Лабораторная работа №5. Применение сверточных нейронных сетей (бинарная классификация)

Данные: Набор данных DogsVsCats, который состоит из изображений различной размерности, содержащих фотографии собак и кошек. Обучающая выборка включает в себя 25 тыс. изображений (12,5 тыс. кошек: cat.0.jpg, …, cat.12499.jpg и 12,5 тыс. собак: dog.0.jpg, …, dog.12499.jpg), а контрольная выборка содержит 12,5 тыс. неразмеченных изображений. Скачать данные, а также проверить качество классификатора на тестовой выборке можно на сайте Kaggle -> [https://www.kaggle.com/c/dogs-vs-cats/data (https://www.kaggle.com/c/dogs-vs-cats/data)](https://www.kaggle.com/c/dogs-vs-cats/data)

In [7]:

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import os
import torch
import torch.nn as nn
import cv2
import matplotlib.pyplot as plt
import torchvision
from torch.utils.data import Dataset, DataLoader, ConcatDataset
from torchvision import transforms
import copy
import tqdm
from PIL import Image

%matplotlib inline
```

Загрузите данные. Разделите исходный набор данных на обучающую, валидационную и контрольную выборки.

In [8]:

```
import zipfile


zip_files = ['test1', 'train']
# Will unzip the files so that you can see them..
for zip_file in zip_files:
    with zipfile.ZipFile("../input/{}.zip".format(zip_file),"r") as z:
        z.extractall(".")
        print("{} unzipped".format(zip_file))
```

```
test1 unzipped
train unzipped
```

In [9]:

```
train_dir = 'train'
test_dir = 'test1'
```

In [10]:

```
files_labels = {os.path.join(train_dir, file_name): 0 if 'cat' in file_name el
se 1
              for file_name in os.listdir(train_dir)}
data = pd.DataFrame.from_dict({'image_file': list(files_labels.keys()), 'label
': list(files_labels.values())})
```

In [11]:

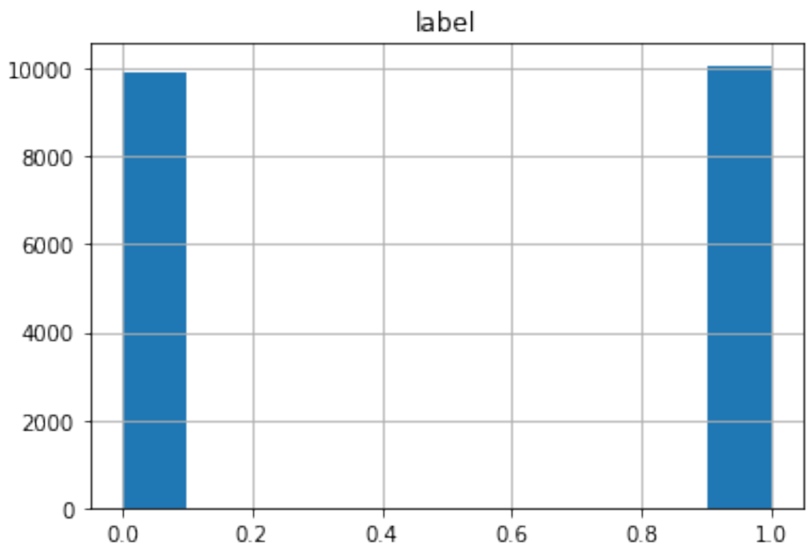
```
from sklearn.model_selection import train_test_split

train_data, test_data = train_test_split(data, test_size=0.2)
test_data, val_data = train_test_split(test_data, test_size=0.25)
```

In [12]:

```
train_data.hist()
```

Out[12]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f3d072
c90f0>]],
      dtype=object)
```

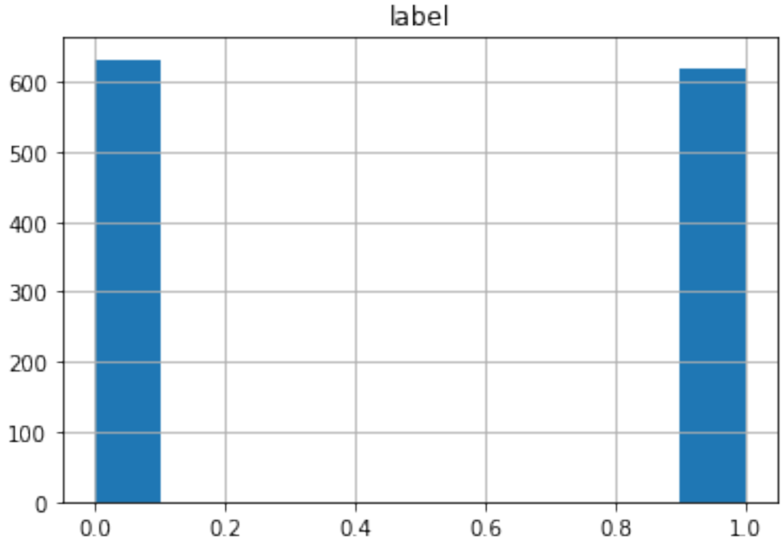


In [13]:

```
val_data.hist()
```

Out[13]:

```
array([[&lt;matplotlib.axes._subplots.AxesSubplot object at 0x7f3d62f
58240&gt;]],
      dtype=object)
```



In [73]:

```
class CatDogDataset(Dataset):
    def __init__(self, data, transform = None):
        self.data = data
        self.transform = transform

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

    def __getitem__(self, idx):
        file = self.data.iloc[idx, 0]
        label = self.data.iloc[idx, 1]
        img = Image.open(file)
        if self.transform:
            img = self.transform(img)

        img = img.numpy()
        return img.astype('float32'), label
```

In [15]:

```
data_transform = transforms.Compose([
    transforms.Resize((128, 128)),
    transforms.ToTensor()
])

train_dataset = CatDogDataset(train_data, transform = data_transform)
val_dataset = CatDogDataset(val_data, transform = data_transform)
```

In [16]:

```
train_loader = DataLoader(train_dataset, batch_size = 32, shuffle=True, num_wo
rkers=4)
val_loader = DataLoader(val_dataset, batch_size = 32, shuffle=False, num_worke
rs=4)
```

In [17]:

```
samples, labels = iter(train_loader).next()
plt.figure(figsize=(16,24))
grid_imgs = torchvision.utils.make_grid(samples[:8])
np_grid_imgs = grid_imgs.cpu().numpy()
# in tensor, image is (batch, width, height), so you have to transpose it to (
width, height, batch) in numpy to show it.
plt.imshow(np.transpose(np_grid_imgs, (1,2,0)))
```

Out[17]:

```
<matplotlib.image.AxesImage at 0x7f3d04643ac8>
```

Реализуйте глубокую нейронную сеть с как минимум тремя сверточными слоями.

In [80]:

```
class CNNModel(nn.Module):
    def __init__(self):
        super(CNNModel, self).__init__()

        self.cnn1 = nn.Conv2d(in_channels=3, out_channels=16, kernel_size=5, s
tride=1, padding=2)
        self.relu1 = nn.ReLU()
        self.maxpool1 = nn.MaxPool2d(kernel_size=2)
        self.cnn2 = nn.Conv2d(in_channels=16, out_channels=32, kernel_size=5,
stride=1, padding=2)
        self.relu2 = nn.ReLU()
        self.maxpool2 = nn.MaxPool2d(kernel_size=2)
        self.cnn3 = nn.Conv2d(in_channels=32, out_channels=16, kernel_size=5,
stride=1, padding=2)
        self.relu3 = nn.ReLU()
        self.maxpool3 = nn.MaxPool2d(kernel_size=2)
        self.fc_preout = nn.Linear(4096, 100)
        self.fc = nn.Linear(100, 2)

    def forward(self, x):
        out = self.cnn1(x)
        out = self.relu1(out)
        out = self.maxpool1(out)
        out = self.cnn2(out)
        out = self.relu2(out)
        out = self.maxpool2(out)
        out = self.cnn3(out)
        out = self.relu3(out)
        out = self.maxpool3(out)
        out = out.view(out.size(0), -1)
        out = self.fc_preout(out)
        out = self.fc(out)

        return out
```

In [43]:

```
def validate(model, val_loader, criterion):
    correct = 0
    total = 0
    total_loss = 0
    for images, labels in val_loader:
        images = images.cuda()
        labels = labels.cuda()

        outputs = model(images)
        loss = criterion(outputs, labels)

        total_loss += loss.item()
        _, predicted = torch.max(outputs.data, 1)

        total += labels.size(0)
        correct += (predicted == labels).sum()
```

```
    accuracy = correct.cpu().numpy() / total
    loss = total_loss / len(val_loader)
    return accuracy, loss

def train(model, train_loader, val_loader, num_epochs, optimizer, criterion, s
cheduler):
    train_acc = []
    val_acc = []
    for epoch in tqdm.tqdm(range(num_epochs)):
        total_loss = 0
        correct = 0
        total = 0
        for i, (images, labels) in enumerate(train_loader):
            images = images.cuda()
            labels = labels.cuda()

            outputs = model(images)
            loss = criterion(outputs, labels)

            optimizer.zero_grad()
            loss.backward()
            optimizer.step()
            scheduler.step()

            total_loss += loss.item()
            _, predicted = torch.max(outputs.data, 1)

            total += labels.size(0)
            correct += (predicted == labels).sum()

        train_loss = total_loss / len(train_loader)
        train_accuracy = correct.cpu().numpy() / total
        accuracy, loss = validate(model, val_loader, criterion)
        # Print Loss
        print(f'[Epoch {epoch+1}/{num_epochs}] Train Loss: {train_loss:.4f}, A
ccuracy: {train_accuracy:.3f}; Val Loss: {loss:.4f}, Accuracy: {accuracy:.3f}'
)
        val_acc.append(accuracy)
        train_acc.append(train_accuracy)

    return train_acc, val_acc
```

In [42]:

```
model = CNNModel().cuda()
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.002, amsgrad=True)
scheduler = torch.optim.lr_scheduler.MultiStepLR(optimizer, milestones=[500,10
00,1500], gamma=0.5)
train(model, train_loader, val_loader, 10, optimizer, criterion, scheduler)
```

```
  0%|          | 0/10 [00:00<?, ?it/s]

 10%|█         | 1/10 [01:26<12:57, 86.34s/it]

[Epoch 1/10] Train Loss: 0.6917, Accuracy: 0.530; Val Loss: 0.6798
, Accuracy: 0.565

 20%|██        | 2/10 [02:50<11:25, 85.74s/it]

[Epoch 2/10] Train Loss: 0.6736, Accuracy: 0.583; Val Loss: 0.6581
, Accuracy: 0.593

 30%|███       | 3/10 [04:14<09:57, 85.31s/it]

[Epoch 3/10] Train Loss: 0.6490, Accuracy: 0.620; Val Loss: 0.6061
, Accuracy: 0.682

 40%|████      | 4/10 [05:40<08:32, 85.38s/it]

[Epoch 4/10] Train Loss: 0.5803, Accuracy: 0.701; Val Loss: 0.5593
, Accuracy: 0.722

 50%|█████     | 5/10 [07:05<07:05, 85.13s/it]

[Epoch 5/10] Train Loss: 0.5335, Accuracy: 0.734; Val Loss: 0.5196
, Accuracy: 0.738
```

```
 60%|██████    | 6/10 [08:30<05:41, 85.33s/it]

[Epoch 6/10] Train Loss: 0.5038, Accuracy: 0.758; Val Loss: 0.5164
, Accuracy: 0.746

 70%|███████   | 7/10 [09:55<04:15, 85.11s/it]

[Epoch 7/10] Train Loss: 0.4852, Accuracy: 0.771; Val Loss: 0.5097
, Accuracy: 0.744

 80%|████████  | 8/10 [11:21<02:50, 85.32s/it]

[Epoch 8/10] Train Loss: 0.4660, Accuracy: 0.781; Val Loss: 0.4841
, Accuracy: 0.768

 90%|█████████ | 9/10 [12:46<01:25, 85.22s/it]

[Epoch 9/10] Train Loss: 0.4475, Accuracy: 0.795; Val Loss: 0.4684
, Accuracy: 0.775

100%|██████████| 10/10 [14:11<00:00, 85.16s/it]

[Epoch 10/10] Train Loss: 0.4334, Accuracy: 0.798; Val Loss: 0.479
3, Accuracy: 0.766
```

In [46]:

```
test_dataset = CatDogDataset(test_data, transform = data_transform)
test_loader = DataLoader(test_dataset, batch_size = 32, shuffle=False, num_wor
kers=4)
accuracy, loss = validate(model, test_loader, criterion)
print(f'Test Loss: {loss:.4f}, Accuracy: {accuracy:.3f}')
```

```
Test Loss: 0.4625, Accuracy: 0.779
```

Примените дополнение данных (data augmentation).

In [54]:

```
data_transform = transforms.Compose([
    transforms.Resize((128, 128)),
    transforms.RandomHorizontalFlip(p=0.5),
    transforms.ToTensor()
])

aug_dataset = CatDogDataset(train_data, transform = data_transform)
aug_loader = DataLoader(aug_dataset, batch_size = 32, shuffle=True, num_worker
s=4)
```

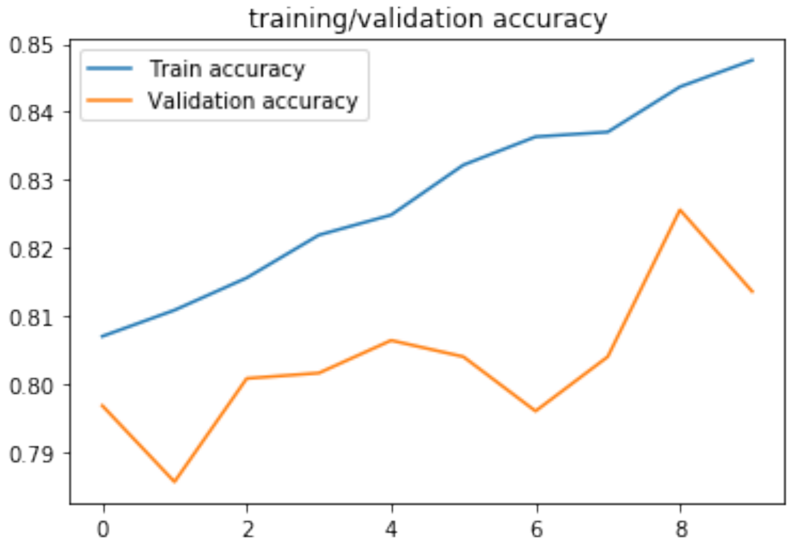
In [ ]:

```
train_acc, val_acc = train(model, aug_loader, val_loader, 10, optimizer, crite
rion, scheduler)
```

[Epoch 10/10] Train Loss: 0.3521, Accuracy: 0.848; Val Loss: 0.4148, Accuracy: 0.814

In [57]:

```
plt.plot(train_acc, label='Train accuracy')
plt.plot(val_acc, label='Validation accuracy')
plt.legend()
plt.title('training/validation accuracy')
plt.show()
```



In [58]:

```
accuracy, loss = validate(model, test_loader, criterion)
print(f'After augmentation Test Loss: {loss:.4f}, Accuracy: {accuracy:.3f}')
```

```
After augmentation Test Loss: 0.4209, Accuracy: 0.815
```

Поэкспериментируйте с готовыми нейронными сетями (например, AlexNet, VGG16, Inception и т.п.), применив передаточное обучение.

In [60]:

```
from torchvision import models
from torch.optim import lr_scheduler

model = models.resnet18(pretrained=True)
num_features = model.fc.in_features
model.fc = nn.Linear(num_features, 2)
model = model.cuda()

criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.002, amsgrad=True)
scheduler = lr_scheduler.CosineAnnealingLR(optimizer, 30)
```

In [63]:

```
ds = ConcatDataset([train_dataset, aug_dataset])
resnet_loader = DataLoader(ds, batch_size = 32, shuffle=True, num_workers=4)
```

In [64]:

```
train_acc, val_acc = train(model, resnet_loader, val_loader, 10, optimizer, cr
iterion, scheduler)
```

```
  0%|          | 0/10 [00:00<?, ?it/s]

 10%|█         | 1/10 [02:53<26:00, 173.34s/it]

[Epoch 1/10] Train Loss: 0.2301, Accuracy: 0.904; Val Loss: 0.1713
, Accuracy: 0.922

 20%|██        | 2/10 [05:51<23:17, 174.65s/it]

[Epoch 2/10] Train Loss: 0.1300, Accuracy: 0.948; Val Loss: 0.1156
, Accuracy: 0.962

 30%|███       | 3/10 [08:48<20:28, 175.47s/it]

[Epoch 3/10] Train Loss: 0.0898, Accuracy: 0.965; Val Loss: 0.1253
, Accuracy: 0.954

 40%|████      | 4/10 [11:45<17:36, 176.06s/it]
```

```
[Epoch 4/10] Train Loss: 0.0660, Accuracy: 0.975; Val Loss: 0.1657
, Accuracy: 0.941
```

```
 50%|█████     | 5/10 [14:36<14:32, 174.56s/it]
```

```
[Epoch 5/10] Train Loss: 0.0554, Accuracy: 0.980; Val Loss: 0.1920
, Accuracy: 0.948
```

```
 60%|██████    | 6/10 [17:34<11:42, 175.51s/it]
```

```
[Epoch 6/10] Train Loss: 0.0455, Accuracy: 0.982; Val Loss: 0.1520
, Accuracy: 0.950
```

```
 70%|███████   | 7/10 [20:31<08:47, 175.94s/it]
```

```
[Epoch 7/10] Train Loss: 0.0334, Accuracy: 0.988; Val Loss: 0.1390
, Accuracy: 0.954
```

```
 80%|████████  | 8/10 [23:29<05:53, 176.52s/it]
```

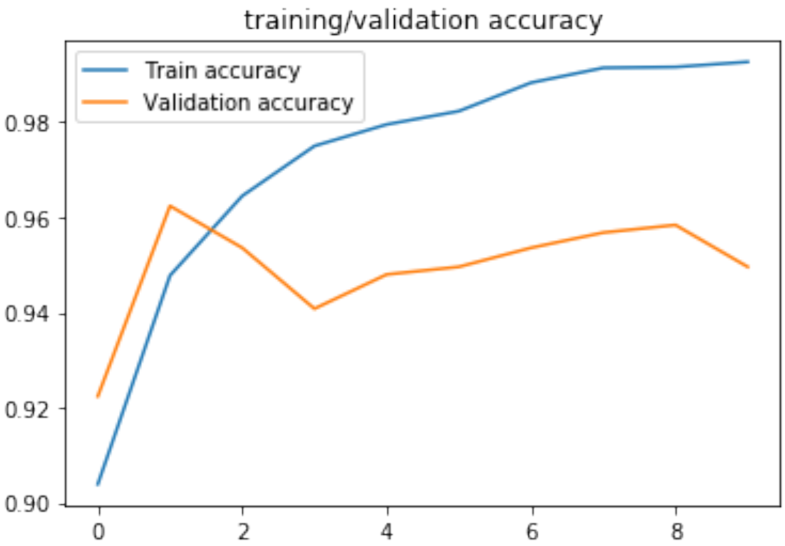
```
[Epoch 8/10] Train Loss: 0.0251, Accuracy: 0.991; Val Loss: 0.1584
, Accuracy: 0.957
```

```
 90%|█████████ | 9/10 [26:29<02:57, 177.46s/it]

[Epoch 9/10] Train Loss: 0.0246, Accuracy: 0.992; Val Loss: 0.1353
, Accuracy: 0.958
```

```
100%|██████████| 10/10 [29:27<00:00, 177.78s/it]

[Epoch 10/10] Train Loss: 0.0209, Accuracy: 0.993; Val Loss: 0.206
7, Accuracy: 0.950
```

In [81]:

```
plt.plot(train_acc, label='Train accuracy')
plt.plot(val_acc, label='Validation accuracy')
plt.legend()
plt.title('training/validation accuracy')
plt.show()
```



In [66]:

```
accuracy, loss = validate(model, test_loader, criterion)
print(f'ResNet18 Test Loss: {loss:.4f}, Accuracy: {accuracy:.3f}')
```

```
ResNet18 Test Loss: 0.1693, Accuracy: 0.949
```

In [68]:

```
filename_pth = 'resnet18_catdog.pth'
torch.save(model.state_dict(), filename_pth)
```

In [75]:

```
files_labels = {os.path.join(train_dir, file_name): file_name for file_name in
os.listdir(train_dir)}
test_data = pd.DataFrame.from_dict({'image_file': list(files_labels.keys()), '
label': list(files_labels.values())})
data_transform = transforms.Compose([
    transforms.Resize((128, 128)),
    transforms.ToTensor()
])

test_ds = CatDogDataset(test_data, transform = data_transform)
testloader = DataLoader(test_ds, batch_size = 32, shuffle=False, num_workers=4
)
fn_list = []
pred_list = []
for x, fn in testloader:
    with torch.no_grad():
        x = x.cuda()
        output = model(x)
        pred = torch.argmax(output, dim=1)
        fn_list += [n[:-4] for n in fn]
        pred_list += [p.item() for p in pred]

submission = pd.DataFrame({"id":fn_list, "label":pred_list})
submission.to_csv('preds_resnet18.csv', index=False)
```

In [79]:

```
samples, _ = iter(testloader).next()
samples = samples.cuda()
fig = plt.figure(figsize=(24, 16))
fig.tight_layout()
output = model(samples[:24])
pred = torch.argmax(output, dim=1)
pred = [p.item() for p in pred]
ad = {0:'cat', 1:'dog'}
for num, sample in enumerate(samples[:12]):
    plt.subplot(4,6,num+1)
    plt.title(ad[pred[num]])
    plt.axis('off')
    sample = sample.cpu().numpy()
    plt.imshow(np.transpose(sample, (1,2,0)))
```

Вывод:

В данной лабораторной мы использовали сверточную нейронную сеть для реализации бинарного классификатора на наборе данных Cats/Dogs. Использовали аугментацию данных и предаточное обучение.