ArtDecode: An Explainable Deep Learning-Based Mobile Application for Multi-Style Artistic Image Classification and Visual Feature Interpretation*

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I. Introduction

Classifying art styles is fundamental to art historical research, curatorial practices, and aesthetic appreciation, offering a crucial framework for understanding artistic evolution and cultural context. Historically, this intricate task has relied heavily on art historians' specialized knowledge and interpretive skills. Concurrently, the past decade has witnessed significant advancements in computer vision and deep learning, leading to transformative breakthroughs in image classification across diverse domains. However, a persistent challenge remains in bridging the inherently objective nature of digital image representation with the complex, often subjective, conceptualizations of art styles [1].

To address this, numerous researchers have explored automated art style classification. Machine learning models, particularly Convolutional Neural Networks (CNNs) and various pre-trained architectures, have emerged as prominent tools for artwork identification. These approaches frequently involve fine-tuning parameters and optimizing network architectures to discern art style elements. Prior studies have effectively utilized features such as distinct color palettes [2] and characteristic brushstroke patterns [3], both crucial elements in differentiating art styles. Despite these efforts, current automated methodologies, alongside traditional manual classification, face notable limitations. Manual art classification requires extensive artistic expertise and is inherently time-consuming, while existing computational models often struggle with the nuanced and subtle variations within art styles, limiting their robustness and scalability across vast and diverse art datasets.

This study addresses these limitations by leveraging computer vision, specifically advanced image classification techniques, for the accurate and automated identification of art styles from digitized artworks. This paper proposes to contribute to existing art style classification frameworks by developing an improved convolutional neural network (CNN) architecture, meticulously optimized to discern the complexities of diverse artistic features. It aims to deliver a highly efficient and accurate preliminary tool that can significantly assist art experts in identifying stylistic inconsistencies, thereby streamlining and enhancing processes for art authentication and attribution. Furthermore, this research holds substantial potential to impact art education, making art historical knowledge more accessible and engaging for broader audiences, including those without a formal art background.

II. Related Work

A. Role of CNNs in Classifying Artistic Styles

Convolutional Neural Networks (CNNs) have become foundational in the field of image classification due to their ability to learn hierarchical visual features. In the context of art, CNNs have been widely adopted to classify artworks by style, genre, artist, and medium. Their layered architecture allows them to capture intricate patterns in brushstrokes, color palettes, and composition, and features that are essential for distinguishing between artistic styles. Studies such as those by Cetinic et al. [4] and DuBois [5] demonstrate the effectiveness of CNNs in art classification, achieving accuracies above 80 percent when trained on curated datasets. CNNs have also been

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extended with attention mechanisms [6], patch-based learning [7], and multi-scale architectures [8], [9] to further enhance their performance in this domain.

B. Key Factors and Challenges Influencing Model Accuracy

Convolutional Neural Networks (CNNs) face key challenges in art classification, notably due to dataset imbalance and scarcity, which can bias learning and hinder generalization for underrepresented styles [5], [10]. Visual similarities between certain styles, such as Impressionism and Post-Impressionism, further complicate classification by blurring stylistic boundaries [10], [11]. Real-world noise like compression artifacts also degrades performance, though some studies, such as Xu and Xu [12], have proposed architectural optimizations to improve robustness. Additionally, while high-performing models like ResNet-50-NTS [6] and BiT [13] offer strong accuracy, their computational demands and the limited effectiveness of training from scratch without transfer learning [14] restrict practical deployment.

C. Comparative Analysis of the Accuracy of Classification Models

Several studies reported classification accuracies below 70 percent, often due to methodological constraints. Iliadis et al. [14] trained Vision Transformers and MLP Mixers from scratch on 21 art style classes, achieving only 39 percent accuracy due to the absence of pre- training and the inherent complexity of the task. Falomir et al. [11] employed qualitative color descriptors with traditional classifiers like k-NN and SVM, reaching about 65 percent accuracy, though their models lacked the representational power of deep learning approaches. Zhao and Zhang [15] explored few- shot learning using the Difference Component model, which improved performance but still struggled with generalization due to limited data. In contrast, transfer learning approaches by Cetinic et al. [A], Sandoval et al. [7], and Zhao et al. [13] achieved significantly higher accuracies (75–95 percent) by leveraging pre-trained models on large datasets like ImageNet. Notably, Li [16] attained 93 percent accuracy with a custom CNN trained from scratch, though this required meticulous architectural design and extensive hyperparameter tuning.

D. Review of Gaps and Implications for Experimental Design

Transfer learning, while effective, often introduces a semantic mismatch between source domains like object recognition and target domains such as art style classification. Additionally, many top-performing models are computationally intensive, making them unsuitable for deployment in resource-limited settings. To address these issues, our study proposes a one-stage training approach using a CNN trained from scratch on the WikiArt dataset, designed to capture domain-specific features without external pre-training. This streamlined architecture aims to balance simplicity, training efficiency, and classification accuracy, contributing to the development of scalable and interpretable models for art classification.

III. Methodology

A. Dataset Description

The dataset utilized for this study is the WikiArt dataset, acquired from Kaggle and originally compiled by Kaggle User Stefano Morelli from WikiArt. This is a comprehensive collection of digitized artworks, representing 80,020 artworks from 1,119 distinct artists across 27 different art styles.

However, there exists a massive class imbalance between art styles where artworks have as little as 98 (Action Painting) or as large as 13,100 (Impressionism). Such a gap comes from the varying number of artists primarily practicing the art style throughout history. Moreover, artworks vary in quality, attributed to the deterioration of materials used in paintings over the passage of time. Artists also contribute to multiple art styles such as Pablo Picasso's artworks existing in Cubism, Fauvism, and Impressionism. Both instances contribute to noise and may affect generalization capability of the model.

Various preprocessing treatments were applied to minimize the effects of class imbalance and improve the quality of the data which shall be discussed further on in this section. A stratified train-test-validation split of 70-15-15 was implemented in the model architecture, ensuring an adequate training data and validation split across all art styles to minimize overfitting and potential biases.

B. Experimental Setup

Two computers were utilized to train models of varying complexity locally through Visual Studio Code. An RTX5070Ti with 16 GB of VRAM served bigger, more complex model architectures, while an RTX3060 with 12GB of VRAM trained simpler, smaller models. Both setups used a TensorFlow 2.10 and Python 3.10 Conda environment that supports GPU model training on a Windows Native Operating System.

C. Data Preprocessing

With the presence of class imbalance and noise within the original dataset, several preprocessing steps are employed to reach the optimal model performance and limit possible classification bias.

Grouping of art styles

Some art styles in the dataset are either progressions over time of a single art style (e.g. Early and High Renaissance) or substyles of a larger artstyle (e.g. Analytical and Synthetic Cubism). Both instances are combined into a single group to reduce the number of classes to be predicted, focusing on the general features of a specific art movement instead of its progression over time. The following are grouped together:

- Impressionism (Impressionism, Post-Impressionism, Pointillism)
- Expressionism (Expressionism, Abstract Expressionism, Action Painting)
- Cubism (Cubism, Synthetic Cubism, Analytical Cubism
- Realism (Realism, New Realism, Contemporary Realism)
- Renaissance (Early, High, Northern, and Late Renaissance)

Grouping of art styles reduced the number of classes from 27 to 16. These styles include Art Nouveau, Baroque, Color Field Painting, Cubism, Expressionism, Fauvism, Impressionism, Minimalism, Naive Art Primitivism, Pop Art, Realism, Renaissance, Rococo, Romanticism, Symbolism, and Ukiyo-e. Each art style is organized into its respective subdirectory within a base directory.

Reduction of Artworks per Style

Even after grouping art styles, there exists a massive class imbalance between art styles with Fauvism only having 934 samples compared to Impressionism with 20010. To have equal representation of classes, samples are reduced down to 900 samples to match the number contained within Fauvism. Artworks from pioneering and defining artists for each art movement are selected and added up to help ensure distinction between art styles. For example, Pablo Picasso is assigned to Cubism as a pioneering artist, making all of his artworks from other art styles not considered in sampling.

Data Cleaning

In combination with reducing the sample size, manual data cleaning was conducted to select high-quality paintings and artworks. Non-paintings (e.g. sculptures and architecture), sketches or Drawings, Paintings with large frames or walls, and black and white paintings are omitted from each selected artist's artwork. It is worth noting that due to the varying art production and conservation across the centuries, some paintings of certain styles are in greater quality than others; thus, the classes are not balanced in terms of quality of painting. After cleaning, each art style consists of around 900 samples, further broken down into around 630 training samples and 135 samples each for validation and testing.

Image Normalization

All images loaded from the base directory were loaded and decoded into 3-channel (RGB) tensor representations. Each decoded image is uniformly resized to a fixed spatial resolution of 224x224 pixels to be normalized into the [0,1] range by dividing by 255.0. Furthermore, the training dataset is shuffled with a buffer size of 1024, randomizing the order of training samples in each epoch for improving model generalization. All datasets are subsequently batched into fixed-size chunks of 32 samples.

D. Model Architecture

The study focused on training and comparing CNN models loosely based on model architectures of state-of-the-art CNNs, specifically AlexNet, VGGNet, and ResNet.

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