# RDDPM: Robust Denoising Diffusion Probabilistic Model for Unsupervised Anomaly Segmentation

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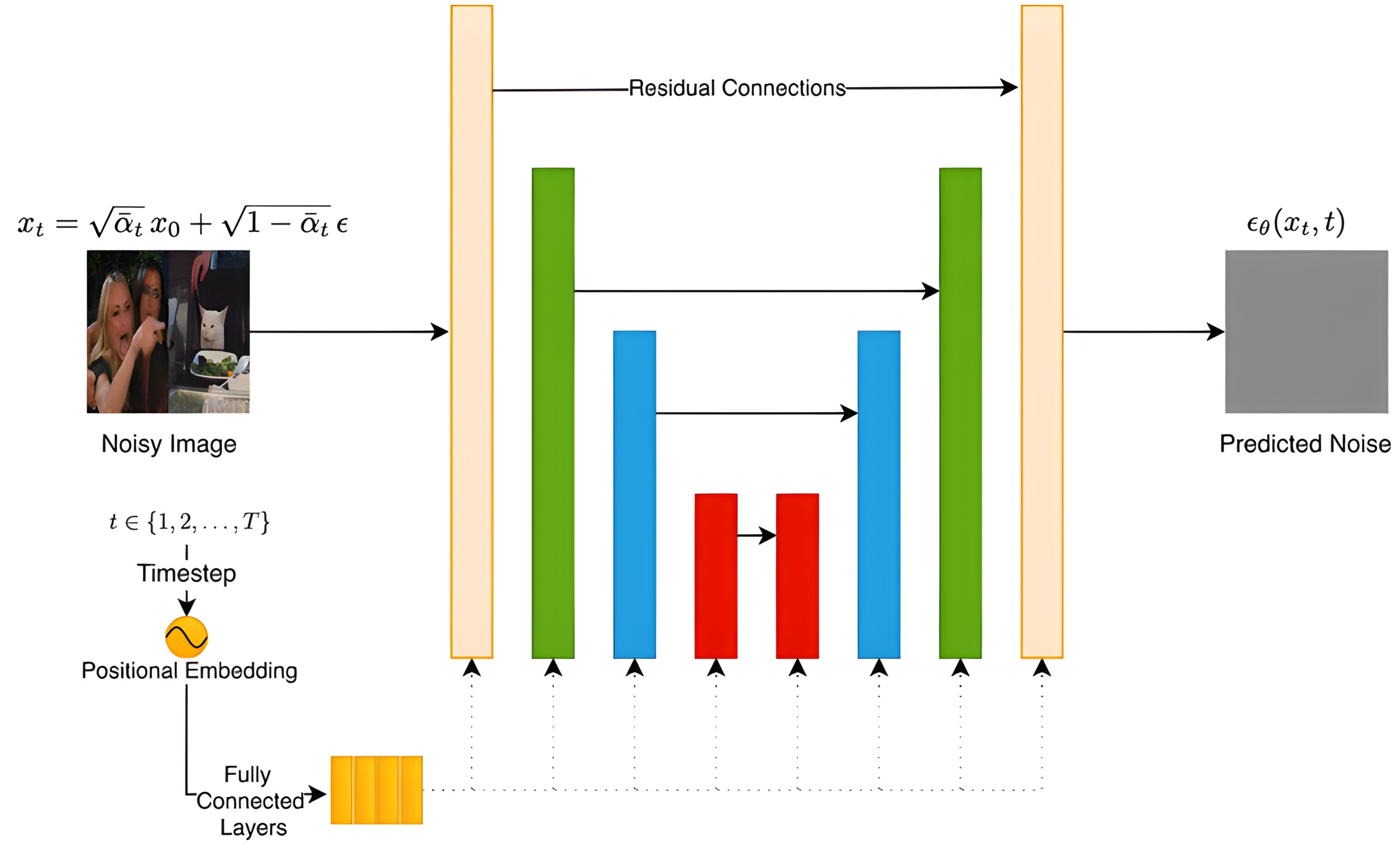
## DDPM as a nonlinear regression

- Learning the backward diffusion process can be interpreted as noise prediction.
- Training can be viewed as a nonlinear regression between U-Net input and output with an effectively infinite number of training pairs.
- The MSE loss used in training is sensitive to outliers.

$$p_\theta(x_{t-1} \mid x_t) = \mathcal{N}(x_t; \mu(x_t, t), \Sigma(x_t, t))$$


$$q(x_t \mid x_{t-1}) = \mathcal{N}\left(x_t; \sqrt{1-\beta_t}x_{t-1}, \beta_t \mathbf{I}\right)$$




## Robust diffusion models

- Instead of MSE loss, we use robust losses to improve generation and anomaly detection performance.
- Least Trimmed Squares (LTS) loss: in each batch, we select the top s samples with the lowest MSE loss.
- Huber loss: for large residuals, we use a linear penalty instead of a quadratic one.

### RDDPM-LTS

**while** Not converged **do**
 $x_0 \sim q(x_0)$
 $t \sim \text{Uniform}(\{1, \ldots, T\})$
 $\epsilon \sim \mathcal{N}(0, I)$
 Take gradient descent step on

$$\nabla_\theta \,\text{Huber}_\delta\left(\epsilon - \epsilon_\theta\left(\sqrt{\bar\alpha_t}x_0 + \sqrt{1-\bar\alpha_t}\epsilon, t\right)\right)$$

$$\text{where} \quad \text{Huber}_\delta(r) = \begin{cases} \frac{1}{2}r^2 & \text{if } |r| \le \delta \\ \delta\left(|r| - \frac{1}{2}\delta\right) & \text{if } |r| > \delta \end{cases}$$

**end while**

### RDDPM-Huber

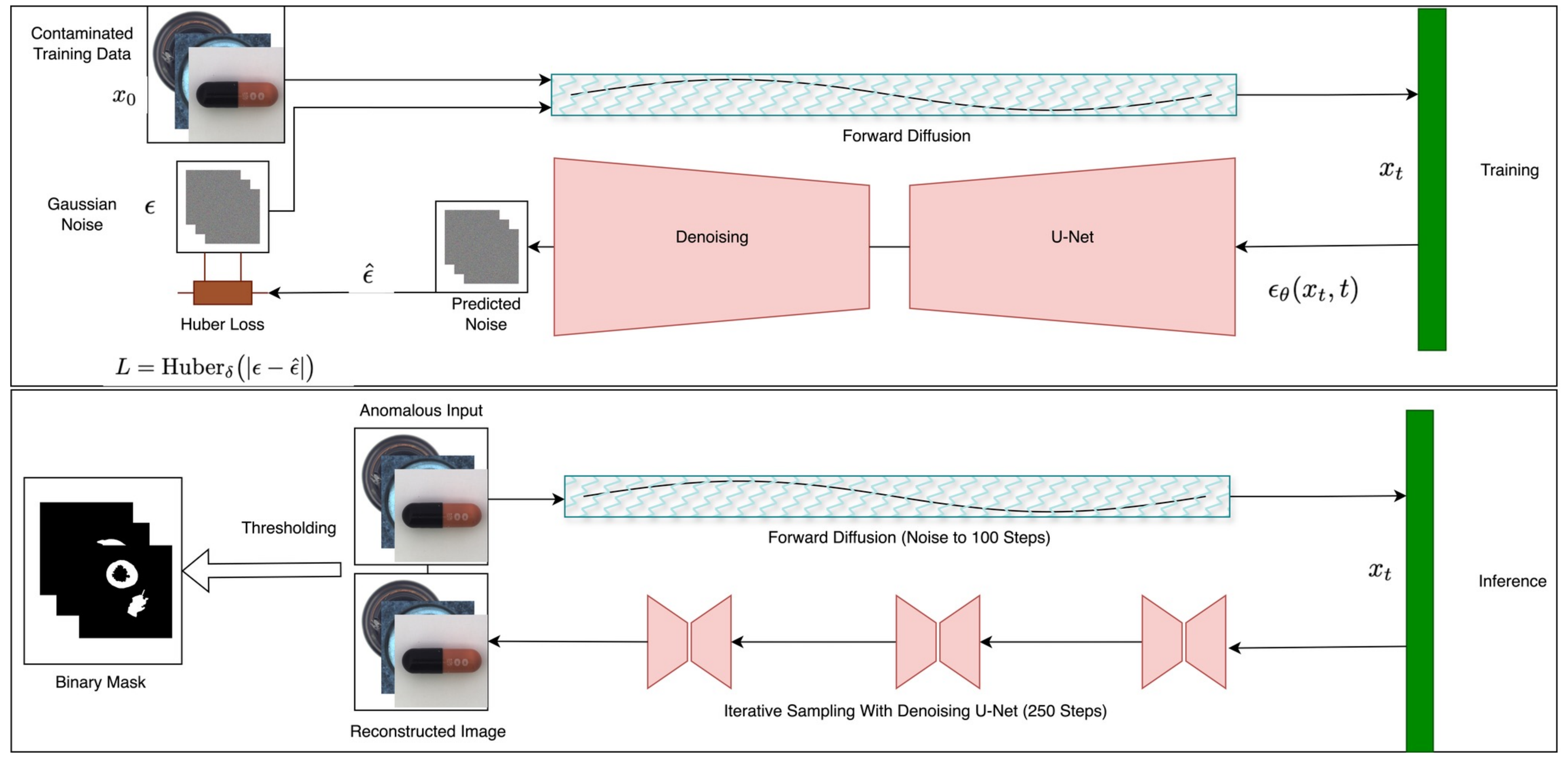
**while** Not converged **do**
 $x_0 \sim q(x_0)$
 $t \sim \text{Uniform}(\{1, \ldots, T\})$
 $\epsilon \sim \mathcal{N}(0, I)$
 Take gradient descent step on

$$\nabla_\theta LTS(\|\epsilon - \epsilon_\theta\left(\sqrt{\bar\alpha_t}x_0 + \sqrt{1-\bar\alpha_t}\epsilon, t\right)\|^2)$$

$$= \sum_{i=1}^{s=\lambda\times B} \nabla_\theta \left\|\epsilon_i - \epsilon_\theta\left(\sqrt{\bar\alpha_{t_i}}x_{0_i} + \sqrt{1-\bar\alpha_{t_i}}\epsilon_i, t_i\right)\right\|^2$$

Where $s \in \{1, \ldots, B\}$ and $\lambda \in (0, 1]$

**end while**




## Performance

| MVTec-Grid | AUROC | AUPRC | MSE |
|---|---|---|---|
| RDDPM | **0.6373** | **0.1803** | 0.0896 |
| AnoDDPM | 0.4734 | 0.0121 | 0.2188 |
| DiffusionAD | 0.5565 | 0.0766 | **0.0863** |

| MVTec-Carpet | AUROC | AUPRC | MSE |
|---|---|---|---|
| RDDPM | **0.5673** | **0.0362** | 0.1246 |
| AnoDDPM | 0.4650 | 0.0234 | 0.2115 |
| DiffusionAD | 0.4909 | 0.0268 | **0.1199** |

| MVTec | AUROC-ID | AUROC-OOD |
|---|---|---|
| RDDPM | **0.78** | **0.71** |
| DDPM | 0.76 | 0.69 |

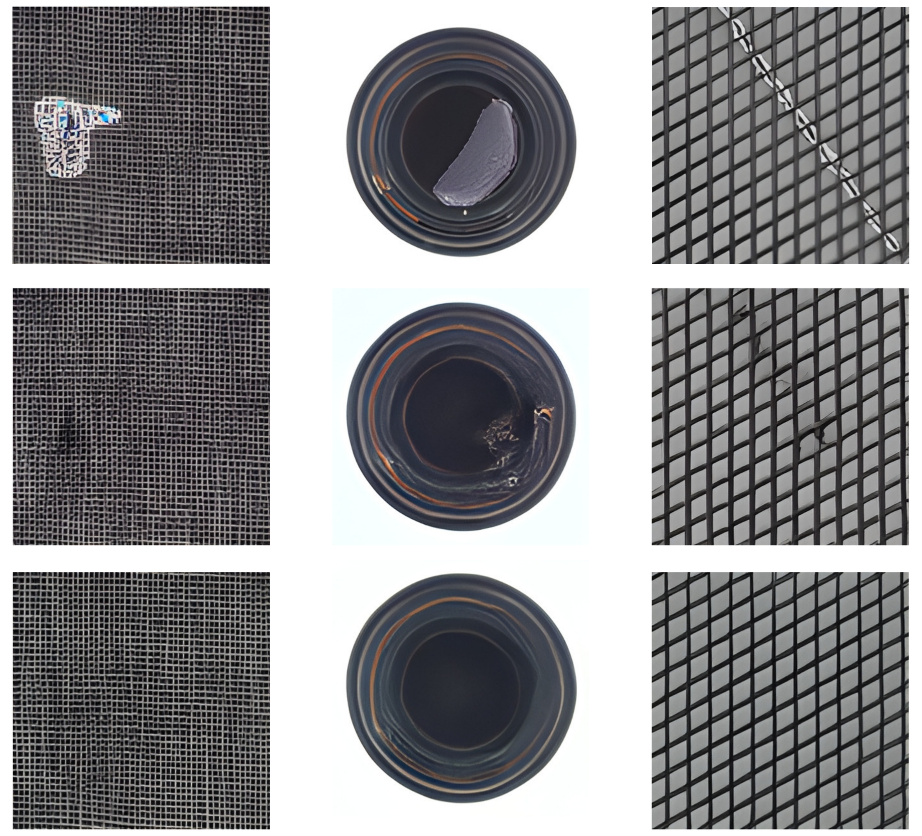
## Example reconstructions by DDPM and RDDPM-Huber

- RDDPM-Huber has cleaner reconstructions when trained under 20% contamination.

**Anomalous**

**DDPM**

**RDDPM -Huber**



**Paper**