

# JenAesthetics Subjective Dataset: Analyzing Paintings by Subjective Scores

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**Abstract.** In the last few years, researchers from the computer vision and image processing community have joined other research groups in searching for the bases of aesthetic judgment of paintings and photographs. One of the most important issues, which has hampered research in the case of paintings compared to photographs, is the lack of subjective datasets available for public use. This issue has not only been mentioned in different publications, but was also widely discussed at different conferences and workshops. In the current work, we perform a subjective test on a recently released dataset of aesthetic paintings. The subjective test not only collects scores based on the subjective quality, but also on other properties that have been linked to aesthetic judgment.

**Keywords:** Computational aesthetics, aesthetic, beauty, color, content, composition, paintings, subjective dataset, JenAesthetics dataset.

## 1 Introduction

In recent years, there has been a growing interest in the topic of aesthetic quality assessment of paintings and photographs in the computer vision and image processing community. This interest has resulted in what is now known as computational aesthetics [12]. Numerous workshops, conferences and special sessions dealing with this topic have attracted researchers in the past few years [2–10, 17–20, 22–24, 28–30, 39]. Due to the nature of this field of research, further progress depends on the availability of datasets for analysis.

Over the years, most research in this field has focused on proposing new methods to evaluate different aesthetic properties [2–11, 17, 18, 20, 21, 23, 24, 28–30, 38, 39]. Although these methods reached interesting results, the lack of a common dataset prevented different methods and approaches to be comparable to one another.

Like in other fields of research that deal with quality assessment of stimuli, such as image and video quality assessment, subjective datasets [32–34, 36, 37]

play an important role for research in this field. Subjective datasets provide researchers with scores given by observers with regard to different properties of a stimuli. Thanks to the many photo-sharing websites nowadays used by professional and amateur photographers, several subjective datasets[8, 17, 19, 20, 22, 23] covering different types and styles of photographs have been introduced to the public. These websites provide the user with a large number of photographs that have been rated subjectively by the community of photographers. The procedure for collecting such datasets is inexpensive both in the sense of time consumption and financial cost. It should be mentioned that a drawback of these datasets is that the scoring of images is not done in a standardized format. This means that the subjective scores were likely given under various viewing condition using different displaying devices. To try to prevent such issues, in the field of image and video quality, subjective tests are normally collected using specific standards such as those described in [13]. Unfortunately, in the aesthetic quality assessment community, there is no specific standard agreed among different research groups with regard to how subjective tests should be performed as of yet.

Unlike for photographs, there has been no public dataset of paintings with subjective scores until recently. Last year, two small subjective datasets have been introduced to the community [2, 39]. However, these datasets fall short of corresponding to the needs of the community, which we will describe in the next section.

In this paper, we take advantage of the JenAesthetics dataset [1, 5, 15], which is available for public use, and perform a subjective test to evaluate different properties of the paintings in this dataset. According to the claims made by Amirshahi et al. [1, 5], the JenAesthetics dataset is one of the largest publicly available datasets and covers a wide range of different styles, art periods, and subject matters. The images in this dataset are colored oil paintings that are all on show in museums and were scanned at a high resolution. The present study will combine the objective data previously provided in [5] with different subjective scores.

The next sections of this article are as follow: Section 2 introduces the previous subjective datasets. Section 3 describes the JenAesthetics subjective dataset. Section 4 evaluates the subjective scores provided by the observers. Finally, Section 5 gives a short conclusion and proposes possible future works to extend this dataset.

## 2 Previous Work

Before the introduction of the two mentioned datasets [2, 39] (Sections 2.1 and 2.2, respectively), other researchers[4, 7, 10, 18, 21, 24, 28] have gathered their own datasets. This was done either by scanning high-quality art books, by ordering digital samples from the museums, or by using their own personal collections. Unfortunately, there is no possibility to release the datasets for other research groups due to copyright restriction, making different approaches incomparable to one another.

**Table 1.** Comparison of different properties between the JenAesthetics subjective dataset and the two datasets introduced in [2] and [39]. NA, not assessed.

Properties	JenAesthetics	[2]	MART[39]
number of images	1628	281	500
number of observers per painting	19 - 21	49	20
total number of observers	134	49	100
scores of individual observers	yes	no	yes
color images	yes	yes	majority
average image size (pixels)	$4583 \times 4434$	$2489 \times 2517$	$513 \times 523$
rating scale	continuous, 1-100	ordinal, 1-4	ordinal, 1-7
art periods/styles	11	NA	1
number of subject matters	16	NA	1
number of artists	410	36	78

In the following subsections, we will give a short summary on the two available subjective datasets [2, 39]. Table 1 lists different properties of the available subjective datasets.

## 2.1 Dataset Introduced in [2]

This dataset, which was introduced in 2013, consists of 281 paintings of different subject matters and art styles. A positive aspect of this dataset is the high number of observers who rated the images. The subjective scoring in this dataset has been done based on a scale of 1-4. Subjective scores show that paintings with bluish or greenish colors are generally given a higher subjective scores compared to paintings with brownish or dark colors [2]. This result confirms findings by Palmer and Schloss [25]. Compared to the JenAesthetics dataset [1, 5, 15], this dataset does not provide information on the art periods which the paintings belong to, and no subject matters are assigned to the paintings.

## 2.2 MART Dataset [39]

This subjective dataset of paintings consists of 500 abstract paintings produced between 1913 and 2008. The paintings were selected from the MART museum in Rovereto, Italy. The images in this dataset were divided into 5 subsets, each consisting of 100 images. 20 observers rated each subset based on a 7-point rating scale. The observers were mostly female (74 females, 26 males) and on average visited 5.5 museums per year. The observers were allowed to spend as much time as they wanted to see and observe a painting before giving a score, but they were advised to rate the paintings in the fastest possible manner. 11 images are in a monochrome format (Table 1). Also, the average pixel size of the images

is relatively small compared to the JenAesthetics and [2] datasets. Unlike the database described in [2] and especially the JenAesthetics dataset, the paintings of this dataset belong to a single art period/style (i.e., abstract art).

### 3 JenAesthetics Subjective Dataset

In collecting the JenAesthetics dataset [1, 5, 15], Amirshahi et al. took advantage of the fact that the Google Art Project (<http://www.googleartproject.com/>) has released a large number of high-quality scanned versions of artworks for public use. Although the artworks in this dataset are mostly from famous painters, this does not guarantee that they will be ranked highly by non-expert observers. The non-expert observers who participated in our experiment were not familiar with most of the paintings and/or painters. The importance of familiarity in evaluating the quality of a photograph or painting has been noticed in different studies [8, 18]. A painting is labelled as familiar in the JenAesthetics subjective dataset if the observer believes that he/she has previously seen the painting or if they know the painter. Moreover, as it will be discussed in Section 4, some famous paintings are not among paintings with the highest subjective scores. This implies that the observers are not necessarily biased towards famous paintings.

As mentioned previously, there is a lack of standards for subjective tests in the field of computational aesthetics. We believe that the following issues have to be taken into account when performing a subjective test of paintings.

1. Tests should be carried out under standard viewing conditions in a controlled environment. This will ensure that the observers are viewing all paintings under the same condition so that the scores are comparable.
2. The observers should not be familiar with the paintings. Different approaches have been taken to prevent the subjective scores from being biased towards a familiar painting. For example, Li et al. [18] removed scores given by observers when they expressed that they were familiar with the painting shown. In our work, we found that the observers were not familiar with the vast majority of paintings evaluated.
3. Multiple properties should be assessed and not just one. For example, if we evaluate the aesthetic quality as well as the observers' liking of the colors, composition, and content of the paintings, as done for the JenAesthetics subjective dataset in the present study, we can correlate each preference with the aesthetic scores given by the observer (see Section 4.2).
4. The visual ability of the observer should be taken into account. Results provided from observers with visual impairment should be treated differently compared to other observers.

In the following sections, we will first provide information on why specific questions/properties were evaluated by the observers (see Section 3.1). We will then describe the experimental procedure (see Section 3.2).

**Table 2.** Questions that the observers were asked for each property in the JenAesthetics subjective dataset. The two terms visible on the rating scale to present the highest and lowest possible scores are also shown.

Property	Question asked	Left side	Right side
Aesthetic	How aesthetic is the image?	not aesthetic	aesthetic
Beauty	How beautiful is the image?	not beautiful	beautiful
Color	Do you like the color of the image?	no	yes
Content	Do you like the content of the image?	no	yes
Composition	Do you like the composition of the image?	no	yes
Artist	Do you know the artist?	no	yes
Familiarity	Are you familiar with this painting?	no	yes

### 3.1 Properties Evaluated

Table 2 gives an overview on the properties evaluated in the JenAesthetics subjective dataset. The main goal for the dataset is to collect subjective scores related to the aesthetic quality of paintings. Previous works have taken different approaches to reach this goal. While Amirshahi et al. [2] used beauty as their measure, Li et al. [19] asked their subjects to give their general opinion about the painting. For the MART dataset [39], the observer was asked to give a score with regard to his/her emotion towards the paintings. In this experiment, the lowest score represents the most negative emotion while the highest score represents the most positive emotion. In the JenAesthetics subjective dataset, we evaluate subjective scores with regard to both aesthetic quality and beauty. The two properties are compared in Section 4.2.

We also evaluated three other properties (i.e., the liking of color, composition and content of the paintings) and studied the relationship between these properties and the aesthetic and beauty scores (see Section 4.2). Previously, Amirshahi et al. [2] and Yanulevskaya et al. [39] used simple color features to predict the aesthetic quality of paintings with a high accuracy. Other works such as [25, 26, 31] have also focused on the importance of color when evaluating the aesthetic quality of images. The composition of an image (for example the rule of thirds) plays an important role in the aesthetic quality of paintings and photographs according to several studies [3, 8, 16, 18, 20, 35, 38]. Finally, it is well known that the content of a painting and/or photograph influences their aesthetic quality. In the JenAesthetics dataset, the content of paintings is represented by the subject matter.

**Table 3.** Statistical information about the JenAesthetics subjective dataset.

Attribute	Value
number of participants	134
number of observers after removing clickers and people with color blindness	130
number of observation sessions	201
age range of the observers	19 to 24 years
mean age	25.4 years
male / female	74 / 60
right / left-handed	122 / 12
with / without glasses	67 / 67
interested / not interested in art	96 / 38
nationality	15 different countries
nationality represented most frequently	109 from Germany

To evaluate whether the subjective scores are in any way biased by being familiar with a painting, the observers’ familiarity towards each painting was assessed. We also asked the observers whether he/she knew the painter. A similar approach was taken by Li et al. [18].

### 3.2 Experimental Procedure

**Participants** 134 participants attended this study; sixty-seven of them took part in two sessions (leading to a total of 201 sessions). Most of them were students, in particular of natural sciences, but other fields of studies and professions were reported also. However, no participant was a student of arts, art history, or any related field. All participants declared having normal or corrected-to-normal visual acuity and gave their written informed consent after receiving an explanation of the procedures. The consent allows us to use and share their subjective scores. Each participant was tested for color blindness using the Ishihara test [14]. Data from observers who were color blind were excluded from the analysis. See Table 3 for additional data on the participants.

**Stimuli** We used the 1628 art images from the JenAesthetics database [1] as stimuli. In every session, a subset of 163 images were rated. Works from 410 painters are available in this dataset. The dataset covers paintings from 11 art periods (Renaissance, Baroque, Classicism, Romanticism, Realism, Impressionism, etc.). Each painting in the dataset is tagged with up to three different subject matters. These subject matters (16 in total) include abstract, landscape, still life, portrait, nude, urban scene, and etc.

**Procedure** The experiment was performed using the PsychoPy [27] program (version 1.77.01) on a BenQ T221W widescreen monitor with a resolution of  $1680 \times 1050$  pixels (WSXGA+). The monitors were calibrated using the same calibration profile with a colorimeter (X-Rite EODIS3 i1Display Pro) in order to create similar conditions for all observers.

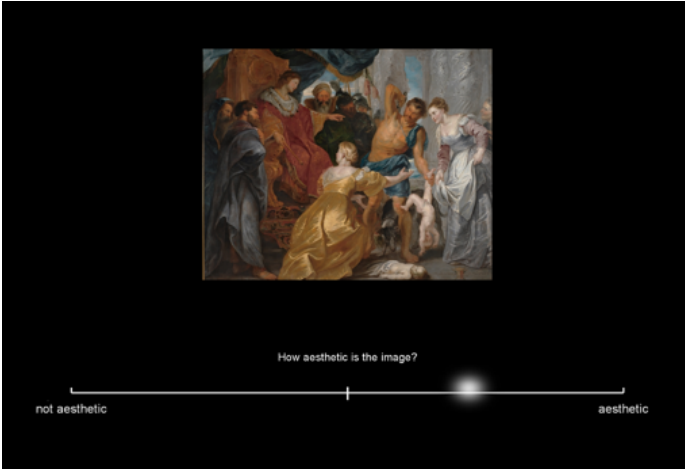
For presentation, each image was scaled so that the longer side of the image was 800 pixels to achieve a constant display on the screen. The images were placed in the middle of the screen on a black background (see Figure 1). Therefore, images were presented with a maximum size of 20.5 cm (longest side) on the computer screen, corresponding to about 19.4 degrees of visual angle (at a viewing distance about 60 cm).

First, twenty images from the dataset that were not used in the rating experiment were presented for three seconds each to get the observer used to the data.

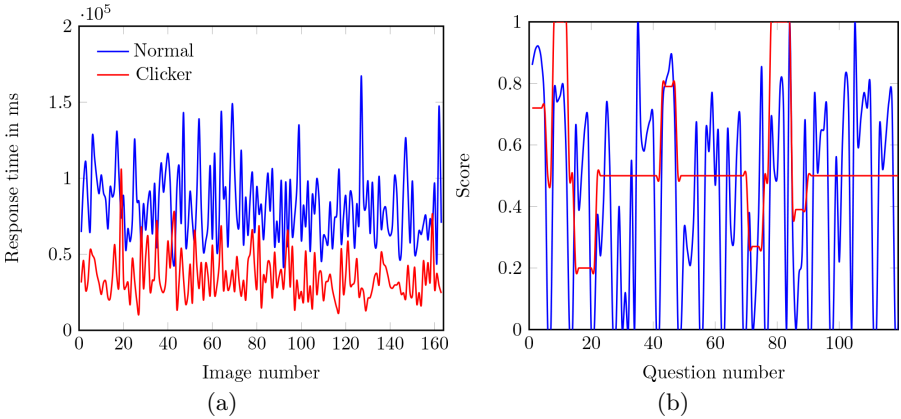
Then, 163 images that were selected randomly from the dataset were presented to the observer in a random order. Careful attention was taken so that no two subsets were identical. In total, each painting was rated by 19 to 21 observers. The participants were asked to rate the images on seven properties using a sliding bar located on the bottom of the screen. The properties were “Aesthetics”, “Beauty”, “Color”, “Content”, “Composition”, “Knowing the artist”, and “Familiarity”. See Table 2 for details on the presented questions. As shown in Figure 1, the questions were presented above the sliding bar. The terms presented in Table 2 indicated the range for the rating at each end of the bar. The observers were instructed that the mentioned phrases on the scoring bar were to represent the two extreme cases for the scores and their scores would not be treated on a binary scale. The participants had no time restrictions for answering each question. After rating, the next question appeared. The image was visible until the last rating was given. Participants who attended a second session were provided with a new randomly selected set of images that shared no images with the images shown in the first session, in which they participated.

## 4 Analysis of the Subjective Scores

The first step in analyzing the subjective scores gathered was to remove the scores that were provided by observers in an improper manner. These scores were mainly provided by what will be referred from here on as clickers. Clickers are observers who provide their results by randomly clicking the score bar, independent of the image content or the question asked. The random clicking of the score bar is mostly performed at a high speed resulting in short response times (Figure 2(a)). Also, clickers tend not to move their mouse for a few questions before moving their mouse to another position (Figure 2(b)). Subjective scores for each property were calculated after removing the scores provided by the clickers. After removing the clickers and the scores provided by people who were color blind, the total number of observers was 130.



**Fig. 1.** Screen-shot from the subjective test for one of the assessed properties (aesthetic quality). The question regarding the assessed property is represented under the painting. Painting by Peter Paul Rubens, about 1617.

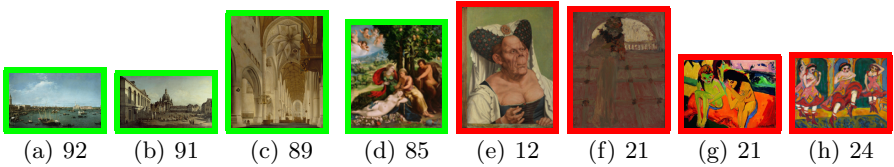


**Fig. 2.** Comparing results from a clicker and a normal observer. (a) Response time spent on each image to score all the seven properties for all the images. (b) Scores given to the seven properties for 17 paintings selected randomly for the same observers whose response times are shown in (a).

#### 4.1 Calculating the Scores

After removing the clickers from the obtained data, the final step in producing a subjective dataset was to calculate a score for each property collected for individual paintings. Among the different options available, we decided that calculating the median value between the scores would be the best possible option. This is mainly to take into account the small chance that some scores are given





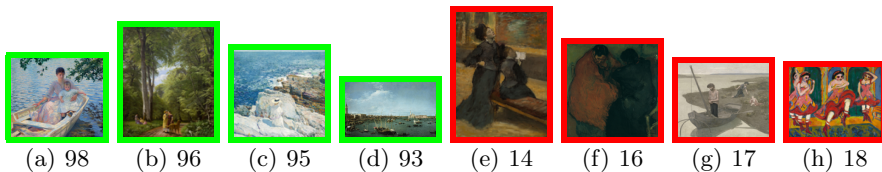
**Fig. 3.** The four paintings ranked highest for their aesthetic quality are marked by a green border ((a)-(d)) and the four paintings ranked lowest by a red border ((e)-(h)). The scores given to each painting is presented below each image. (a) Antonio Canaletto, 1738, (b) Antonio Canaletto, 1749, (c) Pieter Jansz Saenredam, 1648, (d) Dosso Dossi, 1524, (e) Quentin Matsys, 1513, (f) Édouard Vuillard, 1900, (g) Ernst Kirchner, 1910, (h) Ernst Kirchner, 1920.



**Fig. 4.** The four paintings ranked highest for their beauty are marked by a green border ((a)-(d)) and the four paintings ranked lowest with a red border ((e)-(h)). The scores given to each painting is presented below each image. (a) Edmund C. Tarbell, 1892, (b) Antonio Canaletto, 1738, (c) Félix Ziem, 1850, (d) John Constable, 1816, (e) Quentin Matsys, 1513, (f) Ernst Kirchner, 1910, (g) Francisco Goya, 1812, (h) Édouard Vuillard, 1900.

in an incorrect way. For instance, the score might have been given by accidentally clicking the score bar. Using the median scores provides us with a better chance to remove these outliers and achieve a more accurate score. Figures 3-7 represents the four highest rated paintings (marked by a green border) and the four lowest rated paintings (marked by a red border) for the first five properties introduced in Table 2. Figure 8 represents the distribution of the scores for each property. As shown in the figure, the median value of the subjective scores for all properties is around the mid-point of the score range. Note that the subjective scores cover a wide range of the score bar.

As mentioned before (Table 2), the observers were asked two more questions with regard to the familiarity of the paintings and also the painter who created the painting. Results revealed that a majority of the paintings neither looked familiar nor did the observers know the painter (in both cases, 99% had a score less than 10%). This finding suggests that the results for the other five properties cannot have been substantially influenced by familiarity of the observers with the paintings.



**Fig. 5.** The four paintings ranked highest for their color are marked by a green border ((a)-(d)) and the four paintings ranked lowest with a red border ((e)-(h)). The scores given to each painting is presented below each image. (a) Edmund C. Tarbell, 1892, (b) P. C. Skovgaard, 1857, (c) Childe Hassam, 1913, (d) Ernst Kirchner, 1910, (e) Edgar Degas, 1890, (f) Isidre Nonell, 1903, (g) Pierre Puvis de Chavannes, 1881, (h) Ernst Kirchner, 1920.



**Fig. 6.** The four paintings ranked highest for their composition are marked by a green border ((a)-(d)) and the four paintings ranked lowest with a red border ((e)-(h)). The scores given to each painting is presented below each image. (a) Ernst Kirchner, 1910, (b) Johan Christian Dahl, 1839, (c) Viktor Vasnetsov, 1881, (d) John Singleton Copley, 1765, (e) Émile Bernard, 1892, (f) Paul Cézanne, 1877, (g) Isidre Nonell, 1903, (h) Marcus Gheeraerts the Younger, 1591.

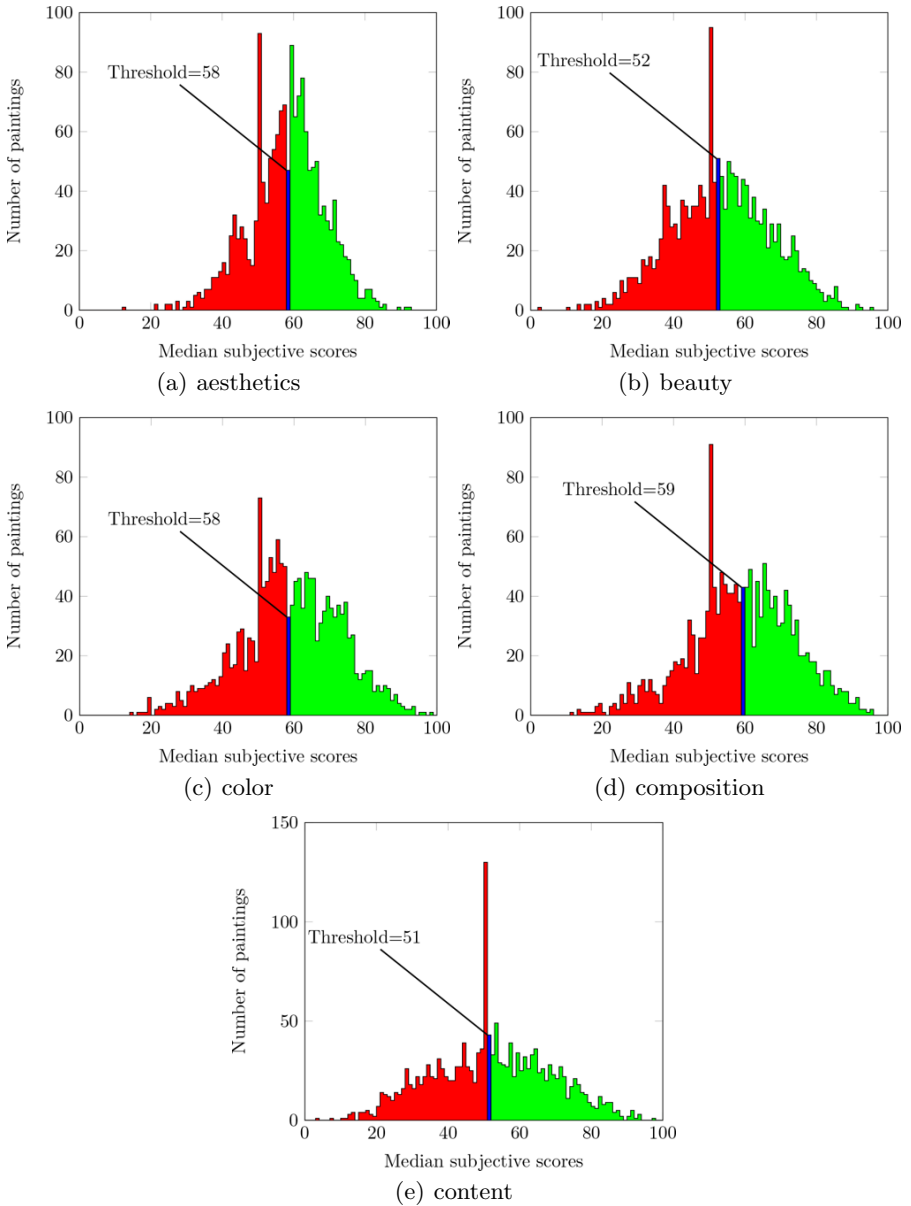


**Fig. 7.** The four paintings ranked highest for their content are marked by a green border ((a)-(d)) and the four paintings ranked lowest with a red border ((e)-(h)). The scores given to each painting is presented below each image. (a) Johan Christian Dahl, 1839, (b) Childe Hassam, 1913, (c) Anton Mauve, 1887, (d) David Teniers the Younger, 1652, (e) Quentin Matsys, 1513, (f) Felice Boselli, 1690, (g) Jusepe de Ribera, 1621, (h) Abraham Staphorst, 1665.

## 4.2 Relationships Between Subjective Scores

Next, we investigated the relationships between the subjective scores of the different properties by calculating the Spearman correlation coefficient.

The following findings deserve further comments:



**Fig. 8.** Histograms representing the score distribution of the median score for different properties evaluated in the JenAesthetics subjective dataset. The blue column represents the median value. Values below the median value are defined as low scores (shown in red) and values above as high scores (shown in green).

**Table 4.**  $\rho$  values calculated for Spearman correlation between subjective scores for different properties. All values are significantly different from zero ( $p < 0.01$ ).

Properties	Aesthetic	Beauty	Color	Composition	Content
Aesthetic	1				
Beauty	0.7802	1			
Color	.6676	.7237	1		
Composition	.7114	.7642	.6506	1	
Content	.6216	.8110	.5945	.7010	1

- The highest correlation rate is seen between liking of content and beauty. The fact that the content and subject matter of a painting plays a crucial role for how an observer evaluates a painting was mentioned previously in [1]. Other works emphasize this fact for other stimuli, such as [16] for webpages.
- The second highest correlation rate is between subjective aesthetic quality and beauty scores. Keeping in mind that the Oxford dictionary defines aesthetic as “concerned with beauty or the appreciation of beauty”, this high correlation is not a surprise.
- Previous studies have related different composition techniques such as the rule of thirds, the golden ratio, etc. to the beauty and aesthetic quality of paintings and photographs [3, 8, 18, 20, 26, 35, 38]. This close relation was also seen for the subjective scores, with the correlation between the quality of composition and beauty being the third highest correlation, and the correlation between aesthetic quality and the quality of composition being the fifth highest correlation.
- With regard to color, studies such as [2, 25, 26, 31] have emphasized the importance of color on subjective aesthetic and beauty scores. This aspect was also seen in the correlation between the color score and scores for beauty and aesthetics.
- The correlation rates between the beauty scores and the mentioned three properties (liking of color, content, and composition) are among the highest (fourth, third, and first, respectively). In contrast, the correlation rates for aesthetic quality with the three properties are not as highly ranked as those of beauty (seventh, fifth, and ninth respectively).

We also implemented a five-fold cross validation classifier using a linear SVM. This was done to enable users of the dataset to compare the present performance of a classifier with their own classifiers based on the subjective scores provided in the present work.

For the case of each property in our classification, we divide the images into two groups (high quality and low quality). The assigning of the groups is done based on the subjective score for each image. If the image has a subjective score greater than  $Median(allscores) + .1$ , the image will be labelled as high

quality and if the subjective score is lower than  $Median(allscores) - .1$ , it will be labelled as low quality. The other remaining properties are used as features in our classifier. Average recognition rates of this classification procedure are listed in Table 5 for different scenarios. From this table we can conclude that:

- High recognition rates were found between subjective aesthetic and beauty scores and the other three properties. This finding was previously seen for the correlation rates (Table 4). This supports the notion that these properties are closely related to the aesthetic and beauty judgement (see Section 3.1).
- Using the subjective scores provided for the liking of color and content together in our feature vector resulted in high recognition rates for beauty. As mentioned, this finding had been previously pointed out in literature.
- Similar to the correlation rates shown in Table 4, the lowest recognition rate is for the scores for content and color. This result is not surprising since the two mentioned properties are usually not related to one another in paintings.

## 5 Discussion and Future Works

In this paper, we present subjective ratings of the previously introduced JenAesthetics dataset. We hope that such a public dataset of paintings along with their subjective scores will provide a significant contribution to the computational aesthetic community. The lack of a publicly available subjective dataset of paintings has been mentioned numerous times in different publications and/or meetings such as the previous VISART workshop. The subjective dataset comprises scores for five different properties (aesthetic, beauty, and liking of color, composition, and content). The scores were gathered by performing 201 observation sessions over 130 observers. The results show that the properties assessed are highly correlated with one another. It was interesting to see that the subjective scores related to color, composition and content had a higher correlation with beauty scores than with aesthetic scores. This finding shows that having a high aesthetic quality, does not necessarily mean that the color, content, or composition are pleasing to the observer as well. The fact that the subjective scores for beauty and aesthetic quality were highly correlated confirms findings from previous studies [1–3, 8, 16, 18, 20, 25, 26, 31, 35, 38].

Compared to previous datasets, the JenAesthetics subjective dataset has a larger number of paintings and covers a wider range of different subject matters, styles and art periods. It also evaluates different properties providing the user with many different scenarios to test and evaluate.

In the future, we will increase the number of images assessed in our subjective dataset. Also, we are planning to extract additional features from the images. Finding the relationship between scores provided in different subgroups, such as males and females, could be an interesting topic of investigation.

**Table 5.** Average recognition rate of five-fold cross validation using different subjective scores as features in a linear SVM. In the first column, A corresponds to subjective scores for aesthetic quality, B for beauty, CL for color, CM for composition, and CN for content.

Feature vector	Aesthetic	Beauty	Color	Composition	Content
A	–	76.37%	73.50%	74.09%	71.99%
B	76.53%	–	76.16%	78.10%	82.77%
CL	72.82%	76.40%	–	73.56%	70.19%
CM	74.59%	77.07%	73.77%	–	76.63%
CN	73.16%	79.80%	69.19%	73.87%	–
A, B	–	–	77.68%	80.63%	82.23%
A, CL	–	82.62%	–	76.19%	75.19%
A, CM	–	82.74%	74.73%	–	77.27%
A, CN	–	85.66%	74.61%	79.79%	–
B, CL	80.96%	–	–	80.02%	82.09%
B, CM	81.54%	–	77.81%	–	84.20%
B, CN	80.23%	–	77.62%	79.86%	–
CL, CM	78.60%	82.36%	–	–	78.13%
CL, CN	77.28%	86.11%	–	78.92%	–
CM, CN	76.46%	84.75%	73.28%	–	–
A, B,CL	–	–	–	80.47%	83.05%
A, B, CM	–	–	77.96%	–	84.76%
A, B, CN	–	–	77.68%	81.18%	–
A, CL, CM	–	85.04%	–	–	79.00%
A, CL, CN	–	88.30%	–	80.59%	–
A, CM, CN	–	87.90%	77.33%	–	–
B, CL, CM	81.56%	–	–	–	84.07%
B, CL, CN	81.03%	–	–	80.23%	–
B, CM, CN	81.59%	–	77.85%	–	–
CL, CM, CN	79.07%	87.42%	–	–	–
A, B, CL, CM	–	–	–	–	84.77%
A, B, CL, CN	–	–	–	81.35%	–
A, B, CM, CN	–	–	78.22%	–	–
A, CL, CM, CN	–	88.68%	–	–	–
B, CL, CM, CN	81.64%	–	–	–	–

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