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 Skin Cancer Data

To do: Take necessary actions to read the data

Importing all the important libraries

In [146]:

```
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
from glob import glob
import warnings
warnings.filterwarnings('ignore')
```

In [ ]:

```
## If you are using the data by mounting the google drive, use the following :
# from google.colab import drive
# drive.mount('/content/gdrive')
#!unzip gdrive/MyDrive/CNN_assignment
##Ref:https://towardsdatascience.com/downloading-datasets-into-google-drive-via-google-


%rm -rf 'Skin cancer ISIC The International Skin Imaging Collaboration'
!gdown --id 1xLfSQUGDl8ezNNbUkpuHOYvSpTyxVhCs
!unzip -o -q CNN_assignment.zip
```

This assignment uses 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.

In [106]:

```
# Defining the path for train and test images
## Todo: Update the paths of the train and test dataset
data_dir_train = pathlib.Path("/content/Skin cancer ISIC The International Skin Imaging
data_dir_test = pathlib.Path('/content/Skin cancer ISIC The International Skin Imaging
```

In [107]:

```
!ls
```

```
 CNN_assignment.zip
 model_plot.png
 sample_data
'Skin cancer ISIC The International Skin Imaging Collaboration'
```

In [108]:

```
image_count_train = len(list(data_dir_train.glob('*/*.jpg')))
print(image_count_train)
image_count_test = len(list(data_dir_test.glob('*/*.jpg')))
print(image_count_test)
```

```
2239
118
```

Load using keras.preprocessing

Let's load these images off disk using the helpful image_dataset_from_directory utility.

Create a dataset

Define some parameters for the loader:

In [109]:

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

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

In [110]:

```
## Write your train dataset here
## Note use seed=123 while creating your dataset using tf.keras.preprocessing.image_dat
## Note, make sure your resize your images to the size img_height*img_width, while writ
train_ds = tf.keras.preprocessing.image_dataset_from_directory(
    data_dir_train,
    seed=123,
    validation_split= 0.2,
    subset= 'training',
    image_size=(img_height,img_width),
    batch_size = batch_size
)
```

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

In [111]:

```
## Write your validation dataset here
## Note use seed=123 while creating your dataset using tf.keras.preprocessing.image_dat
## Note, make sure your resize your images to the size img_height*img_width, while writ
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),
    batch_size = batch_size
)
```

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

In [112]:

```
# List out all the classes of skin cancer and store them in a list.
# You can find the class names in the class_names attribute on these datasets.
# These correspond to the directory names in alphabetical order.
class_names = train_ds.class_names
class_names
```

Out[112]:

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

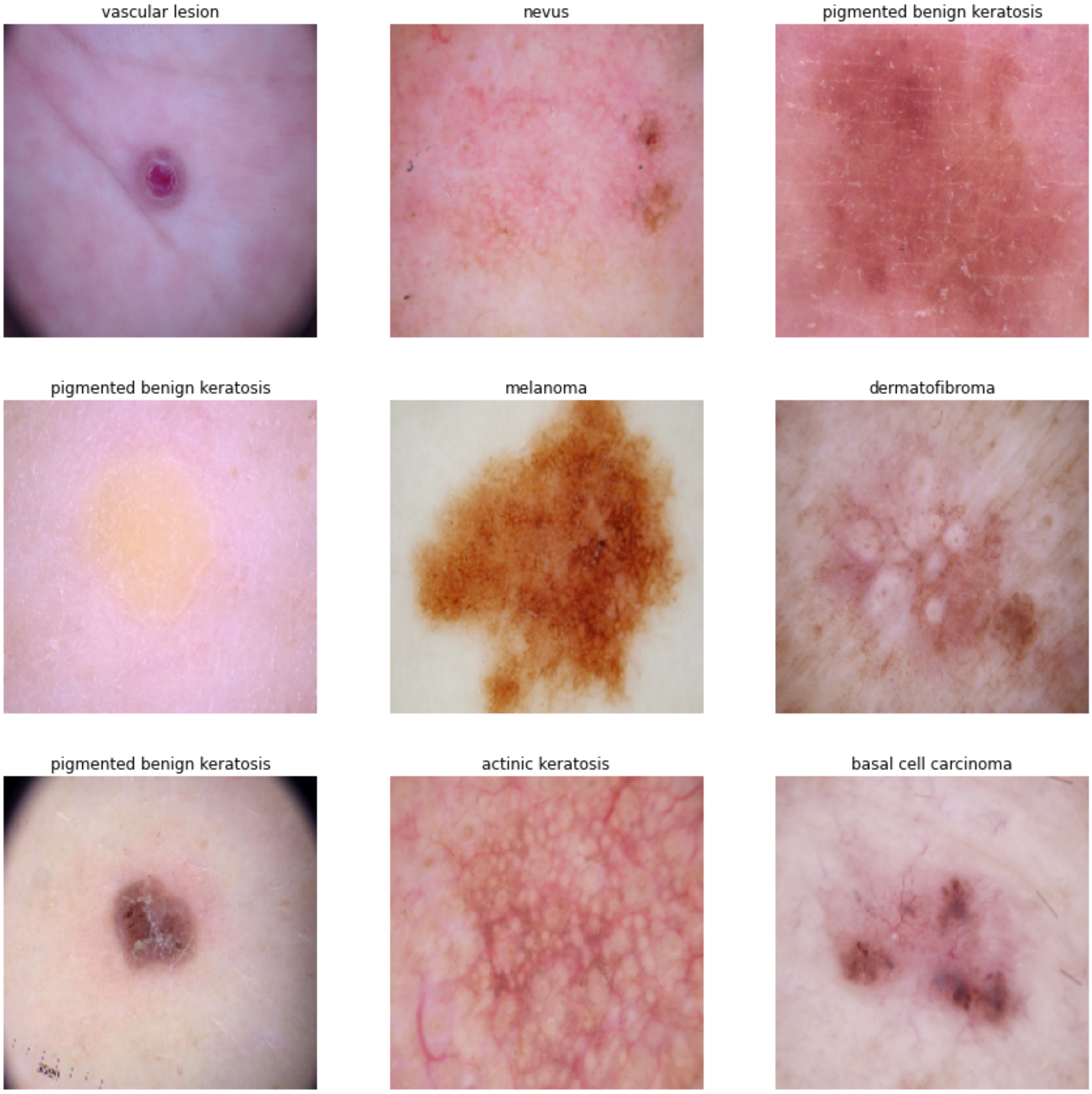
Visualize the data

Todo, create a code to visualize one instance of all the nine classes present in the dataset

In [113]:

```python
### your code goes here, you can use training or validation data to visualize
import matplotlib.pyplot as plt

plt.figure(figsize=(15, 15))
for images, labels in train_ds.take(1):
  for i in range(9):
    ax = plt.subplot(3, 3, i + 1)
    plt.imshow(images[i].numpy().astype("uint8"))
    plt.title(class_names[labels[i]])
    plt.axis("off")
```



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.

In [114]:

```
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)
```

Create the model

Todo: Create a CNN model, which can accurately detect 9 classes present in the dataset. Use `layers.experimental.preprocessing.Rescaling` to normalize pixel values between (0,1). The RGB channel values are in the `[0, 255]` range. This is not ideal for a neural network. Here, it is good to standardize values to be in the `[0, 1]`

In [115]:

```
### Your code goes here
from keras.layers import Dense, Dropout, Flatten, Conv2D, MaxPool2D
num_classes = 9
model = Sequential([
  layers.experimental.preprocessing.Rescaling(1./255, input_shape=(img_height, img_widt
  layers.Conv2D(16, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(32, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(64, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Flatten(),
  layers.Dense(128, activation='relu'),
  layers.Dense(num_classes)
])
```

Compile the model

Choose an appropirate optimiser and loss function for model training

In [116]:

```
### Todo, choose an appropirate optimiser and loss function
model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])
```

In [117]:

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

```
Model: "sequential_21"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 rescaling_19 (Rescaling)    (None, 180, 180, 3)       0         
                                                                 
 conv2d_57 (Conv2D)          (None, 180, 180, 16)      448       
                                                                 
 max_pooling2d_57 (MaxPoolin  (None, 90, 90, 16)       0         
 g2D)                                                            
                                                                 
 conv2d_58 (Conv2D)          (None, 90, 90, 32)        4640      
                                                                 
 max_pooling2d_58 (MaxPoolin  (None, 45, 45, 32)       0         
 g2D)                                                            
                                                                 
 conv2d_59 (Conv2D)          (None, 45, 45, 64)        18496     
                                                                 
 max_pooling2d_59 (MaxPoolin  (None, 22, 22, 64)       0         
 g2D)                                                            
                                                                 
 flatten_19 (Flatten)        (None, 30976)             0         
                                                                 
 dense_44 (Dense)            (None, 128)               3965056   
                                                                 
 dense_45 (Dense)            (None, 9)                 1161      
                                                                 
=================================================================
Total params: 3,989,801
Trainable params: 3,989,801
Non-trainable params: 0
_________________________________________________________________
```

Train the model

In [118]:

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

```
Epoch 1/20
56/56 [==============================] - 14s 70ms/step - loss: 1.8175 - accu
racy: 0.3158 - val_loss: 1.6135 - val_accuracy: 0.4430
Epoch 2/20
56/56 [==============================] - 1s 24ms/step - loss: 1.5158 - accur
acy: 0.4648 - val_loss: 1.5130 - val_accuracy: 0.4922
Epoch 3/20
56/56 [==============================] - 1s 23ms/step - loss: 1.3949 - accur
acy: 0.5089 - val_loss: 1.3946 - val_accuracy: 0.4944
Epoch 4/20
56/56 [==============================] - 1s 23ms/step - loss: 1.2901 - accur
acy: 0.5474 - val_loss: 1.3601 - val_accuracy: 0.5190
Epoch 5/20
56/56 [==============================] - 1s 24ms/step - loss: 1.1835 - accur
acy: 0.5820 - val_loss: 1.4396 - val_accuracy: 0.5034
Epoch 6/20
56/56 [==============================] - 1s 24ms/step - loss: 1.0999 - accur
acy: 0.6088 - val_loss: 1.3980 - val_accuracy: 0.5369
Epoch 7/20
56/56 [==============================] - 1s 24ms/step - loss: 1.0016 - accur
acy: 0.6323 - val_loss: 1.4212 - val_accuracy: 0.5324
Epoch 8/20
56/56 [==============================] - 1s 24ms/step - loss: 0.9411 - accur
acy: 0.6551 - val_loss: 1.3582 - val_accuracy: 0.5593
Epoch 9/20
56/56 [==============================] - 1s 24ms/step - loss: 0.8231 - accur
acy: 0.7048 - val_loss: 1.4639 - val_accuracy: 0.5414
Epoch 10/20
56/56 [==============================] - 1s 24ms/step - loss: 0.7954 - accur
acy: 0.7204 - val_loss: 1.5935 - val_accuracy: 0.5414
Epoch 11/20
56/56 [==============================] - 1s 23ms/step - loss: 0.6651 - accur
acy: 0.7584 - val_loss: 1.6330 - val_accuracy: 0.5459
Epoch 12/20
56/56 [==============================] - 1s 24ms/step - loss: 0.5668 - accur
acy: 0.7891 - val_loss: 1.7141 - val_accuracy: 0.5213
Epoch 13/20
56/56 [==============================] - 1s 23ms/step - loss: 0.4977 - accur
acy: 0.8265 - val_loss: 1.7319 - val_accuracy: 0.5145
Epoch 14/20
56/56 [==============================] - 1s 24ms/step - loss: 0.4099 - accur
acy: 0.8493 - val_loss: 1.8707 - val_accuracy: 0.5257
Epoch 15/20
56/56 [==============================] - 1s 24ms/step - loss: 0.3986 - accur
acy: 0.8677 - val_loss: 1.8504 - val_accuracy: 0.5503
Epoch 16/20
56/56 [==============================] - 1s 24ms/step - loss: 0.3467 - accur
acy: 0.8705 - val_loss: 1.9885 - val_accuracy: 0.4922
Epoch 17/20
56/56 [==============================] - 1s 24ms/step - loss: 0.2689 - accur
acy: 0.8973 - val_loss: 2.0118 - val_accuracy: 0.5481
Epoch 18/20
```

```
56/56 [==============================] - 1s 24ms/step - loss: 0.2635 - accur
acy: 0.8934 - val_loss: 2.1038 - val_accuracy: 0.5593
Epoch 19/20
56/56 [==============================] - 1s 23ms/step - loss: 0.2285 - accur
acy: 0.9102 - val_loss: 2.1650 - val_accuracy: 0.5436
Epoch 20/20
56/56 [==============================] - 1s 24ms/step - loss: 0.1941 - accur
acy: 0.9219 - val_loss: 1.9747 - val_accuracy: 0.5436
```

Visualizing training results

In [119]:

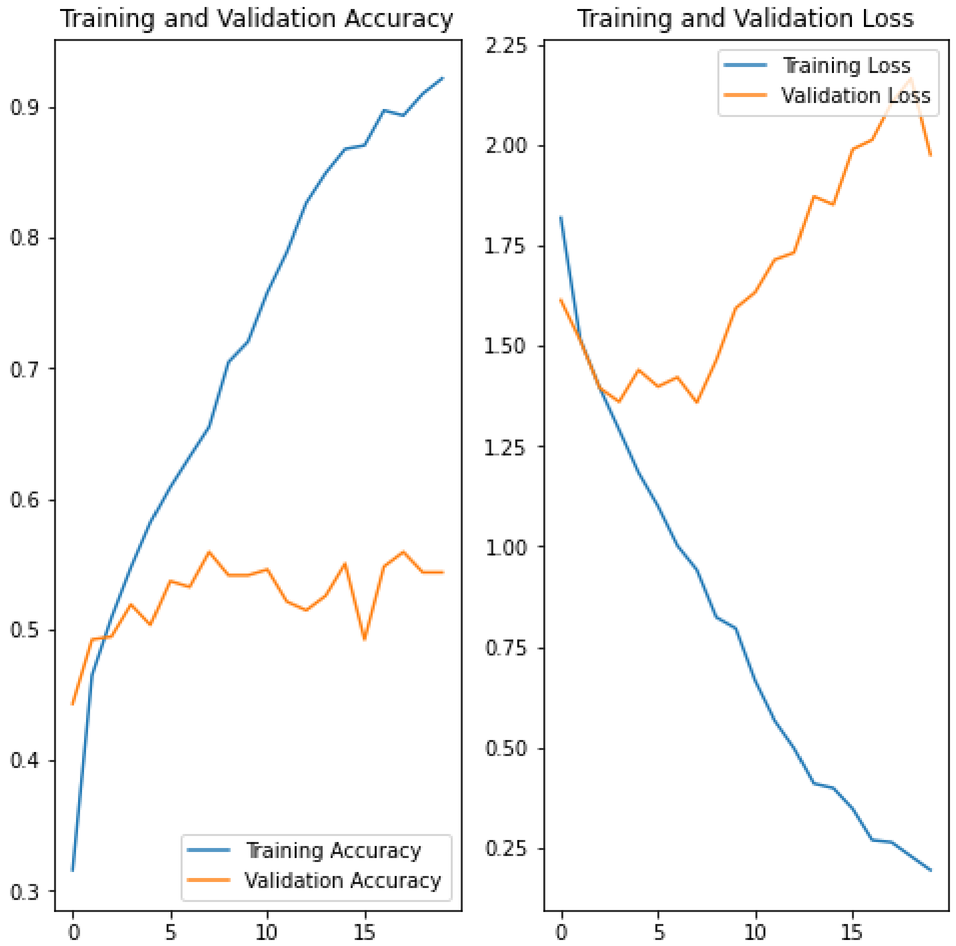
```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

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()
```



Todo: Write your findings after the model fit, see if there is an evidence of model overfit or underfit

Write your findings here

From above graph, training accuracy = 92% but validation accuracy = 54% which is indicating overfitting

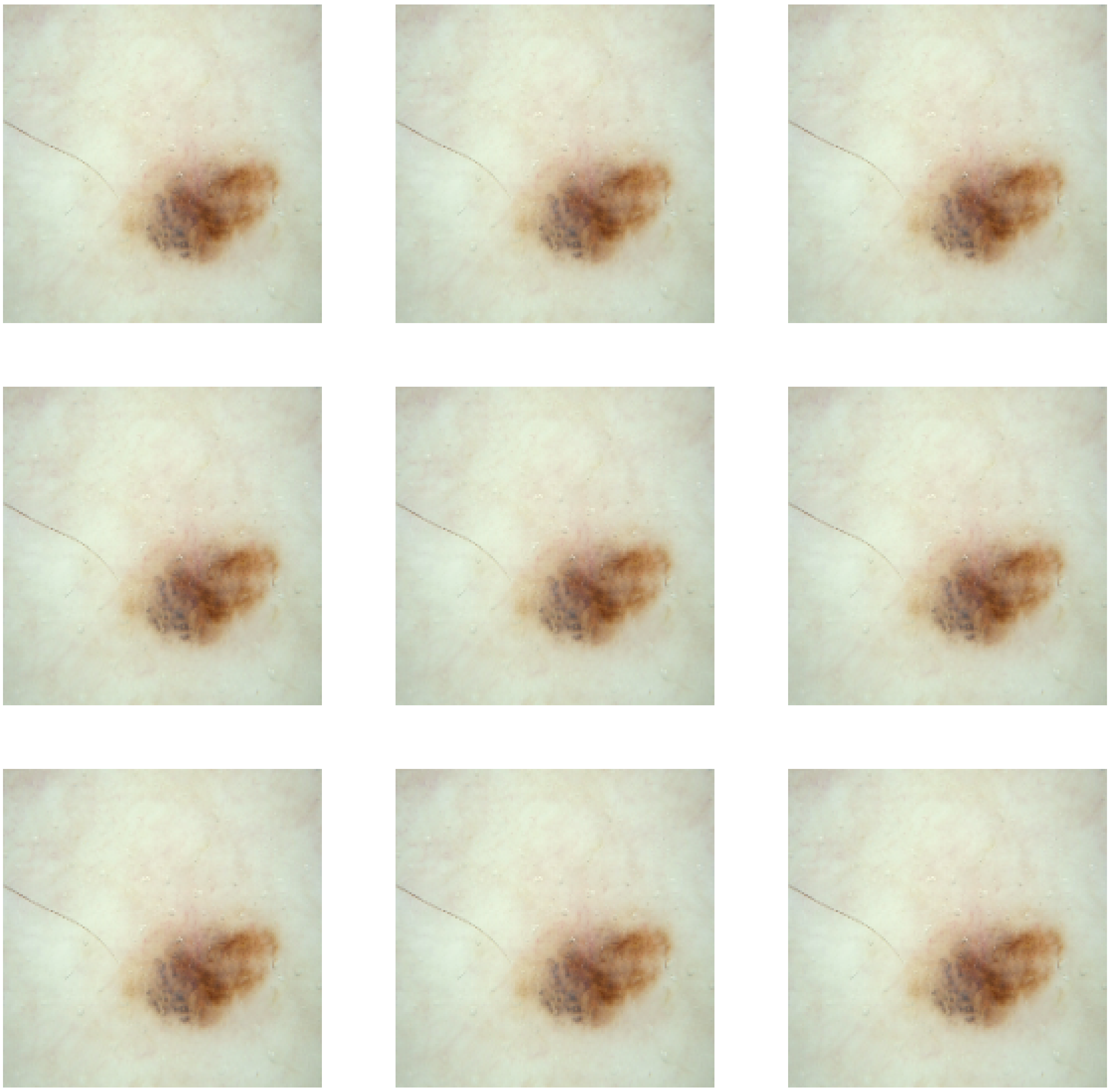
In [120]:

```
# Todo, after you have analysed the model fit history for presence of underfit or overf
data_augmentation = keras.Sequential([
                                      layers.experimental.preprocessing.RandomFlip("ver
                                      layers.experimental.preprocessing.RandomRotation(
                                      layers.experimental.preprocessing.RandomZoom(0.1)
])
```

In [121]:

```
# Todo, visualize how your augmentation strategy works for one instance of training ima

plt.figure(figsize=(10, 10))
for images, labels 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")
```



Todo:

Create the model, compile and train the model

In [122]:

```
## You can use Dropout layer if there is an evidence of overfitting in your findings

model = Sequential([
  data_augmentation,
  layers.experimental.preprocessing.Rescaling(1./255),
  layers.Conv2D(16, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(32, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(64, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Dropout(0.2),
  layers.Flatten(),
  layers.Dense(128, activation='relu'),
  layers.Dense(num_classes)
])
```

Compiling the model

In [123]:

```
model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])
```

Training the model

In [124]:

```
## Your code goes here, note: train your model for 20 epochs
epochs = 20
history = model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs
)
```

```
Epoch 1/20
56/56 [==============================] - 3s 43ms/step - loss: 2.0079 - accur
acy: 0.2985 - val_loss: 1.6843 - val_accuracy: 0.4049
Epoch 2/20
56/56 [==============================] - 2s 40ms/step - loss: 1.6205 - accur
acy: 0.4319 - val_loss: 1.5566 - val_accuracy: 0.4609
Epoch 3/20
56/56 [==============================] - 2s 40ms/step - loss: 1.5515 - accur
acy: 0.4448 - val_loss: 1.5044 - val_accuracy: 0.4676
Epoch 4/20
56/56 [==============================] - 2s 40ms/step - loss: 1.4606 - accur
acy: 0.4855 - val_loss: 1.7323 - val_accuracy: 0.4318
Epoch 5/20
56/56 [==============================] - 2s 40ms/step - loss: 1.4969 - accur
acy: 0.4794 - val_loss: 1.4702 - val_accuracy: 0.4899
Epoch 6/20
56/56 [==============================] - 2s 40ms/step - loss: 1.4127 - accur
acy: 0.5022 - val_loss: 1.3819 - val_accuracy: 0.5123
Epoch 7/20
56/56 [==============================] - 2s 40ms/step - loss: 1.3310 - accur
acy: 0.5279 - val_loss: 1.4481 - val_accuracy: 0.5034
Epoch 8/20
56/56 [==============================] - 2s 40ms/step - loss: 1.3019 - accur
acy: 0.5407 - val_loss: 1.3602 - val_accuracy: 0.5302
Epoch 9/20
56/56 [==============================] - 2s 40ms/step - loss: 1.2692 - accur
acy: 0.5385 - val_loss: 1.4445 - val_accuracy: 0.5101
Epoch 10/20
56/56 [==============================] - 2s 40ms/step - loss: 1.2807 - accur
acy: 0.5396 - val_loss: 1.3955 - val_accuracy: 0.5257
Epoch 11/20
56/56 [==============================] - 2s 39ms/step - loss: 1.2723 - accur
acy: 0.5469 - val_loss: 1.3464 - val_accuracy: 0.5391
Epoch 12/20
56/56 [==============================] - 2s 40ms/step - loss: 1.2179 - accur
acy: 0.5647 - val_loss: 1.3614 - val_accuracy: 0.5324
Epoch 13/20
56/56 [==============================] - 2s 40ms/step - loss: 1.1781 - accur
acy: 0.5698 - val_loss: 1.3716 - val_accuracy: 0.5347
Epoch 14/20
56/56 [==============================] - 2s 39ms/step - loss: 1.1707 - accur
acy: 0.5664 - val_loss: 1.4513 - val_accuracy: 0.4922
Epoch 15/20
56/56 [==============================] - 2s 39ms/step - loss: 1.1367 - accur
acy: 0.5809 - val_loss: 1.3907 - val_accuracy: 0.5168
Epoch 16/20
56/56 [==============================] - 2s 39ms/step - loss: 1.1757 - accur
acy: 0.5776 - val_loss: 1.3595 - val_accuracy: 0.5280
Epoch 17/20
56/56 [==============================] - 2s 40ms/step - loss: 1.1447 - accur
acy: 0.5787 - val_loss: 1.3269 - val_accuracy: 0.5615
```

```
Epoch 18/20
56/56 [==============================] - 2s 40ms/step - loss: 1.1176 - accur
acy: 0.5915 - val_loss: 1.3391 - val_accuracy: 0.5369
Epoch 19/20
56/56 [==============================] - 2s 40ms/step - loss: 1.0858 - accur
acy: 0.6055 - val_loss: 1.3563 - val_accuracy: 0.5481
Epoch 20/20
56/56 [==============================] - 2s 40ms/step - loss: 1.0934 - accur
acy: 0.6066 - val_loss: 1.4071 - val_accuracy: 0.5436
```

Visualizing the results

In [125]:

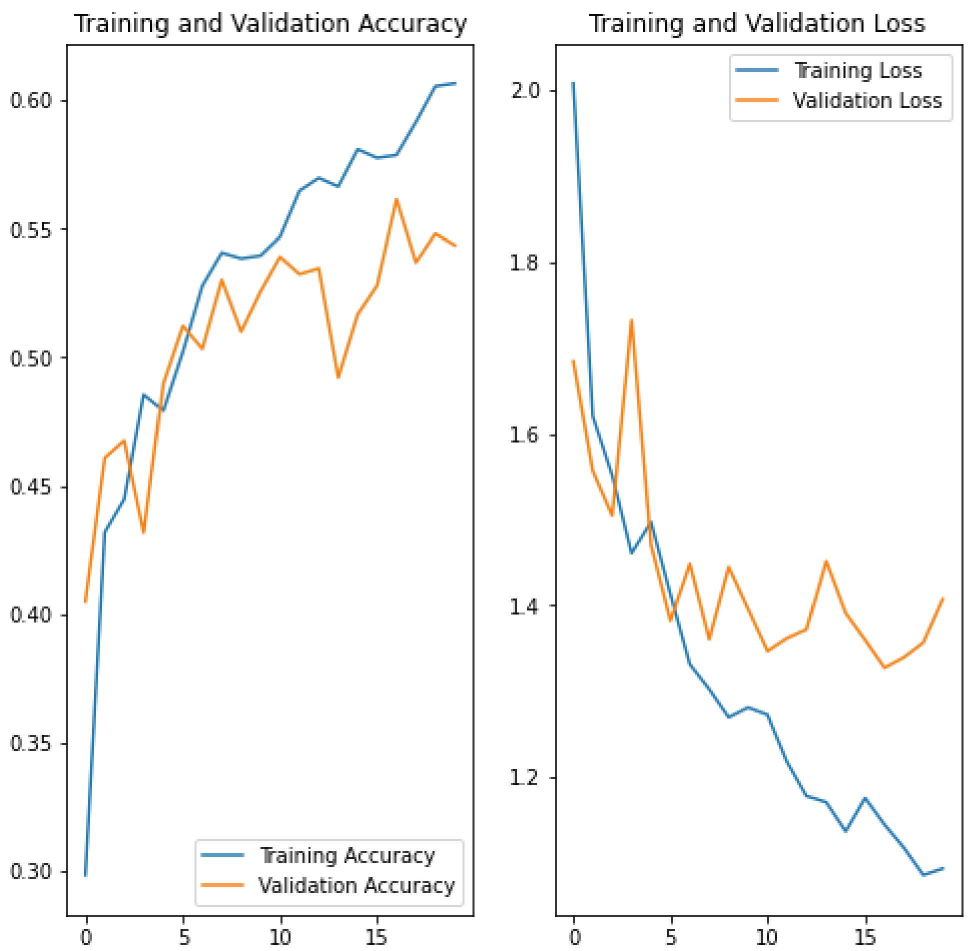
```python
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

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()
```



Todo: Write your findings after the model fit, see if there is an evidence of model overfit or underfit. Do you think there is some improvement now as compared to the previous model run?

Comment:

```
    - After using augumentation data there is improvement now as compared to the p
revious model run.

    - Model is still performing poorly on both trainng and validation data
```

Todo: Find the distribution of classes in the training dataset.

Context: Many times real life datasets can have class imbalance, one class can have proportionately higher number of samples compared to the others. Class imbalance can have a detrimental effect on the final model quality. Hence as a sanity check it becomes important to check what is the distribution of classes in the data.

In [126]:

```python
## Your code goes here.
path_list=[]
lesion_list=[]
for i in class_names:

    for j in data_dir_train.glob(i+'/*.jpg'):
        path_list.append(str(j))
        lesion_list.append(i)
dataframe_dict_original = dict(zip(path_list, lesion_list))
original_df = pd.DataFrame(list(dataframe_dict_original.items()),columns = ['Path','Lab

img_df = original_df[['Label']].value_counts().rename_axis('class_name').reset_index(na
img_df

```

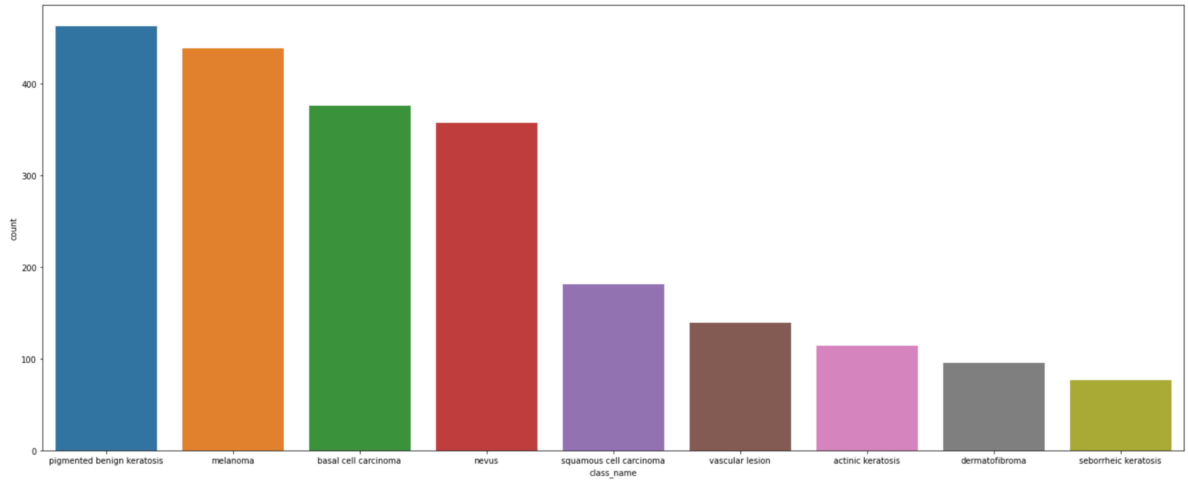
Out[126]:

	class_name	count
0	pigmented benign keratosis	462
1	melanoma	438
2	basal cell carcinoma	376
3	nevus	357
4	squamous cell carcinoma	181
5	vascular lesion	139
6	actinic keratosis	114
7	dermatofibroma	95
8	seborrheic keratosis	77

In [127]:

```
import seaborn as sns
plt.figure(figsize=(25,10))
sns.barplot(x= 'class_name', y = 'count', data=img_df)
plt.show()

```



Todo: Write your findings here:

- Which class has the least number of samples?

- seborrheic keratosis (77 images)

- Which classes dominate the data in terms proportionate number of samples?

- pigmented benign keratosis(462),melanoma(438),basal cell carcinoma(376),nevus(357)

Todo: Rectify the class imbalance

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

In [128]:

```
!pip install Augmentor
```

```
Looking in indexes: https://pypi.org/simple, (https://pypi.org/simple,) http
s://us-python.pkg.dev/colab-wheels/public/simple/ (https://us-python.pkg.de
v/colab-wheels/public/simple/)
Requirement already satisfied: Augmentor in /usr/local/lib/python3.7/dist-pa
ckages (0.2.10)
Requirement already satisfied: Pillow>=5.2.0 in /usr/local/lib/python3.7/dis
t-packages (from Augmentor) (7.1.2)
Requirement already satisfied: tqdm>=4.9.0 in /usr/local/lib/python3.7/dist-
packages (from Augmentor) (4.64.1)
Requirement already satisfied: numpy>=1.11.0 in /usr/local/lib/python3.7/dis
t-packages (from Augmentor) (1.21.6)
Requirement already satisfied: future>=0.16.0 in /usr/local/lib/python3.7/di
st-packages (from Augmentor) (0.16.0)
```

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.

In [129]:

```python
path_to_training_dataset="Skin cancer ISIC The International Skin Imaging Collaboratior
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
```

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

Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x7F90363E0110>:
100%|██████████| 500/500 [00:16<00:00, 29.91 Samples/s]

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

Processing <PIL.JpegImagePlugin.JpegImageFile image mode=RGB size=600x450 at
0x7F9034347F50>: 100%|██████████| 500/500 [00:18<00:00, 27.24 Samples/s]

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

Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x7F9034304890>:
100%|██████████| 500/500 [00:19<00:00, 25.23 Samples/s]

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

Processing <PIL.JpegImagePlugin.JpegImageFile image mode=RGB size=962x674 at
0x7F90364C1C90>: 100%|██████████| 500/500 [01:41<00:00,  4.92 Samples/s]

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

Processing <PIL.Image.Image image mode=RGB size=767x576 at 0x7F9034405DD0>:
100%|██████████| 500/500 [01:19<00:00,  6.29 Samples/s]

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

Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x7F90A050CBD0>:
100%|██████████| 500/500 [00:16<00:00, 30.23 Samples/s]

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

Processing <PIL.JpegImagePlugin.JpegImageFile image mode=RGB size=1024x768 a
t 0x7F904C096F10>: 100%|██████████| 500/500 [00:38<00:00, 12.97 Samples/s]

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

Processing <PIL.JpegImagePlugin.JpegImageFile image mode=RGB size=600x450 at
0x7F903433B310>: 100%|██████████| 500/500 [00:16<00:00, 30.99 Samples/s]
```

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

Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x7F90346FEB50>:
100%|██████████| 500/500 [00:16<00:00, 30.92 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.

In [130]:

```python
image_count_train = len(list(data_dir_train.glob('*/output/*.jpg')))
print(image_count_train)
```

```
4500
```

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

In [131]:

```python
path_list_new = [x for x in glob(os.path.join(data_dir_train, '*','output', '*.jpg'))]
path_list_new

```

Out[131]:

```
['/content/Skin cancer ISIC The International Skin Imaging Collaboration/T
rain/dermatofibroma/output/dermatofibroma_original_ISIC_0026417.jpg_6393d1
19-3431-4b76-8d46-713291129d58.jpg',
 '/content/Skin cancer ISIC The International Skin Imaging Collaboration/T
rain/dermatofibroma/output/dermatofibroma_original_ISIC_0030021.jpg_5a40a2
3f-d1d4-44c6-92d7-74805940b7f2.jpg',
 '/content/Skin cancer ISIC The International Skin Imaging Collaboration/T
rain/dermatofibroma/output/dermatofibroma_original_ISIC_0029891.jpg_07c286
dc-b025-4016-a62d-00cb7e330a9e.jpg',
 '/content/Skin cancer ISIC The International Skin Imaging Collaboration/T
rain/dermatofibroma/output/dermatofibroma_original_ISIC_0031271.jpg_685d4c
36-2404-45b2-aa10-c464b8afb8ed.jpg',
 '/content/Skin cancer ISIC The International Skin Imaging Collaboration/T
rain/dermatofibroma/output/dermatofibroma_original_ISIC_0029297.jpg_913fa6
3a-9e95-49bc-8652-5b3732a76fcf.jpg',
 '/content/Skin cancer ISIC The International Skin Imaging Collaboration/T
rain/dermatofibroma/output/dermatofibroma_original_ISIC_0031344.jpg_b27479
14-f1cb-49be-b4ba-c14b034e8760.jpg',
```

In [132]:

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

Out[132]:

```
['dermatofibroma',
 'dermatofibroma',
 'dermatofibroma',
 'dermatofibroma',
 'dermatofibroma',
 'dermatofibroma',
 'dermatofibroma',
 'dermatofibroma',
 'dermatofibroma',
 'dermatofibroma',
 'dermatofibroma',
 'dermatofibroma',
 'dermatofibroma',
 'dermatofibroma',
 'dermatofibroma',
 'dermatofibroma',
 'dermatofibroma',
 'dermatofibroma',
```

In [133]:

```
dataframe_dict_new = dict(zip(path_list_new, lesion_list_new))
```

In [134]:

```
df2 = pd.DataFrame(list(dataframe_dict_new.items()),columns = ['Path','Label'])
new_df = original_df.append(df2)
```

In [135]:

```
new_df['Label'].value_counts()
```

Out[135]:

```
pigmented benign keratosis    962
melanoma                      938
basal cell carcinoma          876
nevus                         857
squamous cell carcinoma       681
vascular lesion               639
actinic keratosis             614
dermatofibroma                595
seborrheic keratosis          577
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.

Todo: Train the model on the data created using Augmentor

In [136]:

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

Todo: Create a training dataset

In [137]:

```
train_ds = tf.keras.preprocessing.image_dataset_from_directory(
  data_dir_train,
  seed=123,
  validation_split = 0.2,
  subset = "training",
  image_size=(img_height, img_width),
  batch_size=batch_size)
```

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

Todo: Create a validation dataset

In [138]:

```
val_ds = tf.keras.preprocessing.image_dataset_from_directory(
  data_dir_train,
  seed=123,
  validation_split = 0.2,
  subset = 'validation',## Todo choose the correct parameter value, so that only valida
  image_size=(img_height, img_width),
  batch_size=batch_size)
```

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

Todo: Create your model (make sure to include normalization)

In [139]:

```
## your code goes here
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)
```

Todo: Compile your model (Choose optimizer and loss function appropriately)

In [140]:

```
## your code goes here
model = Sequential([
  layers.Rescaling(1./255, input_shape=(img_height, img_width, 3)),

  layers.BatchNormalization(),
  layers.Conv2D(128, 3, padding = 'same', activation='relu'),
  layers.MaxPooling2D(),

  layers.BatchNormalization(),
  layers.Conv2D(256, 3, padding = 'same', activation='relu'),
  layers.MaxPooling2D(),

  layers.BatchNormalization(),
  layers.Conv2D(512, 3, padding = 'same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Dropout(0.4),

  layers.Flatten(),

  layers.BatchNormalization(),
  layers.Dense(128, activation='relu'),

  layers.BatchNormalization(),
  layers.Dense(32, activation='relu'),
  layers.Dropout(0.4),

  layers.Dense(num_classes)
])
```

In [141]:

```
model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])
```

Todo: Train your model

In [142]:

```
epochs = 30
history = model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs
)
```

```
Epoch 1/30
169/169 [==============================] - 64s 229ms/step - loss: 1.8820 - a
ccuracy: 0.3353 - val_loss: 3.2016 - val_accuracy: 0.1158
Epoch 2/30
169/169 [==============================] - 36s 211ms/step - loss: 1.4632 - a
ccuracy: 0.4638 - val_loss: 1.9519 - val_accuracy: 0.2814
Epoch 3/30
169/169 [==============================] - 36s 215ms/step - loss: 1.2724 - a
ccuracy: 0.5336 - val_loss: 1.1598 - val_accuracy: 0.5754
Epoch 4/30
169/169 [==============================] - 36s 213ms/step - loss: 1.1033 - a
ccuracy: 0.5938 - val_loss: 0.9303 - val_accuracy: 0.6763
Epoch 5/30
169/169 [==============================] - 36s 213ms/step - loss: 0.9662 - a
ccuracy: 0.6465 - val_loss: 0.8649 - val_accuracy: 0.6793
Epoch 6/30
169/169 [==============================] - 36s 214ms/step - loss: 0.8397 - a
ccuracy: 0.6981 - val_loss: 0.7615 - val_accuracy: 0.7253
Epoch 7/30
169/169 [==============================] - 36s 214ms/step - loss: 0.7323 - a
ccuracy: 0.7329 - val_loss: 0.7668 - val_accuracy: 0.7127
Epoch 8/30
169/169 [==============================] - 36s 214ms/step - loss: 0.6291 - a
ccuracy: 0.7674 - val_loss: 0.7691 - val_accuracy: 0.7298
Epoch 9/30
169/169 [==============================] - 36s 214ms/step - loss: 0.5639 - a
ccuracy: 0.7921 - val_loss: 0.7363 - val_accuracy: 0.7439
Epoch 10/30
169/169 [==============================] - 36s 214ms/step - loss: 0.4873 - a
ccuracy: 0.8201 - val_loss: 0.5703 - val_accuracy: 0.8018
Epoch 11/30
169/169 [==============================] - 36s 214ms/step - loss: 0.4377 - a
ccuracy: 0.8344 - val_loss: 0.5849 - val_accuracy: 0.8077
Epoch 12/30
169/169 [==============================] - 36s 214ms/step - loss: 0.3605 - a
ccuracy: 0.8655 - val_loss: 0.5746 - val_accuracy: 0.8070
Epoch 13/30
169/169 [==============================] - 36s 214ms/step - loss: 0.3495 - a
ccuracy: 0.8731 - val_loss: 0.7671 - val_accuracy: 0.7372
Epoch 14/30
169/169 [==============================] - 36s 213ms/step - loss: 0.3547 - a
ccuracy: 0.8624 - val_loss: 0.6478 - val_accuracy: 0.8092
Epoch 15/30
169/169 [==============================] - 36s 214ms/step - loss: 0.2910 - a
ccuracy: 0.8906 - val_loss: 0.6231 - val_accuracy: 0.8085
Epoch 16/30
169/169 [==============================] - 36s 214ms/step - loss: 0.2481 - a
ccuracy: 0.9102 - val_loss: 0.5332 - val_accuracy: 0.8263
Epoch 17/30
169/169 [==============================] - 36s 213ms/step - loss: 0.2446 - a
ccuracy: 0.9101 - val_loss: 0.6931 - val_accuracy: 0.8129
Epoch 18/30
```

```
169/169 [==============================] - 36s 213ms/step - loss: 0.2648 - a
ccuracy: 0.8986 - val_loss: 0.6191 - val_accuracy: 0.8151
Epoch 19/30
169/169 [==============================] - 36s 214ms/step - loss: 0.2519 - a
ccuracy: 0.9049 - val_loss: 0.6489 - val_accuracy: 0.8070
Epoch 20/30
169/169 [==============================] - 36s 214ms/step - loss: 0.2282 - a
ccuracy: 0.9177 - val_loss: 0.7648 - val_accuracy: 0.8099
Epoch 21/30
169/169 [==============================] - 36s 213ms/step - loss: 0.2057 - a
ccuracy: 0.9269 - val_loss: 0.7490 - val_accuracy: 0.8070
Epoch 22/30
169/169 [==============================] - 36s 213ms/step - loss: 0.2488 - a
ccuracy: 0.9114 - val_loss: 0.7241 - val_accuracy: 0.8010
Epoch 23/30
169/169 [==============================] - 36s 213ms/step - loss: 0.2001 - a
ccuracy: 0.9251 - val_loss: 0.7374 - val_accuracy: 0.8203
Epoch 24/30
169/169 [==============================] - 36s 214ms/step - loss: 0.1965 - a
ccuracy: 0.9288 - val_loss: 0.7784 - val_accuracy: 0.8151
Epoch 25/30
169/169 [==============================] - 36s 213ms/step - loss: 0.1706 - a
ccuracy: 0.9358 - val_loss: 0.6529 - val_accuracy: 0.8322
Epoch 26/30
169/169 [==============================] - 36s 213ms/step - loss: 0.1599 - a
ccuracy: 0.9420 - val_loss: 0.7501 - val_accuracy: 0.8137
Epoch 27/30
169/169 [==============================] - 36s 214ms/step - loss: 0.1391 - a
ccuracy: 0.9514 - val_loss: 0.6406 - val_accuracy: 0.8359
Epoch 28/30
169/169 [==============================] - 36s 213ms/step - loss: 0.1233 - a
ccuracy: 0.9562 - val_loss: 0.7358 - val_accuracy: 0.8337
Epoch 29/30
169/169 [==============================] - 36s 213ms/step - loss: 0.1315 - a
ccuracy: 0.9516 - val_loss: 0.8800 - val_accuracy: 0.8055
Epoch 30/30
169/169 [==============================] - 36s 214ms/step - loss: 0.1355 - a
ccuracy: 0.9514 - val_loss: 0.8075 - val_accuracy: 0.8048
```

Todo: Visualize the model results

In [143]:

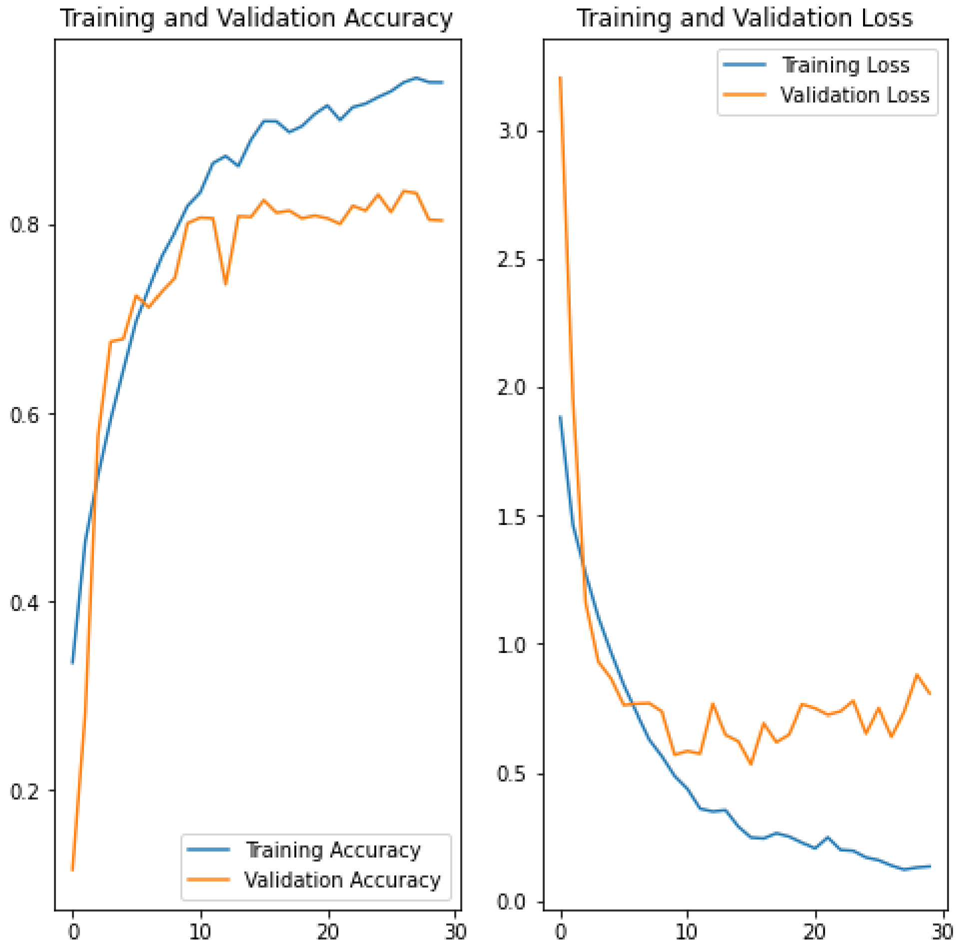
```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

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()
```



Todo: Analyze your results here. Did you get rid of underfitting/overfitting? Did class rebalance help?

Commemts

In the final model, there is no sign of underfitting/overfitting.

Class rebalanced improved the model performance on both training and validation data.

In [144]:

```
print("-----------------------   Accuracy  ----------------------- ")

print("Accuracy            : ", acc[-1])
print("Validation Accuracy : ",val_acc[-1])
print("Loss                : ",loss[-1])
print("Validation Loss     : ", val_loss[-1])
```

```
-----------------------   Accuracy  -----------------------
Accuracy            :  0.9514095187187195
Validation Accuracy :  0.8047512769699097
Loss                :  0.13551045954227448
Validation Loss     :  0.8074936866760254
```

In [145]:

```python
from keras.utils.vis_utils import plot_model
plot_model(model, to_file='model_plot.png', show_shapes=True, show_layer_names=True)
```

Out[145]: