РОССИЙСКИЙ УНИВЕРСИТЕТ ДРУЖБЫ НАРОДОВ

Факультет физико-математических и естественных наук

Кафедра математического моделирования и искусственного интеллекта

ОТЧЕТ ПО КОНТРОЛЬНОЙ РАБОТЕ № 8

Дисциплина: Методы машинного обучения

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Группа: НКНбд-01-21

Москва 2024

Вариант 4

1. Набор данных stl10 с изменением разрешения до 72x72
2. Классы с метками 1,3,5,7,9
3. Требования к архитектуре сети CNN:

   Последовательный API с методом add() при создании

   Функция потерь: категориальная кросс-энтропия

   Кол-во сверточных слоев 5

   Количество фильтров в сверточных слоях 8

   Размеры фильтра 5x5

   Использование слоев dropout
4. Требования к архитектуре сети трансформер:

Функция потерь: разреженная категориальная кросс-энтропия

6. Показатель качества многоклассовой классификации:

максимальная полнота классов, где полнота (recall) класса равна доле правильных предсказаний для всех точек, принадлежащих этому классу.

Решение:

1. Загрузите заданный в индивидуальном задании набор данных с изображениями из Tensorflow Datasets с разбиением на обучающую, валидационную и тестовую выборки. Если при дальнейшей работе с данными возникнет нехватка вычислительных ресурсов, то разрешение изображений можно уменьшить.

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import tensorflow as tf
import tensorflow_datasets as tfds
from PIL import Image, ImageOps
import keras
from keras import layers, models, losses, callbacks
from keras import ops

import json
import re
import string
from IPython.display import display, HTML
```

```
ds = tfds.load("stl10", split=['train[:80%]', 'train[80%:90%]', 'train[90%:]'])
df_train = tfds.as_dataframe(ds[0])
df_test = tfds.as_dataframe(ds[1])
df_val = tfds.as_dataframe(ds[2])
df_train.head(3)
```

	image	label
0	[[[136, 144, 153], [125, 127, 136], [125, 126,...	1
1	[[[70, 132, 186], [81, 139, 189], [143, 176, 2...	0
2	[[[0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], ...	8

Далее: Посмотреть рекомендованные графики

```
df_train.shape, df_test.shape, df_val.shape
```

```
((4000, 2), (500, 2), (500, 2))
```

2. Оставьте в наборе изображения, указанных в индивидуальном задании, и визуализируйте по одному изображению из каждого класса, подписывая изображение меткой класса.

Классы с метками 1,3,5,7,9

```
x = df_train[df_train['label'] == 1]
y = df_train[df_train['label'] == 3]
z = df_train[df_train['label'] == 5]
a = df_train[df_train['label'] == 7]
b = df_train[df_train['label'] == 9]
x['label'] = 0
y['label'] = 1
z['label'] = 2
a['label'] = 3
b['label'] = 4

df_tr1 = pd.concat([x, y, z, a, b])
Y_tr1 = df_tr1['label']
df_tr1 = df_tr1['image']

x = df_test[df_test['label'] == 1]
y = df_test[df_test['label'] == 3]
z = df_test[df_test['label'] == 5]
a = df_test[df_test['label'] == 7]
b = df_test[df_test['label'] == 9]
x['label'] = 0
y['label'] = 1
z['label'] = 2
a['label'] = 3
b['label'] = 4

df_te1 = pd.concat([x, y, z, a, b])
Y_te1 = df_te1['label']
df_te1 = df_te1['image']

x = df_val[df_val['label'] == 1]
y = df_val[df_val['label'] == 3]
z = df_val[df_val['label'] == 5]
a = df_val[df_val['label'] == 7]
b = df_val[df_val['label'] == 9]
x['label'] = 0
y['label'] = 1
z['label'] = 2
a['label'] = 3
b['label'] = 4

df_val1 = pd.concat([x, y, z, a, b])
Y_val1 = df_val1['label']
df_val1 = df_val1['image']


Y_tr1.value_counts()
```

```
  a['label'] = 3
<ipython-input-106-6025acdadeee>:25: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gui
  b['label'] = 4
<ipython-input-106-6025acdadeee>:36: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gui
  x['label'] = 0
<ipython-input-106-6025acdadeee>:37: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gui
  y['label'] = 1
<ipython-input-106-6025acdadeee>:38: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gui
  z['label'] = 2
<ipython-input-106-6025acdadeee>:39: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gui
  a['label'] = 3
<ipython-input-106-6025acdadeee>:40: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gui
  b['label'] = 4
label
4    400
2    399
0    394
1    392
3    391
Name: count, dtype: int64
```

```
Y_tr2 = list(Y_tr1)
Y_te2 = list(Y_te1)
Y_val2 = list(Y_val1)
for i in range(len(Y_tr2)):
    tmp = [0]*5
    tmp[Y_tr2[i]] = 1
    Y_tr2[i] = tmp
for i in range(len(Y_te2)):
    tmp = [0]*5
    tmp[Y_te2[i]] = 1
    Y_te2[i] = tmp
for i in range(len(Y_val2)):
    tmp = [0]*5
    tmp[Y_val2[i]] = 1
    Y_val2[i] = tmp
```

```
Y_tr1 = np.array(Y_tr1)
Y_tr2 = np.array(Y_tr2)
Y_te1 = np.array(Y_te1)
Y_te2 = np.array(Y_te2)
Y_val1 = np.array(Y_val1)
Y_val2 = np.array(Y_val2)
```

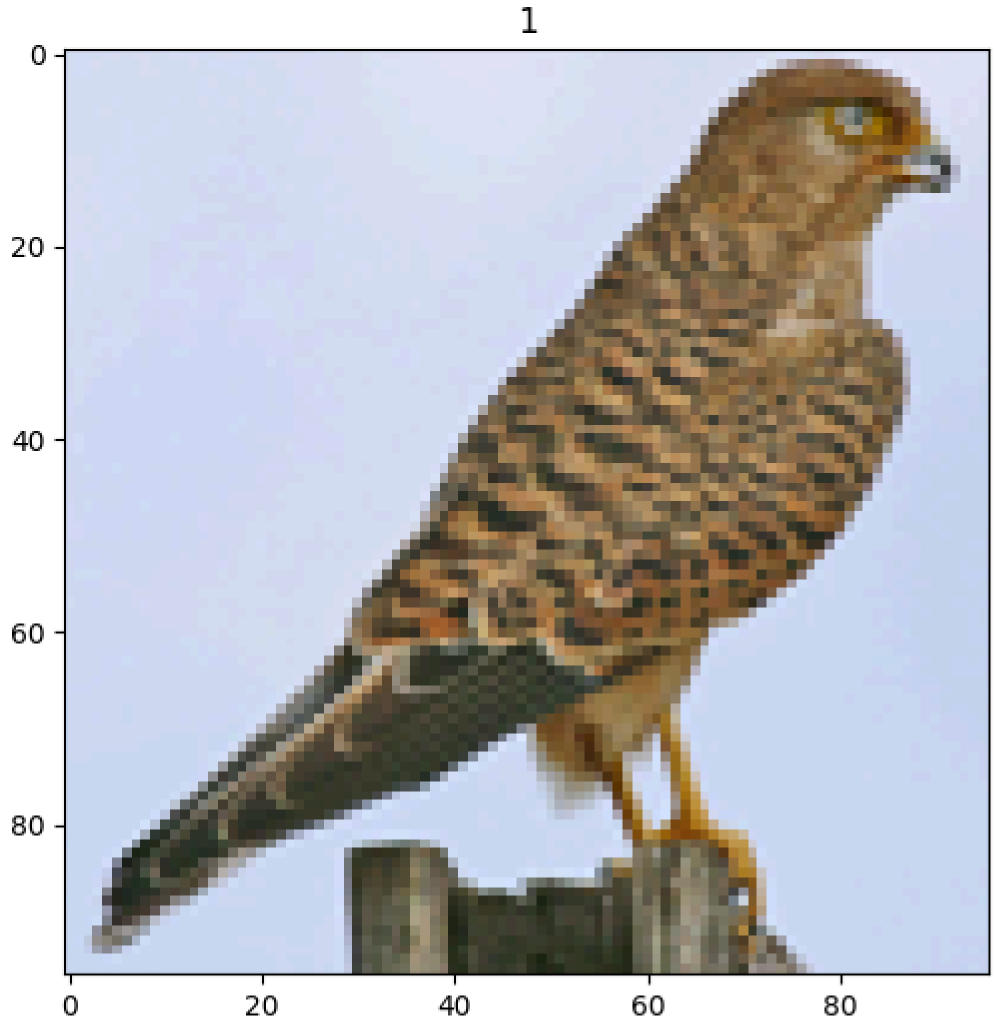
```
df_tr1.shape
```

```
(1976,)
```

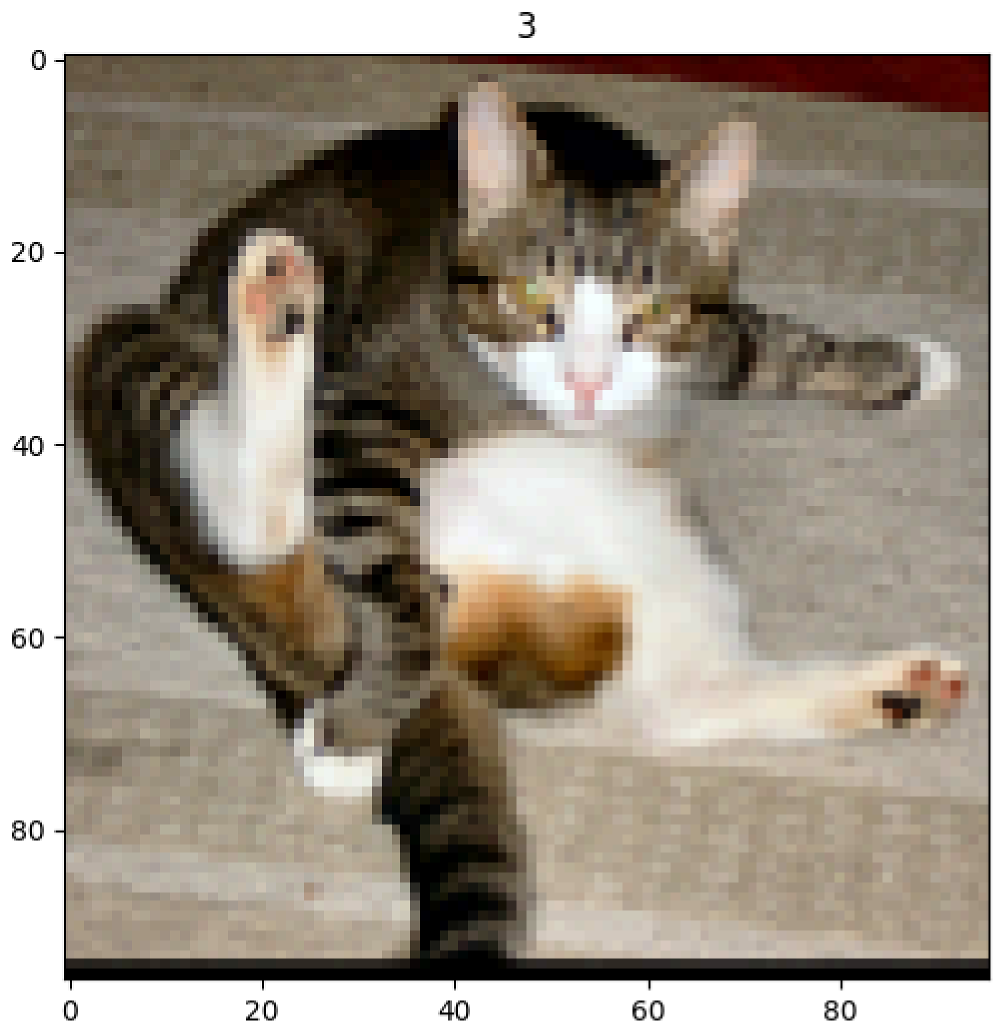
```
df_tr = np.zeros(shape=(df_tr1.shape[0],72,72,3), dtype=np.float32)
df_te  = np.zeros(shape=(df_te1.shape[0],72,72,3), dtype=np.float32)
df_va  = np.zeros(shape=(df_val1.shape[0],72,72,3), dtype=np.float32)

for i in range(len(df_tr1)):
    df_tr[i,:,:,:] = np.array(Image.fromarray(df_tr1.iloc[i]).resize((72,72)))
for i in range(len(df_te1)):
    df_te[i,:,:,:] = np.array(Image.fromarray(df_te1.iloc[i]).resize((72,72)))
for i in range(len(df_val1)):
    df_va[i,:,:,:] = np.array(Image.fromarray(df_val1.iloc[i]).resize((72,72)))

df_tr /= 255
df_te  /= 255
df_va /= 255
```

```
def plot_image(df, i):
    img = df['image'][i]
    plt.figure(figsize=(6, 6))
    plt.imshow(img);
    plt.title(df['label'][i])
    plt.show()
```

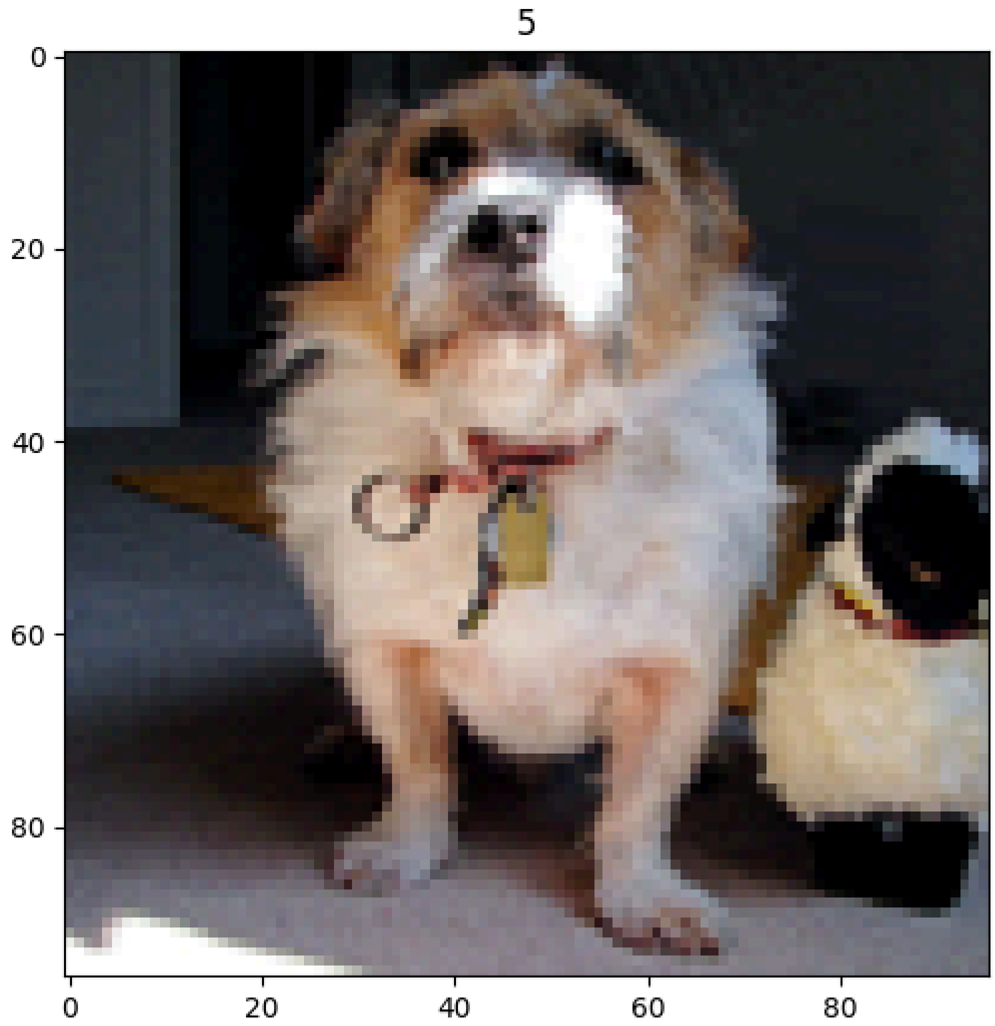
```
plot_image(df_train, 50)
```



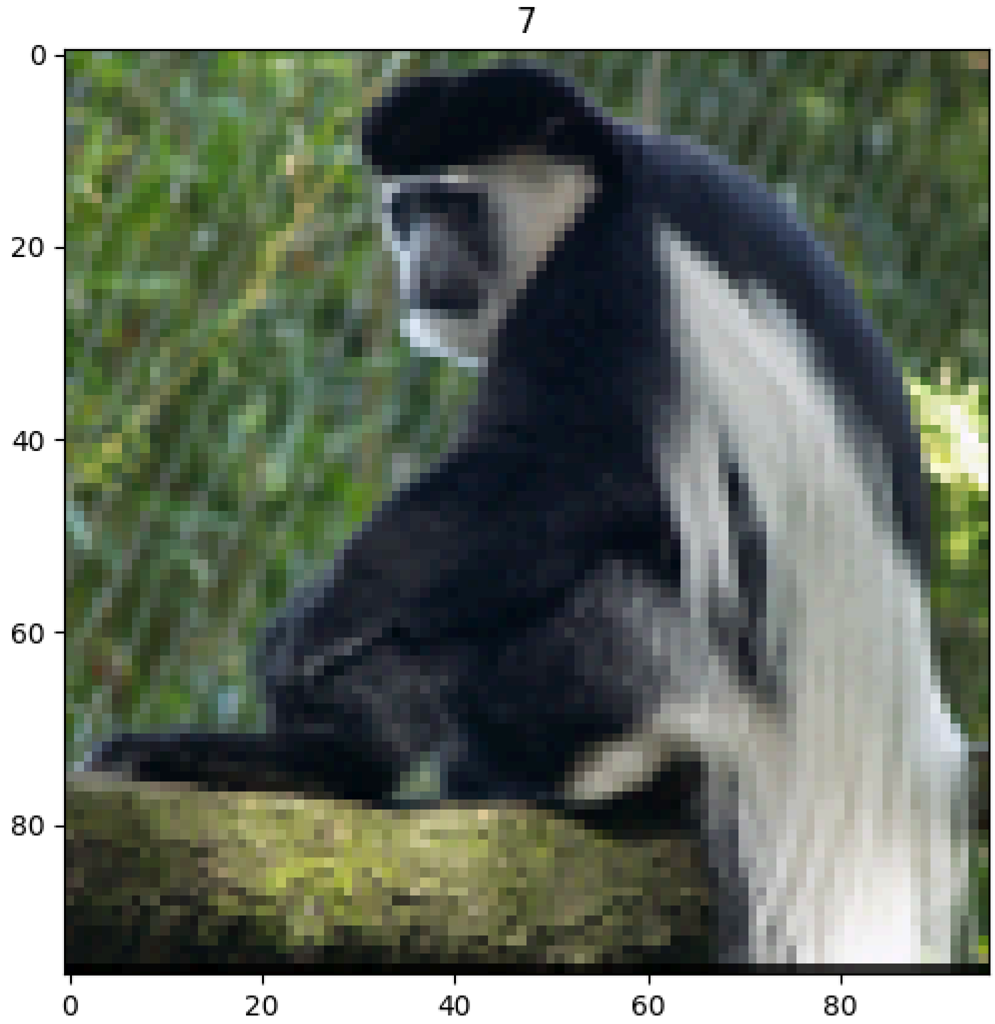

```
plot_image(df_train, 3)
```



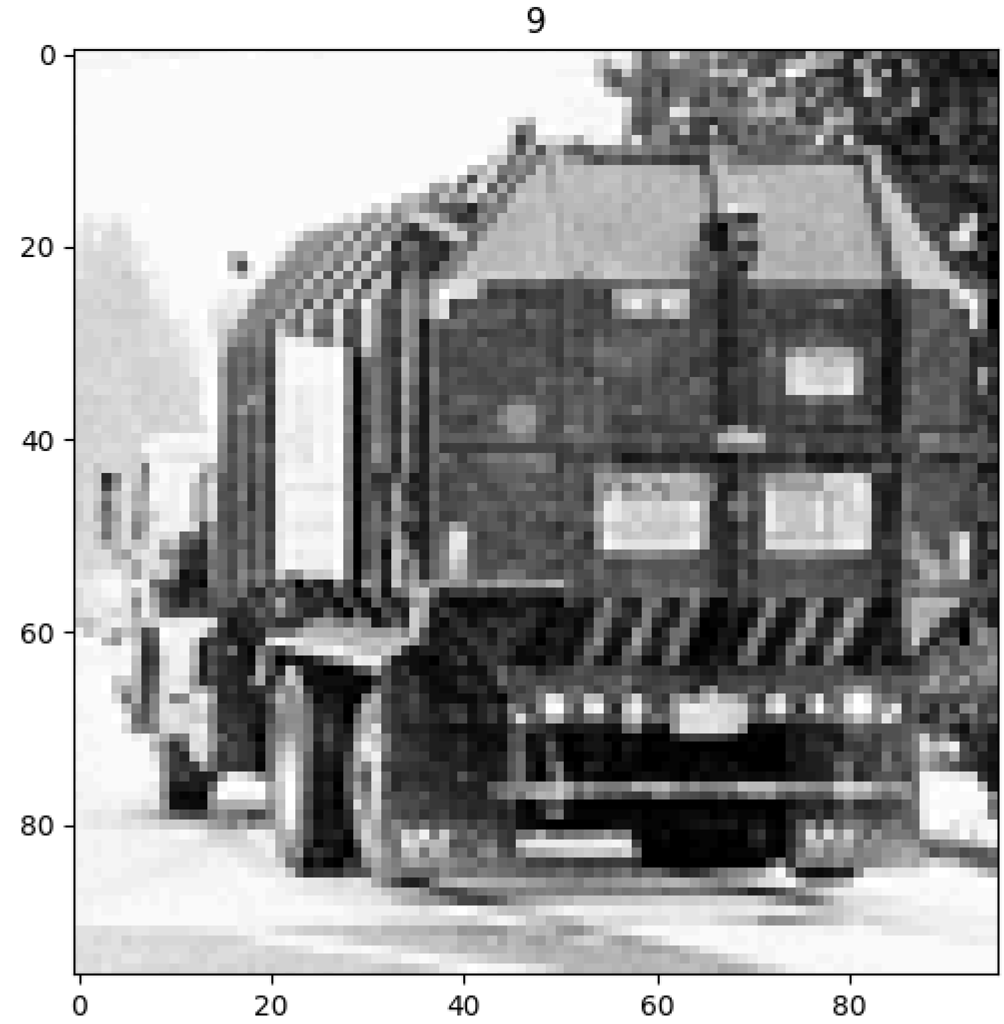

```
plot_image(df_train, 19)
```




```
plot_image(df_train, 17)
```




```
plot_image(df_train, 3969)
```



3. Постройте нейронные сети различных архитектур (MLP, CNN, RNN, трансформер) для задачи многоклассовой классификации изображений (архитектуры и требования к сетям указаны в индивидуальном задании), используя функции потерь, указанные в индивидуальном задании. Подберите такие параметры, как функции активации, оптимизатор, начальная скорость обучения, размер мини-пакета и др. самостоятельно, обеспечивая обучение нейронных сетей. Обучайте нейронные сети с использованием валидационной выборки, сформированной в п. 1. Останавливайте переобучение нейронных сетей в случае роста потерь на валидационной выборке на нескольких эпохах обучения подряд.

Требования к архитектуре сети CNN:

Последовательный API с методом add() при создании

Функция потерь: категориальная кросс-энтропия

Кол-во сверточных слоев 5

Количество фильтров в сверточных слоях 8

Размеры фильтра 5x5

Использование слоев dropout

```
from tensorflow.keras import models
from tensorflow.keras import layers
from keras.regularizers import l1_l2
```

```
cnn = tf.keras.Sequential()
cnn.add(tf.keras.Input(shape=(72, 72, 3)))
cnn.add(tf.keras.layers.Conv2D(filters=8, kernel_size=(5, 5), activation='selu', kernel_regularizer
cnn.add(tf.keras.layers.MaxPool2D(pool_size=(2, 2), padding='same'))
cnn.add(tf.keras.layers.Dropout(0.2))
cnn.add(tf.keras.layers.Conv2D(filters=8, kernel_size=(5, 5), activation='selu', kernel_regularizer
cnn.add(tf.keras.layers.MaxPool2D(pool_size=(2, 2), padding='same'))
cnn.add(tf.keras.layers.Dropout(0.2))
cnn.add(tf.keras.layers.Conv2D(filters=8, kernel_size=(5, 5), activation='selu', kernel_regularizer
cnn.add(tf.keras.layers.MaxPool2D(pool_size=(2, 2), padding='same'))
cnn.add(tf.keras.layers.Dropout(0.2))
cnn.add(tf.keras.layers.Conv2D(filters=8, kernel_size=(5, 5), activation='selu', kernel_regularizer
cnn.add(tf.keras.layers.MaxPool2D(pool_size=(2, 2), padding='same'))
cnn.add(tf.keras.layers.Dropout(0.2))
cnn.add(tf.keras.layers.Conv2D(filters=8, kernel_size=(5, 5), activation='selu', kernel_regularizer
cnn.add(tf.keras.layers.MaxPool2D(pool_size=(2, 2), padding='same'))
cnn.add(tf.keras.layers.Flatten())
cnn.add(tf.keras.layers.Dense(5, activation='softmax'))
```

```
cnn.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.001),
            loss=tf.keras.losses.CategoricalCrossentropy(),
            metrics=[tf.keras.metrics.CategoricalAccuracy(name='accuracy')])
```

```
history1 = cnn.fit(df_tr,
                  Y_tr2,
                  epochs=50,
                  validation_data=(df_va, Y_val2),
                  callbacks=[tf.keras.callbacks.EarlyStopping(monitor='val_loss', patience=3)],
                  batch_size=16
                  )
```

```
Epoch 1/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 16s 106ms/step - accuracy: 0.2289 - loss: 1.9898 - val_accuracy: 0
Epoch 2/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 13s 104ms/step - accuracy: 0.3259 - loss: 1.7757 - val_accuracy: 0
Epoch 3/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 20s 103ms/step - accuracy: 0.3854 - loss: 1.6209 - val_accuracy: 0
Epoch 4/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 13s 102ms/step - accuracy: 0.4092 - loss: 1.5401 - val_accuracy: 0
Epoch 5/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 22s 115ms/step - accuracy: 0.4337 - loss: 1.5090 - val_accuracy: 0
Epoch 6/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 19s 102ms/step - accuracy: 0.4618 - loss: 1.4408 - val_accuracy: 0
Epoch 7/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 13s 105ms/step - accuracy: 0.4660 - loss: 1.4316 - val_accuracy: 0
Epoch 8/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 20s 99ms/step - accuracy: 0.4871 - loss: 1.3741 - val_accuracy: 0
Epoch 9/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 13s 102ms/step - accuracy: 0.4802 - loss: 1.3479 - val_accuracy: 0
Epoch 10/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 21s 102ms/step - accuracy: 0.5158 - loss: 1.3547 - val_accuracy: 0
Epoch 11/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 22s 115ms/step - accuracy: 0.5333 - loss: 1.2755 - val_accuracy: 0
Epoch 12/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 19s 102ms/step - accuracy: 0.5334 - loss: 1.2901 - val_accuracy: 0
```

```
Epoch 13/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 20s 102ms/step - accuracy: 0.5400 - loss: 1.2633 - val_accuracy: 0
Epoch 14/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 12s 100ms/step - accuracy: 0.5327 - loss: 1.2203 - val_accuracy: 0
Epoch 15/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 21s 103ms/step - accuracy: 0.5540 - loss: 1.2310 - val_accuracy: 0
Epoch 16/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 20s 101ms/step - accuracy: 0.5402 - loss: 1.2006 - val_accuracy: 0
```

Требования к архитектуре сети трансформер:

Функция потерь: разреженная категориальная кросс-энтропия

```
learning_rate = 0.001
weight_decay = 0.0001
batch_size = 256
num_epochs = 10  # For real training, use num_epochs=100. 10 is a test value
image_size = 72  # We'll resize input images to this size
patch_size = 6  # Size of the patches to be extract from the input images
num_patches = (image_size // patch_size) ** 2
projection_dim = 64
num_heads = 4
transformer_units = [
    projection_dim * 2,
    projection_dim,
]  # Size of the transformer layers
transformer_layers = 8
mlp_head_units = [
    2048,
    1024,
]  # Size of the dense layers of the final classifier
num_classes = 10
input_shape = (72, 72, 3)
```

```
data_augmentation = tf.keras.Sequential(
    [
        tf.keras.layers.Normalization(),
        tf.keras.layers.Resizing(image_size, image_size),
        tf.keras.layers.RandomFlip("horizontal"),
        tf.keras.layers.RandomRotation(factor=0.02),
        tf.keras.layers.RandomZoom(height_factor=0.2, width_factor=0.2),
    ],
    name="data_augmentation",
)
# Compute the mean and the variance of the training data for normalization.
data_augmentation.layers[0].adapt(df_tr)
```

```
def mlp(x, hidden_units, dropout_rate):
    for units in hidden_units:
        x = layers.Dense(units, activation=keras.activations.gelu)(x)
        x = layers.Dropout(dropout_rate)(x)
    return x
```

```
class Patches( tf.keras.layers.Layer):
    def __init__(self, patch_size):
        super().__init__()
        self.patch_size = patch_size

    def call(self, images):
        input_shape = ops.shape(images)
        batch_size = input_shape[0]
        height = input_shape[1]
        width = input_shape[2]
        channels = input_shape[3]
        num_patches_h = height // self.patch_size
        num_patches_w = width // self.patch_size
        patches = keras.ops.image.extract_patches(images, size=self.patch_size)
        patches = ops.reshape(
            patches,
            (
                batch_size,
                num_patches_h * num_patches_w,
                self.patch_size * self.patch_size * channels,
            ),
        )
        return patches

    def get_config(self):
        config = super().get_config()
        config.update({"patch_size": self.patch_size})
        return config
```

```
plt.figure(figsize=(4, 4))
image = df_tr[np.random.choice(range(df_tr.shape[0]))]
plt.imshow(image)
plt.axis("off")

resized_image = ops.image.resize(
    ops.convert_to_tensor([image]), size=(image_size, image_size)
)
patches = Patches(patch_size)(resized_image)
print(f"Image size: {image_size} X {image_size}")
print(f"Patch size: {patch_size} X {patch_size}")
print(f"Patches per image: {patches.shape[1]}")
print(f"Elements per patch: {patches.shape[-1]}")

n = int(np.sqrt(patches.shape[1]))
plt.figure(figsize=(4, 4))
for i, patch in enumerate(patches[0]):
    ax = plt.subplot(n, n, i + 1)
    patch_img = ops.reshape(patch, (patch_size, patch_size, 3))
    plt.imshow(ops.convert_to_numpy(patch_img))
    plt.axis("off")
```

```
Image size: 72 X 72
Patch size: 6 X 6
Patches per image: 144
Elements per patch: 108
```

```
class PatchEncoder(layers.Layer):
    def __init__(self, num_patches, projection_dim):
        super().__init__()
        self.num_patches = num_patches
        self.projection = layers.Dense(units=projection_dim)
        self.position_embedding = layers.Embedding(
            input_dim=num_patches, output_dim=projection_dim
        )

    def call(self, patch):
        positions = ops.expand_dims(
            ops.arange(start=0, stop=self.num_patches, step=1), axis=0
        )
        projected_patches = self.projection(patch)
        encoded = projected_patches + self.position_embedding(positions)
        return encoded

    def get_config(self):
        config = super().get_config()
        config.update({"num_patches": self.num_patches})
        return config
```

```
def create_vit_classifier():
    inputs = keras.Input(shape=input_shape)
    # Augment data.
    augmented = data_augmentation(inputs)
    # Create patches.
    patches = Patches(patch_size)(augmented)
    # Encode patches.
    encoded_patches = PatchEncoder(num_patches, projection_dim)(patches)

    # Create multiple layers of the Transformer block.
    for _ in range(transformer_layers):
        # Layer normalization 1.
        x1 = layers.LayerNormalization(epsilon=1e-6)(encoded_patches)
        # Create a multi-head attention layer.
        attention_output = layers.MultiHeadAttention(
            num_heads=num_heads, key_dim=projection_dim, dropout=0.1
        )(x1, x1)
        # Skip connection 1.
        x2 = layers.Add()([attention_output, encoded_patches])
        # Layer normalization 2.
        x3 = layers.LayerNormalization(epsilon=1e-6)(x2)
        # MLP.
        x3 = mlp(x3, hidden_units=transformer_units, dropout_rate=0.1)
        # Skip connection 2.
        encoded_patches = layers.Add()([x3, x2])

    # Create a [batch_size, projection_dim] tensor.
    representation = layers.LayerNormalization(epsilon=1e-6)(encoded_patches)
    representation = layers.Flatten()(representation)
    representation = layers.Dropout(0.5)(representation)
    # Add MLP.
    features = mlp(representation, hidden_units=mlp_head_units, dropout_rate=0.5)
    # Classify outputs.
    logits = layers.Dense(num_classes)(features)
    # Create the Keras model.
    model = keras.Model(inputs=inputs, outputs=logits)
    return model
```

```
ViT = create_vit_classifier()
```

```
optimizer = keras.optimizers.AdamW(
    learning_rate=learning_rate, weight_decay=weight_decay
)

ViT.compile(
    optimizer=optimizer,
    loss=keras.losses.SparseCategoricalCrossentropy(from_logits=True),
    metrics=[
        keras.metrics.SparseCategoricalAccuracy(name="accuracy"),
        keras.metrics.SparseTopKCategoricalAccuracy(5, name="top-5-accuracy"),
    ],
)
```

```
checkpoint_filepath = "/content/drive/MyDrive/ViT_checkpoint.weights.h5"
checkpoint_callback = keras.callbacks.ModelCheckpoint(
    checkpoint_filepath,
    monitor="val_accuracy",
    save_best_only=True,
    save_weights_only=True,
)
```

```
history = ViT.fit(
    x=df_tr,
    y=Y_tr1,
    batch_size=batch_size,
    epochs=num_epochs,
    validation_split=0.1,
    callbacks=[checkpoint_callback],
)
```

```
Epoch 1/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 188s 21s/step - accuracy: 0.1859 - loss: 5.7531 - top-5-accuracy: 0.8
Epoch 2/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 182s 18s/step - accuracy: 0.2566 - loss: 2.7459 - top-5-accuracy: 0.9
Epoch 3/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 131s 19s/step - accuracy: 0.2831 - loss: 1.7437 - top-5-accuracy: 0.9
Epoch 4/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 139s 18s/step - accuracy: 0.3420 - loss: 1.5706 - top-5-accuracy: 0.9
Epoch 5/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 141s 20s/step - accuracy: 0.3435 - loss: 1.5725 - top-5-accuracy: 0.9
Epoch 6/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 137s 20s/step - accuracy: 0.3481 - loss: 1.5149 - top-5-accuracy: 0.9
Epoch 7/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 143s 20s/step - accuracy: 0.3815 - loss: 1.4893 - top-5-accuracy: 0.9
Epoch 8/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 134s 18s/step - accuracy: 0.3995 - loss: 1.4288 - top-5-accuracy: 0.9
Epoch 9/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 150s 20s/step - accuracy: 0.3818 - loss: 1.4212 - top-5-accuracy: 1.0
Epoch 10/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 135s 19s/step - accuracy: 0.4149 - loss: 1.3691 - top-5-accuracy: 0.9
```

```
ViT.load_weights(checkpoint_filepath)
```

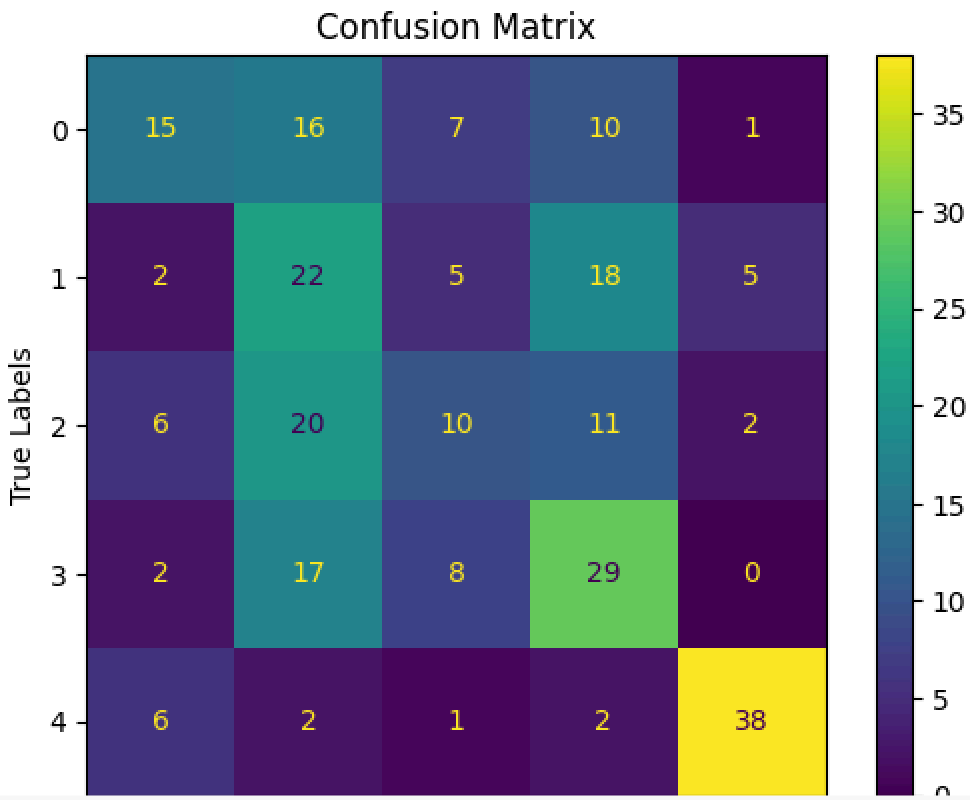
```
_, accuracy, top_5_accuracy = ViT.evaluate(df_te, Y_te1)
print(f"Test accuracy: {round(accuracy * 100, 2)}%")
```

```
8/8 ━━━━━━━━━━━━━━━━━━━━ 5s 557ms/step - accuracy: 0.4287 - loss: 1.3495 - top-5-accuracy: 1.0
Test accuracy: 42.75%
```

4. Вычислите и выведите в отчете матрицы ошибок нейронных сетей (tf.math.confusion_matrix) для обучающей и тестовой выборок.

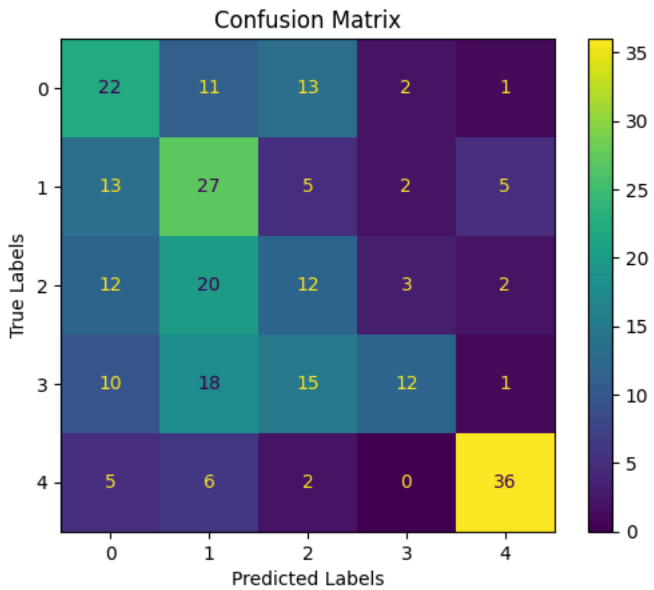
```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

y_pred = cnn.predict(df_te)

y_pred_labels = np.argmax(y_pred, axis=1)

y_true_labels = np.argmax(Y_te2, axis=1)

cm = confusion_matrix(y_true_labels, y_pred_labels)

disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=range(5))
disp.plot()
plt.title('Confusion Matrix')
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```

```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 45ms/step
```



```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

y_pred = ViT.predict(df_te)

y_pred_labels = np.argmax(y_pred, axis=1)

y_true_labels = np.argmax(Y_te2, axis=1)

cm = confusion_matrix(y_true_labels, y_pred_labels)

disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=range(5))
disp.plot()
plt.title('Confusion Matrix')
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```

```
8/8 ━━━━━━━━━━━━━━━━━━━━ 6s 678ms/step
```



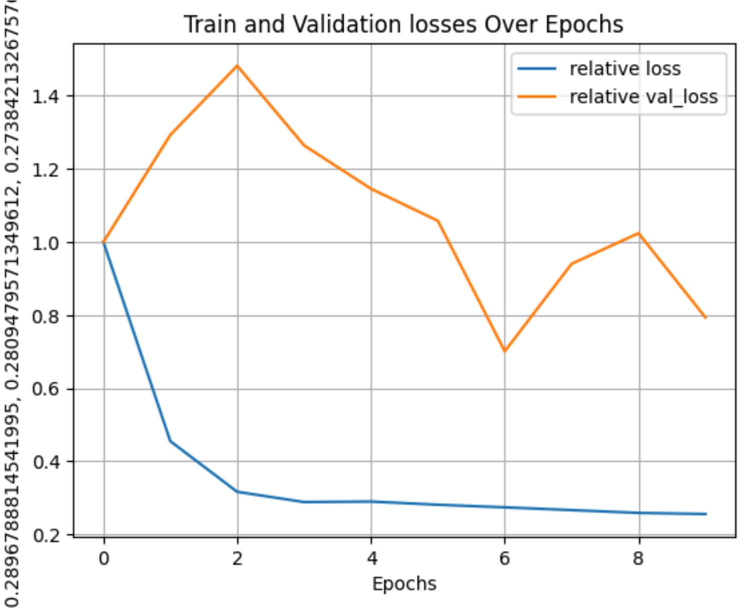
5. Визуализируйте кривые обучения построенных моделей для показателей потерь на обучающей и валидационной выборках на одном рисунке в зависимости от эпохи обучения, подписывая оси и рисунок и создавая легенду. Используйте для визуализации относительные потери (потери, деленные на начальные потери на первой эпохе).

Transformer

```
losses = history.history['loss']
loss0 = history.history['loss'][0]

relative_losses = [loss / loss0 for loss in losses]
```

```
val_losses = history.history['val_loss']
val_loss0 = history.history['val_loss'][0]
relative_val_losses = [val_loss /val_loss0 for val_loss in val_losses]
```

```
plt.plot(relative_losses, label='relative loss')
plt.plot(relative_val_losses, label="relative val_loss")
plt.xlabel("Epochs")
plt.ylabel(relative_losses)
plt.title("Train and Validation losses Over Epochs")
plt.legend()
plt.grid()
plt.show()
```

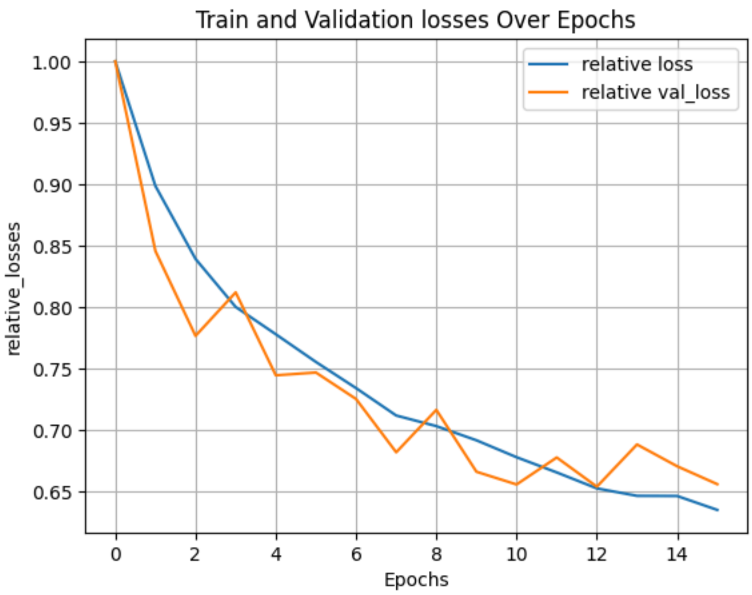


CNN

```
losses = history1.history['loss']
loss0 = history1.history['loss'][0]

relative_losses = [loss / loss0 for loss in losses]
```

```
val_losses = history1.history['val_loss']
val_loss0 = history1.history['val_loss'][0]
relative_val_losses = [val_loss /val_loss0 for val_loss in val_losses]
```

```
plt.plot(relative_losses, label='relative loss')
plt.plot(relative_val_losses, label="relative val_loss")
plt.xlabel("Epochs")
plt.ylabel("relative_losses")
plt.title("Train and Validation losses Over Epochs")
plt.legend()
plt.grid()
plt.show()
```



6. Оцените качество многоклассовой классификации нейронными сетями на тестовой выборке при помощи показателя качества, указанного в индивидуальном задании, и выведите название нейронной сети с лучшим качеством.

Показатель качества многоклассовой классификации: максимальная полнота классов, где полнота (recall) класса равна доле правильных предсказаний для всех точек, принадлежащих этому классу.

```
X1 = cnn.predict(df_te)
X2 = ViT.predict(df_te)
```

```
8/8 ━━━━━━━━━━━━━━━━━━━━ 1s 110ms/step
8/8 ━━━━━━━━━━━━━━━━━━━━ 11s 1s/step
```

```
for i in range(len(X1)):
    for j in range(len(X1[i])):
        if X1[i][j] == min(X1[i]):
            X1[i][j] = 1
        else:
            X1[i][j] = 0
for i in range(len(X2)):
    for j in range(len(X2[i])):
        if X2[i][j] == min(X2[i]):
            X2[i][j] = 1
        else:
            X2[i][j] = 0
```

```
X11 = np.array(X1, dtype=np.int32)
X22 = np.array(X2, dtype=np.int32)
```

```
X22_re = np.resize(X22, (255, 5))
```

```
m1 = tf.keras.metrics.Recall()
m2 = tf.keras.metrics.Recall()

m1.update_state(X11, Y_te2)
m2.update_state(X22_re, Y_te2)
```

```
m1.result().numpy(), m2.result().numpy()
```

```
(0.2, 0.221843)
```