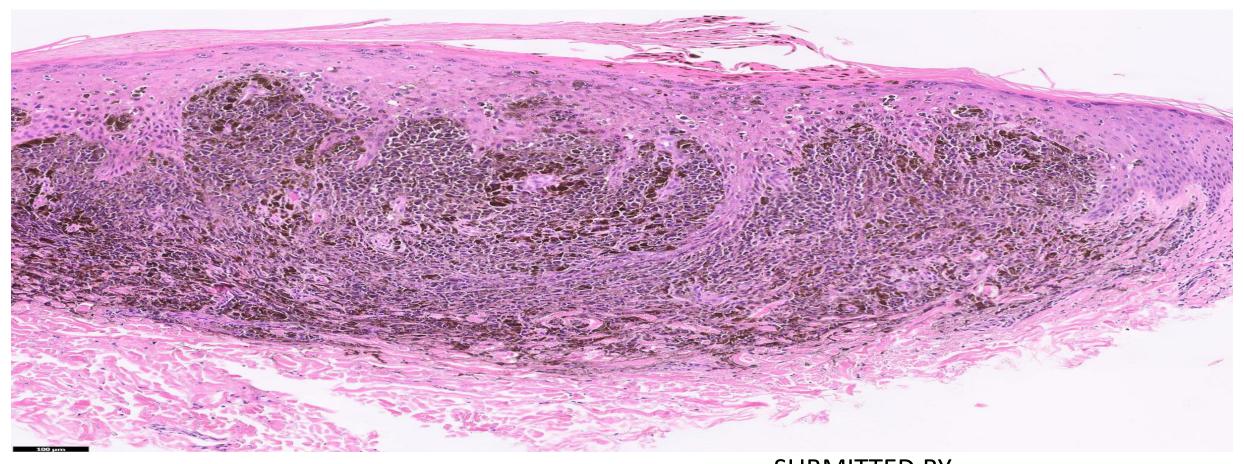
# MELANOMA DETECTION



### **SUBMITTED BY:**

PRINCE FRANCIS
DIBYA RANJAN MOHANTY
PRATIMA PANDEY

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

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## GENERAL INFORMATION

- Melanoma is the most dangerous type of skin cancer. Globally, in 2012, it newly occurred in 232,000 people. In 2015, 3.1 million people had active disease, which resulted in 59,800 deaths. Australia and New Zealand have the highest rates of melanoma in the world. High rates also occur in Northern Europe and North America, while it is less common in Asia, Africa, and Latin America. In the United States, melanoma occurs about 1.6 times more often in men than women. Melanoma has become more common since the 1960s in areas mostly populated by people of European descent.
- For those in whom melanoma has spread, immunotherapy, biological therapy, radiation therapy, or chemotherapy may improve survival. With treatment, the fiver-year survival rates in the United States are 99% among those with localized disease, 65% when the disease has spread to lymph nodes, and 25% among those with distant spread.
- 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

## PROJECT DESCRIPTION

### 1. Data Folder Hierarchy

- Skin cancer ISIC The International Skin Imaging Collaboration
  - Train
    - actinic keratosis
    - basal cell carcinoma
    - Dermatofibroma
    - Melanoma
    - Nevus
    - pigmented benign keratosis
    - seborrheic keratosis
    - squamous cell carcinoma
    - vascular lesion
  - Test
    - actinic keratosis
    - basal cell carcinoma
    - Dermatofibroma
    - Melanoma
    - Nevus
    - pigmented benign keratosis
    - seborrheic keratosis
    - squamous cell carcinoma
    - vascular lesion















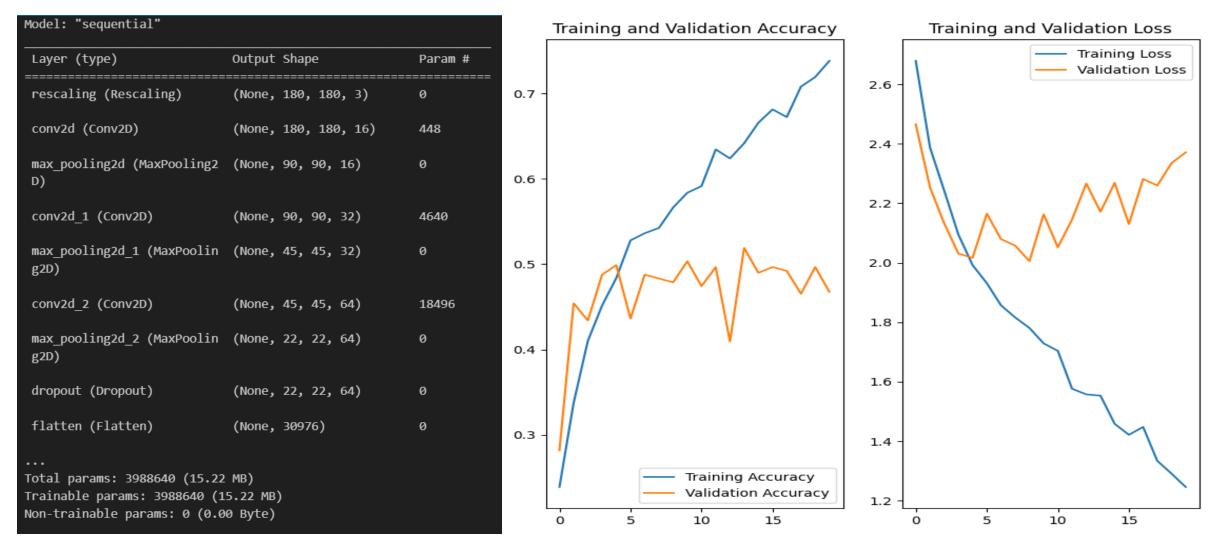






vascular lesion

# 2. Building a simple CNN



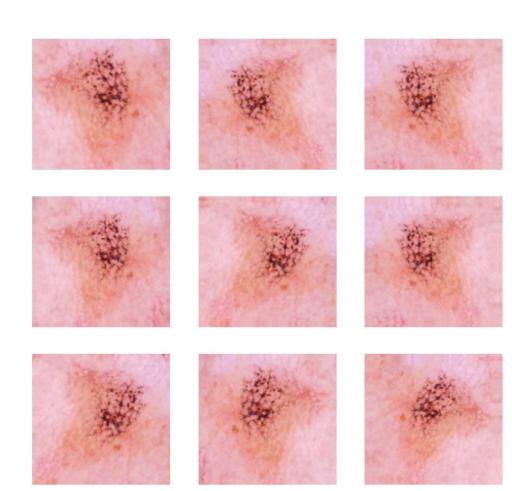
Clearly the CNN is overfitting as per the observation.

# 3. Data Augmentation to reduce overfitting

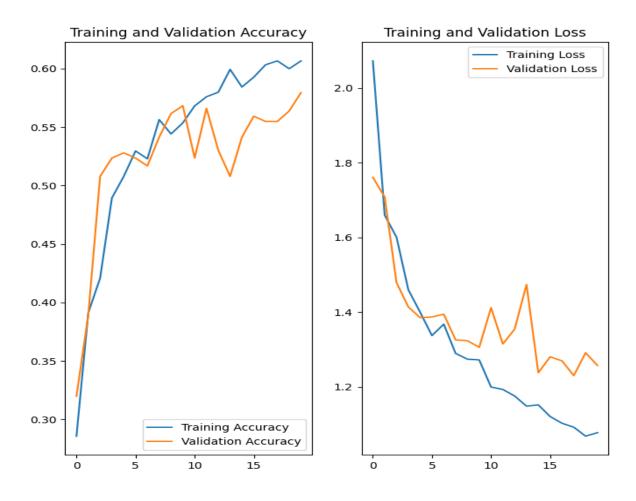
Flip→ Image is flipped horizontally

• Rotation → Image is rotated

• Zoom → Image is zoomed

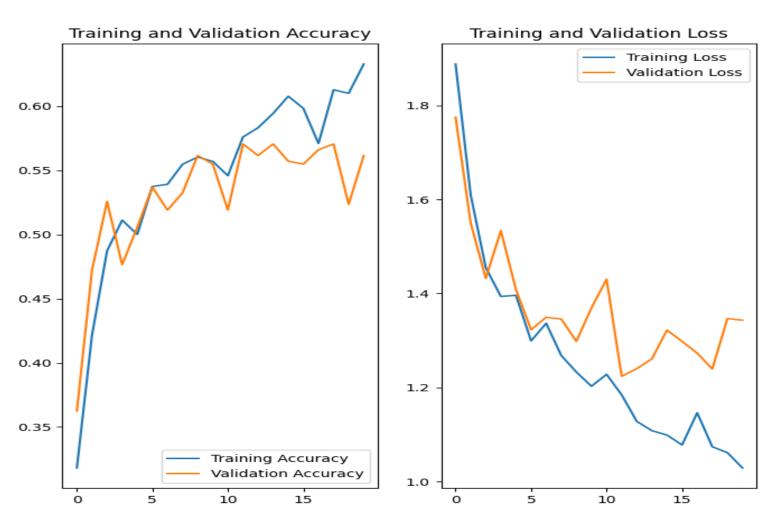


# Data Augmentation(Contd..)



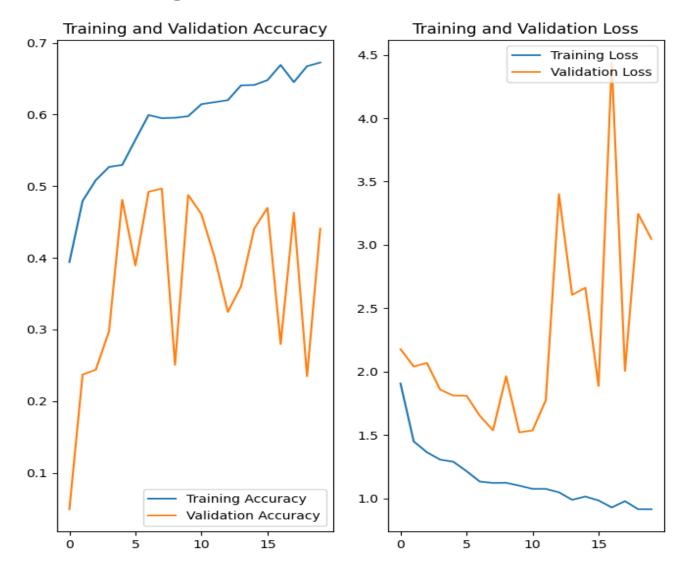
- We can clearly see that the model overfitting has reduced significantly since the training and validation accuracy is very similar.
- This simply means the model is not mugging up all the information.

# 4. Adding Dropout layer



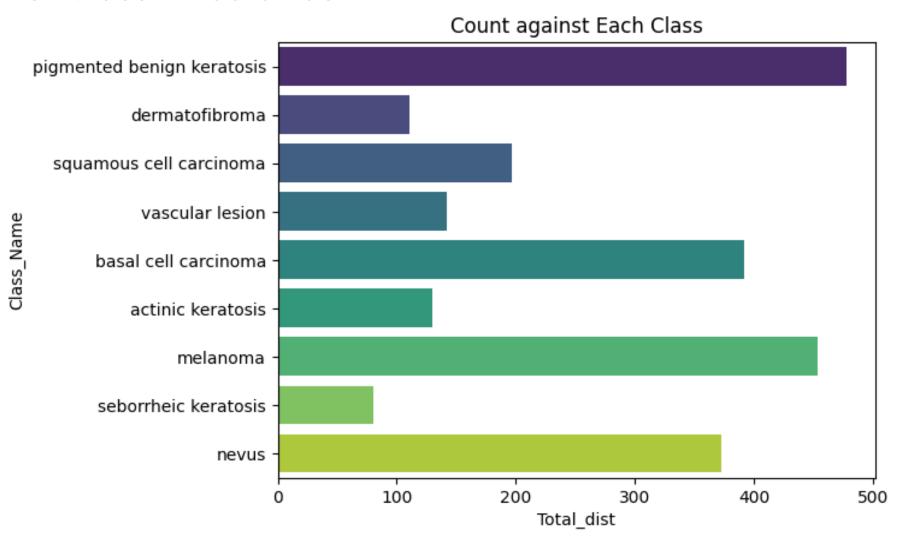
- Adding a Dropout layer and making 25% percent of the weights to reduce overfitting.
- Dropout is a regularization technique.
- Clearly the training and validation accuracy has increased slightly and we have also resolved overfitting.

# 5. Adding Batch Normalization



- Adding a Batch Normalization on top of the augmented and Dropout layer has not improved the model in any sense.
- There is significant overfitting introduced in the model.
- Model is not able to generalize on unseen data.

## 6. Class Imbalance

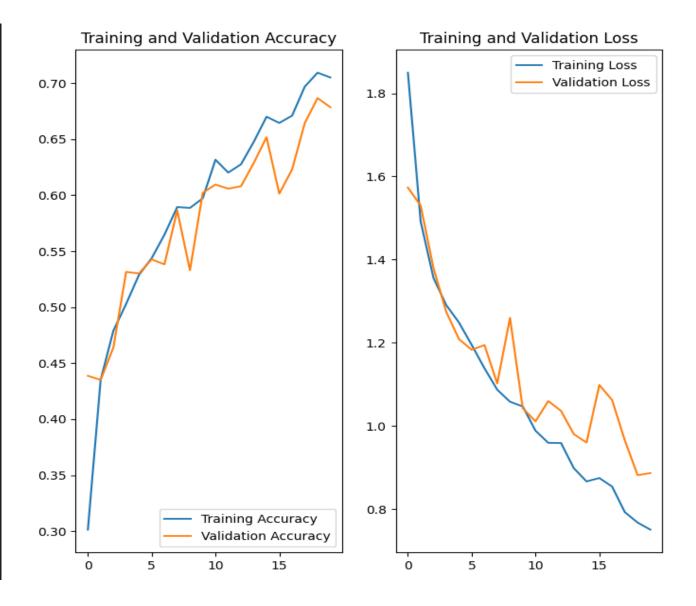


# Handling Class Imbalance (Class imbalance contd...)

- We used the Augmentor library to make 500 samples each each of the classes.
- Each of the 500 samples are stored in an output folder in each of the subdirectories.

# 7.Final Model

Model: "sequential_11"		
Layer (type)	Output Shape	Param #
sequential_1 (Sequential)	(None, 180, 180, 3)	0
rescaling (Rescaling)	(None, 180, 180, 3)	0
conv2d_30 (Conv2D)	(None, 180, 180, 16)	448
<pre>max_pooling2d_30 (MaxPooli ng2D)</pre>	(None, 90, 90, 16)	0
conv2d_31 (Conv2D)	(None, 90, 90, 32)	4640
<pre>max_pooling2d_31 (MaxPooli ng2D)</pre>	(None, 45, 45, 32)	0
conv2d_32 (Conv2D)	(None, 45, 45, 64)	18496
<pre>max_pooling2d_32 (MaxPooli ng2D)</pre>	(None, 22, 22, 64)	0
dropout_10 (Dropout)	(None, 22, 22, 64)	0
Total params: 3989801 (15.22 MB) Trainable params: 3989801 (15.22 MB) Non-trainable params: 0 (0.00 Byte)		



## 8. Conclusion

## Trained Model Output

- Train Accuracy- 70.5%
- Validation Accuracy 67.85%
- Train Loss- 0.77
- Validation Loss 0.84

- Comparing the test and validation accuracies we can say that our initial problem of overfitting has been reduced.
- Data Augmentation, Dropout, and handling class imbalance have significantly helped to improve model accuracy and reduced overfitting.

# Conclusion (Contd....)

- Model evaluation on test set
  - Loss on test set: 0.83
  - Accuracy on test set: 63.8%
- Inference
  - Model is performing significantly well on the test set since our validation accuracy was 67.85%.
  - Our model is performing well on unseen data well.

Model prediction on a random subset of class

## LIBRARIES USED

Below mentioned are all the libraries and modules used in the project

```
## Importing important libraries

∨import pathlib
 import matplotlib.pyplot as plt
 import numpy as np
 import pandas as pd
 import seaborn as sns
 import requests
 import zipfile
 import os
 import tensorflow as tf
 import PIL
 from PIL import Image
 import keras
 # import Augmentor
 from tensorflow import keras
 from tensorflow.keras import layers
 from tensorflow.keras.models import Sequential
 from keras.layers import Conv2D, MaxPool2D, Dropout, Activation, Flatten, Dense, Rescaling, BatchNormalization
 import tensorflow.keras.preprocessing.image as load img
 from keras.utils import image dataset from directory
 from keras.layers import RandomFlip,RandomRotation,RandomZoom
```

**Other mentions:** Notebook has been trained on Google Collab for accelerated computation using GPU.