Classification of Fine Art Paintings by Style and Artist

Team Gold

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Abstract

Labeling artists and styles of fine-art paintings has become increasingly important for art preservation, categorization, and development of virtual Museums. While CNNs have been popularly used for classifying various images, the combination of a CNN-feature extractor followed by a Gradient Boosting classifier appears as a novel high-performance and fast method classifying various attributes of an image simultaneously, facilitating processing large amounts of images and data. The project attempts to classify two fundamental attributes of a painting – artist and style – using this approach via two variants of CNN feature extraction- VGGNet16 and ResNet50. We find that the hybrid ResNet50-XGBoost, the deeper of the two networks, method captures the data better than the VGGNet16-XGBoost method with a classification accuracy of around 78% over 73% for artists and 55% over 52% for painting styles; suggesting better suitability of deeper networks for such tasks.

1 Introduction

With the advent of technology, digital preservation of artworks has become a demanded task. Given the recent spurt in the development of virtual museums, the digitalization of artworks has especially become important. Digitalization of artworks, however, not only requires conversion of art into digital formats but also requires massive ancillary supporting labels and information related to the artwork in the digital space. These, then, becomes crucial to understand the background and placement of paintings.

While gathering painting related information was originally regarded as a task of converting information into digital formats, it is now increasingly being seen through the prism of Artificial Intelligence as a task of classification. Interestingly, this latter approach provides art historians, curators, conservators, and even novice onlookers a tool to build upon and gain from the information. For one, it allows for the creation of an interactive virtual museum experience wherein a complete novice may get to learn about and appreciate the various artworks. For instance, it may point out similarities between styles, allow hyperlinked searches, or a Virtual Reality experience of a style one reads about in the encyclopedia but does not understand. Secondly, it helps domain experts to gather knowledge about an artist's portfolio and aid them in classifying uncategorized paintings that they discover later. Thirdly, this provides for a great connected repository of art knowledge that can act as a library for artworks.

Given this, it becomes pertinent to look at digital artworks through the prism of Artificial Intelligence and classify various attributes related to the artworks. Through this report, we attempt to label the paintings by classifying two very important and fundamental attributes of artworks - the artist and the style.

In the next section, we look at the background of the problem. We then present our work describing the data we used in Section 3 and our methodologies in Section 4. We then present the results in Section 5 and finally conclude in Section 6.

2 Background

Art style recognition has been studied extensively in the literature, most of which focus on the details and texture of fine art paintings, such as the spatial distribution of colors and the spatial organization of regions in the image [3]. This is seen in the works of Liu et al. [10] using pre-computed features from a multi-task dictionary, Shamir et al. [14] and Keren and Daniel [8] who use image segregation followed by extracted discrete cosine and NaiveBayes classifier to predict artists.

Although the use of pre-computed features provides for more interpretability, these classifiers are usually not able to achieve the best accuracy [17]. Convolutional neural networks (CNNs), though, allow automatic feature-learning and, often results in better results [20] [12]. As shown in the work of Tan et al. [17], large-scale classification of fine art paintings with deep convolutional networks achieved an overall accuracy of 68% across styles, genres, and artists, which was optimal among state-of-the-art results. Furthermore, Lu et al. [11] proved that features generated by CNN could achieve a better performance than other existing methods. Therefore, CNNs have become a mainstream technique in image classification problems. Moreover, according to Razavian et al. [15], the features obtained from the CNNs have also become the primary candidates in most visual recognition tasks.

The availability of the pre-trained networks has eased the high computational cost of CNNs [22]. Karayev et al. [7] addressed a similar problem in which they classified artwork on Flickr by style and found that a CNN pre-trained on ImageNet can learn the underlying image features to obtain optimal published performance. Some others have used slightly more sophisticated methods such as to automatically discover style-specific and artist-specific patterns, Liu et al. [10] discovered a dictionary representation by jointly learning an artist-specific dictionary across several artists having painted with the same style. However, not only the results of such methods have only been verified on a certain dataset of small size, which makes it infeasible to apply, but also the remarkable learning ability of pre-trained CNNs overshadows these complex systems in terms of artwork classification [15]. Therefore, pre-trained CNNs seem to be an ideal candidate.

Among the highly acknowledged pre-trained networks, VGGNet and ResNet are both outstanding approaches to the artwork classification problem. VGGNet is a CNN architecture proposed by Karen Simonyan and Andrew Zisserman [16]. It creatively uses multiple smaller size kernels (3x3) rather than a large kernel to capture features of a receptive field [16]. This innovation increases the depth of the network while decreasing the number of parameters which makes the model easier to train but less likely to overfit [12].

Besides, the residual learning framework is one proposed to ease the training of networks that are significantly deeper than those proposed previously, such as VGG nets [5]. Empirical results have shown that these residual networks (ResNet) are easier to optimize from substantially increased depth but still control for lower complexity [5] which entails the identity function. Further, He et al. argued that stacking layers would not degrade network performance because we could simply stack identity functions (layers that do nothing) on the current network, and the final architecture would perform the same [21].

As demonstrated in [22], ResNet50 achieved the highest prediction score in different classification tasks with the smallest training size. Yet, ResNet variants such as ResNet101 and ResNet152 with over 50 convolutional layers are subject to overfitting on training images and thereby unstable [22]. Additionally, VGG networks converge quickly at the first few epochs and achieved high accuracy, comparable with more complex networks such as GoogleNet, with relatively limited training data. On account of the trade-off between computation time and performance, we considered networks that are relatively less complex but still have a preeminent transfer learning capability. Hence, we finally selected VGG16 and ResNet50 as our feature extraction models in the transfer learning part of this project.

In addition to feature extraction, a multi-class classifier is also required to classify artwork by style and artist. There has been extensive research, such as [18] and [19] in applying a combination of CNN and eXtreme Gradient Boosting (XGBoost) to solve image classification tasks. XGBoost is a powerful ensemble learning algorithm that can transform various weak classifiers into a robust classifier for better classification performance with high speed due to its scalability [1] [2]. Such a hybrid model consists of several stacked convolutional layers to automatically learn features from images, followed by XGBoost in the last layer for predicting the class labels. As discussed in [13], the hybrid model performs better than the original CNN and XGBoost models.

Given the considerable data size we have, an efficient and high-performance classifier is required, and XGBoost is such a classifier. Therefore, we decided to employ a hybrid model of two super classifiers: CNN as well as XGBoost in this study, and it is the first time that such hybrid architectures are proposed for the classification of fine-art paintings, which is a unique voice in the existing literature.

3 Data

The data used for the project is obtained from the Painters by Numbers Kaggle Competition[1], which consists of over 100,000 paintings. Each painting is labeled with its respective artist, style, and genre. Therefore, this dataset seems appropriate for classification models to train on and learn the various attributes, including artist and style, of paintings.

Through a panoramic view of the data, we found that the paintings were labeled with multiple sub-style, which can be merged into major art styles, such as Cubism, Renaissance, and Baroque-Rococo as shown in Figure 2. Moreover, from the exploratory data analysis, there were some painting samples by artist and by sub-style which had very few samples (Figure 1); that could be a potential impediment in training and classification.

Given this, for classifying the styles, we chose the 10 major art styles ranging from the central Middle Ages (11th century) to the millennium. These styles help illustrate the evolution of art history. We further merged the original sub-styles into their fundamental art movements, which finally constitute our 10 art styles for classification. Our merge strategy is shown as follows:

1. Analytical Cubism and Synthetic Cubism joined into Cubism

[1] https://www.kaggle.com/c/painter-by-numbers

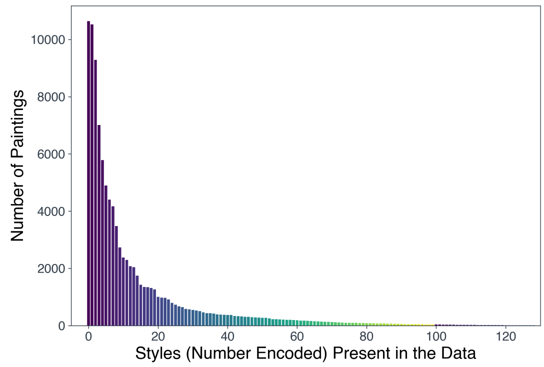

Figure 1: Number of Paintings per Style (as mentioned in the Data)

2. Northern Renaissance, Mannerism, Early Renaissance, and High Renaissance joined into Renaissance
3. Abstract Expressionism joined into Abstract Art
4. Post-Impressionism joined with Impressionism
5. Rococo joined with Baroque

The resulting 10 styles chosen for the classification are presented in Table 1. This processed dataset used to classify Styles consists of 70,901 paintings in total, with each style having at least 2,000 paintings.

Painting Style	Time Period	No. of Paintings
Renaissance	1400-1600	6387
Baroque	1600-1750	7133
Romanticism	1800-1850	9285
Realism	1850-1860	10525
Impressionism	1860-1870	16428
Art Nouveau	1880-1910	4899
Expressionalism	1905-1920	7013
Surrealism	1910-1920	4167
Cubism	1900-1920	2021
Abstract Art	1940+	3053

Table 1: Art Styles and Periods

Further, for artist classification, we selected the most prominent artists, whose paintings are highly-sought after, belonging to the 10 styles in Table 1 and having at least 500 paintings per artist, as available in the dataset. The artists selected were Ivan Aivazovsky, Marc Chagall, Camille Pissarro, Albrecht Durer, Vincent Van Gogh, Paul Cezanne, Martiros Saryan, Ivan Shishkin, Gustave

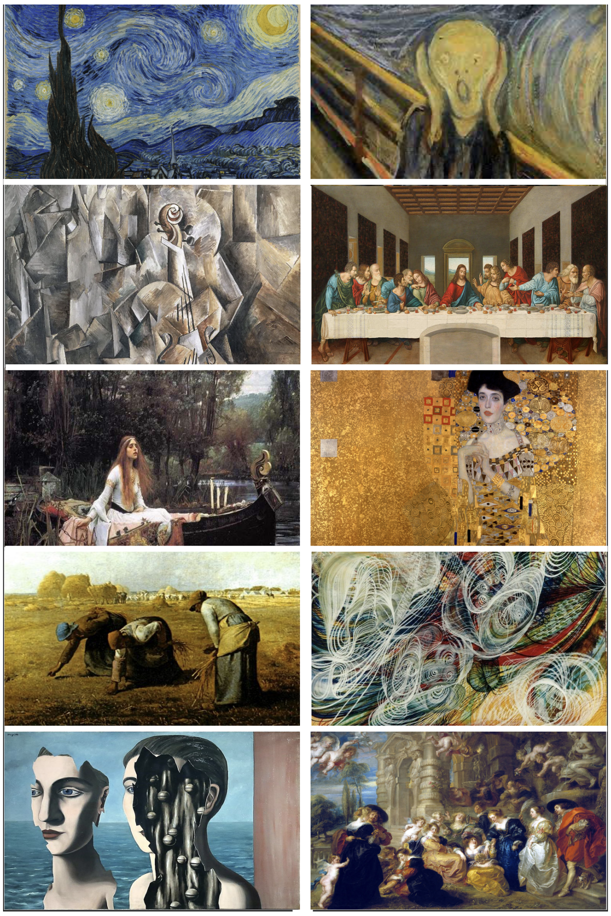

Figure 2: 10 Styles: Column 1 (Top to Bottom)- Impressionism, Cubism, Romanticism, Realism, Surrealism. Column 2 (Top to Bottom) - Expressionism, Renaissance, Art Nouveau, Abstract, Baroque

Dore, Pierre-Auguste Renoir, Rembrandt, and Pablo Picasso. The dataset used to classify artists consisted of 6,000 paintings.

4 Methodology

Taking cue from Section 2, we established a hybrid CNN-XGBoost model, which is essentially a CNN-based encoder-decoder neural network, to classify paintings by artist and style. For the encoder part, we leveraged pre-trained CNNs on the ImageNet dataset to generate features for our fine-art paintings classification. To obtain the best classification performance, we experimented on multiple pre-trained CNN variants, especially the VGG16 and ResNet50 highlighted in [6][4].

To begin with, we applied VGG16 as one of our encoder models for feature extraction. VGG16 is a variant of VGGNet, where the postfix 16 indicates that it has 16 weight layers. In this study, we used the output from its last layer, a vector consists of 25088 elements, as our features extracted for classification. Moreover, we used a pre-trained ResNet50 architecture as our second experiment. ResNet50 is a variant of the ResNet model which has 48 Convolution layers along with a max-pooling layer and an average-pooling layer in its original architecture. This architecture consists of different blocks, where each block uses a shortcut connection. This shortcut connection could be an identity connection or a connection with a convolutional layer [9].

Keras provides ready-to-use VGG16 and ResNet50, which were pre-trained on the ImageNet dataset. These models can only ingest small-size images. Hence, all paintings were resized to 224×224 before be passed to the CNN models. The top fully connected layers of these CNN models were removed so that the output of their last convectional blocks can be used.

Then, for the decoder part of our architecture, the output generated by CNNs was taken as input features for XGBoost, which would further use these features and labels to learn how to predict the artist and style. Figures 3 and 4 show the full view of the architecture of hybrid VGG16-XGBoost model and hybrid ResNet50-XGBoost model respectively.

To speed up computation time and boost efficiency, we stored features extracted by CNNs in the encoder part and separated our training process into two phases. First, we applied the pre-trained VGG16 and ResNet50 as two experiments to generate image features and stored these features into Amazon S3 buckets. Next, XGBoost was used to classify paintings by styles and artists with features generated in the first phase. By doing so, we avoided generating features repeatedly for classification tuning. Lastly, we compared our classification performance in these two experiments, namely the hybrid VGG16-XGBoost model and the hybrid ResNet50-XGBoost model.

The feature extraction task, which is our encoder part, was executed on AWS EC2 t3.2xlarge instances with 8 vCPUs, 32G memory, and 200G SSD space. It is worth noting that a single image feature of VGG16 would cost 1.5 seconds on each

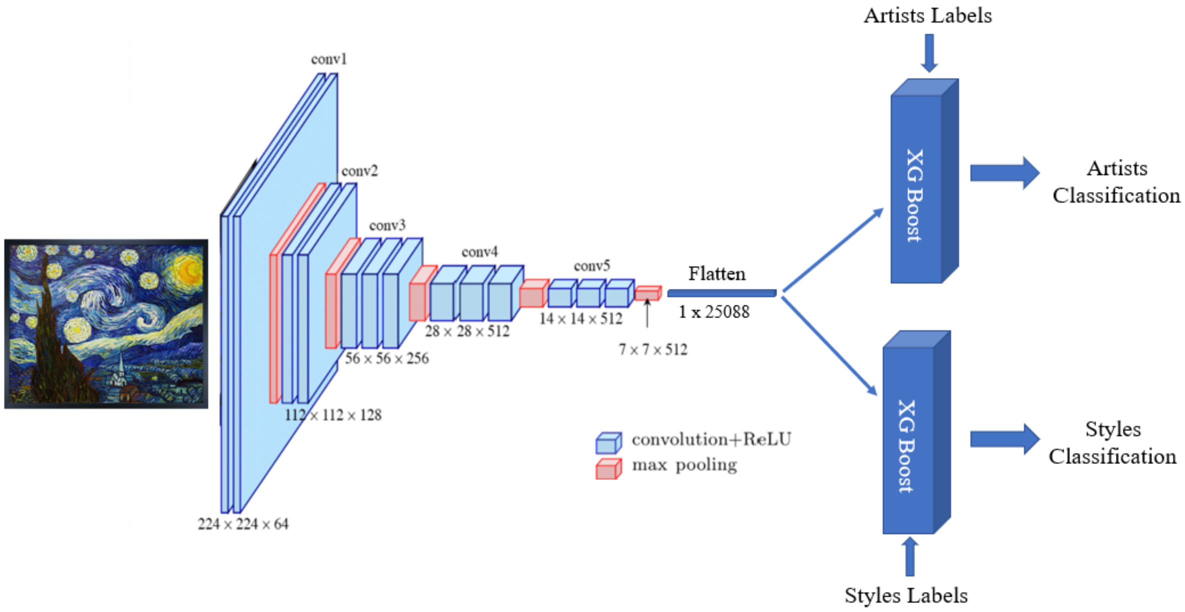

Figure 3: Architecture of Hybrid VGG16-XGBoost Model

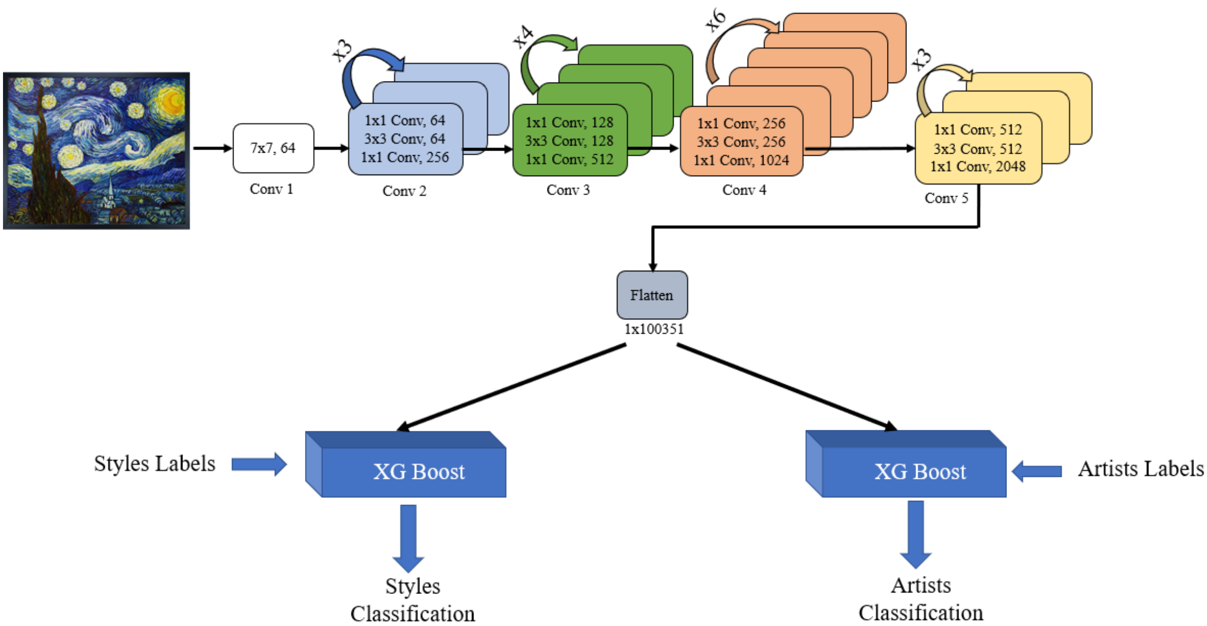

Figure 4: Architecture of Hybrid ResNet50-XGBoost Model

vCPU on average, while that of ResNet50 would take 2 seconds on average. Hence, optimizing the computation time was always the focus of our consideration when we select the model and design the application process.

In the classification aspect, which is our decoder part, the dataset was first split randomly with 33% of the data as the test set and the rest as the training set. The training set was further split into training and validation where we obtained the optimal hyperparameters from the validation results. The XGBoost models were then trained on the entire training data, including training and validation sets, and used to predict on the test set for artists and styles respectively. The train-test split is consistent across two experiments since the prediction only occurs in the decoder part, which uses the same type of model XGBoost.

We selected the first experiment, the hybrid VGG16-XGBoost model, as our baseline both in the classification problems of styles and artists. We believed that our second experiment, the hybrid ResNet50-XGBoost model, would perform better since the encoder network is deeper and presumably learns more image features. To examine the classifier performance, we computed the confusion matrices associated with the classifier as well as the accuracy report, given that this is a multi-class classification problem.

5 Results

From our first experiment-the baseline, based on VGG16-XGBoost, we got an overall average accuracy of 52%. From the confusion matrix in Figure 5, we observed that the model best predicts the Impressionism style with the highest accuracy of 78%. Interestingly, the model misclassified 33% of paintings that should belong to the Expressionism style as Impressionism, which seems plausible due to the similar brush stroke styles. Further, the model performs the lowest when classifying Surrealism with an accuracy of 25%, which again seems plausible as it is more content-based than line or stroke-styled.

In terms of artists, the hybrid VGG16-XGBoost model has an overall accuracy of 73%. As shown in Figure 6, the model could accurately predict 92% of paintings that were composed by Gustave Dore and 95% of those by Ivan Aivazovsky. This

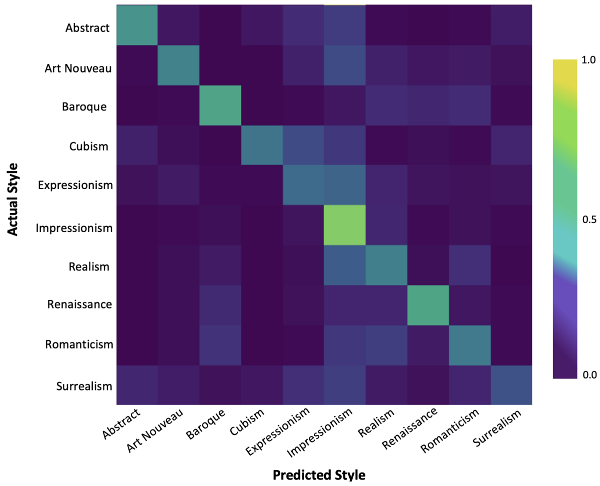

Figure 5: Confusion Matrix of Styles Classified by VGG16-XGBoost

infers that their painting characteristics are unique from the other artists. Interestingly, the model performed the worst on predicting Vincent Van Gogh's paintings with the lowest accuracy of 48%. 12% of Vincent Van Gogh's paintings were misclassified as Pablo Picasso's by this model. The model also misclassified 11% of Ivan Shishkin paintings as Camille Pissarro's. However, this model has an overall accuracy of 75%, and the comparison in Table 2 describes the model performance metrics. Clearly, from this experiment, one can see that the model captures the critical features of some classes better than the others. However, this method is visibly faster and less computationally expensive compared to the next method.

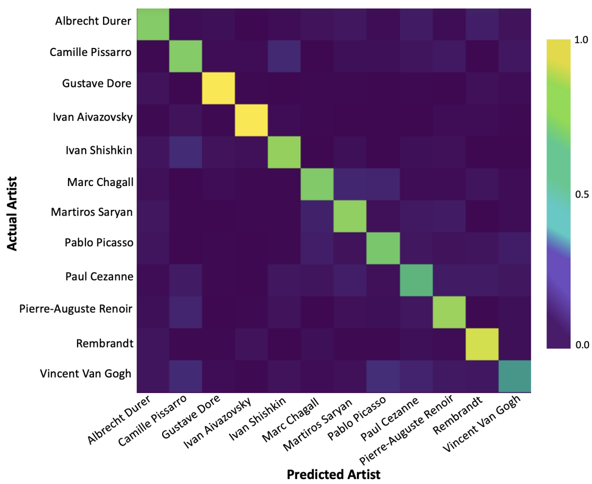

Figure 6: Confusion Matrix of Artists Classified by VGG16-XGBoost

In the second experiment, the hybrid ResNet50-XGBoost model has an overall accuracy of 55%.

According to the confusion matrix in Figure 7. The model best classifies the Renaissance style with an accuracy of 67%. When compared to the VGG16 features, this model performs better in classifying Surrealism, Cubism, and Expressionism which suggests it could capture the features much better.

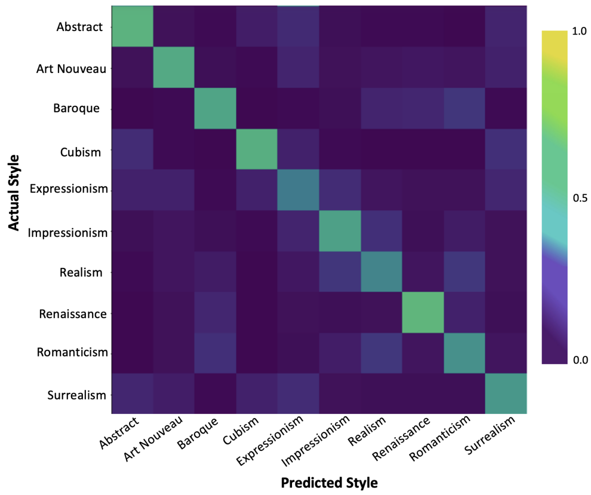

Figure 7: Confusion Matrix of Styles Classified by ResNet50-XGBoost

In the second experiment, the hybrid ResNet50-XGBoost model has an overall accuracy of 78%. According to the confusion matrix in Figure 8, this model performs better than the VGG16-XGBoost model on average. Still, this model predicts Ivan Aivazovsky the best with 95% accuracy and Gustave Dore with 92% accuracy. Also, the model still performs the worst when classifying Vincent Van Gogh's paintings, however, it outperforms VGG16-XGBoost by boosting the prediction accuracy to 60%. Interestingly, when compared to VGG16 features, ResNet50 features improved the prediction accuracy for all artists except Camille Pisarro. As expected, this method performs better but is more time-consuming.

We have chosen the average weighted metrics for the Style Classification and the macro average for the Artist Classification in Table 2 as there appears slight data imbalance in the styles. It can be seen that the hybrid ResNet50-XGBoost model is better than the hybrid VGG16-XGBoost when classifying artists and styles as expected.

The classification of styles is a difficult task because styles can be subjective and there are

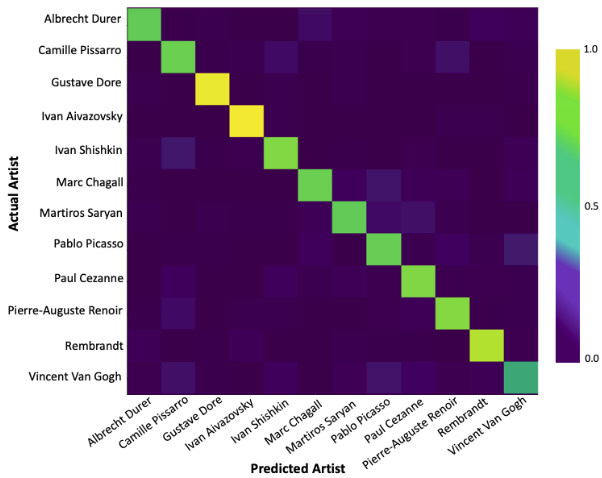

Figure 8: Confusion Matrix of Artists Classified by ResNet50-XGBoost

no clear boundaries for each style. Due to this overlap, the accuracy of the model when predicting styles is not as high as what we obtain for artists. The model performs better when predicting artists. It is possible because artists have their individuality in their paintings which is distinct from others, and the feature extraction can capture these nuances. Hence, the model can classify paintings by artists with more accuracy than styles.

6 Conclusion

This project aims to label paintings by their respective style and artist using the hybrid CNN-XGBoost architecture for facilitating further art digitalization. We examined two different CNN models, VGG16 and ResNet50, to extract features from images, which were then fed into XGBoost for classification of style and artist. This project forayed into hybrid architectures of CNN and XGBoost for the first time for the classification of fine-art paintings based on knowledge from similar computer vision projects. From the project, we find that ResNet50-XGBoost, the deeper CNN, has an edge in aiding digital labeling of paintings with substantial efficiency. Clearly, from this we understand that deeper CNNs could be even more helpful in achieving the task.

However, there are potential limitations of this study. First, our model was trained and tested entirely on images from the Painters by Numbers Kaggle dataset, which is a subset of WikiPaint-

	Artist Classification		Style Classification	
	VGG16-XGBoost	ResNet50-XGBoost	VGG16-XGBoost	ResNet50-XGBoost
Average Accuracy	73%	78%	52%	55%
Average Recall	73%	78%	52%	55%
Average Precision	73%	78%	55%	58%
Average F1-Score	73%	78%	53%	56%

Table 2: Comparison of Model Performance

ing. Therefore, the external validity of this model is restricted. In the future, other fine-art collections database provided by museums could be integrated and trained on to improve the generalizability of the model. Also, we did not use painting colors and texture information to facilitate the classification, which could have been helpful and should be explored going further. Lastly, as explained in Section 2, more advanced models are available, but we could not consider them in this study for comparison due to the limited computational power. They could though be explored further with more resources.

7 Roles

Maobin reviewed the related literature and co-wrote the Section 2 and 4 of the final report. He is also the leader of the proposal and progress report and drafted these two reports. He reviewed the final document and submitted it. Maobin is the Github Lead who managed the project Github and made sure it is well organized throughout the project.

Pranav worked on the classification aspect of the project, training and testing the XGBoost models, and presenting the findings. He also took lead in creating the video and worked on the introduction, results, and conclusion of the final report.

Xinyi contributed to the topic selection, literature review, coding, and was the main writer for the proposal and final reports. She worked on the feature extraction aspect of the project and built the ResNet variants in Keras. She was the leader to integrate and proofread the final report and co-wrote Section 2 and 4. She also contributed to the video presentation and prepared for the script.

Aiman contributed to the topic selection, report writing, especially the Abstract and Introduction and Background sections, and in compiling the reports. She contributed to the classification aspect of the project using XGBoost models and assisted with the findings. She also coordinated the project across the various roles.

8 Timeline of activity

1. Feb. 18th — Kickoff meeting to brainstorm topics
2. Feb. 22nd — Confirmed project topic and set up the Github repository
3. Feb. 23nd — Finished project proposal and submitted
4. Mar 5th — Discussion on the Methods to follow; Feature Extraction and Classification
5. Mar 10th — Discussion on Trained VGGNet Feature Extractions
6. Mar 15th — Discussion on Features to classify
7. Mar. 22nd — Finished project progress report and submitted
8. Mar. 30th — Discussion on what Features to extract and modification in the approach required
9. Apr. 2nd — Completed Feature Extraction with VGG and start new classification for this Data.
10. Apr. 7th — Discussion on VGG extracted dataset and preliminary classification.
11. Apr. 14th — Started ResNet Feature Extraction
12. Apr. 15th — Meeting with Kyle
13. Apr. 17th — Started final report writing
14. Apr. 18th — Completed Feature Extraction with ResNet and started new classification for this Data.
15. Apr. 19th — Creating the Video Presentation.
16. Apr. 20th — Finished project showing video and submitted
17. Apr. 24th — Finished the ResNet version of classification.
18. Apr. 26th — Finished final report and submitted

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Appendix

	precision	recall	f1-score
Abstract	0.41	0.62	0.49
Art Nouveau (Modern)	0.42	0.55	0.48
Baroque	0.56	0.54	0.55
Cubism	0.36	0.65	0.46
Expressionism	0.44	0.41	0.42
Impressionism	0.76	0.56	0.65
Realism	0.45	0.44	0.45
Renaissance	0.55	0.61	0.58
Romanticism	0.41	0.49	0.45
Surrealism	0.30	0.50	0.38
accuracy			0.52
macro avg	0.47	0.54	0.49
weighted avg	0.55	0.52	0.53

Figure 9: Classification Report of Styles Classified by VGG16-XGBoost

	precision	recall	f1-score
Albrecht Durer	0.70	0.72	0.71
Camille Pissarro	0.61	0.65	0.63
Gustave Dore	0.90	0.86	0.88
Ivan Aivazovsky	0.93	0.89	0.91
Ivan Shishkin	0.82	0.70	0.76
Marc Chagall	0.78	0.77	0.77
Martiros Saryan	0.73	0.73	0.73
Pablo Picasso	0.67	0.73	0.70
Paul Cezanne	0.62	0.65	0.64
Pierre-Auguste Renoir	0.70	0.66	0.68
Rembrandt	0.81	0.76	0.78
Vincent van Gogh	0.56	0.67	0.61
accuracy			0.73
macro avg	0.73	0.73	0.73
weighted avg	0.74	0.73	0.74

Figure 10: Classification Report of Artists Classified by VGG16-XGBoost

	precision	recall	f1-score
Abstract	0.48	0.66	0.55
Art Nouveau (Modern)	0.46	0.62	0.52
Baroque	0.59	0.60	0.59
Cubism	0.35	0.64	0.46
Expressionism	0.44	0.42	0.43
Impressionism	0.78	0.58	0.66
Realism	0.48	0.46	0.47
Renaissance	0.61	0.67	0.64
Romanticism	0.45	0.51	0.48
Surrealism	0.32	0.54	0.40
accuracy			0.55
macro avg	0.50	0.57	0.52
weighted avg	0.58	0.55	0.56

Figure 11: Confusion Matrix of Styles Classified by ResNet50-XGBoost

	precision	recall	f1-score
Albrecht Durer	0.79	0.78	0.79
Camille Pissarro	0.67	0.73	0.70
Gustave Dore	0.97	0.91	0.94
Ivan Aivazovsky	0.90	0.89	0.89
Ivan Shishkin	0.83	0.75	0.79
Marc Chagall	0.76	0.79	0.78
Martiros Saryan	0.75	0.78	0.76
Pablo Picasso	0.71	0.68	0.69
Paul Cezanne	0.71	0.66	0.68
Pierre-Auguste Renoir	0.81	0.80	0.80
Rembrandt	0.85	0.84	0.85
Vincent van Gogh	0.57	0.71	0.63
accuracy			0.78
macro avg	0.78	0.78	0.78
weighted avg	0.78	0.78	0.78

Figure 12: Confusion Matrix of Artists Classified by ResNet50-XGBoost