

МОСКОВСКИЙ ГОСУДАРСТВЕННЫЙ ТЕХНИЧЕСКИЙ УНИВЕРСИТЕТ  
им. Н.Э. Баумана

Кафедра «Систем обработки информации и управления»

ОТЧЕТ

**Домашняя работа №1, 2**  
по курсу «Проектирование интеллектуальных систем»

ИСПОЛНИТЕЛЬ:

группа ИУ5-22

Колпаков М.О.

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## ▼ Цель работы.

Подготовить собственный набор данных. Обучить сверточную нейронную сеть на основе собственного набора данных.

## Часть 1

### Подготовка данных

```
import numpy as np
import pandas as pd
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

with zipfile.ZipFile('/content/drive/My Drive/Colab Notebooks/face.zip','r') as zip_ref:
    zip_ref.extractall()

input_folder = '../content/face'

import glob
import pathlib
from tensorflow.keras.applications import MobileNetV2
import tensorflow as tf

data_root = pathlib.Path(input_folder)

#Просматриваем названия все директории, наши будущие классы
for item in data_root.iterdir():
    print(item)

[> ../content/face/woman
  > ../content/face/man

import random
#Получим все пути наших картинок
all_image_paths = list(data_root.glob('*/*'))

#Определим в список все пути наших картинок
all_image_paths = [str(path) for path in all_image_paths]

#Перемешаем в случайном порядке
random.shuffle(all_image_paths)
```

```
#Получим общее кол-во наших картинок
```

```
image_count = len(all_image_paths)
```

```
image_count
```

```
↳ 1961
```

```
all_image_paths[:10]
```

```
↳ ['../content/face/man/face_71.jpg',
    '../content/face/woman/face_50.jpg',
    '../content/face/man/face_1165.jpg',
    '../content/face/man/face_836.jpg',
    '../content/face/man/face_926.jpg',
    '../content/face/woman/face_52.jpg',
    '../content/face/woman/face_1159.jpg',
    '../content/face/man/face_959.jpg',
    '../content/face/man/face_4.jpg',
    '../content/face/woman/face_429.jpg']
```

```
#Выведем в список все наши классы
```

```
label_names = sorted(item.name for item in data_root.glob('*/*') if item.is_dir())
```

```
label_names
```

```
↳ ['man', 'woman']
```

```
#Присвоим индексы нашим классам
```

```
label_to_index = dict((name, index) for index, name in enumerate(label_names))
```

```
label_to_index
```

```
↳ {'man': 0, 'woman': 1}
```

Saved successfully!



каждой картинке относящиеся к этому классу

```
pathlib.Path(path).parent.name]
```

```
for path in all_image_paths]
```

```
#Выведем последние 6 индекса
```

```
print("First 6 labels indices: ", all_image_labels[:6])
```

```
↳ First 6 labels indices: [0, 1, 0, 0, 0, 1]
```

```
img_path = all_image_paths[1]
```

```
img_path
```

```
↳ '../content/face/woman/face_50.jpg'
```

```
#Сырые данные
```

```
img_raw = tf.io.read_file(img_path)
```

```
print(repr(img_raw)[:100]+"...")
```

```
↳ <tf.Tensor: shape=(), dtype=string, numpy=b'\xff\xd8\xff\xe0\x00\x10JFIF\x00\x01\x01'
```

```
#Преобразование в тензор изображения
```

```
img_tensor = tf.image.decode_image(img_raw)
```

```
print(img_tensor.shape)
print(img_tensor.dtype)
```

```
(155, 124, 3)
<dtype: 'uint8'>
```

```
#Установим размер для нашей модели
img_final = tf.image.resize(img_tensor, [102, 80])
img_final = img_final/255.0
print(img_final.shape)
print(img_final.numpy().min())
print(img_final.numpy().max())
```

```
(102, 80, 3)
0.0
1.0
```

```
#Функция декодирования и изменения размера для нашей модели
def preprocess_image(image):
    image = tf.image.decode_jpeg(image, channels=3)
    image = tf.image.resize(image, [128, 128])
    image /= 255.0 # normalize to [0,1] range

    return image
```

```
def load_and_preprocess_image(path):
    image = tf.io.read_file(path)
    return preprocess_image(image)
```

Saved successfully!



```
r_slices(all_image_paths)
```

```
print(path_ds)
```

```
<TensorSliceDataset shapes: (), types: tf.string>
```

```
image_ds = path_ds.map(load_and_preprocess_image, num_parallel_calls=AUTOTUNE)
```

```
#Отообразим несколько преобразованных картинок
import matplotlib.pyplot as plt
```

```
plt.figure(figsize=(8,8))
for n, image in enumerate(image_ds.take(4)):
    plt.subplot(2,2,n+1)
    plt.imshow(image)
    plt.grid(False)
    plt.xticks([])
    plt.yticks([])
```

```
plt.xlabel(all_image_paths[n])
plt.show()
```



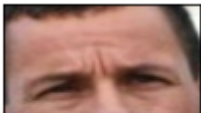
../content/face/man/face\_71.jpg



../content/face/woman/face\_50.jpg



../content/face/man/face\_1165.jpg



Saved successfully!



../content/face/man/face\_836.jpg

#Соберем датасет меток

```
label_ds = tf.data.Dataset.from_tensor_slices(tf.cast(all_image_labels, tf.int64))
```

#Выведем метки

```
for label in label_ds.take(6):
    print(label_names[label.numpy()])
```



```
man
woman
man
man
man
woman
```

#Соберем набор данных с помощью метода zip

```
image_label_ds = tf.data.Dataset.zip((image_ds, label_ds))
```

```
print(image_label_ds)
```

```
↳ <ZipDataset shapes: ((128, 128, 3), ()), types: (tf.float32, tf.int64)>
```

## ▼ Часть 2

### Обучение модели

```
BATCH_SIZE = 32
```

```
# Установка размера буфера перемешивания, равного набору данных, гарантирует
# полное перемешивание данных.
ds = image_label_ds.shuffle(buffer_size=image_count)
ds = ds.repeat()
ds = ds.batch(BATCH_SIZE)
# `prefetch` позволяет датасету извлекать пакеты в фоновом режиме, во время обучения модел
ds = ds.prefetch(buffer_size=AUTOTUNE)
ds
```

```
↳ <PrefetchDataset shapes: ((None, 128, 128, 3), (None,)), types: (tf.float32, tf.int64)>
```

```
ds = image_label_ds.apply(
    tf.data.experimental.shuffle_and_repeat(buffer_size=image_count))
ds = ds.batch(BATCH_SIZE)
ds = ds.prefetch(buffer_size=AUTOTUNE)
ds
```

```
↳ <PrefetchDataset shapes: ((None, 128, 128, 3), (None,)), types: (tf.float32, tf.int64)>
```

Saved successfully!



```
=(128, 128, 3), include_top=False)
```

```
def change_range(image,label):
    return 2*image-1, label
```

```
keras_ds = ds.map(change_range)
```

```
image_batch, label_batch = next(iter(keras_ds))
```

```
feature_map_batch = mobile_net(image_batch)
print(feature_map_batch.shape)
```

```
↳ (32, 4, 4, 1280)
```

```
model = tf.keras.Sequential([
    mobile_net,
    tf.keras.layers.GlobalAveragePooling2D(),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(len(label_names), activation = 'softmax')])
```

```
logit_batch = model(image_batch).numpy()
```

```
print("min logit:", logit_batch.min())
print("max logit:", logit_batch.max())
print()
```

```
print("Shape:", logit_batch.shape)
```

```
↳ min logit: 0.02048682
   max logit: 0.9795132
```

```
Shape: (32, 2)
```

```
model.compile(optimizer=tf.keras.optimizers.Adam(),
              loss='sparse_categorical_crossentropy',
              metrics=["accuracy"])
```

```
model.summary()
```

```
↳ Model: "sequential_1"
```

Layer (type)	Output Shape	Param #
mobilenetv2_1.00_128 (Model)	(None, 4, 4, 1280)	2257984
global_average_pooling2d_1 (	(None, 1280)	0
dropout_1 (Dropout)	(None, 1280)	0
dense_1 (Dense)	(None, 2)	2562

Saved successfully!



```
Non-trainable params: 2,257,984
```

```
steps_per_epoch=tf.math.ceil(len(all_image_paths)/BATCH_SIZE).numpy()
steps_per_epoch
```

```
↳ 62.0
```

```
model = model.fit(ds, epochs=15, steps_per_epoch=15)
```

```
↳
```

```

Epoch 1/15
15/15 [=====] - 6s 373ms/step - loss: 1.0016 - accuracy: 0.5
Epoch 2/15
15/15 [=====] - 5s 365ms/step - loss: 0.5758 - accuracy: 0.7
Epoch 3/15
15/15 [=====] - 6s 367ms/step - loss: 0.4591 - accuracy: 0.8
Epoch 4/15
15/15 [=====] - 6s 371ms/step - loss: 0.3907 - accuracy: 0.8
Epoch 5/15
15/15 [=====] - 6s 368ms/step - loss: 0.3256 - accuracy: 0.8
Epoch 6/15
15/15 [=====] - 5s 366ms/step - loss: 0.3427 - accuracy: 0.8
Epoch 7/15
15/15 [=====] - 6s 376ms/step - loss: 0.3261 - accuracy: 0.8
Epoch 8/15
15/15 [=====] - 6s 367ms/step - loss: 0.2656 - accuracy: 0.9
Epoch 9/15
15/15 [=====] - 6s 368ms/step - loss: 0.2483 - accuracy: 0.9
Epoch 10/15
15/15 [=====] - 6s 369ms/step - loss: 0.2657 - accuracy: 0.8

```

```
print(model.history.keys())
```

```
dict_keys(['loss', 'accuracy'])
```

```
Epoch 13/15
```

```

plt.subplot(211)
plt.plot(model.history['accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['accuracy'])
plt.show()

```

```
plt.subplot(212)
```

Saved successfully!

```

plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['loss'], loc='upper right')
plt.show()

```

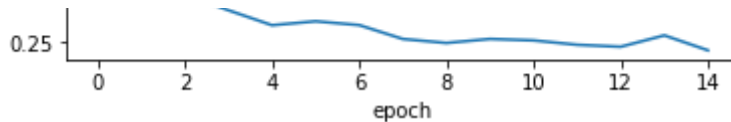
```
↳
```



model accuracy

## Список литературы

- [1] MobileNet: меньше, быстрее, точнее – <https://habr.com/ru/post/352804/>
- [2] Transfer Learning Using Pretrained ConvNets – [https://www.tensorflow.org/alpha/tutorials/images/transfer\\_learning](https://www.tensorflow.org/alpha/tutorials/images/transfer_learning)
- [3] Natural Images – <https://www.kaggle.com/prasunroy/natural-images>
- [4] Load images with tf.data – [https://www.tensorflow.org/alpha/tutorials/load\\_data/images](https://www.tensorflow.org/alpha/tutorials/load_data/images)



Saved successfully!

