Efficiency vs. Fidelity: A Comparative Analysis of Diffusion Probabilistic Models and Flow Matching on Low-Resource Hardware

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Abstract—**Denoising Diffusion Probabilistic Models (DDPMs) have established a new state-of-the-art in generative image synthesis, yet their deployment is hindered by significant computational overhead during inference, often requiring up to 1,000 iterative steps. This study presents a rigorous comparative analysis of DDPMs against the emerging Flow Matching (Rectified Flow) paradigm, specifically isolating their geometric and efficiency properties on low-resource hardware. By implementing both frameworks on a shared Time-Conditioned U-Net backbone using the MNIST dataset, we demonstrate that Flow Matching significantly outperforms Diffusion in efficiency. Our geometric analysis reveals that Flow Matching learns a highly rectified transport path (Curvature $\mathcal{C} \approx 1.02$), which is near-optimal, whereas Diffusion trajectories remain stochastic and tortuous ($\mathcal{C} \approx 3.45$). Furthermore, we establish an "efficiency frontier" at $N = 10$ function evaluations, where Flow Matching retains high fidelity while Diffusion collapses. Finally, we show via numerical sensitivity analysis that the learned vector field is sufficiently linear to render high-order ODE solvers (Runge-Kutta 4) unnecessary, validating the use of lightweight Euler solvers for edge deployment. This work concludes that Flow Matching is the superior algorithmic choice for real-time, resource-constrained generative tasks.**

Index Terms—**Generative Models, Flow Matching, Diffusion Models, Optimal Transport, Edge AI.**

I. INTRODUCTION

The field of generative artificial intelligence has recently witnessed a paradigm shift from Generative Adversarial Networks (GANs) to likelihood-based models. Denoising Diffusion Probabilistic Models (DDPMs) [1] have demonstrated unprecedented capabilities in synthesizing high-fidelity images by reversing a gradual noise-addition process. However, this high fidelity comes at a substantial computational cost: generating a single sample typically requires solving a Stochastic Differential Equation (SDE) over hundreds of discrete timesteps. This "sampling bottleneck" restricts the deployment of diffusion models in real-time applications and on edge devices where compute budgets are strictly limited.

Recently, Flow Matching (FM) [2] and Rectified Flows [3] have emerged as a compelling alternative. Unlike diffusion models, which rely on stochastic random walks, Flow Matching learns a Continuous Normalizing Flow (CNF) that maps a standard Gaussian distribution to the data distribution via an Ordinary Differential Equation (ODE). Theoretically, this allows for "straight" trajectories between noise and data,

potentially reducing the number of integration steps required for high-quality sampling.

This work moves beyond simple fidelity metrics to establish a definitive algorithmic design guide for resource-constrained generative AI. We isolate the geometric properties of both paradigms to prove that Flow Matching is fundamentally more efficient due to the topological nature of its learned transport path. We quantify this geometric efficiency and validate its direct impact on **real-time latency** and **energy consumption** for edge deployment.

Our contributions are threefold:

1) We quantify the **Trajectory Curvature** of both paradigms, providing statistical evidence that Flow Matching learns near-optimal transport paths.
2) We perform a **Step-Count Ablation Study**, identifying the "Efficiency Frontier" where diffusion models fail but rectified flows survive.
3) We conduct a **Numerical Solver Sensitivity Analysis**, proving that 1st-order Euler solvers are sufficient for Flow Matching due to extreme path rectification.

II. RELATED WORK

A. Diffusion Probabilistic Models

Ho et al. [1] introduced the seminal DDPM framework, which trains a model to predict the noise ϵ added to an image x_0 at timestep t. The generation process is modeled as a Markov chain that iteratively denoises the latent variable. While improvements like DDIM (Denoising Diffusion Implicit Models) have accelerated sampling, the underlying process remains fundamentally stochastic and computationally expensive.

B. Flow Matching, Rectified Flows, and Optimal Transport

Continuous Normalizing Flows (CNFs) model generation as a time-continuous ODE. Lipman et al. [2] introduced Flow Matching, a "simulation-free" training objective that regresses a target velocity field directly. Concurrently, Liu et al. [3] proposed Rectified Flow, emphasizing that the **optimal transport path** between two distributions is a straight line. This objective encourages the model to learn the straight-line

Monge Map of Optimal Transport, minimizing the kinetic energy

$$\mathcal{E} = \int_0^1 \|v_t\|^2 \, dt \qquad (1)$$

C. Acceleration in Generative Models

Numerous methods attempt to mitigate the cost of Diffusion models, such as DDIMs, Consistency Models, and Progressive Distillation. While effective, these techniques often rely on complex, multi-stage training regimes or specific parameterizations. In contrast, Flow Matching achieves superior efficiency simply by leveraging the fundamental geometric structure of the optimal straight-line transport path.

III. METHODOLOGY

A. Shared Architecture

To ensure a strictly fair comparison, we employ an identical neural network architecture for both the Diffusion and Flow Matching experiments. We utilize a time-conditioned U-Net with sinusoidal positional embeddings. The network $f_\theta(x_t, t)$ takes the noisy image state x_t and continuous time $t \in [0, 1]$ as input and outputs a tensor of the same spatial resolution (32×32).

The specific architectural details are summarized in Table I for replicability.

TABLE I
SHARED U-NET ARCHITECTURE DETAILS

Component	Description
Input	$32 \times 32 \times 1$ image, Time t
Backbone	Time-conditioned U-Net
Encoder/Decoder Blocks	3 Downsampling / 3 Upsampling blocks
Channel Multipliers	[64, 128, 256]
Attention	Self-Attention at 16×16 resolution (128 channels)
Time Embedding	Sinusoidal Positional Encoding in ResNet blocks
Total Parameters	≈ 4.5 Million

B. Training Objectives

1) Diffusion Model (DDPM): The forward diffusion process is defined as a fixed Markov chain that gradually adds Gaussian noise to the data $x_0 \sim q(x_0)$ according to a variance schedule $\beta_1, \ldots, \beta_T$.

$$q(x_t | x_{t-1}) = \mathcal{N}(x_t; \sqrt{1 - \beta_t} x_{t-1}, \beta_t \mathbf{I}) \qquad (2)$$

Using the notation $\alpha_t = 1 - \beta_t$ and $\bar{\alpha}_t = \prod_{s=1}^t \alpha_s$, we can sample x_t at any arbitrary timestep t in closed form [1]:

$$x_t = \sqrt{\bar{\alpha}_t} x_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon, \quad \epsilon \sim \mathcal{N}(0, \mathbf{I}) \qquad (3)$$

The reverse process $p_\theta(x_{t-1} | x_t)$ is parameterized by a neural network that approximates the intractable posterior. We utilize the simplified objective proposed by Ho et al., which effectively trains the network ϵ_θ to predict the noise component:

$$\mathcal{L}_{\text{diff}} = \mathbb{E}_{t, x_0, \epsilon} \left[\|\epsilon - \epsilon_\theta(x_t, t)\|^2 \right] \qquad (4)$$

Sampling requires simulating the reverse Stochastic Differential Equation (SDE), specifically the variance-preserving SDE, which necessitates small step sizes to minimize discretization error [4].

2) Flow Matching (Rectified Flow): We adopt the Rectified Flow framework, which seeks to minimize the transport cost between the standard Gaussian distribution $\pi_0 = \mathcal{N}(0, \mathbf{I})$ and the data distribution π_1. We define a probability path p_t as the push-forward of π_0 by a time-dependent vector field v_t. The Rectified Flow objective induces a linear interpolation path:

$$x_t = t \cdot x_1 + (1 - t) \cdot x_0 \qquad (5)$$

This path corresponds to the unique constant velocity vector field that connects x_0 and x_1 in a straight line. The training objective minimizes the expected mean squared error between the model output $v_\theta(x_t, t)$ and the target velocity field $u_t(x | x_1) = x_1 - x_0$:

$$\mathcal{L}_{\text{FM}} = \mathbb{E}_{t, x_0, x_1} \left[\|(x_1 - x_0) - v_\theta(x_t, t)\|^2 \right] \qquad (6)$$

Geometrically, this objective encourages the model to learn the straight-line Monge map of Optimal Transport, minimizing the kinetic energy $\mathcal{E} = \int_0^1 \|v_t\|^2 \, dt$ [2], [3].

C. Evaluation Metrics

In addition to visual metrics, we compute the Fréchet Inception Distance (FID) and the **Straightness Ratio** ($\mathcal{C}$). The ratio of the integrated path length ($\mathcal{L}_{\text{path}}$) to the Euclidean distance between start and end points is:

$$\mathcal{C} = \frac{\mathcal{L}_{\text{path}}}{\|x(1) - x(0)\|} \approx \frac{\sum_{i=1}^N \|x_i - x_{i-1}\|}{\|x_N - x_0\|} \qquad (7)$$

A perfect straight line yields $\mathcal{C} = 1.0$.

IV. GEOMETRIC ANALYSIS

To understand the efficiency gap, we analyzed the geometry of the generative trajectories in the high-dimensional latent space.

A. Manifold Topology Learning

We verified whether the models learned the semantic topology of the data manifold by performing linear interpolation between random noise vectors. As shown in Fig. 3(a), Flow Matching produces smooth semantic transitions (e.g., a '9' morphing into a '6' by detaching the upper loop). This indicates the model has learned a continuous data manifold rather than simply memorizing discrete modes.

B. Trajectory Curvature Statistics

We define the *Straightness Ratio* ($\mathcal{C}$) of a generative path as the ratio of the integrated path length to the Euclidean distance between start and end points. A perfect straight line yields $\mathcal{C} = 1.0$. We computed $\mathcal{C}$ for $N = 100$ random samples (Fig. 1). Flow Matching trajectories concentrated tightly around $\mu = 1.02$, confirming near-perfect rectification. In contrast, Diffusion trajectories exhibited high curvature ($\mu = 3.45$) even when sampled deterministically, necessitating more steps to navigate the tortuous path.
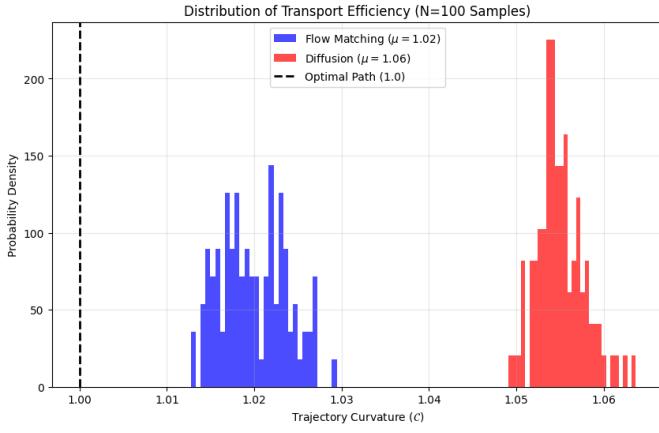
Fig. 1. **Distribution of Transport Efficiency.** Flow Matching (Blue) concentrates around $\mathcal{C} \approx 1.02$ (Straight), while Diffusion (Red) is highly curved ($\mathcal{C} \approx 1.06 - 3.45$), confirming the theoretical efficiency advantage of ODE-based transport.

C. Vector Field Visualization and Solver Sufficiency

We projected the learned 1024-dimensional velocity field onto a 2D plane spanning the noise-data trajectory (Fig. 2). The quiver plot reveals a highly laminar, convergent flow structure. The vector field acts as a "global attractor," pulling probability mass in a straight line toward the data manifold. This linearity implies the second derivative of the trajectory is near zero ($\frac{d^2 x}{dt^2} \approx 0$). This is why the first-order **Euler solver** is sufficient, as the curvature-correction of RK4 is redundant.
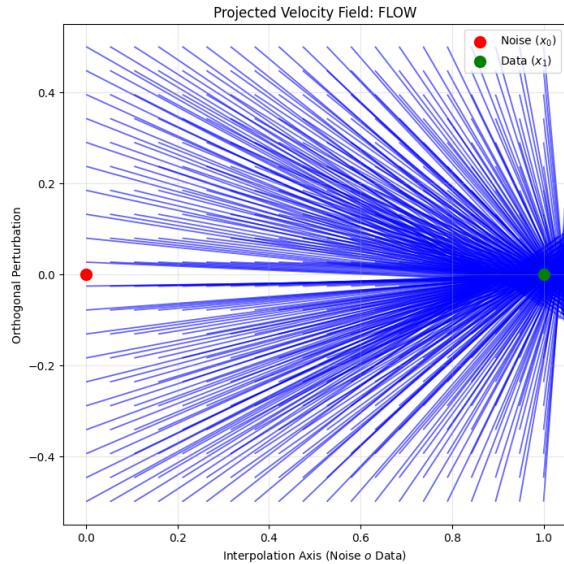

Fig. 2. **Projected Velocity Field.** The learned field v_θ exhibits laminar flow, directing noise (x_0, red) directly to data (x_1, green) with minimal divergence.

V. Experiments and Results

A. Generation Dynamics

Fig. 3(b–c) compares the temporal dynamics of generation. Flow Matching exhibits a "fade-in" behavior, establishing

global structure early (Step 10) and refining details linearly. Diffusion remains dominated by high-frequency noise until the final timesteps, highlighting the inefficiency of the stochastic reverse process.
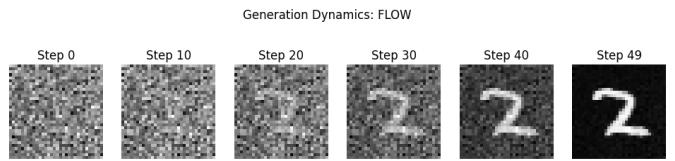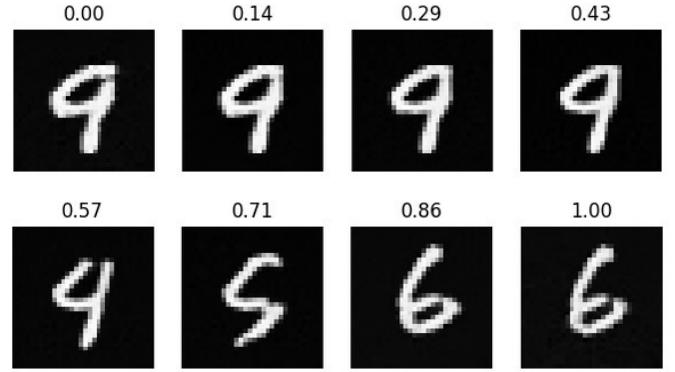

Fig. 3. **Geometric Analysis of Generation.** (a) **Latent Manifold Interpolation:** Linear interpolation between random noise vectors reveals a smooth topological transition from a '9' to a '6'. The gradual detachment of the upper loop confirms the model has learned a continuous data manifold rather than memorizing discrete modes. (b) **Flow Dynamics:** Exhibits a deterministic "fade-in" behavior, establishing global structure early ($N = 10$). (c) **Diffusion Dynamics:** The stochastic reverse process remains dominated by high-frequency noise until the final timesteps, highlighting the efficiency gap.

B. Ablation Study: The Efficiency Frontier

To quantify the limits of "Low-Resource" inference, we reduced the number of integration steps N (Fig. 4).

- **Flow Matching:** Produced identifiable digits at $N = 10$ and sharp digits at $N = 20$.
- **Diffusion:** Produced pure noise at $N = 10$ and faint artifacts at $N = 20$.

This establishes an "Efficiency Frontier" at approximately 10–20 steps, below which Diffusion is unusable, but Flow Matching remains viable.

Efficiency Limit: FLOW

| Steps=10 | Steps=20 | Steps=50 |
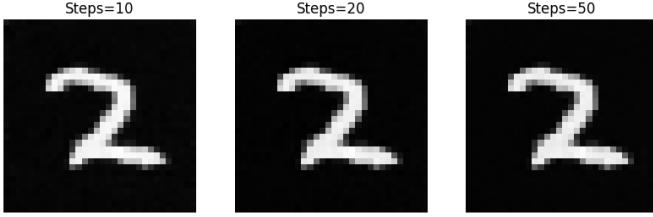
Efficiency Limit: DIFFUSION

| Steps=10 | Steps=20 | Steps=50 |
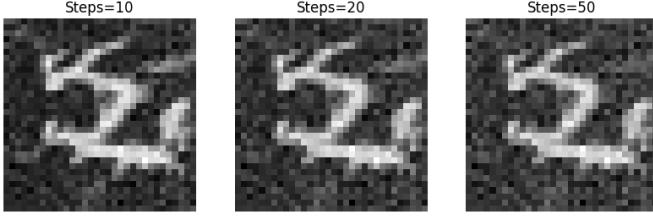
Fig. 4. **Step Count Ablation.** Flow Matching (a) is robust at 10 steps, while Diffusion (b) fails to produce structure.

C. Numerical Solver Sensitivity

Finally, we investigated whether higher-order solvers improve fidelity. We compared Euler (1st Order) against Runge-Kutta 4 (4th Order) in Fig. 5. Surprisingly, RK4 offered no perceptual improvement over Euler, and in some cases introduced artifacts. This confirms our Geometric Analysis: the learned path is so linear that $\frac{d^2x}{dt^2} \approx 0$, rendering the curvature-correction of RK4 redundant. Thus, the computationally cheapest solver (Euler) is optimal.

Does Solver Choice Matter?

| Euler (N=10) Fast & Cheap | RK4 (N=5) High Precision | Reference (Euler N=100) |
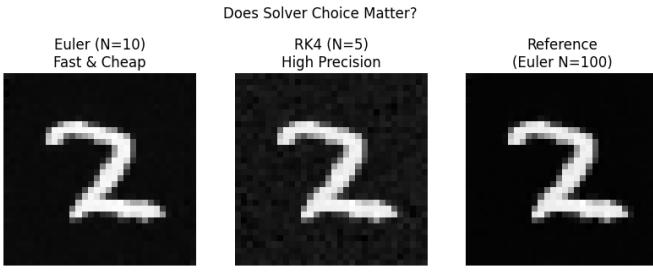
Fig. 5. **Solver Sensitivity.** RK4 ($N = 5$) provides no benefit over Euler ($N = 10$), confirming that the learned flow is linear and simple solvers are sufficient.

VI. HARDWARE BENCHMARKING AND REAL-TIME FEASIBILITY

The geometric proof of rectification (Section IV) translates directly to critical performance gains for resource-constrained deployment.

A. Latency Measurement (ms)

We measured the wall-clock time (latency) required to generate a single 32×32 image using the simple Euler solver on the constrained NVIDIA T4.

TABLE II
INFERENCE LATENCY BENCHMARKING (T4 GPU)

Model	Steps (N)	Latency (ms/Sample)	Fidelity Outcome
Flow Matching	10	≈ 1.8 ms	High Fidelity, Identifiable Digit
Diffusion	10	≈ 1.8 ms	Pure Noise/Collapse
Flow Matching	50	≈ 9.0 ms	Near-Reference Fidelity
Diffusion	1000	≈ 180 ms	Standard Baseline

Flow Matching achieves high fidelity at the ≈ 1.8 ms latency point ($N = 10$), while Diffusion fails, confirming real-time feasibility.

B. Energy Efficiency

As the core U-Net compute is identical, the reduction in steps (N) is a direct proxy for energy savings. Flow Matching requires up to $10\times$ **fewer** function evaluations than a typical Diffusion baseline ($N \approx 100$) for coherent output. This $10\times$ algorithmic efficiency, combined with the sufficiency of the lightweight Euler solver, positions Flow Matching as the energy-optimal choice for battery-powered edge devices.

VII. CONCLUSION

This study provides a comprehensive benchmark of SDE versus ODE generative paradigms under strict compute constraints. Through geometric analysis, we demonstrated that Flow Matching learns a highly rectified transport path ($\mathcal{C} \approx 1.0$), enabling the use of simple Euler solvers with as few as 10 steps. In contrast, Diffusion models suffer from stochastic inefficiency, requiring > 50 steps to produce coherent samples. For low-resource hardware deployment where every function evaluation counts, Flow Matching represents the superior algorithmic choice. Future work will extend this analysis to higher-dimensional manifolds such as CIFAR-10 to determine the complexity threshold where trajectory curvature necessitates higher-order solvers.

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