Problem statement:

Build a CNN based model which can accurately detect melanoma. Melanoma is a type of cancer that can be deadly if not detected early. It accounts for 75% of skin cancer deaths. A solution which can evaluate images and alert the dermatologists about the presence of melanoma has the potential to reduce a lot of manual effort needed in diagnosis.

In [1]:
```
#mount google drive
from google.colab import drive
drive.mount('/content/gdrive')
```

```
Mounted at /content/gdrive
```

In [2]:
```
#unzip the dataset
!unzip "/content/gdrive/MyDrive/SkinCancerDataset.zip" > /dev/null
```

In [3]:
```
#import the required libraries
import pathlib
import os

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

import PIL

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential

from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import ModelCheckpoint,EarlyStopping

from tensorflow.keras.preprocessing.image import load_img
```

In [4]:
```
# Defining the path for train and test images
data_dir_train = pathlib.Path("/content/Skin cancer ISIC The International Skin Imaging Co
data_dir_test = pathlib.Path("/content/Skin cancer ISIC The International Skin Imaging Col
```

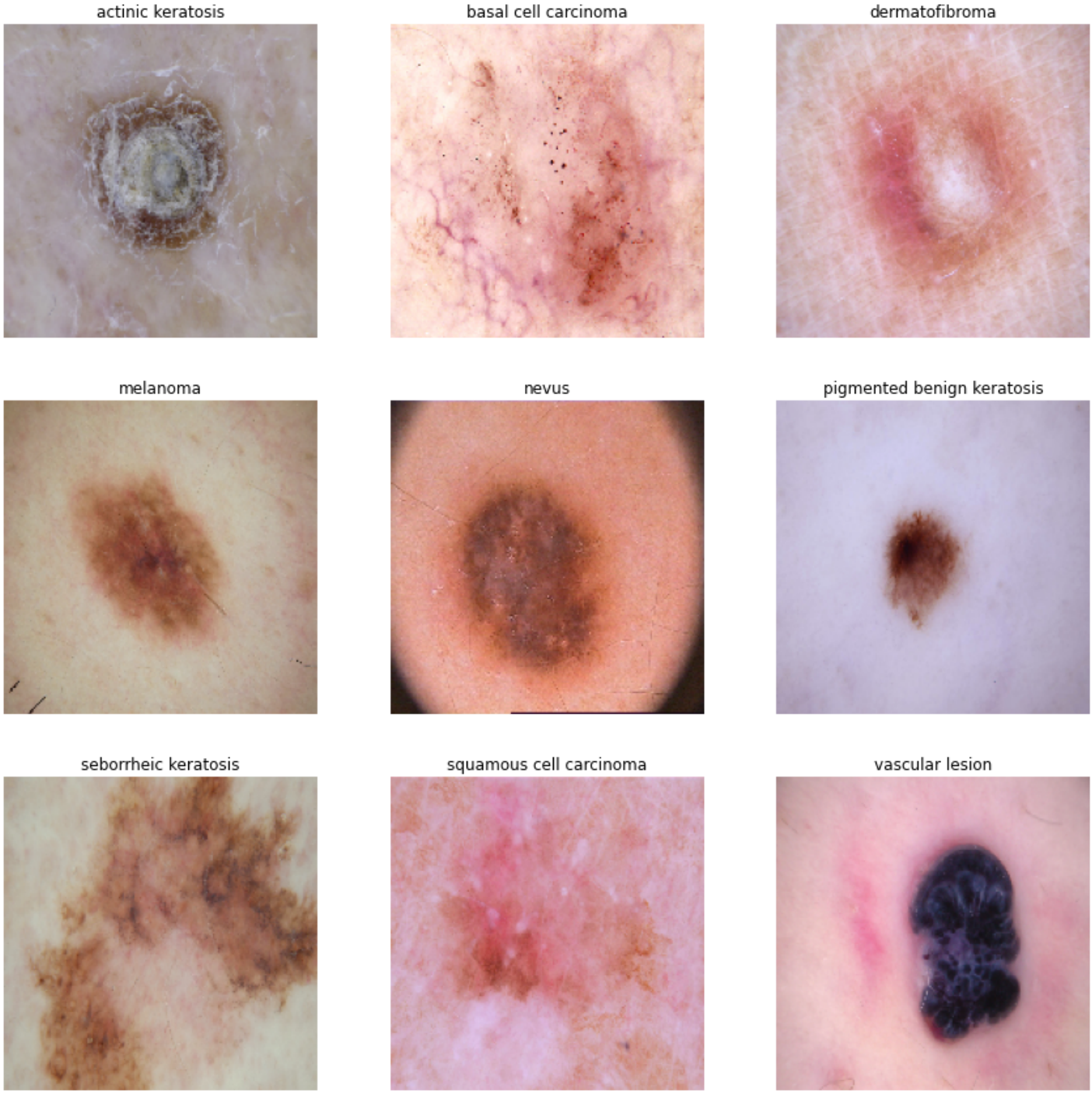
In [5]:
```
# Count the number of image in Train and Test directory
# Using the glob to retrieve files/pathnames matching a specified pattern.

#Train Image count
image_count_train = len(list(data_dir_train.glob('*/*.jpg')))
print(image_count_train)

#Test Image count
image_count_test = len(list(data_dir_test.glob('*/*.jpg')))
print(image_count_test)
```

```
2239
118
```

Data Visualization

In [6]:
```
#Visualize one instance of all the class present in the dataset.

#image_dataset_from_directory() will return a tf.data.Dataset that yields batches of image
#label_mode is categorial, the labels are a float32 tensor of shape (batch_size, num_class
image_dataset = tf.keras.preprocessing.image_dataset_from_directory(data_dir_train,batch_s
                                                                    label_mode='categorica

#all the classes of Skin Cancer
class_names = image_dataset.class_names

#Dictionary to store the path of image as per the class
files_path_dict = {}

for c in class_names:
    files_path_dict[c] = list(map(lambda x:str(data_dir_train)+'/'+c+'/'+x,os.listdir(str

#Visualize image
plt.figure(figsize=(15,15))
index = 0
for c in class_names:
    path_list = files_path_dict[c][:1]
    index += 1
    plt.subplot(3,3,index)
    plt.imshow(load_img(path_list[0],target_size=(180,180)))
    plt.title(c)
    plt.axis("off")
```

```
Found 2239 files belonging to 9 classes.
```



Visualize distribution of classes in the training dataset.

In [7]:

```
def class_distribution_count(directory):

    #count number of image in each classes
    count= []
    for path in pathlib.Path(directory).iterdir():
        if path.is_dir():
            count.append(len([name for name in os.listdir(path)
                              if os.path.isfile(os.path.join(path, name))]))

    #name of the classes
    sub_directory = [name for name in os.listdir(directory)
                     if os.path.isdir(os.path.join(directory, name))]

    #return dataframe with image count and class.
    return pd.DataFrame(list(zip(sub_directory,count)),columns =['Class', 'No. of Image'])

df = class_distribution_count(data_dir_train)
df
```

Out[7]:

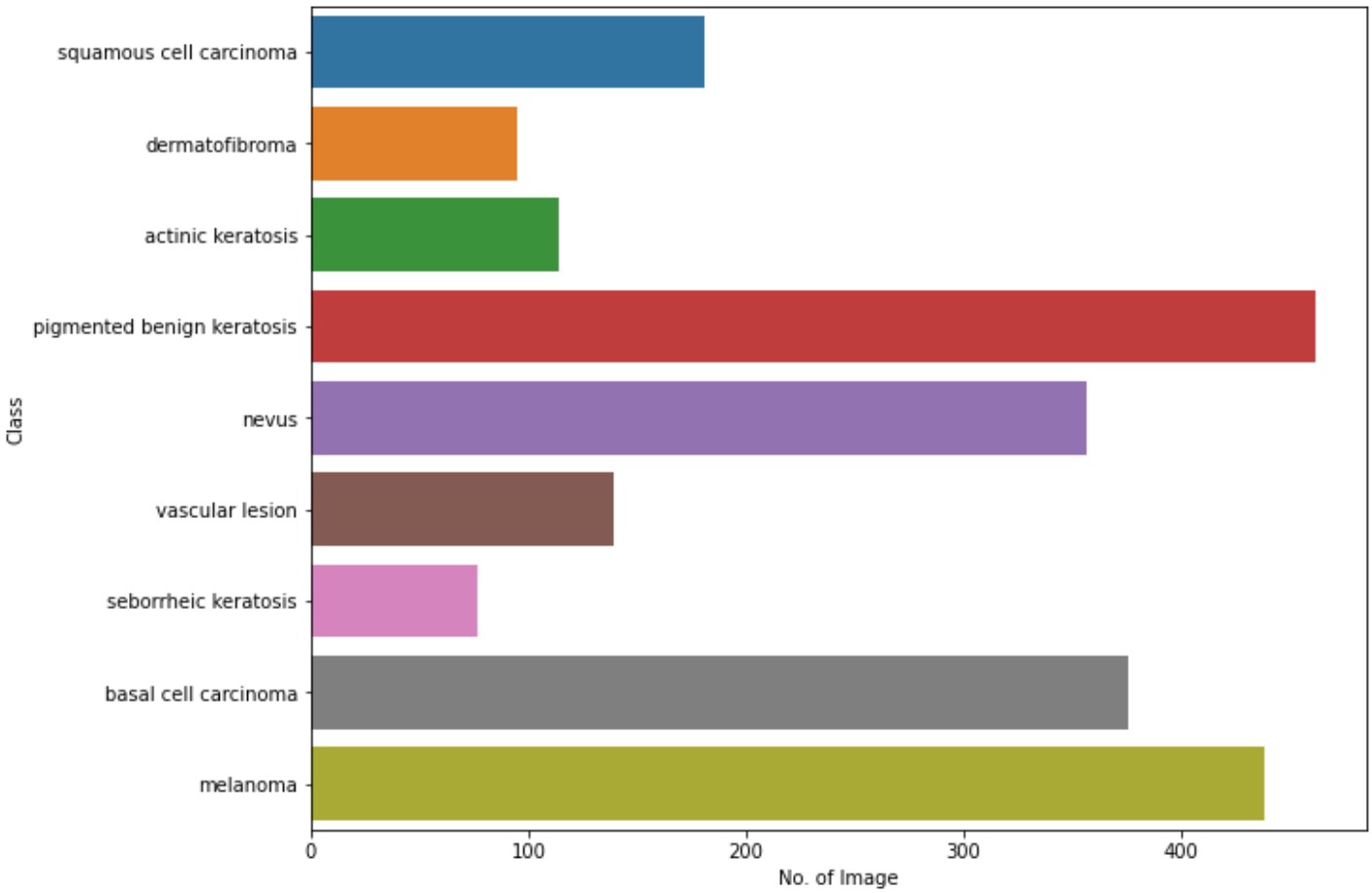
	Class	No. of Image
0	squamous cell carcinoma	181
1	dermatofibroma	95
2	actinic keratosis	114
3	pigmented benign keratosis	462
4	nevus	357
5	vascular lesion	139
6	seborrheic keratosis	77
7	basal cell carcinoma	376
8	melanoma	438

In [8]:

```
#Visualize the Number of image in each class.
import seaborn as sns
plt.figure(figsize=(10, 8))
sns.barplot(x="No. of Image", y="Class", data=df,
            label="Class")
```

Out[8]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f74b43b9390>
```



There is a class imbalance to solve this using a python package 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 [9]:

```
#install Augmentor
```

```
!pip install Augmentor
```

```
Collecting Augmentor
  Downloading Augmentor-0.2.8-py2.py3-none-any.whl (38 kB)
Requirement already satisfied: numpy>=1.11.0 in /usr/local/lib/python3.7/dist-packages (fr
om Augmentor) (1.19.5)
Requirement already satisfied: tqdm>=4.9.0 in /usr/local/lib/python3.7/dist-packages (from
Augmentor) (4.62.3)
Requirement already satisfied: Pillow>=5.2.0 in /usr/local/lib/python3.7/dist-packages (fr
om Augmentor) (7.1.2)
Requirement already satisfied: future>=0.16.0 in /usr/local/lib/python3.7/dist-packages (f
rom Augmentor) (0.16.0)
Installing collected packages: Augmentor
Successfully installed Augmentor-0.2.8
```

In [10]:

```
path_to_training_dataset="/content/Skin cancer ISIC The International Skin Imaging Collabo
import Augmentor
for i in class_names:
    p = Augmentor.Pipeline(path_to_training_dataset + i)
    p.rotate(probability=0.7, max_left_rotation=10, max_right_rotation=10)
    p.sample(500)  #Adding 500 samples per class to make sure that none of the classes are
```

```
Initialised with 114 image(s) found.
Output directory set to /content/Skin cancer ISIC The International Skin Imaging Collabora
tion/Train/actinic keratosis/output.
Processing <PIL.JpegImagePlugin.JpegImageFile image mode=RGB size=600x450 at 0x7F75338535D
0>: 100%|██████████| 500/500 [00:19<00:00, 26.19 Samples/s]
Initialised with 376 image(s) found.
Output directory set to /content/Skin cancer ISIC The International Skin Imaging Collabora
tion/Train/basal cell carcinoma/output.
Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x7F758429DED0>: 100%|████████
█| 500/500 [00:19<00:00, 25.43 Samples/s]
Initialised with 95 image(s) found.
Output directory set to /content/Skin cancer ISIC The International Skin Imaging Collabora
tion/Train/dermatofibroma/output.
Processing <PIL.JpegImagePlugin.JpegImageFile image mode=RGB size=600x450 at 0x7F75336B371
0>: 100%|██████████| 500/500 [00:19<00:00, 25.83 Samples/s]
Initialised with 438 image(s) found.
Output directory set to /content/Skin cancer ISIC The International Skin Imaging Collabora
tion/Train/melanoma/output.
Processing <PIL.Image.Image image mode=RGB size=1024x768 at 0x7F74B3A78B90>: 100%|████████
██| 500/500 [01:33<00:00,  5.34 Samples/s]
Initialised with 357 image(s) found.
Output directory set to /content/Skin cancer ISIC The International Skin Imaging Collabora
tion/Train/nevus/output.
Processing <PIL.Image.Image image mode=RGB size=576x768 at 0x7F75338C8890>: 100%|█████████
| 500/500 [01:36<00:00,  5.19 Samples/s]
Initialised with 462 image(s) found.
Output directory set to /content/Skin cancer ISIC The International Skin Imaging Collabora
tion/Train/pigmented benign keratosis/output.
Processing <PIL.JpegImagePlugin.JpegImageFile image mode=RGB size=600x450 at 0x7F74AE7FFB1
0>: 100%|██████████| 500/500 [00:20<00:00, 24.64 Samples/s]
Initialised with 77 image(s) found.
Output directory set to /content/Skin cancer ISIC The International Skin Imaging Collabora
tion/Train/seborrheic keratosis/output.
Processing <PIL.Image.Image image mode=RGB size=1024x768 at 0x7F74B3B58BD0>: 100%|████████
██| 500/500 [00:47<00:00, 10.46 Samples/s]
Initialised with 181 image(s) found.
Output directory set to /content/Skin cancer ISIC The International Skin Imaging Collabora
tion/Train/squamous cell carcinoma/output.
Processing <PIL.JpegImagePlugin.JpegImageFile image mode=RGB size=600x450 at 0x7F75336EEF9
0>: 100%|██████████| 500/500 [00:19<00:00, 25.78 Samples/s]
```

```
Initialised with 139 image(s) found.
Output directory set to /content/Skin cancer ISIC The International Skin Imaging Collabora
tion/Train/vascular lesion/output.
```

```
Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x7F7533950C50>: 100%|████████
█| 500/500 [00:19<00:00, 25.74 Samples/s]
```

In [11]:

```
#Count total number of image generated by Augmentor.
image_count_train = len(list(data_dir_train.glob('*/output/*.jpg')))
print(image_count_train)
```

```
4500
```

Model Building

In [12]:

```
# train dataset
train_ds = tf.keras.preprocessing.image_dataset_from_directory(data_dir_train, batch_size=
                                                               image_size=(180,180), label
                                                               seed=123,subset="training",
                                                               validation_split=0.2)

#label_mode is categorial, the labels are a float32 tensor of shape (batch_size, num_class
#representing a one-hot encoding of the class index.
```

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

In [13]:

```
# validation dataset
val_ds =tf.keras.preprocessing.image_dataset_from_directory(data_dir_train,batch_size=32,
                                                            image_size=(180,180), label_mo
                                                            seed=123,subset="validation",
                                                            validation_split=0.2)
```

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

In [14]:

```
#tf.data.experimental.AUTOTUNE defines appropriate number of processes that are free for w

#`Dataset.cache()` keeps the images in memory after they're loaded off disk during the fi

#`Dataset.prefetch()` overlaps data preprocessing and model execution while training.


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)
```

In [15]:

```
#CNN Model Architecture

#Sequential allows you to create models layer-by-layer
model = Sequential()

model.add(layers.experimental.preprocessing.Rescaling(1./255,input_shape=(180,180,3)))    #

#First Convulation layer
model.add(layers.Conv2D(32,kernel_size=(3,3),activation='relu'))
model.add(layers.MaxPool2D(pool_size=(2,2)))

#Second Convulation Layer
model.add(layers.Conv2D(64,kernel_size=(3,3),activation='relu'))
model.add(layers.MaxPool2D(pool_size=(2,2)))
```

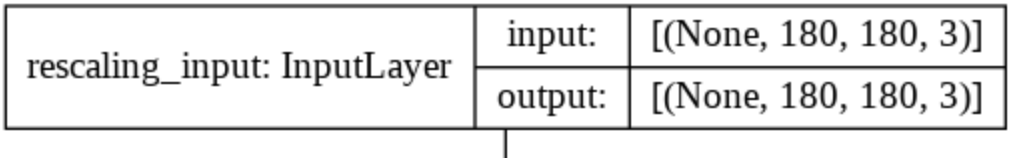
```
#Third Convulation Layer
model.add(layers.Conv2D(128,kernel_size=(3,3),activation='relu'))
model.add(layers.MaxPool2D(pool_size=(2,2)))

#Dropout layer with 50% Fraction of the input units to drop.
model.add(layers.Dropout(0.5))

#Flatten Layer
##Keras.layers.flatten function flattens the multi-dimensional input tensors into a single
model.add(layers.Flatten())

#Dense Layer
model.add(layers.Dense(128,activation='relu'))

#Dropout layer with 25% Fraction of the input units to drop.
model.add(layers.Dropout(0.25))

#Dense Layer with softmax activation function.
#Softmax is an activation function that scales numbers/logits into probabilities.
model.add(layers.Dense(len(class_names),activation='softmax'))

model.summary()
```

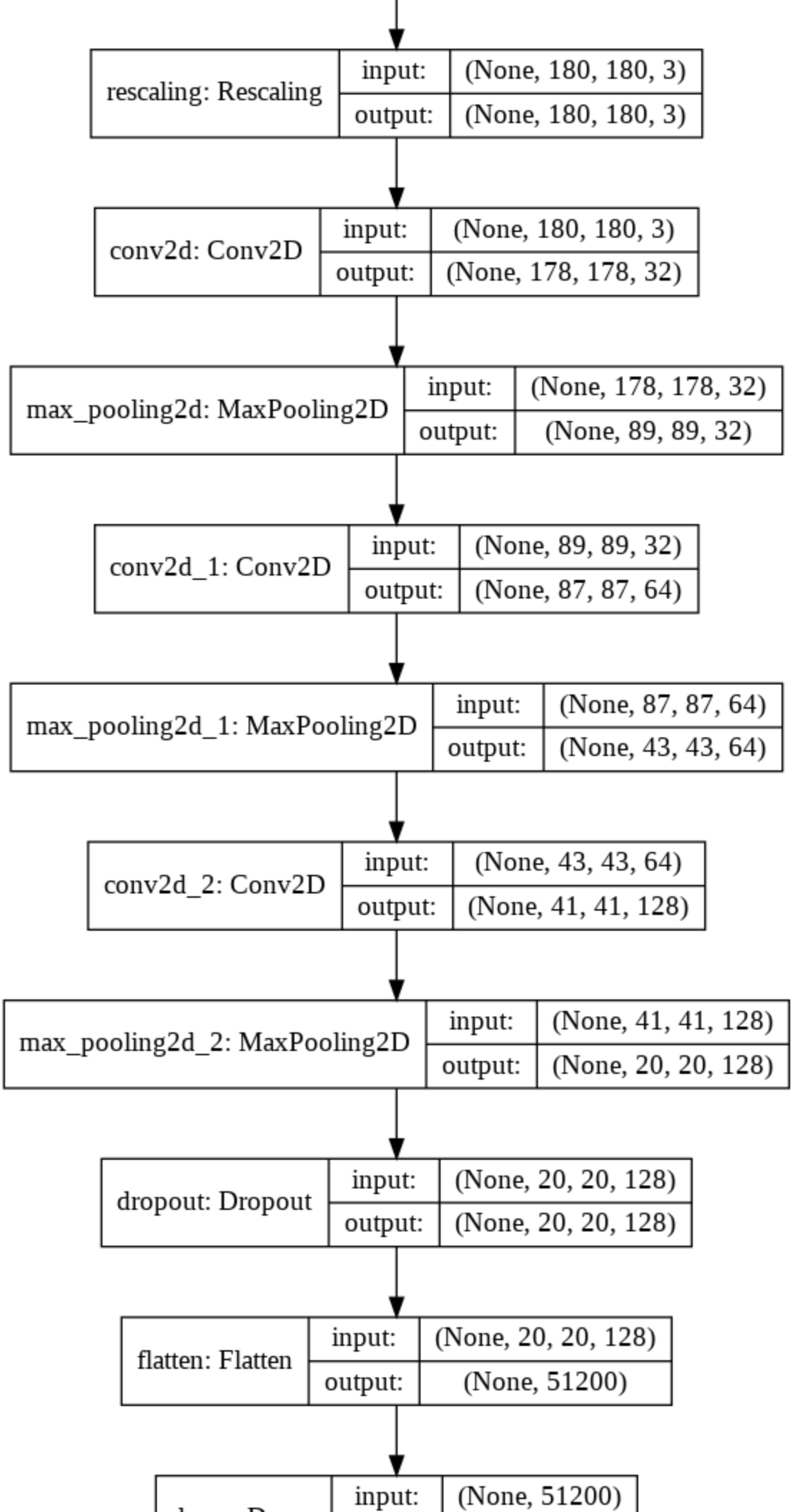
```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
rescaling (Rescaling)        (None, 180, 180, 3)       0
_________________________________________________________________
conv2d (Conv2D)              (None, 178, 178, 32)      896
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 89, 89, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 87, 87, 64)        18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 43, 43, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 41, 41, 128)       73856
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 20, 20, 128)       0
_________________________________________________________________
dropout (Dropout)            (None, 20, 20, 128)       0
_________________________________________________________________
flatten (Flatten)            (None, 51200)             0
_________________________________________________________________
dense (Dense)                (None, 128)               6553728
_________________________________________________________________
dropout_1 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 9)                 1161
=================================================================
Total params: 6,648,137
Trainable params: 6,648,137
Non-trainable params: 0
_________________________________________________________________
```

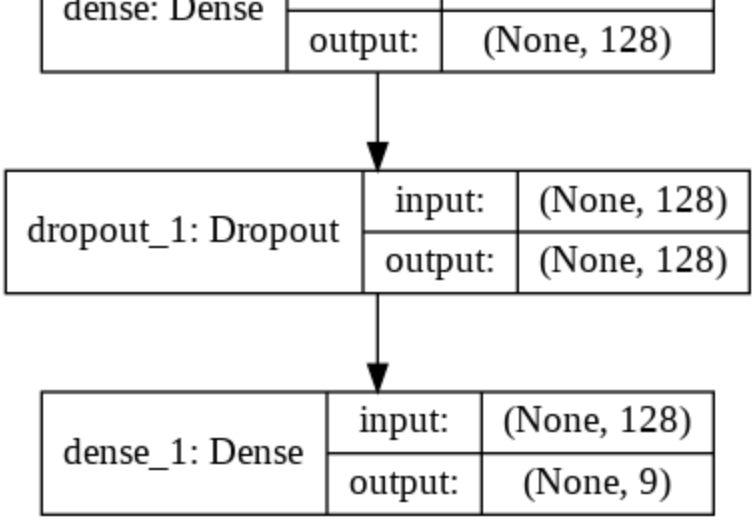
In [16]:

```
# vizualizing the model
from tensorflow.keras.utils import plot_model
plot_model(model, to_file='model_plot.png', show_shapes=True, show_layer_names=True)
```

Out[16]:




rescaling: Rescaling
input: (None, 180, 180, 3)
output: (None, 180, 180, 3)
conv2d: Conv2D
input: (None, 180, 180, 3)
output: (None, 178, 178, 32)
max_pooling2d: MaxPooling2D
input: (None, 178, 178, 32)
output: (None, 89, 89, 32)
conv2d_1: Conv2D
input: (None, 89, 89, 32)
output: (None, 87, 87, 64)
max_pooling2d_1: MaxPooling2D
input: (None, 87, 87, 64)
output: (None, 43, 43, 64)
conv2d_2: Conv2D
input: (None, 43, 43, 64)
output: (None, 41, 41, 128)
max_pooling2d_2: MaxPooling2D
input: (None, 41, 41, 128)
output: (None, 20, 20, 128)
dropout: Dropout
input: (None, 20, 20, 128)
output: (None, 20, 20, 128)
flatten: Flatten
input: (None, 20, 20, 128)
output: (None, 51200)
input: (None, 51200)



In [17]:
```
#Compile the Model

#Adam optimization: is a stochastic gradient descent method that is based on adaptive esti
#categorical_crossentropy: Used as a loss function for multi-class classification model wh

model.compile(optimizer="Adam",loss="categorical_crossentropy",metrics=["accuracy"])

#ModelCheckpoint callback is used in conjunction with training using model.fit() to save a
#so the model or weights can be loaded later to continue the training from the state saved
checkpoint = ModelCheckpoint("model.h5",monitor="val_accuracy",save_best_only=True,mode="a

#Stop training when a monitored metric has stopped improving.
earlystop = EarlyStopping(monitor="val_accuracy",patience=5,mode="auto",verbose=1)
```

In [18]:
```
# Train the model
epochs = 20
history = model.fit(train_ds, validation_data=val_ds, epochs=epochs,callbacks=[checkpoint,
```

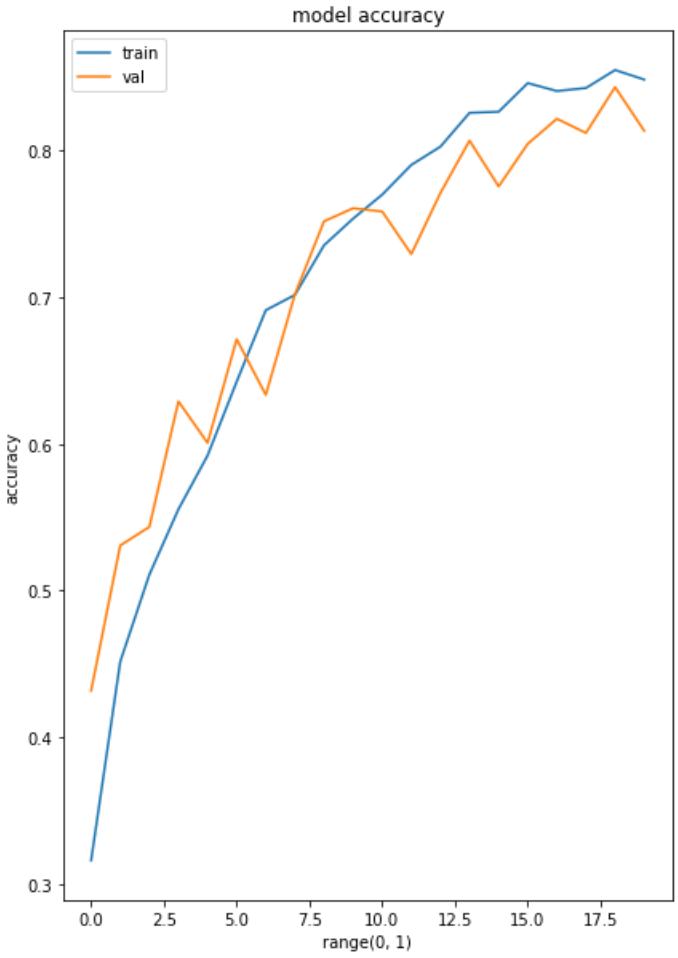
```
Epoch 1/20
169/169 [==============================] - 69s 102ms/step - loss: 1.8030 - accuracy: 0.316
6 - val_loss: 1.5269 - val_accuracy: 0.4321

Epoch 00001: val_accuracy improved from -inf to 0.43207, saving model to model.h5
Epoch 2/20
169/169 [==============================] - 12s 69ms/step - loss: 1.4552 - accuracy: 0.4518
- val_loss: 1.3301 - val_accuracy: 0.5308

Epoch 00002: val_accuracy improved from 0.43207 to 0.53081, saving model to model.h5
Epoch 3/20
169/169 [==============================] - 12s 69ms/step - loss: 1.3019 - accuracy: 0.5109
- val_loss: 1.2471 - val_accuracy: 0.5434

Epoch 00003: val_accuracy improved from 0.53081 to 0.54343, saving model to model.h5
Epoch 4/20
169/169 [==============================] - 12s 69ms/step - loss: 1.1884 - accuracy: 0.5555
- val_loss: 1.0393 - val_accuracy: 0.6288

Epoch 00004: val_accuracy improved from 0.54343 to 0.62880, saving model to model.h5
Epoch 5/20
169/169 [==============================] - 12s 69ms/step - loss: 1.0936 - accuracy: 0.5920
- val_loss: 1.0634 - val_accuracy: 0.6006

Epoch 00005: val_accuracy did not improve from 0.62880
Epoch 6/20
169/169 [==============================] - 12s 69ms/step - loss: 0.9737 - accuracy: 0.6422
- val_loss: 0.8937 - val_accuracy: 0.6711
```

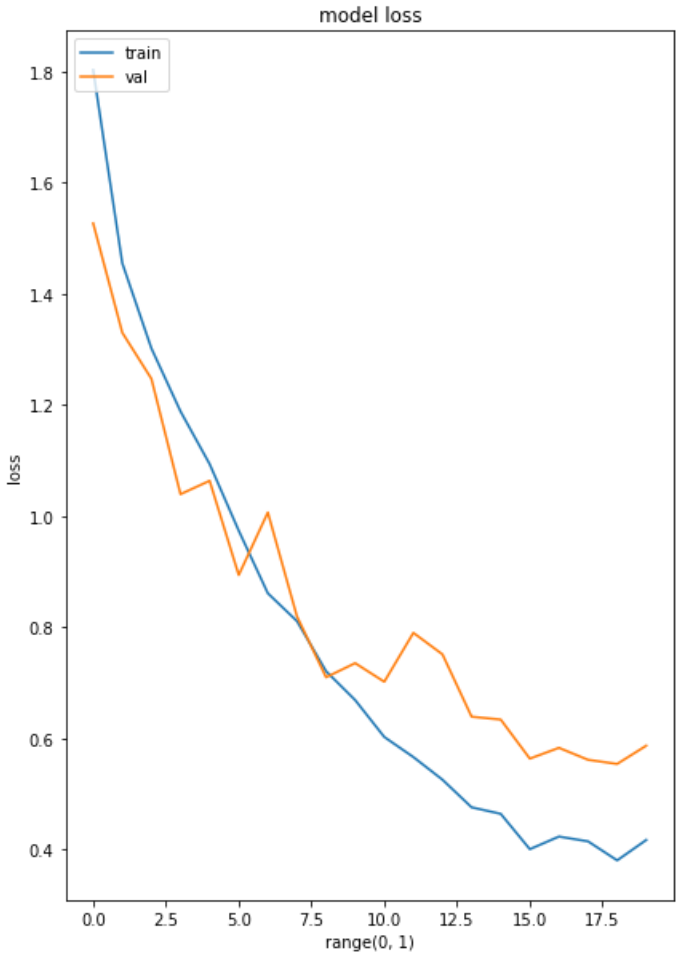
```
Epoch 00006: val_accuracy improved from 0.62880 to 0.67112, saving model to model.h5
Epoch 7/20
169/169 [==============================] - 12s 69ms/step - loss: 0.8609 - accuracy: 0.6908
- val_loss: 1.0064 - val_accuracy: 0.6333

Epoch 00007: val_accuracy did not improve from 0.67112
Epoch 8/20
169/169 [==============================] - 12s 69ms/step - loss: 0.8109 - accuracy: 0.7012
- val_loss: 0.8194 - val_accuracy: 0.7016

Epoch 00008: val_accuracy improved from 0.67112 to 0.70156, saving model to model.h5
Epoch 9/20
169/169 [==============================] - 12s 68ms/step - loss: 0.7206 - accuracy: 0.7350
- val_loss: 0.7097 - val_accuracy: 0.7513

Epoch 00009: val_accuracy improved from 0.70156 to 0.75130, saving model to model.h5
Epoch 10/20
169/169 [==============================] - 12s 69ms/step - loss: 0.6686 - accuracy: 0.7532
- val_loss: 0.7351 - val_accuracy: 0.7602

Epoch 00010: val_accuracy improved from 0.75130 to 0.76021, saving model to model.h5
Epoch 11/20
169/169 [==============================] - 12s 69ms/step - loss: 0.6022 - accuracy: 0.7695
- val_loss: 0.7016 - val_accuracy: 0.7580

Epoch 00011: val_accuracy did not improve from 0.76021
Epoch 12/20
169/169 [==============================] - 12s 68ms/step - loss: 0.5660 - accuracy: 0.7897
- val_loss: 0.7897 - val_accuracy: 0.7290

Epoch 00012: val_accuracy did not improve from 0.76021
Epoch 13/20
169/169 [==============================] - 12s 68ms/step - loss: 0.5252 - accuracy: 0.8021
- val_loss: 0.7509 - val_accuracy: 0.7706

Epoch 00013: val_accuracy improved from 0.76021 to 0.77060, saving model to model.h5
Epoch 14/20
169/169 [==============================] - 12s 69ms/step - loss: 0.4755 - accuracy: 0.8251
- val_loss: 0.6387 - val_accuracy: 0.8062

Epoch 00014: val_accuracy improved from 0.77060 to 0.80624, saving model to model.h5
Epoch 15/20
169/169 [==============================] - 12s 69ms/step - loss: 0.4638 - accuracy: 0.8259
- val_loss: 0.6336 - val_accuracy: 0.7751

Epoch 00015: val_accuracy did not improve from 0.80624
Epoch 16/20
169/169 [==============================] - 12s 69ms/step - loss: 0.4002 - accuracy: 0.8453
- val_loss: 0.5632 - val_accuracy: 0.8040

Epoch 00016: val_accuracy did not improve from 0.80624
Epoch 17/20
169/169 [==============================] - 12s 69ms/step - loss: 0.4229 - accuracy: 0.8399
- val_loss: 0.5827 - val_accuracy: 0.8211

Epoch 00017: val_accuracy improved from 0.80624 to 0.82108, saving model to model.h5
Epoch 18/20
169/169 [==============================] - 12s 68ms/step - loss: 0.4143 - accuracy: 0.8420
- val_loss: 0.5611 - val_accuracy: 0.8114

Epoch 00018: val_accuracy did not improve from 0.82108
Epoch 19/20
169/169 [==============================] - 12s 68ms/step - loss: 0.3800 - accuracy: 0.8542
- val_loss: 0.5537 - val_accuracy: 0.8426
```

```
Epoch 00019: val_accuracy improved from 0.82108 to 0.84261, saving model to model.h5
Epoch 20/20
169/169 [==============================] - 12s 69ms/step - loss: 0.4168 - accuracy: 0.8477
- val_loss: 0.5865 - val_accuracy: 0.8129

Epoch 00020: val_accuracy did not improve from 0.84261
```

In [25]:

```
# Plot the training curves

epochs_range = range(earlystop.stopped_epoch+1)

plt.figure(figsize=(15, 10))
plt.subplot(1, 2, 1)

#Plot Model Accuracy
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel(epochs_range)
plt.legend(['train', 'val'], loc='upper left')

#Plot Model Loss
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel(epochs_range)
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```





Model Prediction

In [29]:

```
from glob import glob
Test_image_path = os.path.join(data_dir_test, class_names[1], '*')
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("Actual Class "+ class_names[1] +'\n'+ "Predictive Class "+pred_class )
```

```
Actual Class basal cell carcinoma
Predictive Class basal cell carcinoma
```