

Importing the libraries

```

import tensorflow as tf
import pandas as pd
import cv2
import warnings
import matplotlib.pyplot as plt
import numpy as np
import matplotlib.pyplot as plt

warnings.filterwarnings("ignore")

from tqdm import tqdm
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.layers import Dense, Activation, Conv2D, MaxPooling2D, Flatten, Dropout, BatchNormalization
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
from tensorflow.keras.utils import to_categorical
from imblearn.over_sampling import SMOTE
from tensorflow import keras
from IPython.display import clear_output
from sklearn.model_selection import train_test_split
from imblearn.under_sampling import RandomUnderSampler
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, accuracy_score, f1_score, classification_report
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.callbacks import ReduceLROnPlateau

```

	image_id	cell_type	is_benign
0	ISIC_0025030	Benign keratosis-like lesions	1.0
1	ISIC_0025661	Benign keratosis-like lesions	1.0

2	ISIC_0027850	Benign keratosis-like lesions	1.0	ed
3	ISIC_0025837	Benign keratosis-like lesions	1.0	back
4	ISIC_0025209	Benign keratosis-like lesions	1.0	back
...
5365	ISIC_0030965	Melanocytic nevi	1.0	NaN
5366	ISIC_0028490	Benign keratosis-like lesions	1.0	NaN
5367	ISIC_0026722	Melanoma	1.0	NaN
5368	ISIC_0029038	Melanocytic nevi	1.0	NaN
5369	ISIC_0032603	Benign keratosis-like lesions	1.0	NaN

5370 rows x 4 columns

```
In [3]: # check for the missing values in the csv

df.isna().sum()

Out[3]: image_id      0
        cell_type    100
        is_benign     100
        localization   13
        dtype: int64

In [4]: # drop the rows with missing values
```

```
df = df.dropna()

In [5]: # again check for missing values

df.isna().sum()

Out[5]: image_id      0
        cell type     0
```

```

localization      0
dtype: int64

```

In [6]:

```

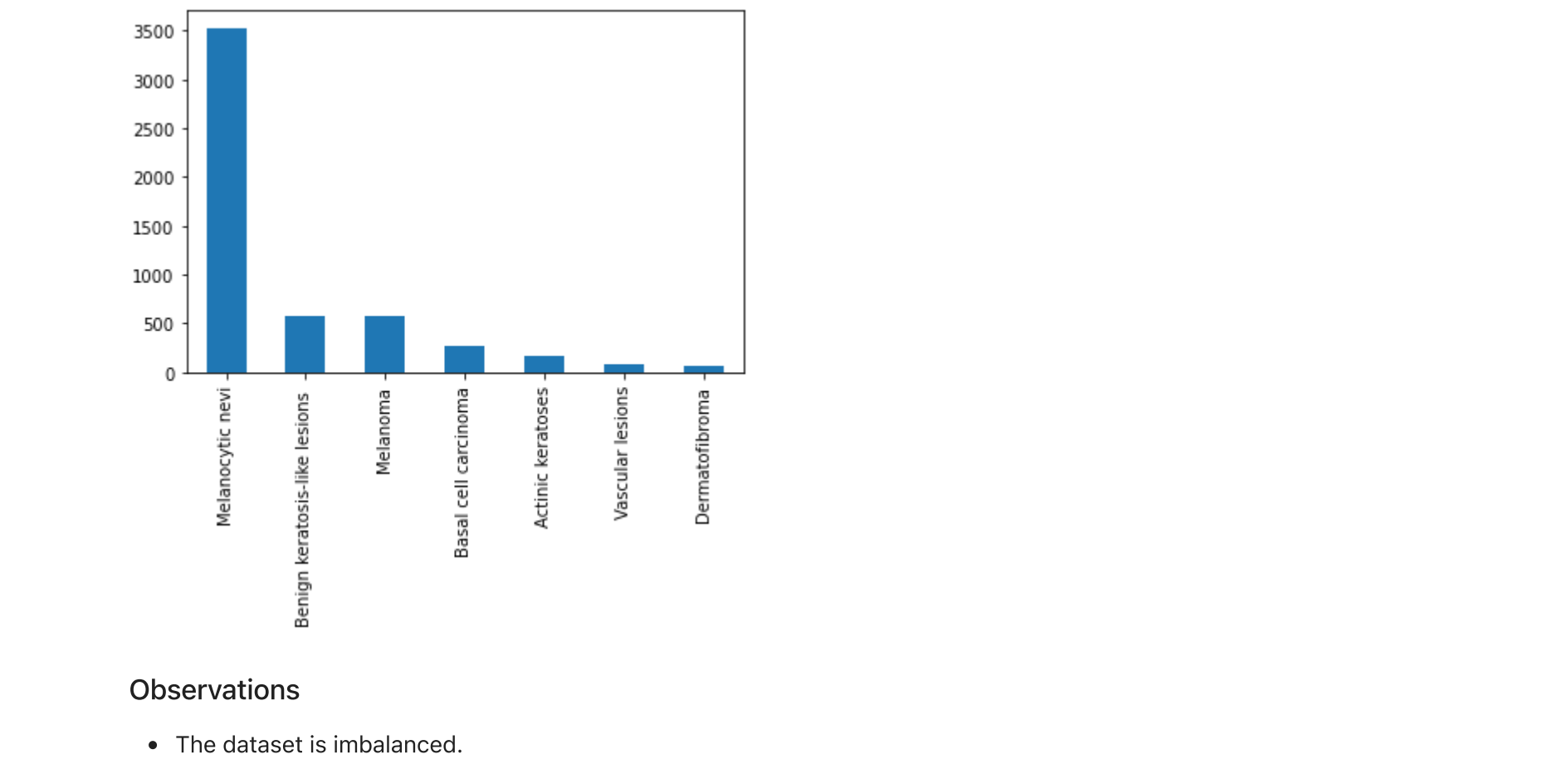
#check the class distribution
print(df['cell_type'].value_counts())
df['cell_type'].value_counts().plot.bar()

```

cell_type	count
Melanocytic nevi	3528

```

      benign_keratosis-like lesions      50
      Melanoma                          576
      Basal cell carcinoma              268
      Actinic keratoses                 169
      Vascular lesions                  74
      Dermatofibroma                    62
      Name: cell_type, dtype: int64
Out[6]: <AxesSubplot:~>
```



```
le = LabelEncoder()
df['cell_type'] = le.fit_transform(df['cell_type'])
```

- ```
There is no missing val
```

```
all_data=[]
labels=[]
for i in tqdm (range(len(df))):
```

```
#print(path)
img=cv2.imread(path)
img=cv2.resize(img,(150,150))
img=cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
img=img*(1/255)
all_data.append(img)
labels.append(df['cell_type'][i])
```

```
In [9]: all_data=np.array(all_data)
labels=np.array(labels)
```

```
In [10]: # Balancing the data using SMOTE Over sampling method
(Synthetic Minority Over Sampling Technique)

sm = SMOTE()
all_data = all_data.reshape(all_data.shape[0],-1)
all_data, labels = sm.fit_resample(all_data, labels)
all_data = all_data.reshape(all_data.shape[0],150,150,3)
```

```
print("Max pixel value = ",all_data.max())

one hot encoding for class label
labels = to_categorical(labels)

print("Shape of images = ",all_data.shape)
print("Shape of labels = ",labels.shape)

Max pixel value = 1.0
```

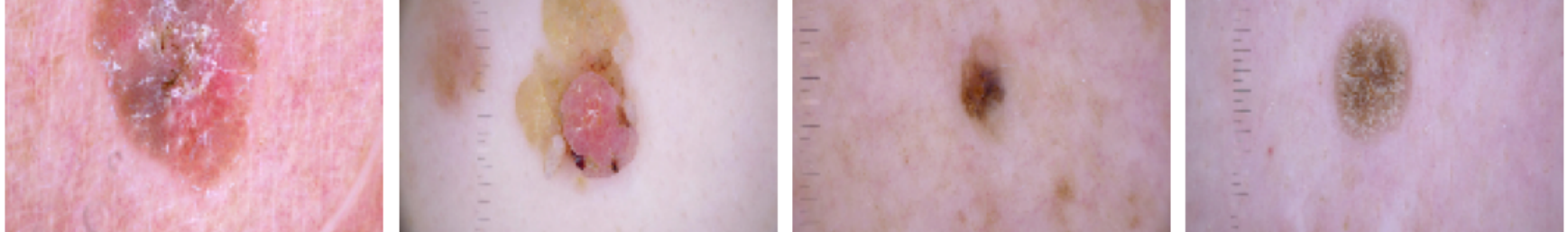
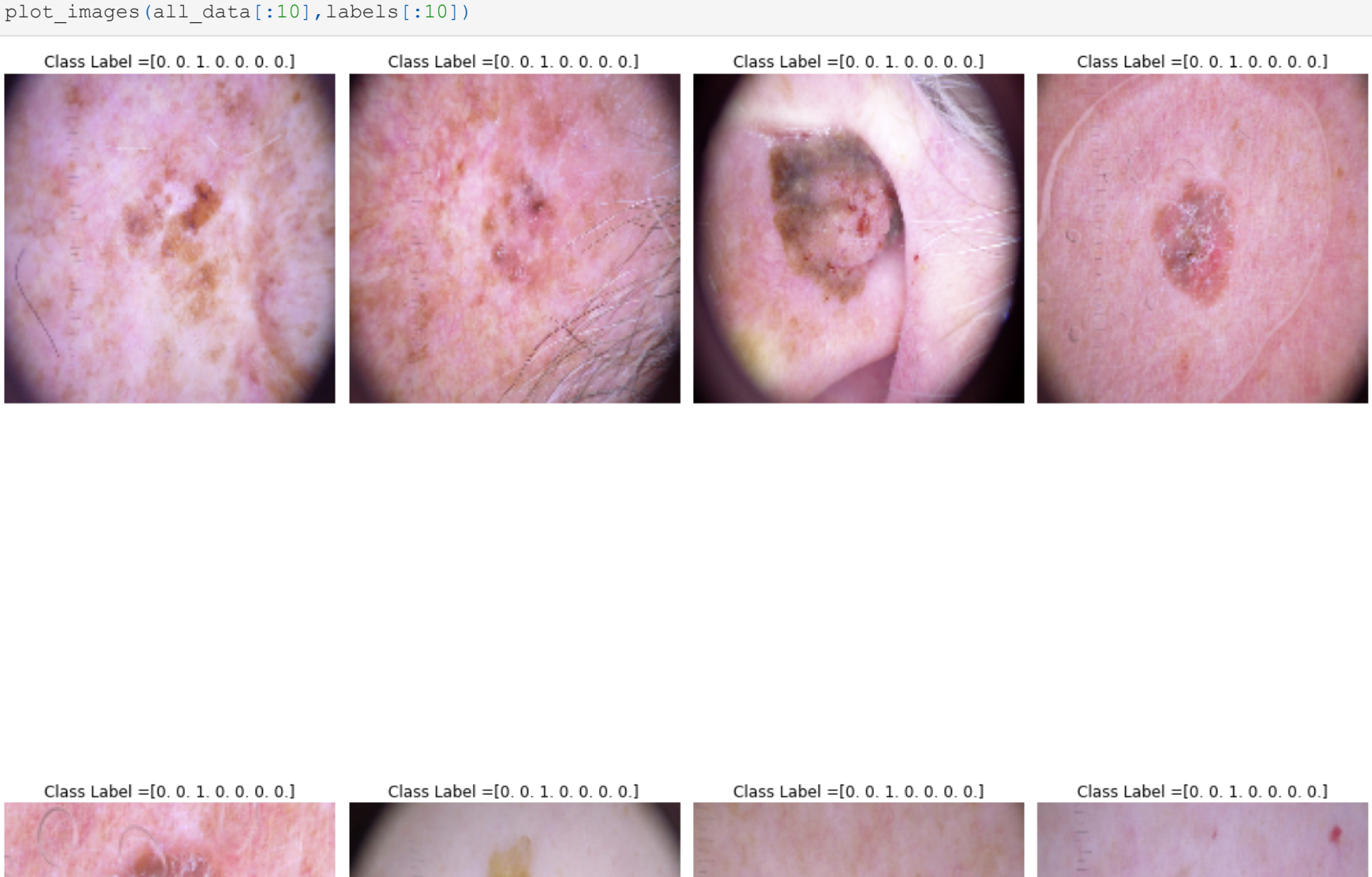
```
Shape of labels = (24696, 7)
```

```
In [12]: # plot Training images

def plot_images(images_arr, labels):
 fig, axes = plt.subplots(2, 4, figsize=(15,20))
 axes = axes.flatten()
 i=0
```

```
ax.imshow(img)
ax.axis('off')
title="Class Label="+str(labels[i])
ax.set_title(title)
i+=1

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



```
In [13]: # Train and valid split
X_train, X_test, y_train, y_test = train_test_split(all_data, labels, test_size=0.3, random_state=42)

del(all_data)
del(labels)
```

```
print("Shape of training labels = ",y_train.shape)
print("Shape of validation images = ",X_test.shape)
print("Shape of validation labels = ",y_test.shape)

Shape of training images = (17287, 150, 150, 3)
Shape of training labels = (17287, 7)
Shape of validation images = (7409, 150, 150, 3)
Shape of validation labels = (7409, 7)
```

```
In [14]: # plot accuracy, loss curve (graph)
class PlotLearning(keras.callbacks.Callback):
 def on_train_begin(self, logs={}):
 self.i = 0
 self.x = []
 self.losses = []
 self.val_losses = []
 self.acc = []
```

```
self.fig = plt.figure()

self.logs = []

def on_epoch_end(self, epoch, logs={}):

 self.logs.append(logs)
 self.x.append(self.i)
```

```
self.val_losses.append(logs.get('val_loss'))
self.acc.append(logs.get('accuracy'))
self.val_acc.append(logs.get('val_accuracy'))
self.i += 1
f, (ax1, ax2) = plt.subplots(1, 2, sharex=True)

clear_output(wait=True)
```

```
ax1.plot(self.x, self.losses, label="loss")
ax1.plot(self.x, self.val_losses, label="val_loss")
ax1.legend()

ax2.plot(self.x, self.acc, label="accuracy")
ax2.plot(self.x, self.val_acc, label="validation accuracy")
ax2.legend()
```

```
accuracy_loss_plot = PlotLearning()
```

```
input_shape = (150, 150, 3)
num_classes = 7

creating sequential model
model = Sequential()

adding extra conv2D, pooling layer(s)
```

```
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', padding = 'Same'))
model.add(MaxPool2D(pool_size = (2, 2)))
model.add(Dropout(0.25))

model.add(Conv2D(64, (3, 3), activation='relu', padding = 'Same'))
model.add(Conv2D(64, (3, 3), activation='relu', padding = 'Same'))
model.add(MaxPool2D(pool_size = (2, 2)))
model.add(Dropout(0.40))
```

```
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes, activation='softmax'))
model.summary()
```

Metal device set to: Apple M1 Pro  
Model: "sequential"

| Layer (type)                 | Output Shape         | Param # |
|------------------------------|----------------------|---------|
| conv2d (Conv2D)              | (None, 150, 150, 32) | 896     |
| conv2d_1 (Conv2D)            | (None, 150, 150, 32) | 9248    |
| max_pooling2d (MaxPooling2D) | (None, 75, 75, 32)   | 0       |

|                                    |                    |       |
|------------------------------------|--------------------|-------|
| dropout (Dropout)                  | (None, 75, 75, 32) | 0     |
| conv2d_2 (Conv2D)                  | (None, 75, 75, 64) | 18496 |
| conv2d_3 (Conv2D)                  | (None, 75, 75, 64) | 36928 |
| max_pooling2d_1 (MaxPooling<br>2D) | (None, 37, 37, 64) | 0     |

|                     |                    |          |
|---------------------|--------------------|----------|
| dropout_1 (Dropout) | (None, 37, 37, 64) | 0        |
| flatten (Flatten)   | (None, 87616)      | 0        |
| dense (Dense)       | (None, 128)        | 11214976 |
| dropout_2 (Dropout) | (None, 128)        | 0        |

```

=====
Total params: 11,281,447
Trainable params: 11,281,447
Non-trainable params: 0

```

```
MA support.
2022-04-24 19:31:07.530228: I tensorflow/core/common_runtime/pluggable_device/pluggable_device_factory.cc:271]
Created TensorFlow device (/job:localhost/replica:0/task:0/device:GPU:0 with 0 MB memory) -> physical Pluggable
Device (device:0, name: METAL, pci bus id: <undefined>)

In [16]: model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=["accuracy"])

Define callbacks
```

[illegible]

## Training the model

```
In [18]: datagen = ImageDataGenerator(
 rotation_range=10, # randomly rotate images in the range (degrees, 0 to 180)
 zoom_range = 0.1 # Randomly zoom image
)
```

```
epochs = 15
batch_size = 128
```

```

verbose = 1, steps_per_epoch=X_train.shape[0] // batch_size
, callbacks=callbacks ,shuffle = True)

```

The left plot shows training and validation loss over 100 epochs. The training loss (blue line) starts at approximately 0.95 and drops sharply to about 0.75 by epoch 10, then continues to decrease more gradually to about 0.65 by epoch 100. The validation loss (orange line) starts at approximately 0.85 and drops sharply to about 0.75 by epoch 10, then continues to decrease more gradually to about 0.65 by epoch 100. The right plot shows training and validation loss over 100 epochs. The training loss (blue line) starts at approximately 0.75 and decreases to about 0.65 by epoch 100. The validation loss (orange line) starts at approximately 0.75 and increases to about 0.85 by epoch 100.



```
ConfusionMatrixDisplay(cm).plot()

check performance
print("Accuracy on test data",accuracy_score(y_true,y_predict))
print(classification_report(y_true,y_predict))

2022-04-24 19:54:32.347804: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113] Plugin
optimizer for device type GPU is enabled.
```

|   | precision | recall | f1-score | support |
|---|-----------|--------|----------|---------|
| 0 | 0.93      | 0.96   | 0.94     | 1044    |
| 1 | 0.92      | 0.95   | 0.93     | 1060    |
| 2 | 0.79      | 0.82   | 0.80     | 1067    |
| 3 | 0.98      | 0.99   | 0.99     | 1040    |
| 4 | 0.92      | 0.57   | 0.70     | 1071    |
| 5 | 0.69      | 0.87   | 0.77     | 1077    |

|              | accuracy | macro avg | weighted avg |
|--------------|----------|-----------|--------------|
| accuracy     | 0.88     | 0.88      | 0.88         |
| macro avg    | 0.89     | 0.88      | 0.88         |
| weighted avg | 0.89     | 0.88      | 0.88         |

<Figure size 1080x720 with 0 Axes>

| Class | Count |
|-------|-------|
| 0     | 1001  |
| 1001  | 29    |
| 29    | 7     |
| 7     | 2     |
| 2     | 0     |
| 0     | 5     |
| 5     | 0     |
| 0     | 0     |

Confusion matrix for the 'True label' vs 'Predicted label' comparison. The matrix shows counts for each combination of true and predicted labels (1, 2, 3, 4). A color bar on the right indicates the count scale from 0 to 800.

|   | 1  | 2    | 3   | 4    |
|---|----|------|-----|------|
| 1 | 27 | 1002 | 11  | 3    |
| 2 | 12 | 29   | 674 | 10   |
| 3 | 0  | 2    | 6   | 1032 |
| 4 | 16 | 25   | 114 | 1    |