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SPIE Lab

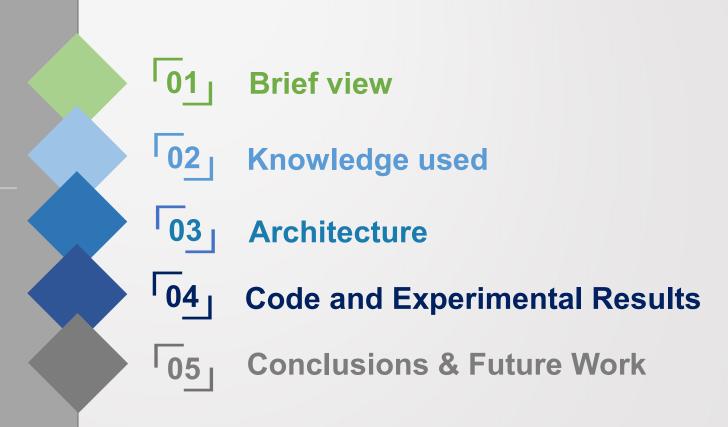
Signal Processing & Intelligent Electronics Lab

A Joint Research Group



CONTENTS





Brief view



About this project

→ Idea comes from:

Location: Yolo

Classification: Homework2

→ Both classification and location

Dataset

- → Dataset of bird classification on Kaggle
- → 12 species out of 400 species in the dataset as classification
- → Use VoTT to mark the location of birds
- →All images are 224 X 224 X 3 color images in jpg format

BIRDS 400 - SPECIES IMAGE CLASSIFICATION

58388Train, 2000 Test, 2000 Validation images 224X224X3 jpg format























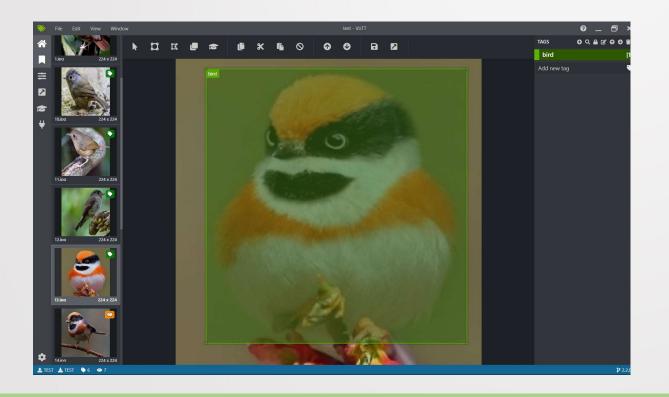






Software that are used in this project

- → Coding: VSCODE and GOOGLE COLLAB
- → Labeling: VOTT



			_	_	
image	xmin	ymin	xmax	ymax	label
ABBOTT	2.665239	2.994652	222.8021	213.2193	BIRD
ABBOTT	13.92513	6.228878	221.6043	210.8235	BIRD
ABBOTT	38.33155	5.031017	219.7177	191.3583	BIRD
ABBOTT	28.4492	10.78075	214.9562	214.1176	BIRD
ABBOTT	18.02781	25.8738	215.615	195.5508	BIRD
ABBOTT	5.989305	28.50909	223.8203	202.139	BIRD
ABBOTT	14.43423	27.79038	209.3262	201.8396	BIRD
ABBOTT	4.791444	29.70695	215.4353	203.3369	BIRD
ABBOTT	12.99679	10.3016	220.4064	196.4492	BIRD
ABBOTT	44.14118	17.00963	211.7219	200.3422	BIRD
ABBOTT	17.66845	2.156151	218.7893	220.4064	BIRD
ABBOTT	44.32086	17.36898	197.6471	198.246	BIRD
ABBOTT	15.57219	15.21284	219.8075	152.1283	BIRD
ABBOTT	17.66845	22.04064	209.446	197.0481	BIRD
ABBOTT	15.27273	3.833156	209.2064	166.5027	BIRD
ABBOTT	4.851341	42.64385	211.6021	185.6684	BIRD
ABBOTT	4.192513	17.48877	222.6225	176.984	BIRD

Knowledge used



Classification



















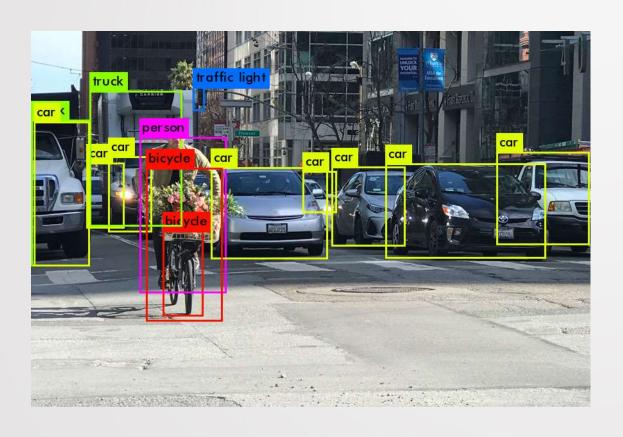






- → Homework2:food classification
- → Use Keras API in Homework2 (keras.applications.inception_v3.InceptionV3)
- → Use another architecture in this program

Location

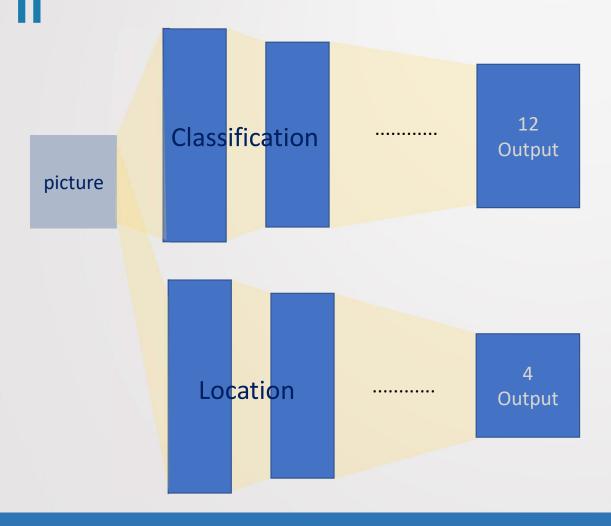


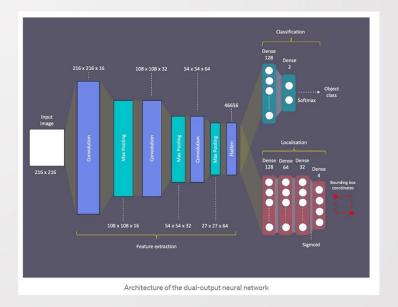
- → Often use Yolo API in object location
- → Use another architecture in this program

Architecture



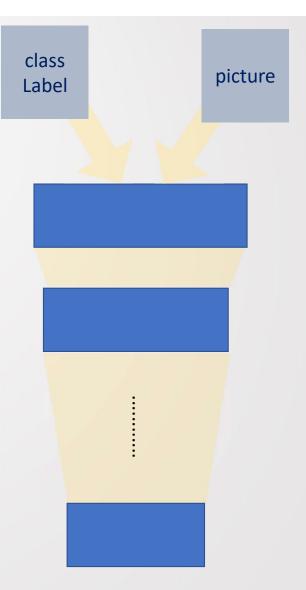
Architecture





Classification

```
## MODEL ##
#create the common input layer
input_shape = (height, width, 3)
input layer = tf.keras.layers.Input(input shape)
#create the base layers
base_layers = layers.Rescaling(1./255, name='bl_1')(input_layer)
base_layers = layers.Conv2D(64, (3,3), padding='same', activation='relu', name='bl_2')(base_layers)
base layers = layers.BatchNormalization()(base layers)
base layers = layers.MaxPooling2D(name='bl 3')(base layers)
base layers = layers.Conv2D(64, (3, 3), activation='relu', name='bl 4')(base layers)
base_layers = layers.MaxPooling2D(pool_size=(2, 2),name='bl_5')(base_layers)
base_layers = layers.BatchNormalization()(base_layers)
base_layers = layers.Conv2D(64, (3, 3), padding='same',activation='relu', name='bl 6')(base layers)
base_layers = layers.MaxPooling2D(name='bl_7')(base_layers)
base_layers = layers.Conv2D(64, (3, 3), activation='relu', name='bl_8')(base_layers)
base_layers = layers.MaxPooling2D(pool_size=(2, 2),name='bl_9')(base_layers)
base_layers = layers.BatchNormalization()(base_layers)
base_layers = layers.Dropout(0.35)(base_layers)
base_layers = layers.Conv2D(64, (3,3), padding='same', activation='relu', name='bl_10')(base_layers)
base layers = layers.MaxPooling2D(name='bl 11')(base layers)
#base_layers = layers.Flatten(name='bl_12')(base_layers)
#create the classifier branch
#classifier branch = base model.output
classifier branch = layers.Flatten()(base layers)
classifier_branch = layers.Dropout(0.5)(classifier_branch)
classifier branch = layers.Dense(512, activation='relu',name='cl_1')(classifier branch)
classifier_branch = layers.BatchNormalization()(classifier_branch)
prediction_ans = layers.Dense(Category_count, activation='softmax',name='cl_head')(classifier_branch)
model_class = tf.keras.Model(input_layer, outputs=[prediction_ans])
print(model_class.summary())
print("prediction ans=",prediction ans)
```



Location

Rol Label

picture

```
##model.##
input shape = (height, width, 3)
input layer = tf.keras.layers.Input(input shape)
model located = layers.Rescaling(1./255, name='ml 1')(input layer)
model located = layers.Conv2D(16, 3, padding='same', activation='relu', name='ml 2')(model located)
model located = layers.MaxPooling2D(name='ml 3')(model located)
model_located = layers.Conv2D(32, 3, padding='same', activation='relu', name='ml_4')(model_located)
model_located = layers.MaxPooling2D(name='ml_5')(model_located)
model_located = layers.Conv2D(64, 3, padding='same', activation='relu', name='ml_6')(model_located)
model located = layers.MaxPooling2D(name='ml 7')(model located)
model_located = layers.Conv2D(128, 3, padding='same', activation='relu', name='ml_8')(model_located)
model located = layers.MaxPooling2D(name='ml 9')(model located)
model_located = layers.Conv2D(256, 3, padding='same', activation='relu', name='ml_10')(model_located)
model located = layers.MaxPooling2D(name='ml 11')(model located)
model located = layers.Flatten(name='ml 12')(model located)
model located = layers.Dense(128, activation='relu', name='ml 13')(model located)
model located = layers.Dense(64, activation='relu', name='ml 14')(model located)
model located = layers.Dense(32, activation='relu', name='ml 15')(model located)
locator ans = layers.Dense(4, activation='sigmoid', name='ml head')(model located)
model_located = tf.keras.Model(input_layer,outputs=[locator_ans])
print(model located.summary())
print("locator ans=",locator ans)
```


Code and Experimental Results

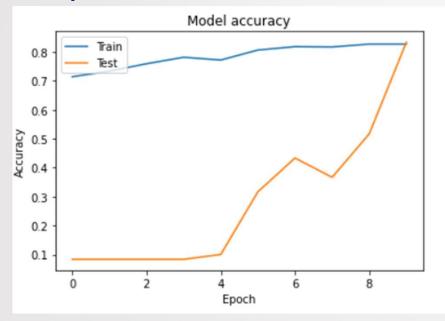


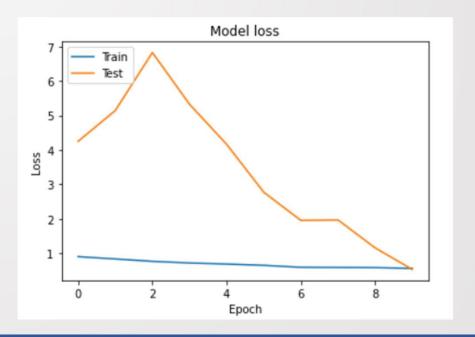
Code

```
import numpy as no
                 import tensorflow as tf
from tensorflow import keras
import pandas as pd
from PIL import leage
from PIL import leage
from PIL import leage
                  import matplotlib.pyplot as plt
                  import pandas as pd
import random
                cl_train_dir = 'D:\program\Images\cl_data_train'
cl_valid_dir = 'D:\program\Images\cl_data_valid'
                  for root, dirs, files in os.walk("D:\program\Images\\test"):
   [14]: def load_img(filename, target_w=224, target_h=224):
                       np_image - Image.open(filename)
np_image - np_array(np_image).astype('float32')/255
np_image - np_reshape(np_image,(224,224,3))
np_image - np_expand_dims(np_image, axis=0)
                       return np_image
In [16]: CATEGORIES - os.listdir(cl_train_dir)
                pic list - os.listdir(tost dir)
               12 CATEGORIES are ['ABBOITS BABBLER', 'AMERICAN GOLDFINCH', 'BANDED PITA', 'BARRED PUFFBIRD', 'BLACK THROATED BUSHIIT', 'CHIPPING SPARRON', 'PAINTED BUNILNG', 'PARADISE TANAGER', 'STRIPPED SMALLON', 'TROPICAL KINGBIRD', 'VIOLET GREEN SMALLON', 'SHITE THROATED BEE BATER']
                results - []
CATE_result -[]
s_point -[]
                 e_point =[]
plt.figure(figsize=(224,224))
                  wild ever that the property that
                  amacestmenesememmeme
for i in range(lon(test_dict)):
    print(test_dict[str(i)])
    ing = load_ing("0:\program\images\\test\\" + test_dict[str(i)])
                        img = load_img( 0.)progict(img)
ret1 = model_class.predict(img)
ret2 = model_located.predict(img)
A = ret1[0]
print("A=")
                        print(%)
print(%)
maxion -np.argnax(A)#原大量可能性--阿CATEGORIES管地程矩
results.append(maxion)
CATE_result.append(cATEGORIES[int(maxion)])
start_point - (int(8[0]*224),int(8[1]*224))
end_point - (int(8[0]*224),int(8[1]*222))
                         s_point.append(start_point)
e_point.append(end_point)
```

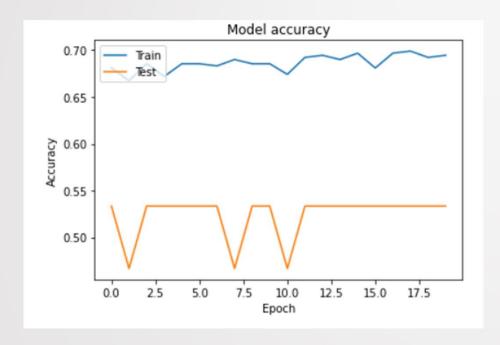
- → Part of the code
- →Input pictures and output pictures, label with bounding box
- →Run the models separated and save as model file, in this main code use the function of load model to load the model in for use.

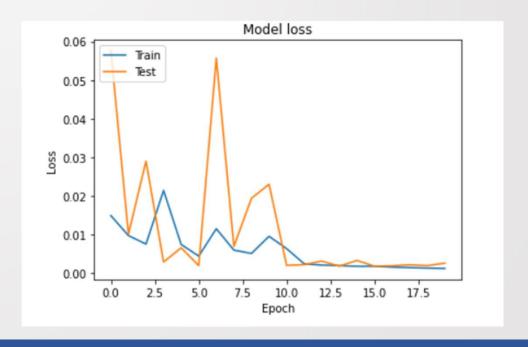
Experiment Result-Classification



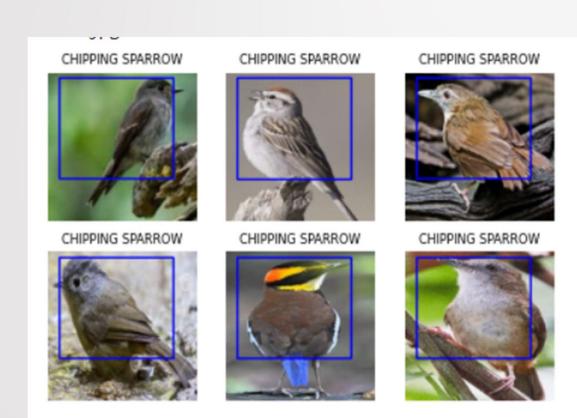


Experiment Result-Location





Experiment Result-Full Program



- → Use Google collab to show this result
- → The bounding box show the location of the birds
- → The tag above shows the species of the bird in the picture

Disadvantages, Reasons and ways to improve

→ Classification is not correct:

The data set isn't big enough and birds are too familiar Or not deep or complex enough to classify those species

→ Location have nearby location

Birds in the pictures have familiar location so can't really show if it is correct just from the pictures in the dataset

→ Ways to improve:

Extend the dataset:

Make the dataset bigger

Get new picture of birds that is in another location

Change architecture:

Make the architecture more complex Use APIs in the program

CHIPPING SPARROW



CHIPPING SPARROW



CHIPPING SPARROW



CHIPPING SPARROW



Conclusions & Future Work



Conclusions and future work

- → Combine two function in machine learning and also combine the knowledge that learned during the semester
- → Learn many information in this project

→ If the correction rate is higher, maybe it can be useful on birds finding and location on bird-watching or researching

Reference

Dataset

https://www.kaggle.com/datasets/gpiosenka/100-bird-species

Code as reference

https://medium.com/nerd-for-tech/building-an-object-detector-in-tensorflow-using-bounding-box-regression-

2bc13992973f

https://www.kaggle.com/code/gowrav143/final-birds-cnn/notebook

https://www.kaggle.com/code/samuiyoru/notebook6561b42683

