Machine Learning
LABORATORY: CNN Homework

NAME:	STUDENT ID#:

Objectives:

- In this assignment, you will train a Convolutional Neural Network (CNN) to classify images of cats and dogs using a dataset and starter template provided to you.
- The template code includes a simple CNN model that serves as a baseline. However, this baseline model does not achieve high accuracy.
- Your goal is to improve the model's performance by modifying and fine-tuning the CNN architecture.
- You are encouraged to: Adjust the layer, add data augmentation and apply regularization techniques such as Dropout, BatchNormalization, or custom pooling strategies.

Part 1. Instruction

- The template code includes a simple CNN model that serves as a baseline. However, this baseline model does not achieve high accuracy.
- Your task is to improve the model's performance by modifying and fine-tuning the CNN architecture.
- You are encouraged to:
    - Adjust layer configurations (number of layers, filters, kernel sizes, activations, etc.)
    - Add data augmentation to improve generalization
    - Apply regularization techniques such as Dropout, BatchNormalization, or custom pooling strategies
- **However**, you are not allowed to use pre-trained models such as VGG, ResNet, EfficientNet, etc. (No transfer learning or model imports from keras.applications).
- Your model should be designed, trained, and fine-tuned by yourself, from scratch using Keras/TensorFlow layers.
- If you're not familiar with TensorFlow or Keras, check these links:
    - Tensorflow Setup Guide https://github.com/JTKostman/keras-tensorflow-windows-installation
    - Keras Quick Start : https://keras.io/getting_started/
- If you're using your **local PC**, you may need to install TensorFlow and Keras manually. If you're using **Google Colab**, they're already installed — but be aware that Colab has **limited training time**.
- Dataset: https://drive.google.com/file/d/1eyrNGFlM83pf-TETo30Cvjm7kYuCFAqu/view?usp=sharing (Also included in the template code for easy loading)

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Part 2. Code Template

Step	Procedure
1	

```
import pandas as pd
import IPython.display as display
import tensorflow as tf
from tensorflow.keras import layers
import numpy as np
import os,random
import matplotlib.pyplot as plt
print(tf.__version__)
```

2	

```
# ========== Download Dataset ==========
#!pip install -U gdown

import gdown, zipfile

file_id = "1eyrNGFlM83pf-TETo30Cvjm7kYuCFAqu"  # <-- from your real zip file link
gdown.download(f"https://drive.google.com/uc?id={file_id}", output="dataset.zip", quiet=False)

with zipfile.ZipFile("dataset.zip", 'r') as zip_ref:
   zip_ref.extractall("dataset")
```

3	

```
# ==========Dataset Preparation ==========
IMAGE_HEIGHT=128
IMAGE_WIDTH=128
BATCH_SIZE=64
def get_pathframe(path):
 '''
 Get all the images paths and its corresponding labels
 Store them in pandas dataframe
 '''
 filenames = os.listdir(path)
 categories = []
 paths=[]
 for filename in filenames:
   paths.append(path+filename)
   category = filename.split('.')[0]
   if category == 'dog':
     categories.append(1)
   else:
     categories.append(0)

 df= pd.DataFrame({
```

```
        'filename': filenames,
        'category': categories,
        'paths':paths
    })
    return df

df=get_pathframe("dataset/dataset/dataset/")
df.tail(5)
```

4

```
# ========== Convert to tensor ==========
def load_and_preprocess_image(path):
    '''
    Load each image and resize it to desired shape
    '''
    image = tf.io.read_file(path)
    image = tf.image.decode_jpeg(image, channels=3)
    image = tf.image.resize(image, [IMAGE_WIDTH, IMAGE_HEIGHT])
    image /= 255.0  # normalize to [0,1] range
    return image

def convert_to_tensor(df):
    '''
    Convert each data and labels to tensor
    '''
    path_ds = tf.data.Dataset.from_tensor_slices(df['paths'])
    image_ds = path_ds.map(load_and_preprocess_image)
    # onehot_label=tf.one_hot(tf.cast(df['category'], tf.int64),2) if
using softmax
    onehot_label=tf.cast(df['category'], tf.int64)
    label_ds = tf.data.Dataset.from_tensor_slices(onehot_label)

    return image_ds,label_ds


X,Y=convert_to_tensor(df)
print("Shape of X in data:", X)
print("Shape of Y in data:", Y)
```

5

```
#Plot Images
dataset=tf.data.Dataset.zip((X,Y)).shuffle(buffer_size=2000)
dataset_train=dataset.take(22500)
dataset_test=dataset.skip(22500)
```


```
dataset_train=dataset_train.batch(BATCH_SIZE, drop_remainder=True)
dataset_test=dataset_test.batch(BATCH_SIZE, drop_remainder=True)
dataset_train

def plotimages(imagesls):
 fig, axes = plt.subplots(1, 5, figsize=(20,20))
 axes = axes.flatten()
 for image,ax in zip(imagesls, axes):
   ax.imshow(image)
   ax.axis('off')

imagesls=[]
for n, image in enumerate(X.take(5)):
 imagesls.append(image)

plotimages(imagesls)
```

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```
#Model Design
def My_CNNmodel():

 model = tf.keras.models.Sequential()
 model.add(layers.Conv2D(8, (3, 3), padding='same',activation='relu',
input_shape=(IMAGE_WIDTH, IMAGE_HEIGHT, 3)))
 model.add(layers.MaxPooling2D(pool_size=(2,2)))
 model.add(layers.Conv2D(16, (3, 3),
padding='same',activation='relu'))
 model.add(layers.MaxPooling2D(pool_size=(2,2)))
 model.add(layers.Conv2D(32, (3, 3),
padding='same',activation='relu'))
 model.add(layers.MaxPooling2D(pool_size=(2,2)))
 model.add(layers.Conv2D(64, (3, 3),
padding='same',activation='relu'))
 model.add(layers.MaxPooling2D(pool_size=(2,2)))
 model.add(layers.Flatten())
 model.add(layers.Dense(512, activation='relu'))
 model.add(layers.Dense(1, activation='sigmoid'))

 opt=tf.keras.optimizers.Adam(0.001)
 model.compile(optimizer=opt,
             loss='binary_crossentropy', #
loss='categorical_crossentropy' if softmax
             metrics=['accuracy'])
```


```
 return model

model=My_CNNmodel()
model.summary()
```

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```
#Training the model
#You can adjust the epochs to get better training results, be aware
with overfitting

hist=model.fit(dataset_train,epochs=2,validation_data=dataset_test)
#Save trained model
model.save("student_ID.keras")
#Save the model with your student ID
```

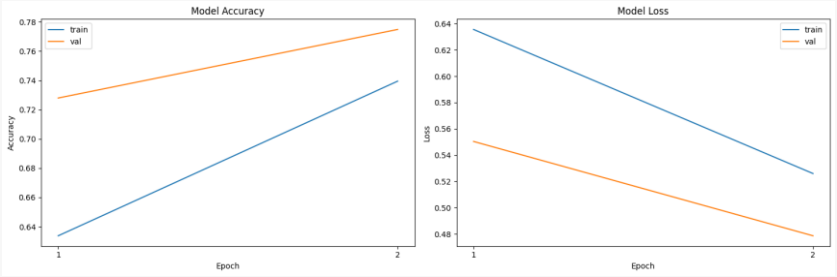
```
#Plot training results
def plot_model_history(model_history, acc='accuracy',
val_acc='val_accuracy'):
   fig, axs = plt.subplots(1, 2, figsize=(15, 5))

   # Accuracy plot
   axs[0].plot(range(1, len(model_history.history[acc]) + 1),
model_history.history[acc])
   axs[0].plot(range(1, len(model_history.history[val_acc]) + 1),
model_history.history[val_acc])
   axs[0].set_title('Model Accuracy')
   axs[0].set_ylabel('Accuracy')
   axs[0].set_xlabel('Epoch')
   axs[0].set_xticks(np.arange(1, len(model_history.history[acc]) +
1))
   axs[0].legend(['train', 'val'], loc='best')

   # Loss plot
   axs[1].plot(range(1, len(model_history.history['loss']) + 1),
model_history.history['loss'])
   axs[1].plot(range(1, len(model_history.history['val_loss']) + 1),
model_history.history['val_loss'])
   axs[1].set_title('Model Loss')
   axs[1].set_ylabel('Loss')
   axs[1].set_xlabel('Epoch')
   axs[1].set_xticks(np.arange(1, len(model_history.history['loss'])
+ 1))
   axs[1].legend(['train', 'val'], loc='best')
```


```
    plt.tight_layout()
    plt.show()
plot_model_history(hist)
```

```
#Evaluate the model
import seaborn as sns
from sklearn.metrics import confusion_matrix, classification_report
import matplotlib.pyplot as plt
import numpy as np

# Evaluate the model
loss, accuracy = model.evaluate(dataset_test)
print("Test: accuracy = %f  ;  loss = %f " % (accuracy, loss))

# Predict values
y_pred = model.predict(dataset_test)
y_p = np.where(y_pred > 0.5, 1, 0)  # for binary classification

# Extract ground truth labels
test_data = dataset_test.unbatch()
y_g = []
for image, label in test_data:
    y_g.append(label.numpy())

# Convert to flat array if needed
y_g = np.array(y_g).flatten()
y_p = y_p.flatten()

# Compute confusion matrix
confusion_mtx = confusion_matrix(y_g, y_p)

# Plot
f, ax = plt.subplots(figsize=(8, 8))
sns.heatmap(confusion_mtx, annot=True, linewidths=0.01, cmap="Blues",
linecolor="gray", fmt='.1f', ax=ax)
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix")
plt.show()
```

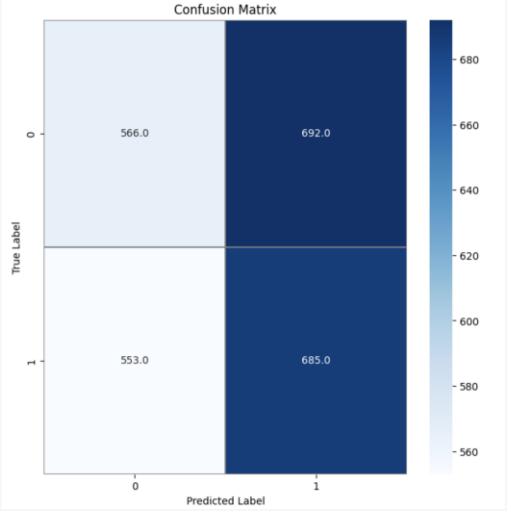
```
# Generate a classification report
report = classification_report(y_g, y_p, target_names=['0','1'])
print(report)
```


```
#Example Output (For references only)
#1. Plot Training Results
```




```
#2. Confusion Matrix
```

```
39/39 ━━━━━━━━━━━━━━━━━━━━ 19s 22ms/step - accuracy: 0.7777 - loss: 0.4819
Test: accuracy = 0.770433  ;  loss = 0.482054
39/39 ━━━━━━━━━━━━━━━━━━━━ 19s 17ms/step
```




```
#3. Classification Report
```

	precision	recall	f1-score	support
0	0.51	0.45	0.48	1258
1	0.50	0.55	0.52	1238
accuracy			0.50	2496
macro avg	0.50	0.50	0.50	2496
weighted avg	0.50	0.50	0.50	2496

```
#4. Model Summary
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 128, 128, 8)	224
max_pooling2d (MaxPooling2D)	(None, 64, 64, 8)	0
conv2d_1 (Conv2D)	(None, 64, 64, 16)	1,168
max_pooling2d_1 (MaxPooling2D)	(None, 32, 32, 16)	0
conv2d_2 (Conv2D)	(None, 32, 32, 32)	4,640
max_pooling2d_2 (MaxPooling2D)	(None, 16, 16, 32)	0
conv2d_3 (Conv2D)	(None, 16, 16, 64)	18,496
max_pooling2d_3 (MaxPooling2D)	(None, 8, 8, 64)	0
flatten (Flatten)	(None, 4096)	0
dense (Dense)	(None, 512)	2,097,664
dense_1 (Dense)	(None, 1)	513

Total params: 2,122,705 (8.10 MB)
Trainable params: 2,122,705 (8.10 MB)
Non-trainable params: 0 (0.00 B)

Grading Assignment & Submission (70%)

Implementation(45%):

1. (5%) **Fine-Tuning:** Adjust model parameters to achieve better accuracy
2. (20%) **Model redesign with techniques:** Redesign the architecture using advanced techniques such as data augmentation, Dropout, BatchNormalization, or self-designed structures (should achieve better accuracy), brief **explain your model summary in the report.**
3. (15%) **Accuracy Improvement:** Demonstrate significantly improved validation accuracy compared to the baseline model. **Explain your performance improvement.**
4. (5%) **Include all evaluation results:** model summary, training plots, confusion matrix, and classification report.

Question(25%):

5. (7%) What changes did you make to the CNN architecture? Why did you choose those modifications, and how did they affect model performance?
6. (8%) What methods did you use to reduce overfitting (if any)? How effective were they? Explain with reference to training/validation curves.
7. (10%) Based on your confusion matrix, what kinds of misclassifications occurred most frequently? What might be causing these errors? How would you attempt to reduce these errors?

Submission :

1. Report: Provide your screenshots of your results in the last pages of this PDF File.
2. Code: Submit your complete Python script in either .py or .ipynb format.
3. Upload both your report and code to the E3 system (**Labs6 Homework Assignment**). Name your files correctly:
    a. Report: StudentID_Lab6_Homework.pdf
    b. Code: StudentID_Lab6_ Homework.py or StudentID_Lab6_Homework.ipynb
4. Deadline: 16:20 PM
5. Plagiarism is **strictly prohibited**. Submitting copied work from other students will result in penalties.

Results and Discussion: