Homework2DenseNet

March 8, 2022

1 Homework 2 DenseNet121

1.1 Loading Libraries

```
[1]: # Importing Libraries
   # Basic Libraries
   import pandas as pd
   import numpy as np
   import matplotlib.pyplot as plt
   import os
   import seaborn as sns
   import datetime
   import time
   # For Feature Engineering
   # For Machine Learning Techniques
   import tensorflow as tf
   from tensorflow import keras
   from tensorflow.keras import layers
   from tensorflow.keras.datasets import cifar10
   from tensorflow.keras.applications import DenseNet121
   from tensorflow.keras.applications.densenet import preprocess_input
   # For Data Anaylsis
   from sklearn.model_selection import train_test_split
```

from tensorflow.keras.preprocessing import image from tensorflow.keras.preprocessing.image import ImageDataGenerator,img to array

from tensorflow.keras.models import Model from tensorflow.keras.optimizers import Adam from tensorflow.keras.callbacks import ModelCheckpoint, ReduceLROnPlateau

 $from\ tensorflow. keras. layers\ import\ Dense, Global Average Pooling 2D, Convolution 2D, Batch Normalization\ from\ tensorflow. keras. layers\ import\ Flatten, Max Pooling 2D, Dropout$

1.1.1 Setting GPU

```
[2]: # Change to markdown if gpu is not set up
     import os
     os.environ["TF_CPP_MIN_LOG_LEVEL"] = "2"
     from tensorflow.python.client import device_lib
     print(device_lib.list_local_devices())
     physical_devices = tf.config.list_physical_devices("GPU")
     tf.config.experimental.set_memory_growth(physical_devices[0], True)
    [name: "/device:CPU:0"
    device_type: "CPU"
    memory_limit: 268435456
    locality {
    }
    incarnation: 9327267842447527460
    xla_global_id: -1
    , name: "/device:GPU:0"
    device_type: "GPU"
    memory_limit: 6273040384
    locality {
      bus_id: 1
      links {
      }
    }
    incarnation: 6856064255926636361
    physical_device_desc: "device: 0, name: NVIDIA GeForce RTX 2070 SUPER, pci bus
```

id: 0000:02:00.0, compute capability: 7.5"

```
xla_global_id: 416903419
```

```
1.2 Loading Data
[3]: # Setting Class Names
     class_names=['airplane', 'automobile', 'bird', 'cat', 'deer',
                  'dog', 'frog', 'horse', 'ship', 'truck']
[4]: # Loading the Dataset
     (x_train,y_train),(x_test,y_test)=cifar10.load_data()
[5]: # Normalizing the Images
     x_train=x_train/255.0
     print(x_train.shape)
    x_test=x_test/255.0
     print(x_test.shape)
    (50000, 32, 32, 3)
    (10000, 32, 32, 3)
    1.3 Splitting the Data
[6]: # 10% of the Orginal Dataset
     x_train10, not_needed1, y_train10, not_needed2 = train_test_split(
```

```
x_train, y_train, test_size=0.90, random_state=42)
```

```
[7]: # 50% of the Orginal Dataset
     x_train50, not_needed1, y_train50, not_needed2 = train_test_split(
         x_train, y_train, test_size=0.50, random_state=42)
```

```
[8]: # 80% of the Orginal Dataset (redundant)
     x_train80, not_needed1, y_train80, not_needed2 = train_test_split(
        x_train, y_train, test_size=0.20, random_state=42)
```

1.4 Setting up Models

```
[9]: # Creating the actual model
      model_10 = tf.keras.applications.DenseNet121(
          include_top=True,
          weights=None,
          input_tensor=None,
          input_shape=(32, 32, 3),
          pooling=None,
          classes=1000,)
[10]: # Setting up Mutiple Models
      model_50 = model_10
      model_80 = model_10
[11]: # Model Compiling
      model_10.compile(loss="sparse_categorical_crossentropy",
                            optimizer="Adam", metrics=["sparse_categorical_accuracy"])
      model_50.compile(loss="sparse_categorical_crossentropy",
                            optimizer="Adam", metrics=["sparse_categorical_accuracy"])
      model_80.compile(loss="sparse_categorical_crossentropy",
                            optimizer="Adam", metrics=["sparse_categorical_accuracy"])
     1.5 Training the Models
[12]: # Fitting the 10% Model
      model 10.fit(x train10,y train10,epochs=25, batch size=32, validation split=0.2)
      \#history10 = model_10.fit(x_train10, y_train10, epochs=25, batch_size=32, u)
```

```
sparse_categorical_accuracy: 0.4300 - val_loss: 2.4747 -
val_sparse_categorical_accuracy: 0.2460
Epoch 4/25
sparse categorical accuracy: 0.4723 - val loss: 2.5736 -
val_sparse_categorical_accuracy: 0.2040
Epoch 5/25
sparse_categorical_accuracy: 0.5095 - val_loss: 2.5524 -
val_sparse_categorical_accuracy: 0.2940
Epoch 6/25
sparse_categorical_accuracy: 0.5545 - val_loss: 1.7555 -
val_sparse_categorical_accuracy: 0.4330
Epoch 7/25
sparse_categorical_accuracy: 0.5968 - val_loss: 2.3706 -
val_sparse_categorical_accuracy: 0.3390
Epoch 8/25
125/125 [============ ] - 9s 73ms/step - loss: 1.0124 -
sparse_categorical_accuracy: 0.6470 - val_loss: 1.8810 -
val_sparse_categorical_accuracy: 0.4050
Epoch 9/25
sparse_categorical_accuracy: 0.6888 - val_loss: 2.2051 -
val_sparse_categorical_accuracy: 0.3710
Epoch 10/25
sparse_categorical_accuracy: 0.7145 - val_loss: 1.8965 -
val_sparse_categorical_accuracy: 0.4610
Epoch 11/25
sparse_categorical_accuracy: 0.7812 - val_loss: 1.7754 -
val_sparse_categorical_accuracy: 0.4660
Epoch 12/25
sparse categorical accuracy: 0.7950 - val loss: 2.4877 -
val_sparse_categorical_accuracy: 0.4430
Epoch 13/25
sparse_categorical_accuracy: 0.8205 - val_loss: 2.0643 -
val_sparse_categorical_accuracy: 0.4570
Epoch 14/25
sparse_categorical_accuracy: 0.8545 - val_loss: 1.9634 -
val_sparse_categorical_accuracy: 0.4640
Epoch 15/25
```

```
sparse_categorical_accuracy: 0.8637 - val_loss: 2.3770 -
   val_sparse_categorical_accuracy: 0.4690
   Epoch 16/25
   sparse categorical accuracy: 0.9072 - val loss: 2.9759 -
   val_sparse_categorical_accuracy: 0.4490
   Epoch 17/25
   sparse_categorical_accuracy: 0.9087 - val_loss: 2.1573 -
   val_sparse_categorical_accuracy: 0.4710
   Epoch 18/25
   sparse_categorical_accuracy: 0.9122 - val_loss: 2.6959 -
   val_sparse_categorical_accuracy: 0.4170
   Epoch 19/25
   sparse_categorical_accuracy: 0.9185 - val_loss: 2.4046 -
   val_sparse_categorical_accuracy: 0.4810
   Epoch 20/25
   sparse_categorical_accuracy: 0.9245 - val_loss: 2.3488 -
   val sparse categorical accuracy: 0.4810
   Epoch 21/25
   sparse_categorical_accuracy: 0.9383 - val_loss: 2.6833 -
   val_sparse_categorical_accuracy: 0.4970
   Epoch 22/25
   sparse_categorical_accuracy: 0.9335 - val_loss: 2.3006 -
   val_sparse_categorical_accuracy: 0.5150
   Epoch 23/25
   sparse_categorical_accuracy: 0.9560 - val_loss: 2.4011 -
   val_sparse_categorical_accuracy: 0.5130
   Epoch 24/25
   sparse categorical accuracy: 0.9680 - val loss: 2.7270 -
   val_sparse_categorical_accuracy: 0.4760
   Epoch 25/25
   sparse_categorical_accuracy: 0.9480 - val_loss: 3.7977 -
   val_sparse_categorical_accuracy: 0.4140
[13]: # Fitting the 50% Model
   model_50.fit(x_train50,y_train50,epochs=25, batch_size=32, validation_split=0.2)
```

```
Epoch 1/25
625/625 [============= ] - 44s 71ms/step - loss: 1.2155 -
sparse categorical accuracy: 0.5900 - val loss: 1.2808 -
val_sparse_categorical_accuracy: 0.5534
Epoch 2/25
625/625 [============= ] - 45s 71ms/step - loss: 0.9159 -
sparse_categorical_accuracy: 0.6811 - val_loss: 0.9580 -
val_sparse_categorical_accuracy: 0.6660
Epoch 3/25
625/625 [=========== ] - 44s 71ms/step - loss: 0.7727 -
sparse_categorical_accuracy: 0.7311 - val_loss: 1.2955 -
val_sparse_categorical_accuracy: 0.5846
Epoch 4/25
625/625 [============ ] - 44s 71ms/step - loss: 0.6411 -
sparse_categorical_accuracy: 0.7758 - val_loss: 1.2529 -
val_sparse_categorical_accuracy: 0.6184
Epoch 5/25
sparse_categorical_accuracy: 0.8106 - val_loss: 0.9847 -
val_sparse_categorical_accuracy: 0.6828
Epoch 6/25
625/625 [=========== ] - 44s 71ms/step - loss: 0.4508 -
sparse_categorical_accuracy: 0.8418 - val_loss: 1.6166 -
val_sparse_categorical_accuracy: 0.6036
Epoch 7/25
625/625 [========== ] - 44s 71ms/step - loss: 0.3576 -
sparse_categorical_accuracy: 0.8761 - val_loss: 1.4494 -
val_sparse_categorical_accuracy: 0.6480
Epoch 8/25
625/625 [============ ] - 44s 71ms/step - loss: 0.2906 -
sparse_categorical_accuracy: 0.8967 - val_loss: 1.2609 -
val_sparse_categorical_accuracy: 0.6894
Epoch 9/25
625/625 [============= ] - 44s 71ms/step - loss: 0.2490 -
sparse_categorical_accuracy: 0.9145 - val_loss: 1.5164 -
val_sparse_categorical_accuracy: 0.6356
Epoch 10/25
sparse_categorical_accuracy: 0.9244 - val_loss: 1.0207 -
val sparse categorical accuracy: 0.7328
Epoch 11/25
625/625 [=========== ] - 43s 68ms/step - loss: 0.1743 -
sparse_categorical_accuracy: 0.9399 - val_loss: 1.6696 -
val_sparse_categorical_accuracy: 0.6480
```

```
Epoch 12/25
sparse_categorical_accuracy: 0.9434 - val_loss: 1.3776 -
val_sparse_categorical_accuracy: 0.6784
Epoch 13/25
sparse categorical accuracy: 0.9476 - val loss: 1.2679 -
val_sparse_categorical_accuracy: 0.7086
Epoch 14/25
625/625 [============ ] - 41s 65ms/step - loss: 0.1390 -
sparse_categorical_accuracy: 0.9519 - val_loss: 1.0181 -
val_sparse_categorical_accuracy: 0.7444
Epoch 15/25
sparse_categorical_accuracy: 0.9572 - val_loss: 1.4486 -
val_sparse_categorical_accuracy: 0.7046
Epoch 16/25
sparse_categorical_accuracy: 0.9612 - val_loss: 1.6245 -
val sparse categorical accuracy: 0.6578
Epoch 17/25
sparse_categorical_accuracy: 0.9623 - val_loss: 1.5455 -
val_sparse_categorical_accuracy: 0.6826
Epoch 18/25
sparse_categorical_accuracy: 0.9642 - val_loss: 1.4584 -
val_sparse_categorical_accuracy: 0.7050
Epoch 19/25
sparse_categorical_accuracy: 0.9673 - val_loss: 1.3788 -
val_sparse_categorical_accuracy: 0.7264
Epoch 20/25
sparse categorical accuracy: 0.9711 - val loss: 1.5430 -
val_sparse_categorical_accuracy: 0.7002
Epoch 21/25
625/625 [============= ] - 49s 78ms/step - loss: 0.0925 -
sparse_categorical_accuracy: 0.9672 - val_loss: 1.7258 -
val_sparse_categorical_accuracy: 0.6658
Epoch 22/25
625/625 [============= ] - 48s 77ms/step - loss: 0.0803 -
sparse_categorical_accuracy: 0.9729 - val_loss: 1.2996 -
val_sparse_categorical_accuracy: 0.7270
Epoch 23/25
625/625 [============= ] - 48s 77ms/step - loss: 0.0820 -
sparse_categorical_accuracy: 0.9722 - val_loss: 1.3716 -
val_sparse_categorical_accuracy: 0.7294
```

```
Epoch 24/25
    sparse_categorical_accuracy: 0.9714 - val_loss: 1.6355 -
    val_sparse_categorical_accuracy: 0.6962
    Epoch 25/25
    sparse_categorical_accuracy: 0.9772 - val_loss: 1.6322 -
    val_sparse_categorical_accuracy: 0.7040
[14]: # Fitting the 80% Model
     model_80.fit(x_train80,y_train80,epochs=25, batch_size=32, validation_split=0.2)
     #history80 = model_80.fit(x train80,y_train80,epochs=25, batch_size=32,__
      \rightarrow validation_split=0.2)
    Epoch 1/25
    1000/1000 [============= ] - 75s 75ms/step - loss: 0.5142 -
    sparse_categorical_accuracy: 0.8465 - val_loss: 0.5194 -
    val_sparse_categorical_accuracy: 0.8328
    Epoch 2/25
    1000/1000 [============= ] - 66s 66ms/step - loss: 0.2670 -
    sparse_categorical_accuracy: 0.9132 - val_loss: 0.8483 -
    val_sparse_categorical_accuracy: 0.7550
    Epoch 3/25
    1000/1000 [============ ] - 66s 66ms/step - loss: 0.1871 -
    sparse_categorical_accuracy: 0.9354 - val_loss: 1.0471 -
    val_sparse_categorical_accuracy: 0.7290
    Epoch 4/25
    1000/1000 [============= ] - 65s 65ms/step - loss: 0.1455 -
    sparse_categorical_accuracy: 0.9506 - val_loss: 0.7504 -
    val_sparse_categorical_accuracy: 0.7970
    Epoch 5/25
    1000/1000 [============= ] - 68s 68ms/step - loss: 0.1210 -
    sparse_categorical_accuracy: 0.9590 - val_loss: 1.0309 -
    val_sparse_categorical_accuracy: 0.7558
    Epoch 6/25
    1000/1000 [============== ] - 65s 65ms/step - loss: 0.1163 -
    sparse_categorical_accuracy: 0.9593 - val_loss: 0.9084 -
    val_sparse_categorical_accuracy: 0.7846
    Epoch 7/25
    1000/1000 [============= ] - 66s 66ms/step - loss: 0.0912 -
    sparse_categorical_accuracy: 0.9685 - val_loss: 0.8923 -
    val_sparse_categorical_accuracy: 0.7968
    Epoch 8/25
    1000/1000 [============== ] - 67s 67ms/step - loss: 0.0928 -
    sparse_categorical_accuracy: 0.9678 - val_loss: 1.2350 -
    val_sparse_categorical_accuracy: 0.7335
    Epoch 9/25
```

```
1000/1000 [============== ] - 81s 81ms/step - loss: 0.0869 -
sparse_categorical_accuracy: 0.9699 - val_loss: 0.9269 -
val_sparse_categorical_accuracy: 0.7884
Epoch 10/25
1000/1000 [============ ] - 71s 71ms/step - loss: 0.0770 -
sparse_categorical_accuracy: 0.9734 - val_loss: 0.8906 -
val sparse categorical accuracy: 0.8089
Epoch 11/25
1000/1000 [============= ] - 66s 66ms/step - loss: 0.0808 -
sparse_categorical_accuracy: 0.9729 - val_loss: 0.8408 -
val_sparse_categorical_accuracy: 0.8062
Epoch 12/25
1000/1000 [============= ] - 65s 65ms/step - loss: 0.0726 -
sparse_categorical_accuracy: 0.9751 - val_loss: 0.9230 -
val_sparse_categorical_accuracy: 0.7937
Epoch 13/25
1000/1000 [============= ] - 65s 65ms/step - loss: 0.0705 -
sparse_categorical_accuracy: 0.9759 - val_loss: 0.9507 -
val_sparse_categorical_accuracy: 0.7881
Epoch 14/25
1000/1000 [============= ] - 64s 64ms/step - loss: 0.0664 -
sparse_categorical_accuracy: 0.9771 - val_loss: 1.1564 -
val_sparse_categorical_accuracy: 0.7659
Epoch 15/25
1000/1000 [============= ] - 65s 65ms/step - loss: 0.0567 -
sparse_categorical_accuracy: 0.9803 - val_loss: 1.0516 -
val_sparse_categorical_accuracy: 0.7989
Epoch 16/25
1000/1000 [============= ] - 65s 65ms/step - loss: 0.0677 -
sparse_categorical_accuracy: 0.9764 - val_loss: 1.2900 -
val_sparse_categorical_accuracy: 0.7604
Epoch 17/25
1000/1000 [============== ] - 65s 65ms/step - loss: 0.0501 -
sparse_categorical_accuracy: 0.9827 - val_loss: 1.0839 -
val sparse categorical accuracy: 0.7843
Epoch 18/25
1000/1000 [============= ] - 64s 64ms/step - loss: 0.0643 -
sparse_categorical_accuracy: 0.9784 - val_loss: 1.0430 -
val_sparse_categorical_accuracy: 0.7824
Epoch 19/25
1000/1000 [============= ] - 67s 67ms/step - loss: 0.0547 -
sparse_categorical_accuracy: 0.9817 - val_loss: 1.1560 -
val_sparse_categorical_accuracy: 0.7794
Epoch 20/25
1000/1000 [============= ] - 65s 65ms/step - loss: 0.0513 -
sparse_categorical_accuracy: 0.9825 - val_loss: 1.0055 -
val_sparse_categorical_accuracy: 0.7976
Epoch 21/25
```

```
1000/1000 [============== ] - 65s 65ms/step - loss: 0.0479 -
sparse_categorical_accuracy: 0.9839 - val_loss: 1.0299 -
val_sparse_categorical_accuracy: 0.7983
Epoch 22/25
1000/1000 [============= ] - 64s 64ms/step - loss: 0.0536 -
sparse_categorical_accuracy: 0.9824 - val_loss: 1.0672 -
val sparse categorical accuracy: 0.7829
Epoch 23/25
1000/1000 [============== ] - 64s 64ms/step - loss: 0.0427 -
sparse_categorical_accuracy: 0.9862 - val_loss: 1.1263 -
val_sparse_categorical_accuracy: 0.7832
Epoch 24/25
1000/1000 [============= ] - 64s 64ms/step - loss: 0.0510 -
sparse_categorical_accuracy: 0.9829 - val_loss: 1.1432 -
val_sparse_categorical_accuracy: 0.7861
Epoch 25/25
1000/1000 [============= ] - 65s 65ms/step - loss: 0.0431 -
sparse_categorical_accuracy: 0.9849 - val_loss: 1.1585 -
val_sparse_categorical_accuracy: 0.7844
```

1.6 Plotting the Models

```
[72]: # Test Error
      temp={}
      temp1={}
      temp2={}
      score = model_10.evaluate(x_test, y_test, verbose=0)
      temp["DenseNet121 10% Test error"] = 1-score[1]
      performance = pd.DataFrame([temp]).T
      score = model_50.evaluate(x_test, y_test, verbose=0)
      temp1["DenseNet121 50% Test error"]=1-score[1]
      performance1 = pd.DataFrame([temp1]).T
      performance = performance.append(performance1)
      score = model_80.evaluate(x_test, y_test, verbose=0)
      temp2["DenseNet121 80% Test error"]=1-score[1]
      performance2 = pd.DataFrame([temp2]).T
      performance = performance.append(performance2)
      performance
```

```
[72]: 0
DenseNet121 10% Test error 0.2593
DenseNet121 50% Test error 0.2593
```



1.6.1 Plotting the 10% Model

plt.plot(history10.history['loss']) plt.title('Model 10% Top-1 Error') plt.ylabel('Loss') plt.xlabel('Epoch') plt.legend(['train'], loc = 'upper left') plt.show()

1.6.2 Plotting the 50% Model

plt.plot(history50.history['loss']) plt.title('Model 50% Top-1 Error') plt.ylabel('Loss') plt.xlabel('Epoch') plt.legend(['train'], loc = 'upper left') plt.show()

1.6.3 Plotting the 80% Model

plt.plot(history80.history['loss']) plt.title('Model 80% Top-1 Error') plt.ylabel('Loss') plt.xlabel('Epoch') plt.legend(['train'], loc = 'upper left') plt.show()

2 Homework 2 My Model

2.1 Setting up the Model

```
[27]: # Designing the Model

custom_model=tf.keras.models.Sequential()
```

```
# Convultions
 # First Layer
custom_model.add(tf.keras.layers.Conv2D(filters=32,kernel_size=3,padding="same",
                                  activation="relu",
 →input_shape=[32,32,3]))
# Max Pooling Layer
custom_model.add(tf.keras.layers.
 →MaxPool2D(pool_size=2,strides=2,padding='valid'))
# Third Layer
custom_model.add(tf.keras.layers.Conv2D(filters=64,kernel_size=3,padding="same",
                                  activation="relu"))
# Max Pooling Layer
custom_model.add(tf.keras.layers.
 →MaxPool2D(pool_size=2,strides=2,padding='valid'))
# Flattening Layer
custom model.add(tf.keras.layers.Flatten())
# Droput Layer
custom_model.add(tf.keras.layers.Dropout(0.5,noise_shape=None,seed=None))
# Neural Network
 # Adding the first fully connected layer
custom_model.add(tf.keras.layers.Dense(units=128,activation='relu'))
# Output Layer
custom_model.add(tf.keras.layers.Dense(units=10,activation='softmax'))
custom_model.summary()
Model: "sequential_2"
Layer (type)
                       Output Shape
                                             Param #
______
conv2d_4 (Conv2D)
                      (None, 32, 32, 32)
                                             896
max_pooling2d_4 (MaxPooling (None, 16, 16, 32)
```

2D)

```
conv2d_5 (Conv2D) (None, 16, 16, 64)
                                                       18496
     max_pooling2d_5 (MaxPooling (None, 8, 8, 64)
     2D)
     flatten_2 (Flatten)
                                (None, 4096)
                                                        0
                               (None, 4096)
     dropout_2 (Dropout)
     dense_4 (Dense)
                                (None, 128)
                                                        524416
     dense_5 (Dense)
                                (None, 10)
                                                        1290
     ______
     Total params: 545,098
     Trainable params: 545,098
     Non-trainable params: 0
[29]: # Setting up the Different Versions
     custom_model_10 = custom_model
     custom_model_50 = custom_model
     custom_model_80 = custom_model
[30]: # Compiling Models
     custom_model_10.compile(loss="sparse_categorical_crossentropy",
                          optimizer="Adam", metrics=["sparse_categorical_accuracy"])
     custom_model_50.compile(loss="sparse_categorical_crossentropy",
                          optimizer="Adam", metrics=["sparse_categorical_accuracy"])
     custom_model_80.compile(loss="sparse_categorical_crossentropy",
                          optimizer="Adam", metrics=["sparse_categorical_accuracy"])
     2.2 Training My Models
```

```
[43]: # Train 10% Model
      custom_model_10.fit(x_train10,y_train10,epochs=25,batch_size=32,__
       →validation_split=0.2)
      \#history10\_2 = custom\_model\_10.fit(x\_train10,y\_train10,epochs=25,batch\_size=32,
       \rightarrow validation_split=0.2)
```

Epoch 1/25

```
sparse_categorical_accuracy: 0.6367 - val_loss: 0.9469 -
val_sparse_categorical_accuracy: 0.6790
Epoch 2/25
sparse categorical accuracy: 0.6905 - val loss: 0.9234 -
val_sparse_categorical_accuracy: 0.6890
Epoch 3/25
125/125 [============= ] - Os 4ms/step - loss: 0.7558 -
sparse_categorical_accuracy: 0.7442 - val_loss: 0.8971 -
val_sparse_categorical_accuracy: 0.7130
Epoch 4/25
125/125 [============= ] - 1s 4ms/step - loss: 0.6541 -
sparse_categorical_accuracy: 0.7740 - val_loss: 0.9213 -
val_sparse_categorical_accuracy: 0.6970
Epoch 5/25
sparse_categorical_accuracy: 0.8012 - val_loss: 0.9280 -
val_sparse_categorical_accuracy: 0.7070
Epoch 6/25
sparse_categorical_accuracy: 0.8267 - val_loss: 0.9431 -
val_sparse_categorical_accuracy: 0.7010
Epoch 7/25
sparse_categorical_accuracy: 0.8575 - val_loss: 0.9496 -
val_sparse_categorical_accuracy: 0.7000
Epoch 8/25
sparse_categorical_accuracy: 0.8723 - val_loss: 1.0057 -
val_sparse_categorical_accuracy: 0.7000
Epoch 9/25
sparse_categorical_accuracy: 0.8827 - val_loss: 0.9781 -
val_sparse_categorical_accuracy: 0.7170
Epoch 10/25
sparse categorical accuracy: 0.9107 - val loss: 1.0438 -
val_sparse_categorical_accuracy: 0.6970
Epoch 11/25
sparse_categorical_accuracy: 0.9185 - val_loss: 1.0469 -
val_sparse_categorical_accuracy: 0.7060
Epoch 12/25
sparse_categorical_accuracy: 0.9193 - val_loss: 1.0901 -
val_sparse_categorical_accuracy: 0.7010
Epoch 13/25
```

```
sparse_categorical_accuracy: 0.9330 - val_loss: 1.1185 -
val_sparse_categorical_accuracy: 0.6970
Epoch 14/25
sparse categorical accuracy: 0.9408 - val loss: 1.1440 -
val_sparse_categorical_accuracy: 0.7160
Epoch 15/25
sparse_categorical_accuracy: 0.9340 - val_loss: 1.1586 -
val_sparse_categorical_accuracy: 0.7010
Epoch 16/25
sparse_categorical_accuracy: 0.9498 - val_loss: 1.1533 -
val_sparse_categorical_accuracy: 0.7130
Epoch 17/25
sparse_categorical_accuracy: 0.9525 - val_loss: 1.1719 -
val_sparse_categorical_accuracy: 0.7100
Epoch 18/25
sparse_categorical_accuracy: 0.9610 - val_loss: 1.2084 -
val_sparse_categorical_accuracy: 0.7020
Epoch 19/25
sparse_categorical_accuracy: 0.9635 - val_loss: 1.1852 -
val_sparse_categorical_accuracy: 0.7040
Epoch 20/25
sparse_categorical_accuracy: 0.9655 - val_loss: 1.2216 -
val_sparse_categorical_accuracy: 0.7000
Epoch 21/25
sparse_categorical_accuracy: 0.9660 - val_loss: 1.2077 -
val_sparse_categorical_accuracy: 0.7090
Epoch 22/25
sparse categorical accuracy: 0.9700 - val loss: 1.3256 -
val_sparse_categorical_accuracy: 0.7020
Epoch 23/25
sparse_categorical_accuracy: 0.9647 - val_loss: 1.2640 -
val_sparse_categorical_accuracy: 0.7000
Epoch 24/25
sparse_categorical_accuracy: 0.9730 - val_loss: 1.2801 -
val_sparse_categorical_accuracy: 0.6930
Epoch 25/25
```

```
sparse_categorical_accuracy: 0.9685 - val_loss: 1.3376 -
    val_sparse_categorical_accuracy: 0.6970
[43]: <keras.callbacks.History at 0x218474ee220>
[44]: # Train 50% Model
    custom_model_50.fit(x_train50,y_train50,epochs=25,batch_size=32,__
     →validation split=0.2)
    \#history50\_2 = custom\_model\_50.fit(x\_train50,y\_train50,epochs=25,batch\_size=32, u)
     \rightarrow validation_split=0.2)
    Epoch 1/25
    sparse_categorical_accuracy: 0.8339 - val_loss: 0.2590 -
    val_sparse_categorical_accuracy: 0.9354
    Epoch 2/25
    625/625 [============ ] - 2s 4ms/step - loss: 0.3501 -
    sparse categorical accuracy: 0.8796 - val loss: 0.2824 -
    val_sparse_categorical_accuracy: 0.9204
    Epoch 3/25
    sparse_categorical_accuracy: 0.9060 - val_loss: 0.2877 -
    val_sparse_categorical_accuracy: 0.9198
    Epoch 4/25
    625/625 [============ ] - 2s 4ms/step - loss: 0.2629 -
    sparse_categorical_accuracy: 0.9096 - val_loss: 0.3217 -
    val_sparse_categorical_accuracy: 0.9064
    Epoch 5/25
    sparse_categorical_accuracy: 0.9194 - val_loss: 0.3758 -
    val_sparse_categorical_accuracy: 0.8918
    Epoch 6/25
    sparse_categorical_accuracy: 0.9256 - val_loss: 0.3469 -
    val_sparse_categorical_accuracy: 0.9034
    Epoch 7/25
    sparse_categorical_accuracy: 0.9323 - val_loss: 0.3592 -
    val_sparse_categorical_accuracy: 0.8998
    Epoch 8/25
    sparse_categorical_accuracy: 0.9311 - val_loss: 0.3576 -
    val_sparse_categorical_accuracy: 0.9018
    Epoch 9/25
    625/625 [=========== ] - 2s 4ms/step - loss: 0.1853 -
```

sparse_categorical_accuracy: 0.9366 - val_loss: 0.3872 -

val_sparse_categorical_accuracy: 0.8884

```
Epoch 10/25
sparse_categorical_accuracy: 0.9395 - val_loss: 0.4205 -
val_sparse_categorical_accuracy: 0.8834
Epoch 11/25
sparse categorical accuracy: 0.9415 - val loss: 0.4134 -
val_sparse_categorical_accuracy: 0.8834
Epoch 12/25
625/625 [============ ] - 2s 4ms/step - loss: 0.1637 -
sparse_categorical_accuracy: 0.9438 - val_loss: 0.4628 -
val_sparse_categorical_accuracy: 0.8670
Epoch 13/25
sparse_categorical_accuracy: 0.9429 - val_loss: 0.4705 -
val_sparse_categorical_accuracy: 0.8676
Epoch 14/25
625/625 [============ ] - 2s 4ms/step - loss: 0.1443 -
sparse_categorical_accuracy: 0.9506 - val_loss: 0.4628 -
val sparse categorical accuracy: 0.8692
Epoch 15/25
sparse_categorical_accuracy: 0.9491 - val_loss: 0.4922 -
val_sparse_categorical_accuracy: 0.8694
Epoch 16/25
625/625 [============= ] - 2s 4ms/step - loss: 0.1535 -
sparse_categorical_accuracy: 0.9488 - val_loss: 0.4892 -
val_sparse_categorical_accuracy: 0.8592
Epoch 17/25
sparse_categorical_accuracy: 0.9503 - val_loss: 0.5376 -
val_sparse_categorical_accuracy: 0.8528
Epoch 18/25
sparse categorical accuracy: 0.9505 - val loss: 0.5298 -
val_sparse_categorical_accuracy: 0.8566
Epoch 19/25
sparse_categorical_accuracy: 0.9504 - val_loss: 0.5401 -
val_sparse_categorical_accuracy: 0.8518
Epoch 20/25
625/625 [============ ] - 2s 4ms/step - loss: 0.1348 -
sparse_categorical_accuracy: 0.9566 - val_loss: 0.5582 -
val_sparse_categorical_accuracy: 0.8480
Epoch 21/25
625/625 [============ ] - 2s 4ms/step - loss: 0.1304 -
sparse_categorical_accuracy: 0.9542 - val_loss: 0.5386 -
val_sparse_categorical_accuracy: 0.8540
```

```
sparse_categorical_accuracy: 0.9560 - val_loss: 0.5511 -
    val_sparse_categorical_accuracy: 0.8472
    Epoch 23/25
    625/625 [============ ] - 2s 4ms/step - loss: 0.1204 -
    sparse categorical accuracy: 0.9589 - val loss: 0.6291 -
    val_sparse_categorical_accuracy: 0.8356
    Epoch 24/25
    625/625 [============ ] - 2s 4ms/step - loss: 0.1449 -
    sparse_categorical_accuracy: 0.9506 - val_loss: 0.6171 -
    val_sparse_categorical_accuracy: 0.8400
    Epoch 25/25
    sparse_categorical_accuracy: 0.9565 - val_loss: 0.6487 -
    val_sparse_categorical_accuracy: 0.8334
[44]: <keras.callbacks.History at 0x218450d5a30>
[45]: # Train 80% Model
     custom_model_80.fit(x_train80,y_train80,epochs=25,batch_size=32,__
     →validation_split=0.2)
     #history80 2 = custom model 80. fit(x train80, y train80, epochs=25, batch size=32,
     \rightarrow validation_split=0.2)
    Epoch 1/25
    sparse_categorical_accuracy: 0.8681 - val_loss: 0.3612 -
    val_sparse_categorical_accuracy: 0.8870
    Epoch 2/25
    1000/1000 [============ ] - 4s 4ms/step - loss: 0.3340 -
    sparse_categorical_accuracy: 0.8895 - val_loss: 0.3338 -
    val_sparse_categorical_accuracy: 0.8940
    Epoch 3/25
    1000/1000 [============= ] - 4s 4ms/step - loss: 0.2856 -
    sparse_categorical_accuracy: 0.9054 - val_loss: 0.3433 -
    val_sparse_categorical_accuracy: 0.8953
    Epoch 4/25
    1000/1000 [============= ] - 4s 4ms/step - loss: 0.2596 -
    sparse_categorical_accuracy: 0.9113 - val_loss: 0.3610 -
    val_sparse_categorical_accuracy: 0.8848
    1000/1000 [============= ] - 4s 4ms/step - loss: 0.2546 -
    sparse_categorical_accuracy: 0.9133 - val_loss: 0.3710 -
    val_sparse_categorical_accuracy: 0.8880
    Epoch 6/25
    1000/1000 [============ ] - 4s 4ms/step - loss: 0.2404 -
```

Epoch 22/25

```
sparse_categorical_accuracy: 0.9193 - val_loss: 0.3735 -
val_sparse_categorical_accuracy: 0.8824
Epoch 7/25
1000/1000 [============ ] - 4s 4ms/step - loss: 0.2267 -
sparse categorical accuracy: 0.9217 - val loss: 0.3778 -
val_sparse_categorical_accuracy: 0.8824
Epoch 8/25
1000/1000 [=========== ] - 4s 4ms/step - loss: 0.2214 -
sparse_categorical_accuracy: 0.9245 - val_loss: 0.4336 -
val_sparse_categorical_accuracy: 0.8671
Epoch 9/25
1000/1000 [============ ] - 4s 4ms/step - loss: 0.2185 -
sparse_categorical_accuracy: 0.9245 - val_loss: 0.4082 -
val_sparse_categorical_accuracy: 0.8791
Epoch 10/25
sparse_categorical_accuracy: 0.9287 - val_loss: 0.4179 -
val_sparse_categorical_accuracy: 0.8769
Epoch 11/25
sparse_categorical_accuracy: 0.9314 - val_loss: 0.4377 -
val sparse categorical accuracy: 0.8705
Epoch 12/25
1000/1000 [============ ] - 4s 4ms/step - loss: 0.1924 -
sparse_categorical_accuracy: 0.9340 - val_loss: 0.4284 -
val_sparse_categorical_accuracy: 0.8716
Epoch 13/25
1000/1000 [============== ] - 4s 4ms/step - loss: 0.1959 -
sparse_categorical_accuracy: 0.9334 - val_loss: 0.4748 -
val_sparse_categorical_accuracy: 0.8604
Epoch 14/25
1000/1000 [============= ] - 4s 4ms/step - loss: 0.1901 -
sparse_categorical_accuracy: 0.9340 - val_loss: 0.4404 -
val_sparse_categorical_accuracy: 0.8691
Epoch 15/25
1000/1000 [============ ] - 4s 4ms/step - loss: 0.1937 -
sparse_categorical_accuracy: 0.9340 - val_loss: 0.4960 -
val_sparse_categorical_accuracy: 0.8543
Epoch 16/25
1000/1000 [============ ] - 4s 4ms/step - loss: 0.1882 -
sparse_categorical_accuracy: 0.9357 - val_loss: 0.5059 -
val_sparse_categorical_accuracy: 0.8489
Epoch 17/25
sparse_categorical_accuracy: 0.9381 - val_loss: 0.5387 -
val_sparse_categorical_accuracy: 0.8505
Epoch 18/25
1000/1000 [============ ] - 4s 4ms/step - loss: 0.1726 -
```

```
sparse_categorical_accuracy: 0.9401 - val_loss: 0.4898 -
     val_sparse_categorical_accuracy: 0.8520
     Epoch 19/25
     1000/1000 [============ ] - 4s 4ms/step - loss: 0.1765 -
     sparse categorical accuracy: 0.9399 - val loss: 0.5162 -
     val sparse categorical accuracy: 0.8471
     Epoch 20/25
     1000/1000 [============= ] - 4s 4ms/step - loss: 0.1787 -
     sparse_categorical_accuracy: 0.9390 - val_loss: 0.5187 -
     val_sparse_categorical_accuracy: 0.8470
     Epoch 21/25
     1000/1000 [============= ] - 4s 4ms/step - loss: 0.1738 -
     sparse_categorical_accuracy: 0.9412 - val_loss: 0.5559 -
     val_sparse_categorical_accuracy: 0.8439
     Epoch 22/25
     1000/1000 [============= ] - 4s 4ms/step - loss: 0.1741 -
     sparse_categorical_accuracy: 0.9408 - val_loss: 0.5191 -
     val_sparse_categorical_accuracy: 0.8515
     Epoch 23/25
     1000/1000 [============ ] - 4s 4ms/step - loss: 0.1677 -
     sparse_categorical_accuracy: 0.9434 - val_loss: 0.5385 -
     val sparse categorical accuracy: 0.8434
     Epoch 24/25
     1000/1000 [============== ] - 4s 4ms/step - loss: 0.1729 -
     sparse_categorical_accuracy: 0.9417 - val_loss: 0.5775 -
     val_sparse_categorical_accuracy: 0.8369
     Epoch 25/25
     1000/1000 [============== ] - 4s 4ms/step - loss: 0.1594 -
     sparse_categorical_accuracy: 0.9455 - val_loss: 0.5809 -
     val_sparse_categorical_accuracy: 0.8349
[45]: <keras.callbacks.History at 0x218450e7f40>
```

2.3 Plotting the Loss of My Model

```
[58]: ## Test Error

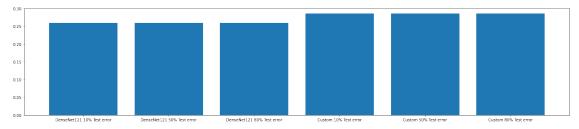
temp3={}
temp4={}
temp5={}

score = custom_model_10.evaluate(x_test, y_test, verbose=0)
temp3["Custom 10% Test error"]=1-score[1]
performance3 = pd.DataFrame([temp3]).T
performance = performance.append(performance3)
```

```
score2 = custom_model_50.evaluate(x_test, y_test, verbose=0)
temp4["Custom 50% Test error"]=1-score[1]
performance4 = pd.DataFrame([temp4]).T
performance = performance.append(performance4)

score3 = custom_model_80.evaluate(x_test, y_test, verbose=0)
temp5["Custom 80% Test error"]=1-score[1]
performance5 = pd.DataFrame([temp5]).T
performance = performance.append(performance5)
```

```
[58]: 0
DenseNet121 10% Test error 0.2593
DenseNet121 50% Test error 0.2593
DenseNet121 80% Test error 0.2593
Custom 10% Test error 0.2862
Custom 50% Test error 0.2862
Custom 80% Test error 0.2862
```



3 Plotting the 10% Model

plt.plot(history10_2.history['loss']) plt.title('Model 10% Top-1 Error') plt.ylabel('Loss') plt.xlabel('Epoch') plt.legend(['train'], loc = 'upper left') plt.show()

4 Plotting the 50% Model

```
plt.plot(history50\_2.history['loss']) \quad plt.title('Model 50\% Top-1 Error') \quad plt.ylabel('Loss') \\ plt.xlabel('Epoch') \quad plt.legend(['train'], loc = 'upper left') \\ plt.show()
```

5 Plotting the 80% Model

```
 plt.plot(history80\_2.history['loss']) \quad plt.title('Model 80\% Top-1 Error') \quad plt.ylabel('Loss') \\ plt.xlabel('Epoch') \quad plt.legend(['train'], loc = 'upper left') \\ plt.show()
```