Interpretable Year Prediction for Post-Medieval French Paintings

Anonymous CVPR submission

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Abstract

The ABSTRACT is to be in fully justified italicized text, at the top of the left-hand column, below the author and affiliation information. Use the word "Abstract" as the title, in 12-point Times, boldface type, centered relative to the column, initially capitalized. The abstract is to be in 10-point, single-spaced type. Leave two blank lines after the Abstract, then begin the main text. Look at previous CVPR abstracts to get a feel for style and length.

1. Introduction

Art–historical scholarship sustains collective cultural memory by tracing the evolution of artistic techniques, iconography, and sociopolitical context [4]. Over the last decade, large museums have accelerated the *digitization* of their holdings, pairing high-resolution images with machine-readable metadata to broaden access and to stimulate computational research [1, 2]. Nevertheless, a critical portion of these digital records still lacks **precise creation dates**. Even world-renowned institutions such as the Louvre routinely catalog paintings with vague labels—e.g., "first half of the 19$^{\text{th}}$ century"—instead of a concrete year.[1] Such imprecision hampers quantitative analyses of temporal trends and complicates provenance verification.

Status quo Previous computer vision work on artworks has concentrated on (i) retrieval of visually similar paintings or shared motifs for influence mapping [7,8], (ii) style or genre classification [5,6], and (iii) artist attribution [10]. Although [9] framed the prediction *year* as a subtask in the OmniArt challenge, to date, *no method targets exact-year dating with interpretable evidence*. Consequently, curators still invest substantial manual effort, often requiring years of specialist training, to narrow broad time ranges into a single year.

Unique Insights. We fill this gap by introducing an *interpretable deep-learning framework* that:

(1) predicts the **precise creation year** of a painting, and

(2) visualizes the **image regions and stylistic cues** that drive the prediction, thereby enhancing scholarly trust.

Focusing exclusively on post-medieval (regarded as encompassing the 15$^{\text{th}}$–20$^{\text{th}}$ centuries) French paintings mitigates geographic heterogeneity while still spanning multiple major movements (Renaissance, Baroque, Neoclassicism, Impressionism). To construct a balanced training corpus, we curate a large set of digitized works with reliable year labels, down-sampling over-represented late-19$^{\text{th}}$ pieces to prevent temporal bias.

Technical challenges. Two obstacles arise. 1) Visual diversity: century-scale shifts in pigments, brushwork, and subject matter create a long-tailed feature distribution. 2) Interpretability: generic saliency methods often highlight irrelevant background pixels, providing little curatorial insight. Instead, we will embed a Grad-CAM++ head and a concept-activation analysis pipeline to identify historically meaningful motifs (e.g., Empire-style uniforms) [3].

Experimental plan. Because no dedicated baselines exist, we establish a new benchmark. We compare our specialist network against: (i) OmniArt, (ii) ImageNet-pretrained CNNs, and (iii) Gemini 2.0, a state-of-the-art multimodal transformer-based foundational model. Evaluation metrics include mean absolute error (MAE) in years and the % of predictions within ± 2 years of ground truth.

Expected outcome. We anticipate decreasing current period-level MAE (~ 25 years on OmniArt [9]) to single-digit year precision while providing curator-credible explanations, thus opening new avenues for automated provenance studies and temporal stylistic analysis.

[1] See, for example, https://collections.louvre.fr/en/ark:/53355/cl010064491.

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