# Introduction

## 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 that can evaluate images and alert dermatologists about the presence of melanoma has the potential to reduce a lot of manual effort needed in diagnosis.

## About the Dataset

The dataset consists of 2357 images of malignant and benign oncological diseases, which were formed from the International Skin Imaging Collaboration (ISIC). All images were sorted according to the classification taken with ISIC, and all subsets were divided into the same number of images, with the exception of melanomas and moles, whose images are slightly dominant.

The data set contains the following diseases:

- Actinic keratosis
- Basal cell carcinoma
- Dermatofibroma
- Melanoma
- Nevus
- Pigmented benign keratosis
- Seborrheic keratosis
- Squamous cell carcinoma
- Vascular lesion

# Preparation

## Setup

```
!pip install pycodestyle
!pip install --index-url https://test.pypi.org/simple/ nbpep8
!pip install Augmentor
```

```
Requirement already satisfied: pycodestyle in /Library/Frameworks/Python.fram
Looking in indexes: https://test.pypi.org/simple/
WARNING: Retrying (Retry(total=4, connect=None, read=None, redirect=None, sta
WARNING: Retrying (Retry(total=3, connect=None, read=None, redirect=None, sta
WARNING: Retrying (Retry(total=2, connect=None, read=None, redirect=None, sta
WARNING: Retrying (Retry(total=1, connect=None, read=None, redirect=None, sta
WARNING: Retrying (Retry(total=0, connect=None, read=None, redirect=None, sta
Could not fetch URL https://test.pypi.org/simple/nbpep8/: There was a problem
ERROR: Could not find a version that satisfies the requirement nbpep8 (from v
ERROR: No matching distribution found for nbpep8
Requirement already satisfied: Augmentor in /Library/Frameworks/Python.framew
Requirement already satisfied: Pillow>=5.2.0 in /Library/Frameworks/Python.fr
Requirement already satisfied: tqdm>=4.9.0 in /Library/Frameworks/Python.fram
Requirement already satisfied: numpy>=1.11.0 in /Library/Frameworks/Python.fr
```

## Imports

```python
import os
from pathlib import Path
import glob
import matplotlib.pyplot as plt
from skimage import io
import Augmentor

import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Input, Conv2D, MaxPooling2D, Flatten, \
        Dense, Dropout
from tensorflow.keras.preprocessing.image import ImageDataGenerator, \
        load_img, img_to_array, DirectoryIterator
from tensorflow.keras.regularizers import l2

from tensorflow.keras.layers import Rescaling, Resizing
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint, \
        ReduceLROnPlateau
from tensorflow.keras.optimizers import Adam

#from nbpep8.nbpep8 import pep8

# pep8(_ih)
```

```python
# # Load the Drive helper and mount
# from google.colab import drive

# # This will prompt for authorization.
# drive.mount('/content/drive')
```

## Setup

## Setup

## Subroutines

```
def plot_accuracy(history):
    """
    Plots the 'accuracy' and 'val_accuracy'
    :param history: history from the model fitting
    :return:
    """
    plt.figure(figsize=(12, 4))

    plt.subplot(1, 2, 1)
    plt.plot(history.history['accuracy'], label='Training Accuracy')
    plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
    plt.legend()
    plt.title('Accuracy')

    plt.subplot(1, 2, 2)
    plt.plot(history.history['loss'], label='Training Loss')
    plt.plot(history.history['val_loss'], label='Validation Loss')
    plt.legend()
    plt.title('Loss')

    plt.show()


def plot_distribution(directory: str):
    """
    Calculates the class distribution in the data directory
    :param directory: dataset directory with class as subdir
    :return: dict of class:sample-count
    """
    print(f"Looking for files under {os.path.abspath(directory)}")
    class_size = dict()
    # Iterate through each subdirectory in the given directory
    for subdir, _, files in os.walk(directory):
        if files:
            condition = str(subdir).split('/')[-1]
            class_size.update({condition.upper(): len(files)})
    return class_size


def distribution(directory: str):
    """
    Calculates the class distribution in the data directory
    :param directory: dataset directory with class as subdir
    :return: dict of class:sample-count
```

```
    """
    class_size = dict()
    # Iterate through each subdirectory in the given directory
    for subdir, _, files in os.walk(directory):
        if files:
            condition = str(subdir).split('/')[-1]
            class_size.update({condition.upper(): len(files)})
    return class_size


# pep8(_ih)
```

## Constants

```
DATA_PATH = '/content/drive/MyDrive/MLAI_Notebooks/data/ISIC_skin_cancer/'
DATA_PATH = '/Users/pchinnas/Learn/AIML/Data/golden/Skin cancer ISIC The Inter
BATCH_SIZE = 32
RANDOM_SEED = 123
MAX_EPOCHS_20 = 20
MAX_EPOCHS_30 = 30
IMG_SIZE = (180, 180)
IMG_CH_SHAPE = (180, 180, 3)
INPUT_SHAPE = (BATCH_SIZE, 180, 180, 3)
AUG_SAMPLE_PER_CLASS_AUGM = 1000
AUG_INC_PER_CLASS_KERAS = 350
AUTOTUNE = tf.data.experimental.AUTOTUNE

# pep8(_ih)
```

## Dataset Creation

```
os.chdir(DATA_PATH)
train_dir = Path("./Train")
test_dir = Path('./Test')
```

```
train_ds = tf.keras.preprocessing.image_dataset_from_directory(
    train_dir,
    shuffle=True,
    image_size=IMG_SIZE,
    batch_size=BATCH_SIZE
)

len(train_ds)
class_names = train_ds.class_names
```

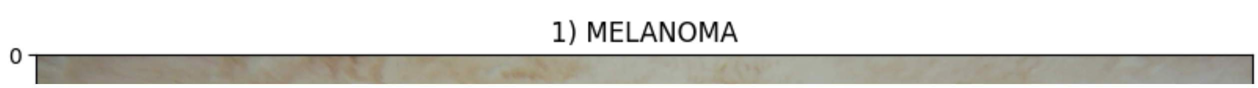
```
Found 8989 files belonging to 9 classes.
```

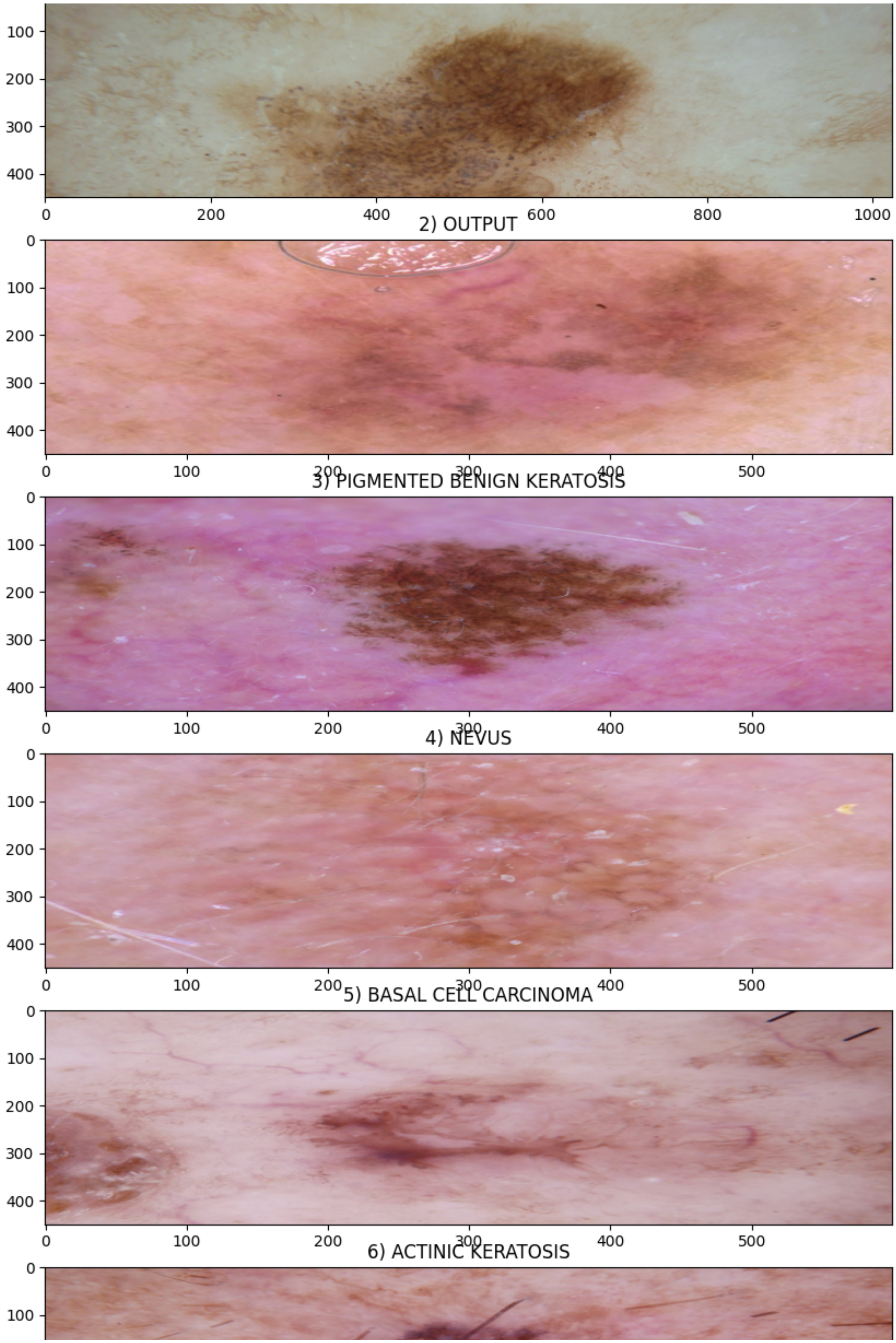
```python
validation_ds = tf.keras.preprocessing.image_dataset_from_directory(
    test_dir,
    shuffle=True,
    image_size=IMG_SIZE,
    batch_size=BATCH_SIZE
)
```

```
Found 118 files belonging to 9 classes.
```

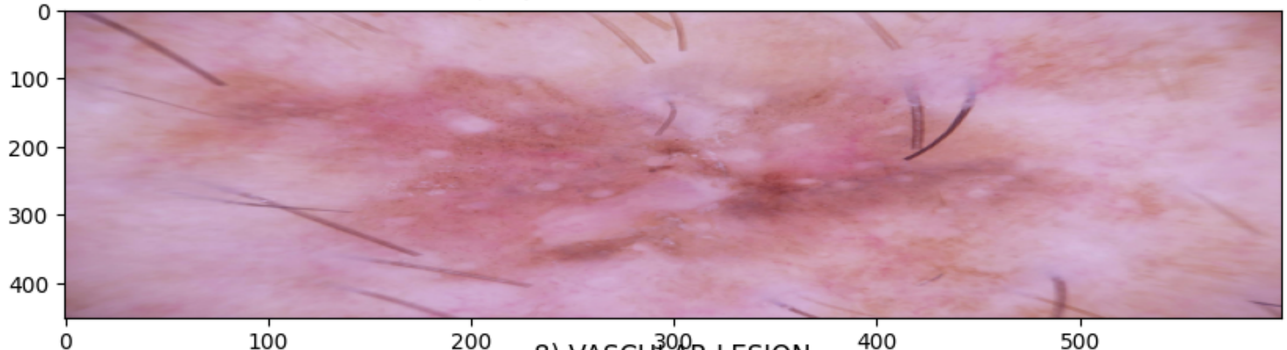
## Visualize the Data

```python
import random

def pick_cond_img(directory: str):
    """
    Picks a random file for each condition
    :param directory:
    :return:
    """
    selected_files = dict()

    # Iterate through each subdirectory in the given directory
    for subdir, _, files in os.walk(directory):
        if files:
            # Pick a random file from the current subdirectory
            selected_file = random.choice(files)
            img_path = os.path.join(subdir, selected_file)
            condition = str(subdir).split('/')[-1]
            selected_files.update({condition.upper(): img_path})
    return selected_files
cond_img = pick_cond_img(train_dir)

f, axes = plt.subplots(len(cond_img), 1, sharey=True, figsize=(10, 30))

i = 0
for cond, img_path in cond_img.items():
    img = io.imread(img_path)
    axes[i].imshow(img, aspect='auto')
    axes[i].title.set_text(str(i+1) + ') ' + cond)
    i += 1
plt.show()

# pep8(_ih)
```

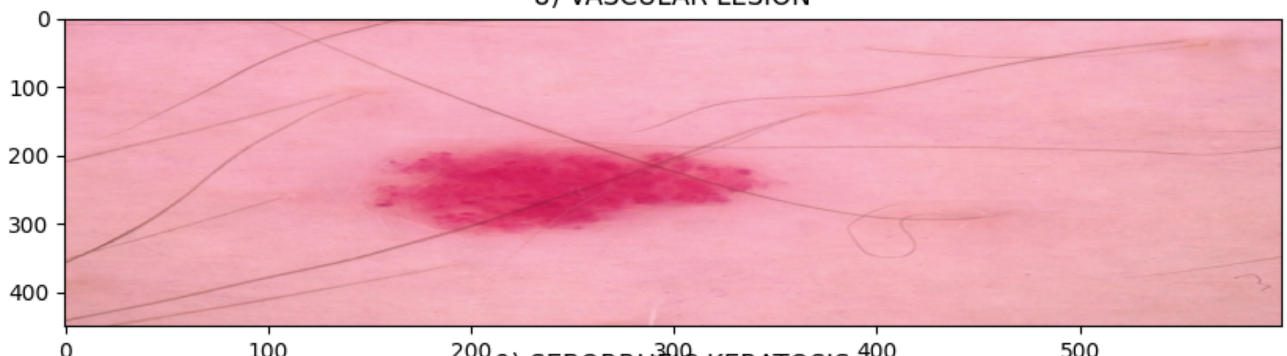



2) OUTPUT
3) PIGMENTED BENIGN KERATOSIS
4) NEVUS
5) BASAL CELL CARCINOMA
6) ACTINIC KERATOSIS


7) SQUAMOUS CELL CARCINOMA

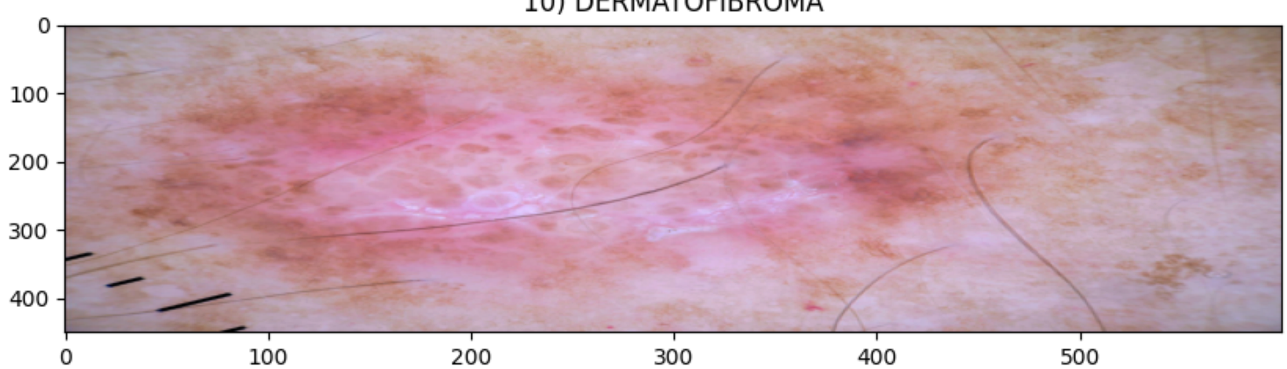



8) VASCULAR LESION




9) SEBORRHEIC KERATOSIS


10) DERMATOFIBROMA



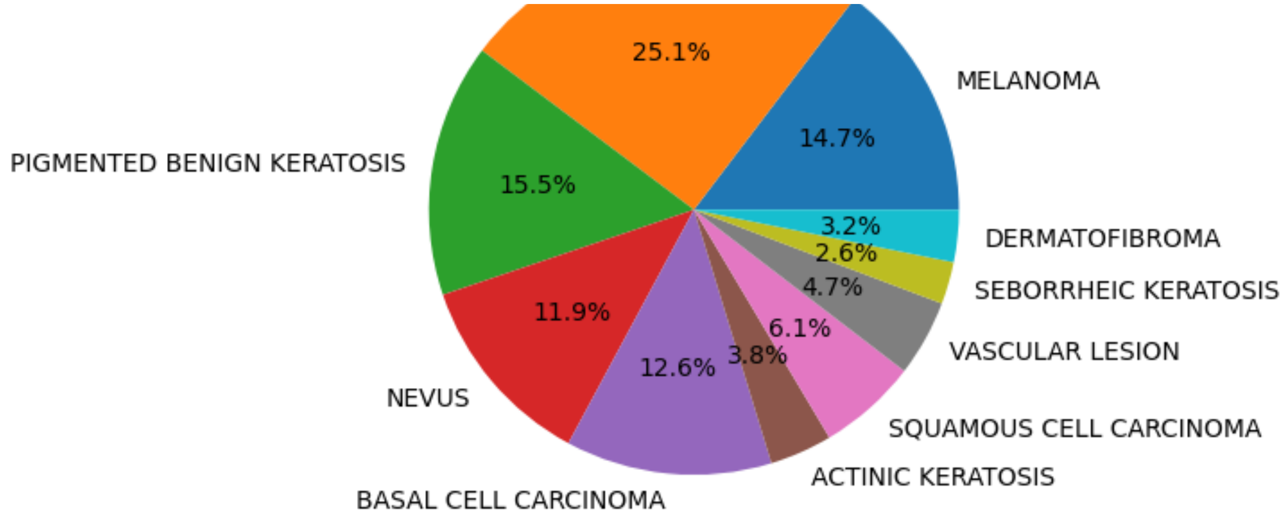
## Model - 1

```
AUTOTUNE = tf.data.experimental.AUTOTUNE
train_ds = train_ds.cache().shuffle(1000).prefetch(buffer_size=AUTOTUNE)
validation_ds = validation_ds.cache() \
    .shuffle(1000).prefetch(buffer_size=AUTOTUNE)

# pep8(_ih)
```

## Class Distribution

```
class_dist = distribution(train_dir)
plt.pie(class_dist.values(), labels=class_dist.keys(), autopct='%1.1f%%')
plt.show()
class_dist
plot_distribution(os.path.join(DATA_PATH, train_dir))

# pep8(_ih)
```

OUTPUT




```
Looking for files under /Users/pchinnas/Learn/AIML/Data/golden/Skin cancer IS:
{'MELANOMA': 438,
 'OUTPUT': 750,
 'PIGMENTED BENIGN KERATOSIS': 462,
 'NEVUS': 357,
 'BASAL CELL CARCINOMA': 376,
 'ACTINIC KERATOSIS': 114,
 'SQUAMOUS CELL CARCINOMA': 181,
 'VASCULAR LESION': 139,
 'SEBORRHEIC KERATOSIS': 77,
 'DERMATOFIBROMA': 95}
```

### Findings

- 'seborrheic keratosis' has 3.4% (77) of the samples and hence is the least
- 'pigmented benign keratosis' has 20.6%(462) at the highest, closely followed by 'melanoma' at 19.6%(438)

## Build

```
from tensorflow.keras.layers import Dense, Dropout, Activation, Flatten, \
    Conv2D, MaxPooling2D, BatchNormalization

model = Sequential([
    Input(shape=IMG_CH_SHAPE, batch_size=BATCH_SIZE),
    Conv2D(32, (3, 3), activation='relu'),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
```

```
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(32, activation='relu'),
    Dense(64, activation='relu'),
    Dense(len(class_names), activation='softmax')
])

# pep8(_ih)
```

```
model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=T
              metrics=['accuracy'])
model.build(INPUT_SHAPE)
model.summary()
```

**Model: "sequential_10"**

| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv2d_22 (Conv2D) | (32, 178, 178, 32) | 896 |
| conv2d_23 (Conv2D) | (32, 176, 176, 64) | 18,496 |
| max_pooling2d_20 (MaxPooling2D) | (32, 88, 88, 64) | 0 |
| conv2d_24 (Conv2D) | (32, 86, 86, 64) | 36,928 |
| max_pooling2d_21 (MaxPooling2D) | (32, 43, 43, 64) | 0 |
| flatten_8 (Flatten) | (32, 118336) | 0 |
| dense_18 (Dense) | (32, 32) | 3,786,784 |
| dense_19 (Dense) | (32, 64) | 2,112 |
| dense_20 (Dense) | (32, 9) | 585 |

**Total params:** 3,845,801 (14.67 MB)
**Trainable params:** 3,845,801 (14.67 MB)
**Non-trainable params:** 0 (0.00 B)

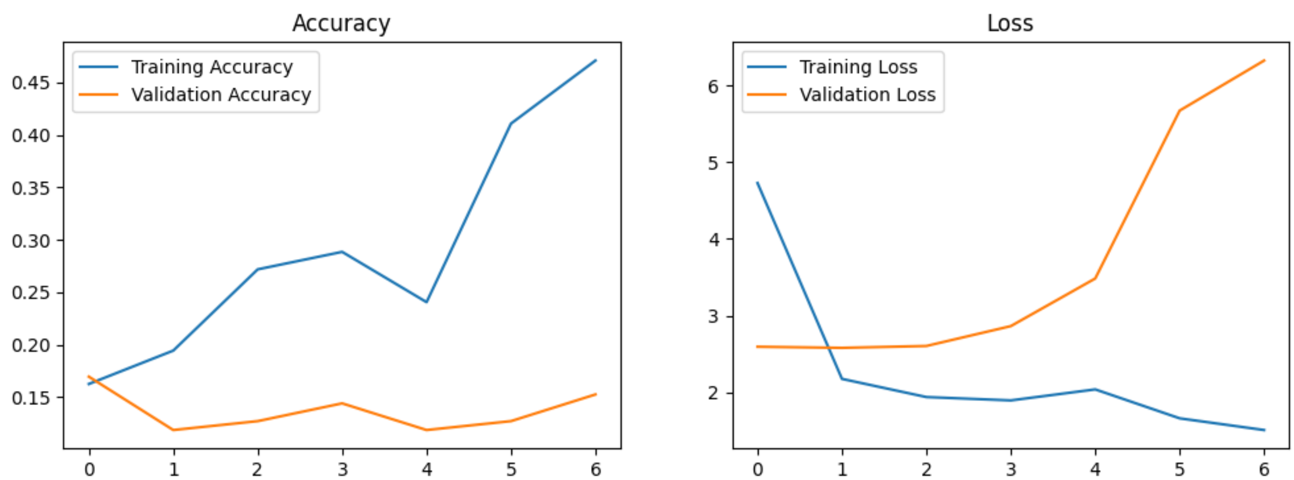
## Train

```
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_we

history = model.fit(
  train_ds,
  validation_data=validation_ds,
  epochs=MAX_EPOCHS_20,
  callbacks=[early_stopping]
)
```

```
print(f"\nBest accuracy: {max(history.history['accuracy'])}")
```

```
Epoch 1/20
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packag
  output, from_logits = _get_logits(
281/281 ━━━━━━━━━━━━━━━━━━━━ 179s 615ms/step - accuracy: 0.1477 - loss: 14.41
Epoch 2/20
281/281 ━━━━━━━━━━━━━━━━━━━━ 181s 642ms/step - accuracy: 0.1929 - loss: 2.131
Epoch 3/20
281/281 ━━━━━━━━━━━━━━━━━━━━ 183s 651ms/step - accuracy: 0.2575 - loss: 1.951
Epoch 4/20
281/281 ━━━━━━━━━━━━━━━━━━━━ 181s 644ms/step - accuracy: 0.3209 - loss: 1.834
Epoch 5/20
281/281 ━━━━━━━━━━━━━━━━━━━━ 187s 667ms/step - accuracy: 0.2050 - loss: 2.060
Epoch 6/20
281/281 ━━━━━━━━━━━━━━━━━━━━ 182s 649ms/step - accuracy: 0.4098 - loss: 1.656
Epoch 7/20
281/281 ━━━━━━━━━━━━━━━━━━━━ 186s 661ms/step - accuracy: 0.4270 - loss: 1.579

Best accuracy: 0.4707976281642914
```

```
plot_accuracy(history)
```




## Findings

- Accuracy is low at** 47.5% **. This can be attributed to the following
  - Not having enough labeled training data can lead to poor generalization. CNNs

require large amounts of diverse data to learn effectively.
    - Imbalanced Dataset: If some classes have significantly more samples than others, the model might become biased toward the more frequent classes, leading to poor performance on the less frequent ones.
- **Overfitting**: When a model performs well on training data but poorly on validation data, it might be overfitting. This can occur if the model is too complex relative to the amount of training data.

## Model - 2

### Build

```
# resize and rescale the value
resize_and_rescale = Sequential([
    tf.keras.layers.Resizing(180, 180),
    tf.keras.layers.Rescaling(1.0/255)
])
```

```
keras_augmentation = Sequential([
    tf.keras.layers.RandomRotation(factor=(-0.2, 0.3)),
    tf.keras.layers.RandomFlip("horizontal_and_vertical")
])
```

```
from tensorflow.keras.layers import Rescaling, Resizing

model = Sequential([
    Input(shape=IMG_CH_SHAPE, batch_size=BATCH_SIZE),
    resize_and_rescale,
    keras_augmentation,
    Conv2D(32, (3, 3), activation='relu'),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(32, activation='relu'),
    Dense(64, activation='relu'),
    Dense(len(class_names), activation='softmax')
])
```

```
model.compile(optimizer='adam',
```

```
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=T
              metrics=['accuracy'])
model.build(INPUT_SHAPE)
model.summary()
```

**Model: "sequential_13"**

| Layer (type) | Output Shape | Param # |
|---|---|---|
| sequential_11 (Sequential) | (32, 180, 180, 3) | 0 |
| sequential_12 (Sequential) | (32, 180, 180, 3) | 0 |
| conv2d_25 (Conv2D) | (32, 178, 178, 32) | 896 |
| conv2d_26 (Conv2D) | (32, 176, 176, 64) | 18,496 |
| max_pooling2d_22 (MaxPooling2D) | (32, 88, 88, 64) | 0 |
| conv2d_27 (Conv2D) | (32, 86, 86, 64) | 36,928 |
| max_pooling2d_23 (MaxPooling2D) | (32, 43, 43, 64) | 0 |
| flatten_9 (Flatten) | (32, 118336) | 0 |
| dense_21 (Dense) | (32, 32) | 3,786,784 |
| dense_22 (Dense) | (32, 64) | 2,112 |
| dense_23 (Dense) | (32, 9) | 585 |

**Total params:** 3,845,801 (14.67 MB)
**Trainable params:** 3,845,801 (14.67 MB)
**Non-trainable params:** 0 (0.00 B)

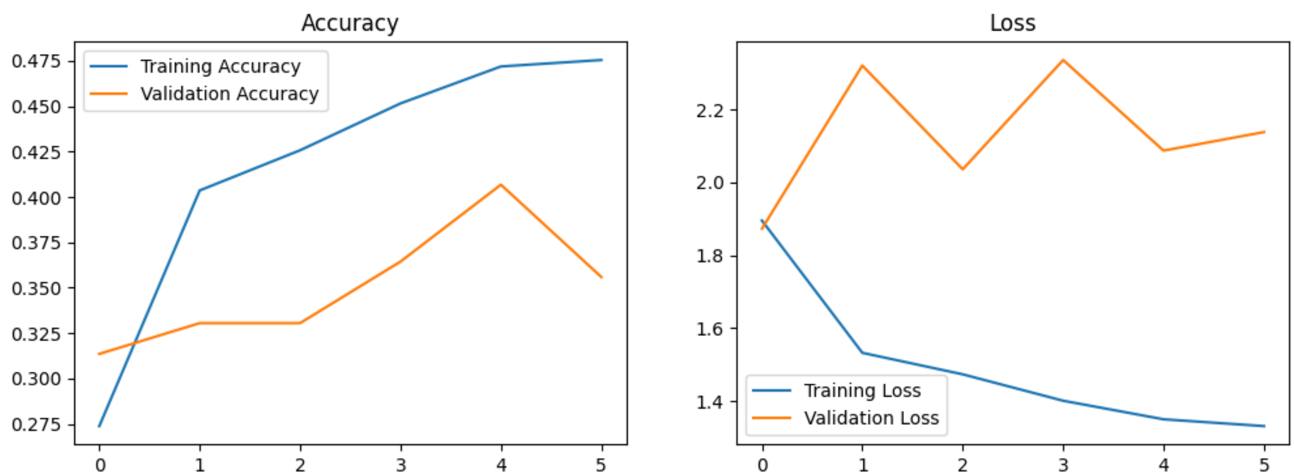
## Train

```
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_we

history = model.fit(
  train_ds,
  validation_data=validation_ds,
  epochs=MAX_EPOCHS_20,
  callbacks=[early_stopping]
)

print(f"\nBest accuracy: {max(history.history['accuracy'])}")
```

```
Epoch 1/20
281/281 ━━━━━━━━━━━━━━━━━━━━ 191s 676ms/step - accuracy: 0.1951 - loss: 2.115
Epoch 2/20
281/281 ━━━━━━━━━━━━━━━━━━━━ 180s 642ms/step - accuracy: 0.4016 - loss: 1.551
Epoch 3/20
```

```
281/281 ━━━━━━━━━━━━━━━━━━━━ 175s 624ms/step - accuracy: 0.4312 - loss: 1.474
Epoch 4/20
281/281 ━━━━━━━━━━━━━━━━━━━━ 192s 683ms/step - accuracy: 0.4440 - loss: 1.418
Epoch 5/20
281/281 ━━━━━━━━━━━━━━━━━━━━ 192s 684ms/step - accuracy: 0.4685 - loss: 1.356
Epoch 6/20
281/281 ━━━━━━━━━━━━━━━━━━━━ 188s 668ms/step - accuracy: 0.4739 - loss: 1.332

Best accuracy: 0.47547000646591187
```

```
1 plot_accuracy(history)
```




## Findings

- Validation accuracy has not improved (**47.5%**)
- There is a clear case of overfitting
- Total trainable params are 3,845,801
- The class imbalance can be a cause of this overfitting
- A good sample size can help the model quality

# Model - 3

## Augmenting Data

```
import Augmentor
for class_name in class_names:
    p = Augmentor.Pipeline(os.path.join(train_dir, class_name))
    p.rotate(probability=0.7, max_left_rotation=10, max_right_rotation=10)
    p.sample(AUG_SAMPLE_PER_CLASS_AUGM)

# pep8(_ih)
```

```
Initialised with 114 image(s) found.
Output directory set to Train/actinic keratosis/output.Processing <PIL.Image.
Initialised with 376 image(s) found.
Output directory set to Train/basal cell carcinoma/output.Processing <PIL.Ima
Initialised with 95 image(s) found.
Output directory set to Train/dermatofibroma/output.Processing <PIL.Image.Ima
Initialised with 438 image(s) found.
Output directory set to Train/melanoma/output.Processing <PIL.Image.Image ima
Initialised with 357 image(s) found.
Output directory set to Train/nevus/output.Processing <PIL.Image.Image image
Initialised with 462 image(s) found.
Output directory set to Train/pigmented benign keratosis/output.Processing <P
Initialised with 77 image(s) found.
Output directory set to Train/seborrheic keratosis/output.Processing <PIL.Ima
Initialised with 181 image(s) found.
Output directory set to Train/squamous cell carcinoma/output.Processing <PIL.
Initialised with 139 image(s) found.
Output directory set to Train/vascular lesion/output.Processing <PIL.Image.Im
```

```
train_ds = tf.keras.preprocessing.image_dataset_from_directory(
    train_dir,
    seed=RANDOM_SEED,
    validation_split=0.2,
    subset='training',
    image_size=IMG_SIZE,
    batch_size=BATCH_SIZE
)

# pep8(_ih)
```

```
Found 11239 files belonging to 9 classes.
Using 8992 files for training.
```

```
validation_ds = tf.keras.preprocessing.image_dataset_from_directory(
    train_dir,
    seed=RANDOM_SEED,
    validation_split=0.2,
    subset='validation',
    image_size=IMG_SIZE,
    batch_size=BATCH_SIZE
)
```

```
# pep8(_ih)
```

```
Found 11239 files belonging to 9 classes.
Using 2247 files for validation.
```

```
train_ds = train_ds.cache().shuffle(1000).prefetch(buffer_size=AUTOTUNE)
validation_ds = validation_ds.cache().prefetch(buffer_size=AUTOTUNE)
```

## Build

```
model = Sequential([
    Input(shape=IMG_CH_SHAPE, batch_size=BATCH_SIZE),

    Rescaling(1.0/255),

    Conv2D(16, (3, 3), activation='relu'),
    BatchNormalization(),
    MaxPooling2D((2, 2)),

    Conv2D(32, (3, 3), activation='relu'),
    BatchNormalization(),
    MaxPooling2D((2, 2)),

    Conv2D(64, (3, 3), activation='relu', kernel_regularizer=l2(0.01)),
    BatchNormalization(),
    MaxPooling2D((2, 2)),

    Conv2D(64, (3, 3), activation='relu', kernel_regularizer=l2(0.01)),
    BatchNormalization(),
    MaxPooling2D((2, 2)),

    # Conv2D(64, (3, 3), activation='relu', kernel_regularizer=l2(0.01)),
    # BatchNormalization(),
    # MaxPooling2D((2, 2)),

    Dropout(0.25),

    Flatten(),

    Dense(128, activation='relu', kernel_regularizer=l2(0.01)),

    Dropout(0.5),

    Dense(len(class_names), activation='softmax')
])

# pep8(_ih)
```

```
adam = Adam(learning_rate=0.0001)

model.compile(optimizer=adam,
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=T
              metrics=['accuracy'])
model.build(INPUT_SHAPE)
model.summary()

# pep8(_ih)
```

**Model: "sequential_16"**

| **Layer (type)** | **Output Shape** | **Param #** |
|---|---|---:|
| rescaling_10 (Rescaling) | (32, 180, 180, 3) | 0 |
| conv2d_36 (Conv2D) | (32, 178, 178, 16) | 448 |
| batch_normalization_19 (BatchNormalization) | (32, 178, 178, 16) | 64 |
| max_pooling2d_32 (MaxPooling2D) | (32, 89, 89, 16) | 0 |
| conv2d_37 (Conv2D) | (32, 87, 87, 32) | 4,640 |
| batch_normalization_20 (BatchNormalization) | (32, 87, 87, 32) | 128 |
| max_pooling2d_33 (MaxPooling2D) | (32, 43, 43, 32) | 0 |
| conv2d_38 (Conv2D) | (32, 41, 41, 64) | 18,496 |
| batch_normalization_21 (BatchNormalization) | (32, 41, 41, 64) | 256 |
| max_pooling2d_34 (MaxPooling2D) | (32, 20, 20, 64) | 0 |
| conv2d_39 (Conv2D) | (32, 18, 18, 64) | 36,928 |
| batch_normalization_22 (BatchNormalization) | (32, 18, 18, 64) | 256 |
| max_pooling2d_35 (MaxPooling2D) | (32, 9, 9, 64) | 0 |
| dropout_16 (Dropout) | (32, 9, 9, 64) | 0 |
| flatten_12 (Flatten) | (32, 5184) | 0 |
| dense_28 (Dense) | (32, 128) | 663,680 |
| dropout_17 (Dropout) | (32, 128) | 0 |
| dense_29 (Dense) | (32, 9) | 1,161 |

**Total params:** 726,057 (2.77 MB)

```
Total params: 726,057 (2.77 MB)
Trainable params: 725,705 (2.77 MB)
Non-trainable params: 352 (1.38 KB)
```

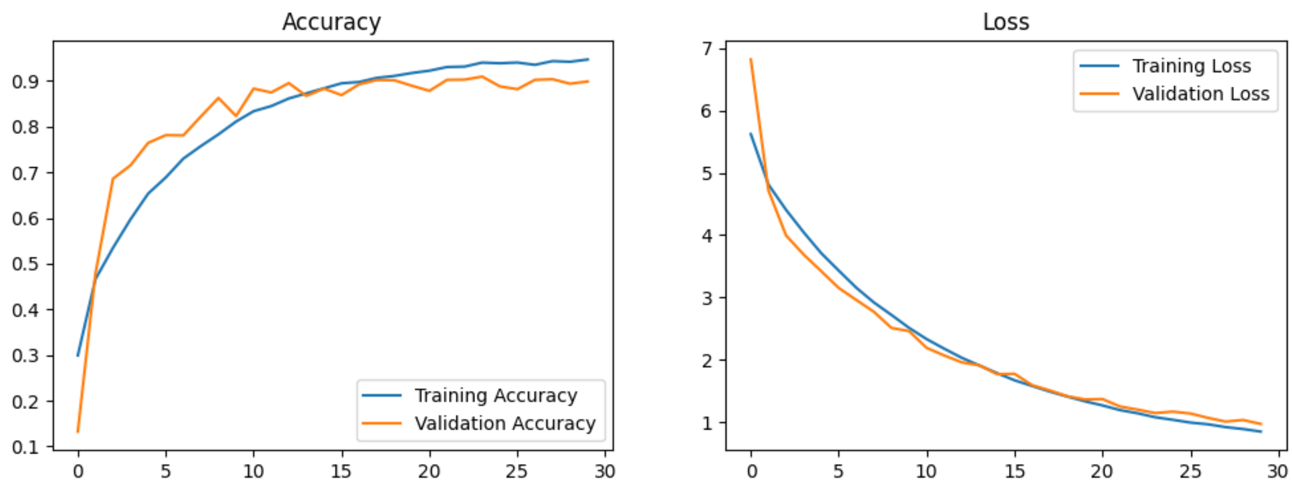
## Train

```
optimizer = Adam(learning_rate=0.0001)
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_weig
checkpoint = ModelCheckpoint("model.keras",monitor="val_loss",save_best_only=Tru
reduce_lr_loss = ReduceLROnPlateau(monitor='val_loss', factor=0.5, patience=7, v

history = model.fit(
    train_ds,
    validation_data=validation_ds,
    epochs=MAX_EPOCHS_30,
    callbacks=[early_stopping, checkpoint, reduce_lr_loss]
)
print(f"\nBest accuracy: {max(history.history['accuracy'])}")

# pep8(_ih)
```

```
Epoch 1/30
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packag
  output, from_logits = _get_logits(
281/281 ━━━━━━━━━━━━━━━━━━━━ 0s 179ms/step - accuracy: 0.2228 - loss: 6.1990
Epoch 1: val_loss improved from inf to 6.82118, saving model to model.keras
281/281 ━━━━━━━━━━━━━━━━━━━━ 60s 194ms/step - accuracy: 0.2231 - loss: 6.1969
Epoch 2/30
281/281 ━━━━━━━━━━━━━━━━━━━━ 0s 174ms/step - accuracy: 0.4506 - loss: 4.8954
Epoch 2: val_loss improved from 6.82118 to 4.71839, saving model to model.ker
281/281 ━━━━━━━━━━━━━━━━━━━━ 51s 183ms/step - accuracy: 0.4507 - loss: 4.8951
Epoch 3/30
281/281 ━━━━━━━━━━━━━━━━━━━━ 0s 174ms/step - accuracy: 0.5290 - loss: 4.4855
Epoch 3: val_loss improved from 4.71839 to 3.99648, saving model to model.ker
281/281 ━━━━━━━━━━━━━━━━━━━━ 51s 183ms/step - accuracy: 0.5291 - loss: 4.4853
Epoch 4/30
281/281 ━━━━━━━━━━━━━━━━━━━━ 0s 173ms/step - accuracy: 0.5857 - loss: 4.1182
Epoch 4: val_loss improved from 3.99648 to 3.69043, saving model to model.ker
281/281 ━━━━━━━━━━━━━━━━━━━━ 51s 182ms/step - accuracy: 0.5857 - loss: 4.1179
Epoch 5/30
281/281 ━━━━━━━━━━━━━━━━━━━━ 0s 173ms/step - accuracy: 0.6489 - loss: 3.7791
Epoch 5: val_loss improved from 3.69043 to 3.42252, saving model to model.ker
281/281 ━━━━━━━━━━━━━━━━━━━━ 51s 182ms/step - accuracy: 0.6489 - loss: 3.7788
Epoch 6/30
281/281 ━━━━━━━━━━━━━━━━━━━━ 0s 175ms/step - accuracy: 0.6840 - loss: 3.4914
Epoch 6: val_loss improved from 3.42252 to 3.15235, saving model to model.ker
281/281 ━━━━━━━━━━━━━━━━━━━━ 52s 184ms/step - accuracy: 0.6840 - loss: 3.4912
Epoch 7/30
281/281 ━━━━━━━━━━━━━━━━━━━━ 0s 176ms/step - accuracy: 0.7282 - loss: 3.1983
Epoch 7: val_loss improved from 3.15235 to 2.95956, saving model to model.ker
281/281 ━━━━━━━━━━━━━━━━━━━━ 52s 186ms/step - accuracy: 0.7282 - loss: 3.1982
Epoch 8/30
281/281 ━━━━━━━━━━━━━━━━━━━━ 0s 170ms/step - accuracy: 0.7519 - loss: 2.9637
```

```
Epoch 8: val_loss improved from 2.95956 to 2.76957, saving model to model.kera
281/281 ━━━━━━━━━━━━━━━━━━━━ 50s 178ms/step - accuracy: 0.7519 - loss: 2.9636
Epoch 9/30
281/281 ━━━━━━━━━━━━━━━━━━━━ 0s 168ms/step - accuracy: 0.7805 - loss: 2.7642
Epoch 9: val_loss improved from 2.76957 to 2.51044, saving model to model.kera
281/281 ━━━━━━━━━━━━━━━━━━━━ 50s 177ms/step - accuracy: 0.7805 - loss: 2.7641
Epoch 10/30
281/281 ━━━━━━━━━━━━━━━━━━━━ 0s 173ms/step - accuracy: 0.8092 - loss: 2.5453
Epoch 10: val_loss improved from 2.51044 to 2.45920, saving model to model.ke
281/281 ━━━━━━━━━━━━━━━━━━━━ 51s 182ms/step - accuracy: 0.8092 - loss: 2.5452
Epoch 11/30
281/281 ━━━━━━━━━━━━━━━━━━━━ 0s 170ms/step - accuracy: 0.8398 - loss: 2.3497
Epoch 11: val_loss improved from 2.45920 to 2.19092, saving model to model.ke
281/281 ━━━━━━━━━━━━━━━━━━━━ 50s 178ms/step - accuracy: 0.8398 - loss: 2.3497
Epoch 12/30
281/281 ━━━━━━━━━━━━━━━━━━━━ 0s 171ms/step - accuracy: 0.8482 - loss: 2.1986
Epoch 12: val_loss improved from 2.19092 to 2.06845, saving model to model.ke
281/281 ━━━━━━━━━━━━━━━━━━━━ 51s 183ms/step - accuracy: 0.8482 - loss: 2.1985
Epoch 13/30
281/281 ━━━━━━━━━━━━━━━━━━━━ 0s 172ms/step - accuracy: 0.8607 - loss: 2.0522
Epoch 13: val_loss improved from 2.06845 to 1.95785, saving model to model.ke
281/281 ━━━━━━━━━━━━━━━━━━━━ 51s 182ms/step - accuracy: 0.8607 - loss: 2.0521
Epoch 14/30
281/281 ━━━━━━━━━━━━━━━━━━━━ 0s 172ms/step - accuracy: 0.8832 - loss: 1.9156
Epoch 14: val_loss improved from 1.95785 to 1.91078, saving model to model.ke
281/281 ━━━━━━━━━━━━━━━━━━━━ 52s 183ms/step - accuracy: 0.8831 - loss: 1.9156
```

```
1 plot_accuracy(history)
```




## Findings

- After increasing the size of the training dataset, the accuracy has improved (**94.6%**).
- Total trainable params are 725,705
- Overfitting is contained with the help of
  - BatchNormalization
  - Dropouts
  - EarlyStopping
- The model also runs with a Learning rate scheduler both with ReduceLROnPlateau and with Adam optimizer with less lr value

## Analysis

```
model.evaluate(validation_ds)
```

```
71/71 ━━━━━━━━━━━━━━━━━━━━ 3s 35ms/step - accuracy: 0.8926 - loss: 0.9721
[0.9695644378662109, 0.8985313773155212]
```

```
print("Best Score:", max(history.history['accuracy']))
```

```
Best Score: 0.9466192126274109
```

```
acc = ['accuracy', 'val_accuracy']
loss = ['loss', 'val_loss']
for s in acc:
    print(s, max(history.history[s]))
for s in loss:
    print(s, min(history.history[s]))

# pep8(_ih)
```

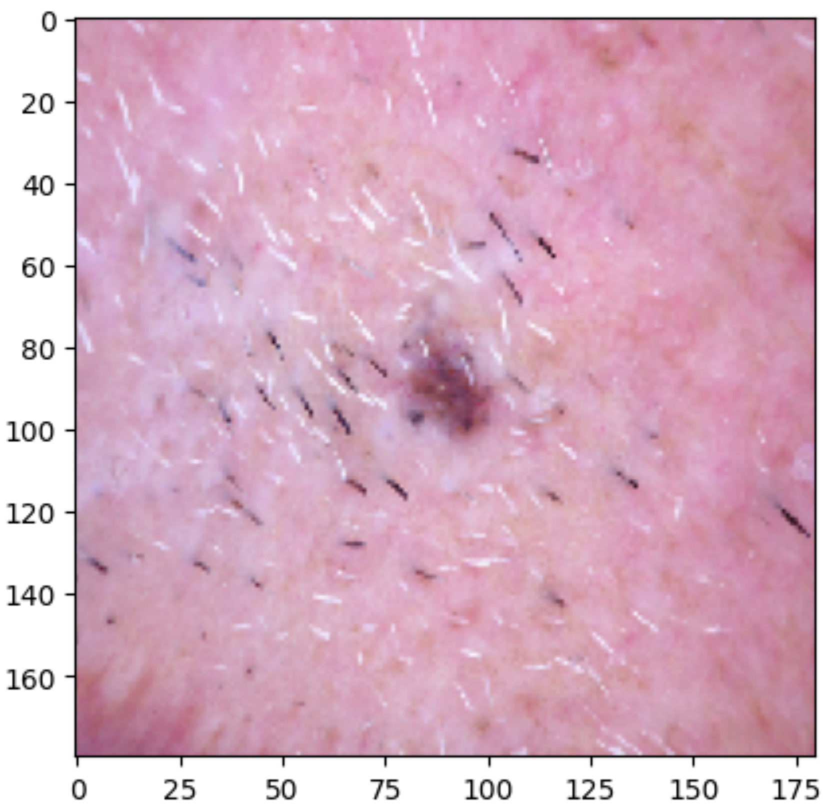
```
accuracy 0.9466192126274109
val_accuracy 0.9092122912406921
loss 0.8464059233665466
val_loss 0.9695644378662109
```

## Prediction:

```
from glob import glob
import numpy as np
class_name = class_names[1]
Test_image_path = os.path.join(test_dir, class_name, '*')
print(Test_image_path)
```

```
print(Test_image_path)
Test_image = glob(Test_image_path)
Test_image = load_img(Test_image[-1], target_size=(180, 180, 3))
plt.imshow(Test_image)
plt.grid(False)

img = np.expand_dims(Test_image, axis=0)
pred = model.predict(img)
pred = np.argmax(pred)
pred_class = class_names[pred]
print(f"Actual Class '{class_name} \nPredictive Class '{pred_class}'")

# pep8(_ih)
```

```
Test/basal cell carcinoma/*
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 67ms/step
Actual Class 'basal cell carcinoma
Predictive Class 'basal cell carcinoma'
```




## Model on Unseen Test data

```
test_ds = tf.keras.preprocessing.image_dataset_from_directory(
    test_dir,
    seed=RANDOM_SEED,
    validation_split=0.2,
    subset='validation',
    image_size=IMG_SIZE,
```

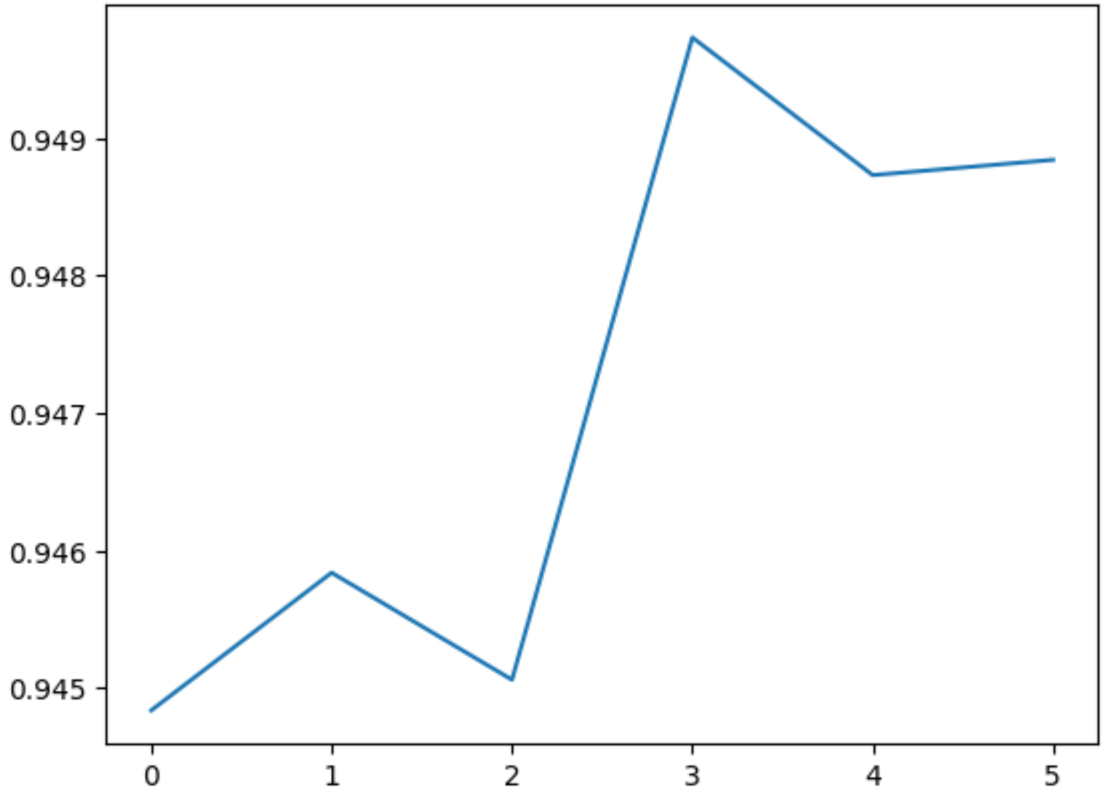
```
    batch_size=BATCH_SIZE
)

```

```
Found 118 files belonging to 9 classes.
Using 23 files for validation.
```

```
optimizer = Adam(learning_rate=0.0001)
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_we
checkpoint = ModelCheckpoint("model.keras",monitor="val_loss",save_best_only=T
reduce_lr_loss = ReduceLROnPlateau(monitor='val_loss', factor=0.5, patience=7,

history = model.fit(
    train_ds,
    validation_data=test_ds,
    epochs=MAX_EPOCHS_30,
    callbacks=[early_stopping, checkpoint, reduce_lr_loss]
)
print(f"\nBest accuracy: {max(history.history['accuracy'])}")

# pep8(_ih)
```

```
Epoch 1/30
281/281 ━━━━━━━━━━━━━━━━━━━━ 0s 173ms/step - accuracy: 0.9450 - loss: 0.8325
Epoch 1: val_loss improved from inf to 3.87447, saving model to model.keras
281/281 ━━━━━━━━━━━━━━━━━━━━ 49s 174ms/step - accuracy: 0.9450 - loss: 0.8325
Epoch 2/30
281/281 ━━━━━━━━━━━━━━━━━━━━ 0s 208ms/step - accuracy: 0.9476 - loss: 0.8045
Epoch 2: val_loss did not improve from 3.87447
281/281 ━━━━━━━━━━━━━━━━━━━━ 59s 209ms/step - accuracy: 0.9476 - loss: 0.8045
Epoch 3/30
281/281 ━━━━━━━━━━━━━━━━━━━━ 0s 164ms/step - accuracy: 0.9447 - loss: 0.7874
Epoch 3: val_loss did not improve from 3.87447
281/281 ━━━━━━━━━━━━━━━━━━━━ 46s 165ms/step - accuracy: 0.9447 - loss: 0.7874
Epoch 4/30
281/281 ━━━━━━━━━━━━━━━━━━━━ 0s 171ms/step - accuracy: 0.9574 - loss: 0.7398
Epoch 4: val_loss did not improve from 3.87447
281/281 ━━━━━━━━━━━━━━━━━━━━ 48s 172ms/step - accuracy: 0.9574 - loss: 0.7399
Epoch 5/30
281/281 ━━━━━━━━━━━━━━━━━━━━ 0s 163ms/step - accuracy: 0.9543 - loss: 0.7281
Epoch 5: val_loss did not improve from 3.87447
281/281 ━━━━━━━━━━━━━━━━━━━━ 46s 164ms/step - accuracy: 0.9542 - loss: 0.7282
Epoch 6/30
281/281 ━━━━━━━━━━━━━━━━━━━━ 0s 167ms/step - accuracy: 0.9561 - loss: 0.7039
Epoch 6: val_loss did not improve from 3.87447
281/281 ━━━━━━━━━━━━━━━━━━━━ 47s 169ms/step - accuracy: 0.9561 - loss: 0.7039

Best accuracy: 0.9497330784797668
```

```
plt.plot(history.history['accuracy'], label='Training Accuracy')
#plt.show()
```




## Conclusion:

- The model is finally up to satisfaction.
- Training and Test paths are defined (train_dir, test_dir)
- Datasets were created (train_ds, validation_ds, test_ds)
- Data for all 9 classes are visualized
- Model-1 built with vanilla daset - accuracy was low and overfitting was noticed
- Model-2 built and run with keras augmentation - accuracy was better but sill low with overfitting
- Model-3 built and run with Augmentor created dataset with steps to curtail overfitting
- Data augmentation done with Keras and Augmentor libraries
- Class distribution was done and imbalance was noticed. It is fixed with Augmentor
- Coded with nbpep8 lib and documentation where it is required.