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The Effect Of Optimizers On CNN Architectures For Art Style Classification

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Abstract: The artistic style of a painting is one of the most frequent semantic criteria used to classify paintings. However, identifying the unique style of a painting is a complex task, and usually only art experts do it, as it requires significant knowledge and expertise. Thus, it is required to employ the advances of deep learning approaches in image processing to present automatic methods to the art community to do such tasks as an enormous number of digital paintings are available on the internet. In this study, we propose a framework to compare the performances of six pre-trained convolutional neural networks (Xception, ResNet50, InceptionV3, InceptionResNetV2, DenseNet121, and EfficientNet B3) for identifying the artistic style of a painting, including Xception architecture, which to our knowledge has never been used for this purpose before. Furthermore, we study the effect of three different optimizers such as (SGD, RMSprop, and Adam) with two learning rates (1e-2 and 1e-4) on the performance of the models using transfer learning to find the best hyper-parameters for each model. Our experiments using two art classification datasets, Pandora18k and Painting-91, indicated that InceptionResNetV2 is the most accurate model for style classification on both datasets when it was trained with an Adam optimizer and a learning rate equal to 1e-4.
Keywords: Computer vision, Image processing, Convolutional neural network, Style Classification, Optimizers, Transfer learning.

1. INTRODUCTION

Studying fine art paintings has attracted so much attention over the years because of their importance as they hold a historical and cultural context behind them. Furthermore, paintings help to better understand the development of human beings in terms of their way of expressing themselves, their feelings, and what was happening around them. Art experts and historians cluster fine art paintings into specific categories such as artist, period of creation, genre, and style in order to ease the process of analyzing, understanding and manipulation. In visual arts, the artistic style is a "...distinctive manner which permits the grouping of artworks into related categories" [1]. It is also called an artistic movement, and it is the unique combination of iconographical, technical, and compositional features that give a piece of artwork its identity[2].

In recent years, researchers have been interested in introducing automatic approaches to the field of fine art painting by using the evolution in computer vision techniques and the great performance of machine learning in the domain of image processing as the number of digital fine art paintings accessible on the web continues to grow exponentially. Many studies automatically investigated the artistic style identification of an artwork during the previous years, which could be grouped into traditional and deep learning approaches.

The earliest studies are the traditional approaches, which concentrated on extracting handcrafted features from the images of the artworks and then used a classifier such as Support Vector Machine (SVM) and K-nearest neighbor (K-NN). Whereas the deep learning approaches are state of the art for painting classification. With the excellent outcomes of convolutional neural networks (CNN) on the largest natural images dataset ImageNet, which contains millions of natural images for image classification, researchers proposed to finetune various CNN architectures for artistic style recognition with transfer learning as the available fine art painting datasets have a small number of labeled images of paintings. Where Transfer learning is the reuse of an already trained model on a large dataset for a specific task to determine a similar purpose that has a small dataset.

In this paper, we propose a framework to compare the performances of six various pre-trained convolutional neural networks (Xception, ResNet50, InceptionV3, IncepResNetV2, DenseNet121, and EfficientNet B3) for identifying the artistic style of a painting by using transfer learning.

The tuning of a pre-trained CNN architecture for a specific task is based on hyper-parameters such as the number of units in each activation layer, the activation function, the number of iterations, the optimizer, and the learning rate. These hyper-parameters are defined before the training, and depending on their configuration, we

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can get different classification results. Setting up the most appropriate weights for the model can lead to the best classification results. Therefore, the hyper-parameters related to the weights (optimizer and learning rate) must be carefully chosen through experiments, as an inappropriate optimizer might get the network stuck at a local minimum without achieving any improvement toward the global minimum. The optimizer is the function that modifies the attributes of a deep neural network (weights and biases) to minimize the loss function and improve the model's accuracy during training. Moreover, the learning rate determines how fast or slow we approach toward the optimal weights with respecting the loss function.

In this paper, we also focus on studying the effect of various optimizers (SGD, RMSprop, and Adam) with different learning rates (1e-2 and 1e-4) on the pre-trained models to find the most accurate hyper-parameters for each model.

The paper is organized into five main sections. Section 2 discusses the main studies in the literature on recognizing the artistic style, whereas Section 3 describes our proposed methodology in detail. Section 4 describes the used datasets to evaluate the models, while Section 5 reports the experimental results and discussion, and finally, we conclude the paper in Section 6.

2. Related work

The subject of classifying fine art paintings has attracted many researchers since the digital versions of paintings became available and accessible on the internet. In this paper, we focus on artistic style identification and recognition. Given that the artistic style of a painting may be understood in terms of texture, colors, or shapes, early studies proposed to automatically identify the unique style of painting by extracting the handcrafted features such as HOG, SIFT, LBP, GIST, GLCM, and applying a machine learning classifier. For example, to categorize a small dataset of images that contained seven art styles, each with 70 paintings Arora [3] tested various classification approaches based on handcrafted features and an SVM classifier.

Investigating both of the handcrafted features individually [4], or combined [5], [6], [7], [8] was proposed to recognize the style of paintings. The combination of different features led to better yet limited results. Florea et al. [9] used boosted ensembles of SVMs to categorize paintings by style on features such as topographical and color histograms. In addition, they constructed a new dataset called Pandora18K. Then in [10], they improved the accuracy of style classification by adding an expert committee with soft voting. The final decision was based on a majority vote of the classification results from evaluating the entire artwork and different random sub-regions.

Afterwards, with the introduction of convolutional neural networks (CNN) and their great results on the largest natural images dataset ImageNet for various tasks, including image classification and object recognition, several studies concentrated on applying CNN architectures for the purpose of style recognition. Tan et al. [11] compared pre-trained convolutional networks and low-level descriptors to categorize paintings to artist, genre, and style. All tasks provided the best performance with the finetuned model. Lecoutre et al. [12] used transfer learning to finetune a pre-trained residual neural network (ResNet50) on the ImageNet dataset for artistic style classification.

Rodriguez et al. [13] suggested boosting the accuracy of style classification with a new method based on subregions classification and transfer learning. The final style was calculated by a weighted sum of the individual-patch classification outcomes. Sandoval et al. [14] expanded the previous study by introducing a two-stage categorization framework based on performing a shallow neural network to the probability vectors obtained by the individual patch. Afterward, in [15], they studied how partial damage to an artwork affects the accuracy of art style identification. The classification of non-damaged artwork was found to be highly accurate when trained on a dataset that included both damaged and non-damaged paintings. Menis et al. [16] proposed to handle the style recognition problem by introducing a stacking ensemble approach, building a super-model composed of models that identify several characteristics of the input and complement one another. In addition, they studied the effect of different data augmentation techniques. Zhao et al. [17] evaluated the results of residual neural network (ResNet) and six of its variants models identifying paintings by artists, styles, and genres, with and without the use of transfer learning.

Taking into consideration the similarities between styles, Mohammadi et al. [18] developed a hierarchical system for categorizing related artistic styles into many super styles known as parents. Then they created one parent classifier and multiple child classifiers to identify both the super style and the style. The experimental findings on the WikiArt dataset revealed an improvement in the DenseNet121 network's average F1 score.

Recently, Efthymiou et al. [19] proposed combining Convolutional Neural Networks (CNNs) and Graph Neural Networks (GNNs) in one architecture called ArtSAGENet, in order to learn both representations of artistic painting visual and semantic simultaneously. In addition, they applied multi-task learning for tag prediction, style classification, creation period estimation, and artist attribution. Pérez and Cozman [20] demonstrated that using Generative Adversarial Networks (GAN) for data augmentation boosts the performance of EfficientNet B0 for style classification.

The previous studies focused on investigating different methodologies and approaches with various CNN models to identify the style of a painting. The choice of the hyperparameters of a model is the main key to achieving good results. The study of different optimizers has not yet been explored in the field of art classification, while it was investigated in many other domains. Agarwal et al. [21] verified the results of convolutional neural networks with different optimization algorithms on the handwritten dataset MNIST and CIFAR 10 datasets. While Verma et al. [22] proposed to compare two different optimizers implemented on CNN architectures to classify COVID-19 X-Ray Images.

In this study, we use transfer learning to evaluate the performance of six pre-trained convolutional neural networks for identifying the artistic style of a painting. In addition, we investigate the effect of a variety of hyper-parameters (including optimizers and learning rates) to determine which combination of hyper-parameters produces the best results for each model.

3. Methodology

In this work, we aim to concentrate on two points. The first is to propose a framework for style classification of a fine art painting, which is illustrated in Figure 1.

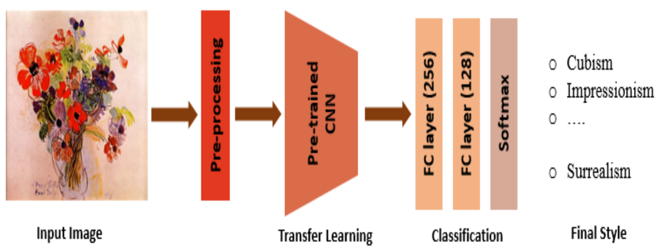

Figure 1. The proposed framework for style recognition

Our framework consists of two essential parts, the first is the data pre-processing, and the second is feature extraction with the use of transfer learning and classification.

A. Data pre-processing :

Before the training, as the images in our datasets (Pandora18k and Painting-91) have variant sizes, we resized all the train and test images in both datasets to a standard resolution of 480x480 and normalized them. We also applied some data augmentation techniques to the training data by randomly flipping the images horizontally, shifting the width and the height, rotating, and slightly zooming. Furthermore, we used the pre-processing input of each model in order to avoid overfitting. Figure 2 presents samples of data augmentation techniques applied to a single image.

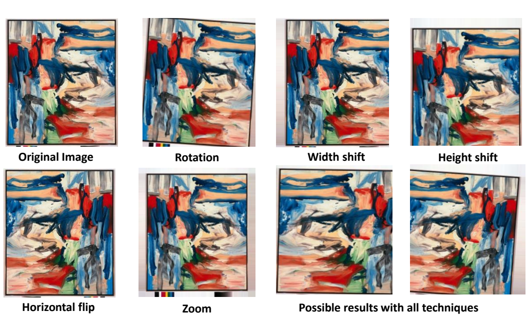

Figure 2. Samples of data augmentation techniques applied on a single image

B. Feature extraction and Classification:

With the use of transfer learning, we initialized the CNN architectures with weights of the pre-trained ImageNet models rather than recreating the entire training process from scratch. We removed the last fully connected layers of each architecture that contains 1,000 classes as output and replaced them with two dense layers that have Swish as an activation function with the values of 256 and 128, respectively, followed by a softmax layer that contains the number of different artistic styles in the input dataset. These layers are randomly initialized. In addition, to prevent overfitting, we inserted batch normalization and dropout layers after each layer. The output of each model is a probability vector representing the various art-style classes to which the image of the artwork may correspond.

During the training, we applied the finetuning process by unfreezing the last four layers of each model and re-training them besides the training of the last fully-connected layers. The maximum accuracy was considered as the final result after 40 iterations (epochs) of training with a batch size of 64. We ran our experiments using Tensorflow 2.3.0 in Windows 11 with Geforce GTX 1660 Super Intel i9 10900k. All the pre-trained models are from Keras[23]. Figure 3 illustrates the details of the training process.

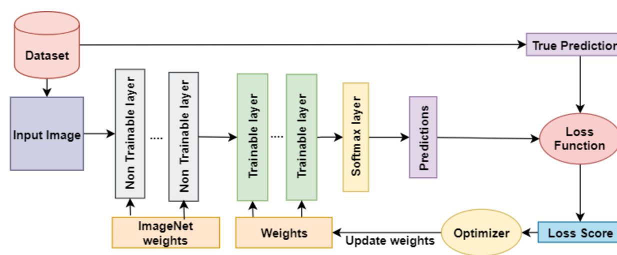

Figure 3. A schematic illustration of the training process

The second point is to study and compare the effect of different optimizers Stochastic Gradient Descent (SGD)[24], Root Mean Square Propagation (RMSprop)[25], and Adaptive Moment Estimation (Adam)[26] with various learning rates 1e-2 and 1e-4 on the performances of six pre-trained CNN architectures (Xception[27], ResNet50[28], InceptionV3[29], InceptionResNetV2[30], DenseNet121[31], and EfficientNet B3[32]) on the ImageNet dataset, which has 1.2 million natural images and 1000 classes[33]. Table 1 presents the most important characteristics of each CNN architecture in terms of the input size, depth, the size of the model, and the number of parameters. InceptionResNetV2 is the largest and deepest model we tested in our study.

4. Datasets

In our experiments, as we aim to identify the artistic style of a painting, we used two standard datasets of fine art paintings collected from free accessible fine-art paintings collections.

Dataset 1: The Painting-91 dataset includes a total of

TABLE I. The characteristics of CNN architectures

Model	Input Image Size	Depth	Size (MB)	Parameters (Millions)
Xception	299 x 299 x 3	81	88	22.9
ResNet-50	224 x 224 x 3	50	96	25.6
InceptionV3	229 x 229 x 3	48	89	23.9
InceptionResNetV2	229 x 229 x 3	164	213.41	56
DenseNet121	224 x 224 x 3	121	33	7,6
EfficientNetB3	300 x 300 x 3	210	48	12.3

4,266 painting images created by 91 different artists. They are classified according to the artist and the style. There are a total of 2,338 paintings that have been categorized according to one of 13 artistic styles. These paintings were created by a total of 50 different artists. 1250 of them were utilized for training, while 1088 of them were used for testing. This dataset, created by Khan et al. [5], is one of the most often utilized datasets for classifying artists and styles. Figure 4 shows a few examples from the dataset; each picture has its corresponding style and artist.

Figure 4. Samples of Painting-91 dataset

Dataset 2: It is called Pandora18K; it was created by Florea et al. [9]. It includes around 18,038 images that engineers and art experts obtained from the internet and sorted them among 18 classes. Figure 5 presents a sample from each style in the dataset. We used 80% of the images in the training and the remaining 20% for testing.

Figure 5. Samples of the 18 classes in Pandora18k

5. Results and discussion

The overall accuracy performance of all our experiments on the two datasets, Painting-91 and Pandora18k, for the artistic style recognition are presented in tables 2 and 3, respectively. The accuracy is defined as the percentage of successfully identified examples relative to the total number of examples. It is calculated as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Where true positive and true negative classification predictions are denoted by TP and TN, respectively, while false positive and false negative classification predictions are denoted by FP and FN, respectively [34]. The percentages in bold represent our best accuracy for identifying the artistic style of a fine-art painting for each optimizer with a specific learning rate.

From Table 2, which presents the results of our experiments on the small dataset Painting-91, we can notice that the pre-trained IncepResNetV2 surpassed all the other tested pre-trained CNN architectures with the SGD optimizer with both learning rates (1e-2 and 1e-4). It is also noticeable that the model with the SGD optimizer and a small learning rate of 1e-4 performed poorly and only achieved an accuracy of 24.26%. The accuracy improved by 48.89% to achieve 73.25% with a bigger learning rate equal to 1e-2. In the case of the RMSprop optimizer with a learning rate equal to 1e-2, the IncepResNetV2 achieved the third best accuracy of 72.06% after ResNet50 and DenseNet121, which achieved 72.15% and 73.99% respectively. Interestingly, in the case of RMSprop and learning rare of 1e-4, the accuracy of IncepResNetV2 increased by 2.94% and achieved the first best accuracy of 75.00% while the accuracy of DenseNet121 decreased by 6.53% and achieved only 67.46%. Similarly, in the case of Adam optimizer with a learning rate equal to 1e-2, the IncepResNetV2 achieved the third best accuracy of 72.89% after ResNet50 and DenseNet121, which achieved 73.07% and 73.99% respectively. Moreover, in the case of Adam and learning rare of 1e-4, the accuracy of IncepResNetV2 increased by 0.18% and achieved the first best accuracy of 75.18% while the accuracy of DenseNet121 decreased by 8.5% and achieved only 65.21%. From the previous results, we can conclude that the best optimizer for each pre-trained model differs from one to another. Additionally, it is crucial to choose an adequate learning rate as the

TABLE II. The results of style classification on Painting-91

Model \ Optimizer	SGD		RMSprop		Adam	
	1e-2	**1e-4**	**1e-2**	**1e-4**	**1e-2**	**1e-4**
Xception	69.67	18.75	67.10	71.51	69.85	71.32
Resnet50	72.15	22.43	72.15	73.16	73.07	72.24
InceptionV3	69.58	19.12	71.69	68.20	70.96	68.66
Incep-ResNetV2	**73.25**	**24.36**	72.06	**75.00**	72.89	**75.18**
DenseNet121	69.29	15.44	**73.99**	67.46	**73.71**	65.44
EfficientNetB3	68.84	13.24	71.42	70.40	71.78	69.21

TABLE III. The results of style classification on Pandora 18k

Model \ Optimizer	SGD		RMSprop		Adam	
	1e-2	**1e-4**	**1e-2**	**1e-4**	**1e-2**	**1e-4**
Xception	62.94	33.49	62.44	65.02	62.72	65.49
Resnet50	66.79	39.57	66.90	66.92	66.65	67.56
InceptionV3	59.02	31.17	61.73	60.04	61.53	59.60
Incep-ResNetV2	**67.56**	**40.21**	66.79	**68.36**	66.79	**68.45**
DenseNet121	64.19	32.41	**68.03**	66.45	**68.07**	66.34
EfficientNetB3	62.89	28.46	63.91	64.66	63.16	65.18

model may fail to achieve good results if an inadequate learning rate is used.

From table 3, which reports the results of our experiments on a larger dataset Pandora18k, we can notice that the results are similar to the results of the small dataset Painting-91. In addition, we can conclude that the size of the dataset does not affect the performance of the pre-trained models, as the best hyper-parameters for a pre-trained model are the same for a small or large dataset.

The pre-trained Xception model, which was investigated for the first time for style recognition, achieved an accuracy of 65.49%, and it performed better than InceptionV3, which achieved 61.73%. The pre-trained IncepResNetV2 surpassed all other models and achieved the best accuracy on both datasets. It achieved 75.18% on the small dataset Painting-91 and 68.45% on the Pandora18k dataset with the Adam optimizer and a learning rate equal to 1e-4.

Figures 6, 7, and 8 show the results of all our experiments on the six pre-trained models for style classification with a different optimizers: SGD, RMSprop, and Adam respectively. Each figure has two subplots: on the top, the results of the Panting-91 dataset, and on the bottom, the results of the Pandora18k dataset. Each pre-trained model has two bars: the blue bar represents the model's accuracy when it was trained with a learning rate of 1e-2, and the orange bar indicates the model's accuracy when it was trained with a learning rate of 1e-4. From the figures, we can notice that the pre-trained Xception model performed better than the pre-trained InceptionV3 model on the Pandora18k dataset. Moreover, the pre-trained ResNet50 model achieved higher accuracy than the pre-trained models Xception, InceptionV3, and EfficientNet B3 on both datasets (Painting-91 and Pandora18k).

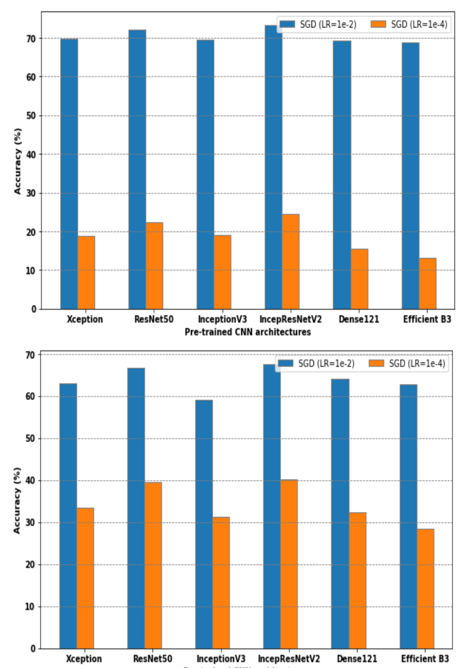

Figure 6. The results of style classification with SGD optimizer on the top: Panting-91 dataset and on the bottom: Pandora18k dataset

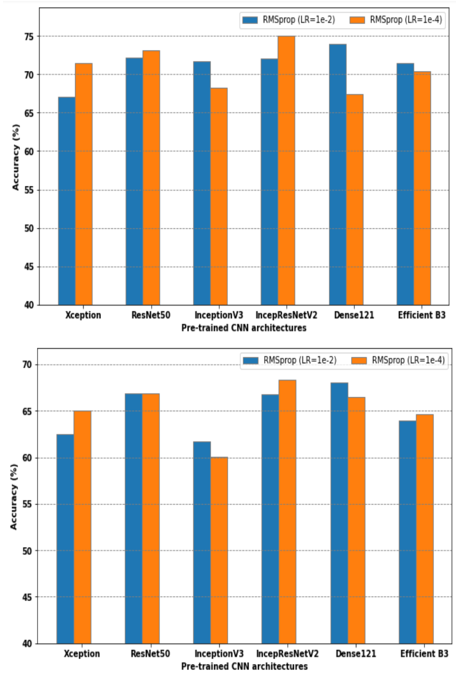

Figure 7. The results of style classification with RMSprop optimizer on the top: Panting-91 dataset and on the bottom: Pandora18k dataset

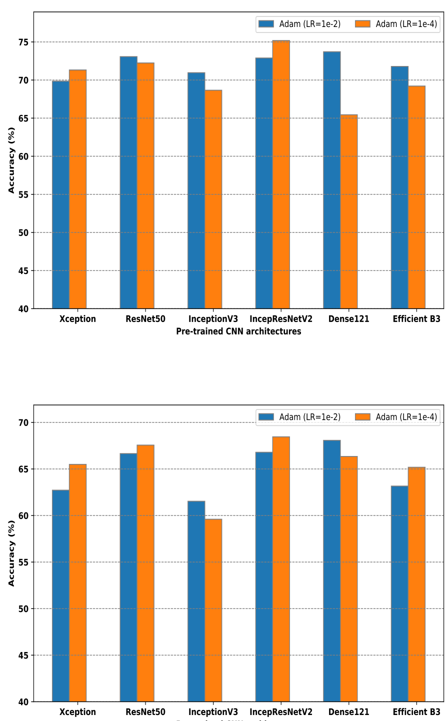

Figure 8. The results of style classification with Adam optimizer on the top: Panting-91 dataset and on the bottom: Pandora18k dataset

Figures 9 and 10 present the confusion matrix of InceptionResNetV2 with Adam optimizer and learning rate 1e-4 on Dataset 1: Painting-91 and Dataset 2: Pandora18k respectively. The diagonal numbers present the average accuracy of each style individually. Figure 9 indicates that classes of styles, Bayantinizim and Early-Renaissance, achieved the best accuracy with 97% and 87%, respectively. The style of Expressionism was confused with Fauvism and Post-Impressionism, while Baroque was confused with Rococo and Romanticism. The confusion between the styles is due to their similarity, as they belong to adjacent periods. Figure 10 indicates the classes Abstract Expressionism and Surrealism were recognized with the highest accuracy of 93% and 88%, respectively. The Renaissance style achieved the lowest accuracy of 56%, and it was mixed up with Neo-classical.

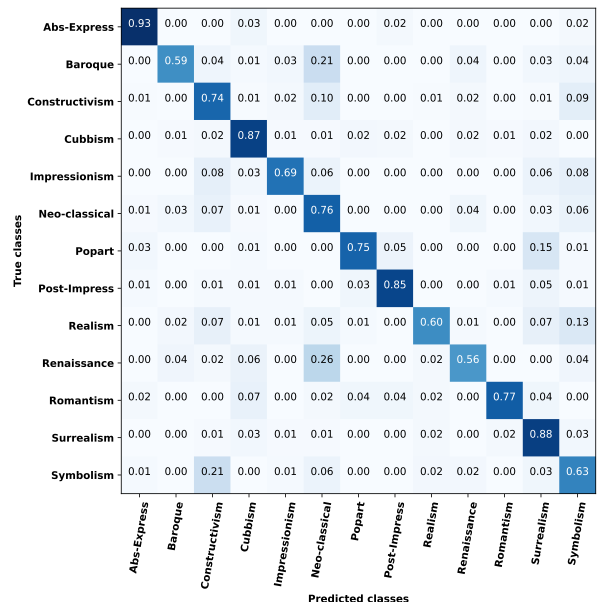

Figure 9. The Confusion Matrix of InceptionResNetV2 with Adam optimizer and learning rate of 1e-4 on the Pandora18k dataset

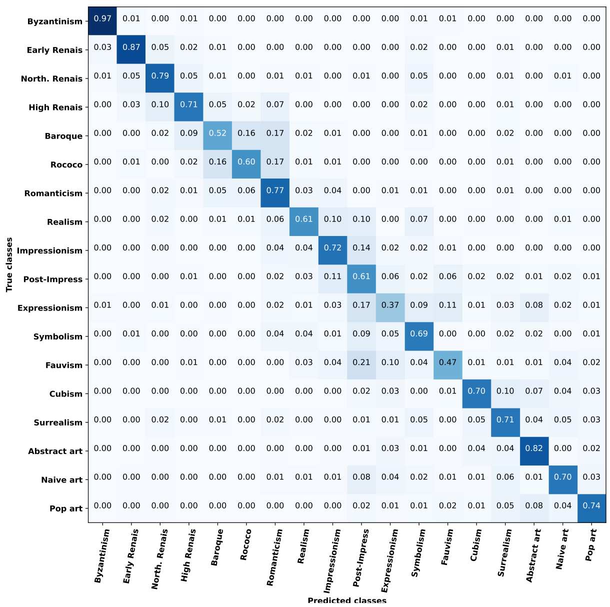

Figure 10. The Confusion matrix of of InceptionResNetV2 with Adam optimizer and learning rate of 1e-4 on the Painting-91 dataset

6. Conclusion

In this study, we proposed a framework to compare the performance of six pre-trained CNN architectures (Xception, ResNet50, InceptionV3, InceptionResNetV2, DenseNet121, and EfficientNet B3) for style classification with transfer learning. Furthermore, we studied the effect of different optimizers (SGD, RMSprop, and Adam) with different learning rates of 1e-2 and 1e-4 on each model. In our studies on two art classification datasets, Painting-91 and Pandora18k, all the pre-trained models performed poorly with the SGD optimizer and a small learning rate (1e-4) and significantly better performed with a higher learning rate (1e-2). This indicates the impact of choosing the correct learning rate, as the model may fail to achieve good results with inadequate hyperparameters. The results of all the pre-trained CNN models with the RMSprop optimizer and the Adam optimizer show similar results when evaluated with the same learning rate. Both are better than the ones with the SGD optimizer. Moreover, we found that the best-performing optimizer and learning rate for a small model are not always the best hyper-parameters for a more profound and larger model. The pre-trained InceptionResNetV2 was the most accurate model for the artistic style classification on both datasets when it was trained with an Adam optimizer and a learning rate equal to 1e-4.

This article has provided a good foundation for further research, which can be used in future studies to increase artistic style recognition accuracy and decrease the ambiguity between specific styles using more complex and diverse classification techniques.

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