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 [1]:
```
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 tensorflow.keras.layers import Dense, Dropout, Flatten, Conv2D, MaxPooling2D
```

Uncomment to read images from Google Drive

In [2]:
```
## If you are using the data by mounting the google drive, use the following :

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

##Ref:https://towardsdatascience.com/downloading-datasets-into-google-drive-via-google-colab-bcb1b30b016
```

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 [3]:
```
# Defining the path for train and test images
## Todo: Update the paths of the train and test dataset
# data_dir_train = pathlib.Path("gdrive/My Drive/UpgradExer5CNNSkin/SkinImg/Train/")
# data_dir_test = pathlib.Path('gdrive/My Drive/UpgradExer5CNNSkin/SkinImg/Test')

data_dir_train = pathlib.Path("./UpgradExer5CNNSkin/SkinImg/Train/")
data_dir_test = pathlib.Path('./UpgradExer5CNNSkin/SkinImg/Test')
```

Train (split for Validation data) and Test data set

In [4]:
```
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 [5]:
```
batch_size = 32
img_height = 180
img_width = 180
```

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

In [6]:
```
## Write your train dataset here
## Note use seed=123 while creating your dataset using tf.keras.preprocessing.image_dataset_from_director
## Note, make sure your resize your images to the size img_height*img_width, while writting the dataset

#train_ds = ##todo

train_ds = tf.keras.preprocessing.image_dataset_from_directory(
  data_dir_train,
  seed=123,
  validation_split = 0.2,
  subset = "training", ## Todo choose the correct parameter value, so that only training data is refered
  image_size = (img_height, img_width),
  batch_size = batch_size)
```

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

In [7]:
```
## Write your validation dataset here
## Note use seed=123 while creating your dataset using tf.keras.preprocessing.image_dataset_from_director
## Note, make sure your resize your images to the size img_height*img_width, while writting the dataset
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 training data is refer
  image_size = (img_height, img_width),
  batch_size = batch_size)
```

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

List of classes

In [8]:
```
# 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
print(class_names)
#len = len(class_names)
```

```
['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

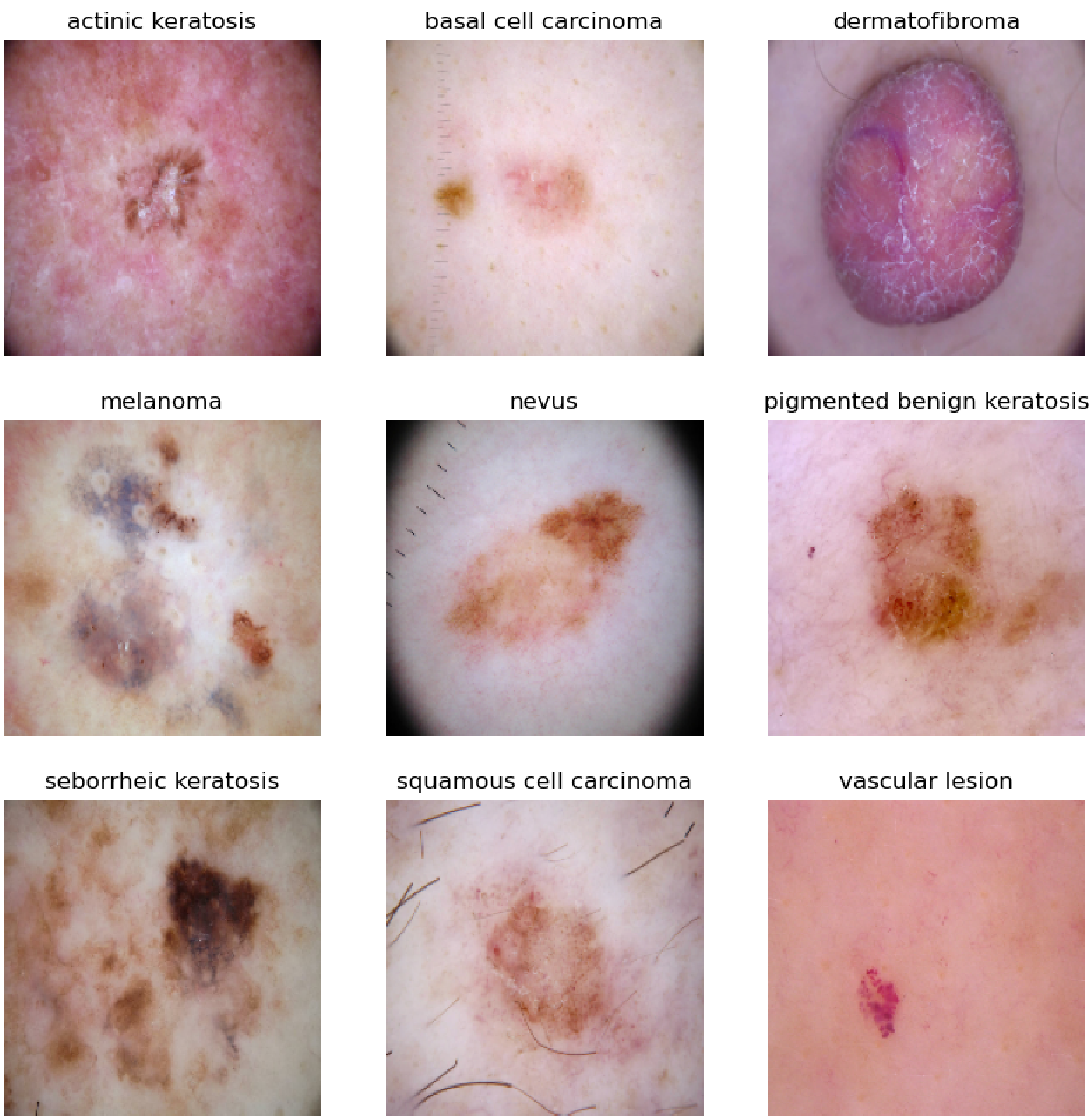
In [9]:
```
import matplotlib.pyplot as plt

### your code goes here, you can use training or validation data to visualize

plt.figure(figsize=(10, 10))

for i in range(len(class_names)):
    filtered_ds = train_ds.filter(lambda x, l: tf.math.equal(l[0], i)).take(1)
    for images, labels in filtered_ds:
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(images[0].numpy().astype("uint8"))
        plt.title(class_names[labels[0]])
        plt.axis("off")
```

```
WARNING:tensorflow:From d:\Users\admin\anaconda3\lib\site-packages\tensorflow\python\autograph\pyct\sta
tic_analysis\liveness.py:83: Analyzer.lamba_check (from tensorflow.python.autograph.pyct.static_analysi
s.liveness) is deprecated and will be removed after 2023-09-23.
Instructions for updating:
Lambda fuctions will be no more assumed to be used in the statement where they are used, or at least in
the same block. https://github.com/tensorflow/tensorflow/issues/56089 (https://github.com/tensorflow/te
nsorflow/issues/56089)
```



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.

In [10]:
```
for image_batch, labels_batch in train_ds:
  print(image_batch.shape)
  print(labels_batch.shape)
  break
```

```
(32, 180, 180, 3)
(32,)
```

`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 [11]:
```
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 [12]:
```
### Your code goes here
# model = tf.keras.Sequential([
#  tf.keras.layers.Rescaling(1./255),
#  tf.keras.layers.Conv2D(32, 3, activation='relu'),
#  tf.keras.layers.MaxPooling2D(),
#  tf.keras.layers.Dropout(0.1),
#  tf.keras.layers.Conv2D(32, 3, activation='relu'),
#  tf.keras.layers.MaxPooling2D(),
#  tf.keras.layers.Dropout(0.1),
#  tf.keras.layers.Conv2D(32, 3, activation='relu'),
#  tf.keras.layers.MaxPooling2D(),
#  tf.keras.layers.Dropout(0.1),
#  tf.keras.layers.Flatten(),
#  tf.keras.layers.Dense(128, activation='relu'),
#  tf.keras.layers.Dense(num_classes)
#  tf.keras.layers.Dropout(0.1)
# ])

num_classes = 9

model = Sequential()
model.add(Conv2D(16,3,padding="same", activation="relu"))
model.add(MaxPooling2D())
model.add(Dropout(0.1))

model.add(Conv2D(32, 3, padding="same", activation="relu"))
model.add(MaxPooling2D())
model.add(Dropout(0.1))

model.add(Conv2D(64, 3, padding="same", activation="relu"))
model.add(MaxPooling2D())

model.add(Dropout(0.1))
model.add(Flatten())
model.add(Dense(128,activation="relu"))
model.add(Dense(num_classes))
model.add(Dropout(0.1))
```

Compile the model

Choose an appropirate optimiser and loss function for model training

In [13]:
```
### Todo, choose an appropirate optimiser and loss function
model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])
```

Train the model

In [14]:
```
# Training and Validation happens Parallel in Batches (epouch).
# As long as the training accuracy gets better we can let the iterations continue.
# In case the training is not accurate we can retune the model

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

```
Epoch 1/20
56/56 [==============================] - 52s 782ms/step - loss: 51.3184 - accuracy: 0.2394 - val_loss:
2.1039 - val_accuracy: 0.3781
Epoch 2/20
56/56 [==============================] - 42s 747ms/step - loss: 1.8411 - accuracy: 0.3549 - val_loss:
1.9932 - val_accuracy: 0.2483
Epoch 3/20
56/56 [==============================] - 42s 752ms/step - loss: 1.7231 - accuracy: 0.3973 - val_loss:
2.1288 - val_accuracy: 0.2215
Epoch 4/20
56/56 [==============================] - 42s 747ms/step - loss: 1.6806 - accuracy: 0.4129 - val_loss:
1.9054 - val_accuracy: 0.3445
Epoch 5/20
56/56 [==============================] - 42s 757ms/step - loss: 1.5984 - accuracy: 0.4291 - val_loss:
2.0002 - val_accuracy: 0.3333
Epoch 6/20
56/56 [==============================] - 43s 763ms/step - loss: 1.5526 - accuracy: 0.4487 - val_loss:
1.9125 - val_accuracy: 0.3199
Epoch 7/20
56/56 [==============================] - 44s 781ms/step - loss: 1.4952 - accuracy: 0.4682 - val_loss:
1.9445 - val_accuracy: 0.3356
Epoch 8/20
56/56 [==============================] - 43s 763ms/step - loss: 1.4434 - accuracy: 0.4844 - val_loss:
1.8135 - val_accuracy: 0.3982
Epoch 9/20
56/56 [==============================] - 42s 747ms/step - loss: 1.4351 - accuracy: 0.4777 - val_loss:
1.6633 - val_accuracy: 0.3870
Epoch 10/20
56/56 [==============================] - 42s 749ms/step - loss: 1.3829 - accuracy: 0.5022 - val_loss:
1.9272 - val_accuracy: 0.3244
Epoch 11/20
56/56 [==============================] - 42s 758ms/step - loss: 1.3582 - accuracy: 0.5123 - val_loss:
1.8587 - val_accuracy: 0.3400
Epoch 12/20
56/56 [==============================] - 45s 800ms/step - loss: 1.3533 - accuracy: 0.5089 - val_loss:
1.6263 - val_accuracy: 0.4631
Epoch 13/20
56/56 [==============================] - 42s 746ms/step - loss: 1.3156 - accuracy: 0.5335 - val_loss:
1.7482 - val_accuracy: 0.4072
Epoch 14/20
56/56 [==============================] - 44s 780ms/step - loss: 1.2398 - accuracy: 0.5575 - val_loss:
1.6596 - val_accuracy: 0.4720
Epoch 15/20
56/56 [==============================] - 44s 780ms/step - loss: 1.1971 - accuracy: 0.5625 - val_loss:
1.7573 - val_accuracy: 0.4094
Epoch 16/20
56/56 [==============================] - 42s 746ms/step - loss: 1.1881 - accuracy: 0.5770 - val_loss:
1.7437 - val_accuracy: 0.4273
Epoch 17/20
56/56 [==============================] - 46s 818ms/step - loss: 1.1671 - accuracy: 0.5859 - val_loss:
1.9293 - val_accuracy: 0.4318
Epoch 18/20
56/56 [==============================] - 44s 789ms/step - loss: 1.0772 - accuracy: 0.6239 - val_loss:
1.8437 - val_accuracy: 0.4251
Epoch 19/20
56/56 [==============================] - 43s 761ms/step - loss: 0.9794 - accuracy: 0.6602 - val_loss:
1.7959 - val_accuracy: 0.4720
Epoch 20/20
56/56 [==============================] - 42s 759ms/step - loss: 0.9580 - accuracy: 0.6607 - val_loss:
1.8658 - val_accuracy: 0.4430
```

In [15]:
```
# View the summary of all layers
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 180, 180, 16)      448

 max_pooling2d (MaxPooling2D  (None, 90, 90, 16)       0
 )

 dropout (Dropout)           (None, 90, 90, 16)        0

 conv2d_1 (Conv2D)           (None, 90, 90, 32)        4640

 max_pooling2d_1 (MaxPooling  (None, 45, 45, 32)       0
 2D)

 dropout_1 (Dropout)         (None, 45, 45, 32)        0

 conv2d_2 (Conv2D)           (None, 45, 45, 64)        18496

 max_pooling2d_2 (MaxPooling  (None, 22, 22, 64)       0
 2D)

 dropout_2 (Dropout)         (None, 22, 22, 64)        0

 flatten (Flatten)           (None, 30976)             0

 dense (Dense)               (None, 128)               3965056

 dense_1 (Dense)             (None, 9)                 1161

 dropout_3 (Dropout)         (None, 9)                 0

=================================================================
Total params: 3,989,801
Trainable params: 3,989,801
Non-trainable params: 0
_________________________________________________________________
```

Visualizing training results

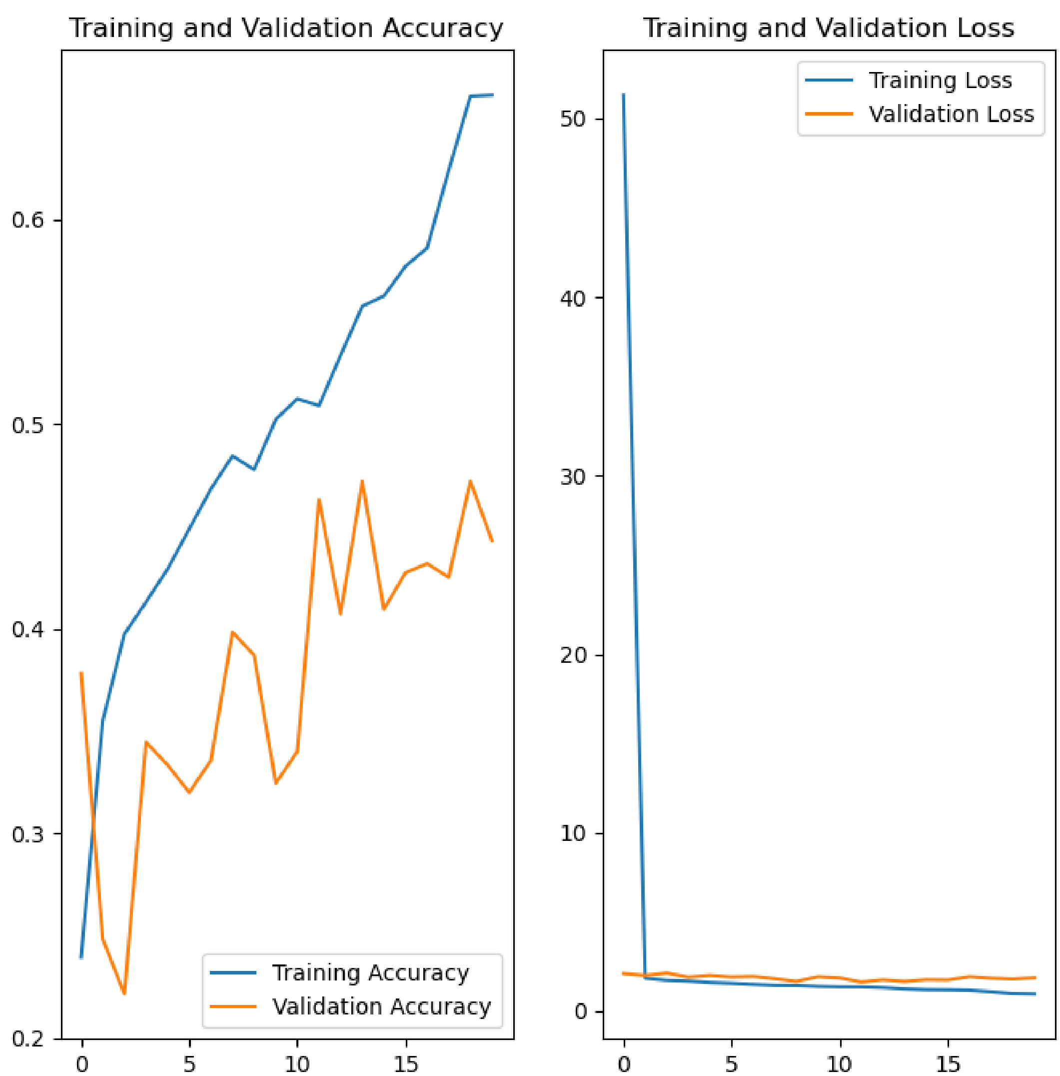
In [16]:
```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

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

Training accuracy is around 60% while Validation accuracy stops around 45%. Use of DropOut has reduced Overfitting. Need to boost validation accuracy using data augmentation. Image Rotation & flipping incorporated.

In [17]:
```
# Todo, after you have analysed the model fit history for presence of underfit or overfit, choose an appr
# Your code goes here


data_augmentation = tf.keras.Sequential([
  layers.RandomFlip("horizontal_and_vertical"),
  layers.RandomRotation(0.2),
])
```

A Sample image with image rotation

In [18]:
```
# Todo, visualize how your augmentation strategy works for one instance of training image.
# Your code goes here

#image = tf.cast(tf.expand_dims(image_batch, 0), tf.float32)

plt.figure(figsize=(10, 10))
for i in range(9):
  augmented_image = data_augmentation(image_batch)
  ax = plt.subplot(3, 3, i + 1)
  #plt.imshow(augmented_image[0])
  plt.imshow((augmented_image[0]).numpy().astype(np.uint8))
  plt.axis("off")
```

```
verter for this op.
WARNING:tensorflow:Using a while_loop for converting Bitcast cause there is no registered converter
for this op.
WARNING:tensorflow:Using a while_loop for converting Bitcast cause there is no registered converter
for this op.
WARNING:tensorflow:Using a while_loop for converting StatelessRandomUniformV2 cause there is no regi
stered converter for this op.
WARNING:tensorflow:Using a while_loop for converting ImageProjectiveTransformV3 cause there is no re
gistered converter for this op.
WARNING:tensorflow:Using a while_loop for converting RngReadAndSkip cause there is no registered con
verter for this op.
WARNING:tensorflow:Using a while_loop for converting Bitcast cause there is no registered converter
for this op.
WARNING:tensorflow:Using a while_loop for converting Bitcast cause there is no registered converter
for this op.
WARNING:tensorflow:Using a while_loop for converting StatelessRandomUniformV2 cause there is no regi
stered converter for this op.
WARNING:tensorflow:Using a while_loop for converting ImageProjectiveTransformV3 cause there is no re
gistered converter for this op.
WARNING:tensorflow:Using a while_loop for converting RngReadAndSkip cause there is no registered con
```

Todo:

Create the model, compile and train the model

In [19]:
```
## You can use Dropout layer if there is an evidence of overfitting in your findings

## Your code goes here

model = Sequential()
model.add(Conv2D(16,3,padding="same", activation="relu"))
model.add(MaxPooling2D())

model.add(Conv2D(32, 3, padding="same", activation="relu"))
model.add(MaxPooling2D())

model.add(Conv2D(64, 3, padding="same", activation="relu"))
model.add(MaxPooling2D())

model.add(Dropout(0.2))

model.add(Flatten())
model.add(Dense(128,activation="relu"))
model.add(Dense(num_classes))
```

Compiling the model

In [20]:
```
## Your code goes here

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

Training the model

In [21]:
```
## Your code goes here, note: train your model for 20 epochs
#history = ## your training code

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

```
Epoch 1/20
56/56 [==============================] - 40s 706ms/step - loss: 33.5445 - accuracy: 0.2779 - val_loss:
1.6129 - val_accuracy: 0.4206
Epoch 2/20
56/56 [==============================] - 38s 683ms/step - loss: 1.5482 - accuracy: 0.4470 - val_loss:
1.7805 - val_accuracy: 0.3512
Epoch 3/20
56/56 [==============================] - 37s 666ms/step - loss: 1.4616 - accuracy: 0.4983 - val_loss:
1.5813 - val_accuracy: 0.4541
Epoch 4/20
56/56 [==============================] - 37s 667ms/step - loss: 1.2441 - accuracy: 0.5653 - val_loss:
1.5885 - val_accuracy: 0.4832
Epoch 5/20
56/56 [==============================] - 40s 710ms/step - loss: 1.1469 - accuracy: 0.6032 - val_loss:
1.5691 - val_accuracy: 0.4944
Epoch 6/20
56/56 [==============================] - 41s 738ms/step - loss: 0.9985 - accuracy: 0.6568 - val_loss:
1.7483 - val_accuracy: 0.4720
Epoch 7/20
56/56 [==============================] - 37s 665ms/step - loss: 0.9072 - accuracy: 0.6858 - val_loss:
1.7251 - val_accuracy: 0.4855
Epoch 8/20
56/56 [==============================] - 43s 773ms/step - loss: 0.7994 - accuracy: 0.7349 - val_loss:
1.8041 - val_accuracy: 0.4720
Epoch 9/20
56/56 [==============================] - 50s 886ms/step - loss: 0.6613 - accuracy: 0.7667 - val_loss:
1.8401 - val_accuracy: 0.5190
Epoch 10/20
56/56 [==============================] - 39s 690ms/step - loss: 0.6581 - accuracy: 0.7801 - val_loss:
2.1573 - val_accuracy: 0.4698
Epoch 11/20
56/56 [==============================] - 38s 676ms/step - loss: 0.6751 - accuracy: 0.7706 - val_loss:
1.8979 - val_accuracy: 0.4407
Epoch 12/20
56/56 [==============================] - 38s 671ms/step - loss: 0.6081 - accuracy: 0.7852 - val_loss:
2.1137 - val_accuracy: 0.4922
Epoch 13/20
56/56 [==============================] - 41s 732ms/step - loss: 0.5023 - accuracy: 0.8147 - val_loss:
2.3080 - val_accuracy: 0.4966
Epoch 14/20
56/56 [==============================] - 41s 729ms/step - loss: 0.4501 - accuracy: 0.8499 - val_loss:
2.0700 - val_accuracy: 0.4743
Epoch 15/20
56/56 [==============================] - 39s 700ms/step - loss: 0.4000 - accuracy: 0.8638 - val_loss:
2.5104 - val_accuracy: 0.4899
Epoch 16/20
56/56 [==============================] - 39s 703ms/step - loss: 0.4119 - accuracy: 0.8566 - val_loss:
2.3285 - val_accuracy: 0.4899
Epoch 17/20
56/56 [==============================] - 41s 727ms/step - loss: 0.3507 - accuracy: 0.8772 - val_loss:
2.3516 - val_accuracy: 0.4765
Epoch 18/20
56/56 [==============================] - 40s 722ms/step - loss: 0.3045 - accuracy: 0.8890 - val_loss:
2.4708 - val_accuracy: 0.4698
Epoch 19/20
56/56 [==============================] - 44s 787ms/step - loss: 0.3240 - accuracy: 0.8823 - val_loss:
2.8071 - val_accuracy: 0.4430
Epoch 20/20
56/56 [==============================] - 44s 783ms/step - loss: 0.3168 - accuracy: 0.8850 - val_loss:
2.7608 - val_accuracy: 0.4698
```

In [22]:
```
test_ds = tf.keras.preprocessing.image_dataset_from_directory(
  data_dir_test,
  seed=123,

  image_size = (img_height, img_width),
  batch_size = batch_size)

loss, acc = model.evaluate(test_ds)
print("Accuracy", acc)
```

```
Found 118 files belonging to 9 classes.
4/4 [==============================] - 5s 164ms/step - loss: 5.7768 - accuracy: 0.2966
Accuracy 0.29661017656326294
```

Visualizing the results

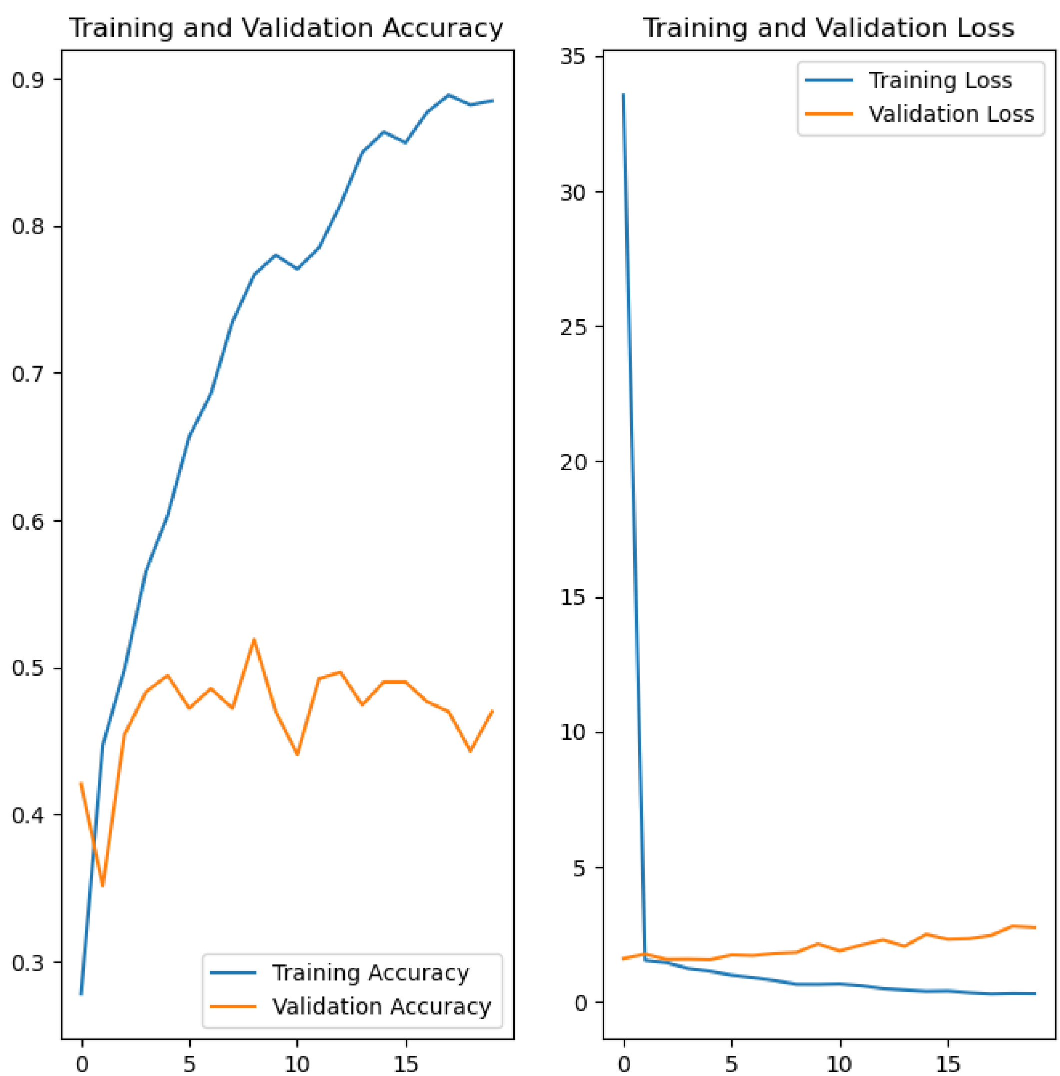
In [23]:
```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

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?

Training accuracy has improved. But Validation accuracy is still low. So its still overfitting.

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 [24]:
```
## Your code goes here.

from glob import glob
train_image_names = glob(r'./UpgradExer5CNNSkin/SkinImg/Train/*/*.jpg')
print("Total number of training images: ", len(train_image_names))

#print(train_image_names)
# make train_image_names as serie object
train_image_names = pd.Series(train_image_names)

# train_df: a dataframe with 2 field: Filename, ClassId
train_df = pd.DataFrame()

# generate Filename field
train_df['Filename'] = train_image_names.map(lambda img_name: img_name.split("\\")[-1])

# generate ClassId field
train_df['ClassId'] = train_image_names.map(lambda img_name: (img_name.split("\\")[-2]))

train_df.head()

class_id_distribution = train_df['ClassId'].value_counts()
class_id_distribution.head(10)
```

```
Total number of training images:  2239
```

Out[24]:
```
pigmented benign keratosis    462
melanoma                      438
basal cell carcinoma          376
nevus                         357
squamous cell carcinoma       181
vascular lesion               139
actinic keratosis             114
dermatofibroma                 95
seborrheic keratosis           77
Name: ClassId, dtype: int64
```

Todo: Write your findings here:

- Which class has the least number of samples?

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

Least Samples in seborrheic keratosis 77

Following classes dominate

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 [25]:
```
#!pip install Augmentor
```

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 [26]:
```
path_to_training_dataset="./UpgradExer5CNNSkin/SkinImg/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 ./UpgradExer5CNNSkin/SkinImg/Train/actinic keratosis\output.

Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x1DC826DA3A0>: 100%|█| 500/500 [00:08<00:0
0, 56.70 Samples/

Initialised with 376 image(s) found.
Output directory set to ./UpgradExer5CNNSkin/SkinImg/Train/basal cell carcinoma\output.

Processing <PIL.JpegImagePlugin.JpegImageFile image mode=RGB size=600x450 at 0x1DC8265A430>: 100%|█| 50
0/500 [00:09<00:

Initialised with 95 image(s) found.
Output directory set to ./UpgradExer5CNNSkin/SkinImg/Train/dermatofibroma\output.

Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x1DC84399130>: 100%|█| 500/500 [00:08<00:0
0, 55.97 Samples/

Initialised with 438 image(s) found.
Output directory set to ./UpgradExer5CNNSkin/SkinImg/Train/melanoma\output.

Processing <PIL.JpegImagePlugin.JpegImageFile image mode=RGB size=767x576 at 0x1DC8263CA60>: 100%|█| 50
0/500 [00:47<00:

Initialised with 357 image(s) found.
Output directory set to ./UpgradExer5CNNSkin/SkinImg/Train/nevus\output.

Processing <PIL.Image.Image image mode=RGB size=1504x1129 at 0x1DC84230130>: 100%|█| 500/500 [00:45<00:
00, 11.01 Sample

Initialised with 462 image(s) found.
Output directory set to ./UpgradExer5CNNSkin/SkinImg/Train/pigmented benign keratosis\output.

Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x1DC825AE850>: 100%|█| 500/500 [00:10<00:0
0, 49.06 Samples/

Initialised with 77 image(s) found.
Output directory set to ./UpgradExer5CNNSkin/SkinImg/Train/seborrheic keratosis\output.

Processing <PIL.Image.Image image mode=RGB size=1024x768 at 0x1DC842CB760>: 100%|█| 500/500 [00:22<00:0
0, 22.65 Samples

Initialised with 181 image(s) found.
Output directory set to ./UpgradExer5CNNSkin/SkinImg/Train/squamous cell carcinoma\output.

Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x1DC84359D30>: 100%|█| 500/500 [00:09<00:0
0, 53.13 Samples/

Initialised with 139 image(s) found.
Output directory set to ./UpgradExer5CNNSkin/SkinImg/Train/vascular lesion\output.

Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x1DC8432EEE0>: 100%|█| 500/500 [00:10<00:0
0, 49.91 Samples/
```

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 [27]:
```
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 [28]:
```
from glob import glob
path_list = [x for x in glob(os.path.join(data_dir_train, '*', '*.jpg'))]
path_list_new = [x for x in glob(os.path.join(data_dir_train, '*','output', '*.jpg'))]
```

In [29]:
```
lesion_list     = [os.path.basename((os.path.dirname(y))) for y in glob(os.path.join(data_dir_train, '*'
lesion_list_new = [os.path.basename(os.path.dirname(os.path.dirname(y))) for y in glob(os.path.join(data_
```

In [30]:
```
dataframe_dict = dict(zip(path_list, lesion_list))
dataframe_dict_new = dict(zip(path_list_new, lesion_list_new))
```

In [31]:
```
original_df = pd.DataFrame(list(dataframe_dict.items()),columns = ['Path','Label'])
df2 = pd.DataFrame(list(dataframe_dict_new.items()),columns = ['Path','Label'])
new_df = original_df.append(df2)
```

```
C:\Users\admin\AppData\Local\Temp\ipykernel_16544\739838753.py:3: FutureWarning: The frame.append metho
d is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  new_df = original_df.append(df2)
```

Distribution of data across classes including augmented data

In [32]:
```
new_df['Label'].value_counts()
```

Out[32]:
```
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 [33]:
```
batch_size = 32
img_height = 180
img_width = 180
```

Todo: Create a training dataset

In [34]:
```
data_dir_train=  "./UpgradExer5CNNSkin/SkinImg/Train/"
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 [35]:
```
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 validation data is refe
  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 [36]:
```
## your code goes here

model = tf.keras.Sequential([
  tf.keras.layers.Rescaling(1./255),
  tf.keras.layers.Conv2D(32, 3, activation='relu'),
  tf.keras.layers.MaxPooling2D(),
  tf.keras.layers.Conv2D(32, 3, activation='relu'),
  tf.keras.layers.MaxPooling2D(),
  tf.keras.layers.Conv2D(32, 3, activation='relu'),
  tf.keras.layers.MaxPooling2D(),
  tf.keras.layers.Flatten(),
  tf.keras.layers.Dense(128, activation='relu'),
  tf.keras.layers.Dense(num_classes)
])
```

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

In [37]:
```
## your code goes here

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

Todo: Train your model

In [38]:
```
epochs = 30
history = model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs
)
```

```
Epoch 1/30
169/169 [==============================] - 159s 927ms/step - loss: 1.8898 - accuracy: 0.2717 - val_los
s: 1.6057 - val_accuracy: 0.3846
Epoch 2/30
169/169 [==============================] - 149s 878ms/step - loss: 1.4960 - accuracy: 0.4375 - val_los
s: 1.4491 - val_accuracy: 0.4736
Epoch 3/30
169/169 [==============================] - 148s 870ms/step - loss: 1.3066 - accuracy: 0.5070 - val_los
s: 1.2650 - val_accuracy: 0.5434
Epoch 4/30
169/169 [==============================] - 144s 850ms/step - loss: 1.1501 - accuracy: 0.5746 - val_los
s: 1.2830 - val_accuracy: 0.5256
Epoch 5/30
169/169 [==============================] - 155s 916ms/step - loss: 1.0435 - accuracy: 0.6226 - val_los
s: 1.1470 - val_accuracy: 0.5694
Epoch 6/30
169/169 [==============================] - 146s 860ms/step - loss: 0.8895 - accuracy: 0.6738 - val_los
s: 1.0483 - val_accuracy: 0.6340
Epoch 7/30
169/169 [==============================] - 153s 900ms/step - loss: 0.7768 - accuracy: 0.7253 - val_los
s: 1.0870 - val_accuracy: 0.6013
Epoch 8/30
169/169 [==============================] - 157s 925ms/step - loss: 0.6422 - accuracy: 0.7672 - val_los
s: 0.9604 - val_accuracy: 0.6867
Epoch 9/30
169/169 [==============================] - 147s 868ms/step - loss: 0.5396 - accuracy: 0.8099 - val_los
s: 0.9842 - val_accuracy: 0.7030
Epoch 10/30
169/169 [==============================] - 143s 840ms/step - loss: 0.5107 - accuracy: 0.8153 - val_los
s: 0.8404 - val_accuracy: 0.7246
Epoch 11/30
169/169 [==============================] - 151s 892ms/step - loss: 0.3698 - accuracy: 0.8709 - val_los
s: 0.9539 - val_accuracy: 0.7246
Epoch 12/30
169/169 [==============================] - 143s 843ms/step - loss: 0.3263 - accuracy: 0.8861 - val_los
s: 0.7684 - val_accuracy: 0.7832
Epoch 13/30
169/169 [==============================] - 143s 845ms/step - loss: 0.2769 - accuracy: 0.9008 - val_los
s: 0.9096 - val_accuracy: 0.7617
Epoch 14/30
169/169 [==============================] - 150s 885ms/step - loss: 0.3002 - accuracy: 0.8969 - val_los
s: 0.7740 - val_accuracy: 0.7810
Epoch 15/30
169/169 [==============================] - 151s 887ms/step - loss: 0.2224 - accuracy: 0.9225 - val_los
s: 0.7988 - val_accuracy: 0.7906
Epoch 16/30
169/169 [==============================] - 148s 874ms/step - loss: 0.2287 - accuracy: 0.9182 - val_los
s: 0.8876 - val_accuracy: 0.7684
Epoch 17/30
169/169 [==============================] - 158s 933ms/step - loss: 0.2027 - accuracy: 0.9264 - val_los
s: 0.7992 - val_accuracy: 0.7951
Epoch 18/30
169/169 [==============================] - 148s 872ms/step - loss: 0.1883 - accuracy: 0.9282 - val_los
s: 0.9459 - val_accuracy: 0.7751
Epoch 19/30
169/169 [==============================] - 154s 907ms/step - loss: 0.1532 - accuracy: 0.9429 - val_los
s: 0.8246 - val_accuracy: 0.8033
Epoch 20/30
169/169 [==============================] - 150s 883ms/step - loss: 0.1429 - accuracy: 0.9440 - val_los
s: 0.8164 - val_accuracy: 0.8137
Epoch 21/30
169/169 [==============================] - 153s 905ms/step - loss: 0.1318 - accuracy: 0.9496 - val_los
s: 0.8676 - val_accuracy: 0.8062
Epoch 22/30
169/169 [==============================] - 168s 988ms/step - loss: 0.1256 - accuracy: 0.9509 - val_los
s: 0.8999 - val_accuracy: 0.8010
Epoch 23/30
169/169 [==============================] - 164s 966ms/step - loss: 0.2021 - accuracy: 0.9282 - val_los
s: 0.8774 - val_accuracy: 0.8025
Epoch 24/30
169/169 [==============================] - 146s 858ms/step - loss: 0.1219 - accuracy: 0.9514 - val_los
```

```
s: 1.0118 - val_accuracy: 0.7803
Epoch 25/30
169/169 [==============================] - 146s 860ms/step - loss: 0.1261 - accuracy: 0.9492 - val_los
s: 0.9898 - val_accuracy: 0.7892
Epoch 26/30
169/169 [==============================] - 145s 857ms/step - loss: 0.1412 - accuracy: 0.9451 - val_los
s: 1.0156 - val_accuracy: 0.7981
Epoch 27/30
169/169 [==============================] - 145s 857ms/step - loss: 0.1143 - accuracy: 0.9547 - val_los
s: 1.0109 - val_accuracy: 0.8048
Epoch 28/30
169/169 [==============================] - 146s 860ms/step - loss: 0.1108 - accuracy: 0.9560 - val_los
s: 1.0315 - val_accuracy: 0.7832
Epoch 29/30
169/169 [==============================] - 153s 905ms/step - loss: 0.1642 - accuracy: 0.9373 - val_los
s: 1.0671 - val_accuracy: 0.8107
Epoch 30/30
169/169 [==============================] - 145s 857ms/step - loss: 0.1097 - accuracy: 0.9542 - val_los
s: 1.0126 - val_accuracy: 0.8174
```

Todo: Visualize the model results

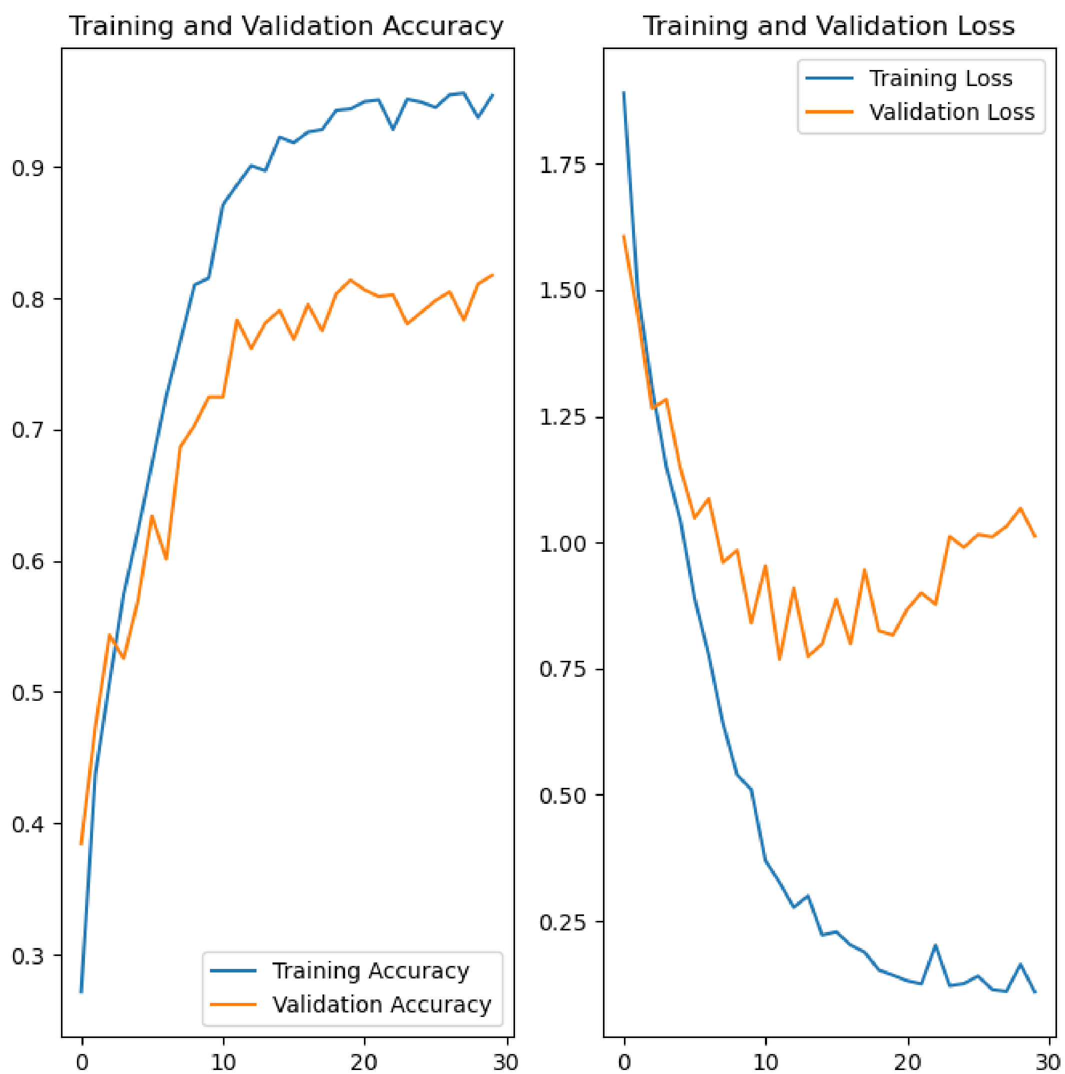
In [39]:
```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

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()
```



In [40]:
```
test_ds = tf.keras.preprocessing.image_dataset_from_directory(
  data_dir_test,
  seed=123,
  image_size = (img_height, img_width),
  batch_size = batch_size)

loss, acc = model.evaluate(test_ds)
print("Accuracy", acc)
```

```
Found 118 files belonging to 9 classes.
4/4 [==============================] - 4s 229ms/step - loss: 8.4599 - accuracy: 0.3051
Accuracy 0.3050847351551056
```

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

Rebalancing the class must have helped address underfitting of few classes with very less data (images).

Overall Overfitting is addressed as we see the Validation Accuracy has increased.

In [41]:
```
from keras.preprocessing.image import ImageDataGenerator
test_generator = ImageDataGenerator()
test_data_generator = test_generator.flow_from_directory(
 data_dir_test , # Put your path here
     target_size=(img_width, img_height),
    batch_size=32,
    shuffle=False)
test_steps_per_epoch = np.math.ceil(test_data_generator.samples / test_data_generator.batch_size)

predictions = model.predict_generator(test_data_generator, steps=test_steps_per_epoch)
# Get most likely class
predicted_classes = np.argmax(predictions, axis=1)
```

```
Found 118 images belonging to 9 classes.

C:\Users\admin\AppData\Local\Temp\ipykernel_16544\2016176624.py:10: UserWarning: `Model.predict_generat
or` is deprecated and will be removed in a future version. Please use `Model.predict`, which supports g
enerators.
  predictions = model.predict_generator(test_data_generator, steps=test_steps_per_epoch)
```

In [42]:
```
true_classes = test_data_generator.classes
class_labels = list(test_data_generator.class_indices.keys())
```

In [43]:
```
import sklearn.metrics as metrics
report = metrics.classification_report(true_classes, predicted_classes, target_names=class_labels)
print(report)
```

```
                          precision    recall  f1-score   support

       actinic keratosis       0.00      0.00      0.00        16
    basal cell carcinoma       0.39      0.44      0.41        16
          dermatofibroma       0.67      0.12      0.21        16
                melanoma       0.17      0.12      0.14        16
                   nevus       0.31      0.94      0.46        16
pigmented benign keratosis       0.39      0.56      0.46        16
    seborrheic keratosis       0.00      0.00      0.00         3
 squamous cell carcinoma       0.29      0.12      0.17        16
         vascular lesion       0.67      0.67      0.67         3

                accuracy                           0.33       118
               macro avg       0.32      0.33      0.28       118
            weighted avg       0.32      0.33      0.27       118
```

In [ ]:

In [ ]: