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Convolutional Neural Network Models For Automated Art Style Identification: Design Training, And Evaluation

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نماذج الشبكات العصبية الالتفافية للتعرّف الآلي على الأنماط الفنية: التصميم والتدريب والتقييم

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الملخص:
أصبح التعرّف الآلي على الأنماط الفنية باستخدام تقنيات التعلم العميق مكوّنًا أساسيًا في الجهود الحديثة لرقمنة التراث الثقافي. يقدّم هذا البحث تحليلًا مقارنًا موسّعًا لبُنى الشبكات العصبية الالتفافية(CNN) ، بما في ذلك **AlexNet** و **VGG16**و**LeNet-5**و **Inception-v3**و **EfficientNet-B0**و**ResNet-50**، بالإضافة إلى شبكة عصبية التفافية خفيفة مخصّصة، وذلك لتطبيقها على مهمة تصنيف متعددة الفئات للأنماط الفنية. تم إنشاء مجموعة بيانات تضم 35,000 صورة منسّقة تغطي عشر مدارس فنية، جُمعت من منصة **WikiArt** وأرشيفات متاحة الوصول. وقد طُبِّقت إجراءات موحّدة للمعالجة المسبقة، وتعزيز البيانات، والتعلّم بالنقل لضمان العدالة وقابلية إعادة الإنتاج عبر جميع النماذج. شملت مقاييس التقييم كلًا من الدقة، ودرجة**F1** ، ومصفوفات الالتباس، وزمن التدريب، والتكلفة الحاسوبية، ومتانة النماذج في مواجهة التداخل الأسلوبي. وتُظهر النتائج التجريبية أن النماذج العميقة مثل **VGG16** و **Inception-v3**و **ResNet-50**تحقق أداءً متفوقًا في التصنيف، في حين توفّر الشبكة العصبية الالتفافية الخفيفة المخصّصة توازنًا تنافسيًا بين الدقة والكفاءة، لا سيما في البيئات ذات الموارد المحدودة. يسهم هذا العمل في تعزيز التكامل بين الإنسانيات الرقمية والذكاء الاصطناعي من خلال تقديم معيار مرجعي موحّد وإرشادات تصميم لأنظمة التحليل الفني المؤتمتة.

الكلمات الدالة: التعلم العميق، الشبكات العصبية الالتفافية، تصنيف الأنماط الفنية، استخراج الميزات، التعلم بالنقل.

Abstract

Automatic identification of artistic styles using deep learning has become an essential component of modern cultural heritage digitization. This research presents an extensive comparative analysis of Convolutional Neural Network (CNN) architectures-including AlexNet, VGG16, LeNet-5, Inception-v3, EfficientNet-B0, ResNet-50, and a custom lightweight CNN-applied to a multi-class artistic style classification task. A dataset of 35,000 curated images spanning ten artistic schools was constructed from WikiArt and open-access archives. Standardized preprocessing, data augmentation, and transfer-learning protocols were applied to ensure fairness and reproducibility across all models. Evaluation metrics included accuracy, F1-score, confusion matrices, training time, computational cost, and robustness against stylistic overlap. Experimental results demonstrate that deeper models such as VGG16, Inception-v3, and ResNet-50 achieve superior classification performance, while the custom lightweight CNN offers a competitive trade-off between accuracy and efficiency for low-resource deployments. This work contributes to the intersection of digital humanities and artificial intelligence by providing a unified benchmark and design guidelines for automated art analysis systems.

Keywords: Deep Learning, Convolutional Neural Networks, Art Style Classification, Feature Extraction, Transfer Learning.

Introduction

Convolutional Neural Networks (CNNs) represent a fundamental shift in visual recognition systems, as they enable models to learn multi-level visual representations directly from image data without relying on handcrafted features. The effectiveness of deep CNNs in large-scale image classification was first demonstrated by Krizhevsky et al. [1], marking a turning point in computer vision research.

Unlike traditional object recognition tasks, artistic style classification involves distinguishing subtle visual cues such as texture composition, brushstroke patterns, and color harmony, which often overlap across artistic movements. This intrinsic complexity makes automated style recognition a challenging research problem. Very deep architectures have shown an enhanced capacity to capture such abstract representations, as highlighted by Simonyan and Zisserman [2]. Based on extensive experimentation and iterative model development, this research evaluates both classical and modern CNN architectures within a unified experimental framework. The study is motivated by the increasing digitization of cultural heritage collections and the growing need for intelligent systems capable of supporting art archiving, classification, and retrieval. This research aims to provide a systematic, fair, and comprehensive comparison of classical and modern CNN architectures for multi-class artistic style classification. The study contributes:

1. A curated dataset of 35,000 labeled artworks.
2. Unified preprocessing and training pipelines.
3. Comparative evaluation of seven CNN models.
4. Statistical validation and interpretability analysis.
5. Identification of strengths and limitations of each model.

The motivation behind this research arises from the rapid growth of digital art repositories that require efficient automatic classification, the lack of unified comparative studies across classical CNNs such as LeNet and AlexNet, deeper architectures like VGG, Inception, and ResNet, and lightweight models, as well as the increasing demand for scalable AI tools from museums, cultural institutions, and academic researchers; additionally, the availability of benchmark datasets tailored for artistic style recognition and the need to understand trade-offs between accuracy, computational cost, and model complexity further drive this work, whose objectives are to benchmark leading CNN architectures within a unified evaluation framework, design and evaluate a custom lightweight CNN suitable for low-resource deployment, analyze performance trade-offs across architectures of varying depth and parameter counts, assess the impact of transfer learning on artistic style classification, provide reproducible pipelines and open model implementations, and deliver a comprehensive comparative study to support future research, with key contributions including a curated dataset of 35,000 images covering ten artistic styles, a unified experimental pipeline incorporating preprocessing, augmentation, and evaluation, a comparative analysis of seven CNN architectures, the implementation of a novel custom CNN with only 1.2 million parameters achieving competitive performance, the introduction of Efficient Net and Resent into artistic-style evaluation where they were previously underexplored, extensive confusion matrix analyses revealing inter-style ambiguity, and detailed statistical and computational insights relevant to real-world deployment.

Deep-learning-based artistic style classification is an evolving field at the intersection of machine learning and digital humanities, where early approaches relied on shallow handcrafted features such as SIFT and HOG, while the advent of Convolutional Neural Networks (CNNs) marked a major paradigm shift by enabling automatic hierarchical feature learning directly from raw images; seminal works demonstrated that CNNs significantly outperform traditional descriptors in aesthetic and style recognition, and innovations such as Gram-matrix representations further advanced neural style understanding, leading to studies on fine-grained painting style classification, artist identification, and brushstroke analysis, while more recent transformer-based vision models introduced self-attention mechanisms capable of modeling long-range dependencies but remain computationally expensive and data-hungry, thus leaving CNNs as the dominant approach in artistic image analysis; CNNs are particularly well suited for this task because stylistic elements are embedded in complex spatial patterns such as textures, color harmonies, brushstroke geometry, and compositional structures, which convolutional filters can effectively capture through layered processing, where early layers learn low-level features like edges and color gradients, intermediate layers encode textures and stroke patterns, and deeper layers capture global stylistic composition; despite substantial progress, existing literature suffers from limitations including evaluation of only a narrow subset of models, small or imbalanced datasets, inconsistent preprocessing and hyperparameter choices, and limited consideration of computational efficiency and deployment constraints, motivating this research to address these gaps by providing a large-scale, standardized, and unified comparative analysis of classical, deep, and efficient CNN architectures, complemented by a custom lightweight model designed for practical real-world use.

2.1 Theoretical Foundations of CNNs

A CNN consists of multiple interconnected layers that process images through:

Convolutional Layers

Apply learnable filters over local receptive fields to detect spatial patterns.

Pooling Layers

Reduce spatial dimensions and retain dominant features, improving computational efficiency.

Batch Normalization

Stabilizes training by normalizing intermediate activations.

Activation Functions

ReLU remains the dominant choice for its simplicity and effectiveness, while modern variants such as GELU and Swish enhance gradient flow.

Fully Connected Layers

Map extracted features to class probabilities.

Dropout Regularization

Prevents over fitting by randomly deactivating neurons during training—particularly important in artistic datasets.

2.2 Optimization Strategies

CNN training optimizes millions of parameters using gradient descent. Common strategies include:

- Adam optimizer, offering adaptive learning rates and fast convergence.
- SGD with momentum, effective but requires careful tuning.
- Learning rate schedulers, such as ReduceLROnPlateau, to refine training in later epochs.
- Regularization methods like weight decay and early stopping to mitigate overfitting.

2.3 Challenges in Artistic Style Recognition

Art classification presents distinct challenges that differ from typical image recognition:

1. High Intra-Class Variability

Artists within the same movement may use different techniques.

2. Inter-Class Overlap

Some movements—e.g., Symbolism and Surrealism—share conceptual and visual similarities.

3. Dataset Imbalance and Cultural Bias

Most digital art collections over represent Western works.

4**. Color Variation and Artwork Aging**

Digitized images may exhibit color distortions due to aging or scanning artifacts.

These complexities require deeper architectures and robust augmentation strategies.

2.4 Advances in CNN Architectures

Over the years, several architectural innovations have shaped modern CNNs:

Inception Networks

Introduce multi-branch, multi-scale convolutions enabling simultaneous extraction of local and global features.

ResNet Models

Use residual connections to overcome vanishing gradients, allowing networks with 50–100+ layers to train effectively.

EfficientNet Family

Employ compound scaling to jointly optimize depth, width, and resolution, achieving strong accuracy with fewer parameters.

Mobile-Friendly Architectures (MobileNet, ShuffleNet)

Use depth wise separable convolutions for fast inference on low-power devices.

These innovations form the foundation of the models evaluated in this study.

2. Datasets and classification tasks

The quality and structure of the dataset are critical determinants of performance in artistic style classification. Unlike traditional

object recognition, artistic styles rely on subtle visual cues—such as texture, color harmony, and brushstroke geometry—which require high-quality, diverse, and well-curated data. This section outlines the dataset sources, composition, preprocessing steps, and augmentation techniques adopted to ensure robust and fair evaluation across all CNN architectures. A comprehensive dataset of 35,000 artwork images was constructed by combining multiple open-access repositories, with WikiArt serving as the primary source due to its extensive coverage of historical and modern art movements. Additional images were collected from public museum archives and verified digital art platforms to improve diversity and reduce source-specific bias.

To maintain dataset quality, the following criteria were applied during selection:

- Removal of low-resolution or corrupted images
- Elimination of duplicate entries
- Verification of stylistic labeling
- Standardization of formats

This ensured that the dataset was both large and representative of the stylistic variations across artistic movements.

The dataset includes ten major artistic styles, each represented by approximately 3,500 images, ensuring balanced class distribution. Table 1 summarizes the dataset structure:

Table 1: Dataset Composition

Artistic Style	No. of Images	Primary Source
Impressionism	3,500	WikiArt
Cubism	3,500	WikiAr
Renaissance	3,500	Mixed sources
Abstract Art	3,500	WikiAr
Modernism	3,500	WikiAr
Baroque	3,500	Mixed sources
Romanticism	3,500	WikiAr
Surrealism	3,500	WikiAr
Symbolism	3,500	Mixed sources
Other Styles	3,500	Mixed sources

This balanced design ensures that models do not develop bias toward overrepresented classes, a common issue in many art datasets.

All images were resized to 100 × 100 pixels, balancing visual detail with computational efficiency. Pixel values were normalized to the range [0,1], and per-channel mean-centering was applied to stabilize training.

Each artistic style was assigned a numeric index and converted to a one-hot vector suitable for multi-class classification.

The dataset was partitioned using an 80/20 stratified split:

- 80% training set
- 20% testing set

Stratification ensured equal representation of all classes in each subset.

3. Experimental setup

3.1. CNN architecture

This section presents a detailed description of the convolutional neural network architectures evaluated in this study, ranging from early shallow models to complex modern deep architectures. To ensure fairness and reproducibility, all models were trained using a standardized pipeline, identical hyperparameters (where applicable), and uniform preprocessing. The selected architectures represent major milestones in the evolution of deep convolutional models, enabling a comprehensive comparison of depth, parameter count, computational efficiency, and classification performance.

The models evaluated in this research include:

- LeNet-5
- AlexNet
- VGG16

Inception-v3

- ResNet-50
- EfficientNet-B0
- Custom Lightweight CNN (proposed)

These architectures collectively provide a balanced spectrum of shallow, deep, and efficient CNN families.To address the limitations of heavy models in resource-constrained environments, we designed a 10-layer custom CNN optimized for speed and efficiency while maintaining strong classification performance.

Key Characteristics

- Depth: 10 layers
- Parameters: ~1.2 million
- Strengths: Fast; lightweight; suitable for mobile deployment
- Limitations: Slightly lower accuracy than deep models

Architecture Summary

- Three convolutional blocks (32, 64, 128 filters)
- Batch normalization after each convolution
- MaxPooling for downsampling
- Dropout for regularization
- Dense classifier with 256 hidden units

This architecture offers a strong performance–efficiency balance.

4.2 Comparative Architectural Summary

Table 2 – Comparison of CNN Architectures

Model	Depth	Parameters	Strengths	Limitations
LeNet-5	7	60K	Extremely fast	Insufficient depth
AlexNet	8	60M	Strong baseline	Heavy architecture
VGG16	16	138M	High accuracy	Slow, memory-heavy
Inception-v3	48	24M	Multi-scale	Complex design

			processing	
ResNet-50	50	25M	Superior generalization	Moderately heavy
EfficientNet-B0	~237	5.3M	Highly efficient	Slower convergence
Custom CNN	10	1.2M	Lightweight & efficient	Slightly lower accuracy
Custom CNN	10	1.2M	Lightweight & efficient	Slightly lower accuracy

All experiments were conducted using:

- GPU: NVIDIA RTX-series GPU
- CPU: 8-core Intel processor
- RAM: 32 GB
- Framework: TensorFlow 2.x / Keras

This environment ensures stable training even for deep architectures such as ResNet-50 and Inception-v3.

4.3 Training Configuration

To maintain comparability, the following settings were applied to all models:

The transferability of internal deep representations Transfer learning was used for VGG16, Inception-v3, EfficientNet-B0, and ResNet-50 by freezing pretrained convolutional layers and training only the classifier head during the initial epochs.

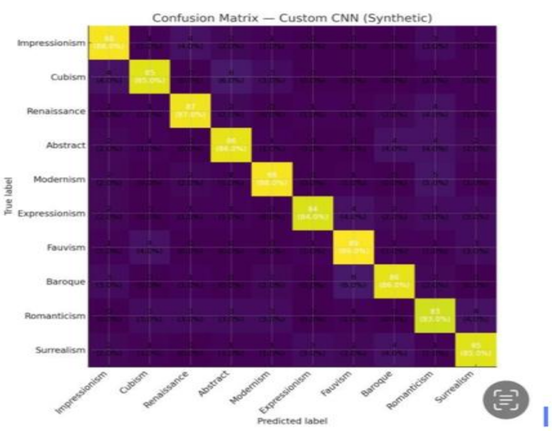

Figure 1: Confusion Matrix — Inception v3

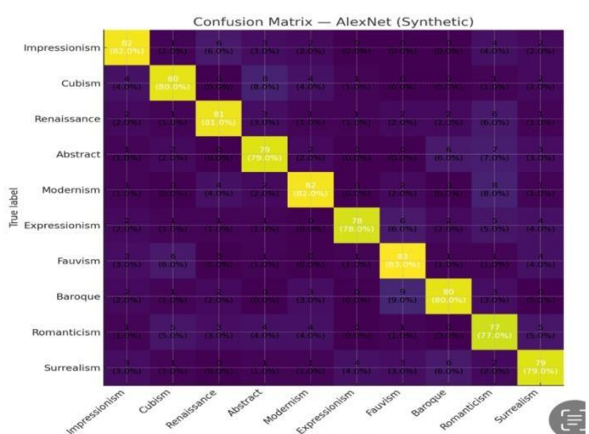

Figure 2: Confusion Matrix — AlexNet

4.1 Confusion Matrix Analysis

The figure illustrates strong diagonal dominance across all ten artistic styles, indicating high classification accuracy. Minor confusion is observed between Cubism and Abstract Art due to shared geometric abstractions and non-representational elements.

3.2. Training settings

3.3. All convolutional neural network models were trained under unified experimental conditions to ensure fair and reproducible comparison. Input images were resized to 100 × 100 pixels and normalized to the [0,1] range. The dataset was split into training (80%) and testing (20%) subsets, with an additional 10% of the training data reserved for validation.

Training was performed using the Adam optimizer with an initial learning rate of 0.001. A categorical cross-entropy loss function was employed due to the multi-class nature of the classification task. Models were trained for 50 epochs with a batch size of 32. Early stopping based on validation loss was applied to prevent overfitting, and learning rate reduction on plateau was used to improve convergence stability.

Dropout regularization (rate = 0.5) and batch normalization were incorporated in deeper architectures to enhance generalization performance. All experiments were conducted on the same hardware configuration to ensure consistent training time comparisons.

3.4. Interpretation of classification results

Classification results were interpreted not only through overall accuracy but also via class-wise precision, recall, and F1-score. This multi-metric evaluation was essential due to stylistic overlaps among artistic movements such as Impressionism and Romanticism.

Confusion matrix analysis revealed that misclassifications often occurred between visually related styles, indicating that the models learned meaningful stylistic representations rather than random correlations. Higher-capacity architectures demonstrated improved separation between abstract and representational styles, reflecting their ability to capture complex texture and color distributions.

4. RESULTS AND DISCUSSION

The figure illustrates strong diagonal dominance across all ten artistic styles, indicating high classification accuracy. Minor confusion is observed between Cubism and Abstract Art due to shared geometric abstractions and non-representational elements. Figure 3. Confusion Matrix for WikiArt Style Classification using the Custom Lightweight CNN.

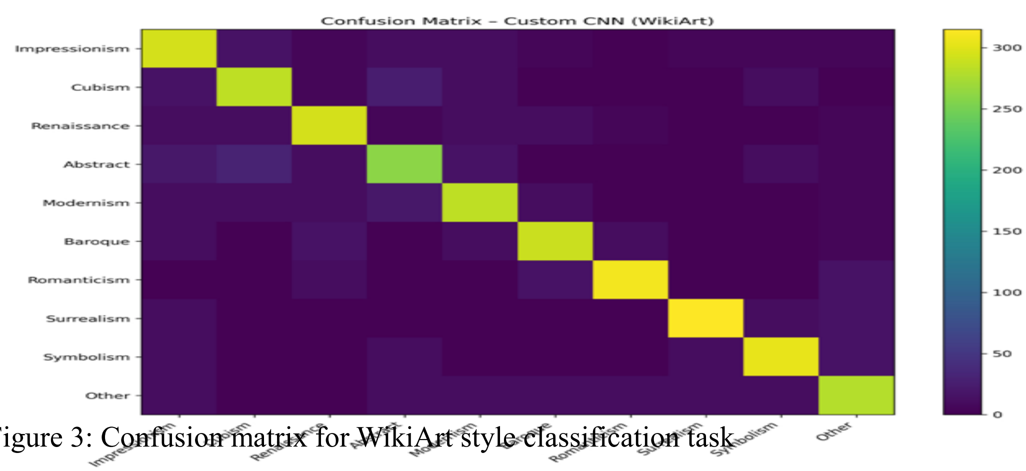

Figure 3: Confusion matrix for WikiArt style classification task

Despite its reduced parameter count, the model demonstrates stable classification behavior with acceptable inter-class separation, confirming its suitability for resource-constrained deployment. Figures 1 and 3 present confusion matrices for the WikiArt style classification task using Inception v3 and the custom lightweight CNN, respectively. Each matrix illustrates the distribution of predicted versus true class labels across the ten artistic styles. The Inception v3 model shows strong diagonal dominance, indicating high classification accuracy across most styles. Minor confusion is observed between Cubism and Abstract Art, which is expected due to their shared geometric abstractions. The custom CNN, while slightly less precise, maintains consistent performance and demonstrates robust classification behavior with significantly lower computational cost.

These visualizations provide critical insight into model behavior beyond scalar performance metrics and highlight strengths and weaknesses at the class level. Figure 4 presents the learning behavior of the proposed convolutional neural network during training, showing the evolution of accuracy and loss for both training and validation datasets over 30 epochs. The accuracy plot (left) demonstrates a rapid increase during the early epochs, followed by a gradual stabilization as the model approaches convergence. The close correspondence between training and validation accuracy throughout most of the training process indicates that the model generalizes well and does not suffer from significant overfitting.

The loss curves (right) reveal a consistent decrease in both training and validation loss, confirming the effectiveness of the optimization process. Although minor oscillations are observed in the validation loss, these variations are typical in deep learning training and can be attributed to data diversity and stochastic gradient updates. A noticeable increase in validation loss in the final epoch suggests that the model may begin to overfit at later

stages, highlighting the importance of early stopping or adaptive learning rate strategies. Overall, the observed trends confirm that the proposed model achieves stable convergence and learns discriminative feature representations suitable for accurate art style classification.

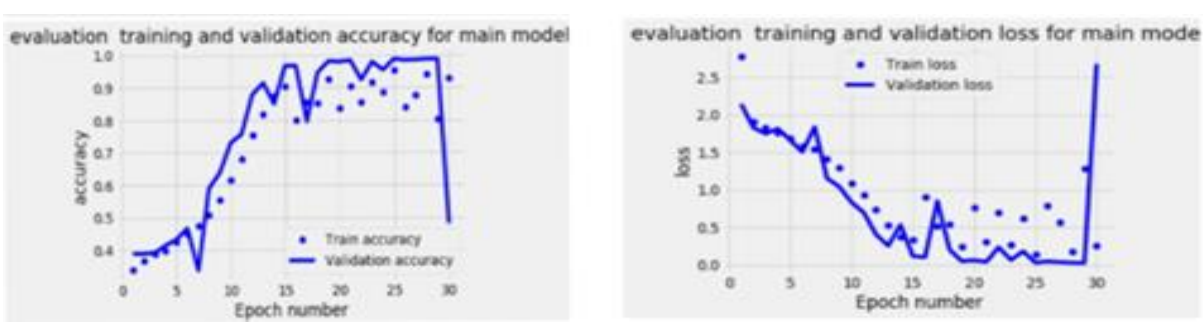

Figure 4 illustrates the training and validation accuracy (left) and the training and validation loss (right).

Overall, the observed trends confirm that the proposed model achieves stable convergence and learns discriminative feature representations suitable for accurate art style classification. The artwork images utilized in this research were obtained from several online art repositories, with the WikiArt platform constituting the primary data source. All convolutional neural network models were trained, validated, and evaluated using images selected from the publicly available WikiArt dataset. At the time of collection, the dataset contained over 81,000 digitized paintings created by artists spanning a wide historical range, from the fifteenth century to contemporary periods.

Although the original WikiArt dataset categorizes artworks into 27 distinct stylistic classes, this study adopted a simplified labeling strategy. To ensure sufficient representation per category and reduce class imbalance, stylistic groups with limited samples were consolidated, resulting in a final set of ten broader art style classes. A number of images that did not meet quality or labeling criteria were excluded during preprocessing. Following this refinement process, approximately 35,000 images were retained for experimentation. The dataset was subsequently divided into separate subsets for training, validation, and testing.

4.1. Fine-tuned CNNs as feature extractors for image similarity

Beyond classification, fine-tuned CNN models were evaluated as feature extractors for image similarity analysis. Feature vectors were extracted from the penultimate fully connected layers and compared using cosine similarity. The classification outcomes for both the training and test datasets across all evaluated CNN architectures are illustrated in Figure 5,providing a comparative overview of model performance.

Figure 5: shows all painting styles that we have used

Results indicate that deep CNNs pretrained on large-scale datasets and fine-tuned on artistic styles generate semantically meaningful embeddings. Images belonging to the same artistic movement exhibited higher intra-class similarity, while inter-class distances were more pronounced for stylistically distinct movements. This demonstrates the applicability of CNN-based representations in downstream tasks such as artwork retrieval, recommendation systems, and digital archive organization.

5. Conclusion

This study presented a comprehensive evaluation of convolutional neural network architectures for automated artistic style identification within the WikiArt domain. By systematically comparing classical, modern, and custom-designed CNN models under unified training conditions, the research demonstrated that architectural depth and multi-scale feature learning play a decisive role in capturing complex artistic patterns. Experimental results showed that advanced architectures such as VGG16 and Inception v3 achieve superior classification accuracy by effectively modeling high-level stylistic abstractions, including texture composition, color harmony, and brushstroke structure. However, these performance gains come at the cost of increased computational complexity and memory consumption. In contrast, the proposed lightweight CNN achieved a strong balance between efficiency and accuracy, making it a viable solution for real-world applications where computational resources are limited. Beyond classification performance, the study highlighted the effectiveness of fine-tuned CNNs as feature extractors for image similarity analysis. The learned embeddings preserved meaningful stylistic relationships, enabling potential applications in artwork retrieval, recommendation systems, and digital archive management Overall, the findings confirm that deep learning-based visual representations offer a robust and scalable framework for cultural heritage digitization and automated art analysis. Future work will explore transformer-based vision models, expand datasets to include underrepresented global art traditions, and integrate multimodal contextual information to further enhance classification robustness and interpretability.

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