

▼ Libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers

from keras.applications.densenet import DenseNet121
from keras.applications.xception import Xception
from keras.applications.densenet import preprocess_input
from keras.optimizers import Adam, SGD, Adamax
from keras.models import Model, load_model
from keras.layers import *
from sklearn.model_selection import train_test_split
from keras.callbacks import *

from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Embedding, LSTM, Conv1D, MaxPool1D
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, accuracy_score
from tensorflow.keras import regularizers
```

▼ Train test split

```
from google.colab import drive
drive.mount('/content/drive',force_remount=True)

Mounted at /content/drive

image_size = (224, 224)
batch_size = 32

train_ds, val_ds = tf.keras.utils.image_dataset_from_directory(
    "/content/drive/MyDrive/BM1000",
    validation_split=0.25,
    subset="both",
    seed=1337,
    image_size=image_size,
    batch_size=batch_size,
)

Found 5850 files belonging to 7 classes.
Using 4388 files for training.
Using 1462 files for validation.

train_ds

<_PrefetchDataset element_spec=(TensorSpec(shape=(None, 224, 224, 3), dtype=tf.float32, name=None), TensorSpec(shape=(None,), dtype=tf.int32, name=None))>

class_names = train_ds.class_names
print(class_names)
num_classes = len(class_names)
print(num_classes)

['BAS', 'EOS', 'HAC', 'LYT', 'MON', 'NGB', 'NGS']
7
```

▼ Data Augmentation

```
data_augmentation = keras.Sequential(
    [
        layers.RandomFlip("horizontal",
                           input_shape=(224,
                                           224,
                                           3)),
        layers.RandomRotation(0.2),
        layers.RandomZoom(0.2),
        layers.RandomContrast(0.2),
        layers.RandomBrightness(0.2)
    ]
)

train_ds = train_ds.map(
    lambda x, y: (data_augmentation(x, training=True), y))
```

▼ Configure the dataset for performance

Make sure to use buffered prefetching, so you can yield data from disk without having I/O become blocking. These are two important methods you should use when loading data:

Dataset.cache keeps the images in memory after they're loaded off disk during the first epoch. This will ensure the dataset does not become a bottleneck while training your model. If your dataset is too large to fit into memory, you can also use this method to create a performant on-disk cache.

Dataset.prefetch overlaps data preprocessing and model execution while training.

```
AUTOTUNE = tf.data.AUTOTUNE

train_ds = train_ds.cache().shuffle(1000).prefetch(buffer_size=AUTOTUNE)
val_ds = val_ds.cache().prefetch(buffer_size=AUTOTUNE)
```

Custom Callbacks

```
import time
### Define a class for custom callback
class MyCallback(keras.callbacks.Callback):
    def __init__(self, model, base_model, patience, stop_patience, threshold, factor, batches, initial_epoch, epochs, ask_epoch):
        super(MyCallback, self).__init__()
        self.model = model
        self.base_model = base_model
        self.patience = patience # specifies how many epochs without improvement before learning rate is adjusted
        self.stop_patience = stop_patience # specifies how many times to adjust lr without improvement to stop training
        self.threshold = threshold # specifies training accuracy threshold when lr will be adjusted based on validation loss
        self.factor = factor # factor by which to reduce the learning rate
        self.batches = batches # number of training batch to runn per epoch
        self.initial_epoch = initial_epoch
        self.epochs = epochs
        self.ask_epoch = ask_epoch
        self.ask_epoch_initial = ask_epoch # save this value to restore if restarting training
        # callback variables
        self.count = 0 # how many times lr has been reduced without improvement
        self.stop_count = 0
        self.best_epoch = 1 # epoch with the lowest loss
        self.initial_lr = float(tf.keras.backend.get_value(model.optimizer.lr)) # get the initial learning rate and save it
        self.highest_tracc = 0.0 # set highest training accuracy to 0 initially
        self.lowest_vloss = np.inf # set lowest validation loss to infinity initially
        self.best_weights = self.model.get_weights() # set best weights to model's initial weights
        self.initial_weights = self.model.get_weights() # save initial weights if they have to get restored

# Define a function that will run when train begins
def on_train_begin(self, logs= None):
    msg = '{0:^8s}{1:^10s}{2:^9s}{3:^9s}{4:^9s}{5:^9s}{6:^9s}{7:^10s}{8:10s}{9:^8s}'.format('Epoch', 'Loss', 'Accuracy', 'V_loss', 'V_acc',
    print(msg)
    self.start_time = time.time()

def on_train_end(self, logs= None):
    stop_time = time.time()
    tr_duration = stop_time - self.start_time
    hours = tr_duration // 3600
    minutes = (tr_duration - (hours * 3600)) // 60
    seconds = tr_duration - ((hours * 3600) + (minutes * 60))
    msg = f'training elapsed time was {str(hours)} hours, {minutes:4.1f} minutes, {seconds:4.2f} seconds'
    print(msg)
    self.model.set_weights(self.best_weights) # set the weights of the model to the best weights

def on_train_batch_end(self, batch, logs= None):
    acc = logs.get('accuracy') * 100 # get batch accuracy
    loss = logs.get('loss')
    msg = '{0:20s}processing batch {1:} of {2:5s}- accuracy= {3:5.3f} - loss: {4:8.5f}'.format(' ', str(batch), str(self.batches),
    print(msg, '\r', end= '') # prints over on the same line to show running batch count

def on_epoch_begin(self, epoch, logs= None):
    self.ep_start = time.time()

# Define method runs on the end of each epoch
def on_epoch_end(self, epoch, logs= None):
    ep_end = time.time()
    duration = ep_end - self.ep_start

    lr = float(tf.keras.backend.get_value(self.model.optimizer.lr)) # get the current learning rate
    current_lr = lr
    acc = logs.get('accuracy') # get training accuracy
    v_acc = logs.get('val_accuracy') # get validation accuracy
    loss = logs.get('loss') # get training loss for this epoch
    v_loss = logs.get('val_loss') # get the validation loss for this epoch

    if acc < self.threshold: # if training accuracy is below threshold adjust lr based on training accuracy
        monitor = 'accuracy'
        if epoch == 0:
            pimprov = 0.0
        else:
            pimprov = (acc - self.highest_tracc) * 100 / self.highest_tracc # define improvement of model progres

    if acc > self.highest_tracc: # training accuracy improved in the epoch
        self.highest_tracc = acc # set new highest training accuracy
        self.best_weights = self.model.get_weights() # training accuracy improved so save the weights
        self.count = 0 # set count to 0 since training accuracy improved
        self.stop_count = 0 # set stop counter to 0
        if v_loss < self.lowest_vloss:
            self.lowest_vloss = v_loss
        self.best_epoch = epoch + 1 # set the value of best epoch for this epoch

    else:
        # training accuracy did not improve check if this has happened for patience number of epochs
        # if so adjust learning rate
```

```
        if self.count >= self.patience - 1: # lr should be adjusted
            lr = lr * self.factor # adjust the learning by factor
            tf.keras.backend.set_value(self.model.optimizer.lr, lr) # set the learning rate in the optimizer
            self.count = 0 # reset the count to 0
            self.stop_count = self.stop_count + 1 # count the number of consecutive lr adjustments
            self.count = 0 # reset counter
            if v_loss < self.lowest_vloss:
                self.lowest_vloss = v_loss
        else:
            self.count = self.count + 1 # increment patience counter

    else: # training accuracy is above threshold so adjust learning rate based on validation loss
        monitor = 'val_loss'
        if epoch == 0:
            pimprov = 0.0
        else:
            pimprov = (self.lowest_vloss - v_loss ) * 100 / self.lowest_vloss
        if v_loss < self.lowest_vloss: # check if the validation loss improved
            self.lowest_vloss = v_loss # replace lowest validation loss with new validation loss
            self.best_weights = self.model.get_weights() # validation loss improved so save the weights
            self.count = 0 # reset count since validation loss improved
            self.stop_count = 0
            self.best_epoch = epoch + 1 # set the value of the best epoch to this epoch
        else: # validation loss did not improve
            if self.count >= self.patience - 1: # need to adjust lr
                lr = lr * self.factor # adjust the learning rate
                self.stop_count = self.stop_count + 1 # increment stop counter because lr was adjusted
                self.count = 0 # reset counter
                tf.keras.backend.set_value(self.model.optimizer.lr, lr) # set the learning rate in the optimizer
            else:
                self.count = self.count + 1 # increment the patience counter
            if acc > self.highest_tracc:
                self.highest_tracc = acc

    msg = f'{str(epoch + 1):^3s}/{str(self.epochs):4s} {loss:^9.3f}{acc * 100:^9.3f}{v_loss:^9.5f}{v_acc * 100:^9.3f}{current_lr:^9.5f}{1}
    print(msg)

    if self.stop_count > self.stop_patience - 1: # check if learning rate has been adjusted stop_count times with no improvement
        msg = f' training has been halted at epoch {epoch + 1} after {self.stop_patience} adjustments of learning rate with no improvement'
        print(msg)
        self.model.stop_training = True # stop training

    else:
        if self.ask_epoch != None:
            if epoch + 1 >= self.ask_epoch:
                msg = 'enter H to halt training or an integer for number of epochs to run then ask again'
                print(msg)
                ans = input('')
                if ans == 'H' or ans == 'h':
                    msg = f'training has been halted at epoch {epoch + 1} due to user input'
                    print(msg)
                    self.model.stop_training = True # stop training
                else:
                    try:
                        ans = int(ans)
                        self.ask_epoch += ans
                        msg = f' training will continue until epoch ' + str(self.ask_epoch)
                        print(msg)
                        msg = '{0:^8s}{1:^10s}{2:^9s}{3:^9s}{4:^9s}{5:^9s}{6:^9s}{7:^10s}{8:10s}{9:^8s}'.format('Epoch', 'Loss', 'Accurac
                        print(msg)
                    except:
                        print('Invalid')
```

▼ DenseNet121

```
base_model=tf.keras.applications.DenseNet121(include_top= False, weights= "imagenet", input_shape= (224,224,3), pooling= 'max')
```

Downloading data from [https://storage.googleapis.com/tensorflow/keras-applications/densenet/densenet121\\_weights\\_tf\\_dim\\_ordering\\_tf\\_kernels/29084464/29084464](https://storage.googleapis.com/tensorflow/keras-applications/densenet/densenet121_weights_tf_dim_ordering_tf_kernels/29084464/29084464) [=====] - 0s 0us/step



```
model = Sequential([
    layers.Rescaling(1./255, input_shape=(224, 224, 3)),
    base_model,
    BatchNormalization(axis= -1, momentum= 0.99, epsilon= 0.001),
    Dense(256, kernel_regularizer= regularizers.l2(l= 0.016), activity_regularizer= regularizers.l1(0.006),
        bias_regularizer= regularizers.l1(0.006), activation= 'relu'),
    Dropout(rate= 0.45, seed= 123),
    Dense(7, activation= 'softmax')
])

model.compile(Adamax(learning_rate= 0.001, weight_decay=0.02), loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=False), metrics=

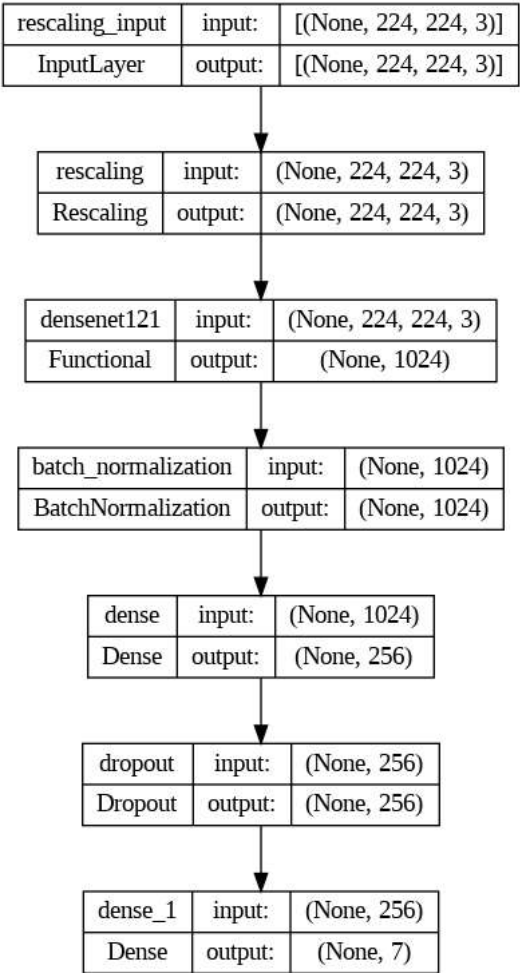
model.summary()
```

Model: "sequential\_3"

Layer (type)	Output Shape	Param #
rescaling (Rescaling)	(None, 224, 224, 3)	0
densenet121 (Functional)	(None, 1024)	7037504
batch_normalization (Batch Normalization)	(None, 1024)	4096

dense (Dense)	(None, 256)	262400
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 7)	1799
=====		
Total params: 7305799 (27.87 MB)		
Trainable params: 7220103 (27.54 MB)		
Non-trainable params: 85696 (334.75 KB)		

```
keras.utils.plot_model(model, show_shapes=True)
```



```
train = np.concatenate([y for x, y in train_ds], axis=0)
len(train)

4388
```

```
batch_size = 40
epochs = 40
patience = 1 # number of epochs to wait to adjust lr if monitored value does not improve
stop_patience = 3 # number of epochs to wait before stopping training if monitored value does not improve
threshold = 0.9 # if train accuracy is < threshold adjust monitor accuracy, else monitor validation loss
factor = 0.5 # factor to reduce lr by
freeze = False # if true free weights of the base model
ask_epoch = 5 # number of epochs to run before asking if you want to halt training
#batches = int(np.ceil(len(train_ds.labels) / batch_size))
batches = int(np.ceil(4388 / batch_size))
```

```
callbacks = [MyCallback(model= model, base_model= base_model, patience= patience,
                        stop_patience= stop_patience, threshold= threshold, factor= factor,
                        batches= batches, initial_epoch= 0, epochs= epochs, ask_epoch= ask_epoch )]
```

```
history = model.fit(x= train_ds, epochs= epochs, verbose= 0, callbacks= callbacks,
                    validation_data= val_ds, validation_steps= None, shuffle= False,
                    initial_epoch= 0)
```

Epoch	Loss	Accuracy	V_loss	V_acc	LR	Next LR	Monitor	% Improv	Duration
1 /40	6.633	39.198	6.60142	48.632	0.00100	0.00100	accuracy	0.00	560.09
2 /40	4.334	61.987	3.70347	71.956	0.00100	0.00100	accuracy	58.14	225.13
3 /40	3.350	70.214	2.84616	78.659	0.00100	0.00100	accuracy	13.27	224.53
4 /40	2.684	74.499	2.44648	75.308	0.00100	0.00100	accuracy	6.10	219.65
5 /40	2.255	76.185	2.04556	77.702	0.00100	0.00100	accuracy	2.26	225.51
enter H to halt training or an integer for number of epochs to run then ask again									
5									
training will continue until epoch 10									
Epoch	Loss	Accuracy	V_loss	V_acc	LR	Next LR	Monitor	% Improv	Duration
6 /40	1.915	78.077	1.82772	76.334	0.00100	0.00100	accuracy	2.48	224.72
7 /40	1.664	78.829	1.64515	74.419	0.00100	0.00100	accuracy	0.96	224.78
8 /40	1.468	78.965	1.36977	80.096	0.00100	0.00100	accuracy	0.17	228.07
9 /40	1.303	80.059	1.36763	75.923	0.00100	0.00100	accuracy	1.39	228.67
10 /40	1.206	80.059	1.13806	80.096	0.00100	0.00050	accuracy	0.00	224.36
enter H to halt training or an integer for number of epochs to run then ask again									
6									
training will continue until epoch 16									
Epoch	Loss	Accuracy	V_loss	V_acc	LR	Next LR	Monitor	% Improv	Duration
11 /40	1.055	82.566	0.99145	83.037	0.00050	0.00050	accuracy	3.13	222.71
12 /40	0.973	83.888	1.00610	81.874	0.00050	0.00050	accuracy	1.60	220.24
13 /40	0.924	84.868	0.93076	83.105	0.00050	0.00050	accuracy	1.17	220.42

```
14 /40      0.886   84.594   0.94095   81.737   0.00050   0.00025   accuracy   -0.32   219.42
15 /40      0.808   86.805   0.89385   83.242   0.00025   0.00025   accuracy    2.28   221.06
16 /40      0.779   87.056   0.84956   83.926   0.00025   0.00025   accuracy    0.29   220.47
enter H to halt training or an integer for number of epochs to run then ask again
5
training will continue until epoch 21
Epoch   Loss   Accuracy   V_loss   V_acc   LR   Next LR   Monitor   % Improv   Duration
17 /40   0.755   87.306   0.84766   84.405   0.00025   0.00025   accuracy   0.29   219.54
18 /40   0.743   87.717   0.92366   80.780   0.00025   0.00025   accuracy   0.47   220.05
19 /40   0.727   87.717   0.87074   82.490   0.00025   0.00013   accuracy   0.00   221.27
20 /40   0.705   88.446   0.85363   82.627   0.00013   0.00013   accuracy   0.83   218.76
21 /40   0.691   88.605   0.82662   83.311   0.00013   0.00013   accuracy   0.18   219.18
enter H to halt training or an integer for number of epochs to run then ask again
5
training will continue until epoch 26
Epoch   Loss   Accuracy   V_loss   V_acc   LR   Next LR   Monitor   % Improv   Duration
22 /40   0.690   88.195   0.80776   83.721   0.00013   0.00006   accuracy  -0.46   224.47
23 /40   0.669   89.312   0.84311   82.490   0.00006   0.00006   accuracy   0.80   221.20
24 /40   0.657   89.152   0.79415   84.884   0.00006   0.00003   accuracy  -0.18   220.28
25 /40   0.644   89.813   0.81428   83.926   0.00003   0.00003   accuracy   0.56   218.35
26 /40   0.642   89.904   0.85606   81.737   0.00003   0.00003   accuracy   0.10   218.79
enter H to halt training or an integer for number of epochs to run then ask again
5
training will continue until epoch 31
Epoch   Loss   Accuracy   V_loss   V_acc   LR   Next LR   Monitor   % Improv   Duration
27 /40   0.643   89.676   0.80592   83.858   0.00003   0.00002   accuracy  -0.25   220.40
28 /40   0.646   89.380   0.80939   83.721   0.00002   0.00001   accuracy  -0.58   219.49
29 /40   0.626   90.087   0.81368   83.447   0.00001   0.00000   val_loss  -2.46   218.14
training has been halted at epoch 29 after 3 adjustments of learning rate with no improvement
training elapsed time was 2.0 hours, 9.0 minutes, 57.85 seconds)
```

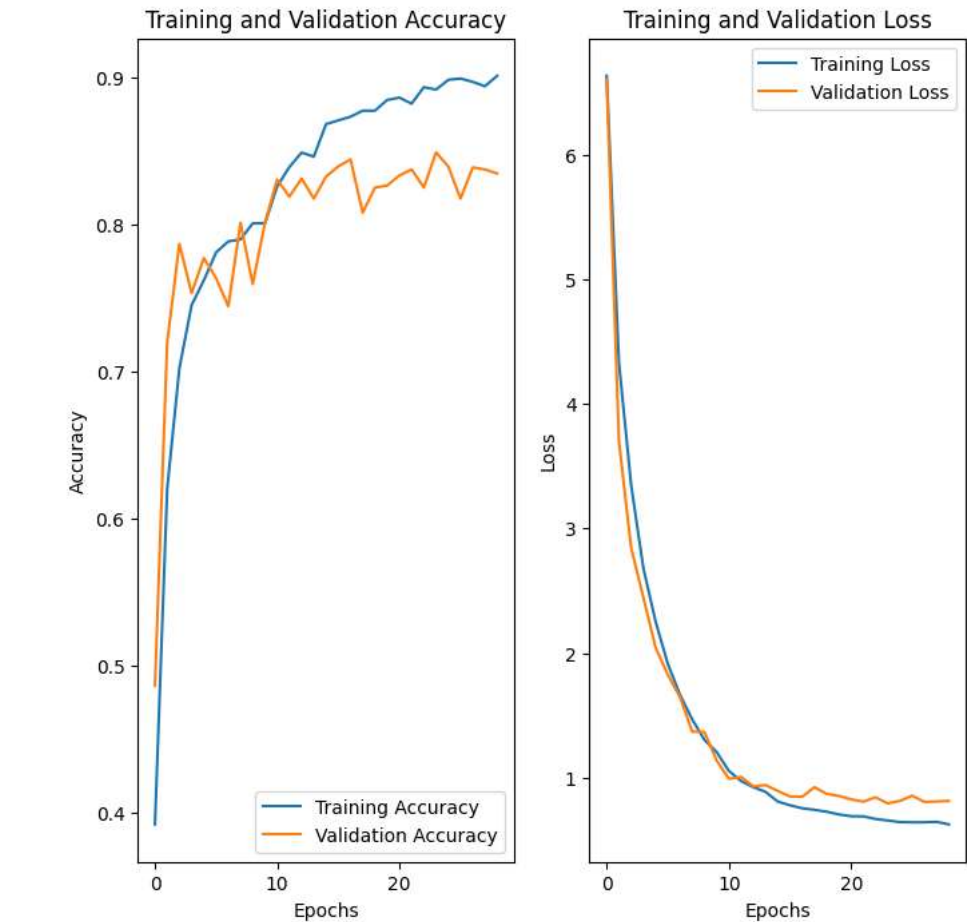
#Create plots of the loss and accuracy on the training and validation sets:

```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

loss = history.history['loss']
val_loss = history.history['val_loss']

plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(acc, label='Training Accuracy')
plt.plot(val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.title('Training and Validation Accuracy')
```

```
plt.subplot(1, 2, 2)
plt.plot(loss, label='Training Loss')
plt.plot(val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.title('Training and Validation Loss')
plt.show()
```



```
y_test = np.concatenate([y for x, y in val_ds], axis=0)
y_pred = model.predict(val_ds)
y_pred_classes = np.argmax(y_pred, axis=1)
accuracy_score(y_test, y_pred_classes)
```

```
print(classification_report(y_test, y_pred_classes, target_names=class_names))
```

	precision	recall	f1-score	support
BAS	0.88	0.75	0.81	110
EOS	0.89	0.97	0.93	255
HAC	0.82	0.81	0.81	93
LYT	0.96	0.77	0.85	265
MON	0.66	0.93	0.78	255
NGB	0.75	0.76	0.75	235
NGS	0.90	0.68	0.78	249
accuracy			0.82	1462
macro avg	0.84	0.81	0.82	1462
weighted avg	0.84	0.82	0.82	1462