Art-Style Classification Using MobileNetV2: A Deep Learning Approach

Zhengyang Wang [a]
School of Information Science and Engineering, Lanzhou University, Lanzhou, Gansu, China

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Abstract: Painting, as a significant component of human culture, carries historical and cultural information while shaping aesthetic perceptions. However, the complexity of artistic styles often makes it challenging for the general public to comprehend them in depth. Leveraging artificial intelligence to popularize art knowledge and facilitate the recognition and understanding of artistic styles intuitively has thus become increasingly important. This study applies MobileNetV2 to develop an art style classification system that automatically identifies eight painting genres, including Abstract Art and Romanticism, showcasing their historical and cultural significance. The research is based on the WikiArt dataset, covering eight classic painting styles with approximately 3,600 images. By employing data preprocessing, transfer learning, and the MobileNetV2 model, the system achieves art-style classification, with data augmentation and hyperparameter optimization enhancing model performance. The target accuracy for the system is set at ≥65%. This study aims to provide an innovative tool for art education and aesthetic appreciation by implementing artificial intelligence techniques for the automatic classification of classical painting styles. The findings contribute to enhancing public understanding and appreciation of painting art while advancing practical applications of artificial intelligence in the art domain.

1 INTRODUCTION

The classification and management of art styles have long posed significant challenges due to the inherent complexity and diversity of artistic creations. Each art style often embodies unique visual features, making it difficult to accurately classify them using traditional methods (Saleh & Elgammal, 2015; Tan et al., 2018). Recent advancements in deep learning have opened new avenues for addressing such challenges, especially in visual classification tasks. Convolutional Neural Networks (CNNs), as representative models of deep learning, have demonstrated exceptional capabilities in image classification, achieving superior performance compared to traditional machine learning algorithms (Krizhevsky et al., 2017; Simonyan, 2014). For instance, CNNs are particularly effective when dealing with large-scale datasets, significantly outperforming traditional models like Support Vector Machines (SVMs) in terms of accuracy and efficiency (Wang et al., 2020) . These advancements underscore the transformative potential of deep learning in addressing complex classification problems in diverse domains, including art.

This study aims to leverage the MobileNetV2 model, a state-of-the-art deep learning architecture known for its efficiency and adaptability, to classify paintings into eight distinct art styles. By focusing on MobileNetV2, this research investigates how the model manages intricate visual patterns and characteristics linked to various art styles. The process includes adjusting the MobileNetV2 model to enhance its effectiveness in classifying artistic styles. Moreover, the study assesses the model's capability by examining both its classification accuracy and computational efficiency.Through this approach, the research seeks to identify potential limitations and propose avenues for future improvements in art style classification tasks.

The use of deep learning techniques for art style classification marks a major advancement in streamlining art management processes. Beyond its practical implications, this study provides valuable

[a] https://orcid.org/0009-0006-2954-0758

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insights into the nuanced characteristics of different artistic styles. By bridging the gap between artificial intelligence and cultural heritage, this research contributes to the growing body of knowledge on AI-driven solutions for artistic and cultural domains, underscoring the transformative potential of deep learning in revolutionizing traditional fields.

The structure of this paper reflects the logical progression of the research. It begins with an explanation of the dataset and data preprocessing techniques, along with the specific configuration of the MobileNetV2 model employed in this study. Following this, the results are presented and analyzed, offering insights into the model's strengths and areas where improvement is needed. The paper concludes by summarizing the research findings, discussing the limitations, and proposing potential directions for future work. By emphasizing the capabilities of MobileNetV2, this study aims to advance the boundaries of art style classification and lay the groundwork for more sophisticated AI-based solutions in the arts.

2 DATA AND METHOD

2.1 Data Collection and Description

The data used in this study comes from the publicly available art database WikiArt. WikiArt provides a rich collection of paintings, covering various art styles and artists. The dataset includes eight style categories: Abstract Art, Baroque, Cubism, Impressionism, Post-Impressionism, Realism, Romanticism, and Surrealism. Each style comprises representative works from approximately five artists, with each category containing 345 to 500 images, for a total of 3,606 paintings.

Data augmentation was employed to improve the model's generalization and mitigate overfitting. Data augmentation is described as a strategy to prevent overfitting via regularization, addressing two major concerns: generating more data from a limited dataset and minimizing overfitting (Maharana et al., 2022). Common techniques implemented in this study include image flipping, brightness adjustment, cropping, and rotation. These augmentations effectively reduce model overfitting to specific image features and improve performance on the test set.

The dataset was divided into training and testing subsets using an 80:20 split, resulting in 2,885 images in the training set and 721 in the test set. Each image was resized to a uniform input size of 160×160 pixels to ensure data consistency.

2.2 Model Introduction

This study adopts MobileNetV2 as the base model due to its lightweight architecture and efficiency. MobileNetV2 leverages depthwise separable convolutions to significantly reduce computational complexity and the number of model parameters, making it ideal for resource-constrained environments (Sandler et al., 2028). Moreover, by incorporating transfer learning, pre-trained weights from large-scale datasets such as ImageNet provide robust feature extraction capabilities, even when working with small-scale datasets. This approach has been shown to enhance classification performance and minimize overfitting in tasks similar to art-style classification (Gulzar, 2023). Additionally, MobileNetV2's simple yet effective design ensures compatibility with deployment on edge devices, making it highly practical for real-world applications.

3 RESULTS AND DISCUSSION

3.1 Experimental Setup

The experiment was conducted on the Edge Impulse platform, which supports rapid model development and deployment. The configuration details for the neural network training are summarized in Table 1.

Table 1. Neural Network Training Configuration.

Category	Setting	Value
Training settings	Number of training cycles	15
	Use learned optimizer	Disabled
	Learning rate	0.0003
	Training processor	CPU
	Data augmentation	Enabled
Advanced training settings	Validation set size	20%
	Split train/validation by key	Not used
	Batch size	32
	Auto-weight classes	Enabled

	Profile int8 model	Disabled
Neural Network architecture	Model structure	MobileNetV2 160x160 0.35
	Input layer features	76,800 features
	Final dense layer	None
	Dropout	0.1

3.2 Experimental Results

Table 2 provides a summary of MobileNetV2's classification performance on various art styles, detailing metrics like accuracy, F1-score, recall, precision, and the overall ROC value.

In the classification results, styles such as Cubism and Impressionism performed relatively well, with accuracy exceeding 70%. In contrast, Romanticism and Surrealism exhibited weaker classification performance, which may be attributed to the complexity of these styles and the similarity of features between samples.

The results offer a detailed summary of the model's performance, emphasizing notable strengths and weaknesses, which are examined more thoroughly in the next section.

Table 2. Experiment Result

Art Style	Accuracy(%)	F1 Score	Precision	Recall	ROC
Abstract Art	66.1	0.70	0.76	0.66	0.94
Baroque	69.7	0.70	0.71	0.70	
Cubism	89.1	0.85	0.81	0.89	
Impressionism	73.1	0.70	0.66	0.73	
Post-Impressionism	62.4	0.64	0.65	0.62	
Realism	60.6	0.59	0.57	0.61	
Romanticism	53.3	0.57	0.62	0.53	
Surrealism	69.5	0.68	0.66	0.70	
Overall	67.6	0.67	0.68	0.68	

3.3 Results and Discussion

The experimental results demonstrate that the art style classification system based on MobileNetV2 performs relatively stably across most categories. However, certain categories, particularly Romanticism and Surrealism, exhibit relatively lower classification accuracy. This may be attributed to the transitional characteristics of art styles. Some artists' works are created during historical transitions or periods of transformation, such as the shift from Classicism to Romanticism or from Impressionism to Post-Impressionism. These transitional works often blend characteristics of different styles, increasing the difficulty for the model to classify them accurately.

Another significant challenge stems from the overlapping features of different art styles. As Vuttipittayamongkol et al. emphasized, class overlap has a more pronounced negative impact on classification accuracy compared to class imbalance, as it leads to misclassifications even when datasets are balanced (Vuttipittayamongkol et al., 2020). This issue is further exacerbated by the multi-stylistic nature of certain artists, who create works that simultaneously reflect characteristics of multiple styles, such as Romanticism and Realism. Consequently, the training data for categories like Romanticism may include traces of features from other styles, increasing the risk of confusion for the model.

Additionally, the ambiguity in sample features plays a crucial role. Certain artworks exhibit high visual similarity across different styles due to the use of similar techniques or color treatments. For instance, Romanticism and Surrealism share commonalities in expressing emotions and fantasy, while Impressionism and Post-Impressionism often overlap in brushstroke techniques. Such ambiguities align with findings from Vuttipittayamongkol et al., who emphasized that addressing overlapping features is critical to improving model performance (Vuttipittayamongkol et al., 2020) . These factors collectively make it challenging for the model to clearly distinguish between styles, necessitating more sophisticated approaches to mitigate their impact.

To address these challenges, several improvements were made in the data processing for this experiment. By rigorously screening the training data, transitional-style artworks were further filtered out to ensure the representativeness and purity of each style category, thereby reducing feature confusion between categories. Furthermore, the sample size was increased, particularly for categories with complex or easily confusable style features. By expanding the artwork samples, the model's understanding of stylistic diversity was further enhanced.

Future research could focus on introducing multi-label classification methods to enable the model to identify multiple stylistic features that may coexist within a single artwork. This approach aligns with the advancements discussed by Coulibaly et al., who proposed a Multi-Branch Neural Network (MBNN) framework for multi-label classification (Coulibaly et al., 2022). Their work highlights the potential of combining multitask learning and transfer learning to enhance the performance of classification models, particularly for datasets with overlapping features or complex label structures (Coulibaly et al., 2022). By applying similar methodologies, art style classification systems can better reflect the complexity and diversity of art styles.

Additionally, incorporating external information, such as the creation dates of artworks or background information about the artists, could provide richer contextual support for classification and enhance the model's recognition capability. Coulibaly et al. also emphasized the role of external information through pre-trained feature extractors and attention mechanisms to improve classification accuracy (Coulibaly et al., 2022). Inspired by this, future models could leverage contextual data to more effectively identify complex and transitional styles.

4 CONCLUSIONS

This study successfully developed a deep learning-based system for art style classification, utilizing the MobileNetV2 model combined with techniques such as data augmentation and transfer learning.

The system achieved satisfactory accuracy in classifying eight representative art styles. This achievement not only provides technical support for automated art style recognition but also offers valuable insights into the intersection of artificial intelligence and cultural heritage preservation.

However, despite these successes, the system's performance is still limited by challenges such as the overlapping complexity between art styles and the lack of diverse annotated datasets. These limitations indicate that there is room for improvement in data preprocessing and feature extraction.

Building on the findings in Section 3.3, future work could focus on introducing multi-label classification methods to better capture the coexistence of multiple stylistic features within a single artwork. Additionally, integrating contextual data, such as creation dates or artist backgrounds, could enhance classification robustness and provide richer insights. As highlighted in (Yu et al., 2021), combining transfer learning with external contextual data is a promising approach to address the challenges of multi-label classification, offering improved model versatility and generalization. Furthermore, the outcomes of this study contribute not only to art education and cultural dissemination but also to potential applications in cultural heritage preservation and digital management, thereby driving technological innovation in the art domain.

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