A Robust Deep Model for Classification of Peptic Ulcer and Other Digestive Tract Disorders Using Endoscopic Images

packages that need to install to run this code

- pip install **tensrflow** || in case of GPU use pip install **tensrflow-gpu**
- pip install **imblearn**
- pip install **tensorflow-addons**
- pip install **matplotlib**
- pip install **seaborn**
- pip install **keras**
- pip install **scikit-learn**

Dataset Link

File modified to run on colab

Follow the below instructions

- Instructions to add dataset in colab from kaggle Link
- download dataset in your current directory or another and carefully add path in the **WORKING_DIRECTORY** variable

In [ ]:

```
!pip install tensorflow
!pip install keras
!pip install imblearn
!pip install matplotlib
!pip install seaborn
!pip install scikit-learn
!pip install tensorflow-addons
```

Importing Libraries

In [ ]:

```
import numpy as np
import random

#   Plotting
import seaborn as sns
import matplotlib.pyplot as plt


#   DataGenerator to read images and rescale images
from tensorflow.keras.preprocessing.image import ImageDataGenerator

import tensorflow as tf
import tensorflow_addons as tfa

#   count each class samples
from collections import Counter

#   callbacks
from tensorflow.keras.callbacks import ReduceLROnPlateau
```

```
#   evaluate precison recall and f1-score of each class of model
from sklearn.metrics import classification_report
#   Show performance of a classification model
from sklearn.metrics import confusion_matrix

#   Different layers
from keras.models import Sequential
from tensorflow.keras.layers import Input
from tensorflow.keras.layers import Flatten
from tensorflow.keras.layers import AveragePooling2D
from tensorflow.keras.layers import Convolution2D
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Dropout
from tensorflow.keras.layers import ReLU
from tensorflow.keras.layers import Softmax

# split dataset to train, validation and test set
from sklearn.model_selection import train_test_split

#   callbacks
from keras import callbacks

#   ADASYN from imblance library
from imblearn.over_sampling import BorderlineSMOTE

#   Optimizer
from tensorflow.keras.optimizers import Adam

from sklearn.metrics import roc_curve, auc
from itertools import cycle
```

Define directory of dataset & Classes names

In [ ]:

```
### Set Path Here before running the code
WORKING_DIRECTORY = ".\\dataset\\"

CLASSES = ['Ampulla of Vater',
           'Angiectasia',
           'Blood-fresh',
           'Blood-hematin',
           'Erosion',
           'Erythema',
           'Foreign body',
           'Ileocecal valve',
           'Lymphangiectasia',
           'Normal clean mucosa',
           'Polyp',
           'Pylorus',
           'Reduced Mucosal',
           'Ulcer'
           ]

IMG_SIZE = 128
```

Load Images, Rescale Images, and seperate from data generator & Label One Hot encoding

In [ ]:

```
X, y = [], []

## Images rescaling
datagen = ImageDataGenerator(rescale=1.0/255.0)
```

```
#   Load images by resizing and shuffling randomly

#   set batch size to the total number of images
batch_size_datagen = 18827
train_dataset = datagen.flow_from_directory(WORKING_DIRECTORY,
                                            target_size=(IMG_SIZE, IMG_SIZE),
                                            batch_size=batch_size_datagen,
                                            shuffle=True)

### Seperate Dataset from  Data Genrator
X, y = train_dataset.next()
```

In [ ]:

```
samples_before = len(X)
print("Images shape :\t", X.shape)
print("Labels shape :\t", y.shape)
```

In [ ]:

```
#   Number of samples in classes
print("Number of samples in each class:\t", sorted(Counter(np.argmax(y, axis=1)).items()))

#   class labels as per indices
print("Classes Names according to index:\t", train_dataset.class_indices)
```

Show some random samples from the origional dataset

In [ ]:

```
#   show some samples from the dataset randomly
fig = plt.figure(figsize=(10,8))

rows = 4
columns = 4

for i in range(rows * columns):
    fig.add_subplot(rows, columns, i+1)
    num = random.randint(0, len(X)-1 )
    plt.imshow(X[num])
    plt.axis('off')
    plt.title(CLASSES[(np.argmax(y[num]))], fontsize=8)
plt.axis('off')
plt.show()
```

Apply ADASYN Algorithm to OverSample the dataset

In [ ]:

```
#   reshaping the images to 1D
X = X.reshape(-1, IMG_SIZE * IMG_SIZE * 3)

#   Oversampling method to remove imbalance class problem
X, y = BorderlineSMOTE().fit_resample(X, y)

#   reshape images to images size of 208, 176, 3
X = X.reshape(-1, IMG_SIZE, IMG_SIZE, 3)

samples_after = len(X)
print("Number of samples after SMOTETomek :\t", sorted(Counter(np.argmax(y, axis=1)).items
```

Show some random samples from the Generated dataset

In [ ]:

```
fig = plt.figure(figsize=(10,8))
```

```
rows = 4
columns = 4

for i in range(rows * columns):
    fig.add_subplot(rows, columns, i+1)
    num = random.randint(samples_before, samples_after - 1 )
    plt.imshow(X[num])
    plt.axis('off')
    plt.title(CLASSES[(np.argmax(y[num]))], fontsize=8)
plt.axis('off')
plt.show()
```

Splitting dataset for Training, Validation & Testing

In [ ]:

```
#   10% split to validation and 90% split to train set
X_train, x_val, y_train, y_val = train_test_split(X,y, test_size = 0.1)

#   10% split to test from 90% of train and 80% remains in train set
X_train, x_test, y_train, y_test = train_test_split(X_train,y_train, test_size = 0.1)

# Number of samples after train test split
print("Number of samples after splitting into Training, validation & test set\n")

print("Train     \t",sorted(Counter(np.argmax(y_train, axis=1)).items()))
print("Validation\t",sorted(Counter(np.argmax(y_val, axis=1)).items()))
print("Test      \t",sorted(Counter(np.argmax(y_test, axis=1)).items()))
```

In [ ]:

```
#   to free memeory we don't need this one as we split our data
del X, y
```

Model Architecture

In [ ]:

```
from keras.initializers import GlorotUniformV2

init = GlorotUniformV2

model = Sequential()

model.add(Convolution2D(16, 5, activation="relu", input_shape=(IMG_SIZE, IMG_SIZE, 3), ker
model.add(AveragePooling2D(pool_size=(2,2)))

model.add(Convolution2D(32, 5, activation="relu", kernel_initializer=init))
model.add(AveragePooling2D(pool_size=(2,2)))

model.add(Convolution2D(64, 5, activation="relu", kernel_initializer=init))
model.add(AveragePooling2D(pool_size=(2,2)))

model.add(Convolution2D(128, 5, activation="relu", kernel_initializer=init))
model.add(AveragePooling2D(pool_size=(2,2)))

model.add(Dropout(0.1))

model.add(Flatten())

model.add(Dense(256, activation="relu", kernel_initializer=init))
model.add(Dropout(0.3))

model.add(Dense(14, activation="softmax", kernel_initializer=init))
```

```
model.summary()
```

Compiling the Model

In [ ]:

```
### Model Compilation
model.compile(
    optimizer = Adam(learning_rate=0.0001),
    loss = tf.keras.losses.CategoricalCrossentropy(name='loss'),
    metrics=[
        tf.keras.metrics.CategoricalAccuracy(name='acc'),
        tf.keras.metrics.AUC(name='auc'),
        tfa.metrics.F1Score(num_classes=14),
        tf.metrics.Precision(name="precision"),
        tf.metrics.Recall(name="recall") ])
```

Defining CALLBACKS to reduce Learning Rate

In [ ]:

```
# callbacks used in model to perform well
rop_callback = ReduceLROnPlateau(monitor="val_loss", patience=2)
CALLBACKS = [rop_callback]
```

Training of the Model

In [ ]:

```
#   declare to run on small gpu create batch sizes of images
valAug = ImageDataGenerator()

#   defining batch size
batch_size = 32

history = model.fit(valAug.flow(X_train, y_train, batch_size=batch_size, shuffle = True),
steps_per_epoch=len(X_train) // batch_size,
validation_data=valAug.flow(x_val, y_val, batch_size=batch_size, shuffle = True),
validation_steps=len(x_val) // batch_size,
epochs= 2,
batch_size=batch_size,
callbacks = CALLBACKS
)
```

Evaluation of Model with the Test data

In [ ]:

```
### Evaluate Model
test_scores = model.evaluate(x_test, y_test, batch_size = 32)


print("\n\nTesting Loss : \t\t {0:0.6f}".format(test_scores[0] ))
print("Testing Accuracy : \t {0:0.6f} %".format(test_scores[1] * 100))
print("Testing AC : \t\t {0:0.6f} %".format(test_scores[2] * 100))
print("Testing F1-Score : \t {0:0.6f} %".format(
    ((test_scores[3][0] + test_scores[3][1] + test_scores[3][2] + test_scores[3][3] +
    test_scores[3][4] + test_scores[3][5] + test_scores[3][6] + test_scores[3][7] +
    test_scores[3][8] + test_scores[3][9] + test_scores[3][10] + test_scores[3][11]+
    test_scores[3][12]+ test_scores[3][13])/14) * 100))
print("Testing Precision : \t {0:0.6f} %".format(test_scores[4] * 100))
print("Testing Recall : \t {0:0.6f} %".format(test_scores[5] * 100))
```

Model Training graphs

- Accuracy
- Loss
- AUC
- Precision
- Recall
- F1-Score

In [ ]:

```
plt.plot(history.history['acc'], 'b')
plt.plot(history.history['val_acc'], 'g')
plt.title("Model Accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend(["train", "val"])
plt.show()
```

In [ ]:

```
plt.plot(history.history['loss'], 'b')
plt.plot(history.history['val_loss'], 'g')
plt.title("Model Loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend(["train", "val"])
plt.show()
```

In [ ]:

```
plt.plot(history.history['auc'], 'b')
plt.plot(history.history['val_auc'], 'g')
plt.title("Model AUC")
plt.xlabel("Epochs")
plt.ylabel("AUC")
plt.legend(["train", "val"])
plt.show()
```

In [ ]:

```
plt.plot(history.history['precision'], 'b')
plt.plot(history.history['val_precision'], 'g')
plt.title("Model Precision")
plt.xlabel("Epochs")
plt.ylabel("Precision")
plt.legend(["train", "val"])
plt.show()
```

In [ ]:

```
plt.plot(history.history['recall'], 'b')
plt.plot(history.history['val_recall'], 'g')
plt.title("Model Recall")
plt.xlabel("Epochs")
plt.ylabel("Recall")
plt.legend(["train", "val"])
plt.show()
```

In [ ]:

```
plt.plot(history.history['f1_score'])
plt.plot(history.history['val_f1_score'])
plt.title("Model F1-Score")
plt.xlabel("Epochs")
plt.ylabel("F1-Score")
plt.show()
```

Test set Evaluation

- Classification Report
- Confusion Matrix
- ROC Curve
- Extension ROC Multiclass

In [ ]:

```
pred_labels = model.predict(x_test, batch_size=32)

def roundoff(arr):
    arr[np.argwhere(arr != arr.max())] = 0
    arr[np.argwhere(arr == arr.max())] = 1
    return arr

for labels in pred_labels:
    labels = roundoff(labels)

print(classification_report(y_test, pred_labels, target_names=CLASSES))
```

In [ ]:

```
pred_ls = np.argmax(pred_labels, axis=1)
test_ls = np.argmax(y_test, axis=1)

conf_arr = confusion_matrix(test_ls, pred_ls)

plt.figure(figsize=(10, 8), dpi=80, facecolor='w', edgecolor='k')

ax = sns.heatmap(conf_arr, cmap='Greens', annot=True, fmt='d', xticklabels= CLASSES, ytick

plt.title('Confusion Matrix of Model', fontweight='bold', fontsize=14.0)
plt.xlabel('Predictions', fontweight='bold', fontsize=13)
plt.ylabel('Ground Truth', fontweight='bold', fontsize=13)
plt.tight_layout()
plt.show(ax)
```

In [ ]:

```
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(14):
    fpr[i], tpr[i], _ = roc_curve(y_test[:, i], pred_labels[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Compute micro-average ROC curve and ROC area
fpr["micro"], tpr["micro"], _ = roc_curve(y_test.ravel(), pred_labels.ravel())
roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])

plt.figure()
lw = 2
plt.plot(
    fpr[2],
    tpr[2],
    color="darkorange",
    lw=lw,
    label="ROC curve (area = %0.4f)" % roc_auc[2])

plt.plot([0, 1], [0, 1], color="navy", lw=lw, linestyle="--")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver operating characteristic ")
plt.legend(loc="lower right")
plt.show()
```

In [ ]:

```
n_classes = 14
# First aggregate all false positive rates
all_fpr = np.unique(np.concatenate([fpr[i] for i in range(n_classes)]))

# Then interpolate all ROC curves at this points
mean_tpr = np.zeros_like(all_fpr)
for i in range(n_classes):
    mean_tpr += np.interp(all_fpr, fpr[i], tpr[i])

# Finally average it and compute AUC
mean_tpr /= n_classes

fpr["macro"] = all_fpr
tpr["macro"] = mean_tpr
roc_auc["macro"] = auc(fpr["macro"], tpr["macro"])

# Plot all ROC curves
plt.figure(figsize=(10, 8))
plt.plot(
    fpr["micro"],
    tpr["micro"],
    label="micro-average ROC curve (area = {0:0.4f})".format(roc_auc["micro"]),
    color="deeppink",
    linestyle=":",
    linewidth=4,
)

plt.plot(
    fpr["macro"],
    tpr["macro"],
    label="macro-average ROC curve (area = {0:0.4f})".format(roc_auc["macro"]),
    color="navy",
    linestyle=":",
    linewidth=4,
)

for i in range(n_classes):
    plt.plot(
        fpr[i],
        tpr[i],
        lw=lw,
        label="ROC curve of class {0} (area = {1:0.4f})".format(i, roc_auc[i]),
    )

plt.plot([0, 1], [0, 1], "k--", lw=lw)
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Some extension of Receiver operating characteristic to multiclass")
plt.legend(loc="lower right")
plt.show()
```

Saving Model for Future Use

In [ ]:

```
#    To save the model in the current directory
model.save(".\\model.h5")
```