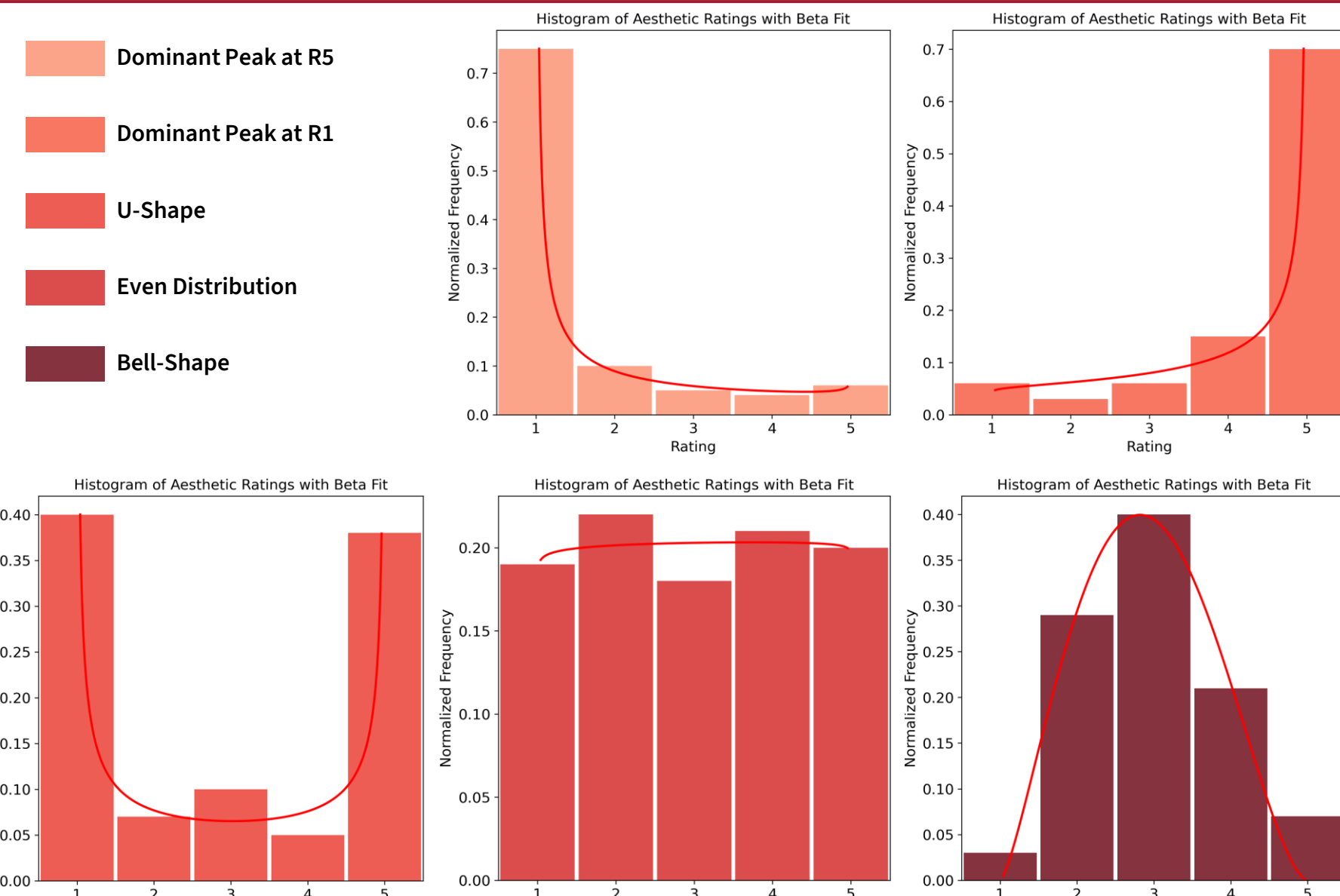


Analysing consensus in aesthetic judgements of images with low semantic content

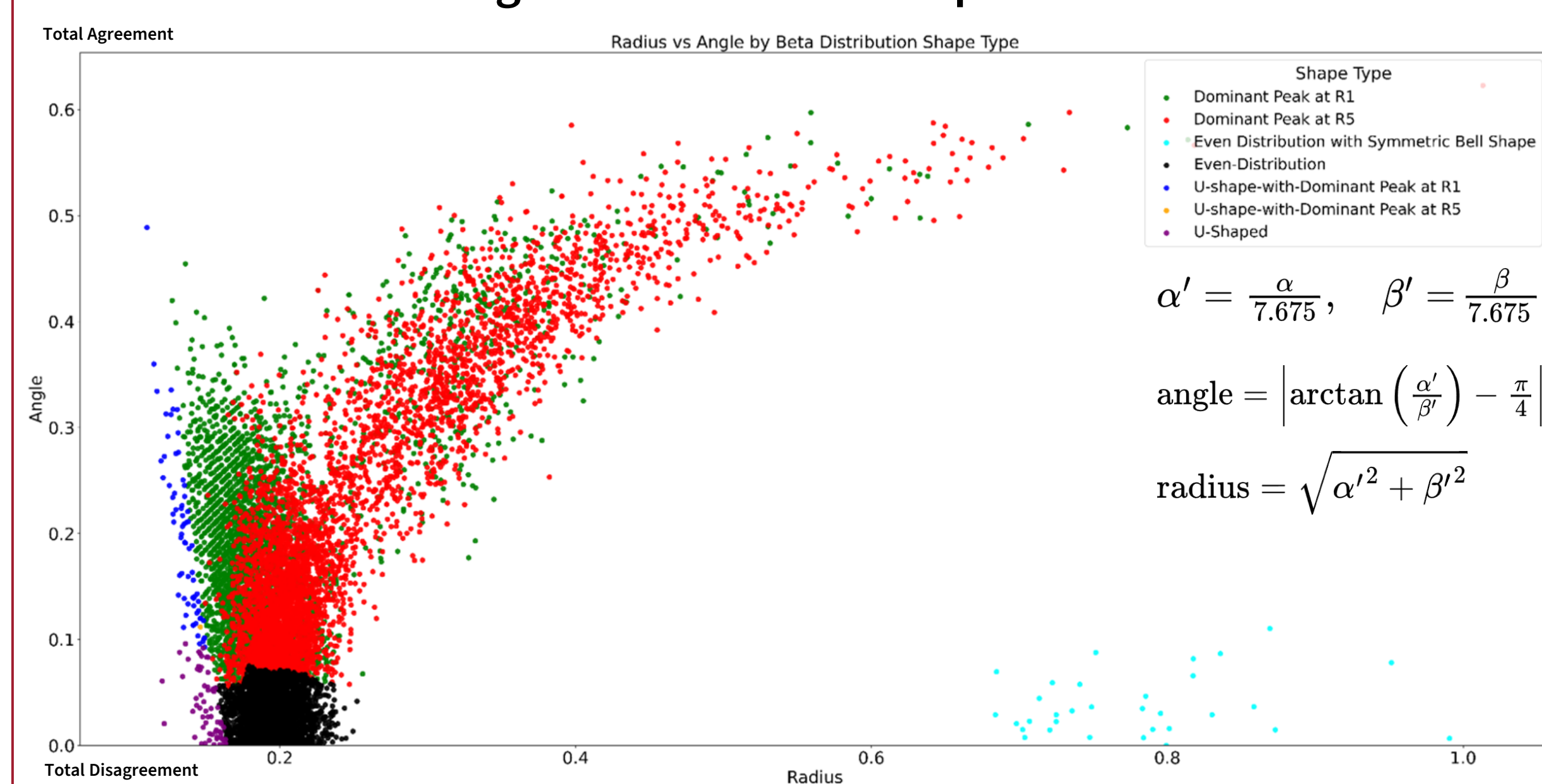
1- Motivation

- Aesthetic experiences are influenced by both universal sensory features and cultural or individual preferences.
- Previous work [1]: Low-level visual features correlate with aesthetic responses in minimal semantic content (MSC) images [2].
- Observations shows that some images have clear Agreement (everyone rated similarly), others showed strong disagreement—e.g., U-shaped distributions (some rated 1, others rated 5).
- This disagreement, especially in the absence of semantic content, points Which low-level visual features drive consensus vs. disagreement in aesthetic judgments?
- We aim to quantify this Agreement/Disagreement and investigate whether it can be predicted from low-level visual features.



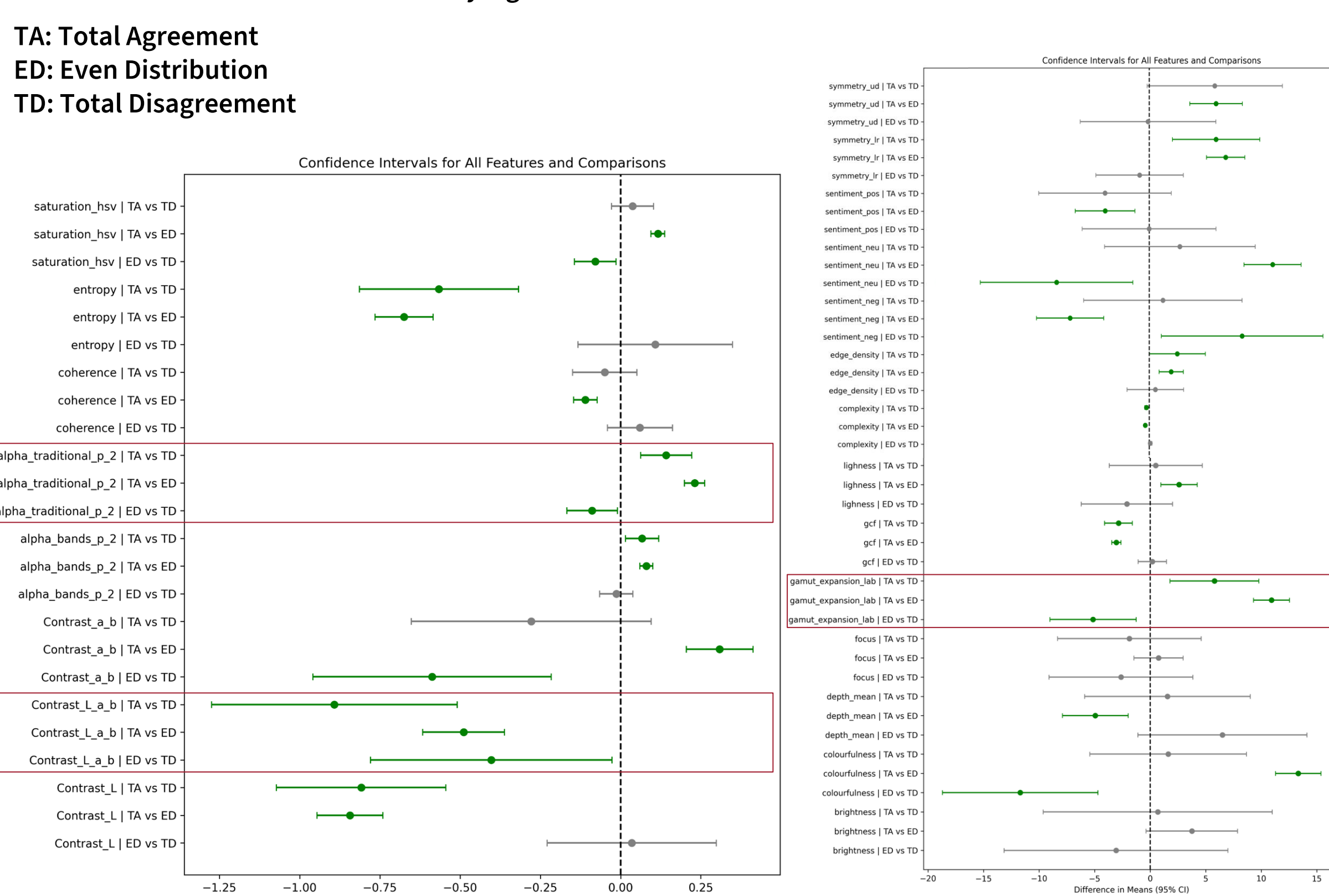
4- Experiments and Results

Calculate Radius & Angle and Plot the data points:



Confidence Interval:

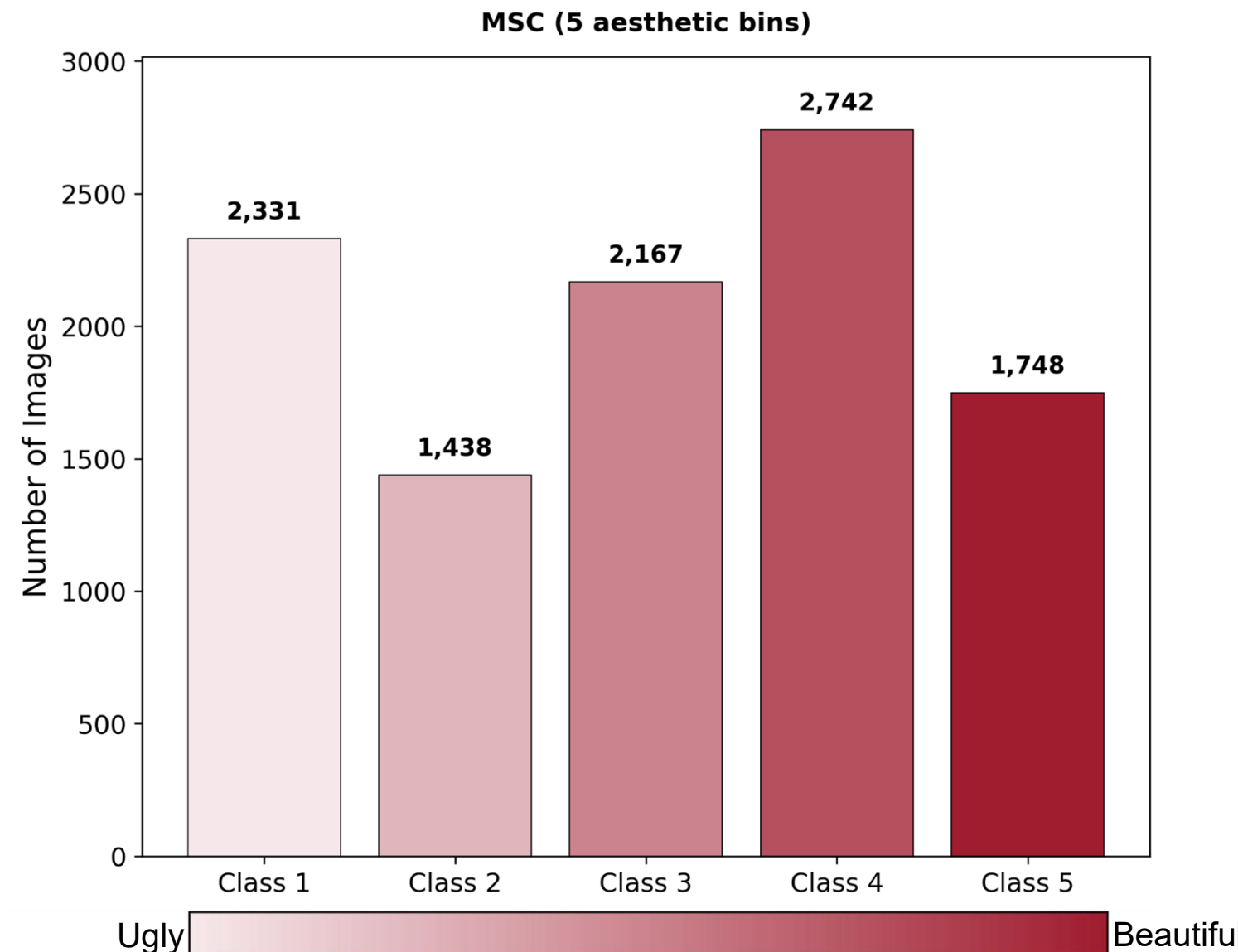
Differences are considered statistically significant when the 95% confidence interval does not include 0.



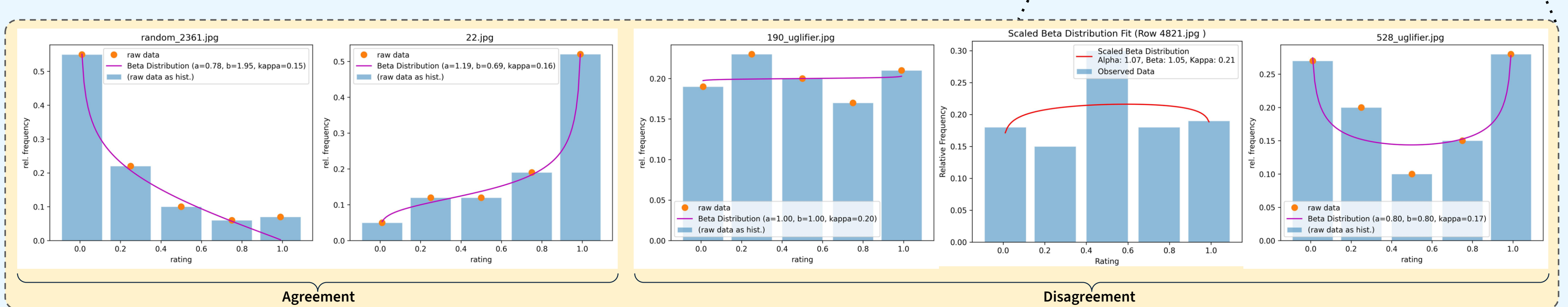
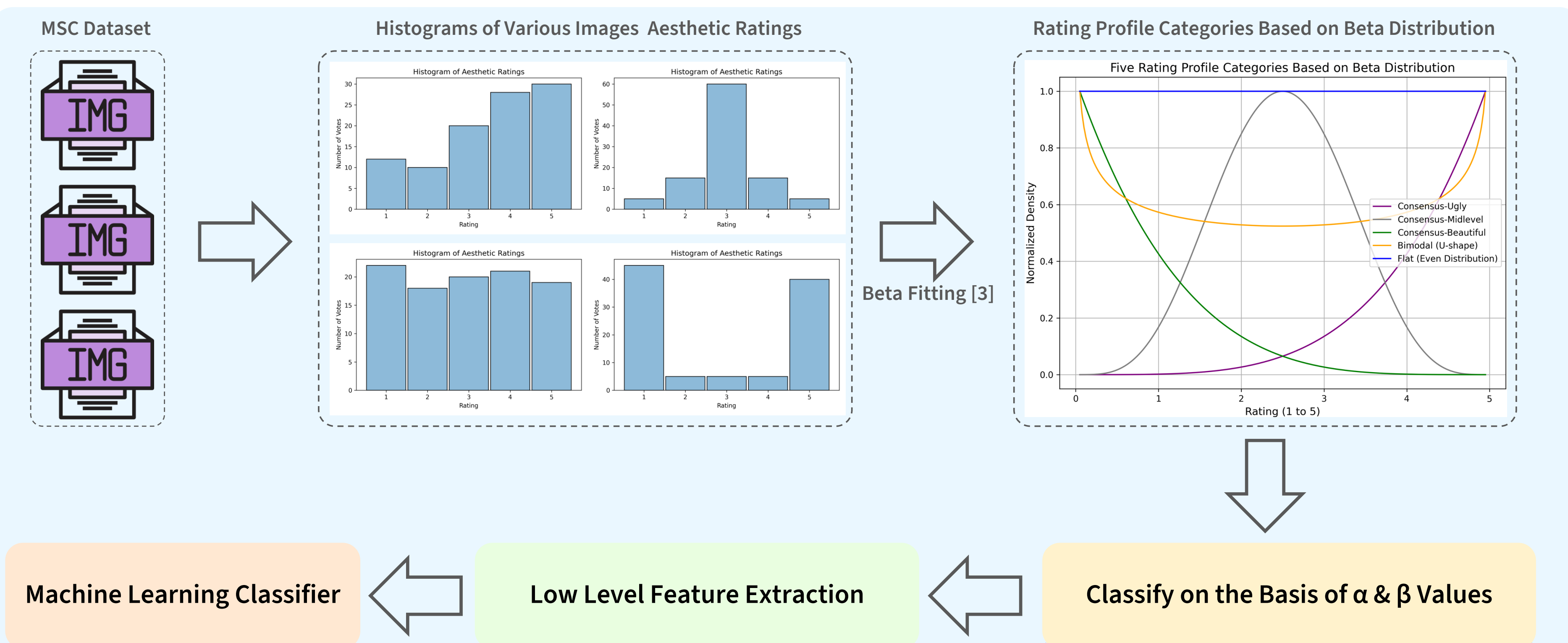
2- Methodology

Dataset:

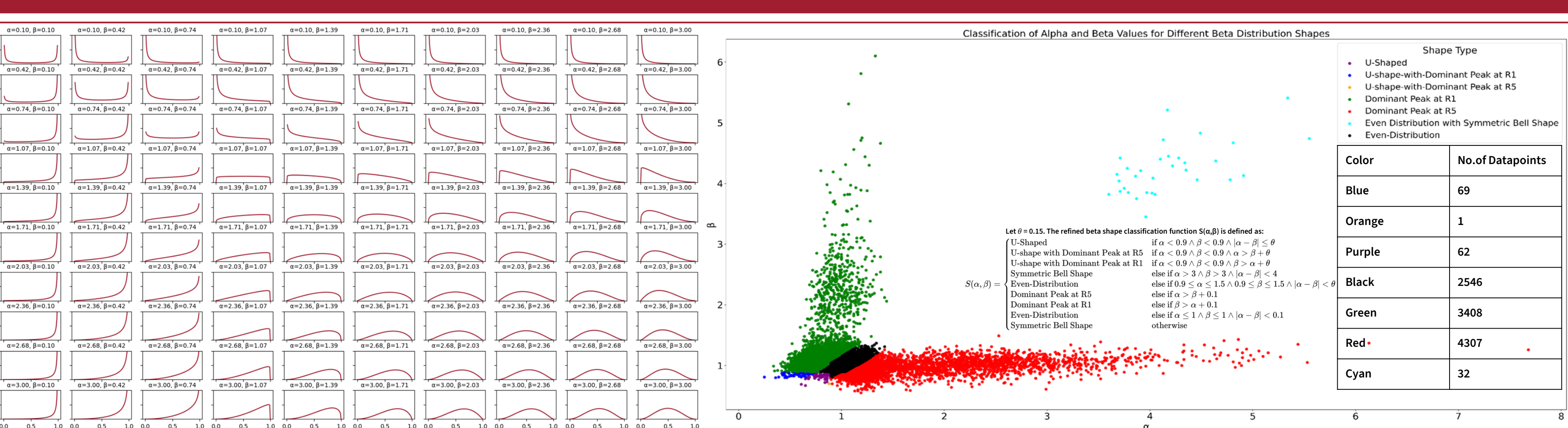
- MSC (Minimal Semantic Content) dataset created to remove semantic content.
- It contains images with only natural objects.
- No man-made objects, people or animals.
- MSC dataset consists of 10426 images.
- Each image rated by 100 individuals on a 1–5 aesthetic scale.



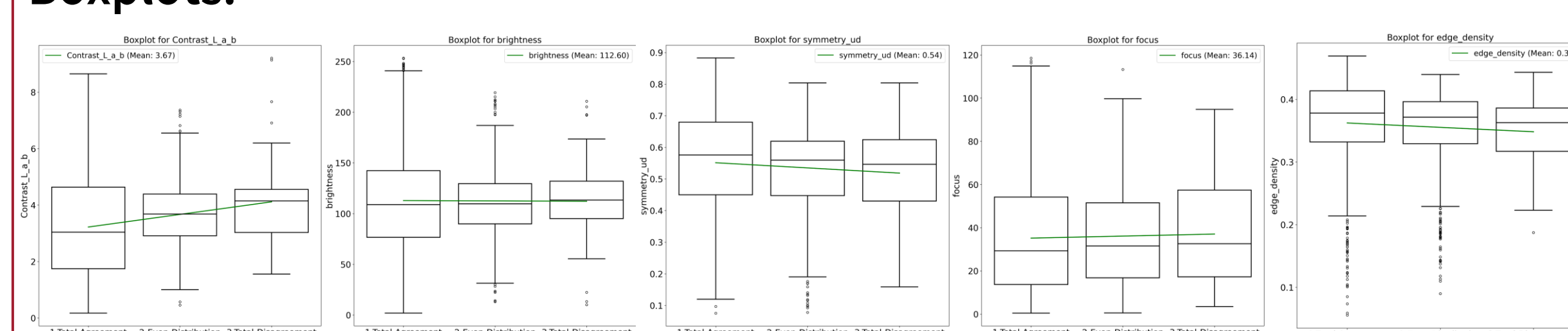
Workflow:



3- Distribution of Images according to Alpha & Beta values



Boxplots:



Low-Level Feature Classification:

We trained three different classifiers (SVM, Random Forest, XGBoost) to predict Total Agreement R1, Total Agreement R5, Total Disagreement using:

- Basic low-level features (Symmetry_lr, alpha_traditional_p_2, complexity, sentiment_pos, sentiment_neu, Contrast_L_a_b, Contrast_a_b, Gamut Expansion, saturation_hsv, lightness, Focus symmetry_ud, alpha_bands_p_2, coherence, sentiment_neg, depth_mean, Contrast_L, GCF, colorfulness)
- Deep features extracted using ResNet50
- Oversampling on training set to balance minority classes

Best accuracy (0.8775) achieved using XGBoost with all features + ResNet50.

Model	Features Set	Accuracy
XGBoost	All Basic Features + ResNet50	0.8775
XGBoost	Selected Basic Features + ResNet50	0.8562
XGBoost	All Basic Features	0.8162

Deep visual features (ResNet50) combined with handcrafted ones significantly improve classification performance, especially with XGBoost.

5- Conclusion

- This study provides evidences that low-level visual features contribute significantly to explaining patterns of aesthetic consensus in images with minimal semantic content.
- We trained machine learning models using both low-level features and deep features from ResNet50. The best-performing model, XGBoost, achieved an accuracy of 87.75%, highlight that consensus judgments are not random but can be systematically predicted from quantitative image properties.
- In addition to classification performance, we performed statistical analysis of aesthetic categories (Total Agreement, Even Distribution, Total Disagreement) revealed significant differences (95% Confidence Interval) for key features (Contrast_L_a_b, Gamut Expansion_lab, Fourier Alpha Traditional_p_2). Results show that these features significantly differ across consensus types and may serve as reliable indicators of aesthetic agreement or disagreement.
- Moreover Boxplot trends further suggest that some features systematically vary across categories, indicating that some visual features consistently increase or decrease depending on the level of consensus.

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