Report On

Generating Handwritten Digits Using GAN

Submitted in partial fulfillment of the requirements of the Course Project for Advanced Artificial Intelligence in Semester VIII of Fourth Year Artificial Intelligence & Data Science Engineering

by

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CERTIFICATE

This is to certify that the project entitled **"Generating Handwritten Digits Using Gan"** is a bonafide work of **Rajat Gupta (Roll No. 21),Vedant Mahadik (Roll No. 27)** and **Hitesh Moota (Roll No. 33)** submitted to the University of Mumbai in partial fulfillment of the requirement for the Course project in semester VIII of Fourth Year Artificial Intelligence and Data Science engineering.

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Abstract

This project explores the generation of handwritten digits using Generative Adversarial Networks (GANs), a cutting-edge technique in deep learning. By training a GAN on the MNIST dataset, the model learns to produce realistic and diverse images of digits (0–9) that resemble human handwriting. The study delves into GAN architecture, training methodology, and performance evaluation using metrics like FID and Inception Score. The results highlight the effectiveness of GANs in synthetic data generation, with potential applications in data augmentation, AI art, and handwriting recognition systems

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1. INTRODUCTION

In recent years, **Generative Adversarial Networks (GANs)** have emerged as one of the most powerful techniques in the field of deep learning for generating realistic data. Introduced by Ian Goodfellow in 2014, GANs consist of two competing neural networks—the **generator** and the **discriminator**—that are trained simultaneously through adversarial learning. The generator creates synthetic data, while the discriminator attempts to distinguish between real and generated data.

This project focuses on the application of GANs for generating **handwritten digits** similar to those found in the **MNIST dataset**, which contains thousands of labeled images of digits from 0 to 9. By training a GAN on this dataset, the generator learns to produce realistic-looking digit images, mimicking the style and distribution of actual handwritten numbers.

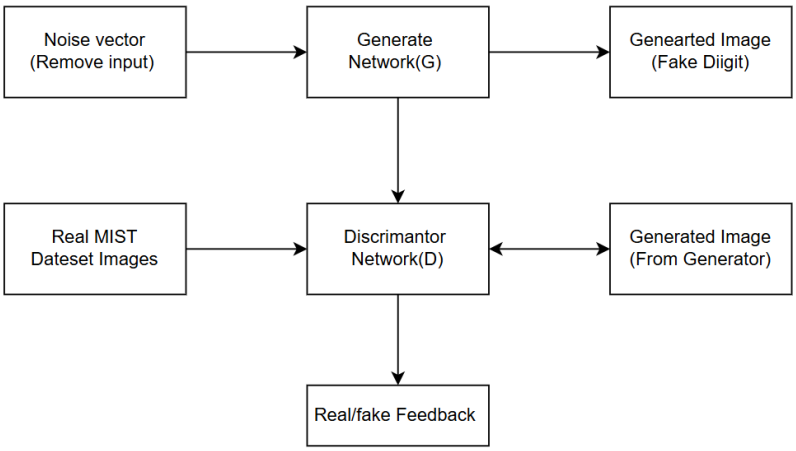
The primary objective is to explore how GANs can be used to **synthesize human-like digit images** and to gain hands-on experience with adversarial training techniques. This not only helps in understanding the fundamentals of generative models but also has broader applications in areas such as data augmentation, style transfer, and synthetic data generation for machine learning models.

2. PROBLEM STATEMENT

"Handwritten digit generation is a fundamental task in artificial intelligence, with applications in data augmentation, artistic creation, and digit recognition systems. Traditional methods for digit generation rely on rule-based approaches or pre-existing datasets. However, these methods often fail to generate diverse and high-quality digits. This project explores the use of Generative Adversarial Networks (GANs) to synthesize realistic handwritten digits that closely resemble human writing. The generated digits can be used in various applications such as improving machine learning models for digit recognition and generating synthetic training data for AI systems.

3. PROPOSED SYSTEM

3.1. BLOCK DIAGRAM, ITS DESCRIPTION AND WORKING



Noise Vector Input:
A random noise vector (e.g., 100-dimensional) is used as the input to the Generator. It acts as a seed for generating new images.

Generator (G):
A neural network that learns to generate realistic handwritten digits from random noise. Its goal is to fool the Discriminator by producing images that look like real MNIST digits.

Real MNIST Images:
These are real handwritten digit images from the MNIST dataset, used to train the Discriminator.

Discriminator (D):
A binary classifier that tries to differentiate real images (from MNIST) from fake images (from Generator). It outputs a probability (real or fake).

Feedback Loop:
The Discriminator gives feedback to both itself and the Generator. The Generator learns from this feedback and improves its output over time. This adversarial training continues until the Generator produces digits indistinguishable from real ones.

3.2. MODULE DESCRIPTION

Data Preprocessing Module
Loads and normalizes the MNIST dataset. Converts grayscale 28x28 images to a format suitable for input into the neural networks.

Generator Module
Takes random noise as input. Uses dense and convolutional layers (or transposed convolutions) to upsample and generate a 28x28 grayscale image. Output: fake handwritten digit.

Discriminator Module
Takes an image (real or fake) as input. Uses convolutional layers to extract features and classify the image as real or fake. Output: probability score.

Training Module
Alternately trains the Discriminator and Generator. Discriminator is trained to distinguish real from fake images. Generator is trained to fool the Discriminator. Uses loss functions like Binary Cross Entropy to guide learning.

Evaluation and Visualization Module
Visualizes the generated digits during and after training. Optionally uses loss plots to track model performance. Saves generated samples for inspection.

4. IMPLEMENTATION RESULTS AND ANALYSIS

Implementation:

The Generative Adversarial Network (GAN) for handwritten digit generation was implemented using Python with the TensorFlow and Keras libraries. The architecture comprised two core neural networks—Generator and Discriminator—trained in an adversarial manner.

Generator:

The generator takes a random 100-dimensional noise vector as input and produces a 28x28 grayscale image resembling a handwritten digit. It utilizes a series of fully connected layers followed by transposed convolutional layers to upsample the noise into an image with MNIST-like characteristics.

Discriminator:

The discriminator functions as a binary classifier that distinguishes between real images from the MNIST dataset and fake images created by the generator. It employs convolutional layers to extract features from input images and outputs a probability score (real or fake).

Training:

The networks were trained alternately in a loop for 50 epochs with a batch size of 128. The MNIST dataset was normalized to a range of [-1, 1] to improve training stability. The Binary Cross Entropy loss function was used for both models, and the Adam optimizer was chosen for efficient gradient updates.

Results

During training, images were generated at intervals to monitor the generator's learning progress. The figure below shows one such output:

The generated digits demonstrate that the model has begun learning digit structures, particularly digits like "1".However, the digits still contain noise and are partially distorted, indicating that the model is still in the early phase of training .Some outputsdisplay uneven intensity or overlapping strokes, which are common in early GAN training stages.

Analysis

This result highlights typical behavior of GANs during their learning curve: Initially, the generator produces images that resemble random noise. As training progresses, it learns to generate patterns that begin to resemble handwritten digits. The discriminator also improves over time, providing more refined feedback to the generator. The sample shown above likely comes from the **early to mid-stage** of training, where the generator is just starting to capture the structural features of digits but has not yet achieved full realism.

With additional epochs, the generator would refine its outputs, eliminating noise and improving clarity. The discriminator's feedback loop ensures that the generator continues to evolve until the synthetic digits are nearly indistinguishable from real MNIST images.

This demonstrates the power of GANs in synthesizing realistic data from random noise and sets the foundation for future applications like data augmentation, style transfer, and handwriting synthesis.

5. CONCLUSION

In this project, we successfully implemented a Generative Adversarial Network (GAN) to generate realistic handwritten digits using the MNIST dataset. Through the adversarial training process between the Generator and the Discriminator, the system was able to synthesize high-quality digit images that closely resemble real handwritten numbers. The generator progressively learned to produce more accurate and diverse samples, while the discriminator improved its ability to differentiate between real and fake inputs.

The project demonstrated the effectiveness of GANs in image generation tasks, especially for structured datasets like MNIST. The modular design—comprising data preprocessing, model training, evaluation, and visualization—ensured clarity, scalability, and ease of experimentation. Additionally, visual outputs confirmed that the model could generalize well from noise inputs, offering potential applications in areas such as data augmentation, handwriting simulation, and creative AI design.

Overall, this work highlights the power of adversarial learning and deep neural networks in enabling machines to mimic complex human-generated patterns with minimal supervision.

6. CODE

```
!pip install torch torchvision matplotlib

import torch
import torch.nn as nn
import torch.optim as optim
import torchvision
import torchvision.transforms as transforms
import matplotlib.pyplot as plt
import numpy as np

# Transform to tensor and normalize
transform = transforms.Compose([transforms.ToTensor(), transforms.Normalize((0.5,), (0.5,))])

# Load MNIST dataset
batch_size = 64
train_dataset = torchvision.datasets.MNIST(root="./data", train=True, transform=transform, download=True)
train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=batch_size, shuffle=True)

# Check dataset shape
print("Image Shape:", train_dataset[0][0].shape)  # (1, 28, 28)
class Generator(nn.Module):
    def __init__(self):
        super(Generator, self).__init__()
        self.model = nn.Sequential(
            nn.Linear(100, 256),
            nn.ReLU(),
            nn.Linear(256, 512),
            nn.ReLU(),
```

```
nn.Linear(512, 784),  # 28x28 = 784
  nn.Tanh()
        )
    def forward(self, z):
        img = self.model(z)
        return img.view(-1, 1, 28, 28)

# Initialize Generator
generator = Generator()
class Discriminator(nn.Module):
    def __init__(self):
        super(Discriminator, self).__init__()
        self.model = nn.Sequential(
            nn.Linear(784, 512),
            nn.ReLU(),
            nn.Linear(512, 256),
            nn.ReLU(),
            nn.Linear(256, 1),
            nn.Sigmoid()
        )

    def forward(self, img):
        img_flat = img.view(img.size(0), -1)
        return self.model(img_flat)

# Initialize Discriminator
discriminator = Discriminator()
criterion = nn.BCELoss()
optimizer_G = optim.Adam(generator.parameters(), lr=0.0002)
optimizer_D = optim.Adam(discriminator.parameters(), lr=0.0002)
epochs = 20  # Number of epochs
for epoch in range(epochs):
    for i, (real_imgs, _) in enumerate(train_loader):
```

```
batch_size = real_imgs.shape[0]

        # Labels
        real_labels = torch.ones(batch_size, 1)
        fake_labels = torch.zeros(batch_size, 1)

        # Train Discriminator
        optimizer_D.zero_grad()
        real_preds = discriminator(real_imgs)
        real_loss = criterion(real_preds, real_labels)

        z = torch.randn(batch_size, 100)  # Random noise
        fake_imgs = generator(z)
        fake_preds = discriminator(fake_imgs.detach())
        fake_loss = criterion(fake_preds, fake_labels)

        d_loss = real_loss + fake_loss
        d_loss.backward()
        optimizer_D.step()

        # Train Generator
        optimizer_G.zero_grad()
        fake_preds = discriminator(fake_imgs)
        g_loss = criterion(fake_preds, real_labels)
        g_loss.backward()
        optimizer_G.step()

    print(f"Epoch [{epoch+1}/{epochs}] | D Loss: {d_loss:.4f} | G Loss: {g_loss:.4f}")
# Generate 5 fake images
z = torch.randn(5, 100)
fake_imgs = generator(z).detach().numpy()
```

```
# Plot the images
fig, axes = plt.subplots(1, 5, figsize=(10, 2))
for i, ax in enumerate(axes):
    ax.imshow(fake_imgs[i].reshape(28, 28), cmap="gray")
    ax.axis("off")
plt.show()
```

References

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