In [ ]:
```python
import numpy as np
import matplotlib.pyplot as plt
import torch
from torch import nn
import torchvision
import torchvision.transforms as transforms
from torchvision.datasets import ImageFolder
import torchvision.models as models
from torch.utils.data import TensorDataset, ConcatDataset, DataLoader,Sub
from sklearn.model_selection import KFold
import os
from torchinfo import summary
```

In [4]:
```python
device = "cuda" if torch.cuda.is_available() else "cpu"
```

In [ ]:
```python
class DeepLens(nn.Module):
    def __init__(self,normalized_r2):
        super(DeepLens, self).__init__()
        self.normalized_r2 = normalized_r2

    # Step 2: Use another ResNet-18 for vector A
        self.resnet_A = models.resnet18(pretrained=True)

#         for param in self.resnet_B.parameters():  # Freeze ResNet-18 pa
#             param.requires_grad = False

        self.features_A = nn.Sequential(*list(self.resnet_A.children())[:
        self.features_A.add_module('flatten', nn.Flatten())
        self.features_A.add_module('dropout', nn.Dropout(p=0.4))  # Addin
        self.relu = nn.ReLU(inplace=True)
        self.features_A.add_module('linear', nn.Linear(12800, 22500))

    # Step 3: Use another ResNet-18 for vector B
        self.resnet_B = models.resnet18(pretrained=True)

#         for param in self.resnet_B.parameters():  # Freeze ResNet-18 pa
#             param.requires_grad = False

        self.features_B = nn.Sequential(*list(self.resnet_B.children())[:
        self.features_B.add_module('flatten', nn.Flatten())
        self.features_B.add_module('dropout', nn.Dropout(p=0.4))  # Addin
#         self.relu = nn.ReLU(inplace=True)
        self.features_B.add_module('linear', nn.Linear(12800, 22500))

        # Step 5: Neural layer and softmax

        self.neural_layer1 = nn.Linear(22500,5625 )
        self.neural_layer2 = nn.Linear(5625, 128)
        self.neural_layer3 = nn.Linear(128, 3)
        self.dropout = nn.Dropout(p=0.4)  # Adding dropout layer

    def forward(self, x):

        # Step 2: Extract features A

        features_A = self.features_A(x)
        features_A = self.relu(features_A)
        features_A = features_A.view(features_A.size(0), -1)
```

```python
        # Step 3: Extract features B

        features_B = self.features_B(x)
        features_B = self.relu(features_B)
        features_B = features_B.view(features_B.size(0), -1)

        # Step 4: Physics equation C = I - B * (distance from center of i
        C = features_A - features_B * (self.normalized_r2)

        # Step 5: Neural layer and softmax
        output = self.neural_layer1(C)
        output = self.relu(output)
        output = self.dropout(output)

        output = self.neural_layer2(output)
        output = self.relu(output)
        output = self.dropout(output) # Applying dropout

        output = self.neural_layer3(output)

        return output
```

In [7]:

```python
transformer=transforms.Compose([
    transforms.Resize((150,150)),
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(degrees=10),
    transforms.ToTensor(),  #0-255 to 0-1, numpy to tensors
    transforms.Normalize([0.5,0.5,0.5], # 0-1 to [-1,1] , formula (x-mean
                        [0.5,0.5,0.5])
])
```

In [8]:

```python
grid_size = 150

# Initialize an empty tensor to store distances
r2 = torch.zeros(grid_size * grid_size)

# Compute distances for each pixel
for i in range(grid_size):
    for j in range(grid_size):
        r2[grid_size * i + j] = ((74.5 - i) ** 2 + (74.5 - j) ** 2)

# Verify the size of dis
print("Size of dis tensor:", r2.size())

# Find the maximum value in the r2 tensor
max_r2 = r2.max()
normalized_r2 = r2/max_r2

# Move r2 tensor to CUDA if available
normalized_r2 = normalized_r2.cuda()
```

```
Size of dis tensor: torch.Size([22500])
```

In [9]:

```python
encoder = DeepLens(normalized_r2).to(device)
```

```
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:208: UserWarning: The parameter 'pretrained' is deprecated since 0.13 and may be removed in the future, please use 'weights' instead.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a weight enum or `None` for 'weights' are deprecated since 0.13 and may be removed in the future. The current behavior is equivalent to passing `weights=ResNet18_Weights.IMAGENET1K_V1`. You can also use `weights=ResNet18_Weights.DEFAULT` to get the most up-to-date weights.
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/resnet18-f37072fd.pth" to /root/.cache/torch/hub/checkpoints/resnet18-f37072fd.pth
100%|██████████| 44.7M/44.7M [00:00<00:00, 148MB/s]
```

In [10]:
```
train_path = '/kaggle/input/gsoc-pinn1/new_dataset_PINN/train'
```

In [11]:
```
class_folders = torchvision.datasets.ImageFolder(train_path,transform=tra
```

In [12]:
```
torch.cuda.empty_cache()
```

In [13]:
```
from torch.optim.lr_scheduler import StepLR
optimizer = torch.optim.RMSprop(encoder.parameters(), lr=0.01, weight_dec
# Define the scheduler
scheduler = StepLR(optimizer, step_size=10, gamma=0.1, verbose=True)
```

```
/usr/local/lib/python3.10/dist-packages/torch/optim/lr_scheduler.py:62: UserWarning: The verbose parameter is deprecated. Please use get_last_lr() to access the learning rate.
  warnings.warn(
```

In [16]:
```
num_epochs = 10
num_folds = 3
best_accuracy = 0.0
loss_fn = nn.CrossEntropyLoss()
# Initialize KFold object
kf = KFold(n_splits=num_folds, shuffle=True)

# Loop through each fold
for fold, (train_index, val_index) in enumerate(kf.split(class_folders)):
    print(f"Fold {fold + 1}/{num_folds}")

    dataset_train = Subset(class_folders, train_index)
    dataset_valid = Subset(class_folders, val_index)

    train_loader = torch.utils.data.DataLoader(
        dataset_train, batch_size=64, shuffle=True
    )
    val_loader = torch.utils.data.DataLoader(
        dataset_valid, batch_size=32, shuffle=True
    )

    # Training loop
    for epoch in range(num_epochs):
        # Set model to training mode
        encoder.train()

        train_accuracy = 0.0
        train_loss = 0.0
```

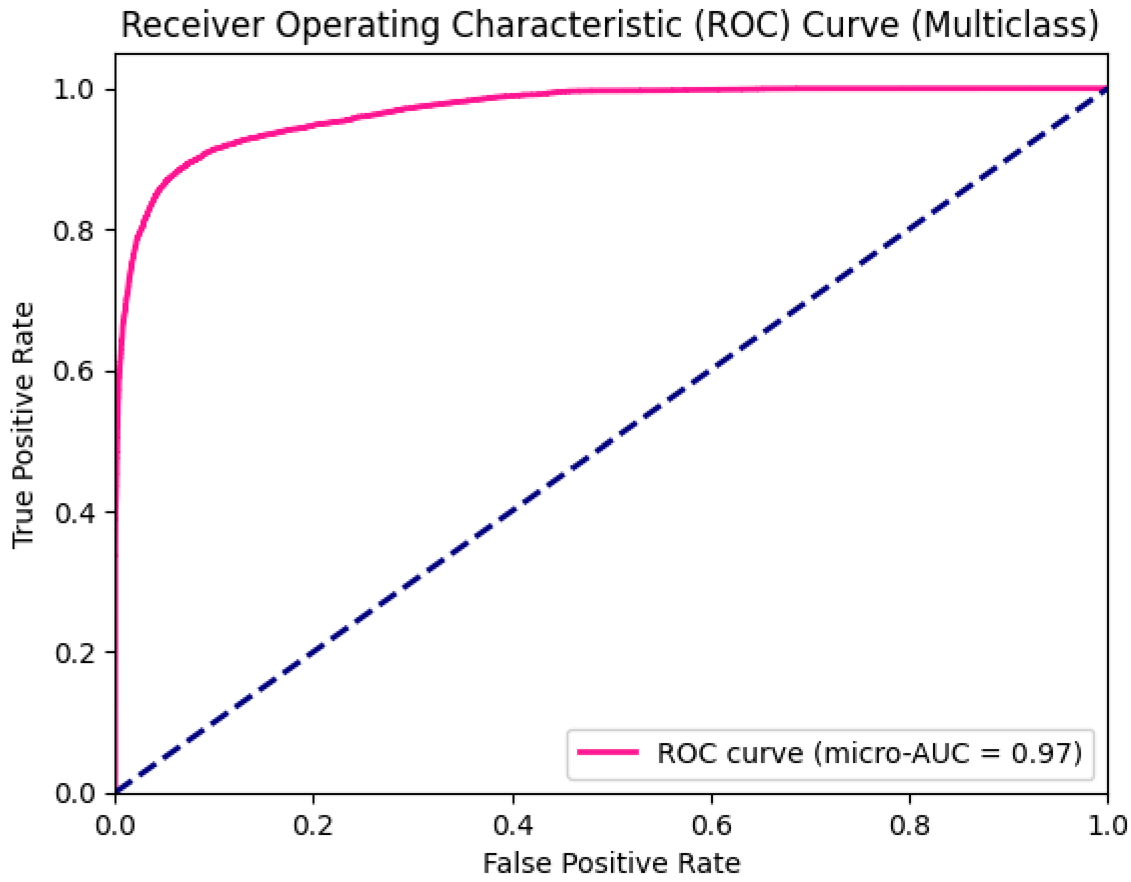
```
        for i, (images, labels) in enumerate(train_loader):
            if torch.cuda.is_available():
                images = images.cuda()
                labels = labels.cuda()

            optimizer.zero_grad()
            outputs = encoder(images)
            loss = loss_fn(outputs, labels)
            loss.backward()
            optimizer.step()

            train_loss += loss.item() * images.size(0)
            _, prediction = torch.max(outputs.data, 1)
            train_accuracy += int(torch.sum(prediction == labels.data))

        train_accuracy = train_accuracy / len(train_index)
        train_loss = train_loss / len(train_index)

        # Validation loop
        encoder.eval()

        val_accuracy = 0.0
        val_loss = 0.0

        for i, (images, labels) in enumerate(val_loader):
            if torch.cuda.is_available():
                images = images.cuda()
                labels = labels.cuda()

            outputs = encoder(images)
            loss = loss_fn(outputs, labels)
            val_loss += loss.item()* images.size(0)  # Accumulate the los
            _, prediction = torch.max(outputs.data, 1)
            val_accuracy += int(torch.sum(prediction == labels.data))

        # Compute average loss and accuracy
        val_loss /= len(val_index)
        val_accuracy = val_accuracy / len(val_index)

        print(f"Epoch [{epoch + 1}/{num_epochs}], Train Loss: {train_loss

        # Save the best model
        if val_accuracy > best_accuracy:
            torch.save(encoder.state_dict(), 'best_model.pth')
            best_accuracy = val_accuracy

print(f"Best Validation Accuracy: {best_accuracy}")
```

```
Fold 1/5
Epoch [1/5], Train Loss: 1.101, Train Accuracy: 0.340, Val Loss: 1.096, Va
lidation Accuracy: 0.368
Epoch [2/5], Train Loss: 1.096, Train Accuracy: 0.351, Val Loss: 1.086, Va
lidation Accuracy: 0.387
Epoch [3/5], Train Loss: 1.053, Train Accuracy: 0.419, Val Loss: 1.004, Va
lidation Accuracy: 0.459
Epoch [4/5], Train Loss: 0.902, Train Accuracy: 0.547, Val Loss: 0.821, Va
lidation Accuracy: 0.614
Epoch [5/5], Train Loss: 0.734, Train Accuracy: 0.669, Val Loss: 0.759, Va
lidation Accuracy: 0.648
Fold 2/5
Epoch [1/5], Train Loss: 0.614, Train Accuracy: 0.740, Val Loss: 0.893, Va
lidation Accuracy: 0.647
Epoch [2/5], Train Loss: 0.538, Train Accuracy: 0.779, Val Loss: 0.933, Va
lidation Accuracy: 0.626
Epoch [3/5], Train Loss: 0.493, Train Accuracy: 0.800, Val Loss: 0.484, Va
lidation Accuracy: 0.804
Epoch [4/5], Train Loss: 0.457, Train Accuracy: 0.816, Val Loss: 0.515, Va
lidation Accuracy: 0.799
Epoch [5/5], Train Loss: 0.421, Train Accuracy: 0.833, Val Loss: 0.471, Va
lidation Accuracy: 0.813
Fold 3/5
Epoch [1/5], Train Loss: 0.410, Train Accuracy: 0.839, Val Loss: 0.924, Va
lidation Accuracy: 0.737
Epoch [2/5], Train Loss: 0.382, Train Accuracy: 0.852, Val Loss: 0.548, Va
lidation Accuracy: 0.802
Epoch [3/5], Train Loss: 0.367, Train Accuracy: 0.858, Val Loss: 0.504, Va
lidation Accuracy: 0.826
Epoch [4/5], Train Loss: 0.345, Train Accuracy: 0.866, Val Loss: 0.406, Va
lidation Accuracy: 0.842
Epoch [5/5], Train Loss: 0.336, Train Accuracy: 0.871, Val Loss: 0.557, Va
lidation Accuracy: 0.775
Fold 4/5
Epoch [1/5], Train Loss: 0.335, Train Accuracy: 0.872, Val Loss: 0.338, Va
lidation Accuracy: 0.866
Epoch [2/5], Train Loss: 0.317, Train Accuracy: 0.879, Val Loss: 0.378, Va
lidation Accuracy: 0.859
Epoch [3/5], Train Loss: 0.310, Train Accuracy: 0.883, Val Loss: 0.353, Va
lidation Accuracy: 0.858
Epoch [4/5], Train Loss: 0.297, Train Accuracy: 0.887, Val Loss: 0.299, Va
lidation Accuracy: 0.882
Epoch [5/5], Train Loss: 0.291, Train Accuracy: 0.889, Val Loss: 0.298, Va
lidation Accuracy: 0.885
Fold 5/5
Epoch [1/5], Train Loss: 0.285, Train Accuracy: 0.892, Val Loss: 0.299, Va
lidation Accuracy: 0.888
Epoch [2/5], Train Loss: 0.278, Train Accuracy: 0.896, Val Loss: 0.334, Va
lidation Accuracy: 0.877
Epoch [3/5], Train Loss: 0.270, Train Accuracy: 0.899, Val Loss: 0.387, Va
lidation Accuracy: 0.869
Epoch [4/5], Train Loss: 0.258, Train Accuracy: 0.904, Val Loss: 0.301, Va
lidation Accuracy: 0.891
Epoch [5/5], Train Loss: 0.258, Train Accuracy: 0.904, Val Loss: 0.266, Va
lidation Accuracy: 0.900
Best Validation Accuracy: 0.9003333333333333
```

In [19]:

```
test_path='/kaggle/input/gsoc-pinn1/new_dataset_PINN/val'
test_loader=DataLoader(
    torchvision.datasets.ImageFolder(test_path,transform=transformer),
```

```
    batch_size=32, shuffle=True
)
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import label_binarize

y_score_list = []
y_true_list = []

# Evaluate model
encoder.eval()
for images, labels in test_loader:
    if torch.cuda.is_available():
        images = images.cuda()
        labels = labels.cuda()

    with torch.no_grad():
        y_score_batch = encoder(images)

    y_score_list.append(y_score_batch.cpu().numpy())
    y_true_list.append(labels.cpu().numpy())

y_score = np.vstack(y_score_list)
y_true = np.hstack(y_true_list)

# Binarize the ground truth labels
y_true_bin = label_binarize(y_true, classes=np.unique(y_true))

# Compute ROC curve and ROC area for each class
n_classes = y_score.shape[1]
fpr = dict()
tpr = dict()
roc_auc = dict()

for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_true_bin[:, i], y_score[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Compute micro-average ROC curve and ROC area
fpr["micro"], tpr["micro"], _ = roc_curve(y_true_bin.ravel(), y_score.rav
roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])

# Plot ROC curve
plt.figure()
plt.plot(fpr["micro"], tpr["micro"], color='deeppink', lw=2, label=f'ROC
plt.plot([0, 1], [0, 1], color='navy', lw=2, 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 (ROC) Curve (Multiclass)')
plt.legend(loc='lower right')
plt.show()
```


Receiver Operating Characteristic (ROC) Curve (Multiclass)
True Positive Rate
False Positive Rate
ROC curve (micro-AUC = 0.97)
0.0
0.2
0.4
0.6
0.8
1.0