

# Applying Neural Networks For Classification of Skin Cancer Lesions

Using Deep Learning for Early Detection

by: Nicholas Kondis

#### The Impacts of Skin Cancer

More people are diagnosed with skin cancers than all other types of cancers combined

1 in 5 Americans will develop skin cancer by age 70

In the US, on average, more than 2 people die from skin cancer every hour

With early detection, the survival rate of skin cancer is over 99 percent

Effective identification of types of skin cancers allows efficient use of resources and therapies

The annual cost of treating skin cancers in the U.S. is estimated at \$8.1 billion

# Benefits Of Early Identification of Skin Cancer

- 1. Improved Survival Rates
- 2. Less Aggressive/Invasive Treatment
- 3. Lower Healthcare Costs
- 4. Better Cosmetic Outcomes
- 5. Decreased Risk of Metastasis
- 6. Enhanced Monitoring and Follow-Up
- 7. Psychological Benefits

# Proposed Solution: Creating a deployable model for identifying skin cancer types using deep learning

Creating and optimizing a CNN a Deep Learning Model

Modifying pretrained models to find the most effective model

Employing an ensemble model to find the most effective classification

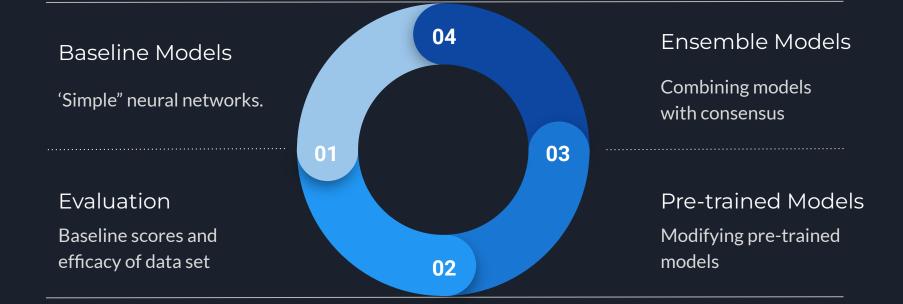


#### Data Pre-Processing

Although the dataset HAM10000 is generally a clean dataset, it does contain substantial imbalances as, of the seven types of lesions included in the data, NV was represented in 67%.

I solved this by oversampling the smaller classes to balance the sata classes..

#### Project Flow



## Creating Baseline Models

Initial (Baseline) CNN models::

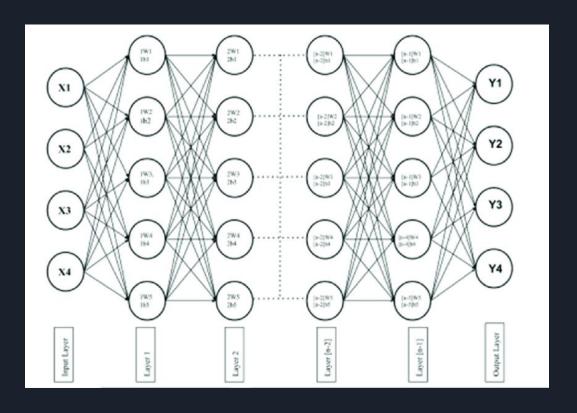
#### 12 layer model

Conv2D -> BatchNormalization -> MaxPooling2D -> Conv2D -> BatchNormalization -> MaxPooling2D -> Conv2D -> BatchNormalization -> MaxPooling2D -> Flatten -> Dense -> Dropout Dense

#### 15 layer model

Conv2D -> BatchNormalization -> MaxPooling2D -> Conv2D -> BatchNormalization -> BatchNormalization -> MaxPooling2D -> Conv2D -> BatchNormalization -> MaxPooling2D -> Conv2D -> BatchNormalization -> MaxPooling2D -> Flatten -> Dense -> Dropout Dense

## Creating Baseline Models \*\*



## Using Pre-trained Models

ResNet-50 is a convolutional neural network that is 50 layers deep. It is a pre-trained on ImageNet database. \*\*\*

**<u>EfficientNet</u>** scales all dimensions of depth/width/resolution using a compound coefficient. \*\*\*\*

<u>Inception v3</u> is a convolutional neural network for assisting in image analysis from GoogLeNet.\*\*\*\*\*

VGG-16 is a convolutional neural network that is 16 layers deep trained on the ImageNet database.\*\*\*\*\*\*

**DenseNet** is an extension of (CNN) which attempts to increase the number of skip connections.\*\*\*\*\*\*\*

<u>NASNet</u> is a type of convolutional neural network discovered through neural architecture search, most similar to biological brains..\*\*\*\*\*\*\*

Xception is a CNN that is 71 layers deep, pretrained on the ImageNet database.\*\*\*\*\*\*\*\*

## Evaluating The Models

Accuracy and loss curves during training.

Precision, Recall, and F1-Score for each class.

Confusion matrix and classification report

# Combining The Models Ensemble Model

After evaluating each model, I will combine the models to create an ensemble model, weighting equally each model's predictions.

All models may not necessarily be used (based on performance.

#### References:

- \* https://www.skincancer.org/skin-cancer-information/skin-cancer-facts/
- \*\*\* https://paperswithcode.com/method/efficientnet
- \*\*\*\* https://keras.io/api/applications/inceptionv3/
- \*\*\*\*\* https://www.geeksforgeeks.org/vgg-16-cnn-model/
- \*\*\*\*\*\*<u>https://medium.com/@alejandro.itoaramendia/densenet-a-complete-guide-84fedef21dcc</u>
- \*\*\*\*\*\*\*https://paperswithcode.com/model/nasnet?variant=nasnetalarge
- \*\*\*\*\*\*\*\*https://www.mathworks.com/help/deeplearning/ref/xception.html