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# Лабораторна робота №5

**Проектування та реалізація програмних систем з нейронними мережами** Згорткові нейронні мережі типу Іпсертіоп

Київ 2023

Завдання: Написати програму, що реалізує згорткову нейронну мережу Inception V3 для розпізнавання об'єктів на зображеннях. Створити власний дата сет з папки на диску, навчити нейронну мережу на цьому датасеті розпізнавати породу Вашої улюбленої собаки чи кота. Навчену нейронну мережу зберегти на комп'ютер написати програму, що відкриває та аналізує зображення.

#### Виконання роботи

```
import os
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
from google.colab import files
path = os.path.join(os.getcwd(), '/content/drive/MyDrive/Dataset/laboratory5/
datagen = tf.keras.preprocessing.image.ImageDataGenerator(
    rescale=1./255,
   validation_split=0.3
)
train_generator = datagen.flow_from_directory(
   path,
   target size=(150,150),
   batch size=32,
   shuffle=True,
   subset='training'
)
validation_generator = datagen.flow_from_directory(
   path,
   target_size=(150,150),
   batch_size=32,
   shuffle=True,
   subset='validation'
)
```

```
pre_trained_model = tf.keras.applications.inception_v3.InceptionV3(
    input_shape=(150, 150, 3),
    include_top=False,
    weights='imagenet'
)

for layer in pre_trained_model.layers:
    layer.trainable = False

last_layer = pre_trained_model.get_layer('mixed10')
last_layer_output = last_layer.output

x = tf.keras.layers.GlobalAveragePooling2D()(last_layer_output)
output = tf.keras.layers.Dense(2, activation='softmax')(x)
model = tf.keras.Model(pre_trained_model.input, output)
model.summary()
```

```
batch_normalization_276 (Batch (None, 3, 3, 384) 1152
                                                             ['conv2d_276[0][0]']
 Normalization)
 batch_normalization_279 (Batch (None, 3, 3, 384) 1152
                                                             ['conv2d_279[0][0]']
 Normalization)
 batch_normalization_280 (Batch (None, 3, 3, 384) 1152
                                                             ['conv2d_280[0][0]']
 Normalization)
 conv2d_281 (Conv2D)
                             (None, 3, 3, 192)
                                                  393216
                                                             ['average_pooling2d_26[0][0]']
 batch_normalization_273 (Batch (None, 3, 3, 320) 960
                                                             ['conv2d_273[0][0]']
 Normalization)
 activation_275 (Activation)
                              (None, 3, 3, 384)
                                                             ['batch_normalization_275[0][0]']
 activation_276 (Activation)
                             (None, 3, 3, 384)
                                                             ['batch_normalization_276[0][0]']
 activation_279 (Activation)
                              (None, 3, 3, 384) 0
                                                             ['batch_normalization_279[0][0]']
 activation_280 (Activation)
                             (None, 3, 3, 384)
                                                             ['batch_normalization_280[0][0]']
 batch_normalization_281 (Batch (None, 3, 3, 192) 576
                                                             ['conv2d_281[0][0]']
 Normalization)
 activation_273 (Activation)
                             (None, 3, 3, 320) 0
                                                             ['batch_normalization_273[0][0]']
 mixed9_1 (Concatenate)
                              (None, 3, 3, 768) 0
                                                             ['activation_275[0][0]
                                                               'activation_276[0][0]']
 concatenate_5 (Concatenate)
                              (None, 3, 3, 768)
                                                             ['activation_279[0][0]'
                                                               activation_280[0][0]')
 activation_281 (Activation)
                              (None, 3, 3, 192) 0
                                                             ['batch_normalization_281[0][0]']
 mixed10 (Concatenate)
                              (None, 3, 3, 2048) 0
                                                             ['activation_273[0][0]',
                                                               'mixed9_1[0][0]'
                                                              'concatenate_5[0][0]',
'activation_281[0][0]']
 global_average_pooling2d_2 (Gl (None, 2048)
                                                             ['mixed10[0][0]']
 obalAveragePooling2D)
 dense_2 (Dense)
                            (None, 2)
                                                 4098
                                                              ['global_average_pooling2d_2[0][0
Total params: 21,806,882
Trainable params: 4,098
Non-trainable params: 21,802,784
model.compile(
     optimizer=tf.keras.optimizers.RMSprop(learning rate=0.0001),
     loss='categorical crossentropy',
     metrics=['accuracy']
)
```

conv2d\_273 (Conv2D)

Normalization)

(None, 3, 3, 320)

batch\_normalization\_275 (Batch (None, 3, 3, 384) 1152

655360

['mixed9[0][0]']

['conv2d\_275[0][0]']

history = model.fit(train\_generator, epochs=30, validation\_data=validation\_generator)

```
Epoch 8/30
2/2 [=====
                  ========] - 5s 3s/step - loss: 0.7598 - accuracy: 0.7174 - val_loss: 0.9034 - val_accuracy: 0.6111
Epoch 9/30
2/2 [======
           Epoch 10/30
2/2 [=====
             ========== ] - 3s 2s/step - loss: 0.6801 - accuracy: 0.7391 - val loss: 0.8456 - val accuracy: 0.6111
Epoch 11/30
2/2 [===
                    :=======] - 5s 3s/step - loss: 0.6457 - accuracy: 0.7826 - val_loss: 0.8564 - val_accuracy: 0.6667
Epoch 12/30
                          ===] - 3s 3s/step - loss: 0.6116 - accuracy: 0.7609 - val_loss: 0.8071 - val_accuracy: 0.6667
2/2 [===
Epoch 13/30
                      =======] - 3s 2s/step - loss: 0.6066 - accuracy: 0.7609 - val_loss: 0.8532 - val_accuracy: 0.6667
2/2 [=====
Epoch 14/30
2/2 [=====
              :=========] - 5s 4s/step - loss: 0.5672 - accuracy: 0.7609 - val loss: 0.7781 - val accuracy: 0.6667
Epoch 15/30
              2/2 [======
Epoch 16/30
               ========] - 3s 2s/step - loss: 0.5457 - accuracy: 0.7391 - val_loss: 0.7096 - val_accuracy: 0.6667
2/2 [=====
Epoch 17/30
                  ========== ] - 4s 3s/step - loss: 0.4990 - accuracv: 0.7826 - val loss: 0.6939 - val accuracv: 0.6667
2/2 [=====
Epoch 18/30
2/2 [=====
              ==========] - 3s 3s/step - loss: 0.4676 - accuracy: 0.8261 - val_loss: 0.6685 - val_accuracy: 0.6667
Epoch 19/30
              ==========] - 3s 1s/step - loss: 0.4478 - accuracy: 0.8261 - val loss: 0.6748 - val accuracy: 0.7222
2/2 [=====
Epoch 20/30
2/2 [======
              :==========] - 5s 3s/step - loss: 0.4287 - accuracy: 0.8478 - val_loss: 0.5973 - val_accuracy: 0.6667
Epoch 21/30
2/2 [=====
                  ========] - 4s 2s/step - loss: 0.4075 - accuracy: 0.8478 - val loss: 0.5742 - val accuracy: 0.7778
Epoch 22/30
2/2 [======
               ==========] - 3s 3s/step - loss: 0.3824 - accuracy: 0.8478 - val_loss: 0.5853 - val_accuracy: 0.6667
Enoch 23/30
              2/2 [=====
Epoch 24/30
              =========] - 5s 4s/step - loss: 0.3805 - accuracy: 0.8696 - val loss: 0.5704 - val accuracy: 0.7222
2/2 [======
Epoch 25/30
2/2 [===
                           ==] - 3s 2s/step - loss: 0.3350 - accuracy: 0.8478 - val_loss: 0.5561 - val_accuracy: 0.8333
Epoch 26/30
2/2 [====
                          ===] - 3s 2s/step - loss: 0.3050 - accuracy: 0.8696 - val_loss: 0.5736 - val_accuracy: 0.7222
Epoch 27/30
2/2 [=====
                          ===] - 3s 2s/step - loss: 0.2943 - accuracy: 0.8478 - val_loss: 0.5924 - val_accuracy: 0.7222
Epoch 28/30
2/2 [=====
               :=========] - 5s 4s/step - loss: 0.2791 - accuracy: 0.8696 - val loss: 0.5415 - val accuracy: 0.8333
Epoch 29/30
                 ========] - 3s 2s/step - loss: 0.2533 - accuracy: 0.8913 - val_loss: 0.5177 - val_accuracy: 0.8333
2/2 [=====
Epoch 30/30
              2/2 [=======
model.save('lab5 model')
WARNING:absl:Found untraced functions such as _jit_compiled_convolution_op, _jit_compi
```

## !zip -r /content/lab5-model.zip /content/lab5 model

```
adding: content/lab5_model/ (stored 0%)
adding: content/lab5_model/keras_metadata.pb (deflated 96%)
adding: content/lab5_model/assets/ (stored 0%)
adding: content/lab5_model/fingerprint.pb (stored 0%)
adding: content/lab5_model/variables/ (stored 0%)
adding: content/lab5_model/variables/variables.index (deflated 79%)
adding: content/lab5_model/variables/variables.data-00000-of-00001 (deflated 7%)
adding: content/lab5_model/saved_model.pb (deflated 92%)
```

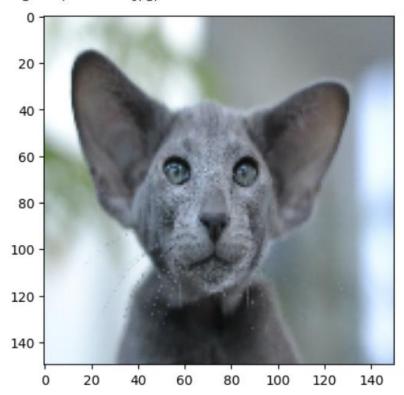
```
files.download("/content/lab5-model.zip")
```

### Перевіримо:

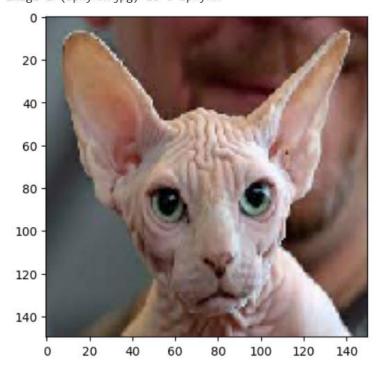
```
files_dir = os.path.join(os.getcwd(), 'drive/MyDrive/Dataset/Check')
files_names = os.listdir(files_dir)
names = ['Other','Sphynx']
classes = []
i = 1
for item in files names:
 img_path = os.path.join(files_dir, item)
 img = tf.keras.utils.load_img(img_path, target_size=(150, 150))
 img = tf.keras.utils.img_to_array(img) / 255
 img = np.expand\_dims(img, axis=0)
 img = np.vstack([img])
 pred = model.predict(img, batch_size=10)
 num = np.argmax(pred)
 print(f'image {i} ({files_names[i-1]}) is a {names[num]}')
 plt.imshow(img[0])
 plt.show()
 i += 1
```

### Результат:

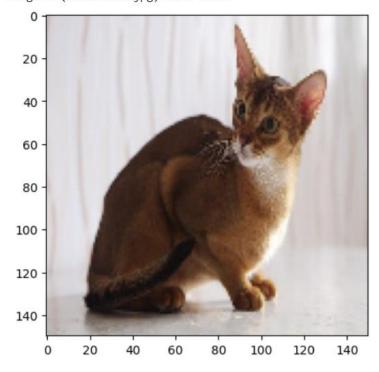
```
1/1 [======] - 0s 72ms/step image 1 (oriental.jpg) is a Other
```



1/1 [======] - 0s 73ms/step image 2 (Sphynx.jpg) is a Sphynx



1/1 [======] - 0s 73ms/step image 3 (oriental1.jpg) is a Other



**Висновок:** Виконуючи дану лабораторну роботу, я реалізував згорткову нейронну мережу типу Inception для розпізнавання котів породи Сфінкса на зображеннях. Використовувався власний маленький датасет.