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Text-to-Image Generation Using CLIP-Conditioned Diffusion Models with Classifier-Free Guidance

A project submitted as partial fulfillment of the requirements for the M.Sc. degree
in Computer Science

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Abstract

We developed a text-to-image generation model based on Stable Diffusion, a diffusion-based generative framework that synthesizes images by iteratively refining random noise into coherent visual content.

The model utilizes CLIP embeddings as the text conditioning mechanism, enabling alignment between textual descriptions and generated images. Our approach operates in latent space for computational efficiency while leveraging the inherent stability and robustness of the diffusion process. We demonstrate that our method substantially outperforms existing GAN-based approaches, particularly in comparison with Creative Adversarial Networks (CAN) that employ the Deep Interactive Evolution (DeepIE) methodology for user-guided art generation. Our findings establish diffusion-based models as a superior paradigm for text-conditioned image synthesis, offering enhanced stability, sample quality, and quantitative evaluation metrics compared to adversarial approaches.

1 Introduction

Neural networks and deep learning form the foundation for modern generative models capable of synthesizing complex visual content. Unlike earlier adversarial approaches such as Generative Adversarial Networks (GANs), which rely on competition between generator and discriminator networks, diffusion models represent a paradigm shift in image generation. Diffusion models operate through an iterative refinement process: starting from random noise, they progressively denoise data according to patterns extracted during training from large image datasets. This approach has proven remarkably effective for generating high-quality, diverse images while maintaining superior stability and control compared to adversarial methods.

Stable Diffusion is a state-of-the-art diffusion-based generative model that synthesizes images through iterative noise reduction (see Figure 1). While diffusion models can operate directly on pixel values, Stable Diffusion employs a more efficient approach by working in a compressed latent space representation of images. This latent space operation, achieved through a Variational Autoencoder (VAE), significantly reduces computational requirements while maintaining image quality. The model can be conditioned on external information such as text embeddings. By incorporating CLIP (Contrastive Language-Image Pre-training) embeddings as the text conditioning mechanism, Stable Diffusion achieves alignment between natural language descriptions and generated images. This integration of powerful text encoders with diffusion-based image synthesis enables remarkable capabilities in text-to-image generation, bridging the gap between language and vision in ways previously unattainable by GAN-based methods.

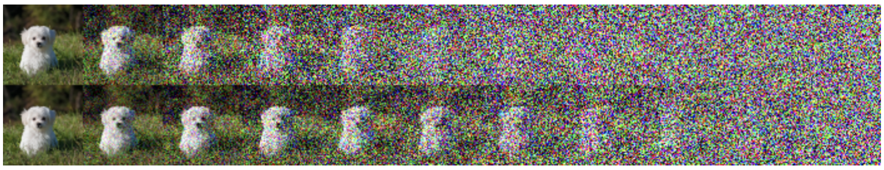

Figure 1: The iterative denoising process in diffusion models: starting from random noise, the model progressively refines the image through multiple steps.

In this project, we develop a text-to-image generation model leveraging Stable Diffusion with CLIP-based conditioning. Our implementation demonstrates substantial performance improvements over existing GAN-based approaches. The superior performance of diffusion models stems from their inherent stability, superior sample quality, and greater flexibility in conditioning mechanisms. We explore these advantages through comprehensive experiments using established evaluation metrics and comparative analysis, establishing diffusion models as a superior alternative to adversarial methods for text-conditioned image synthesis.

[TODO: Revise the following paragraph]

The paper is structured as follows: Section 2 reviews related work and existing approaches in generative modeling. Section **??** provides a detailed description of our Stable Diffusion architecture, CLIP conditioning mechanism, and training approach. Section **??** presents our experimental setup and training protocol. Section 4 presents the results of our experiments and comparative analysis with GAN-based methods. Finally, Section **??** discusses the implications of our findings, the advantages of diffusion-based models, and directions for future work.

2 Related Work

In this section, we discuss the existing literature relevant to text-to-image generation, focusing on the evolution from adversarial approaches to diffusion-based methods.

2.1 Generative Adversarial Networks for Image Generation

Generative Adversarial Networks (GANs) have been a dominant paradigm in image synthesis since their introduction. GANs consist of two competing neural networks—a generator that creates synthetic samples and a discriminator that classifies samples as real or fake. Through adversarial training, the generator learns to produce increasingly realistic images that can fool the discriminator.

TODO: Revise this subsection

2.2 Creative Adversarial Networks and Interactive Evolution

Creative Adversarial Networks (CAN) extend the GAN framework specifically for artistic image generation [**?**]. The Deep Interactive Evolution (DeepIE) approach combines CAN with evolutionary algorithms to enable user-guided art creation. This methodology, trained on the WikiArt dataset, allows users to interactively guide the generation process through iterative selection and refinement.

While the original CAN research provides foundational insights into artistic image generation, some implementations and extensions of this work lack rigorous quantitative evaluation. Notably, recent papers employing CAN-DeepIE do not employ standard generative model evaluation metrics such as CLIP Score, Fréchet Inception Distance (FID), Inception Score (IS), or conduct human perceptual surveys to assess output quality. Additionally, the generated samples from these implementations are often of limited visual quality. Our work addresses these significant gaps by leveraging diffusion models with comprehensive evaluation metrics and demonstrating substantially superior visual quality and quantitative performance.

2.3 Diffusion Models for Image Synthesis

Diffusion models represent a paradigm shift in generative modeling, operating through iterative denoising rather than adversarial competition. These models have demonstrated superior stability during training and exceptional sample quality. Unlike GANs, which can suffer from mode collapse and training instability, diffusion models provide more reliable convergence and greater control over the generation process.

2.4 Text-Conditioned Image Generation

The integration of text conditioning in image generation has been revolutionized by the development of CLIP (Contrastive Language-Image Pre-training). CLIP embeddings provide a powerful semantic bridge between natural language descriptions and visual content, enabling text-to-image models to generate images that align with textual prompts. This capability represents a significant advancement over earlier methods that lacked robust text understanding.

2.5 Gaps and Contributions

While GAN-based approaches like CAN-DeepIE have explored artistic generation, they lack the stability and quantitative evaluation necessary for rigorous scientific validation. Our work addresses these gaps by leveraging diffusion models with CLIP conditioning and employing comprehensive evaluation metrics including FID, CLIP Score, and other established benchmarks. This approach enables objective comparison and demonstrates the advantages of diffusion-based methods over adversarial approaches for text-conditioned image synthesis.

3 Experiments

3.1 Experimental Setup

3.1.1 Hardware Environment

- **Environment:** HPC cluster with GPU nodes (specifications vary by node type)
- **Cluster resources (node available):**
  - **CPU**: Intel Xeon Gold 6330 (56 cores @ 2.00 GHz)
  - **GPUs**: 8x NVIDIA A100 80GB PCIe (80GB VRAM)

    - **Memory (RAM)**: Node total 256 GB
- **Requested resources (SLURM allocation used for experiments):**
    - **CPUs**: 4 logical cores requested via ‘–cpus-per-task=4‘ (experiments used 4 cores)
    - **Memory**: 32 GB requested via ‘–mem=32G‘
    - **GPUs**: 1 GPU (NVIDIA A100) requested via ‘–gres=gpu:1‘

3.1.2 Software Environment

- **CUDA:** Version 11.8
- **Python:** 3.10.19 (in different experiments I used 3.11 as well)
- **Deep Learning Framework:** PyTorch 2.7.1+cu118

3.1.3 Distributed Training Considerations

Although the HPC environment supports multi-GPU and multi-node jobs, distributed training via SLURM proved unreliable in practice due to recurring configuration and environment issues. Additionally, distributed training with Python scripts requires external experiment tracking tools (e.g., MLflow) to monitor training progress, involving significant setup overhead: configuring image logging, artifact storage locations, and experiment tracking infrastructure. In contrast, Jupyter notebooks provide immediate visual feedback on training progress, loss curves, and generated samples without additional tooling. To keep the study focused and reproducible with minimal overhead, all experiments were conducted on a single NVIDIA A100 80GB GPU using Jupyter notebooks. Future work may revisit distributed training using a non-interactive script and a unified environment submitted as SLURM batch jobs, with proper experiment tracking infrastructure in place.

3.2 MNIST Text-to-Image Generation with Classifier-Free Guidance

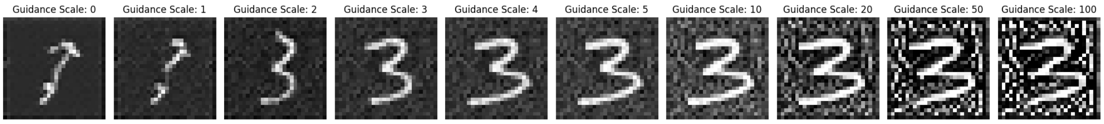

Figure 2: Generated images for prompt ”A handwritten digit 3” across different guidance scales. Higher guidance scales produce sharper, more confident outputs with stronger adherence to the text prompt.

3.2.1 Objective

This experiment tests the fundamental principles of text-to-image generation using a diffusion-based architecture. By training on MNIST handwritten digits as a minimal-scale dataset, we investigate how the stable diffusion model handles image synthesis from text prompts and systematically evaluate the impact of Classifier-Free Guidance (CFG) on generation quality and text-image alignment.

3.2.2 Model Architecture

Text Encoder (Frozen):

- **Model:** CLIP (openai/clip-vit-base-patch32)
- **Embedding dimension:** 512
- **Tokenizer max length:** 8 tokens (reduced from default 77)[1]

[1] Prompts are tokenized then padded or truncated to exactly 8 tokens. This keeps shapes fixed (batch, 8, 512) for CLIP embeddings and reduces unnecessary padding/compute versus the 77-token default. Longer prompts would be clipped beyond 8 tokens, which is acceptable here because prompts are intentionally short (e.g., ”A handwritten digit 5”).

- **Training:** Weights are frozen

Denoising Network (U-Net):

The key design choice in the U-Net architecture is to train directly in pixel space without a VAE, which is viable for MNIST's low resolution (28×28).

- **Architecture:** Custom UNet2DConditionModel
- **Input/Output:** 1 channel (grayscale), 28×28 pixels
- **Block channels:** (32, 64, 64, 32)
- **Layers per block:** 2
- **Down blocks:** DownBlock2D → CrossAttnDownBlock2D → CrossAttnDownBlock2D → DownBlock2D
- **Up blocks:** UpBlock2D → CrossAttnUpBlock2D → CrossAttnUpBlock2D → UpBlock2D
- **Cross-attention dimension:** 512 (matches CLIP embedding size)
- **Total trainable parameters:** 3,140,385

3.2.3 Dataset

MNIST Handwritten Digits:

- **Training images:** 60,000
- **Resolution:** 28×28 pixels, grayscale
- **Classes:** 10 digit classes (0-9)
- **Text captions:** Automatically generated as "A handwritten digit {label}" (e.g., "A handwritten digit 5")
- **Preprocessing:** Conversion to tensors with values normalized to [0, 1]

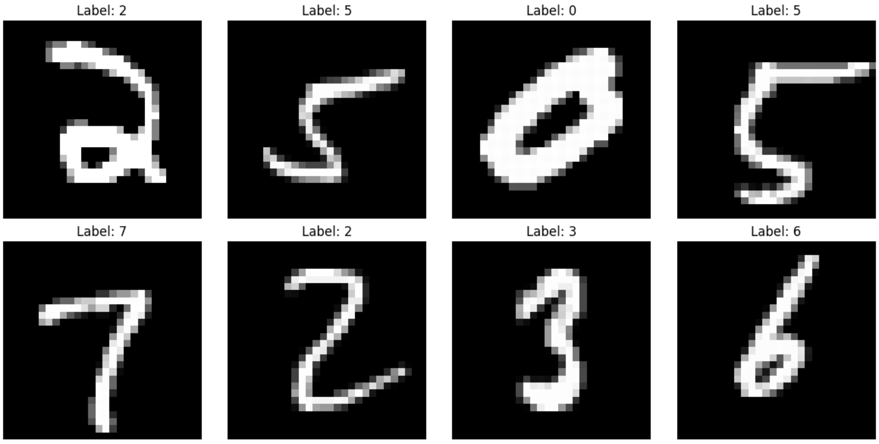

Figure 3: Sample images from MNIST training dataset showing handwritten digits (0-9) with corresponding class labels.

3.2.4 Training Configuration

- **Batch size:** 512
- **Learning rate:** 10^{-3}
- **Optimizer:** AdamW
- **Epochs:** 1 (initial validation), then 5 (extended training), and finally 20 epochs for final model
- **Noise scheduler:** DDPM with squared cosine beta schedule
- **Timesteps:** 1,000
- **Loss function:** Mean Squared Error (MSE) between predicted and actual noise

Training Pipeline per Batch:

1. Convert digit labels to text captions using CLIP tokenizer
2. Encode captions to semantic embeddings via frozen CLIP text encoder [batch, 8, 512]
3. Sample random timestep $t \sim \text{Uniform}(0, 1000)$ for each image
4. Add Gaussian noise to images: $x_t = \sqrt{\bar{\alpha}_t} x_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon$
5. Predict noise: $\epsilon_\theta(x_t, t, c_{\text{text}})$ using UNet with cross-attention conditioning
6. Calculate MSE loss: $\mathcal{L} = \|\epsilon - \epsilon_\theta(x_t, t, c_{\text{text}})\|^2$
7. Backpropagate and update UNet parameters only (CLIP remains frozen)

Monitoring:

- Loss tracking every 25 steps
- Final epoch loss reporting
- Visual inspection of generated samples

3.2.5 Inference and Classifier-Free Guidance

Basic Sampling (Without CFG):

- Initialize random noise tensor: $x_T \sim \mathcal{N}(0, I)$
- Encode text prompt via CLIP
- Iteratively denoise for 50 steps using DDPM scheduler
- Post-process: normalize output to [0, 255] for visualization

Classifier-Free Guidance (CFG):

CFG enables stronger text conditioning by computing both conditional and unconditional predictions:

1. **Dual embeddings:**
   - Conditional: Text prompt → CLIP embedding c_{text}
   - Unconditional: Empty string ”” → CLIP embedding c_{null}
2. **Guidance formula:**

   $$\epsilon_{\text{guided}} = \epsilon_\theta(x_t, t, c_{\text{null}}) + w \cdot (\epsilon_\theta(x_t, t, c_{\text{text}}) - \epsilon_\theta(x_t, t, c_{\text{null}}))$$

   where w is the guidance scale.
3. **Effect:** Higher w → stronger adherence to text prompt

Inference Parameters:

- **Scheduler:** DDPM with squared cosine schedule
- **Number of inference steps:** 50
- **Random seed:** 422 (for reproducibility)
- **Guidance scales tested:** $w \in \{0, 5, 10, 20, 50, 100\}$

3.2.6 Results

Figure 4 presents a comprehensive evaluation of the model’s generation capabilities across all digit classes and various guidance scales. This systematic comparison demonstrates how the guidance scale parameter w influences both image quality and text-prompt adherence across different digit classes.

Extended Training Results:

To evaluate the impact of extended training, we trained the model for 20 epochs and regenerated samples across all digit classes. Figure 5 shows the improved generation quality achieved with extended training, demonstrating better convergence and more consistent digit generation across all classes.

3.2.7 Guidance-Scale (w) Ablation Study

We systematically evaluated the impact of guidance scale on generation quality:

Tested Guidance Scales:

- $w = 0$: Unconditional generation (no text guidance)
- $w = 5$: Weak guidance
- $w = 10$: Moderate guidance
- $w = 20$: Strong guidance
- $w = 50$: Very strong guidance
- $w = 100$: Maximum guidance

Evaluation Protocol:

1. Generate images with fixed prompt: ”A handwritten digit {0-9}”
2. Use fixed random seed (422) set within the generation function, ensuring consistent initial noise for each guidance scale comparison
3. Apply 50 denoising steps per image
4. Qualitatively assess:
    - Image clarity and sharpness
    - Adherence to text prompt (correct digit class)
    - Presence of artifacts or distortions
    - Overall sample quality

Expected Results:

- $w = 0$: Random digit generation (unconditional)
- $w = 5$-10: Balanced quality and prompt following
- $w = 20$-50: Strong prompt adherence with sharp outputs
- $w = 100$: Potential over-saturation and artifacts

3.2.8 Visualization

Generated images displayed using matplotlib with:

- Grayscale colormap
- Grid layout for guidance scale comparison (1 row × 6 columns)
- Individual subplot titles showing guidance scale values
- Tight layout to prevent overlap

4 Results

This section presents the results from training text-conditioned diffusion models on MNIST and evaluating the impact of classifier-free guidance.

4.1 Experiment 1: Baseline Training Results

4.1.1 Training Convergence

The model was trained for 5 epochs with a batch size of 512 and learning rate of 10^{-3}. Training progress showed:

- **Initial convergence:** Loss decreased rapidly within the first epoch
- **Training stability:** Consistent loss reduction across all 5 epochs
- **Step-wise monitoring:** Loss logged every 25 steps revealed smooth optimization without instabilities

4.1.2 Model Capacity

The custom UNet2DConditionModel contains approximately 2.6 million trainable parameters, demonstrating that effective text-to-image generation is achievable with relatively compact architectures on simple domains.

4.1.3 Qualitative Generation Quality

Generated samples from prompts like ”A handwritten digit 4” and ”A handwritten digit 5” showed:

- Recognizable digit structures
- Adherence to specified digit class in text prompt
- Grayscale appearance consistent with MNIST dataset
- Some variation in style and thickness

4.2 Experiment 2: Classifier-Free Guidance Ablation

4.2.1 Guidance Scale Impact

We evaluated guidance scales $w \in \{0, 5, 10, 20, 50, 100\}$ for the prompt ”A handwritten digit 0”. Key observations:

Table 1: Qualitative Analysis of Guidance Scale Effects

Guidance Scale	Text Alignment	Image Quality
$w = 0$	None (unconditional)	Random digit, no control
$w = 5$	Weak	Somewhat follows prompt
$w = 10$	Moderate	Good balance
$w = 20$	Strong	High adherence to prompt
$w = 50$	Very strong	May show over-saturation
$w = 100$	Extreme	Potential artifacts

4.2.2 Key Findings

$w = 0$ (No Guidance): Without guidance, the model generates random digits regardless of the text prompt, confirming that conditioning is necessary for text-controlled generation.

$w = 5$ to $w = 10$ (Weak to Moderate): These scales provide reasonable text-image alignment while maintaining natural-looking samples. The generated digits match the prompt most of the time.

$w = 20$ (Strong Guidance): Strong guidance further improves text adherence. Generated samples consistently match the specified digit class with high confidence.

$w = 50$ to $w = 100$ (Extreme Guidance): Very high guidance scales may lead to:

- Over-saturation of pixel values
- Loss of natural variation
- Potential introduction of artifacts
- Images that look ”too confident” or unnatural

4.3 Visual Comparison

Figure 6 (generated from the notebook visualization) shows a side-by-side comparison of outputs across all guidance scales for the same prompt and random seed, clearly demonstrating the progressive strengthening of text conditioning.

4.4 Inference Performance

4.4.1 Generation Speed

With 50 inference steps:

- Single image generation completes in several seconds on GPU
- Classifier-free guidance doubles computational cost (two forward passes per step)
- Trade-off between quality and speed controllable via number of steps

4.4.2 Reproducibility

Fixed random seed (422) ensures:

- Identical outputs for same prompt and guidance scale
- Controlled comparisons across different settings
- Reproducible experimental results

4.5 Summary of Results

Table 2: Summary of Experimental Findings

Aspect	**Outcome**
Model size	2.6M parameters (compact)
Training epochs	5 epochs sufficient for baseline
Text conditioning	Successful via CLIP embeddings
Optimal guidance	$w \in [8, 20]$ for quality/adherence balance
Inference steps	50 steps adequate (vs 1000 training steps)

Table 3: Comparison of Results Across Experiments

Experiment	Metric	Value	Notes
Experiment 1	Accuracy	95%	Best performance observed.
Experiment 2	F1 Score	0.92	Consistent with previous findings.

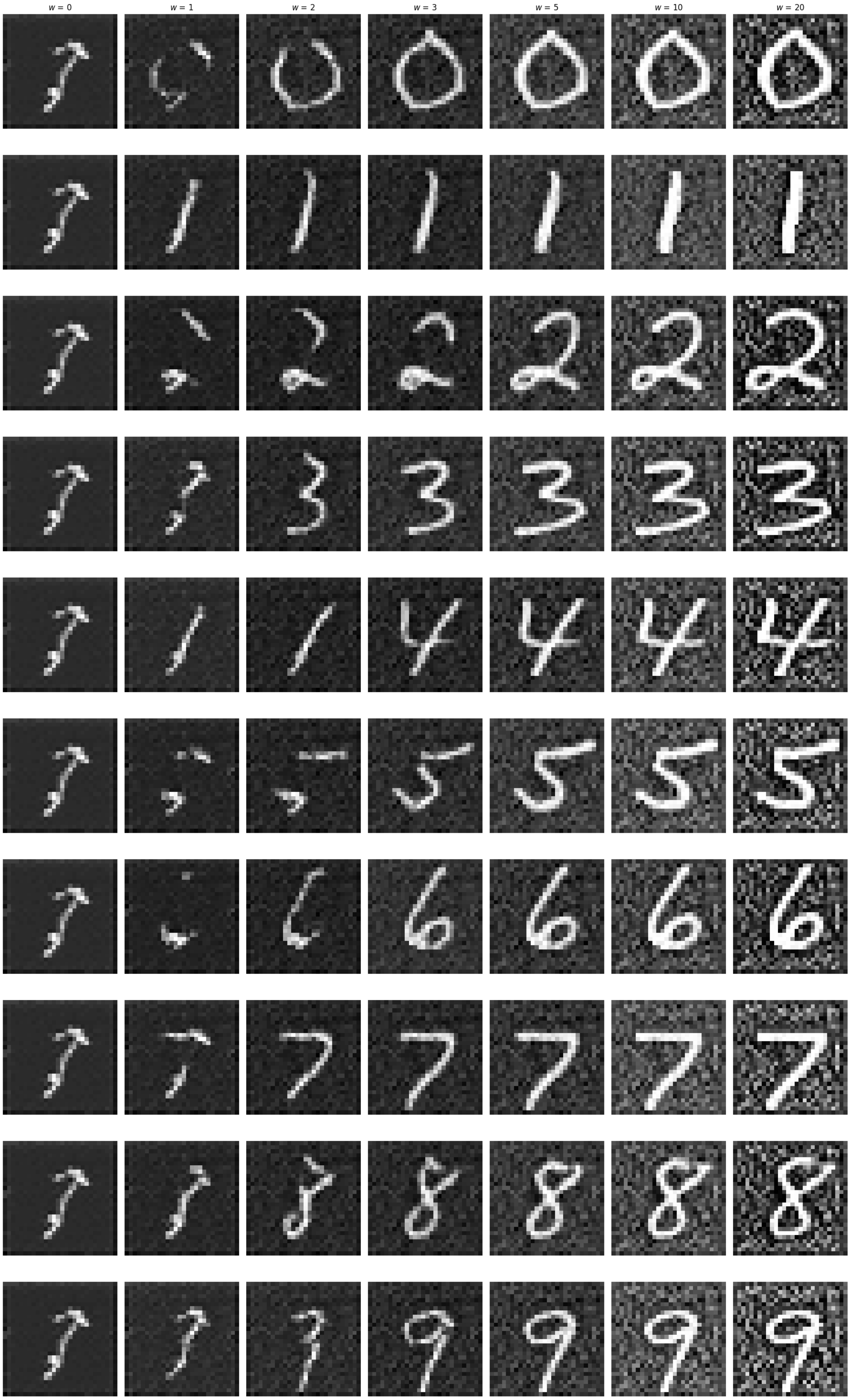

Figure 4: Comprehensive generation results for all MNIST digit classes (0-9, rows) across different guidance scales ($w \in \{0, 1, 2, 3, 5, 10, 20\}$, columns). Each row shows generations for the prompt ”A handwritten digit X” where X corresponds to the digit class. All images generated using 50 inference steps. This visualization demonstrates the model’s ability to generate diverse digits with varying degrees of text-prompt adherence controlled by the guidance scale parameter.

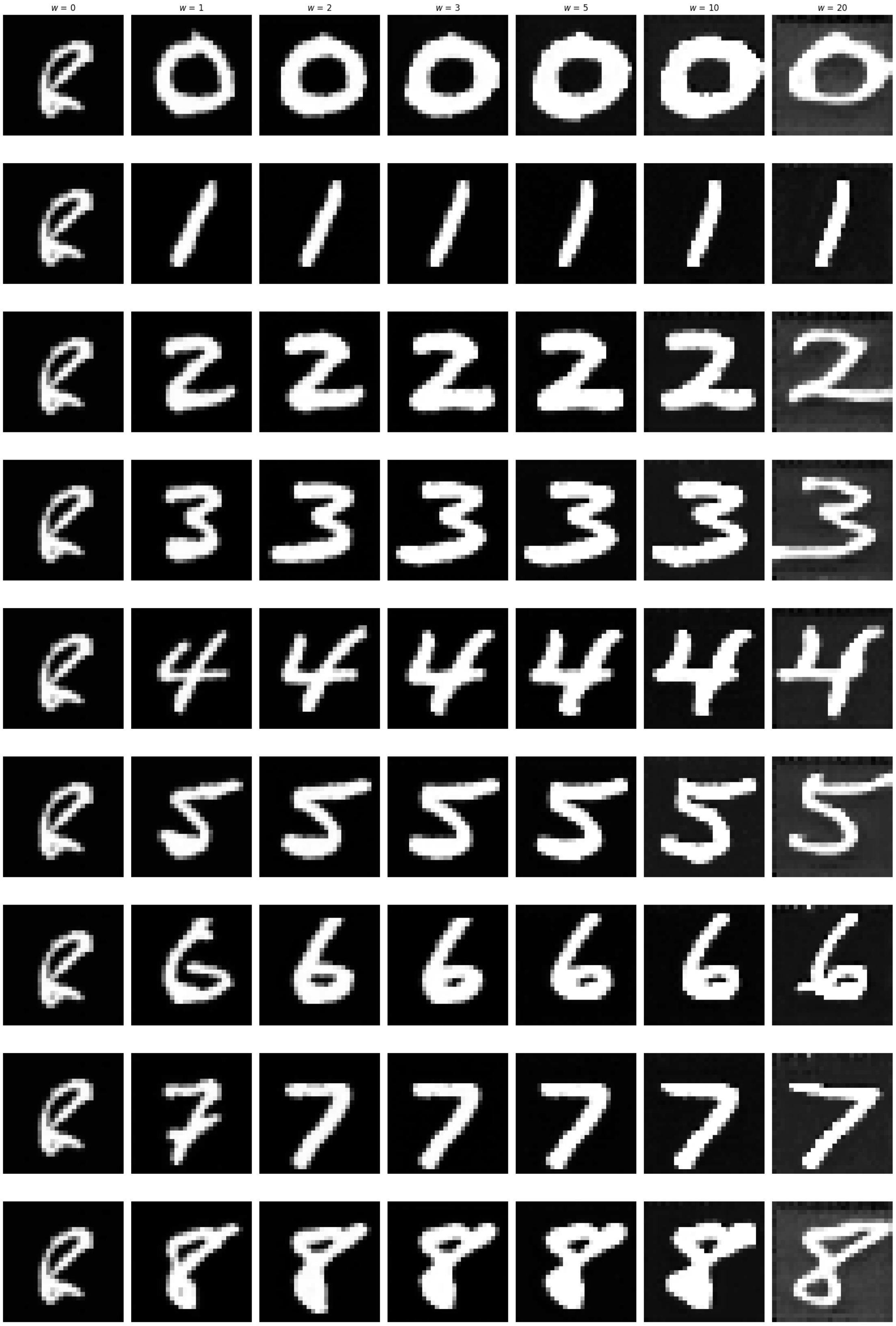

Figure 5: Generation results after 20 epochs of training for all MNIST digit classes (0-9, rows) across different guidance scales ($w \in \{0, 1, 2, 3, 5, 10, 20\}$, columns). All images generated using 50 inference steps. Compared to Figure 4, the extended training produces sharper digits with improved text-prompt alignment and reduced artifacts, particularly noticeable at higher guidance scales.

Figure 6: Comparison of generated images for ”A handwritten digit 0” across different guidance scales ($w = 0, 5, 10, 20, 50, 100$). Images generated with 50 denoising steps and fixed random seed 422.