Using Machine Learning to Classify Art Style in Naturalism and Realism

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Abstract
Art styles have evolved over time in response to changing cultural, societal, and artistic influences. The naturalism and realism art styles emerged as artistic and philosophical movements in the 19th century, and while they had some similarities, they also had some important differences. There is, however, a challenge in fully recognizing and understanding the complexities of these art styles. This study aims to investigate how machine learning techniques, including LeNet, Pretrained ResNet-50, and Pretrained MobileNetV3 models, can be used to classify naturalism and realism art styles. The Pretrained MobileNetV3 model demonstrates superior performance for the classification of naturalism and realism, achieving an accuracy rate of 95% and outperforming other models in terms of Precision, Recall, F1-score, and overall accuracy. This model's effectiveness in accurately classifying naturalism and realism art styles holds promise for various applications in art analysis, interpretation, and curation. This research contributes to advancing the understanding and application of machine learning in the field of art style classification. By utilizing suitable machine learning models, art researchers, historians, curators, and museum professionals will be able to analyze extensive art collections efficiently.

Keywords: Classification, Machine Learning, Naturalism, Realism

Introduction

The development of art styles over time reflects the evolving cultural, societal, and artistic influences, shaping the trajectory of artistic movements. Naturalism and realism have captivated audiences across generations, presenting distinct approaches to visual representation. While both emerged as artistic and philosophical movements in the 19th century and share some similarities, they also have important differences (Hauser, 1999; Novak, 2007). Naturalism meticulously captures reality, paying close attention to detail and emphasizing the influence of environmental, hereditary, and social factors on individuals (Silviani & Rinjani, 2022). On the other hand, realism primarily focuses on accurately observing and depicting everyday life without delving into the underlying causes of human behavior. It often centers on ordinary subjects and the experiences of everyday life (PUTRA et al., 2017).

However, understanding the complexities of these art styles and discerning their differences can be daunting and overwhelming. Thus, machine learning, with its ability to recognize patterns and make informed decisions to distinguish the styles. Using the concept to learn the data from the dataset and train to adapt the new information given (Alzubaidi et al., 2021; Lee & Shin, 2020). As a result, it is expected that classification in machine learning will yield high-accuracy results.

Therefore, the primary objective of this study is to investigate the application of various machine learning techniques in art classification. This comprehensive approach has significant implications for the broader art analysis and interpretation field. Art researchers, historians, curators, and museum professionals can efficiently analyze extensive art collections by employing different machine learning models, such as LeNet, Pretrained ResNet-50, and Pretrained MobileNetV3. This multi-model exploration offers valuable insights that contribute to understanding Naturalism and Realism, their prevalence, and distinguishing characteristics. Furthermore, it enriches our knowledge of these art styles and their cultural significance, expanding the horizons of art analysis and interpretation through the utilization of various machine learning techniques.

Methods

A. Dataset and Data Acquisition

The dataset used in this study was sourced from the Wikiart dataset, a vast collection of annotated artwork encompassing approximately 80,000 artworks categorized by genre, artist, and style class. For this research, a specific subset of data was carefully chosen from the Naturalism and Realism style classes. We selected 240 artworks and divided them into 120 artworks from each class to ensure a balance in representation. The dataset predominantly consisted of oil paintings, with images limited to the jpg/jpeg format for consistency purposes. In order to facilitate effective model training and evaluation, an 80:20 split was implemented, allocating 80% (100 images) of the dataset for training and reserving 20% (20 images) for validation. Figure 1 provides an overview of the dataset and its composition. This commonly used split ratio was employed to maintain the continuity of features and strike a balance between the training and evaluation phases (Amir et al., 2023; Joseph & Vakayil, 2022). The specific distribution of training and validation images can be seen in Table 1.

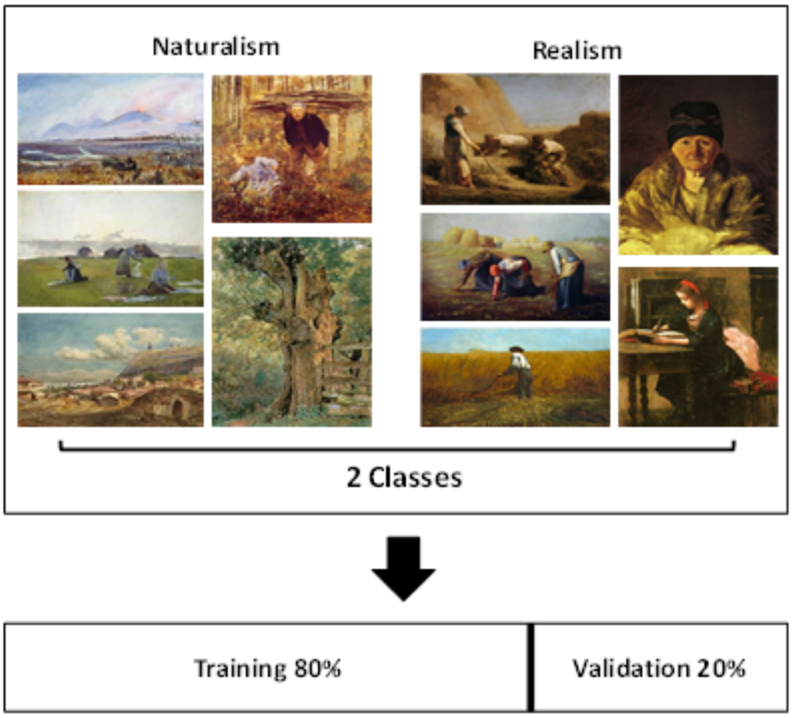

Figure 1: Dataset Composition

Class	Training	Validation
Naturalism	100	20
Realism	100	20

Table 1: Dataset for Classification

B. Architecture Data Processing

The image classification architecture consists of several key components. First, the input image is scanned to identify unique characteristics specific to paintings, focusing on elements such as brushstrokes, color palettes, and composition that contribute to the artistic style. Next, features are extracted using convolutional layers to capture distinct patterns and details. As the model progresses, the features are condensed and abstracted by reducing pixel dimensions. These condensed features pass through interconnected layers, where intermediate neurons help extract abstract features and understand complex relationships. The transformed features are then used in the image classification layer, applying machine learning techniques to assign the image to predefined categories. The method also involves training and validation, where the model learns from labeled data, adjusting parameters to minimize prediction differences. Validation assesses the model's performance on unseen images, ensuring its ability to generalize and accurately classify new paintings. This integrated approach of architecture and method enables accurate recognition of painting characteristics and classification into specific styles (Figure 2).

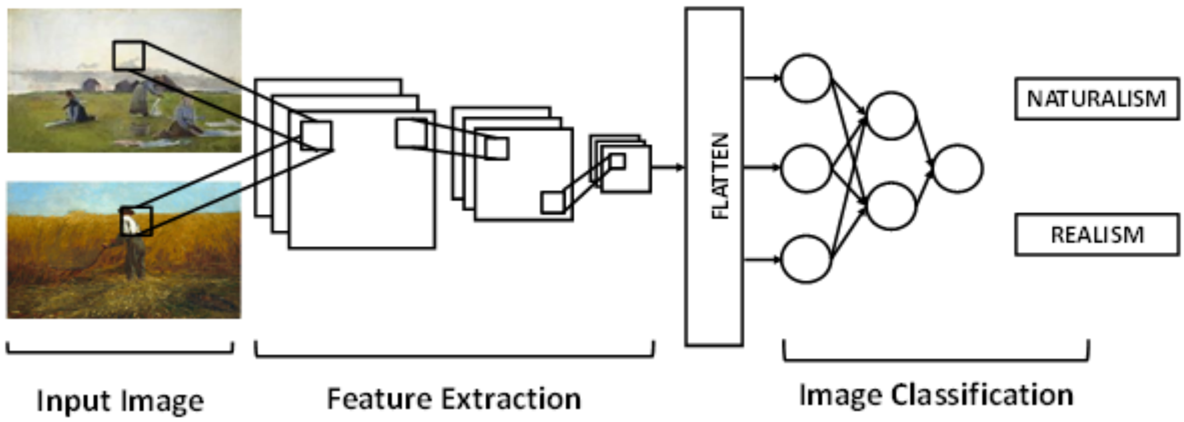

Figure 2: Architecture of Image Classification Method

C. Machine Learning Models

This study used several machine learning models LeNet, Pretrained ResNet-50, and Pretrained MobileNetV3, to classify naturalism and realism art styles. The model used a loss function with cross entropy error, optimization function, and learning parameters such as Recall, Precision, F-1 Score, and Accuracy. The performance is compared based on the metric performance of each model.

LeNet
LeNet is widely used in machine learning classification, especially for image classification, because it extracts hierarchical features, handles translation invariance, leverages local connectivity, shares parameters efficiently, and captures spatial hierarchies (Khan et al., 2020). These qualities make LeNet highly effective in recognizing and differentiating objects within images while efficiently processing large datasets.

Pretrained ResNet-50
The Pretrained ResNet-50 is a deep learning architecture consisting of 50 layers that have been trained on a large dataset of images from ImageNet (Rezende et al., 2017). It is selected for its smaller parameter size, enabling faster model loading and training (Ikechukwu et al., 2021). The proposed solution involves pre-processing the data, training the model using the Pretrained ResNet-50, and performing image classification.

Pretrained MobileNetV3
The Pretrained MobileNetV3 model is well-known for its robustness in extracting features from the input image (Alsenan et al., 2021). This lightweight convolutional neural network model has gained recognition for its ability to achieve a harmonious balance between accuracy and computational efficiency (Abd Elaziz et al., 2021).

Results

The performance metrics of the three models are compared and summarized in Table 2. Figure 3 displays the results of the LeNet model, Figure 4 showcases the performance of the Pretrained ResNet50 model, and Figure 5 presents the outcomes achieved using the Pretrained MobileNetV3 model.

Model Performance Comparison	LeNet		Pretrained ResNet-50		Pretrained MobileNetV3	
	Natural	Realism	Natural	Realism	Natural	Realism
Precision	71%	74%	83%	100%	91%	100%
Recall	75%	70%	100%	80%	100%	90%
F1-Score	73%	72%	91%	89%	95%	95%
Accuracy	73%		90%		95%	

Note: Natural, Naturalism.

Table 2: Dataset for Classification

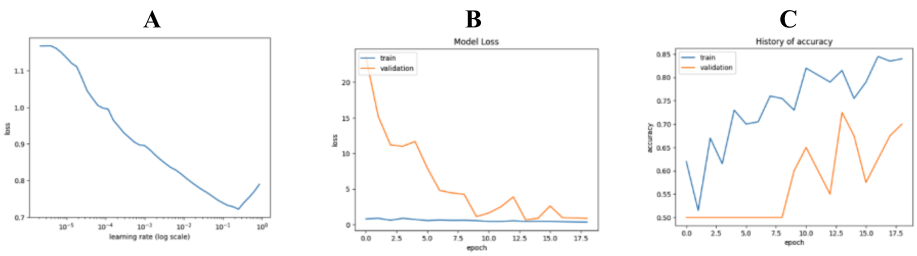

Figure 3: Result of LeNet model. The learning rate (A), model loss during training and validation (B), the accuracy during the training and validation (C)

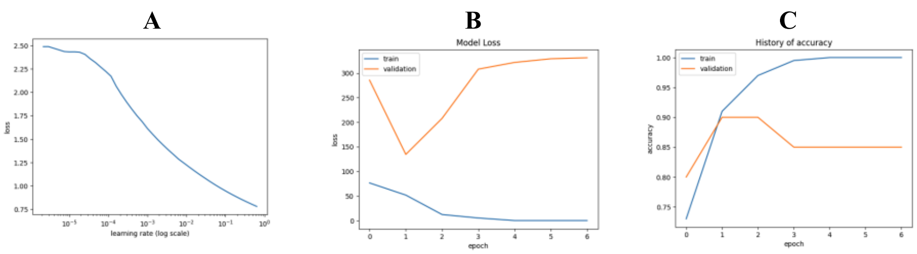

Figure 4: Result of Pretrained ResNet-50 model. The learning rate (A), model loss during training and validation (B), the accuracy during the training and validation (C)

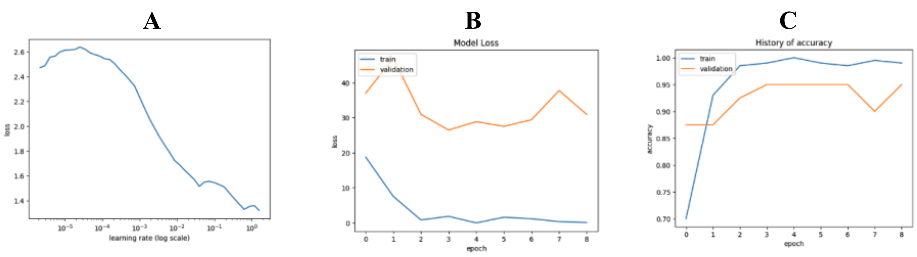

Figure 5: Result of Pretrained MobileNetV3 model. The learning rate (A), model loss during training and validation (B), the accuracy during the training and validation (C)

All models demonstrated proficiency in accurately classifying samples of naturalism and realism from a dataset of 240 images, achieving an impressive mean accuracy rate of 86%. The evaluation of the model's performance, considering Precision, Recall, and F1-score metrics, provided additional validation of its effectiveness in distinguishing between the two art styles.

Discussion

From the results, it is evident that each model demonstrates varying levels of performance in classifying naturalism and realism. The Pretrained MobileNetV3 model demonstrated superior performance across all metrics with all values above 90%. It achieved an impressive accuracy rate of 95%, indicating the model's strong capability in accurately classifying the dataset. The second highest was the Pretrained ResNet-50 model, which showed notable performance as it attained an accuracy rate of 90%, showcasing its effectiveness in distinguishing between naturalism and realism. The LeNet model was the lowest. However, it showed a good performance with an overall accuracy of 73%.

Based on the comparison of these models, it is evident that the Pretrained MobileNetV3 model outperformed the other models in terms of precision, recall, F1-score, and overall accuracy. This superiority can be attributed to its architecture, which creates deeper networks that positively impact model accuracy and efficiency during training (Horry et al., 2020). Its superior performance highlights its potential as a highly effective model for classifying naturalism and realism art styles. The model's ability to accurately distinguish between naturalism and realism holds promise for various applications in the field of art analysis, interpretation, and curation.

However, there is still a limitation in this study. First, the evaluation was conducted using a relatively small dataset of 240 samples, which may not fully represent the entire range of naturalism and realism artworks. Future research should aim to utilize larger and more diverse datasets to validate the models' performance in different contexts. Last, while the Pretrained MobileNetV3 model demonstrated superior performance in this study, it is worth exploring other machine learning models and ensemble techniques to assess their effectiveness in art style classification.

Conclusion

In conclusion, this study investigated the application of machine learning for art style classification. The models demonstrated varying performance levels in classifying naturalism and realism, with the Pretrained MobileNetV3 model surpassing others in all metrics. It effectively distinguished between art styles, particularly in classic painting. The application of this comprehensive approach has a significant impact on the field of art analysis and interpretation and is useful to art researchers, historians, curators, and museum professionals in order to analyze extensive collections of art in a systematic manner.

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