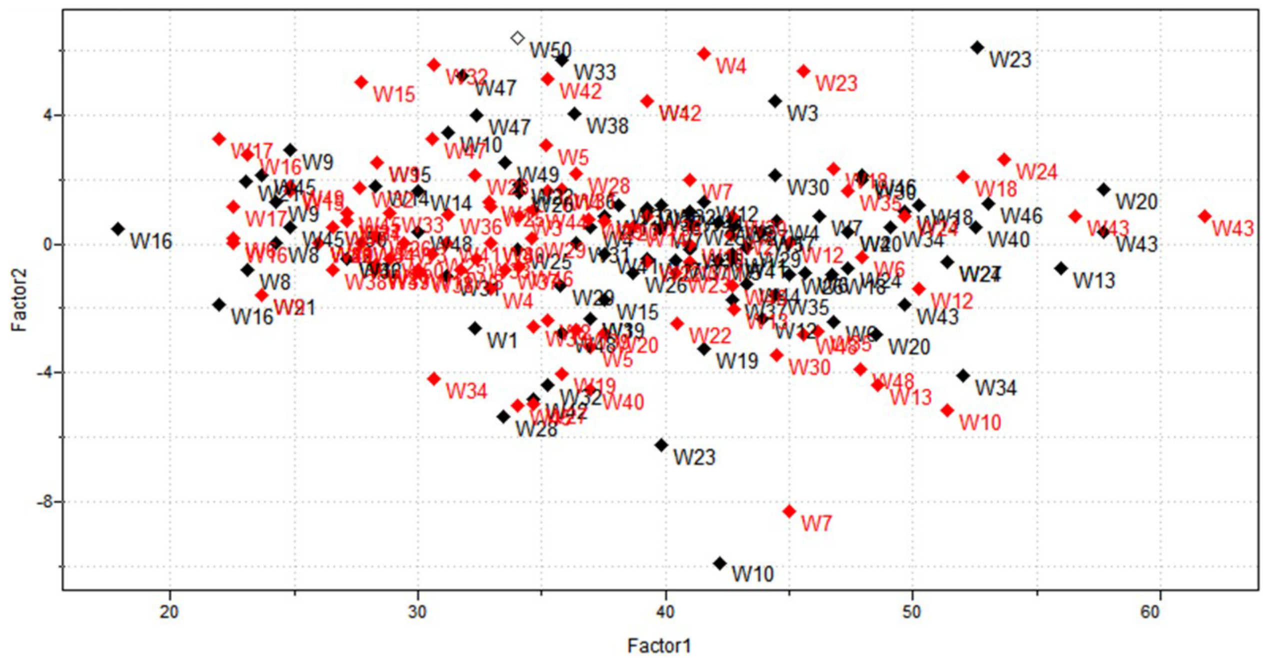
Figure 3: PCA results for set 3.

W is the abbreviation used for female samples and M is the abbreviation for male samples. The smiling feature is represented by the black colour and the natural feature by the red colour



A

Females



B

Males

Table 7: SIMCA results for set 3

	Preview in Natural's class	Preview in Smiling's class	Misclassified
Women			
Natural	62	35	3
Smiling	56	40	4
Men			
Natural	62	37	1
Smiling	46	48	6

Table 8: PLS results for set 3

	# PCs	% cumulated variance	RMSEV	Q^2	RMSEC	R^2
Women						
Natural	1	99.31	6	0.07	5.65	0.07
Smiling	1	99.22	6	0.09	5.75	0.09
Men						
Natural	2	99.87	6	0.75	5.85	0.76
Smiling	2	99.82	8	0.60	7.44	0.62

#PCs = Principal Component; % cumulated variance = amount of information according to the number of optimal principal components; RMSEV = Root Mean Square Error of Validation; Q^2 = internal correlation coefficient model cross validation; RMSEC = Root Mean Square Error of Calibration; R^2 = correlation coefficient for calibration

Table 9: Univariate Regression results for set 3

	Equation	R^2
Natural	$y = 0.35x + 14.10$	0.07
Smiling	$y = 0.38x + 11.76$	0.09
Natural	$y = 0.77x + 7.61$	$R^2 = 0.76$
Smiling	$y = 0.64x + 11.94$	$R^2 = 0.58$

x = raw matrix; y = dependent variable

DISCUSSION

With the technological advances transforming life and routine, new forms of communication have been introduced through mobile devices, such as smartphones and tablets, and these devices have been presented as new means of socialization and communication through social networks and apps.[21] The task of estimating age aims to use computers algorithms to estimate the age of a person based on features extracted from the face image.[22]

When composing the samples for this study, we observed that both the apps put the facial images of the individuals in the same sex in which they were previously allocated, showing a standard in the division of classification of the samples according to the sex, independent of the facial expression or app, that is, there was a low number of sex classification errors, because others types of facial information, such as identity and sex, are more accurate when compared to the estimation of facial age, in which it's very challenging to accurately predict the age of a facial image, because the human facial aging is a slow process influenced by many internal and external factors, like the hair length, caps, glasses or other loose items of clothing, which can cover a lot of facial features related to the age estimates, besides that, the hair length can be a sex specific factor.[10]

When we tested the classification by app or facial expression, there was no standard in the separation of both, demonstrating that there isn't a feature that differentiates the results between the apps or facial expressions studied.

About the regression analysis techniques used in the study, to verify the correlation between the replicates and the real age of the individuals, when the results are separated only by sex, using all the replicates for the two apps and two facials expressions, we observed a correlation practically null between the age estimated and real age in Patzelt[11] verified the Photo Age app (Version1.5, © 2012, Percipo Inc., San Francisco, CA, USA) selecting 10 individuals (6 women and 4 men), of whom six photos were taken (three with the apparent smile and three with the natural face), these individuals were analysed by the cited app and by one hundred evaluator randomly selected to a future comparison. The subjects' real ages were between 42.1 ± 22.6 and the result found was: for the app between 43.1 ± 18.2; and for the evaluators between 41.5 ± 19.0. It has been women's data (R^2 0.12), and the highest correlations were observed for men's (R^2 0.77), which are responsible for influencing the general data and arriving at a reasonable correlation (R^2 0.68). This result can be justified by the fact that environmental factors, such as depressive symptoms, social class, social security and economic stability, have a greater influence on the visual estimation in women, when compared to the men's, influencing in the skin wrinkling and hair loss for example,[9] as Rexbye[23] observed in his study, that the effect of chronological age on perceived age in males is 3 years for visual age of 1 year, in females 2,5 for 1 year visually, a slightly greater effect. There is the hormonal factor too, that interferes with women's aging, because over time there is a decrease in oestrogen and progesterone levels, decreasing also the amount of collagen and elasticity of the skin, contributing to the wrinkling of the skin.[24] This fact can be explained because in women there are more factors that influence the apparent age, such as hormonal, genetic and environmental factors, which there are not for men.

When we observe the correlation of the estimated age by each of the facial expression in each sex, with both apps, there is still a low result for the women's, which does not occur in men, however, the natural expression presents a slightly higher of the correlation coefficient in both sex. This is not the case of the study by Sheretz[25], who photographed twenty-seven patients between 22 and 75 years old, males and females, with natural facial expression and smiling. This author found that there was no difference between the ages judged by the observers in both expressions, however, the ways of estimating the age of the individuals in the both studies cited were distinct, in addition to the sample with a superior mean age when compared with the mean age used in our study, which may also be a factor of divergence.[23,25,26]

demonstrated that the estimate age with the PhotoAge software app is a reliable procedure, with results comparable to the selected evaluators, besides the fact that it could be used as a method of estimating age. In our study, when we analysed the correlation between the ages estimated by each app in each sex (without the two facial expression) and the real ages of the individuals, we still found a low correlation for female, and a higher correlation for male, and we can even say that the App B presented a higher correlation coefficient. However, as we can see, the number of individuals in the different samples of the two studies cited are divergent, in the Patzelt[11] study ten individuals were selected six women and four men, and in the sample of our research, 100 individuals were selected (50 female and 50 male), being a relevant factor for the difference in correlation between the app studied and the real age of the individuals.

Therefore, considering the difficulties and limitations of the applications, it could be used as initial and auxiliary method in forensic investigations in the field of Forensic Dentistry, considering the importance of dentist´s knowledge in estimates of age by facial images for criminal cases, especially in male, because there is a significant correlation.

CONCLUSIONS

The results of this study show that the App B is slightly better for both sexes, compared to the App A but ultimately, both apps fail to determine the age for women, in natural and smiling photos. For men, the result was satisfactory, where the natural photo presented the least errors, thus it could be applied as an initial and auxiliary method for age estimation in images.

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