# FlowLensing: Simulating Gravitational Lensing with Flow Matching

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NEURAL INFORMATION PROCESSING SYSTEMS

## Abstract

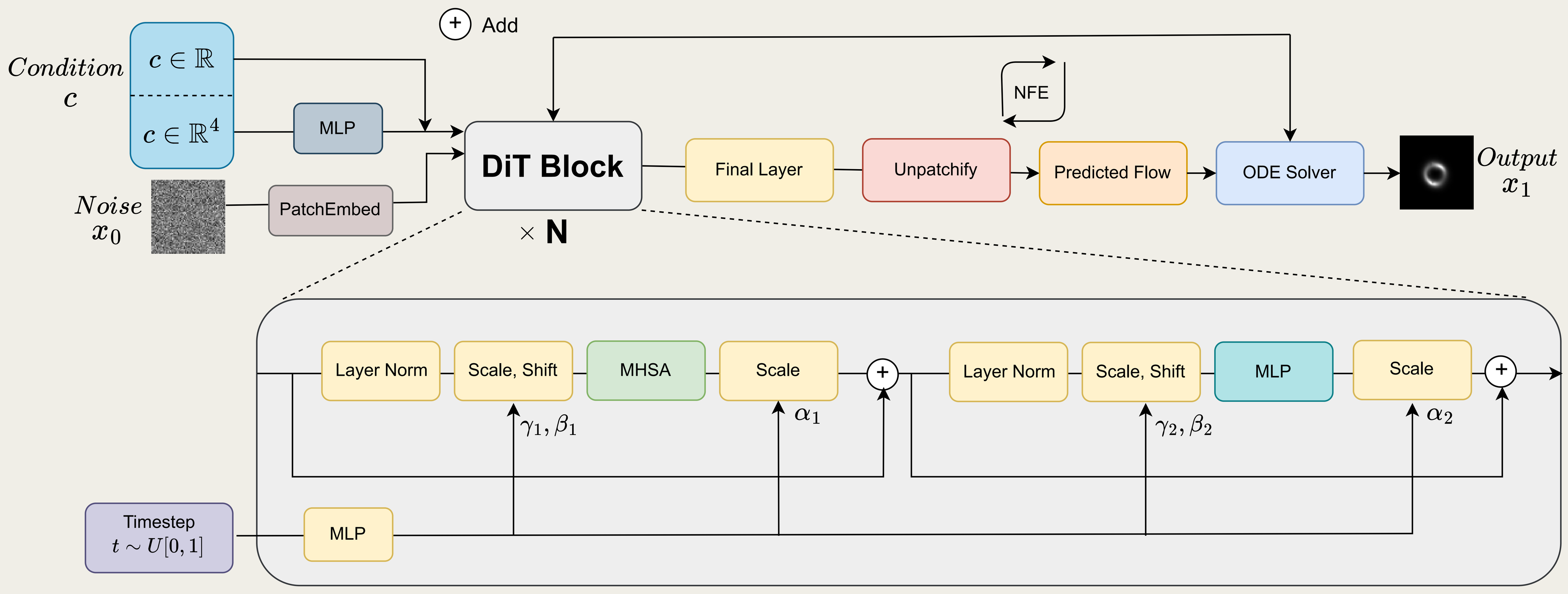



Figure 1. Overview of the FlowLensing architecture.

Gravitational lensing simulations are computationally expensive, with classical ray-tracing methods taking prohibitively long for large-scale dark matter studies. FlowLensing is a flow-matching model with Diffusion Transformer backbone that generates high-fidelity lensed images **200**× faster than traditional simulators. It handles both discrete dark matter classes and continuous lensing parameters while maintaining physical consistency critical for cosmological surveys.

## Overview

- **Background:** Gravitational lensing is a powerful probe for dark matter substructure studies. Accurate analysis requires large-scale simulations, yet traditional ray-tracing methods are prohibitively slow for statistical studies involving complex dark matter models.
- **Challenges:** Classical simulators like lenstronomy take excessive time for intensive dark matter models. Existing deep learning approaches struggle with fidelity, conditioning control, or require long sampling chains leading to slow inference.
- **Objective:** Introduce and evaluate FlowLensing, a flow-matching model with Diffusion Transformer backbone, designed to generate physically consistent lensed images from astrophysical parameters while achieving **200**× speedup over classical methods.

## Dataset

- **Dark Matter Classes (Discrete):** 89,104 simulated 64×64 grayscale lensing images across three regimes—(1) CDM without substructure, (2) CDM with truncated NFW subhalos, and (3) Axionic dark matter ($m \approx 10^{-23}$ eV) represented via vortex-like defects.
- **Lensing Parameters (Continuous):** 30,000 CDM-only images conditioned on continuous variables: Einstein radius ($\theta_E$), source coordinates $(x, y)$, and subhalo mass function slope $(\beta)$. These enable regression-based control and interpolation of physical properties.
- **Simulation Setup:** All images generated using lenstronomy, reproducing Euclid-like survey conditions. Each host lens follows a sheared isothermal ellipse profile, and each source uses a Sersic light profile. Datasets include instrumental effects, PSF convolution, and pixel noise to emulate realistic observations.
- **Normalization:** Images are preprocessed through contrast stretching, mean-centering, and rescaling to $[-1, 1]$ to stabilize transformer training, improve gradient flow, and ensure consistent dynamic range across lensing configurations.

## Methodology

FlowLensing implements a compact, diffusion-transformer–based flow matching model tailored for strong gravitational lensing simulation. Instead of iterative stochastic denoising, it learns a direct, continuous mapping from Gaussian noise to astrophysically realistic lensed images.

$$x_t = (1-t)x_0 + tx_1, \quad v^*(x_t, t) = x_1 - x_0, \tag{1}$$

where $x_0 \sim \mathcal{N}(0, I)$ and $x_1 \sim p_{\text{data}}$ are noise and real lensing samples. The model predicts the velocity field $v_\theta(x_t, t, c)$ and is trained by minimizing the mean squared error:

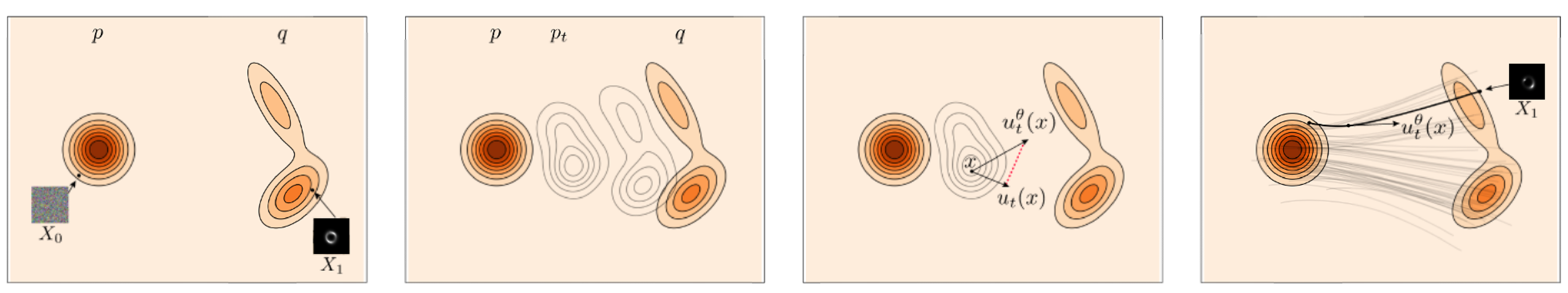
$$\mathcal{L}(\theta) = \mathbb{E}_{x_0, x_1, t, c}\left[\|v_\theta(x_t, t, c) - (x_1 - x_0)\|^2\right]. \tag{2}$$

**Conditioning:** Two conditioning modes were implemented: (i) *Discrete* — dark matter classes (CDM, Axion, NoSubstructure) embedded via a learned lookup table, and (ii) *Continuous* — lensing parameters $(\theta_E, x, y, \beta)$ projected through an MLP into the transformer's latent space. Classifier-free guidance with dropout probability $p_{\text{drop}} = 0.1$ was used for controllable generation:

$$\tilde{v}_\theta = v_\theta(x_t, t, \emptyset) + w(v_\theta(x_t, t, c) - v_\theta(x_t, t, \emptyset)), \tag{3}$$

where $w$ is the guidance scale.

**Outcome:** This setup enables physically consistent, high-fidelity image synthesis with over **200**× **speedup** compared to Lenstronomy/PyAutoLens, preserving substructure information crucial for dark matter inference.



**(a)** Data. **(b)** Path design. **(c)** Training. **(d)** Sampling.

Figure 2. Illustration of the flowmatching framework showing the continuoustrajectories between data and noisesamples. Figure adapted from Meta AI's **flow_matching** repository.

## Results & Discussion

- **Metrics:** MSE, PSNR, SSIM for image quality; FID for distribution matching; Classification AUC and Regression R² for physical consistency.
- **Baseline:** DDPM with U-Net backbone (1000 NFE steps).
- FlowLensing achieves **200**× **speedup (0.36s vs 4.8s per sample)** with superior image quality (PSNR: 68.68, SSIM: 0.9993).
- Perfect classification (AUC: 1.00) for all dark matter classes and strong parameter regression (R²: 0.833-0.945) demonstrate physical consistency.

Table 1. Reconstruction Quality

| Model | MSE | FID | Latency (s) | PSNR | SSIM |
|---|---|---|---|---|---|
| DDPM | 0.0110 | 87.31 | 4.8 | 30.78 | 0.8870 |
| **FlowLensing** | **0.0108** | **1.61** | **0.36** | **68.68** | **0.9993** |

Table 2. Downstream Evaluation (AUC / $R^2$)

| | AUC | | $R^2$ | | | |
|---|---|---|---|---|---|---|
| Class | Ours | Base | $x$ | $y$ | $\beta$ | $\theta_E$ |
| CDM | **1.00** | 0.92 | 0.945 | 0.940 | 0.833 | Const. (1.281) |
| Axion | **1.00** | 0.91 | | | | |
| No Substructure | **1.00** | 0.75 | | | | |

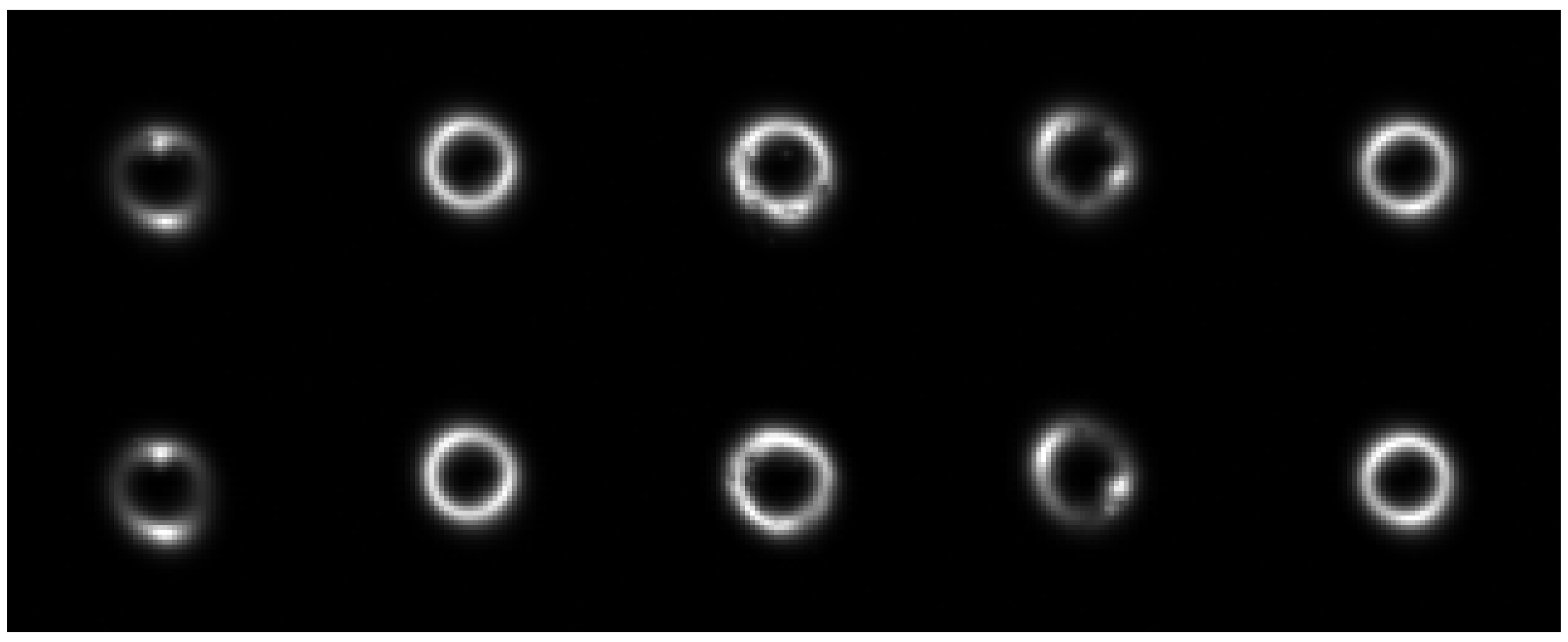


Figure 3. Comparison of real (top) and generated (bottom) images from FlowLensing, both sharing the same continuous lensing parameters.

## Conclusion

- **Summary:** FlowLensing enables scalable gravitational lensing simulation with **200**× speedup over classical methods while maintaining high fidelity and physical consistency across dark matter models.
- **Future Work:** Integrate lensing equations directly into architecture for deeper physical fidelity and benchmark against GANs and VAEs to explore generative approach trade-offs.

For more details, please refer to the full paper: **arXiv:2510.07878**

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