Импортируем библиотеки, качаем датасет

```
import os
import random
import torchvision
import torchmetrics
from torchmetrics.functional import char_error_rate
import torch
from sklearn import metrics
import torch.nn as nn
from PIL import Image, ImageOps
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from tqdm import tqdm
```

```
!unzip 'CCPD2019-dl1.zip'
```

Показать скрытые выходные данные

```
device = 'cuda' if torch.cuda.is_available() else 'cpu'
device
```

```
'cuda'
```

Алфавит, encoding/decoding для inputs/outputs

```
provinces = ["皖", "沪", "津", "渝", "冀", "晋", "蒙", "辽",
             "吉", "黑", "苏", "浙", "京", "闽", "赣", "鲁",
             "豫", "鄂", "湘", "粤", "桂", "琼", "川", "贵",
             "云", "藏", "陕", "甘", "青", "宁", "新", "警",
             "学", "O"]

ads = ['A', 'B', 'C', 'D', 'E', 'F', 'G', 'H',
       'J', 'K', 'L', 'M', 'N', 'P', 'Q', 'R',
       'S', 'T', 'U', 'V', 'W', 'X', 'Y', 'Z',
       '0', '1', '2', '3', '4', '5', '6', '7',
       '8', '9', 'O']

alphabet = provinces + ads
```

```
OOV_TOKEN = '<OOV>'
CTC_BLANK = '<BLANK>'

class Tokenizer:

    def __init__(self, alphabet):
        self.char_map = {value: idx + 2 for (idx, value) in enumerate(alphabet)}
        self.char_map[CTC_BLANK] = 0
        self.char_map[OOV_TOKEN] = 1
        self.rev_char_map = {val: key for key, val in self.char_map.items()}
```

```python
    def encode(self, word_list):
        enc_words = [self.char_map[char] if char in self.char_map
             else self.char_map[OOV_TOKEN]
             for char in word_list]
        return enc_words

    def get_num_chars(self):
        return len(self.char_map)

    def decode(self, enc_word_list):
        word_chars = ''
        for idx, char_enc in enumerate(enc_word_list):
            if (
                char_enc != self.char_map[OOV_TOKEN]
                and char_enc != self.char_map[CTC_BLANK]
                and not (idx > 0 and char_enc == enc_word_list[idx - 1])
            ):
                word_chars += self.rev_char_map[char_enc]
        return word_chars
```

Класс датасета и даталоадеры + collate_fn

```python
class OCRDataSet(torch.utils.data.Dataset):
    def __init__(self, data_path, names, tokenizer):
        self.data_path = data_path
        self.tokenizer = tokenizer
        self.names = names
        self.dataset = []
        self.labels = []
        self.encoded_labels = []
        self.shape = [0] * 2
        self.aug = torchvision.transforms.Compose(
            [
                torchvision.transforms.ToTensor()
                #torchvision.transforms.Normalize(mean, std)
            ]
        )
        for i in tqdm(range(len(self.names))):
            image = Image.open(self.data_path + self.names[i]).convert("RGB")
            #image = ImageOps.grayscale(image) # делал один канал, но по итогу оставил все 3
            image = image.resize((200, 32))
            image = self.aug(image)

            self.dataset.append(image)
            self.labels.append(self.names[i][-11:-4])
            self.encoded_labels.append(self.tokenizer.encode(self.names[i][-11:-4]))


    def __getitem__(self, idx):
        encoded_label = torch.LongTensor(self.encoded_labels[idx])
        return self.dataset[idx], self.labels[idx], encoded_label

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


train_path = 'CCPD2019-dl1/train/'
```

```
test_path = 'CCPD2019-dl1/test/'

train_names = os.listdir(train_path)
test_names = os.listdir(test_path)
```

```
tokenizer = Tokenizer(alphabet)
test = OCRDataSet(test_path, test_names, tokenizer)
```

```
100%|██████████| 9999/9999 [00:05<00:00, 1791.32it/s]
```

```
test[0][0].shape
```

```
torch.Size([3, 32, 200])
```

```
train = OCRDataSet(train_path, train_names, tokenizer)
```

```
100%|██████████| 199980/199980 [01:49<00:00, 1823.43it/s]
```

```
def collate_fn(batch):
    images, texts, enc_texts = zip(*batch)
    images = torch.stack(images, 0)
    enc_pad_texts = torch.nn.utils.rnn.pad_sequence(enc_texts, batch_first=True, padding_value=0)
    return images, texts, enc_pad_texts
```

```
train_loader = torch.utils.data.DataLoader(train,
                                           batch_size=80,
                                           shuffle=True,
                                           collate_fn=collate_fn)

test_loader = torch.utils.data.DataLoader(test,
                                          batch_size=80,
                                          shuffle=False,
                                          collate_fn=collate_fn)
```

```
sample = train[4][0]
plt.axis('off')
plt.imshow(sample.permute(1, 2, 0))
```

```
<matplotlib.image.AxesImage at 0x7f7fc5164820>
```

Модель:

CNN + BiLSTM

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

```
        self.relu = nn.ReLU()

        self.conv1 = nn.Conv2d(in_channels=3, out_channels=64, kernel_size=3, stride=1, padding=1)
        self.maxpool1 = nn.MaxPool2d(kernel_size=2, stride=2)

        self.conv3_1 = nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, stride=1, padding=1)
        self.maxpool3 = nn.MaxPool2d(kernel_size=(1,2), stride=2)

        self.conv5 = nn.Conv2d(in_channels=128, out_channels=256, kernel_size=3, stride=1, padding=1)
        self.batchnorm2 = nn.BatchNorm2d(256)

        self.maxpool4 = nn.MaxPool2d(kernel_size=(1,2), stride=2)
        self.conv6 = nn.Conv2d(in_channels=256, out_channels=256, kernel_size=2, stride=1, padding=0)

    def forward(self, x):

        x = self.relu(self.conv1(x))
        x = self.maxpool1(x)
        x = self.relu(self.conv3_1(x))
        x = self.maxpool3(x)
        x = self.relu(x)
        x = self.relu(self.conv5(x))
        x = self.batchnorm2(x)
        x = self.maxpool4(x)
        x = self.relu(self.conv6(x))

        return x


class BiLSTM(nn.Module):
    def __init__(self, input_size, hidden_size, num_layers, dropout=0.15):
        super().__init__()
        self.lstm = nn.LSTM(
            input_size, hidden_size, num_layers,
            dropout=dropout, batch_first=True, bidirectional=True)

    def forward(self, x):
        out, _ = self.lstm(x)
        return out


class CRNN(nn.Module):
    def __init__(
        self, number_class_symbols, time_feature_count=21, lstm_hidden=100,
        lstm_len=2,
    ):
        super().__init__()
        self.feature_extractor = CNNFe()
        self.avg_pool = nn.AdaptiveAvgPool2d(
            (time_feature_count, time_feature_count))
        self.bilstm = BiLSTM(time_feature_count, lstm_hidden, lstm_len)
        self.classifier = nn.Sequential(
            nn.Linear(lstm_hidden * 2, time_feature_count),
            nn.GELU(),
            nn.Dropout(0.1),
            nn.Linear(time_feature_count, number_class_symbols)
        )

    def forward(self, x):
```

```
        x = self.feature_extractor(x)
        b, c, h, w = x.size()
        x = x.view(b, c * h, w)
        x = self.avg_pool(x)
        x = x.transpose(1, 2)
        x = self.bilstm(x)
        x = self.classifier(x)
        x = x.permute(1, 0, 2)
        x = nn.functional.log_softmax(x, dim=2)
        return x
```

Инициализация модели и функции тренировки и валидации

взял интересный шедулер, который нашел в одной из реализаций CTC-loss, он при ухудшении/не изменении loss-а, понижает lr

```
model = CRNN(tokenizer.get_num_chars())
criterion = torch.nn.CTCLoss(blank=0, reduction='mean', zero_infinity=True)
optimizer = torch.optim.Adam(model.parameters(), lr=2e-4)
scheduler = torch.optim.lr_scheduler.ReduceLROnPlateau(
    optimizer, factor=0.5, patience=2, verbose=True
)
```

```
a = model(test[0][0].unsqueeze(0))
a.shape # time_feature x batch x vocab_size
```

```
torch.Size([21, 1, 70])
```

```
def train_epoch(model, train_loader, optimizer, criterion):
    epoch_loss = 0
    total_step = len(train_loader)
    model.train(True)
    model.to(device)
    for i, (images, labels, encoded_labels) in enumerate(train_loader):

        batch_s = images.shape[0]
        images = images.to(device)
        labels = labels
        encoded_labels = encoded_labels.to(device)
        outputs = model(images)

        input_lengths = torch.full(
                size=(batch_s,), fill_value=outputs.size(0), dtype=torch.long
        )
        target_lengths = torch.full(
            size=(batch_s,), fill_value=encoded_labels.size(1), dtype=torch.long
        )

        loss = criterion(
            outputs, encoded_labels, input_lengths, target_lengths
        )

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

```
        epoch_loss += loss.item()

    return epoch_loss / total_step


def val_epoch(model, test_loader):
    epoch_loss = 0
    preds = []
    total_step = len(test_loader)
    model.train(False)
    model.to(device)
    for i, (images, labels, encoded_labels) in enumerate(test_loader):
        with torch.no_grad():
            batch_s = images.shape[0]
            images = images.to(device)
            labels = labels
            encoded_labels = encoded_labels.to(device)
            outputs = model(images)

            input_lengths = torch.full(
                    size=(batch_s,), fill_value=outputs.size(0), dtype=torch.long
            )
            target_lengths = torch.full(
                size=(batch_s,), fill_value=encoded_labels.size(1), dtype=torch.long
            )

            loss = nn.CTCLoss(blank=0)(
                outputs, encoded_labels, input_lengths, target_lengths
            )
            epoch_loss += loss.item()
            preds.extend(outputs.argmax(2).T)

    return epoch_loss / total_step, preds
```

Тренируем модель

```
epoches = 8
real_test = np.array(test.labels)
real_train = np.array(train.labels)
for i in tqdm(range(epoches)):
    decoded = []
    train_loss = train_epoch(model, train_loader, optimizer, criterion)
    test_loss, val_preds = val_epoch(model, test_loader)
    test_answers = np.array(list(map(output_decoder, val_preds)))
    acc = (real_test == test_answers).sum() / 9999

    scheduler.step(test_loss)
    print(f'Epoch: {i + 1}; Train_loss: {train_loss}; Test_loss: {test_loss};\n Eval Accuracy: {acc}')
```

```
 12%|█         | 1/8 [00:31<03:42, 31.85s/it]Epoch: 1; Train_loss: 1.4445627773061396; Test_loss: 0
 Eval Accuracy: 0.9227922792279228
 25%|██        | 2/8 [01:03<03:11, 31.92s/it]Epoch: 2; Train_loss: 0.050318637614697216; Test_loss:
 Eval Accuracy: 0.9482948294829483
 38%|███       | 3/8 [01:34<02:37, 31.51s/it]Epoch: 3; Train_loss: 0.022383602664619685; Test_loss:
 Eval Accuracy: 0.9442944294429443
 50%|█████     | 4/8 [02:06<02:06, 31.52s/it]Epoch: 4; Train_loss: 0.014354023332661017; Test_loss:
 Eval Accuracy: 0.9581958195819582
 62%|██████    | 5/8 [02:37<01:34, 31.46s/it]Epoch: 5; Train_loss: 0.010359219936467707; Test_loss:
```

```
Eval Accuracy: 0.9566956695669567
 75%|███████▌  | 6/8 [03:09<01:03, 31.70s/it]Epoch: 6; Train_loss: 0.007967271547275596; Test_loss:
Eval Accuracy: 0.9657965796579658
 88%|████████▊ | 7/8 [03:41<00:31, 31.79s/it]Epoch: 7; Train_loss: 0.006686707442335319; Test_loss:
Eval Accuracy: 0.9660966096609661
100%|██████████| 8/8 [04:13<00:00, 31.71s/it]Epoch: 8; Train_loss: 0.005419347418146208; Test_loss:
Eval Accuracy: 0.9706970697069707
```

Получим предикты на тест выборку

```
def output_decoder(output):
    output = output
    output = output.tolist()
    output = tokenizer.decode(output)
    return output
```

```
loss, test_preds = val_epoch(model, test_loader)
```

```
comparation_test = np.array(test.labels)
test_answers = np.array(list(map(output_decoder, test_preds)))
```

Посчитаем Accuracy

```
(test_answers == comparation_test).sum() / 9999
```

```
0.9706970697069707
```

Посчитаем CER

```
char_error_rate(test_answers, comparation_test).item()
```

```
0.005386252887547016
```

Посмотрим на результаты и на "плохие" картинки

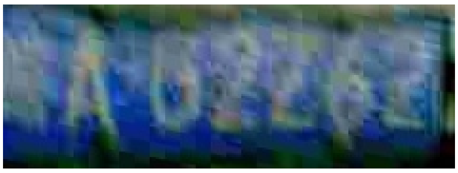
```
df = pd.DataFrame({"true": comparation_test,  "predict": test_answers}, index=np.arange(9999))

df['Errors in predict'] = ''

for i in range(df.shape[0]):
    ref = df.loc[i, "true"]
    output = df.loc[i, "predict"]
    df.loc[i, 'Errors in predict'] = int(char_error_rate(output, ref).item() * 7)

df = df.sort_values(by = 'Errors in predict', ascending=False)
df.head(10)
```

	true	predict	Errors in predict
3791	皖AK927W	皖44	6
2025	皖AG2Z62	皖AW5QQ	5
1750	皖A2W003	皖A6JFF4	5
1684	皖AMQ059	苏ANNK59	4
5885	皖Q99066	皖0LQ0066	4
8458	皖AJ915C	皖AM51EZ	4
6953	皖AYU642	皖LU1A2	4
3417	皖AN8N55	皖AQU55	3
6381	皖AZ7M69	皖A469	3

```
def show_image(image_name):
    img = Image.open(test_path + image_name)
    return img
```

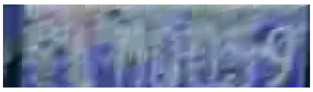
```
show_image('1609-皖AK927W.jpg')
```

```
show_image('0374-皖AG2Z62.jpg')
```



```
show_image('0607-皖A2W003.jpg')
```

```
show_image('0201-皖AMQ059.jpg')
```



```
show_image('0388-皖Q99066.jpg')
```

Выводы

Результаты довольно хорошие, на 1000 символов модель дак мы видим - сэмплы с плохим распознаванием либо плохо задетекчены, либо с плохим качеством, либо часть текста отсвечивает.

Что можно сделать?

1. Подобрать хорошие аугментации, чтобы модель меньше ошибалась на плохо обрезанных фото

2. Дополнительно пройтись детектором как раз для таких семплов

3. Вместо LSTM попробовать Transformer, вместо CTC-loss попробовать CE-loss

4. Естественно, потюнить параметры, можно и выход модельки потюнить, во время последних экспериментов оставил 21 (в 3 раза больше чем символов в названии, для бланков хватит)

5. Можно заметить, что модель плохо определяет текст на картинках, где текст под каким-либо углом, т.е. ее надо дополнительно обучать на такие семплы, которые можно достать с помощью аугментаций