Classification of Fine-Art Paintings with Simulated Partial Damages

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***Abstract*—Recognition of an artistic style of a painting is a complex task that requires significant knowledge and expertise. This paper is a continuation of our previous studies aiming to develop an automatic style classification method. While our previous research was limited to the analysis of paintings with no visible damages, this study investigates the effect of partial damage to a painting on the accuracy of the automatic style recognition. A two-stage approach was adapted with images being first classified patch by patch by a convolutional neural network (CNN) and then by a shallow neural network (NN) trained to make the final decision based on the outcomes achieved by individual patches (image sub-regions). The partial damage was simulated by superimposing randomly positioned circles with randomized pixel values. It was found that the combination of damaged and non-damaged painting in the training dataset and the strengthening role of the final decision-making classifier increase the system's robustness to partial damages, while at the same time maintaining a relatively high classification accuracy of non-damaged artworks.**

Keywords— Art analysis, Fine-art classification, Convolutional neural networks, Transfer learning, Image classification

I. Introduction

Art conservation and restoration are vital activities for the maintenance and preservation of cultural heritage. Restoration can be defined as the action of returning the artwork to its original condition using various reparation techniques, such as cleaning or inpainting [1]. The restoration of valuable artworks is usually carried out by experienced academic experts who have accumulated knowledge and experience over the years.

The first step in the task of painting restoration is to determine the artistic movement to which the painting belongs and, if possible, to identify the author of the painting. Given this information, the curator can make decisions about the appropriate materials, colors, and shapes to be restored, as well as the chemicals and techniques that can be used to clean the affected area. The recognition of an artist or the artistic style is not an easy task and requires not only a lengthily training and years of experience but also a personal talent of the restorer.

In the last years, there has been a constant growth of interest in applying computer vision techniques to categorization, analysis, and restoration of artworks. The ongoing systematic digitalization of fine-art collections and the development of new machine learning methods sparked an interest in introducing automatic approaches and objective measures into the fine art assessment, making it no longer an exclusive task undertaken by expert historians and curators.

Paintings are generally classified according to different criteria, i.e., the historical period, medium, author, and style. Because in many cases, a painting style is defined by its artistic period, stylistic classification is a complex task due to the smooth transitions between the historical periods and the unrelated visual characteristics that belong to the same artistic movement [2, 3]. The difficulty in the identification of the period of a painting increases when the piece presents damages or deteriorations due to environmental storage conditions or accidents.

Due to the recent advancements in deep learning systems and the availability of large databases with millions of annotated images, computer vision tasks such as classification, recognition, detection, and localization of objects in natural images have shown impressive outcomes [4, 5]. However, the application of these techniques in the fine-art field continues to be a challenge due to the subjective character in human annotation and the variations in the interpretation and perception of the different elements of art.

As shown in our previous study [6], the style recognition task can be replaced or supported by an automatic process, where a machine learning model is trained in a supervised way to emulate the job of an art expert. While in [6], this concept was validated using images of fine art paintings that had no visible damages, in this study, we aim to show that an automatic style recognition can be extended to paintings with partial damages (i.e., loss of spatial information).

The classification method introduced in [6] included two stages. Firstly, the image was split into several sub-regions (or patches), and a convolutional neural network (CNN) classifier was applied to perform a separate style recognition for each patch. The outcomes were then consolidated into a final decision using a shallow neural network (NN) trained on the class probability outcomes achieved for individual patches. A similar approach was applied in this study to determine the effect of partial damage to the painting on the accuracy of style classification. The damage was simulated by superimposing into the undamaged images, randomly positioned circles filled up with randomized pixel values. Different sizes of circles simulated different extend of the

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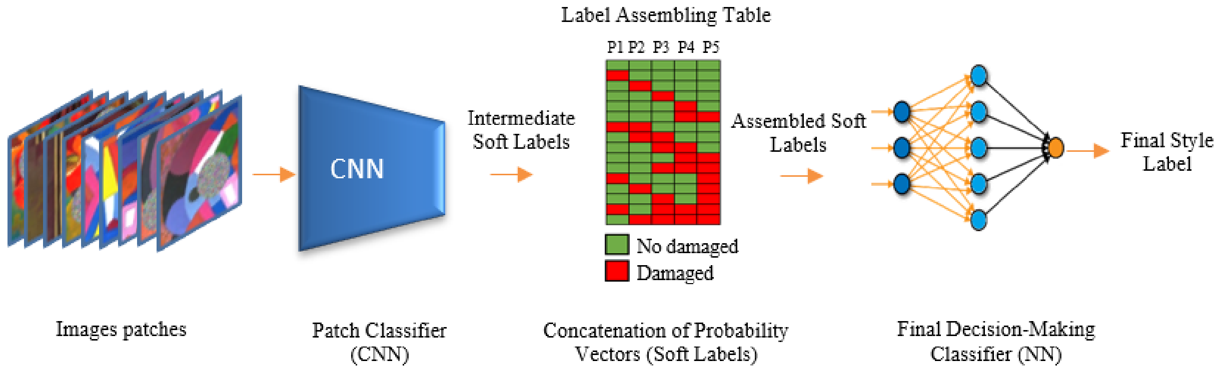

Fig. 1. The artistic style classification framework

damage. A comparison between the same two-stage system trained on clean, undamaged images and a mixture of undamaged and damaged images of paintings was included.

The remainder of this paper is organized into four sections: A brief summary of related works is presented in Section II. Section III describes the proposed methodology. The experimental setup is presented in Section IV. Results and discussion are included in Section V. Final conclusions and future work are given in Section VI.

II. RELATED WORKS

Several studies have addressed the problem of painting classification using deep Convolutional Neural Networks (CNN). CNNs were applied either as feature extractors or pre-trained models, allowing to transfer the knowledge from the more general task of image object recognition to the specific task of an artistic style recognition. The application of pre-trained networks was particularly attractive as it reduced the data and training time requirements while maintaining high classification accuracy [7].

Some of the first Deep Learning (DL) studies of the fine art classification implemented CNN models to extract features to be trained with linear classifiers such as the Support Vector Machine (SVM), or the k-nearest neighbor (k-NN) [8-11]. However, it was shortly shown that these methods could be significantly outperformed by the transfer learning approach based on the many existing pre-trained image classification networks [12, 13].

Over the last few years, the fine-tuning of a pre-trained CNN has become a standard benchmark for the classification of fine art paintings and fine art analysis [14-17]. Several variants have been investigated to improve the classification accuracy. A two-path classification approach was, for example, proposed in [18], where the outcomes of the CNN (content path) and the output of a network based on the gram-matrices features (texture path) were combined to determine the stylistic category of the painting. A similar structure was investigated in [19]. However, in this study, the CNN features were combined with brush stroke information.

Patch-based schemes have been explored in various classification studies. Multi-resolution or subregion analysis has demonstrated higher performance than schemes based on only one resized image. Different ways of combining the classification outcomes of individual subregions have been explored in [11, 20-22]. A Deep multibranch neural network was proposed in [23], where two branches classified different sub-regions of interest, and the third branch analyzed a randomly selected region. To reduce the scale dependency, the training images were given at different scales.

In one of the very recent works, a combination of CNN and Markov random fields for the panting authorship recognition was investigated [24]. The method applied a three-level pyramid structure, where each level contains a CNN. The levels differ by the scale of the input images. Thus, if the first level uses the basic CNN input size image, the second level uses two times, and the third level three times the basic size image. The first-level CNN classifies the whole image, the CNN in the second level classifies four patches, and the CNN in the third level classifies sixteen patches. Intermediate decisions combining the individual patch classification are made by the Markov random fields over the soft labels generated by the classifiers. The final category label is decided by applying an entropy exponential fusion scheme over the output of the three levels.

The use of a second classifier as a fusion method of the independent outputs from intermediate classification stages has been shown to give higher performance than simple majority voting, or either weighted or unweighted sum fusion schemes. In [6], for example, a shallow final decision-making neural network was used to ensemble the outcomes of CNN patch-based classifiers. The soft labels (probability vectors) generated by the five independent patch-based classifiers were concatenated into single vectors used to train a shallow neural network inferring the final artistic style category. The current study extends this approach to the classification of images containing partial damages.

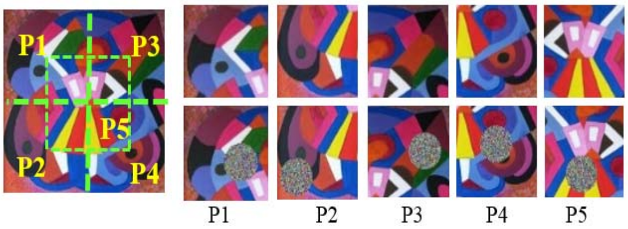

Fig. 2. An example of the patch generation for a given image. P1-P5 are image patches. The top row shows patches without damage, and the bottom row shows patches with simulated damages.

III. Method

A. *Style Classification Framework – training process*

As shown in Fig. 1, the classification framework consisted of four main steps: (i) extraction of image patches with the presence or absence of simulated damages; (ii) patch classification with a CNN model to obtain intermediate soft labels (style probability vectors) based on individual patches, (iii) concatenation of the soft labels of every path according to the patch assembling table, and (iv) the second classification process of the ensembled probabilities vectors to decide the final style category. The patch classifiers were trained on actual images (patches), whereas the final classifier was trained on concatenated probability vectors given by the patch classifiers.

1) *Patch Generation and Damage Simulation*

In the first step of the classification framework shown in Fig. 1, each painting was upsized to double the required CNN input dimensions. The enlarged images were then dived into five squared patches of the same size, including four corner patches and a fifth central patch. There was 25% of overlapping between patches. Fig. 2 shows an example of splitting an image into five patches.

Due to the unpredictable nature of potential damages to fine art paintings, the classification framework was expected to infer the categorical style disregarding the sizes and locations of the damaged spots. To simulate potential damages occurring in different locations, a copy of the five patches was created for each image in the database, and a single simulated damage region was superimposed onto each patch. The damage was simulated as a randomly positioned circle with randomly generated RGB pixel values ranging from 0 to 255 and different radius values. This way, for each painting in the dataset, ten patches were generated, five with simulated damages and five without damages. The reason for using the RGB color palette rather than a monochromatic approach to simulate the damage was to minimize distortion to the original color palette of the painting. In real-life applications, damages of different shapes or colors can be covered in digitized images by circles with randomized RGB pixel values to achieve conditions similar to our experiments. Fig.2 shows an example of image patches. The top row contains patches without damage, and the bottom row shows patches with simulated damages.

P1	P2	P3	P4	P5
0	0	0	0	0
1	0	0	0	0
0	1	0	0	0
0	0	1	0	0
0	0	0	1	0
0	0	0	1	1
1	1	0	0	0
0	1	1	0	0
0	0	1	1	0
0	0	0	1	1
0	0	1	1	1
1	0	0	0	1
0	1	0	0	1
0	0	1	0	1
1	0	1	1	1
0	1	1	1	1

No damaged

Damaged

Fig. 3. An example of a patch label assembling table generating training examples with different amounts and locations of simulated damages. P1-P5 image patches. Red blocks (1) represent patches containing simulated damage and green (0) without damage.

2) *Patch Classification*

After patch generation, an existing pre-trained CNN model was fine-tuned to individually classify all image patches with and without damages. This process generated intermediate style classification labels given as class probability vectors (soft labels). Since each image was represented by five undamaged and five damaged patches number of training data was doubled compared to training data used to classify only undamaged images.

3) *Assembling Intermediate Labels*

The intermediate soft labels produced by fine-tuning of the CNN model were concatenated into single vectors to create data vectors to train the final decision-making classifier. The training data for the final decision-making classifier included samples representing damaged and undamaged images. The amount and the location of damage represented by the data used to train the final decision-making classifier were controlled by a binary patch label assembling table. The probabilities vectors of the individual patch classification of an image are concatenated in every possible combination according to the presence or absence of damage in each patch. Given a k number of image patches, with two probable binary states, damaged (1) or not damaged (0), the possible combinations

Fig. 4. An example of an image corresponding to the label assembling table with a row coded as [1,0,0,1,1].

of assembly vectors are 2^k. In the case of k=5 patches, the number of possible scenarios is 32.

An example of a label assembling table is shown in Fig. 3. It allowed representing each training image by different combinations of soft labels obtained through the CNN-based classification of damaged and undamaged patches. By choosing which patch contained damage or not, multiple assembled soft labels were generated for each picture in the training data, each with different amounts and locations of damages. Therefore, the free of damage scenario is [0,0,0,0,0], and the scenario with damage in all regions of the painting is [1,1,1,1,1].

However, due to the overlapping of the fifth patch, the scenario with four patches with no damage and the fifth with damaged area [0,0,0,0,1] do not occur during the testing process.

Fig. 4 shows an example of an image corresponding to an assembling table row codded as [1,0,0,1,1]. It can be seen that patches P1, P4, and P5 contain damaged areas.

4) Training the Final Decision-Making Classifier

In the last step of the style recognition framework, a final decision-maker classifier is trained on the concatenated probability vectors. A shallow, fully connected Neural Network (NN) model was applied. Due to the combination of the soft labels of all possible scenarios of damaged and undamaged patches, the feature matrix input to the second classifier is significantly bigger (32 times) than the feature matrix of a standard classification training process for undamaged images, which has only one concatenation scenario per image.

B. Style Classification Framework – inference process

The inference process follows the four steps of the training process but with important differences. In the first step, each painting image in the testing set is resized to the double of the input dimensions required for the CNN, and before the generation of the five patches, a random circle is introduced to simulate a damaged area. In the second step, the individual patch classification is performed using the CNN model previously trained. In the third step, the five probability vectors of each image are assembled in a unique vector that serves as input to the second classifier, where the final style label is inferred as the output.

IV. EXPERIMENTAL SETUP

A. Image Data

The proposed methodology was tested experimentally using a dataset of 14,380 images representing Western and non-Western fine art paintings. In total, the dataset contained examples of 20 different artistic styles. It included eighteen styles represented by images sourced from the Paintings Dataset for Recognizing the Art movement (Pandora 18K) [25]. The Pandora dataset was introduced in [26] as a high-quality artistic database. The high quality of this dataset was ensured by the art expert revision and correction of the labeling process. The remaining two styles represented the Australian Aboriginal style and the Japanese Ukiyo-e movement. Images representing these two styles were collected by the authors. The Australian Aboriginal style pictures were obtained from different online galleries that are members of the Australia Aboriginal Art Association [27], and the Ukiyo-e images were extracted from the open Wikiart dataset [28]. The style representation was balanced to 719 (5%) sample images per style. Fig. 5 shows the style labels and the percentage distribution of the experimental dataset.

B. Training and Testing Settings

The image patch classification task was conducted using the existing pre-trained image classification CNN model ResNet-50 [29]. It was fine-tuned to recognize 20 different fine art categories. The ResNet-50 model has a residual network block architecture consisting of 50 layers. The required image input size is 224 by 224 pixels. The network

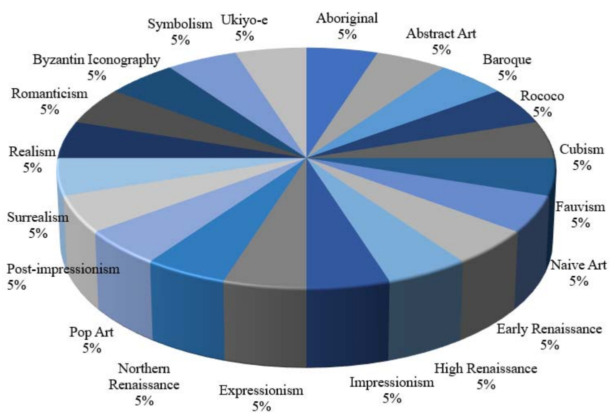

Fig. 5. Style labels (classes) and their percentage distribution in the experimental dataset.

TABLE I. CLASSIFICATION ACCURACY (%) FOR DIFFERENT EXPERIMENTAL SCENARIOS.

	Baseline	**Two-stage approach – trained undamaged images**		**Two-stage approach – trained undamaged and damaged images**	
Model	**CNN-NP-ND**	**CNN/NN-P-ND**		**CNN/NN-P-D**	
		CNN-P-ND	**NN-P-ND**	**CNN -P-D**	**NN-P-D**
Training details	Fine-tuned ResNet-50	Fine-tuned ResNet-50	NN-2 hidden layers	Fine-tuned ResNet-50	NN-5 hidden layers
	11504 (Undamaged images)	57520 (Undamaged patches)	11504 (Probability vectors)	115040 (57520 Undamaged patches and 57520 damaged patches with 45 pixel radius circles)	368128 (Probability vectors)
Testing details	2876 (Undamaged images)	14380 (Undamaged patches)	2876 (Probability vectors)	14380 (Undamaged patches)	2876 (Probability vectors)
Test (undamaged images) - Average Accuracy	**58.96%**	53.48%	**65.17%**	56.88%	**66.78%**

is defined by 25.6 million of parameters, and the network's storage size is 96 MB. The ResNet-50 model was pre-trained to perform a general task of natural image classification using the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) dataset, containing 1.2 million images with 1,000 classes [2]. The training/testing procedure used 80% of the total image data for training of the style recognition system, and the remaining 20% for testing.

C. *Experimental scenarios*

To compare the performance of the proposed framework for the classification of partially damaged paintings against the standard classification, a baseline and two-stage classification systems trained on undamaged images were implemented. The description of the three experimental scenarios is presented below.

1) CNN-NP–ND

This was the simplest baseline case where only a single CNN was trained to classify whole images. The paintings were not split into patches, and no damage was introduced. A ResNet-50 CNN model was fine-tuned. The images were resized to the dimension required by the CNN input layer (224 pixels x 224 pixels).

2) CNN/NN–P-ND

A two-stage painting classification framework was implemented. Therefore, two classifiers were trained. A CNN for the patch classification, and a fully connected Neural Network (NN) for the classification of the concatenated probability vectors generated by the CNN.

a) CNN–P-ND

CNN-P-ND is the first classification stage. A CNN was trained to classify patches individually. As shown in Fig.2, the images were split into five patches, and the classification was performed patch by patch. No damage was introduced to the patches during the training process. The CNN implemented was a fine-tuned ResNet-50 model.

b) NN–P-ND

NN–P-ND is the second classification stage. A Neural Network with two hidden layers was implemented for the classification of the concatenated probability vectors generated by the CNN. Due to the fact that no damages were introduced into the paintings during the training process, the five probability vectors of each image were assembled in a unique vector.

3) CNN/NN–P-D

This scenario applied the proposed two-stage method for classification of paintings with simulated partial damages, described in Section III.

a) CNN–P-D

CNN-P-D is the first classification stage. A fine-tuned ResNet-50 CNN model was trained to classify patches individually. As previously explained, ten patches were generated for each image in the training dataset. Five patches without damages and five patches with random damage added. A 45-pixel radius circle was used to simulate the damage in the painting patches, filling up 13% of the size of the patch.

b) NN–P-D

NN–P-D is the final decision-making neural network. It has five hidden layers trained on the probability vectors obtained during the first stage of classification. In this case, for a given input image, 32 probability vectors are assembled during the training process.

D. *Performance evaluation*

The average classification accuracy was used to evaluate the classification performance. The classification accuracy is defined as:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

Where *TP* and *TN* indicate the number of true positive and true negative classification predictions, respectively, and *FP* and *FN* denote the false positive and false negative

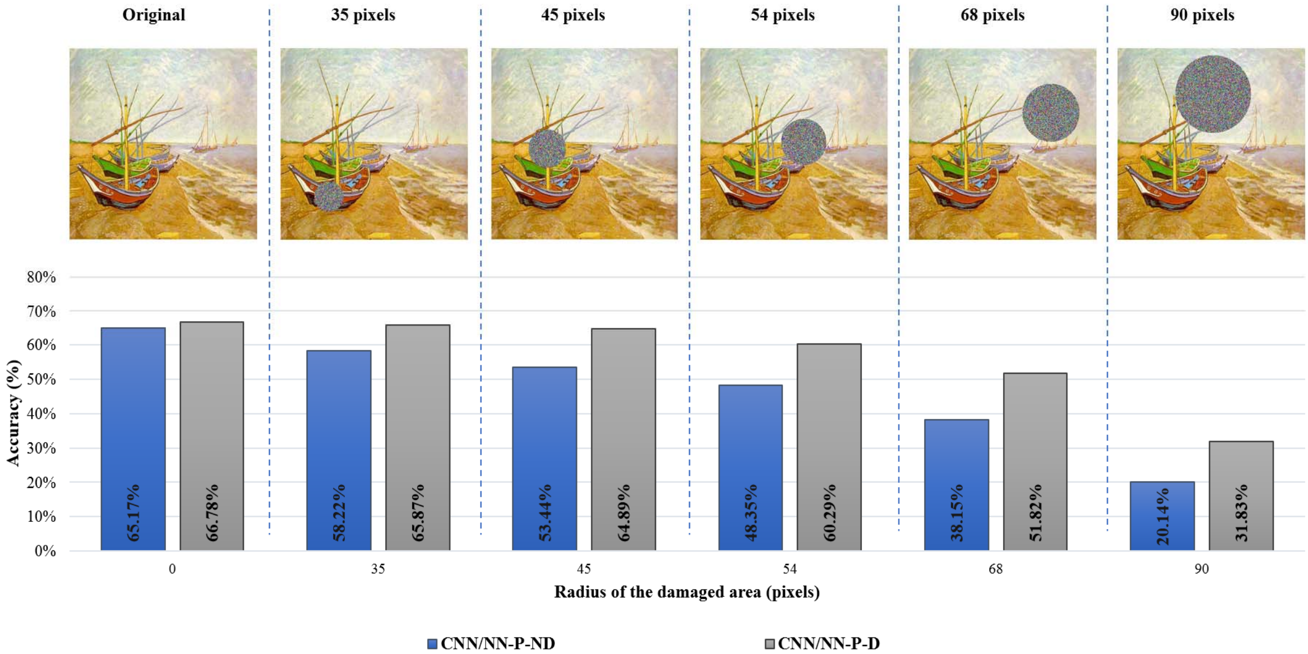

Fig. 6. Classification results with different radius of the circular simulated damaged area, for the framework model CNN/NN-P-ND, trained without damaged images, and the proposed CNN/NN-P-D model trained with paintings containing damaged areas. The top row shows examples of pictures with damages simmulated as circles with different radius values (0 (original), 35, 45, 54, 68 and 90 pixels).

classification predictions [30]. The reported results corresponded to the averaged classification accuracy over all classes.

E. Testing procedure

The performance of the proposed method was evaluated across six independent experiments, each one of them with a different radius of the simulated damaged area. The same test image dataset was used in each experiment, but the area of damage introduced to each image was changed for every experiment. The first experiment was performed using the original test images without the damage, and for the remaining five experiments, the values of the damaged area radius were 35, 45, 54, 68, and 90 pixels. The circle position was randomly generated; in this way, the patches affected by the simulated damage were arbitrary in each image.

V. RESULTS AND DISCUSSION

A. Classification of undamaged images

The training details and classification results obtained in the three experimental scenarios using a test dataset without the introduction of simulated damages are presented in Table I.

A comparison between experimental scenarios involving two-stage classification (CNN/NN–P-ND and CNN/NN-P-D) and the baseline scenario using only a single classifier (CNN-NP-ND) shows that the two-stage approaches clearly outperformed the baseline. While the single-stage approach produced an accuracy of 59%, the two-stage methods led to 65% to 67%.

Looking at the first classifier of the two-stage scenarios (CNN-P-ND and CNN-P-D) versus the baseline scenario (CNN-NP-ND), corresponding to the implementation of a fine-tuned CNN model, it can be observed that the best results were obtained when the undamaged paintings were classified as a whole without splitting into patches (CNN-NP-ND, 59%). Therefore, the individual subregion classification of the painting produces a lower recognition accuracy than the baseline classification, which indicates the importance of the second classification stage for the final stylistic decision.

However, when the first classifier of the two-stage scenarios (CNN-P-ND and CNN-P-D) are compared; the first classifier of the proposed method, trained on a mixture of undamaged and damaged patches, provided better results (CNN-P-D, 56.8% accuracy) than the CNN trained only on undamaged paintings (CNN-P-ND, 53.5%, accuracy). This could be due to the fact that CNN-P-D was trained with twice the number of patches of the CNN-P-ND, which produced an effect of data augmentation leading to an improvement in the classification accuracy.

Considering the final outcomes of the two-stage scenarios after the application of the second classifier corresponding to the decision-making neural network (NN-P-ND and NN-P-D), the proposed method trained on a mixture of damaged and undamaged patches (CNN/NN-P-D, 67 %) outperformed by almost 2%, the scenario trained using only clean patches (CNN/NN–P-ND, 65%).

B. System Sensitivity to the Damage Size

To determine the sensitivity of the proposed two-stage approach to the size of the damaged area present in the tested paintings, additional experiments were conducted, as explained in section IV. Namely, the performance of the two-stage scenarios (CNN/NN-P-ND and CNN/NN-P-D) were compared across six experiments using different values of the damaged area radius in the testing images; 0 (original), 35, 45, 54, 68, 90 pixels corresponding to 0%, 8%, 13%, 18%, 29%, and 51%, of the patch area, respectively.

The classification results obtained for the six different values of the damage radius and an example of the panting in each experimental case are presented in Fig. 6.

It can be observed that while the proposed method trained on mixtures of damaged and undamaged images (CNN/NN-P-D) in all cases outperforms the system trained on undamaged paintings only (CNN/NN-P-ND), the overall performance of both systems decays monotonically with the increasing radius area of the damage. Thus, the performance of the CNN/NN-P-ND reduces from 58% accuracy for the radius of 35 pixels to 20% for the radius of 90 pixels. In comparison, the corresponding performance of the CNN/NN-P-D decreases from about 66% to 32%.

The 35- and 45-pixel radius tests exhibit the highest accuracies of the testing classification of damaged images with the CNN/NN-P-D system. For a 35-pixel radius test, the accuracy achieved is only 0.9% lower than the accuracy reached with undamaged images (67%), while the accuracy obtained in the 45-pixel radius test is 1.9% lower than the accuracy obtained with the undamaged image experiment. The 54-pixel radius test achieved an accuracy of 60.29% with a decrease of 6.5%, while the accuracy in the scenarios with 68- and 90-pixels radius decrease significantly by 15% and 35%, respectively, when compared to the results where undamaged imaged are used.

Therefore, when the size of the simulated damaged area in a test painting is less or similar to the size of the simulated damaged used during the training process (45 pixels), the CNN/NN-P-D system is able to infer the style of the painting with high accuracy, however, for larger areas, the error in the classification grows. Increasing the area of the simulated damage also increases the number of patches affected, thus making it more challenging to infer the style.

The CNN/NN-P-ND scenario yields a decrease in the accuracy by 7.39%, 12.06%, 17.15%, 27.35%, and 45.37% when the results of each damaged painting tests are compared to those obtained in the classification of undamaged paintings. Thus, the performance of the CNN/NN-P-ND scenario is most sensitive to the loss of information caused by the damage than the CNN/NN-P-D framework. Consequently, the addition of images containing damages during the training process is vital to the increase of the model generalization and to make the classification system robust to a partial loss of information.

VI. Conclusions and Future Work

The study investigated the classification of fine-art paintings with simulated partial damages. The adaptation of the training process using a combination of damaged and undamaged patches increased the system's robustness in the presence of small damaged areas in the classified images. A comparison between the benchmark approaches and the proposed framework showed that the latter yields better results in the classification of art images with and without damages.

Future work will investigate the application of the style classification to an automatic image inpainting techniques aiming to reconstruct missing or damaged painting areas.

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