In [1]:
```
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader
from sklearn.model_selection import train_test_split
import torchvision.transforms as transforms
from bisect import bisect
torch.cuda.is_available()
```

Out[1]: True

In [2]:
```
import pandas as pd
import pyarrow.parquet as pq

# def read_parquet_in_chunks(file_path, chunk_size=100):
#     dfs = []
#     pf = pq.ParquetFile(file_path)
#     for i in range(0, pf.num_row_groups, chunk_size):
#         chunk = pf.read_row_group(i).to_pandas()
#         dfs.append(chunk)
#     return pd.concat(dfs, ignore_index=True)

file1 = 'QCDToGGQQ_IMGjet_RH1all_jet0_run0_n36272.test.snappy.parquet'
file2 = 'QCDToGGQQ_IMGjet_RH1all_jet0_run1_n47540.test.snappy.parquet'
file3 = 'QCDToGGQQ_IMGjet_RH1all_jet0_run2_n55494.test.snappy.parquet'

# df1 = read_parquet_in_chunks(file1)
# df2 = read_parquet_in_chunks(file2)
# df3 = read_parquet_in_chunks(file3)

# # Combine the DataFrames
# df = pd.concat([df1, df2, df3], ignore_index=True)
```

In [3]:
```
class ParquetDataset(Dataset):
    def __init__(self, file_path):
        self.file_path = file_path
        self.parquet_file = pq.ParquetFile(file_path)
        self.num_row_groups = self.parquet_file.num_row_groups

    def __len__(self):
        return self.num_row_groups

    def __getitem__(self, idx):
        row_group = self.parquet_file.read_row_group(idx).to_pandas()
        image_data = row_group['X_jets'].iloc[0]
        label = row_group['y'].iloc[0]

        # Stack the image data
        image_data = np.stack([np.stack(channel) for channel in image_data], axis=0
        image_data = torch.tensor(image_data, dtype=torch.float)

        # Explicitly cast label to an integer
        label = int(label)
        label = torch.tensor(label, dtype=torch.long)

        return image_data, label
```

In [4]:
```
from torch.utils.data import ConcatDataset

dataset1 = ParquetDataset(file1)
dataset2 = ParquetDataset(file2)
dataset3 = ParquetDataset(file3)


dataset = ConcatDataset([dataset1, dataset2, dataset3])
```

In [5]:
```
from torch.utils.data import random_split

train_size = int(0.8 * len(dataset))
test_size = len(dataset) - train_size
train_dataset, test_dataset = random_split(dataset, [train_size, test_size])

train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)
```

In [6]:
```
from e2cnn import gspaces
from e2cnn import nn as enn

r2_act = gspaces.Rot2dOnR2(N=8)  # N: Number of discrete rotations

class EquivariantNetwork(nn.Module):
    def __init__(self, n_classes):
        super(EquivariantNetwork, self).__init__()

        self.input_type = enn.FieldType(r2_act, 3 * [r2_act.trivial_repr])
        self.output_type = enn.FieldType(r2_act, 24 * [r2_act.regular_repr])

        self.layer1 = enn.R2Conv(self.input_type, self.output_type, kernel_size=3,
        self.relu1 = enn.ReLU(self.output_type)

        self.pool1 = enn.R2Conv(self.output_type, self.output_type, kernel_size=3,

        self.gpool = enn.GroupPooling(self.output_type)

        self.fc1 = nn.Linear(24 * 63 * 63, 64)
        self.fc2 = nn.Linear(64, n_classes)

    def forward(self, x):
        x = enn.GeometricTensor(x, self.input_type)
        x = self.relu1(self.layer1(x))
        x = self.pool1(x)
        x = self.gpool(x)
        x = x.tensor.view(x.tensor.shape[0], -1)
        x = torch.relu(self.fc1(x))
        x = self.fc2(x)
        return x
```

In [7]:
```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
num_classes = 2
equivariant_net = EquivariantNetwork(num_classes)
equivariant_net = equivariant_net.to(device)
```

```
C:\Users\roder\anaconda3\envs\pt2.0\lib\site-packages\e2cnn\nn\modules\r2_conv\ba
sisexpansion_singleblock.py:80: UserWarning: indexing with dtype torch.uint8 is n
ow deprecated, please use a dtype torch.bool instead. (Triggered internally at
C:\cb\pytorch_1000000000000\work\aten\src\ATen/native/IndexingUtils.h:28.)
  full_mask[mask] = norms.to(torch.uint8)
```

In [8]:
```
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(equivariant_net.parameters(), lr=0.0001)
```

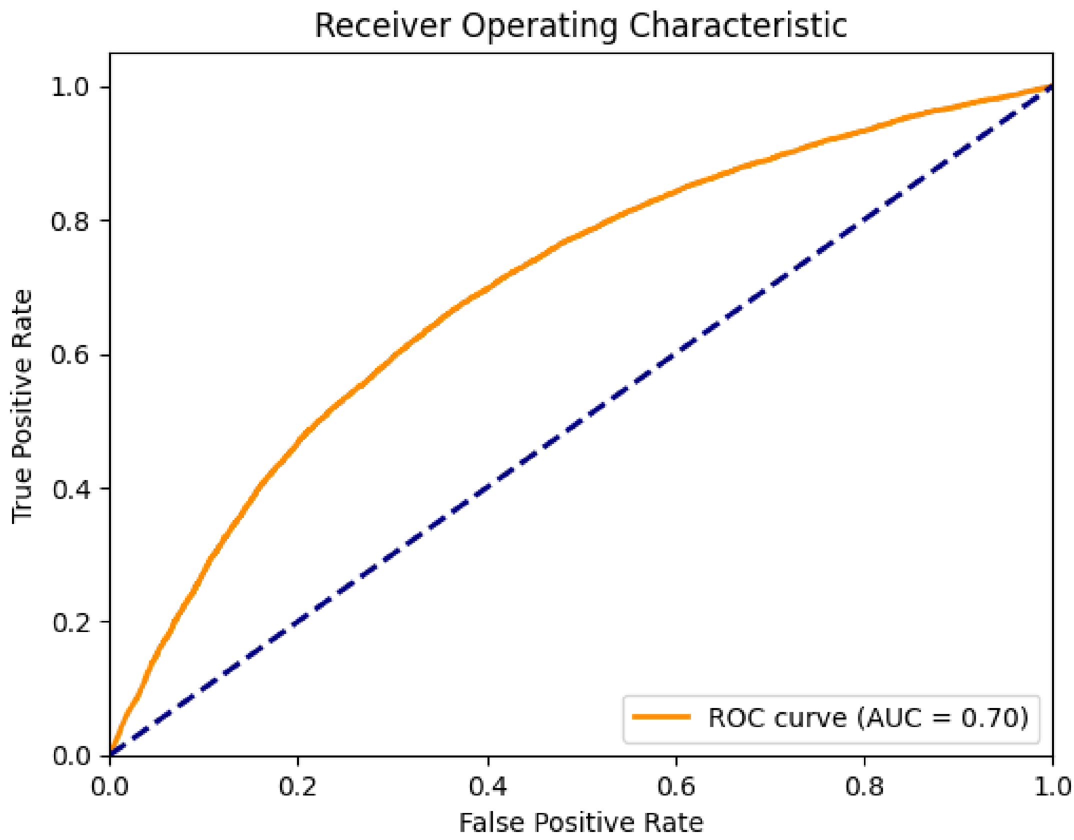
In [9]:
```
num_epochs = 10
reg_factor = 0.01

for epoch in range(num_epochs):
    equivariant_net.train()
    running_loss = 0.0

    for images, labels in train_loader:
        images, labels = images.to(device), labels.to(device)

        optimizer.zero_grad()

        outputs = equivariant_net(images)
        loss = criterion(outputs, labels)
        loss += l2_regularization(vgg16, reg_factor)

        loss.backward()

        optimizer.step()

        running_loss += loss.item()

    print(f"Epoch {epoch+1}/{num_epochs}, Loss: {running_loss/len(train_loader)}")
```

```
Epoch 1/10, Loss: 0.5989298875342831
Epoch 2/10, Loss: 0.5589273914399586
Epoch 3/10, Loss: 0.5243561527286149
Epoch 4/10, Loss: 0.4817090367589776
Epoch 5/10, Loss: 0.4291343157605607
Epoch 6/10, Loss: 0.3651678797767794
Epoch 7/10, Loss: 0.2865716498831788
Epoch 8/10, Loss: 0.20833704907991507
Epoch 9/10, Loss: 0.13208005041207027
Epoch 10/10, Loss: 0.08407282102115061
```

In [10]:
```
# Set the model to evaluation mode
equivariant_net.eval()

# Initialize variables for accuracy calculation
correct = 0
total = 0
# Disable gradient computation to save memory and speed up the evaluation
with torch.no_grad():
    for images, labels in test_loader:
        images, labels = images.to(device), labels.to(device)

        # Make predictions
        outputs = equivariant_net(images)

        # Get the predicted class (highest value)
        _, predicted = torch.max(outputs.data, 1)

        # Update the total number of samples and the number of correct predictions
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

# Calculate the accuracy
accuracy = correct / total
print(f'Accuracy of the model on the test dataset: {accuracy * 100:.2f}%')
```

```
Accuracy of the model on the test dataset: 65.02%
```

In [11]:
```
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt
# Set the model to evaluation mode
equivariant_net.eval()

# Initialize lists to store true labels and predicted probabilities
y_true = []
y_probs = []

# Disable gradient computation to save memory and speed up the evaluation
with torch.no_grad():
    for images, labels in test_loader:
        images, labels = images.to(device), labels.to(device)

        # Make predictions
        outputs = equivariant_net(images)

        # Get the probability of the positive class (class 1)
        probs = torch.nn.functional.softmax(outputs, dim=1)
        probs = probs[:, 1].cpu().numpy()

        y_probs.extend(probs)
        y_true.extend(labels.cpu().numpy())

# Compute ROC curve and AUC score
fpr, tpr, _ = roc_curve(y_true, y_probs)
roc_auc = auc(fpr, tpr)

# Plot the ROC curve
plt.figure()
lw = 2
plt.plot(fpr, tpr, color='darkorange', lw=lw, label='ROC curve (AUC = %0.2f)' % roc
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```



In [12]:
```
torch.save(equivariant_net.state_dict(), 'equivariant_net.pt')
```

In [ ]:

In [ ]: