KENNESAW STATE
UNIVERSITY

CS 4732
MACHINE VISION

Assignment 4

Deep Learning for Classification

INSTRUCTOR

Dr. Sanghoon Lee

Your Name: Max Haviv
KSU ID: 001029496

1. ABSTRACT

In this assignment I completed sub assignment 1 using resnet18 as my pre-trained CNN. I tried multiple iterations with different epochs and learning rates. After my tests I found that a learning rate of 0.00001 and around 50 epochs was the most optimal resulting in an accuracy of around 86%.

2. TEST RESULTS

2.1 Test Results for sub-assignment 1

```
Epoch 1, Loss: 0.0039790409548273335
Epoch 2, Loss: 0.003750155640019517
Epoch 3, Loss: 0.002033684272246602
Epoch 4, Loss: 0.0030683944661329694
Epoch 5, Loss: 0.002543058608756455
Epoch 6, Loss: 0.002931990280225583
Epoch 7, Loss: 0.0028892753189175974
Epoch 8, Loss: 0.003243433594239825
Epoch 9, Loss: 0.003143631530642973
Epoch 10, Loss: 0.0027715327210927287
Epoch 11, Loss: 0.0024575523829181833
Epoch 12, Loss: 0.0023910129580516294
Epoch 13, Loss: 0.0024291942555616803
Epoch 14, Loss: 0.0023222514627508615
Epoch 15, Loss: 0.002478572413151366
Epoch 16, Loss: 0.0033562958008584347
Epoch 17, Loss: 0.003717732568659207
Epoch 18, Loss: 0.0038745278050463486
Epoch 19, Loss: 0.001667392508992889
Epoch 20, Loss: 0.0036924970752998084
Epoch 21, Loss: 0.0013029080188691848
Epoch 22, Loss: 0.0014445296985166082
Epoch 23, Loss: 0.0013958163530446211
Epoch 24, Loss: 0.004078942514115271
Epoch 25, Loss: 0.003914051018800253
...
Epoch 47, Loss: 0.0066763756340115915
Epoch 48, Loss: 0.0003646231810870338
Epoch 49, Loss: 0.0007930591644480071
Epoch 50, Loss: 0.0007511932794222108
```

```
tensor([0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
        1, 0, 1, 0, 0, 1, 1, 0])
tensor([1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0,
        0, 0, 1, 1, 1, 1, 1, 1])
tensor([0, 0])
Accuracy of the model on the test images: 87.88%
```

Fig(1) Loss and accuracy of resnet18 0.00001 learning rate 50 epochs

```
Epoch 1, Loss: 0.003367181418006986
Epoch 2, Loss: 0.003274787724713871
Epoch 3, Loss: 0.0024337158592758474
Epoch 4, Loss: 0.002631116701935052
Epoch 5, Loss: 0.0024942651333048184
Epoch 6, Loss: 0.0032738906400212983
Epoch 7, Loss: 0.003392056964250854
Epoch 8, Loss: 0.0018793405957722943
Epoch 9, Loss: 0.0017234047563159513
Epoch 10, Loss: 0.0017093696019065056
Epoch 11, Loss: 0.0038820461076521226
Epoch 12, Loss: 0.004237439381937109
Epoch 13, Loss: 0.001403989263081829
Epoch 14, Loss: 0.004784800199219225
Epoch 15, Loss: 0.004576498432382071
Epoch 16, Loss: 0.0013413256476361463
Epoch 17, Loss: 0.0013709554180560872
Epoch 18, Loss: 0.004447110895980657
Epoch 19, Loss: 0.0012905172104965387
Epoch 20, Loss: 0.004211737024181084
Epoch 21, Loss: 0.0012847804373804232
Epoch 22, Loss: 0.004273584380687907
Epoch 23, Loss: 0.004004898238274838
Epoch 24, Loss: 0.0017216785408643433
Epoch 25, Loss: 0.003612162770000413
...
tensor([1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0,
        0, 1, 1, 0, 1, 0, 1, 1])
tensor([0, 0])
Accuracy of the model on the test images: 75.76%
```

Fig (2) Loss and Accuracy of resnet18 0.0001 learning rate 100 epochs

```
Epoch 1, Loss: 0.0014524684805814394
Epoch 2, Loss: 0.002649517838593123
Epoch 3, Loss: 0.001128183148714355
Epoch 4, Loss: 0.008624348658995869
Epoch 5, Loss: 0.010659116715308756
Epoch 6, Loss: 0.01055364942736199
Epoch 7, Loss: 0.007389268522596545
Epoch 8, Loss: 0.0017448591814894 62
Epoch 9, Loss: 0.0035044803693600668
Epoch 10, Loss: 0.0010896535003231658
Epoch 11, Loss: 0.0007680510152638654
Epoch 12, Loss: 0.007218558500712948
Epoch 13, Loss: 0.00050396463518476 67
Epoch 14, Loss: 0.009306877039749799
Epoch 15, Loss: 0.00872166611341187
Epoch 16, Loss: 0.0007290429062416582
Epoch 17, Loss: 0.0013301045514266315
Epoch 18, Loss: 0.002674480356594932
Epoch 19, Loss: 0.004941692612050573
Epoch 20, Loss: 0.000767583397112004
Epoch 21, Loss: 0.0006581556472333024
Epoch 22, Loss: 0.0007491728675040753
Epoch 23, Loss: 0.005106643480085677
Epoch 24, Loss: 0.0024840161494243933
Epoch 25, Loss: 0.001332726575985029
 ...
tensor([0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1,
        0, 0, 1, 0, 1, 0, 0, 1])
tensor([0, 0])
Accuracy of the model on the test images: 66.67%
```

Fig (3) Loss and Accuracy of resnet18 0.0001 learning rate 50 epochs

As shown in the above figures, figure 1 shows the best accuracy with a learning rate of 0.00001 and 50 epochs. I then tested to see if the accuracy would improve over more epochs as shown in figure 2 (resnet18 0.00001 learning rate 50 epochs). This did not drastically harm the performance but it did not improve the results only decreasing the accuracy by around 10%. Lastly in figure 3 I show that with a learning rate of 0.0001 and 50 epochs that the accuracy takes a drastic hit with only correctly identifying around 66% of test cases. From these tests I can conclude that a learning rate of 0.00001 is most optimal and around 50 epochs is the most optimal for this dataset.

I can confirm this by also taking a look at the ROC curve and confusion matrix of the first test (resnet18 0.00001 learning rate 50 epochs) which was the most accurate with 87% accuracy. As you can see in figure 4 the ROC curve shows a drastic increase in true positive rate with a steadying out around 0.9 for the true positive rate. This is consistent with other machine learning models in training as the true positive rate grows rapidly then steadies out over each epoch. Lastly in figure 5 the confusion matrix is shown. This confusion matrix shows a total of 30 true positives and 22 true negatives while having only 4 false positives and 10 false negatives. What can be concluded from this confusion matrix is that the model that resnet18 model is good at predicting true for a patient with DR but has a hard time producing false for a patient without DR as seen with the much higher false negative rate.

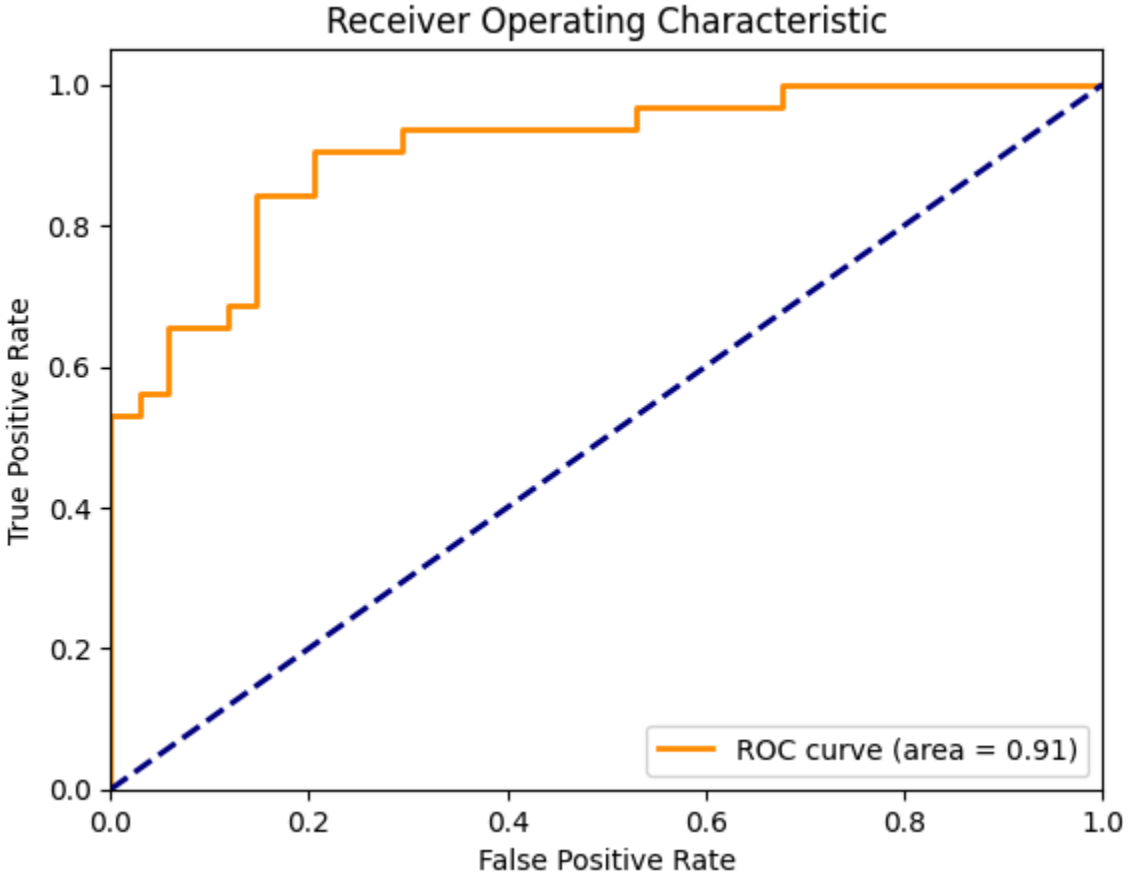


Fig (4) ROC curve of resnet18 0.00001 learning rate and 50 epochs

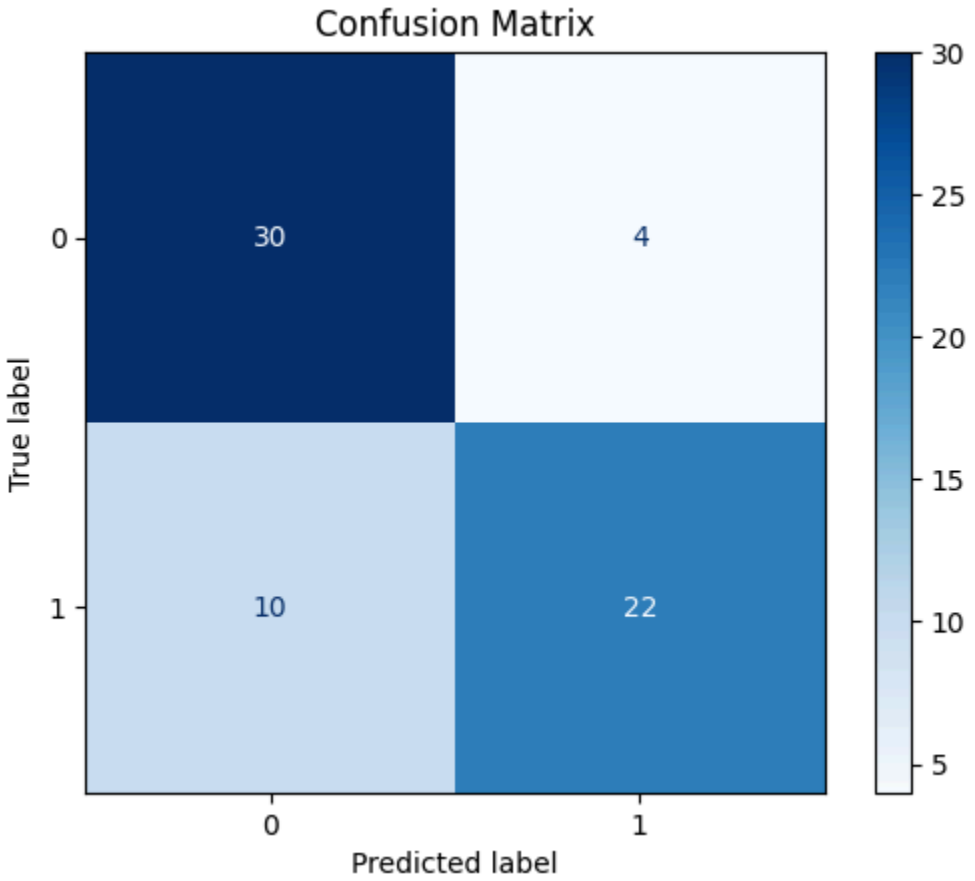


Fig (5) Confusion matrix of resnet18 0.00001 learning rate and 50 epochs

3. Discussion

I learned a lot from this assignment. This was the first time that I have ever worked with a CNN and worked with pre-trained CNNs. I had some issues early on when I was initially using AlexNet for my pre-trained model. I could not get the model to work at all as it would always either only predict all positive or all negative. I tried to adjust learning rates and epochs yet nothing would help. I eventually switched to resnet18 and it worked immediately. I am not sure exactly what went wrong but I had no issues once I switched over to resnet18. I also learned that you really don't need a high learning rate or high amount of epochs to train these models. I wasn't super aware of the overfitting issues when I had worked on previous neural networks but here I definitely saw some overfitting and underfitting.

4. CODE

In [301…

```
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import os

# - Separate images in train and test into two groups as DR and nonDR:
# o NonDR : Label 0
# o DR : Label 3 & Label 4 (You don’t need to use Label 1 and Label 2)

image_files = [f for f in os.listdir("Test") if os.path.isfile(os.path.join(

testnonDR = []
testDR = []

for image in image_files:
  label = image.split("-")[1].split('.')[0]
  # nonDR
  if (label == "0"):
    testnonDR.append((os.path.join("Test",image), 0))
  elif (label == "3" or label == "4"):
    testDR.append((os.path.join("Test",image), 1))

image_files = [f for f in os.listdir("Train") if os.path.isfile(os.path.joir

trainnonDR = []
trainDR = []

for image in image_files:
  label = image.split("-")[1].split('.')[0]
  # nonDR
  if (label == "0"):
    trainnonDR.append((os.path.join("Train",image), 0))
  elif (label == "3" or label == "4"):
    trainDR.append((os.path.join("Train",image), 1))
```

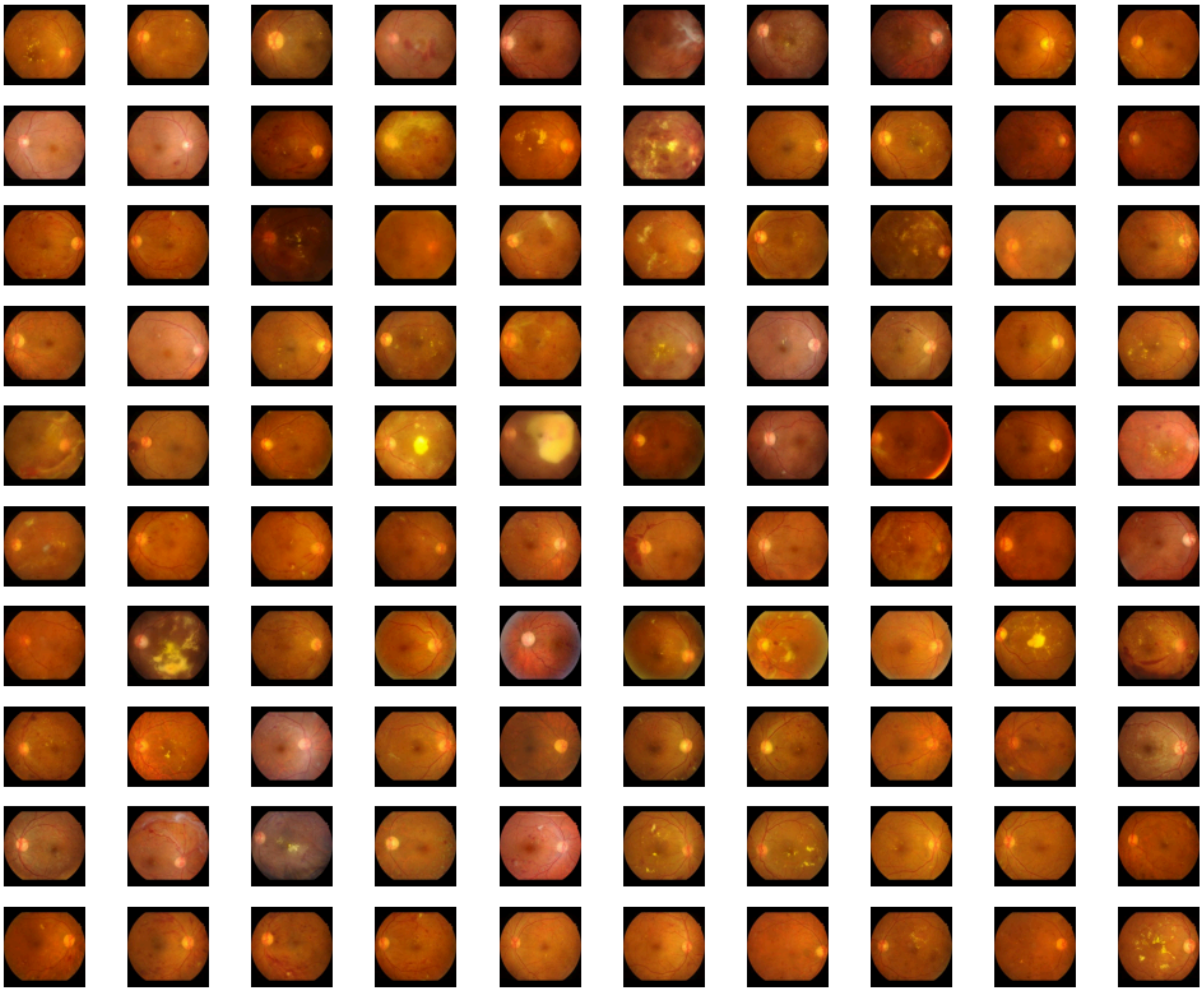
Montage Train DR

In [302…

```
fig, axes = plt.subplots(10, 10, figsize=(10, 8))

for i, ax in enumerate(axes.flat):
  ax.imshow(mpimg.imread(trainDR[i][0]), cmap='gray')
  ax.axis('off')

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



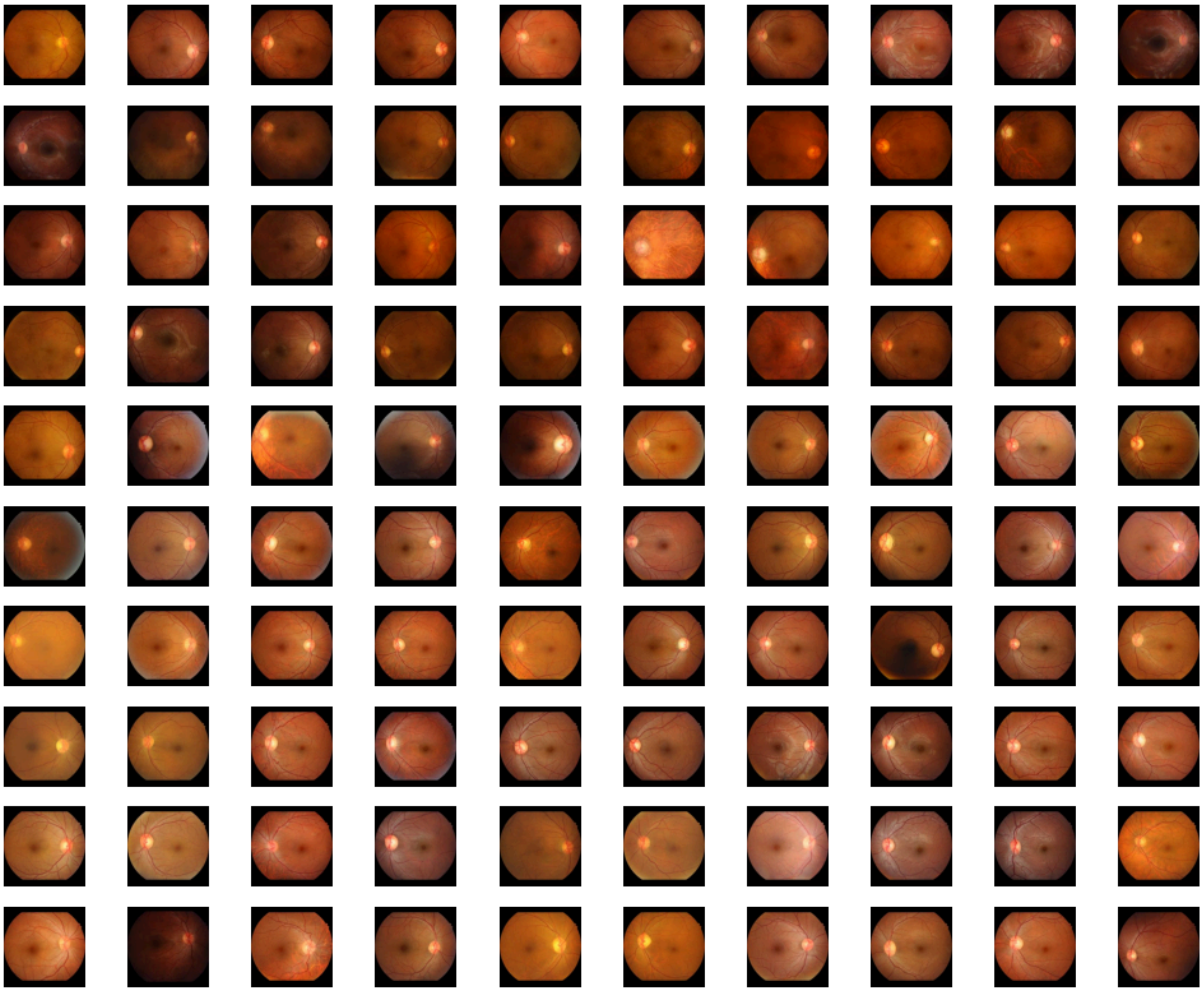
Montage Train non DR

In [303…

```
fig, axes = plt.subplots(10, 10, figsize=(10, 8))

for i, ax in enumerate(axes.flat):
  ax.imshow(mpimg.imread(trainnonDR[i][0]), cmap='gray')
  ax.axis('off')

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



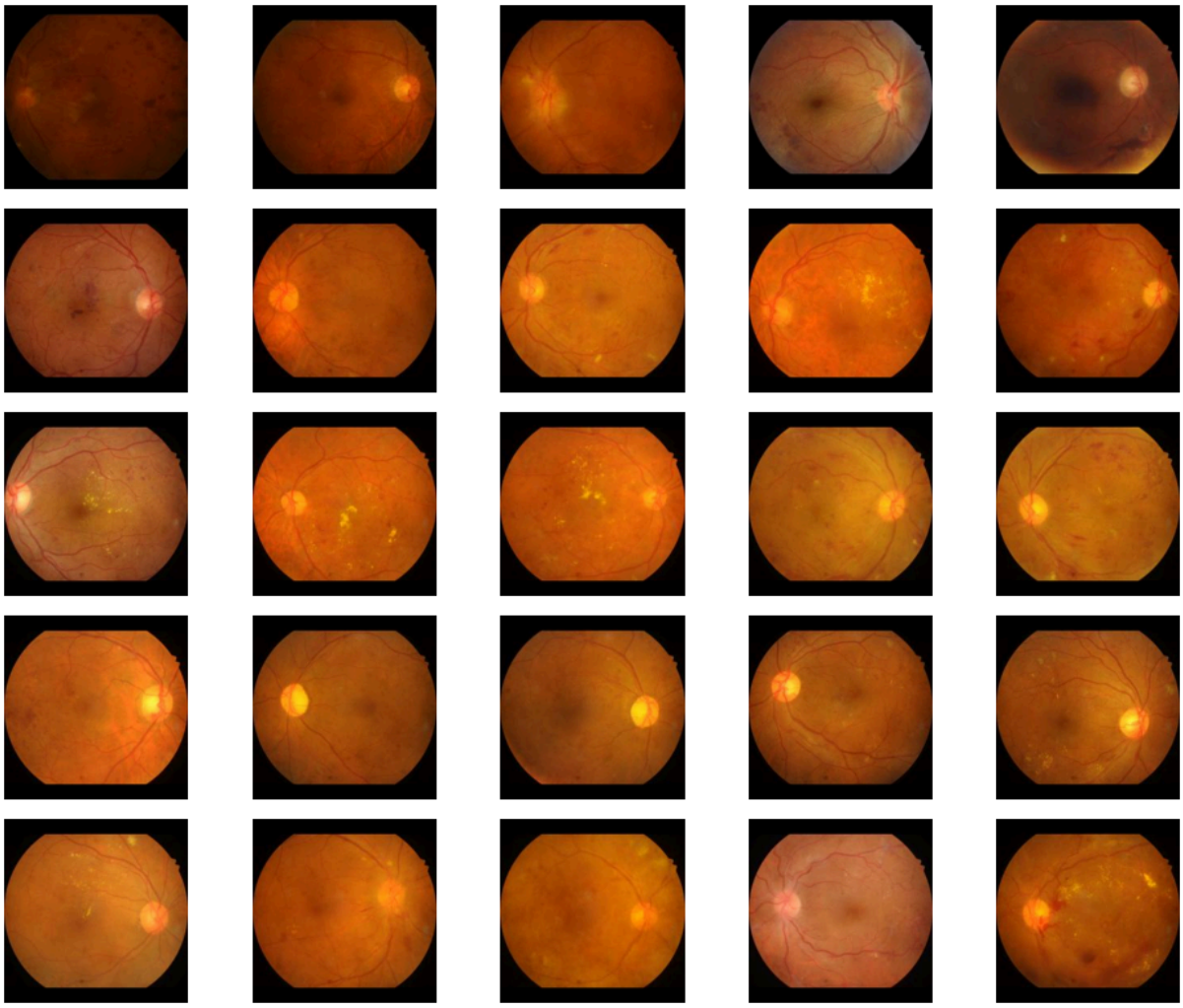
Montage Test DR

In [304…

```
fig, axes = plt.subplots(5, 5, figsize=(10, 8))

for i, ax in enumerate(axes.flat):
  ax.imshow(mpimg.imread(testDR[i][0]), cmap='gray')
  ax.axis('off')

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



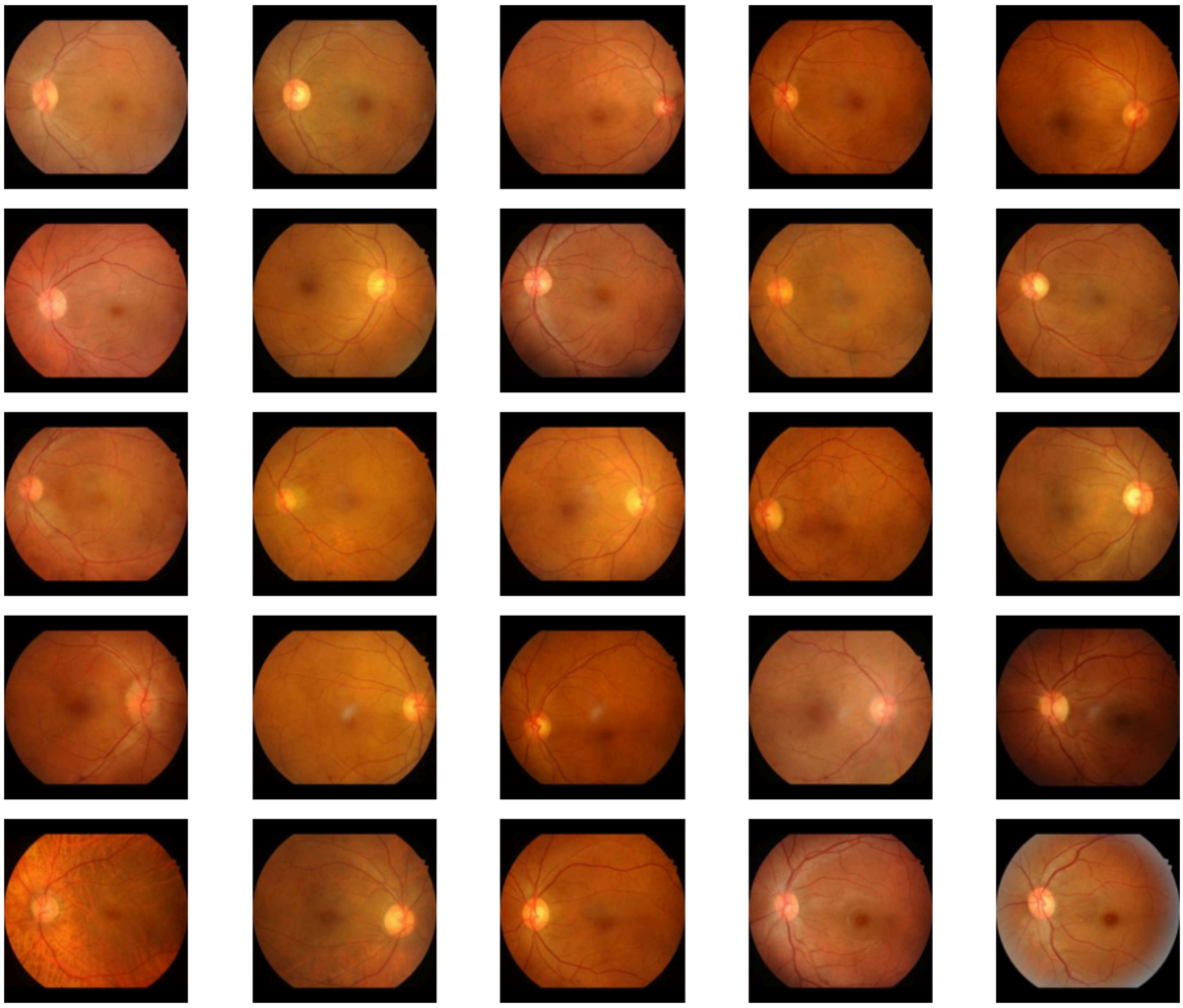
Montage Test non Dr

In [305…

```
fig, axes = plt.subplots(5, 5, figsize=(10, 8))

for i, ax in enumerate(axes.flat):
  ax.imshow(mpimg.imread(testnonDR[i][0]), cmap='gray')
  ax.axis('off')

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



Merge label 0 and label 3-4

In [306…

```
import random

trainSet = trainDR + trainnonDR
random.shuffle(trainSet)

testSet = testDR + testnonDR
random.shuffle(testSet)
```

Download Pretained AlexNet from pytorch

In [307…

```
import torch
import torchvision.models as models

model = models.resnet18(weights=models.ResNet18_Weights.DEFAULT)
model.fc = torch.nn.Linear(model.fc.in_features, 2)
```

In [308…

```
from torchvision import transforms
from torch.utils.data import DataLoader, Dataset
from PIL import Image
```

```
transform = transforms.Compose([
  transforms.Resize((224,224)),
  transforms.ToTensor(),
])

for i in range(len(trainSet)):
  img = Image.open(trainSet[i][0])
  img = transform(img)

  trainSet[i] = (img, trainSet[i][1])
```

In [309…
```
for i in range(len(testSet)):
  img = Image.open(testSet[i][0])
  img = transform(img)

  testSet[i] = (img, testSet[i][1])
```

In [310…
```
train_loader = DataLoader(trainSet, batch_size=32, shuffle=True)
test_loader = DataLoader(testSet, batch_size=32, shuffle=True)
```

resnet18 0.00001 learning rate 50 epochs

In [311…
```
import torch.optim as optim

criterion = torch.nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.00001)

for epoch in range(50):
  model.train()

  running_loss = 0

  for inputs, labels in train_loader:
    outputs = model(inputs)
    loss = criterion(outputs, labels)
    loss.backward()
    optimizer.step()

  running_loss += loss.item()

  print(f'Epoch {epoch+1}, Loss: {running_loss/len(trainSet)}')
```

```
Epoch 1, Loss: 0.003979040954827335
Epoch 2, Loss: 0.003750155640019517
Epoch 3, Loss: 0.002033684272246602
Epoch 4, Loss: 0.0030683944661329694
Epoch 5, Loss: 0.002543058608756455
Epoch 6, Loss: 0.002931990280225583
Epoch 7, Loss: 0.0028892753189175974
Epoch 8, Loss: 0.003243433594239825
Epoch 9, Loss: 0.003143631530642973
Epoch 10, Loss: 0.0027715327210927287
Epoch 11, Loss: 0.0024575523829181833
Epoch 12, Loss: 0.0023910129580516294
Epoch 13, Loss: 0.0024291942555616803
Epoch 14, Loss: 0.0023222514627508615
Epoch 15, Loss: 0.002478572413151366
Epoch 16, Loss: 0.0033562958008584347
Epoch 17, Loss: 0.003717732568659207
Epoch 18, Loss: 0.0038745278050463486
Epoch 19, Loss: 0.001667392508992889
Epoch 20, Loss: 0.0036924970752998084
Epoch 21, Loss: 0.0013029080188691848
Epoch 22, Loss: 0.0014445296985166082
Epoch 23, Loss: 0.0013958163530446211
Epoch 24, Loss: 0.004078942514115271
Epoch 25, Loss: 0.003914051018800253
Epoch 26, Loss: 0.006035046354805913
Epoch 27, Loss: 0.001207933583612108
Epoch 28, Loss: 0.0029593492760268633
Epoch 29, Loss: 0.004643747314868734
Epoch 30, Loss: 0.003944213288303479
Epoch 31, Loss: 0.002857551500491131
Epoch 32, Loss: 0.002119366992772321
Epoch 33, Loss: 0.002048092825403473
Epoch 34, Loss: 0.0019086494983866057
Epoch 35, Loss: 0.0015877702124851686
Epoch 36, Loss: 0.0013154096872426192
Epoch 37, Loss: 0.0011424048865351696
Epoch 38, Loss: 0.00545952663347415
Epoch 39, Loss: 0.0007470308110871667
Epoch 40, Loss: 0.007014095551308955
Epoch 41, Loss: 0.0005497945189939863
Epoch 42, Loss: 0.0004468760253854299
Epoch 43, Loss: 0.0006195369397619818
Epoch 44, Loss: 0.006771795480631669
Epoch 45, Loss: 0.0003972805253726499
Epoch 46, Loss: 0.006668717016969673
Epoch 47, Loss: 0.0066763756340115915
Epoch 48, Loss: 0.0003646231810870338
Epoch 49, Loss: 0.0007930591644480071
Epoch 50, Loss: 0.0007511932794222108
```

In [312…

```
model.eval()

correct = 0
total = 0
```

```
with torch.no_grad():
  for inputs, label in test_loader:
    outputs = model(inputs)
    _, predicted = torch.max(outputs.data, 1)
    total += len(label)
    print(predicted)
    correct += (predicted == label).sum().item()

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

```
tensor([0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0,
0,
        1, 0, 1, 0, 0, 1, 1, 0])
tensor([1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, 0,
0,
        0, 0, 1, 1, 1, 1, 1, 1])
tensor([0, 0])
Accuracy of the model on the test images: 87.88%
```

resnet18 0.00001 learning rate 100 epochs

In [317…

```
# reset model
model = models.resnet18(weights=models.ResNet18_Weights.DEFAULT)
model.fc = torch.nn.Linear(model.fc.in_features, 2)
```

In [318…

```
optimizer = optim.Adam(model.parameters(), lr=0.00001)

for epoch in range(100):
  model.train()

  running_loss = 0

  for inputs, labels in train_loader:
    outputs = model(inputs)
    loss = criterion(outputs, labels)
    loss.backward()
    optimizer.step()

  running_loss += loss.item()

  print(f'Epoch {epoch+1}, Loss: {running_loss/len(trainSet)}')

model.eval()

correct = 0
total = 0

with torch.no_grad():
  for inputs, label in test_loader:
    outputs = model(inputs)
    _, predicted = torch.max(outputs.data, 1)
    total += len(label)
    print(predicted)
    correct += (predicted == label).sum().item()
```

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

```
Epoch 1, Loss: 0.003367181418006986
Epoch 2, Loss: 0.003274787724713871
Epoch 3, Loss: 0.0024337158592758474
Epoch 4, Loss: 0.002631116701935052
Epoch 5, Loss: 0.0024942651333048184
Epoch 6, Loss: 0.0032738906400212983
Epoch 7, Loss: 0.003392056964250854
Epoch 8, Loss: 0.0018793405957722943
Epoch 9, Loss: 0.0017234047563159513
Epoch 10, Loss: 0.0017093696019065056
Epoch 11, Loss: 0.0038820461076521226
Epoch 12, Loss: 0.004237439381937109
Epoch 13, Loss: 0.001403989263081829
Epoch 14, Loss: 0.004784800199219225
Epoch 15, Loss: 0.004576498432382071
Epoch 16, Loss: 0.0013413256476361463
Epoch 17, Loss: 0.0013709554180560872
Epoch 18, Loss: 0.004447110895980657
Epoch 19, Loss: 0.0012905172104965387
Epoch 20, Loss: 0.004211737024181084
Epoch 21, Loss: 0.0012847804373804232
Epoch 22, Loss: 0.004273584380687907
Epoch 23, Loss: 0.004004898238274838
Epoch 24, Loss: 0.0017216785408643433
Epoch 25, Loss: 0.003612162770000413
Epoch 26, Loss: 0.003189810055239191
Epoch 27, Loss: 0.002124352909711548
Epoch 28, Loss: 0.0020302752112600127
Epoch 29, Loss: 0.002300867542682455
Epoch 30, Loss: 0.002020842370356103
Epoch 31, Loss: 0.002518472040673638
Epoch 32, Loss: 0.0018096794646073873
Epoch 33, Loss: 0.0022945216193737223
Epoch 34, Loss: 0.0020184836962807502
Epoch 35, Loss: 0.001950434905545721
Epoch 36, Loss: 0.002171667865278192
Epoch 37, Loss: 0.001413072825405848
Epoch 38, Loss: 0.0013511730539195732
Epoch 39, Loss: 0.0033430672805133035
Epoch 40, Loss: 0.0010220384087544006
Epoch 41, Loss: 0.003815468183287387
Epoch 42, Loss: 0.004571317234855682
Epoch 43, Loss: 0.0018786171067085712
Epoch 44, Loss: 0.002661397716878453
Epoch 45, Loss: 0.002938705195712672
Epoch 46, Loss: 0.0029372605368321045
Epoch 47, Loss: 0.001893326930034949
Epoch 48, Loss: 0.0014511368849861946
Epoch 49, Loss: 0.001963229262875212
Epoch 50, Loss: 0.001782058046021814
Epoch 51, Loss: 0.003239985569905678
Epoch 52, Loss: 0.0027092398372605617
Epoch 53, Loss: 0.0012772668892307504
Epoch 54, Loss: 0.0025727843959971624
Epoch 55, Loss: 0.002167096165831451
Epoch 56, Loss: 0.001331825432610419
```

```
Epoch 57, Loss: 0.001035366772677648
Epoch 58, Loss: 0.001263096174841261
Epoch 59, Loss: 0.0020750626515785545
Epoch 60, Loss: 0.000963825312106062
Epoch 61, Loss: 0.002535745095650046
Epoch 62, Loss: 0.0009920889301522696
Epoch 63, Loss: 0.0025461258127531653
Epoch 64, Loss: 0.002004599060993714
Epoch 65, Loss: 0.0024581117852652584
Epoch 66, Loss: 0.0005004923747207404
Epoch 67, Loss: 0.002348156986533436
Epoch 68, Loss: 0.00058033291235972
Epoch 69, Loss: 0.0008152813763006188
Epoch 70, Loss: 0.0025840536165794045
Epoch 71, Loss: 0.0036668656864982637
Epoch 72, Loss: 0.0013322542613582388
Epoch 73, Loss: 0.0012766197033893274
Epoch 74, Loss: 0.002972202542227066
Epoch 75, Loss: 0.0023778150517652936
Epoch 76, Loss: 0.0007962611166883536
Epoch 77, Loss: 0.0019156459704447349
Epoch 78, Loss: 0.0005165083978890445
Epoch 79, Loss: 0.0005869578990490983
Epoch 80, Loss: 0.0015899667712037202
Epoch 81, Loss: 0.0015033819796046394
Epoch 82, Loss: 0.0005019799976497309
Epoch 83, Loss: 0.001694286263870358
Epoch 84, Loss: 0.001847614110211918
Epoch 85, Loss: 0.0005271538570233356
Epoch 86, Loss: 0.0017420828110513056
Epoch 87, Loss: 0.0010861120103398186
Epoch 88, Loss: 0.00048551456241756097
Epoch 89, Loss: 0.003065701588582436
Epoch 90, Loss: 0.0022045698611188953
Epoch 91, Loss: 0.0019066457850459948
Epoch 92, Loss: 0.0002024741372245759
Epoch 93, Loss: 0.0024761794142222127
Epoch 94, Loss: 0.001933122539334724
Epoch 95, Loss: 0.0032409086301632894
Epoch 96, Loss: 0.003112450879835433
Epoch 97, Loss: 0.0002458204845046255
Epoch 98, Loss: 0.001515407854480966
Epoch 99, Loss: 0.00020010665001108489
Epoch 100, Loss: 0.0009982742456146716
tensor([0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 1, 1,
1,
        1, 1, 0, 1, 1, 0, 0, 1])
tensor([1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0,
0,
        0, 1, 1, 0, 1, 0, 1, 1])
tensor([0, 0])
Accuracy of the model on the test images: 75.76%
```

resnet18 0.00001 learning rate 75 epochs

In [321…

```
# reset model
model = models.resnet18(weights=models.ResNet18_Weights.DEFAULT)
model.fc = torch.nn.Linear(model.fc.in_features, 2)

optimizer = optim.Adam(model.parameters(), lr=0.00001)

for epoch in range(75):
  model.train()

  running_loss = 0

  for inputs, labels in train_loader:
    outputs = model(inputs)
    loss = criterion(outputs, labels)
    loss.backward()
    optimizer.step()

  running_loss += loss.item()

  print(f'Epoch {epoch+1}, Loss: {running_loss/len(trainSet)}')

model.eval()

correct = 0
total = 0

with torch.no_grad():
  for inputs, label in test_loader:
    outputs = model(inputs)
    _, predicted = torch.max(outputs.data, 1)
    total += len(label)
    print(predicted)
    correct += (predicted == label).sum().item()

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

```
Epoch 1, Loss: 0.0018907897899123017
Epoch 2, Loss: 0.0019058022749563136
Epoch 3, Loss: 0.003579891145461264
Epoch 4, Loss: 0.0035323795177593306
Epoch 5, Loss: 0.0034616777405200765
Epoch 6, Loss: 0.0021617301243288508
Epoch 7, Loss: 0.002977751804233061
Epoch 8, Loss: 0.0025622900357970004
Epoch 9, Loss: 0.0023845186029426784
Epoch 10, Loss: 0.002884398638506344
Epoch 11, Loss: 0.003306969826323513
Epoch 12, Loss: 0.003290341521979306
Epoch 13, Loss: 0.003259401377073058
Epoch 14, Loss: 0.0021203767928631855
Epoch 15, Loss: 0.002807232656367558
Epoch 16, Loss: 0.002547218178032901
Epoch 17, Loss: 0.0024815872021686242
Epoch 18, Loss: 0.0020970409946219
Epoch 19, Loss: 0.001546251518717072
Epoch 20, Loss: 0.004600640400838295
Epoch 21, Loss: 0.004342324538917393
Epoch 22, Loss: 0.0032634718872693726
Epoch 23, Loss: 0.0017464726815427788
Epoch 24, Loss: 0.0029364374361149533
Epoch 25, Loss: 0.00247048798238257
Epoch 26, Loss: 0.0025541144586258826
Epoch 27, Loss: 0.0018507766352553311
Epoch 28, Loss: 0.0015308782748211219
Epoch 29, Loss: 0.0014709971758178236
Epoch 30, Loss: 0.0009501302752513366
Epoch 31, Loss: 0.005831047254777604
Epoch 32, Loss: 0.0071284283923731704
Epoch 33, Loss: 0.007279001321310199
Epoch 34, Loss: 0.007603735775335289
Epoch 35, Loss: 0.006457943860658876
Epoch 36, Loss: 0.0061243016432231505
Epoch 37, Loss: 0.0014601447238996334
Epoch 38, Loss: 0.0014407621979249591
Epoch 39, Loss: 0.003408723072319179
Epoch 40, Loss: 0.0025749046514934137
Epoch 41, Loss: 0.00316934873157902
Epoch 42, Loss: 0.0036358582834325414
Epoch 43, Loss: 0.004039306121113699
Epoch 44, Loss: 0.0043626230514467
Epoch 45, Loss: 0.0046626640201078776
Epoch 46, Loss: 0.0013814997580264793
Epoch 47, Loss: 0.0021028059465875884
Epoch 48, Loss: 0.003533430136595255
Epoch 49, Loss: 0.0021230160958108273
Epoch 50, Loss: 0.0018321470527797358
Epoch 51, Loss: 0.002129700165314433
Epoch 52, Loss: 0.0034246340336038907
Epoch 53, Loss: 0.00213578447757528
Epoch 54, Loss: 0.0017616233937007445
Epoch 55, Loss: 0.0039184566601705
Epoch 56, Loss: 0.001847662350546989
```

```
Epoch 57, Loss: 0.003178523440305361
Epoch 58, Loss: 0.00405645092173773
Epoch 59, Loss: 0.002046503445517692
Epoch 60, Loss: 0.004179865469728462
Epoch 61, Loss: 0.001491960500464829
Epoch 62, Loss: 0.001986188183498754
Epoch 63, Loss: 0.0030856457201887196
Epoch 64, Loss: 0.0019872800849291138
Epoch 65, Loss: 0.004164688318156083
Epoch 66, Loss: 0.003228315583462845
Epoch 67, Loss: 0.00318464509244095
Epoch 68, Loss: 0.003078308086914775
Epoch 69, Loss: 0.0019532460646870535
Epoch 70, Loss: 0.0023852605300190848
Epoch 71, Loss: 0.001778661508968368
Epoch 72, Loss: 0.003341324134559483
Epoch 73, Loss: 0.0017906103848483311
Epoch 74, Loss: 0.0033439163567954926
Epoch 75, Loss: 0.0037508432967189686
tensor([1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1,
1,
        1, 0, 0, 1, 0, 1, 1, 0])
tensor([0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0,
0,
        1, 0, 0, 1, 0, 0, 0, 0])
tensor([1, 1])
Accuracy of the model on the test images: 86.36%
```

resnet18 0.0001 learning rate 50 epochs

In [322…

```python
# reset model
model = models.resnet18(weights=models.ResNet18_Weights.DEFAULT)
model.fc = torch.nn.Linear(model.fc.in_features, 2)

optimizer = optim.Adam(model.parameters(), lr=0.0001)

for epoch in range(50):
  model.train()

  running_loss = 0

  for inputs, labels in train_loader:
    outputs = model(inputs)
    loss = criterion(outputs, labels)
    loss.backward()
    optimizer.step()

  running_loss += loss.item()

  print(f'Epoch {epoch+1}, Loss: {running_loss/len(trainSet)}')

model.eval()

correct = 0
total = 0
```

```
with torch.no_grad():
  for inputs, label in test_loader:
    outputs = model(inputs)
    _, predicted = torch.max(outputs.data, 1)
    total += len(label)
    print(predicted)
    correct += (predicted == label).sum().item()

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

```
Epoch 1, Loss: 0.0014524684805814394
Epoch 2, Loss: 0.002649517838593123
Epoch 3, Loss: 0.00112818314871435 5
Epoch 4, Loss: 0.008624348658995869
Epoch 5, Loss: 0.010659116715308756
Epoch 6, Loss: 0.01055364942736199
Epoch 7, Loss: 0.007389268522596545
Epoch 8, Loss: 0.001744859181489462
Epoch 9, Loss: 0.0035044803693600668
Epoch 10, Loss: 0.0010896535003231658
Epoch 11, Loss: 0.0007680510152638654
Epoch 12, Loss: 0.007218558500712948
Epoch 13, Loss: 0.0005039646351847667
Epoch 14, Loss: 0.009306877039749799
Epoch 15, Loss: 0.00872166611341187
Epoch 16, Loss: 0.0007290429062416582
Epoch 17, Loss: 0.0013301045514266315
Epoch 18, Loss: 0.002674480356594932
Epoch 19, Loss: 0.004941692612050573
Epoch 20, Loss: 0.000767583397112004
Epoch 21, Loss: 0.0006581556472333024
Epoch 22, Loss: 0.0007491728675040753
Epoch 23, Loss: 0.005106643480085677
Epoch 24, Loss: 0.0024840161494243933
Epoch 25, Loss: 0.001332726575985029
Epoch 26, Loss: 0.008167193557501767
Epoch 27, Loss: 0.00030043341422359305
Epoch 28, Loss: 0.0103153477383031
Epoch 29, Loss: 0.008656885837302598
Epoch 30, Loss: 0.005264028037104625
Epoch 31, Loss: 0.002562110062239235
Epoch 32, Loss: 0.0009896705354697974
Epoch 33, Loss: 0.0003240911819127747
Epoch 34, Loss: 0.01409124771444714
Epoch 35, Loss: 0.01670229017502603
Epoch 36, Loss: 3.9155768948074445e-05
Epoch 37, Loss: 4.122990404585456e-05
Epoch 38, Loss: 0.01700399450754841
Epoch 39, Loss: 0.014857337632531786
Epoch 40, Loss: 0.00013902638440929963
Epoch 41, Loss: 0.011077393817530532
Epoch 42, Loss: 0.005466240853187175
Epoch 43, Loss: 0.0013141884877987872
Epoch 44, Loss: 0.004005145933841453
Epoch 45, Loss: 0.0052103852483549006
Epoch 46, Loss: 0.008439271830399213
Epoch 47, Loss: 0.0008265522783368479
Epoch 48, Loss: 0.0010077176390918777
Epoch 49, Loss: 0.0007389164620336392
Epoch 50, Loss: 0.00060172106505368
tensor([1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1,
1,
        1, 0, 1, 1, 1, 0, 1, 1])
tensor([0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1,
1,
        0, 0, 1, 0, 1, 0, 0, 1])
```

```
tensor([0, 0])
Accuracy of the model on the test images: 66.67%
```

Plot ROC curve for the best result and show the confusion matrix.

resnet18 0.000001 learning rate 50 epochs

In [324…

```python
# reset model
model = models.resnet18(weights=models.ResNet18_Weights.DEFAULT)
model.fc = torch.nn.Linear(model.fc.in_features, 2)

optimizer = optim.Adam(model.parameters(), lr=0.000001)

for epoch in range(50):
  model.train()

  running_loss = 0

  for inputs, labels in train_loader:
    outputs = model(inputs)
    loss = criterion(outputs, labels)
    loss.backward()
    optimizer.step()

  running_loss += loss.item()

  print(f'Epoch {epoch+1}, Loss: {running_loss/len(trainSet)}')

model.eval()

y_true = []
y_scores = []

# Set model to evaluation mode
model.eval()
with torch.no_grad():
  for inputs, labels in test_loader:
    outputs = model(inputs)
    probabilities = torch.softmax(outputs, dim=1)

    y_true.extend(labels.numpy())
    y_scores.extend(probabilities.numpy()[:, 1])
```

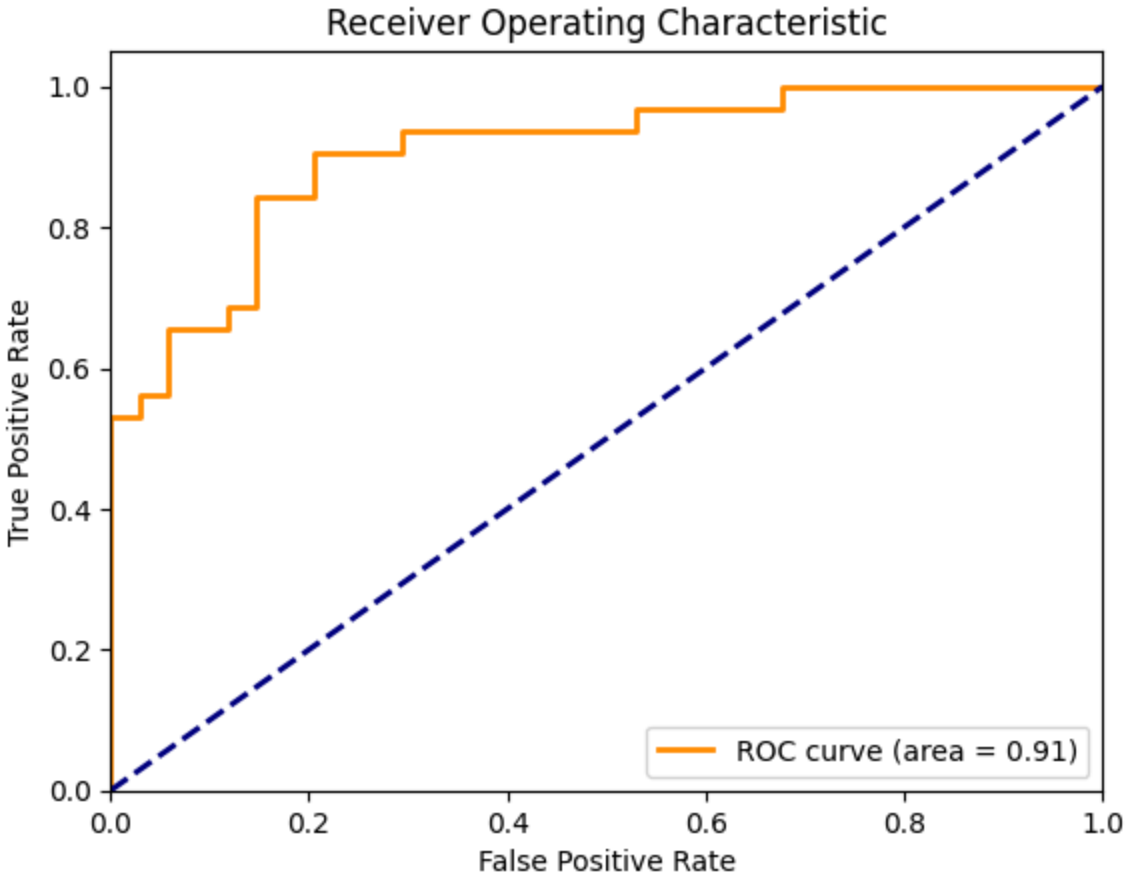
```
Epoch 1, Loss: 0.002972601452690154
Epoch 2, Loss: 0.0029478003542710834
Epoch 3, Loss: 0.0029348519989488655
Epoch 4, Loss: 0.002885742873997076
Epoch 5, Loss: 0.0029010049100052057
Epoch 6, Loss: 0.002549519566710357
Epoch 7, Loss: 0.002767976156004672
Epoch 8, Loss: 0.0029683122375132043
Epoch 9, Loss: 0.002568285057053028
Epoch 10, Loss: 0.002715041433326929
Epoch 11, Loss: 0.0025690838056779556
Epoch 12, Loss: 0.002724224955191408
Epoch 13, Loss: 0.0026795622903549253
Epoch 14, Loss: 0.0027320484706863817
Epoch 15, Loss: 0.002633232087012859
Epoch 16, Loss: 0.0026438825325279386
Epoch 17, Loss: 0.0026442271726140718
Epoch 18, Loss: 0.0026930860508276797
Epoch 19, Loss: 0.0026550946996369714
Epoch 20, Loss: 0.002700044023387627
Epoch 21, Loss: 0.0025589714254386693
Epoch 22, Loss: 0.002870504958156482
Epoch 23, Loss: 0.0027255455343639804
Epoch 24, Loss: 0.002935999098454932
Epoch 25, Loss: 0.002911213307065259
Epoch 26, Loss: 0.0028979555642094593
Epoch 27, Loss: 0.0025856877579299394
Epoch 28, Loss: 0.002904387763502069
Epoch 29, Loss: 0.0024562065239546365
Epoch 30, Loss: 0.0028896981176235333
Epoch 31, Loss: 0.0030100885996094937
Epoch 32, Loss: 0.002989376333437077
Epoch 33, Loss: 0.002445269187600696
Epoch 34, Loss: 0.0026470218651025675
Epoch 35, Loss: 0.002885935371487985
Epoch 36, Loss: 0.002916487738316161
Epoch 37, Loss: 0.002962239289562062
Epoch 38, Loss: 0.00289166947747019
Epoch 39, Loss: 0.002515865439106982
Epoch 40, Loss: 0.002480468629399162
Epoch 41, Loss: 0.0025414022026358876
Epoch 42, Loss: 0.002823966486444733
Epoch 43, Loss: 0.0025408724866488566
Epoch 44, Loss: 0.0027609701750343414
Epoch 45, Loss: 0.00232171965944164
Epoch 46, Loss: 0.002865936969504746
Epoch 47, Loss: 0.0028457414315368416
Epoch 48, Loss: 0.0027812661363920813
Epoch 49, Loss: 0.0027923449468056053
Epoch 50, Loss: 0.0025079869574609896
```

In [329…

```
from sklearn.metrics import roc_curve, auc, confusion_matrix, ConfusionMatri
fpr, tpr, thresholds = roc_curve(y_true, y_scores)
roc_auc = auc(fpr, tpr)

plt.figure()
```

```
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)
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')
plt.legend(loc='lower right')
plt.show()
```



In [327…

```
y_pred = np.array([1 if score >= 0.5 else 0 for score in y_scores])
cm = confusion_matrix(y_true, y_pred)

# Plot confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=[0, 1])
disp.plot(cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.show()
```