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Geometric Pictorial Language of the Female Body in Feminist Visual Narratives

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Abstract. Narratives of feminist visual stories are increasingly placing the female body as an object of self-perception, bodily agency, and storytelling rather than an external observation. Computer vision methods may quantify formal qualities of art pieces, but geometric transformation and surface texture have been little investigated in connection with feminist iconography in a replicable framework. A collection of 160 public oil paintings has been collected into two classes of 80 pieces each: 80 paintings containing feminist narratives and 80 paintings not containing feminist narratives. Body regions of the female body are localized using Grounding DINO and SAM2 models and corrected by hand, while geometry and surface texture measurements are performed, together with annotations for agency, gaze reversal, bodily reconstruction, and situated actions by two coders. On a validation set of 40 paintings, IoU has a mean value of 0.892, while Dice score is equal to 0.943. Five-fold cross-validation experiments have been carried out and random forests have yielded a result of AUC=0.887, F1=0.823 and accuracy of 0.831, outperforming logistic regression. Using SHAP analysis, the importance of agency, corner density, bodily reconstruction, and apparent impasto has been established as the most important predictors. The conclusion is that angular restructuring, contour discontinuities, and surface activity carry meaningful information related to feminist narrative structure.

Keywords: Feminist Painting, Female Body, Geometric Form, Pictorial Narrative, Computer Vision

1. Introduction

The contemporary feminist approach to painting has been moving away from the traditional representation of the body as a passive visual object by reconsidering gaze, presence of bodies, and the representation of the subjects. The modern feminist image practices have drawn attention to the issue of female subjectivity and identity through the representation that could change the interaction of the viewer and represented body [1]. The recent research into visual arts has also addressed the body as a communication medium for experience, memories, and self-perception [2]. In addition to these approaches, computer vision enables the segmentation of figures and analysis of the contours, compositions, and textures, but not the formal measures alone explain the narrative meanings of the feminist images. For this reason, the iconography is combined with female-body segmentation, geometry, apparent impasto, and classification techniques.

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2. Literature review

2.1. Feminist iconography of the female body

The female body in feminist iconography is viewed as a battlefield that is defined by cultural values, power structures, and bodily self-definition. It has been found that images of women reflect the process of construction and control of the ideal body within a certain culture [3]. In other studies, it was demonstrated that women artists of the contemporary period redefine the female body as an instrument of resistance and identity negotiation against the backdrop of local tradition and the outside gaze [4]. Thus, traditional interpretations of the female figure become more complex: bodily fragmentation can be a sign of vulnerability, resistance, or reconstruction, and the reversed gaze changes the narrative focus to the subject.

2.2. Expressive mechanisms of geometric oil-painting form

More recent academic work concerning visual practice by women makes note of the fact that re-storytelling the body of the woman is about appropriating or interrupting the representational codes already available rather than substituting one imagery form for another [5]. In the case of contemporary female painters from China, the same point has been demonstrated in terms of how materials and embodied practice can make statements about gender through different forms of creative practice [6]. Such a geometric form in an oil painting, for instance, can be understood to disrupt the conventional understanding of the body in terms of distorted angles, compression of proportion, disintegration of mass, and transformation of spatial occupation. Impasto in the painting, while adding to its textural quality, can only be observed digitally through texture alone.

2.3. Computational analysis of pictorial narrative

While computational analysis of art has evolved beyond stylistic categorization into spatial models of pictorial structure, large-scale datasets for art works that have semantic structure suggest that segmentation of visual regions is feasible as a tool for analyzing compositional structure in art [7]. Research on segmentation of paintings additionally reveals that art images have boundary ambiguity and art domain specificity different from regular photographic images [8]. Multiscale analysis using machine learning techniques to analyze paintings also reveals that complex stylistic patterns can be recognized while generating meaningful comparisons at the same time [9]. While these advancements pave the way for automated measurements, narrative meaning cannot be derived from mere formal descriptions. The spatial framework for geometry and texture analysis is formed by female-body masks, while human iconographic coding provides the semantic element required.

3. Experimental methods

3.1. Public oil-painting corpus construction

Corpus consists of 160 images drawn from freely available galleries from The Metropolitan Museum of Art, Art Institute of Chicago, Cleveland Museum of Art, Smithsonian Open Access and Wikimedia Commons. Corpus is comprised of 80 feminist narrative paintings and 80 comparison paintings. All images should depict at least one recognisable female body, should have high enough resolution to allow for contour analysis and should be allowed for research purposes. Grouping is determined by information provided by the museum or other sources such as published literature.

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Additional metadata includes artist name, image title, date, source of the image, its size and group category. Annotation of agency, gaze reversal, bodily reconstruction and situated actions is done independently by two coders using codebook of predefined categories. Disagreement is reviewed only after calculation of inter-coder agreement rate, to avoid reaching consensus to inflate agreement. Images are standardised to RGB format while maintaining aspect ratio and without any stylistic enhancements prior to segmentation. Subset of 40 images is drawn equally from both groups and is used for manual validation, while full set of 160 images is used for features comparison and classification.

3.2. Geometric feature extraction of the female body

Grounding DINO first detects female-body regions from the text prompt "female person," after which SAM2 generates pixel-level masks. Artistic-image AI research identifies substantial domain gaps and emphasizes geometry-aware feature extraction, so every generated mask is inspected and corrected in CVAT before measurement [10]. Segmentation reliability on the 40-image validation subset is quantified by Intersection over Union, as shown in Formula (1).

$$IoU(M,G)=\frac{|M\cap G|}{|M\cup G|} \tag{1}$$

M denotes the generated body mask and G the manually verified reference mask. Dice score is reported as a secondary overlap metric, and recurrent errors are categorized by occlusion, clothing-body ambiguity, and low-contrast boundaries. Corrected contours are then used to calculate body-area proportion, corner density, curvature continuity, principal-axis deviation, contour compactness, and line-orientation entropy. Directional organization is summarized by normalized orientation entropy, as shown in Formula (2).

$$H_o=-\frac{\sum_{k=1}^{K} p_k \ln p_k}{\ln K} \tag{2}$$

Here, p_k denotes the proportion of orientations in bin k and K the total number of bins. Lower entropy represents stronger directional concentration, whereas higher entropy represents dispersed orientation structure. All geometric variables are z-standardized using corpus-level means and standard deviations before feature fusion. Group differences are tested using two-sided Welch t-tests with Cohen's d for standardized effect size.

3.3. Narrative feature fusion modeling

Feature extraction is performed only within the boundaries of the masked female body images since the background as well as frame and other compositional elements should not be included in the narrative model. Gabor energy reflects oriented frequency responses, Local Binary Pattern Histograms represent local microtexture, while variances of the gradient and Laplacian reflect intensity variations. The recent work on computational painting uses the combination of segmentation with Local Binary Patterns descriptors [11]. Four standardized components are combined with equal weights to define the apparent-impasto index, as shown in Formula (3).

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$$I_{app}=\frac{1}{4}\left[z\left(E_G\right)+z\left(H_{LBP}\right)+z\left(V_\nabla\right)+z\left(V_\Delta\right)\right] \tag{3}$$

Here, z denotes standardization, E_G denotes mean Gabor energy, H_{LBP} denotes Local Binary Pattern histogram entropy, V_∇ denotes gradient variance, and V_Δ denotes Laplacian variance. The index represents visible digital texture rather than physical paint thickness. Geometric variables, the apparent-impasto index, and four iconographic annotations are concatenated into feature vector x. Logistic regression estimates feminist-narrative probability, as shown in Formula (4).

$$P(y=1|x)=\frac{1}{1+\exp\left[-\left(\beta_0+\sum_{j=1}^{p}\beta_j x_j\right)\right]} \tag{4}$$

Beta-zero is the intercept and beta-j is the coefficient of feature x-j. A random forest provides a nonlinear comparison using the identical input matrix. Stratified five-fold cross-validation preserves the 80-to-80 class balance and reports AUC, F1 score, accuracy, and fold variation, while SHAP values quantify the magnitude and direction of individual feature contributions.

4. Results

4.1. Geometric differentiation after body segmentation

The 40-image validation subset produced a mean IoU of 0.892 and a mean Dice score of 0.943, indicating stable localization of female-body regions after manual correction. Residual errors occurred mainly around partially occluded limbs, clothing-body boundaries, and low-contrast contours. As shown in Table 1, the feminist-narrative group exhibited higher corner density than the comparison group, 0.184 versus 0.137, with d = 0.78 and p < 0.001. Curvature continuity decreased from 0.714 to 0.641, d = -0.69, p < 0.001, indicating greater contour interruption. Orientation entropy increased from 0.667 to 0.731, d = 0.61, p < 0.001, while body-area proportion increased from 0.332 to 0.384, d = 0.47, p = 0.004. Principal-axis deviation increased from 14.2 degrees to 18.7 degrees, and contour compactness declined from 0.648 to 0.592. Corner density produced the largest standardized separation, identifying angular restructuring as the clearest geometric difference between the two groups.

Table 1. Geometric feature differences between the two painting groups

Measure	Feminist-Narrative Group	Comparison Group	Effect Size	p-value
Corner density	0.184	0.137	0.78	<0.001
Curvature continuity	0.641	0.714	-0.69	<0.001
Principal-axis deviation	18.7	14.2	0.55	0.001
Contour compactness	0.592	0.648	-0.58	<0.001
Orientation entropy	0.731	0.667	0.61	<0.001
Body-area proportion	0.384	0.332	0.47	0.004

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4.2. Feature contribution in narrative recognition

Five-fold cross-validation showed that logistic regression achieved AUC 0.842, F1 0.781, and accuracy 0.794, whereas random forest reached AUC 0.887, F1 0.823, and accuracy 0.831. Their fold-level AUC standard deviations were 0.031 and 0.026, indicating limited variation across validation folds. As shown in Figure 1, mean absolute SHAP values were highest for agency at 0.118, corner density at 0.103, bodily reconstruction at 0.091, and apparent impasto at 0.077. Orientation entropy contributed 0.064, followed by gaze reversal at 0.058, body-area proportion at 0.049, and curvature continuity at 0.045. Higher corner density, stronger apparent impasto, and positive bodily-reconstruction coding increased the predicted probability of the feminist-narrative class. The random forest exceeded logistic regression by 0.045 AUC, indicating that nonlinear interactions among geometric, textural, and iconographic variables supplied additional discriminative information beyond additive effects. Across the five folds, random-forest AUC remained between 0.851 and 0.918, supporting stable comparative performance.

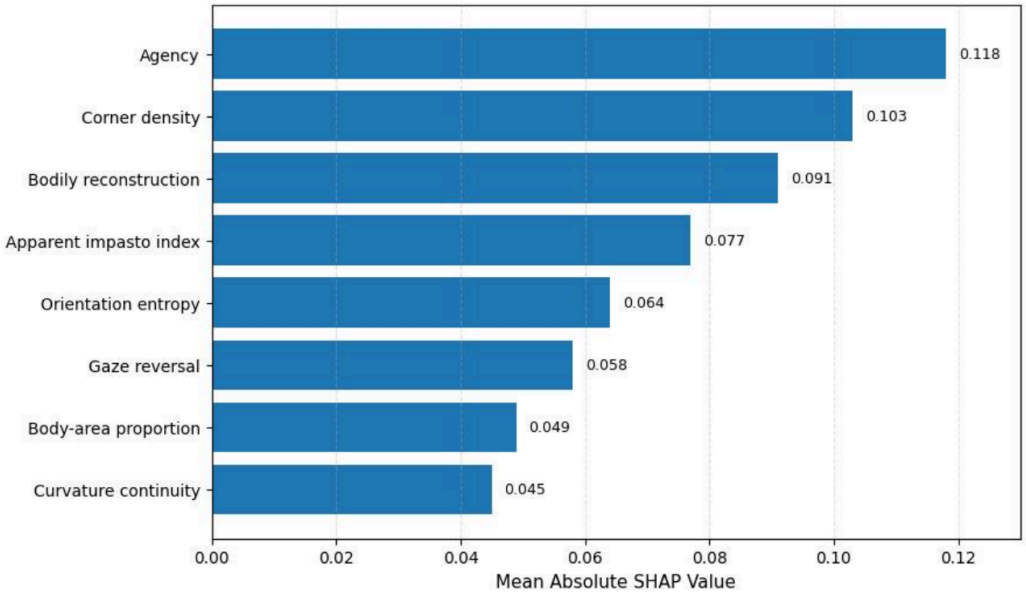

Figure 1. SHAP feature contribution profile for feminist narrative recognition

5. Discussion

From the presence of corner density in the context of the group comparison and SHAP analysis, it is reasonable to say that angular restructuring relates to narrative structure instead of being just a stylistic surface characteristic. In connection with the influence of such characteristics on the bodily reconstruction and agency, it can be said that formal deformation becomes important from the point of view of narrative if it occurs together with the change in the position of the body and representation. Reduced continuity of the curvature and increased entropy of orientation mean that fragmentation and orientation complexity are associated with the departure from realistic representation; however, these factors alone do not guarantee the feminist meaning. The apparent-impasto index affects discrimination through the surface activity, but this relationship is confined to digital texture and thus does not provide claims about the thickness of the real paint. The AUC of 0.045 advantage of the random forest means that the narrative recognition depends on nonlinear interactions of the geometrical, texture, and iconographic factors, not just their addition. This

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dependency is dependent on the corpus since it does not create any universal visual code even if the selected paintings are considered.

6. Conclusion

There is an established connection between the geometry of the female body, perceived surface quality, and feminist iconography categories within 160 publicly available oil paintings. The segmentation model yielded IoU of 0.892 and Dice of 0.943; Random Forest generated AUC of 0.887, F1 of 0.823, and accuracy of 0.831. Female agency, corners, body reconstruction, and perceived impasto are the factors contributing most to the recognition of narratives. It was shown that there is an empirical connection between the formally measurable features and visual interpretation of the painting with the use of semiotic annotation. There are limitations in terms of a small dataset size, poor digital representations of art pieces, subjective encoding of narratives, and inability to measure physical thickness of paint by a two-dimensional image.

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