

In [1]: `from tensorflow.keras import layers`

C:\Users\krishnendu\Desktop\sample_project\env\lib\site-packages\scipy__init__.py:146: UserWarning: A NumPy version >=1.16.5 and <1.23.0 is required for this version of SciPy (detected version 1.24.3
 warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}")

In [2]: `import pathlib`

In [3]: `import tensorflow as tf`

In [4]: `from tensorflow import keras
 from tensorflow.keras.models import Sequential`

In [5]: `import matplotlib.pyplot as plt
 import numpy as np
 import pandas as pd
 import os
 import PIL`

In [6]: `''' train_ds have totle 2239
 test_ds have totle 118 files
 totle =2357 files , and train and test have 9 classe
 ...`

Out[6]: ' train_ds have totle 2239\n test_ds have totle 118 files \n totle =2357 files , and train and test have 9 classe \n'

Create a dataset

Some parameter of data loader

In [7]: `batch_size = 32 # the number of images to be processed in each batch during training
 #that the model will process 32 images at a time before updating the weights.

 channel = 3 # indicates the number of color channels in the images. In this case, 3
 # representing the Red, Green, and Blue (RGB) channels.

 img_height = 180
 img_width = 180 #images will be resized or cropped to these dimensions`

In [8]: `# Writing the train dataset
 # Resize the images with the mentioned image dimensions

 train_data = keras.preprocessing.image_dataset_from_directory(r"Skin cancer ISIC T1",
 shuffle=True,
 image_size=(img_height, img_width),
 batch_size=batch_size,
)`

Found 2239 files belonging to 9 classes.

In [9]: `len(train_data)`

Out[9]: 70

The totle files is 2239 and btach_size is 32

$\text{totole_batch} = (2239/32) \sim 70$

its mean 70 iteration

```
In [10]: ## Numbar of classes in the training data set
train_data.class_names
```

```
Out[10]: ['act_keratosis',
'basal_carc',
'dermatofibroma',
'melanoma',
'nevus',
'pig_kerato',
'sebo_kerato',
'squamous_car',
'vas_lesion']
```

- 'act_keratosis' : 'actinic keratosis',
- 'basal_carc' : 'basal cell carcinoma',
- 'dermatofibroma' : 'dermatofibroma',
- 'melanoma' : 'melanoma',
- 'nevus' : 'nevus',
- 'pig_kerato' : 'pigmented benign keratosis',
- 'sebo_kerato' : 'seborrheic keratosis',
- 'squamous_car' : 'squamous cell carcinoma',
- 'vas_lesion' : 'vascular lesion'

```
In [11]: # Writting the validation dataset
# Resize the images with the mentioned image dimensions

val_data = keras.preprocessing.image_dataset_from_directory(r"Skin cancer ISIC The
                                                            shuffle=True,
                                                            image_size=(img_height,
                                                            batch_size=batch_size)
                                                            )
```

Found 118 files belonging to 9 classes.

The totle files is 118 and btach_size is 32

$\text{totole_batch} = (118/32) \sim 4$

its mean 4 iteration

```
In [12]: len(val_data)
```

```
Out[12]: 4
```

```
In [13]: ## Numbar of classes in the validation data set
val_data.class_names
```

```
Out[13]: ['act_keratosis',  
          'basal_carc',  
          'dermatofibroma',  
          'melanoma',  
          'nevus',  
          'pig_kerato',  
          'sebo_kerato',  
          'squamous_car',  
          'vas_lesion']
```

```
In [14]: val_data
```

```
Out[14]: <BatchDataset element_spec=(TensorSpec(shape=(None, 180, 180, 3), dtype=tf.float32, name=None), TensorSpec(shape=(None,), dtype=tf.int32, name=None))>
```

```
In [15]: train_data
```

```
Out[15]: <BatchDataset element_spec=(TensorSpec(shape=(None, 180, 180, 3), dtype=tf.float32, name=None), TensorSpec(shape=(None,), dtype=tf.int32, name=None))>
```

The data type is tensor

```
In [16]: # convert simple form  
# fetch 1 batch , 1 batch have 32 files  
for img_batch, label_batch in val_data.take(1):  
    print("This is one batch shape : ", img_batch.shape)  
    print("The label shape is :", label_batch.shape)
```

```
This is one batch shape : (32, 180, 180, 3)  
The label shape is : (32,)
```

```
In [17]: ## Normal form  
for img_batch, label_batch in train_data.take(1):  
    print(img_batch.numpy())  
    print("\n")  
    print("Convergt the label in numeric",label_batch.numpy())
```

```

[[[170.41667 150.45833 149.41666 ]
  [173.875 156.625 160. ]
  [176.875 157.91667 163.16667 ]
  ...
  [161.7084 135.37503 141.62503 ]
  [160.375 133.5 143.125 ]
  [159.62502 134.37502 143.37505 ]]]

[[172.83334 153.08333 152.08333 ]
  [174.875 158.75 162.125 ]
  [176. 157.375 159.91666 ]
  ...
  [161.91669 137.0416 143.74994 ]
  [161.75 136.875 146.75 ]
  [161.04167 136.66669 149.2083 ]]]

[[174.625 154.20833 154.29166 ]
  [176.625 157.125 163.25 ]
  [175.91667 158.79167 161.75 ]
  ...
  [161.58331 139.83331 150.66663 ]
  [162.875 139.875 152.375 ]
  [163.7917 139.75 150.45839 ]]]

...

[[157.33334 131.875 132.91667 ]
  [157.125 132.125 131.625 ]
  [150.54166 125.16667 125.41667 ]
  ...
  [148.0416 121.416565 125.666626]
  [144.25 117. 121.875 ]
  [142.95833 113.95833 117.29164 ]]]

[[154.91667 130.45833 131.20833 ]
  [158.125 132.125 134.625 ]
  [154.20833 125.875 128.79167 ]
  ...
  [146.2916 117.99994 121.83325 ]
  [145.125 116.5 119.75 ]
  [141.99997 115.874954 117.16666 ]]]

[[159.58334 130.70834 133.41667 ]
  [157.875 131.25 134.375 ]
  [156.66666 128.79166 132.33334 ]
  ...
  [142.99994 116.50006 119.66669 ]
  [142.375 113.375 117.875 ]
  [145.99994 117.99994 116.99994 ]]]

[[[195.79167 134.91667 130.375 ]
  [195.75 134.25 130.375 ]
  [193.5 130.91666 128.33333 ]
  ...
  [187.00006 121.83331 126.00006 ]
  [187.25 125.625 122.5 ]
  [185.83331 125.12508 123.625046]]]

[[196.29167 133.75 130.91667 ]
  [198.375 133.5 139.25 ]
  [194.58333 128.16667 127.333336]
  ...
  [186.29147 127.458405 130.12479 ]

```

```

[[[216.73334 152.73334 106.73333 ]
  [217.      154.      110.      ]
  [217.01295 155.01295 108.01296 ]
  ...
  [219.72217 157.72217 108.72217 ]
  [215.63333 153.63333 103.9      ]
  [220.42929 162.42929 115.69596 ]]]

[[[213.65445 150.65445 106.65444 ]
  [217.00333 154.00333 111.003334]
  [216.1      155.1      110.1      ]
  ...
  [217.62216 157.62216 107.62217 ]
  [219.83669 159.63669 109.73669 ]
  [217.80998 160.60999 115.70998 ]]]

[[[216.39075 151.89075 104.39074 ]
  [217.20001 152.70001 108.86667 ]
  [217.9352  153.4352  107.60185 ]
  ...
  [216.72217 154.48145 106.71281 ]
  [215.03333 155.03333 103.033325]
  [216.53523 155.53523 110.535225]]]

...

[[[224.59816 155.59816 116.59816 ]
  [224.39987 155.39987 114.23325 ]
  [225.5556  156.5556  115.555595]
  ...
  [227.4166  163.69443 119.97226 ]
  [228.      166.49988 127.33325 ]
  [233.28703 173.28703 136.28703 ]]]

[[[227.44449 158.44449 116.54452 ]
  [224.13004 153.13004 110.92996 ]
  [228.50002 156.20007 112.70555 ]
  ...
  [230.14449 166.35008 127.37209 ]
  [234.96335 172.06339 129.26346 ]
  [233.83438 172.03445 135.13449 ]]]

[[[225.41516 152.78186 117.948364]
  [224.      154.3667  118.5332  ]
  [226.92595 157.45563 121.19078 ]
  ...
  [229.53142 165.80925 120.364914]
  [232.6544  174.0211  134.0211  ]
  [228.24432 168.61102 129.77753 ]]]]

```

Convergt the label in numeric [1 5 4 4 1 3 7 7 5 1 1 8 5 5 7 5 7 5 8 8 5 5 4 1 5 2
7 1 4 4 3 4]

```
In [18]: class_names = train_data.class_names
```

Visualize the data

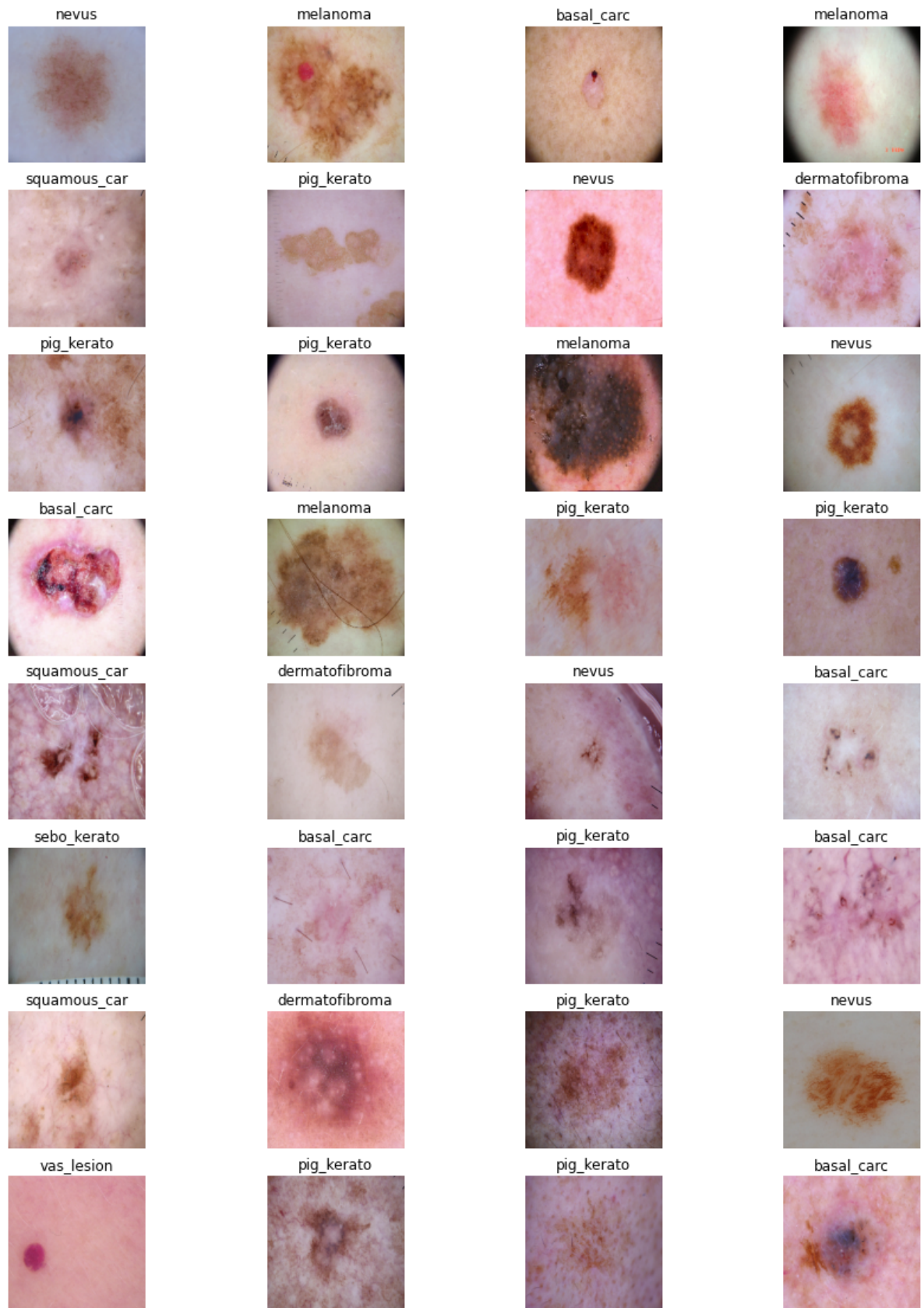
Todo, create a code to visualize one instance of all the nine classes present in the dataset

```
In [19]: import matplotlib.pyplot as plt
plt.figure(figsize=(15,20))

# The visualisation of training data has been done here
for image_batch , labels_batch in train_data.take(1):
    print(image_batch.shape)
    print(labels_batch.numpy())
    for i in range(32):
        plt.subplot(8,4,i+1)
        plt.imshow(image_batch[i].numpy().astype('uint8'))
        plt.title(class_names[labels_batch[i]])
        plt.axis('off')
```

(32, 180, 180, 3)

[4 3 1 3 7 5 4 2 5 5 3 4 1 3 5 5 7 2 4 1 6 1 5 1 7 2 5 4 8 5 5 1]



The *img_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 [20]: # increass the perfomance
autotune = tf.data.experimental.AUTOTUNE
train_data = train_data.shuffle(1000).prefetch(buffer_size= autotune)
val_data = val_data.shuffle(1000).prefetch(buffer_size = autotune)

In [21]: # Resize and Rescale the values
resize_and_resacle = keras.Sequential([
    keras.layers.experimental.preprocessing.Resizing(img_height,img_width),
    keras.layers.experimental.preprocessing.Rescaling(1.0/255)
])

In [22]: ## Data augentation
data_augmentation = keras.Sequential([
    keras.layers.experimental.preprocessing.RandomFlip('horizontal_and_vertical'),
    keras.layers.experimental.preprocessing.RandomRotation(0.3)
])
```

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 [23]: from tensorflow.keras.layers import Dense, Dropout, Activation, Flatten, Conv2D, MaxPooling2D

In [24]: input_shape = (batch_size , img_height , img_width , channel)
n_class = len(class_names)

In [25]: ## CREAT CNN MODEL
model = Sequential()

model.add(resize_and_resacle)
model.add(data_augmentation)

## Covlutional Layes
model.add(Conv2D(32,kernel_size=(3,3),padding='same', activation='relu',input_shape=input_shape))
model.add(Conv2D(64,kernel_size=(3,3),padding='same', activation='relu'))
model.add(MaxPooling2D(2,2))

model.add(Conv2D(64,kernel_size = (3,3), padding= 'same', activation= 'relu'))
model.add(MaxPooling2D(2,2))
model.add(Flatten())

## Add dense layers to connect the layers
model.add(Dense(32, activation= 'relu'))
model.add(Dense(64, activation= 'relu'))

## Add dropout as regularisation
model.add(Dropout(0.10))
model.add(Dense(n_class))
```

Compile the model

Choose an appropriate optimiser and loss function for model training

In CNN models, various optimizers and loss functions are used to train the network effectively and optimize the learning process. Here are some commonly used optimizers and loss functions in CNN models, along with their functionalities and typical usage:

Optimizers:

Stochastic Gradient Descent (SGD):

Functionality: SGD is a classic optimization algorithm that updates the model's weights based on the gradients computed on small batches of training data. Usage: SGD is a simple optimizer often used as a baseline. It can be effective for training shallow CNN models or when dealing with limited computational resources.

Adam:

Functionality: Adam is an adaptive optimization algorithm that combines the benefits of both AdaGrad and RMSProp. It adjusts the learning rate adaptively based on the gradients' magnitudes. Usage: Adam is a popular optimizer choice in CNN models. It performs well across a wide range of problems and provides faster convergence compared to SGD.

Adagrad:

Functionality: Adagrad adapts the learning rate for each parameter based on the historical gradients. It reduces the learning rate more for frequently updated parameters. Usage: Adagrad is suitable when dealing with sparse data or when different features have significantly different frequencies. It can handle learning rate scheduling automatically.

RMSProp:

Functionality: RMSProp also adapts the learning rate based on the moving average of squared gradients. It divides the learning rate by a running average of the recent gradient magnitudes. Usage: RMSProp is effective in dealing with non-stationary or noisy gradients. It is commonly used in CNN models and performs well in various scenarios.

Loss Functions:

Binary Crossentropy:

Functionality: Binary Crossentropy is used for binary classification tasks, where the model predicts probabilities for two classes. Usage: Binary Crossentropy is typically used as the loss function in the output layer of CNN models when performing binary classification tasks.

Categorical Crossentropy:

Functionality: Categorical Crossentropy is suitable for multi-class classification tasks, where the model predicts probabilities across multiple mutually exclusive classes. Usage: Categorical Crossentropy is commonly used as the loss function in the output layer of CNN models for multi-class classification tasks.

Mean Squared Error (MSE):

Functionality: MSE calculates the average squared difference between the predicted and target values. It is often used for regression tasks. Usage: MSE is commonly used as the loss function in CNN models when performing regression tasks, such as predicting continuous values or coordinates.

Sparse Categorical Crossentropy:

Functionality: Sparse Categorical Crossentropy is similar to Categorical Crossentropy but accepts integer labels instead of one-hot encoded vectors. Usage: Sparse Categorical Crossentropy is used as the loss function in the output layer of CNN models for multi-class classification tasks with integer labels.

```
In [26]: ### Here we have to choose an appropriate optimiser and also a loss function
model.compile(optimizer= 'adam',
              loss = keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              #expected to be a logits tensor. By #default, we assume that `y_pre
              #CNN models for multi-class classification tasks with integer labels
              metrics=['accuracy'])
```

```
In [27]: model.build(input_shape)
```

WARNING:tensorflow:Using a while_loop for converting RngReadAndSkip 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 Bitcast cause there is no registered converter for this op.
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WARNING:tensorflow:Using a while_loop for converting StatelessRandomUniformV2 cause there is no registered converter for this op.
WARNING:tensorflow:Using a while_loop for converting ImageProjectiveTransformV3 cause there is no registered converter for this op.

```
In [28]: # View the summary of all layers
model.summary()
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
=====		
sequential (Sequential)	(32, 180, 180, 3)	0
sequential_1 (Sequential)	(None, 180, 180, 3)	0
conv2d (Conv2D)	(None, 180, 180, 32)	896
conv2d_1 (Conv2D)	(None, 180, 180, 64)	18496
max_pooling2d (MaxPooling2D)	(None, 90, 90, 64)	0
conv2d_2 (Conv2D)	(None, 90, 90, 64)	36928
max_pooling2d_1 (MaxPooling2D)	(None, 45, 45, 64)	0
flatten (Flatten)	(None, 129600)	0
dense (Dense)	(None, 32)	4147232
dense_1 (Dense)	(None, 64)	2112
dropout (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 9)	585
=====		
Total params: 4,206,249		
Trainable params: 4,206,249		
Non-trainable params: 0		

```
In [29]: epochs = 10

history = model.fit(train_data, validation_data= val_data, epochs=epochs)
```

Epoch 1/10

WARNING:tensorflow:Using a while_loop for converting RngReadAndSkip cause there is no registered converter for this op.
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WARNING:tensorflow:Using a while_loop for converting ImageProjectiveTransformV3 cause there is no registered converter for this op.

70/70 [=====] - 220s 3s/step - loss: 2.0347 - accuracy: 0.2144 - val_loss: 2.1485 - val_accuracy: 0.2288

Epoch 2/10

70/70 [=====] - 226s 3s/step - loss: 1.8645 - accuracy: 0.3198 - val_loss: 2.3261 - val_accuracy: 0.3220

Epoch 3/10

70/70 [=====] - 206s 3s/step - loss: 1.6526 - accuracy: 0.4288 - val_loss: 2.0924 - val_accuracy: 0.3475

Epoch 4/10

70/70 [=====] - 197s 3s/step - loss: 1.5123 - accuracy: 0.4730 - val_loss: 2.1662 - val_accuracy: 0.3390

Epoch 5/10

70/70 [=====] - 202s 3s/step - loss: 1.4644 - accuracy: 0.5060 - val_loss: 2.1836 - val_accuracy: 0.3305

Epoch 6/10

70/70 [=====] - 206s 3s/step - loss: 1.3763 - accuracy: 0.5252 - val_loss: 2.0576 - val_accuracy: 0.3729

Epoch 7/10

70/70 [=====] - 203s 3s/step - loss: 1.3472 - accuracy: 0.5284 - val_loss: 2.1824 - val_accuracy: 0.3814

Epoch 8/10

70/70 [=====] - 209s 3s/step - loss: 1.3252 - accuracy: 0.5360 - val_loss: 2.1387 - val_accuracy: 0.3814

Epoch 9/10
 70/70 [=====] - 221s 3s/step - loss: 1.3099 - accuracy: 0.5333 - val_loss: 2.1448 - val_accuracy: 0.3814
 Epoch 10/10
 70/70 [=====] - 209s 3s/step - loss: 1.2863 - accuracy: 0.5395 - val_loss: 1.9936 - val_accuracy: 0.3559

```
In [30]: # accuracy of model each epochs
print("Accuracy propagation :",history.history['accuracy'])
print('\n')
# validation accuracy of model each epochs
print("Validation accuracy propagation :",history.history['val_accuracy'])
print('\n')

#Loss of model each epochs
print("Loss propagation through epochs",history.history["loss"])
```

Accuraccy propagation : [0.21438142657279968, 0.31978562474250793, 0.42876285314559937, 0.47297900915145874, 0.506029486656189, 0.5252344608306885, 0.528360903263092, 0.5359535217285156, 0.5332737565040588, 0.5395265817642212]

Validation accuracy propagation : [0.2288135588169098, 0.32203391194343567, 0.347457617521286, 0.33898305892944336, 0.3305084705352783, 0.37288135290145874, 0.381359412956238, 0.3813559412956238, 0.3813559412956238, 0.35593220591545105]

Loss propagation through epochs [2.034680128097534, 1.8644813299179077, 1.6525657176971436, 1.5122623443603516, 1.464416742324829, 1.3762773275375366, 1.3471523523330688, 1.3252204656600952, 1.3099390268325806, 1.2862755060195923]

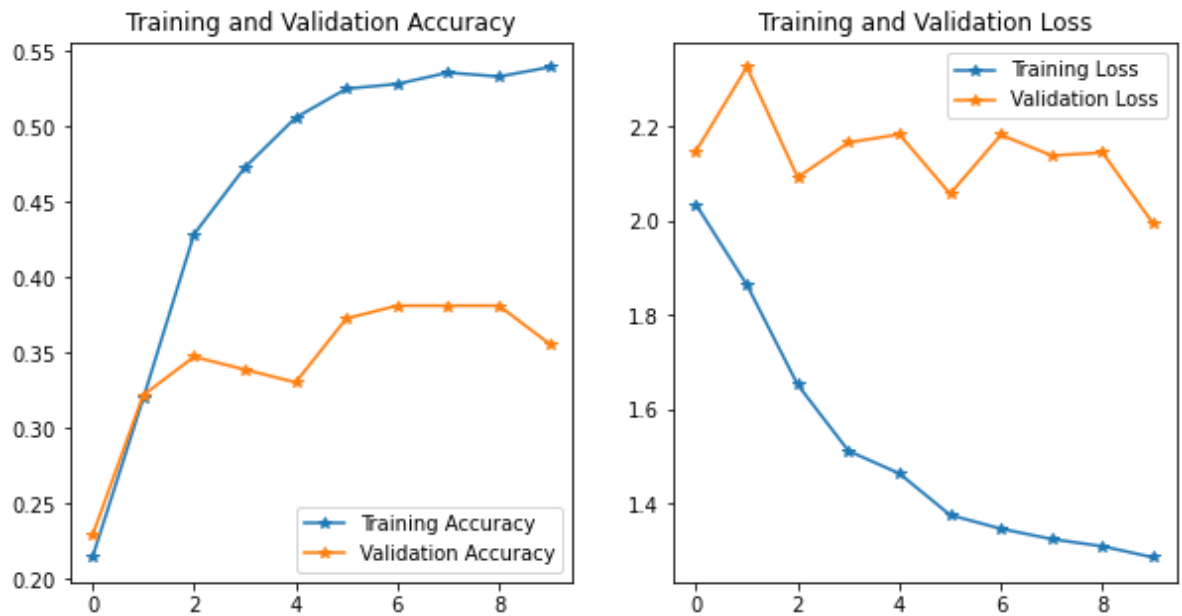
```
In [31]: acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

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

epochs_range = range(epochs)

plt.figure(figsize=(10, 5))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy',marker = '*')
plt.plot(epochs_range, val_acc, label='Validation Accuracy',marker = '*')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

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



Findings of the model (Underfit or Overfit)

The **Training_accuracy** = 0.50 and the **Validation accuracy** = 0.35 Which both are very less, So the model is clearly **underfit**

Sol = We will different augmentation to create more datas.

```
In [32]: import warnings

# Ignore all warnings
warnings.filterwarnings("ignore")

# Your code here

# Reset warning behavior (optional)
warnings.resetwarnings()
```

```
In [33]: data_augmentation = keras.Sequential([
    keras.layers.experimental.preprocessing.RandomFlip('horizontal', input_shape=(img_height, img_width, 3)),
    keras.layers.experimental.preprocessing.RandomRotation(0.1),
    keras.layers.experimental.preprocessing.RandomZoom(0.1)
])
```

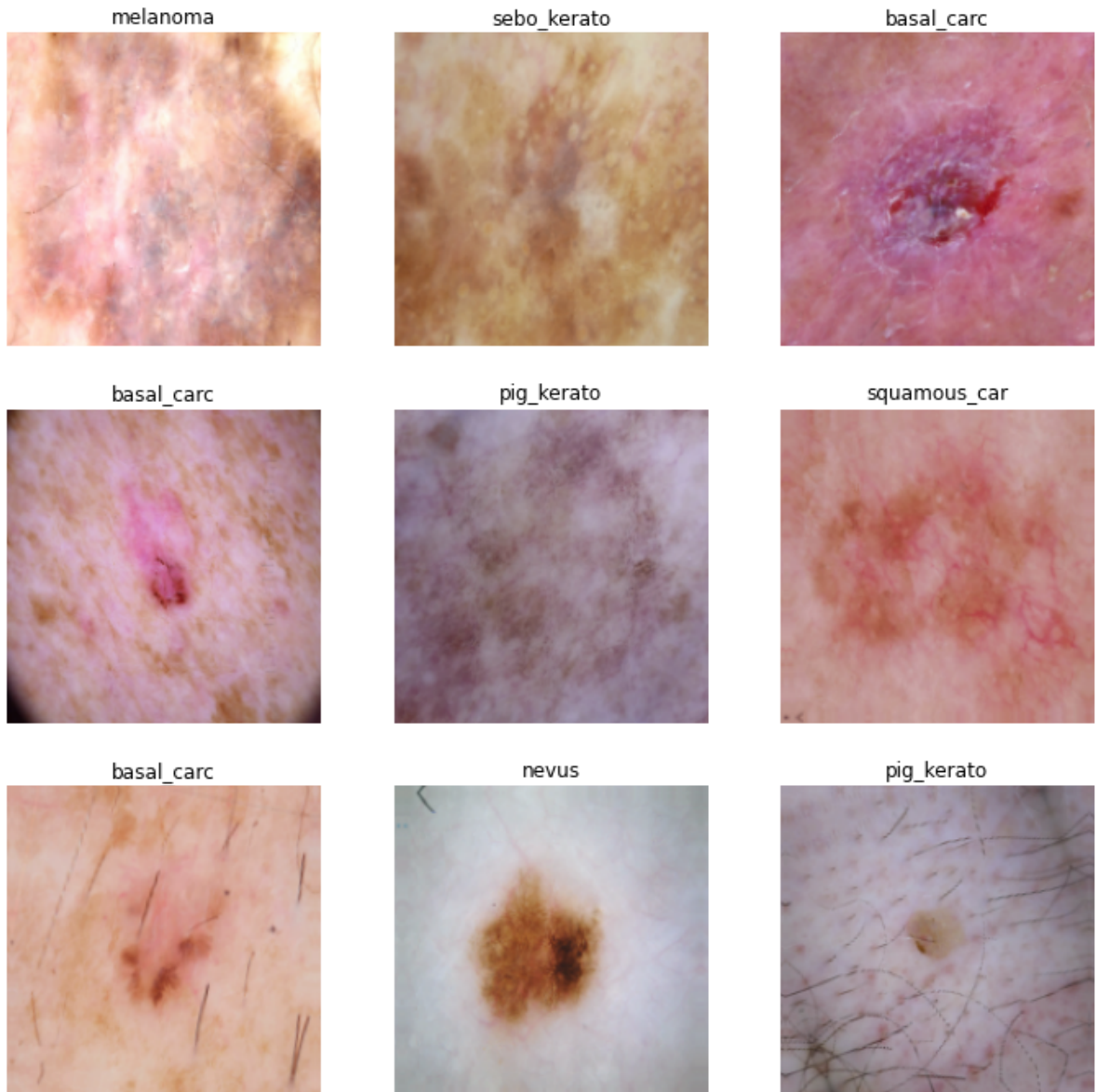
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WARNING:tensorflow:Using a while_loop for converting ImageProjectiveTransformV3 cause there is no registered converter for this op.

```
In [34]: # Todo, visualize how your augmentation strategy works for one instance of training
# Your code goes here
plt.figure(figsize=(12, 12))
for images, labels in train_data.take(1):
    for i in range(9):
        augmented_images = data_augmentation(images)
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(augmented_images[i].numpy().astype("uint8"))
        plt.title(class_names[labels[i]])
        plt.axis("off")
```

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 registered converter for this op.

WARNING:tensorflow:Using a while_loop for converting ImageProjectiveTransformV3 cause there is no registered converter for this op.



Create the model, compile and train the model

In [35]: *## You can use Dropout Layer if there is an evidence of overfitting in your finding*

Your code goes here

```
model = Sequential()
model.add(data_augmentation)
model.add(resize_and_resacle)

model.add(Conv2D(16, kernel_size= (3,3), padding='same',activation='relu'))
model.add(MaxPooling2D(2,2))

model.add(Conv2D(32,kernel_size=(3,3), padding='same',activation='relu'))
model.add(MaxPooling2D(2,2))
```



```
model.add(Conv2D(64, kernel_size=(3,3), padding='same',activation='relu'))
model.add(MaxPooling2D(2,2))

model.add(Dropout(0.2))
model.add(Flatten())

model.add(Dense(128,activation='relu'))
model.add(Dense(n_class))
```

WARNING:tensorflow:Using a while_loop for converting RngReadAndSkip 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 Bitcast cause there is no registered converter for this op.
WARNING:tensorflow:Using a while_loop for converting StatelessRandomUniformV2 cause there is no registered converter for this op.
WARNING:tensorflow:Using a while_loop for converting ImageProjectiveTransformV3 cause there is no registered converter for this op.
WARNING:tensorflow:Using a while_loop for converting RngReadAndSkip 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 Bitcast cause there is no registered converter for this op.
WARNING:tensorflow:Using a while_loop for converting StatelessRandomUniformV2 cause there is no registered converter for this op.
WARNING:tensorflow:Using a while_loop for converting ImageProjectiveTransformV3 cause there is no registered converter for this op.

Compiling the model

```
In [36]: model.compile(optimizer='adam',
                      loss=keras.losses.SparseCategoricalCrossentropy(from_logits=True),
                      metrics=['accuracy'])
```

Training the model

```
In [37]: history = model.fit(train_data , validation_data= val_data, epochs=10)
```

Epoch 1/10

WARNING:tensorflow:Using a while_loop for converting RngReadAndSkip 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 Bitcast cause there is no registered converter for this op.
WARNING:tensorflow:Using a while_loop for converting StatelessRandomUniformV2 cause there is no registered converter for this op.
WARNING:tensorflow:Using a while_loop for converting ImageProjectiveTransformV3 cause there is no registered converter for this op.
WARNING:tensorflow:Using a while_loop for converting RngReadAndSkip 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 Bitcast cause there is no registered converter for this op.
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WARNING:tensorflow:Using a while_loop for converting ImageProjectiveTransformV3 cause there is no registered converter for this op.
WARNING:tensorflow:Using a while_loop for converting RngReadAndSkip 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.
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WARNING:tensorflow:Using a while_loop for converting StatelessRandomUniformV2 cause there is no registered converter for this op.
WARNING:tensorflow:Using a while_loop for converting ImageProjectiveTransformV3 cause there is no registered converter for this op.
WARNING:tensorflow:Using a while_loop for converting RngReadAndSkip 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 Bitcast cause there is no registered converter for this op.
WARNING:tensorflow:Using a while_loop for converting StatelessRandomUniformV2 cause there is no registered converter for this op.
WARNING:tensorflow:Using a while_loop for converting ImageProjectiveTransformV3 cause there is no registered converter for this op.
70/70 [=====] - 62s 708ms/step - loss: 2.0961 - accuracy: 0.2309 - val_loss: 2.2464 - val_accuracy: 0.1780

Epoch 2/10

70/70 [=====] - 61s 765ms/step - loss: 1.7298 - accuracy: 0.3573 - val_loss: 2.1644 - val_accuracy: 0.2458

Epoch 3/10

70/70 [=====] - 62s 728ms/step - loss: 1.5145 - accuracy: 0.4640 - val_loss: 2.5041 - val_accuracy: 0.3136

Epoch 4/10

70/70 [=====] - 62s 758ms/step - loss: 1.4057 - accuracy: 0.5083 - val_loss: 2.0894 - val_accuracy: 0.4068

Epoch 5/10

70/70 [=====] - 61s 756ms/step - loss: 1.3915 - accuracy: 0.5074 - val_loss: 2.0829 - val_accuracy: 0.3305

Epoch 6/10

70/70 [=====] - 58s 730ms/step - loss: 1.3095 - accuracy: 0.5458 - val_loss: 2.2683 - val_accuracy: 0.3559

Epoch 7/10

70/70 [=====] - 63s 769ms/step - loss: 1.2741 - accuracy: 0.5440 - val_loss: 2.2635 - val_accuracy: 0.3305

Epoch 8/10

70/70 [=====] - 60s 732ms/step - loss: 1.2622 - accuracy: 0.5502 - val_loss: 2.1194 - val_accuracy: 0.3559

Epoch 9/10

70/70 [=====] - 60s 743ms/step - loss: 1.2709 - accuracy:

0.5476 - val_loss: 2.3111 - val_accuracy: 0.3051

Epoch 10/10

70/70 [=====] - 62s 740ms/step - loss: 1.1920 - accuracy:

0.5744 - val_loss: 2.2799 - val_accuracy: 0.2797

Visualizing the results

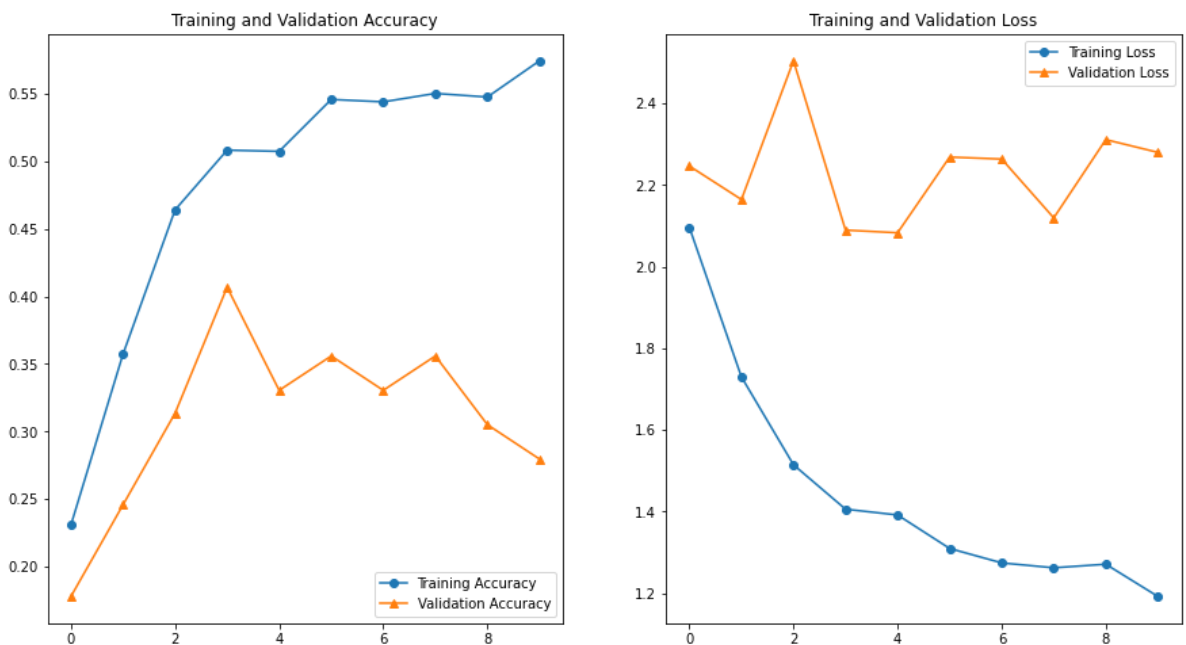
```
In [38]: acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

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

epochs_range = range(epochs)

plt.figure(figsize=(15, 8))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy',marker = 'o')
plt.plot(epochs_range, val_acc, label='Validation Accuracy',marker = '^')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss',marker = 'o')
plt.plot(epochs_range, val_loss, label='Validation Loss',marker = '^')
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? This model like underfitting beacuse

Traning accuracy = 57 and

Validation accuracy = 44

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 [40]: data_dir = pathlib.Path(r"Skin cancer ISIC The International Skin Imaging Collabora
```

```
In [41]: image_count_train = len(list(data_dir.glob('*/*.jpg'))) ## How many images are there
print(image_count_train)
```

2239

```
In [42]: class_names
```

```
Out[42]: ['act_keratosis',
          'basal_carc',
          'dermatofibroma',
          'melanoma',
          'nevus',
          'pig_kerato',
          'sebo_kerato',
          'squamous_car',
          'vas_lesion']
```

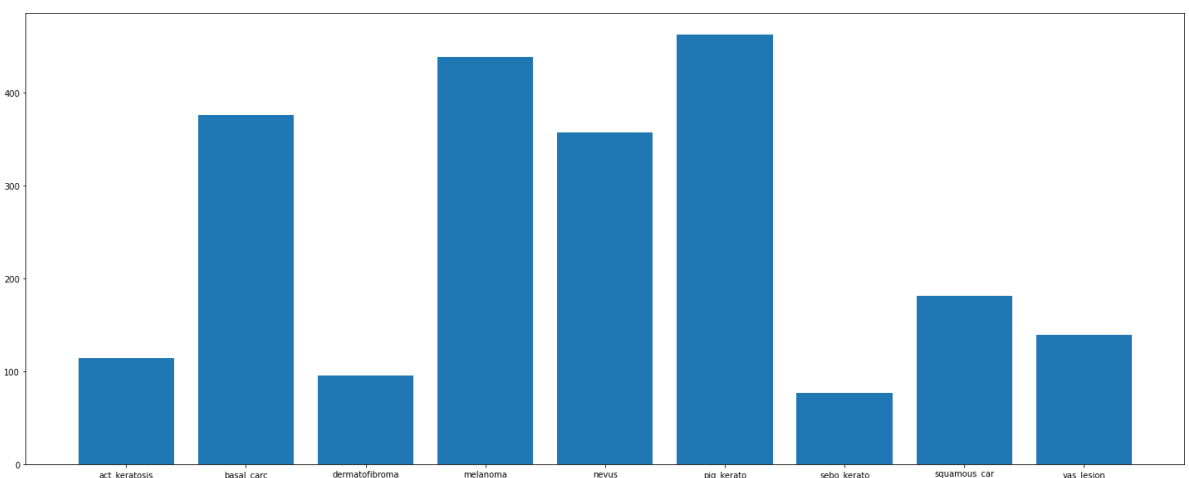
```
In [43]: #plot number of images in each Class
count=[]
for name in class_names:
    count.append(len(list(data_dir.glob(name+'/*.jpg'))))
```

```
In [44]: count
```

```
Out[44]: [114, 376, 95, 438, 357, 462, 77, 181, 139]
```

```
In [45]: plt.figure(figsize=(25,10))
plt.bar(class_names,count)
```

```
Out[45]: <BarContainer object of 9 artists>
```



So clearly there is a class imbalance in the data set.

Todo: Write your findings here:

- Which class has the least number of samples?

- Which classes dominate the data in terms proportionate number of samples? Todo: Rectify the class imbalance Context: You can use a python package known as Augmentor (<https://augmentor.readthedocs.io/en/master/>) to add more samples across all classes so that none of the classes have very few samples.

In []:

In [46]: `import Augmentor as aug`

To use Augmentor, the following general procedure is followed:

Instantiate a **Pipeline** object pointing to a directory containing your initial image data set.

Define a number of operations to perform on this data set using your **Pipeline** object.

Execute these operations by calling the **Pipeline's sample()** method.

In [47]: `data_dir`Out[47]: `WindowsPath('Skin cancer ISIC The International Skin Imaging Collaboration/Train')`

```
In [48]: path_to_training_dataset=str(data_dir)+'/'
for i in class_names:
    p = aug.Pipeline(path_to_training_dataset + str(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
```

Initialised with 114 image(s) found.

Output directory set to Skin cancer ISIC The International Skin Imaging Collaboration\Train\act_keratosis\output.

Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x14F0E6E7580>: 100%|█| 500/500 [00:07<00:00, 71.30 Samples/

Initialised with 376 image(s) found.

Output directory set to Skin cancer ISIC The International Skin Imaging Collaboration\Train\basal_carc\output.

Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x14F0E5A0DC0>: 100%|█| 500/500 [00:06<00:00, 72.11 Samples/

Initialised with 95 image(s) found.

Output directory set to Skin cancer ISIC The International Skin Imaging Collaboration\Train\dermatofibroma\output.

Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x14F0CA203A0>: 100%|█| 500/500 [00:07<00:00, 63.22 Samples/

Initialised with 438 image(s) found.

Output directory set to Skin cancer ISIC The International Skin Imaging Collaboration\Train\melanoma\output.

Processing <PIL.Image.Image image mode=RGB size=1024x768 at 0x14F0D0134C0>: 100%|█| 500/500 [00:30<00:00, 16.26 Samples/

Initialised with 357 image(s) found.

Output directory set to Skin cancer ISIC The International Skin Imaging Collaboration\Train\nevus\output.

Processing <PIL.Image.Image image mode=RGB size=1024x768 at 0x14F1120D8D0>: 100%|█| 500/500 [00:43<00:00, 11.54 Samples/

Initialised with 462 image(s) found.

Output directory set to Skin cancer ISIC The International Skin Imaging Collaboration\Train\pig_kerato\output.

Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x14F07842C80>: 100%|█| 500/500 [00:12<00:00, 39.21 Samples/

Initialised with 77 image(s) found.

Output directory set to Skin cancer ISIC The International Skin Imaging Collaboration\Train\sebo_kerato\output.

```
Processing <PIL.Image.Image image mode=RGB size=1024x768 at 0x14F11178DF0>: 100%|
| 500/500 [00:25<00:00, 19.32 Samples
Initialised with 181 image(s) found.
Output directory set to Skin cancer ISIC The International Skin Imaging Collaborat
ion\Train\squamous_car\output.
Processing <PIL.JpegImagePlugin.JpegImageFile image mode=RGB size=600x450 at 0x14F
0C8EEE60>: 100%| 500/500 [00:12<00:
Initialised with 139 image(s) found.
Output directory set to Skin cancer ISIC The International Skin Imaging Collaborat
ion\Train\vas_lesion\output.
Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x14F0E6E7A90>: 100%|
500/500 [00:13<00:00, 35.84 Samples/
```

In [49]: *#Augmentor has stored the augmented images in the output sub-directory of each of*
#Lets take a look at total count of augmented images.

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

4500

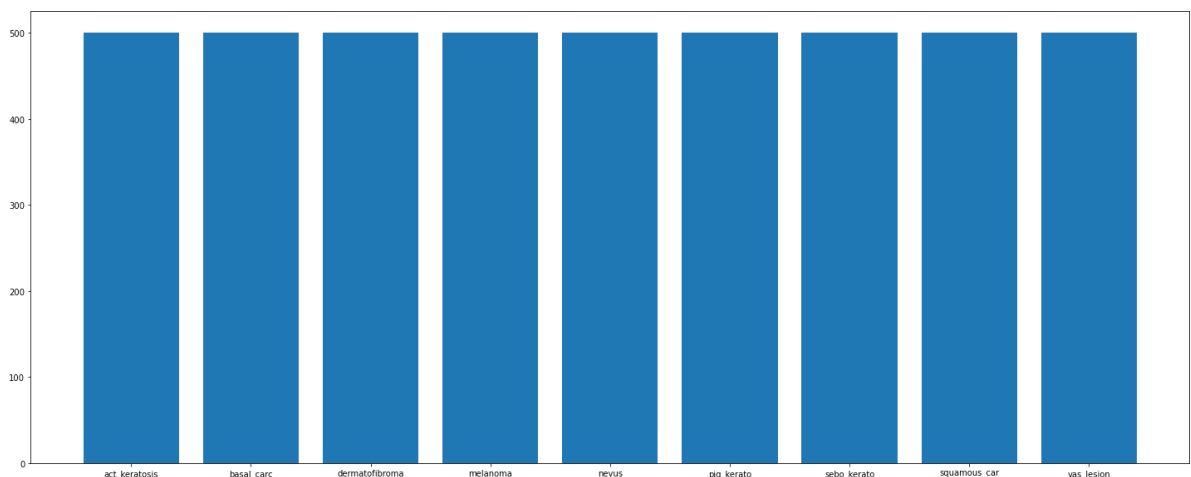
In [50]: class_names

Out[50]: ['act_keratosis',
'basal_carc',
'dermatofibroma',
'melanoma',
'nevus',
'pig_kerato',
'sebo_kerato',
'squamous_car',
'vas_lesion']

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

In [52]: *# Check the distribution of data again.*
count=[]
for name in class_names:
count.append(len(list(data_dir.glob(name+'*/*output/*.jpg'))))
plt.figure(figsize=(25,10))
plt.bar(class_names,count)

Out[52]: <BarContainer object of 9 artists>



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

```
In [53]: import os  
         from glob import glob
```

```
In [55]: path_list_new = [x for x in glob(os.path.join(data_dir, '*', 'output', '*.jpg'))]  
         path_list_new
```

```

\\output\\basal_carc_original_ISIC_0031442.jpg_8a07da38-4adf-4185-b9d8-05ad5da1b62
b.jpg',
'Skin cancer ISIC The International Skin Imaging Collaboration\\Train\\basal_carc
\\output\\basal_carc_original_ISIC_0031450.jpg_29e8dbfc-164b-472b-87b1-ea8d8448b2c
5.jpg',
'Skin cancer ISIC The International Skin Imaging Collaboration\\Train\\basal_carc
\\output\\basal_carc_original_ISIC_0031450.jpg_3e83bbad-6c75-4871-8197-00a9ffe9693
b.jpg',
'Skin cancer ISIC The International Skin Imaging Collaboration\\Train\\basal_carc
\\output\\basal_carc_original_ISIC_0031450.jpg_a4b97b8a-02b1-4fde-bd6d-aebd9e58c35
d.jpg',
'Skin cancer ISIC The International Skin Imaging Collaboration\\Train\\basal_carc
\\output\\basal_carc_original_ISIC_0031470.jpg_5009c4e1-71cb-40dc-83e4-ac53dbcd283
2.jpg',
'Skin cancer ISIC The International Skin Imaging Collaboration\\Train\\basal_carc
\\output\\basal_carc_original_ISIC_0031470.jpg_695091f7-a053-480c-a323-72bd1fa1821
8.jpg',
'Skin cancer ISIC The International Skin Imaging Collaboration\\Train\\basal_carc
\\output\\basal_carc_original_ISIC_0031489.jpg_74b9a0b6-357b-4459-b012-61678929d69
d.jpg',
'Skin cancer ISIC The International Skin Imaging Collaboration\\Train\\basal_carc
\\output\\basal_carc_original_ISIC_0031513.jpg_027af825-64bc-409b-a01a-3709ae7ed1d
5.jpg',
'Skin cancer ISIC The International Skin Imaging Collaboration\\Train\\basal_carc
\\output\\basal_carc_original_ISIC_0031520.jpg_b581c67c-b6f6-4fe9-88b8-2030605113a
6.jpg',
'Skin cancer ISIC The International Skin Imaging Collaboration\\Train\\basal_carc
\\output\\basal_carc_original_ISIC_0031526.jpg_2cd439b7-4683-425b-86a1-3bf466b1c2b
a.jpg',
'Skin cancer ISIC The International Skin Imaging Collaboration\\Train\\basal_carc
\\output\\basal_carc_original_ISIC_0031526.jpg_43c2374d-a532-4b95-aa7e-87228a6bb0b
0.jpg',
'Skin cancer ISIC The International Skin Imaging Collaboration\\Train\\basal_carc
\\output\\basal_carc_original_ISIC_0031531.jpg_5e300e81-75db-47b6-a273-342331f0d5b
5.jpg',
'Skin cancer ISIC The International Skin Imaging Collaboration\\Train\\basal_carc
\\output\\basal_carc_original_ISIC_0031552.jpg_ec99455b-71ab-43a3-981d-e6f01363c1b
5.jpg',
'Skin cancer ISIC The International Skin Imaging Collaboration\\Train\\basal_carc
\\output\\basal_carc_original_ISIC_0031597.jpg_09bb4e39-131e-4705-8630-856ba751d2c
f.jpg',
'Skin cancer ISIC The International Skin Imaging Collaboration\\Train\\basal_carc
\\output\\basal_carc_original_ISIC_0031597.jpg_a5bd89a7-5b82-4524-83f7-1d2374d49d5
2.jpg',
'Skin cancer ISIC The International Skin Imaging Collaboration\\Train\\basal_carc
\\output\\basal_carc_original_ISIC_0031614.jpg_641b24e9-1dea-4dd3-80f2-56041b248c1
6.jpg',
'Skin cancer ISIC The International Skin Imaging Collaboration\\Train\\basal_carc
\\output\\basal_carc_original_ISIC_0031614.jpg_a4eee3c5-761a-4a9b-a019-18e90e437dd
3.jpg',
'Skin cancer ISIC The International Skin Imaging Collaboration\\Train\\basal_carc
\\output\\basal_carc_original_ISIC_0031614.jpg_cfd93c14-dd95-4013-b263-c0bef4d3d27
b.jpg',
'Skin cancer ISIC The International Skin Imaging Collaboration\\Train\\basal_carc
\\output\\basal_carc_original_ISIC_0031614.jpg_e843140b-e0b2-4e3c-90cd-a89c668bd1d
3.jpg',
...]
```

```
In [58]: lesion_list_new = [os.path.basename(os.path.dirname(os.path.dirname(y))) for y in lesion_list_new]
```

```
Out[58]: 4500
```



```
In [60]: dataframe_dict_new = dict(zip(path_list_new,lesion_list_new))
path_list = []
class_name = []
for name in class_names:
    for file in data_dir.glob(name + '/*.jpg'):
        path_list.append(file)
        class_name.append(name)
```

```
In [61]: dataframe_dict_original=dict(zip(path_list,class_name))
original_df=pd.DataFrame(list(dataframe_dict_original.items()),columns=['Path','Label'])
```

```
In [62]: original_df
```

```
Out[62]:
```

	Path	Label
0	Skin cancer ISIC The International Skin Imagin...	act_keratosis
1	Skin cancer ISIC The International Skin Imagin...	act_keratosis
2	Skin cancer ISIC The International Skin Imagin...	act_keratosis
3	Skin cancer ISIC The International Skin Imagin...	act_keratosis
4	Skin cancer ISIC The International Skin Imagin...	act_keratosis
...
2234	Skin cancer ISIC The International Skin Imagin...	vas_lesion
2235	Skin cancer ISIC The International Skin Imagin...	vas_lesion
2236	Skin cancer ISIC The International Skin Imagin...	vas_lesion
2237	Skin cancer ISIC The International Skin Imagin...	vas_lesion
2238	Skin cancer ISIC The International Skin Imagin...	vas_lesion

2239 rows × 2 columns

```
In [63]: df2 = pd.DataFrame(list(dataframe_dict_new.items()),columns=['Path','Label'])
```

```
In [64]: new_df = original_df.append(df2)
```

C:\Users\krishnendu\AppData\Local\Temp\ipykernel_9100\1731109560.py:1: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.

```
new_df = original_df.append(df2)
```

```
In [65]: new_df
```

Out[65]:

	Path	Label
0	Skin cancer ISIC The International Skin Imagin...	act_keratosis
1	Skin cancer ISIC The International Skin Imagin...	act_keratosis
2	Skin cancer ISIC The International Skin Imagin...	act_keratosis
3	Skin cancer ISIC The International Skin Imagin...	act_keratosis
4	Skin cancer ISIC The International Skin Imagin...	act_keratosis
...
4495	Skin cancer ISIC The International Skin Imagin...	vas_lesion
4496	Skin cancer ISIC The International Skin Imagin...	vas_lesion
4497	Skin cancer ISIC The International Skin Imagin...	vas_lesion
4498	Skin cancer ISIC The International Skin Imagin...	vas_lesion
4499	Skin cancer ISIC The International Skin Imagin...	vas_lesion

6739 rows × 2 columns

In [66]: new_df['Label'].value_counts()

Out[66]:

pig_kerato	962
melanoma	938
basal_carc	876
nevus	857
squamous_car	681
vas_lesion	639
act_keratosis	614
dermatofibroma	595
sebo_kerato	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.

Create training set

In [67]:

```
traing_ds = keras.preprocessing.image_dataset_from_directory(data_dir, image_size=(
    validation_split= 0.2
```

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

Create validation set

In [68]:

```
validation_ds = keras.preprocessing.image_dataset_from_directory(data_dir, image_si:
    validation_split= 0.2
```

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

Create your model again (make sure to include normalization)

```
In [73]: ## code
AUTOTUNE = tf.data.experimental.AUTOTUNE

traing_ds = traing_ds.cache().shuffle(1000).prefetch(buffer_size=AUTOTUNE)
validation_ds = validation_ds.cache().prefetch(buffer_size = AUTOTUNE)

model = Sequential([
    layers.experimental.preprocessing.Rescaling(1.0/255),
    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.MaxPool2D(),
    layers.Dropout(0.2),
    layers.Flatten(),
    layers.Dense(128, activation='relu'),
    layers.Dense(n_class)
])
```

```
In [74]: ### Compile the model
model.compile(optimizer='adam',
              loss = keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])
```

```
In [75]: ## fitting the model
epochs = 15

history = model.fit(
    traing_ds,
    validation_data= validation_ds,
    epochs=epochs
)
```

```

Epoch 1/15
169/169 [=====] - 166s 862ms/step - loss: 1.7510 - accuracy: 0.3414 - val_loss: 1.4119 - val_accuracy: 0.4744
Epoch 2/15
169/169 [=====] - 128s 760ms/step - loss: 1.3289 - accuracy: 0.5013 - val_loss: 1.2801 - val_accuracy: 0.5204
Epoch 3/15
169/169 [=====] - 119s 704ms/step - loss: 1.1579 - accuracy: 0.5692 - val_loss: 1.0667 - val_accuracy: 0.6192
Epoch 4/15
169/169 [=====] - 130s 768ms/step - loss: 1.0073 - accuracy: 0.6350 - val_loss: 1.0693 - val_accuracy: 0.6169
Epoch 5/15
169/169 [=====] - 118s 697ms/step - loss: 0.8675 - accuracy: 0.6845 - val_loss: 0.9737 - val_accuracy: 0.6696
Epoch 6/15
169/169 [=====] - 130s 770ms/step - loss: 0.7022 - accuracy: 0.7526 - val_loss: 0.8874 - val_accuracy: 0.7030
Epoch 7/15
169/169 [=====] - 130s 766ms/step - loss: 0.6026 - accuracy: 0.7858 - val_loss: 0.9500 - val_accuracy: 0.7008
Epoch 8/15
169/169 [=====] - 135s 799ms/step - loss: 0.4842 - accuracy: 0.8288 - val_loss: 0.9211 - val_accuracy: 0.7275
Epoch 9/15
169/169 [=====] - 128s 757ms/step - loss: 0.4013 - accuracy: 0.8591 - val_loss: 0.7939 - val_accuracy: 0.7654
Epoch 10/15
169/169 [=====] - 119s 702ms/step - loss: 0.3378 - accuracy: 0.8809 - val_loss: 0.9107 - val_accuracy: 0.7699
Epoch 11/15
169/169 [=====] - 125s 740ms/step - loss: 0.3033 - accuracy: 0.8871 - val_loss: 0.8715 - val_accuracy: 0.7832
Epoch 12/15
169/169 [=====] - 123s 726ms/step - loss: 0.2778 - accuracy: 0.9002 - val_loss: 0.7481 - val_accuracy: 0.7988
Epoch 13/15
169/169 [=====] - 126s 745ms/step - loss: 0.2326 - accuracy: 0.9173 - val_loss: 0.9936 - val_accuracy: 0.7765
Epoch 14/15
169/169 [=====] - 126s 744ms/step - loss: 0.2065 - accuracy: 0.9251 - val_loss: 0.7799 - val_accuracy: 0.8196
Epoch 15/15
169/169 [=====] - 132s 779ms/step - loss: 0.1819 - accuracy: 0.9347 - val_loss: 0.8565 - val_accuracy: 0.7988

```

Visualize the model results

```

In [77]: acc = history.history['accuracy']
         val_acc = history.history['val_accuracy']

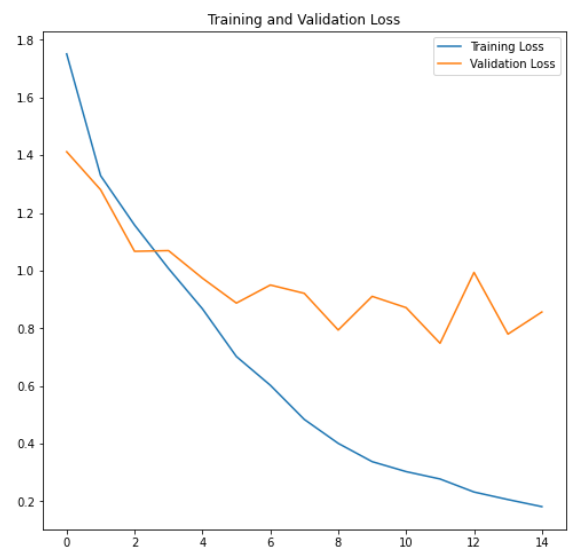
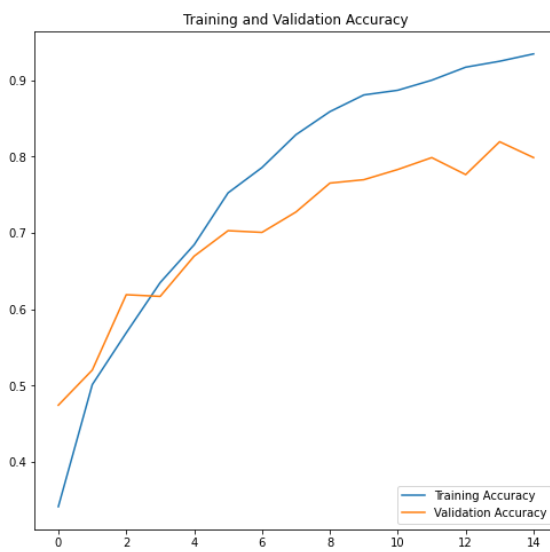
         loss = history.history['loss']
         val_loss = history.history['val_loss']

         epochs_range = range(epochs)

         plt.figure(figsize=(18, 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()
```



This is good

Traning Accuracy = 93

Validation Accuracy = 80

thats good

In []: