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Toward the Automatic Retrieval and Annotation of Outsider Art images: A Preliminary Statement

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Abstract

The aim of this position paper is to establish an initial approach to the automatic classification of digital images about the Outsider Art style of painting. Specifically, we explore whether is it possible to classify non-traditional artistic styles by using the same features that are used for classifying traditional styles? Our research question is motivated by two facts. First, art historians state that non-traditional styles are influenced by factors "outside" of the world of art. Second, some studies have shown that several artistic styles confound certain classification techniques. Following current approaches to style prediction, this paper utilises Deep Learning methods to encode image features. Our preliminary experiments have provided motivation to think that, as is the case with traditional styles, Outsider Art can be computationally modelled with objective means by using training datasets and CNN models. Nevertheless, our results are not conclusive due to the lack of a large available dataset on Outsider Art. Therefore, at the end of the paper, we have mapped future lines of action, which include the compilation of a large dataset of Outsider Art images and the creation of an ontology of Outsider Art. This research forms part of a wider project called "Semantic Analysis of Text Corpora in the Outsider Art Domain".

Keywords: Outsider Art, visual aesthetics, artistic styles

1. Introduction

This paper is about the computational analysis of visual aesthetics. We focus our attention on Outsider Art, which is considered by some as the "unsightly style".

At present, aesthetics constitutes a field of interest for scientists working in Artificial Intelligence, particularly in the context of paintings. Five of the main tasks in this field are: the prediction of ratings, the detection of forgery in paintings, artist identification, genre recognition and style prediction. First, the prediction of ratings (Talebi and Milanfar, 2017) captures the technical and semantic level characteristics associated with emotions and beauty in images in order to categorize images in two classes: low and high quality. Second, the detection of forgery in paintings (Mane, 2017) assumes that an artist's brushwork is characterized by signature features that can be detected automatically. Third, "artist identification is the task of identifying the artist of a painting given no other information about it" (Viswanathan, 2017). Fourth, genre recognition in paintings (Agarwal et al., 2015) focuses on classifying works of art according to the (type of) scene that is depicted by the artist. Finally, style prediction uses both low-level and semantic features in order to group paintings according to their shared properties. Several studies on style prediction will be commented on this paper.

Recently, deep learning methods have been growing in popularity for style classification because they can achieve state-of-the-art performance in this field. For example, Deep Convolutional Neural Networks models such as AlexNet, VGGNet and ResNet have been applied to the classification of traditional painting styles with varying success thanks to the existence of large scale datasets of digital paintings. However, to the best of our knowledge, there are no attempts to classify, retrieve and annotate the Outsider Art style.

1.1. Traditional art styles

While the expression "artistic genre" is used to divide artworks according to the themes depicted (e.g. landscape, self-portrait, marine, religious, etc.), the term "artistic style" is used to refer to groups of works that have similar but not rigorously defined properties. This set of distinctive characteristics "permits the grouping of artworks into related art movements" (Bar et al., 2014). For example, Impressionism is characterised by the use of flurried brushstrokes to represent the subject with gesture and illusion (e.g. the painter Pierre-Auguste Renoir), Expressionism uses vivid and unrealistic colors to depict the subject as it appears to the artist (e.g. Wassily Kandinsky), in Abstraction the subject is reduced to its dominant colors, shapes or patterns (e.g. Piet Mondrian) and Baroque emphasize exaggerated motion and easily interpreted detail to produce drama and exuberance (e.g. Peter Paul Rubens). Figure 1 shows 5 different art styles, along with a brief description.

Art style divisions are often identified by art historians based on the experience of looking at other works of art and the historical context. However, this is not an easy task since the limits between art styles are vague or blurred. Indeed, a style can span many different painters, periods and artistic schools. For example, Goya's technique influenced both late Romanticism and Impressionism and Pablo Picasso painted in both surrealist and cubist styles.

1.2. Outsider Art and non-traditional art styles

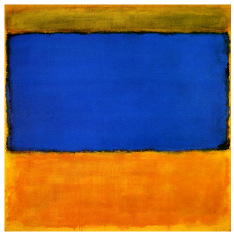
Previous artistic styles are part of the mainstream art world, which means that they all have culture as "an inescapable aspect of image production" (Chadwick, 2015, p. 17). In practical terms, this means that a painter in the mainstream is inspired by the work of those who had gone before

Action Painting *paint is randomly splashed onto the canvas*

Contemporary Realism *depicts the real rather than the ideal*

New Realism *daily existence of common people*

Synthetic Cubism *simple geometric shapes, interlocking planes and collage*



Color Field Painting *large areas of a single colour*

Figure 1: Some examples of traditional artistic styles.

him/her but the artist is not conscious that he/she is "imitating" another work of art.

In contrast, there is the art created outside the boundaries of official culture or "Anti-cultural art" as described by Jean Dubuffet in 1949. The condition of "non-traditional" or, more specifically, "outsider" artist applies to people who have very little contact with the mainstream art world and for this reason have developed extreme unconventional ideas based on spontaneous inventions (see Figure 2a-b). We are therefore talking about psychiatric hospital patients, children, self-taught artists, people in prison or with autism, etc. The art of these "anti-intellectual, anti-professional, anti-academic" people (Cottom, 2003) resists analysis with traditional art criteria, while the use of non-artistic criteria such as personality features, prevents the consideration of the results of the creative process (you are looking at the person not at the work of art). This is the thinking of the Outsider art collector John Soldano, for whom "the only way for me to honestly define outsider art is by artists" and the arts writer Priscilla Frank who says that "while other genres like Abstract Expressionism or Cubism denote a specific set of aesthetic guidelines or artistic traditions, the label 'outsider art' reflects more the life story and mental or emotional aptitude of the artist" (Frank, 2017).

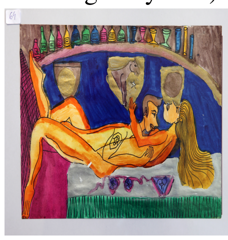
From a stylistic point of view, outsider artists paint obsessively repetitive images or themes (see Figure 2c). This might indicate an attempt to overcome the "horror vacui" (fear of empty space), bring order to mental chaos and provide reassurance that they are in control. It could be said that the outsider's vocabulary "oscillates back and forth between the ordered and monotonous filling of the surface of the work and the rhythmic and dynamic variation between the void and fullness of the composition" (Raw Vision magazine). Outsider Artists paint by physical impulse rather than intellectually. For that reason, subjects such as sexuality and eroticism can erupt in the most raw, emphatic and uncontrolled way (see Figure 2d). In some cases, the artworks appear to reveal dark desires which are not often played out in reality. These, and a number of other characteristics, make Outsider Art unattractive for a large part of the population and art historians.

In a larger sense, Outsider Art label covers an expanded range of non-traditional art styles such as art brut, naïve art, self-taught art, art singulier, visionary art, insane art, raw art, folk art, etc. All these form part of a continuum of artistic terms with blurred lines between them that are the tip of the iceberg of a potential task of classification of non-traditional art styles. In this article we use the terms **non-traditional** and **outsider** styles interchangeably.

(a) *Untitled* by Theodore H. Gordon (artbrut.ch)

(b) *Baby Beau Vine* by Lori Field (cumberlandgallery.com)

(c) *Untitled* (2016) by Stephanie Hill (creativegrowth.org)



(d) *Untitled* by Ramón Esteve (marginarte.com)

Figure 2: Some examples of Outsider Art paintings.

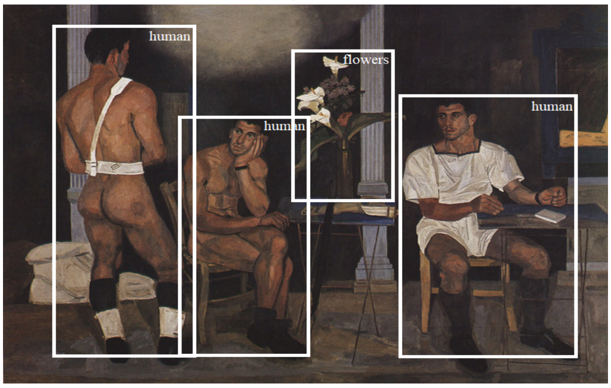
1.3. Classifying art style automatically in painting

Studies addressing the topic of the computational analysis of works of art are based on extracting a set of image features and using them to train different classifiers. Various formal image features such as line, color, texture or brush strokes and functional image features such as expression, content, composition and meaning (iconography) can be used to classify art styles automatically for paintings.

2. Related works

Classifying an artistic style automatically in painting has been the subject of much recent work that can be loosely divided into hand-crafted features and CNN-based features (training from scratch and pre-trained models). The former category (see Figure 3a) is a past tendency based in the use of computer vision methods to model handcrafted low-level features (e.g., color histograms, SIFT/GIST descriptor, texture, edges, brightness and gradient) that can be used by machine learning methods (e.g., SVM). The latter category (see Figure 3b) is a growing tendency and uses a Convolutional Neural Network (CNN) that encodes image content (semantic features) from a very large set of data (Zhao et al., 2017). Some examples of these two methods are briefly described below.

(a)



(b)

Figure 3: (a) low-level features (adapted from Condorovici et al. (2015) and (b) semantic features: object detection.

2.1. Handcrafted low-level features

Gunsel et al. (2005) trained an SVM classifier to discriminate between five painting styles. Their system computes a 6-dimensional vector of low level features. The authors report 90% accuracy with a low number of false positives. **Jiang et al. (2006)** classified traditional Chinese paintings into one of the two styles, Gongbi (traditional Chinese realistic painting) or Xieyi (freehand style) by using low-level features. They reported an accuracy rate of around 90% when combining decision tree and SVMs classifiers. **Wallraven et al. (2009)** tested how well several low-level features describe images from 11 different art periods. The authors found than "computational classifiers created from the participant data are able to categorize art periods with a performance of around 66%". The overall conclusion was that images grouped by humans corresponded better with the canonical art periods than those clustered by the computer.
Siddiquie et al. (2009) obtained good results in the classification of seven different painting styles by using multiple kernel learning in conjunction with low-level features (with accuracy rates of 76% to 92%). **Zujovic et al. (2009)** reported an overall accuracy rate of 69.1% when classifying five different genres. They used the AdaBoost classifier and, as features, steerable filters, as well as edge information extracted by a canny edge detector. **Shamir et al. (2010)** achieved an accuracy of 91.0% by using a set of low-level features on paintings by nine artists working in three different styles. **Culjak et al. (2011)** reported a 60.2% accuracy rate in the classification of six styles (including Naïve Art). They chose texture and color as low-level features and tested a range of classifiers, such as SVM.
Condorovici et al. (2015) achieved an overall detection rate of 72.24% on a database containing 4119 images from 8 painting styles (SVM). The authors selected features relevant for human perception and assessed the contribution of each feature. The overall conclusion is that the Dominant Color Volume features play a more important role for the automatic identification of artistic style.

2.2. CNN-based features

In the task of classifying 25 different painting styles from the Wikipainting dataset, **Karayev et al. (2014)** calculated through the confusion matrix up to 0.81 accuracy at predicting the Ukiyo-e style. They also found that the DeCAF, a deep CNN originally trained for object recognition, performs best for the task of classifying novel images according to their style. This leads them to conclude that some styles are closely related to image content, that is, the existence of certain objects in the painting.
Bar et al. (2014) examine binarized features derived from a Deep Neural Network in order to identify the style of paintings. They apply PiCoDes ("Picture Codes"), a very compact image descriptor, to learn a compact binary representation of an image. Their baseline was extracted from a CNN trained on the ImageNet dataset and implemented in Decaf, a deep convolutional activation feature for generic visual recognition. Their results show an improvement in performance with CNN-based features (0.43% accuracy) as well as their binarized version to distinguish 27 painting styles compared to hand-crafted low level descriptors (0.37% accuracy) such as Edge texture information and color histogram.
Mao et al. (2017) implemented DeepArt, a unified framework that can learn simultaneously both the contents and style of visual arts from a large number of digital artworks with multi-labels. The architecture of the framework is constructed by dual feature extraction paths that can extract style features and content features, respectively. The content feature representation path is generated on the basis of a VGG-16 network and the style feature representation path is built by adopting a Gram matrix to the filter responses in certain layers of the VGG-16 network. According to the authors, embedding the two output features in a single representation can be used to further improve two tasks: the automatic retrieval and annotation of digital artworks.
With the goal of outperforming the state-of-the-art, **Hong and Kim (2017)** trained a CNN on an art painting dataset of 30,000 distorted (projected, rotated, scaled, etc.) images

to simulate real-world displaying conditions. Three different architectures of CNN were tested on this dataset: the first architecture was derived from AlexNet (Krizhevsky et al., 2012), the second architecture was inspired by VGGNet (Simonyan and Zisserman, 2014) and the third architecture was a smaller version of the second one which used a smaller filter size ($11 \to 7$) in the beginning and fewer neurons in fully-connected layers. The latter architecture performed best, obtaining low test error rates by optimizing its parameters with the Adam algorithm. According to the researchers, the proposed CNN-based method outperformed the previous state-of-the-art with a test error rate of 15.6% to 2%.

In order to identify the best training setup for the style classification of paintings, **Cetinic et al. (2018)** compared different CNN fine-tuning strategies performed on a WikiArt subset of 27 classes in which each class contains more than 800 paintings. They used visual features (e.g. edges or blobs) and content features (e.g. scenes and objects in paintings) derived from the layers of a CNN pre-trained on the ImageNet dataset (CaffeNet). Overall results indicate a lower accuracy for style classification due to the overlapping of visual properties between classes and the great diversity of content depicted in each style. The most distinctively categorized style was Ukiyo-e (84%) and the least distinctive was Academism, which was misclassified. On the basis of these results, researchers conclude that style is not only associated with mere visual characteristics and the content of paintings, but is often a contextually dependent concept.

Yang et al. (2018) argue that the style classification of painted images should consider the historical context in conjunction with traditional visual descriptors. Based on this observation, they built a multimodal CNN framework that considers origin time, birthplace and art movement in order to classify paintings into styles. Taking into account these three factors, Yang and colleagues achieved good performances on three datasets: 77.76% on Painting91 (13 style categories), 70.59% on OilPainting (17 image styles) and 73.28% on Pandora (12 art styles). They compared this multimodal method with single label method in the Painting91 dataset. The comparison results show that multimodal method can effectively identify painting style categories based on art history context knowledge.

Elgammal et al. (2018) adapted three main networks (AlexNet, VGGNet and ResNet) and variations in the training strategies for classifying 20 style classes. Their results showed that pre-training and fine-tuned networks outperform networks trained from scratch: with accuracy rates of 63.7% versus 55.2%. However, researchers consider that "the fine-tuned models could be outperformed if sufficient data is available to train a style-classification network from scratch". Additionally, by using Principle Component Analysis, they established that only few factors are discriminant enough to characterize different styles in art history. These factors are related to Wölfflin's five pairs modes of visual variation (Wölfflin, 1950): linear/painterly, planar/recessional, closed form/open form, multiplicity/unity, absolute clarity/relative clarity.

3. Preliminary experiments

Previous research has reported heterogeneous performances for the style classification of fine art paintings, depending on the type of features used and the number of categories created. Nevertheless, there is a significant degree of agreement on the prevalence of binarized features derived from a deep neural network over hand-crafted low level descriptors. But, can these findings be considered valid for non-traditional artistic styles? Such a question arises due to the fact that, as described in the Introduction, non-traditional styles are influenced by factors "outside" of the world of art. Additionally, Florea et al. (2016) showed that several artistic styles resist certain classification techniques.
Two different experiments were conducted in order to achieve a first approach to the classification of non-traditional styles. These experiments perform the binary and multiclass classification of Outsider Art and traditional styles.

3.1. Experimental setup

To study the performance correlation between Outsider Art and traditional styles, we trained, validated, and tested different networks using images from WikiArt and Outsider Art datasets. WikiArt is the largest public available dataset and contains 82,653 images classified in 27 artistic styles. It is fair to note that: *(i)* the "Wikiart collection [...] contains various paintings from different styles that are erroneously labeled" (Elgammal et al., 2018, p. 6) and *(ii)* this is an unbalanced dataset as seen in Figure 4. For its part, the Outsider Art dataset merges 2,405 images labeled as Naïve Art from WikiArt, which is considered very close to the Outsider Art style (Van Heddeghem, 2016, p. 13), and 1,232 Outsider Art images collected specifically for this paper (in total 3,616 images). In the experiments, the number of images and classes was reduced in order to work with balanced data.

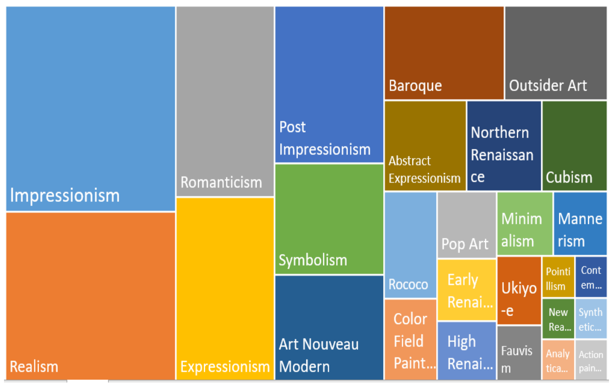


Figure 4: Original distribution of 27 styles: 26 traditional styles from WikiArt and the Outsider Art style (in the upper-right corner).

3.2. Classification from scratch

This experiment aims at answering the following scientific question: Does the Outsider style show a performance in the task of classifying paintings comparable to those of the

	Outsider	Cubism	Baroque	Abstract	Renaissance	Romanticism	Expressionism	Modern	Realism	Impressionism	%
Outsider	40,3	62,3	82,2	72,7	75	77,2	62,5	67,5	77	72	**72,04**
Cubism	62,3	40,9	82,5	77,1	68,9	76,5	58	66,5	76,4	70,6	**70,98**
Baroque	82,2	82,5	40,8	83,8	70	67,8	79,9	80	73,1	79,9	**77,69**
Abstract	72,7	77,1	83,8	44,3	79,2	80,2	73,5	70,1	81,1	80,6	**77,59**
Renaissance	75	68,9	70	79,2	37,2	71,9	67,7	70,3	73,9	75,3	**72,47**
Romanticism	77,2	76,5	67,8	80,2	71,9	42,5	70,9	70	62,3	71,3	**72,01**
Expressionism	62,5	58	79,9	73,5	67,7	70,9	40,1	62,3	71,9	66,2	**68,10**
Modern	67,5	66,5	80	70,1	70,3	70	62,3	42,5	72	67,5	**69,58**
Realism	77	76,4	73,1	81,1	73,9	62,3	71,9	72	37,5	64,3	**72,44**
Impressionism	72	70,6	79,9	80,6	75,3	71,3	66,2	67,5	64,3	46,9	**71,97**
	72,04	**70,98**	**77,69**	**77,59**	**72,47**	**72,01**	**68,10**	**69,58**	**72,44**	**71,97**	72,49

Figure 5: Accuracies between pairs of classes/styles.

traditional styles? To answer this question, we trained several Convolutional Neural Networks to classify different pairs of traditional and non-traditional artistic styles.
In this regard, WikiArt and Outsider Art datasets were used as basis categories for mapping the problem to multiple binary classification tasks (e.g. Cubism versus Outsider Art). Datasets were balanced by selecting 2,561 images per class and merging similar styles in ten basic categories: Cubism (CUB), Baroque (BAR), Abstract (ABS), Renaissance (REN), Romanticism (ROM), Expressionism (EXP), Modern Art (MOD), Realism (REA), Impressionism (IMP) and Outsider Art (OUT). As a result, the final dataset included 10 categories and **25,610** images that were resized to 28 $\times$ 21 pixels.
We trained several Convolutional Neural Networks from scratch using Keras API with Tensorflow as backend. Accuracies were obtained with 100 epochs because our tests indicate that using a number of epochs greater than 100 does not increase the performance significantly. Additionally, as is usually done in the literature, 70% of data were used for training, 20% of data for validation and 10% for testing. During the classification, all styles were crossed with each other in order to obtain the accuracies listed in Figure 5. The left hand column in the same Figure contains the average accuracy (%) obtained by each style.
In general, our results suggest that the task of classifying the Outsider Art style does not differ from classifying traditional styles. The classification of Outsider Art achieves a general average accuracy of 72,04%, which is below the average for Baroque (77,69%) and above the average for Expressionism (68,10%). This may indicate that, in contrast to what art historians state, this so-called anti-cultural art can be analyzed under the same parameters and conditions as mainstream art.
These preliminary results also show that Outsider Art is closely related to Cubism, Expressionism and Modern Art, resulting in poor accuracies (62.3%, 62.5% and 67.5%, respectively). Indeed, these three styles of art present the lowest average accuracy levels of the entire classification (70.9%, 69.5% and 68.1%, respectively). These analyses further show that while it is relatively easy for the classifier to differentiate Outsider Art from Baroque (82.2% of accuracy), Cubism and Expressionism are the pair of traditional styles that are more difficult to classify (58% of accuracy), while Baroque is the easiest style to classify.
However, although this seems obvious, it is important to emphasise that while style classification accuracies between pairs of styles are high (the estimated average efficiency levels are about 72,49%, see Figure 5), test accuracies drop dramatically when we classify three or more categories under a basic configuration: 3 styles/categories (62,4%), 4 styles/categories (52,2%), and so on, until the 10 styles (23,6%). In other words, it is essential to find features which can discriminate among multiple artistic styles. The second part of the following experiment tackles this issue.

3.3. Classification using a pre-trained model

This second experiment aims at answering the following scientific question: Is it possible to improve accuracy for Outsider Art style classification by using pre-trained models? Pre-trained models, such as ImageNet, VGGNet and ResNet use fine-tuned features that were originally trained on a different but correlated problem, to match the current problem. We trained a ResNet-18 model[1] to perform a **binary classification problem**: traditional versus Outsider Art styles. The dataset used is balanced, containing 2,028 images, 1,014 for Outsider Art and 1,014 for traditional art (homogeneously sampling 39 images for each of the 26 styles of traditional art from WikiArt). The test set is also balanced and has 416 images (208 for each category with the same sampling of 8 images for each of the 26 styles). The training is done for 40 epochs using pre-trained weights from ImageNet[2]. The batch size used is 128, weight decay 5e-4, momentum 0.9. Learning rate for blocks 1, 2 and 3 of ResNet-18 is set to 0.001 and the block 4 and the classifiers have a learning rate of 0.01. All learning rates are multiplied by 0.1 at epochs 20, 30 and 35. The model selected for classification is the one in the last epoch as no validation set was built due to the lack of data. The loss used is binary cross-entropy. Under this fine-tuned configuration, an accuracy of 84.3% was achieved. This accuracy outperforms all previous accuracies based on CNN trained from scratch, which means that repurposing and fine-tuning features can be used to obtain better feature rep-

[1]https://arxiv.org/abs/1512.03385
[2]https://ieeexplore.ieee.org/document/5206848

resentations of the Outsider Art style.
We have also trained a ResNet-18 model to perform a **multiclass classification problem**. The loss used is cross-entropy. The dataset is the same as that used in the experiment described in Section 3.2. with 224x224 crops extracted from the images resized to 256 in the smallest side (preserving the aspect ratio). The training was done for 120 epochs using pre-trained weights from ImageNet. Batch size used is 256, weight decay 5e-4, momentum 0.9. Initial learning rates are: for classifier 0.01, for blocks 3 and 4 0.001 and the rest of the parameters 0.0001. All learning rates are multiplied by 0.1 at epochs 70 and 100. The model selected for classification is the one in the best epoch of validation, whose accuracy is 61.17188 (see Figure 6). The test accuracy is 61.9141 (per class, Abstract: 0.9414, Baroque: 0.7891, Cubism: 0.8672, Expressionism: 0.5508, Impressionism: 0.5938, Modern: 0.5938, Outsider: 0.7695, Realism: 0.5273, Renaissance: 0.7695, Romanticism: 0.8047). This result agrees with the results from researchers in section 2.2., showing once again that there are no significant differences in classifying traditional and non-traditional art styles.

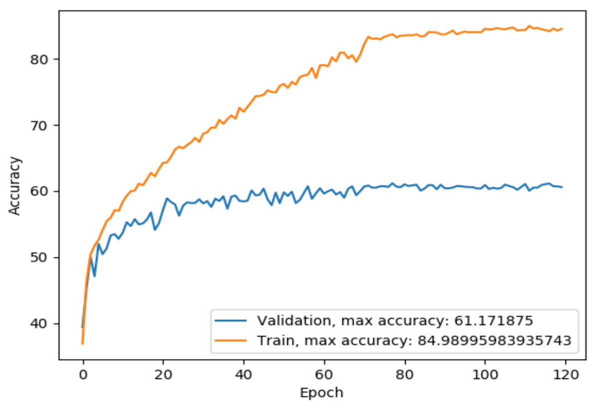


Figure 6: Validation and training accuracies with respect to the Epochs.

4. Conclusion and future work

This position paper has analysed the possibility of classifying non-traditional artistic styles by using the same binarized features that are used for classifying traditional styles. The first part of the paper introduces the theoretical elements that constitute a framework for understanding the problem. The second part describes the state-of-the-art on classifying art styles automatically in paintings. Due to the good accuracy performance of Deep Learning-based methods for classifying traditional art styles, it was suggested to apply them to classify non-traditional art styles (i.e. Outsider Art). Our preliminary experiments have provided good reasons to think that, as is the case with traditional styles, the Outsider Art can be computationally modelled by objective means.
Additionally, in accordance with theoretical (Frank, 2017) and applied (Yang et al., 2018) studies, we assume that the automatic classification of the Outsider Art style should consider **a multimodal approach based on an analysis of images, as well as text**. From our point of view, this two-fold strategy will involve (i) the compilation of a big dataset of Outsider Art images and (ii) the creation of an ontology of Outsider Art.
On the one hand, the image dataset will contain thousands of digital paintings in the Outsider Art style that can be used by machine learning algorithm. This resource can be integrated with the Outsider Art ontology to obtain a multi-modal dataset for understanding Outsider Art, similar to that suggested by (Garcia and Vogiatzis, 2019).
On the other hand, the Outsider Art ontology will focus on representing part of our existing knowledge of this artistic style in a machine-readable language. A particular feature of the Outsider Art knowledge is that it includes both aesthetic entities and social/medical issues, for example: "*(Gaston Chaissac) suffered from tuberculosis, and for a time, produced art while convalescing in a sanitorium*" (Wikipedia). Therefore, the source text that we will use for ontology learning is a representative set of scientific books, papers, magazines and web pages. Additionally, we will integrate in our model some existing ontologies and terminologies such as the Conceptual Reference Model (CIDOC CRM) (Le Boeuf et al., 2019), the Europeana Data Model (EDM) (Europeana, 2017), the Art & Architecture Thesaurus (Alexiev et al., 2017)), the Cultural Objects Name Authority (CONA) (Harpring, 2019a), the Getty Iconography Authority (AI) (Harpring, 2019b) and the Getty Union List of Artist Names (ULAN) (Harpring, 2019c).
Currently, we are in the first phase of the project and aim to semi-automatically construct an exhaustive corpus that consists of semantically tagged texts. Our purpose is to apply this corpus to the construction of a large-scale corpus through the automatic retrieval and annotation of new texts. In the second phase of the project, we will extract the ontology from the corpus and we will use the ontology for automatic image annotation and retrieval.

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