

The background is a dark blue gradient. On the left, there is a large, semi-transparent circular image of a circuit board. Overlaid on the top left of this circle are two overlapping triangles: a blue one in front and a light green one behind. In the top right corner, there is a 3D perspective view of a circuit board's traces.

# Skin cancer detection using DL models

Iraklis Evangelinos

# Overview

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# Introduction

Skin cancer is the most prevalent type of cancer. Melanoma, specifically, is responsible for 75% of skin cancer deaths, despite being the least common skin cancer. The only diagnosis involves having each mole examined by a dermatologist, therefore most moles go unchecked, emphasizing only the ones most likely to be cancer.

Melanoma, if diagnosed early has a 98% recovery rate, with the percentages plummeting if it is given time to progress.

Building AI models capable of examining and classifying skin lesions as malignant or benign in a matter of seconds can be of great use in diagnosing melanoma early.



# The dataset

The dataset used is the 2018 ISIC Melanoma Classification dataset, consisting of 10,015 images of different skin lesions, along with the diagnosis provided by a dermatologist.

- 1627 images are classified as cancerous or malignant
- 8388 images are classified as benign

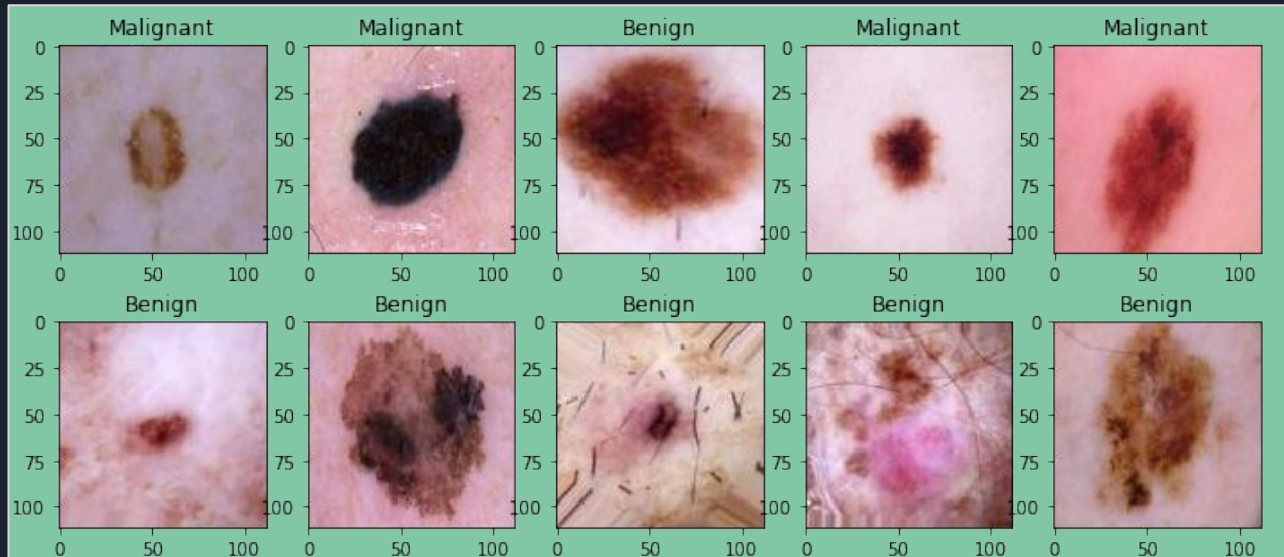
The dataset is imbalanced, over representing the benign cases. This is expected, as it stems from the nature of the phenomenon.

Measures were taken during the training phase to mitigate the side effects.

# Data visualisation and preparation

The data consists of a folder with the 10,015 images and a .csv file containing the particular type of diagnosis for the lesion. In total there are 10 labels, which are converted into two: Malignant or Benign.

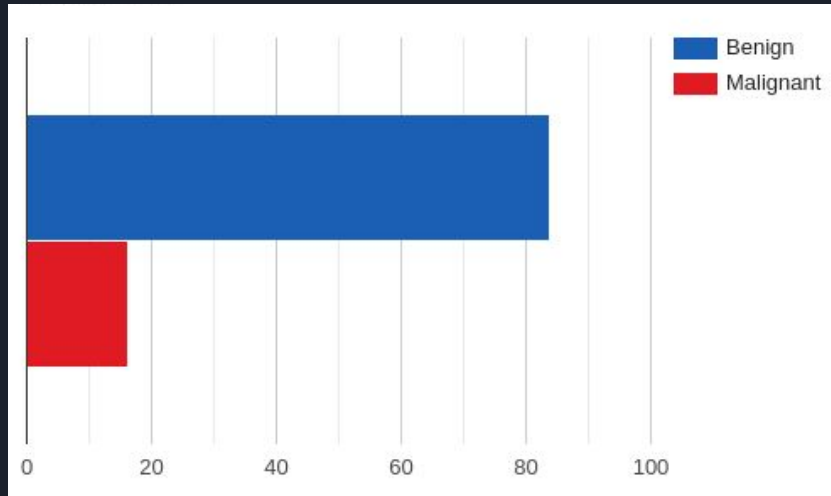
A sample is plotted in order to visualise the data:



# Data visualisation and preparation

Separate the malignant from the benign images into separate folders, keep 10% in a different folder as a testing dataset.

The distribution between the two class labels is shown below:





# Data visualisation and preparation

Augmentation is used in order to create more of the minority class for the training dataset, by applying the following transformations to a subset of the dataset:

- Horizontal flip
- Vertical flip
- Zoom
- Random rotation

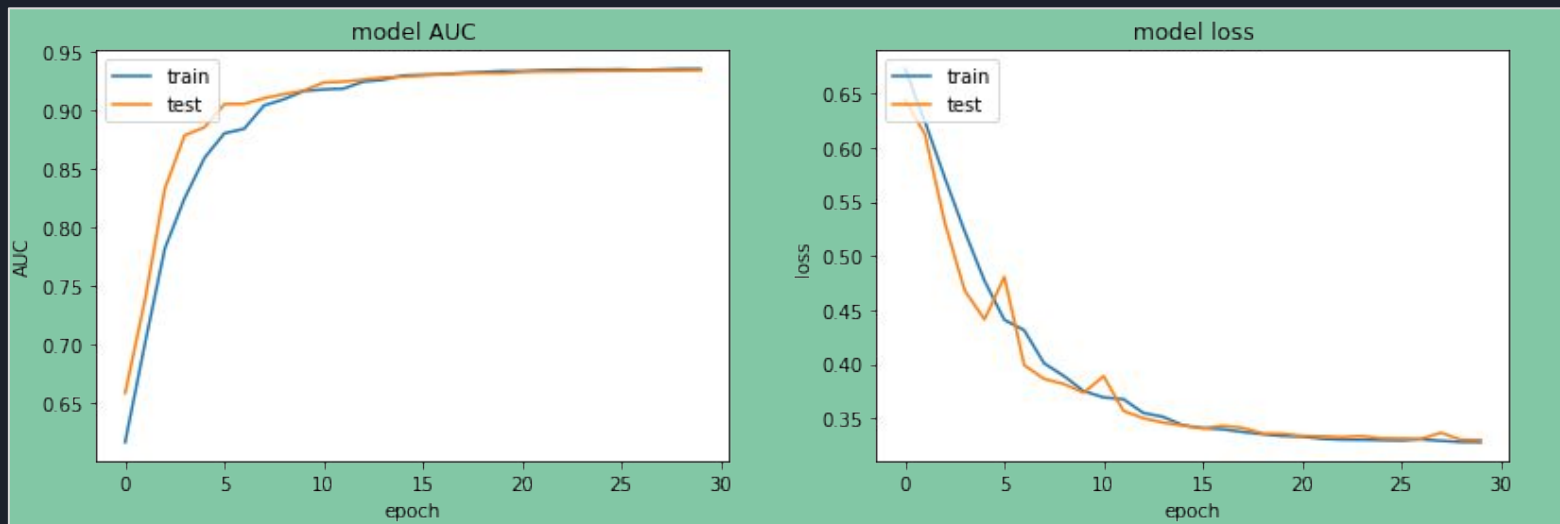
No image transformations that distort the image were applied in order to preserve the lesion's characteristics unaltered.

The final result was a test set comprised of 8059 benign and 7548 malignant images.

# The CNN model

The CNN model's hyperparameters ranged from 2-4 layers, the number of FC layers and their size, along with computational complexity constraints.

The model was optimized with respect to the AUC metric.

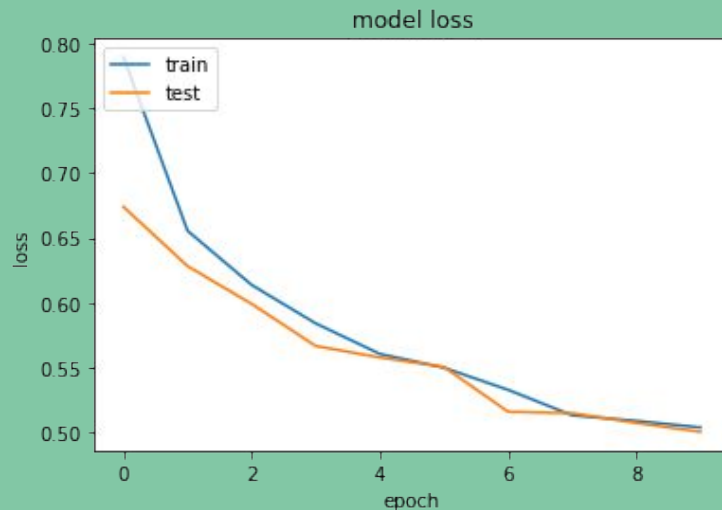
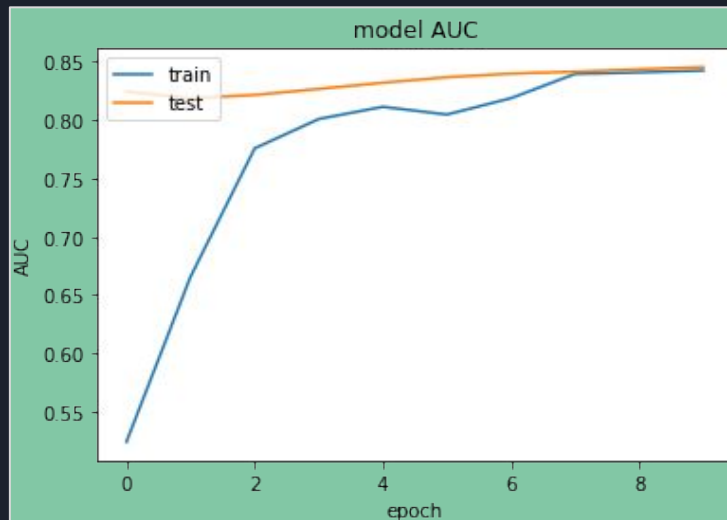




# The ResNet50 model

The pretrained ResNet50 model was used as a way to compare the best performing CNN to top-tier pretrained models.

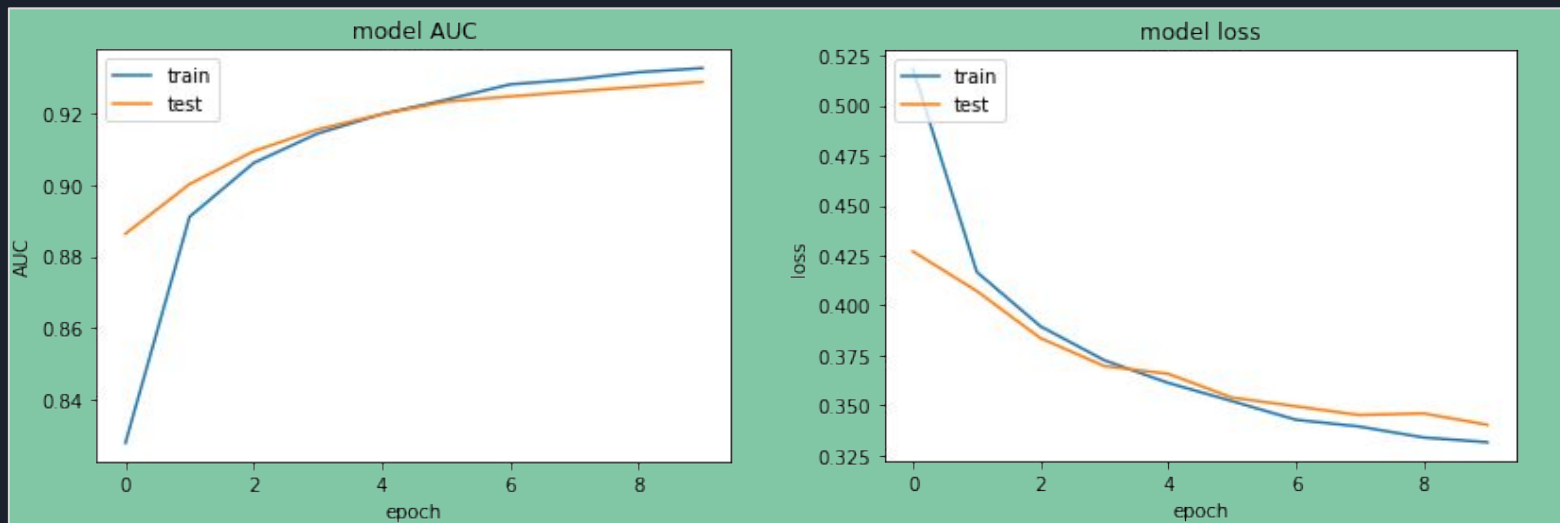
One FC layer(size=512) connected the ResNet50 model to the classification node



# The VGG19 model

The pretrained VGG19 model was also used, outperforming all other models after training for 10 epochs.

One FC layer(size=512) connected the ResNet50 model to the classification node





# Conclusion

The CNN model's performance increased dramatically through fine tuning the parameters.

Compared to the pretrained state of the art models it was able to perform fairly well, given the size of the parameters of the final model was ~25million.

Both VGG and ResNet outclassed the simple CNN solution that was provided, although this was to be expected.

An interesting note was that fine tuning the final layer gave VGG19 ~1% improvement during testing.

Thank you!