Problem statement: To build a CNN based model which can accurately detect melanoma. Melanoma is a type of cancer that can be deadly if not detected early. It accounts for 75% of skin cancer deaths. A solution which can evaluate images and alert the dermatologists about the presence of melanoma has the potential to reduce a lot of manual effort needed in diagnosis.

Importing all the important libraries

```
#import libraries

import pathlib
import tensorflow as tf
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import os
import PIL
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential
```

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

```
Mounted at /content/gdrive
```

```
# Unzip the dataset
!unzip "/content/gdrive/MyDrive/CNN_assignment.zip" > /dev/null
```

A dataset of about 2357 images of skin cancer types. The dataset contains 9 sub-directories in each train and test subdirectories. The 9 sub-directories contains the images of 9 skin cancer types respectively.

```
# Defining the path for train and test images
data_dir_train = pathlib.Path("/content/Skin cancer ISIC The International Skin Imaging Collaboration/Train/")
data_dir_test = pathlib.Path("/content/Skin cancer ISIC The International Skin Imaging Collaboration/Test/")
```

```
# Count the number of image in Train and Test directory
# Using the glob to retrieve files/pathnames matching a specified pattern.

#Train Image count
image_count_train = len(list(data_dir_train.glob('*/*.jpg')))
print(image_count_train)

#Test Image count
image_count_test = len(list(data_dir_test.glob('*/*.jpg')))
print(image_count_test)
```

```
2239
118
```

Create a dataset

Define some parameters for the loader:

```
batch_size = 32
img_height = 180
img_width = 180
```

Use 80% of the images for training, and 20% for validation.

```
#Train datset
train_ds =
tf.keras.preprocessing.image_dataset_from_directory(data_dir_train,bat
ch_size=batch_size,image_size=(img_height,img_width),label_mode='categ
orical',

seed=123,subset="training",validation_split=0.2)
```

```
Found 2239 files belonging to 9 classes.
Using 1792 files for training.
```

```
#Validation Dataset
val_ds
=tf.keras.preprocessing.image_dataset_from_directory(data_dir_train,ba
tch_size=batch_size,image_size=(img_height,img_width),label_mode='cate
gorical',

seed=123,subset="validation",validation_split=0.2)
```

```
Found 2239 files belonging to 9 classes.
Using 447 files for validation.
```

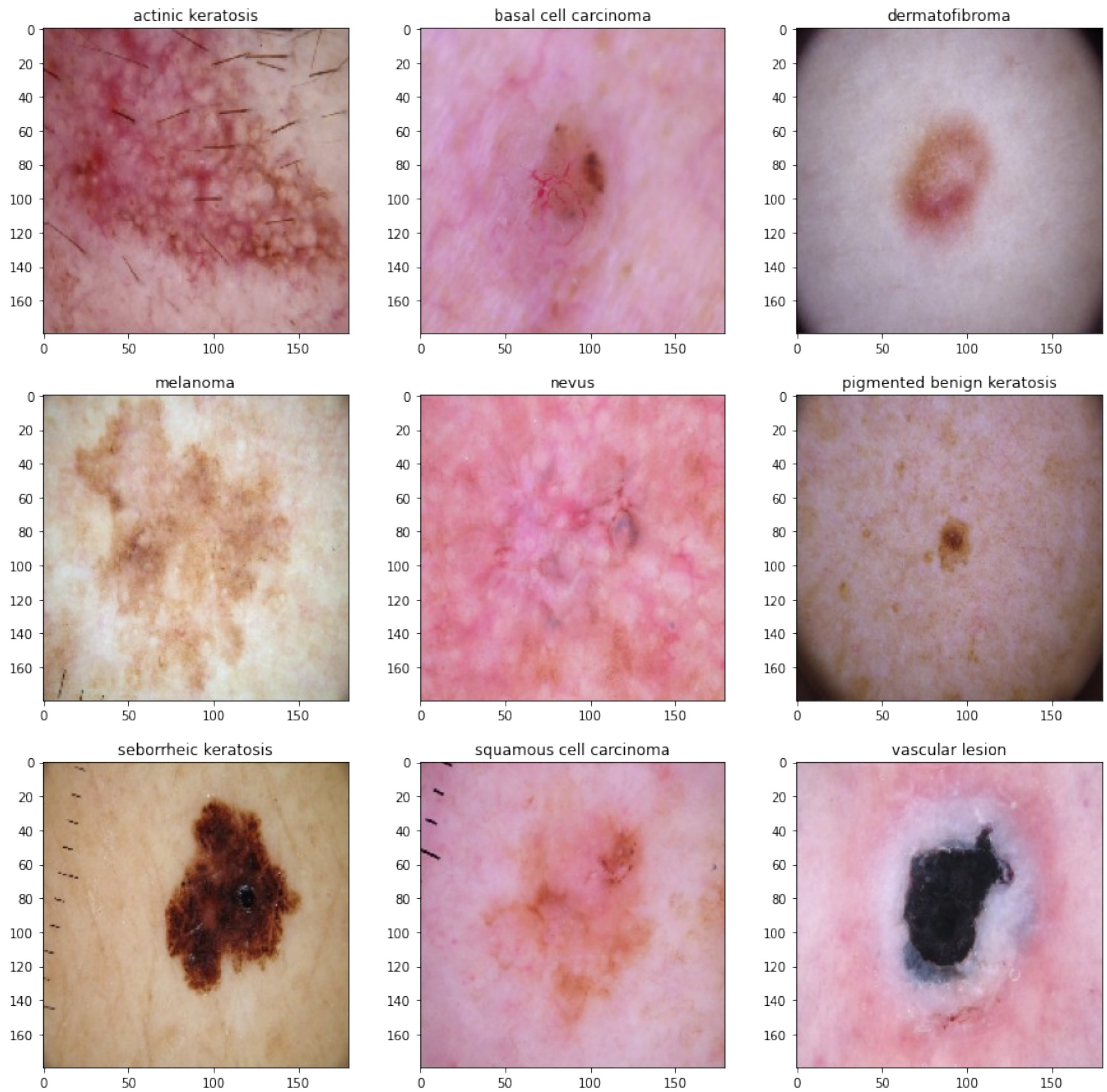
```
#All the classes of skin cancer.
class_names = train_ds.class_names
print(class_names)
```

```
['actinic keratosis', 'basal cell carcinoma', 'dermatofibroma',
'melanoma', 'nevus', 'pigmented benign keratosis', 'seborrheic
keratosis', 'squamous cell carcinoma', 'vascular lesion']
```

Visualize the data

```
import matplotlib.pyplot as plt
from tensorflow.keras.preprocessing.image import load_img

#Dictionary to store the path of image as per the class
files_path_dict = {}

for c in class_names:
```

```
    files_path_dict[c] = list(map(lambda x:str(data_dir_train)
+'/'+c+'/'+x,os.listdir(str(data_dir_train)+'/'+c)))

#Visualize image
plt.figure(figsize=(15,15))
index = 0
for c in class_names:
    path_list = files_path_dict[c][:1]
    index += 1
    plt.subplot(3,3,index)

plt.imshow(load_img(path_list[0],target_size=(img_height,img_width)))
    plt.title(c)
```



The `image_batch` is a tensor of the shape `(32, 180, 180, 3)`. This is a batch of 32 images of shape `180x180x3` (the last dimension refers to color channels RGB). The `label_batch` is a tensor of the shape `(32,)`, these are corresponding labels to the 32 images.

`Dataset.cache()` keeps the images in memory after they're loaded off disk during the first epoch.

`Dataset.prefetch()` overlaps data preprocessing and model execution while training.

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

Model Creation

```
input_shape = (img_height,img_width,3)

model = Sequential()    #Sequential allows you to create models layer-
by-layer

#First Convulation Layer
model.add(layers.experimental.preprocessing.Rescaling(1./255,input_sha
pe=input_shape))
model.add(layers.Conv2D(32,kernel_size=(3,3),activation='relu'))
model.add(layers.MaxPool2D(pool_size=(2,2)))

#Second Convulation Layer
model.add(layers.Conv2D(64,kernel_size=(3,3),activation='relu'))
model.add(layers.MaxPool2D(pool_size=(2,2)))

#Third Convulation Layer
model.add(layers.Conv2D(128,kernel_size=(3,3),activation='relu'))
model.add(layers.MaxPool2D(pool_size=(2,2)))

model.add(layers.Flatten())   #Keras.layers.flatten function flattens
the multi-dimensional input tensors into a single dimension.

#Dense Layer
model.add(layers.Dense(512,activation='relu'))

#Dense Layer
model.add(layers.Dense(128,activation='relu'))

#Dense Layer with softmax activation function.
#Softmax is an activation function that scales numbers/logits into
probabilities.
model.add(layers.Dense(len(class_names),activation='softmax'))
```

Compile the model

```
#Adam optimization: is a stochastic gradient descent method that is
based on adaptive estimation of first-order and second-order moments.
#categorical_crossentropy: Used as a loss function for multi-class
classification model where there are two or more output labels.

model.compile(optimizer='Adam',
              loss="categorical_crossentropy",
              metrics=['accuracy'])

# summary of all layers
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
rescaling (Rescaling)        (None, 180, 180, 3)       0
_________________________________________________________________
conv2d (Conv2D)              (None, 178, 178, 32)      896
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 89, 89, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 87, 87, 64)        18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 43, 43, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 41, 41, 128)       73856
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 20, 20, 128)       0
_________________________________________________________________
flatten (Flatten)            (None, 51200)             0
_________________________________________________________________
dense (Dense)                (None, 512)               26214912
_________________________________________________________________
dense_1 (Dense)              (None, 128)               65664
_________________________________________________________________
dense_2 (Dense)              (None, 9)                 1161
=================================================================
Total params: 26,374,985
Trainable params: 26,374,985
Non-trainable params: 0
_________________________________________________________________
```

Train the model

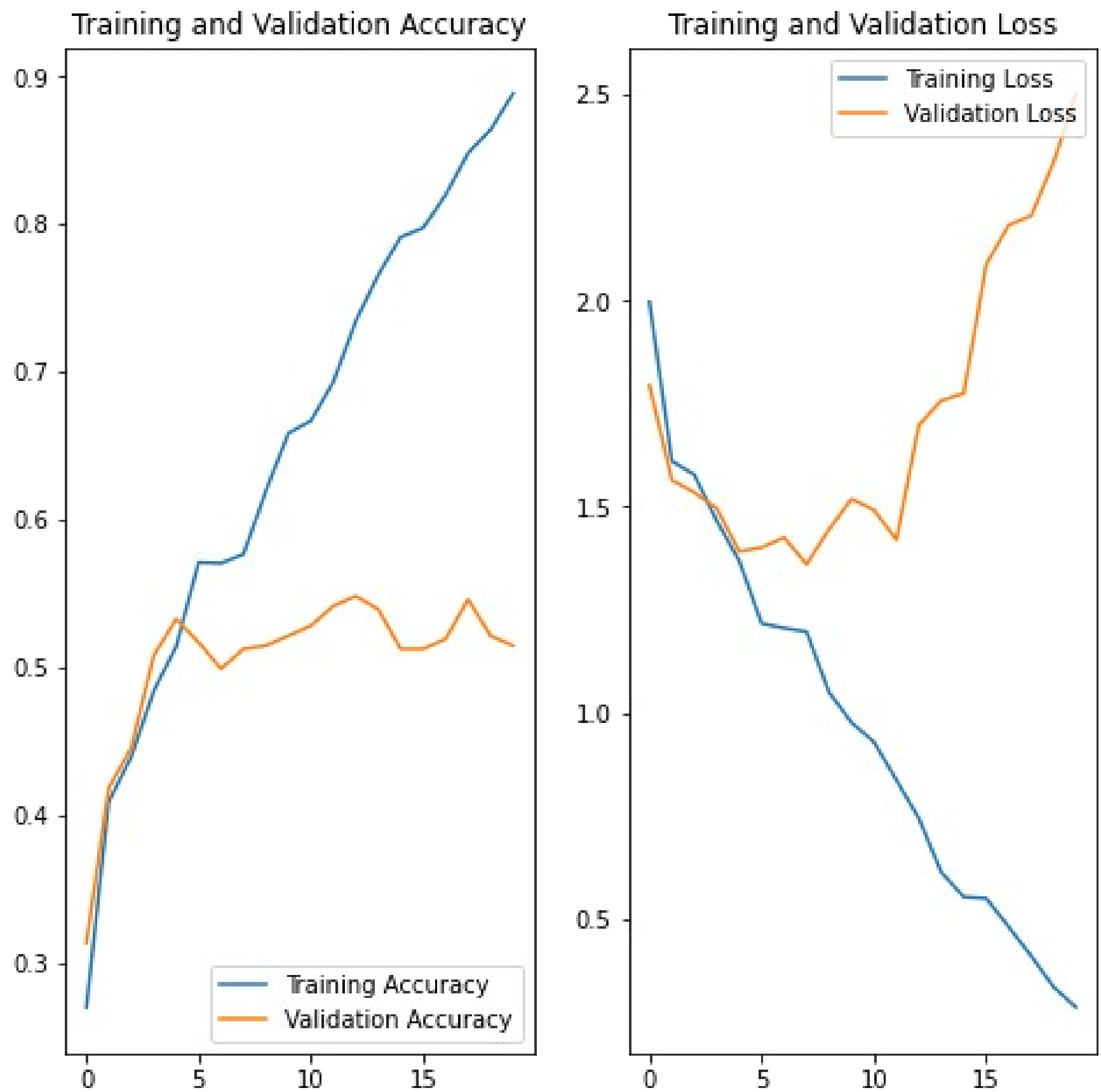
```
epochs = 20
history = model.fit(
  train_ds,
  validation_data=val_ds,
```

```
  epochs=epochs
)

Epoch 1/20
56/56 [==============================] - 51s 139ms/step - loss: 1.9974
- accuracy: 0.2695 - val_loss: 1.7946 - val_accuracy: 0.3132
Epoch 2/20
56/56 [==============================] - 4s 78ms/step - loss: 1.6104 -
accuracy: 0.4090 - val_loss: 1.5644 - val_accuracy: 0.4183
Epoch 3/20
56/56 [==============================] - 4s 78ms/step - loss: 1.5775 -
accuracy: 0.4392 - val_loss: 1.5345 - val_accuracy: 0.4452
Epoch 4/20
56/56 [==============================] - 4s 78ms/step - loss: 1.4652 -
accuracy: 0.4838 - val_loss: 1.4956 - val_accuracy: 0.5078
Epoch 5/20
56/56 [==============================] - 4s 78ms/step - loss: 1.3683 -
accuracy: 0.5140 - val_loss: 1.3912 - val_accuracy: 0.5324
Epoch 6/20
56/56 [==============================] - 4s 77ms/step - loss: 1.2163 -
accuracy: 0.5709 - val_loss: 1.4011 - val_accuracy: 0.5168
Epoch 7/20
56/56 [==============================] - 4s 77ms/step - loss: 1.2053 -
accuracy: 0.5703 - val_loss: 1.4251 - val_accuracy: 0.4989
Epoch 8/20
56/56 [==============================] - 4s 77ms/step - loss: 1.1963 -
accuracy: 0.5765 - val_loss: 1.3598 - val_accuracy: 0.5123
Epoch 9/20
56/56 [==============================] - 4s 77ms/step - loss: 1.0492 -
accuracy: 0.6194 - val_loss: 1.4452 - val_accuracy: 0.5145
Epoch 10/20
56/56 [==============================] - 4s 77ms/step - loss: 0.9761 -
accuracy: 0.6585 - val_loss: 1.5185 - val_accuracy: 0.5213
Epoch 11/20
56/56 [==============================] - 4s 78ms/step - loss: 0.9290 -
accuracy: 0.6669 - val_loss: 1.4921 - val_accuracy: 0.5280
Epoch 12/20
56/56 [==============================] - 4s 78ms/step - loss: 0.8361 -
accuracy: 0.6931 - val_loss: 1.4196 - val_accuracy: 0.5414
Epoch 13/20
56/56 [==============================] - 4s 77ms/step - loss: 0.7434 -
accuracy: 0.7344 - val_loss: 1.6979 - val_accuracy: 0.5481
Epoch 14/20
56/56 [==============================] - 4s 77ms/step - loss: 0.6123 -
accuracy: 0.7656 - val_loss: 1.7575 - val_accuracy: 0.5391
Epoch 15/20
56/56 [==============================] - 4s 77ms/step - loss: 0.5529 -
accuracy: 0.7913 - val_loss: 1.7751 - val_accuracy: 0.5123
Epoch 16/20
56/56 [==============================] - 4s 77ms/step - loss: 0.5492 -
```

```
accuracy: 0.7974 - val_loss: 2.0880 - val_accuracy: 0.5123
Epoch 17/20
56/56 [==============================] - 4s 77ms/step - loss: 0.4801 -
accuracy: 0.8198 - val_loss: 2.1833 - val_accuracy: 0.5190
Epoch 18/20
56/56 [==============================] - 4s 77ms/step - loss: 0.4094 -
accuracy: 0.8482 - val_loss: 2.2062 - val_accuracy: 0.5459
Epoch 19/20
56/56 [==============================] - 4s 77ms/step - loss: 0.3341 -
accuracy: 0.8638 - val_loss: 2.3358 - val_accuracy: 0.5213
Epoch 20/20
56/56 [==============================] - 4s 77ms/step - loss: 0.2847 -
accuracy: 0.8884 - val_loss: 2.5026 - val_accuracy: 0.5145
```

Visualizing training results

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

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

epochs_range = range(epochs)

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

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



Model is overfitting. From the above Training vs Validation accuracy graph we can see that as the epoch increases the difference between Training accuracy and validation accuracy increases.

```
#Data augumentation strategy.

rescale = tf.keras.Sequential([
  #To rescale an input in the [0, 255] range to be in the [0, 1] range

  layers.experimental.preprocessing.Rescaling(1./255)
])

data_augmentation = tf.keras.Sequential([
  #Randomly flip each image horizontally and vertically.

layers.experimental.preprocessing.RandomFlip("horizontal_and_vertical"
```

```
),

  #Randomly rotate each image.
  layers.experimental.preprocessing.RandomRotation(0.2),

  #Randomly zoom each image during training.
  layers.experimental.preprocessing.RandomZoom(0.2),

  #Randomly translate each image during training.
  layers.experimental.preprocessing.RandomTranslation(0.1, 0.1)
])


#Visualize the augmentation image
plt.figure(figsize=(10, 10))
for images, _ in train_ds.take(1):
    for i in range(9):
        augmented_images = data_augmentation(images)
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(augmented_images[0].numpy().astype("uint8"))
        plt.axis("off")
```

```
## Model 2 Creation

#Dropout layer: randomly sets input units to 0 with a frequency of 
rate at each step during training time,
#which helps prevent overfitting.Inputs not set to 0 are scaled up by 
1/(1 - rate) such that the sum over all inputs is unchanged.


## Your code goes here
model2 = Sequential()                          #Sequential allows you to 
create models layer-by-layer

model2.add(data_augmentation)                  #Augmentation layer
model2.add(rescale)                            #Rescaling layer

#First Convulation Layer
model2.add(layers.Conv2D(32,kernel_size=(3,3),activation='relu'))
```

```
model2.add(layers.MaxPool2D(pool_size=(2,2)))

#Dropout layer with 25% Fraction of the input units to drop.
model2.add(layers.Dropout(0.25))

#Second Convulation Layer
model2.add(layers.Conv2D(64,kernel_size=(3,3),activation='relu'))
model2.add(layers.MaxPool2D(pool_size=(2,2)))

#Dropout layer with 25% Fraction of the input units to drop.
model2.add(layers.Dropout(0.25))

#Third Convulation Layer
model2.add(layers.Conv2D(128,kernel_size=(3,3),activation='relu'))
model2.add(layers.MaxPool2D(pool_size=(2,2)))

#Keras.layers.flatten function flattens the multi-dimensional input
tensors into a single dimension.
model2.add(layers.Flatten())

#Dense Layer
model2.add(layers.Dense(512,activation='relu'))

#Dense Layer
model2.add(layers.Dense(128,activation='relu'))

#Dropout layer with 50% Fraction of the input units to drop.
model2.add(layers.Dropout(0.50))

#Dense Layer with softmax activation function.
#Softmax is an activation function that scales numbers/logits into
probabilities.
model2.add(layers.Dense(len(class_names),activation='softmax'))
```

Compiling the model

```
model2.compile(optimizer='Adam',
              loss="categorical_crossentropy",
              metrics=['accuracy'])
```

Training the model

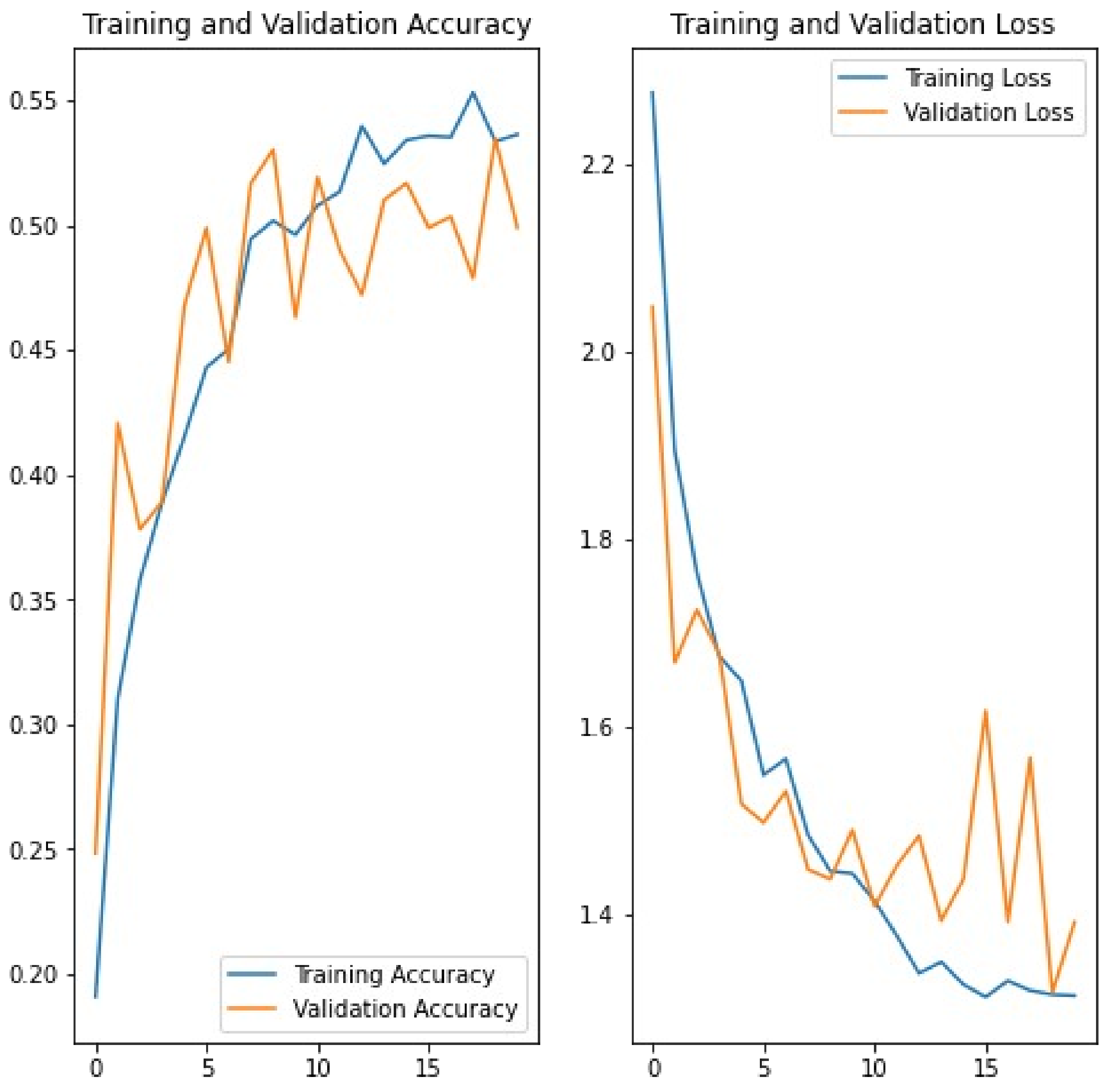
```
epochs =20
history =
model2.fit(train_ds,epochs=epochs,validation_data=val_ds,verbose=1)

Epoch 1/20
56/56 [==============================] - 8s 97ms/step - loss: 2.2754 -
```

```
accuracy: 0.1908 - val_loss: 2.0474 - val_accuracy: 0.2483
Epoch 2/20
56/56 [==============================] - 5s 92ms/step - loss: 1.8945 -
accuracy: 0.3103 - val_loss: 1.6684 - val_accuracy: 0.4206
Epoch 3/20
56/56 [==============================] - 5s 92ms/step - loss: 1.7640 -
accuracy: 0.3577 - val_loss: 1.7247 - val_accuracy: 0.3781
Epoch 4/20
56/56 [==============================] - 5s 92ms/step - loss: 1.6752 -
accuracy: 0.3890 - val_loss: 1.6779 - val_accuracy: 0.3893
Epoch 5/20
56/56 [==============================] - 5s 92ms/step - loss: 1.6490 -
accuracy: 0.4152 - val_loss: 1.5178 - val_accuracy: 0.4676
Epoch 6/20
56/56 [==============================] - 5s 93ms/step - loss: 1.5488 -
accuracy: 0.4431 - val_loss: 1.4979 - val_accuracy: 0.4989
Epoch 7/20
56/56 [==============================] - 5s 93ms/step - loss: 1.5659 -
accuracy: 0.4503 - val_loss: 1.5313 - val_accuracy: 0.4452
Epoch 8/20
56/56 [==============================] - 5s 92ms/step - loss: 1.4849 -
accuracy: 0.4944 - val_loss: 1.4482 - val_accuracy: 0.5168
Epoch 9/20
56/56 [==============================] - 5s 93ms/step - loss: 1.4464 -
accuracy: 0.5017 - val_loss: 1.4376 - val_accuracy: 0.5302
Epoch 10/20
56/56 [==============================] - 5s 93ms/step - loss: 1.4438 -
accuracy: 0.4961 - val_loss: 1.4902 - val_accuracy: 0.4631
Epoch 11/20
56/56 [==============================] - 5s 93ms/step - loss: 1.4143 -
accuracy: 0.5078 - val_loss: 1.4087 - val_accuracy: 0.5190
Epoch 12/20
56/56 [==============================] - 5s 91ms/step - loss: 1.3773 -
accuracy: 0.5134 - val_loss: 1.4523 - val_accuracy: 0.4899
Epoch 13/20
56/56 [==============================] - 5s 93ms/step - loss: 1.3375 -
accuracy: 0.5396 - val_loss: 1.4840 - val_accuracy: 0.4720
Epoch 14/20
56/56 [==============================] - 5s 91ms/step - loss: 1.3496 -
accuracy: 0.5246 - val_loss: 1.3937 - val_accuracy: 0.5101
Epoch 15/20
56/56 [==============================] - 5s 91ms/step - loss: 1.3255 -
accuracy: 0.5340 - val_loss: 1.4377 - val_accuracy: 0.5168
Epoch 16/20
56/56 [==============================] - 5s 91ms/step - loss: 1.3123 -
accuracy: 0.5357 - val_loss: 1.6170 - val_accuracy: 0.4989
Epoch 17/20
56/56 [==============================] - 5s 91ms/step - loss: 1.3295 -
accuracy: 0.5352 - val_loss: 1.3920 - val_accuracy: 0.5034
Epoch 18/20
```

```
56/56 [==============================] - 5s 91ms/step - loss: 1.3191 -
accuracy: 0.5530 - val_loss: 1.5669 - val_accuracy: 0.4787
Epoch 19/20
56/56 [==============================] - 5s 92ms/step - loss: 1.3149 -
accuracy: 0.5335 - val_loss: 1.3170 - val_accuracy: 0.5347
Epoch 20/20
56/56 [==============================] - 5s 91ms/step - loss: 1.3137 -
accuracy: 0.5363 - val_loss: 1.3919 - val_accuracy: 0.4989
```

Visualizing the results

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

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

epochs_range = range(epochs)

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

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



- After using data augumentation and dropout layer overfitting issue is reduce.
- Model Performance is still not increased. Will check the distribution of classes in the training set to check is there have class imbalance.

Class Imbalance Detection

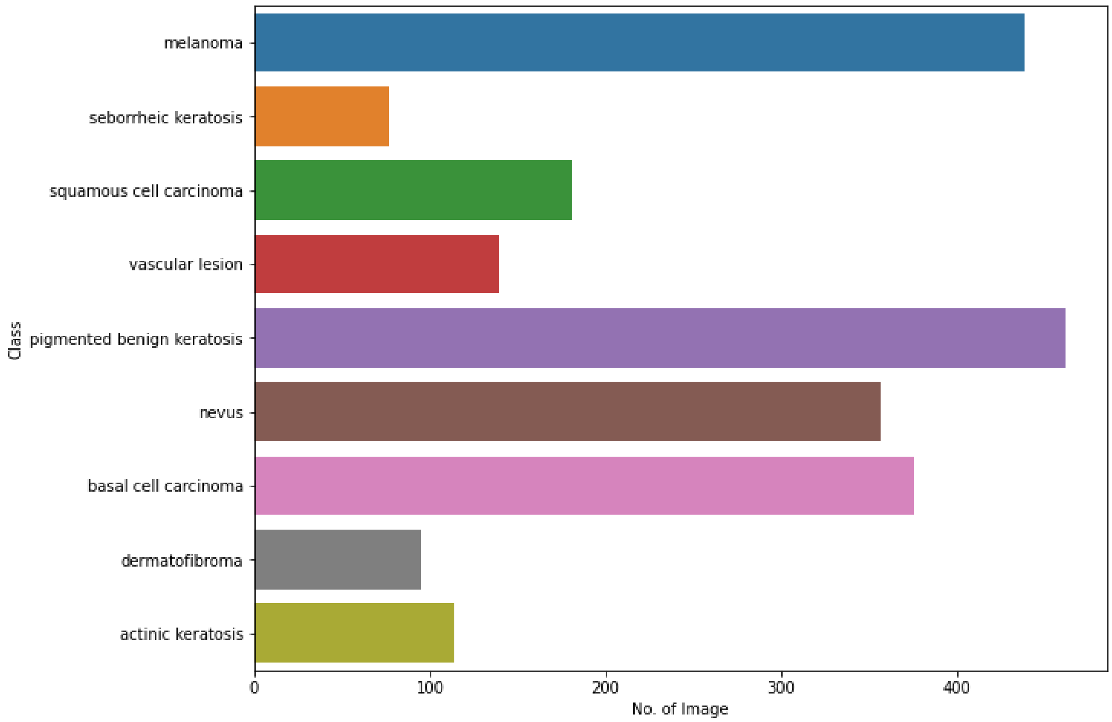
```
def class_distribution_count(directory):

    #count number of image in each classes
    count= []
    for path in pathlib.Path(directory).iterdir():
        if path.is_dir():
            count.append(len([name for name in os.listdir(path)
                               if os.path.isfile(os.path.join(path,
name))]))
```

```
    #name of the classes
    sub_directory = [name for name in os.listdir(directory)
                    if os.path.isdir(os.path.join(directory, name))]

    #return dataframe with image count and class.
    return pd.DataFrame(list(zip(sub_directory,count)),columns
=['Class', 'No. of Image'])

df = class_distribution_count(data_dir_train)
df
```

```
                        Class  No. of Image
0                    melanoma           438
1        seborrheic keratosis            77
2     squamous cell carcinoma           181
3             vascular lesion           139
4  pigmented benign keratosis           462
5                       nevus           357
6        basal cell carcinoma           376
7              dermatofibroma            95
8           actinic keratosis           114
```

```
#Visualize the Number of image in each class.
import seaborn as sns
plt.figure(figsize=(10, 8))
sns.barplot(x="No. of Image", y="Class", data=df,
            label="Class")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7d5879b610>
```



- seborrheic keratosis has the least number of samples only 77.
- pigmented benign keratosis (462 Samples), melanoma (438 Samples), basal cell carcinoma (376 Samples), and nevus (357 Samples) classes dominates the data in terms proportionate number of samples .

Rectify the class imbalance

Use a python package known as `Augmentor` (https://augmentor.readthedocs.io/en/master/) to add more samples across all classes so that none of the classes have very few samples.

```
!pip install Augmentor
```

```
Collecting Augmentor
  Downloading Augmentor-0.2.8-py2.py3-none-any.whl (38 kB)
Requirement already satisfied: future>=0.16.0 in
/usr/local/lib/python3.7/dist-packages (from Augmentor) (0.16.0)
Requirement already satisfied: Pillow>=5.2.0 in
/usr/local/lib/python3.7/dist-packages (from Augmentor) (7.1.2)
Requirement already satisfied: tqdm>=4.9.0 in
/usr/local/lib/python3.7/dist-packages (from Augmentor) (4.62.3)
Requirement already satisfied: numpy>=1.11.0 in
/usr/local/lib/python3.7/dist-packages (from Augmentor) (1.19.5)
Installing collected packages: Augmentor
Successfully installed Augmentor-0.2.8
```

To use `Augmentor`, the following general procedure is followed:

1. Instantiate a `Pipeline` object pointing to a directory containing your initial image data set.
2. Define a number of operations to perform on this data set using your `Pipeline` object.
3. Execute these operations by calling the `Pipeline`’s `sample()` method.

```
path_to_training_dataset="/content/Skin cancer ISIC The International Skin Imaging Collaboration/Train/"
import Augmentor
for i in class_names:
    p = Augmentor.Pipeline(path_to_training_dataset + i)
    p.rotate(probability=0.7, max_left_rotation=10, max_right_rotation=10)
    p.sample(500) ## We are adding 500 samples per class to make sure that none of the classes are sparse.
```

```
Initialised with 114 image(s) found.
Output directory set to /content/Skin cancer ISIC The International Skin Imaging Collaboration/Train/actinic keratosis/output.

Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x7F7DD4F36FD0>: 100%|██████████| 500/500 [00:19<00:00, 25.31 Samples/s]

Initialised with 376 image(s) found.
Output directory set to /content/Skin cancer ISIC The International Skin Imaging Collaboration/Train/basal cell carcinoma/output.

Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x7F7DD4FE2450>: 100%|██████████| 500/500 [00:20<00:00, 24.98 Samples/s]

Initialised with 95 image(s) found.
Output directory set to /content/Skin cancer ISIC The International Skin Imaging Collaboration/Train/dermatofibroma/output.

Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x7F7E4F34FBD0>: 100%|██████████| 500/500 [00:19<00:00, 25.43 Samples/s]

Initialised with 438 image(s) found.
Output directory set to /content/Skin cancer ISIC The International Skin Imaging Collaboration/Train/melanoma/output.

Processing <PIL.Image.Image image mode=RGB size=3072x2304 at 0x7F7DD4D7BFD0>: 100%|██████████| 500/500 [01:53<00:00,  4.40 Samples/s]

Initialised with 357 image(s) found.
Output directory set to /content/Skin cancer ISIC The International Skin Imaging Collaboration/Train/nevus/output.
```

```
Processing <PIL.JpegImagePlugin.JpegImageFile image mode=RGB
size=1504x1129 at 0x7F7E4F4DE050>: 100%|██████████| 500/500
[01:14<00:00,  6.71 Samples/s]

Initialised with 462 image(s) found.
Output directory set to /content/Skin cancer ISIC The International
Skin Imaging Collaboration/Train/pigmented benign keratosis/output.

Processing <PIL.Image.Image image mode=RGB size=600x450 at
0x7F7D587ECE90>: 100%|██████████| 500/500 [00:20<00:00, 24.64
Samples/s]

Initialised with 77 image(s) found.
Output directory set to /content/Skin cancer ISIC The International
Skin Imaging Collaboration/Train/seborrheic keratosis/output.

Processing <PIL.JpegImagePlugin.JpegImageFile image mode=RGB
size=1024x768 at 0x7F7D57FCFED0>: 100%|██████████| 500/500
[00:47<00:00, 10.54 Samples/s]

Initialised with 181 image(s) found.
Output directory set to /content/Skin cancer ISIC The International
Skin Imaging Collaboration/Train/squamous cell carcinoma/output.

Processing <PIL.Image.Image image mode=RGB size=600x450 at
0x7F7EC49553D0>: 100%|██████████| 500/500 [00:19<00:00, 25.63
Samples/s]

Initialised with 139 image(s) found.
Output directory set to /content/Skin cancer ISIC The International
Skin Imaging Collaboration/Train/vascular lesion/output.

Processing <PIL.Image.Image image mode=RGB size=600x450 at
0x7F7E4F2C73D0>: 100%|██████████| 500/500 [00:19<00:00, 25.70
Samples/s]
```

Augmentor has stored the augmented images in the output sub-directory of each of the sub-directories of skin cancer types.. Lets take a look at total count of augmented images.

```
#Count total number of image generated by Augmentor.
image_count_train = len(list(data_dir_train.glob('*/output/*.jpg')))
print(image_count_train)

4500
```

see the distribution of augmented data after adding new images to the original training data.

```
from glob import glob
path_list = [x for x in glob(os.path.join(data_dir_train,
'*','output', '*.jpg'))]
#path_list

lesion_list_new =
[os.path.basename(os.path.dirname(os.path.dirname(y))) for y in
```

```
glob(os.path.join(data_dir_train, '*','output', '*.jpg'))]
#lesion_list_new

dataframe_dict_new = dict(zip(path_list, lesion_list_new))

#dataframe that store path and label of the images generated by
Augmentor
df2 = pd.DataFrame(list(dataframe_dict_new.items()),columns =
['Path','Label'])

#label count.
df2['Label'].value_counts()
```

```
pigmented benign keratosis    500
seborrheic keratosis          500
dermatofibroma                500
melanoma                      500
squamous cell carcinoma       500
actinic keratosis             500
vascular lesion               500
nevus                         500
basal cell carcinoma          500
Name: Label, dtype: int64
```

So, now we have added 500 images to all the classes to maintain some class balance. We can add more images as we want to improve training process.

Train the model on the data created using Augmentor

```
batch_size = 32
img_height = 180
img_width = 180
```

Create a training dataset

```
data_dir_train="/content/Skin cancer ISIC The International Skin
Imaging Collaboration/Train/"

#Training dataset.
train_ds = tf.keras.preprocessing.image_dataset_from_directory(
  data_dir_train,
  seed=123,
  validation_split = 0.2,    #20% fraction of data to reserve for
validation.
  subset = "training",
  image_size=(img_height, img_width),label_mode='categorical',
#label_mode='categorical' means that the labels are encoded as a
categorical vector
  batch_size=batch_size)
```

```
Found 6739 files belonging to 9 classes.
Using 5392 files for training.
```

Create a validation dataset

```
#Validation dataset.
val_ds = tf.keras.preprocessing.image_dataset_from_directory(
  data_dir_train,
  seed=123,
  validation_split = 0.2,
  subset = "validation",
  image_size=(img_height, img_width),label_mode='categorical',
#label_mode='categorical' means that the labels are encoded as a
categorical vector
  batch_size=batch_size)
```

```
Found 6739 files belonging to 9 classes.
Using 1347 files for validation.
```

Create model

```
#Model

model3 = Sequential()

model3.add(rescale)   #Rescaling Layer

#First Convulation layer
model3.add(layers.Conv2D(32,kernel_size=(2,2),activation='relu'))
model3.add(layers.MaxPool2D(pool_size=(2,2)))
model3.add(layers.Dropout(0.25))

#Second Convulation Layer
model3.add(layers.Conv2D(64,kernel_size=(2,2),activation='relu'))
model3.add(layers.MaxPool2D(pool_size=(2,2)))
model3.add(layers.Dropout(0.25))

#Third Convulation Layer
model3.add(layers.Conv2D(128,kernel_size=(2,2),activation='relu'))
model3.add(layers.MaxPool2D(pool_size=(2,2)))

#Flatten Layer
model3.add(layers.Flatten())

#Dense Layer
model3.add(layers.Dense(512,activation='relu'))

#Dropout layer
model3.add(layers.Dropout(0.25))

#Batch normalization: is a method used to make artificial neural
networks faster and more stable through normalization
#of the layers' inputs by re-centering and re-scaling.
model3.add(layers.BatchNormalization())
```

```python
#Dense Layer
model3.add(layers.Dense(128,activation='relu'))

#Dropout layer with 50% Fraction of the input units to drop.
model3.add(layers.Dropout(0.50))

#Batch normalization
model3.add(layers.BatchNormalization())

#Dense layer with Softmax activation function.
model3.add(layers.Dense(len(class_names),activation='softmax'))
```

Compile Model

```python
model3.compile(optimizer='Adam',
              loss="categorical_crossentropy",
              metrics=['accuracy'])
```

Train your model

```python
epochs = 50
history =
model3.fit(train_ds,epochs=epochs,validation_data=val_ds,verbose=1)
```

```
Epoch 1/50
169/169 [==============================] - 33s 181ms/step - loss:
2.4487 - accuracy: 0.1825 - val_loss: 4.1381 - val_accuracy: 0.1359
Epoch 2/50
169/169 [==============================] - 32s 186ms/step - loss:
1.8023 - accuracy: 0.3418 - val_loss: 2.4640 - val_accuracy: 0.1693
Epoch 3/50
169/169 [==============================] - 32s 186ms/step - loss:
1.5857 - accuracy: 0.3986 - val_loss: 1.9945 - val_accuracy: 0.2517
Epoch 4/50
169/169 [==============================] - 33s 187ms/step - loss:
1.5265 - accuracy: 0.4201 - val_loss: 1.5896 - val_accuracy: 0.3831
Epoch 5/50
169/169 [==============================] - 33s 187ms/step - loss:
1.4334 - accuracy: 0.4609 - val_loss: 1.3672 - val_accuracy: 0.4937
Epoch 6/50
169/169 [==============================] - 32s 185ms/step - loss:
1.3552 - accuracy: 0.4800 - val_loss: 1.3817 - val_accuracy: 0.4722
Epoch 7/50
169/169 [==============================] - 32s 187ms/step - loss:
1.2997 - accuracy: 0.5056 - val_loss: 1.4254 - val_accuracy: 0.4640
Epoch 8/50
169/169 [==============================] - 32s 185ms/step - loss:
1.2361 - accuracy: 0.5254 - val_loss: 1.2275 - val_accuracy: 0.5449
Epoch 9/50
169/169 [==============================] - 32s 186ms/step - loss:
```

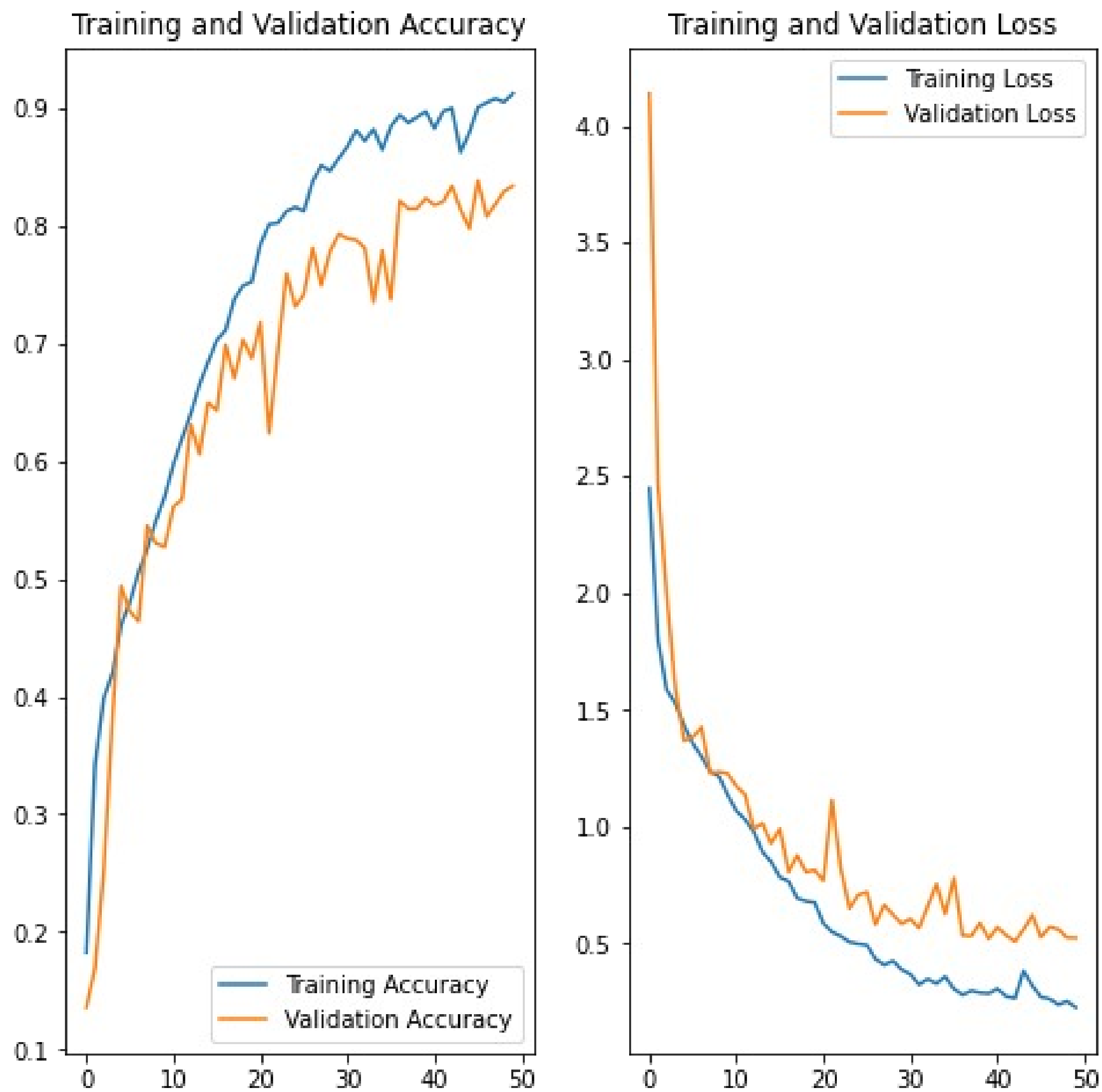
```
1.2146 - accuracy: 0.5493 - val_loss: 1.2341 - val_accuracy: 0.5301
Epoch 10/50
169/169 [==============================] - 32s 183ms/step - loss:
1.1354 - accuracy: 0.5695 - val_loss: 1.2274 - val_accuracy: 0.5271
Epoch 11/50
169/169 [==============================] - 32s 183ms/step - loss:
1.0676 - accuracy: 0.5972 - val_loss: 1.1729 - val_accuracy: 0.5612
Epoch 12/50
169/169 [==============================] - 32s 184ms/step - loss:
1.0303 - accuracy: 0.6191 - val_loss: 1.1371 - val_accuracy: 0.5672
Epoch 13/50
169/169 [==============================] - 32s 183ms/step - loss:
0.9785 - accuracy: 0.6404 - val_loss: 0.9895 - val_accuracy: 0.6310
Epoch 14/50
169/169 [==============================] - 33s 187ms/step - loss:
0.8914 - accuracy: 0.6647 - val_loss: 1.0143 - val_accuracy: 0.6058
Epoch 15/50
169/169 [==============================] - 31s 179ms/step - loss:
0.8498 - accuracy: 0.6843 - val_loss: 0.9272 - val_accuracy: 0.6496
Epoch 16/50
169/169 [==============================] - 31s 181ms/step - loss:
0.7827 - accuracy: 0.7027 - val_loss: 0.9905 - val_accuracy: 0.6429
Epoch 17/50
169/169 [==============================] - 32s 182ms/step - loss:
0.7659 - accuracy: 0.7111 - val_loss: 0.8056 - val_accuracy: 0.6986
Epoch 18/50
169/169 [==============================] - 32s 184ms/step - loss:
0.6931 - accuracy: 0.7378 - val_loss: 0.8763 - val_accuracy: 0.6704
Epoch 19/50
169/169 [==============================] - 32s 184ms/step - loss:
0.6807 - accuracy: 0.7489 - val_loss: 0.8052 - val_accuracy: 0.7030
Epoch 20/50
169/169 [==============================] - 32s 183ms/step - loss:
0.6751 - accuracy: 0.7522 - val_loss: 0.8132 - val_accuracy: 0.6875
Epoch 21/50
169/169 [==============================] - 32s 182ms/step - loss:
0.5856 - accuracy: 0.7838 - val_loss: 0.7683 - val_accuracy: 0.7179
Epoch 22/50
169/169 [==============================] - 33s 187ms/step - loss:
0.5487 - accuracy: 0.8012 - val_loss: 1.1119 - val_accuracy: 0.6236
Epoch 23/50
169/169 [==============================] - 32s 184ms/step - loss:
0.5309 - accuracy: 0.8023 - val_loss: 0.8205 - val_accuracy: 0.6941
Epoch 24/50
169/169 [==============================] - 32s 185ms/step - loss:
0.5050 - accuracy: 0.8121 - val_loss: 0.6481 - val_accuracy: 0.7595
Epoch 25/50
169/169 [==============================] - 33s 187ms/step - loss:
0.4980 - accuracy: 0.8157 - val_loss: 0.7069 - val_accuracy: 0.7313
Epoch 26/50
```

```
169/169 [==============================] - 32s 186ms/step - loss:
0.4924 - accuracy: 0.8123 - val_loss: 0.7194 - val_accuracy: 0.7416
Epoch 27/50
169/169 [==============================] - 31s 179ms/step - loss:
0.4326 - accuracy: 0.8374 - val_loss: 0.5811 - val_accuracy: 0.7810
Epoch 28/50
169/169 [==============================] - 32s 182ms/step - loss:
0.4078 - accuracy: 0.8513 - val_loss: 0.6638 - val_accuracy: 0.7491
Epoch 29/50
169/169 [==============================] - 32s 183ms/step - loss:
0.4247 - accuracy: 0.8464 - val_loss: 0.6210 - val_accuracy: 0.7780
Epoch 30/50
169/169 [==============================] - 32s 186ms/step - loss:
0.3875 - accuracy: 0.8572 - val_loss: 0.5844 - val_accuracy: 0.7929
Epoch 31/50
169/169 [==============================] - 32s 185ms/step - loss:
0.3672 - accuracy: 0.8672 - val_loss: 0.6045 - val_accuracy: 0.7892
Epoch 32/50
169/169 [==============================] - 32s 183ms/step - loss:
0.3238 - accuracy: 0.8809 - val_loss: 0.5658 - val_accuracy: 0.7877
Epoch 33/50
169/169 [==============================] - 32s 184ms/step - loss:
0.3468 - accuracy: 0.8718 - val_loss: 0.6590 - val_accuracy: 0.7810
Epoch 34/50
169/169 [==============================] - 32s 183ms/step - loss:
0.3277 - accuracy: 0.8820 - val_loss: 0.7535 - val_accuracy: 0.7350
Epoch 35/50
169/169 [==============================] - 32s 184ms/step - loss:
0.3568 - accuracy: 0.8644 - val_loss: 0.6257 - val_accuracy: 0.7788
Epoch 36/50
169/169 [==============================] - 32s 184ms/step - loss:
0.3045 - accuracy: 0.8843 - val_loss: 0.7786 - val_accuracy: 0.7372
Epoch 37/50
169/169 [==============================] - 32s 184ms/step - loss:
0.2791 - accuracy: 0.8939 - val_loss: 0.5336 - val_accuracy: 0.8211
Epoch 38/50
169/169 [==============================] - 32s 184ms/step - loss:
0.2966 - accuracy: 0.8874 - val_loss: 0.5314 - val_accuracy: 0.8144
Epoch 39/50
169/169 [==============================] - 32s 184ms/step - loss:
0.2881 - accuracy: 0.8921 - val_loss: 0.5872 - val_accuracy: 0.8144
Epoch 40/50
169/169 [==============================] - 32s 181ms/step - loss:
0.2850 - accuracy: 0.8971 - val_loss: 0.5198 - val_accuracy: 0.8233
Epoch 41/50
169/169 [==============================] - 32s 187ms/step - loss:
0.3055 - accuracy: 0.8826 - val_loss: 0.5687 - val_accuracy: 0.8174
Epoch 42/50
169/169 [==============================] - 32s 183ms/step - loss:
0.2729 - accuracy: 0.8971 - val_loss: 0.5346 - val_accuracy: 0.8203
```

```
Epoch 43/50
169/169 [==============================] - 31s 181ms/step - loss:
0.2646 - accuracy: 0.8999 - val_loss: 0.5081 - val_accuracy: 0.8337
Epoch 44/50
169/169 [==============================] - 32s 182ms/step - loss:
0.3819 - accuracy: 0.8624 - val_loss: 0.5588 - val_accuracy: 0.8137
Epoch 45/50
169/169 [==============================] - 32s 182ms/step - loss:
0.3193 - accuracy: 0.8789 - val_loss: 0.6199 - val_accuracy: 0.7973
Epoch 46/50
169/169 [==============================] - 31s 181ms/step - loss:
0.2699 - accuracy: 0.9006 - val_loss: 0.5255 - val_accuracy: 0.8382
Epoch 47/50
169/169 [==============================] - 31s 179ms/step - loss:
0.2617 - accuracy: 0.9045 - val_loss: 0.5703 - val_accuracy: 0.8077
Epoch 48/50
169/169 [==============================] - 32s 181ms/step - loss:
0.2378 - accuracy: 0.9078 - val_loss: 0.5595 - val_accuracy: 0.8181
Epoch 49/50
169/169 [==============================] - 32s 181ms/step - loss:
0.2516 - accuracy: 0.9050 - val_loss: 0.5245 - val_accuracy: 0.8293
Epoch 50/50
169/169 [==============================] - 32s 186ms/step - loss:
0.2257 - accuracy: 0.9121 - val_loss: 0.5234 - val_accuracy: 0.8337
```

Visualize the model results

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

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

epochs_range = range(epochs)

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

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



- As per the final model (model3) Training accuracy and validation accuracy increases.
- Model overfitting issue is solved.
- Class rebalance helps in augmentation and achieving the best Training and validation accuracy.