Complex PyTorch for Music Genre Classification

In [23]:
```
# 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 *

# 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
```

In [2]:
```
import os
import shutil
from sklearn.model_selection import train_test_split

# Path to the folder containing subfolders for each class
data_folder = 'Data/genres_original'

# List of subfolder names (class names)
class_names = os.listdir(data_folder)
class_names.remove('.DS_Store')

# Create train and test directories
train_dir = 'data/train'
test_dir = 'data/test'
os.makedirs(train_dir, exist_ok=True)
os.makedirs(test_dir, exist_ok=True)

# Split ratio (adjust as needed)
test_size = 0.16

# Loop through each class
for class_name in class_names:
    class_folder = os.path.join(data_folder, class_name)
```

```
    class_files = os.listdir(class_folder)

    # Split files into train and test sets
    train_files, test_files = train_test_split(class_files, test_size=tes

    # Create class subdirectories in train and test folders
    train_class_dir = os.path.join(train_dir, class_name)
    test_class_dir = os.path.join(test_dir, class_name)
    os.makedirs(train_class_dir, exist_ok=True)
    os.makedirs(test_class_dir, exist_ok=True)

    # Move train files
    for train_file in train_files:
        src_path = os.path.join(class_folder, train_file)
        dest_path = os.path.join(train_class_dir, train_file)
        shutil.copy(src_path, dest_path)

    # Move test files
    for test_file in test_files:
        src_path = os.path.join(class_folder, test_file)
        dest_path = os.path.join(test_class_dir, test_file)
        shutil.copy(src_path, dest_path)

print("Data split and saved successfully.")
```

```
Data split and saved successfully.
```

In [3]:

```
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, target) in enumerate(train_loader):
        data, target = data.to(device), target.to(device)
        if complexify: data = data.type(torch.complex64)
        if data_fn != None: data = data_fn(data)
        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, target in test_loader:
            data, target = data.to(device), target.to(device)
            if complexify:
                data = data.type(torch.complex64)
            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
```

Data Preparation

In [4]:
```
DATASET_PATH = "Data/genres_original/"
SAMPLE_RATE = 22050
TRACK_DURATION = 30 # measured in seconds
SAMPLES_PER_TRACK = SAMPLE_RATE * TRACK_DURATION
BATCH_SIZE = 32
NUM_EPOCHS = 20
```

In [5]:
```
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 [6]:
```
class MusicFeatureExtractor:
    def __init__(self, FFT_size=2048, HOP_SIZE=512, mel_filter_num=13, dc
        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
        return frames

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

    def met_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 +
        freqs = self.met_to_freq(mels)
        return np.floor((self.FFT_size + 1) / sample_rate * freqs).astype

    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.linsp
            filters[n, filter_points[n + 1]: filter_points[n + 2]] = np.l
        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
        for i in range(1, self.dct_filter_num):
            basis[i, :] = np.cos(i * samples) * np.sqrt(2.0 / self.mel_fi
        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.sha
        for n in range(audio_fft.shape[1]):
            audio_fft[:, n] = fft.fft(audio_winT[:, n], axis=0)[:audio_ff
        audio_fft = np.transpose(audio_fft)
        audio_fft = np.square(np.abs(audio_fft))
        freq_min = 0
        freq_high = sample_rate / 2
        filter_points, mel_freqs = self.get_filter_points(freq_min, freq_
        filters = self.get_filters(filter_points)
        audio_filtered = np.dot(filters, np.transpose(audio_fft))
        audio_filtered = np.maximum(audio_filtered, self.epsilon)  # Repl
        audio_log = 10.0 * np.log10(audio_filtered)
        dct_filters = self.dct()
        cepstral_coefficents = np.dot(dct_filters, audio_log)
        return np.array([cepstral_coefficents])
```

```
class MusicFeatureExtractorComplex:
    def __init__(self, FFT_size=2048, HOP_SIZE=512, mel_filter_num=13, dc
        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
        return frames

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

    def met_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 +
        freqs = self.met_to_freq(mels)
        return np.floor((self.FFT_size + 1) / sample_rate * freqs).astype

    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.linsp
            filters[n, filter_points[n + 1]: filter_points[n + 2]] = np.l
        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
        for i in range(1, self.dct_filter_num):
            basis[i, :] = np.cos(i * samples) * np.sqrt(2.0 / self.mel_fi
        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.sha
        for n in range(audio_fft.shape[1]):
            audio_fft[:, n] = fft.fft(audio_winT[:, n], axis=0)[:audio_ff
        audio_fft = np.transpose(audio_fft)
        freq_min = 0
        freq_high = sample_rate / 2
```

```
        filter_points, mel_freqs = self.get_filter_points(freq_min, freq_
        filters = self.get_filters(filter_points)
        audio_filtered = np.dot(filters, np.transpose(audio_fft))
        audio_filtered[audio_filtered == 0] = self.epsilon # Replace zerc
        audio_log = 10.0 * np.log10(audio_filtered)
        dct_filters = self.dct()
        cepstral_coefficents = np.dot(dct_filters, audio_log)
        return np.array([cepstral_coefficents])
```

In [7]:
```
class GenreDatasetMFCC(Dataset):

    def __init__(self, train_path, n_fft=2048, hop_length=512, num_segmen
        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.mfcc_extractor = MusicFeatureExtractor(
            FFT_size=n_fft, HOP_SIZE=hop_length, mel_filter_num = mel_fil
        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,
        if random.random() < 0.5:
            signal = librosa.effects.time_stretch(signal, rate=random.uni
        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_leng
            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_signa
        cur_mfcc = self.mfcc_extractor.get_mfcc_features(cur_signal, samp
        cur_mfcc = self.adjust_shape(cur_mfcc)
        return torch.tensor(cur_mfcc, dtype=torch.float32), target
```

```
class GenreDatasetPhaseMFCC(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 = MusicFeatureExtractorComplex(
            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 = self.mfcc_extractor.get_mfcc_features(cur_signal, samp
        cur_mfcc = self.adjust_shape(cur_mfcc)
        return torch.tensor(cur_mfcc, dtype=torch.complex64), target
```

1. No phase data

In [8]:
```
train_dataset = GenreDatasetMFCC("Data/train/", n_fft=2048, hop_length=51
test_dataset = GenreDatasetMFCC("Data/test/", n_fft=2048, hop_length=512,
train_loader = torch.utils.data.DataLoader(dataset=train_dataset, shuffle
test_loader = torch.utils.data.DataLoader(dataset=test_dataset, shuffle=F
```

In [9]:
```
class RealNet(nn.Module):

    def __init__(self):
        super(RealNet, self).__init__()
        self.conv1 = nn.Conv2d(1, 10, 2, 1)
        self.bn   = nn.BatchNorm2d(10)
        self.conv2 = nn.Conv2d(10, 20, 2, 1)
        self.fc1 = nn.Linear(30*2*20, 500)
        self.fc2 = nn.Linear(500, 10)

    def forward(self,x):
        x = self.conv1(x)
        x = F.relu(x)
        x = F.max_pool2d(x, 2, 2)
        x = self.bn(x)
        x = self.conv2(x)
        x = F.relu(x)
        x = F.max_pool2d(x, 2, 2)
        x = x.view(-1,30*2*20)
        x = self.fc1(x)
        x = F.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 = RealNet().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,
          complexify = False)

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: 2.316185  Accuracy: 3.12%
Train Epoch:   0 [  3200/  8390 ( 38%)] Loss: 2.077888  Accuracy: 24.47%
Train Epoch:   0 [  6400/  8390 ( 76%)] Loss: 1.776363  Accuracy: 30.16%
Epoch 0 - Time: 176.49s - Train Loss: 1.842231 - Train Accuracy: 32.15%
Test Loss: 1.759411 - Test Accuracy: 38.69%

Train Epoch:   1 [     0/  8390 (  0%)] Loss: 1.773670  Accuracy: 40.62%
Train Epoch:   1 [  3200/  8390 ( 38%)] Loss: 1.957644  Accuracy: 43.38%
Train Epoch:   1 [  6400/  8390 ( 76%)] Loss: 1.535713  Accuracy: 43.69%
Epoch 1 - Time: 175.82s - Train Loss: 1.561373 - Train Accuracy: 43.74%
Test Loss: 1.565164 - Test Accuracy: 41.88%

Train Epoch:   2 [     0/  8390 (  0%)] Loss: 1.569602  Accuracy: 40.62%
Train Epoch:   2 [  3200/  8390 ( 38%)] Loss: 1.500369  Accuracy: 48.55%
Train Epoch:   2 [  6400/  8390 ( 76%)] Loss: 1.554265  Accuracy: 49.10%
Epoch 2 - Time: 182.97s - Train Loss: 1.428993 - Train Accuracy: 48.75%
Test Loss: 1.465071 - Test Accuracy: 46.12%

Train Epoch:   3 [     0/  8390 (  0%)] Loss: 1.148391  Accuracy: 59.38%
Train Epoch:   3 [  3200/  8390 ( 38%)] Loss: 1.240188  Accuracy: 50.84%
Train Epoch:   3 [  6400/  8390 ( 76%)] Loss: 1.676979  Accuracy: 50.84%
Epoch 3 - Time: 175.02s - Train Loss: 1.357373 - Train Accuracy: 50.77%
Test Loss: 1.657636 - Test Accuracy: 43.38%

Train Epoch:   4 [     0/  8390 (  0%)] Loss: 0.997623  Accuracy: 59.38%
Train Epoch:   4 [  3200/  8390 ( 38%)] Loss: 1.197162  Accuracy: 53.87%
Train Epoch:   4 [  6400/  8390 ( 76%)] Loss: 1.274162  Accuracy: 53.34%
Epoch 4 - Time: 187.68s - Train Loss: 1.274983 - Train Accuracy: 53.99%
Test Loss: 1.743243 - Test Accuracy: 44.62%

Train Epoch:   5 [     0/  8390 (  0%)] Loss: 1.174444  Accuracy: 53.12%
Train Epoch:   5 [  3200/  8390 ( 38%)] Loss: 1.106565  Accuracy: 56.25%
Train Epoch:   5 [  6400/  8390 ( 76%)] Loss: 1.058037  Accuracy: 56.16%
Epoch 5 - Time: 179.67s - Train Loss: 1.214539 - Train Accuracy: 56.94%
Test Loss: 1.398109 - Test Accuracy: 51.44%

Train Epoch:   6 [     0/  8390 (  0%)] Loss: 0.910724  Accuracy: 62.50%
Train Epoch:   6 [  3200/  8390 ( 38%)] Loss: 1.512703  Accuracy: 58.88%
Train Epoch:   6 [  6400/  8390 ( 76%)] Loss: 0.951155  Accuracy: 58.80%
Epoch 6 - Time: 177.37s - Train Loss: 1.167653 - Train Accuracy: 58.67%
Test Loss: 1.608052 - Test Accuracy: 43.88%

Train Epoch:   7 [     0/  8390 (  0%)] Loss: 1.153452  Accuracy: 56.25%
Train Epoch:   7 [  3200/  8390 ( 38%)] Loss: 1.605653  Accuracy: 61.88%
Train Epoch:   7 [  6400/  8390 ( 76%)] Loss: 1.263472  Accuracy: 61.04%
Epoch 7 - Time: 2114.84s - Train Loss: 1.114955 - Train Accuracy: 60.64%
Test Loss: 1.444405 - Test Accuracy: 50.56%

Train Epoch:   8 [     0/  8390 (  0%)] Loss: 0.997894  Accuracy: 59.38%
Train Epoch:   8 [  3200/  8390 ( 38%)] Loss: 0.927493  Accuracy: 61.36%
Train Epoch:   8 [  6400/  8390 ( 76%)] Loss: 1.140884  Accuracy: 62.33%
Epoch 8 - Time: 307.90s - Train Loss: 1.058625 - Train Accuracy: 62.94%
Test Loss: 1.366964 - Test Accuracy: 53.06%

Train Epoch:   9 [     0/  8390 (  0%)] Loss: 1.066264  Accuracy: 65.62%
Train Epoch:   9 [  3200/  8390 ( 38%)] Loss: 1.137856  Accuracy: 65.28%
Train Epoch:   9 [  6400/  8390 ( 76%)] Loss: 1.076037  Accuracy: 64.46%
Epoch 9 - Time: 178.32s - Train Loss: 1.033641 - Train Accuracy: 63.69%
Test Loss: 1.412204 - Test Accuracy: 52.81%
```

```
Train Epoch:  10 [     0/  8390 (  0%)] Loss: 0.944797  Accuracy: 68.75%
Train Epoch:  10 [  3200/  8390 ( 38%)] Loss: 0.705615  Accuracy: 67.61%
Train Epoch:  10 [  6400/  8390 ( 76%)] Loss: 1.042045  Accuracy: 66.34%
Epoch 10 - Time: 174.27s - Train Loss: 0.969864 - Train Accuracy: 66.11%
Test Loss: 1.472573 - Test Accuracy: 52.00%

Train Epoch:  11 [     0/  8390 (  0%)] Loss: 1.073031  Accuracy: 65.62%
Train Epoch:  11 [  3200/  8390 ( 38%)] Loss: 1.021653  Accuracy: 67.14%
Train Epoch:  11 [  6400/  8390 ( 76%)] Loss: 0.704792  Accuracy: 67.27%
Epoch 11 - Time: 169.76s - Train Loss: 0.925578 - Train Accuracy: 67.58%
Test Loss: 1.561576 - Test Accuracy: 52.25%

Train Epoch:  12 [     0/  8390 (  0%)] Loss: 1.120808  Accuracy: 59.38%
Train Epoch:  12 [  3200/  8390 ( 38%)] Loss: 1.080361  Accuracy: 69.15%
Train Epoch:  12 [  6400/  8390 ( 76%)] Loss: 1.099876  Accuracy: 68.89%
Epoch 12 - Time: 170.53s - Train Loss: 0.903229 - Train Accuracy: 68.64%
Test Loss: 1.646151 - Test Accuracy: 53.06%

Train Epoch:  13 [     0/  8390 (  0%)] Loss: 0.975203  Accuracy: 56.25%
Train Epoch:  13 [  3200/  8390 ( 38%)] Loss: 0.643761  Accuracy: 71.10%
Train Epoch:  13 [  6400/  8390 ( 76%)] Loss: 0.590223  Accuracy: 70.88%
Epoch 13 - Time: 171.76s - Train Loss: 0.851645 - Train Accuracy: 70.70%
Test Loss: 1.415567 - Test Accuracy: 53.56%

Train Epoch:  14 [     0/  8390 (  0%)] Loss: 0.651511  Accuracy: 81.25%
Train Epoch:  14 [  3200/  8390 ( 38%)] Loss: 0.735180  Accuracy: 71.88%
Train Epoch:  14 [  6400/  8390 ( 76%)] Loss: 1.041193  Accuracy: 72.22%
Epoch 14 - Time: 171.69s - Train Loss: 0.811780 - Train Accuracy: 72.17%
Test Loss: 1.562119 - Test Accuracy: 54.25%

Train Epoch:  15 [     0/  8390 (  0%)] Loss: 0.853154  Accuracy: 65.62%
Train Epoch:  15 [  3200/  8390 ( 38%)] Loss: 1.031863  Accuracy: 73.51%
Train Epoch:  15 [  6400/  8390 ( 76%)] Loss: 0.822448  Accuracy: 73.03%
Epoch 15 - Time: 178.36s - Train Loss: 0.778017 - Train Accuracy: 72.94%
Test Loss: 1.672464 - Test Accuracy: 50.94%

Train Epoch:  16 [     0/  8390 (  0%)] Loss: 0.686605  Accuracy: 78.12%
Train Epoch:  16 [  3200/  8390 ( 38%)] Loss: 0.703789  Accuracy: 76.33%
Train Epoch:  16 [  6400/  8390 ( 76%)] Loss: 0.488479  Accuracy: 74.63%
Epoch 16 - Time: 173.46s - Train Loss: 0.747625 - Train Accuracy: 73.99%
Test Loss: 1.446513 - Test Accuracy: 55.50%

Train Epoch:  17 [     0/  8390 (  0%)] Loss: 0.429874  Accuracy: 90.62%
Train Epoch:  17 [  3200/  8390 ( 38%)] Loss: 0.538253  Accuracy: 76.52%
Train Epoch:  17 [  6400/  8390 ( 76%)] Loss: 0.879903  Accuracy: 75.25%
Epoch 17 - Time: 174.48s - Train Loss: 0.725593 - Train Accuracy: 75.01%
Test Loss: 1.639021 - Test Accuracy: 51.94%

Train Epoch:  18 [     0/  8390 (  0%)] Loss: 1.111452  Accuracy: 65.62%
Train Epoch:  18 [  3200/  8390 ( 38%)] Loss: 0.493201  Accuracy: 78.06%
Train Epoch:  18 [  6400/  8390 ( 76%)] Loss: 1.000018  Accuracy: 76.99%
Epoch 18 - Time: 173.06s - Train Loss: 0.691851 - Train Accuracy: 76.60%
Test Loss: 1.669921 - Test Accuracy: 53.88%

Train Epoch:  19 [     0/  8390 (  0%)] Loss: 0.497625  Accuracy: 84.38%
Train Epoch:  19 [  3200/  8390 ( 38%)] Loss: 0.629276  Accuracy: 78.65%
Train Epoch:  19 [  6400/  8390 ( 76%)] Loss: 1.373169  Accuracy: 77.88%
Epoch 19 - Time: 172.69s - Train Loss: 0.655765 - Train Accuracy: 77.43%
Test Loss: 1.952313 - Test Accuracy: 50.94%
```

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FINAL RESULTS:
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epoch_times: [176.49259638786316, 175.82231879234314, 182.96968507766724,
175.01975083351135, 187.68068408966064, 179.67215514183044, 177.3721632957
4585, 2114.843255996704, 307.8959949016571, 178.3186070919037, 174.2747299
671173, 169.76471304893494, 170.52626276016235, 171.7625710964203, 171.689
70608711243, 178.36060214042664, 173.4625279903412, 174.47915482521057, 17
3.05771207809448, 172.68643403053284]
train_losses: [1.8422306057151037, 1.561372934634449, 1.4289932237326644,
1.3573728212873444, 1.2749834552066017, 1.214539316546826, 1.1676533497471
846, 1.114954732301581, 1.05862481038989, 1.0336408935885393, 0.9698635776
534336, 0.9255781260155539, 0.9032293719644765, 0.8516452396643981, 0.8117
804636482064, 0.7780174973584314, 0.7476246215346205, 0.725593437561552,
0.6918507014749614, 0.6557649082809914]
train_accuracies: [32.145411203814064, 43.74255065554231, 48.7485101311084
6, 50.77473182359952 4, 53.99284862932062, 56.93682955899881, 58.6650774731
8236, 60.64362336114422, 62.94398092967819, 63.69487485101311, 66.11442193
087008, 67.58045292014303, 68.64123957091776, 70.70321811680571, 72.169249
10607867, 72.94398092967819, 73.99284862932062, 75.00595947556614, 76.6030
989272944, 77.42550655542313]
test_losses: [1.7594111448526382, 1.5651644814014434, 1.4650710982084274,
1.6576355692744256, 1.7432427006959914, 1.3981089863181113, 1.608052256107
3303, 1.4444050145149232, 1.3669641822576524, 1.4122039565443993, 1.472573
2989609241, 1.5615760169923305, 1.6461506137251853, 1.4155672320723534, 1.
5621185782551765, 1.6724637657403947, 1.4465129046142102, 1.63902138382196
43, 1.6699206562340259, 1.9523125983774663]
test_accuracies: [38.6875, 41.875, 46.125, 43.375, 44.625, 51.4375, 43.87
5, 50.5625, 53.0625, 52.8125, 52.0, 52.25, 53.0625, 53.5625, 54.25, 50.937
5, 55.5, 51.9375, 53.875, 50.9375]
```

In [10]:

```python
class ComplexNet(nn.Module):

    def __init__(self):
        super(ComplexNet, self).__init__()
        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):
        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(-1,30*2*20)
        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 = ComplexNet().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: 2.298491  Accuracy: 12.50%
Train Epoch:   0 [  3200/  8390 ( 38%)] Loss: 1.557620  Accuracy: 33.94%
Train Epoch:   0 [  6400/  8390 ( 76%)] Loss: 1.463058  Accuracy: 37.13%
Epoch 0 - Time: 207.23s - Train Loss: 1.700529 - Train Accuracy: 38.96%
Test Loss: 1.837249 - Test Accuracy: 37.88%

Train Epoch:   1 [     0/  8390 (  0%)] Loss: 1.486362  Accuracy: 50.00%
Train Epoch:   1 [  3200/  8390 ( 38%)] Loss: 1.224142  Accuracy: 49.57%
Train Epoch:   1 [  6400/  8390 ( 76%)] Loss: 1.203180  Accuracy: 50.39%
Epoch 1 - Time: 209.31s - Train Loss: 1.394651 - Train Accuracy: 50.64%
Test Loss: 1.502434 - Test Accuracy: 50.50%

Train Epoch:   2 [     0/  8390 (  0%)] Loss: 1.243697  Accuracy: 59.38%
Train Epoch:   2 [  3200/  8390 ( 38%)] Loss: 1.305529  Accuracy: 55.72%
Train Epoch:   2 [  6400/  8390 ( 76%)] Loss: 1.287207  Accuracy: 55.64%
Epoch 2 - Time: 208.01s - Train Loss: 1.276541 - Train Accuracy: 55.55%
Test Loss: 1.503635 - Test Accuracy: 48.88%

Train Epoch:   3 [     0/  8390 (  0%)] Loss: 1.319306  Accuracy: 59.38%
Train Epoch:   3 [  3200/  8390 ( 38%)] Loss: 0.906786  Accuracy: 60.33%
Train Epoch:   3 [  6400/  8390 ( 76%)] Loss: 1.429709  Accuracy: 59.17%
Epoch 3 - Time: 218.88s - Train Loss: 1.162604 - Train Accuracy: 59.06%
Test Loss: 1.531845 - Test Accuracy: 48.00%

Train Epoch:   4 [     0/  8390 (  0%)] Loss: 0.983407  Accuracy: 71.88%
Train Epoch:   4 [  3200/  8390 ( 38%)] Loss: 1.189449  Accuracy: 63.40%
Train Epoch:   4 [  6400/  8390 ( 76%)] Loss: 1.243121  Accuracy: 62.38%
Epoch 4 - Time: 227.79s - Train Loss: 1.098549 - Train Accuracy: 62.16%
Test Loss: 1.480476 - Test Accuracy: 53.19%

Train Epoch:   5 [     0/  8390 (  0%)] Loss: 0.945691  Accuracy: 68.75%
Train Epoch:   5 [  3200/  8390 ( 38%)] Loss: 1.595011  Accuracy: 65.38%
Train Epoch:   5 [  6400/  8390 ( 76%)] Loss: 1.228773  Accuracy: 65.13%
Epoch 5 - Time: 217.21s - Train Loss: 1.021704 - Train Accuracy: 65.40%
Test Loss: 1.419648 - Test Accuracy: 53.19%

Train Epoch:   6 [     0/  8390 (  0%)] Loss: 1.023521  Accuracy: 65.62%
Train Epoch:   6 [  3200/  8390 ( 38%)] Loss: 0.868787  Accuracy: 68.22%
Train Epoch:   6 [  6400/  8390 ( 76%)] Loss: 1.304474  Accuracy: 67.35%
Epoch 6 - Time: 214.13s - Train Loss: 0.936772 - Train Accuracy: 67.21%
Test Loss: 1.766144 - Test Accuracy: 49.94%

Train Epoch:   7 [     0/  8390 (  0%)] Loss: 1.172550  Accuracy: 68.75%
Train Epoch:   7 [  3200/  8390 ( 38%)] Loss: 0.928560  Accuracy: 69.12%
Train Epoch:   7 [  6400/  8390 ( 76%)] Loss: 1.150136  Accuracy: 68.58%
Epoch 7 - Time: 219.18s - Train Loss: 0.899686 - Train Accuracy: 68.67%
Test Loss: 1.508090 - Test Accuracy: 52.62%

Train Epoch:   8 [     0/  8390 (  0%)] Loss: 0.720141  Accuracy: 84.38%
Train Epoch:   8 [  3200/  8390 ( 38%)] Loss: 0.978278  Accuracy: 72.87%
Train Epoch:   8 [  6400/  8390 ( 76%)] Loss: 1.115881  Accuracy: 72.17%
Epoch 8 - Time: 211.72s - Train Loss: 0.826719 - Train Accuracy: 71.47%
Test Loss: 1.482925 - Test Accuracy: 52.94%

Train Epoch:   9 [     0/  8390 (  0%)] Loss: 0.771082  Accuracy: 68.75%
Train Epoch:   9 [  3200/  8390 ( 38%)] Loss: 0.770933  Accuracy: 74.91%
Train Epoch:   9 [  6400/  8390 ( 76%)] Loss: 0.638593  Accuracy: 74.52%
Epoch 9 - Time: 211.68s - Train Loss: 0.775972 - Train Accuracy: 73.81%
Test Loss: 2.327325 - Test Accuracy: 46.06%
```

```
Train Epoch:  10 [     0/  8390 (  0%)] Loss: 0.718460  Accuracy: 81.25%
Train Epoch:  10 [  3200/  8390 ( 38%)] Loss: 0.490445  Accuracy: 76.45%
Train Epoch:  10 [  6400/  8390 ( 76%)] Loss: 0.763847  Accuracy: 74.47%
Epoch 10 - Time: 220.81s - Train Loss: 0.768677 - Train Accuracy: 73.90%
Test Loss: 1.624778 - Test Accuracy: 50.06%

Train Epoch:  11 [     0/  8390 (  0%)] Loss: 0.837381  Accuracy: 71.88%
Train Epoch:  11 [  3200/  8390 ( 38%)] Loss: 0.955065  Accuracy: 76.76%
Train Epoch:  11 [  6400/  8390 ( 76%)] Loss: 0.871415  Accuracy: 76.32%
Epoch 11 - Time: 217.77s - Train Loss: 0.710534 - Train Accuracy: 75.29%
Test Loss: 1.927030 - Test Accuracy: 46.62%

Train Epoch:  12 [     0/  8390 (  0%)] Loss: 0.437259  Accuracy: 84.38%
Train Epoch:  12 [  3200/  8390 ( 38%)] Loss: 0.542547  Accuracy: 75.96%
Train Epoch:  12 [  6400/  8390 ( 76%)] Loss: 0.763151  Accuracy: 76.43%
Epoch 12 - Time: 220.09s - Train Loss: 0.679895 - Train Accuracy: 76.85%
Test Loss: 1.866881 - Test Accuracy: 52.62%

Train Epoch:  13 [     0/  8390 (  0%)] Loss: 0.471891  Accuracy: 78.12%
Train Epoch:  13 [  3200/  8390 ( 38%)] Loss: 0.483762  Accuracy: 79.39%
Train Epoch:  13 [  6400/  8390 ( 76%)] Loss: 0.462755  Accuracy: 79.00%
Epoch 13 - Time: 205.67s - Train Loss: 0.640420 - Train Accuracy: 78.55%
Test Loss: 1.900124 - Test Accuracy: 50.31%

Train Epoch:  14 [     0/  8390 (  0%)] Loss: 0.535412  Accuracy: 78.12%
Train Epoch:  14 [  3200/  8390 ( 38%)] Loss: 1.018734  Accuracy: 80.38%
Train Epoch:  14 [  6400/  8390 ( 76%)] Loss: 0.481601  Accuracy: 79.80%
Epoch 14 - Time: 202.46s - Train Loss: 0.605839 - Train Accuracy: 79.49%
Test Loss: 1.946474 - Test Accuracy: 53.69%

Train Epoch:  15 [     0/  8390 (  0%)] Loss: 0.608204  Accuracy: 75.00%
Train Epoch:  15 [  3200/  8390 ( 38%)] Loss: 0.225345  Accuracy: 79.27%
Train Epoch:  15 [  6400/  8390 ( 76%)] Loss: 0.510582  Accuracy: 79.23%
Epoch 15 - Time: 201.00s - Train Loss: 0.586624 - Train Accuracy: 79.30%
Test Loss: 2.127388 - Test Accuracy: 55.38%

Train Epoch:  16 [     0/  8390 (  0%)] Loss: 0.638399  Accuracy: 65.62%
Train Epoch:  16 [  3200/  8390 ( 38%)] Loss: 0.393152  Accuracy: 82.05%
Train Epoch:  16 [  6400/  8390 ( 76%)] Loss: 0.281390  Accuracy: 81.00%
Epoch 16 - Time: 205.50s - Train Loss: 0.547327 - Train Accuracy: 81.12%
Test Loss: 2.033684 - Test Accuracy: 50.81%

Train Epoch:  17 [     0/  8390 (  0%)] Loss: 0.874391  Accuracy: 68.75%
Train Epoch:  17 [  3200/  8390 ( 38%)] Loss: 0.404561  Accuracy: 82.77%
Train Epoch:  17 [  6400/  8390 ( 76%)] Loss: 0.610093  Accuracy: 82.11%
Epoch 17 - Time: 206.37s - Train Loss: 0.536022 - Train Accuracy: 81.75%
Test Loss: 1.759946 - Test Accuracy: 56.44%

Train Epoch:  18 [     0/  8390 (  0%)] Loss: 0.479482  Accuracy: 87.50%
Train Epoch:  18 [  3200/  8390 ( 38%)] Loss: 0.659766  Accuracy: 84.65%
Train Epoch:  18 [  6400/  8390 ( 76%)] Loss: 0.344141  Accuracy: 84.05%
Epoch 18 - Time: 221.55s - Train Loss: 0.496238 - Train Accuracy: 83.54%
Test Loss: 2.168570 - Test Accuracy: 49.31%

Train Epoch:  19 [     0/  8390 (  0%)] Loss: 0.513600  Accuracy: 75.00%
Train Epoch:  19 [  3200/  8390 ( 38%)] Loss: 0.243855  Accuracy: 83.66%
Train Epoch:  19 [  6400/  8390 ( 76%)] Loss: 0.496647  Accuracy: 83.19%
Epoch 19 - Time: 204.48s - Train Loss: 0.496304 - Train Accuracy: 82.96%
Test Loss: 1.894559 - Test Accuracy: 55.88%
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FINAL RESULTS:
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epoch_times: [207.22970986366272, 209.30913090705872, 208.01324605941772,
218.8806028366089, 227.79374074935913, 217.20957016944885, 214.13214111328
125, 219.17577195167542, 211.7231628894806, 211.67860794067383, 220.808238
9831543, 217.77472281455994, 220.09114789962769, 205.66677808761597, 202.4
6442699432373, 200.99517726898193, 205.49894618988037, 206.37325477600098,
221.5477020740509, 204.48290991783142]
train_losses: [1.700529125355582, 1.3946505498340112, 1.2765410285414631,
1.1626035025101582, 1.098549397619626, 1.0217041275428451, 0.9367715119178
058, 0.8996856087491713, 0.8267188028979847, 0.7759724028465402, 0.7686765
82297296, 0.7105342651369008, 0.6798951057077364, 0.6404201299634599, 0.60
58392998485165, 0.5866240029230373, 0.5473274279186744, 0.5360223032136,
0.4962378031083646, 0.4963039540550636]
train_accuracies: [38.963051251489865, 50.64362336114422, 55.5542312276519
7, 59.05840286054827, 62.157330154946365, 65.39928486293206, 67.2109654350
4171, 68.66507747318236, 71.46603098927294, 73.81406436233611, 73.89749702
026222, 75.29201430274136, 76.8533969010727, 78.54588796185935, 79.4874851
0131108, 79.29678188319429, 81.12038140643624, 81.75208581644816, 83.53992
84862932, 82.95589988081049]
test_losses: [1.8372494512796402, 1.5024336314201354, 1.5036351738870144,
1.5318452209234237, 1.4804760238528252, 1.4196479684114456, 1.766143504083
1566, 1.508089792728424, 1.482925257012248, 2.3273247413337232, 1.62477848
79803657, 1.9270301645994186, 1.866880871206522, 1.900124378465116, 1.9464
739935845137, 2.127388111501932, 2.033684199824929, 1.7599458007141948, 2.
168570462167263, 1.8945587299019098]
test_accuracies: [37.875, 50.5, 48.875, 48.0, 53.1875, 53.1875, 49.9375, 5
2.625, 52.9375, 46.0625, 50.0625, 46.625, 52.625, 50.3125, 53.6875, 55.37
5, 50.8125, 56.4375, 49.3125, 55.875]
```

In [11]:

```python
train_dataset = GenreDatasetPhaseMFCC("Data/train/", n_fft=2048, hop_leng
test_dataset = GenreDatasetPhaseMFCC("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

class ComplexNet(nn.Module):

    def __init__(self):
        super(ComplexNet, self).__init__()
        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):
        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(-1,30*2*20)
        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 = ComplexNet().to(device)
optimizer = torch.optim.SGD(model.parameters(), lr=0.01, momentum=0.9)

metrics_dict_e3 = {
    '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_e3.items():
    print(f'{key}: {value}')
```

```
Train Epoch:   0 [     0/  8390 (  0%)] Loss: 2.413850  Accuracy: 15.62%
Train Epoch:   0 [  3200/  8390 ( 38%)] Loss: 2.207769  Accuracy: 19.09%
Train Epoch:   0 [  6400/  8390 ( 76%)] Loss: 1.834011  Accuracy: 23.13%
Epoch 0 - Time: 223.27s - Train Loss: 2.042803 - Train Accuracy: 25.22%
Test Loss: 1.984808 - Test Accuracy: 29.25%

Train Epoch:   1 [     0/  8390 (  0%)] Loss: 2.062810  Accuracy: 25.00%
Train Epoch:   1 [  3200/  8390 ( 38%)] Loss: 1.839269  Accuracy: 32.21%
Train Epoch:   1 [  6400/  8390 ( 76%)] Loss: 1.721043  Accuracy: 32.73%
Epoch 1 - Time: 337.22s - Train Loss: 1.861055 - Train Accuracy: 32.40%
Test Loss: 1.878305 - Test Accuracy: 31.12%

Train Epoch:   2 [     0/  8390 (  0%)] Loss: 1.635835  Accuracy: 40.62%
Train Epoch:   2 [  3200/  8390 ( 38%)] Loss: 1.928107  Accuracy: 34.10%
Train Epoch:   2 [  6400/  8390 ( 76%)] Loss: 2.216387  Accuracy: 34.76%
Epoch 2 - Time: 286.50s - Train Loss: 1.809655 - Train Accuracy: 34.35%
Test Loss: 1.889286 - Test Accuracy: 30.88%

Train Epoch:   3 [     0/  8390 (  0%)] Loss: 1.787891  Accuracy: 37.50%
Train Epoch:   3 [  3200/  8390 ( 38%)] Loss: 1.962163  Accuracy: 37.10%
Train Epoch:   3 [  6400/  8390 ( 76%)] Loss: 1.804685  Accuracy: 36.35%
Epoch 3 - Time: 319.34s - Train Loss: 1.759352 - Train Accuracy: 36.33%
Test Loss: 1.856480 - Test Accuracy: 35.00%

Train Epoch:   4 [     0/  8390 (  0%)] Loss: 1.647825  Accuracy: 40.62%
Train Epoch:   4 [  3200/  8390 ( 38%)] Loss: 1.899797  Accuracy: 38.24%
Train Epoch:   4 [  6400/  8390 ( 76%)] Loss: 1.599051  Accuracy: 37.06%
Epoch 4 - Time: 298.26s - Train Loss: 1.723030 - Train Accuracy: 37.53%
Test Loss: 1.867167 - Test Accuracy: 31.50%

Train Epoch:   5 [     0/  8390 (  0%)] Loss: 1.510139  Accuracy: 50.00%
Train Epoch:   5 [  3200/  8390 ( 38%)] Loss: 1.432850  Accuracy: 38.06%
Train Epoch:   5 [  6400/  8390 ( 76%)] Loss: 1.950091  Accuracy: 38.56%
Epoch 5 - Time: 378.20s - Train Loss: 1.717170 - Train Accuracy: 38.20%
Test Loss: 1.821705 - Test Accuracy: 34.25%

Train Epoch:   6 [     0/  8390 (  0%)] Loss: 1.339843  Accuracy: 53.12%
Train Epoch:   6 [  3200/  8390 ( 38%)] Loss: 1.512588  Accuracy: 40.01%
Train Epoch:   6 [  6400/  8390 ( 76%)] Loss: 1.511724  Accuracy: 39.80%
Epoch 6 - Time: 327.84s - Train Loss: 1.674332 - Train Accuracy: 39.89%
Test Loss: 1.803232 - Test Accuracy: 34.06%

Train Epoch:   7 [     0/  8390 (  0%)] Loss: 1.740120  Accuracy: 40.62%
Train Epoch:   7 [  3200/  8390 ( 38%)] Loss: 1.243231  Accuracy: 40.78%
Train Epoch:   7 [  6400/  8390 ( 76%)] Loss: 1.950737  Accuracy: 40.80%
Epoch 7 - Time: 353.24s - Train Loss: 1.654439 - Train Accuracy: 40.87%
Test Loss: 1.895607 - Test Accuracy: 32.88%

Train Epoch:   8 [     0/  8390 (  0%)] Loss: 1.482600  Accuracy: 53.12%
Train Epoch:   8 [  3200/  8390 ( 38%)] Loss: 1.587255  Accuracy: 42.85%
Train Epoch:   8 [  6400/  8390 ( 76%)] Loss: 1.714218  Accuracy: 42.54%
Epoch 8 - Time: 297.25s - Train Loss: 1.620706 - Train Accuracy: 42.05%
Test Loss: 1.815371 - Test Accuracy: 36.19%

Train Epoch:   9 [     0/  8390 (  0%)] Loss: 1.766228  Accuracy: 34.38%
Train Epoch:   9 [  3200/  8390 ( 38%)] Loss: 1.787615  Accuracy: 43.38%
Train Epoch:   9 [  6400/  8390 ( 76%)] Loss: 1.693290  Accuracy: 42.96%
Epoch 9 - Time: 287.32s - Train Loss: 1.599723 - Train Accuracy: 42.90%
Test Loss: 1.834403 - Test Accuracy: 34.81%
```

```
Train Epoch:  10 [     0/  8390 (  0%)] Loss: 1.723920  Accuracy: 40.62%
Train Epoch:  10 [  3200/  8390 ( 38%)] Loss: 1.512322  Accuracy: 43.47%
Train Epoch:  10 [  6400/  8390 ( 76%)] Loss: 1.607760  Accuracy: 43.05%
Epoch 10 - Time: 1177.41s - Train Loss: 1.586791 - Train Accuracy: 43.02%
Test Loss: 1.872561 - Test Accuracy: 31.62%

Train Epoch:  11 [     0/  8390 (  0%)] Loss: 1.793006  Accuracy: 34.38%
Train Epoch:  11 [  3200/  8390 ( 38%)] Loss: 1.809574  Accuracy: 45.85%
Train Epoch:  11 [  6400/  8390 ( 76%)] Loss: 1.698219  Accuracy: 44.29%
Epoch 11 - Time: 8451.60s - Train Loss: 1.559433 - Train Accuracy: 44.22%
Test Loss: 1.905067 - Test Accuracy: 34.38%

Train Epoch:  12 [     0/  8390 (  0%)] Loss: 1.667610  Accuracy: 37.50%
Train Epoch:  12 [  3200/  8390 ( 38%)] Loss: 1.469992  Accuracy: 45.11%
Train Epoch:  12 [  6400/  8390 ( 76%)] Loss: 1.860880  Accuracy: 44.92%
Epoch 12 - Time: 210.94s - Train Loss: 1.559958 - Train Accuracy: 44.17%
Test Loss: 1.800275 - Test Accuracy: 34.94%

Train Epoch:  13 [     0/  8390 (  0%)] Loss: 1.479374  Accuracy: 37.50%
Train Epoch:  13 [  3200/  8390 ( 38%)] Loss: 1.582445  Accuracy: 44.71%
Train Epoch:  13 [  6400/  8390 ( 76%)] Loss: 1.403867  Accuracy: 45.20%
Epoch 13 - Time: 217.98s - Train Loss: 1.539376 - Train Accuracy: 45.44%
Test Loss: 1.738834 - Test Accuracy: 38.12%

Train Epoch:  14 [     0/  8390 (  0%)] Loss: 1.457347  Accuracy: 43.75%
Train Epoch:  14 [  3200/  8390 ( 38%)] Loss: 1.363334  Accuracy: 48.79%
Train Epoch:  14 [  6400/  8390 ( 76%)] Loss: 1.780651  Accuracy: 47.59%
Epoch 14 - Time: 245.03s - Train Loss: 1.514394 - Train Accuracy: 46.85%
Test Loss: 1.863470 - Test Accuracy: 35.62%

Train Epoch:  15 [     0/  8390 (  0%)] Loss: 1.374776  Accuracy: 43.75%
Train Epoch:  15 [  3200/  8390 ( 38%)] Loss: 1.330341  Accuracy: 46.91%
Train Epoch:  15 [  6400/  8390 ( 76%)] Loss: 1.671826  Accuracy: 46.72%
Epoch 15 - Time: 301.61s - Train Loss: 1.497057 - Train Accuracy: 46.82%
Test Loss: 1.824527 - Test Accuracy: 36.12%

Train Epoch:  16 [     0/  8390 (  0%)] Loss: 1.425750  Accuracy: 46.88%
Train Epoch:  16 [  3200/  8390 ( 38%)] Loss: 1.448989  Accuracy: 48.45%
Train Epoch:  16 [  6400/  8390 ( 76%)] Loss: 1.449083  Accuracy: 47.43%
Epoch 16 - Time: 299.60s - Train Loss: 1.486795 - Train Accuracy: 47.54%
Test Loss: 1.906221 - Test Accuracy: 34.56%

Train Epoch:  17 [     0/  8390 (  0%)] Loss: 1.887340  Accuracy: 31.25%
Train Epoch:  17 [  3200/  8390 ( 38%)] Loss: 1.329155  Accuracy: 49.69%
Train Epoch:  17 [  6400/  8390 ( 76%)] Loss: 1.594913  Accuracy: 49.00%
Epoch 17 - Time: 300.35s - Train Loss: 1.454458 - Train Accuracy: 48.92%
Test Loss: 1.837543 - Test Accuracy: 37.62%

Train Epoch:  18 [     0/  8390 (  0%)] Loss: 1.328355  Accuracy: 53.12%
Train Epoch:  18 [  3200/  8390 ( 38%)] Loss: 1.780887  Accuracy: 49.01%
Train Epoch:  18 [  6400/  8390 ( 76%)] Loss: 1.542195  Accuracy: 48.49%
Epoch 18 - Time: 295.70s - Train Loss: 1.448089 - Train Accuracy: 48.90%
Test Loss: 1.878924 - Test Accuracy: 34.25%

Train Epoch:  19 [     0/  8390 (  0%)] Loss: 1.354482  Accuracy: 59.38%
Train Epoch:  19 [  3200/  8390 ( 38%)] Loss: 1.856767  Accuracy: 50.19%
Train Epoch:  19 [  6400/  8390 ( 76%)] Loss: 1.144183  Accuracy: 49.91%
Epoch 19 - Time: 248.67s - Train Loss: 1.423151 - Train Accuracy: 49.58%
Test Loss: 1.881986 - Test Accuracy: 35.38%
```

```
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FINAL RESULTS:
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epoch_times: [223.27179288864136, 337.2176299095154, 286.5028817653656, 319.344908952713, 298.26079392433167, 378.1967351436615, 327.8363778591156, 353.2444438934326, 297.2461521625519, 287.32417821884155, 1177.4050579071045, 8451.597054958344, 210.93699979782104, 217.97601509094238, 245.02782487869263, 301.6087737083435, 299.5960121154785, 300.3493719100952, 295.69727897644043, 248.66599893569946]
train_losses: [2.042802960363053, 1.8610548781984635, 1.8096553337483006, 1.7593516279722898, 1.7230299820426767, 1.7171696833981813, 1.6743323070402363, 1.6544389388033451, 1.6207061751198222, 1.5997228954584544, 1.5867910953878446, 1.55943332191642, 1.5599576771714305, 1.539376305259821, 1.5143942514448676, 1.497057060931475, 1.4867947952437948, 1.4544576249504817, 1.4480891391521191, 1.4231507835042385]
train_accuracies: [25.220500595947556, 32.39570917759237, 34.35041716328963, 36.32896305125149, 37.532777115613825, 38.20023837902264, 39.892729439809294, 40.87008343265793, 42.05005959475566, 42.896305125148984, 43.01549463647199, 44.219308700834326, 44.17163289630513, 45.43504171632896, 46.853396901072706, 46.8176400476758, 47.54469606674613, 48.91537544696067, 48.903456495828365, 49.582836710369484]
test_losses: [1.9848083889484405, 1.8783054047822951, 1.8892862010002136, 1.8564798241853715, 1.867166874408722, 1.821704980134964, 1.8032320165634155, 1.895607076883316, 1.8153707492351532, 1.834402973651886, 1.8725606411695481, 1.905067165493965, 1.8002750039100648, 1.7388343811035156, 1.8634701204299926, 1.824527004957199, 1.9062212073802949, 1.837543227672577, 1.8789236879348754, 1.8819858026504517]
test_accuracies: [29.25, 31.125, 30.875, 35.0, 31.5, 34.25, 34.0625, 32.875, 36.1875, 34.8125, 31.625, 34.375, 34.9375, 38.125, 35.625, 36.125, 34.5625, 37.625, 34.25, 35.375]
```
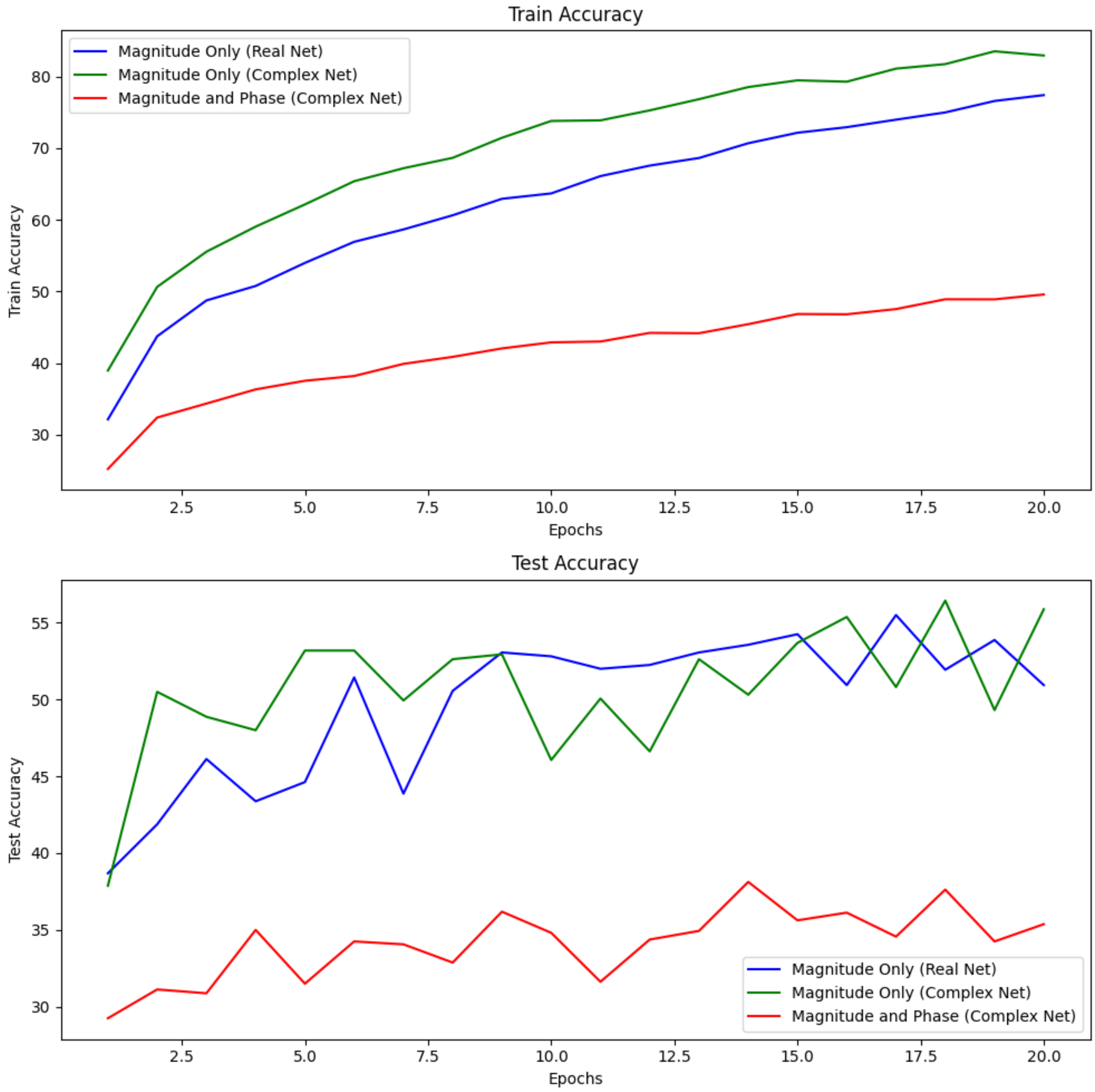
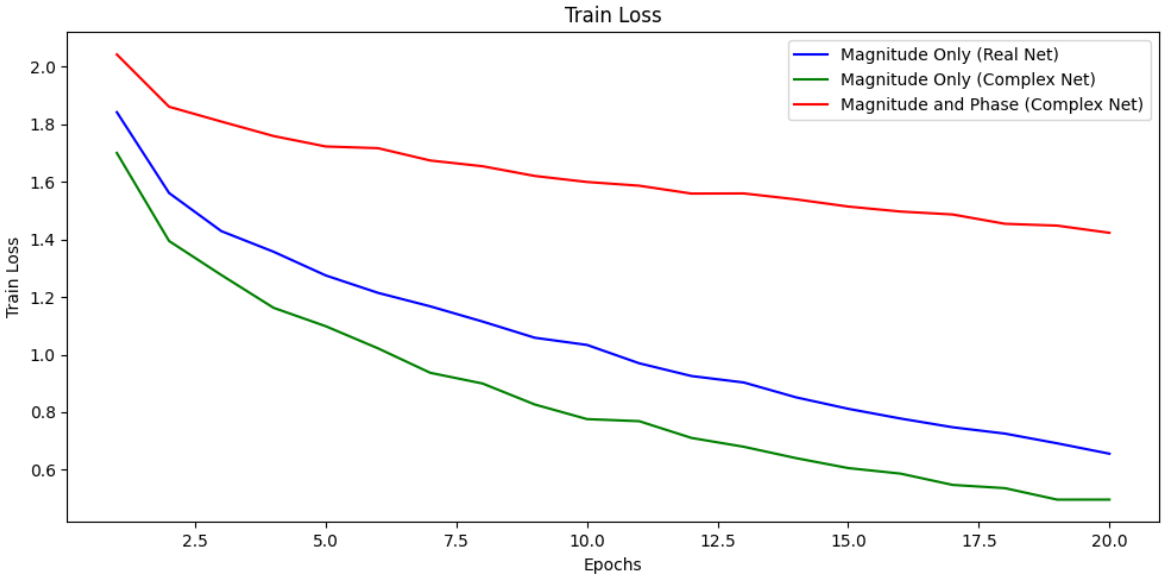

Plots

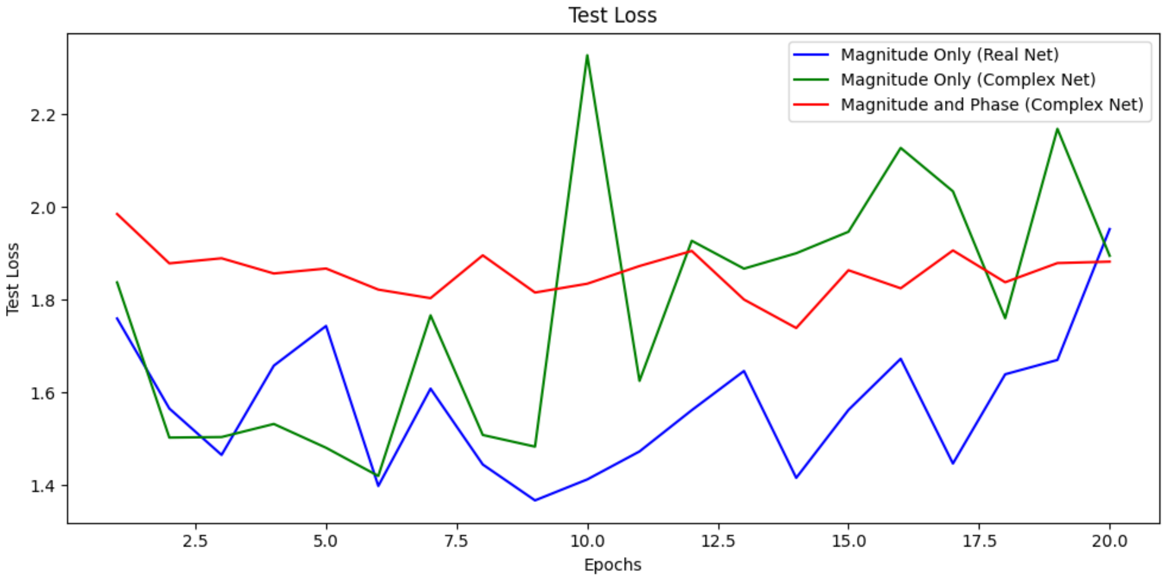
In [22]:

```python
# Data for the four scenarios
data = {
    "Magnitude Only (Real Net)": metrics_dict_e1,
    "Magnitude Only (Complex Net)": metrics_dict_e2,
    "Magnitude and Phase (Complex Net)": metrics_dict_e3
}

# Data for plotting
epochs = range(1, 21)
colors = ['b', 'g', 'r', 'm', 'y']
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=scenar

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=scenari

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,

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, c

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, colc
axes.set_title("Time")
axes.set_xlabel("Epochs")
axes.set_ylabel("Time (secs)")
axes.legend()
```


Train Accuracy
Magnitude Only (Real Net)
Magnitude Only (Complex Net)
Magnitude and Phase (Complex Net)
Train Accuracy
30
40
50
60
70
80
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Epochs
Test Accuracy
Test Accuracy
30
35
40
45
50
55
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Epochs
Magnitude Only (Real Net)
Magnitude Only (Complex Net)
Magnitude and Phase (Complex Net)






```
Out[22]: <matplotlib.legend.Legend at 0x2b9e9f790>
```