The art painting style Classifier based on Logic Aggregators and qualitative colour Descriptors (C-LAD)

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Abstract

This paper presents C-LAD, an art painting style classifier based on colours and logic aggregators which yields explanations of its categorisations. First, the more representative colour traits for the Baroque, the Impressionism, and the Post-Impressionism styles are introduced as fuzzy notions. Then, categorisations of the three styles are proposed using these colour features and logic aggregators, and the C-LAD algorithm is defined. Finally, the algorithm is tested on 90 paintings of the QArt-Dataset and on 247 paintings of the Paintings-91-PIB dataset, and the competitive results achieved are analysed.

1 Introduction

This paper is a contribution to the challenge of classifying paintings in art styles using artificial intelligence (AI). In the literature, this problem has mainly been tackled using machine learning algorithms (e.g. neural networks, support vector machines, deep learning, etc.): for instance, traditional Chinese paintings were classified by Jiang et al. [17] using colours and support vector machines (SVMs); Karayev et al. [18] trained deep neural networks on object recognition for style categorisation of artworks; the work of Condorovici et al. [3] presents a fusion scheme based on combining Multi-Layer Perceptron classified data with SVMs; and Falomir et al. [12, 13] categorised painting styles using qualitative colour descriptors, k-nearest neighbors algorithms and SVMs.

In general, machine learning methods applied to painting style categorisation provide high accuracy rates, but they usually do not follow the *explainable AI principle* (i.e. they cannot provide reasons to users regarding why an item is classified in a category). Recent works on explainable AI deal with classifications of films, wines and places [5], or leaves [1]. Regarding painting categorisation in explainable AI, Costa et al. [4] presented the ℓ-SHE classifier, which is the first research work that integrates qualitative descriptors and t-norm based logics for art painting style categorisation with explanations. The authors defined three versions of the ℓ-SHE classifier, depending on the logic selected. Although the ℓ-SHE algorithm yields reasons of its classifications, it has two main disadvantages, which motivated the work we present in this paper: it gets an accuracy rate lower than other art painting style classifiers in the literature; and it does not integrate logic aggregators in the categorisations of the art styles. Indeed, according to the theory of Dujmović [8], logic aggregators can be utilised in mathematical models of human evaluation reasoning, since in general they yield a closer approximation to related human evaluation process than t-norm based logics do.

Thus this paper presents and evaluates the art painting style Classifier based on Logic Aggregators and qualitative colour Descriptors (C-LAD). This classifier categorises paintings from the Baroque, the Impressionism and the Post-Impressionism styles. Moreover, the C-LAD algorithm tackles and solves the before mentioned disadvantages of previous

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work in the literature of art painting categorisation in explainable AI. In this way, the three main features of the C-LAD algorithm represent a significant advance in the field: (i) the classifier uses logic aggregators and integrates the subjective aggregation theory developed by Dujmović [8]; (ii) it yields reasons regarding why a painting belongs to a certain style, and it also provides explanations about why some paintings may belong to another art style, giving a second classification option in some hard-fought cases; (iii) the general accuracy rates shown by the C-LAD categorisation for the selected datasets are higher than the other art painting style classifiers in the literature of explainable AI.

2 Preliminaries

This section contains the preliminaries of the paper. First, the two datasets used in this paper, the QArt-Dataset and Painting-91-BIP datasets, are presented. Then, we briefly sketch the computational model for Qualitative Colour Description (QCD model) introduced by Falomir et al. [9, 11]. Finally, logic aggregators and their different types [8] are briefly recalled and exemplified in the context of evaluating the style of a painting.

The QArt-Dataset contains 90 images (30 paintings for each style) and the Painting-91-BIP dataset includes 247 images (74 for the Baroque style, 82 for the Impressionism style and 91 for the Post-Impressionism style). For each art style, both datasets consider two representative authors: Velázquez and Vermeer for the Baroque style, Monet and Renoir for the Impressionism style, and Gauguin and van Gogh for the Post-Impressionism style (see Fig. 1 for some examples).

B

I

PI

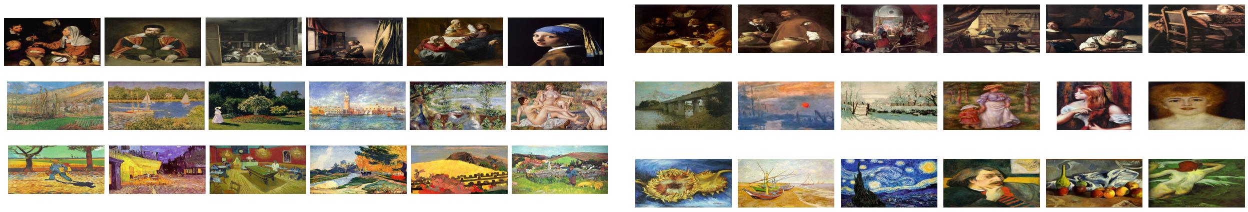

Figure 1: Extracts from the QArt-Dataset (left) and the Painting-91-BIP dataset (right): paintings corresponding to the Baroque style (B), the Impressionist style (I) and the Post-Impressionist style (PI). All rights by Wikimedia commons, public domain.

The QCD model [9, 11] defines a reference system in the Hue Saturation Ligthness (HSL) colour space for qualitative colour naming. It is defined as $QCRS = \{UH, US, UL, QC_{NAME1\ldots5}, QC_{INT1\ldots5}\}$, where UH, US, UL are the units of Hue, Saturation and Lightness, repectively, $QC_{NAME1\ldots5}$ refers to the colour names, and $QC_{INT1\ldots5}$ refers to the intervals of HSL coordinates associated with each colour. The chosen QC_{NAME} are: QC_{NAME_1} = {*black, dark_grey, grey, light_grey, white*}, QC_{NAME_2} = {*red, orange, yellow, green, turquoise, blue, purple, pink*}, QC_{NAME_3} = {*pale_* + QC_{NAME_2}}, QC_{NAME_4} = {*light_* + QC_{NAME_2}}, and QC_{NAME_5} = {*dark_* + QC_{NAME_2} }. In order to determine a colour name, the QCD proceeds as explained in Table 1. Using this model, colour frequencies of any digital image have been extracted and expressed as Prolog facts [4], i.e. we describe digital images with Prolog facts, as shown in Fig. 2.

Table 1: Reference HSL intervals for colour names (QC_{INT}).

	colour	UH	US	UL
QC_{LAB_1}	*black*	[0, 360]	$[0, \min\{20, 2\,UL, 200 - 2\,UL\}]$	$(0, 20]$
	dark_grey			$(20, 40]$
	grey			$(40, 60]$
	light_grey			$(60, 80]$
	white			$(80, 100]$
QC_{LAB_2}	*red*	(335, 360] ∪ [0, 20]	$(50, \min\{100, 2\,UL, 200 - 2\,UL\}]$	$(40, 60]$
	orange	(20, 50]		
	yellow	(50, 80]		
	green	(80, 160]		
	turquoise/cyan	(160, 200]		
	blue	(200, 239]		
	purple	(239, 297]		
	pink/magenta	(297, 335]		
QC_{LAB_3}	$pale\_QC_{LAB_2}$	Idem	$(20, 50]$	$(40, 60]$
QC_{LAB_3}	$light\_QC_{LAB_2}$	Idem	$(20, 200 - 2UL]$	$(60, 90]$
QC_{LAB_3}	$dark\_QC_{LAB_2}$	Idem	$(20, 2UL]$	$(10, 40]$

Dujmović introduced logic aggregators, i.e. functions that aggregate two or more degrees of truth and return a degree of truth in a way similar to observable patterns of human reasoning [7, 8]. The meaning and role of inputs and outputs of logic aggregators can be used as the necessary restrictive conditions that filter those functions and properties that have

```
colour_painting(v10, black, 0.362).
colour_painting(v10, dark_turquoise, 0.056).
colour_painting(v10, dark_grey, 0.117).
...
colour_painting(v10, light_green, 0.014).
colour_painting(v10, light_orange, 0.010).
...
colour_painting(v10, pale_yellow, 0.0128).
colour_painting(v10, white, 0.021).
```

Figure 2: *Equestrian Portrait of Prince Balthasar Charles* (Velázquez). All rights by Wikimedia commons, public domain.

potential to serve in mathematical models of human evaluation reasoning. In this paper we use these functions to categorise art painting styles, as shown in next section. Let us now recall the main definitions on logic aggregators.

An *aggregator* $A : [0,1]^n \to [0,1]$ [7, Definition 1] is defined as a nondecreasing function in each argument (where $n > 1$ and $[0,1]$ is the unit interval of the real numbers) and such that satisfies boundary conditions of idempotency in extreme points 0 and 1. An aggregator $A : [0,1]^n \to [0,1]$ is a *logic aggregator* [7, Definition 2] if A is a continuous function that satisfies the following sensitivity conditions: for every $x_1, \ldots, x_n \in [0,1]$ and $1 \leq i \leq n$, $A(x_1, \ldots, x_n) > 0$ if $x_i > 0$; and $A(x_1, \ldots, x_n) < 1$ if $x_i < 1$. From now on, let $A : [0,1]^n \to [0,1]$ be a logic aggregator.

In the process of classifying a picture into a painting style, humans may have input percepts of the degrees of adequacy of the picture with respect to the different distinctive traits of the painting styles. The distinctive colour features can be regarded in a natural way as fuzzy notions [4]. According to Dujmović [8], humans would aggregate the degrees corresponding to the different traits to create a composite percept, assigning a degree of membership of a picture to the different painting styles. In the remainder of the section characteristic patterns of human aggregative reasoning related to the art painting style categorisation are identified, based on this aggregation theory.

Pattern 1. Idempotent Aggregation. This aggregation pattern is based on the assumption that the membership degree to an art style must be between the lowest and the highest value of the colour traits of this style. Formally, it is said that A is *idempotent* [7, Definition 3] if for every $x_1, \ldots, x_n \in [0,1]$, $\min(x_1, \ldots, x_n) \leq A(x_1, \ldots, x_n) \leq \max(x_1, \ldots, x_n)$.

Pattern 2. Noncommutativity. Observe that for each painting style, each colour trait may have its degree of importance. Hence it is essential to model asymmetry, which can be represented using different weights of the arguments. Formally, it is said that A is *asymmetric* [7, Definition 5] if for every $x_1, \ldots, x_n \in [0,1]$, $i \neq j$, $x_i \neq x_j$, we have that $A(x_1, \ldots, x_i, \ldots, x_j, \ldots, x_n) \neq A(x_1, \ldots, x_j, \ldots, x_i, \ldots, x_n)$. Asymmetry is usually realised using different weights of arguments. Weights are assumed to be positive and normalized: $0 < w_i < 1$, $\sum_i w_i = 1$.

Pattern 3. The use of Annihilators. An annihilator is an extreme value of suitability (either 0 or 1) of a feature which is sufficient to decide the result of aggregation regardless of the values of other inputs. In the case of necessary conditions the annihilator is 0: if some mandatory requirement for a painting style is not satisfied, the painting is not classified in this style. In a dual case of sufficient conditions the annihilator is 1. The aggregators that support annihilators 0 and 1 are called *hard*, and aggregators that do not support annihilators are called *soft*. Although many examples of the use of hard aggregators in human aggregation can be observed [8], we believe that art is too diverse to justify the use of annihilators. For instance, a high level of darkness is distinctive of the Baroque style but other art styles can also present a high level of darkness (as for instance the Romanticism style). Conversely, the absence of this distinctive trait is not enough to discard this style: some Baroque paintings show few use of dark colours. Formally, it is said that A has an *annihilator* $a \in [0,1]$ *in the argument* i (where $1 \leq i \leq n$) [7, Definition 13] if for every $x_1, \ldots, x_n \in [0,1]$, the following holds: if $x_i = a$, then $A(x_1, \ldots, x_i, \ldots, x_n) = a$. Furthermore, it is said that A has *homogeneous annihilators*, either if A does not have annihilators, or if A has the same annihilator in all arguments. Homogeneous aggregators are called *hard* if they have 0 as annihilator in all the arguments, and are called *soft* if 0 is not an annihilator for any argument. A soft conjunction that has homogeneous annihilators is called *partial soft conjunction* [7, Definition 18]; and asymmetric partial conjunctions are denoted by Δ. The formula interpreting the soft partial conjunction [8, Figure 2.4.24], Δ, has the following expression: $\frac{\alpha_\theta-\alpha}{\alpha_\theta-0.5}(\Sigma_{i=1}^n W_i x_i) + \frac{\alpha-0.5}{\alpha_\theta-0.5}(\Sigma_{i=1}^n W_i x_i^R)^{\frac{1}{R}}$, where $\alpha = 9/14, \alpha_\theta = 0.75$ and R is obtained from [8, Table 2.4.16]. As shown in next section, we categorise the art styles under study using asymmetric partial conjunctions.

3 Art painting style categorisation based on QCDs and logic aggregators

In this section we propose distinctive colour traits for the painting styles under study. Note that in this work we expand the set of colour traits defined in [4]. Using the Qart-Dataset, the value of these colour features are then calibrated. Furthermore, a formula in order to categorise each style is defined using these characteristic colour features and logic aggregators. Finally, the parametrisation of the formulas categorising each style is explained.

With the aim of defining the different colour traits for the three styles, the QCD model was extended in [4, Def.1] as follows: *dark_colours* $= \{$*black, dark_(red,orange,yellow,green,turquoise,blue,purple,pink,grey)*$\}$,

pale_colours $= \{$*pale_(red,orange,yellow,green,turquoise,blue,purple,pink,grey)*$\}$,

light_colours $= \{$*white,light_(red,orange,yellow,green,turquoise,blue,purple,pink)*$\}$,

grey_hue $= \{grey, pale\_grey, light\_grey, dark\_grey\}$ (analogously for *red_hue, orange_hue, yellow_hue, green_hue, turquoise_hue, blue_hue, purple_hue, pink_hue*) *warm_hue* $= \{$*red_hue,orange_hue,yellow_hue*$\}$, and

vivid_colours $= \{$*red, orange, yellow, green, turquoise, blue, purple, pink*$\}$.

In addition to this extension of the QCD model, let us add the following: *red_colours*={*red, orange, pale_red, light_red, dark_red, pale_orange, dark_orange, light_orange*}. Now we proceed with the categorisations of the styles.

Mainly, the Baroque painting shows a high level of darkness provided by the use of dark colours (black colour and dark tones of other colours) [21]. Since most of the Baroque creations correspond to indoor scenes, this darkness is emphasised by a modest use of light-pale colours, which contrast with the dark colours and, at the same time, exaggerate the lightness in the composition [15]. Consequently, Baroque paintings are lacking in pale colours, since a too much frequent use of them might break this contrast effect between dark and light-pale colours. Moreover, Baroque compositions include a high proportion of peroxide-based yellows, oranges and reds, according to Grygar [14]. Considering these colour features outlined by the art experts, we propose to use the following distinctive colour traits for the Baroque style: $\underline{darkness\_level}$: the accumulative sum of the frequencies of *dark_colours*; $\underline{no\_paleness\_level}$: the total frequency of colours that are not *pale_colours*; $\underline{contrast\_level}$: the total frequency of $dark$ and $pale$ colours; $\underline{red\_colours}$: the relation between the amount of *red_colours* in a painting, and the total number of qualitative colours (QCs) in the painting. From now on, let p be a digital image. The categorisation of the Baroque style, $B(p)$, is formalised with logic aggregators as follows:

$$W_1 \text{ darkness\_level}(p) \, \Delta \, W_2 \text{ no\_paleness\_level}(p) \, \Delta \, W_3 \text{ contrast\_level}(p) \, \Delta \, W_4 \text{ red\_colours}(p).$$

Regarding colour features in the Impressionism style, the literature [19, 20] explains that the development of synthetic pigments provided artists with vibrant shades of blue and green. Hence a bigger number of colours and hues is expected in comparison to more ancient art styles, such as the Baroque style. In addition, the Impressionists captured the effects of sunlight by painting en *plein air* (outdoors), and thereby the blue of the sky or the sea, light colours and grey shadows are common in this style [6, 2]. The characteristic colour features proposed are thus: $\underline{diversityofHues}$: all the QCs in a painting are grouped according to their hues and they are related to the total number of hues in QCD, which is 11 ($|\{vivid\_colours\} \cup \{black,white\}| = 11$); $\underline{diversityofQCDs}$: the relation between the amount of qualitative colours (including all their pale-, light-, and dark- variants) in a painting, and the total number of QCs possible (i.e. 37); $\underline{bluish\_level}$: the total frequency of the QCs extracted as having blue hue; $\underline{greyish\_level}$: the total frequency of the QCs extracted as having grey hue. This definition of the Impressionism, $I(p)$, is formalised as:

$$W_1' \text{ diversityofHues}(p) \, \Delta \, W_2' \text{ diversityofQCDs}(p) \, \Delta \, W_3' \text{ bluish\_level}(p) \, \Delta \, W_4' \text{ greyish\_level}(p).$$

The Post-Impressionist style breaks the tendency of representing colours as appearing in reality [15, 16]. The Post-Impressionists looked for expressiveness using colours arbitrarily[1], and hence colours with pure hues (i.e. *vivid colours*) are present in their paintings. Post-Impressionist paintings show hues of reds, oranges and yellows (*warm colours*); and frequently they have colour contrasts, specially blue vs. yellow and red vs. green [19]. The traits proposed are: $\underline{vividness\_level}$: the total frequency of the QCs extracted as having pure hue; $\underline{warm\_colours\_level}$: the total frequency of the QCs extracted as having warm hue; $\underline{contrast\_blue\_yellow\_level}$: the total frequency of $bluish$ and $yellowish$ (i.e. the total frequency of *yellow, pale_yellow* and *dark_yellow*) colours bounded to 1; $\underline{contrast\_red\_green\_level}$: the total frequency of $reddish$ and $green\_colours$ colours bounded to 1. The Post-Impressionism, $\underline{PI(p)}$, is formalised as:

$$W_1'' \text{ vividness\_level}(p) \, \Delta \, W_2'' \text{ warm\_colours\_level}(p) \, \Delta \, W_3'' \text{ contrast\_blue\_yellow\_level}(p) \, \Delta \, W_4'' \text{ contrast\_red\_green\_level}(p).$$

In order to calibrate the distinctive colour traits of each art style, we have considered the mean of each of these features in all the images of the QArt-Dataset:

Colour trait	$darkness\_level$	$no\_paleness\_level$	$contrast\_level$	$red\_colours$	$diversityofHues$
Mean	0.5004	0.7760	0.7247	0.3721	0.7121
Colour trait	$diversityofQCDs$	$bluish\_level$	$greyish\_level$	$vividness\_level$	$warm\_colours\_level$
Mean	0.5426	0.0860	0.3330	0.0558	0.3704
Colour trait	$contrast\_blue\_yellow\_level$	$contrast\_red\_green\_level$			
Mean	0.1486	0.2954			

[1] C. Tate. Post-Impressionism. http://www.tate.org.uk/art/art-terms/p/post-impressionism, accessed 14 April 2018.

Notice that, although all the values of the colour traits are normalised, their means are quite dispar in such a way that a priori some features are more significant than others. For instance, a painting might show 0.75 of $no\_paleness\_level$ and 0.25 of $bluish\_level$. Hence the model should give more importance to the $bluish\_level$ feature of the painting than to the $no\_paleness\_level$ trait, since in this case the $bluish\_level$ feature is specially relevant to determine the art style. Thus we need to calibrate the values of the colour traits. In order to do it, we consider the mean of all the colour traits, which is 0.4098. Then, the calibrated colour feature, indicated by $*$, is obtained as follows: $darkness\_level(p)^* = max\{darkness\_level(p) - (0.5004 - 0.4098), 0\}, \ldots,$ $contrast\_red\_green\_level(p)^* = vividness\_level(p) + (0.4098 - 0.0558)$, etc. That is, the difference between the general mean of the all the colour features and the mean of the colour trait considered is added or substracted (depending on the mean of the colour trait considered) to the value of the colour trait for p.

Finally, in order to obtain the weights corresponding to the colour traits distinctive of the Baroque style ($W_1, \ldots, W_4$), we have considered the mean of each of these features. We explain the procedure for the colour trait $darkness\_level$. The mean for $darkness\_level$ is denoted by $\overline{x_{dly}}$, where *dl* denotes *darkness_level* and y is substituted by B, I, PI, depending on the art style selected. For instance, $\overline{x_{dlB}}$ denotes the mean of the $darkness\_level$ of the 30 Baroque paintings in the QArt-Dataset. The other colour traits of the Baroque are denoted by npl, cl and rc. The results obtained are shown next.

art painting style	$\overline{x_{dly}}$	$\overline{x_{nply}}$	$\overline{x_{cly}}$	$\overline{x_{rcy}}$
Baroque (B)	0.67	0.50	0.59	0.49
Impressionism (I)	0.33	0.36	0.38	0.38
Post-Impressionism (PI)	0.24	0.37	0.28	0.36

From these data, we obtain the differences between the mean of the colour trait for the Baroque style and the mean of this feature for the other styles: $dif_{dl} = \frac{(\overline{x_{dlB}} - \overline{x_{dlI}}) + (\overline{x_{dlB}} - \overline{x_{dlPI}})}{2} = 0.38, dif_{npl} = 0.15, dif_{cl} = 0.26$, and $dif_{rc} = 0.12$. The highest difference must correspond to the highest weight, because a higher difference indicates that the colour trait is more distinctive for the art style selected. In this case, it corresponds to the $darkness\_level$ (i.e. *dl*). The weights are thus obtained by solving the system of linear equations $\{W_1 + W_2 + W_3 + W_4 = 1, W_1 = 2.61W_2, W_1 = 1.48W_3, W_1 = 3.10W_4\}$, whose solutions are $W_1 = 0.42, W_2 = 0.16, W_3 = 0.28$, and $W_4 = 0.14$. With respect to the other styles, we proceed analogously and obtain that $W_1', W_2', W_3', W_4', W_1'', W_2'', W_3'', W_4''$. Therefore we have parametrised the three formulas that categorise the Baroque, the Impressionism and the Post-Impressionism styles.

4 The C-LAD algorithm

In this section we define the art painting style Classifier based on Logic Aggregators and qualitative colour Descriptors (C-LAD) and show some examples of responses produced by the C-LAD categorisation for paintings of the QArt-Dataset.

We define first the *evaluation degree* for p to belong to an art style as:

$$ebAS(p) = \begin{cases} (B_{st}, B(p)) & \text{if } max\{B(p), I(p), PI(p)\} = B(p) \text{ and } PI(p) \neq B(p) \neq I(p); \\ (I_{st}, I(p)) & \text{if } max\{B(p), I(p), PI(p)\} = I(p) \text{ and} B(p) \neq I(p) \neq PI(p); \\ (PI_{st}, PI(p)) & \text{if } max\{B(p), I(p), PI(p)\} = PI(p) \text{ and} B(p) \neq PI(p) \neq I(p); \\ (Unk_{st}, I(p)) & \text{otherwise.} \end{cases}$$

Since the C-LAD algorithm has to give a second option in difficult cases, a function between evaluation degrees, Sim, is defined: $Sim_{B,I}(p) = |B(p) - I(p)|$, $Sim_{B,PI}(p) = |B(p) - PI(p)|$, and $Sim_{I,PI}(p) = |I(p) - PI(p)|$, where $Sim_{B,I}(p)$ stands for the closeness between the Baroque and the Impressionism evaluation degrees of p, and $Sim_{B,PI}(p), Sim_{I,PI}(p)$ are described analogously. The C-LAD algorithm categorises paintings as follows:

1. If $edAS = (B_{st}, B(p))$, then "p is a Baroque painting." & $explanation_{\text{C-LAD}}(B, p)$.
   - If $Sim_{B(p),I(p)} \leq 0.15$, then "Although p is categorised in the Baroque style, there are reasons to believe that it may belong to the Impressionism." & $explanation_{\text{C-LAD}}(I, p)$.
   - If $Sim_{B(p),PI(p)} \leq 0.15$, then "Although p is categorised in the Baroque style, there are reasons to believe that it may belong to the Post-Impressionist." & $explanation_{\text{C-LAD}}(PI, p)$.
2. If $edAS = (I_{st}, I(p))$, then "p is an Impressionist painting." & $explanation_{\text{C-LAD}}(I, p)$.
   - If $Sim_{B(p),I(p)} \leq 0.15$, then "Although p is categorised in the Impressionist style, there are reasons to believe that it may belong to the Baroque." & $explanation_{\text{C-LAD}}(B, p)$.

- If $Sim_{I(p),PI(p)} \leq 0.15$, then "Although p is categorised in the Impressionist style, there are reasons to believe that it may belong to the Post-Impressionism." & $explanation_{\text{C-LAD}}(PI, p)$.

3. If $edAS = (PI_{st}, PI(p))$, then "p is a Post-Impressionist painting." $explanation_{\text{C-LAD}}(PI, p)$.
   - If $Sim_{B(p),PI(p)} \leq 0.15$, then "Although p is categorised in the Post-Impressionist style, there are reasons to believe that it may belong to the Baroque." & $explanation_{\text{C-LAD}}(B, p)$.
   - If $Sim_{I(p),PI(p)} \leq 0.15$, then "Although p is categorised in the Post-Impressionist style, there are reasons to believe that it may belong to the Impressionism." & $explanation_{\text{C-LAD}}(I, p)$.
4. If $edAS = (Unk_{st}, I(p))$, then "p could not be classified."

In addition, explanations for specific characteristics in each art style can also be provided. For instance, let us consider the colour trait $darkness\_level$ as significant for classifying p into the Baroque style, whenever $darkness\_level(p)$ is higher than the mean of the $darkness\_level$ of the 30 Baroque paintings in the QArt-Dataset, say $\overline{darkness\_level}$ (and analogously for the rest of the distinctive colour traits). Hence this mean plays the role of a threshold. That is, if this is the case, the presence of this feature must appear as an explanation/evidence for p classified into this style. For the Baroque style, $explanation_{\text{C-LAD}}(B, p)$ provided by C-LAD are the following (the rest of the explanations are analogous):

If $darkness\_level(p) \geq \overline{darkness\_level}$, then "The darkness evidences the Baroque style."

If $no\_paleness\_level(p) \geq \overline{no\_paleness\_level}$, then "The contrast of $dark$ and $pale$ colours evidences this style."

If $contrast\_level(p) \geq \overline{contrast\_level}$, then "The lack of $pale$ colours evidences this style."

If $red\_colours(p) \geq \overline{red\_colours}$, then "The high proportion of peroxide-based yellows, oranges and reds evidences this style."

The C-LAD algorithm has been implemented in the program language R[2], but let us recall that the values of the colour traits were obtained using Swi-Prolog, as explained in [4, Section 6]. A random image in the QArt-Dataset of each style has been selected as a running example (see Figure 3), and the categorisation and the explanations provided by C-LAD for these paintings are:

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v4 is a Baroque painting. The darkness evidences the Baroque style.
The contrast of dark and pale colours evidences this style.
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rn5 is an Impressionist painting. The variety of hues evidences
the Impressionism style.The diversity of qualitative colours
evidences the Impressionism style. The amount of bluish evidences
this style. The amount of grey colour evidences this style.
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```
rn5 is an Impressionist painting. The variety of hues evidences
the Impressionism style.The diversity of qualitative colours
evidences the Impressionism style. The amount of bluish evidences
this style. The amount of grey colour evidences this style.
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V4 | rn5 | vg10 | v3, outlier for C-LAD | rn3, outlier for C-LAD | vg3, outlier for C-LAD

Figure 3: The first three images are examples used to show the responses provided by C-LAD. The other images are examples of paintings misclassified from the QArt-Dataset (Section 5). All rights by Wikimedia commons, public domain.

5 Evaluating the C-LAD algorithm

This section shows and discusses the results obtained when classifying the 90 images in the QArt-Dataset using the C-LAD algorithm. The results for the 247 images in the Painting-91-BIP dataset are only highlighted at the end of the section.

Table 2 shows the confusion matrix obtained for the three art styles in the QArt-Dataset. The blue cells correspond to the correct classifications: on the left, correct classifications where C-LAD is sure (✓); on the right, correct classifications where C-LAD is not sure and yields an alternative style as a second opinion (**?**). The rest of the cells correspond to the outliers: in each column, the cell on the left indicates the outliers in that C-LAD does not give a second opinion (✓); and the cell on the right shows the outliers in that the second opinion given classifies correctly the painting (**?**). Let us indicate that, when the algorithm is doubting, it provides two possible styles as a result. The first option (highest certainty) is the one considered as a correct classification. If the second opinion (lowest certainty) is the correct one, it is not counted as a correct classification and it appears in a column corresponding to a different style.

The highest accuracy is obtained for the **Baroque style** (93.7% – 28/30), and 82.1% of correct classifications (23/28) C-LAD certainly categorises the painting, without yielding a second opinion. An outlier of the Baroque style is the

[2] https://www.r-project.org/.

Table 2: Confusion matrix for C-LAD using the QArt-Dataset.

	Baroque		Impressionism		Post-Impressionism	
	✓	?	✓	?	✓	?
Baroque	23	5	0	1	1	0
Impressionism	3	2	8	13	2	2
Post-Impressionism	2	0	1	4	12	11

painting *The Surrender of Breda* ($v3$, Figure 3), from Velázquez, which is categorised as an Impressionist painting, but in fact C-LAD warns that there is evidence to belong to the Baroque style. The **Impressionism style** obtains an accuracy of 70.0% (21/30). In 44.4% of the misclassifications obtained, C-LAD warns that there is evidence to belong to the Impressionist style. An example of an outlier in this style is *Composition, Five Bathers* ($rn3$, Figure 3) by Renoir, for which $B(rn3) = 0.42$, $I(rn3) = 0.31$, and $PI(rn3) = 0.58$. The **Post-Impressionism** style gets 76.7% of accuracy rate (23/30). Observe that 71.4% of the outliers are categorised in the Impressionism style. In addition, in 57.1% of the misclassifications C-LAD warns that there is evidence to believe that a painting belongs to the Post-Impressionist style. An example of an outlier in the Post-Impressionist style is *Paysage de Bretagne. Le moulin David* ($gg11$, Figure 3) by Gauguin, for which $B(gg11) = 0.33$, $I(gg11) = 0.55$, and $PI(gg11) = 0.44$ (in this case C-LAD warns that there is evidence $gg11$ to belong to the Post-Impressionism style). The general accuracy rate got by C-LAD in the QArt-Dataset is 80.0%. Table 3 shows the confusion matrix obtained for the three art styles in the 247 images of the Painting-91-BIP dataset. Note that the total accuracy rate got by C-LAD in the Painting-91-BIP dataset is 64.0%.

Table 3: Confusion matrix for C-LAD using the QArt-Dataset.

	Baroque		Impressionism		Post-Impressionism	
	✓	?	✓	?	✓	?
Baroque	53	13	0	1	1	6
Impressionism	25	10	21	16	17	3
Post-Impressionism	9	10	10	7	36	19

6 Conclusions and future work

The C-LAD algorithm has been presented and tested on the QArt-Dataset and the Painting-91-BIP datasets. The results obtained are similar to other research works as [12, 13]. Furthermore, contrary to the art painting classifiers based on machine learning methods, the C-LAD classification provides explanations of right classifications, and also of some of the outliers by giving a second option. In comparison to the ℓ-SHE classifier, which also yields explanations of the results obtained, the C-LAD algorithm has some advantages: (i) it adds a larger number of explanations of its classifications; (ii) it integrates the subjective aggregation theory developed by Dujmović [8]; (iii) and the accuracy obtained is significantly higher (80.0% vs. 73.3% for the best version of ℓ-SHE in the QArt-Dataset; and 64.0% vs. 60.2% for the best version of ℓ-SHE in the Painting-91-BIP dataset).

Regarding future work, we intend to improve the function $ebAS$ in order to solve any event of a tied evaluation degree that may appear in future testings of the algorithm. Other future work includes a detailed comparison of the different approaches for art painting style classification. We also plan to design a classifier that mixes qualitative colour descriptors, logic aggregators and art genres data. Finally, future research should aim to add new art styles to the dataset in order to define categorisations of a larger number of styles.

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