```
from google.colab import drive
drive.mount('/content/drive', force remount=True)
    Mounted at /content/drive
!pip install -q libtiff
!pip install -q tqdm
# import the necessary packages
import matplotlib.pyplot as plt
import sys
import os
from pathlib import Path
from libtiff import TIFF
import numpy as np
from typing import List
from tqdm.notebook import tqdm
from time import sleep
from PIL import Image
import IPython.display
import tensorflow as tf
from sklearn.metrics import balanced accuracy score
from keras.optimizers import SGD, RMSprop, Adam
from keras import optimizers, Model, callbacks
from sklearn.metrics import mean squared error
from keras.utils import plot model
from sklearn.preprocessing import StandardScaler, MinMaxScaler
```

Класс Dataset

Предназначен для работы с наборами данных, хранящихся на Google Drive, обеспечивает чтение изображений и соответствующих меток, а также формирование пакетов (батчей).

```
class Dataset:
    def __init__(self, name, gdrive_dir):
        self.name = name
        self.is_loaded = False
        p = Path("/content/drive/MyDrive/" + gdrive_dir + name + '.npz')
        if p.exists():
            print(f'[INFO] Loading dataset {self.name} from npz...')
            np_obj = np.load(str(p))
            self.images = np_obj['data']
            self.labels = np_obj['labels']
            self.n files = self.images.shape[0]
```

```
self.is loaded = True
        print(f'[INFO] Done. Dataset {name} consists of {self.n files}
def image(self, i):
    # read i-th image in dataset and return it as numpy array
    if self.is loaded:
        return self.images[i, :, :, :]
def images seq(self, n=None):
    # sequential access to images inside dataset (is needed for testing
    for i in range(self.n files if not n else n):
        yield self.image(i)
def random image with label(self):
    # get random image with label from dataset
    i = np.random.randint(self.n files)
    return self.image(i), self.labels[i]
def random batch with labels(self, n):
    # create random batch of images with labels (is needed for training
    indices = np.random.choice(self.n files, n)
    imgs = []
    for i in indices:
        imgs.append(self.image(i))
    logits = np.array([self.labels[i] for i in indices])
    return np.array(imgs), logits
def image with label(self, i: int):
    # return i-th image with label from dataset
    return self.image(i), self.labels[i]
```

Класс Model

Предназначен для работы с нейросетью. Обеспечивает загрузку, обучение, тестирование и сохранение нейронной сети, отображение дополнительной информации об алгоритме обучения.

```
class Model:
```

```
def __init__(self):
    chanDim = -1
    self.model = tf.keras.models.Sequential(
        [tf.keras.layers.Conv2D(8, (3, 3), padding="same", activation='input_shape=(224, 224, 3)),
```

```
ti.keras.layers.MaxPoolingZD(pool size=(2, 2)),
      tf.keras.layers.Conv2D(64, (3, 3), padding="same", activation='r
      tf.keras.layers.MaxPooling2D(data format='channels last'),
      tf.keras.layers.Conv2D(128, (3, 3), padding="same", activation='
      tf.keras.layers.MaxPooling2D(data format='channels last'),
      tf.keras.layers.Conv2D(256, (3, 3), padding="same", activation='r
      tf.keras.layers.MaxPooling2D(data format='channels last'),
      tf.keras.layers.Conv2D(512, (3, 3), padding="same", activation='r
      tf.keras.layers.MaxPooling2D(data format='channels last'),
      tf.keras.layers.Dropout(0.5),
      tf.keras.layers.Flatten(),
      tf.keras.layers.Dense(1000, kernel regularizer=tf.keras.regulariz
      tf.keras.layers.Activation("relu"),
      tf.keras.layers.Dropout(0.3),
      tf.keras.layers.Dense(512, kernel regularizer=tf.keras.regularize
      tf.keras.layers.Activation("relu"),
      tf.keras.layers.Dropout(0.3),
      tf.keras.layers.Dense(256, kernel regularizer=tf.keras.regularize
      tf.keras.layers.Activation("relu"),
      tf.keras.layers.Dropout(0.3),
      tf.keras.layers.Dense(9),
      tf.keras.layers.Activation("softmax")
      ])
    self.save_dir = "/content/drive/MyDrive/nn tasks/"
def save model(self, name: str):
    # save model to SAVE DIR folder on gdrive with name 'name'
    #self.save dir += name
    self.model.save(self.save dir + "model-res/" + name + " model.h5")
    self.model.save weights(self.save dir + "model-res/" + name + " mod
    plot model(self.model, to file=self.save dir + "model-res/" + name
def load(self, name: str, is checkpoint=False):
    p1 = Path(self.save dir + "model-res/" + name + ".h5")
    p2 = Path(self.save_dir + "model-res/best_checkpoint/")
```

```
self.model = None
    if is checkpoint and p2.exists():
      self.model = tf.keras.models.load model(p2)
    elif pl.exists():
      self.model = tf.keras.models.load model(p1)
    return model
def train(self, dataset: Dataset, is showing history=True):
    # you can add some plots for better visualization,
    self.INIT LR = 6e-4
    self.EPOCHS = 100
    self.BS = 64
    print(f"[INFO] split and shuffle the data...")
    d train images 1, d train labels 1 = dataset.random batch with labe
    n train = int(dataset.n files * 0.92)
    d train images = d train images 1[0:n train]
    d train labels = d train labels 1[0:n train]
    #LBL1
    d val images = d train images 1[n train:dataset.n files]
    d val labels = d train labels 1[n train:dataset.n files]
    #scaler = MinMaxScaler()
    #X = scaler.fit transform(d train images)
    #X_val = scaler.fit_transform(d_val_images)
    optA = Adam(learning rate=self.INIT LR)
    self.model.compile(loss=tf.keras.losses.SparseCategoricalCrossentro
      metrics=["accuracy"])
    #LBL2
    checkpoint = callbacks.ModelCheckpoint(self.save dir + "model-res/b
save weights only=False, save freq='epoch') #mode='auto',
    callbacks list = [checkpoint]
    #LBL3
    print(f"[INFO] training network...")
    self.History = self.model.fit(d train images, d train labels, valid
    print(f'[INFO] training done')
    #LBL4
    self.show history(str(n train))
def test_on_dataset(self, dataset: Dataset, limit=None):
    # you can upgrade this code if you want to speed up testing using b
    predictions = []
```

```
n = dataset.n files if not limit else int(dataset.n files * limit)
        for img in tqdm(dataset.images seq(n), total=n):
            predictions.append(self.test on image(img))
        return predictions
    def test on image(self, img):
        # todo: replace this code
        prediction = self.model.predict(np.array(img))
        return np.argmax(prediction)
    def evaluate model(self, dataset: Dataset):
        print("[INFO] evaluating network...")
        result = self.model.evaluate(dataset.images, dataset.labels, batch
        print('test loss, test acc:', result)
        predictions = self.model.predict(dataset.images)
        pred = []
        print("MSE (test y, predictions)")
        for i in range(0, len(dataset.labels)):
          pred.append(predictions[i].max())
        print(mean squared error(dataset.labels, pred, squared=False))
    def show history(self, size):
        N = np.arange(0, self.EPOCHS)
        plt.style.use("ggplot")
        plt.figure()
        plt.plot(N, self.History.history["loss"], label="train loss")
        plt.plot(N, self.History.history["accuracy"], label="train_acc")
        plt.plot(N, self.History.history["val_loss"], label="test_loss")
        plt.plot(N, self.History.history["val accuracy"], label="test acc")
        plt.title("Training Los")
        plt.xlabel("Epoch #")
        plt.ylabel("Loss, accuracy")
        plt.legend()
        plt.savefig(self.save dir + "model-res/history training on " + size
PROJECT DIR = "nn tasks/"
EVALUATE ONLY = False
TEST ON LARGE DATASET = True
TTCCIIF CLACCEC = ('ADT'')
                                 ' מתח'
                                        'TVM'
                                                'MIIC'
                                                       'MIIC'
                                                              ' MODM'
                                                                      ' Cmp '
```

model.train(dataset_train, is_showing_history=True)

model.save model('best')

model.load('best')

else:

```
[INFO] split and shuffle the data...
[INFO] training network...
Epoch 1/100
Epoch 00001: val_accuracy improved from -inf to 0.42361, saving model to /conten-
INFO:tensorflow:Assets written to: /content/drive/MyDrive/nn tasks/model-res/bes
Epoch 2/100
Epoch 00002: val accuracy improved from 0.42361 to 0.62153, saving model to /con
INFO:tensorflow:Assets written to: /content/drive/MyDrive/nn_tasks/model-res/bes-
Epoch 3/100
Epoch 00003: val_accuracy did not improve from 0.62153
Epoch 4/100
Epoch 00004: val accuracy improved from 0.62153 to 0.70139, saving model to /con
INFO:tensorflow:Assets written to: /content/drive/MyDrive/nn tasks/model-res/bes
Epoch 5/100
Epoch 00005: val_accuracy improved from 0.70139 to 0.77431, saving model to /con-
INFO:tensorflow:Assets written to: /content/drive/MyDrive/nn tasks/model-res/bes
Epoch 6/100
Epoch 00006: val accuracy improved from 0.77431 to 0.80625, saving model to /con
INFO:tensorflow:Assets written to: /content/drive/MyDrive/nn_tasks/model-res/bes-
Epoch 7/100
Epoch 00007: val accuracy improved from 0.80625 to 0.81250, saving model to /con-
INFO:tensorflow:Assets written to: /content/drive/MyDrive/nn tasks/model-res/bes
Epoch 8/100
Epoch 00008: val accuracy improved from 0.81250 to 0.85556, saving model to /con
INFO:tensorflow:Assets written to: /content/drive/MyDrive/nn tasks/model-res/bes
Epoch 9/100
Epoch 00009: val accuracy did not improve from 0.85556
Epoch 10/100
Epoch 00010: val accuracy improved from 0.85556 to 0.89444, saving model to /con
INFO:tensorflow:Assets written to: /content/drive/MyDrive/nn tasks/model-res/bes-
Epoch 11/100
Epoch 00011: val_accuracy improved from 0.89444 to 0.91736, saving model to /con-
INFO:tensorflow:Assets written to: /content/drive/MyDrive/nn tasks/model-res/bes-
Epoch 12/100
```

```
Epoch 00012: val_accuracy did not improve from 0.91736
Epoch 13/100
Epoch 00013: val accuracy did not improve from 0.91736
Epoch 14/100
Epoch 00014: val_accuracy improved from 0.91736 to 0.93681, saving model to /con-
INFO:tensorflow:Assets written to: /content/drive/MyDrive/nn tasks/model-res/bes
Epoch 15/100
Epoch 00015: val_accuracy did not improve from 0.93681
Epoch 16/100
Epoch 00016: val accuracy did not improve from 0.93681
Epoch 17/100
Epoch 00017: val_accuracy did not improve from 0.93681
Epoch 18/100
Epoch 00018: val_accuracy did not improve from 0.93681
Epoch 19/100
Epoch 00019: val accuracy improved from 0.93681 to 0.94097, saving model to /con
INFO:tensorflow:Assets written to: /content/drive/MyDrive/nn tasks/model-res/bes
Epoch 20/100
Epoch 00020: val accuracy did not improve from 0.94097
Epoch 21/100
Epoch 00021: val accuracy improved from 0.94097 to 0.94306, saving model to /con
INFO:tensorflow:Assets written to: /content/drive/MyDrive/nn tasks/model-res/bes
Epoch 22/100
Epoch 00022: val accuracy improved from 0.94306 to 0.96111, saving model to /con
INFO:tensorflow:Assets written to: /content/drive/MyDrive/nn_tasks/model-res/bes-
Epoch 23/100
Epoch 00023: val accuracy did not improve from 0.96111
Epoch 24/100
Epoch 00024: val accuracy did not improve from 0.96111
Epoch 25/100
```

Epoch 00025: val_accuracy improved from 0.96111 to 0.96458, saving model to /con-

```
INFO:tensorflow:Assets written to: /content/drive/MyDrive/nn tasks/model-res/bes
Epoch 26/100
Epoch 00026: val accuracy did not improve from 0.96458
Epoch 27/100
Epoch 00027: val accuracy did not improve from 0.96458
Epoch 28/100
Epoch 00028: val accuracy did not improve from 0.96458
Epoch 29/100
Epoch 00029: val accuracy did not improve from 0.96458
Epoch 30/100
Epoch 00030: val accuracy improved from 0.96458 to 0.96875, saving model to /con-
INFO:tensorflow:Assets written to: /content/drive/MyDrive/nn_tasks/model-res/bes-
Epoch 31/100
Epoch 00031: val accuracy did not improve from 0.96875
Epoch 32/100
Epoch 00032: val accuracy did not improve from 0.96875
Epoch 33/100
Epoch 00033: val accuracy did not improve from 0.96875
Epoch 34/100
Epoch 00034: val accuracy did not improve from 0.96875
Epoch 35/100
Epoch 00035: val accuracy did not improve from 0.96875
Epoch 36/100
Epoch 00036: val accuracy did not improve from 0.96875
Epoch 37/100
Epoch 00037: val_accuracy did not improve from 0.96875
Epoch 38/100
Epoch 00038: val accuracy did not improve from 0.96875
Epoch 39/100
```

```
_poon occos. var_accarac, ara noc impr
Epoch 40/100
Epoch 00040: val_accuracy did not improve from 0.96875
Epoch 41/100
Epoch 00041: val accuracy did not improve from 0.96875
Epoch 42/100
Epoch 00042: val accuracy did not improve from 0.96875
Epoch 43/100
Epoch 00043: val_accuracy improved from 0.96875 to 0.97500, saving model to /con-
INFO:tensorflow:Assets written to: /content/drive/MyDrive/nn_tasks/model-res/bes-
Epoch 44/100
Epoch 00044: val_accuracy did not improve from 0.97500
Epoch 45/100
Epoch 00045: val_accuracy did not improve from 0.97500
Epoch 46/100
Epoch 00046: val accuracy did not improve from 0.97500
Epoch 47/100
Epoch 00047: val accuracy did not improve from 0.97500
Epoch 48/100
Epoch 00048: val accuracy improved from 0.97500 to 0.97917, saving model to /con
INFO:tensorflow:Assets written to: /content/drive/MyDrive/nn tasks/model-res/bes
Epoch 49/100
Epoch 00049: val accuracy did not improve from 0.97917
Epoch 50/100
Epoch 00050: val accuracy did not improve from 0.97917
Epoch 51/100
Epoch 00051: val accuracy did not improve from 0.97917
Epoch 52/100
Epoch 00052: val accuracy did not improve from 0.97917
Epoch 53/100
```

```
Epoch UUU53: Val_accuracy ald not improve from U.9/91/
Epoch 54/100
Epoch 00054: val_accuracy did not improve from 0.97917
Epoch 55/100
Epoch 00055: val_accuracy did not improve from 0.97917
Epoch 56/100
Epoch 00056: val accuracy did not improve from 0.97917
Epoch 57/100
Epoch 00057: val_accuracy improved from 0.97917 to 0.98472, saving model to /con-
INFO:tensorflow:Assets written to: /content/drive/MyDrive/nn_tasks/model-res/bes-
Epoch 58/100
Epoch 00058: val_accuracy did not improve from 0.98472
Epoch 59/100
Epoch 00059: val accuracy did not improve from 0.98472
Epoch 60/100
Epoch 00060: val accuracy did not improve from 0.98472
Epoch 61/100
Epoch 00061: val accuracy did not improve from 0.98472
Epoch 62/100
Epoch 00062: val accuracy did not improve from 0.98472
Epoch 63/100
Epoch 00063: val accuracy did not improve from 0.98472
Epoch 64/100
Epoch 00064: val accuracy did not improve from 0.98472
Epoch 65/100
Epoch 00065: val accuracy did not improve from 0.98472
Epoch 66/100
Epoch 00066: val accuracy did not improve from 0.98472
Epoch 67/100
Epoch 00067: val accuracy did not improve from 0.98472
```

```
Epoch 68/100
Epoch 00068: val_accuracy did not improve from 0.98472
Epoch 69/100
Epoch 00069: val accuracy did not improve from 0.98472
Epoch 70/100
Epoch 00070: val accuracy did not improve from 0.98472
Epoch 71/100
Epoch 00071: val_accuracy did not improve from 0.98472
Epoch 72/100
Epoch 00072: val_accuracy did not improve from 0.98472
Epoch 73/100
Epoch 00073: val accuracy did not improve from 0.98472
Epoch 74/100
Epoch 00074: val accuracy did not improve from 0.98472
Epoch 75/100
Epoch 00075: val accuracy did not improve from 0.98472
Epoch 76/100
Epoch 00076: val accuracy did not improve from 0.98472
Epoch 77/100
Epoch 00077: val accuracy did not improve from 0.98472
Epoch 78/100
Epoch 00078: val accuracy did not improve from 0.98472
Epoch 79/100
Epoch 00079: val accuracy did not improve from 0.98472
Epoch 80/100
Epoch 00080: val accuracy did not improve from 0.98472
Epoch 81/100
Epoch 00081: val accuracy did not improve from 0.98472
Epoch 82/100
```

```
Epoch 00082: val_accuracy did not improve from 0.98472
Epoch 83/100
Epoch 00083: val_accuracy did not improve from 0.98472
Epoch 84/100
Epoch 00084: val accuracy did not improve from 0.98472
Epoch 85/100
Epoch 00085: val accuracy did not improve from 0.98472
Epoch 86/100
Epoch 00086: val accuracy did not improve from 0.98472
Epoch 87/100
Epoch 00087: val accuracy did not improve from 0.98472
Epoch 88/100
Epoch 00088: val_accuracy did not improve from 0.98472
Epoch 89/100
Epoch 00089: val_accuracy did not improve from 0.98472
Epoch 90/100
Epoch 00090: val accuracy did not improve from 0.98472
Epoch 91/100
Epoch 00091: val accuracy did not improve from 0.98472
Epoch 92/100
Epoch 00092: val_accuracy did not improve from 0.98472
Epoch 93/100
Epoch 00093: val accuracy did not improve from 0.98472
Epoch 94/100
Epoch 00094: val accuracy did not improve from 0.98472
Epoch 95/100
Epoch 00095: val accuracy did not improve from 0.98472
Epoch 96/100
```

model.evaluate model(dataset test)

```
[INFO] evaluating network...
   test loss, test acc: [0.4413629472255707, 0.9511111378669739]
   MSE (test_y, predictions)
   3.9812546
   437/437 [----- tobs: 0.4743 - accutat
img, lbl = dataset test.random image with label()
pred = model.test on image([img])
TISSUE CLASSES[pred], pred, TISSUE CLASSES[lbl], lbl
   ('DEB', 2, 'DEB', 2)
   Epoch 00100: val accuracy did not improve from 0.98472
#LOADING MODEL FROM BEST CHECKPOINT
mm = model.load("best model", is checkpoint=True)
     1/.5
mm.evaluate model(dataset test)
   [INFO] evaluating network...
   test loss, test acc: [0.44866058230400085, 0.9546666741371155]
   MSE (test_y, predictions)
   3.9859054
      25 -
img, lbl = dataset test.random image with label()
pred = model.test on image([img])
TISSUE CLASSES[pred], pred, TISSUE CLASSES[lbl], lbl
   ('STR', 7, 'STR', 7)
img, lbl = dataset train.random image with label()
print()
print(f'Got numpy array of shape {img.shape}, and label with code {lbl}.')
print(f'Label code corresponds to {TISSUE CLASSES[lbl]} class.')
pil img = Image.fromarray(img)
IPython.display.display(pil img)
```

Got numpy array of shape (224, 224, 3), and label with code 2. Label code corresponds to DEB class.



