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# Human age estimation ability and factors affect the estimation

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## Abstract

Number of studies that are focused on estimating age from facial images are increasing every day. These studies are performed largely by automatic systems. Altough these techniques have given better results, they have not reached successful estimation levels as human made, yet. Being able to identify the significant decision-making variables that influence people's estimations is one of the things that can improve these systems. The aim of this study is to examine the success rate of human observers' estimations and to draw attention to what affects those estimations. In this study an age estimation survey was offered; people were asked whether they trust themselves about age estimation and which factors affect their estimations. Participants have been provided with an online survey created using Google Forms. A total of 223 people participated in the study, 66 male and 157 female. In general total 5 images were estimated correctly out of 12, 7 were estimated incorrectly. The ages of all participants (face images of 12 individuals) were estimated correctly with an average of 30.08%. The majority of participants (77,6%) claim to trust their judgement on some level and to make correct estimations overall. When the frequency of factor designation was examined, it was discovered that the majority of participants (65,17%) were focused on the wrinkles on faces (the study includes general face, eyes and mouth.). It is expected that future studies would yield improved results by increasing the number of factors affecting age estimation and including more machine learning studies.

**Key Words:** Age estimation, estimation ability, identification, skin aging, wrinkle

## *İnsanların yaş tahmin yeteneği ve tahminlerini etkileyen faktörler*

## Öz

*Yüz görüntülerinden yaş tahminine odaklanan çalışmaların sayısı her geçen gün artmaktadır. Bu çalışmalar büyük ölçüde otomatik sistemler tarafından gerçekleştirilmektedir. Bu teknikler daha iyi sonuçlar vermiş olsa da henüz insan yapımı kadar başarılı tahmin seviyelerine ulaşamamıştır. İnsanların tahminlerini etkileyen önemli karar verme değişkenlerini belirleyebilmek, bu sistemleri geliştirebilecek şeylerden biridir. Bu çalışmanın amacı, insan gözlemcilerin tahminlerinin başarı oranını incelemek ve bu tahminleri neyin etkilediğine dikkat çekmektir. Bu çalışmada bir yaş tahmin anketi sunulmuştur. İnsanlara yaş tahmini konusunda kendilerine güvenip güvenmedikleri ve tahminlerini hangi faktörlerin etkilediği sorulmuştur. Katılımcılara Google Forms kullanılarak oluşturulmuş bir çevrimiçi anket sunulmuştur. Çalışmaya 66 erkek ve 157 kadın olmak üzere toplam 223 kişi katılmıştır. Genel olarak 12 görüntüden 5'i doğru tahmin edilmiş, 7'si yanlış tahmin edilmiştir. Tüm katılımcıların yaşları (12 kişinin yüz görüntüleri) ortalama %30,08 oranında doğru tahmin edilmiştir. Katılımcıların çoğunluğu (%77,6) kendi tahminlerine bir düzeyde güvendiklerini ve genel olarak doğru tahminlerde bulunduklarını ifade etmişlerdir. Faktör belirleme sıklığı incelendiğinde, katılımcıların çoğunluğunun (%65,17) yüzlerdeki kırışıklıklara odaklandığı görülmüştür (çalışma genel yüz, gözler ve ağza yer vermektedir). Gelecekteki çalışmaların yaş tahminini etkileyen faktör sayısını artırarak ve daha fazla makine öğrenimi çalışması dahil ederek daha iyi sonuçlar vermesi beklenmektedir.*

**Anahtar Kelimeler:** *Yaş tahmini, tahmin becerisi, kimliklendirme, cilt yaşlanması, kırışıklıklar*

## Introduction

Facial aging, which affects self-perception and how individuals are viewed by others, manifests itself through facial features such as wrinkles, folds, poor skin tone and texture, and uneven distribution of soft tissues (Gupta & Gilchrest, 2005; Reilly et al., 2015). Youthful faces typically reflect a mix of symmetrical and balanced features (Swift et al., 2021). With aging, bones remodels, fat pads reposition, and skin wrinkles and sags (Coleman & Grover, 2006). Although facial aging is similar regardless of sex or race/ethnicity, the rate and extent of facial feature change varies among individuals (Rossi et al., 2017; Alexis et al., 2019). The rates of bone remodeling, photodamage, wrinkle development, and soft tissue redistribution differ by race (Swift et al., 2021).

People can have information about a person's age by looking at a face image (Han et al., 2013). Although many studies have performed about this subject, there is limited information about how to make correct estimation from face images (Kumar et al., 2011).

The number of age estimation from face images studies are increasing everyday. However automatic systems cannot make estimations as successful as humans (Anguluu et al., 2018). For reformation about this subject, one of the important issues is to determine what people are focused when they make estimations.

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Skin is the organ which protects humans from dehydration, also cosmetically important (Blanpain & Fuchs, 2006). Skin aging is caused by both internal and external factors. Internal aging is a physiological process. In this process, fine wrinkles, thinning and drying occurs. External aging comes from air pollution, irregular/poor nutrition and exposure to intense sun light for long time. At this stage wrinkles occur in skin, loss of elasticity happens and the skin takes a rough look (Zhang & Duan, 2018). Cells of the skin get harm due to exposure of sun light. As a result, spots appear on the skin and the skin color changes (Zimbler et al., 2001).

The factors that affect perceived face aging include diet, genetic structure, ethnicity and cosmetic products (Anguluu et al., 2018). In addition to that some researches assert that also facial expression affects age estimation (Guo & Wang, 2012; Nguyen et al., 2014). Wrinkles that occur at expressions such as smiling, frowning etc. affect estimation accuracy in the age estimation state (Anguluu et al., 2018).

That type of studies can provide some information for the performances of age estimation methods. At the same time the accuracy of age estimation has not reported by people in large scale for many data base used in automatic age estimation studies (Han et al., 2013).

The aim of this study is to reveal how successfully human participants make age estimations based on facial images and to evaluate which factors affect this estimation. Thus, it is aimed to contribute to studies measuring machine-human performance in terms of data presentation and to bring up-to-date approaches to studies conducted in this direction.

## Material and Method

In the online survey section of the study conducted in Google Forms, facial images of a total of 12 people (5 male and 7 female), over the age of 18 were used. The front face images of 12 people included in the survey were randomly selected from the author's doctoral thesis database consisting of facial images, regardless of sex and age range. These 12 people, whose images were taken without makeup, have no surgery or scars on their faces, and have not had any plastic surgery. The selection of 12 people was made entirely based on the time it would take to complete the survey. The time was kept short for the participants, thus preventing them from getting bored and leaving the survey unfinished. There was no restriction on the duration of the face images remaining on the screen during the estimation, and participants were allowed to advance the page. In addition to demographic information such as sex, age, and profession, the online survey includes questions such as whether people are confident in estimating the age, whether they estimate the ages of the people around them, and how successful they are in these estimations. After these questions;

- Facial images of 12 people previously recorded in the system are shown the screen at random.
- Participants estimate the age ranges for these people (18-24, 25-29, 30-34...85-89, 90 or above)
- The person's real age is then presented on the screen, and participants are required to remark on whether or not the person shows their age based on their own estimates.
- Finally, they are asked to choose the most effective options in their comments (such as skin brightness, skin dullness, and wrinkles around the face, eyes and mouth).

This study included 223 participants (66 male, 157 female) between the ages of 18-66. The highest rate (19.73%) among the participants' professional groups (such as health, education, law enforcement) was educators. The question "Do you guess the age of people around you in your daily life?" was answered positively by over 50% (33,6% yes, 57,4% sometimes). Those who answered "yes" and "sometimes" to this question were asked whether they guessed correctly and the highest rate (42,2%) answered "usually". Tables were generated that show the frequencies and percentages of the participants' responses to the questions. The Chi-Square test was used to evaluate the established cross-tables. The significance level was set at 0.05, and a statistically significant difference was found in the tables with p values less than 0.05.

## Results

In the estimation made about 12 face images, 223 participants made a more or less balanced distribution about all the images except the 4 face images. However, the reason why the estimation about the 4 images mentioned are shown in the tables and the main attention is wanted to be drawn to these images is that 3 images had a 55% and above rate of estimation (higher than the other images) and 1 image had almost half of the focus on 2 different answers. The following are some comments on these people and their rates:

- 150 people (67,26%) said the person in the first image "looks older"
- 200 people (89,68%) said the person in the fourth image "shows age"
- 123 people (55,15) said the person in the sixth image "looks younger"
- While 100 people (44,84%) said "shows age" about the person in the ninth image, 92 people (41,25%) said "looks older"

With the participants' permission, the first and ninth images are shown in Figures 1 and 2, respectively. Images of the other participants were not given because publication permission was unable to be obtained from them.

**Figure 1.** *The facial image of the participant in the survey, of whom 150 of the 223 people who participated in the survey said "looks older" (Real age: 21 [Published with permission of the participant]*

The age estimation comments were compared to the categories developed for those who estimated correctly and those who did not estimate correctly. Tables 1 and 2 provide the evaluations for selected images and all images, respectively. Table 1 shows a significant difference in the distribution of categorical variables for selected images ($p<0.001$).

Participants who estimated a person's age were first asked if they were confident in their estimation. The true/false answers were statistically compared

**Figure 2.** *The facial image of the participant in the survey, of whom 100 of the 223 people who participated in the survey said "shows age" and 92 said "looks older" (Real age: 73) [Published with permission of the participant]*

with the comments about whether the individual in the image shows his/her age or not (Table 1). There is a correlation in the estimated age range of the four people determined to have the most extreme values as a result of the frequency analysis. The values for the 1st, 4th, 6th and 9th images, from which the extreme data were obtained, are presented in Table 1. The data for the other images are not included in the table because average values were obtained.

A significant difference in the distribution of the estimating success categories to the self-confidence categories was discovered in the evaluations given for all images for the fifth image ($p=0.009$).

Face images of 12 people were used in the study. Before the age estimation of these people was made, the participants were asked whether they were confident in their age estimation. People's self-confidence was examined in this direction by true/false estimations (Table 2).

There is a correlation in the estimated age range of the four people identified as having the most extreme values as a result of frequency analysis and the comments made on the estimate.

**Table 1.** *Participants' true/false answers to questions related to the real age of the person in the selected image*

| | | Looks older | | | Looks much older | | | Looks younger | | | Looks much younger | | | Shows age | | | Total | | | p |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | False | True | Total | False | True | Total | False | True | Total | False | True | Total | False | True | Total | False | True | Total | |
| 1 | n | 131 | 19 | 150 | 4 | 0 | 4 | 2 | 1 | 3 | 4 | 0 | 4 | 11 | 51 | 62 | 152 | 71 | 223 | p<0.001* |
| | % | 87.3% | 12.7% | 100.0% | 100.0% | 0.0% | 100.0% | 66.7% | 33.3% | 100.0% | 100.0% | 0.0% | 100.0% | 17.7% | 82.3% | 100.0% | 68.2% | 31.8% | 100.0% | |
| 4 | n | 7 | 1 | 8 | 0 | 1 | 1 | 1 | 6 | 7 | 0 | 7 | 7 | 1 | 199 | 200 | 9 | 214 | 223 | p<0.001* |
| | % | 87.5% | 12.5% | 100.0% | 0.0% | 100.0% | 100.0% | 14.3% | 85.7% | 100.0% | 0.0% | 100.0% | 100.0% | 0.5% | 99.5% | 100.0% | 4.0% | 96.0% | 100.0% | |
| 6 | n | 6 | 1 | 7 | 0 | 0 | 0 | 121 | 2 | 123 | 50 | 1 | 51 | 20 | 22 | 42 | 197 | 26 | 223 | p<0.001* |
| | % | 85.7% | 14.3% | 100.0% | 0 | 0 | 0 | 98.4% | 1.6% | 100.0% | 98.0% | 2.0% | 100.0% | 47.6% | 52.4% | 100.0% | 88.3% | 11.7% | 100.0% | |
| 9 | n | 89 | 3 | 92 | 18 | 0 | 18 | 13 | 0 | 13 | 0 | 0 | 0 | 47 | 53 | 100 | 167 | 56 | 223 | p<0.001* |
| | % | 96.7% | 3.3% | 100.0% | 100.0% | 0.0% | 100.0% | 100.0% | 0.0% | 100.0% | 0 | 0 | 0 | 47.0% | 53.0% | 100.0% | 74.9% | 25.1% | 100.0% | |

* There was a significant difference in the distribution of estimate statement groups to estimation accuracy groups (p<0,001)

**Table 2.** *Participants' estimation success vs. self-confidence for all images*

| | | Trust a little | | Trust much | | Never trust | | Don't trust much | | Total | | p |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | False | True | False | True | False | True | False | True | False | True | |
| **1** | n | 103 | 48 | 11 | 11 | 4 | 0 | 34 | 12 | 152 | 71 | 0.075 |
| | % | 68.2% | 31.8% | 50.0% | 50.0% | 100.0% | 0.0% | 73.9% | 26.1% | 68.2% | 31.8% | |
| **2** | n | 112 | 39 | 15 | 7 | 4 | 0 | 36 | 10 | 167 | 56 | 0.370 |
| | % | 74.2% | 25.8% | 68.2% | 31.8% | 100.0% | 0.0% | 78.3% | 21.7% | 74.9% | 25.1% | |
| **3** | n | 128 | 23 | 21 | 1 | 3 | 1 | 43 | 3 | 195 | 28 | 0.184 |
| | % | 84.8% | 15.2% | 95.5% | 4.5% | 75.0% | 25.0% | 93.5% | 6.5% | 87.4% | 12.6% | |
| **4** | n | 5 | 146 | 1 | 21 | 1 | 3 | 2 | 44 | 9 | 214 | 0.491 |
| | % | 3.3% | 96.7% | 4.5% | 95.5% | 25.0% | 75.0% | 4.3% | 95.7% | 4.0% | 96.0% | |
| **5** | n | 87 | 64 | 7 | 15 | 4 | 0 | 30 | 16 | 128 | 95 | 0.009 |
| | % | 57.6% | 42.4% | 31.8% | 68.2% | 100.0% | 0.0% | 65.2% | 34.8% | 57.4% | 42.6% | |
| **6** | n | 134 | 17 | 20 | 2 | 3 | 1 | 40 | 6 | 197 | 26 | 0.849 |
| | % | 88.7% | 11.3% | 90.9% | 9.1% | 75.0% | 25.0% | 87.0% | 13.0% | 88.3% | 11.7% | |
| **7** | n | 129 | 22 | 19 | 3 | 2 | 2 | 39 | 7 | 189 | 34 | 0.434 |
| | % | 85.4% | 14.6% | 86.4% | 13.6% | 50.0% | 50.0% | 84.8% | 15.2% | 84.8% | 15.2% | |
| **8** | n | 76 | 75 | 6 | 16 | 2 | 2 | 26 | 20 | 110 | 113 | 0.141 |
| | % | 50.3% | 49.7% | 27.3% | 72.7% | 50.0% | 50.0% | 56.5% | 43.5% | 49.3% | 50.7% | |
| **9** | n | 113 | 38 | 17 | 5 | 3 | 1 | 34 | 12 | 167 | 56 | 0.993 |
| | % | 74.8% | 25.2% | 77.3% | 22.7% | 75.0% | 25.0% | 73.9% | 26.1% | 74.9% | 25.1% | |
| **10** | n | 120 | 31 | 18 | 4 | 2 | 2 | 36 | 10 | 176 | 47 | 0.618 |
| | % | 79.5% | 20.5% | 81.8% | 18.2% | 50.0% | 50.0% | 78.3% | 21.7% | 78.9% | 21.1% | |
| **11** | n | 128 | 23 | 18 | 4 | 4 | 0 | 40 | 6 | 190 | 33 | 0.658 |
| | % | 84.8% | 15.2% | 81.8% | 18.2% | 100.0% | 0.0% | 87.0% | 13.0% | 85.2% | 14.8% | |
| **12** | n | 84 | 67 | 9 | 13 | 3 | 1 | 28 | 18 | 124 | 99 | 0.380 |
| | % | 55.6% | 44.4% | 40.9% | 59.1% | 75.0% | 25.0% | 60.9% | 39.1% | 55.6% | 44.4% | |

**Table 3.** *Comparisons of the person's real age in the first image and his/her facial image*

| Age range | | Looks older | Looks much older | Looks much younger | Looks younger | Shows age | Total | p |
|---|---|---|---|---|---|---|---|---|
| 18-24 | Count | 19 | 0 | 0 | 1 | 51 | 71 | **<0.001*** |
| | %within age range | 26.8% | 0.0% | 0.0% | 1.4% | 71.8% | 100.0% | |
| | % of Total | 8.5% | 0.0% | 0.0% | 0.4% | 22.9% | 31.8% | |
| 25-29 | Count | 117 | 3 | 3 | 2 | 11 | 136 | |
| | %within age range | 86.0% | 2.2% | 2.2% | 1.5% | 8.1% | 100.0% | |
| | % of Total | 52.5% | 1.3% | 1.3% | 0.9% | 4.9% | 61.0% | |
| 30-34 | Count | 12 | 0 | 1 | 0 | 0 | 13 | |
| | %within age range | 92.3% | 0.0% | 7.7% | 0.0% | 0.0% | 100.0% | |
| | % of Total | 5.4% | 0.0% | 0.4% | 0.0% | 0.0% | 5.8% | |
| 35-39 | Count | 2 | 1 | 0 | 0 | 0 | 3 | |
| | %within age range | 66.7% | 33.3% | 0.0% | 0.0% | 0.0% | 100.0% | |
| | % of Total | 0.9% | 0.4% | 0.0% | 0.0% | 0.0% | 1.3% | |
| Total | Count | 150 | 4 | 4 | 3 | 62 | 223 | |
| | %within age range | 67.3% | 1.8% | 1.8% | 1.3% | 27.8% | 100.0% | |
| | % of Total | 67.3% | 1.8% | 1.8% | 1.3% | 27.8% | 100.0% | |

* As a result of the chi-square test, a significant difference was found in terms of the distribution of age groups into estimation groups (p<0.001).

Tables 3-6 show the evaluations of the real age of the person in the image and the facial image based on the answers given by the four selected participants. The chi-square test was used to evaluate the tables. A statistically significant difference was discovered between the real age and the estimated comment categories by examining the answers of the person in the first image in Table 3 (p<0.001).

**Table 4.** *Comparisons of the person's real age in the fourth image and his/her facial image*

| Age range | | Looks older | Looks much older | Looks much younger | Looks younger | Shows age | Total | p |
|---|---|---|---|---|---|---|---|---|
| 18-24 | Count | 1 | 1 | 7 | 6 | 199 | 214 | **<0.001*** |
| | %within age range | 0.5% | 0.5% | 3.3% | 2.8% | 93.0% | 100.0% | |
| | % of Total | 0.4% | 0.4% | 3.1% | 2.7% | 89.2% | 96.0% | |
| 25-29 | Count | 6 | 0 | 0 | 1 | 1 | 8 | |
| | %within age range | 75.0% | 0.0% | 0.0% | 12.5% | 12.5% | 100.0% | |
| | % of Total | 2.7% | 0.0% | 0.0% | 0.4% | 0.4% | 3.6% | |
| 30-34 | Count | 1 | 0 | 0 | 0 | 0 | 1 | |
| | %within age range | 100.0% | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% | |
| | % of Total | 0.4% | 0.0% | 0.0% | 0.0% | 0.0% | 0.4% | |
| Total | Count | 8 | 1 | 7 | 7 | 200 | 223 | |
| | %within age range | 3.6% | 0.4% | 3.1% | 3.1% | 89.7% | 100.0% | |
| | % of Total | 3.6% | 0.4% | 3.1% | 3.1% | 89.7% | 100.0% | |

* As a result of the chi-square test, a significant difference was found in terms of the distribution of age groups into estimation groups (p<0.001).

**Table 5.** *Comparisons of the person's real age in the sixth image and his/her facial image*

| Age range | | Looks older | Looks much older | Looks younger | Shows age | Total | p |
|---|---|---|---|---|---|---|---|
| 40-44 | Count | 0 | 2 | 0 | 1 | 3 | **<0.001*** |
| | %within age range | 0.0% | 66.7% | 0.0% | 33.3% | 100.0% | |
| | % of Total | 0.0% | 0.9% | 0.0% | 0.4% | 1.3% | |
| 45-49 | Count | 0 | 1 | 1 | 0 | 2 | |
| | %within age range | 0.0% | 50.0% | 50.0% | 0.0% | 100.0% | |
| | % of Total | 0.0% | 0.4% | 0.4% | 0.0% | 0.9% | |
| 50-54 | Count | 1 | 12 | 10 | 1 | 24 | |
| | %within age range | 4.2% | 50.0% | 41.7% | 4.2% | 100.0% | |
| | % of Total | 0.4% | 5.4% | 4.5% | 0.4% | 10.8% | |
| 55-59 | Count | 0 | 25 | 32 | 0 | 57 | |
| | %within age range | 0.0% | 43.9% | 56.1% | 0.0% | 100.0% | |
| | % of Total | 0.0% | 11.2% | 14.3% | 0.0% | 25.6% | |
| 60-64 | Count | 2 | 10 | 42 | 3 | 57 | |
| | %within age range | 3.5% | 17.5% | 73.7% | 5.3% | 100.0% | |
| | % of Total | 0.9% | 4.5% | 18.8% | 1.3% | 25.6% | |
| 65-69 | Count | 1 | 0 | 36 | 13 | 50 | |
| | %within age range | 2.0% | 0.0% | 72.0% | 26.0% | 100.0% | |
| | % of Total | 0.4% | 0.0% | 16.1% | 5.8% | 22.4% | |
| 70-74 | Count | 1 | 1 | 2 | 22 | 26 | |
| | %within age range | 3.8% | 3.8% | 7.7% | 84.6% | 100.0% | |
| | % of Total | 0.4% | 0.4% | 0.9% | 9.9% | 11.7% | |
| 75-79 | Count | 2 | 0 | 0 | 1 | 3 | |
| | %within age range | 66.7% | 0.0% | 0.0% | 33.3% | 100.0% | |
| | % of Total | 0.9% | 0.0% | 0.0% | 0.4% | 1.3% | |
| 80-84 | Count | 0 | 0 | 0 | 1 | 1 | |
| | %within age range | 0.0% | 0.0% | 0.0% | 100.0% | 100.0% | |
| | % of Total | 0.0% | 0.0% | 0.0% | 0.4% | 0.4% | |
| Total | Count | 7 | 51 | 123 | 42 | 223 | |
| | %within age range | 3.1% | 22.9% | 55.2% | 18.8% | 100.0% | |
| | % of Total | 3.1% | 22.9% | 55.2% | 18.8% | 100.0% | |

* As a result of the chi-square test, a significant difference was found in terms of the distribution of age groups into estimation groups (p<0.001).

In Table 4, a statistically significant difference was discovered between the participant in the fourth image's real age and estimated comment categories ($p<0.001$).

A statistically significant differences was discovered between the real age and the estimated comment categories after analyzing the data of the participant in the sixth image in Table 5. ($p<0.001$).

A statistically significant differences was found between the real age and the estimated comment categories after analyzing the data of the participant in the nineth image in Table 6 ($p<0.001$).

Following their age estimation, those who took part in the survey were asked which variables influenced their age estimation. The factors skin brightness, dullness, oiliness, no wrinkles, few wrinkles, more wrinkles, wrinkles around the eyes, and wrinkles around the mouth were given to the participants in the desired number of options. As a result, Figure 3 shows the selection ratios of the factors affecting age estimation for the first image, in which the expression "looks older" is highly selected.

**Table 6.** *Comparisons of the person's real age in the nineth image and his/her facial image*

| Age range | | Looks older | Looks much older | Looks younger | Shows age | Total | p |
|---|---|---|---|---|---|---|---|
| 40-44 | Count | 1 | 0 | 0 | 0 | 1 | **<0.001*** |
| | %within age range | 100.0% | 0.0% | 0.0% | 0.0% | 100.0% | |
| | % of Total | 0.4% | 0.0% | 0.0% | 0.0% | 0.4% | |
| 60-64 | Count | 0 | 0 | 1 | 0 | 1 | |
| | %within age range | 0.0% | 0.0% | 100.0% | 0.0% | 100.0% | |
| | % of Total | 0.0% | 0.0% | 0.4% | 0.0% | 0.4% | |
| 65-69 | Count | 1 | 0 | 5 | 7 | 13 | |
| | %within age range | 7.7% | 0.0% | 38.5% | 53.8% | 100.0% | |
| | % of Total | 0.4% | 0.0% | 2.2% | 3.1% | 5.8% | |
| 70-74 | Count | 3 | 0 | 0 | 53 | 56 | |
| | %within age range | 5.4% | 0.0% | 0.0% | 94.6% | 100.0% | |
| | % of Total | 1.3% | 0.0% | 0.0% | 23.8% | 25.1% | |
| 75-79 | Count | 17 | 1 | 4 | 36 | 58 | |
| | %within age range | 29.3% | 1.7% | 6.9% | 62.1% | 100.0% | |
| | % of Total | 7.6% | 0.4% | 1.8% | 16.1% | 26.0% | |
| 80-84 | Count | 55 | 7 | 2 | 2 | 66 | |
| | %within age range | 83.3% | 10.6% | 3.0% | 3.0% | 100.0% | |
| | % of Total | 24.7% | 3.1% | 0.9% | 0.9% | 29.6% | |
| 85-89 | Count | 14 | 10 | 0 | 1 | 25 | |
| | %within age range | 56.0% | 40.0% | 0.0% | 4.0% | 100.0% | |
| | % of Total | 6.3% | 4.5% | 0.0% | 0.4% | 11.2% | |
| 90 or above | Count | 1 | 0 | 1 | 1 | 3 | |
| | %within age range | 33.3% | 0.0% | 33.3% | 33.3% | 100.0% | |
| | % of Total | 0.4% | 0.0% | 0.4% | 0.4% | 1.3% | |
| Total | Count | 92 | 18 | 13 | 100 | 223 | |
| | %within age range | 41.3% | 8.1% | 5.8% | 44.8% | 100.0% | |
| | % of Total | 41.3% | 8.1% | 5.8% | 44.8% | 100.0% | |

* As a result of the chi-square test, a significant difference was found in terms of the distribution of age groups into estimation groups ($p<0.001$).

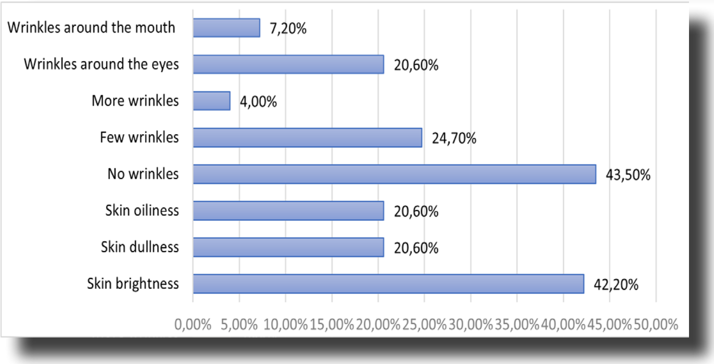


**Figure 3.** *The distribution of the factors affecting age estimation selected for the individual in the first image, for whom the majority of participants reported that "look older".*

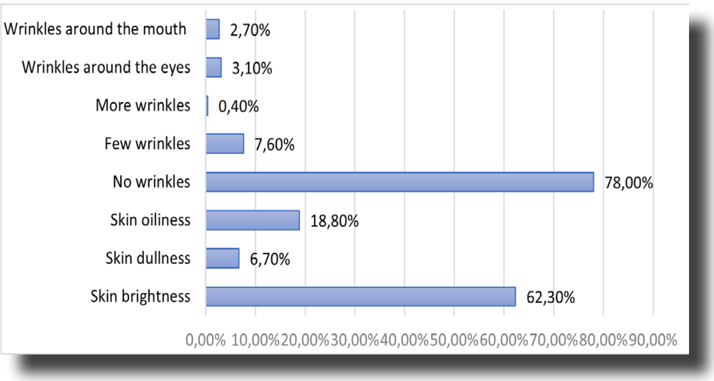


**Figure 4.** *The distribution of factors affecting age estimation was chosen for the person in the fourth image, which the majority of participants said "shows age".*

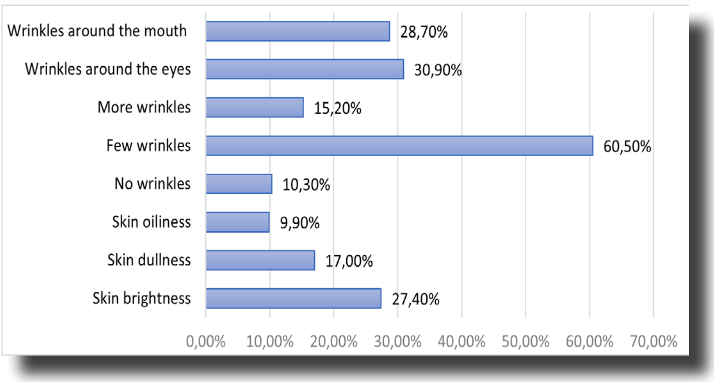


**Figure 5.** *The distribution of factors affecting age estimation was chosen for the person in the sixth image, who, according to the majority of participants, "looks younger".*

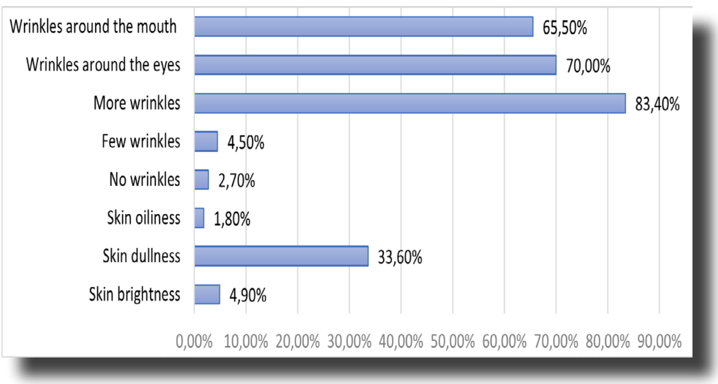


**Figure 6.** *The distribution of factors affecting age estimation was chosen for the person in the ninth image, which the participants stated "shows age" nearly half "looks older".*

Figure 4 shows the distribution of factors affecting age estimation for the person in the fourth image, in which the participants chosen to "shows age".

Figure 5 shows an explanation of the factors affecting the age estimation for the person in the sixth image, who "looks younger".

Figure 6 shows the factors affecting the age estimation of the person in the 9th image, in which 100 of the 223 participants "shows age" and 92 of them "looks older".

## Discussion

There are no studies in the literature that estimate age from facial images using surveys with participants. Similar research, however, has been examined and compared to the available data.

People cannot obtain perfect outcomes when estimating age based on face features. People estimate age based on factors such as the person's ethnicity, the general observable conditions of the face, and the person's actual ability to perceive and process facial information (Lanitis et al., 2004). In this study, in accordance with the statement, age estimation was made correctly by 30,08%. Among the factors presented in the study (skin brightness, dullness, wrinkles around the mouth, wrinkles around the eyes), people stated that they mostly focused on wrinkles and made their estimations. The rate of those who stated that they made their estimations by focusing on the general face, wrinkles around the mouth and eyes is higher (65.17%).

A study that used facial wrinkles to estimate age from a facial image found that age estimation utilizing wrinkle information provided reliable results. The largest incorrect estimation was done with a difference of 20 years in the study, which used 20 facial images, while the exact estimation of the real age of 2 people was made (Jana et al., 2015). In this study, among the factors affecting age estimation, individuals preferred wrinkles on the skin to a large amount over skin dullness, oiliness, and brightness.

Two steps were used in a study in which 51 facial images were shown to 29 human observers. Only grayscale facial regions were displayed to the observers in one stage, whereas all color images were shown in the other. The estimate in the first stage was based just on the face, whereas the estimate in the second stage was based on information such as the face, hair, skin color, clothing, and background. The study also examined the algorithms' capacity to estimate age and compared it to human observers. When looking at the average total error of age estimation in years, 4 out of 8 algorithms (Kernel AGing pattErn Subspace – KAGES: 6.18, AGing pattErn Subspace – AGES: 6.77, Weighed Appearance Specific – WAS: 8.06, Support Vector Machines – SVM: 7.25) gave better results than the second stage test (6.23) (Geng et al., 2008). People's clothes, hair, accessories, and so on are not considered in the facial images used in this study. Only expressionless biometric images were allowed, and participants were supposed to make estimates based on these faces.

Jana et al. (2013) analyzed the effect of age groups on age estimation in their study. The accuracy of age estimation was 96% for two age group categories, 84% for three age group categories, and 62% for four age group categories. As a result, it was found that as the number of categories increases, the classification's accuracy falls (Jana et al., 2013). Sezgin et al. (2017) analyzed the age estimation reliability of eyewitnesses and discovered that the accuracy of estimating the exact age of persons with a 5-age range was 41.44%, and the accuracy of estimating the exact age of people with a 10-age range was 62.73% (Sezgin et al., 2017). Except for the options of 18-24 and above 90 years of age (all other groups), age groups with a 4-year difference were determined in this study. The ranges are kept small in this case to make responses more realistic. For instance, if a person's age is estimated using a 10-year range, the observer will choose this option because the estimated age is 25, while the options are 25-35. As a result, simply looking at the answer here will need determining whether the person is 25 or 34. When the age range is kept small, characterizing someone as "in his/her early 20s" or "late 20s" seems more current.

Lanitis et al. (2004) showed to 20 volunteers various facial images and asked them to estimate their age. They compared these estimations to those made by machines. While humans are shown the whole face image for estimating age, machines are shown general information from only the inner part of the face. According to the study's results, human observers made more accurate estimations (3.64 years) than all of the machines examined (Lanitis et al., 2004). In this research, full-face images were used.

## Conclusions

In this study, which was conducted to examine how confident people are in age estimation, how successful they are in this area, and which factors affect them, it is seen that the overall success rate is low when looking at correct estimates. The small number of images presented in the survey (12) is likely to have influenced this result. Although it was possible to continue the study with a larger number of images in the first stage, images were used in small numbers because participants would lose focus if the survey took too long to complete, and they would either abandon the study or give random answers.

One of the most important components of this research is determining what influences human observers when estimating age. Looking at the results, it was discovered that wrinkles on the skin drew the most attention. In future studies, the number of factors mentioned here should be increased. Some participants indicated in their feedback at the end of the survey that they also paid attention to the beard/moustache, glasses, age spots etc., but they were unable to write these down because those options did not exist.

In such studies, problems occur in the data collection phase because people are reluctant to share their facial images. In future studies, more images can be used, the number of questions can be reduced (in order to shorten the completion time), and the number of factors affecting age estimation can surely be enhanced. It is hoped that by doing so, more successful results would be obtained, and that this will contribute more to machine learning researches in this subject.

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