In [1]:
```
!pip install torchmetrics, albumentations
```

```
Requirement already satisfied: torchmetrics in /opt/conda/lib/python3.10/site-packages (0.11.0)
Requirement already satisfied: packaging in /opt/conda/lib/python3.10/site-packages (from torchmetrics) (21.3)
Requirement already satisfied: torch>=1.8.1 in /opt/conda/lib/python3.10/site-packages (from torchmetrics) (1.13.1+cu11
6)
Requirement already satisfied: numpy>=1.17.2 in /opt/conda/lib/python3.10/site-packages (from torchmetrics) (1.24.1)
Requirement already satisfied: typing-extensions in /opt/conda/lib/python3.10/site-packages (from torch>=1.8.1->torchme
trics) (4.3.0)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in /opt/conda/lib/python3.10/site-packages (from packaging->tor
chmetrics) (3.0.9)
```

Libraries

In [4]:
```
import os
import torch
import torchvision
import torchmetrics
import cv2
from torchmetrics.functional import char_error_rate
from sklearn import metrics
import torch.nn as nn
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from tqdm import tqdm
import albumentations as A
from albumentations.pytorch import ToTensorV2
```

In [5]:
```
device = 'cuda' if torch.cuda.is_available() else 'cpu'
device
```

Out[5]: 'cuda'

In [ ]:
```
torch.random.manual_seed(777)
torch.cuda.random.manual_seed_all(777)
torch.cuda.random.manual_seed(777)
```

Loading Data and Preprocessing

In [71]:
```
!unzip -qq 'CCPD2019-dl1.zip'
```

```
replace CCPD2019-dl1/test/0287-皖AYX440.jpg? [y]es, [n]o, [A]ll, [N]one, [r]ename: ^C
```

In [6]:
```
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"]

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
```

In [7]:
```
CTC_BLANK = '<CTC>'

class Tokenizer:

    def __init__(self, alphabet):
        self.char_dict = {val: i + 1 for (i, val) in enumerate(alphabet)}
        self.char_dict[CTC_BLANK] = 0
        self.rev_char_dict = self.reverse_dict(self.char_dict)

    def tokenize(self, word_list):
        tokens = [self.char_dict[char] if char in self.char_dict
             else self.char_dict[OOV_TOKEN]
             for char in word_list]
        return tokens

    def untokenize(self, tokenized_words):
        untokens = ''
        for idx, token in enumerate(tokenized_words):
            if not (idx > 0 and token == tokenized_words[idx - 1]) and token != self.char_dict[CTC_BLANK]:
                untokens += self.rev_char_dict[token]
        return untokens

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

    @staticmethod
    def reverse_dict(d):
        return {v: k for k, v in d.items()}
```

In [8]:
```
SIZE = 224
transforms = A.Compose([
    A.Resize(32, SIZE),
    A.Normalize(),
    ToTensorV2()
])
```

In [155]:
```
class OCRDataSet(torch.utils.data.Dataset):
    def __init__(self, img_folder, tokenizer, transforms):
        super().__init__()
        self.img_folder = img_folder
        self.tokenizer = tokenizer
        self.dataset = []
        self.labels = []
        self.tokenized_labels = []
        self.img_name = []
        self.transforms = transforms
        self._get_data_from_folder()

    def _get_data_from_folder(self):
            for img_name in tqdm(os.listdir(self.img_folder)):
               img = cv2.imread(os.path.join(self.img_folder, img_name))
               img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
               transformed = self.transforms(image=img)
               img_tensor = transformed['image']
               self.dataset.append(img_tensor)
               self.labels.append(img_name[-11:-4])
               self.img_name.append(img_name)
               self.tokenized_labels.append(torch.LongTensor(self.tokenizer.tokenize(img_name[-11:-4])))

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

    def __getitem__(self, idx):
        return self.dataset[idx], self.labels[idx], self.tokenized_labels[idx]

    def get_img_name(self, idx):
        return self.img_name[idx]
```

In [156]:
```
train_folder = 'CCPD2019-dl1/train/'
test_folder = 'CCPD2019-dl1/test/'
```

In [157]:
```
tokenizer = Tokenizer(alphabet)
train_dataset = OCRDataSet(train_folder, tokenizer, transforms)
test_dataset = OCRDataSet(test_folder, tokenizer, transforms)
```

```
100%|██████████| 199980/199980 [01:38<00:00, 2038.84it/s]
100%|██████████| 9999/9999 [00:05<00:00, 1987.42it/s]
```

In [101]:
```
def collate(batch):
    imgs, labels, tok_labels = zip(*batch)
    imgs = torch.stack(imgs, 0)
    tok_pad_labels = torch.nn.utils.rnn.pad_sequence(tok_labels, batch_first=True, padding_value=0)
    return imgs, labels, tok_pad_labels
```

In [102]:
```
train_dataloader = torch.utils.data.DataLoader(train_dataset,
                                               batch_size=128,
                                               shuffle=True,
                                               collate_fn=collate)

test_dataloader = torch.utils.data.DataLoader(test_dataset,
                                              batch_size=128,
                                              shuffle=False,
                                              collate_fn=collate)
```

MODEL

In [103]:
```
class CNN_encoder(nn.Module):
    def __init__(self):
        super().__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.conv2 = nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, stride=1, padding=1)
        self.maxpool2 = nn.MaxPool2d(kernel_size=(1,2), stride=2)

        self.conv3 = nn.Conv2d(in_channels=128, out_channels=256, kernel_size=3, stride=1, padding=1)
        self.batchnorm = nn.BatchNorm2d(256)
        self.maxpool3 = nn.MaxPool2d(kernel_size=(1,2), stride=2)

        self.conv4 = 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.conv2(x)))
        x = self.maxpool2(x)
        x = self.batchnorm(self.relu(self.conv3(x)))
        x = self.maxpool3(x)
        x = self.relu(self.conv4(x))

        return x


class BiLSTM_decoder(nn.Module):
    def __init__(self, input_size, hidden_size, num_layers, dropout=0.2):
        super().__init__()
        self.lstm = nn.LSTM(
            input_size, hidden_size, num_layers,
            dropout=dropout, batch_first=True, bidirectional=True)

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

```
class CRNN(nn.Module):
    def __init__(
        self, number_class_symbols, time_feature_count=16, lstm_hidden=128,
        lstm_len=2,
    ):
        super().__init__()
        self.encoder = CNN_encoder()
        self.avg_pool = nn.AdaptiveAvgPool2d(
            (time_feature_count, time_feature_count))
        self.decoder = BiLSTM_decoder(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.encoder(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.decoder(x)
        x = self.classifier(x)
        x = x.permute(1, 0, 2)
        x = nn.functional.log_softmax(x, dim=2)
        return x
```

Training

In [135]:
```
import math
import torch
import torch.optim

from typing import TYPE_CHECKING, Any, Callable, Optional

if TYPE_CHECKING:
    from torch.optim.optimizer import _params_t
else:
    _params_t = Any

class MADGRAD(torch.optim.Optimizer):
    def __init__(
        self, params: _params_t, lr: float = 1e-2, momentum: float = 0.9,
        weight_decay: float = 0, eps: float = 1e-6, decouple_decay=False,
    ):
        if momentum < 0 or momentum >= 1:
            raise ValueError(f"Momentum {momentum} must be in the range [0,1)")
        if lr <= 0:
            raise ValueError(f"Learning rate {lr} must be positive")
        if weight_decay < 0:
            raise ValueError(f"Weight decay {weight_decay} must be non-negative")
        if eps < 0:
            raise ValueError(f"Eps must be non-negative")

        defaults = dict(lr=lr, eps=eps, momentum=momentum,
                        weight_decay=weight_decay, decouple_decay=decouple_decay)
        super().__init__(params, defaults)

    @property
    def supports_memory_efficient_fp16(self) -> bool:
        return False

    @property
    def supports_flat_params(self) -> bool:
        return True

    def step(self, closure: Optional[Callable[[], float]] = None) -> Optional[float]:
        """Performs a single optimization step.
        Arguments:
            closure (callable, optional): A closure that reevaluates the model
```

```
                and returns the loss.
        """
        loss = None
        if closure is not None:
            loss = closure()

        # step counter must be stored in state to ensure correct behavior under
        # optimizer sharding
        if 'k' not in self.state:
            self.state['k'] = torch.tensor([0], dtype=torch.long)
        k = self.state['k'].item()

        for group in self.param_groups:
            eps = group["eps"]
            lr = group["lr"] + eps
            decay = group["weight_decay"]
            momentum = group["momentum"]
            decouple_decay = group["decouple_decay"]

            ck = 1 - momentum
            lamb = lr * math.pow(k + 1, 0.5)

            for p in group["params"]:
                if p.grad is None:
                    continue
                grad = p.grad.data
                state = self.state[p]

                if "grad_sum_sq" not in state:
                    state["grad_sum_sq"] = torch.zeros_like(p.data).detach()
                    state["s"] = torch.zeros_like(p.data).detach()
                    if momentum != 0:
                        state["x0"] = torch.clone(p.data).detach()

                if momentum != 0.0 and grad.is_sparse:
                    raise RuntimeError("momentum != 0 is not compatible with sparse gradients")

                grad_sum_sq = state["grad_sum_sq"]
                s = state["s"]

                # Apply weight decay
                if decay != 0 and not decouple_decay:
```

```
                if grad.is_sparse:
                    raise RuntimeError("weight_decay option is not compatible with sparse gradients")

                grad.add_(p.data, alpha=decay)

            if grad.is_sparse:
                grad = grad.coalesce()
                grad_val = grad._values()

                p_masked = p.sparse_mask(grad)
                grad_sum_sq_masked = grad_sum_sq.sparse_mask(grad)
                s_masked = s.sparse_mask(grad)

                # Compute x_0 from other known quantities
                rms_masked_vals = grad_sum_sq_masked._values().pow(1 / 3).add_(eps)
                x0_masked_vals = p_masked._values().addcdiv(s_masked._values(), rms_masked_vals, value=1)

                # Dense + sparse op
                grad_sq = grad * grad
                grad_sum_sq.add_(grad_sq, alpha=lamb)
                grad_sum_sq_masked.add_(grad_sq, alpha=lamb)

                rms_masked_vals = grad_sum_sq_masked._values().pow_(1 / 3).add_(eps)

                if eps == 0:
                    rms_masked_vals[rms_masked_vals == 0] = float('inf')

                s.add_(grad, alpha=lamb)
                s_masked._values().add_(grad_val, alpha=lamb)

                # update masked copy of p
                p_kp1_masked_vals = x0_masked_vals.addcdiv(s_masked._values(), rms_masked_vals, value=-1)
                # Copy updated masked p to dense p using an add operation
                p_masked._values().add_(p_kp1_masked_vals, alpha=-1)
                p.data.add_(p_masked, alpha=-1)
            else:
                if momentum == 0:
                    # Compute x_0 from other known quantities
                    rms = grad_sum_sq.pow(1 / 3).add_(eps)
                    x0 = p.data.addcdiv(s, rms, value=1)
                else:
                    x0 = state["x0"]
```

```
                    # Accumulate second moments
                    grad_sum_sq.addcmul_(grad, grad, value=lamb)
                    rms = grad_sum_sq.pow(1 / 3).add_(eps)

                    if eps == 0:
                        rms[rms == 0] = float('inf')

                    # Update s
                    s.data.add_(grad, alpha=lamb)

                    if decay != 0 and decouple_decay:
                        p_old = p.data.clone()

                    # Step
                    if momentum == 0:
                        p.data.copy_(x0.addcdiv(s, rms, value=-1))
                    else:
                        z = x0.addcdiv(s, rms, value=-1)

                        # p is a moving average of z
                        p.data.mul_(1 - ck).add_(z, alpha=ck)

                    if decay != 0 and decouple_decay:
                        p.data.add_(p_old, alpha=-lr*decay)


        self.state['k'] += 1
        return loss
```

In [140]:

```
model = CRNN(tokenizer.get_num_chars())
criterion = torch.nn.CTCLoss(blank=0, reduction='sum', zero_infinity=True)
optimizer = MADGRAD(model.parameters(), lr=4e-5)
scheduler = torch.optim.lr_scheduler.ReduceLROnPlateau(
    optimizer, factor=0.5, patience=2, verbose=True
)
```

In [141]:
```
def train_epoch(model, train_dataloader, optimizer, criterion):
    epoch_loss = 0
    model.train()
    model.to(device)
    for (imgs, labels, tokenized_labels) in train_dataloader:

        b_size = imgs.shape[0]
        imgs = imgs.to(device)
        labels = labels
        tokenized_labels = tokenized_labels.to(device)
        outputs = model(imgs)

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

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

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

        epoch_loss += loss.item()

    return epoch_loss / len(train_dataloader)


def val_epoch(model, test_dataloader):
    epoch_loss = 0
    preds = []
    total_step = len(test_dataloader)
    model.eval()
    model.to(device)
    for i, (imgs, labels, tokenized_labels) in enumerate(test_dataloader):
        with torch.no_grad():
            b_size = imgs.shape[0]
```

```
            imgs = imgs.to(device)
            tokenized_labels = tokenized_labels.to(device)
            outputs = model(imgs)

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

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

    return epoch_loss / total_step, preds
```

In [142]:

```
def output_untokenizer(output):
    output = output.tolist()
    output = tokenizer.untokenize(output)
    return output
```

In [143]:
```
from sklearn.metrics import accuracy_score

n_epoch = 8
y_test = np.array(test_dataset.labels)
y_train = np.array(train_dataset.labels)
for i in tqdm(range(n_epoch)):
    decoded = []
    train_loss = train_epoch(model, train_dataloader, optimizer, criterion)
    test_loss, test_preds = val_epoch(model, test_dataloader)
    _, train_preds = val_epoch(model, train_dataloader)
    test_preds = np.array(list(map(output_untokenizer, test_preds)))
    train_preds = np.array(list(map(output_untokenizer, train_preds)))
    print(f'Epoch: {i + 1}; Test_loss: {test_loss}')
    print(f'Test_accuracy: {accuracy_score(y_test, test_preds)}, Test_CER: {char_error_rate(y_test, test_preds)} ')
    scheduler.step(test_loss)
```

```
  0%|          | 0/8 [00:00<?, ?it/s]

Epoch: 1; Test_loss: 0.17336191133230547

 12%|█▎        | 1/8 [00:57<06:41, 57.35s/it]

Test_accuracy: 0.8038803880388039, Test_CER: 0.038601361215114594
Epoch: 2; Test_loss: 0.07018297578243515

 25%|██▌       | 2/8 [01:56<05:49, 58.21s/it]

Test_accuracy: 0.9266926692669267, Test_CER: 0.01418916042894125
Epoch: 3; Test_loss: 0.059420637014215884

 38%|███▊      | 3/8 [02:52<04:47, 57.42s/it]

Test_accuracy: 0.9438943894389439, Test_CER: 0.010730717331171036
Epoch: 4; Test_loss: 0.07773811828722305

 50%|█████     | 4/8 [03:48<03:47, 56.78s/it]

Test_accuracy: 0.9283928392839284, Test_CER: 0.014091351069509983
Epoch: 5; Test_loss: 0.058232629926627665

 62%|██████▎   | 5/8 [04:45<02:50, 56.91s/it]

Test_accuracy: 0.9481948194819482, Test_CER: 0.009708737954497337
```

```
Epoch: 6; Test_loss: 0.05124230934690118

 75%|███████▌  | 6/8 [05:43<01:54, 57.10s/it]

Test_accuracy: 0.9521952195219522, Test_CER: 0.009102600626647472
Epoch: 7; Test_loss: 0.039478539975501506

 88%|████████▊ | 7/8 [06:40<00:57, 57.37s/it]

Test_accuracy: 0.9617961796179618, Test_CER: 0.007258698344230652
Epoch: 8; Test_loss: 0.04685749313307785

100%|██████████| 8/8 [07:37<00:00, 57.20s/it]

Test_accuracy: 0.9553955395539554, Test_CER: 0.008060482330620289
```

Calculate metrics on Test Dataset

Accuracy ont Test

In [144]:
```
accuracy_score(y_test, test_preds)
```

Out[144]:
```
0.9553955395539554
```

CER

In [145]:
```
char_error_rate(y_test, test_preds).item()
```

Out[145]:
```
0.008060482330620289
```

Check on bad samples

In [158]:
```
cers = []
for i in range(len(y_test)):
    cer = char_error_rate(y_test[i], test_preds[i]).item()
    cers.append((i, cer))
cers = sorted(cers, key=lambda x: x[1], reverse=True)
```

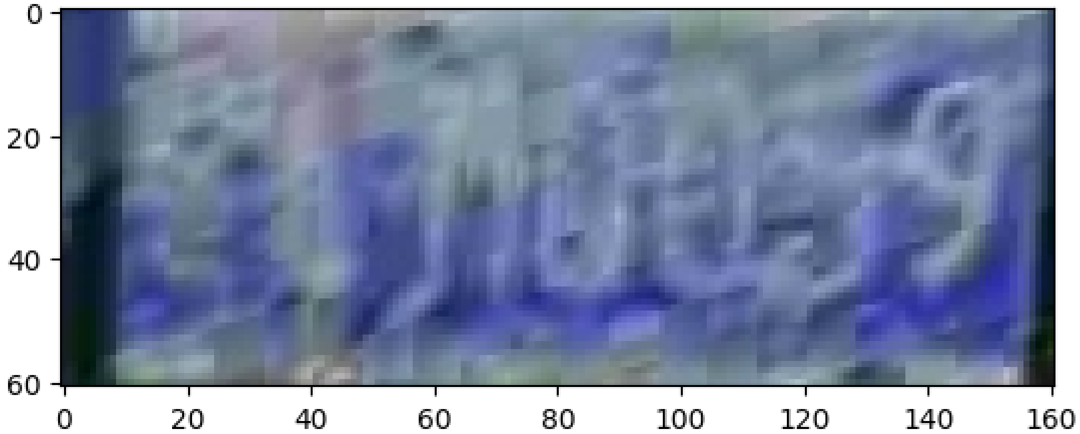
In [159]:
```
cers[0][0]
```

Out[159]:
```
1684
```

In [162]:
```
bad_imgs = []
for i in range(10):
    img_name = test_dataset.get_img_name(cers[i][0])
    img = cv2.imread(os.path.join(test_folder, img_name))
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    bad_imgs.append(img)
```

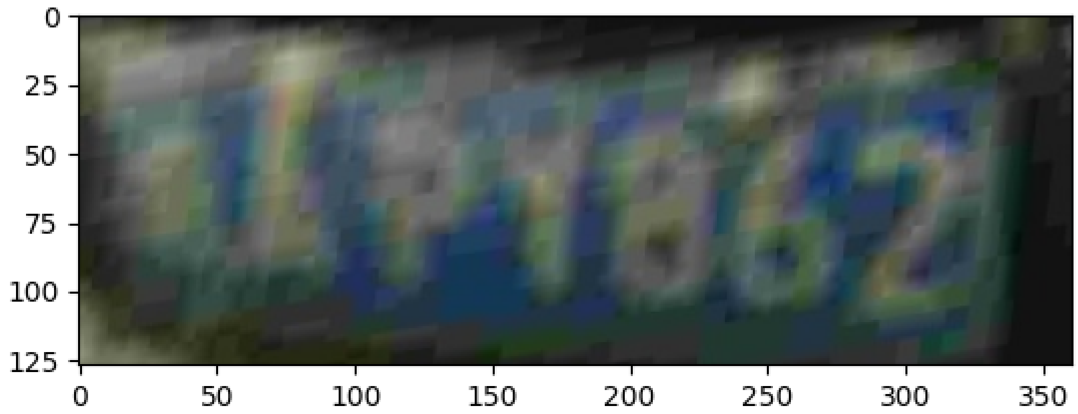
In [163]:
```
plt.imshow(bad_imgs[0])
```

Out[163]:
```
<matplotlib.image.AxesImage at 0x7fae20266560>
```



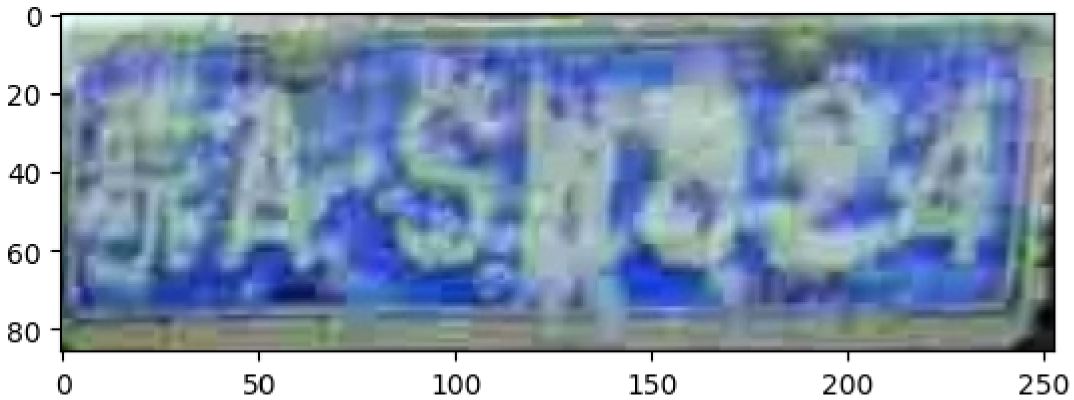
In [164]:
```
plt.imshow(bad_imgs[1])
```

Out[164]:
```
<matplotlib.image.AxesImage at 0x7fae202af6a0>
```



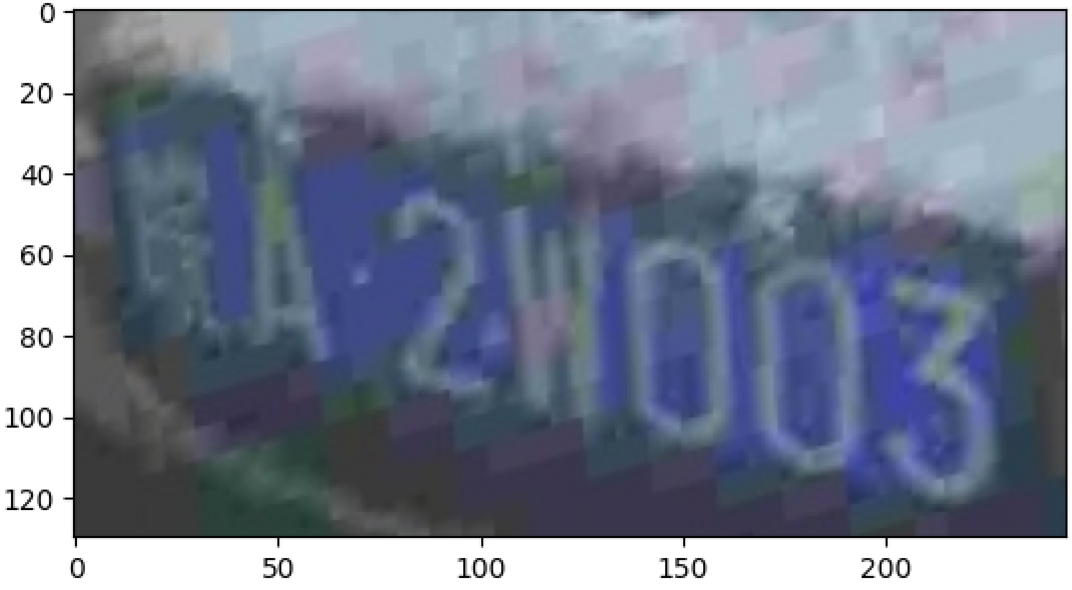
In [165]:
```
plt.imshow(bad_imgs[2])
```

Out[165]:
```
<matplotlib.image.AxesImage at 0x7fae2012dc30>
```



In [166]:
```
plt.imshow(bad_imgs[3])
```

Out[166]:
```
<matplotlib.image.AxesImage at 0x7fae201924d0>
```



In [ ]:

Results and Summary

1. Общие наблюдения и результаты: Данный способ решения хорошо справляется с задачей OCR, модель себя показала плохо на семплах, которые имеют плохое качество изображения, имеют блюр, засвечивания
2. Недостатки решения Тут стоит отметить, что модель может ошибаться на семплах, где все не так плохо с качеством, но текст находится под углом и мы это не учитываем
3. Способы улучшения 1) Аугментации, с небольшим поворотом текста, тк модель может ошибаться на семплах, где текст под углом. Аугментации с блюром, контрастностью 2) Тюнинг параметров модели 3) Попробовать другие Encoder модели, взять свертку глубже

или же попробовать Visual Tranformer 4) Попробовать другие Decoder модели 5) Возможно стоит попробовать попытасться улучшить качество исходных изображений с помощью предобученного Super Resolution GAN'a и уже на них тренировать нашу модель

In [ ]:

```
```