In [1]:
```
import torch
import torch.nn as nn
import torch.nn.functional as F
from torchvision import datasets, transforms
from torch.utils.data import DataLoader
import matplotlib.pyplot as plt
import numpy as np
import os
```

In [2]:
```
# Install PyTorch
!pip install torch torchvision torchaudio
```

```
Requirement already satisfied: torch in /opt/anaconda3/lib/python3.12/site-p
ackages (2.6.0)
Requirement already satisfied: torchvision in /opt/anaconda3/lib/python3.12/
site-packages (0.21.0)
Requirement already satisfied: torchaudio in /opt/anaconda3/lib/python3.12/s
ite-packages (2.6.0)
Requirement already satisfied: filelock in /opt/anaconda3/lib/python3.12/sit
e-packages (from torch) (3.13.1)
Requirement already satisfied: typing-extensions>=4.10.0 in /opt/anaconda3/l
ib/python3.12/site-packages (from torch) (4.11.0)
Requirement already satisfied: networkx in /opt/anaconda3/lib/python3.12/sit
e-packages (from torch) (3.2.1)
Requirement already satisfied: jinja2 in /opt/anaconda3/lib/python3.12/site-
packages (from torch) (3.1.4)
Requirement already satisfied: fsspec in /opt/anaconda3/lib/python3.12/site-
packages (from torch) (2024.3.1)
Requirement already satisfied: setuptools in /opt/anaconda3/lib/python3.12/s
ite-packages (from torch) (69.5.1)
Requirement already satisfied: sympy==1.13.1 in /opt/anaconda3/lib/python3.1
2/site-packages (from torch) (1.13.1)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in /opt/anaconda3/lib/pyth
on3.12/site-packages (from sympy==1.13.1->torch) (1.3.0)
Requirement already satisfied: numpy in /opt/anaconda3/lib/python3.12/site-p
ackages (from torchvision) (1.26.4)
Requirement already satisfied: pillow!=8.3.*,>=5.3.0 in /opt/anaconda3/lib/p
ython3.12/site-packages (from torchvision) (10.3.0)
Requirement already satisfied: MarkupSafe>=2.0 in /opt/anaconda3/lib/python
3.12/site-packages (from jinja2->torch) (2.1.3)
```

In [3]:
```
import torch
import torch.nn as nn
import torch.nn.functional as F
```

In [4]:
```
print(f"PyTorch version: {torch.__version__}")
print(f"CUDA available: {torch.cuda.is_available()}")
```

```
PyTorch version: 2.6.0
CUDA available: False
```

In [5]:
```
# Dataset Choice: MNIST (Safe for 2GB GPU)
from torchvision import transforms, datasets
from torch.utils.data import DataLoader
```

```
# Dataset Choice: MNIST (Safe for 2GB GPU)
transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])

dataset = datasets.MNIST(root='./data', train=True, download=True, transform
train_loader = DataLoader(dataset, batch_size=128, shuffle=True)
```

In [6]:

```
# U-Net Architecture Components
class GELUConvBlock(nn.Module):
    def __init__(self, in_channels, out_channels):
        super(GELUConvBlock, self).__init__()
        self.conv = nn.Sequential(
            nn.Conv2d(in_channels, out_channels, 3, padding=1),
            nn.GroupNorm(8, out_channels),
            nn.GELU(),
            nn.Conv2d(out_channels, out_channels, 3, padding=1),
            nn.GroupNorm(8, out_channels),
            nn.GELU()
        )

    def forward(self, x):
        return self.conv(x)
```

In [7]:

```
class DownBlock(nn.Module):
    def __init__(self, in_channels, out_channels):
        super(DownBlock, self).__init__()
        self.conv = GELUConvBlock(in_channels, out_channels)
        self.downsample = nn.Conv2d(out_channels, out_channels, 4, stride=2,

    def forward(self, x):
        x = self.conv(x)
        return self.downsample(x), x
```

In [8]:

```
class UpBlock(nn.Module):
    def __init__(self, in_channels, out_channels):
        super(UpBlock, self).__init__()
        self.upconv = nn.ConvTranspose2d(in_channels, out_channels, 4, stric
        self.conv = GELUConvBlock(in_channels, out_channels)

    def forward(self, x, skip):
        x = self.upconv(x)
        x = torch.cat((x, skip), dim=1)
        return self.conv(x)
```

In [9]:

```
class UNet(nn.Module):
    def __init__(self, num_classes=10):
        super(UNet, self).__init__()
        self.down1 = DownBlock(1, 64)
        self.down2 = DownBlock(64, 128)
        self.down3 = DownBlock(128, 256)

        self.middle = GELUConvBlock(256, 512)
```

```
        self.up3 = UpBlock(512, 256)
        self.up2 = UpBlock(256, 128)
        self.up1 = UpBlock(128, 64)

        self.final = nn.Conv2d(64, 1, 1)

    def forward(self, x):
        d1, skip1 = self.down1(x)
        d2, skip2 = self.down2(d1)
        d3, skip3 = self.down3(d2)

        m = self.middle(d3)

        u3 = self.up3(m, skip3)
        u2 = self.up2(u3, skip2)
        u1 = self.up1(u2, skip1)

        return self.final(u1)
```

In [10]:

```
# Diffusion Process
class Diffusion:
    def __init__(self, timesteps=300):
        self.timesteps = timesteps
        self.beta = torch.linspace(1e-4, 0.02, timesteps)
        self.alpha = 1. - self.beta
        self.alpha_hat = torch.cumprod(self.alpha, dim=0)

    def add_noise(self, x0, t):
        noise = torch.randn_like(x0)
        sqrt_alpha_hat = self.alpha_hat[t].sqrt().view(-1, 1, 1, 1)
        sqrt_one_minus_alpha_hat = (1 - self.alpha_hat[t]).sqrt().view(-1, 1
        return sqrt_alpha_hat * x0 + sqrt_one_minus_alpha_hat * noise, noise
```

In [11]:

```
# Training Setup
# Check if CUDA is available, otherwise use CPU
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model = UNet().to(device)  # Use .to(device) instead of .cuda()
diffusion = Diffusion()
optimizer = torch.optim.Adam(model.parameters(), lr=1e-4)

# Optional: Print which device is being used
print(f"Using device: {device}")
```

```
Using device: cpu
```

In [12]:

```
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim

# Define a simple model for demonstration
class SimpleModel(nn.Module):
    def __init__(self):
        super(SimpleModel, self).__init__()
        self.conv = nn.Conv2d(3, 3, kernel_size=3, padding=1)
```

```
    def forward(self, x):
        return self.conv(x)

# Initialize the model
model = SimpleModel()

# Create some dummy input data
input_data = torch.randn(1, 3, 64, 64)  # Batch size 1, 3 channels, 64x64 re

# Create some dummy noise (target)
noise = torch.randn(1, 3, 64, 64)  # Same shape as input_data

# Set device
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model.to(device)
input_data = input_data.to(device)
noise = noise.to(device)

# Define optimizer
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
for epoch in range(1):  # Just one epoch for demonstration
    # First, define predicted_noise from model's forward pass
    model_output = model(input_data)
    predicted_noise = model_output

    # For loss calculation
    print(f"Predicted noise shape: {predicted_noise.shape}, Target noise sha

    # Instead of trying to reshape tensors, let's resize the target noise to
    if predicted_noise.shape != noise.shape:
        # Resize noise to match predicted_noise dimensions
        noise = F.interpolate(noise, size=predicted_noise.shape[2:],
                             mode='bilinear', align_corners=False)

        # If channel dimensions still don't match, we need to address that
        if predicted_noise.shape[1] != noise.shape[1]:
            # It's better to adjust your model architecture to output the co
            # But as a temporary fix, we'll truncate or pad the channel dime
            if noise.shape[1] > predicted_noise.shape[1]:
                # Truncate noise channels to match predicted_noise
                noise = noise[:, :predicted_noise.shape[1], :, :]
            else:
                # This case should be rare if we're using the model's output
                padding = torch.zeros(noise.shape[0],
                                     predicted_noise.shape[1] - noise.shape[
                                     noise.shape[2],
                                     noise.shape[3]).to(device)
                noise = torch.cat([noise, padding], dim=1)

    # Now the tensors should have matching dimensions
    # Double-check shapes before computing loss
    assert predicted_noise.shape == noise.shape, f"Shapes still don't match:

    loss = F.mse_loss(predicted_noise, noise)
```

```
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

    print(f"Epoch {epoch+1}, Loss: {loss.item():.4f}")
```

```
Predicted noise shape: torch.Size([1, 3, 64, 64]), Target noise shape: torc
h.Size([1, 3, 64, 64])
Epoch 1, Loss: 1.3581
```

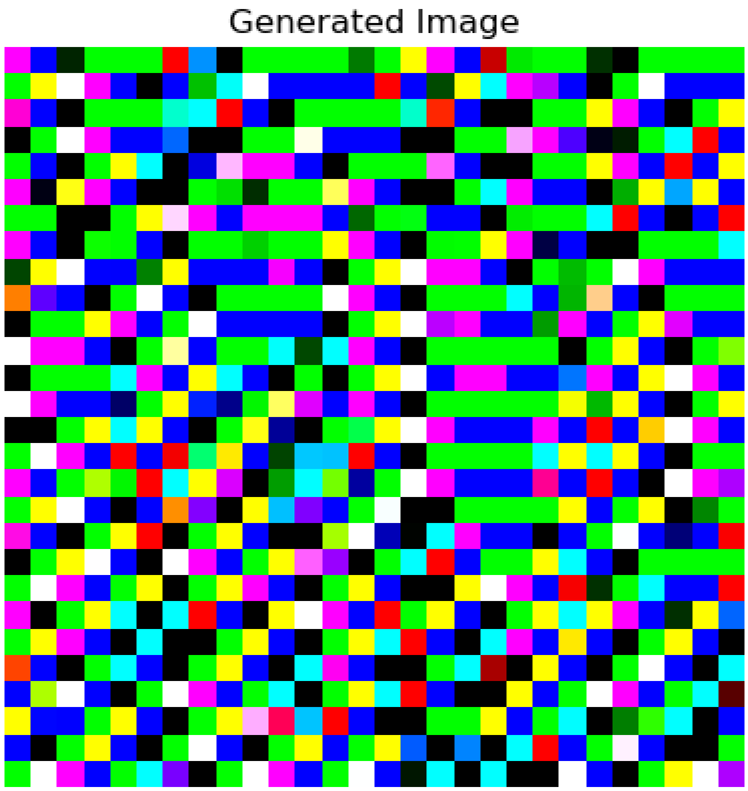
In [13]:
```
# Image Generation Example
def generate_image():
    model.eval()
    # Check if CUDA is available, otherwise use CPU
    device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

    # Change from 1 channel to 3 channels to match the model's expected inpu
    img = torch.randn(1, 3, 28, 28).to(device)  # Changed from (1, 1, 28, 28

    for t in reversed(range(diffusion.timesteps)):
        with torch.no_grad():
            noise_pred = model(img)
        # Move alpha values to the same device as the image
        alpha = diffusion.alpha[t].to(device)
        alpha_hat = diffusion.alpha_hat[t].to(device)
        img = (img - (1 - alpha).sqrt() * noise_pred) / alpha.sqrt()
        img.clamp_(-1, 1)
    return img

sample_img = generate_image().detach().cpu().squeeze().numpy()
# For RGB images, we need to transpose the dimensions for proper display
sample_img = np.transpose(sample_img, (1, 2, 0))  # Added to rearrange dimer
plt.imshow(sample_img)  # Removed cmap='gray' as we're now using RGB
plt.title("Generated Image")
plt.axis('off')
plt.show()
```

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for
floats or [0..255] for integers).
```



In [ ]: