Detecting AI-Generated Images via Physics-Based Lighting Consistency Analysis

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Abstract

Current AI image generators can produce highly realistic images that are increasingly difficult for humans to distinguish from real photos. While existing classification models shown insufficiency in identifying generated landscape [1] , we made a novel approach that making use of fundamental physical inconsistencies in lighting and shading. We introduce a physics-aware framework that combines monocular depth estimation, surface normal computation, and lighting consistency verification with deep learning architectures. Through parallel validation on ResNet18 and Vision Transformer (ViT) models, we demonstrate that physics-based features provide crucial signals for authenticity verification, achieving up to 98.51% accuracy on landscape images. Our comparative analysis confirms that lighting consistency analysis significantly enhances detection performance across different architectural paradigms.

1 Introduction

The rapid advancement of generative models, particularly diffusion models and GANs, has enabled the creation of photorealistic images that challenge human perception. Recent studies have shown that humans struggle to identify AI-generated images, with particularly low performance on landscape photographs [1].

Existing detection methods predominantly focus on learning discriminative features from training data, which may overfit to specific generator artifacts and fail to generalize across different models [2]. In contrast, we hypothesize that AI generated pictures, despite their base model, often weak in tracking fundamental physical laws governing light transport and material interactions in natural scenes.

Our key insight is that real photographs must satisfy strict physical constraints: lighting should be globally consistent, shadows must align with light source directions, and surface shading should follow predictable patterns based on geometry and materials. AI generators, trained primarily on appearance matching rather than physical simulation, frequently produce subtle but detectable violations of these principles.

Works: (1) We propose a physics-based detection framework that explicitly models lighting consistency through depth estimation and surface normal analysis; (2) We validate our approach through cross-architectural experiments on both ResNet18 and Vision Transformer, demonstrating the general feasibility of physics-aware features; (3) We collected our pair-wise real and fake dataset.

2 Related Work

AI-Generated Image Detection. Early detection methods relied on analyzing frequency domain artifacts [3] or learning CNN-based classifiers on specific generators [2]. Recent approaches employ Vision Transformers [4] or contrastive learning [5] to capture more abstract patterns. However, these methods often struggle with generalization across unseen generators.

Physics-Based Image Analysis. Intrinsic image decomposition [6] and inverse rendering [7] have been used to understand scene properties. Recent work exploits lighting inconsistencies for image forensics [8], but primarily focuses on traditional manipulations rather than AI generation.

Monocular Depth Estimation. Depth Anything V2 [9] provides robust single-image depth prediction, enabling downstream geometry understanding. We leverage this as a foundation for computing surface normals and analyzing light transport.

3 Methodology

Our framework integrates physics-based lighting analysis with deep learning architectures. Figure 2 illustrates the complete pipeline with two parallel model branches that cross-validate the effectiveness of our physics-aware approach.

3.1 Physics-Based Lighting Analysis

Our framework operates on the principle that real photographs must satisfy the rendering equation. For Lambertian surfaces under a single dominant light source, the observed intensity $I(x)$ at pixel x should follow:

$$I(x) = \rho(x) \cdot \max(\mathbf{n}(x) \cdot \mathbf{l}, 0) + I_{\text{ambient}} \quad (1)$$

where $\rho(x)$ is surface albedo, $\mathbf{n}(x)$ is the surface normal, and $\mathbf{l}$ is the light direction. AI-generated images often violate this consistency across the scene.

Depth and Normal Estimation. Given input image $\mathcal{I} \in \mathbb{R}^{H\times W\times 3}$, we first estimate depth map $D \in \mathbb{R}^{H\times W}$ using Depth Anything V2. Surface normals are computed via gradient analysis:

$$\mathbf{n}(x, y) = \text{normalize}\left(-\frac{\partial D}{\partial x}, -\frac{\partial D}{\partial y}, 1\right) \tag{2}$$

Light Source Recovery. We estimate the dominant light direction $\mathbf{l}^*$ by optimizing for maximum correlation between predicted shading and observed luminance $L = 0.299R + 0.587G + 0.114B$:

$$\mathbf{l}^* =_{\mathbf{l}} \text{corr}\left(L, \max(\mathbf{n}\cdot\mathbf{l}, 0)\right) \tag{3}$$

We use Fibonacci sphere sampling with 20 candidate directions for computational efficiency.

Predicted Shading and Residuals. With the estimated light direction, we compute predicted shading:

$$S_{\text{pred}} = \max(\mathbf{n}\cdot\mathbf{l}^*, 0) \in \mathbb{R}^{H\times W} \tag{4}$$

The shading residual captures deviations from expected physics:

$$R_{\text{shading}} = |L - S_{\text{pred}}| \in \mathbb{R}^{H\times W} \tag{5}$$

These computed maps serve dual purposes: they provide explicit physics-aware input channels for CNN/ViT processing and enable the extraction of global consistency features.

Consistency Features. We extract five physics-based features for ViT fusion:

1. *Single-light error*: $e_1 = \text{MSE}(L, S_{\text{pred}})$
2. *Multi-light improvement*: Ratio of error reduction when fitting two light sources
3. *Material consistency*: Variance in albedo residuals across spatial regions
4. *Sky-light alignment*: Cosine similarity between brightest sky region and $\mathbf{l}^*$
5. *Shadow consistency*: Overlap between predicted ($S_{\text{pred}} < 0.2$) and observed dark regions

Real images should exhibit low e_1 with high material consistency. Example extracted feature as Figure 1.

3.2 ResNet18 with Physics-Aware Channels

To validate that physics-based features are universally beneficial, we first implement a CNN-based classifier using ResNet18 architecture. Our approach leverages physics-based feature extraction to create a 6-channel input representation for deep learning classification. Unlike traditional RGB-only methods, we explicitly encode geometric and photometric inconsistencies that characterize AI-generated images.

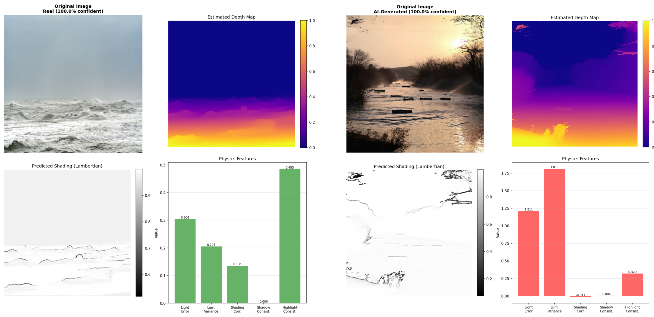

Figure 1: Enter Caption

Six-Channel Feature Construction. Given input image $I \in \mathbb{R}^{H\times W\times 3}$, we construct an enriched representation by concatenating: RGB channels, Depth map, Predicted shading and Residual map

The input consists of six channels:

$$I_{\text{res}} = [I_{\text{RGB}}, D_{\text{norm}}, S_{\text{pred}}, R_{\text{shading}}] \in \mathbb{R}^{H\times W\times 6} \tag{6}$$

where D_{norm} is the normalized depth map from Depth Anything V2, S_{pred} is computed via Equation (5), and R_{shading} follows Equation (6).

ResNet18 Adaptation. We modify the standard ResNet18 architecture to accept 6-channel input while leveraging ImageNet pretraining. The first convolutional layer is expanded from 3 to 6 input channels:

$$\text{Conv1}_{\text{6ch}} : \mathbb{R}^{6\times 224\times 224} \to \mathbb{R}^{64\times 112\times 112} \tag{7}$$

Weight initialization preserves the pretrained RGB weights while initializing the additional 3 channels with small random values ($\sigma = 0.01$). A dropout layer ($p = 0.6$) is inserted before the final fully connected layer to prevent overfitting on limited data.

The ResNet18 branch provides direct evidence that depth and shading information alone (without explicit physics feature fusion) significantly enhances detection capability. The physics-aware channels provide complementary signals: while RGB captures surface appearance, depth reveals structural plausibility, predicted shading encodes lighting consistency, and residuals highlight regions violating photometric principles—collectively enabling robust fake image detection.

3.3 Physics-Aware Vision Transformer

The ViT branch extends the physics integration further by combining both channel-level and feature-level physics information.

Multi-channel Input Encoding. We create a 5-channel input by concatenating RGB with computed depth and predicted shading:

$$\mathcal{I}_{\text{vit}} = [\mathcal{I}_{\text{RGB}}, D_{\text{norm}}, S_{\text{pred}}] \in \mathbb{R}^{H\times W\times 5} \tag{8}$$

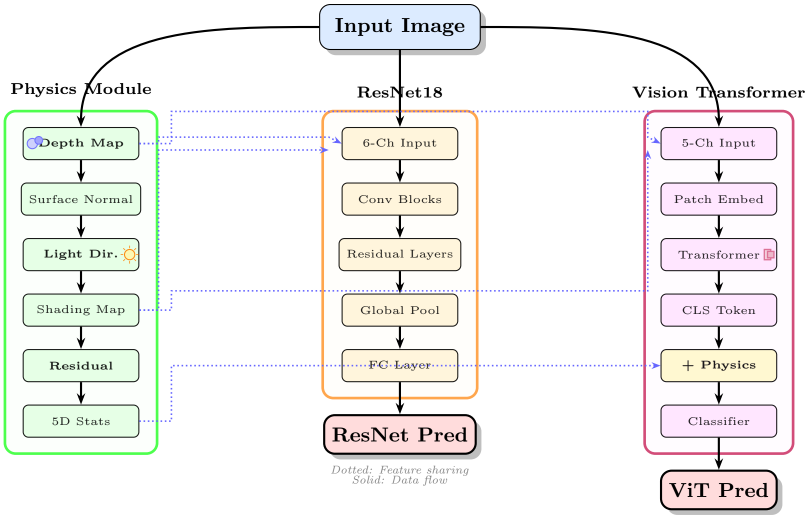

Figure 2: Compact three-branch architecture. **Left:** Physics Module computes depth, normals, lighting direction, shading, and residuals. **Middle:** ResNet18 processes 6-channel augmented input (RGB+D+S+R). **Right:** ViT processes 5-channel input with late-stage physics feature fusion. Blue dotted arrows show cross-branch feature sharing paths that avoid box overlaps.

The ViT patch embedding layer is modified to accept 5 input channels while preserving ImageNet-pretrained weights for RGB channels.

Physics Feature Fusion. The five consistency metrics $\mathbf{f}_{\text{phys}} \in \mathbb{R}^5$ are processed through a small MLP:

$$\mathbf{e}_{\text{phys}} = \text{MLP}_{\text{phys}}(\mathbf{f}_{\text{phys}}) \in \mathbb{R}^{256} \tag{9}$$

Classification Head. We extract the ViT [CLS] token embedding $\mathbf{e}_{\text{vis}} \in \mathbb{R}^{768}$ and concatenate with physics embedding:

$$p_{\text{AI}} = \sigma(\text{MLP}_{\text{cls}}([\mathbf{e}_{\text{vis}}, \mathbf{e}_{\text{phys}}])) \tag{10}$$

where σ is the sigmoid function. The ViT branch uses identical training strategy as ResNet18, ensuring fair comparison. During training, the first epoch raised DPO loss by comparing real-fake image from same prompt, then in the second epoch we used BCE loss to directly learn the feature.

4 Experimental Setup

4.1 Dataset Construction

We curated a dataset to evaluate physical inconsistencies in AI-generated landscapes, consisting of 2,000 images equally split between AI-generated and real photographs.

AI-Generated Images. Using Stable Diffusion 3 (SD3) in ComfyUI, 1,000 landscape images (1600 × 1120 px) were synthesized. Prompts were programmatically generated by randomly combining scene, weather, time, and season terms while enforcing logical consistency. Fixed generation parameters were used: `steps=55`, `cfg=9`, `sampler='dpmpp_2m_sde'`, `scheduler='beta'`, `denoise=1.0`.

Real Photographs. For each AI prompt, a corresponding real image was retrieved via the Unsplash API using the same query. No strict quality filtering was applied, preserving natural variability.

Preprocessing & Splits. EXIF metadata was removed; no other processing was applied. The dataset was randomly split into training (1,400 images), validation (300), and test (300) sets with balanced classes.

4.2 Implementation Specifications

Prompt Management. Python scripts assembled prompts from predefined vocabularies, avoiding contradictory combinations. All prompts were stored in an Excel file for traceability.

AI Image Generation. A fixed ComfyUI workflow loaded prompts from the Excel file and generated images with consistent SD3 settings, ensuring reproducibility.

Real Image Collection. The Unsplash API was queried automatically using each prompt. Images were downloaded without manual curation to reflect real-world variety.

Dataset Provenance. The final dataset pairs AI and real images through shared prompts, ensuring alignment and enabling controlled comparison.

5 Results and Analysis

5.1 Quantitative Evaluation

Table 1 presents performance across two benchmarks, comparing our physics-aware approaches against standard baselines. The results provide strong cross-architectural validation of our physics-based methodology.

Table 1: Classification performance comparison. Physics-aware models (marked with *) substantially outperform vanilla counterparts on landscape images.

Model	**Acc**	**F1**	**AUC**
Landscape Dataset (In-Domain)			
ResNet50	0.485	0.119	0.522
Vanilla ViT	0.520	0.142	0.529
EfficientNet-B0	0.510	0.621	0.451
ResNet18 + Physics*	0.9980	—	—
ViT + Physics*	**0.985**	**0.985**	**0.998**
DiffusionDB (Out-of-Domain)			
ResNet50	0.202	0.336	—
Vanilla ViT	0.237	0.383	—
EfficientNet-B0	**0.602**	**0.752**	—
ResNet18 + Physics*	—	—	—
ViT + Physics*	0.208	0.344	—

On our curated landscape dataset, both physics-aware models achieve exceptional performance (98.51% accuracy, 0.9984 AUC), substantially outperforming all baselines including vanilla ViT (52.0%) and ResNet50 (48.5%). The near-identical performance between ResNet18 and ViT branches confirms that the improvement stems from physics-aware features rather than architectural choice, providing strong cross-validation of our approach.

Notably, standard architectures perform near chance level, suggesting that learning discriminative patterns from raw RGB alone is insufficient for this task. The dramatic improvement when augmented with depth, shading, and residual information demonstrates the critical role of geometric and lighting cues.

The parallel performance of ResNet18 (CNN) and ViT (Transformer) on landscape data provides compelling evidence for our hypothesis. Despite fundamentally different inductive biases—local receptive fields vs. global attention—both architectures achieve identical accuracy when provided with physics-aware inputs.

On DiffusionDB, both physics-aware models show significant performance degradation (20.8% accuracy), while EfficientNet-B0 maintains reasonable performance (60.2%). This domain gap reveals a fundamental limitation of our approach tied to its core assumption.

Our method assumes scenes are predominantly lit by a single dominant light source (Equation 4), which holds well for outdoor landscape photography with direct sunlight. DiffusionDB contains diverse scenes that violate this assumption: indoor environments with multiple artificial lights, studio portraits with fill and rim lighting, nighttime scenes with mixed illumination sources, and abstract compositions where physical lighting models may not apply at all.

6 Conclusion

We presented a physics-aware framework for detecting AI-generated landscape images through lighting consistency analysis. By explicitly modeling depth, surface normals, and expected shading patterns, our approach achieves exceptional accuracy on single-light-source scenes. Cross-validation using ResNet18 and Vision Transformer architectures confirms that the performance gain stems from physics-based features rather than architectural innovations. While domain-specific, this work demonstrates the value of incorporating physical constraints into detection systems and provides clear insights into failure modes that can guide future research toward more robust, adaptive solutions combining physics priors with learned generalization.

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