Medical AI Sorcerers

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Presentation Outline

- Intro and Background
- Dataset
- Baseline Models
- Final Model Architecture
- Model Evaluation
- Results
- Challenges

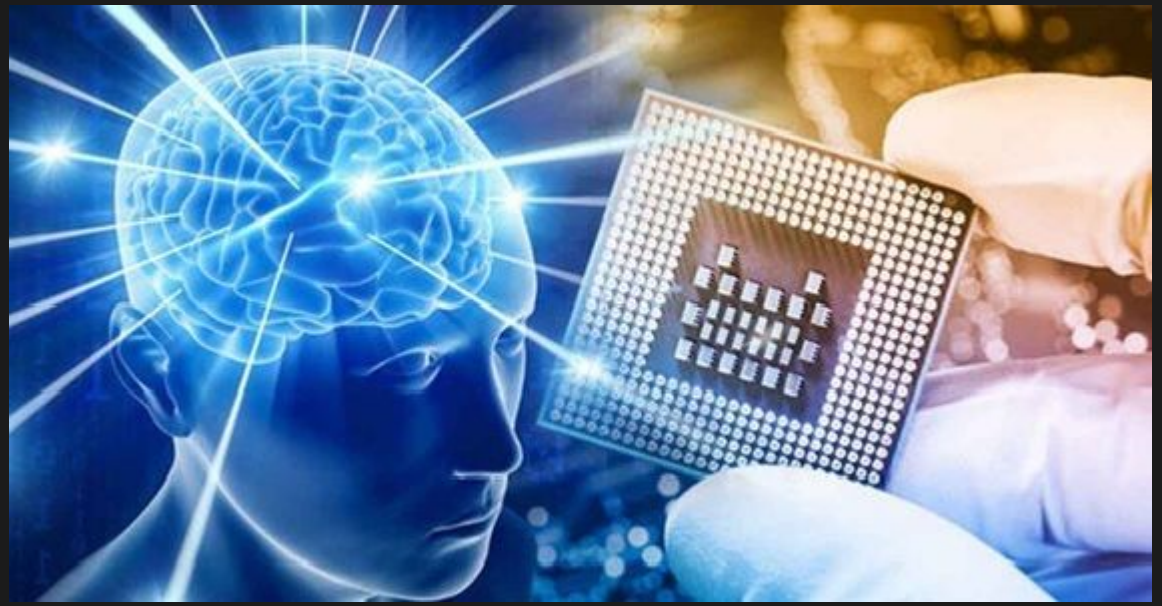
Skin Cancer Classification

- To enable faster, more accurate, and accessible diagnosis of skin cancer, potentially improving early detection and patient outcomes

Background

- Skin cancer types
  - Benign
  - Malignant

- Deep learning models excel at distinguishing patterns in images



Previous Solutions

DeepSkin

- DenseNet169 and ResNet50
- Attempts to address class imbalance in training data

U-Net and MobileNetV3

- Combines a standard U-Net and an Improved MobileNetV3
- Uses HAM-10000 dataset

Melanoma Skin Cancer Detection

- Identification of melanoma, the most deadly type of skin cancer
- Features custom built CNN Model architecture

Dataset

01

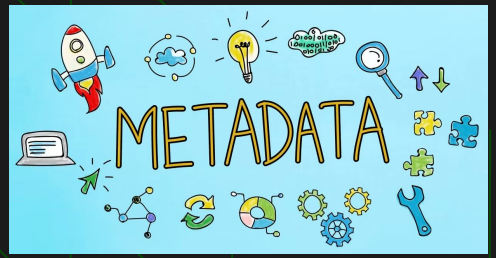
Source: ISIC

The International Skin Imaging Collaboration is developing proposed Digital Image Communication in Medicine standards and engages the dermatology and computer science communities to improve diagnostic accuracy with the aid of AI.

02

Skin Lesion Images

Approved medical quality images of skin lesions



03

Image Metadata

Values associated with each image

Data Cleansing and Balancing

Metadata

- ➔ Focused on 3 main variables for training
  - ◆ Approx. Age
  - ◆ Approx. Size
  - ◆ Approx. Location

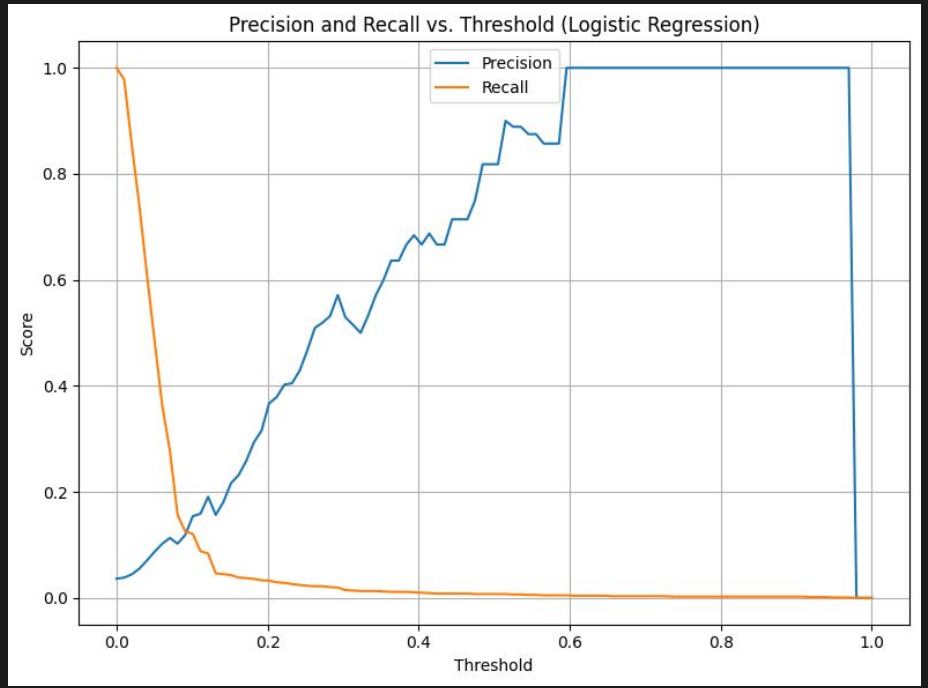
Benign/Malignant Balancing

- ➔ 96% Benign Observations
- ➔ Augmented Malignant Observations

Milestone Recaps

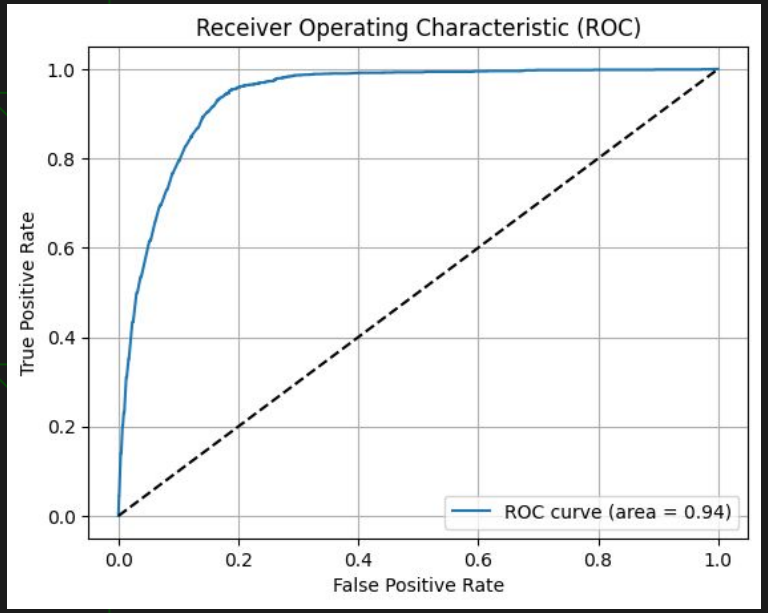
Baseline Models

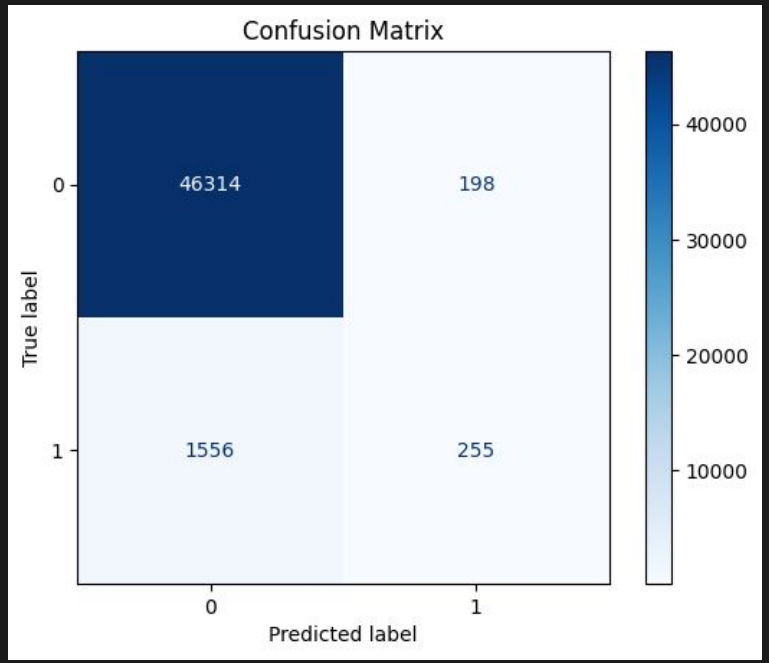
1. Metadata Linear Regression



Baseline Models

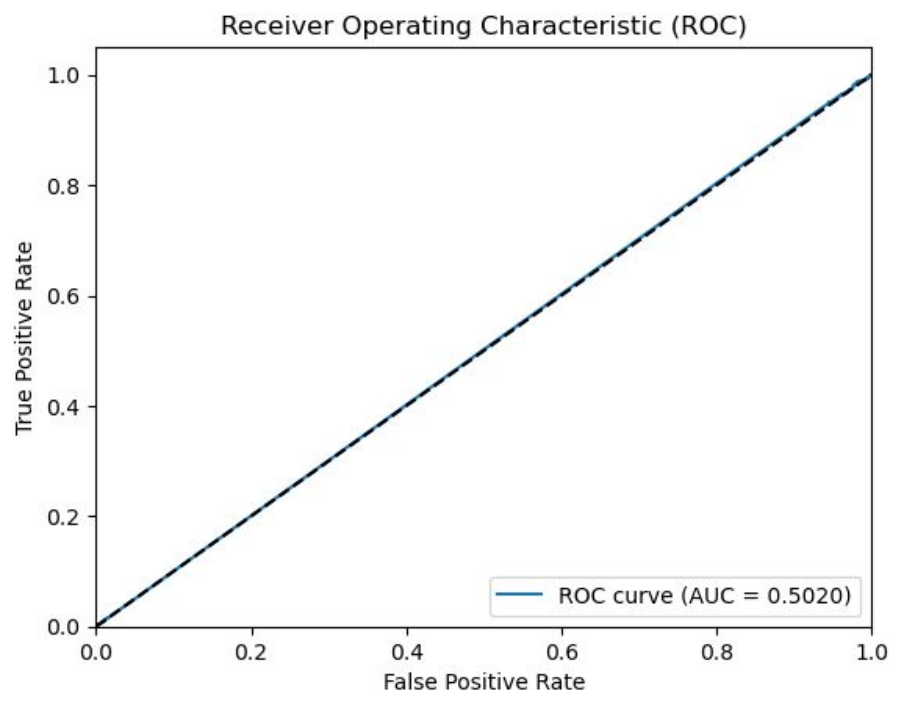
2. Metadata MLP

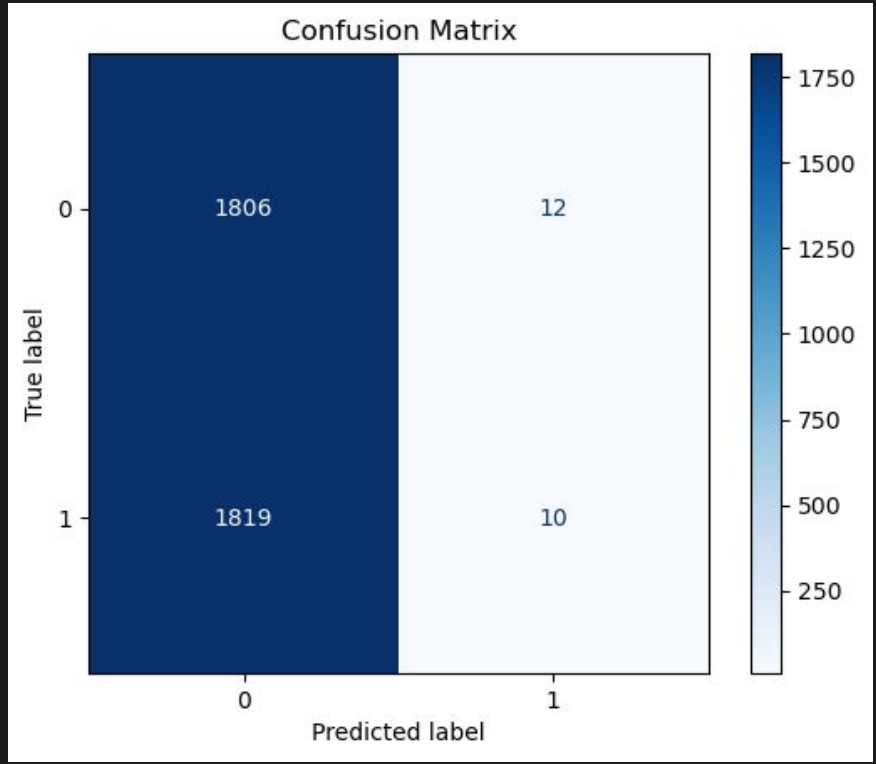




Baseline Models

3. Image CNN





Final Model Architecture

- Used **MobileNetV2** base model
- Fine tuned weights further
- 2D Global Average Pooling
- Binary Classification

Base Model
MobileNetV2

keras.applications.MobileNetV2

- ➔ Keras image classification model
- ➔ “uses inverted residual blocks with bottlenecking features”
- ➔ Pretrained on ImageNet
- ➔ Good balance between performance and computational cost
- ➔ Used pretrained weights and froze

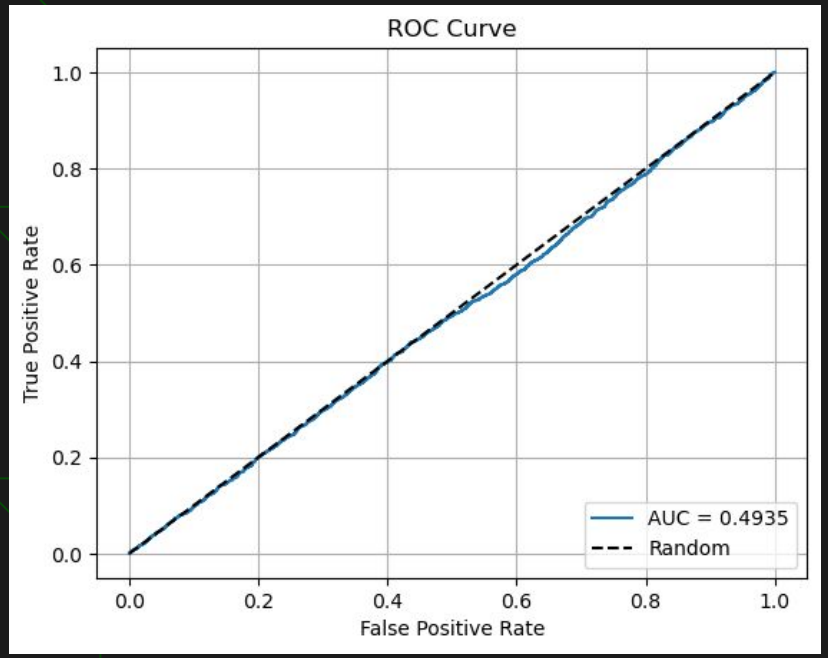
Training Details

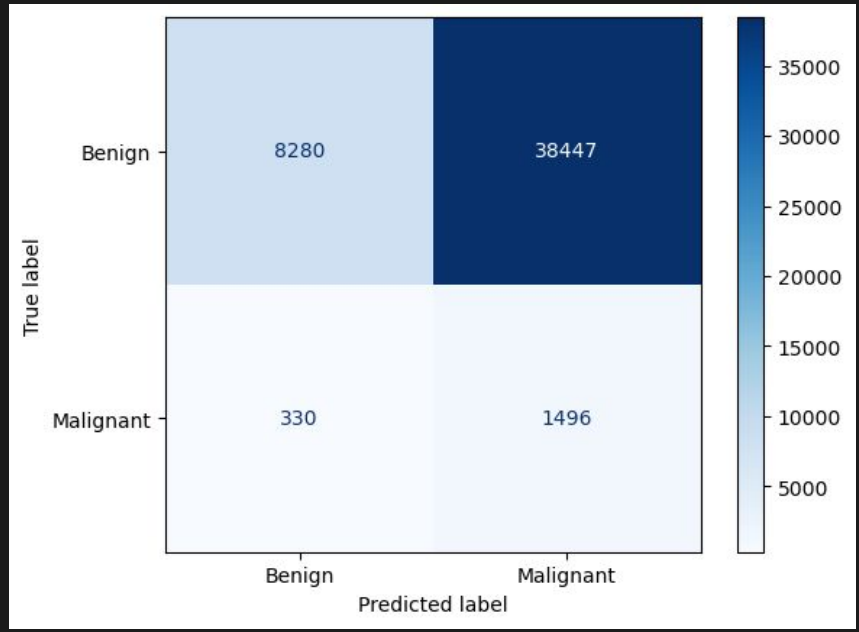
- **Optimizer**
  Adam
- **Learning Rate**
  0.001
- **Loss Function**
  Binary Cross Entropy
- **Regularization**
  Earlystopping

Results

Binary: Balanced Train and Validation

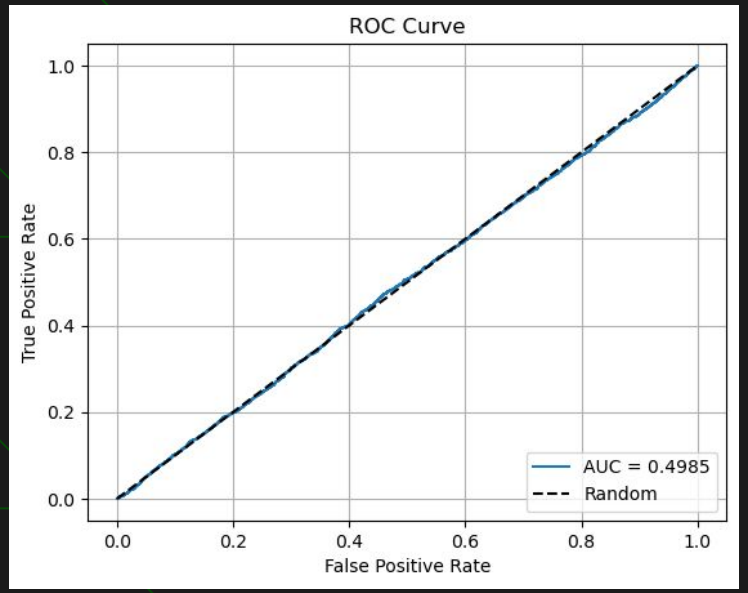
- Using balanced image data for training, and evaluated using balanced data

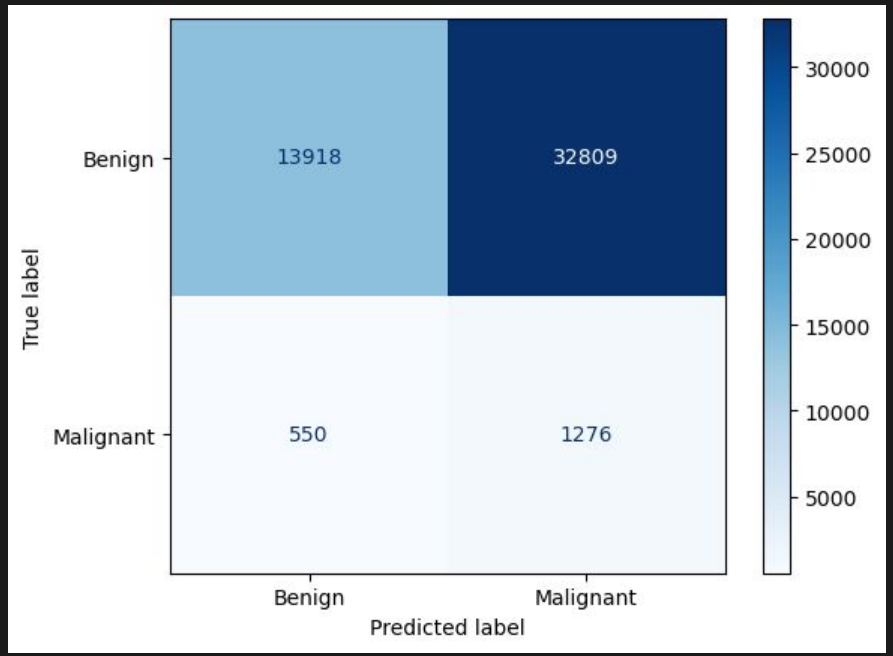




Binary: Balanced Train, Unbalanced Validation

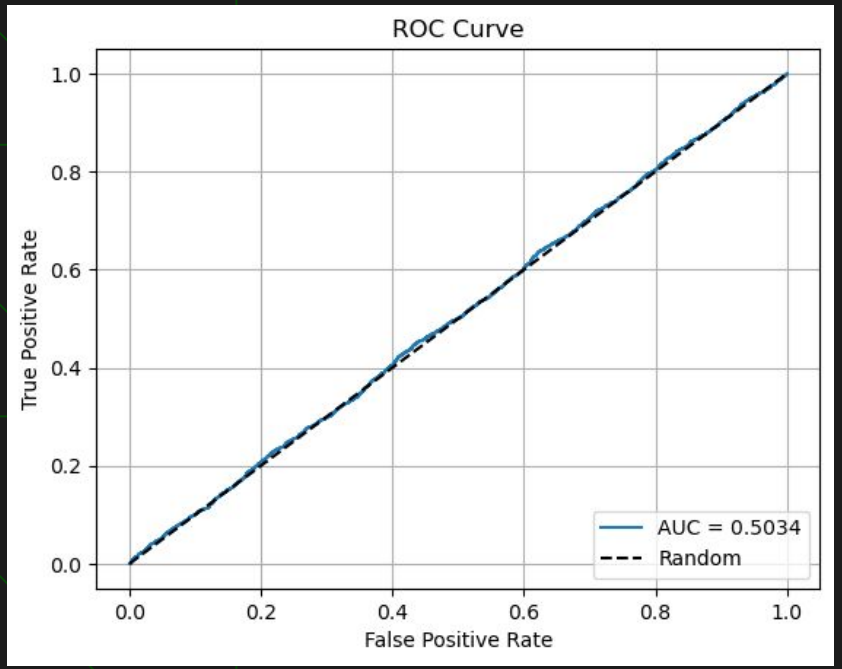
- Using balanced image data for training, but evaluated on unbalanced/original data splits

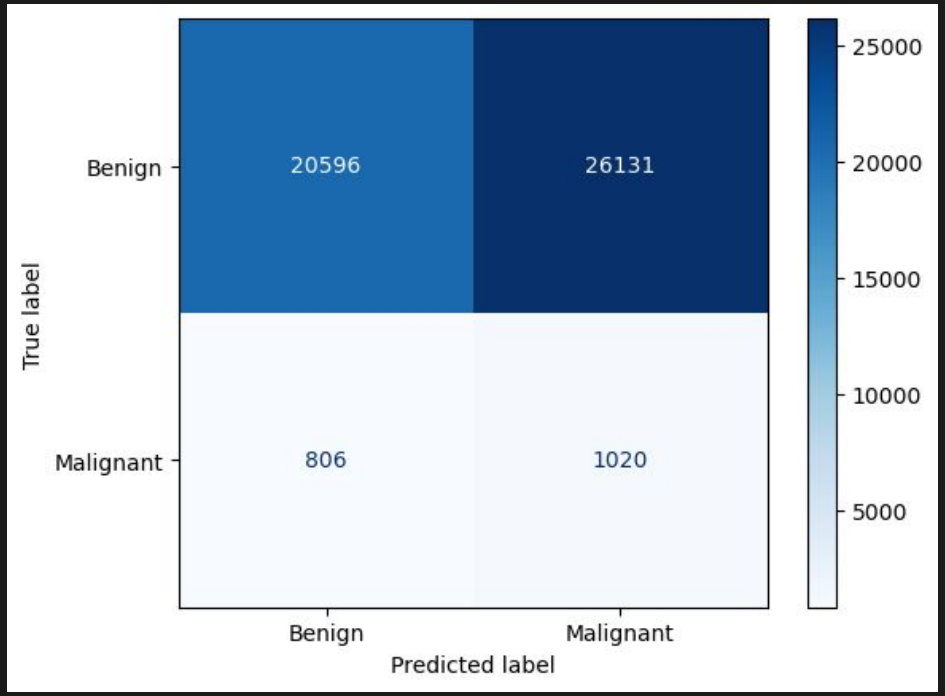




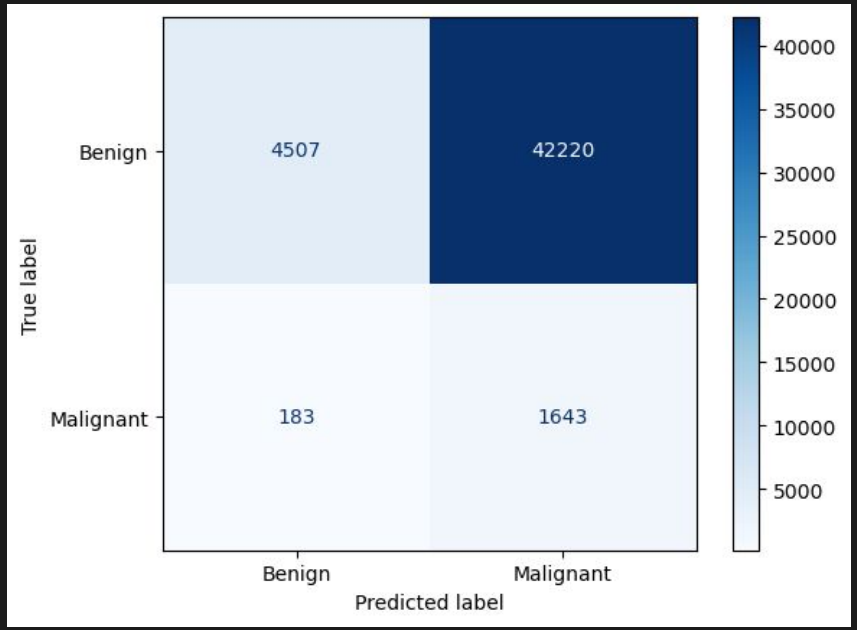
Binary: Balanced Train, Unbal Val, Augmented Data

- Using augmented and balanced image data for training, but evaluated on unbalanced data splits

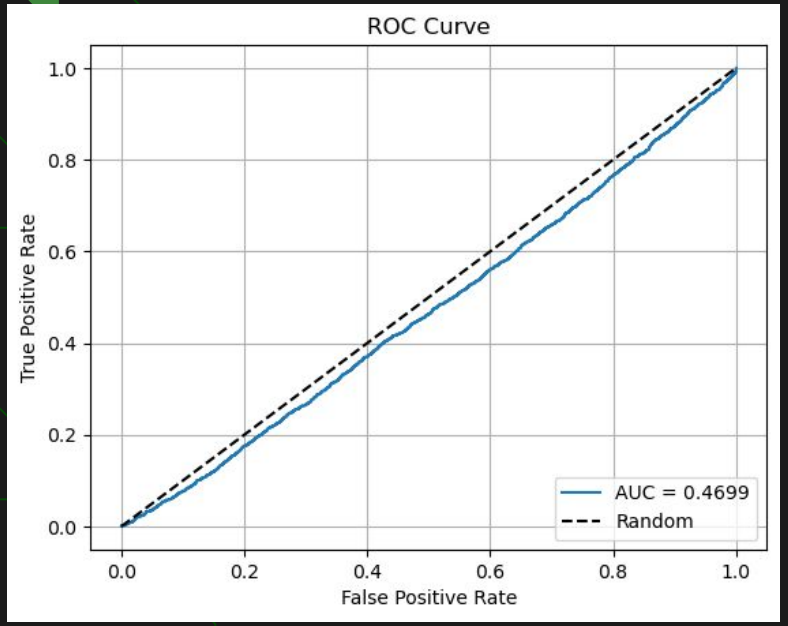


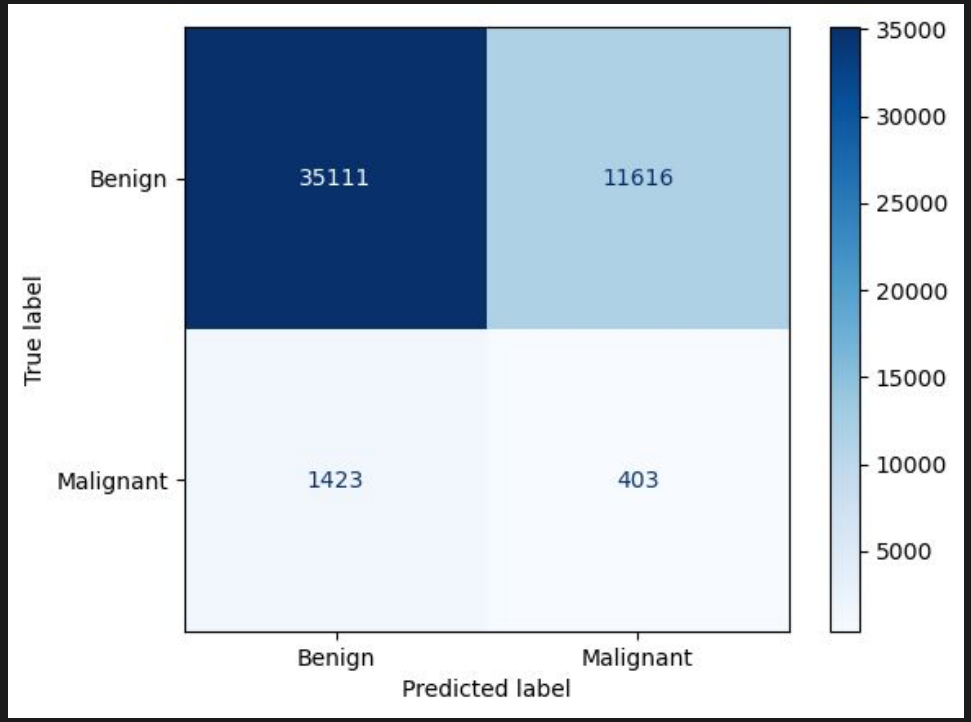


Binary: RESN50 base model



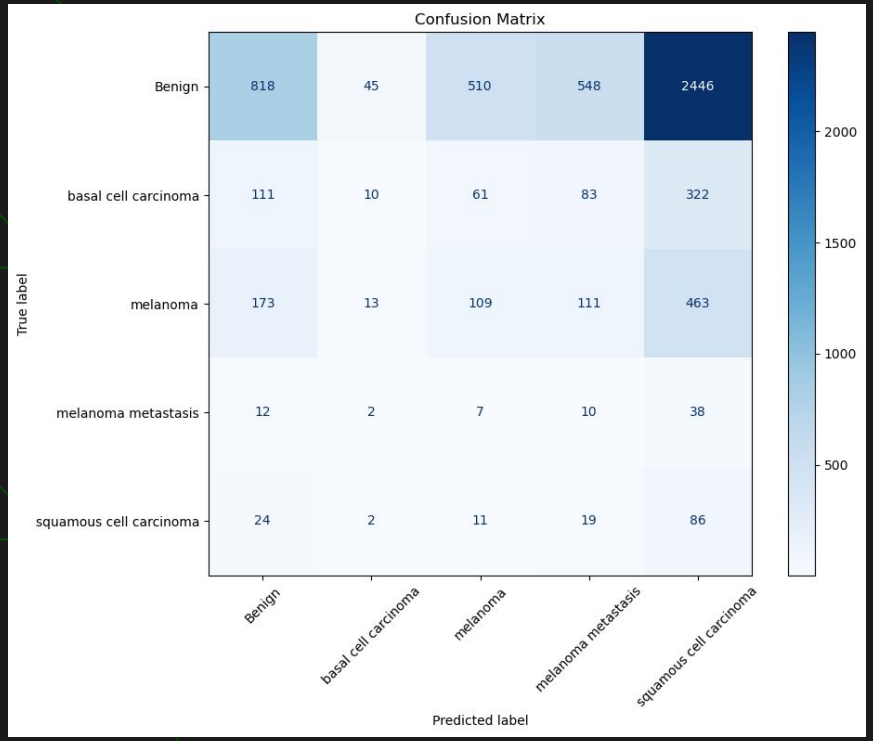
Binary: Adding in the metadata



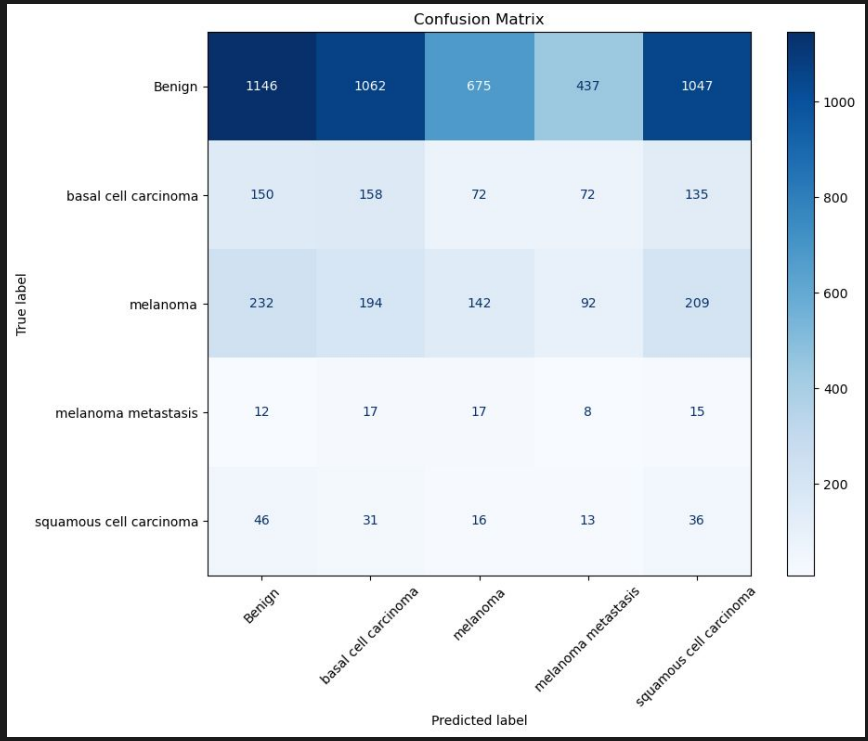


Multiclass Classification

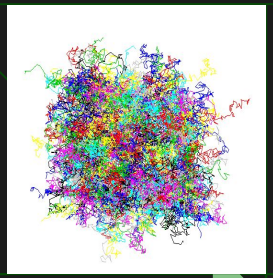
With Unfreezing



No Unfreezing



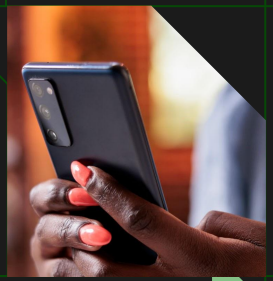
Challenges



01

Large Image Dataset

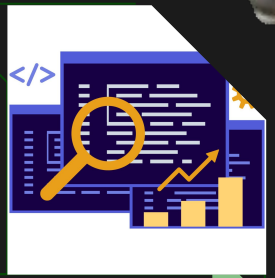
- ISIC API issues when working with such large (>500,000) image sets
- Lack of detailed diagnosis information
- Lack of malignant lesion representation



02

Combining Models

- Model compatibility made it difficult for us to combine/concatenate our architectures into a larger single model

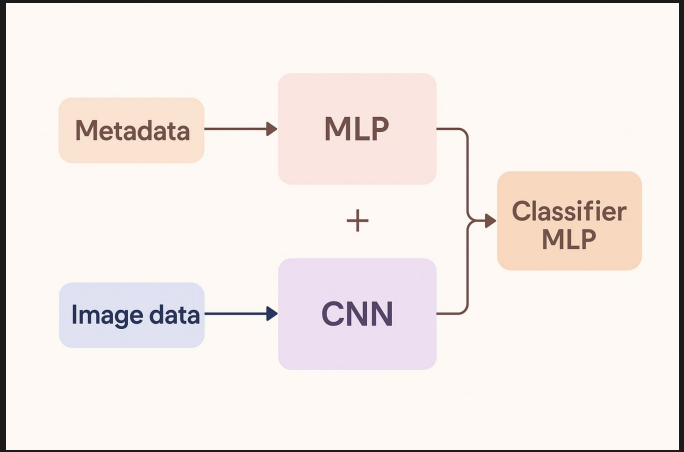


03

Image Metadata

- Incomplete values for metadata categories
- Needed to be processed alongside image set, further complicating task

Future Steps



Architecture

Include more complex model features, ie. skip connection, residual connection, etc

Dataset

Expand our database for training and evaluation, especially malignant lesions

Baseline Model

Test effectiveness with other various baseline models, ie. EfficientNet, DenseNet, etc

Thank You!

References

https://keras.io/api/applications/mobilenet/
https://keras.io/api/applications/resnet/