

Complex PyTorch for Music Genre Classification

```
In [28]: # Complex pytorch
import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import DataLoader
from torchvision import datasets, transforms
from complexPyTorch.complexLayers import *
from complexPyTorch.complexFunctions import *
from torch_geometric.nn import GCNConv
from torch_geometric.data import Data

# Plot
import matplotlib.pyplot as plt
import seaborn as sns
import time

# Load Data
import numpy as np
import json
import os
import math
import librosa
import pathlib
from scipy.spatial.distance import cdist
from torch.utils.data import Dataset
from sklearn.model_selection import train_test_split
import random

# MFCCS
from scipy.io import wavfile
import scipy.fftpack as fft
from scipy.signal import get_window
```

Data Preparation

```
In [29]: DATASET_PATH = "Data/train"
SAMPLE_RATE = 22050
TRACK_DURATION = 30 # measured in seconds
SAMPLES_PER_TRACK = SAMPLE_RATE * TRACK_DURATION
BATCH_SIZE = 32
NUM_EPOCHS = 50
```

```
In [30]: genre_list = os.listdir(DATASET_PATH)
if '.DS_Store' in genre_list: genre_list.remove('.DS_Store')
genre_mappings = dict(zip(genre_list, range(len(genre_list))))
print(genre_mappings)
```

```
{'pop': 0, 'metal': 1, 'disco': 2, 'blues': 3, 'reggae': 4, 'classical': 5, 'rock': 6, 'hiphop': 7, 'country': 8, 'jazz': 9}
```

MFCCS

```

In [31]: class MusicFeatureExtractorComplex2:
    def __init__(self, FFT_size=2048, HOP_SIZE=512, mel_filter_num=13, dct_filter_num=13, epsilon=1e-10):
        self.FFT_size = FFT_size
        self.HOP_SIZE = HOP_SIZE
        self.mel_filter_num = mel_filter_num
        self.dct_filter_num = dct_filter_num
        self.epsilon = 1e-10 # Added to log to avoid log10(0)

    def normalize_audio(self, audio):
        audio = audio / np.max(np.abs(audio))
        return audio

    def frame_audio(self, audio):
        frame_num = int((len(audio) - self.FFT_size) / self.HOP_SIZE) + 1
        frames = np.zeros((frame_num, self.FFT_size))
        for n in range(frame_num):
            frames[n] = audio[n * self.HOP_SIZE: n * self.HOP_SIZE + self.FFT_size]
        return frames

    def freq_to_mel(self, freq):
        return 2595.0 * np.log10(1.0 + freq / 700.0)

    def mel_to_freq(self, mels):
        return 700.0 * (10.0 ** (mels / 2595.0) - 1.0)

    def get_filter_points(self, fmin, fmax, sample_rate):
        fmin_mel = self.freq_to_mel(fmin)
        fmax_mel = self.freq_to_mel(fmax)
        mels = np.linspace(fmin_mel, fmax_mel, num=self.mel_filter_num + 1)
        freqs = self.mel_to_freq(mels)
        return np.floor((self.FFT_size + 1) / sample_rate * freqs).astype(int)

    def get_filters(self, filter_points):
        filters = np.zeros((len(filter_points) - 2, int(self.FFT_size / 2)))
        for n in range(len(filter_points) - 2):
            filters[n, filter_points[n]: filter_points[n + 1]] = np.linspace(0, 1, filter_points[n + 1] - filter_points[n])
            filters[n, filter_points[n + 1]: filter_points[n + 2]] = np.linspace(1, 0, filter_points[n + 2] - filter_points[n + 1])
        return filters

    def dct(self):
        basis = np.empty((self.dct_filter_num, self.mel_filter_num))
        basis[0, :] = 1.0 / np.sqrt(self.mel_filter_num)
        samples = np.arange(1, 2 * self.mel_filter_num, 2) * np.pi / (2.0 * self.FFT_size)
        for i in range(1, self.dct_filter_num):
            basis[i, :] = np.cos(i * samples) * np.sqrt(2.0 / self.mel_filter_num)
        return basis

    def get_mfcc_features(self, audio, sample_rate):
        audio = self.normalize_audio(audio)
        audio_framed = self.frame_audio(audio)
        window = get_window("hann", self.FFT_size, fftbins=True)
        audio_win = audio_framed * window
        audio_winT = np.transpose(audio_win)
        audio_fft = np.empty((int(1 + self.FFT_size // 2), audio_winT.shape[1]))
        for n in range(audio_fft.shape[1]):
            audio_fft[:, n] = fft.fft(audio_winT[:, n], axis=0)[:audio_fft.shape[0]]
        audio_fft = np.transpose(audio_fft)
        mag_fft = np.square(np.abs(audio_fft))
        phase_fft = np.angle(audio_fft)

```

```

freq_min = 0
freq_high = sample_rate / 2
filter_points, mel_freqs = self.get_filter_points(freq_min, freq_high)
filters = self.get_filters(filter_points)
audio_filtered = np.dot(filters, np.transpose(mag_fft))
phase_filtered = np.dot(filters, np.transpose(phase_fft))
audio_filtered = np.maximum(audio_filtered, self.epsilon) # Replace negative values
audio_log = 10.0 * np.log10(audio_filtered)
dct_filters = self.dct()
cepstral_coefficients = np.dot(dct_filters, audio_log)
phase_coefficients = np.dot(dct_filters, phase_filtered)
return np.array([cepstral_coefficients]), np.array([phase_coefficients])

```

In [32]: **class** GenreDatasetMFCC(Dataset):

```

def __init__(self, train_path, n_fft=2048, hop_length=512, num_segments=10,
             cur_path = pathlib.Path(train_path),
             self.files = []):
    for i in list(cur_path.rglob("*.wav")):
        for j in range(num_segments):
            self.files.append([j, i])
    self.samples_per_segment = int(SAMPLES_PER_TRACK / num_segments)
    self.n_fft = n_fft
    self.hop_length = hop_length
    self.num_segments = num_segments
    self.dct_filter_num = dct_filter_num
    self.training = training

def apply_augmentations(self, signal):
    # Apply augmentations to the audio signal
    if random.random() < 0.5:
        signal = librosa.effects.pitch_shift(signal, sr=SAMPLE_RATE,
                                             pitch_shift=random.uniform(-12, 12))
    if random.random() < 0.5:
        signal = librosa.effects.time_stretch(signal, rate=random.uniform(0.8, 1.2))
    return signal

def adjust_shape(self, sequence, max_sequence_length = 126):
    current_length = sequence.shape[2]
    if current_length < max_sequence_length:
        padding = np.zeros((1, 13, max_sequence_length - current_length))
        padded_sequence = np.concatenate((sequence, padding), axis=2)
    else:
        padded_sequence = sequence[:, :, :max_sequence_length]
    return padded_sequence

def __len__(self):
    return len(self.files)

def __getitem__(self, idx):
    cur_file = self.files[idx]
    d = cur_file[0]
    file_path = cur_file[1]
    target = genre_mappings[str(file_path).split("/")[-2]]
    signal, sample_rate = librosa.load(file_path, sr=SAMPLE_RATE)
    start = self.samples_per_segment * d
    finish = start + self.samples_per_segment
    cur_signal = signal[start:finish]
    if self.training: cur_signal = self.apply_augmentations(cur_signal)
    cur_mfcc = self.mfcc_extractor.get_mfcc_features(cur_signal, sample_rate)
    cur_mfcc = self.adjust_shape(cur_mfcc)

```

```

        return torch.tensor(cur_mfcc, dtype=torch.float32), target

class GenreDatasetPhaseMFCC2(GenreDatasetMFCC):

    def __init__(self, train_path, n_fft=2048, hop_length=512, num_segmen
        super().__init__(train_path, n_fft, hop_length, num_segments, mel
        self.mfcc_extractor = MusicFeatureExtractorComplex2(
            FFT_size=n_fft, HOP_SIZE=hop_length, mel_filter_num = mel_fil

    def __getitem__(self, idx):
        cur_file = self.files[idx]
        d = cur_file[0]
        file_path = cur_file[1]
        target = genre_mappings[str(file_path).split("/") [2]]
        signal, sample_rate = librosa.load(file_path, sr=SAMPLE_RATE)
        start = self.samples_per_segment * d
        finish = start + self.samples_per_segment
        cur_signal = signal[start:finish]
        if self.training: cur_signal = self.apply_augmentations(cur_signa
        cur_mfcc, cur_phase = self.mfcc_extractor.get_mfcc_features(cur_s
        cur_mfcc, cur_phase = self.adjust_shape(cur_mfcc), self.adjust_sh
        return torch.tensor(cur_mfcc, dtype=torch.float32), torch.tensor(

```

```

In [33]: train_dataset = GenreDatasetPhaseMFCC2("Data/train/", n_fft=2048, hop_len
test_dataset = GenreDatasetPhaseMFCC2("Data/test/", n_fft=2048, hop_length
train_loader = torch.utils.data.DataLoader(dataset=train_dataset, shuffle
test_loader = torch.utils.data.DataLoader(dataset=test_dataset, shuffle=F

```

1. Simple Graph Net (Only magnitude)

```

In [34]: def train(model, device, train_loader, test_loader, optimizer, epoch, met
    model.train()
    total_loss = 0
    correct = 0
    total_samples = len(train_loader.dataset)
    start_time = time.time()

    for batch_idx, (data, data2, target) in enumerate(train_loader):
        data, data2, target = data.to(device), data2.to(device), target.t
        optimizer.zero_grad()
        output = model(data)
        loss = F.nll_loss(output, target)
        loss.backward()
        optimizer.step()
        total_loss += loss.item()
        pred = output.argmax(dim=1, keepdim=True)
        correct += pred.eq(target.view_as(pred)).sum().item()

    if batch_idx % 100 == 0:
        batch_accuracy = 100. * correct / ((batch_idx + 1) * len(data
        print('Train Epoch: {:3} [{:6}/{:6} ({:3.0f}%)]\tLoss: {:.6f}
            epoch,
            batch_idx * len(data),
            total_samples,
            100. * batch_idx / len(train_loader),
            loss.item(),
            batch_accuracy)
    )

```

```

end_time = time.time()
epoch_times = metrics_dict['epoch_times']
epoch_times.append(end_time - start_time)
epoch_loss = total_loss / len(train_loader)
epoch_accuracy = 100. * correct / total_samples
train_losses = metrics_dict['train_losses']
train_accuracies = metrics_dict['train_accuracies']
train_losses.append(epoch_loss)
train_accuracies.append(epoch_accuracy)
print('Epoch {} - Time: {:.2f}s - Train Loss: {:.6f} - Train Accuracy

# Evaluate on test data
model.eval()
test_loss = 0
correct = 0
with torch.no_grad():
    for data, data2, target in test_loader:
        data, data2, target = data.to(device), data2.to(device), target.to(device)
        output = model(data)
        test_loss += F.nll_loss(output, target, reduction='sum').item()
        pred = output.argmax(dim=1, keepdim=True)
        correct += pred.eq(target.view_as(pred)).sum().item()

test_loss /= len(test_loader.dataset)
test_accuracy = 100. * correct / len(test_loader.dataset)
test_losses = metrics_dict['test_losses']
test_accuracies = metrics_dict['test_accuracies']
test_losses.append(test_loss)
test_accuracies.append(test_accuracy)
print('Test Loss: {:.6f} - Test Accuracy: {:.2f}%\n'.format(test_loss, test_accuracy))

```

```

In [35]: class ComplexGraphNet(nn.Module):
    def __init__(self):
        super(ComplexGraphNet, self).__init__()
        self.gnn_layer = GCNConv(in_channels=126, out_channels=126, node_size=126)
        self.conv1 = ComplexConv2d(1, 10, 2, 1)
        self.bn = ComplexBatchNorm2d(10)
        self.conv2 = ComplexConv2d(10, 20, 2, 1)
        self.fc1 = ComplexLinear(30*2*20, 500)
        self.fc2 = ComplexLinear(500, 10)

    def forward(self, x): # Pass edge_index for GNN
        batch_size, _, num_nodes, node_size = x.size()
        edge_index = torch.tensor([[i, j] for i in range(num_nodes) for j in range(num_nodes)])
        x = x.view(-1, num_nodes, node_size) # Reshape for batch process
        x = self.gnn_layer(x, edge_index)
        x = x.unsqueeze(1)

        x = x.type(torch.complex64)
        x = self.conv1(x)
        x = complex_relu(x)
        x = complex_max_pool2d(x, 2, 2)
        x = self.bn(x)
        x = self.conv2(x)
        x = complex_relu(x)
        x = complex_max_pool2d(x, 2, 2)
        x = x.view(batch_size, -1) # Reshape back to batched form
        x = self.fc1(x)
        x = complex_relu(x)

```

```
x = self.fc2(x)
x = x.abs()
x = F.log_softmax(x, dim=1)
return x

device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model = ComplexGraphNet().to(device)
optimizer = torch.optim.SGD(model.parameters(), lr=0.01, momentum=0.9)

metrics_dict_e1 = {
    'epoch_times': [],
    'train_losses': [],
    'train_accuracies': [],
    'test_losses': [],
    'test_accuracies': []
}

for epoch in range(NUM_EPOCHS):
    train(model,
          device,
          train_loader,
          test_loader,
          optimizer,
          epoch,
          metrics_dict_e1)

print("-"*100)
print("-"*100)
print("FINAL RESULTS:")
print("-"*100)
for key, value in metrics_dict_e1.items():
    print(f'{key}: {value}')
```

Train Epoch: 0 [0/ 8390 (0%)] Loss: 2.283815 Accuracy: 9.38%
Train Epoch: 0 [3200/ 8390 (38%)] Loss: 2.285956 Accuracy: 15.53%
Train Epoch: 0 [6400/ 8390 (76%)] Loss: 2.140933 Accuracy: 17.06%
Epoch 0 – Time: 233.97s – Train Loss: 2.234477 – Train Accuracy: 17.37%
Test Loss: 2.186637 – Test Accuracy: 20.44%

Train Epoch: 1 [0/ 8390 (0%)] Loss: 2.173024 Accuracy: 25.00%
Train Epoch: 1 [3200/ 8390 (38%)] Loss: 2.406570 Accuracy: 19.15%
Train Epoch: 1 [6400/ 8390 (76%)] Loss: 2.102077 Accuracy: 19.45%
Epoch 1 – Time: 226.15s – Train Loss: 2.182805 – Train Accuracy: 19.19%
Test Loss: 2.154018 – Test Accuracy: 20.75%

Train Epoch: 2 [0/ 8390 (0%)] Loss: 2.015391 Accuracy: 34.38%
Train Epoch: 2 [3200/ 8390 (38%)] Loss: 2.243402 Accuracy: 19.06%
Train Epoch: 2 [6400/ 8390 (76%)] Loss: 2.275811 Accuracy: 19.56%
Epoch 2 – Time: 236.52s – Train Loss: 2.171332 – Train Accuracy: 19.48%
Test Loss: 2.191294 – Test Accuracy: 17.31%

Train Epoch: 3 [0/ 8390 (0%)] Loss: 2.239104 Accuracy: 9.38%
Train Epoch: 3 [3200/ 8390 (38%)] Loss: 2.304262 Accuracy: 20.39%
Train Epoch: 3 [6400/ 8390 (76%)] Loss: 2.138627 Accuracy: 20.20%
Epoch 3 – Time: 238.93s – Train Loss: 2.166512 – Train Accuracy: 19.83%
Test Loss: 2.181513 – Test Accuracy: 18.69%

Train Epoch: 4 [0/ 8390 (0%)] Loss: 2.182257 Accuracy: 15.62%
Train Epoch: 4 [3200/ 8390 (38%)] Loss: 2.212053 Accuracy: 20.45%
Train Epoch: 4 [6400/ 8390 (76%)] Loss: 2.122830 Accuracy: 21.21%
Epoch 4 – Time: 239.38s – Train Loss: 2.143740 – Train Accuracy: 20.86%
Test Loss: 2.133375 – Test Accuracy: 22.38%

Train Epoch: 5 [0/ 8390 (0%)] Loss: 2.226711 Accuracy: 18.75%
Train Epoch: 5 [3200/ 8390 (38%)] Loss: 2.121426 Accuracy: 21.10%
Train Epoch: 5 [6400/ 8390 (76%)] Loss: 1.933081 Accuracy: 21.39%
Epoch 5 – Time: 236.68s – Train Loss: 2.138812 – Train Accuracy: 21.49%
Test Loss: 2.176407 – Test Accuracy: 18.31%

Train Epoch: 6 [0/ 8390 (0%)] Loss: 2.114547 Accuracy: 12.50%
Train Epoch: 6 [3200/ 8390 (38%)] Loss: 2.301475 Accuracy: 22.03%
Train Epoch: 6 [6400/ 8390 (76%)] Loss: 2.247961 Accuracy: 21.08%
Epoch 6 – Time: 237.03s – Train Loss: 2.130672 – Train Accuracy: 21.20%
Test Loss: 2.145782 – Test Accuracy: 21.50%

Train Epoch: 7 [0/ 8390 (0%)] Loss: 2.018586 Accuracy: 37.50%
Train Epoch: 7 [3200/ 8390 (38%)] Loss: 2.011729 Accuracy: 21.04%
Train Epoch: 7 [6400/ 8390 (76%)] Loss: 2.357390 Accuracy: 22.05%
Epoch 7 – Time: 239.32s – Train Loss: 2.122056 – Train Accuracy: 21.80%
Test Loss: 2.176117 – Test Accuracy: 19.69%

Train Epoch: 8 [0/ 8390 (0%)] Loss: 2.233269 Accuracy: 18.75%
Train Epoch: 8 [3200/ 8390 (38%)] Loss: 2.092553 Accuracy: 20.39%
Train Epoch: 8 [6400/ 8390 (76%)] Loss: 2.221566 Accuracy: 21.10%
Epoch 8 – Time: 242.28s – Train Loss: 2.119308 – Train Accuracy: 21.44%
Test Loss: 2.113507 – Test Accuracy: 22.31%

Train Epoch: 9 [0/ 8390 (0%)] Loss: 1.932667 Accuracy: 37.50%
Train Epoch: 9 [3200/ 8390 (38%)] Loss: 2.014356 Accuracy: 22.71%
Train Epoch: 9 [6400/ 8390 (76%)] Loss: 2.107163 Accuracy: 22.62%
Epoch 9 – Time: 240.29s – Train Loss: 2.099407 – Train Accuracy: 22.24%
Test Loss: 2.145893 – Test Accuracy: 19.19%

Train Epoch: 10 [0/ 8390 (0%)] Loss: 2.220515 Accuracy: 15.62%
Train Epoch: 10 [3200/ 8390 (38%)] Loss: 2.189619 Accuracy: 21.94%
Train Epoch: 10 [6400/ 8390 (76%)] Loss: 1.973737 Accuracy: 22.68%
Epoch 10 – Time: 241.49s – Train Loss: 2.108154 – Train Accuracy: 22.80%
Test Loss: 2.145267 – Test Accuracy: 22.25%

Train Epoch: 11 [0/ 8390 (0%)] Loss: 2.138165 Accuracy: 18.75%
Train Epoch: 11 [3200/ 8390 (38%)] Loss: 2.291169 Accuracy: 23.05%
Train Epoch: 11 [6400/ 8390 (76%)] Loss: 2.173194 Accuracy: 22.84%
Epoch 11 – Time: 237.19s – Train Loss: 2.095983 – Train Accuracy: 22.82%
Test Loss: 2.097750 – Test Accuracy: 23.88%

Train Epoch: 12 [0/ 8390 (0%)] Loss: 1.984829 Accuracy: 25.00%
Train Epoch: 12 [3200/ 8390 (38%)] Loss: 1.933785 Accuracy: 23.58%
Train Epoch: 12 [6400/ 8390 (76%)] Loss: 1.954490 Accuracy: 23.97%
Epoch 12 – Time: 233.34s – Train Loss: 2.078130 – Train Accuracy: 24.18%
Test Loss: 2.239533 – Test Accuracy: 18.81%

Train Epoch: 13 [0/ 8390 (0%)] Loss: 2.180044 Accuracy: 15.62%
Train Epoch: 13 [3200/ 8390 (38%)] Loss: 1.909034 Accuracy: 24.29%
Train Epoch: 13 [6400/ 8390 (76%)] Loss: 2.191316 Accuracy: 23.17%
Epoch 13 – Time: 231.77s – Train Loss: 2.090801 – Train Accuracy: 23.71%
Test Loss: 2.107307 – Test Accuracy: 25.00%

Train Epoch: 14 [0/ 8390 (0%)] Loss: 2.004154 Accuracy: 21.88%
Train Epoch: 14 [3200/ 8390 (38%)] Loss: 1.827421 Accuracy: 24.16%
Train Epoch: 14 [6400/ 8390 (76%)] Loss: 2.039760 Accuracy: 24.61%
Epoch 14 – Time: 228.70s – Train Loss: 2.073023 – Train Accuracy: 24.37%
Test Loss: 2.113122 – Test Accuracy: 21.69%

Train Epoch: 15 [0/ 8390 (0%)] Loss: 2.098036 Accuracy: 12.50%
Train Epoch: 15 [3200/ 8390 (38%)] Loss: 1.838435 Accuracy: 23.73%
Train Epoch: 15 [6400/ 8390 (76%)] Loss: 2.227892 Accuracy: 24.07%
Epoch 15 – Time: 228.27s – Train Loss: 2.051294 – Train Accuracy: 24.35%
Test Loss: 2.088547 – Test Accuracy: 26.12%

Train Epoch: 16 [0/ 8390 (0%)] Loss: 2.222553 Accuracy: 18.75%
Train Epoch: 16 [3200/ 8390 (38%)] Loss: 2.005491 Accuracy: 25.31%
Train Epoch: 16 [6400/ 8390 (76%)] Loss: 2.025543 Accuracy: 25.36%
Epoch 16 – Time: 228.22s – Train Loss: 2.059692 – Train Accuracy: 25.40%
Test Loss: 2.077507 – Test Accuracy: 25.62%

Train Epoch: 17 [0/ 8390 (0%)] Loss: 2.034314 Accuracy: 18.75%
Train Epoch: 17 [3200/ 8390 (38%)] Loss: 1.842534 Accuracy: 28.56%
Train Epoch: 17 [6400/ 8390 (76%)] Loss: 2.120786 Accuracy: 27.05%
Epoch 17 – Time: 226.93s – Train Loss: 2.034155 – Train Accuracy: 26.52%
Test Loss: 2.073564 – Test Accuracy: 24.38%

Train Epoch: 18 [0/ 8390 (0%)] Loss: 2.023822 Accuracy: 25.00%
Train Epoch: 18 [3200/ 8390 (38%)] Loss: 1.873845 Accuracy: 26.64%
Train Epoch: 18 [6400/ 8390 (76%)] Loss: 2.002745 Accuracy: 26.00%
Epoch 18 – Time: 227.17s – Train Loss: 2.036771 – Train Accuracy: 25.69%
Test Loss: 2.069038 – Test Accuracy: 25.81%

Train Epoch: 19 [0/ 8390 (0%)] Loss: 2.088804 Accuracy: 21.88%
Train Epoch: 19 [3200/ 8390 (38%)] Loss: 1.972812 Accuracy: 25.93%
Train Epoch: 19 [6400/ 8390 (76%)] Loss: 1.902578 Accuracy: 25.47%
Epoch 19 – Time: 228.38s – Train Loss: 2.030699 – Train Accuracy: 26.22%
Test Loss: 2.080796 – Test Accuracy: 24.94%

Train Epoch: 20 [0/ 8390 (0%)] Loss: 1.757594 Accuracy: 31.25%
Train Epoch: 20 [3200/ 8390 (38%)] Loss: 2.131952 Accuracy: 25.93%
Train Epoch: 20 [6400/ 8390 (76%)] Loss: 1.976331 Accuracy: 25.65%
Epoch 20 – Time: 234.30s – Train Loss: 2.032363 – Train Accuracy: 25.85%
Test Loss: 2.099731 – Test Accuracy: 25.19%

Train Epoch: 21 [0/ 8390 (0%)] Loss: 1.994877 Accuracy: 21.88%
Train Epoch: 21 [3200/ 8390 (38%)] Loss: 2.212613 Accuracy: 25.96%
Train Epoch: 21 [6400/ 8390 (76%)] Loss: 1.958855 Accuracy: 25.64%
Epoch 21 – Time: 225.82s – Train Loss: 2.027406 – Train Accuracy: 26.23%
Test Loss: 2.047946 – Test Accuracy: 25.31%

Train Epoch: 22 [0/ 8390 (0%)] Loss: 2.057194 Accuracy: 28.12%
Train Epoch: 22 [3200/ 8390 (38%)] Loss: 1.830850 Accuracy: 27.51%
Train Epoch: 22 [6400/ 8390 (76%)] Loss: 1.977901 Accuracy: 27.15%
Epoch 22 – Time: 225.02s – Train Loss: 2.001441 – Train Accuracy: 26.96%
Test Loss: 2.053808 – Test Accuracy: 25.69%

Train Epoch: 23 [0/ 8390 (0%)] Loss: 2.087957 Accuracy: 18.75%
Train Epoch: 23 [3200/ 8390 (38%)] Loss: 1.934952 Accuracy: 28.22%
Train Epoch: 23 [6400/ 8390 (76%)] Loss: 2.093279 Accuracy: 27.61%
Epoch 23 – Time: 224.18s – Train Loss: 1.999862 – Train Accuracy: 27.32%
Test Loss: 2.041623 – Test Accuracy: 25.56%

Train Epoch: 24 [0/ 8390 (0%)] Loss: 1.804892 Accuracy: 37.50%
Train Epoch: 24 [3200/ 8390 (38%)] Loss: 2.206030 Accuracy: 27.78%
Train Epoch: 24 [6400/ 8390 (76%)] Loss: 1.932141 Accuracy: 27.08%
Epoch 24 – Time: 224.50s – Train Loss: 1.996928 – Train Accuracy: 27.57%
Test Loss: 2.081249 – Test Accuracy: 24.62%

Train Epoch: 25 [0/ 8390 (0%)] Loss: 1.818998 Accuracy: 37.50%
Train Epoch: 25 [3200/ 8390 (38%)] Loss: 2.048907 Accuracy: 28.50%
Train Epoch: 25 [6400/ 8390 (76%)] Loss: 2.009765 Accuracy: 27.57%
Epoch 25 – Time: 224.85s – Train Loss: 1.990574 – Train Accuracy: 27.56%
Test Loss: 2.069043 – Test Accuracy: 24.44%

Train Epoch: 26 [0/ 8390 (0%)] Loss: 1.843599 Accuracy: 37.50%
Train Epoch: 26 [3200/ 8390 (38%)] Loss: 2.136900 Accuracy: 27.44%
Train Epoch: 26 [6400/ 8390 (76%)] Loss: 1.867156 Accuracy: 27.89%
Epoch 26 – Time: 227.72s – Train Loss: 1.986620 – Train Accuracy: 28.12%
Test Loss: 2.048724 – Test Accuracy: 24.69%

Train Epoch: 27 [0/ 8390 (0%)] Loss: 1.889203 Accuracy: 31.25%
Train Epoch: 27 [3200/ 8390 (38%)] Loss: 1.977899 Accuracy: 28.34%
Train Epoch: 27 [6400/ 8390 (76%)] Loss: 2.176792 Accuracy: 27.83%
Epoch 27 – Time: 226.10s – Train Loss: 1.995100 – Train Accuracy: 27.88%
Test Loss: 2.056802 – Test Accuracy: 25.62%

Train Epoch: 28 [0/ 8390 (0%)] Loss: 1.990392 Accuracy: 31.25%
Train Epoch: 28 [3200/ 8390 (38%)] Loss: 1.947343 Accuracy: 27.88%
Train Epoch: 28 [6400/ 8390 (76%)] Loss: 2.123044 Accuracy: 28.00%
Epoch 28 – Time: 223.05s – Train Loss: 1.985914 – Train Accuracy: 27.91%
Test Loss: 2.034711 – Test Accuracy: 25.69%

Train Epoch: 29 [0/ 8390 (0%)] Loss: 1.824628 Accuracy: 43.75%
Train Epoch: 29 [3200/ 8390 (38%)] Loss: 1.940703 Accuracy: 29.21%
Train Epoch: 29 [6400/ 8390 (76%)] Loss: 2.051470 Accuracy: 28.28%
Epoch 29 – Time: 223.30s – Train Loss: 1.970584 – Train Accuracy: 28.46%
Test Loss: 2.062386 – Test Accuracy: 26.69%

Train Epoch: 30 [0/ 8390 (0%)] Loss: 1.932767 Accuracy: 31.25%
Train Epoch: 30 [3200/ 8390 (38%)] Loss: 2.009117 Accuracy: 29.02%
Train Epoch: 30 [6400/ 8390 (76%)] Loss: 1.938020 Accuracy: 28.51%
Epoch 30 – Time: 221.56s – Train Loss: 1.964117 – Train Accuracy: 28.62%
Test Loss: 2.015479 – Test Accuracy: 28.25%

Train Epoch: 31 [0/ 8390 (0%)] Loss: 1.612053 Accuracy: 43.75%
Train Epoch: 31 [3200/ 8390 (38%)] Loss: 1.733670 Accuracy: 29.73%
Train Epoch: 31 [6400/ 8390 (76%)] Loss: 1.920024 Accuracy: 29.20%
Epoch 31 – Time: 223.11s – Train Loss: 1.956306 – Train Accuracy: 29.24%
Test Loss: 2.053814 – Test Accuracy: 27.62%

Train Epoch: 32 [0/ 8390 (0%)] Loss: 1.901363 Accuracy: 25.00%
Train Epoch: 32 [3200/ 8390 (38%)] Loss: 1.922382 Accuracy: 30.14%
Train Epoch: 32 [6400/ 8390 (76%)] Loss: 2.035112 Accuracy: 29.73%
Epoch 32 – Time: 220.86s – Train Loss: 1.951182 – Train Accuracy: 29.58%
Test Loss: 2.034440 – Test Accuracy: 25.69%

Train Epoch: 33 [0/ 8390 (0%)] Loss: 1.991580 Accuracy: 25.00%
Train Epoch: 33 [3200/ 8390 (38%)] Loss: 1.911169 Accuracy: 30.82%
Train Epoch: 33 [6400/ 8390 (76%)] Loss: 1.893150 Accuracy: 30.53%
Epoch 33 – Time: 225.68s – Train Loss: 1.944604 – Train Accuracy: 29.99%
Test Loss: 2.033751 – Test Accuracy: 25.94%

Train Epoch: 34 [0/ 8390 (0%)] Loss: 1.752453 Accuracy: 31.25%
Train Epoch: 34 [3200/ 8390 (38%)] Loss: 1.883572 Accuracy: 30.17%
Train Epoch: 34 [6400/ 8390 (76%)] Loss: 1.837702 Accuracy: 29.49%
Epoch 34 – Time: 223.98s – Train Loss: 1.946527 – Train Accuracy: 29.62%
Test Loss: 2.073126 – Test Accuracy: 26.44%

Train Epoch: 35 [0/ 8390 (0%)] Loss: 2.025464 Accuracy: 25.00%
Train Epoch: 35 [3200/ 8390 (38%)] Loss: 1.954219 Accuracy: 29.95%
Train Epoch: 35 [6400/ 8390 (76%)] Loss: 1.886833 Accuracy: 29.94%
Epoch 35 – Time: 223.24s – Train Loss: 1.936648 – Train Accuracy: 29.68%
Test Loss: 2.020539 – Test Accuracy: 27.81%

Train Epoch: 36 [0/ 8390 (0%)] Loss: 1.900638 Accuracy: 25.00%
Train Epoch: 36 [3200/ 8390 (38%)] Loss: 1.862369 Accuracy: 30.14%
Train Epoch: 36 [6400/ 8390 (76%)] Loss: 1.809317 Accuracy: 30.36%
Epoch 36 – Time: 227.75s – Train Loss: 1.942515 – Train Accuracy: 30.13%
Test Loss: 2.031603 – Test Accuracy: 25.81%

Train Epoch: 37 [0/ 8390 (0%)] Loss: 2.025652 Accuracy: 21.88%
Train Epoch: 37 [3200/ 8390 (38%)] Loss: 1.811957 Accuracy: 30.32%
Train Epoch: 37 [6400/ 8390 (76%)] Loss: 2.013695 Accuracy: 30.66%
Epoch 37 – Time: 222.05s – Train Loss: 1.927433 – Train Accuracy: 30.36%
Test Loss: 2.051604 – Test Accuracy: 26.31%

Train Epoch: 38 [0/ 8390 (0%)] Loss: 1.649459 Accuracy: 43.75%
Train Epoch: 38 [3200/ 8390 (38%)] Loss: 2.124419 Accuracy: 31.37%
Train Epoch: 38 [6400/ 8390 (76%)] Loss: 1.922676 Accuracy: 30.77%
Epoch 38 – Time: 230.87s – Train Loss: 1.921546 – Train Accuracy: 31.20%
Test Loss: 2.057478 – Test Accuracy: 28.44%

Train Epoch: 39 [0/ 8390 (0%)] Loss: 2.099957 Accuracy: 18.75%
Train Epoch: 39 [3200/ 8390 (38%)] Loss: 2.118045 Accuracy: 31.87%
Train Epoch: 39 [6400/ 8390 (76%)] Loss: 1.844247 Accuracy: 31.67%
Epoch 39 – Time: 227.03s – Train Loss: 1.904664 – Train Accuracy: 31.55%
Test Loss: 2.079740 – Test Accuracy: 24.88%

Train Epoch: 40 [0/ 8390 (0%)] Loss: 2.131852 Accuracy: 25.00%
Train Epoch: 40 [3200/ 8390 (38%)] Loss: 1.620973 Accuracy: 31.68%
Train Epoch: 40 [6400/ 8390 (76%)] Loss: 2.101529 Accuracy: 31.31%
Epoch 40 – Time: 226.69s – Train Loss: 1.911417 – Train Accuracy: 31.11%
Test Loss: 2.053170 – Test Accuracy: 26.00%

Train Epoch: 41 [0/ 8390 (0%)] Loss: 1.750316 Accuracy: 34.38%
Train Epoch: 41 [3200/ 8390 (38%)] Loss: 1.904465 Accuracy: 30.69%
Train Epoch: 41 [6400/ 8390 (76%)] Loss: 1.963924 Accuracy: 31.19%
Epoch 41 – Time: 225.56s – Train Loss: 1.904321 – Train Accuracy: 31.17%
Test Loss: 2.053985 – Test Accuracy: 27.31%

Train Epoch: 42 [0/ 8390 (0%)] Loss: 1.974954 Accuracy: 28.12%
Train Epoch: 42 [3200/ 8390 (38%)] Loss: 1.891893 Accuracy: 31.96%
Train Epoch: 42 [6400/ 8390 (76%)] Loss: 1.921841 Accuracy: 32.59%
Epoch 42 – Time: 225.97s – Train Loss: 1.895247 – Train Accuracy: 32.32%
Test Loss: 1.997389 – Test Accuracy: 28.06%

Train Epoch: 43 [0/ 8390 (0%)] Loss: 1.914194 Accuracy: 31.25%
Train Epoch: 43 [3200/ 8390 (38%)] Loss: 1.982564 Accuracy: 32.67%
Train Epoch: 43 [6400/ 8390 (76%)] Loss: 2.258419 Accuracy: 32.65%
Epoch 43 – Time: 223.78s – Train Loss: 1.899233 – Train Accuracy: 32.44%
Test Loss: 2.024002 – Test Accuracy: 27.38%

Train Epoch: 44 [0/ 8390 (0%)] Loss: 1.560061 Accuracy: 50.00%
Train Epoch: 44 [3200/ 8390 (38%)] Loss: 1.845327 Accuracy: 32.92%
Train Epoch: 44 [6400/ 8390 (76%)] Loss: 2.210847 Accuracy: 32.40%
Epoch 44 – Time: 226.01s – Train Loss: 1.893218 – Train Accuracy: 32.04%
Test Loss: 2.061902 – Test Accuracy: 24.31%

Train Epoch: 45 [0/ 8390 (0%)] Loss: 1.775600 Accuracy: 43.75%
Train Epoch: 45 [3200/ 8390 (38%)] Loss: 1.951963 Accuracy: 32.24%
Train Epoch: 45 [6400/ 8390 (76%)] Loss: 1.674304 Accuracy: 31.95%
Epoch 45 – Time: 225.07s – Train Loss: 1.889554 – Train Accuracy: 32.03%
Test Loss: 2.012643 – Test Accuracy: 28.81%

Train Epoch: 46 [0/ 8390 (0%)] Loss: 1.857784 Accuracy: 34.38%
Train Epoch: 46 [3200/ 8390 (38%)] Loss: 1.889494 Accuracy: 33.79%
Train Epoch: 46 [6400/ 8390 (76%)] Loss: 1.861357 Accuracy: 32.76%
Epoch 46 – Time: 225.23s – Train Loss: 1.875798 – Train Accuracy: 32.97%
Test Loss: 2.018404 – Test Accuracy: 28.50%

Train Epoch: 47 [0/ 8390 (0%)] Loss: 2.024217 Accuracy: 31.25%
Train Epoch: 47 [3200/ 8390 (38%)] Loss: 1.554365 Accuracy: 32.58%
Train Epoch: 47 [6400/ 8390 (76%)] Loss: 1.847797 Accuracy: 31.98%
Epoch 47 – Time: 224.48s – Train Loss: 1.879617 – Train Accuracy: 32.55%
Test Loss: 2.083142 – Test Accuracy: 27.81%

Train Epoch: 48 [0/ 8390 (0%)] Loss: 1.864645 Accuracy: 37.50%
Train Epoch: 48 [3200/ 8390 (38%)] Loss: 2.004141 Accuracy: 32.12%
Train Epoch: 48 [6400/ 8390 (76%)] Loss: 1.954044 Accuracy: 32.56%
Epoch 48 – Time: 222.04s – Train Loss: 1.873967 – Train Accuracy: 32.67%
Test Loss: 2.052414 – Test Accuracy: 26.94%

Train Epoch: 49 [0/ 8390 (0%)] Loss: 1.916777 Accuracy: 40.62%
Train Epoch: 49 [3200/ 8390 (38%)] Loss: 1.728014 Accuracy: 33.48%
Train Epoch: 49 [6400/ 8390 (76%)] Loss: 1.615704 Accuracy: 33.26%
Epoch 49 – Time: 1162.20s – Train Loss: 1.856905 – Train Accuracy: 33.05%
Test Loss: 2.021979 – Test Accuracy: 28.06%

FINAL RESULTS:

```
epoch_times: [233.97046875953674, 226.14852595329285, 236.52325081825256,
238.92535185813904, 239.38257002830505, 236.6788511276245, 237.02662801742
554, 239.32301020622253, 242.27710700035095, 240.29133009910583, 241.49365
496635437, 237.19384503364563, 233.34383893013, 231.7748110294342, 228.695
59788703918, 228.27052807807922, 228.22335124015808, 226.9341676235199, 22
7.17398810386658, 228.38212084770203, 234.2978479862213, 225.821125984191
9, 225.02131295204163, 224.1751549243927, 224.49942111968994, 224.85096287
727356, 227.71697902679443, 226.1047580242157, 223.05186772346497, 223.297
59693145752, 221.56133818626404, 223.107741355896, 220.85710501670837, 22
5.68304800987244, 223.97671675682068, 223.2411026954651, 227.7453482151031
5, 222.0526521205902, 230.87250208854675, 227.02583384513855, 226.69209814
071655, 225.56455397605896, 225.97482013702393, 223.7847821712494, 226.007
67278671265, 225.06873416900635, 225.23424696922302, 224.47550320625305, 2
22.03592991828918, 1162.1967041492462]
train_losses: [2.234476645029228, 2.1828049061862567, 2.171332196879933,
2.166512229515396, 2.1437400169954954, 2.138811717051586, 2.13067216045073
86, 2.1220557052670546, 2.1193076758894303, 2.099406872996847, 2.108154222
2554446, 2.0959825861545007, 2.0781302060789733, 2.0908009400804533, 2.073
023048066001, 2.051294315862292, 2.0596924214872696, 2.0341545625497366,
2.0367706076789447, 2.0306985701313454, 2.0323631217461506, 2.027406216577
7194, 2.0014411761560513, 1.9998621972462602, 1.9969276835900227, 1.990574
1105552848, 1.9866200831100231, 1.9950999772275677, 1.985913817664139, 1.9
705841104492887, 1.9641166929980272, 1.9563061344714565, 1.951182177958597
6, 1.9446035810099302, 1.9465266179492455, 1.9366483128707828, 1.942514810
853332, 1.9274329051716637, 1.9215455496584186, 1.9046635550397042, 1.9114
173896440112, 1.9043212164449328, 1.8952473711421471, 1.899233222917746,
1.8932179776766829, 1.8895541998266263, 1.8757984788363216, 1.879616890699
8088, 1.873966821732412, 1.8569049575856624]
train_accuracies: [17.36591179976162, 19.189511323003575, 19.4755661501787
86, 19.833134684147794, 20.858164481525627, 21.489868891537544, 21.2038140
64362337, 21.799761620977353, 21.442193087008345, 22.240762812872468, 22.8
00953516090583, 22.824791418355186, 24.183551847437425, 23.70679380214541
3, 24.37425506555423, 24.35041716328963, 25.399284862932063, 26.5196662693
68294, 25.68533969010727, 26.221692491060786, 25.852205005959476, 26.23361
1442193087, 26.96066746126341, 27.31823599523242, 27.568533969010726, 27.5
5661501787843, 28.116805721096544, 27.878426698450536, 27.914183551847437,
28.462455303933254, 28.61740166865316, 29.237187127532778, 29.582836710369
488, 29.9880810488677, 29.61859356376639, 29.67818831942789, 30.1311084624
55305, 30.357568533969012, 31.203814064362337, 31.549463647199048, 31.1084
62455303933, 31.168057210965436, 32.32419547079857, 32.44338498212157, 32.
038140643623365, 32.02622169249106, 32.967818831942786, 32.55065554231228,
32.66984505363528, 33.05125148986889]
test_losses: [2.1866367852687834, 2.154017615318298, 2.1912943744659423,
2.1815134119987487, 2.1333746206760407, 2.176407445669174, 2.1457816970348
36, 2.176116580963135, 2.1135067558288574, 2.145893280506134, 2.1452674436
569215, 2.0977504682540893, 2.2395331597328187, 2.1073072028160094, 2.1131
2224149704, 2.088547270298004, 2.077507041692734, 2.0735635244846344, 2.06
90382504463196, 2.080795907974243, 2.0997307825088503, 2.0479457080364227,
2.0538084936141967, 2.041623057126999, 2.0812490618228914, 2.0690434098243
715, 2.0487236738204957, 2.0568019306659697, 2.0347112727165224, 2.0623856
341838835, 2.015479021072388, 2.0538138830661774, 2.0344402396678927, 2.03
37510764598847, 2.0731262707710267, 2.0205389261245728, 2.031603275537490
6, 2.0516035866737368, 2.057477984428406, 2.079739997386932, 2.05316980123
```

5199, 2.0539849162101746, 1.9973892450332642, 2.0240018010139464, 2.0619021534919737, 2.0126427090168, 2.018404322862625, 2.0831423473358153, 2.0524144637584687, 2.02197856426239]

test accuracies: [20.4375, 20.75, 17.3125, 18.6875, 22.375, 18.3125, 21.5, 19.6875, 22.3125, 19.1875, 22.25, 23.875, 18.8125, 25.0, 21.6875, 26.125, 25.625, 24.375, 25.8125, 24.9375, 25.1875, 25.3125, 25.6875, 25.5625, 24.625, 24.4375, 24.6875, 25.625, 25.6875, 26.6875, 28.25, 27.625, 25.6875, 25.9375, 26.4375, 27.8125, 25.8125, 26.3125, 28.4375, 24.875, 26.0, 27.3125, 28.0625, 27.375, 24.3125, 28.8125, 28.5, 27.8125, 26.9375, 28.0625]

2. Simple Graph Net (Magnitude + phase wieghts)

```
In [36]: def train(model, device, train_loader, test_loader, optimizer, epoch, metrics_dict):
    model.train()
    total_loss = 0
    correct = 0
    total_samples = len(train_loader.dataset)
    start_time = time.time()

    for batch_idx, (data, data2, target) in enumerate(train_loader):
        data, data2, target = data.to(device), data2.to(device), target.to(device)
        optimizer.zero_grad()
        output = model([data, data2])
        loss = F.nll_loss(output, target)
        loss.backward()
        optimizer.step()
        total_loss += loss.item()
        pred = output.argmax(dim=1, keepdim=True)
        correct += pred.eq(target.view_as(pred)).sum().item()

    if batch_idx % 100 == 0:
        batch_accuracy = 100. * correct / ((batch_idx + 1) * len(data_loader.dataset))
        print('Train Epoch: {:3} [{:6}/{:6}] ({:3.0f}%) \t Loss: {:.6f}'.format(
            epoch,
            batch_idx * len(data_loader.dataset),
            total_samples,
            100. * batch_idx / len(train_loader.dataset),
            loss.item(),
            batch_accuracy))

    end_time = time.time()
    epoch_times = metrics_dict['epoch_times']
    epoch_times.append(end_time - start_time)
    epoch_loss = total_loss / len(train_loader)
    epoch_accuracy = 100. * correct / total_samples
    train_losses = metrics_dict['train_losses']
    train_accuracies = metrics_dict['train_accuracies']
    train_losses.append(epoch_loss)
    train_accuracies.append(epoch_accuracy)
    print('Epoch {} - Time: {:.2f}s - Train Loss: {:.6f} - Train Accuracy: {:.2f}%'.format(
        epoch, end_time - start_time, epoch_loss, epoch_accuracy))

    # Evaluate on test data
    model.eval()
    test_loss = 0
    correct = 0
    with torch.no_grad():
        for data, data2, target in test_loader:
```

```

        data, data2, target = data.to(device), data2.to(device), target
        output = model([data, data2])
        test_loss += F.nll_loss(output, target, reduction='sum').item()
        pred = output.argmax(dim=1, keepdim=True)
        correct += pred.eq(target.view_as(pred)).sum().item()

test_loss /= len(test_loader.dataset)
test_accuracy = 100. * correct / len(test_loader.dataset)
test_losses = metrics_dict['test_losses']
test_accuracies = metrics_dict['test_accuracies']
test_losses.append(test_loss)
test_accuracies.append(test_accuracy)
print('Test Loss: {:.6f} - Test Accuracy: {:.2f}%\n'.format(test_loss, test_accuracy))

```

```

In [37]: class ComplexGraphNet(nn.Module):
    def __init__(self):
        super(ComplexGraphNet, self).__init__()
        self.gnn_layer = GCNConv(in_channels=126, out_channels=126, node_size=126)
        self.conv1 = ComplexConv2d(1, 10, 2, 1)
        self.bn = ComplexBatchNorm2d(10)
        self.conv2 = ComplexConv2d(10, 20, 2, 1)
        self.fc1 = ComplexLinear(30*2*20, 500)
        self.fc2 = ComplexLinear(500, 10)

    def forward(self, x): # Pass edge_index for GNN
        x, phase_data = x[0], x[1]
        batch_size, _, num_nodes, node_size = x.size()
        edge_index = torch.tensor([[i, j] for i in range(num_nodes) for j in range(num_nodes)])
        phase_data = torch.mean(phase_data.view(-1, num_nodes, node_size), dim=-1)
        edge_weight = torch.tensor([torch.mean(np.abs(phase_data[edge_index[i][0], edge_index[i][1]])),
                                     for i in range(len(edge_index[0]))])

        x = x.view(-1, num_nodes, node_size) # Reshape for batch process
        x = self.gnn_layer(x, edge_index, edge_weight)
        x = x.unsqueeze(1)

        x = x.type(torch.complex64)
        x = self.conv1(x)
        x = complex_relu(x)
        x = complex_max_pool2d(x, 2, 2)
        x = self.bn(x)
        x = self.conv2(x)
        x = complex_relu(x)
        x = complex_max_pool2d(x, 2, 2)
        x = x.view(batch_size, -1) # Reshape back to batched form
        x = self.fc1(x)
        x = complex_relu(x)
        x = self.fc2(x)
        x = x.abs()
        x = F.log_softmax(x, dim=1)
        return x

device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model = ComplexGraphNet().to(device)
optimizer = torch.optim.SGD(model.parameters(), lr=0.01, momentum=0.9)

metrics_dict_e2 = {
    'epoch_times': [],
    'train_losses': [],
    'train_accuracies': [],
}

```

```
        'test_losses': [],  
        'test accuracies': []  
    }  
  
    for epoch in range(NUM_EPOCHS):  
        train(model,  
              device,  
              train_loader,  
              test_loader,  
              optimizer,  
              epoch,  
              metrics_dict_e2)  
  
    print("-"*100)  
    print("-"*100)  
    print("FINAL RESULTS:")  
    print("-"*100)  
    for key, value in metrics_dict_e2.items():  
        print(f'{key}: {value}')
```

Train Epoch: 0 [0/ 8390 (0%)] Loss: 2.479136 Accuracy: 6.25%
Train Epoch: 0 [3200/ 8390 (38%)] Loss: 2.111964 Accuracy: 16.49%
Train Epoch: 0 [6400/ 8390 (76%)] Loss: 2.072670 Accuracy: 18.86%
Epoch 0 – Time: 1216.79s – Train Loss: 2.162852 – Train Accuracy: 19.68%
Test Loss: 2.109093 – Test Accuracy: 22.25%

Train Epoch: 1 [0/ 8390 (0%)] Loss: 1.894730 Accuracy: 25.00%
Train Epoch: 1 [3200/ 8390 (38%)] Loss: 2.064820 Accuracy: 22.62%
Train Epoch: 1 [6400/ 8390 (76%)] Loss: 2.095362 Accuracy: 23.46%
Epoch 1 – Time: 237.43s – Train Loss: 2.037587 – Train Accuracy: 24.28%
Test Loss: 2.066230 – Test Accuracy: 23.56%

Train Epoch: 2 [0/ 8390 (0%)] Loss: 2.163065 Accuracy: 21.88%
Train Epoch: 2 [3200/ 8390 (38%)] Loss: 2.177595 Accuracy: 26.21%
Train Epoch: 2 [6400/ 8390 (76%)] Loss: 1.961488 Accuracy: 26.90%
Epoch 2 – Time: 3536.20s – Train Loss: 1.987517 – Train Accuracy: 26.82%
Test Loss: 2.096034 – Test Accuracy: 21.19%

Train Epoch: 3 [0/ 8390 (0%)] Loss: 2.063694 Accuracy: 25.00%
Train Epoch: 3 [3200/ 8390 (38%)] Loss: 1.783233 Accuracy: 26.98%
Train Epoch: 3 [6400/ 8390 (76%)] Loss: 2.109796 Accuracy: 27.33%
Epoch 3 – Time: 255.05s – Train Loss: 1.977226 – Train Accuracy: 27.37%
Test Loss: 1.984386 – Test Accuracy: 26.75%

Train Epoch: 4 [0/ 8390 (0%)] Loss: 1.770829 Accuracy: 46.88%
Train Epoch: 4 [3200/ 8390 (38%)] Loss: 1.907099 Accuracy: 26.30%
Train Epoch: 4 [6400/ 8390 (76%)] Loss: 2.030431 Accuracy: 26.40%
Epoch 4 – Time: 338.99s – Train Loss: 1.973808 – Train Accuracy: 26.90%
Test Loss: 1.946919 – Test Accuracy: 28.12%

Train Epoch: 5 [0/ 8390 (0%)] Loss: 1.673114 Accuracy: 53.12%
Train Epoch: 5 [3200/ 8390 (38%)] Loss: 1.919456 Accuracy: 28.34%
Train Epoch: 5 [6400/ 8390 (76%)] Loss: 2.014733 Accuracy: 29.12%
Epoch 5 – Time: 249.76s – Train Loss: 1.922926 – Train Accuracy: 29.37%
Test Loss: 1.960438 – Test Accuracy: 29.12%

Train Epoch: 6 [0/ 8390 (0%)] Loss: 1.968090 Accuracy: 25.00%
Train Epoch: 6 [3200/ 8390 (38%)] Loss: 1.901110 Accuracy: 29.86%
Train Epoch: 6 [6400/ 8390 (76%)] Loss: 2.166843 Accuracy: 30.22%
Epoch 6 – Time: 260.97s – Train Loss: 1.913745 – Train Accuracy: 30.00%
Test Loss: 2.020193 – Test Accuracy: 25.06%

Train Epoch: 7 [0/ 8390 (0%)] Loss: 1.990562 Accuracy: 28.12%
Train Epoch: 7 [3200/ 8390 (38%)] Loss: 1.973588 Accuracy: 31.13%
Train Epoch: 7 [6400/ 8390 (76%)] Loss: 1.772776 Accuracy: 30.99%
Epoch 7 – Time: 290.29s – Train Loss: 1.895390 – Train Accuracy: 31.13%
Test Loss: 2.053939 – Test Accuracy: 31.88%

Train Epoch: 8 [0/ 8390 (0%)] Loss: 1.993796 Accuracy: 25.00%
Train Epoch: 8 [3200/ 8390 (38%)] Loss: 1.942533 Accuracy: 31.50%
Train Epoch: 8 [6400/ 8390 (76%)] Loss: 1.756390 Accuracy: 30.89%
Epoch 8 – Time: 2350.99s – Train Loss: 1.899573 – Train Accuracy: 30.83%
Test Loss: 2.063662 – Test Accuracy: 28.69%

Train Epoch: 9 [0/ 8390 (0%)] Loss: 1.870236 Accuracy: 43.75%
Train Epoch: 9 [3200/ 8390 (38%)] Loss: 1.853202 Accuracy: 31.96%
Train Epoch: 9 [6400/ 8390 (76%)] Loss: 1.817463 Accuracy: 32.51%
Epoch 9 – Time: 1119.26s – Train Loss: 1.858082 – Train Accuracy: 32.37%
Test Loss: 1.877559 – Test Accuracy: 30.88%

Train Epoch: 10 [0/ 8390 (0%)] Loss: 1.855305 Accuracy: 28.12%
Train Epoch: 10 [3200/ 8390 (38%)] Loss: 1.746241 Accuracy: 32.09%
Train Epoch: 10 [6400/ 8390 (76%)] Loss: 1.742811 Accuracy: 32.70%
Epoch 10 – Time: 1714.28s – Train Loss: 1.838106 – Train Accuracy: 32.60%
Test Loss: 1.843091 – Test Accuracy: 33.31%

Train Epoch: 11 [0/ 8390 (0%)] Loss: 1.638626 Accuracy: 46.88%
Train Epoch: 11 [3200/ 8390 (38%)] Loss: 1.710752 Accuracy: 34.38%
Train Epoch: 11 [6400/ 8390 (76%)] Loss: 1.678067 Accuracy: 33.78%
Epoch 11 – Time: 685.16s – Train Loss: 1.824078 – Train Accuracy: 33.58%
Test Loss: 1.925280 – Test Accuracy: 30.50%

Train Epoch: 12 [0/ 8390 (0%)] Loss: 1.972635 Accuracy: 21.88%
Train Epoch: 12 [3200/ 8390 (38%)] Loss: 1.832804 Accuracy: 33.35%
Train Epoch: 12 [6400/ 8390 (76%)] Loss: 1.663738 Accuracy: 34.67%
Epoch 12 – Time: 229.54s – Train Loss: 1.800104 – Train Accuracy: 34.56%
Test Loss: 1.895443 – Test Accuracy: 29.94%

Train Epoch: 13 [0/ 8390 (0%)] Loss: 1.694533 Accuracy: 46.88%
Train Epoch: 13 [3200/ 8390 (38%)] Loss: 2.048083 Accuracy: 34.31%
Train Epoch: 13 [6400/ 8390 (76%)] Loss: 1.721056 Accuracy: 35.49%
Epoch 13 – Time: 247.96s – Train Loss: 1.801329 – Train Accuracy: 35.18%
Test Loss: 2.059045 – Test Accuracy: 28.69%

Train Epoch: 14 [0/ 8390 (0%)] Loss: 1.800010 Accuracy: 31.25%
Train Epoch: 14 [3200/ 8390 (38%)] Loss: 1.848253 Accuracy: 35.61%
Train Epoch: 14 [6400/ 8390 (76%)] Loss: 1.741197 Accuracy: 35.54%
Epoch 14 – Time: 228.88s – Train Loss: 1.772695 – Train Accuracy: 35.88%
Test Loss: 1.796405 – Test Accuracy: 36.19%

Train Epoch: 15 [0/ 8390 (0%)] Loss: 1.862352 Accuracy: 34.38%
Train Epoch: 15 [3200/ 8390 (38%)] Loss: 1.758721 Accuracy: 36.26%
Train Epoch: 15 [6400/ 8390 (76%)] Loss: 1.585711 Accuracy: 36.72%
Epoch 15 – Time: 225.72s – Train Loss: 1.766506 – Train Accuracy: 36.84%
Test Loss: 1.717395 – Test Accuracy: 36.69%

Train Epoch: 16 [0/ 8390 (0%)] Loss: 1.405506 Accuracy: 56.25%
Train Epoch: 16 [3200/ 8390 (38%)] Loss: 1.843312 Accuracy: 37.53%
Train Epoch: 16 [6400/ 8390 (76%)] Loss: 1.662048 Accuracy: 36.63%
Epoch 16 – Time: 227.74s – Train Loss: 1.762409 – Train Accuracy: 36.71%
Test Loss: 1.860578 – Test Accuracy: 30.94%

Train Epoch: 17 [0/ 8390 (0%)] Loss: 1.506352 Accuracy: 46.88%
Train Epoch: 17 [3200/ 8390 (38%)] Loss: 1.742810 Accuracy: 37.41%
Train Epoch: 17 [6400/ 8390 (76%)] Loss: 1.585670 Accuracy: 37.00%
Epoch 17 – Time: 229.74s – Train Loss: 1.733406 – Train Accuracy: 37.16%
Test Loss: 1.890041 – Test Accuracy: 33.00%

Train Epoch: 18 [0/ 8390 (0%)] Loss: 1.732439 Accuracy: 31.25%
Train Epoch: 18 [3200/ 8390 (38%)] Loss: 1.549548 Accuracy: 38.18%
Train Epoch: 18 [6400/ 8390 (76%)] Loss: 1.562699 Accuracy: 38.03%
Epoch 18 – Time: 236.13s – Train Loss: 1.706303 – Train Accuracy: 38.25%
Test Loss: 1.805835 – Test Accuracy: 31.38%

Train Epoch: 19 [0/ 8390 (0%)] Loss: 1.522326 Accuracy: 53.12%
Train Epoch: 19 [3200/ 8390 (38%)] Loss: 1.878907 Accuracy: 39.14%
Train Epoch: 19 [6400/ 8390 (76%)] Loss: 1.591529 Accuracy: 38.68%
Epoch 19 – Time: 231.99s – Train Loss: 1.693270 – Train Accuracy: 39.06%
Test Loss: 1.893017 – Test Accuracy: 31.00%

Train Epoch: 20 [0/ 8390 (0%)] Loss: 1.637941 Accuracy: 34.38%
Train Epoch: 20 [3200/ 8390 (38%)] Loss: 1.428763 Accuracy: 38.27%
Train Epoch: 20 [6400/ 8390 (76%)] Loss: 1.534950 Accuracy: 38.63%
Epoch 20 – Time: 230.55s – Train Loss: 1.689023 – Train Accuracy: 39.01%
Test Loss: 1.742904 – Test Accuracy: 35.69%

Train Epoch: 21 [0/ 8390 (0%)] Loss: 1.540716 Accuracy: 46.88%
Train Epoch: 21 [3200/ 8390 (38%)] Loss: 1.768099 Accuracy: 39.29%
Train Epoch: 21 [6400/ 8390 (76%)] Loss: 1.482714 Accuracy: 39.23%
Epoch 21 – Time: 234.37s – Train Loss: 1.677518 – Train Accuracy: 39.01%
Test Loss: 1.751613 – Test Accuracy: 38.19%

Train Epoch: 22 [0/ 8390 (0%)] Loss: 1.777973 Accuracy: 43.75%
Train Epoch: 22 [3200/ 8390 (38%)] Loss: 1.748068 Accuracy: 39.88%
Train Epoch: 22 [6400/ 8390 (76%)] Loss: 1.431685 Accuracy: 40.66%
Epoch 22 – Time: 234.67s – Train Loss: 1.657473 – Train Accuracy: 40.64%
Test Loss: 1.876027 – Test Accuracy: 32.38%

Train Epoch: 23 [0/ 8390 (0%)] Loss: 2.058917 Accuracy: 25.00%
Train Epoch: 23 [3200/ 8390 (38%)] Loss: 1.625033 Accuracy: 38.83%
Train Epoch: 23 [6400/ 8390 (76%)] Loss: 1.697508 Accuracy: 39.80%
Epoch 23 – Time: 224.09s – Train Loss: 1.652329 – Train Accuracy: 40.42%
Test Loss: 1.726458 – Test Accuracy: 38.56%

Train Epoch: 24 [0/ 8390 (0%)] Loss: 1.661963 Accuracy: 37.50%
Train Epoch: 24 [3200/ 8390 (38%)] Loss: 1.884388 Accuracy: 41.43%
Train Epoch: 24 [6400/ 8390 (76%)] Loss: 1.717796 Accuracy: 41.00%
Epoch 24 – Time: 226.88s – Train Loss: 1.633753 – Train Accuracy: 41.20%
Test Loss: 1.755266 – Test Accuracy: 39.50%

Train Epoch: 25 [0/ 8390 (0%)] Loss: 2.029453 Accuracy: 21.88%
Train Epoch: 25 [3200/ 8390 (38%)] Loss: 1.803970 Accuracy: 41.62%
Train Epoch: 25 [6400/ 8390 (76%)] Loss: 1.742526 Accuracy: 41.48%
Epoch 25 – Time: 241.10s – Train Loss: 1.638339 – Train Accuracy: 41.25%
Test Loss: 1.831373 – Test Accuracy: 35.31%

Train Epoch: 26 [0/ 8390 (0%)] Loss: 1.667392 Accuracy: 43.75%
Train Epoch: 26 [3200/ 8390 (38%)] Loss: 1.706036 Accuracy: 43.75%
Train Epoch: 26 [6400/ 8390 (76%)] Loss: 1.283091 Accuracy: 41.93%
Epoch 26 – Time: 242.64s – Train Loss: 1.636386 – Train Accuracy: 41.80%
Test Loss: 1.872317 – Test Accuracy: 37.25%

Train Epoch: 27 [0/ 8390 (0%)] Loss: 1.798654 Accuracy: 37.50%
Train Epoch: 27 [3200/ 8390 (38%)] Loss: 1.548966 Accuracy: 40.69%
Train Epoch: 27 [6400/ 8390 (76%)] Loss: 1.751830 Accuracy: 42.37%
Epoch 27 – Time: 227.35s – Train Loss: 1.597866 – Train Accuracy: 42.66%
Test Loss: 1.769318 – Test Accuracy: 35.69%

Train Epoch: 28 [0/ 8390 (0%)] Loss: 1.510158 Accuracy: 40.62%
Train Epoch: 28 [3200/ 8390 (38%)] Loss: 1.709183 Accuracy: 43.53%
Train Epoch: 28 [6400/ 8390 (76%)] Loss: 1.747401 Accuracy: 42.75%
Epoch 28 – Time: 226.97s – Train Loss: 1.610359 – Train Accuracy: 42.72%
Test Loss: 1.805375 – Test Accuracy: 37.50%

Train Epoch: 29 [0/ 8390 (0%)] Loss: 1.620673 Accuracy: 43.75%
Train Epoch: 29 [3200/ 8390 (38%)] Loss: 1.735744 Accuracy: 43.16%
Train Epoch: 29 [6400/ 8390 (76%)] Loss: 1.518578 Accuracy: 43.52%
Epoch 29 – Time: 222.71s – Train Loss: 1.580171 – Train Accuracy: 43.17%
Test Loss: 1.713054 – Test Accuracy: 37.12%

Train Epoch: 30 [0/ 8390 (0%)] Loss: 1.523651 Accuracy: 43.75%
Train Epoch: 30 [3200/ 8390 (38%)] Loss: 1.402524 Accuracy: 42.82%
Train Epoch: 30 [6400/ 8390 (76%)] Loss: 1.423656 Accuracy: 43.17%
Epoch 30 – Time: 221.71s – Train Loss: 1.588955 – Train Accuracy: 43.31%
Test Loss: 1.720405 – Test Accuracy: 40.56%

Train Epoch: 31 [0/ 8390 (0%)] Loss: 1.578195 Accuracy: 53.12%
Train Epoch: 31 [3200/ 8390 (38%)] Loss: 1.480698 Accuracy: 45.45%
Train Epoch: 31 [6400/ 8390 (76%)] Loss: 1.441470 Accuracy: 45.94%
Epoch 31 – Time: 224.97s – Train Loss: 1.546672 – Train Accuracy: 45.16%
Test Loss: 1.775559 – Test Accuracy: 38.19%

Train Epoch: 32 [0/ 8390 (0%)] Loss: 1.695147 Accuracy: 37.50%
Train Epoch: 32 [3200/ 8390 (38%)] Loss: 1.325187 Accuracy: 44.86%
Train Epoch: 32 [6400/ 8390 (76%)] Loss: 1.499307 Accuracy: 44.71%
Epoch 32 – Time: 232.97s – Train Loss: 1.528269 – Train Accuracy: 45.01%
Test Loss: 1.851925 – Test Accuracy: 35.56%

Train Epoch: 33 [0/ 8390 (0%)] Loss: 1.566870 Accuracy: 37.50%
Train Epoch: 33 [3200/ 8390 (38%)] Loss: 1.623017 Accuracy: 46.81%
Train Epoch: 33 [6400/ 8390 (76%)] Loss: 1.333343 Accuracy: 46.13%
Epoch 33 – Time: 222.50s – Train Loss: 1.519943 – Train Accuracy: 45.77%
Test Loss: 1.797330 – Test Accuracy: 38.19%

Train Epoch: 34 [0/ 8390 (0%)] Loss: 1.530742 Accuracy: 53.12%
Train Epoch: 34 [3200/ 8390 (38%)] Loss: 1.340442 Accuracy: 46.26%
Train Epoch: 34 [6400/ 8390 (76%)] Loss: 1.714650 Accuracy: 46.25%
Epoch 34 – Time: 371.90s – Train Loss: 1.506658 – Train Accuracy: 46.63%
Test Loss: 1.941669 – Test Accuracy: 35.25%

Train Epoch: 35 [0/ 8390 (0%)] Loss: 1.191646 Accuracy: 65.62%
Train Epoch: 35 [3200/ 8390 (38%)] Loss: 1.346883 Accuracy: 46.75%
Train Epoch: 35 [6400/ 8390 (76%)] Loss: 1.417341 Accuracy: 46.50%
Epoch 35 – Time: 839.33s – Train Loss: 1.492409 – Train Accuracy: 46.16%
Test Loss: 1.755629 – Test Accuracy: 39.75%

Train Epoch: 36 [0/ 8390 (0%)] Loss: 1.476019 Accuracy: 46.88%
Train Epoch: 36 [3200/ 8390 (38%)] Loss: 1.865099 Accuracy: 46.26%
Train Epoch: 36 [6400/ 8390 (76%)] Loss: 1.578250 Accuracy: 47.51%
Epoch 36 – Time: 260.74s – Train Loss: 1.480662 – Train Accuracy: 47.54%
Test Loss: 1.746769 – Test Accuracy: 41.62%

Train Epoch: 37 [0/ 8390 (0%)] Loss: 1.372396 Accuracy: 65.62%
Train Epoch: 37 [3200/ 8390 (38%)] Loss: 1.404371 Accuracy: 48.58%
Train Epoch: 37 [6400/ 8390 (76%)] Loss: 1.312795 Accuracy: 47.89%
Epoch 37 – Time: 238.93s – Train Loss: 1.456575 – Train Accuracy: 47.79%
Test Loss: 1.713381 – Test Accuracy: 40.44%

Train Epoch: 38 [0/ 8390 (0%)] Loss: 1.285304 Accuracy: 46.88%
Train Epoch: 38 [3200/ 8390 (38%)] Loss: 1.466446 Accuracy: 47.06%
Train Epoch: 38 [6400/ 8390 (76%)] Loss: 1.480421 Accuracy: 47.50%
Epoch 38 – Time: 225.90s – Train Loss: 1.466263 – Train Accuracy: 47.52%
Test Loss: 1.734649 – Test Accuracy: 39.38%

Train Epoch: 39 [0/ 8390 (0%)] Loss: 1.281939 Accuracy: 56.25%
Train Epoch: 39 [3200/ 8390 (38%)] Loss: 1.203103 Accuracy: 49.04%
Train Epoch: 39 [6400/ 8390 (76%)] Loss: 1.221993 Accuracy: 48.69%
Epoch 39 – Time: 233.83s – Train Loss: 1.438474 – Train Accuracy: 48.75%
Test Loss: 1.698388 – Test Accuracy: 41.25%

Train Epoch: 40 [0/ 8390 (0%)] Loss: 1.390738 Accuracy: 50.00%
Train Epoch: 40 [3200/ 8390 (38%)] Loss: 1.468864 Accuracy: 48.05%
Train Epoch: 40 [6400/ 8390 (76%)] Loss: 1.655652 Accuracy: 49.02%
Epoch 40 – Time: 234.83s – Train Loss: 1.442420 – Train Accuracy: 48.86%
Test Loss: 1.713381 – Test Accuracy: 40.88%

Train Epoch: 41 [0/ 8390 (0%)] Loss: 1.223912 Accuracy: 46.88%
Train Epoch: 41 [3200/ 8390 (38%)] Loss: 1.173113 Accuracy: 48.42%
Train Epoch: 41 [6400/ 8390 (76%)] Loss: 1.541021 Accuracy: 48.74%
Epoch 41 – Time: 240.24s – Train Loss: 1.412495 – Train Accuracy: 48.99%
Test Loss: 1.804260 – Test Accuracy: 40.00%

Train Epoch: 42 [0/ 8390 (0%)] Loss: 1.315914 Accuracy: 56.25%
Train Epoch: 42 [3200/ 8390 (38%)] Loss: 1.457621 Accuracy: 50.93%
Train Epoch: 42 [6400/ 8390 (76%)] Loss: 1.301119 Accuracy: 49.56%
Epoch 42 – Time: 228.13s – Train Loss: 1.408532 – Train Accuracy: 49.81%
Test Loss: 1.848636 – Test Accuracy: 36.69%

Train Epoch: 43 [0/ 8390 (0%)] Loss: 1.095912 Accuracy: 68.75%
Train Epoch: 43 [3200/ 8390 (38%)] Loss: 1.502681 Accuracy: 52.04%
Train Epoch: 43 [6400/ 8390 (76%)] Loss: 1.337117 Accuracy: 50.92%
Epoch 43 – Time: 231.53s – Train Loss: 1.396336 – Train Accuracy: 50.35%
Test Loss: 1.700084 – Test Accuracy: 42.94%

Train Epoch: 44 [0/ 8390 (0%)] Loss: 1.331070 Accuracy: 53.12%
Train Epoch: 44 [3200/ 8390 (38%)] Loss: 1.648317 Accuracy: 51.79%
Train Epoch: 44 [6400/ 8390 (76%)] Loss: 1.354382 Accuracy: 51.85%
Epoch 44 – Time: 234.37s – Train Loss: 1.361948 – Train Accuracy: 51.42%
Test Loss: 1.661956 – Test Accuracy: 42.50%

Train Epoch: 45 [0/ 8390 (0%)] Loss: 1.314737 Accuracy: 62.50%
Train Epoch: 45 [3200/ 8390 (38%)] Loss: 1.620541 Accuracy: 53.00%
Train Epoch: 45 [6400/ 8390 (76%)] Loss: 1.276034 Accuracy: 51.38%
Epoch 45 – Time: 237.77s – Train Loss: 1.358715 – Train Accuracy: 51.16%
Test Loss: 1.723875 – Test Accuracy: 39.81%

Train Epoch: 46 [0/ 8390 (0%)] Loss: 1.273015 Accuracy: 53.12%
Train Epoch: 46 [3200/ 8390 (38%)] Loss: 1.205081 Accuracy: 51.89%
Train Epoch: 46 [6400/ 8390 (76%)] Loss: 1.084803 Accuracy: 51.94%
Epoch 46 – Time: 230.29s – Train Loss: 1.345437 – Train Accuracy: 52.11%
Test Loss: 1.786524 – Test Accuracy: 40.50%

Train Epoch: 47 [0/ 8390 (0%)] Loss: 1.356501 Accuracy: 46.88%
Train Epoch: 47 [3200/ 8390 (38%)] Loss: 1.344147 Accuracy: 52.26%
Train Epoch: 47 [6400/ 8390 (76%)] Loss: 1.232960 Accuracy: 52.39%
Epoch 47 – Time: 235.62s – Train Loss: 1.351638 – Train Accuracy: 52.31%
Test Loss: 1.924757 – Test Accuracy: 37.25%

Train Epoch: 48 [0/ 8390 (0%)] Loss: 1.029061 Accuracy: 65.62%
Train Epoch: 48 [3200/ 8390 (38%)] Loss: 1.407160 Accuracy: 52.13%
Train Epoch: 48 [6400/ 8390 (76%)] Loss: 1.230066 Accuracy: 52.91%
Epoch 48 – Time: 237.75s – Train Loss: 1.333594 – Train Accuracy: 53.11%
Test Loss: 1.675849 – Test Accuracy: 42.44%

Train Epoch: 49 [0/ 8390 (0%)] Loss: 1.518033 Accuracy: 46.88%
Train Epoch: 49 [3200/ 8390 (38%)] Loss: 1.227060 Accuracy: 52.78%
Train Epoch: 49 [6400/ 8390 (76%)] Loss: 1.245394 Accuracy: 53.25%
Epoch 49 – Time: 228.26s – Train Loss: 1.321129 – Train Accuracy: 53.13%
Test Loss: 1.728029 – Test Accuracy: 41.00%

FINAL RESULTS:

```
epoch_times: [1216.786159992218, 237.43125772476196, 3536.2034180164337, 2
55.0527946949005, 338.98512411117554, 249.76298189163208, 260.968131065368
65, 290.2906048297882, 2350.9871430397034, 1119.262617111206, 1714.2808780
670166, 685.1609690189362, 229.54470205307007, 247.95893597602844, 228.884
4177722931, 225.72268295288086, 227.74287104606628, 229.74079060554504, 23
6.1341609954834, 231.98818516731262, 230.55307173728943, 234.3666918277740
5, 234.67452025413513, 224.09229612350464, 226.87726593017578, 241.1005702
0187378, 242.64449501037598, 227.35298085212708, 226.97432398796082, 222.7
1014785766602, 221.70982909202576, 224.96943998336792, 232.96854400634766,
222.49809098243713, 371.89834690093994, 839.3271780014038, 260.740571022203
37, 238.9295699596405, 225.8984100818634, 233.8280041217804, 234.825166702
2705, 240.2430510520935, 228.12757992744446, 231.5294008255005, 234.373477
22053528, 237.76521015167236, 230.28806805610657, 235.62296104431152, 237.
7456498146057, 228.25890517234802]
train_losses: [2.162851532906976, 2.0375869633587262, 1.9875167171463712,
1.9772260184506423, 1.973807847226849, 1.9229257152280734, 1.9137453100153
508, 1.8953898330681196, 1.899573454420075, 1.8580818735916196, 1.83810602
11713078, 1.824077689920673, 1.8001040738957528, 1.8013294184480915, 1.772
6950404298214, 1.7665060276293572, 1.7624088416572745, 1.7334060755394798,
1.706302819816211, 1.6932695644502422, 1.6890230351731976, 1.6775176966463
337, 1.657472894846938, 1.6523291555069786, 1.6337526204021833, 1.63833934
61467655, 1.6363864782202335, 1.5978663550078414, 1.6103589298160932, 1.58
0170889392154, 1.588955131650881, 1.546672313267948, 1.5282688573116565,
1.5199425070340398, 1.506657939375812, 1.492409292978185, 1.48066221894198
7, 1.4565749753067512, 1.4662629063347823, 1.4384736666697582, 1.442420180
5172985, 1.4124947722631556, 1.408531955407776, 1.3963362629177005, 1.3619
47868844025, 1.358714550961065, 1.3454369156415227, 1.3516383494129618, 1.
3335936713309688, 1.3211287958476379]
train_accuracies: [19.67818831942789, 24.27890345649583, 26.81764004767580
5, 27.36591179976162, 26.90107270560191, 29.36829558998808, 30.0, 31.13230
0357568536, 30.834326579261024, 32.37187127532777, 32.598331346841476, 33.
57568533969011, 34.56495828367104, 35.18474374255066, 35.87604290822408, 3
6.841477949940405, 36.7103694874851, 37.163289630512516, 38.2479141835518
5, 39.05840286054827, 39.01072705601907, 39.01072705601907, 40.64362336114
422, 40.417163289630516, 41.203814064362334, 41.25148986889154, 41.7997616
2097736, 42.65792610250298, 42.717520858164484, 43.1704410011919, 43.31346
84147795, 45.160905840286055, 45.00595947556615, 45.76877234803337, 46.626
936829559, 46.162097735399286, 47.54469606674613, 47.794994040524436, 47.5
20858164481524, 48.74851013110846, 48.85578069129917, 48.98688915375447, 4
9.80929678188319, 50.345649582836714, 51.418355184743746, 51.1561382598331
35, 52.109654350417166, 52.31227651966627, 53.1108462455304, 53.1346841477
9499]
test_losses: [2.109093050956726, 2.066229785680771, 2.0960341399908065, 1.
9843857073783875, 1.9469191420078278, 1.9604377828538417, 2.02019314527511
6, 2.0539393174648284, 2.0636624544113875, 1.877559413909912, 1.8430911654
233932, 1.92527961820364, 1.8954430627822876, 2.059045124053955, 1.7964048
707485198, 1.7173949246108533, 1.8605775427818299, 1.890041069984436, 1.80
5834757089615, 1.893017338514328, 1.7429044938087463, 1.751613089442253,
1.8760265758633614, 1.7264579290151596, 1.7552662622928619, 1.831373276114
4639, 1.87231743901968, 1.7693175518512725, 1.805375024974346, 1.713054386
973381, 1.7204049178957939, 1.7755592098832131, 1.8519245845079422, 1.7973
303461819887, 1.9416690100729466, 1.755628821849823, 1.7467694664001465,
1.7133814676105976, 1.734649378284812, 1.698387702703476, 1.71338147729635
```

25, 1.8042599228024483, 1.8486363255977631, 1.7000837564468383, 1.6619563192129134, 1.7238749971985816, 1.7865237033367156, 1.9247570157051086, 1.6758494615554809, 1.7280293914675713]

test accuracies: [22.25, 23.5625, 21.1875, 26.75, 28.125, 29.125, 25.0625, 31.875, 28.6875, 30.875, 33.3125, 30.5, 29.9375, 28.6875, 36.1875, 36.6875, 30.9375, 33.0, 31.375, 31.0, 35.6875, 38.1875, 32.375, 38.5625, 39.5, 35.3125, 37.25, 35.6875, 37.5, 37.125, 40.5625, 38.1875, 35.5625, 38.1875, 35.25, 39.75, 41.625, 40.4375, 39.375, 41.25, 40.875, 40.0, 36.6875, 42.9375, 42.5, 39.8125, 40.5, 37.25, 42.4375, 41.0]

Plots

```
In [40]: # Data for the four scenarios
data = {
    "GNN Path 1": metrics_dict_e1,
    "GNN Path 2": metrics_dict_e2,
}

# Data for plotting
epochs = range(1, 51)
colors = ['b', 'g', 'r', 'm', 'y', 'c', 'k', '#FF5733', '#7E4DFF']
scenarios = list(data.keys())

fig, axes = plt.subplots(2, 1, figsize=(10, 10))

for i, scenario in enumerate(scenarios):
    axes[0].plot(epochs, data[scenario]["train_accuracies"], label=scenario)

axes[0].set_title("Train Accuracy")
axes[0].set_xlabel("Epochs")
axes[0].set_ylabel("Train Accuracy")
axes[0].legend()

for i, scenario in enumerate(scenarios):
    axes[1].plot(epochs, data[scenario]["test_accuracies"], label=scenario)

axes[1].set_title("Test Accuracy")
axes[1].set_xlabel("Epochs")
axes[1].set_ylabel("Test Accuracy")
axes[1].legend()

plt.tight_layout()
plt.show()

fig, axes = plt.subplots(2, 1, figsize=(10, 10))

for i, scenario in enumerate(scenarios):
    axes[0].plot(epochs, data[scenario]["train_losses"], label=scenario, color=colors[i])

axes[0].set_title("Train Loss")
axes[0].set_xlabel("Epochs")
axes[0].set_ylabel("Train Loss")
axes[0].legend()

for i, scenario in enumerate(scenarios):
    axes[1].plot(epochs, data[scenario]["test_losses"], label=scenario, color=colors[i])

axes[1].set_title("Test Loss")
```

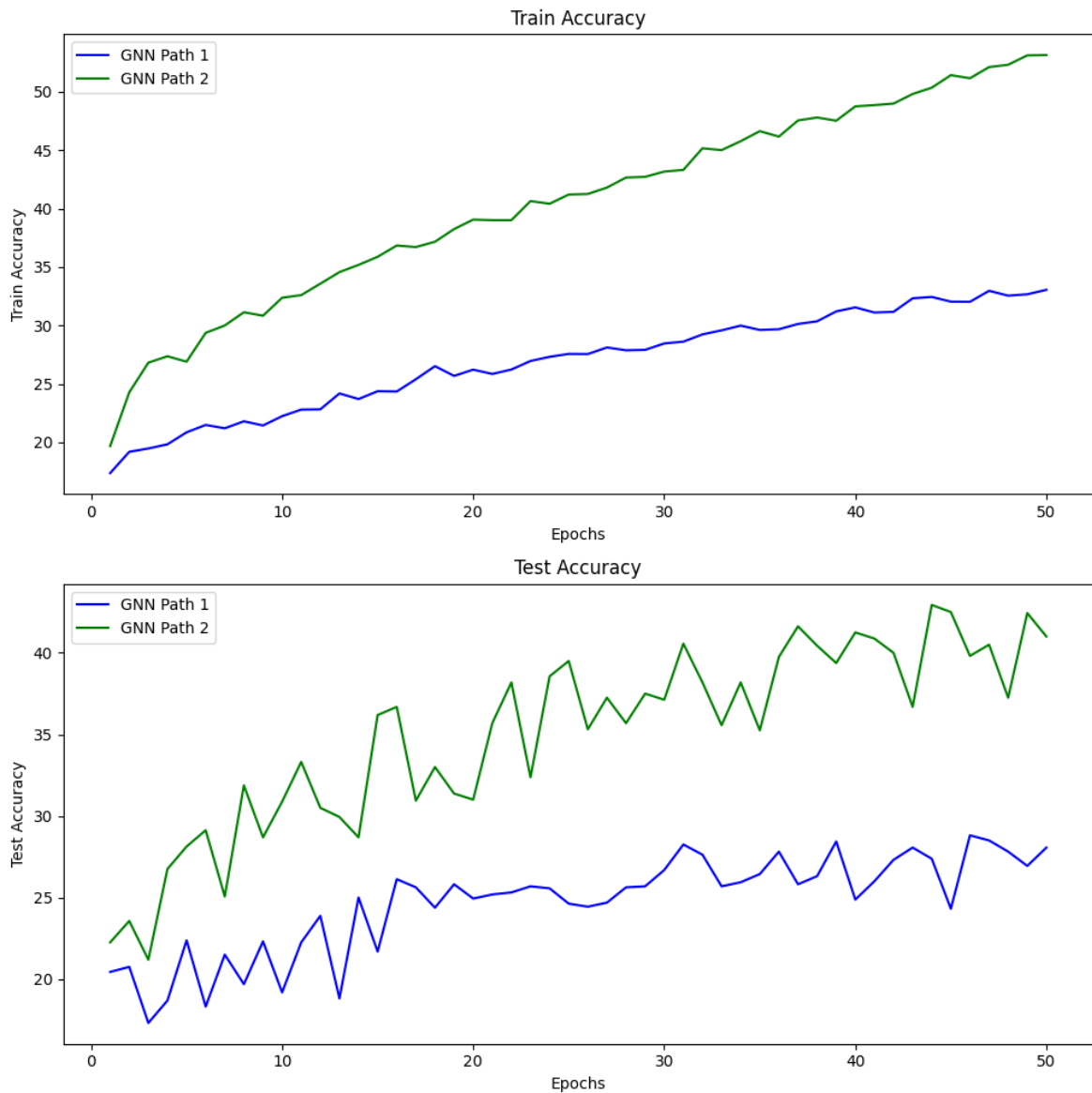
```

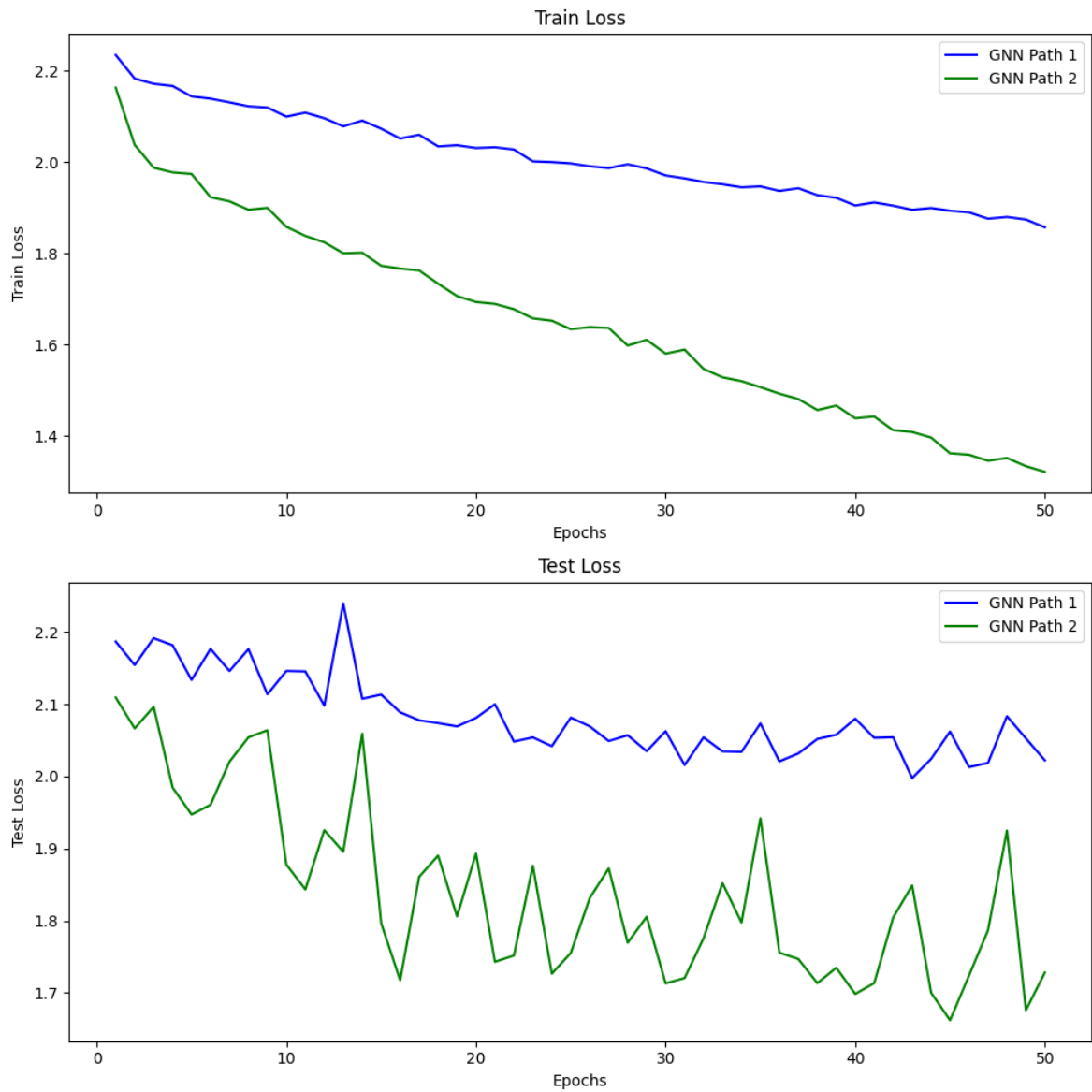
axes[1].set_xlabel("Epochs")
axes[1].set_ylabel("Test Loss")
axes[1].legend()

plt.tight_layout()
plt.show()

fig, axes = plt.subplots(1, 1, figsize=(10, 5))
for i, scenario in enumerate(scenarios):
    axes.plot(epochs, data[scenario]["epoch_times"], label=scenario, color=i)
axes.set_title("Time")
axes.set_xlabel("Epochs")
axes.set_ylabel("Time (secs)")
axes.legend()

```





Out[40]: <matplotlib.legend.Legend at 0x2af840c50>

