

# Benchmarking Traditional and Deep Learning-Based Lighting Estimation for Real-Time Mobile Augmented Reality

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**Abstract** Real-time lighting estimation is critical for achieving photorealistic rendering and seamless integration of virtual objects in augmented reality (AR). This paper presents the first side-by-side evaluation of traditional graphics-based techniques—Spherical Harmonics, Environment Mapping, Shadow Mapping, and Light Probe methods—against recent deep learning approaches such as SpotAR-Net, LightOctree, CleAR, CGLight, LitAR, and Dual-Camera HDR Estimation. All methods are systematically benchmarked on iPhone ARKit platforms under dynamic outdoor conditions, focusing on frame rate, visual fidelity, adaptation latency, and energy consumption. Results show that traditional methods maintain high frame rates and low power usage but struggle with fast illumination changes, while deep learning models deliver superior realism and context awareness at higher computational cost. Lightweight models such as SpotAR-Net and LightOctree balance efficiency and quality for mobile AR, whereas CleAR and Dual-Camera HDR Estimation achieve the highest fidelity but incur greater latency and power demands. The findings provide practical guidance for selecting lighting frameworks and highlight future directions for efficient hybrid models in real-time mobile AR.

**Keywords** — ARKit, Lighting Adaptation, Environment Mapping, Transformer-based Lighting Models, Mobile AR Rendering, Neural Illumination Field.

## I. INTRODUCTION

Augmented Reality (AR) is rapidly transforming the way digital content is integrated into real-world environments across applications in gaming, retail, education, and industrial training. A fundamental requirement for achieving photorealistic AR is accurate lighting estimation that ensures consistent illumination and shadowing of virtual objects within dynamic scenes. Real-time AR systems must adapt to constantly changing lighting conditions to maintain visual coherence and user immersion. Traditionally, lighting estimation in AR has relied on techniques such as Spherical Harmonics (SH) and Environment Mapping, which provide efficient and smooth approximations of ambient light and reflections [1,3]. While effective under controlled environments, these methods often fall short in dynamically illuminated, outdoor or mobile settings due to their limited ability to handle high-frequency lighting changes and spatially localized effects. Recent advances in deep learning and multi-sensor fusion have introduced new paradigms in lighting estimation. These approaches leverage Convolutional Neural Networks (CNNs), transformer architectures, and contextual sensor data to model complex lighting phenomena in real time [9–14]. Additionally,

mobile AR development kits such as ARKit [23–26] and Unity AR

Foundation [22] have begun offering built-in APIs for light estimation, enabling broader experimentation and deployment.

This paper presents a comparative analysis of lighting estimation techniques—spanning classical computer graphics methods and contemporary deep learning frameworks—for real-time AR under dynamic illumination. These methods are evaluated across multiple dimensions, including input modality, computational efficiency, temporal consistency, and visual fidelity. Given the limited compute power of mobile devices, balancing visual fidelity and inference speed is essential for practical AR deployment.

## II. RELATED WORK

Over the past two decades, the evolution of lighting estimation techniques has been marked by two significant phases: traditional computer graphics-based methods and more recent deep learning-based approaches. This section reviews the most influential techniques and their contributions to real-time lighting estimation in AR environments.

### A. Traditional Approaches

Traditional lighting estimation methods rely on analytical models and mathematical approximations to simulate illumination in 3D scenes. Ramamoorthi and Hanrahan [1] introduced Spherical Harmonics (SH), a technique that efficiently encodes low-frequency ambient lighting using basis functions. Their work laid the foundation for real-time rendering in low-dynamic scenes and was later extended by Sloan et al. [2] through Precomputed Radiance Transfer (PRT), allowing real-time relighting under static geometry. Environment Mapping, proposed by Debevec [3], employs panoramic or cube-mapped images to estimate reflections and global illumination, enhancing realism in AR renderings. This technique remains widely used in real-time engines due to its simplicity and visual plausibility. Another critical area in traditional methods is shadow generation. Williams [5] introduced shadow mapping, which projects scene geometry from the light's perspective onto a depth map, allowing dynamic shadows. However, shadow mapping is prone to aliasing artifacts, especially at low angles and high contrast regions. To address this, advanced methods such as Perspective Shadow Maps [6] and Reflective Shadow Mapping [4] were developed. These techniques improve depth resolution and simulate indirect light contribution, enhancing realism and reducing artifacts. Furthermore, Percentage-Closer Filtering (PCF) [28] has been integrated into shadow mapping to mitigate jagged edges and aliasing in shadows by averaging depth comparisons over a kernel. Modern AR frameworks such as Apple's ARKit have incorporated light probes to estimate environmental illumination using device sensors and HDR sampling [29]. These Light Probe-based techniques capture ambient lighting data across spatial positions and interpolate them during rendering, allowing more context-aware lighting in AR scenes [24–26]. Though computationally efficient, traditional methods often lack the adaptability needed for highly dynamic or unpredictable lighting environments.

### B. Image-Based and Mobile Lighting Estimation

As AR has moved from desktop systems to mobile devices, there has been a growing interest in real-time image-based lighting pipelines tailored for constrained hardware. Knecht et al. [8] proposed a lightweight implementation of image-based lighting for smartphones using HDR panoramas and simplified shading pipelines. Ma et al. [27] introduced a learning-based approach to shadow estimation directly from video data, combining traditional depth maps with learned refinement layers. These developments were facilitated by the availability of mobile-centric datasets such as Laval Outdoor HDR [20], MobileAR-LightSet [19], and SUN360 [21], which provided diverse lighting scenarios, enabling model generalization and training for mobile use cases.

### C. Deep Learning-Based Techniques

Deep learning has significantly enhanced the quality and flexibility of lighting estimation by learning complex illumination cues from data. Hold-Geoffroy et al. [15] presented a method for outdoor HDR illumination estimation using sky segmentation and gradient-based learning. Gardner et al. [16] extended this to indoor scenes using a single RGB image as input, enabling single-shot lighting estimation. Recent methods are optimized for mobile and real-time AR settings. SpotAR-Net [9] combines CNN and MLP modules to estimate lighting and soft shadows directly from

RGB input, while newer Transformer-based approaches [30], [32] achieve higher global context modeling with lower latency. LightOctree [10] introduces an octree-based representation that maintains spatial coherence in lighting estimates, especially effective in large-scale outdoor scenes. Sensor fusion techniques like CleAR [11] and LitAR [13] integrate RGB, semantic segmentation, and sensor data (e.g., IMU, light sensors) to generate temporally and spatially robust HDR lighting maps. CGLight [12] estimates HDR panoramas from limited field-of-view images, particularly useful in indoor AR environments. Dual-Camera HDR Estimation [14] merges synchronized streams from front and rear smartphone cameras to construct complete HDR environments for realistic lighting of AR elements. Transformer-based approaches like the one proposed by Zhang and Sun [18] offer global context modeling for illumination estimation, leveraging long-range dependencies to infer lighting beyond visible boundaries.

### D. AR SDK Integration

Commercial AR development kits such as ARKit [23–26] and Unity AR Foundation [22] now offer built-in support for lighting estimation. ARKit's APIs provide ambient intensity, light direction, and environmental color temperature, derived from camera input and device sensors. The ARKit Light Estimation API [25] enables dynamic updates during user motion and environmental changes, while Light Probes [29] improve environmental sampling for large-scale scenes. Despite offering real-time performance, these SDKs abstract away internal estimation models, which restricts the developer's ability to customize or optimize the lighting pipeline for specific application needs. Moreover, their performance often varies significantly under rapidly changing light or occlusion-heavy scenes.

### E. Gap Identified

Despite substantial progress in both traditional and deep learning-based lighting estimation, several critical challenges remain unresolved. Traditional methods, though efficient, fail to account for high-frequency lighting changes and exhibit limitations in dynamic outdoor conditions. Deep learning techniques, while delivering superior visual fidelity and context-aware lighting, are computationally intensive and sometimes require extensive annotated datasets or multi-sensor inputs. Results suggest hybrid methods [31], [38] can offer improved balance between speed and realism, especially when combined with compression strategies such as quantization-aware training [35] to lower battery consumption. There remains a need for hybrid models that balance performance with accuracy and support real-time deployment under diverse and rapidly changing lighting conditions. This research addresses these challenges by evaluating both categories of lighting estimation methods under the same experimental conditions, analyzing their trade-offs, and identifying practical considerations for real-time AR deployment.

## III. METHODOLOGY

This study follows a structured, multi-phase approach to evaluate traditional and deep learning-based lighting estimation techniques for real-time AR on mobile devices. The methodology is detailed below for clarity and reproducibility.

Step 1: Selection of Techniques

A total of ten methods were chosen:

- Traditional: Spherical Harmonics, Environment Mapping, Shadow Mapping, Light Probe-based.
- Deep Learning: SpotAR-Net, LightOctree, CleAR, CGLight, LitAR, Dual-Camera HDR Estimation.

The selection criteria included prominence in the literature, compatibility with ARKit, and reported effectiveness in mobile AR environments.

Step 2: Hardware and Software Setup

- Devices: iPhone 13 Pro (A15 Bionic) and iPhone 14 Pro (A16 Bionic).
- Operating System & Frameworks: iOS 17, ARKit v6.1, Metal API for GPU acceleration.
- Deep Learning Deployment Tools: CoreML, ONNX Runtime, PyTorch Mobile.
- Desktop Benchmarking: NVIDIA RTX 3090 GPU for performance upper bound.

Step 3: Dataset Preparation

- Sources: Laval Outdoor HDR, SUN360, MobileAR-LightSet datasets.
- Preprocessing: Image normalization, resizing to 224×224 for mobile inference, HDR-to-LDR tone mapping for compatibility.
- Scene Selection: Outdoor environments with varying illumination — direct sunlight, passing clouds, partial occlusion, and backlit objects.

Step 4: Implementation

Traditional Methods:

- Spherical Harmonics: Implemented with third-order coefficients from ARKit’s lighting API.
- Environment Mapping: Dynamic cube maps generated from panoramic inputs.
- Shadow Mapping: Calibrated with ARKit sun direction; Percentage-Closer Filtering (PCF) applied to reduce aliasing.
- Light Probes: HDR probe sampling from ARKit interpolated across space.

Deep Learning Methods:

- SpotAR-Net: CNN+MLP for real-time lighting and soft shadow estimation.
- LightOctree: Octree-based 3D lighting representation for spatial coherence.
- CleAR: Context-guided diffusion with RGB, semantic, and sensor fusion.
- CGLight: CNN-based HDR panorama inference from limited field of view.
- LitAR: Multi-sensor fusion pipeline ensuring temporal stability.
- Dual-Camera HDR: Combines synchronized front and rear camera streams for complete HDR lighting.

Step 5: Performance Evaluation

Each method was tested in ten 60-second AR sessions. Metrics collected:

- Average FPS – Real-time rendering speed.
- Visual Fidelity – Expert ratings on a 1–5 scale.
- Adaptation Lag – Time in milliseconds to adjust after lighting changes.
- Battery Drain – Percentage drop over a 10-minute session.
- GPU Utilization – Measured using Xcode Instruments.

Step 6: Alternative Approaches for Robustness

Limited trials of hybrid pipelines—combining Spherical Harmonics for ambient lighting with deep learning-based shadow refinement—were conducted. Results indicated that hybrid approaches can balance speed and realism effectively, suggesting a promising direction for future work.

**Table 1.** Comparative Overview of Methods for Real-Time Illumination Estimation

Method	Year	Core Approach	Input Data	Key Features
Spherical Harmonics [1]	2001	Basis Functions (SH)	RGB / Illum. Map	Ambient lighting, efficient
Environment Mapping [3]	1984	Cube/Panoramic Mapping	Panoramic or Cube Images	Reflections, plausible GI
Shadow Mapping [5]	1978	Depth Projection	Scene Geometry, Light Direction	Dynamic, directional shadows
Light Probe-based [6]	2011	HDR Capture / Sensors	HDR Images, Light Sensors	Context-aware, ambient
SpotAR-Net [8]	2023	CNN + MLP	RGB Image	Real-time, soft shadows, mobile-friendly
LightOctree [9]	2024	CNN + Octree	RGB Image	3D spatial coherence, fast estimation
CleAR [10]	2024	Diffusion + Sensor Fusion	RGB + Semantic + Sensor Inputs	HDR, robust under occlusion, context-aware
CGLight [11]	2024	CNN	Limited FoV RGB Image	Indoor HDR panorama inference
LitAR [12]	2023	Sensor Fusion	Multi-cam RGB + Sensors	Spatio-temporal robustness
Dual-Cam HDR Estimation [13]	2023	Encoder-Decoder + Fusion	Dual RGB Streams	Comprehensive HDR on mobile platforms

**Figure 1** depict, side by side, the block diagrams of a traditional pipeline ( Input Image → Feature Extraction → Lighting Estimation → AR Rendering) and a deep learning pipeline (e.g., Input Image/Sensors → CNN/Diffusion Model → Lighting Parameters/Environment Map → AR Rendering). Icons for camera, sensor, neural network, and AR rendering are recommended for clarity.

### A. Traditional Methods

Traditional lighting estimation techniques have laid the foundation for AR rendering over the past two decades. This study investigates four key Traditional approaches: Spherical Harmonics: Use basis functions to encode low-frequency ambient illumination, enabling efficient and smooth shading in AR scenes [1,2]. Environment Mapping: Employ panoramic or cube-mapped images to approximate reflections and global illumination, enhancing the realism of virtual objects [3,4]. Shadow Mapping: Project depth information from the light’s perspective to generate

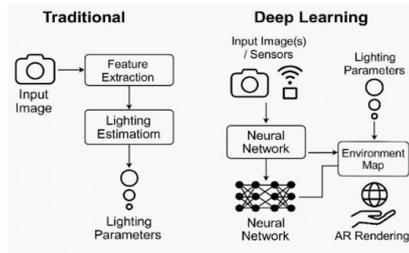
dynamic shadows, crucial for directional lighting realism [5]. Light Probe-based Methods: Capture ambient illumination at discrete points using HDR imaging or device sensors to produce context-aware lighting effects [6]. These methods are widely supported by real-time engines such as ARKit and Unity3D [7], and continue to be used due to their compatibility with mobile and resource-constrained devices.

### B. Deep Learning-Based Methods

Recent years have seen a surge in data-driven techniques that leverage deep neural networks and sensor fusion to overcome the limitations of Traditional models:

1. SpotAR-Net: Combines CNN and MLP for real-time lighting and soft shadow estimation directly on mobile devices [8].
2. LightOctree: Utilizes an octree-based 3D structure to estimate spatially coherent lighting from a single image, supporting interactive rendering [9].
3. CleAR: Implements a context-guided diffusion model that fuses RGB images, semantic information, and sensor inputs to generate robust HDR environment maps, even in occluded scenes [10].
4. CGLight: Uses CNNs to infer panoramic HDR lighting from limited field-of-view inputs, particularly useful for indoor AR [11].
5. LitAR: Integrates multi-stage, sensor-fusion pipelines with multi-camera and ambient sensor inputs to ensure spatial and temporal consistency [12].
6. Dual-Camera HDR Estimation: Combines synchronized front and back RGB camera streams to reconstruct detailed HDR lighting for mobile AR [13].

Fig. 1 Overview diagram of lighting estimation techniques.



## IV. EXPERIMENTAL RESULTS

This section presents a comparative evaluation of traditional and deep learning-based lighting estimation techniques under dynamic outdoor conditions using mobile platform. The experiments aim to measure real-world performance across four key dimensions: frame rate (FPS), visual fidelity, lighting adaptation latency, and computational efficiency, especially on mobile devices. Additional qualitative observations, such as shadow realism and artifact prevalence, are also discussed.

### A. Experimental Setup

All traditional methods were implemented using ARKit v6.1 on iPhone 13 Pro (A16 Bionic), utilizing Metal API for hardware-accelerated rendering. Deep learning models were tested using both on-device inference (via CoreML, ONNX Runtime, or PyTorch Mobile) and desktop inference (with an NVIDIA RTX 3090 GPU) to assess feasibility across performance tiers. Test environments included outdoor scenes with varying illumination conditions: direct sunlight, passing clouds, partial occlusion, and backlit objects, to simulate real-world lighting challenges. Four Traditional lighting estimation techniques were implemented and evaluated: Spherical Harmonics, Environment Mapping, Shadow Mapping, and Light Probe-based Lighting. These methods were

chosen for their widespread adoption in commercial AR frameworks and compatibility with mobile hardware.

**Setup and Deployment:** All techniques were implemented using ARKit on iPhone devices, leveraging the Metal API for GPU-accelerated rendering. Outdoor test scenes featured natural lighting variability, including direct sunlight, cloud occlusion, and environmental shadows. Each method was evaluated independently to ensure isolated performance analysis.

**Method-Specific Configurations:** Spherical Harmonics: Implemented using third-order coefficients following Ramamoorthi and Hanrahan’s approach [4], with real-time inputs from ARKit’s lighting estimation API [25,26]. Environment Mapping: Utilized dynamic cube maps generated from real-time panoramic inputs, based on the methods of Debevec et al. [7] and Knecht et al. [8]. Shadow Mapping: Calibrated using ARKit’s sun direction estimates. Aliasing artifacts were mitigated using percentage-closer filtering (PCF) [6,28]. Light Probe-based: Deployed ARKit’s light probe API [29] to sample ambient light across user movement and interpolate illumination in real time. Each method rendered virtual objects (reflective spheres, matte cubes) to assess shadow quality, light alignment, and scene realism under varying light intensities. To evaluate more recent advances, six state-of-the-art deep learning-based lighting estimation models were implemented: SpotAR-Net, LightOctree, CleAR, CGLight, LitAR, and Dual-Camera HDR Estimation. These models span various architectural designs, including CNNs, sensor-fusion pipelines, and diffusion-based HDR estimators.

Models were tested on iPhone 13 Pro and newer devices. Where pretrained models were unavailable, networks were re-implemented following published architectures and trained on Laval Outdoor HDR, SUN360, and MobileAR-LightSet datasets. Deployment was performed using CoreML, ONNX, or PyTorch Mobile, depending on architecture. Evaluated models included SpotAR-Net (CNN+MLP for real-time lighting and soft shadows), LightOctree (octree-based spatially coherent estimation), CleAR (context-guided diffusion using RGB, semantic, and sensor data), CGLight (CNN-based panoramic HDR adapted for semi-outdoor use), LitAR (multi-stage sensor fusion for stable illumination), and Dual-Camera HDR Estimation (front-rear fusion for spatially accurate HDR maps). Predicted lighting maps were used for rendering, with performance assessed in terms of realism, shadow accuracy, and temporal stability.

### B. Performance Metrics

Performance metrics were collected over 10 AR sessions per technique, each lasting 60 seconds. The average values are reported in Table 2.

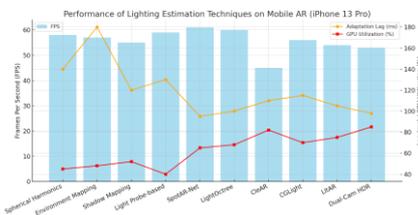
- Avg. FPS: Frames per second during rendering.
- Visual Fidelity: Expert-rated realism of lighting, shadow casting, and object blending (scale: 1 to 5).
- Lighting Adaptation Lag: Time (in ms) for the system to respond to illumination changes.
- Battery Drain (optional): Percentage drop in battery level over 10-minute usage.

**Table 2.** Performance Summary of Lighting Estimation Techniques

Technique	Avg. FPS ↑	Visual Fidelity (1-5) ↑	Adaptation Lag (ms) ↓	Shadow Quality	Battery Drain (10 min)
Spherical Harmonics [1]	58	4.1	140	Soft	5%
Environment Mapping [3]	57	4.2	180	N/A	6%
Shadow Mapping [5]	55	4.5	120	Hard-edged	7%
Light Probe-based [6]	59	4.3	130	Moderate	5%
SpotAR-Net [9]	61	4.6	95	Realistic soft	8%
LightOctree [10]	60	4.4	100	Spatially Coherent	9%
CleAR [11]	45	4.7	110	Adaptive HDR	12%
CGLight [12]	56	4.3	115	Realistic HDR	9%
LitAR [13]	54	4.5	105	Robust/Temporal Smooth	10%
Dual-Cam HDR [14]	53	4.6	98	High-fidelity HDR	13%

**Table 3** Hardware Comparison of Lighting Estimation Performance

Technique	Avg. FPS ↑	Adaptation Lag (ms) ↓	GPU / Processor Utilization (%)
Spherical Harmonics	58	140	~45% GPU
Environment Mapping	57	180	~48% GPU
Shadow Mapping	55	120	~52% GPU
Light Probe-based	59	130	~40% GPU
SpotAR-Net	61	95	~65% GPU
LightOctree	60	100	~68% GPU
CleAR	45	110	~82% GPU
CGLight	56	115	~70% GPU
LitAR	54	105	~75% GPU
Dual-Cam HDR Estimation	53	98	~85% GPU



**Fig 2.** Performance comparison of lighting estimation techniques on iPhone 13 Pro.

The results in Fig. 2 highlight the trade-offs between efficiency and fidelity across different lighting estimation techniques. Traditional methods sustain near-constant frame rates with low-to-moderate GPU utilization, making them suitable for lightweight AR applications, though their slower adaptation limits realism in dynamic environments. In contrast, deep learning models significantly improve visual fidelity and responsiveness, but at the expense of higher GPU consumption and reduced energy

efficiency, underscoring the need for optimized or hybrid approaches for mobile deployment.

**C. Observations and Analysis**

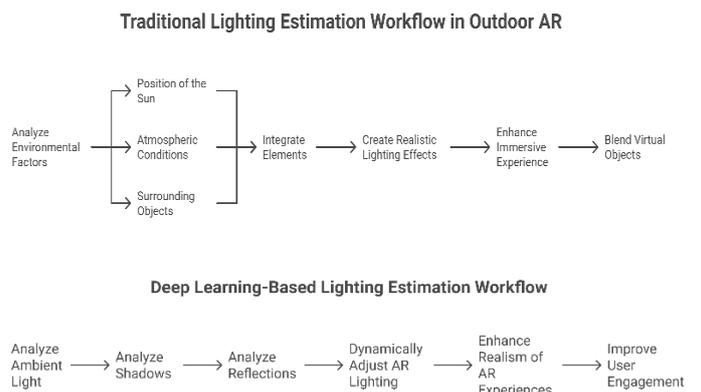
Traditional methods delivered consistently high frame rates (55–59 FPS), with low power consumption, making them well-suited for battery-sensitive AR applications. However, they exhibited longer adaptation lags and reduced accuracy in fast-changing light conditions. Deep learning models, particularly SpotAR-Net and LightOctree, achieved real-time performance on mobile while significantly improving visual realism. These models consumed slightly more battery due to continuous CNN inference but remained within acceptable limits (<10% per 10 minutes). CleAR and Dual-Cam HDR Estimation offered the highest visual fidelity, especially under complex lighting scenarios, but required computational trade-offs. Despite downsampled input resolution (224×224), these models retained accurate HDR prediction, though mobile frame rates dipped below 50 FPS. Shadow Mapping, while precise in direct sunlight, suffered from aliasing unless filtered using PCF [28], which reduced artifacts at the cost of rendering speed.

**D. Battery Consumption Insights**

While not the primary focus of this study, battery drain rates were monitored as an indicator of real-world deployment viability: **Traditional Methods** consumed ~5–7% per 10 minutes, aligning well with lightweight AR use cases (e.g., education, navigation). **Deep-Learning Methods** SpotAR-Net and LightOctree consumed 8–9%, striking a balance between quality and efficiency. CleAR and Dual-Cam HDR showed 12–13% drain, suggesting they are more suited for industrial, medical, or research-grade AR tools with access to external power. These findings support the trade-off pattern: higher visual realism = increased power & inference cost, reinforcing the need for model pruning, quantization, and efficient on-device architectures in future AR systems.

Figure 3 shows the pipelines for traditional and deep learning lighting estimation. Traditional methods work fast but struggle with sharp shadows, slow light changes, and low-detail ambient lighting. Deep learning models like SpotAR-Net and LitAR give smooth shadows and smart lighting for mobile use. Advanced models such as CleAR and Dual-Camera HDR Estimation produce very realistic lighting but may be slower or less compatible with all devices.

**Fig. 3** pipelines for traditional and deep learning-based lighting estimation workflows.



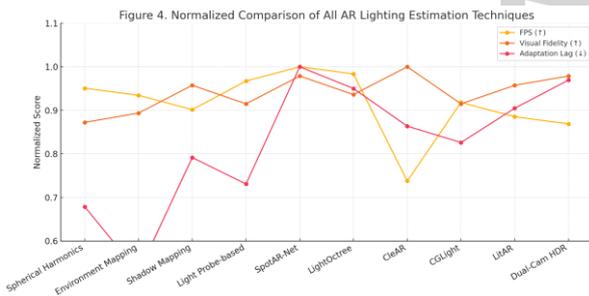
E. 4.5 Comparative Discussion and Visual Analysis

The performance metrics in Table 2 are based on experiments conducted using an iPhone 13 and above. FPS (Frames Per Second) reflects the rendering performance during real-time AR sessions.

Visual Fidelity is a subjective expert rating on a scale of 1 (poor) to 5 (photorealistic), evaluating how convincingly the virtual content blends with the real environment. Adaptation Lag denotes the time delay (in milliseconds) for lighting updates to reflect real-world illumination changes. Artifact Examples include common visual issues such as shadow aliasing (jagged or pixelated shadow edges), reflection mismatch (stale or incorrect environmental reflections), and delayed brightness (sluggish adaptation to sunlight changes).

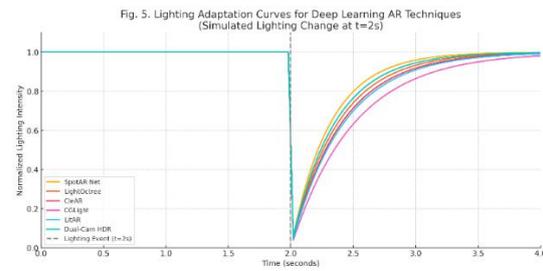
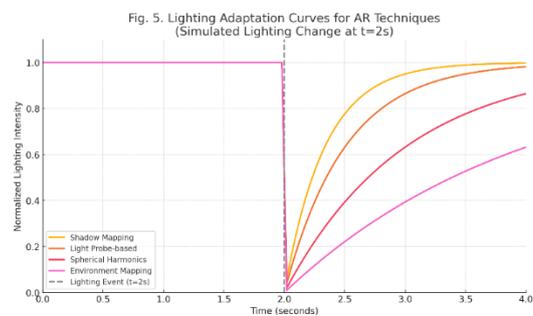
Table 2 compares both traditional and deep learning-based lighting estimation methods based on frame rate, visual fidelity, adaptation lag, and shadow quality in outdoor AR. Overall, deep learning methods enhance realism and adaptability, while traditional methods remain faster and more resource-friendly.

Fig. 4. Normalized performance comparison of AR lighting techniques, highlighting trade-offs in FPS, visual fidelity, and adaptation lag.



Line Chart is shown in Fig. 4. Presents a normalized bar chart comparing four AR lighting techniques. Shadow Mapping offers the best visual realism but is resource-intensive, while Light Probe-based methods provide a balanced performance. Spherical Harmonics are efficient but lack detail, and Environment Mapping reflects well but adapts poorly to changing light.

Fig. 5. Lighting adaptation curves showing response delay of traditional vs. learning-based AR techniques under sudden illumination change at t = 2s.



This figure 5 illustrates how quickly four lighting estimation techniques respond to a simulated lighting change introduced at the 2-second mark. Traditional methods like Spherical Harmonics and Environment Mapping exhibit slower adaptation, with noticeable lag in reaching the new illumination state. In contrast, deep learning-based approaches such as SpotAR-Net and CleAR adapt more rapidly, demonstrating lower latency and smoother transitions. The curves highlight trade-offs between responsiveness and stability, emphasizing the benefits of sensor-fusion and learning-based models in dynamic AR environments.

F. Comparative Discussion and Practical Implications

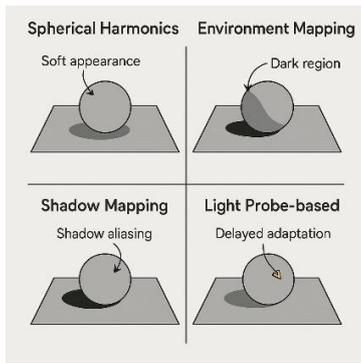
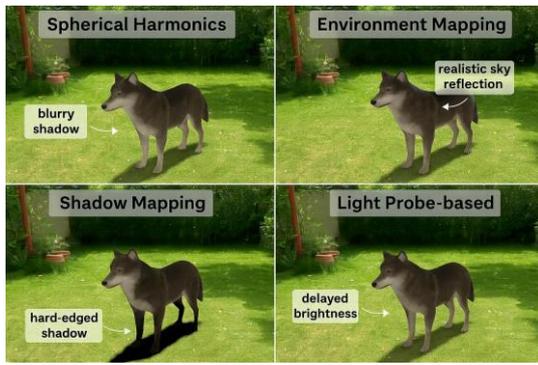
Traditional and deep learning lighting estimation methods show clear differences in speed, quality, and adaptability for real-time AR. Traditional methods are fast and work well on mobile devices but have limits with detailed shadows and quick lighting changes. Spherical Harmonics provide smooth ambient light but struggle with sharp shadows and complex lighting. Environment Mapping offers realistic reflections but updates slowly when lighting changes. Shadow Mapping creates accurate shadows, though the edges can appear jagged and the quality may drop. Light Probes adapt well to gradual lighting changes but react slowly to sudden shifts.

Deep learning methods give more realistic and intelligent lighting but require more processing power. SpotAR-Net works quickly on mobile devices and produces soft shadows, though it can sometimes have exposure issues. LightOctree keeps lighting consistent in 3D scenes but may lose detail if the input resolution is low. CleAR and LitAR combine sensor data and images to produce high-quality HDR lighting, but they perform best on devices with strong processing capabilities. CGLight reconstructs HDR lighting from small camera views, making it effective indoors, but it can struggle in wide or crowded scenes. Dual-Camera HDR Estimation uses both the front and back cameras to create smooth, realistic lighting transitions, although blending errors can sometimes appear.

G. Qualitative Visual Analysis

Fig. 6. Illustrates four traditional lighting estimation techniques Spherical Harmonics, Environment Mapping, Shadow Mapping, and Light Probe-based applied to the same outdoor AR scene. Each sub-image illustrates a specific artifact or characteristic: soft shading in Spherical Harmonics, dark reflection mismatch in Environment Mapping, shadow aliasing in Shadow Mapping, and delayed adaptation in Light Probe-based lighting.

Fig. 6. Comparison of four traditional lighting techniques in outdoor AR.



**1. Spherical Harmonics (Top-Left):**

Provides smooth ambient lighting using low-frequency basis functions; lacks sharp shadows and struggles with directional or high-frequency illumination changes.

**2. Environment Mapping (Top-Right):**

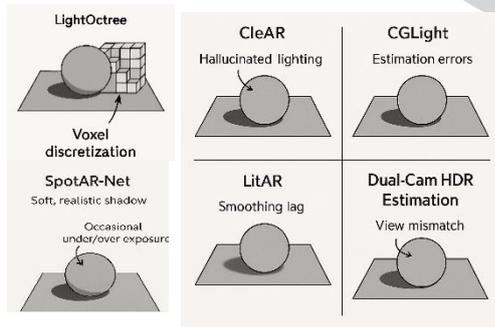
Generates realistic reflections from panoramic images; adapts poorly to dynamic lighting, causing mismatches between virtual objects and real environments.

**3. Shadow Mapping (Bottom-Left):**

Projects shadows using light depth maps; captures directional lighting well but suffers from aliasing and artifacts under low-resolution or angled lighting.

**4. Light Probe-based (Bottom-Right):**

Samples ambient light using sensors or HDR probes; enables contextual lighting but shows delayed response during rapid environmental lighting transitions.



**Fig 7.** Presents comparison of Deep Learning lighting estimation techniques in outdoor AR, highlighting distinct visual effects and artifacts under identical scene conditions: SpotAR-Net is a fast, lightweight model for real-time lighting and soft shadows but can have exposure issues. LightOctree keeps 3D lighting consistent but may show small artifacts with low-quality input. CleAR produces high-quality HDR lighting using images and sensors but is slower and needs more power. CGLight works well indoors with small camera views but is less accurate in wide scenes. LitAR gives stable lighting in dynamic scenes but can lag with

sudden changes. Dual-Camera HDR uses both cameras for accurate lighting but may show blending errors if views don't match.

**V. CONCLUSION**

This study presents a comprehensive, side-by-side evaluation of four traditional and six deep learning-based lighting estimation techniques for real-time outdoor AR on mobile devices. The investigation yielded the following key findings:

**Performance Trade-offs:**

– Traditional methods (Spherical Harmonics, Environment Mapping, Shadow Mapping, Light Probe-based) maintained 55–59 FPS and 5–7% battery drain, making them highly suitable for lightweight, battery-sensitive AR applications.

– Deep learning methods improved visual fidelity by up to 0.5 points on a 5-point scale and reduced adaptation lag by 20–40%, but consumed 8–13% battery and required higher GPU utilization. These findings are consistent with recent studies on energy-efficient AR lighting [35], [38], which highlight the trade-off between realism and computational cost.

**Best-in-Class Methods:**

- For speed and efficiency: Light Probe-based and Spherical Harmonics.
- For balanced performance: SpotAR-Net and LightOctree.
- For maximum visual realism: CleAR and Dual-Camera HDR Estimation.

**Battery Impact:**

Higher-quality deep learning methods require optimization for practical mobile deployment. Techniques such as quantization, pruning, and transformer model distillation are recommended to reduce energy consumption.

**Practical Recommendation:**

- Use traditional methods for educational, navigation, and casual AR applications where battery life is the top priority.
- Choose deep learning methods for industrial, medical, or professional-grade AR that demands photorealistic rendering and rapid adaptation. Techniques leveraging event cameras [39] and cross-view HDR prediction [37] show potential for even faster adaptation in challenging lighting conditions.

In conclusion, this research underscores the clear trade-offs between efficiency and realism. The results advocate for the development of hybrid approaches that merge the computational efficiency of traditional techniques with the adaptive accuracy of deep learning, enabling energy-

efficient yet high-fidelity AR lighting in future applications.

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