

# PROJECT DECISION LOG

Inter IIT Tech Meet 2025

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## BRIEF SUMMARY

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This document captures the critical engineering decisions for the mobile-optimized **AI Driven Photo Editing App**. The system targets four core capabilities: **Text-Based Segmentation**, **Image Re-lighting**, **Object Removal**, and **Object/Background Replacement**.

## CORE ACHIEVEMENT

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Successfully transitioned from server-grade SOTA models (SAM3, DPT, SD-XL) to hybrid, CPU-compatible architectures (MobileSAM, MiDaS-small, LaMa-Dilated, SD v1.5) optimized for local mobile deployment.

## 1 MODULE: TEXT-BASED SEGMENTATION

*Objective: Achieve on-device text-guided segmentation with latency under 15 seconds.*

### DL-01 Evaluating SAM3 for Deployment

[REJECTED]

#### CONTEXT

Baseline model was Vanilla SAM3, selected for SOTA performance.

#### TECHNICAL ANALYSIS

Mobile devices lack the GPU power required for SAM3.

- **Baseline Latency (CPU):** 2.47 minutes (148s) – Infeasible.
- **Quantization (INT8):** Reduced to 129s – Still too slow.

**Final Verdict:** Abandon SAM3. Architectural overhead is too high for mobile CPUs.

### DL-02 Hybrid CLIP + MobileSAM

[PIVOT]

#### CONTEXT

Pivoted to **CLIP** (Text Encoder) + **MobileSAM** (Mask Generator).

#### BOTTLENECK DISCOVERY

Accuracy was preserved, but inference spiked to **76 seconds**.

- **Cause:** CLIP had to evaluate *every* candidate mask against the text embedding.

**Final Verdict:** Adopt Architecture, Optimization Required. CLIP evaluation is the new critical path.

### DL-03 Prompt-Guided Search Reduction

[OPTIMIZED]

#### INNOVATION

Introduced **Prompt-Aware Mask Filtering**. Use prompt semantics (e.g., “person on the left”) to discard irrelevant masks spatially *before* embedding generation.

#### RESULTS

- Latency dropped from 76s → **27s**.

**Final Verdict:** Integrated. First configuration to achieve CPU viability.

### DL-04 Deploying Tiny-CLIP

[DEPLOYED]

#### STRATEGY

Replaced standard CLIP with **Tiny-CLIP** to minimize encoder latency.

#### PERFORMANCE MATRIX

- Tiny-CLIP + MobileSAM:  $\approx 17s$ .
- **Tiny-CLIP + Pruning (Combined):  $\approx 13s$ .**

**Final Verdict:** Production Ready. Final shipping configuration.



Figure 1: Output by Final Architecture with an Average Latency of 13 sec

## 2 MODULE: RELIGHTING PIPELINE

*Objective: Physics-accurate relighting with intuitive mobile controls.*

### DL-01 Depth Estimator Selection

[SELECTED]

#### ANALYSIS

**MiDaS-small** selected over Large DPT. It provides the best balance of smoothness for shading and CPU/GPU-constrained inference speed.

**Final Verdict:** MiDaS-small. Sets the geometric foundation.

### DL-03/04 Physics Core & Gesture Mapping

[ARCHITECTED]

#### STRATEGY

Implemented an analytic shading engine (Lambertian + Phong) to capture basic physics.

#### UX DESIGN

Mapped swipes to directional light vectors and taps to point-light positions.

**Final Verdict:** Hybrid Approach. Physics provides the controllable baseline; User gestures map directly to 3D light vectors.

### DL-06/09 Refinement Network & Domain Gap

[STRATEGY]

#### MODEL

**Tiny RelightNet:** A lightweight network receiving RGB, Depth, Normals, and Physics-Shading.

#### TRAINING INNOVATION

Training on raw images failed. We corrected this by generating physics output on-the-fly during training to match the inference domain.

**Final Verdict:** Adopted. The network learns to *refine* physics rather than learn lighting from scratch.

## DL-12 Final Pipeline Architecture

[FROZEN]

### SYSTEM FLOWCHART

Input → MiDaS(Depth) → Normals → Physics Shading → Tiny RelightNet → Output

**Final Verdict:** Deployed. Exported to ONNX (FP16/INT8) for NNAPI acceleration.

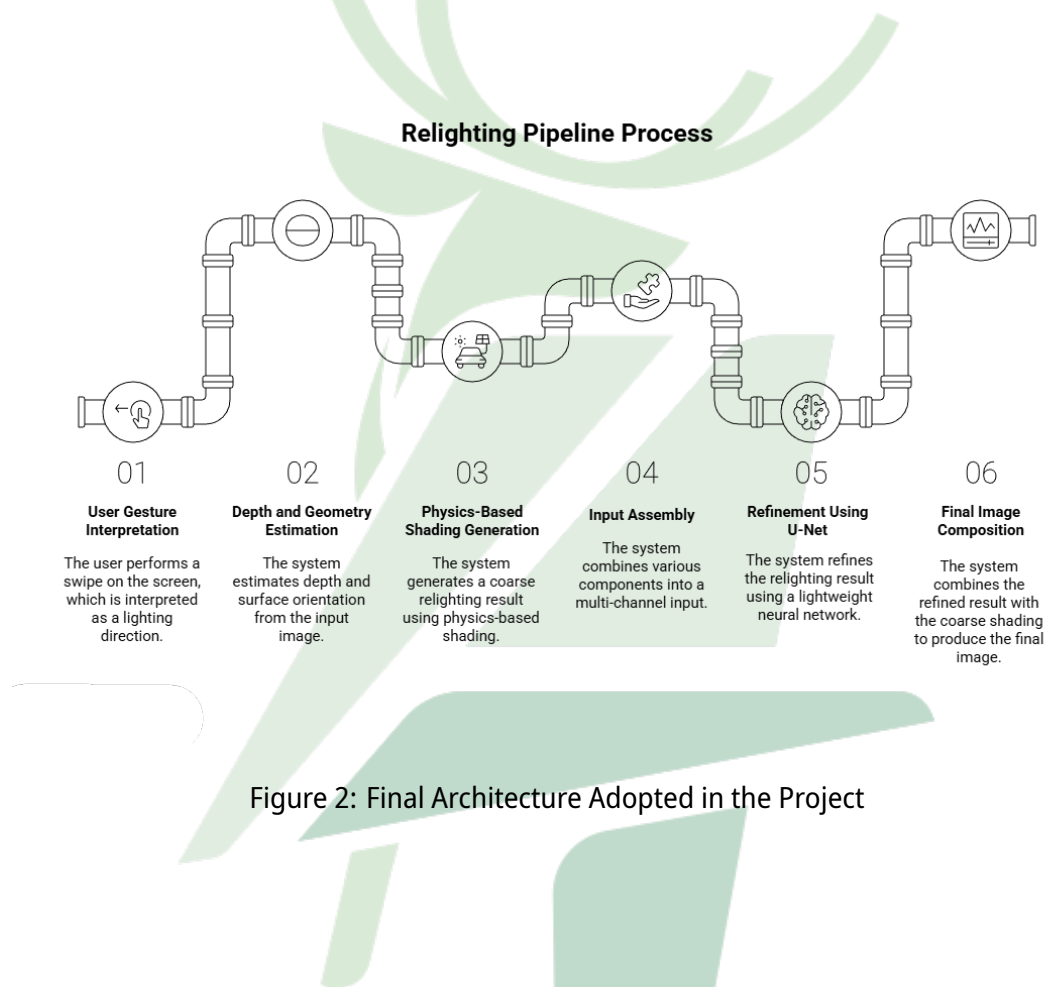


Figure 2: Final Architecture Adopted in the Project

### 3 MODULE: OBJECT REMOVAL

*Objective: High-fidelity object removal with minimal footprint.*

#### DL-01 Model Selection Benchmark

[SELECTED]

##### CANDIDATES EVALUATED

- **LaMa-Dilated:** 0.54s latency. Sharp structure, best balance.
- **LaMa-Fourier:** 9s latency. Good quality, but too slow for interactive use.
- **Big LaMa:** 23s latency. High resource consumption, infeasible for mobile.
- **AOT-GAN:** 0.39s latency. Fast, but smeared textures.
- **MI-GAN:** 0.05s latency. Blurry blobs (Failure).

**Final Verdict:** LaMa-Dilated. Chosen for superior structural completion.

#### DL-02 Classical Approaches

[REJECTED]

##### CONTEXT

Tested OpenCV methods (Telea, Navier-Stokes).

##### RESULT

Extremely fast but texture-less and blurry. Unsuitable for photo-editing quality standards.

**Final Verdict:** Dropped. Useful only for benchmarking.

#### DL-03 Quantization Strategy

[MODIFIED]

##### EXPERIMENTS

- **FP16:** Size → 226 MB (39% drop). Negligible quality loss.
- **INT8:** Some degradations (color shifts, 43% filter error).

**Final Verdict:** FP16 Adopted. INT8 rejected due to visual artifacts.

#### DL-05 Final Pipeline Decision

[DEPLOYED]

##### CONFIGURATION

Mask (MobileSAM) → LaMa-Dilated (FP16) → Post-Processing

**Final Verdict:** Production Ready. Compact, quantized, and stable across various mask shapes.

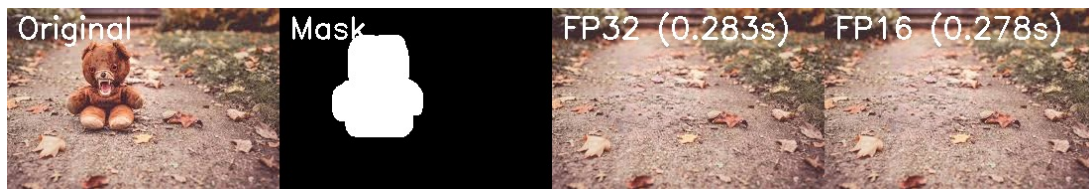


Figure 3: Output Comparison for FP16 Quantized Model

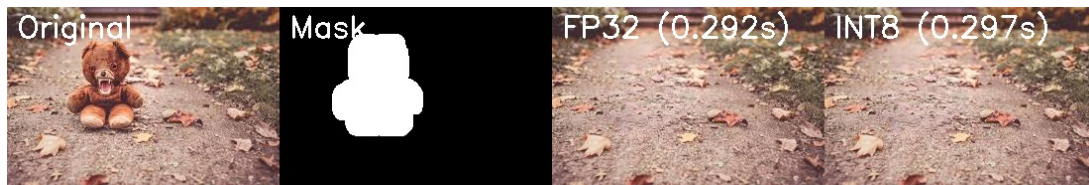


Figure 4: Output Comparison for INT8 Quantized Model

## 4 MODULE: OBJECT REPLACEMENT

*Objective: Generative object replacement on CPU-only mobile hardware.*

### DL-01 Base Diffusion Model

[SELECTED]

#### BENCHMARK

Compared **Stable Diffusion v1.5** vs. **DreamShaper**.

#### RESULT

SD v1.5 consistently ran faster across all setups while providing predictable results. DreamShaper had a slight speed penalty.

**Final Verdict:** Stable Diffusion v1.5. Selected for lower CPU latency.

### DL-02 Step Budget Definition

[CONSTRAINED]

#### ANALYSIS

Full quality requires 20-50 steps, which is infeasible on CPU.

- **5 Steps:**  $\approx$  32–43 seconds.
- **20 Steps:**  $\approx$  103–127 seconds.

**Final Verdict:** 5-Step Budget. Established as the practical ceiling for mobile CPU inference.

### DL-03 Scheduler Selection

[SELECTED]

#### COMPARISON

Tested Default, Euler\_a, DDIM, and LCM.

#### IMPROVEMENT

While DDIM was effective, we subsequently integrated the **LCM (Latent Consistency Model) Scheduler**. This advanced scheduler is designed to produce high-fidelity images in as few as 4-8 steps, significantly reducing latency while withstanding accuracy drop-offs common in low-step regimes.

**Final Verdict:** LCM Scheduler Adopted. It offered the best trade-off for CPU-based inference.

## DL-04/05 Final Configuration & Limitations

[PROTOTYPE]

### CONFIGURATION

**SD v1.5 + LCM + 5 Steps.**

### STATUS

This configuration brings generation time within an acceptable window on CPU. However, complex prompts may still require more time.

**Final Verdict:** Good Enough for Prototype. Recognized as CPU-heavy; suitable for proof-of-concept but requires NPU/GPU for production refinement.



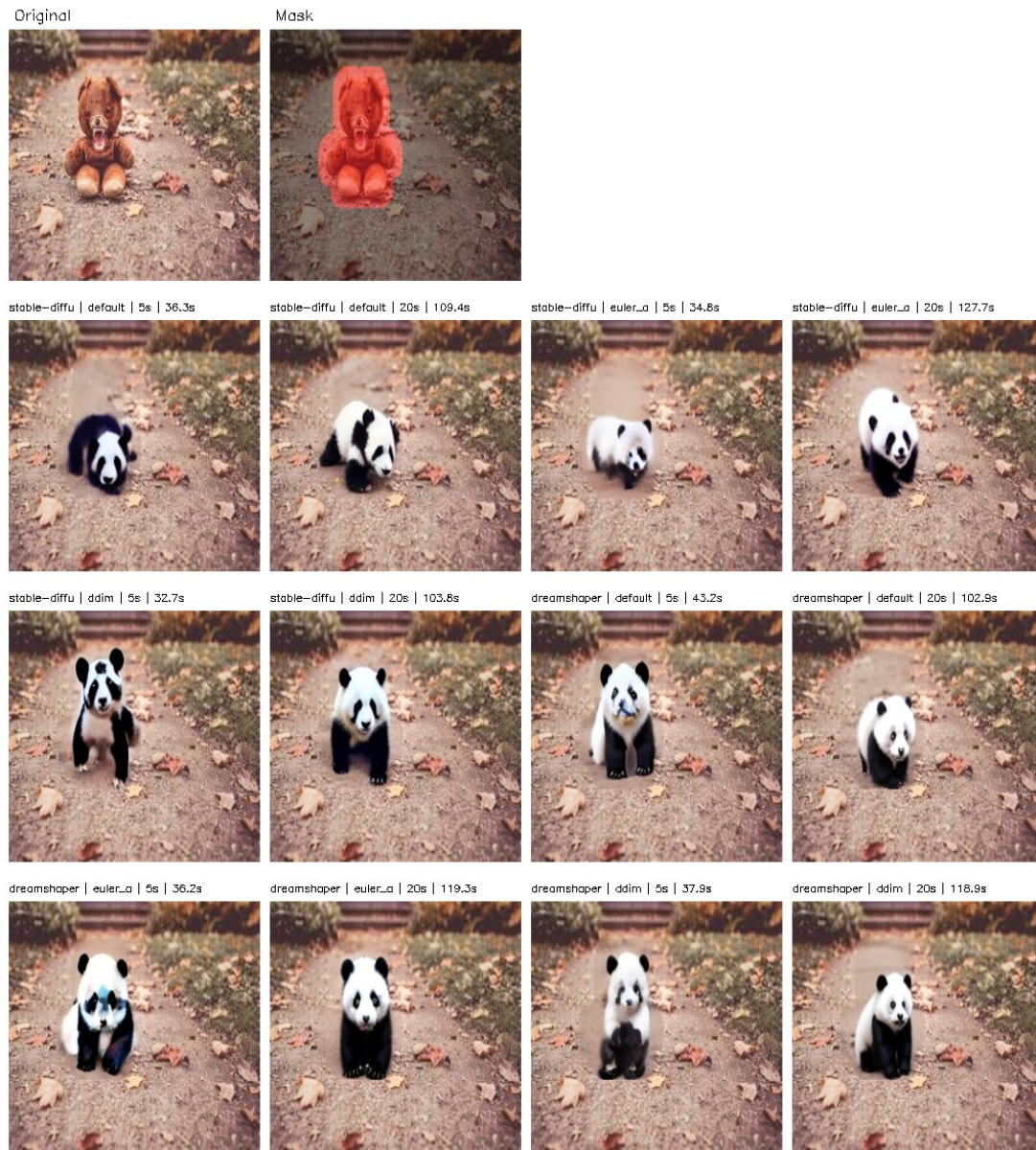


Figure 5: Outputs From Various Diffusion Models for the Prompt "A baby Panda"