MELANOMA DETECTION ASSIGNMENT

1.0.1 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 dermatologists about the presence of melanoma has the potential to reduce a lot of manual effort needed in diagnosis.

1.0.2 Importing all the important libraries

 # Install Augmentor

[ ]:
```
!pip install Augmentor

# Import necessary libraries
import pathlib
import os
import glob
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers, regularizers, Sequential
from tensorflow.keras.models import Sequential
from tensorflow.keras.callbacks import ReduceLROnPlateau, EarlyStopping
from tensorflow.keras.preprocessing import image_dataset_from_directory
import Augmentor
from google.colab import drive
```

```
Collecting Augmentor
  Downloading Augmentor-0.2.12-py2.py3-none-any.whl (38 kB)
Requirement already satisfied: Pillow>=5.2.0 in /usr/local/lib/python3.10/dist-
packages (from Augmentor) (9.4.0)
Requirement already satisfied: tqdm>=4.9.0 in /usr/local/lib/python3.10/dist-
packages (from Augmentor) (4.66.4)
Requirement already satisfied: numpy>=1.11.0 in /usr/local/lib/python3.10/dist-
packages (from Augmentor) (1.25.2)
```

```
Installing collected packages: Augmentor
Successfully installed Augmentor-0.2.12
```

1.0.3 Importing Skin Cancer Data

[ ]:
```
# Mounting the Google Drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[ ]:
```
# Defining the path for train and test images
data_dir_train = pathlib.Path("/content/drive/MyDrive/Dataset/Train")
data_dir_test = pathlib.Path('/content/drive/MyDrive/Dataset/Test')
augmented_data_dir = pathlib.Path("/content/drive/MyDrive/Dataset/
 ↪AugmentedDataset")

image_count_train = len(list(data_dir_train.glob('*/*.jpg')))
print(f"Training Image Count: {image_count_train}")
image_count_test = len(list(data_dir_test.glob('*/*.jpg')))
print(f"Testing Image Count: {image_count_test}")
```

```
Training Image Count: 2239
Testing Image Count: 118
```

1.0.4 Dataset Creation

[ ]:
```
# Defining the parameters for the loader:
batch_size = 32
img_height = 180
img_width = 180

# Using 80% of the images for training, and 20% for validation.
train_ds = tf.keras.preprocessing.image_dataset_from_directory(
  data_dir_train,
  validation_split=0.2,
  subset="training",
  seed=123,
  image_size=(img_height, img_width),
  batch_size=batch_size)

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

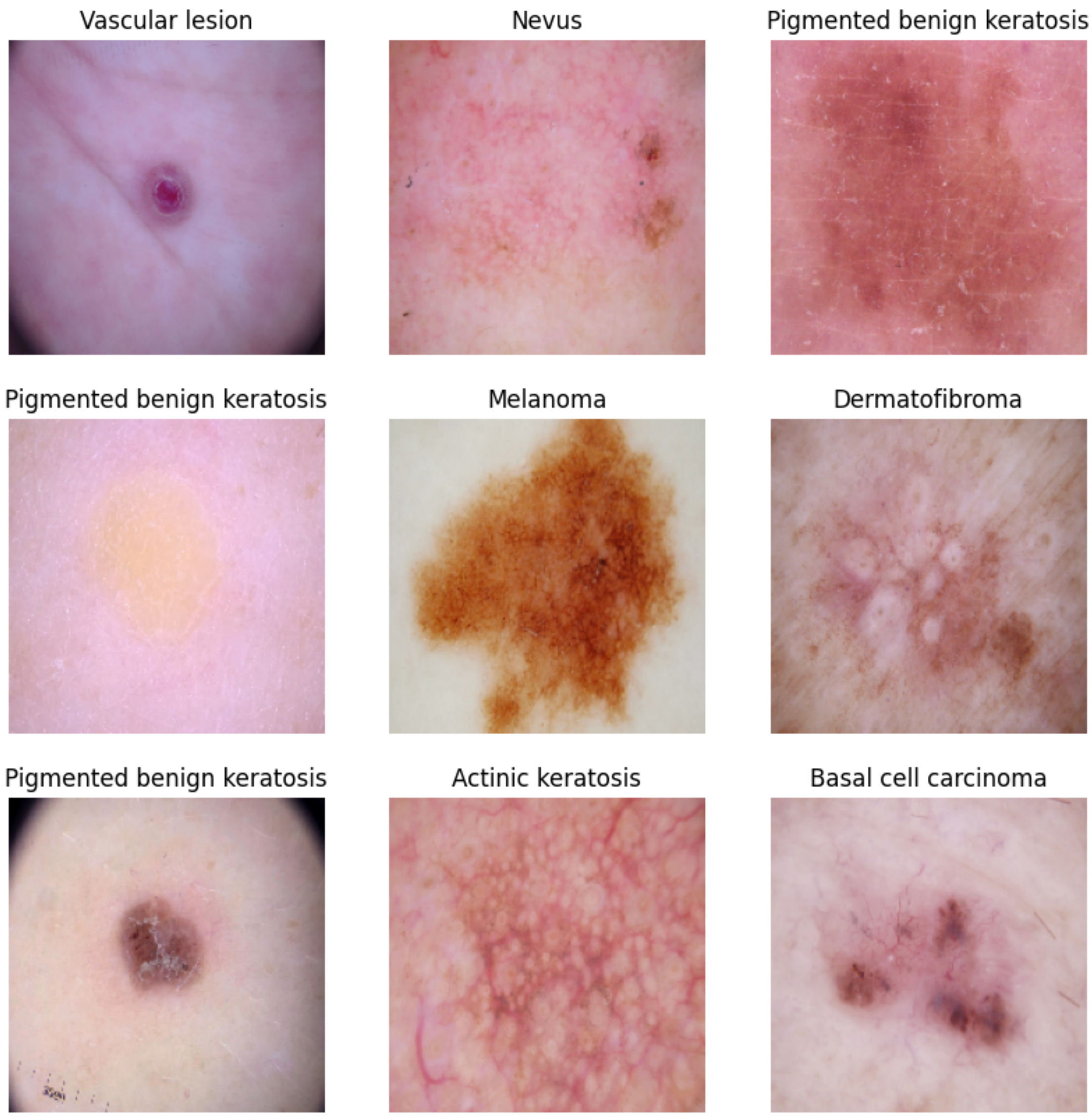
```
# Creating the test dataset
test_ds = tf.keras.preprocessing.image_dataset_from_directory(
  data_dir_test,
  image_size=(img_height, img_width),
  batch_size=batch_size)

# Listing out all the classes of skin cancer and store them in a list
class_names = train_ds.class_names
print(f"Class Names: {class_names}")
```

```
Found 2239 files belonging to 9 classes.
Using 1792 files for training.
Found 2239 files belonging to 9 classes.
Using 447 files for validation.
Found 118 files belonging to 9 classes.
Class Names: ['Actinic keratosis', 'Basal cell carcinoma', 'Dermatofibroma',
'Melanoma', 'Nevus', 'Pigmented benign keratosis', 'Seborrheic keratosis',
'Squamous cell carcinoma', 'Vascular lesion']
```

1.0.5 Data Visualization

[ ]:
```
plt.figure(figsize=(10, 10))
for images, labels in train_ds.take(1):
    for i in range(9):
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(images[i].numpy().astype("uint8"))
        plt.title(class_names[labels[i]])
        plt.axis("off")
plt.show()
```



1.0.6 Data Cache and Prefetch

[ ]:
```
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)
test_ds = test_ds.cache().prefetch(buffer_size=AUTOTUNE)
```

1.0.7 Model Creation

[ ]:
```python
# Creation
def build_model():
    model = Sequential([
        layers.experimental.preprocessing.Rescaling(1./255,␣
 ↪input_shape=(img_height, img_width, 3)),
        layers.Conv2D(32, 3, padding='same', activation='relu'),
        layers.MaxPooling2D(),
        layers.Conv2D(64, 3, padding='same', activation='relu'),
        layers.MaxPooling2D(),
        layers.Conv2D(128, 3, padding='same', activation='relu'),
        layers.MaxPooling2D(),
        layers.Flatten(),
        layers.Dense(128, activation='relu'),
        layers.Dropout(0.5),
        layers.Dense(len(class_names), activation='softmax')
    ])
    return model

# Compilation
def compile_model(model):
    model.compile(optimizer='adam',
                  loss=tf.keras.losses.SparseCategoricalCrossentropy(),
                  metrics=['accuracy'])
    return model

# Viewing the summary of all layers
model = build_model()
model = compile_model(model)
model.summary()
```

```
Model: "sequential"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling (Rescaling)       (None, 180, 180, 3)       0

 conv2d (Conv2D)             (None, 180, 180, 32)      896

 max_pooling2d (MaxPooling2  (None, 90, 90, 32)        0
 D)

 conv2d_1 (Conv2D)           (None, 90, 90, 64)        18496

 max_pooling2d_1 (MaxPoolin  (None, 45, 45, 64)        0
 g2D)
```

```
 conv2d_2 (Conv2D)           (None, 45, 45, 128)       73856

 max_pooling2d_2 (MaxPoolin  (None, 22, 22, 128)       0
 g2D)

 flatten (Flatten)           (None, 61952)             0

 dense (Dense)               (None, 128)               7929984

 dropout (Dropout)           (None, 128)               0

 dense_1 (Dense)             (None, 9)                 1161

=================================================================
Total params: 8024393 (30.61 MB)
Trainable params: 8024393 (30.61 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

1.0.8 Model Training

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

```
Epoch 1/20
56/56 [==============================] - 129s 559ms/step - loss: 2.1684 -
accuracy: 0.2260 - val_loss: 1.9218 - val_accuracy: 0.2953
Epoch 2/20
56/56 [==============================] - 1s 26ms/step - loss: 1.8762 - accuracy:
0.3471 - val_loss: 1.7750 - val_accuracy: 0.3289
Epoch 3/20
56/56 [==============================] - 1s 26ms/step - loss: 1.7412 - accuracy:
0.3834 - val_loss: 1.6493 - val_accuracy: 0.4273
Epoch 4/20
56/56 [==============================] - 1s 26ms/step - loss: 1.6818 - accuracy:
0.4079 - val_loss: 1.6118 - val_accuracy: 0.4698
Epoch 5/20
56/56 [==============================] - 1s 27ms/step - loss: 1.6183 - accuracy:
0.4235 - val_loss: 1.5647 - val_accuracy: 0.4698
Epoch 6/20
56/56 [==============================] - 1s 26ms/step - loss: 1.5286 - accuracy:
0.4710 - val_loss: 1.4562 - val_accuracy: 0.5324
Epoch 7/20
56/56 [==============================] - 1s 26ms/step - loss: 1.4675 - accuracy:
```

```
0.4894 - val_loss: 1.4384 - val_accuracy: 0.5056
Epoch 8/20
56/56 [==============================] - 1s 26ms/step - loss: 1.5478 - accuracy:
0.4503 - val_loss: 1.6253 - val_accuracy: 0.4385
Epoch 9/20
56/56 [==============================] - 2s 27ms/step - loss: 1.4772 - accuracy:
0.5039 - val_loss: 1.4144 - val_accuracy: 0.5347
Epoch 10/20
56/56 [==============================] - 1s 26ms/step - loss: 1.3858 - accuracy:
0.5140 - val_loss: 1.4009 - val_accuracy: 0.5324
Epoch 11/20
56/56 [==============================] - 1s 26ms/step - loss: 1.3270 - accuracy:
0.5340 - val_loss: 1.3998 - val_accuracy: 0.5347
Epoch 12/20
56/56 [==============================] - 1s 26ms/step - loss: 1.3580 - accuracy:
0.5290 - val_loss: 1.3802 - val_accuracy: 0.5280
Epoch 13/20
56/56 [==============================] - 1s 26ms/step - loss: 1.2572 - accuracy:
0.5491 - val_loss: 1.4008 - val_accuracy: 0.5391
Epoch 14/20
56/56 [==============================] - 1s 26ms/step - loss: 1.2222 - accuracy:
0.5603 - val_loss: 1.4591 - val_accuracy: 0.5145
Epoch 15/20
56/56 [==============================] - 1s 26ms/step - loss: 1.2351 - accuracy:
0.5658 - val_loss: 1.3488 - val_accuracy: 0.5459
Epoch 16/20
56/56 [==============================] - 1s 26ms/step - loss: 1.1809 - accuracy:
0.5798 - val_loss: 1.3342 - val_accuracy: 0.5593
Epoch 17/20
56/56 [==============================] - 1s 26ms/step - loss: 1.1637 - accuracy:
0.5731 - val_loss: 1.3652 - val_accuracy: 0.5481
Epoch 18/20
56/56 [==============================] - 1s 26ms/step - loss: 1.1134 - accuracy:
0.6150 - val_loss: 1.3543 - val_accuracy: 0.5570
Epoch 19/20
56/56 [==============================] - 1s 26ms/step - loss: 1.0484 - accuracy:
0.6256 - val_loss: 1.3746 - val_accuracy: 0.5391
Epoch 20/20
56/56 [==============================] - 1s 26ms/step - loss: 1.0567 - accuracy:
0.6116 - val_loss: 1.6144 - val_accuracy: 0.5615
```

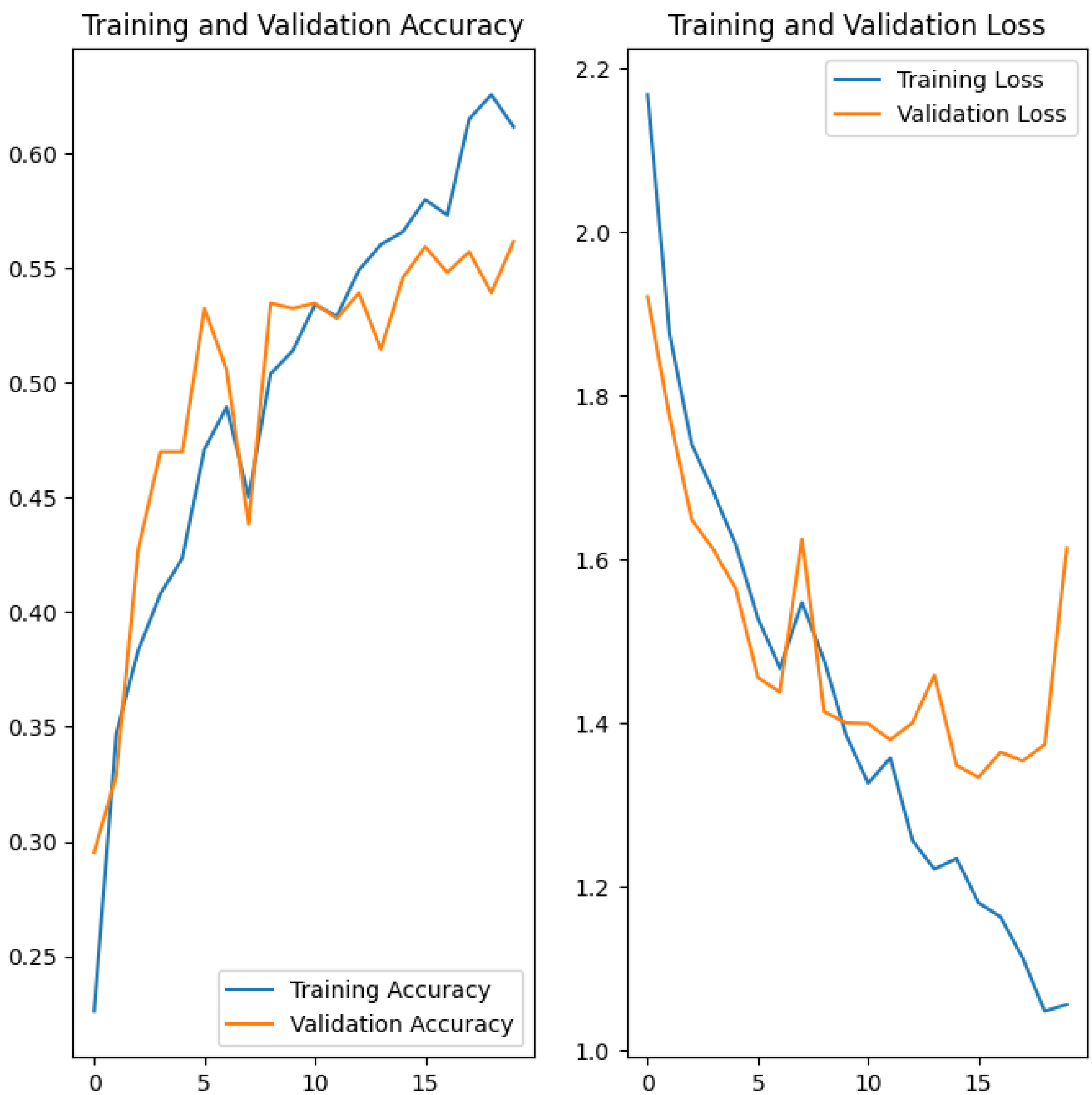
1.0.9 Visualizing training results

[ ]:
```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']
```

```
epochs_range = range(epochs)

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

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



[ ]:
```python
# Evaluating the model on the test dataset
test_loss, test_acc = model.evaluate(test_ds, verbose=2)
print(f'\nTest accuracy: {test_acc}')
```

```
4/4 - 13s - loss: 3.6811 - accuracy: 0.3644 - 13s/epoch - 3s/step

Test accuracy: 0.3644067943096161
```

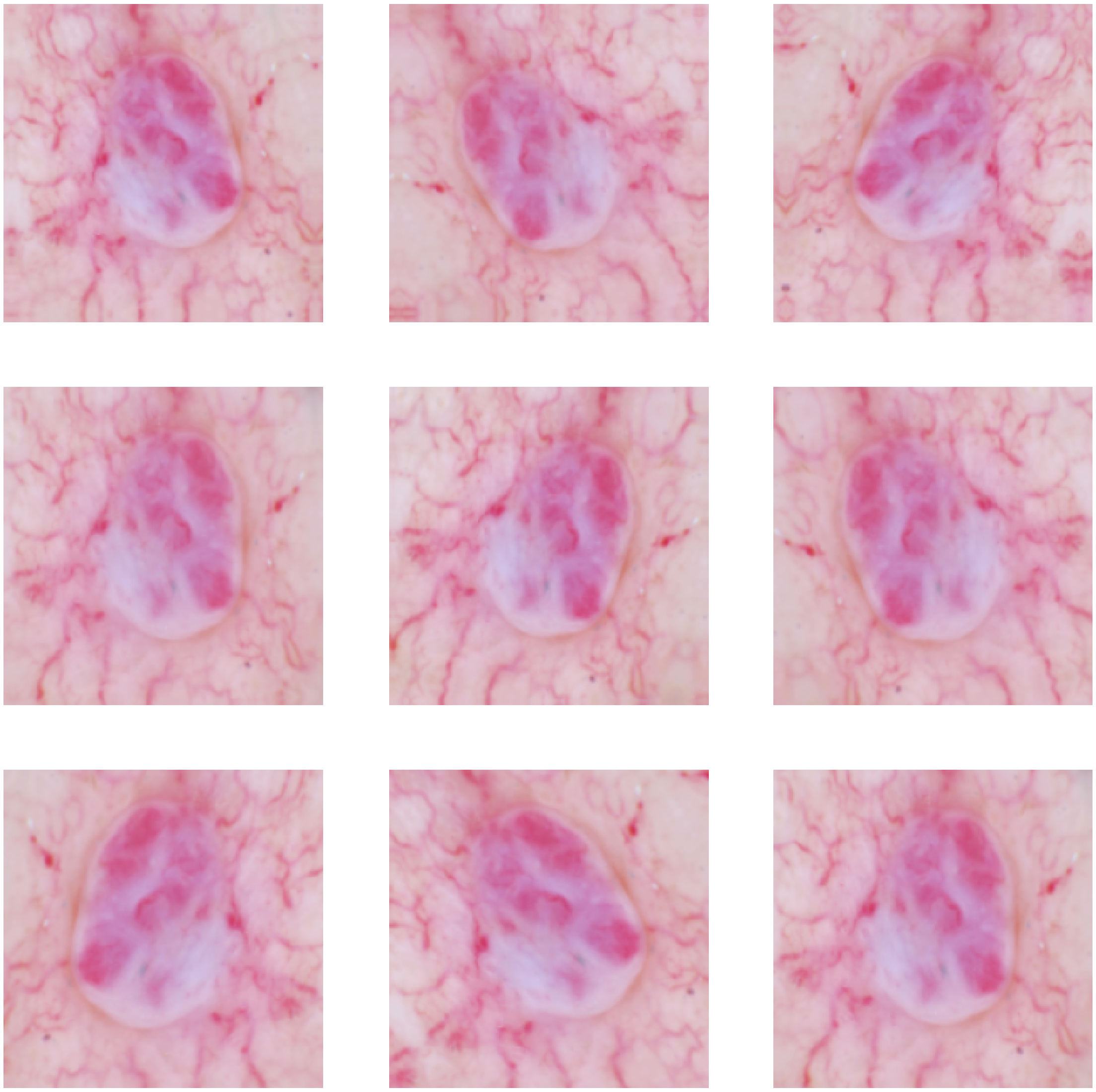
1.0.10 Findings:

1. The model was relatively simple but showed signs of overfitting.
2. The test accuracy was significantly lower than the validation accuracy, indicating poor generalization.

1.0.11 Data Augmentation

[ ]:
```python
data_augmentation = keras.Sequential(
  [
    layers.experimental.preprocessing.RandomFlip("horizontal",␣
 ↪input_shape=(img_height, img_width, 3)),
    layers.experimental.preprocessing.RandomRotation(0.1),
    layers.experimental.preprocessing.RandomZoom(0.1),
    layers.Lambda(lambda x: tf.image.random_brightness(x, max_delta=0.1)),
    layers.Lambda(lambda x: tf.image.random_contrast(x, lower=0.9, upper=1.1)),
  ]
)
```

[ ]:
```python
# Checking the performance of data augmentation strategy
for image, _ in train_ds.take(1):
    plt.figure(figsize=(10, 10))
    first_image = image[0]
    for i in range(9):
        ax = plt.subplot(3, 3, i + 1)
        augmented_image = data_augmentation(tf.expand_dims(first_image, 0))
        plt.imshow(augmented_image[0].numpy().astype("uint8"))
        plt.axis("off")
    plt.show()
```



1.0.12 Model Creation

[ ]:
```
def build_improved_model():
    model = Sequential([
        data_augmentation,
        layers.experimental.preprocessing.Resizing(img_height, img_width),  #␣
↪Resizing layer after augmentation
        layers.experimental.preprocessing.Rescaling(1./255),

        layers.Conv2D(32, 3, padding='same', activation='relu',␣
↪kernel_regularizer=regularizers.l2(0.001)),
        layers.BatchNormalization(),
        layers.MaxPooling2D(),
```

```
        layers.Dropout(0.3),

        layers.Conv2D(64, 3, padding='same', activation='relu',␣
 ↪kernel_regularizer=regularizers.l2(0.001)),
        layers.BatchNormalization(),
        layers.MaxPooling2D(),
        layers.Dropout(0.3),

        layers.Conv2D(128, 3, padding='same', activation='relu',␣
 ↪kernel_regularizer=regularizers.l2(0.001)),
        layers.BatchNormalization(),
        layers.MaxPooling2D(),
        layers.Dropout(0.4),

        layers.Conv2D(256, 3, padding='same', activation='relu',␣
 ↪kernel_regularizer=regularizers.l2(0.001)),
        layers.BatchNormalization(),
        layers.GlobalAveragePooling2D(),
        layers.Dropout(0.5),

        layers.Dense(512, activation='relu', kernel_regularizer=regularizers.
 ↪l2(0.001)),
        layers.Dropout(0.5),
        layers.Dense(len(class_names), activation='softmax')
    ])
    return model

better_model = build_improved_model()
better_model = compile_model(model)
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling (Rescaling)       (None, 180, 180, 3)       0

 conv2d (Conv2D)             (None, 180, 180, 32)      896

 max_pooling2d (MaxPooling2  (None, 90, 90, 32)        0
 D)

 conv2d_1 (Conv2D)           (None, 90, 90, 64)        18496

 max_pooling2d_1 (MaxPoolin  (None, 45, 45, 64)        0
 g2D)
```

```
 conv2d_2 (Conv2D)           (None, 45, 45, 128)       73856

 max_pooling2d_2 (MaxPoolin  (None, 22, 22, 128)       0
 g2D)

 flatten (Flatten)           (None, 61952)             0

 dense (Dense)               (None, 128)               7929984

 dropout (Dropout)           (None, 128)               0

 dense_1 (Dense)             (None, 9)                 1161

=================================================================
Total params: 8024393 (30.61 MB)
Trainable params: 8024393 (30.61 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

1.0.13 Model Training

[ ]:
```python
early_stopping = EarlyStopping(monitor='val_loss', patience=5,
 ↪restore_best_weights=True)
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.5, patience=3,
 ↪min_lr=1e-6)

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

```
Epoch 1/20
56/56 [==============================] - 3s 31ms/step - loss: 1.0290 - accuracy:
0.6334 - val_loss: 1.4281 - val_accuracy: 0.5459 - lr: 0.0010
Epoch 2/20
56/56 [==============================] - 1s 26ms/step - loss: 0.9262 - accuracy:
0.6635 - val_loss: 1.4914 - val_accuracy: 0.5660 - lr: 0.0010
Epoch 3/20
56/56 [==============================] - 1s 27ms/step - loss: 0.9269 - accuracy:
0.6590 - val_loss: 1.3993 - val_accuracy: 0.5660 - lr: 0.0010
Epoch 4/20
56/56 [==============================] - 1s 26ms/step - loss: 0.8851 - accuracy:
0.6708 - val_loss: 1.4431 - val_accuracy: 0.5548 - lr: 0.0010
Epoch 5/20
56/56 [==============================] - 1s 26ms/step - loss: 0.8492 - accuracy:
0.6814 - val_loss: 1.6038 - val_accuracy: 0.5459 - lr: 0.0010
```

```
Epoch 6/20
56/56 [==============================] - 1s 26ms/step - loss: 0.8776 - accuracy:
0.6858 - val_loss: 1.5606 - val_accuracy: 0.5817 - lr: 0.0010
Epoch 7/20
56/56 [==============================] - 1s 26ms/step - loss: 0.7733 - accuracy:
0.7093 - val_loss: 1.6196 - val_accuracy: 0.5839 - lr: 5.0000e-04
Epoch 8/20
56/56 [==============================] - 2s 27ms/step - loss: 0.7066 - accuracy:
0.7288 - val_loss: 1.7577 - val_accuracy: 0.5570 - lr: 5.0000e-04
```

1.0.14 Visualizing training results

[ ]:
```python
# Visualizing the training results
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs_range = range(len(acc))

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()
```


```
[ ]: # Evaluating the model on the test dataset
test_loss, test_acc = better_model.evaluate(test_ds, verbose=2)
print(f'\nTest accuracy: {test_acc}')
```

```
4/4 - 0s - loss: 2.9797 - accuracy: 0.4407 - 45ms/epoch - 11ms/step

Test accuracy: 0.4406779706478119
```

1.0.15 Findings:

1. The model with data augmentation and regularization showed better performance and generalization compared to the basic model.
2. Test accuracy improved but was still significantly lower than validation accuracy, indicating room for improvement in generalization.

1.0.16 Finding the distribution of classes in the training dataset

[ ]:
```
def analyze_class_distribution(dataset):
    class_counts = {}
    for images, labels in dataset.unbatch():
        label = labels.numpy()  # convert the tensor to a numpy value
        class_name = class_names[label]
        if class_name in class_counts:
            class_counts[class_name] += 1
        else:
            class_counts[class_name] = 1
    return class_counts

class_distribution = analyze_class_distribution(train_ds)
print("Class Distribution in Training Data:", class_distribution)
```

1.0.17 Rectification of Class imbalances

[ ]:
```
def augment_data_balanced(class_names, source_dir, target_dir, sample_size=500):
    for class_name in class_names:
        p = Augmentor.Pipeline(source_directory=str(source_dir / class_name),␣
 ↪output_directory=str(target_dir / class_name))
        p.rotate(probability=0.7, max_left_rotation=10, max_right_rotation=10)
        p.flip_left_right(probability=0.5)
        p.zoom_random(probability=0.5, percentage_area=0.8)
        p.random_contrast(probability=0.5, min_factor=0.7, max_factor=1.3)
        p.random_brightness(probability=0.5, min_factor=0.7, max_factor=1.3)
        p.sample(sample_size)

augment_data_balanced(class_names, data_dir_train, augmented_data_dir,␣
 ↪sample_size=500)
```

```
Initialised with 114 image(s) found.
Output directory set to /content/drive/MyDrive/Dataset/AugmentedDataset/Actinic
keratosis.

Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x7EA57829FFD0>:
100%|      | 500/500 [00:08<00:00, 61.34 Samples/s]

Initialised with 376 image(s) found.
Output directory set to /content/drive/MyDrive/Dataset/AugmentedDataset/Basal
cell carcinoma.

Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x7EA5781A1FC0>:
100%|      | 500/500 [00:05<00:00, 90.85 Samples/s]
Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x7EA57829F5B0>:
100%|      | 500/500 [00:05<00:00, 84.59 Samples/s]

Initialised with 438 image(s) found.
```

```
Output directory set to
/content/drive/MyDrive/Dataset/AugmentedDataset/Melanoma.

Processing <PIL.Image.Image image mode=RGB size=1024x768 at 0x7EA55BF0BCA0>:
100%|      | 500/500 [00:23<00:00, 21.70 Samples/s]

Initialised with 357 image(s) found.
Output directory set to /content/drive/MyDrive/Dataset/AugmentedDataset/Nevus.

Processing <PIL.Image.Image image mode=RGB size=1024x768 at 0x7EA6262B26E0>:
100%|      | 500/500 [00:18<00:00, 26.46 Samples/s]

Initialised with 462 image(s) found.
Output directory set to
/content/drive/MyDrive/Dataset/AugmentedDataset/Pigmented benign keratosis.

Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x7EA55BF42080>:
100%|      | 500/500 [00:05<00:00, 93.27 Samples/s]

Initialised with 77 image(s) found.
Output directory set to
/content/drive/MyDrive/Dataset/AugmentedDataset/Seborrheic keratosis.

Processing <PIL.Image.Image image mode=RGB size=1024x768 at 0x7EA57811EBC0>:
100%|      | 500/500 [00:10<00:00, 49.00 Samples/s]

Initialised with 181 image(s) found.
Output directory set to /content/drive/MyDrive/Dataset/AugmentedDataset/Squamous
cell carcinoma.

Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x7EA55BF37970>:
100%|      | 500/500 [00:05<00:00, 86.35 Samples/s]

Initialised with 139 image(s) found.
Output directory set to /content/drive/MyDrive/Dataset/AugmentedDataset/Vascular
lesion.

Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x7EA57829FAC0>:
100%|      | 500/500 [00:06<00:00, 81.58 Samples/s]
```

1.0.18 Dataset Creation

[ ]:
```python
# Training Dataset Creation
augmented_train_ds = image_dataset_from_directory(
    augmented_data_dir,
    validation_split=0.2,
    subset="training",
    seed=123,
    image_size=(img_height, img_width),
    batch_size=batch_size)

augmented_val_ds = image_dataset_from_directory(
    augmented_data_dir,
```

```
    validation_split=0.2,
    subset="validation",
    seed=123,
    image_size=(img_height, img_width),
    batch_size=batch_size)

AUTOTUNE = tf.data.experimental.AUTOTUNE
augmented_train_ds = augmented_train_ds.cache().shuffle(1000).
 ↪prefetch(buffer_size=AUTOTUNE)
augmented_val_ds = augmented_val_ds.cache().prefetch(buffer_size=AUTOTUNE)
```

```
Found 4500 files belonging to 9 classes.
Using 3600 files for training.
Found 4500 files belonging to 9 classes.
Using 900 files for validation.
```

1.0.19 Model Creation

[ ]:
```
def build_improved_model():
    model = Sequential([
        layers.experimental.preprocessing.Rescaling(1./255,␣
 ↪input_shape=(img_height, img_width, 3)),
        layers.Conv2D(32, 3, padding='same', activation='relu'),
        layers.BatchNormalization(),
        layers.MaxPooling2D(),
        layers.Dropout(0.3),

        layers.Conv2D(64, 3, padding='same', activation='relu'),
        layers.BatchNormalization(),
        layers.MaxPooling2D(),
        layers.Dropout(0.3),

        layers.Conv2D(128, 3, padding='same', activation='relu'),
        layers.BatchNormalization(),
        layers.MaxPooling2D(),
        layers.Dropout(0.4),

        layers.Conv2D(256, 3, padding='same', activation='relu'),
        layers.BatchNormalization(),
        layers.GlobalAveragePooling2D(),
        layers.Dropout(0.5),

        layers.Dense(256, activation='relu', kernel_regularizer=regularizers.
 ↪l2(0.01)),
        layers.Dropout(0.5),
        layers.Dense(len(class_names), activation='softmax')
    ])
```

```python
    optimizer = optimizers.Adam(learning_rate=0.0001)
    model.compile(optimizer=optimizer,
                  loss='sparse_categorical_crossentropy',
                  metrics=['accuracy'])
    return model

improved_model = build_improved_model()
improved_model.summary()
```

```
Model: "sequential_5"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling_4 (Rescaling)     (None, 180, 180, 3)       0

 conv2d_15 (Conv2D)          (None, 180, 180, 32)      896

 batch_normalization_12 (Ba  (None, 180, 180, 32)      128
 tchNormalization)

 max_pooling2d_12 (MaxPooli  (None, 90, 90, 32)        0
 ng2D)

 dropout_16 (Dropout)        (None, 90, 90, 32)        0

 conv2d_16 (Conv2D)          (None, 90, 90, 64)        18496

 batch_normalization_13 (Ba  (None, 90, 90, 64)        256
 tchNormalization)

 max_pooling2d_13 (MaxPooli  (None, 45, 45, 64)        0
 ng2D)

 dropout_17 (Dropout)        (None, 45, 45, 64)        0

 conv2d_17 (Conv2D)          (None, 45, 45, 128)       73856

 batch_normalization_14 (Ba  (None, 45, 45, 128)       512
 tchNormalization)

 max_pooling2d_14 (MaxPooli  (None, 22, 22, 128)       0
 ng2D)

 dropout_18 (Dropout)        (None, 22, 22, 128)       0

 conv2d_18 (Conv2D)          (None, 22, 22, 256)       295168
```

```
 batch_normalization_15 (Ba  (None, 22, 22, 256)       1024
 tchNormalization)

 global_average_pooling2d_3  (None, 256)               0
  (GlobalAveragePooling2D)

 dropout_19 (Dropout)        (None, 256)               0

 dense_8 (Dense)             (None, 512)               131584

 dropout_20 (Dropout)        (None, 512)               0

 dense_9 (Dense)             (None, 9)                 4617

=================================================================
Total params: 526537 (2.01 MB)
Trainable params: 525577 (2.00 MB)
Non-trainable params: 960 (3.75 KB)
_________________________________________________________________
```

1.0.20 Model Training

[ ]:
```
class_distribution = analyze_class_distribution(augmented_train_ds)
total_count = sum(class_distribution.values())
class_weights = {i: total_count/class_distribution[class_name] for i,␣
 ↪class_name in enumerate(class_names)}

early_stopping = EarlyStopping(monitor='val_loss', patience=5,␣
 ↪restore_best_weights=True)
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.2, patience=2,␣
 ↪min_lr=0.00001)

history = improved_model.fit(
  augmented_train_ds,
  validation_data=augmented_val_ds,
  epochs=30,
  callbacks=[early_stopping, reduce_lr],
  class_weight=class_weights
)
```

```
Epoch 1/30
225/225 [==============================] - 78s 310ms/step - loss: 20.0258 -
accuracy: 0.2529 - val_loss: 4.9879 - val_accuracy: 0.1217 - lr: 1.0000e-04
Epoch 2/30
225/225 [==============================] - 11s 50ms/step - loss: 18.3093 -
accuracy: 0.3264 - val_loss: 4.7404 - val_accuracy: 0.1994 - lr: 1.0000e-04
Epoch 3/30
```

```
225/225 [==============================] - 11s 50ms/step - loss: 17.5156 -
accuracy: 0.3556 - val_loss: 4.2156 - val_accuracy: 0.3233 - lr: 1.0000e-04
Epoch 4/30
225/225 [==============================] - 11s 50ms/step - loss: 17.0114 -
accuracy: 0.3718 - val_loss: 3.9623 - val_accuracy: 0.3739 - lr: 1.0000e-04
Epoch 5/30
225/225 [==============================] - 11s 50ms/step - loss: 16.5868 -
accuracy: 0.4019 - val_loss: 3.8629 - val_accuracy: 0.4011 - lr: 1.0000e-04
Epoch 6/30
225/225 [==============================] - 11s 50ms/step - loss: 16.1585 -
accuracy: 0.4149 - val_loss: 3.8980 - val_accuracy: 0.3950 - lr: 1.0000e-04
Epoch 7/30
225/225 [==============================] - 11s 50ms/step - loss: 15.7979 -
accuracy: 0.4253 - val_loss: 3.6999 - val_accuracy: 0.4372 - lr: 1.0000e-04
Epoch 8/30
225/225 [==============================] - 11s 50ms/step - loss: 15.4173 -
accuracy: 0.4478 - val_loss: 3.6538 - val_accuracy: 0.4478 - lr: 1.0000e-04
Epoch 9/30
225/225 [==============================] - 11s 50ms/step - loss: 15.2694 -
accuracy: 0.4447 - val_loss: 3.5769 - val_accuracy: 0.4628 - lr: 1.0000e-04
Epoch 10/30
225/225 [==============================] - 11s 50ms/step - loss: 14.8204 -
accuracy: 0.4663 - val_loss: 3.8217 - val_accuracy: 0.4233 - lr: 1.0000e-04
Epoch 11/30
225/225 [==============================] - 11s 50ms/step - loss: 14.5142 -
accuracy: 0.4806 - val_loss: 4.0233 - val_accuracy: 0.3683 - lr: 1.0000e-04
Epoch 12/30
225/225 [==============================] - 11s 50ms/step - loss: 14.1310 -
accuracy: 0.4844 - val_loss: 3.8803 - val_accuracy: 0.3683 - lr: 2.0000e-05
Epoch 13/30
225/225 [==============================] - 11s 50ms/step - loss: 14.0050 -
accuracy: 0.4932 - val_loss: 3.8189 - val_accuracy: 0.3828 - lr: 2.0000e-05
Epoch 14/30
225/225 [==============================] - 11s 51ms/step - loss: 13.8877 -
accuracy: 0.5010 - val_loss: 3.5558 - val_accuracy: 0.4444 - lr: 1.0000e-05
Epoch 15/30
225/225 [==============================] - 11s 50ms/step - loss: 13.8137 -
accuracy: 0.5079 - val_loss: 4.0291 - val_accuracy: 0.3550 - lr: 1.0000e-05
Epoch 16/30
225/225 [==============================] - 11s 50ms/step - loss: 13.8458 -
accuracy: 0.5044 - val_loss: 4.1680 - val_accuracy: 0.3472 - lr: 1.0000e-05
Epoch 17/30
225/225 [==============================] - 11s 50ms/step - loss: 13.6997 -
accuracy: 0.5119 - val_loss: 3.5828 - val_accuracy: 0.4494 - lr: 1.0000e-05
Epoch 18/30
225/225 [==============================] - 11s 50ms/step - loss: 13.7969 -
accuracy: 0.5006 - val_loss: 3.7696 - val_accuracy: 0.4022 - lr: 1.0000e-05
Epoch 19/30
```

```
225/225 [==============================] - 11s 50ms/step - loss: 13.6749 -
accuracy: 0.5135 - val_loss: 3.6785 - val_accuracy: 0.4272 - lr: 1.0000e-05
```

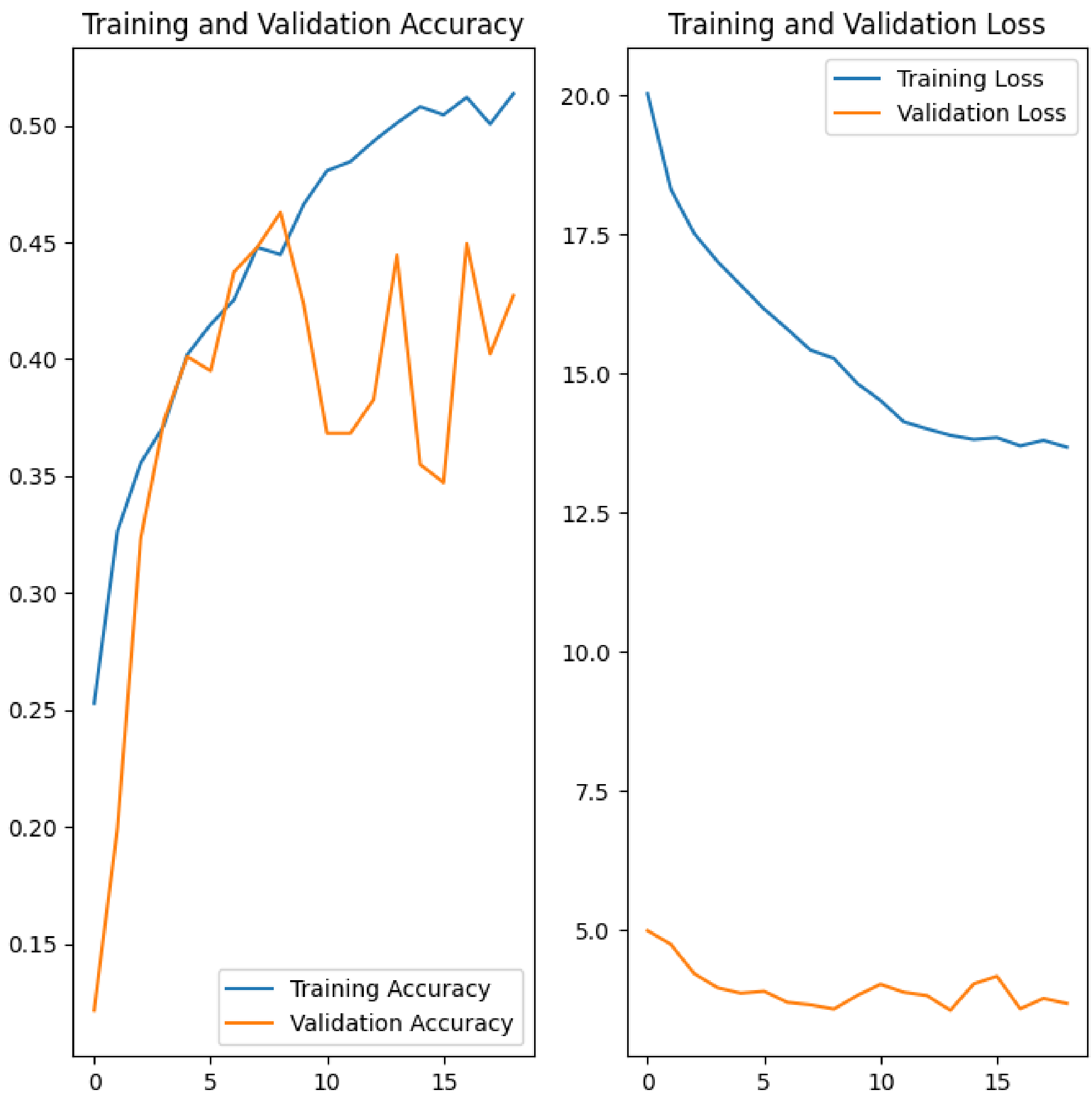
1.0.21 Visualizing training results

[ ]:

```python
# Visualizing training results (Third model)
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs_range = range(len(acc))

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()
```



1.0.22 Findings:

1. This model showed better generalization with augmented and balanced data, but overfitting persisted.
2. Although the training accuracy improved, the validation and test accuracies were not as high as desired.
3. The use of class weights helped address class imbalance but did not fully solve generalization issues.

1.0.23 Evaluting the model for the test dataset

[ ]:
```python
# Evaluating the model on the test dataset
test_loss, test_acc = improved_model.evaluate(test_ds, verbose=2)
print(f'\nTest accuracy: {test_acc}')
```

```
4/4 - 9s - loss: 4.9886 - accuracy: 0.2881 - 9s/epoch - 2s/step

Test accuracy: 0.2881355881690979
```