Automatic Exposure Estimation for Exterior Real Estate Photo Editing in Adobe Photoshop

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***Abstract*—Manual exposure adjustment in Adobe Camera Raw (ACR) is a repetitive, time-consuming, and error-prone step in high-volume real estate photo editing. This paper presents a fully automatic exposure estimation method tailored to exterior real estate photography. We first identify two robust measurements: entropy and weighted variance of the luminance histogram. These metrics reliably characterise desirable tonal distribution under a fixed production ACR preset, and we empirically demonstrate that both are unimodal functions of exposure in this domain, ensuring a single well-defined optimum. This property is leveraged to develop an efficient directed search algorithm. The algorithm exploits the unimodality of the metrics and the practical observation that optimal corrections are typically small. As a result, it dramatically reduces the number of required Photoshop evaluations compared with exhaustive search while still locating the global optimum. The proposed method is completely unsupervised, requires no training data, and integrates seamlessly into existing ACR/Photoshop workflows. Experiments on large real production datasets show that the automatically estimated exposures are perceptually indistinguishable from those set by experienced human editors. They deliver the same visual quality while being both highly precise and substantially faster than manual editing, which eliminates one of the most labour-intensive steps in professional real estate post-production pipelines.**

Keywords—Exposure Estimation, Image Processing, Automation, Real Estate, Photo Editing.

I. INTRODUCTION

High-quality photographs are crucial in real estate marketing, as professional images significantly increase viewer engagement, lead to faster sales, and command higher listing prices [1]. In professional workflows, raw images captured on-site are usually processed in Adobe Photoshop, with the initial step performed in its built-in raw converter, ACR. A fixed preset is typically applied to standardise parameters such as contrast, highlights, shadows, whites, blacks, and colour profile, after which the editor manually adjusts the Exposure slider to achieve balanced brightness and tonal distribution. This manual exposure setting is essential for preventing underexposed facades or overexposed skies, which are common issues in exterior real estate scenes with high dynamic range.

Automating this exposure adjustment offers substantial benefits in high-volume production environments, where large numbers of images are edited each month. Manual tuning is time-consuming, repetitive, and susceptible to human error or inconsistency due to fatigue, resulting in occasional overexposure or underexposure that affects the final image quality.

Also, the built-in "Auto" button in ACR is not always suitable for exterior real estate photography. Designed for general-purpose images, it attempts to simultaneously optimise multiple parameters across the Light and Colour panels, which can lead to unnatural results. Even when constrained to adjust only exposure while preserving other preset values, the resulting exposure estimate remains inaccurate and unacceptable in numerous cases due to its generic tuning.

Automatic exposure correction has been widely studied in the broader fields of image enhancement and computational photography [2-9]. In recent years, learning-based exposure correction methods have become dominant. Afifi et al. suggested a multi-scale deep neural network that learns to correct exposure by mapping poorly exposed images to enhanced outputs [10]. Eyiokur et al. introduced an exposure correction model trained with perceptual and feature-level losses, demonstrating strong performance on benchmark datasets [11].

To reduce reliance on paired training data and subjective ground truth, several unsupervised and zero-reference approaches have been suggested. Sun et al. introduced an unsupervised exposure correction framework guided by illumination component decomposition [12]. Zero-shot and zero-reference methods, such as ZSDECNet and generative exposure correction with adaptive fusion, further eliminate the need for external datasets by optimising internal statistical and perceptual objectives [13], [14]. Closely related work in low-light image enhancement (including illumination map estimation [15], deep Retinex decomposition [16], and zero-reference curve estimation [17]) shares similar motivations and has inspired many recent exposure correction models [18], [19].

Despite substantial progress, existing exposure correction methods are primarily designed for general-purpose photography and aim to produce a fully enhanced output image. Most approaches operate on rendered images (typically after camera processing) and manipulate pixel intensities to improve appearance, rather than estimating an explicit exposure parameter within the raw development pipeline. Consequently, they are not designed to set or optimise camera-level exposure controls such as the Exposure slider in ACR. Moreover, they do not account for domainspecific constraints in real estate workflows, where a fixed ACR preset with aggressive highlight recovery and shadow lifting is applied, and the only intended manual adjustment is the Exposure parameter.

This paper addresses this gap by proposing a fully automatic exposure estimation method tailored to exterior real estate photography in ACR. We identify robust histogram-based metrics (entropy and weighted variance of luminance) that effectively capture desirable tonal distribution under fixed presets. We empirically demonstrate that both metrics are unimodal functions of exposure in this domain, enabling efficient optimisation. Leveraging this property, we develop a fast directed search algorithm that locates the optimum with minimal Photoshop evaluations.

The paper is organised as follows: Section II details the proposed method, Section III presents experimental results, and Section IV concludes.

II. Proposed Method

In this section, a fully automatic method is proposed for setting the optimal exposure value (EV) when opening raw files in Adobe Photoshop (specifically in its built-in raw processor, ACR) for exterior real estate photographs. The approach aims to automate the manual exposure setting step in the editing workflow, reducing time consumption and minimising human error in processing large volumes of images. We leverage robust statistical measures derived from the luminance histogram of the raw image to determine the optimal EV. Specifically, weighted variance and entropy are employed as fitness functions to model the exposure optimisation problem. Given the unimodal nature of these measures with respect to exposure in typical exterior real estate scenes, the task is formulated as a unimodal optimisation problem, and a fast search algorithm is introduced to efficiently find the peak with minimal evaluations.

A. Overview of the Workflow

The standard manual workflow for editing exterior real estate raw photos involves opening the file in ACR, applying a company-specific preset (e.g., contrast, highlights, shadows, whites, blacks, profile), and then manually adjusting the exposure slider to achieve a visually pleasant photo. This manual adjustment is subjective and time-intensive, particularly for batches of thousands of images, and can lead to inconsistencies due to fatigue or perceptual bias, resulting in overexposed or underexposed images.

The proposed method automates this exposure adjustment by analysing the luminance histogram of the processed image under the preset. We integrate with Photoshop via JavaScript Extend Script (JSX) to dynamically set exposure values, open the raw file in ACR, and retrieve the histogram. This script ensures the preset is applied, and the histogram (a 256-bin array representing luminance distribution) is obtained for analysis.

B. Histogram-Based Metrics for Exposure Optimisation

We focus on the luminance histogram $H = [h_0, h_1, \dots, h_{255}]$, where h_i is the number of pixels with luminance value i. For the ACR rendered RGB image, luminance L is computed as:

$$L = 0.299R + 0.587G + 0.114B \tag{1}$$

where *R*, *G*, and *B* represent red, green, and blue channels, respectively.

While exposure perception can indeed be influenced by individual colour channels (e.g., saturated blue skies versus green lawns), our method optimises based on Photoshop's Luminosity histogram, which applies a perceptually weighted combination of RGB channels (approximately 30% red, 59% green, 11% blue) to reflect human brightness perception rather than raw channel sums or chroma extremes. In exterior real estate photography, where professional editors prioritise balanced tonal distribution and natural brightness under typical daylight conditions, this luminance-focused approach closely aligns with human-edited results and established industry workflows. Moreover, by relying on a simple, single-channel luminosity metric rather than more computationally intensive chroma-aware metrics, our method achieves high efficiency and scalability, enabling fast processing of large batches of images without sacrificing alignment with professional exposure standards.

Following the luminance histogram, several traditional histogram-based statistics were analysed to investigate whether a fixed tonal target could reliably represent well-exposed images. Table I summarises the quantitative measurements obtained from nine images (shown in Fig. 1) whose exposures were manually adjusted by a professional editor in ACR. The evaluated metrics include the luminance mean, median, peak intensity, a high-percentile indicator, standard deviation, and the derived statistic (Mean + Std). If a single global statistic were a reliable indicator of optimal exposure, one would expect its value to remain relatively consistent across professionally edited images. However, the results in Table I demonstrate substantial variation across all reported metrics. For example, the mean luminance ranges from 134.5 to 158.3, the median from 125 to 177, the peak value from 163 to 247, and the standard deviation from 43.2 to 64.3. Similar variability is observed for the derived metric (Mean + Std) which spans from 188.7 to 221.5. These results indicate that professionally balanced exposures do not converge toward a fixed value of conventional histogram statistics. Instead, the tonal characteristics of correctly exposed images depend strongly on scene content, brightness distribution, and contrast. Consequently, enforcing exposure adjustment based on a predefined target for these traditional metrics (e.g., forcing the mean or median to a constant value) would not reliably reproduce expert exposure decisions. This observation motivates the adoption of metrics that characterise the overall distribution and information content of the luminance histogram, rather than relying on individual brightness statistics.

TABLE I. Luminance histogram statistics for nine professionally exposed images, illustrating the variability of common exposure-related metrics.

Image	Mean	Median	Peak	Percentile	Std	Mean + Std
1	153.9	155	242	0.61	62.1	216.1
2	145.5	154	194	0.47	43.2	188.7
3	158.3	177	213	0.45	63.2	221.5
4	156.9	173	245	0.49	63.8	220.7
5	138.5	147	219	0.66	57.0	195.5
6	148.8	159	189	0.45	45.7	194.5
7	134.5	146	247	0.79	64.3	198.9
8	136.0	125	235	1.14	56.3	192.3
9	135.1	139	163	0.86	58.9	194.0

Fig. 1. Images corresponding to Table I and III (arranged from top-left to bottom-right in the same order as rows 1–9). Only the company's fixed ACR preset is applied; exposure is set to 0 in all cases.

To quantify tonal distribution, two metrics are computed: entropy and weighted variance.

- **Entropy (E)**: Measures the information content or spread of the histogram. Higher entropy values indicate a broader and more evenly distributed use of tonal levels, which is commonly associated with improved utilisation of the dynamic range and increased potential for detail recovery. It is defined as:

$$E = -\sum_{i=0}^{255} p_i \log_2(p_i + \epsilon) \quad (2)$$

where $p_i = h_i / \sum h_j$ is the normalised probability, and $\epsilon = 10^{-10}$ avoids log of zero.

- **Weighted Variance (V)**: Measures the spread of luminance values around the mean, reflecting the degree of tonal distribution in the image. It is defined as:

$$V = \sum_{i=0}^{255} p_i \, (i - \mu)^2 \quad (3)$$

where $\mu = \sum_{i=0}^{255} i p_i$ is the weighted mean luminance. The weights are the normalized probabilities p_i (as defined in Eq. (2)), which are derived directly from the image's pixel luminance distribution, making this metric inherently adaptive to scene content. This naturally emphasizes tonal regions with more pixels (e.g., shadows in facade-heavy scenes or highlights in sky-dominated ones), promoting generalization across architectural styles without scene-specific priors. This choice prioritizes overall dynamic range spread, which aligns with real estate aesthetics by enhancing detail recovery across varying architectural elements without assuming fixed tonal biases.

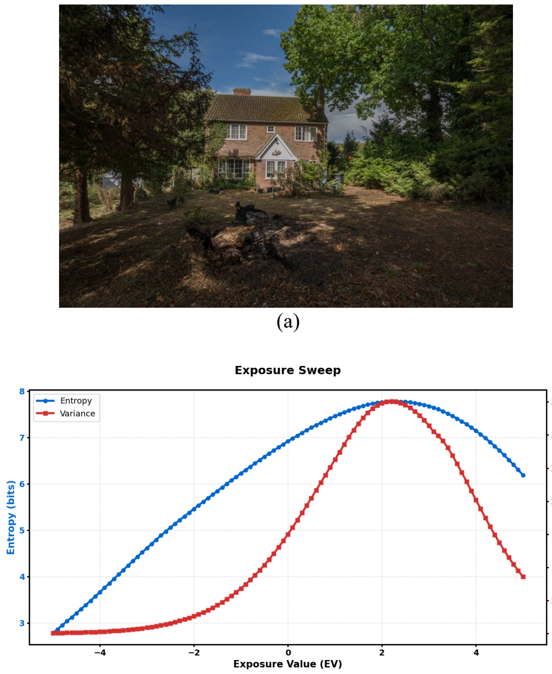
These metrics are computed for various possible exposure values EV $\in [-5,5]$ in ACR where EV shifts the luminance histogram.

C. Unimodality of Metrics in Exterior Real Estate Scenes

Empirical analysis on over 1,000 exterior real estate photos from the different times of the year shows that both entropy and variance are unimodal functions of exposure, with a single maximum (see Fig. 2 for a representative example).

This unimodality arises from the typical scene characteristics in real estate photography: high dynamic range with bright skies, reflective surfaces, and shadowed buildings.

- As exposure increases from low values, shadows are lifted (aided by the shadow boost preset), spreading the histogram from the left (dark tones) toward the centre, increasing variance and entropy.
- The variance peaks when the tonal distribution utilises the full 0–255 range without significant clipping.
- Further increases cause highlights (e.g., sky or white facades) to clip to 255, compressing the distribution on the right and decreasing variance/entropy.



(a)

(b)

Fig. 2. Unimodality of measurements. (a) typical Exterior real estate photograph rendered in ACR at exposure = 0, (b) variance and entropy of (a) when ACR exposure sweeps through its boundaries (−5 to +5).

The strong highlights recovery (preset) delays clipping, ensuring a smooth, single-peaked curve. The unimodal property of entropy and variance allow treating exposure estimation as a unimodal optimisation problem, enabling efficient search algorithms.

Fig. 2 illustrates this for a sample image, showing variance (red) and entropy (blue) vs. exposure, both exhibiting unimodal shapes with maxima near optimal values.

Note that the proposed approach is tailored to single-raw inputs for exterior real estate photography, reflecting common high-volume workflows where bracketing is not routinely used for exteriors (unlike many interior scenes with high contrast from windows). While the unimodality of the metrics could potentially extend to selecting an optimal frame from bracketed sequences or tone-mapping guide for HDR merging, such extensions are beyond the current scope focused on seamless integration into existing single-image ACR/Photoshop pipelines without additional capture or merging steps.

D. Fast Search Algorithm for Optimal Exposure

Given the unimodality, full grid search over $[-5,5]$ with 0.1 resolution requires ~100 evaluations per image, which is computationally expensive because each evaluation needs to open ACR separately. We propose a coarse-to-fine search starting near 0 exposure values, as photographers typically set in-camera exposure close to optimal, and editors usually make small adjustments around 0. In other words, as we get closer to zero the probability of finding optimal EV increases. Therefore, we consider this idea in the proposed search algorithm.

As Fig. 2 illustrates, while both entropy and weighted variance are unimodal functions of exposure, the entropy curve often exhibits a relatively flat region around its maximum. This flatness increases the likelihood of multiple near-optimal exposure values, making precise localisation challenging. In contrast, the weighted variance curve is noticeably sharper at its peak, rendering it a more reliable and stable objective for optimisation. Consequently, in the proposed search algorithm depicted in Fig. 3, the objective function f is defined as the weighted variance of the luminance histogram (Eq. (3)).

The algorithm evaluates variance at incremental steps, branching based on gradient direction, refining around the peak with a fixed resolution. Entropy is computed for all evaluated points, and the final EV is selected as the one closer to zero between variance and entropy maxima, prioritising stability in real estate scenes. The algorithm is robust to noise, as unimodality guarantees convergence to the global maximum.

Fig. 3 illustrates the proposed directed search algorithm in generalised form, with step size h and search radius Ra. In this figure, $x_{\max}$ and $f_{\max}$ denote the optimal exposure and its corresponding weighted variance, respectively. In our implementation, we use $h = 0.25$ and $Ra = 2.75$. This choice provides a significant reduction in the number of evaluations while keeping the resulting exposure error well below the level that is typically noticeable by professional editors under standard real estate viewing conditions.

The algorithm begins by evaluating variance at $+h$ and $-h$, immediately discarding half of the search space based on which side yields the higher value. It performs hill-climbing by advancing in steps of $2h$ in the direction of increasing variance, starting from near zero.

It continues until the objective no longer improves, after which it performs local refinement by evaluating up to two additional points at offsets of $\pm h$. This strategy exploits the key practical observation in professional real estate photography: when the original raw file is correctly exposed in-camera, the optimal ACR exposure correction is typically very close to zero. Therefore, most images require only 4–6 function evaluations, while images needing larger corrections naturally require a few more (yet still far fewer than a full grid search).

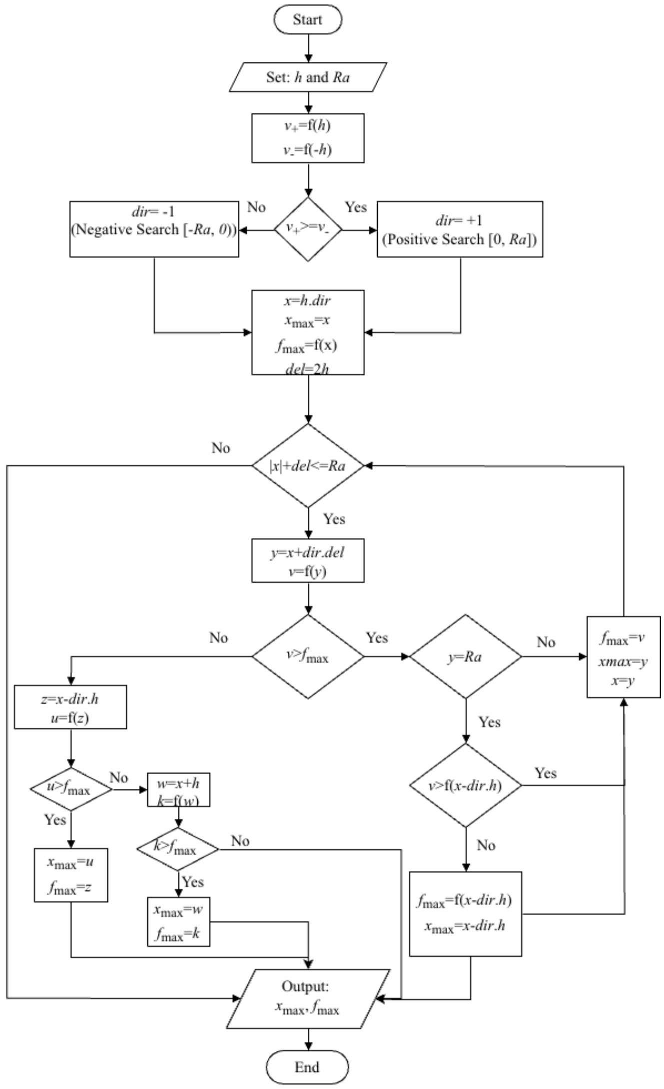


Fig. 3. Flowchart of the proposed search algorithm.

Experimental results in Section III confirm that the proposed method reduces the average number of Photoshop evaluations per image by more than 75% compared to exhaustive search, while achieving virtually identical perceptual quality.

Once the peak exposure for weighted variance (EV_v) is identified, the algorithm leverages the fact that entropy has been computed for all evaluated points during the variance search (incurring no additional Photoshop calls). The optimal entropy exposure (EV_e) is then determined as the value maximising entropy across this finite set of points. This dual-metric evaluation ensures a comprehensive assessment of tonal distribution, as entropy complements variance by emphasising information richness, which is particularly valuable in high-dynamic-range exterior scenes where uniform tone spread prevents loss of detail in skies or shadows.

To select the final exposure value (EV_f), the algorithm compares $|EV_e|$ and $|EV_v|$, choosing the one closer to zero:

$$EV_f = \begin{cases} EV_e & \text{if } |EV_e| < |EV_v| \\ EV_v & \text{otherwise} \end{cases} \tag{4}$$

This rule prioritises stability and aligns with practical real estate photography, where in-camera exposures are typically near-optimal, and large ACR corrections are rare. By favouring the near-zero peak, the method reduces over-correction risks while ensuring the selected value balances sharpness (variance) and detail (entropy), resulting in manual editor-like results with minimal deviation from zero.

III. Experimental Results

To evaluate the proposed automatic exposure estimation algorithm, we tested it on approximately 1,000 exterior real-estate photographs captured on different dates in 2025 and compared the results quantitatively and qualitatively with those produced by professional human photo editors (hereafter referred to as manual editors).

Table II summarises the number of Photoshop evaluations required to find the optimal exposure value in the positive search branch ([0, R]) with h=0.25 and R=2.75, as the negative branch is symmetric. The table lists representative paths from the algorithm, the corresponding number of evaluations, and the evaluated EV points. Across our dataset of approximately 1,000 real estate exterior images, the proposed algorithm required an average of 5.6 Photoshop evaluations per image, compared with 23 evaluations for an exhaustive grid search over the same range [−2.75, +2.75] at 0.25 steps. This corresponds to a ~4 times speed-up (76% fewer evaluations).

To quantitatively evaluate the proposed method, we reported the automatically estimated exposure values with those set by manual editors for 9 representative exterior real estate photographs (Fig. 1). The results, summarised in Table III, demonstrate strong alignment between the automatic and manual exposures. For each image, the maximum entropy and variance are listed, along with the exposures at which they occur (EV (Entropy) and EV (Variance)). The final automatic exposure (EV (Auto)) is selected as the value closer to zero between these two peaks, ensuring robustness and perceptual stability.

As shown, the absolute difference between EV (Auto) and EV (Manual) is consistently small. This indicates that the method effectively captures the tonal balance preferred by professional editors, avoiding overexposure or underexposure while requiring minimal computational overhead. On the full dataset of approximately 1000 images, similar trends hold, confirming the reliability of the algorithm for production use.

TABLE II. Number of Photoshop evaluations required by the proposed directed search algorithm (h = 0.25, Ra = 2.75) as a function of location of maximum of variance in the positive direction.

Max	**Number of Tries**	**Evaluated Exposure Points (EV)**
0.00	4	−0.25, 0, 0.25, 0.75
0.25	5	−0.25, 0, 0.25, 0.5, 0.75
0.5	5	−0.25, 0, 0.25, 0.5, 0.75
0.75	6	−0.25, 0.25, 0.5, 0.75, 1, 1.25
1.00	6	−0.25, 0.25, 0.5, 0.75, 1, 1.25
1.25	7	−0.25, 0.25, 0.75, 1, 1.25, 1.5, 1.75
1.50	7	−0.25, 0.25, 0.75, 1, 1.25, 1.5, 1.75
1.75	8	−0.25, 0.25, 0.75, 1.25, 1.5, 1.75, 2, 2.25
2.00	8	−0.25, 0.25, 0.75, 1.25, 1.5, 1.75, 2, 2.25
2.25	9	−0.25, 0.25, 0.75, 1.25, 1.75, 2, 2.25, 2.5, 2.75
2.50	9	−0.25, 0.25, 0.75, 1.25, 1.75, 2, 2.25, 2.5, 2.75
2.75	8	−0.25, 0.25, 0.75, 1.25, 1.75, 2.25, 2.5, 2.75

TABLE III. Quantitative comparison of automatic exposure estimation with manual editor settings on nine representative images (shown in Fig. 1). Columns report maximum entropy and variance values, their corresponding exposure values, the final automatic exposure EV (Auto), and the manual exposure EV (Manual).

Image	Ent	Var	EV (Ent)	EV (Var)	EV (Auto)	EV (Manual)
1	7.5257	3875.43	-0.50	-0.25	-0.25	-0.20
2	7.2723	1928.05	0.00	0.25	0.00	0.00
3	7.7375	3986.35	-0.50	-0.25	-0.25	-0.10
4	7.7080	4059.14	-0.50	-0.25	-0.25	-0.25
5	7.6749	3321.58	2.25	2.50	2.25	2.10
6	7.3262	2147.35	0.50	1.00	0.50	0.50
7	7.7789	4194.36	0.25	0.50	0.25	0.20
8	7.5028	3146.69	0.50	0.75	0.50	0.55
9	7.7560	3464.75	-1.00	-1.00	-1.00	-1.05

In addition to the quantitative comparison presented in Table III, we conducted a qualitative assessment to evaluate perceptual differences between the automatic and manual results. Fig. 4 shows the final edited images for the case exhibiting the largest exposure discrepancy in Table III (image 3), where the proposed method estimates −0.25 while the manual editor used −0.10 (a difference of only 0.15). The top image uses the manual editor's exposure setting, and the bottom image uses the automatically estimated exposure. All subsequent post-processing steps in Photoshop are identical in both versions.

Fig. 4. Visual comparison for the image with the largest exposure discrepancy in Table III (image 3). Top: final edit using the manual editor's exposure; bottom: final edit using the automatically estimated exposure. All post-ACR editing steps are identical in both versions.

As can be seen in Fig. 4, the visual difference is extremely subtle and barely perceptible under standard viewing conditions (screen and print). This confirms that even in the worst-case scenario within our dataset, the proposed automatic exposure estimation produces results that are practically indistinguishable from those of an experienced human editor, validating its suitability for production use in large-scale real estate photo editing workflows.

IV. Conclusion

We introduced an efficient and robust automatic exposure estimation technique specifically designed for exterior real estate photography in ACR. By exploiting the unimodal nature of entropy and weighted variance under a fixed production preset, combined with a directed search that starts near zero and requires on average only 5.6 evaluations per image, the method delivers exposure values that match professional manual settings with remarkable accuracy. Both quantitative metrics and side-by-side visual comparison confirm that the results are perceptually indistinguishable from those of experienced editors, while eliminating the most repetitive and error-prone step in the current workflow. The algorithm is lightweight, requires no training, and integrates seamlessly into existing Photoshop/ACR pipelines, making it immediately suitable for large-scale commercial deployment.

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