



Synthesize Privacy-Preserving High-Resolution Images via Private Textual Intermediaries







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Main Result

We introduce SPTI, a training-free yet effective pipeline to synthesize high resolution images under differential private constraints.

- SPTI uses text modality as intermediaries: Our pipeline uses text to generate key information for image modality under DP constraints;
- SPTI performs well: delivering superior performance over traditional PE method;
- SPTI is easy to extend: our method can extended to other modality like sound, etc.

Algorithm 1 SPTI: Privately Synthesize High-Resolution Images via Private Text Intermediaries

Require: Private image dataset D, Aug_PE, Aug_PE_Image_Voting, text_voting **Ensure:** Synthetic images \mathcal{D}'

- : if text voting = true then
- Convert images $\mathcal D$ to text descriptions $\mathcal T$ via a captioning model
- Apply Private Evolution on text: $T' = Aug_PE(T)$
- Apply Private Evolution with image-voting: $T' = Aug_PE_Image_Voting(D)$
- 6: end if
- 7: Generate synthetic images \mathcal{D}' from \mathcal{T}' using a text-to-image diffusion model 8: return \mathcal{D}'

Overview of the Synthesis via Private Textual Intermediaries (SPTI) framework

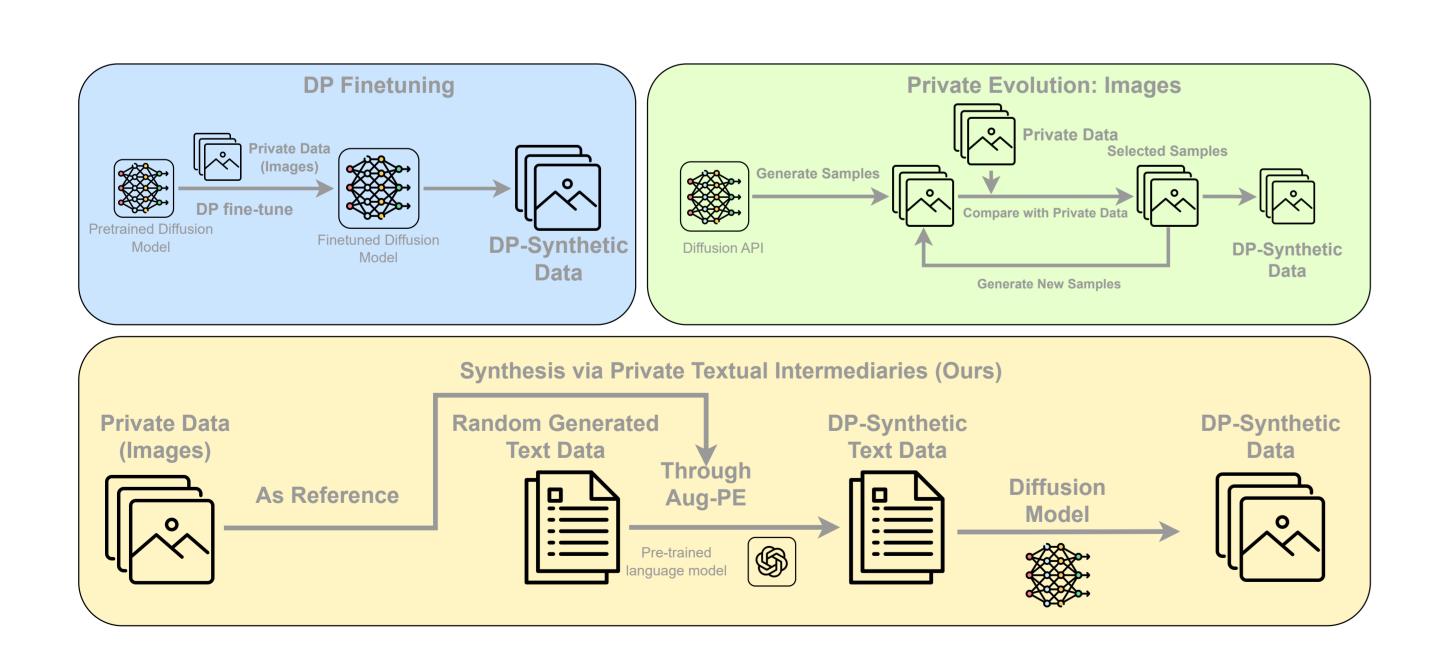


Figure 1. Top-left: DP-finetune method. Top-right: Private Evolution (PE) on images. Bottom: SPTI. Private image data is served as reference. A modified Augmented Private Evolution (Aug-PE) method is then applied to synthesize DP text data, which is subsequently transformed into DP synthetic images using a diffusion model API.

Privacy Analysis

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SPTI ensures differential privacy by restricting all private-data access to the Private Evolution module (Aug_PE / Aug_PE_Image_Voting). This module uses private image embeddings only to guide voting over text candidates.

Voting Mechanism

Each private embedding votes for its nearest generated image, forming a histogram H. Adding Gaussian noise $\mathcal{N}(0, \sigma^2 \mathbf{I})$ to H applies the Gaussian mechanism.

DP Guarantee

The histogram has L_2 sensitivity 1. With Gaussian noise of variance σ^2 applied for G iterations, SPTI satisfies (ε, δ) -DP whenever:

$$\Phi\left(\frac{\sqrt{G}}{2\sigma} - \frac{\varepsilon\sigma}{\sqrt{G}}\right) - e^{\varepsilon}\Phi\left(-\frac{\sqrt{G}}{2\sigma} - \frac{\varepsilon\sigma}{\sqrt{G}}\right) \le \delta.$$

Post-Processing

All later steps—text mutation and diffusion-based image generation—use only the privatized histogram. By post-processing immunity, they add no privacy cost.

Performance of *SPTI*

		$\varepsilon=10$	arepsilon=5 $arepsilon=1$
LSUN Bedroom	SPTI (ours)	25.88	25.87 26.39
	PE image	41.72	41.08 40.36
	DP-finetune	31.28	31.34 31.76
European Art	SPTI (ours)	41.42	42.71 57.64
	PE image	76.25	74.41 76.50
	DP-finetune	61.10	61.82 63.97
Wave-ui-25k	SPTI (ours)	20.16	22.53 35.18
	PE image	39.28	48.95 50.45
	DP-finetune	49.84	52.09 62.08

Table 1. FID values (lower is better) across multiple datasets to compare three different DP methods: SPTI, PE Image, and DP-finetune.

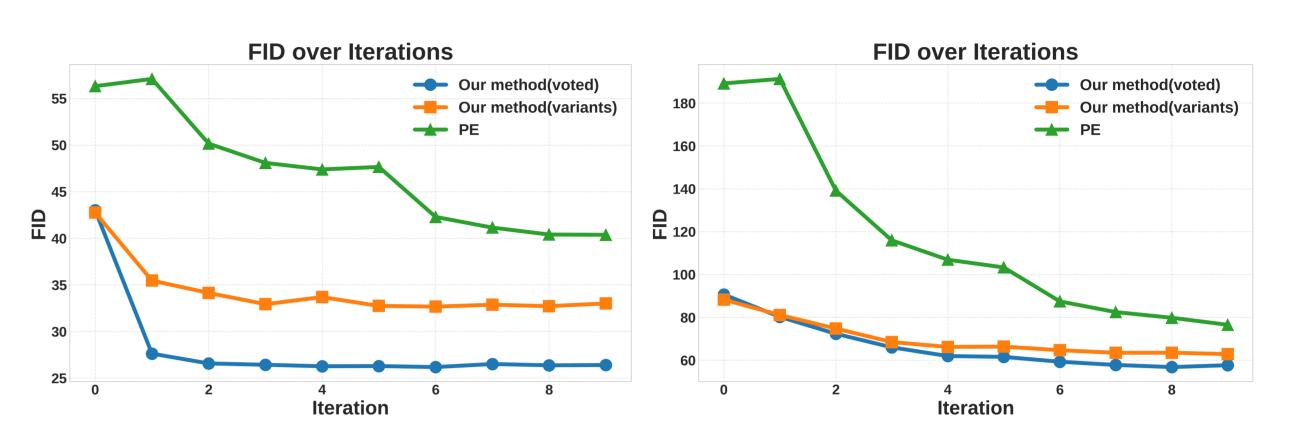


Figure 2. (FID lower is better). Quality of synthesized image samples in each iteration.

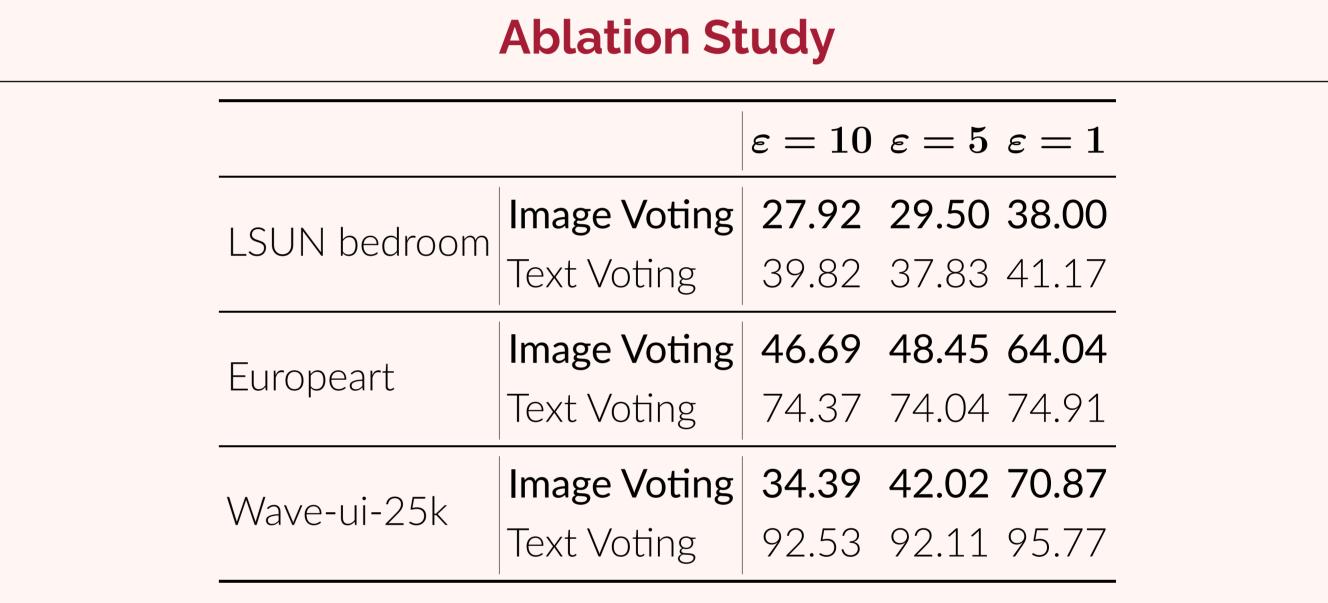


Table 2. FID values (lower is better) across multiple datasets to compare the SPTI method with Image Voting and that with Text Voting.

	SDXL-Turbo	SDXL-base-1.0	Infinity
Meta-Llama-3-8B-Instruct	26.71	25.42	30.66
qwen-plus	26.65	24.44	31.28

Table 3. FID (lower is better) on LSUN Bedroom with $\epsilon = 1.0$, tested using different LLM and diffusion APIs.

Downstream Task

We also validate the quality of generated images in downstream tasks. To be more specific, we test the classification accuracy on CelebA dataset using WRN-40-4 model.



Figure 3. Left: samples generated by SPTI. Right: samples generated by PE method.