```
!unzip -qq CCPD2019-dl1.zip
In [12]: !pip install torchmetrics pybind11 fastwer scikit-learn matplotlib
         Requirement already satisfied: torchmetrics in /opt/conda/lib/python3.10/site-pack
         ages (0.11.0)
         Requirement already satisfied: pybind11 in /opt/conda/lib/python3.10/site-packages
         (2.10.3)
         Requirement already satisfied: fastwer in /opt/conda/lib/python3.10/site-packages
         (0.1.3)
         Requirement already satisfied: scikit-learn in /opt/conda/lib/python3.10/site-pack
         ages (1.2.0)
         Collecting matplotlib
           Downloading matplotlib-3.6.2-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86
         _64.whl (11.8 MB)
                                                      - 11.8/11.8 MB 9.4 MB/s eta 0:00:00:0
         0:0100:01
         Requirement already satisfied: numpy>=1.17.2 in /opt/conda/lib/python3.10/site-pac
         kages (from torchmetrics) (1.24.1)
         Requirement already satisfied: packaging in /opt/conda/lib/python3.10/site-package
         s (from torchmetrics) (21.3)
         Requirement already satisfied: torch>=1.8.1 in /opt/conda/lib/python3.10/site-pack
         ages (from torchmetrics) (1.13.1+cu116)
         Requirement already satisfied: joblib>=1.1.1 in /opt/conda/lib/python3.10/site-pac
         kages (from scikit-learn) (1.2.0)
         Requirement already satisfied: threadpoolctl>=2.0.0 in /opt/conda/lib/python3.10/s
         ite-packages (from scikit-learn) (3.1.0)
         Requirement already satisfied: scipy>=1.3.2 in /opt/conda/lib/python3.10/site-pack
         ages (from scikit-learn) (1.10.0)
         Collecting kiwisolver>=1.0.1
           Downloading kiwisolver-1.4.4-cp310-cp310-manylinux_2_12_x86_64.manylinux2010_x86
         _64.whl (1.6 MB)
                                                      - 1.6/1.6 MB 5.6 MB/s eta 0:00:0000:01
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         Requirement already satisfied: pillow>=6.2.0 in /opt/conda/lib/python3.10/site-pac
         kages (from matplotlib) (9.4.0)
         Requirement already satisfied: pyparsing>=2.2.1 in /opt/conda/lib/python3.10/site-
         packages (from matplotlib) (3.0.9)
         Collecting cycler>=0.10
           Downloading cycler-0.11.0-py3-none-any.whl (6.4 kB)
         Requirement already satisfied: python-dateutil>=2.7 in /opt/conda/lib/python3.10/s
         ite-packages (from matplotlib) (2.8.2)
         Collecting fonttools>=4.22.0
           Downloading fonttools-4.38.0-py3-none-any.whl (965 kB)
                                                     - 965.4/965.4 kB 6.6 MB/s eta 0:00:000
         0:0100:01
         Collecting contourpy>=1.0.1
           Downloading contourpy-1.0.6-cp310-cp310-manylinux 2 17 x86 64.manylinux2014 x86
         64.whl (296 kB)
                                                    - 296.1/296.1 kB 5.3 MB/s eta 0:00:00a
         0:00:01
         Requirement already satisfied: six>=1.5 in /opt/conda/lib/python3.10/site-packages
         (from python-dateutil>=2.7->matplotlib) (1.16.0)
         Requirement already satisfied: typing-extensions in /opt/conda/lib/python3.10/site
         -packages (from torch>=1.8.1->torchmetrics) (4.3.0)
         Installing collected packages: kiwisolver, fonttools, cycler, contourpy, matplotli
         Successfully installed contourpy-1.0.6 cycler-0.11.0 fonttools-4.38.0 kiwisolver-
```

1.4.4 matplotlib-3.6.2

In [13]: import torch

```
import torchvision
        import fastwer
        import torchmetrics
        import os
        import gc
        import numpy as np
        import matplotlib.pyplot as plt
        from torch import nn
        from torchvision import transforms
        from PIL import Image
        from tqdm.notebook import tqdm
        from sklearn.metrics import accuracy_score
In [2]: path = 'CCPD2019-dl1/'
        dictionary = ["皖", "沪", "津", "渝", "冀", "晋", "蒙", "辽",
                     "吉","黑","苏","浙","京","闽","赣","鲁",
                     "豫","鄂","湘","粤","桂","琼","川","贵"
                         ,"藏","陕","甘","青","宁","新",
                                                             "警",
                     "学", "O", 'A', 'B', 'C', 'D', 'E', 'F', 'G', 'H',
               'J', 'K', 'L', 'M', 'N', 'P', 'Q', 'R',
                  , 'T', 'U', 'V', 'W', 'X', 'Y', 'Z'
               '0', '1', '2', '3', '4', '5', '6', '7',
               '8', '9', '0']
        unknown = '<U>'
        blank = '<B>'
In [3]: class Tokenizer:
            def __init__(self, labels):
                self.char2id = {}
                self.char2id[unknown] = 0
                self.char2id[blank] = 1
                for i, label in enumerate(labels):
                        self.char2id[label] = i + 2
                self.id2char = {v:k for k, v in self.char2id.items()}
            def encode(self, label):
                enc_label = [self.char2id[char] if char in self.char2id else self.char2id[u
                return enc_label
            def __len__(self):
                return len(self.char2id)
            def decode(self, enc_list):
                decoded_list = ''
                for i, char in enumerate(enc_list):
                    if (char != self.char2id[unknown] and char != self.char2id[blank] and r
                        decoded_list += self.id2char[char]
                return decoded list
In [4]: class Dataset(torch.utils.data.Dataset):
            def __init__(self, path, transform, tokenizer):
                super(). init ()
                self.files = [file for file in os.listdir(path) if file[0] != '.']
                self.t = transform
                self.labels = [file.split('-')[-1].split('.')[0] for file in self.files]
```

```
self.path = path
self.alphabet = {}
self.tokenizer = tokenizer
self.encoded_labels = [self.tokenizer.encode(label) for label in self.label

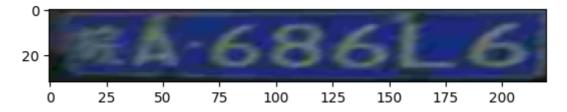
def __len__(self):
    return len(self.files)

def __getitem__(self, ind):
    image = Image.open(f'{self.path}{self.files[ind]}')
    img = self.t(image)
    label = self.labels[ind]
    return img, label, self.encoded_labels[ind]
```

```
In [7]: len(train_dataset), len(test_dataset)
```

Out[7]: (199980, 9999)

```
In [18]: plt.imshow(test_dataset[3][0].permute(1, 2, 0))
    plt.show()
```



```
In [7]: class Encoder(nn.Module):
    def __init__(self):
        super().__init__()
        self.layers = nn.Sequential(
```

```
nn.MaxPool2d(kernel_size = 2, stride = 2),
                 Downsample(in channels=64, out channels=128, kernel size=3, stride=1),
                 nn.MaxPool2d(kernel_size = (1,2), stride = 2),
                 Downsample(in_channels=128, out_channels=256, kernel_size=3, stride=1),
                 nn.MaxPool2d(kernel_size = (1,2), stride = 2),
                 Downsample(in_channels=256, out_channels=128, kernel_size=3, stride=1),
             def forward(self, inputs):
                 x = self.layers(inputs)
                 return x
In [8]: class BiLSTM(nn.Module):
             def __init__(self, input_dim, hidden_dim, num_layers, dropout = 0.1):
                 super().__init__()
                 self.rnn = nn.LSTM(input_dim, hidden_dim, num_layers, dropout = dropout, ba
             def forward(self, inputs):
                 outputs, _ = self.rnn(inputs)
                 return outputs
         class CRNN(nn.Module):
             def __init__(self, output_dim, hidden_dim, max_len = 15, num_layers = 2):
                 super().__init__()
                 self.encoder = Encoder()
                 self.avg_pool = nn.AdaptiveAvgPool2d((max_len, max_len))
                 self.rnn = BiLSTM(max_len, hidden_dim, num_layers)
                 self.classify_layer = nn.Sequential(
                     nn.Linear(hidden_dim * 2, max_len),
                     nn.GELU(),
                     nn.Dropout(0.1),
                     nn.Linear(max_len, output_dim)
                 )
             def forward(self, inputs):
                 outp = self.encoder(inputs)
                 b, c, h, w = outp.shape
                 outp = outp.view(b, c * h, w)
                 outp = self.avg_pool(outp)
                 outp = outp.transpose(1,2)
                 outp = self.rnn(outp)
                 outp = self.classify_layer(outp)
                 outp = outp.permute(1, 0, 2)
                 outp = nn.functional.log_softmax(outp, dim=2)
                 return outp
 In [9]: def collate_fn(batch):
             images, labels, encoded_labels = zip(*batch)
             images = torch.stack(images, 0)
             encoded labels = torch.nn.utils.rnn.pad sequence(torch.tensor(encoded labels),
             return images, labels, encoded_labels
In [10]: def train_epoch(model,
                        dataset,
                        loss,
                        optimizer,
```

Downsample(in\_channels=3, out\_channels=64, kernel\_size=3, stride=1, use\_bat

scheduler,

```
device):
model.train()
epoch loss = 0
model = model.to(device)
for img, label, encoded_label in tqdm(dataset):
    batch = img.shape[0]
   img = img.to(device)
   optimizer.zero_grad()
   preds = model(img)
   p_labels = torch.full(size = (batch,), fill_value = preds.size(0), dtype =
   t_labels = torch.full(size = (batch,), fill_value = encoded_label.size(1),
   b_loss = loss(preds, encoded_label, p_labels, t_labels)
   epoch_loss += b_loss.item()
   b_loss.backward()
   optimizer.step()
return epoch_loss / len(dataset)
```

```
In [11]: def eval_epoch(model,
                         dataset,
                         loss,
                         device):
             model.eval()
             epoch_loss = 0
             model = model.to(device)
             for img, label, encoded_label in tqdm(dataset):
                 with torch.no_grad():
                     batch = img.shape[0]
                     img = img.to(device)
                     encoded_label = encoded_label.to(device)
                     preds = model(img)
                     p_labels = torch.full(size = (batch,), fill_value = preds.size(0), dtyr
                     t_labels = torch.full(size = (batch,), fill_value = encoded_label.size(
                     b_loss = loss(preds, encoded_label, p_labels, t_labels)
                     epoch loss += b loss.item()
             return epoch_loss / len(dataset)
```

scheduler,

```
device):
             model.cuda()
             loss.to(device)
             test_dataloader = torch.utils.data.DataLoader(test_dataset,
                                                            batch_size = batch_size,
                                                            shuffle = False,
                                                            collate_fn = collate_fn)
             train_dataloader = torch.utils.data.DataLoader(train_dataset,
                                                             batch_size = batch_size,
                                                             shuffle = True,
                                                             collate_fn = collate_fn)
             for epoch i in range(epochs):
                 print(f'Epoch {epoch_i+1}')
                 train_loss = train_epoch(model, train_dataloader, loss, optimizer, schedule
                 eval_loss = eval_epoch(model, test_dataloader, loss, device)
                 scheduler.step(eval_loss)
                 print(f'Train CTC: {train_loss}')
                 print(f'Eval CTC: {eval_loss}')
                 print()
             torch.save(model, f'model_ep{epoch_i+1}.pt')
In [13]: model = CRNN(max_len = 15, hidden_dim = 200, output_dim = len(train_dataset.tokeniz
         CTC = nn.CTCLoss(blank = 1, reduction = 'mean', zero_infinity = True)
         optimizer = torch.optim.Adam(model.parameters(), lr = 1e-4)
         scheduler = torch.optim.lr_scheduler.ReduceLROnPlateau(optimizer, factor=0.8, patie
         gc.collect()
         torch.cuda.empty_cache()
         train_model(
             model = model,
             train dataset = train dataset,
             test_dataset = test_dataset,
             batch size = 128,
             loss = CTC,
             optimizer = optimizer,
             scheduler = scheduler,
             epochs = 10,
             device = 'cuda'
         Epoch 1
           0%|
                         | 0/1563 [00:00<?, ?it/s]
           0%|
                         | 0/79 [00:00<?, ?it/s]
         Train CTC: 3.0028658341842815
         Eval CTC: 2.0103080891355685
         Epoch 2
           0%|
                         | 0/1563 [00:00<?, ?it/s]
                         | 0/79 [00:00<?, ?it/s]
         Train CTC: 0.9231137104013069
         Eval CTC: 0.2196903477741193
         Epoch 3
```

> | 0/1563 [00:00<?, ?it/s] | 0/79 [00:00<?, ?it/s]

0%|

```
Train CTC: 0.20089744116755837
         Eval CTC: 0.10001567105137849
         Epoch 4
           0%
                         | 0/1563 [00:00<?, ?it/s]
           0%|
                         | 0/79 [00:00<?, ?it/s]
         Train CTC: 0.10375405463818473
         Eval CTC: 0.07591616317535503
         Epoch 5
           0%
                         | 0/1563 [00:00<?, ?it/s]
           0%
                         | 0/79 [00:00<?, ?it/s]
         Train CTC: 0.06926006894089133
         Eval CTC: 0.0693979582431007
         Epoch 6
           0%|
                         | 0/1563 [00:00<?, ?it/s]
                         | 0/79 [00:00<?, ?it/s]
         Train CTC: 0.05219624730772074
         Eval CTC: 0.06486983366216285
         Epoch 7
           0%
                         | 0/1563 [00:00<?, ?it/s]
           0%|
                         | 0/79 [00:00<?, ?it/s]
         Train CTC: 0.04214400670807558
         Eval CTC: 0.07545892772252989
         Epoch 8
           0%
                         | 0/1563 [00:00<?, ?it/s]
                         | 0/79 [00:00<?, ?it/s]
         Train CTC: 0.035413823933033745
         Eval CTC: 0.06186418796563816
         Epoch 9
           0% l
                         | 0/1563 [00:00<?, ?it/s]
                         | 0/79 [00:00<?, ?it/s]
         Train CTC: 0.03099549728221071
         Eval CTC: 0.05557966011663298
         Epoch 10
           0%|
                         | 0/1563 [00:00<?, ?it/s]
                         | 0/79 [00:00<?, ?it/s]
         Train CTC: 0.027535500582867682
         Eval CTC: 0.0651401086055373
In [14]: def predict(model, dataset, tokenizer, device = 'cuda'):
             model.eval()
             preds = []
             real = []
             epoch loss = 0
             model = model.to(device)
             test_dataloader = torch.utils.data.DataLoader(dataset, batch_size = 1, shuffle
             for img, label, encoded_label in tqdm(test_dataloader):
                 with torch.no_grad():
                      batch = img.shape[0]
                      img = img.to(device)
                      encoded_label = encoded_label.to(device)
                      pred = model(img)
```

```
In [15]: accuracy = torchmetrics.CharErrorRate()
    preds, real_labels = predict(model, test_dataset, tokenizer)
    print('CER:', accuracy(preds, real_labels).item())
    print('Accuracy:', accuracy_score(preds, real_labels))
```

0% | 0/9999 [00:00<?, ?it/s]

CER: 6.995199680328369

Accuracy: 0.948794879488