In [20]:

```
!pip install Augmentor
```

```
Defaulting to user installation because normal site-packages is not writeable
Collecting Augmentor
  Downloading Augmentor-0.2.10-py2.py3-none-any.whl (38 kB)
Requirement already satisfied: numpy>=1.11.0 in c:\users\pc\appdata\roaming\python\python
39\site-packages (from Augmentor) (1.23.1)
Requirement already satisfied: future>=0.16.0 in c:\programdata\anaconda3\lib\site-packag
es (from Augmentor) (0.18.2)
Requirement already satisfied: Pillow>=5.2.0 in c:\programdata\anaconda3\lib\site-package
s (from Augmentor) (9.0.1)
Requirement already satisfied: tqdm>=4.9.0 in c:\programdata\anaconda3\lib\site-packages
(from Augmentor) (4.64.0)
Requirement already satisfied: colorama in c:\programdata\anaconda3\lib\site-packages (fr
om tqdm>=4.9.0->Augmentor) (0.4.4)
Installing collected packages: Augmentor
Successfully installed Augmentor-0.2.10
```

```
WARNING: Ignoring invalid distribution -cs (c:\users\pc\appdata\roaming\python\python39\s
ite-packages)
WARNING: Ignoring invalid distribution -cos (c:\users\pc\appdata\roaming\python\python39\
site-packages)
WARNING: Ignoring invalid distribution -cs (c:\users\pc\appdata\roaming\python\python39\s
ite-packages)
WARNING: Ignoring invalid distribution -cos (c:\users\pc\appdata\roaming\python\python39\
site-packages)
WARNING: Ignoring invalid distribution -cs (c:\users\pc\appdata\roaming\python\python39\s
ite-packages)
WARNING: Ignoring invalid distribution -cos (c:\users\pc\appdata\roaming\python\python39\
site-packages)
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ite-packages)
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site-packages)
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ite-packages)
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site-packages)
WARNING: Ignoring invalid distribution -cs (c:\users\pc\appdata\roaming\python\python39\s
ite-packages)
WARNING: Ignoring invalid distribution -cos (c:\users\pc\appdata\roaming\python\python39\
site-packages)
WARNING: Ignoring invalid distribution -cs (c:\users\pc\appdata\roaming\python\python39\s
ite-packages)
WARNING: Ignoring invalid distribution -cos (c:\users\pc\appdata\roaming\python\python39\
site-packages)
```

In [21]:

```
import Augmentor
```

In [1]:

```
from pathlib import Path
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 sklearn.model_selection import train_test_split as tts
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from keras.layers import Conv2D,MaxPool2D,GlobalMaxPool2D,Reshape,Dense,Dropout,BatchNor
```

```
malization,Flatten
from keras import Model
from keras.callbacks import ModelCheckpoint, EarlyStopping, ReduceLROnPlateau, Callback
from keras.optimizers import Adam,Adamax,RMSprop,Nadam,SGD
from tensorflow.keras import layers
```

In [2]:

```
data_dir_train=pathlib.Path(r"F:\Python Works\Malenoma Detection\Malenoma\Skin cancer ISI
C The International Skin Imaging Collaboration\Train")
data_dir_test=pathlib.Path(r"F:\Python Works\Malenoma Detection\Malenoma\Skin cancer ISIC
The International Skin Imaging Collaboration\Test")
```

Create Dataset

In [3]:

```
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
```

In [4]:

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

In [5]:

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

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

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

In [7]:

In [7]:

```
# 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)
```

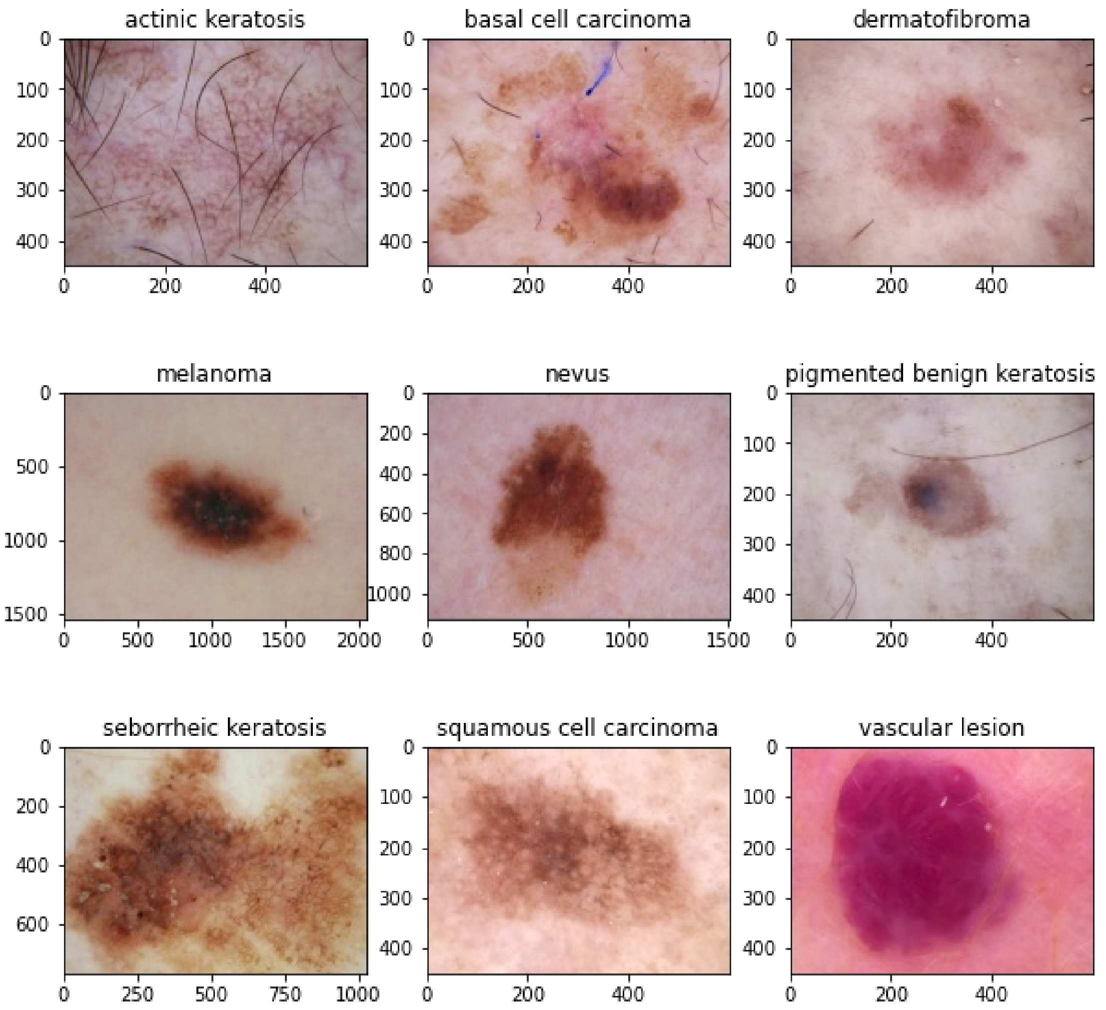
```
['actinic keratosis', 'basal cell carcinoma', 'dermatofibroma', 'melanoma', 'nevus', 'pig
mented benign keratosis', 'seborrheic keratosis', 'squamous cell carcinoma', 'vascular le
sion']
```

Visualizate the data

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

In [8]:

```
### your code goes here, you can use training or validation data to visualize
import matplotlib.pyplot as plt
plt.figure(figsize=(10,10))
for i in range(9):
    plt.subplot(3, 3, i + 1)
    image = plt.imread(str(list(data_dir_train.glob(class_names[i]+'/*.jpg'))[1]))
    plt.title(class_names[i])
    plt.imshow(image)
```



In [9]:

```
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

In [27]:

```
data_normalize=Sequential([
                    layers.experimental.preprocessing.Rescaling(1./255)
])
def downsample(channels, inputs):
    x = keras.layers.BatchNormalization(momentum=0.99)(inputs)
    x = keras.layers.LeakyReLU(0.03)(x)
    x = keras.layers.Conv2D(channels, 1, padding='same', use_bias=False)(x)
    x = keras.layers.MaxPool2D(3)(x)

    return x

def resblock(channels, inputs):
    x = keras.layers.BatchNormalization(momentum=0.99)(inputs)
    x = keras.layers.LeakyReLU(0.03)(x)
    x = keras.layers.Conv2D(channels, 3, padding='same', use_bias=False)(x)
    x = keras.layers.BatchNormalization(momentum=0.99)(x)
    x = keras.layers.LeakyReLU(0.03)(x)
    x = keras.layers.Conv2D(channels, 3, padding='same', use_bias=False)(x)
    return keras.layers.add([x, inputs])

def create_network(input_size, channels, n_blocks=2, depth=4):
    # input
    inputs = keras.Input(shape=(input_size, input_size, 3))
    x=data_normalize(inputs)
    x = keras.layers.Conv2D(channels, 3, padding='same', use_bias=False)(inputs)
    # residual blocks
    for d in range(depth):
        channels = channels * 2
        x = downsample(channels, x)
        for b in range(n_blocks):
            x = resblock(channels, x)
    x=Dropout(.25)(x)
    x = keras.layers.BatchNormalization(momentum=0.99)(x)
    x = keras.layers.LeakyReLU(0.03)(x)
    outputs = keras.layers.Conv2D(256,(1,1))(x)

    outputs=MaxPool2D((2,2))(outputs)
    outputs=Dropout(.25)(outputs)
    outputs = keras.layers.Conv2D(128,(3,3))(outputs)
    #outputs = keras.layers.Conv2D(64,(3,3),2)(outputs)
    #outputs = keras.layers.Conv2D(32,(3,3), 2)(outputs)
    #outputs = keras.layers.Conv2D(16,(3,3), 2)(outputs)
    outputs = keras.layers.Conv2D(64,(1,1))(outputs)



    model = keras.Model(inputs=inputs, outputs=outputs)
    return model
```

In [28]:

```
model = create_network(input_size=180, channels=64, n_blocks=1, depth=3)
```

In [29]:

```
headModel=model.output
headModel=Flatten()(headModel)
headModel=Dense(9,activation="softmax")(headModel)
model = Model(inputs=model.input, outputs=headModel)
```

In [30]:

```
model.summary()
```

```
Model: "model_3"
________________________________________________________________________________
__________
 Layer (type)                   Output Shape         Param #     Connected to
```

```
 Layer (type)                   Output Shape         Param #     Connected to

==================================================================================
=========
 input_2 (InputLayer)           [(None, 180, 180, 3  0           []

                                )]


 conv2d_23 (Conv2D)             (None, 180, 180, 64  1728        ['input_2[0][0]']

                                )


 batch_normalization_10 (BatchN  (None, 180, 180, 64  256        ['conv2d_23[0][0]']

 ormalization)                  )


 leaky_re_lu_10 (LeakyReLU)     (None, 180, 180, 64  0           ['batch_normalization_10
[0][0]']
                                )


 conv2d_24 (Conv2D)             (None, 180, 180, 12  8192        ['leaky_re_lu_10[0][0]']

                                8)


 max_pooling2d_12 (MaxPooling2D  (None, 60, 60, 128)  0          ['conv2d_24[0][0]']

 )


 batch_normalization_11 (BatchN  (None, 60, 60, 128)  512        ['max_pooling2d_12[0][0]
']
 ormalization)


 leaky_re_lu_11 (LeakyReLU)     (None, 60, 60, 128)  0           ['batch_normalization_11
[0][0]']

 conv2d_25 (Conv2D)             (None, 60, 60, 128)  147456      ['leaky_re_lu_11[0][0]']


 batch_normalization_12 (BatchN  (None, 60, 60, 128)  512        ['conv2d_25[0][0]']

 ormalization)


 leaky_re_lu_12 (LeakyReLU)     (None, 60, 60, 128)  0           ['batch_normalization_12
[0][0]']

 conv2d_26 (Conv2D)             (None, 60, 60, 128)  147456      ['leaky_re_lu_12[0][0]']


 add_3 (Add)                    (None, 60, 60, 128)  0           ['conv2d_26[0][0]',

                                                                  'max_pooling2d_12[0][
0]']
```

```
 batch_normalization_13 (BatchN  (None, 60, 60, 128)  512         ['add_3[0][0]']
 ormalization)

 leaky_re_lu_13 (LeakyReLU)     (None, 60, 60, 128)  0           ['batch_normalization_13
[0][0]']

 conv2d_27 (Conv2D)             (None, 60, 60, 256)  32768       ['leaky_re_lu_13[0][0]']

 max_pooling2d_13 (MaxPooling2D  (None, 20, 20, 256)  0          ['conv2d_27[0][0]']
 )

 batch_normalization_14 (BatchN  (None, 20, 20, 256)  1024       ['max_pooling2d_13[0][0]
']
 ormalization)

 leaky_re_lu_14 (LeakyReLU)     (None, 20, 20, 256)  0           ['batch_normalization_14
[0][0]']

 conv2d_28 (Conv2D)             (None, 20, 20, 256)  589824      ['leaky_re_lu_14[0][0]']

 batch_normalization_15 (BatchN  (None, 20, 20, 256)  1024       ['conv2d_28[0][0]']
 ormalization)

 leaky_re_lu_15 (LeakyReLU)     (None, 20, 20, 256)  0           ['batch_normalization_15
[0][0]']

 conv2d_29 (Conv2D)             (None, 20, 20, 256)  589824      ['leaky_re_lu_15[0][0]']

 add_4 (Add)                    (None, 20, 20, 256)  0           ['conv2d_29[0][0]',
                                                                  'max_pooling2d_13[0][
0]']

 batch_normalization_16 (BatchN  (None, 20, 20, 256)  1024       ['add_4[0][0]']
 ormalization)

 leaky_re_lu_16 (LeakyReLU)     (None, 20, 20, 256)  0           ['batch_normalization_16
[0][0]']

 conv2d_30 (Conv2D)             (None, 20, 20, 512)  131072      ['leaky_re_lu_16[0][0]']

 max_pooling2d_14 (MaxPooling2D  (None, 6, 6, 512)   0           ['conv2d_30[0][0]']
 )
```

```
 ,

 batch_normalization_17 (BatchN  (None, 6, 6, 512)   2048        ['max_pooling2d_14[0][0]
']
 ormalization)

 leaky_re_lu_17 (LeakyReLU)     (None, 6, 6, 512)    0           ['batch_normalization_17
[0][0]']

 conv2d_31 (Conv2D)             (None, 6, 6, 512)    2359296     ['leaky_re_lu_17[0][0]']

 batch_normalization_18 (BatchN  (None, 6, 6, 512)   2048        ['conv2d_31[0][0]']

 ormalization)

 leaky_re_lu_18 (LeakyReLU)     (None, 6, 6, 512)    0           ['batch_normalization_18
[0][0]']

 conv2d_32 (Conv2D)             (None, 6, 6, 512)    2359296     ['leaky_re_lu_18[0][0]']

 add_5 (Add)                    (None, 6, 6, 512)    0           ['conv2d_32[0][0]',

                                                                  'max_pooling2d_14[0][
0]']

 dropout_4 (Dropout)            (None, 6, 6, 512)    0           ['add_5[0][0]']

 batch_normalization_19 (BatchN  (None, 6, 6, 512)   2048        ['dropout_4[0][0]']

 ormalization)

 leaky_re_lu_19 (LeakyReLU)     (None, 6, 6, 512)    0           ['batch_normalization_19
[0][0]']

 conv2d_33 (Conv2D)             (None, 6, 6, 256)    131328      ['leaky_re_lu_19[0][0]']

 max_pooling2d_15 (MaxPooling2D  (None, 3, 3, 256)   0           ['conv2d_33[0][0]']

 )

 dropout_5 (Dropout)            (None, 3, 3, 256)    0           ['max_pooling2d_15[0][0
]']

 conv2d_34 (Conv2D)             (None, 1, 1, 128)    295040      ['dropout_5[0][0]']

 conv2d_35 (Conv2D)             (None, 1, 1, 64)     8256        ['conv2d_34[0][0]']
```

```
 flatten_3 (Flatten)            (None, 64)          0           ['conv2d_35[0][0]']


 dense_3 (Dense)                (None, 9)           585         ['flatten_3[0][0]']


==========================================================================================
=========
Total params: 6,813,129
Trainable params: 6,807,625
Non-trainable params: 5,504
__________________________________________________________________________________________
_________
```

Compile the model

In [31]:

```
opt=Adam(learning_rate=2.0000e-04)
model.compile(loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True), opti
mizer=opt, metrics=['accuracy']) # Regression loss is MSE

#checkpoint = ModelCheckpoint("model-{accuracy:.2f}.h5", monitor="val_accuracy", verbose=
1, save_best_only=True,
                             #save_weights_only=True, mode="max", period=1) # Checkpoint
best validation model
stop = EarlyStopping(monitor="val_accuracy", patience=7, mode="max") # Stop early, if the
validation error deteriorates
reduce_lr = ReduceLROnPlateau(monitor="val_accuracy", factor=0.2, patience=2, min_lr=1e-
10, verbose=1, mode="max")
```

Train the model

In [32]:

```
epochs = 30
history = model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs,
    callbacks=[ stop, reduce_lr]
)
```

```
Epoch 1/30
56/56 [==============================] - 119s 2s/step - loss: 2.1374 - accuracy: 0.3811 -
val_loss: 3.7394 - val_accuracy: 0.1834 - lr: 2.0000e-04
Epoch 2/30
56/56 [==============================] - 119s 2s/step - loss: 1.5332 - accuracy: 0.4888 -
val_loss: 2.7887 - val_accuracy: 0.2707 - lr: 2.0000e-04
Epoch 3/30
56/56 [==============================] - 119s 2s/step - loss: 1.2508 - accuracy: 0.5910 -
val_loss: 1.7880 - val_accuracy: 0.3893 - lr: 2.0000e-04
Epoch 4/30
56/56 [==============================] - 119s 2s/step - loss: 1.0754 - accuracy: 0.6205 -
val_loss: 1.5158 - val_accuracy: 0.4541 - lr: 2.0000e-04
Epoch 5/30
56/56 [==============================] - 119s 2s/step - loss: 0.8870 - accuracy: 0.6780 -
val_loss: 1.3321 - val_accuracy: 0.5056 - lr: 2.0000e-04
Epoch 6/30
56/56 [==============================] - 120s 2s/step - loss: 0.7907 - accuracy: 0.7087 -
val_loss: 1.6100 - val_accuracy: 0.5280 - lr: 2.0000e-04
Epoch 7/30
56/56 [==============================] - 120s 2s/step - loss: 0.6809 - accuracy: 0.7533 -
val_loss: 1.2852 - val_accuracy: 0.5459 - lr: 2.0000e-04
Epoch 8/30
56/56 [==============================] - 120s 2s/step - loss: 0.6272 - accuracy: 0.7746 -
```

```
val_loss: 1.4748 - val_accuracy: 0.5593 - lr: 2.0000e-04
Epoch 9/30
56/56 [==============================] - 120s 2s/step - loss: 0.4903 - accuracy: 0.8253 -
val_loss: 1.5015 - val_accuracy: 0.5727 - lr: 2.0000e-04
Epoch 10/30
56/56 [==============================] - 119s 2s/step - loss: 0.3830 - accuracy: 0.8638 -
val_loss: 1.4345 - val_accuracy: 0.5906 - lr: 2.0000e-04
Epoch 11/30
56/56 [==============================] - 120s 2s/step - loss: 0.2983 - accuracy: 0.8828 -
val_loss: 1.6338 - val_accuracy: 0.5280 - lr: 2.0000e-04
Epoch 12/30
56/56 [==============================] - ETA: 0s - loss: 0.2728 - accuracy: 0.9135
Epoch 12: ReduceLROnPlateau reducing learning rate to 3.9999998989515007e-05.
56/56 [==============================] - 120s 2s/step - loss: 0.2728 - accuracy: 0.9135 -
val_loss: 1.4865 - val_accuracy: 0.5772 - lr: 2.0000e-04
Epoch 13/30
56/56 [==============================] - 120s 2s/step - loss: 0.1430 - accuracy: 0.9537 -
val_loss: 1.3796 - val_accuracy: 0.6197 - lr: 4.0000e-05
Epoch 14/30
56/56 [==============================] - 120s 2s/step - loss: 0.0880 - accuracy: 0.9743 -
val_loss: 1.3649 - val_accuracy: 0.6242 - lr: 4.0000e-05
Epoch 15/30
56/56 [==============================] - 120s 2s/step - loss: 0.0769 - accuracy: 0.9766 -
val_loss: 1.3848 - val_accuracy: 0.6331 - lr: 4.0000e-05
Epoch 16/30
56/56 [==============================] - 120s 2s/step - loss: 0.0634 - accuracy: 0.9838 -
val_loss: 1.4050 - val_accuracy: 0.6353 - lr: 4.0000e-05
Epoch 17/30
56/56 [==============================] - 120s 2s/step - loss: 0.0550 - accuracy: 0.9883 -
val_loss: 1.4455 - val_accuracy: 0.6331 - lr: 4.0000e-05
Epoch 18/30
56/56 [==============================] - ETA: 0s - loss: 0.0494 - accuracy: 0.9888
Epoch 18: ReduceLROnPlateau reducing learning rate to 7.999999797903002e-06.
56/56 [==============================] - 120s 2s/step - loss: 0.0494 - accuracy: 0.9888 -
val_loss: 1.4728 - val_accuracy: 0.6309 - lr: 4.0000e-05
Epoch 19/30
56/56 [==============================] - 120s 2s/step - loss: 0.0411 - accuracy: 0.9916 -
val_loss: 1.4816 - val_accuracy: 0.6398 - lr: 8.0000e-06
Epoch 20/30
56/56 [==============================] - 120s 2s/step - loss: 0.0419 - accuracy: 0.9916 -
val_loss: 1.4949 - val_accuracy: 0.6465 - lr: 8.0000e-06
Epoch 21/30
56/56 [==============================] - 120s 2s/step - loss: 0.0372 - accuracy: 0.9950 -
val_loss: 1.5024 - val_accuracy: 0.6488 - lr: 8.0000e-06
Epoch 22/30
56/56 [==============================] - 120s 2s/step - loss: 0.0365 - accuracy: 0.9911 -
val_loss: 1.5067 - val_accuracy: 0.6443 - lr: 8.0000e-06
Epoch 23/30
56/56 [==============================] - ETA: 0s - loss: 0.0357 - accuracy: 0.9955
Epoch 23: ReduceLROnPlateau reducing learning rate to 1.5999999959603884e-06.
56/56 [==============================] - 119s 2s/step - loss: 0.0357 - accuracy: 0.9955 -
val_loss: 1.5144 - val_accuracy: 0.6443 - lr: 8.0000e-06
Epoch 24/30
56/56 [==============================] - 120s 2s/step - loss: 0.0351 - accuracy: 0.9939 -
val_loss: 1.5186 - val_accuracy: 0.6443 - lr: 1.6000e-06
Epoch 25/30
56/56 [==============================] - ETA: 0s - loss: 0.0309 - accuracy: 0.9944
Epoch 25: ReduceLROnPlateau reducing learning rate to 3.200000037395512e-07.
56/56 [==============================] - 120s 2s/step - loss: 0.0309 - accuracy: 0.9944 -
val_loss: 1.5215 - val_accuracy: 0.6421 - lr: 1.6000e-06
Epoch 26/30
56/56 [==============================] - 120s 2s/step - loss: 0.0358 - accuracy: 0.9944 -
val_loss: 1.5226 - val_accuracy: 0.6398 - lr: 3.2000e-07
Epoch 27/30
56/56 [==============================] - ETA: 0s - loss: 0.0349 - accuracy: 0.9927
Epoch 27: ReduceLROnPlateau reducing learning rate to 6.399999961104187e-08.
56/56 [==============================] - 120s 2s/step - loss: 0.0349 - accuracy: 0.9927 -
val_loss: 1.5245 - val_accuracy: 0.6421 - lr: 3.2000e-07
Epoch 28/30
56/56 [==============================] - 120s 2s/step - loss: 0.0343 - accuracy: 0.9939 -
val_loss: 1.5243 - val_accuracy: 0.6421 - lr: 6.4000e-08
```

In [34]:

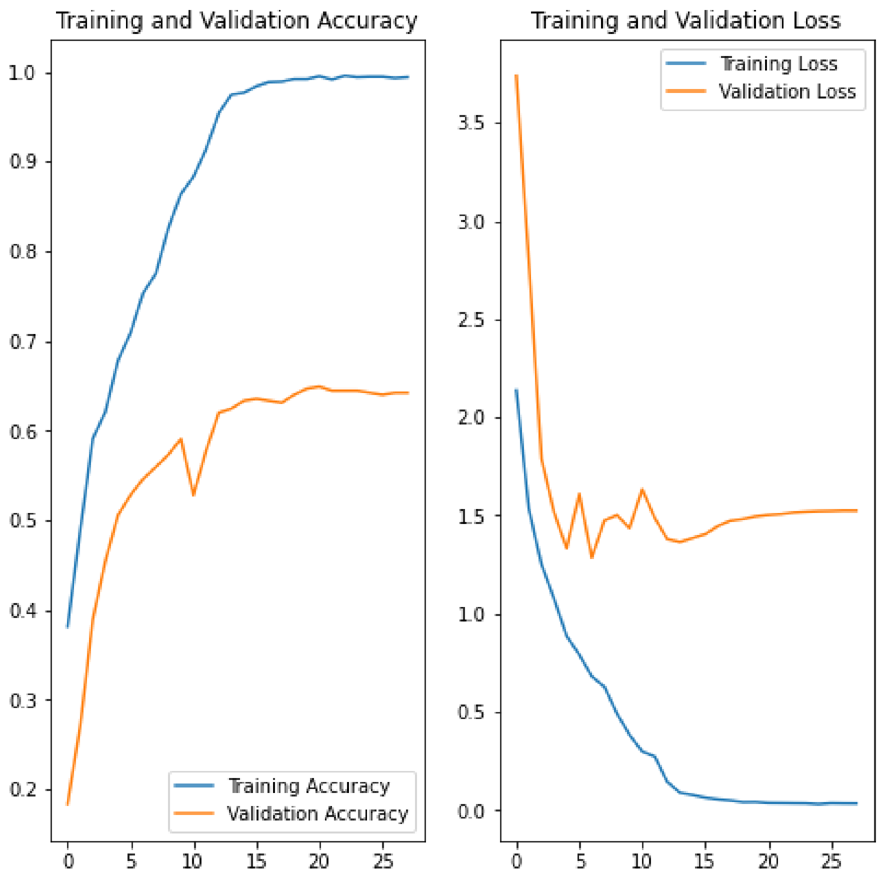
```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

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

epochs_range = history.epoch

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()
```



There is a clear indication of overfitting , but the lifecycle of model for training and validation set is same , the accuracy rises till around 8th epoch , after 10th epoch the learning becomes saturated which is shown both by train and validation accuracy.

The only difference is that the validation set , model was bit volatile.

Choose data augmentation technique

In [10]:

```
data_augument = keras.Sequential([
                             layers.experimental.preprocessing.Rescaling(1./255),
                             layers.experimental.preprocessing.RandomFlip(mode="horizont
al_and_vertical",input_shape=(img_height,img_width,3)),
                             layers.experimental.preprocessing.RandomRotation(0.2, fill_
```

```
mode='reflect'),
                                layers.experimental.preprocessing.RandomZoom(height_factor=
(0.2, 0.3), width_factor=(0.2, 0.3), fill_mode='reflect')
])
```

Create model

In [11]:

```
def downsample(channels, inputs):
    x = keras.layers.BatchNormalization(momentum=0.99)(inputs)
    x = keras.layers.LeakyReLU(0.03)(x)
    x = keras.layers.Conv2D(channels, 1, padding='same', use_bias=False)(x)
    x = keras.layers.MaxPool2D(3)(x)

    return x

def resblock(channels, inputs):
    x = keras.layers.BatchNormalization(momentum=0.99)(inputs)
    x = keras.layers.LeakyReLU(0.03)(x)
    x = keras.layers.Conv2D(channels, 3, padding='same', use_bias=False)(x)
    x = keras.layers.BatchNormalization(momentum=0.99)(x)
    x = keras.layers.LeakyReLU(0.03)(x)
    x = keras.layers.Conv2D(channels, 3, padding='same', use_bias=False)(x)
    return keras.layers.add([x, inputs])

def create_network(input_size, channels, n_blocks=2, depth=4):
    # input
    inputs = keras.Input(shape=(input_size, input_size, 3))
    x=data_augument(inputs)
    x = keras.layers.Conv2D(channels, 3, padding='same', use_bias=False)(inputs)
    # residual blocks
    for d in range(depth):
        channels = channels * 2
        x = downsample(channels, x)
        for b in range(n_blocks):
            x = resblock(channels, x)
    x=Dropout(.25)(x)
    x = keras.layers.BatchNormalization(momentum=0.99)(x)
    x = keras.layers.LeakyReLU(0.03)(x)
    outputs = keras.layers.Conv2D(256,(1,1))(x)

    outputs=MaxPool2D((2,2))(outputs)
    outputs=Dropout(.25)(outputs)
    outputs = keras.layers.Conv2D(128,(3,3))(outputs)
    #outputs = keras.layers.Conv2D(64,(3,3),2)(outputs)
    #outputs = keras.layers.Conv2D(32,(3,3), 2)(outputs)
    #outputs = keras.layers.Conv2D(16,(3,3), 2)(outputs)
    outputs = keras.layers.Conv2D(64,(1,1))(outputs)



    model = keras.Model(inputs=inputs, outputs=outputs)
    return model
```

In [12]:

```
model = create_network(input_size=180, channels=16, n_blocks=1, depth=3)
headModel=model.output
headModel=Flatten()(headModel)
headModel=Dense(9,activation="softmax")(headModel)
model = Model(inputs=model.input, outputs=headModel)
```

In [13]:

```
opt=Adam(learning_rate=2.0000e-04)
model.compile(loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True), opti
mizer=opt, metrics=['accuracy']) # Regression loss is MSE

#checkpoint = ModelCheckpoint("model-{accuracy:.2f}.h5", monitor="val_accuracy", verbose=
```

```
1, save_best_only=True,
                                   #save_weights_only=True, mode="max", period=1) # Checkpoint best validation model
stop = EarlyStopping(monitor="val_accuracy", patience=7, mode="max") # Stop early, if the validation error deteriorates
reduce_lr = ReduceLROnPlateau(monitor="val_accuracy", factor=0.2, patience=2, min_lr=1e-10, verbose=1, mode="max")
```

In [14]:

```
epochs = 20
history = model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs,
    callbacks=[ stop, reduce_lr]
)
```

```
Epoch 1/20
```

```
C:\Users\PC\AppData\Roaming\Python\Python39\site-packages\tensorflow\python\util\dispatch.py:1082: UserWarning: "`sparse_categorical_crossentropy` received `from_logits=True`, but the `output` argument was produced by a sigmoid or softmax activation and thus does not represent logits. Was this intended?"
  return dispatch_target(*args, **kwargs)
```

```
56/56 [==============================] - 28s 457ms/step - loss: 2.1254 - accuracy: 0.3125 - val_loss: 2.2728 - val_accuracy: 0.2081 - lr: 2.0000e-04
Epoch 2/20
56/56 [==============================] - 25s 447ms/step - loss: 1.5237 - accuracy: 0.4821 - val_loss: 1.9964 - val_accuracy: 0.2774 - lr: 2.0000e-04
Epoch 3/20
56/56 [==============================] - 25s 446ms/step - loss: 1.2917 - accuracy: 0.5564 - val_loss: 1.7984 - val_accuracy: 0.3356 - lr: 2.0000e-04
Epoch 4/20
56/56 [==============================] - 25s 444ms/step - loss: 1.1247 - accuracy: 0.5971 - val_loss: 1.5975 - val_accuracy: 0.4855 - lr: 2.0000e-04
Epoch 5/20
56/56 [==============================] - 25s 446ms/step - loss: 0.9928 - accuracy: 0.6468 - val_loss: 1.4673 - val_accuracy: 0.5011 - lr: 2.0000e-04
Epoch 6/20
56/56 [==============================] - 25s 444ms/step - loss: 0.7949 - accuracy: 0.7232 - val_loss: 1.4071 - val_accuracy: 0.4966 - lr: 2.0000e-04
Epoch 7/20
56/56 [==============================] - 25s 445ms/step - loss: 0.7055 - accuracy: 0.7433 - val_loss: 1.4668 - val_accuracy: 0.5168 - lr: 2.0000e-04
Epoch 8/20
56/56 [==============================] - 25s 446ms/step - loss: 0.6321 - accuracy: 0.7751 - val_loss: 1.4369 - val_accuracy: 0.5280 - lr: 2.0000e-04
Epoch 9/20
56/56 [==============================] - 25s 450ms/step - loss: 0.4832 - accuracy: 0.8259 - val_loss: 1.4817 - val_accuracy: 0.5324 - lr: 2.0000e-04
Epoch 10/20
56/56 [==============================] - 25s 445ms/step - loss: 0.4195 - accuracy: 0.8577 - val_loss: 1.4721 - val_accuracy: 0.5593 - lr: 2.0000e-04
Epoch 11/20
56/56 [==============================] - 25s 445ms/step - loss: 0.3262 - accuracy: 0.9029 - val_loss: 1.5220 - val_accuracy: 0.5772 - lr: 2.0000e-04
Epoch 12/20
56/56 [==============================] - 25s 446ms/step - loss: 0.2436 - accuracy: 0.9314 - val_loss: 1.6744 - val_accuracy: 0.5123 - lr: 2.0000e-04
Epoch 13/20
56/56 [==============================] - ETA: 0s - loss: 0.2096 - accuracy: 0.9386
Epoch 13: ReduceLROnPlateau reducing learning rate to 3.9999998989515007e-05.
56/56 [==============================] - 25s 445ms/step - loss: 0.2096 - accuracy: 0.9386 - val_loss: 1.5805 - val_accuracy: 0.5660 - lr: 2.0000e-04
Epoch 14/20
56/56 [==============================] - 25s 446ms/step - loss: 0.1438 - accuracy: 0.9598 - val_loss: 1.5014 - val_accuracy: 0.5772 - lr: 4.0000e-05
Epoch 15/20
56/56 [==============================] - ETA: 0s - loss: 0.1026 - accuracy: 0.9754
Epoch 15: ReduceLROnPlateau reducing learning rate to 7.999999797903002e-06.
56/56 [==============================] - 25s 446ms/step - loss: 0.1026 - accuracy: 0.9754
```

```
56/56 [==============================] - 25s 446ms/step - loss: 0.1026 - accuracy: 0.9754
- val_loss: 1.4951 - val_accuracy: 0.5705 - lr: 4.0000e-05
Epoch 16/20
56/56 [==============================] - 25s 455ms/step - loss: 0.0837 - accuracy: 0.9872
- val_loss: 1.4988 - val_accuracy: 0.5682 - lr: 8.0000e-06
Epoch 17/20
56/56 [==============================] - ETA: 0s - loss: 0.0837 - accuracy: 0.9849
Epoch 17: ReduceLROnPlateau reducing learning rate to 1.5999999959603884e-06.
56/56 [==============================] - 26s 457ms/step - loss: 0.0837 - accuracy: 0.9849
- val_loss: 1.5094 - val_accuracy: 0.5727 - lr: 8.0000e-06
Epoch 18/20
56/56 [==============================] - 25s 454ms/step - loss: 0.0804 - accuracy: 0.9877
- val_loss: 1.5169 - val_accuracy: 0.5772 - lr: 1.6000e-06
```

In [15]:

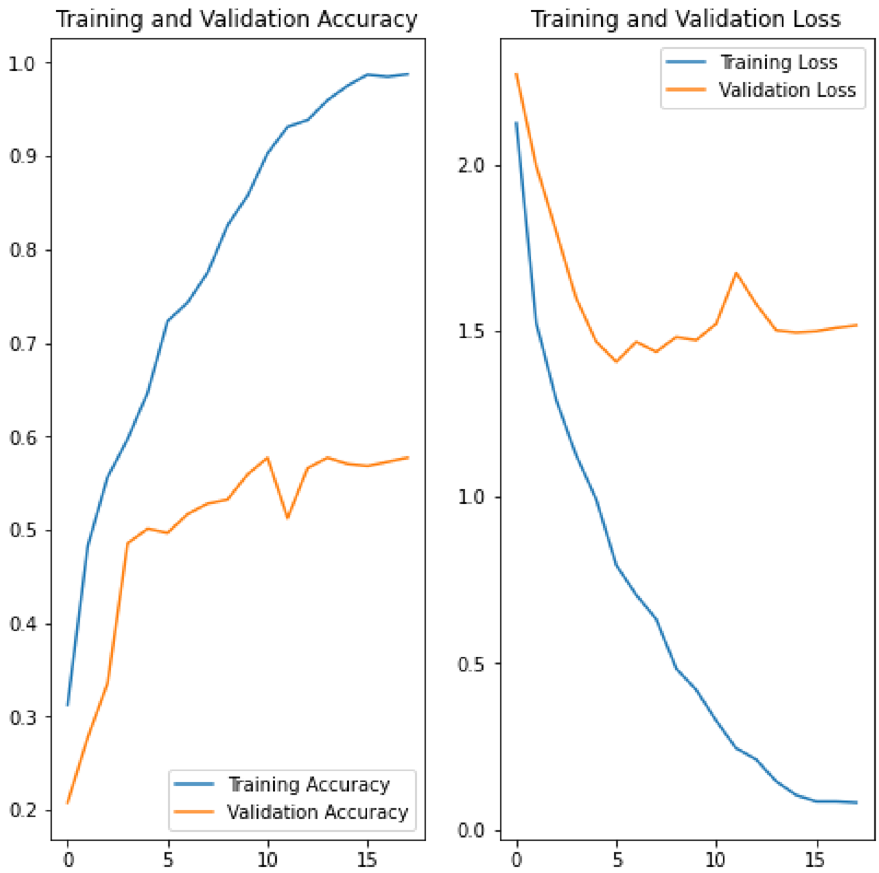
```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

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

epochs_range = history.epoch

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()
```



We see the model keeps on learning over training set , the accuracy does not get saturated , it keeps on increasing, but after 3rd epoch the accuracy saturates on validation data

Find the distribution of classes in the training dataset.

In [16]:

```
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','Labe
l'])
original_df
```

Out[16]:

	Path	Label
0	F:\Python Works\Malenoma Detection\Malenoma\Sk...	actinic keratosis
1	F:\Python Works\Malenoma Detection\Malenoma\Sk...	actinic keratosis
2	F:\Python Works\Malenoma Detection\Malenoma\Sk...	actinic keratosis
3	F:\Python Works\Malenoma Detection\Malenoma\Sk...	actinic keratosis
4	F:\Python Works\Malenoma Detection\Malenoma\Sk...	actinic keratosis
...	...	...
2234	F:\Python Works\Malenoma Detection\Malenoma\Sk...	vascular lesion
2235	F:\Python Works\Malenoma Detection\Malenoma\Sk...	vascular lesion
2236	F:\Python Works\Malenoma Detection\Malenoma\Sk...	vascular lesion
2237	F:\Python Works\Malenoma Detection\Malenoma\Sk...	vascular lesion
2238	F:\Python Works\Malenoma Detection\Malenoma\Sk...	vascular lesion

2239 rows × 2 columns

In [17]:

```
dataframe_dict_original = dict(zip(path_list, lesion_list))
original_df = pd.DataFrame(list(dataframe_dict_original.items()),columns = ['Path','Labe
l'])
original_df
```

Out[17]:

	Path	Label
0	F:\Python Works\Malenoma Detection\Malenoma\Sk...	actinic keratosis
1	F:\Python Works\Malenoma Detection\Malenoma\Sk...	actinic keratosis
2	F:\Python Works\Malenoma Detection\Malenoma\Sk...	actinic keratosis
3	F:\Python Works\Malenoma Detection\Malenoma\Sk...	actinic keratosis
4	F:\Python Works\Malenoma Detection\Malenoma\Sk...	actinic keratosis
...	...	...
2234	F:\Python Works\Malenoma Detection\Malenoma\Sk...	vascular lesion
2235	F:\Python Works\Malenoma Detection\Malenoma\Sk...	vascular lesion
2236	F:\Python Works\Malenoma Detection\Malenoma\Sk...	vascular lesion
2237	F:\Python Works\Malenoma Detection\Malenoma\Sk...	vascular lesion
2238	F:\Python Works\Malenoma Detection\Malenoma\Sk...	vascular lesion

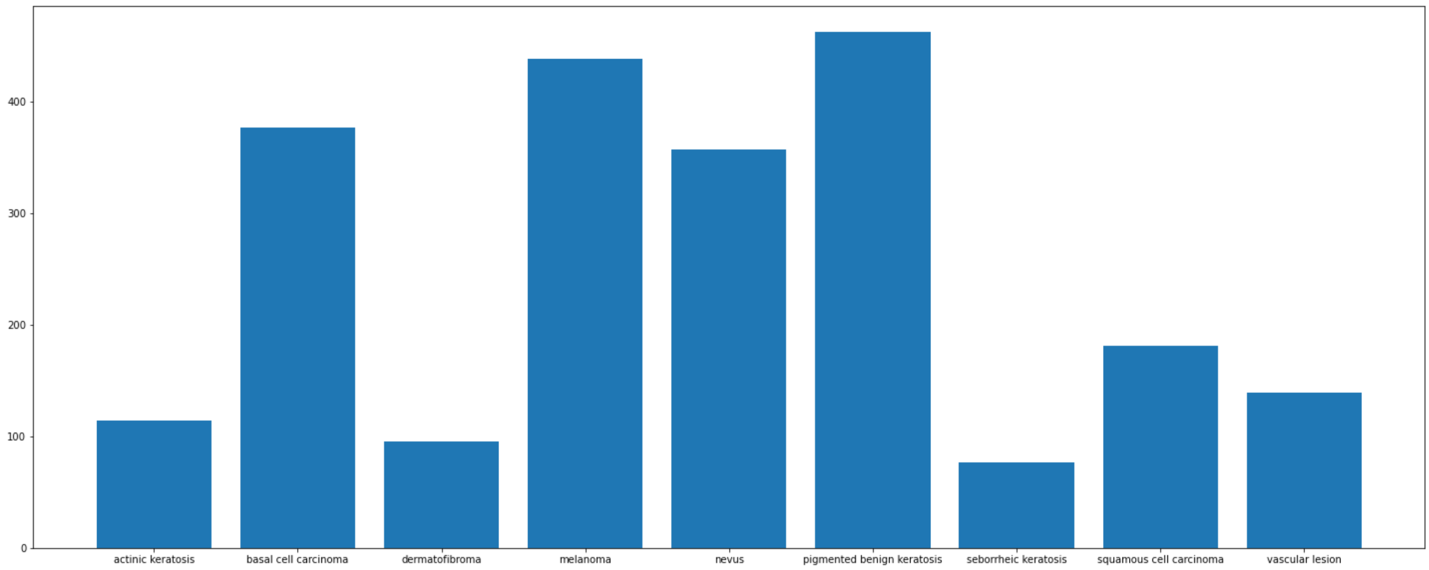
2239 rows × 2 columns

In [18]:

```
count=[]
for i in class_names:
    count.append(len(list(data_dir_train.glob(i+'/*.jpg'))))
plt.figure(figsize=(25,10))
plt.bar(class_names,count)
```

Out[18]:

```
<BarContainer object of 9 artists>
```



- **Which class has the least number of samples?**
- **Which classes dominate the data in terms proportionate number of samples?**

Answer-1 :- squamous cell carcinoma has least number of samples

Answer-2:- actinic keratosis and dermatofibroma have proportionate number of classes. melanoma and pigmented benign keratosis have proprtionate number of classes

Rectify the class imbalance

In [22]:

```
for i in class_names:
    p = Augmentor.Pipeline(r"F:\Python Works\Malenoma Detection\Malenoma\Skin cancer ISIC The International Skin Imaging Collaboration\Train",save_format='jpg')
    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 2239 image(s) found.
Output directory set to F:\Python Works\Malenoma Detection\Malenoma\Skin cancer ISIC The International Skin Imaging Collaboration\Train\output.
```

```
Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x207FC417280>: 100%|█| 500/500 [00:03<00:00, 159.12 Samples
```

```
Initialised with 2239 image(s) found.
Output directory set to F:\Python Works\Malenoma Detection\Malenoma\Skin cancer ISIC The International Skin Imaging Collaboration\Train\output.
```

```
Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x207F6C6F100>: 100%|█| 500/500 [00:03<00:00, 135.09 Samples
```

```
Initialised with 2239 image(s) found.
Output directory set to F:\Python Works\Malenoma Detection\Malenoma\Skin cancer ISIC The International Skin Imaging Collaboration\Train\output.
```

```
Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x207F634F760>: 100%|█| 500/500 [00:04<00:00, 102.57 Samples
```

```
Initialised with 2239 image(s) found.
Output directory set to F:\Python Works\Malenoma Detection\Malenoma\Skin cancer ISIC The International Skin Imaging Collaboration\Train\output.
```

```
Processing <PIL.Image.Image image mode=RGB size=963x629 at 0x207FA098F40>: 100%|█| 500/500 [00:04<00:00, 113.38 Samples
```

```
Initialised with 2239 image(s) found.
Output directory set to F:\Python Works\Malenoma Detection\Malenoma\Skin cancer ISIC The International Skin Imaging Collaboration\Train\output.
```

```
Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x207F69C93A0>: 100%|█| 500/500 [00:04<00:00, 105.16 Samples
```

```
Initialised with 2239 image(s) found.
Output directory set to F:\Python Works\Malenoma Detection\Malenoma\Skin cancer ISIC The International Skin Imaging Collaboration\Train\output.
```

```
Processing <PIL.Image.Image image mode=RGB size=1024x768 at 0x207FA07E580>: 100%|█| 500/500 [00:05<00:00, 97.02 Samples
```

```
Initialised with 2239 image(s) found.
Output directory set to F:\Python Works\Malenoma Detection\Malenoma\Skin cancer ISIC The International Skin Imaging Collaboration\Train\output.
```

```
Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x207F6BEC550>: 100%|█| 500/500 [00:05<00:00, 90.52 Samples/
```

```
Initialised with 2239 image(s) found.
Output directory set to F:\Python Works\Malenoma Detection\Malenoma\Skin cancer ISIC The International Skin Imaging Collaboration\Train\output.
```

```
Processing <PIL.JpegImagePlugin.JpegImageFile image mode=RGB size=600x450 at 0x207FA16D1C0>: 100%|█| 500/500 [00:06<00:
```

```
Initialised with 2239 image(s) found.
Output directory set to F:\Python Works\Malenoma Detection\Malenoma\Skin cancer ISIC The International Skin Imaging Collaboration\Train\output.
```

```
Processing <PIL.Image.Image image mode=RGB size=1024x768 at 0x207F81D37C0>: 100%|█| 500/500 [00:05<00:00, 97.69 Samples
```

In [23]:

```python
#Distribution of augmented data set
data_dir_train1 = pathlib.Path("F:\Python Works\Malenoma Detection\Malenoma\Skin cancer ISIC The International Skin Imaging Collaboration\Train\output")
image_count_train1 = len(list(data_dir_train1.glob('*/*.jpg')))
print(image_count_train1)
```

```
4500
```

In [24]:

```python
for i in class_names:

    for j in data_dir_train1.glob(i+'/*.jpg'):
        path_list.append(str(j))
        lesion_list.append(i)
dataframe_dict_original = dict(zip(path_list, lesion_list))
new_df = pd.DataFrame(list(dataframe_dict_original.items()),columns = ['Path','Label'])
new_df
```

Out[24]:

	Path	Label
0	F:\Python Works\Malenoma Detection\Malenoma\Sk...	actinic keratosis
1	F:\Python Works\Malenoma Detection\Malenoma\Sk...	actinic keratosis
2	F:\Python Works\Malenoma Detection\Malenoma\Sk...	actinic keratosis
3	F:\Python Works\Malenoma Detection\Malenoma\Sk...	actinic keratosis

4	**F:\Python Works\Malenoma Detection\Malenoma\Sk...**	**actinic keratosis**
...	**...**	**...**
6734	**F:\Python Works\Malenoma Detection\Malenoma\Sk...**	**vascular lesion**
6735	**F:\Python Works\Malenoma Detection\Malenoma\Sk...**	**vascular lesion**
6736	**F:\Python Works\Malenoma Detection\Malenoma\Sk...**	**vascular lesion**
6737	**F:\Python Works\Malenoma Detection\Malenoma\Sk...**	**vascular lesion**
6738	**F:\Python Works\Malenoma Detection\Malenoma\Sk...**	**vascular lesion**

6739 rows × 2 columns

In [25]:

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

Out[25]:

```
melanoma                      1365
pigmented benign keratosis    1357
basal cell carcinoma          1146
nevus                         1062
squamous cell carcinoma        520
vascular lesion                435
actinic keratosis              340
dermatofibroma                 294
seborrheic keratosis           220
Name: Label, dtype: int64
```

In [31]:

```
data_dir_train1=pathlib.Path(r"F:\Python Works\Malenoma Detection\Malenoma\Skin cancer ISIC The International Skin Imaging Collaboration\Train")
image_count_train1 = len(list(data_dir_train1.glob('*/*.jpg')))
print(image_count_train1)
```

```
6739
```

In [32]:

```
train_ds = tf.keras.preprocessing.image_dataset_from_directory(
  data_dir_train1,
  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.
```

In [33]:

```
val_ds = tf.keras.preprocessing.image_dataset_from_directory(
  data_dir_train1,
  seed=123,
  validation_split = 0.2,
  subset = 'validation',
  image_size=(img_height, img_width),
  batch_size=batch_size)
```

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

Final Model

In [34]:

```
#Data Augmentation
```

```
data_augument = keras.Sequential([
                              layers.experimental.preprocessing.Rescaling(1./255),
                              layers.experimental.preprocessing.RandomFlip(mode="horizont
al_and_vertical",input_shape=(img_height,img_width,3)),
                              layers.experimental.preprocessing.RandomRotation(0.2, fill_
mode='reflect'),
                              layers.experimental.preprocessing.RandomZoom(height_factor=
(0.2, 0.3), width_factor=(0.2, 0.3), fill_mode='reflect')
])
```

In [35]:

```
def downsample(channels, inputs):
    x = keras.layers.BatchNormalization(momentum=0.99)(inputs)
    x = keras.layers.LeakyReLU(0.03)(x)
    x = keras.layers.Conv2D(channels, 1, padding='same', use_bias=False)(x)
    x = keras.layers.MaxPool2D(3)(x)

    return x

def resblock(channels, inputs):
    x = keras.layers.BatchNormalization(momentum=0.99)(inputs)
    x = keras.layers.LeakyReLU(0.03)(x)
    x = keras.layers.Conv2D(channels, 3, padding='same', use_bias=False)(x)
    x = keras.layers.BatchNormalization(momentum=0.99)(x)
    x = keras.layers.LeakyReLU(0.03)(x)
    x = keras.layers.Conv2D(channels, 3, padding='same', use_bias=False)(x)
    return keras.layers.add([x, inputs])

def create_network(input_size, channels, n_blocks=2, depth=4):
    # input
    inputs = keras.Input(shape=(input_size, input_size, 3))
    x=data_augument(inputs)
    x = keras.layers.Conv2D(channels, 3, padding='same', use_bias=False)(inputs)
    # residual blocks
    for d in range(depth):
        channels = channels * 2
        x = downsample(channels, x)
        for b in range(n_blocks):
            x = resblock(channels, x)
    x=Dropout(.25)(x)
    x = keras.layers.BatchNormalization(momentum=0.99)(x)
    x = keras.layers.LeakyReLU(0.03)(x)
    outputs = keras.layers.Conv2D(256,(1,1))(x)

    outputs=MaxPool2D((2,2))(outputs)
    outputs=Dropout(.25)(outputs)
    outputs = keras.layers.Conv2D(128,(3,3))(outputs)
    #outputs = keras.layers.Conv2D(64,(3,3),2)(outputs)
    #outputs = keras.layers.Conv2D(32,(3,3), 2)(outputs)
    #outputs = keras.layers.Conv2D(16,(3,3), 2)(outputs)
    outputs = keras.layers.Conv2D(64,(1,1))(outputs)



    model = keras.Model(inputs=inputs, outputs=outputs)
    return model
```

In [36]:

```
model = create_network(input_size=180, channels=16, n_blocks=1, depth=3)
headModel=model.output
headModel=Flatten()(headModel)
headModel=Dense(9,activation="softmax")(headModel)
model = Model(inputs=model.input, outputs=headModel)
```

In [37]:

```
opt=Adam(learning_rate=2.0000e-04)
model.compile(loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True), opti
mizer=opt, metrics=['accuracy']) # Regression loss is MSE
```

```
#checkpoint = ModelCheckpoint("model-{accuracy:.2f}.h5", monitor="val_accuracy", verbose=1, save_best_only=True,
                             #save_weights_only=True, mode="max", period=1) # Checkpoint best validation model
stop = EarlyStopping(monitor="val_accuracy", patience=7, mode="max") # Stop early, if the validation error deteriorates
reduce_lr = ReduceLROnPlateau(monitor="val_accuracy", factor=0.2, patience=2, min_lr=1e-10, verbose=1, mode="max")
```

In [38]:

```
epochs = 20
history = model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs,
    callbacks=[ stop, reduce_lr]
)
```

```
Epoch 1/20
```

```
C:\Users\PC\AppData\Roaming\Python\Python39\site-packages\tensorflow\python\util\dispatch.py:1082: UserWarning: "`sparse_categorical_crossentropy` received `from_logits=True`, but the `output` argument was produced by a sigmoid or softmax activation and thus does not represent logits. Was this intended?"
  return dispatch_target(*args, **kwargs)
```

```
169/169 [==============================] - 81s 470ms/step - loss: 1.7237 - accuracy: 0.4273 - val_loss: 1.7392 - val_accuracy: 0.3630 - lr: 2.0000e-04
Epoch 2/20
169/169 [==============================] - 82s 485ms/step - loss: 1.2134 - accuracy: 0.5658 - val_loss: 1.0900 - val_accuracy: 0.6221 - lr: 2.0000e-04
Epoch 3/20
169/169 [==============================] - 83s 491ms/step - loss: 1.0378 - accuracy: 0.6276 - val_loss: 0.9910 - val_accuracy: 0.6563 - lr: 2.0000e-04
Epoch 4/20
169/169 [==============================] - 83s 487ms/step - loss: 0.8909 - accuracy: 0.6819 - val_loss: 0.8950 - val_accuracy: 0.6852 - lr: 2.0000e-04
Epoch 5/20
169/169 [==============================] - 83s 489ms/step - loss: 0.7555 - accuracy: 0.7302 - val_loss: 0.8668 - val_accuracy: 0.6793 - lr: 2.0000e-04
Epoch 6/20
169/169 [==============================] - 83s 488ms/step - loss: 0.6751 - accuracy: 0.7533 - val_loss: 0.7603 - val_accuracy: 0.7231 - lr: 2.0000e-04
Epoch 7/20
169/169 [==============================] - 83s 488ms/step - loss: 0.5929 - accuracy: 0.7917 - val_loss: 1.0119 - val_accuracy: 0.6392 - lr: 2.0000e-04
Epoch 8/20
169/169 [==============================] - 82s 486ms/step - loss: 0.5242 - accuracy: 0.8077 - val_loss: 0.6914 - val_accuracy: 0.7327 - lr: 2.0000e-04
Epoch 9/20
169/169 [==============================] - 82s 485ms/step - loss: 0.4418 - accuracy: 0.8364 - val_loss: 0.7443 - val_accuracy: 0.7305 - lr: 2.0000e-04
Epoch 10/20
169/169 [==============================] - 82s 484ms/step - loss: 0.3871 - accuracy: 0.8574 - val_loss: 0.5987 - val_accuracy: 0.7944 - lr: 2.0000e-04
Epoch 11/20
169/169 [==============================] - 82s 484ms/step - loss: 0.3515 - accuracy: 0.8698 - val_loss: 0.6030 - val_accuracy: 0.7981 - lr: 2.0000e-04
Epoch 12/20
169/169 [==============================] - 82s 487ms/step - loss: 0.3404 - accuracy: 0.8739 - val_loss: 0.6849 - val_accuracy: 0.7476 - lr: 2.0000e-04
Epoch 13/20
169/169 [==============================] - 82s 486ms/step - loss: 0.2901 - accuracy: 0.8897 - val_loss: 0.5186 - val_accuracy: 0.8010 - lr: 2.0000e-04
Epoch 14/20
169/169 [==============================] - 82s 485ms/step - loss: 0.2639 - accuracy: 0.8982 - val_loss: 0.4557 - val_accuracy: 0.8411 - lr: 2.0000e-04
Epoch 15/20
169/169 [==============================] - 82s 486ms/step - loss: 0.2701 - accuracy: 0.8939 - val_loss: 0.5287 - val_accuracy: 0.8211 - lr: 2.0000e-04
Epoch 16/20
```

```
Epoch 16/20
169/169 [==============================] - 82s 485ms/step - loss: 0.2585 - accuracy: 0.90
17 - val_loss: 0.4720 - val_accuracy: 0.8419 - lr: 2.0000e-04
Epoch 17/20
169/169 [==============================] - 82s 486ms/step - loss: 0.2341 - accuracy: 0.90
54 - val_loss: 0.5138 - val_accuracy: 0.8114 - lr: 2.0000e-04
Epoch 18/20
169/169 [==============================] - 83s 490ms/step - loss: 0.1777 - accuracy: 0.92
86 - val_loss: 0.4462 - val_accuracy: 0.8434 - lr: 2.0000e-04
Epoch 19/20
169/169 [==============================] - 82s 487ms/step - loss: 0.1778 - accuracy: 0.93
14 - val_loss: 0.4180 - val_accuracy: 0.8552 - lr: 2.0000e-04
Epoch 20/20
169/169 [==============================] - 83s 491ms/step - loss: 0.2160 - accuracy: 0.91
62 - val_loss: 0.5734 - val_accuracy: 0.8062 - lr: 2.0000e-04
```

In [39]:

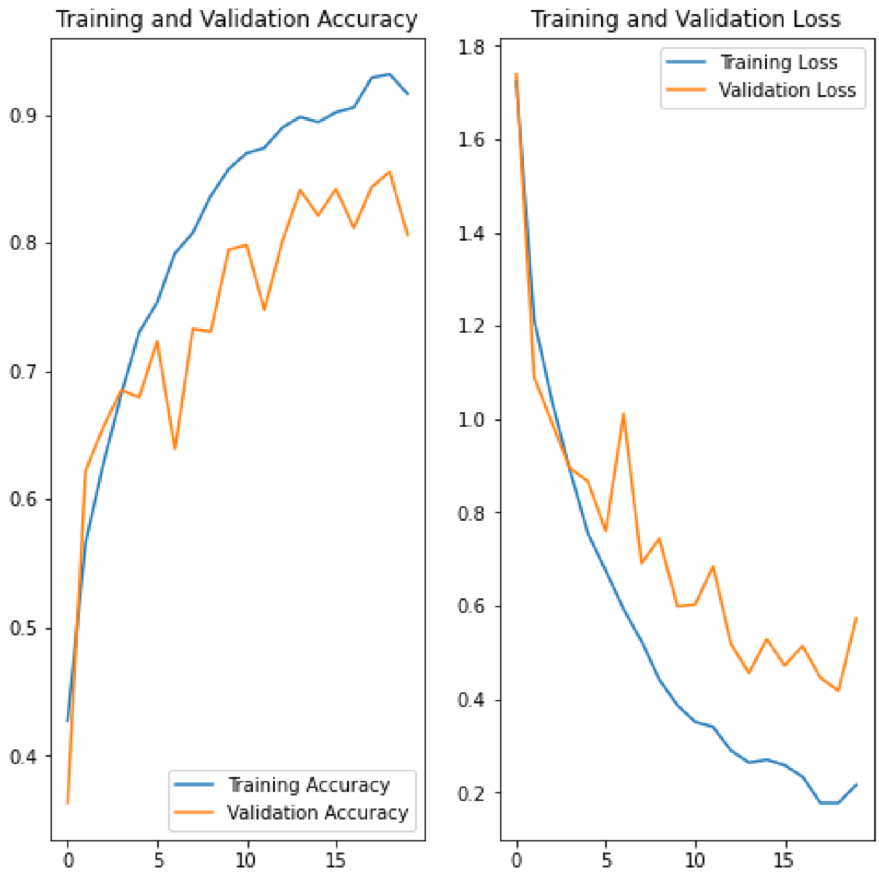
```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

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

epochs_range = history.epoch

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()
```



We see as compared to previous models , accuracy and loss over training and validation set shows steady increase and decrease. The model exhibits similar learning curve path over train and validation set, it's just that

model performanc over validation set is more volatile. There is a bit over-fitting seen.

In [ ]: