InceptionResNetV2

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
import os
import shutil
import numpy as np
import pandas as pd
import tensorflow as tf
import matplotlib.pyplot as plt
import seaborn as sns
import cv2
import itertools
import sklearn
from sklearn.metrics import classification_report
from keras.applications import *
from keras.layers import *
from keras.models import Model, load_model
from keras.optimizers import Adam
from sklearn.utils import class_weight
from tqdm import tqdm
from keras.preprocessing.image import ImageDataGenerator
from keras.applications.resnet_v2 import preprocess_input as base_preprocess
from keras.callbacks import ReduceLROnPlateau, EarlyStopping, ModelCheckpoint
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score, roc_curve, RocCurveDisplay,
from sklearn.utils.multiclass import unique_labels
from collections import Counter
from pathlib import Path
from sklearn.model_selection import train_test_split
from keras.utils import to_categorical
from PIL import Image
from sklearn.preprocessing import LabelEncoder
from sklearn.utils.class_weight import compute_class_weight
```

Load data

```
data = np.load('/content/drive/MyDrive/SC Lab/Dataset/data.npy',mmap_mode='r')
labels = np.load('/content/drive/MyDrive/SC Lab/Dataset/labels.npy',mmap_mode='r')
```

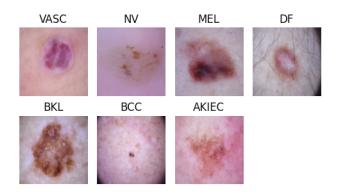
```
print("Data shape:", data.shape)
print("Labels shape:", labels.shape)
```

```
Data shape: (10015, 224, 224, 3)
Labels shape: (10015, 7)
```

Loading Images from the data

```
# Get unique class labels and their corresponding indices in the data array
unique_classes = np.unique(labels, axis=1)
# Create a dictionary to store one data sample from each class
```

```
class_samples = {}
# Map class indices to their corresponding names
class_names = {0: "AKIEC", 1: "BCC", 2: "BKL", 3: "DF", 4: "MEL", 5: "NV", 6: "VASC"}
# Select one data sample from each class
for class_label in unique_classes:
    class_indices = np.where(np.all(labels = class_label, axis=1))[0]
    class_samples[tuple(class_label)] = data[class_indices[0]]
# Plot the images in 2 rows
plt.figure(figsize=(5, 3))
for i, (class_label, image_data) in enumerate(class_samples.items()):
    class_index = np.argmax(class_label) # Get the index of the class
    class_name = class_names[class_index] # Get the corresponding class name
   plt.subplot(2, 4, i + 1)
    plt.imshow(image_data)
    plt.title(f'{class_name}')
    plt.axis('off')
plt.tight_layout()
plt.show()
```



Frequency of the data

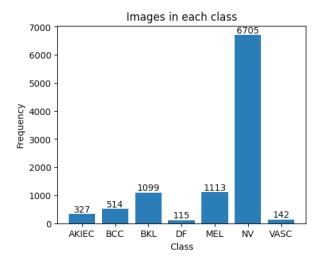
```
# Sum the one-hot encoded labels along the rows to get the frequency of each class
class_counts = np.sum(labels, axis=0)

# Map class indices to their corresponding names
class_names = {0: "AKIEC", 1: "BCC", 2: "BKL", 3: "DF", 4: "MEL", 5: "NV", 6: "VASC"}

# Plot the class frequencies
plt.figure(figsize=(5, 4))
plt.bar([class_names[class_idx] for class_idx in range(len(class_names))], class_counts)
plt.xlabel('Class')
plt.ylabel('Frequency')
plt.title('Images in each class')

# Annotate the bars with the class frequencies (integer format)
for i, count in enumerate(class_counts):
    plt.text(i, count, str(int(count)), ha='center', va='bottom')

plt.show()
```



Split Data

```
# Split the data into train, test, and validation sets
train_data, test_data, train_labels, test_labels = train_test_split(data, labels, test_size=0.1,stratify=labels,
random_state=42)
train_data, val_data, train_labels, val_labels = train_test_split(train_data, train_labels,
test_size=0.1,stratify=train_labels, random_state=42)
```

Augmentation

```
# Create an ImageDataGenerator for data augmentation during training (optional)
datagen = ImageDataGenerator(
    rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True
)
```

Callbacks

```
lr_reduce = ReduceLROnPlateau(monitor = 'val_accuracy', factor = 0.5, patience = 5,mode='max', min_lr = 1e-
4,verbose = 1)
#early_stop = EarlyStopping(monitor = "val_loss", patience = 5, verbose=1)
saved_model = '/content/drive/MyDrive/SC Lab/Saved Model/InceptionResNetV2.h5'
model_chkpt = ModelCheckpoint(saved_model ,save_best_only = True, monitor = 'val_accuracy',verbose = 1)
# callback_list = [early_stop, model_chkpt, lr_reduce]
callback_list = [model_chkpt, lr_reduce]
```

InceptionResNetV2 Model

Model Training

```
epochs = 30
batch_size = 16
history = model.fit(datagen.flow(train_data, train_labels, batch_size=batch_size),
              validation_data=(val_data, val_labels),
              epochs=epochs,
              callbacks=callback_list)
Epoch 1/30
507/507 [==========] - ETA: Os - loss: 0.9252 - accuracy: 0.6775
Epoch 1: val_accuracy improved from -inf to 0.62084, saving model to /content/drive/MyDrive/SC Lab/Saved
Model/irnv2.h5
- val_accuracy: 0.6208 - lr: 0.0010
Epoch 2/30
507/507 [========== ] - ETA: 0s - loss: 0.8627 - accuracy: 0.6958
Epoch 2: val_accuracy improved from 0.62084 to 0.66851, saving model to /content/drive/MyDrive/SC Lab/Saved
Model/irnv2.h5
- val_accuracy: 0.6685 - lr: 0.0010
Epoch 3/30
507/507 [==========] - ETA: Os - loss: 0.8543 - accuracy: 0.6999
Epoch 3: val_accuracy improved from 0.66851 to 0.73392, saving model to /content/drive/MyDrive/SC Lab/Saved
Model/irnv2.h5
- val_accuracy: 0.7339 - lr: 0.0010
Epoch 4/30
507/507 [=========== ] - ETA: 0s - loss: 0.7961 - accuracy: 0.7113
Epoch 4: val_accuracy improved from 0.73392 to 0.74390, saving model to /content/drive/MyDrive/SC Lab/Saved
Model/irnv2.h5
- val_accuracy: 0.7439 - lr: 0.0010
Epoch 5/30
507/507 [============== ] - ETA: Os - loss: 0.7459 - accuracy: 0.7281
Epoch 5: val_accuracy did not improve from 0.74390
```

```
- val_accuracy: 0.7140 - lr: 0.0010
Epoch 6/30
507/507 [=========== ] - ETA: Os - loss: 0.7452 - accuracy: 0.7369
Epoch 6: val_accuracy improved from 0.74390 to 0.77051, saving model to /content/drive/MyDrive/SC Lab/Saved
Model/irnv2.h5
- val_accuracy: 0.7705 - lr: 0.0010
Epoch 7/30
Epoch 7: val_accuracy did not improve from 0.77051
- val_accuracy: 0.7328 - lr: 0.0010
Epoch 8/30
507/507 [=========== ] - ETA: 0s - loss: 0.7350 - accuracy: 0.7367
Epoch 8: val_accuracy did not improve from 0.77051
- val_accuracy: 0.7118 - lr: 0.0010
Epoch 9/30
507/507 [============ ] - ETA: Os - loss: 0.6796 - accuracy: 0.7531
Epoch 9: val_accuracy did not improve from 0.77051
- val_accuracy: 0.7284 - lr: 0.0010
Epoch 10/30
507/507 [==========] - ETA: 0s - loss: 0.6743 - accuracy: 0.7522
Epoch 10: val_accuracy improved from 0.77051 to 0.78160, saving model to /content/drive/MyDrive/SC Lab/Saved
Model/irnv2.h5
507/507 [============ - 639s 1s/step - loss: 0.6743 - accuracy: 0.7522 - val_loss: 0.6519 -
val_accuracy: 0.7816 - lr: 0.0010
Epoch 11/30
507/507 [===========] - ETA: 0s - loss: 0.6500 - accuracy: 0.7651
Epoch 11: val_accuracy did not improve from 0.78160
- val_accuracy: 0.7450 - lr: 0.0010
Epoch 12/30
Epoch 12: val_accuracy did not improve from 0.78160
- val_accuracy: 0.7095 - lr: 0.0010
Epoch 13/30
507/507 [===========] - ETA: Os - loss: 0.6381 - accuracy: 0.7667
Epoch 13: val_accuracy did not improve from 0.78160
- val_accuracy: 0.7738 - lr: 0.0010
Epoch 14/30
Epoch 14: val_accuracy improved from 0.78160 to 0.79601, saving model to /content/drive/MyDrive/SC Lab/Saved
Model/irnv2.h5
val_accuracy: 0.7960 - lr: 0.0010
Epoch 15/30
507/507 [========= ] - ETA: 0s - loss: 0.5962 - accuracy: 0.7824
```

```
Epoch 15: val_accuracy did not improve from 0.79601
- val_accuracy: 0.7882 - lr: 0.0010
Epoch 16/30
Epoch 16: val_accuracy did not improve from 0.79601
- val_accuracy: 0.7517 - lr: 0.0010
Epoch 17/30
Epoch 17: val_accuracy did not improve from 0.79601
- val_accuracy: 0.7838 - lr: 0.0010
Epoch 18/30
507/507 [========== ] - ETA: 0s - loss: 0.5623 - accuracy: 0.7919
Epoch 18: val_accuracy improved from 0.79601 to 0.80044, saving model to /content/drive/MyDrive/SC Lab/Saved
Model/irnv2.h5
val_accuracy: 0.8004 - lr: 0.0010
Epoch 19/30
Epoch 19: val_accuracy did not improve from 0.80044
- val_accuracy: 0.7384 - lr: 0.0010
Epoch 20/30
Epoch 20: val_accuracy did not improve from 0.80044
- val_accuracy: 0.7572 - lr: 0.0010
Epoch 21/30
507/507 [==========] - ETA: Os - loss: 0.5599 - accuracy: 0.7993
Epoch 21: val_accuracy did not improve from 0.80044
- val_accuracy: 0.7927 - 1r: 0.0010
Epoch 22/30
507/507 [===========] - ETA: Os - loss: 0.5230 - accuracy: 0.8069
Epoch 22: val_accuracy improved from 0.80044 to 0.80377, saving model to /content/drive/MyDrive/SC Lab/Saved
Model/irnv2.h5
val_accuracy: 0.8038 - 1r: 0.0010
Epoch 23/30
507/507 [==========] - ETA: 0s - loss: 0.5223 - accuracy: 0.8110
Epoch 23: val_accuracy did not improve from 0.80377
- val_accuracy: 0.8038 - lr: 0.0010
Epoch 24/30
507/507 [============ ] - ETA: Os - loss: 0.5060 - accuracy: 0.8151
Epoch 24: val_accuracy improved from 0.80377 to 0.82927, saving model to /content/drive/MyDrive/SC Lab/Saved
val_accuracy: 0.8293 - 1r: 0.0010
Epoch 25/30
```

```
507/507 [=========== - ETA: Os - loss: 0.5118 - accuracy: 0.8101
Epoch 25: val_accuracy did not improve from 0.82927
- val_accuracy: 0.8093 - lr: 0.0010
Epoch 26/30
Epoch 26: val_accuracy did not improve from 0.82927
- val_accuracy: 0.8160 - lr: 0.0010
Epoch 27/30
Epoch 27: val_accuracy did not improve from 0.82927
- val_accuracy: 0.7838 - 1r: 0.0010
Epoch 28/30
Epoch 28: val_accuracy improved from 0.82927 to 0.83259, saving model to /content/drive/MyDrive/SC Lab/Saved
Model/irnv2.h5
507/507 [============ - 733s 1s/step - loss: 0.4669 - accuracy: 0.8289 - val_loss: 0.4702 -
val_accuracy: 0.8326 - lr: 0.0010
Epoch 29/30
507/507 [==========] - ETA: 0s - loss: 0.4517 - accuracy: 0.8385
Epoch 29: val_accuracy did not improve from 0.83259
- val_accuracy: 0.8126 - lr: 0.0010
Epoch 30/30
Epoch 30: val_accuracy did not improve from 0.83259
- val_accuracy: 0.8060 - lr: 0.0010
model= load_model('/content/drive/MyDrive/SC Lab/Saved Model/irnv2.h5')
epochs = 20
batch_size = 16
history = model.fit(datagen.flow(train_data, train_labels, batch_size=batch_size),
          validation_data=(val_data, val_labels),
          epochs=epochs,
          callbacks=callback_list)
Epoch 1/20
Epoch 1: val_accuracy improved from -inf to 0.81264, saving model to /content/drive/MyDrive/SC Lab/Saved
Model/irnv2.h5
- val_accuracy: 0.8126 - lr: 0.0010
Epoch 2/20
507/507 [========== ] - ETA: 0s - loss: 0.4483 - accuracy: 0.8366
Epoch 2: val_accuracy did not improve from 0.81264
```

```
- val_accuracy: 0.8004 - lr: 0.0010
Epoch 3/20
Epoch 3: val_accuracy did not improve from 0.81264
- val_accuracy: 0.8038 - lr: 0.0010
Epoch 4/20
Epoch 4: val_accuracy improved from 0.81264 to 0.82816, saving model to /content/drive/MyDrive/SC Lab/Saved
Model/irnv2.h5
- val_accuracy: 0.8282 - lr: 0.0010
Epoch 5/20
Epoch 5: val_accuracy did not improve from 0.82816
- val_accuracy: 0.8027 - lr: 0.0010
Epoch 6/20
Epoch 6: val_accuracy did not improve from 0.82816
- val_accuracy: 0.8093 - lr: 0.0010
Epoch 7/20
Epoch 7: val_accuracy improved from 0.82816 to 0.82927, saving model to /content/drive/MyDrive/SC Lab/Saved
Model/irnv2.h5
- val_accuracy: 0.8293 - lr: 0.0010
Epoch 8/20
Epoch 8: val_accuracy did not improve from 0.82927
- val_accuracy: 0.8049 - lr: 0.0010
Epoch 9/20
507/507 [===========] - ETA: Os - loss: 0.4073 - accuracy: 0.8572
Epoch 9: val_accuracy improved from 0.82927 to 0.83370, saving model to /content/drive/MyDrive/SC Lab/Saved
- val_accuracy: 0.8337 - lr: 0.0010
Epoch 10/20
Epoch 10: val_accuracy improved from 0.83370 to 0.84257, saving model to /content/drive/MyDrive/SC Lab/Saved
Model/irnv2.h5
- val_accuracy: 0.8426 - lr: 0.0010
Epoch 11/20
507/507 [============] - ETA: Os - loss: 0.3504 - accuracy: 0.8720
Epoch 11: val_accuracy did not improve from 0.84257
- val_accuracy: 0.8237 - lr: 0.0010
Epoch 12/20
507/507 [=========== ] - ETA: 0s - loss: 0.3531 - accuracy: 0.8726
```

```
Epoch 12: val_accuracy did not improve from 0.84257
507/507 [=========:: - 172s 339ms/step - loss: 0.3531 - accuracy: 0.8726 - val_loss: 0.5454
- val_accuracy: 0.8182 - lr: 0.0010
Epoch 13/20
Epoch 13: val_accuracy did not improve from 0.84257
- val_accuracy: 0.8126 - lr: 0.0010
Epoch 14/20
Epoch 14: val_accuracy did not improve from 0.84257
- val_accuracy: 0.8160 - lr: 0.0010
Epoch 15/20
507/507 [========== ] - ETA: 0s - loss: 0.3342 - accuracy: 0.8788
Epoch 15: val_accuracy did not improve from 0.84257
Epoch 15: ReduceLROnPlateau reducing learning rate to 0.0005000000237487257.
- val_accuracy: 0.8404 - lr: 0.0010
Epoch 16/20
507/507 [==========] - ETA: 0s - loss: 0.2606 - accuracy: 0.9093
Epoch 16: val_accuracy improved from 0.84257 to 0.86475, saving model to /content/drive/MyDrive/SC Lab/Saved
Model/irnv2.h5
- val_accuracy: 0.8647 - lr: 5.0000e-04
Epoch 17/20
507/507 [===========] - ETA: 0s - loss: 0.2465 - accuracy: 0.9107
Epoch 17: val_accuracy did not improve from 0.86475
- val_accuracy: 0.8348 - 1r: 5.0000e-04
Epoch 18/20
Epoch 18: val_accuracy did not improve from 0.86475
- val_accuracy: 0.8514 - lr: 5.0000e-04
Epoch 19/20
Epoch 19: val_accuracy did not improve from 0.86475
- val_accuracy: 0.8636 - lr: 5.0000e-04
Epoch 20/20
Epoch 20: val_accuracy did not improve from 0.86475
- val_accuracy: 0.8537 - 1r: 5.0000e-04
```

```
model= load_model('/content/drive/MyDrive/SC Lab/Saved Model/irnv2.h5')
```

```
epochs = 10
batch_size = 16
```

```
Epoch 1/10
Epoch 1: val_accuracy improved from -inf to 0.85366, saving model to /content/drive/MyDrive/4.2/SC
Lab/Project/Saved Model/irnv2.h5
- val_accuracy: 0.8537 - lr: 5.0000e-04
Epoch 2/10
507/507 [============= ] - ETA: Os - loss: 0.2259 - accuracy: 0.9181
Epoch 2: val_accuracy did not improve from 0.85366
- val_accuracy: 0.8492 - 1r: 5.0000e-04
Epoch 3/10
Epoch 3: val_accuracy improved from 0.85366 to 0.85698, saving model to /content/drive/MyDrive/4.2/SC
Lab/Project/Saved Model/irnv2.h5
- val_accuracy: 0.8570 - lr: 5.0000e-04
Epoch 4/10
Epoch 4: val_accuracy did not improve from 0.85698
- val_accuracy: 0.8570 - lr: 5.0000e-04
Epoch 5/10
507/507 [===========] - ETA: Os - loss: 0.2082 - accuracy: 0.9278
Epoch 5: val_accuracy did not improve from 0.85698
- val_accuracy: 0.8503 - lr: 5.0000e-04
Epoch 6/10
507/507 [===========] - ETA: 0s - loss: 0.2059 - accuracy: 0.9305
Epoch 6: val_accuracy did not improve from 0.85698
- val_accuracy: 0.8559 - 1r: 5.0000e-04
Epoch 7/10
Epoch 7: val_accuracy did not improve from 0.85698
- val_accuracy: 0.8559 - lr: 5.0000e-04
Epoch 8/10
507/507 [============= ] - ETA: Os - loss: 0.1911 - accuracy: 0.9324
Epoch 8: val_accuracy improved from 0.85698 to 0.86585, saving model to /content/drive/MyDrive/4.2/SC
Lab/Project/Saved Model/irnv2.h5
- val_accuracy: 0.8659 - 1r: 5.0000e-04
Epoch 9/10
507/507 [==========] - ETA: 0s - loss: 0.1701 - accuracy: 0.9414
Epoch 9: val_accuracy did not improve from 0.86585
```

```
- val_accuracy: 0.8592 - lr: 5.0000e-04
Epoch 10/10
Epoch 10: val_accuracy improved from 0.86585 to 0.87140, saving model to /content/drive/MyDrive/4.2/SC
Lab/Project/Saved Model/irnv2.h5
- val_accuracy: 0.8714 - lr: 5.0000e-04
model= load_model('/content/drive/MyDrive/SC Lab/Saved Model/InceptionResNetV2.h5')
history = model.fit(datagen.flow(train_data, train_labels, batch_size=batch_size),
           validation_data=(val_data, val_labels),
           epochs=15.
           callbacks=callback_list)
Epoch 1/15
Epoch 1: val_accuracy improved from -inf to 0.86807, saving model to /content/drive/MyDrive/4.2/SC
Lab/Project/Saved Model/irnv2.h5
- val_accuracy: 0.8681 - lr: 5.0000e-04
Epoch 2/15
Epoch 2: val_accuracy did not improve from 0.86807
- val_accuracy: 0.8592 - lr: 5.0000e-04
Epoch 3/15
507/507 [========== ] - ETA: 0s - loss: 0.1610 - accuracy: 0.9444
Epoch 3: val_accuracy did not improve from 0.86807
- val_accuracy: 0.8614 - lr: 5.0000e-04
Epoch 4/15
507/507 [========== ] - ETA: 0s - loss: 0.1570 - accuracy: 0.9459
Epoch 4: val_accuracy did not improve from 0.86807
- val_accuracy: 0.8625 - 1r: 5.0000e-04
Epoch 5/15
507/507 [==========] - ETA: Os - loss: 0.1459 - accuracy: 0.9485
Epoch 5: val_accuracy did not improve from 0.86807
- val_accuracy: 0.8348 - lr: 5.0000e-04
Epoch 6/15
```

507/507 [=============] - ETA: Os - loss: 0.1434 - accuracy: 0.9465

Lab/Project/Saved Model/irnv2.h5

Epoch 7/15

- val_accuracy: 0.8703 - lr: 5.0000e-04

- val_accuracy: 0.8614 - lr: 5.0000e-04

Epoch 7: val_accuracy did not improve from 0.87029

Epoch 6: val_accuracy improved from 0.86807 to 0.87029, saving model to /content/drive/MyDrive/4.2/SC

```
Epoch 8/15
Epoch 8: val_accuracy did not improve from 0.87029
- val_accuracy: 0.8703 - lr: 5.0000e-04
Epoch 9/15
Epoch 9: val_accuracy did not improve from 0.87029
- val_accuracy: 0.8614 - lr: 5.0000e-04
Epoch 10/15
507/507 [===========] - ETA: Os - loss: 0.1247 - accuracy: 0.9565
Epoch 10: val_accuracy did not improve from 0.87029
- val_accuracy: 0.8537 - 1r: 5.0000e-04
Epoch 11/15
Epoch 11: val_accuracy did not improve from 0.87029
Epoch 11: ReduceLROnPlateau reducing learning rate to 0.0002500000118743628.
- val_accuracy: 0.8636 - lr: 5.0000e-04
Epoch 12/15
Epoch 12: val_accuracy improved from 0.87029 to 0.87251, saving model to /content/drive/MyDrive/4.2/SC
Lab/Project/Saved Model/irnv2.h5
- val_accuracy: 0.8725 - lr: 2.5000e-04
Epoch 13/15
Epoch 13: val_accuracy did not improve from 0.87251
- val_accuracy: 0.8537 - lr: 2.5000e-04
Epoch 14/15
507/507 [===========] - ETA: Os - loss: 0.0812 - accuracy: 0.9731
Epoch 14: val_accuracy did not improve from 0.87251
- val_accuracy: 0.8681 - lr: 2.5000e-04
Epoch 15/15
507/507 [===========] - ETA: 0s - loss: 0.0748 - accuracy: 0.9741
Epoch 15: val_accuracy did not improve from 0.87251
- val_accuracy: 0.8681 - lr: 2.5000e-04
```

```
model= load_model('/content/drive/MyDrive/SC Lab/Saved Model/InceptionResNetV2.h5')
```

Test Accuracy

```
test_loss, test_accuracy = model.evaluate(test_data, test_labels)
print("Test Accuracy:", test_accuracy)
```

```
32/32 [========] - 10s 210ms/step - loss: 0.6894 - accuracy: 0.8573
Test Accuracy: 0.8572854399681091
```

Classification Report

```
# Make predictions on the test data
predictions = model.predict(test_data)

# Convert predictions and true labels to integer format
predicted_labels = np.argmax(predictions, axis=1)

# test_labels = test_data.classes
true_labels = np.argmax(test_labels, axis=1)

# Calculate the classification report
report = classification_report(true_labels, predicted_labels)

# Print the classification report
print("Classification Report:")
print(report)
```

```
32/32 [======] - 19s 174ms/step
Classification Report:
           precision recall f1-score support
                               0.55
         0
                0.68
                       0.45
                                         33
         1
                0.81
                       0.69
                                0.74
                                          51
         2
                0.64
                        0.79
                                0.71
                                          110
         3
               0.50
                       0.58
                               0.54
                                          12
         4
               0.80
                       0.54
                               0.65
                                          111
         5
                0.92
                        0.96
                                0.94
                                          671
         6
                0.92
                        0.79
                               0.85
                                         14
   accuracy
                                 0.86
                                         1002
                0.75
                        0.69
                                0.71
                                         1002
  macro avg
weighted avg
                0.86
                        0.86
                                 0.85
                                         1002
```

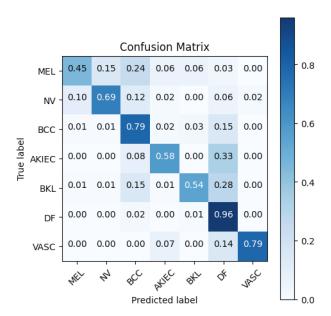
Confusion Matrix

```
# Calculate the confusion matrix
cm = confusion_matrix(true_labels, predicted_labels)
cm
```

```
array([[ 15, 5, 8, 2, 2, 1,
                            0],
     [ 5, 35,
             6, 1, 0, 3,
                            1],
     [ 1,
          1, 87, 2, 3, 16,
                            0],
     [ 0, 0, 1, 7, 0, 4,
                            0],
     [ 1, 1, 17, 1, 60, 31,
     [ 0,
          1, 16, 0, 10, 644,
                            0],
     [ 0,
          0,
             0, 1, 0, 2, 11]])
```

```
cmap=plt.cm.Blues):
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
        print('Confusion matrix, without normalization')
    # print(cm)
    plt.figure(figsize=(5, 5))
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    {\tt plt.yticks(tick\_marks,\ classes)}
    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.tight_layout()
cm_plot_labels = ["MEL", "NV", "BCC", "AKIEC", "BKL", "DF", "VASC"]
plot_confusion_matrix(cm, cm_plot_labels, title='Confusion Matrix', normalize=True)
```

Normalized confusion matrix



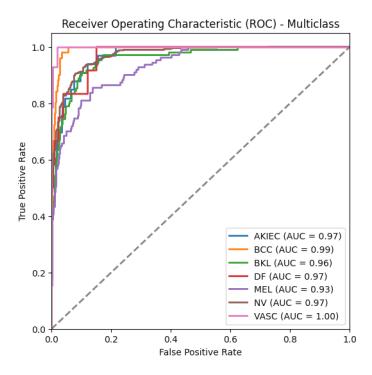
ROC-AUC curve

```
# Define class names
class_names = ['AKIEC', 'BCC', 'BKL', 'DF', 'MEL', 'NV', 'VASC']

# Make predictions on the test data
predictions = model.predict(test_data)
```

```
# Get the number of classes
num_classes = test_labels.shape[1]
# Initialize a figure to plot ROC curves
plt.figure(figsize=(6, 6))
# Loop through each class
for class_index in range(num_classes):
    # Compute ROC curve and ROC AUC for the current class
    fpr, tpr, thresholds = roc_curve(test_labels[:, class_index], predictions[:, class_index])
    roc_auc = auc(fpr, tpr)
    # Plot ROC curve for the current class
    plt.plot(fpr, tpr, lw=2, label=f'{class_names[class_index]} (AUC = {roc_auc:.2f})')
# Plot the diagonal line (random chance)
plt.plot([0, 1], [0, 1], color='gray', linestyle='--', lw=2)
# Set plot properties
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) - Multiclass')
plt.legend(loc='lower right')
# Display the plot
plt.show()
```

```
32/32 [============] - 5s 160ms/step
```



Misclass Classification

```
!pip install tf-keras-vis
```

```
Collecting tf-keras-vis

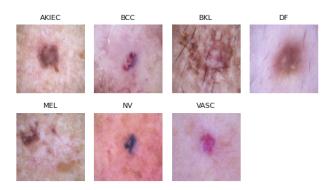
Downloading tf_keras_vis-0.8.5-py3-none-any.whl (52 kB)
```

[90m

```
%reload_ext autoreload
%autoreload 2
%matplotlib inline
from tensorflow.python.client import device_lib
device_list = device_lib.list_local_devices()
gpus = [device.name for device in device_list if device.device_type = 'GPU']
print('TensorFlow recognized {} GPUs'.format(len(gpus)))
```

TensorFlow recognized 1 GPUs

```
image_titles = ['AKIEC', 'BCC', 'BKL', 'DF', 'MEL', 'NV', 'VASC']
num_images = len(image_titles)
# Convert one-hot encoded labels to integer labels
test_labels_int = np.argmax(test_labels, axis=1)
# Find the indices of the first image from each class
class_indices = [np.where(test_labels_int = i)[0][0] for i in range(len(image_titles))]
# Create an array to store the images
image_array = []
# Create subplots with 2 rows
num_rows = 2
num_cols = (num_images + 1) // num_rows
fig, ax = plt.subplots(num_rows, num_cols, figsize=(5, 3))
for i, title in enumerate(image_titles):
    row = i // num_cols
    col = i % num_cols
    ax[row, col].set_title(title, fontsize=8)
    # Display the image from test data
    img = test_data[class_indices[i]]
    image_array.append(img) # Store the image in the array
    ax[row, col].imshow(img)
    ax[row, col].axis('off')
# Remove any empty subplots
for i in range(len(image_titles), num_rows * num_cols):
   row = i // num_cols
    col = i % num_cols
    fig.delaxes(ax[row, col])
plt.tight_layout()
plt.show()
```



```
from tf_keras_vis.utils.model_modifiers import ReplaceToLinear

replace2linear = ReplaceToLinear()

# Instead of using the ReplaceToLinear instance above,
# you can also define the function from scratch as follows:
def model_modifier_function(cloned_model):
    cloned_model.layers[-1].activation = tf.keras.activations.linear
```

```
from tf_keras_vis.utils.scores import CategoricalScore

# 1 is the imagenet index corresponding to Goldfish, 294 to Bear and 413 to Assault Rifle.
score = CategoricalScore([0, 1, 2, 3, 4, 5, 6])

# Instead of using CategoricalScore object,
# you can also define the function from scratch as follows:
def score_function(output):
    # The `output` variable refers to the output of the model,
    # so, in this case, `output` shape is `(3, 1000)` i.e., (samples, classes).
    return (output[0][1][2][3][4][5][6])
```

Faster Scorecam

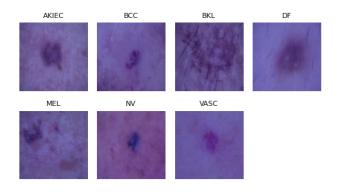
```
for i, title in enumerate(image_titles):
    row = i // num_cols
    col = i % num_cols

heatmap = np.uint8(cm.jet(cam[i])[..., :3] * 255)
    ax[row, col].set_title(title, fontsize=8)
    ax[row, col].imshow(image_array[i])
    ax[row, col].imshow(heatmap, cmap='jet', alpha=0.5)
    ax[row, col].axis('off')

# Remove any empty subplots
for i in range(len(image_titles), num_rows * num_cols):
    row = i // num_cols
    col = i % num_cols
    f.delaxes(ax[row, col])

plt.tight_layout()
plt.show()
```

3/3 [========] - 6s 654ms/step



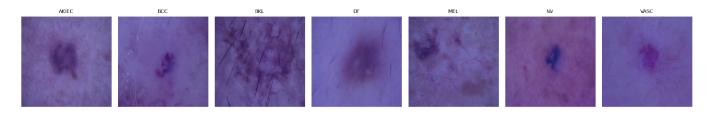
```
CPU times: user 17.4 s, sys: 351 ms, total: 17.7 s
Wall time: 27.4 s
```

```
%time
from matplotlib import pyplot as plt, cm
from tf_keras_vis.scorecam import Scorecam
# Assuming you have already defined model and replace2linear
# Create ScoreCAM object
scorecam = Scorecam(model, model_modifier=replace2linear)
\ensuremath{\mathtt{\#}} Generate heatmaps with Faster-ScoreCAM
cam = scorecam(score, X, penultimate_layer=-1, max_N=10)
# Calculate the number of images
num_images = len(image_titles)
# Create a single row plot
fig, axes = plt.subplots(1, num_images, figsize=(15, 5))
for i, title in enumerate(image_titles):
    heatmap = np.uint8(cm.jet(cam[i])[..., :3] * 255)
    combined_image = cv2.addWeighted(image_array[i], 0.5, heatmap, 0.5, 0)
    axes[i].set_title(title, fontsize=8)
```

```
axes[i].imshow(combined_image)
   axes[i].axis('off')

plt.tight_layout()
plt.show()
```

```
3/3 [======] - 19s 1s/step
```

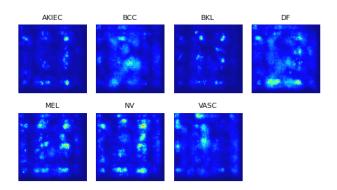


```
CPU times: user 19.9 s, sys: 1.01 s, total: 20.9 s
Wall time: 40.4 s
```

SmoothGrad

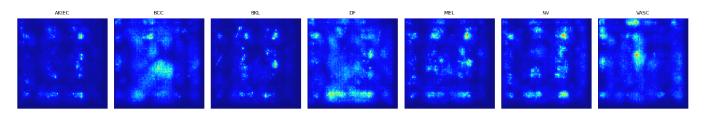
```
%time
from tensorflow.keras import backend as K
from tf_keras_vis.saliency import Saliency
# Create Saliency object.
saliency = Saliency(model,
                    model_modifier=replace2linear,
                    clone=True)
# Generate saliency map with smoothing that reduce noise by adding noise
saliency_map = saliency(score,
                        smooth_samples=20, # The number of calculating gradients iterations.
                        smooth_noise=0.20) # noise spread level.
## Since v0.6.0, calling `normalize()` is NOT necessary.
# saliency_map = normalize(saliency_map)
# Calculate the number of rows and columns for subplots
num_rows = 2
num_cols = (num_images + 1) // num_rows
# Render
f, ax = plt.subplots(nrows=num_rows, ncols=num_cols, figsize=(5, 3))
for i, title in enumerate(image_titles):
    row = i // num_cols
   col = i % num_cols
    ax[row, col].set_title(title, fontsize=8)
    ax[row, col].imshow(saliency_map[i], cmap='jet')
    ax[row, col].axis('off')
# Remove any empty subplots
for i in range(len(image_titles), num_rows * num_cols):
   row = i // num_cols
   col = i % num_cols
   f.delaxes(ax[row, col])
```

```
plt.tight_layout()
plt.show()
```



```
CPU times: user 25.5 s, sys: 545 ms, total: 26 s
Wall time: 29.3 s
```

```
%time
from tensorflow.keras import backend as K
from tf_keras_vis.saliency import Saliency
# Create Saliency object.
saliency = Saliency(model, model_modifier=replace2linear, clone=True)
# Generate saliency maps with smoothing that reduces noise by adding noise
saliency_maps = saliency(score, X, smooth_samples=20, smooth_noise=0.20)
# Calculate the number of images
num_images = len(image_titles)
# Create a single row plot
fig, axes = plt.subplots(1, num_images, figsize=(15, 5))
for i, title in enumerate(image_titles):
    axes[i].set_title(title, fontsize=8)
   axes[i].imshow(saliency_maps[i], cmap='jet')
   axes[i].axis('off')
plt.tight_layout()
plt.show()
```



```
CPU times: user 29.8 s, sys: 754 ms, total: 30.6 s
Wall time: 50.3 s
```