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Batch: 2022-2026

Branch: AI-ML

Experiment 1

Title: Implement a Simple GAN for generating 1D Sine Waves using PyTorch

Objectives:

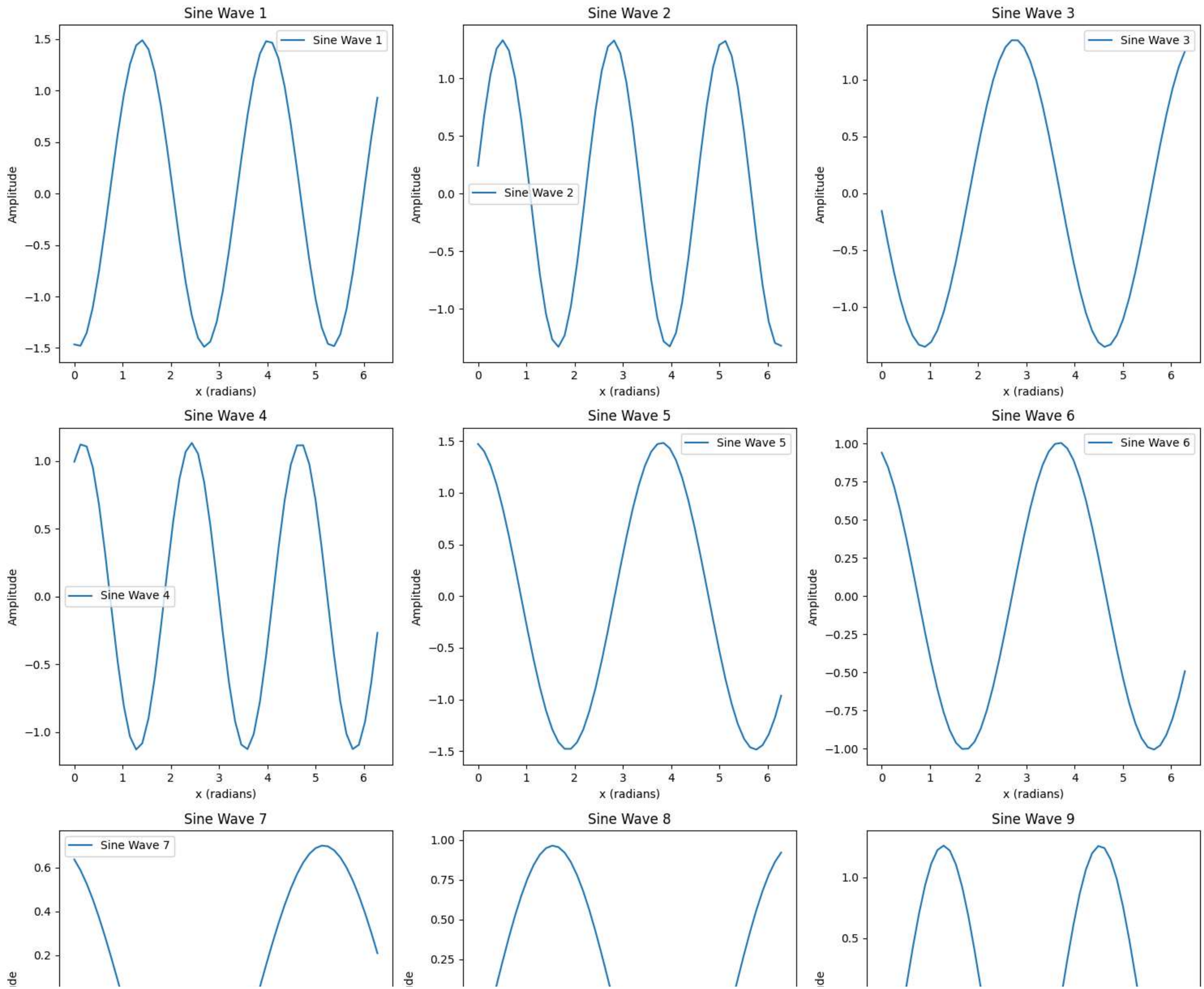
1. Implement a simple GAN using PyTorch to generate synthetic 1D sine wave data.
2. Understand the roles of the generator and discriminator in GANs.
3. Learn the training process of GANs and evaluate performance visually through plots.

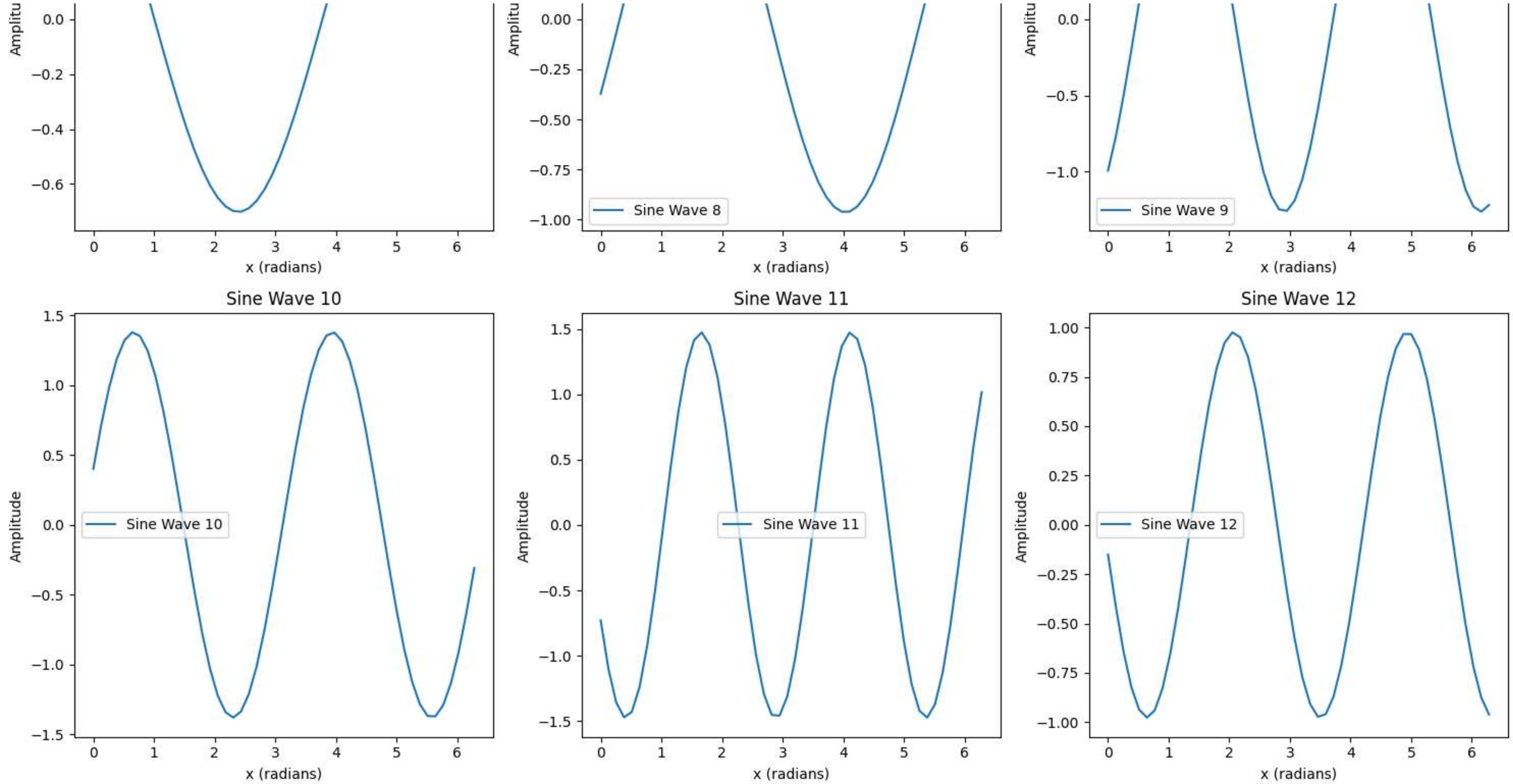
```
#Import the necessary libraries
import torch                      #Importing the PyTorch Library
import torch.nn as nn
import matplotlib.pyplot as plt
import numpy as np


#Setting Hyperparameters

#Model Configuration
lr = 0.001                #Learning Rate to determine step-size and rate of convergence
batch_size = 32           #Batch Size determines number of samples processed in parallel
epochs = 5000             #Number of Epochs or Training Cycles
```

```
#Model Architecture
latent_dim = 10          #The size of the Noise Vector fed as input to the Generator.
hidden_dim = 32          #The number of Neurons per Hidden Layer of the Generator and the Discriminator.
output_dim = 50          #Number of Sine Wave Points generated is 50.


# Generator Architecture

class Generator(nn.Module):                    #Generator Class

    def __init__(self, latent_dim, output_dim): #Constructor
        super(Generator, self).__init__()
        self.model = nn.Sequential(
            nn.Linear(latent_dim, 128),
            nn.ReLU(),
            nn.BatchNorm1d(128),  # Batch Normalization
            nn.Linear(128, 256),
            nn.ReLU(),
            nn.BatchNorm1d(256),
            nn.Linear(256, output_dim),
            nn.Tanh()  # Ensures the output is between -1 and 1
        )

    def forward(self, z):                 #Method for Forward Pass
        return self.model(z)



# Discriminator Network

class Discriminator(nn.Module):    #Discriminator Class

    def __init__(self, output_dim):

        super(Discriminator, self).__init__()
        self.model = nn.Sequential(
            nn.Linear(output_dim, 256),
            nn.LeakyReLU(0.2),
            nn.Linear(256, 128),
            nn.LeakyReLU(0.2),
            nn.Linear(128, 1),
```

```
            nn.Sigmoid()  # Output between 0 and 1
        )

    def forward(self, x):
        return self.model(x)


#Instantiate Networks

generator = Generator(latent_dim,output_dim)

discriminator = Discriminator(output_dim)


#Loss Function

loss = nn.BCELoss()        #Binary Cross Entropy Loss as distinguishing real and fake is a Binary Classification task. (0 or 1)



#Optimizer for tuning parameters

import torch.optim as optim

#Optimizers

optimizer_g = optim.Adam(generator.parameters(),lr=lr)

optimizer_d = optim.Adam(discriminator.parameters(),lr=lr)




# Function to generate the dataset of real Sine Waves with random phase, frequency, and amplitude.

def generate_real_sine_waves(batch_size, output_dim, num_waves=12):

    x = np.linspace(0, 2 * np.pi, output_dim) #A total of points equal to output_dim in the range of (0,2*pi)

    real_waves = []
```

```python
    for _ in range(num_waves):
        amplitude = np.random.uniform(0.5, 1.5)  # Random amplitude
        phase = np.random.uniform(0, 2 * np.pi)  # Random phase
        frequency = np.random.uniform(1, 3)     # Random frequency
        sine_wave = amplitude * np.sin(frequency * x + phase)
        real_waves.append(sine_wave)
    return torch.tensor(real_waves, dtype=torch.float32)



#Visualizing the real dataset of Sine Waves

num_waves = 12
real_data = generate_real_sine_waves(batch_size,output_dim,num_waves=12)

# Create subplots
rows = num_waves // 3  # Number of rows
cols = 3       # Number of columns
fig, axes = plt.subplots(rows, cols, figsize=(15, 5 * rows))

# Plot each sine wave in its subplot
x = np.linspace(0, 2 * np.pi, output_dim)
for idx, ax in enumerate(axes.flat):
    ax.plot(x, real_data[idx], label=f"Sine Wave {idx + 1}")
    ax.set_title(f"Sine Wave {idx + 1}")
    ax.set_xlabel("x (radians)")
    ax.set_ylabel("Amplitude")
    ax.legend()

plt.tight_layout()
plt.show()
```

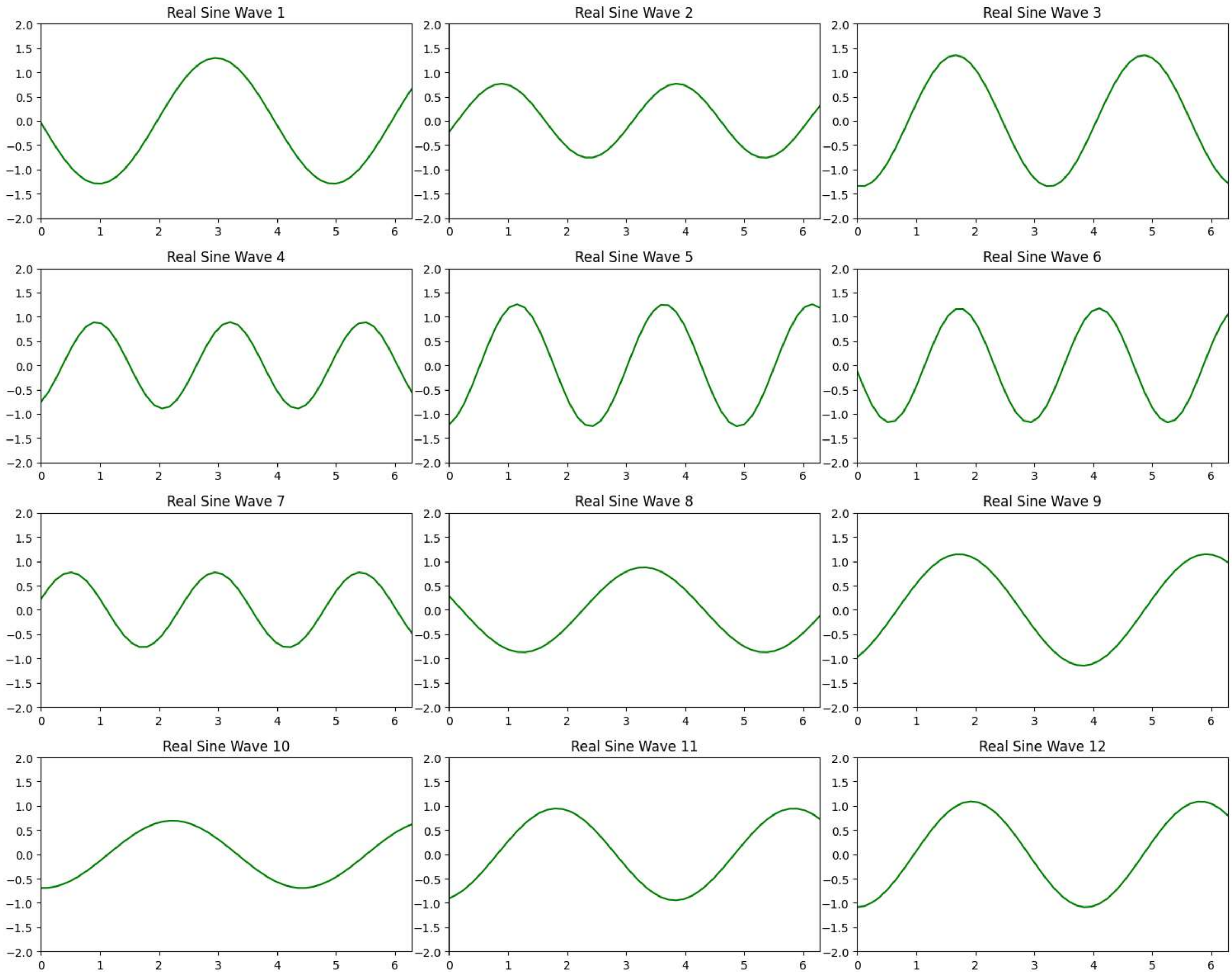

Sine Wave 1
Sine Wave 2
Sine Wave 3
Sine Wave 4
Sine Wave 5
Sine Wave 6
Sine Wave 7
Sine Wave 8
Sine Wave 9
Amplitude
x (radians)

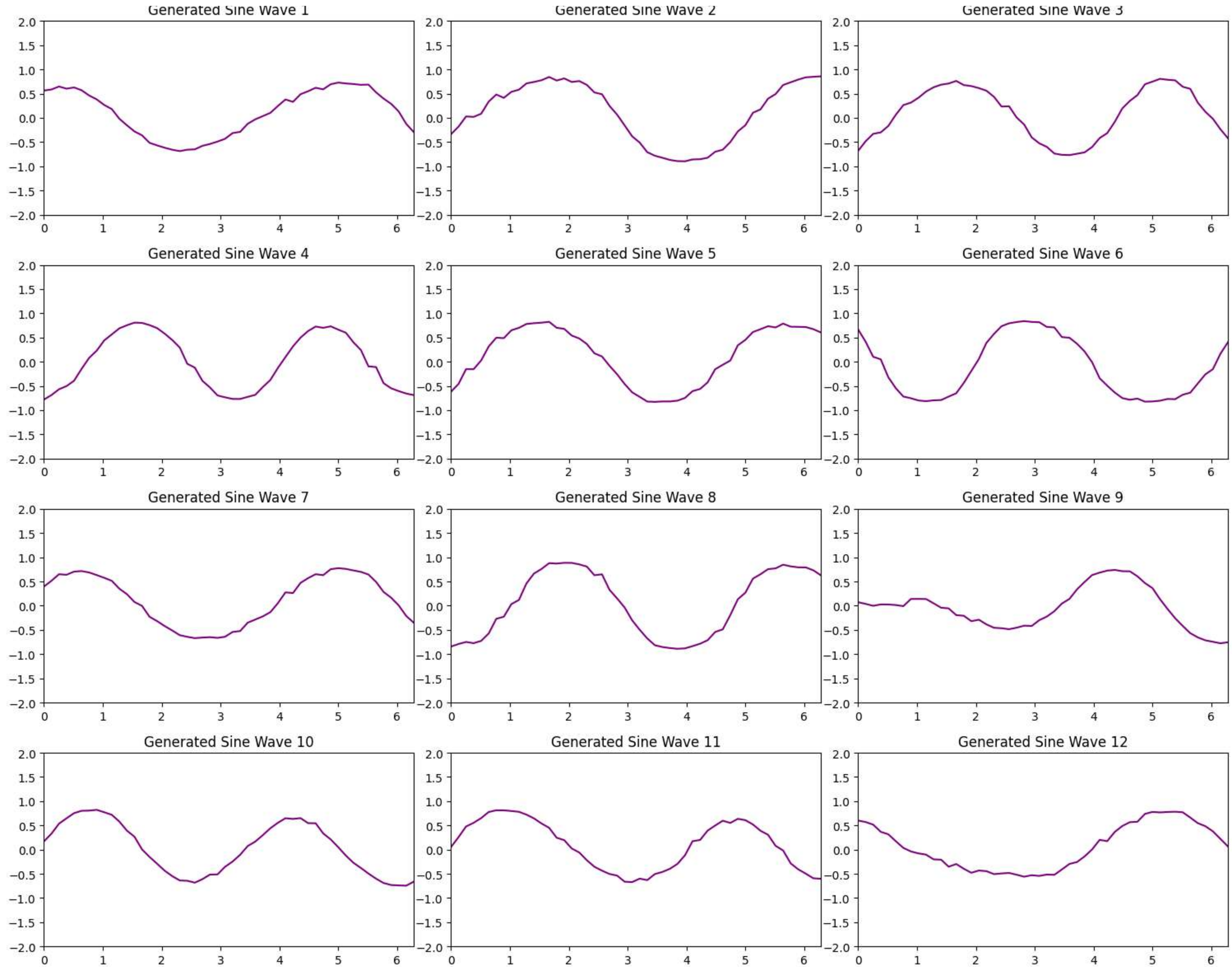

Amplitu
x (radians)
Sine Wave 8
Sine Wave 9
Sine Wave 10
Sine Wave 11
Sine Wave 12
Amplitude

```
criterion = nn.BCELoss()


# Training Process
for epoch in range(epochs):
    for _ in range(batch_size):
        # Step 1: Train the Discriminator
        real_data = generate_real_sine_waves(batch_size, output_dim, num_waves=batch_size)
        latent_vectors = torch.randn(batch_size, latent_dim)  # Random latent vectors
        fake_data = generator(latent_vectors)

        real_labels = torch.ones((batch_size, 1))  # Label for real data
        fake_labels = torch.zeros((batch_size, 1))  # Label for fake data

        # Calculate the loss for real and fake data
        real_loss = criterion(discriminator(real_data), real_labels)
        fake_loss = criterion(discriminator(fake_data.detach()), fake_labels)
        d_loss = real_loss + fake_loss

        # Update Discriminator's weights
        optimizer_d.zero_grad()
        d_loss.backward()
        optimizer_d.step()

        # Step 2: Train the Generator
        latent_vectors = torch.randn(batch_size, latent_dim)  # New random latent vectors
        fake_data = generator(latent_vectors)
        g_loss = criterion(discriminator(fake_data), real_labels)  # Fake data should fool the discriminator

        # Update Generator's weights
        optimizer_g.zero_grad()
        g_loss.backward()
        optimizer_g.step()


    # Visualization every 100 epochs
    if epoch % 100 == 0:
        print(f"Epoch {epoch}, Discriminator Loss: {d_loss.item()}, Generator Loss: {g_loss.item()}")

        # Visualize real data in green
```

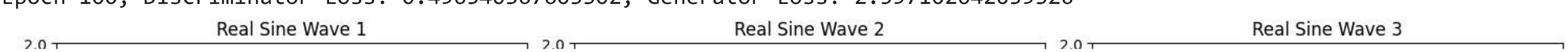
```
real_data_plot = generate_real_sine_waves(batch_size, output_dim, num_waves=12).detach().numpy()
fig, axs = plt.subplots(4, 3, figsize=(15, 12))  # 4 rows, 3 columns
axs = axs.flatten()
for i, ax in enumerate(axs):
    ax.plot(np.linspace(0, 2 * np.pi, output_dim), real_data_plot[i], color='green')  # Green for real data
    ax.set_title(f"Real Sine Wave {i + 1}")
    ax.set_xlim(0, 2 * np.pi)
    ax.set_ylim(-2, 2)
plt.tight_layout()
plt.show()

# Visualizing generated data in purple
latent_vectors = torch.randn(12, latent_dim)  # Generate new random latent vectors
fake_data_plot = generator(latent_vectors).detach().numpy()
fig, axs = plt.subplots(4, 3, figsize=(15, 12))  # 4 rows, 3 columns
axs = axs.flatten()
for i, ax in enumerate(axs):
    ax.plot(np.linspace(0, 2 * np.pi, output_dim), fake_data_plot[i], color='purple')  # Purple for synthetic data
    ax.set_title(f"Generated Sine Wave {i + 1}")
    ax.set_xlim(0, 2 * np.pi)
    ax.set_ylim(-2, 2)
plt.tight_layout()
plt.show()
```

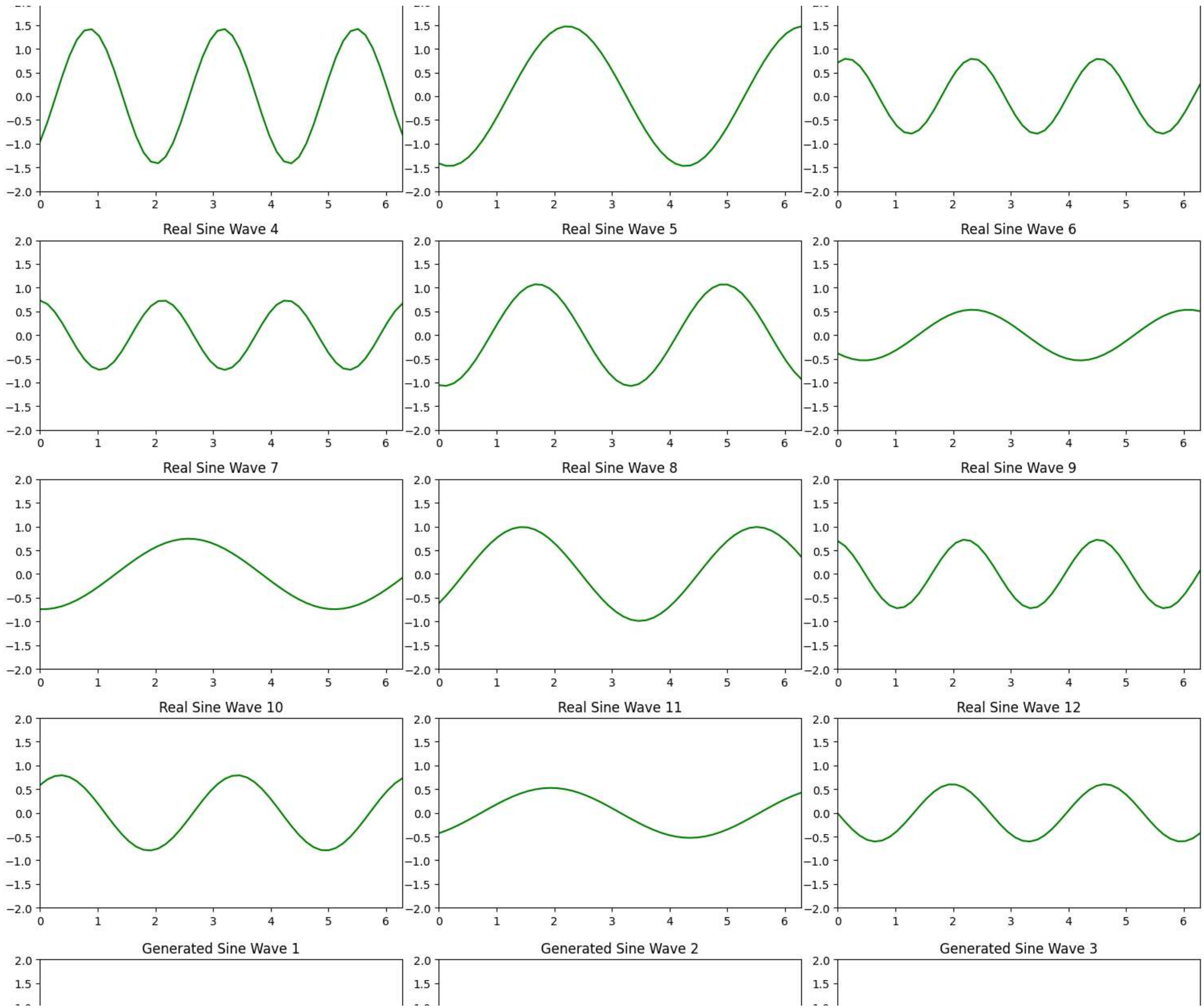
Epoch 0, Discriminator Loss: 0.7593666315078735, Generator Loss: 2.3158233165740967





Epoch 100, Discriminator Loss: 0.496540367603302, Generator Loss: 2.597102642059326




Real Sine Wave 4
Real Sine Wave 5
Real Sine Wave 6
Real Sine Wave 7
Real Sine Wave 8
Real Sine Wave 9
Real Sine Wave 10
Real Sine Wave 11
Real Sine Wave 12
Generated Sine Wave 1
Generated Sine Wave 2
Generated Sine Wave 3