SKIN JOB

Data Model Dermatology

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Course: DSE I2100
Instructor: Michael Grossberg

Introduction

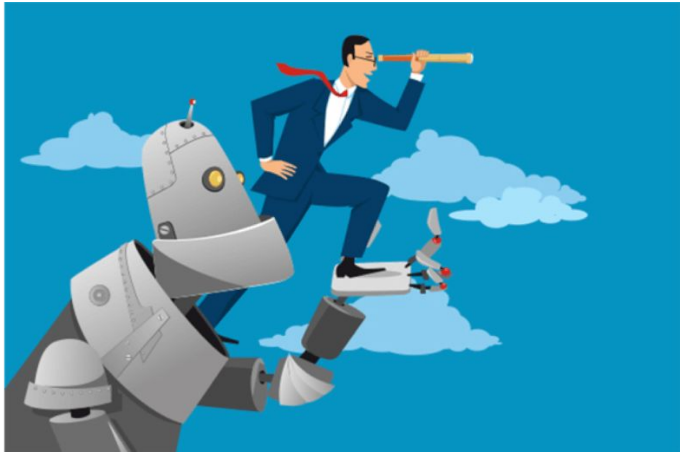
- Project Overview
- Research Purpose
- Why We Cares
- Data introduction
- Exploratory Data Analysis
- Methods
- Evaluation
- Conclusion

Project Overview

In this project, we incorporated a series of machine learning techniques to help us build a model that can distinguish skin cancers from other tumors. A convulsion neural network model was selected and built with the accuracy of matching human benchmark. Alongside, we also identified few key features that affect the model Training.

Research Purpose

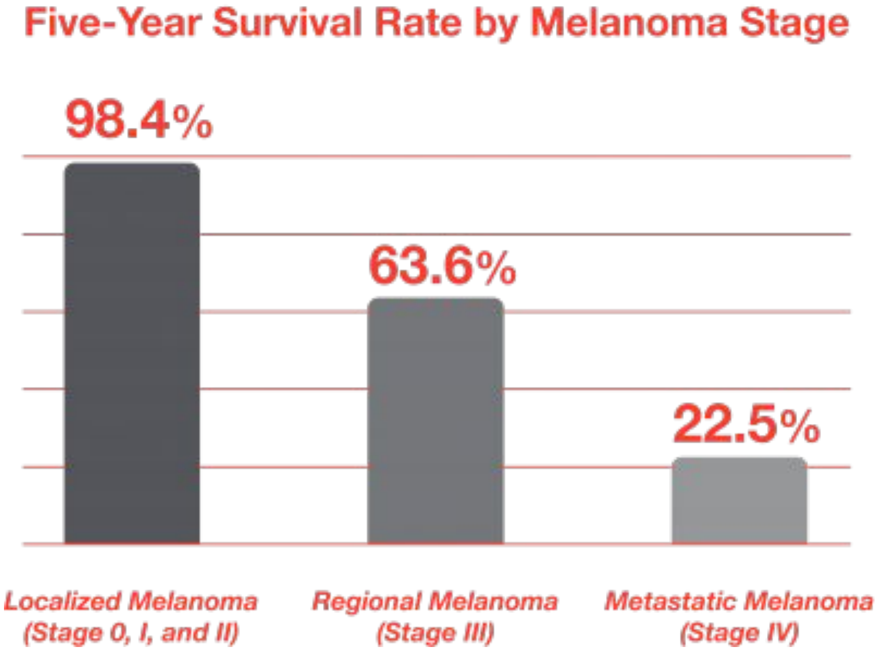
- Objective:
  - Use image data to classify skin lesions
  - Emphasize on recall and precision rate of skin cancers
- Benchmark:
  - Human accuracy: 67-75%
- Our goal
  - Match or better human benchmark
  - Achieve higher F1 score for skin cancers



Why we care?

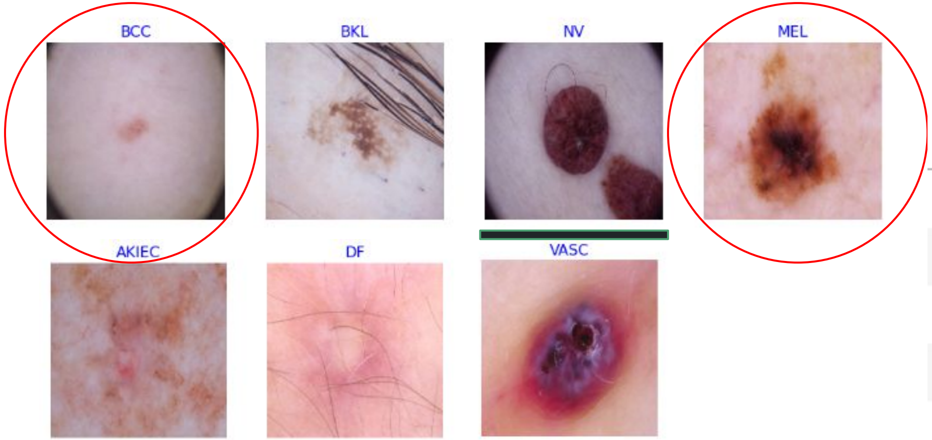
Limited screening methods
Once malignancy is confirmed, usually late stage
Accurate skin cancer detection at earlier stage is the key:

1. Improved survival
2. Improved clinical outcomes
3. Improved quality of life



Data Introduction

- Dataset: HAM10000: Human Against Machine with 10000 training images
- What:
  - 10015 dermatoscopic images
  - Types of label: 5 benign + 2 malignant
    - Benign: (AKIEC, BKL, DF,NV, VASC), **Malignant:** (**BCC, MEL)**
    - NV most common label
  - Variables:
    - lesion_id, image_id, dx, dx_type, age and localization



	lesion_id	image_id	dx	dx_type	age	sex	localization
0	HAM_0000118	ISIC_0027419	bkl	histo	80.0	male	scalp
1	HAM_0000118	ISIC_0025030	bkl	histo	80.0	male	scalp
2	HAM_0002730	ISIC_0026769	bkl	histo	80.0	male	scalp
3	HAM_0002730	ISIC_0025661	bkl	histo	80.0	male	scalp
4	HAM_0001466	ISIC_0031633	bkl	histo	75.0	male	ear

Data Introduction

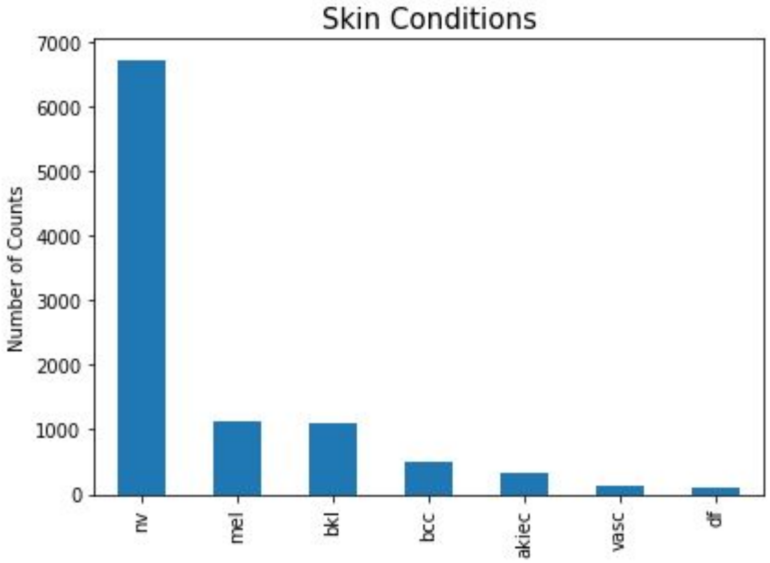
- Who:
  - International Skin Imaging Collaboration (ISIC) archive
  - Standard source for dermatoscopic image analysis research
- When: 2018 challenges
- Why: Enhance the diagnostic accuracy for distinguishing melanoma from other tumors

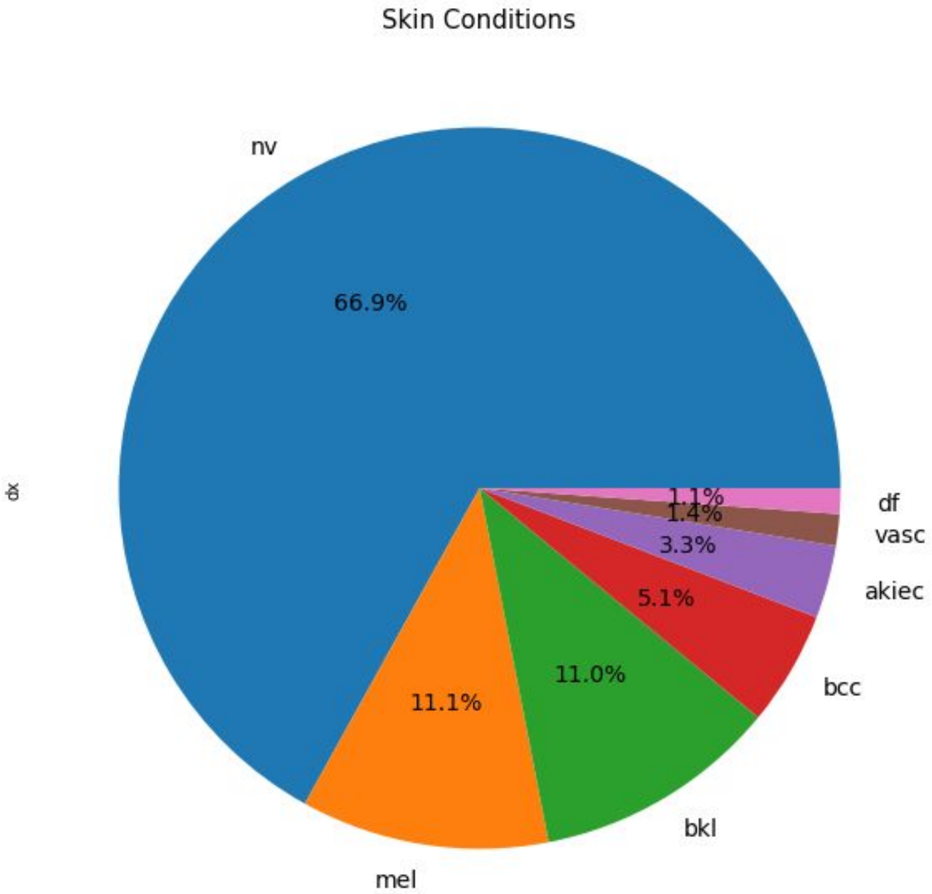
Exploratory Data Analysis

- Missing Data in Age
  - Replaced with average mean

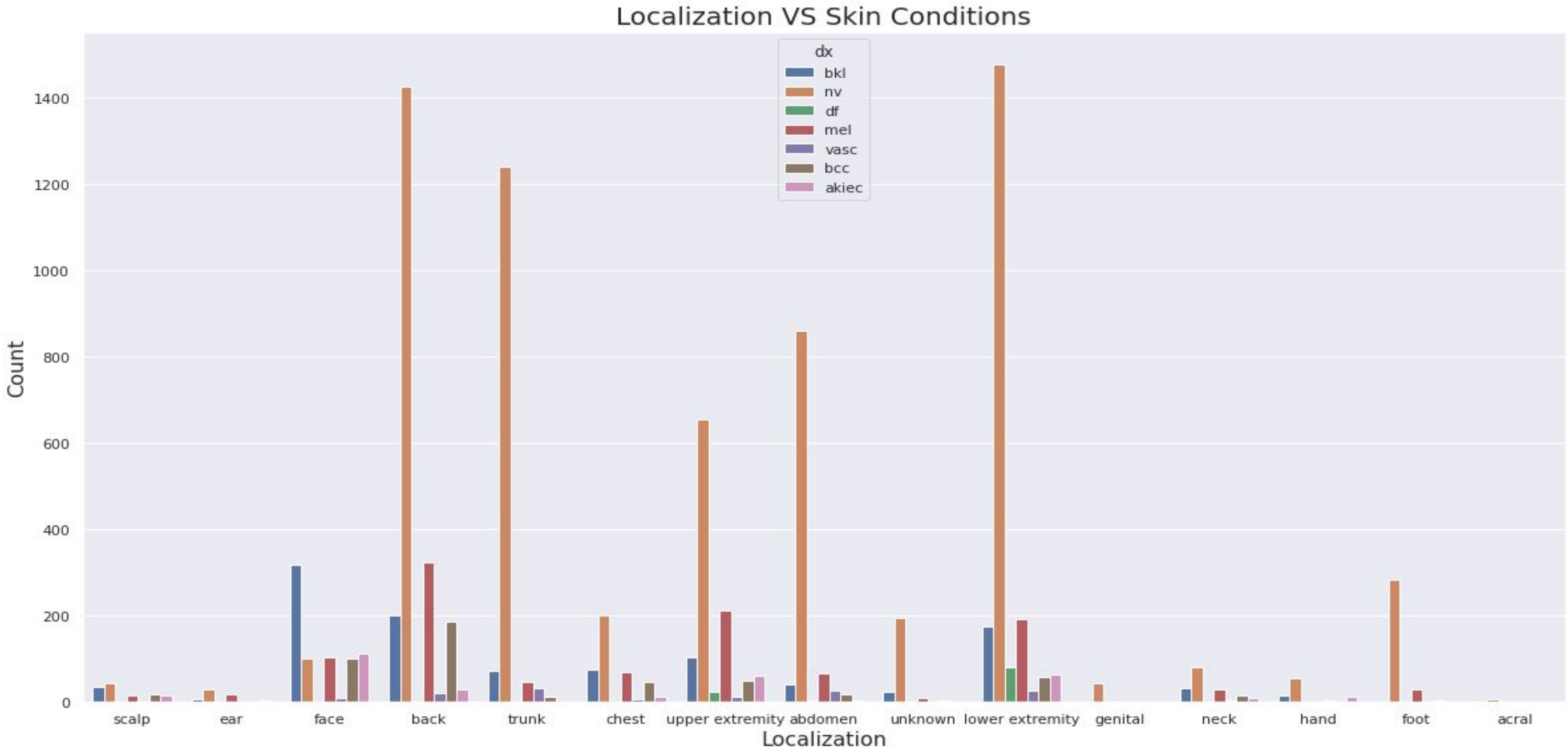
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10015 entries, 0 to 10014
Data columns (total 7 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   lesion_id     10015 non-null  object
 1   image_id      10015 non-null  object
 2   dx            10015 non-null  object
 3   dx_type       10015 non-null  object
 4   age           9958 non-null   float64
 5   sex           10015 non-null  object
 6   localization  10015 non-null  object
dtypes: float64(1), object(6)
memory usage: 547.8+ KB
```

EDA - Imbalance Data

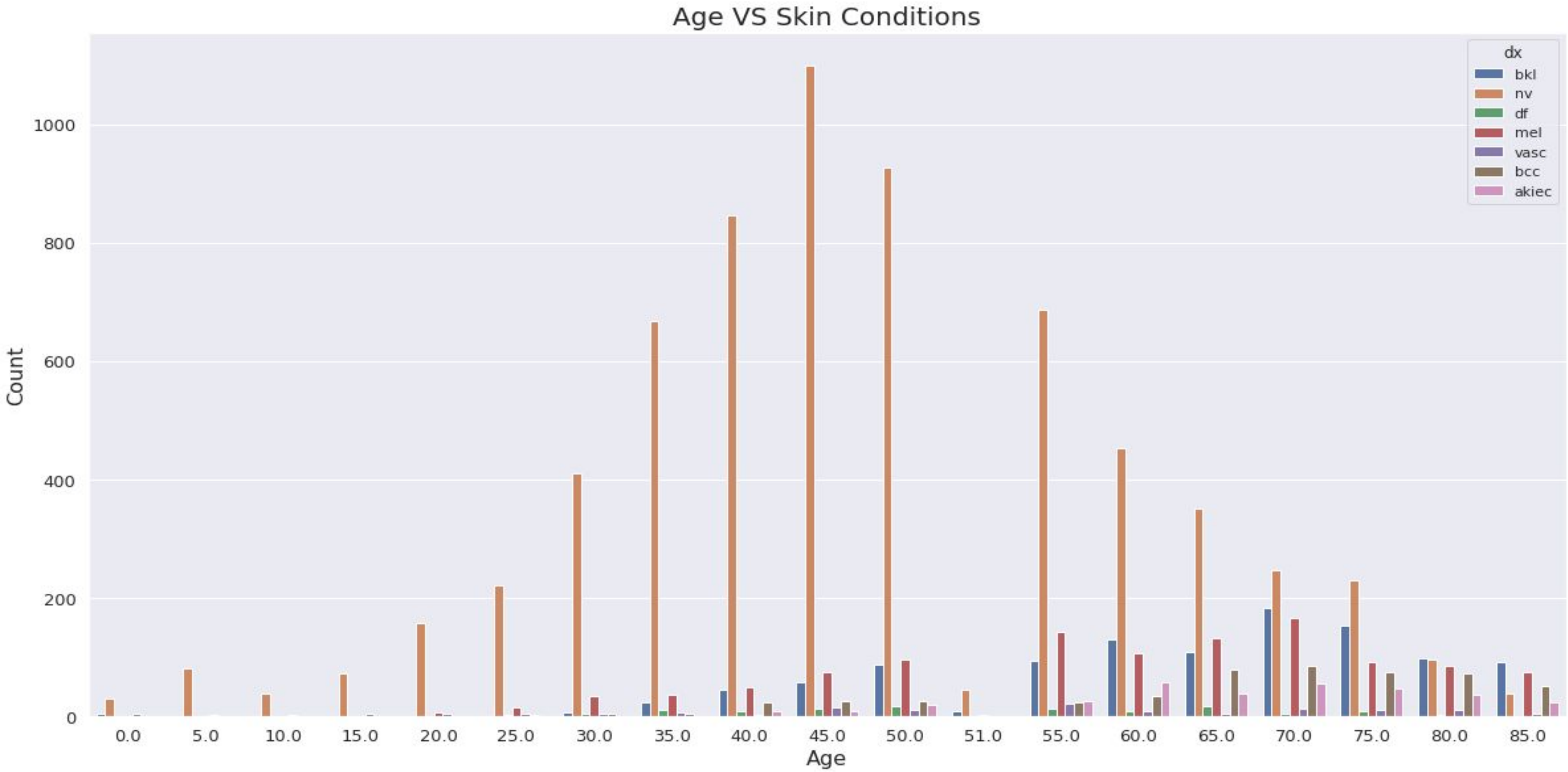




EDA - Bivariate Analysis



EDA - Bivariate Analysis



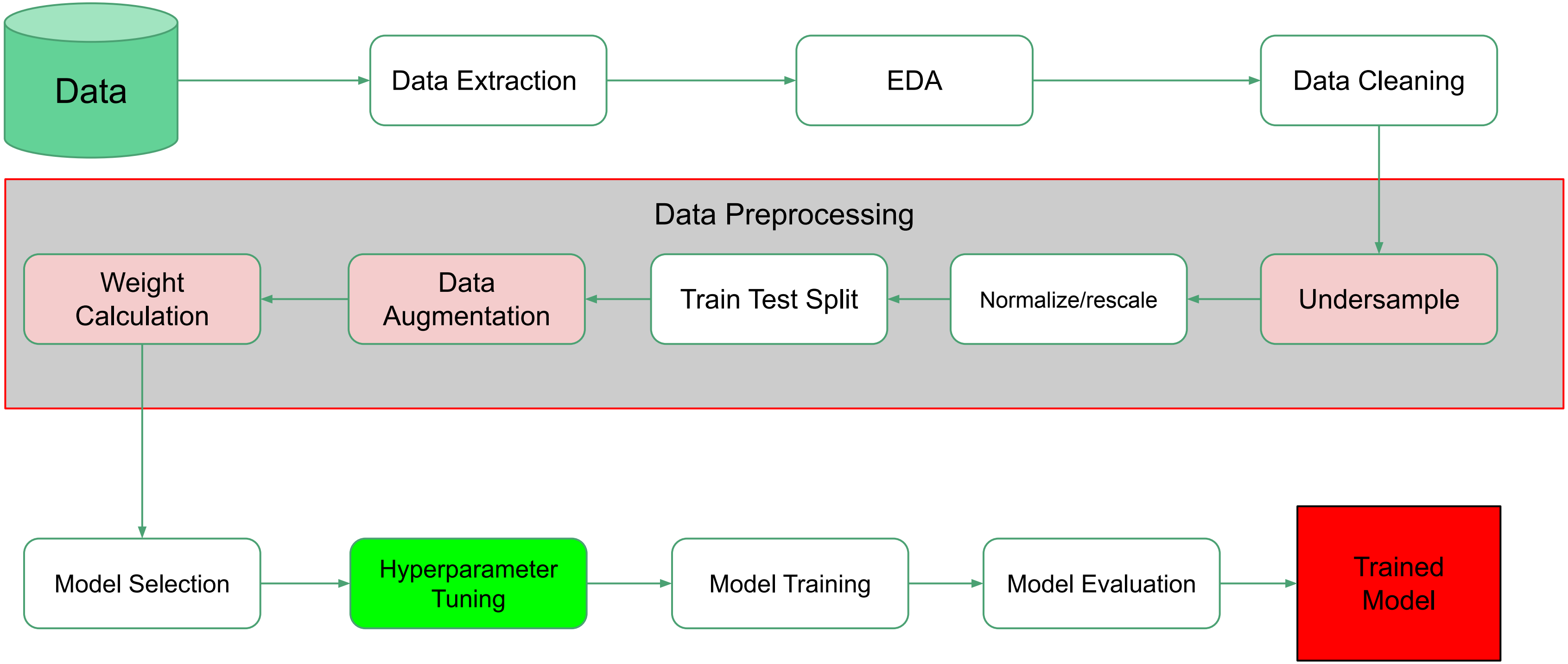
Feature Selection

- Image Data
  - 90x90
- Age
- Localization

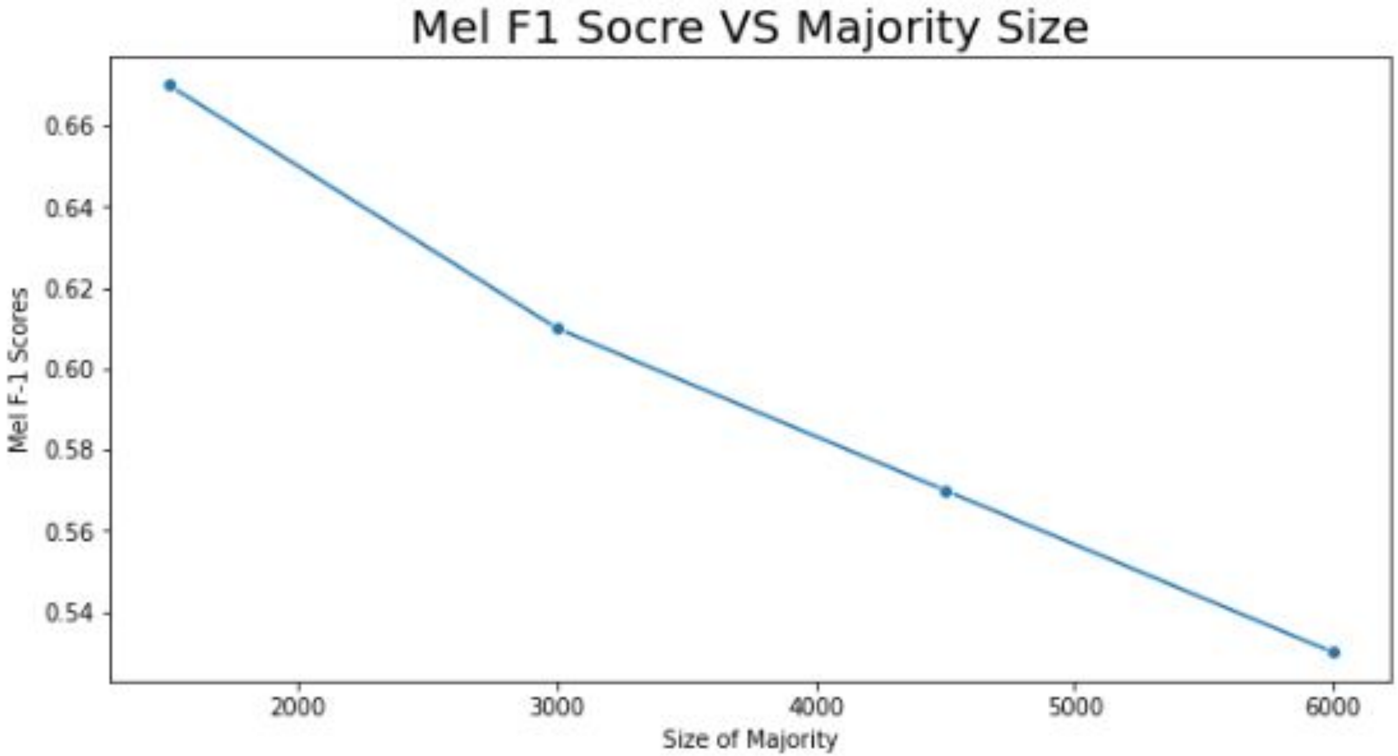
Model Improvement with Age and Localization:

Models	Val accuracy	Mel F1 Score	Bcc F1 Score
Ridge Classifier	9.30%	0.11	0.1
Logistic Classifier	11.81%	0.16	0.04
SVC	9.02%	0.05	0.12
Random Forest	7.51%	0.04	0.05
DNN	3.65%	0.15	0.03

Pipeline Flow Chart



Undersample



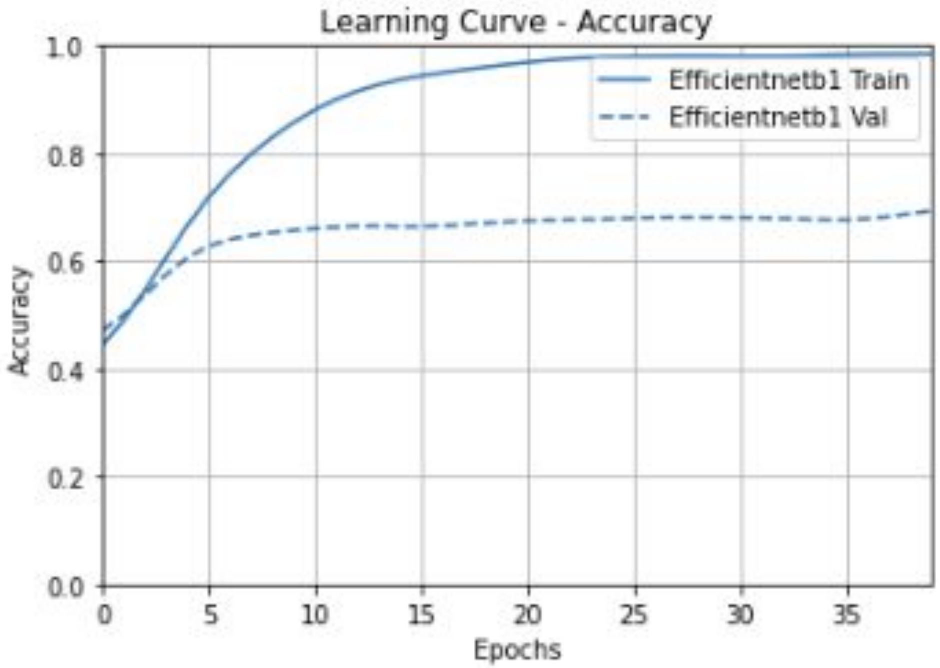
Model Selection

- Sklearn Models
  - Ridge Classifier
  - Logistic Classifier
  - SVC
  - Random Forest
- Keras Models
  - DNN (Dense Neural Network)
  - CNN (Convolutional Neural Network)
  - CNN with EfficientNetB1

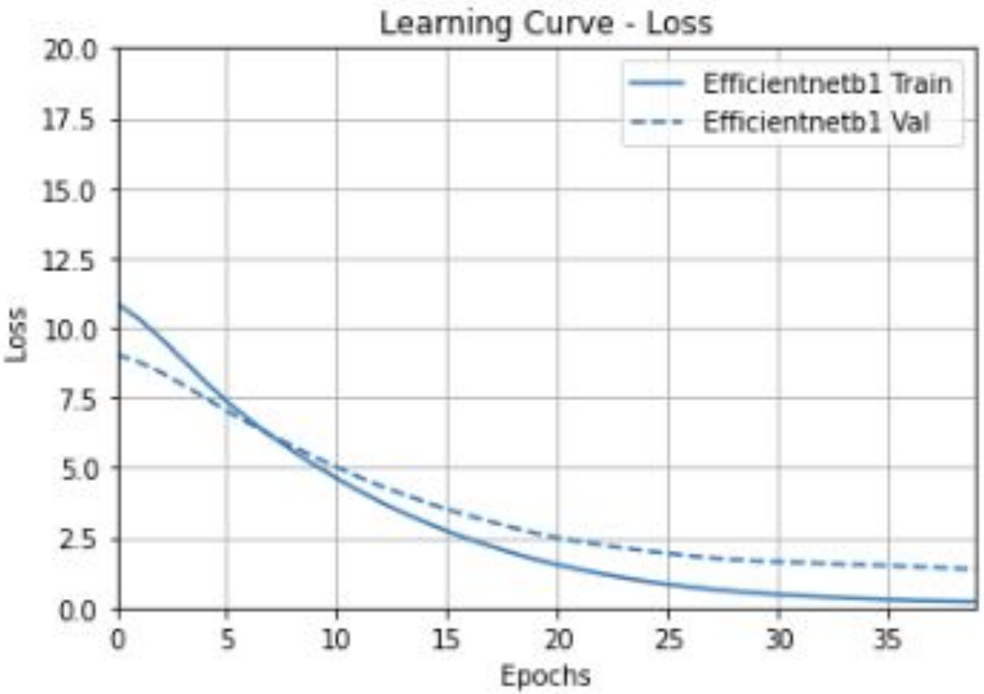
Model Selection

Models	Val accuracy	Mel F1 Score	Bcc F1 Score	Train - Val
Ridge Classifier	62.06%	0.45	0.33	8.14%
Logistic Classifier	67.57%	0.50	0.43	11.36%
SVC	72.72%	0.49	0.55	16.88%
Random Forest	68.93%	0.48	0.35	11.57%
DNN	71.65%	0.42	0.34	2.39%
CNN	75.23%	0.45	0.48	7.59%
CNN (EfficientNet B1)	81.53%	0.55	0.62	15.42%

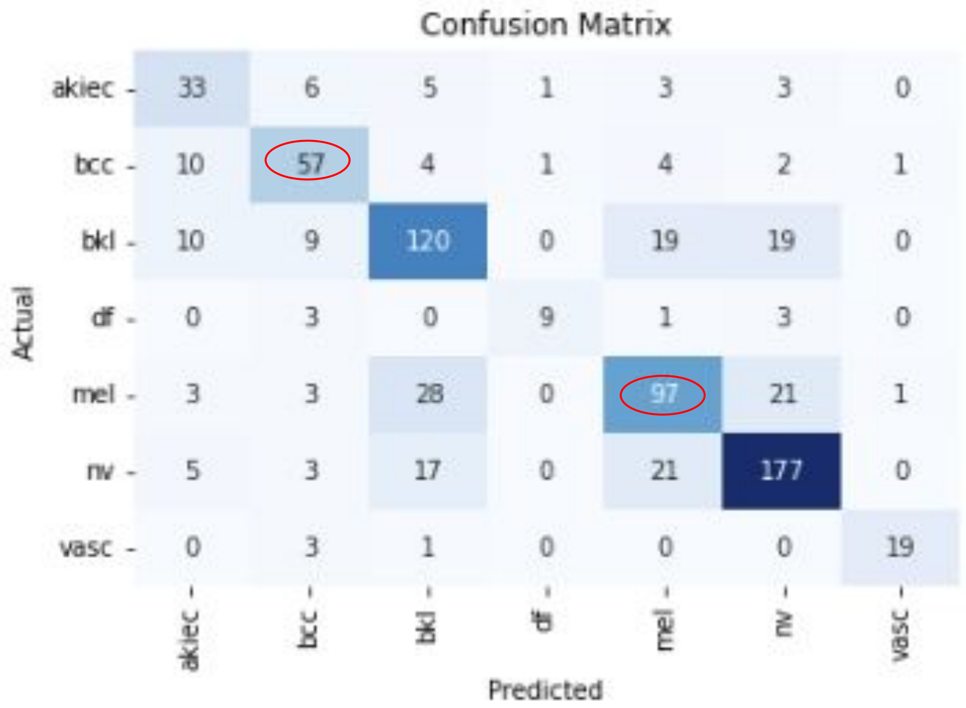
Learning Curve - Accuracy



Learning Curve - Loss



Confusion Matrix



- Mel: 97 out of 153
- Bcc: 57 out of 79

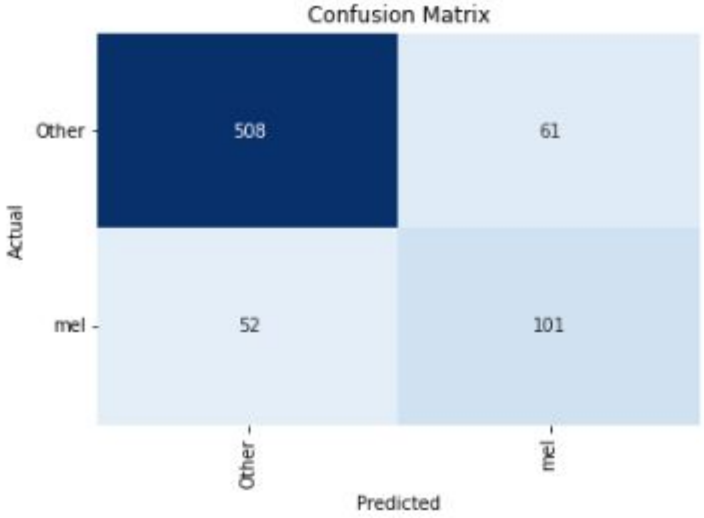
Classification Report

```
Classification Report:
============================================================
              precision    recall  f1-score   support

       akiec       0.54      0.65      0.59        51
         bcc       0.68      0.72      0.70        79
         bkl       0.69      0.68      0.68       177
          df       0.82      0.56      0.67        16
         mel       0.67      0.63      0.65       153
          nv       0.79      0.79      0.79       223
        vasc       0.90      0.83      0.86        23

    accuracy                           0.71       722
   macro avg       0.73      0.69      0.71       722
weighted avg       0.71      0.71      0.71       722
```

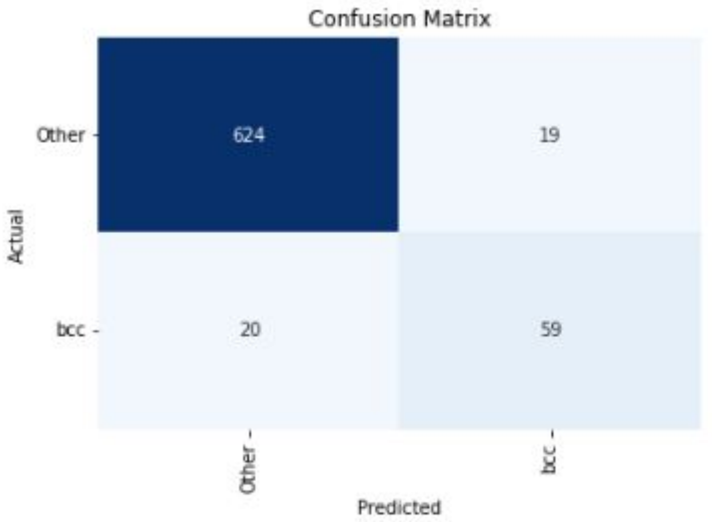
One vs Rest - Mel



Classification Report:

	precision	recall	f1-score	support
other	0.91	0.89	0.90	569
mel	0.62	0.66	0.64	153
accuracy			0.84	722
macro avg	0.77	0.78	0.77	722
weighted avg	0.85	0.84	0.85	722

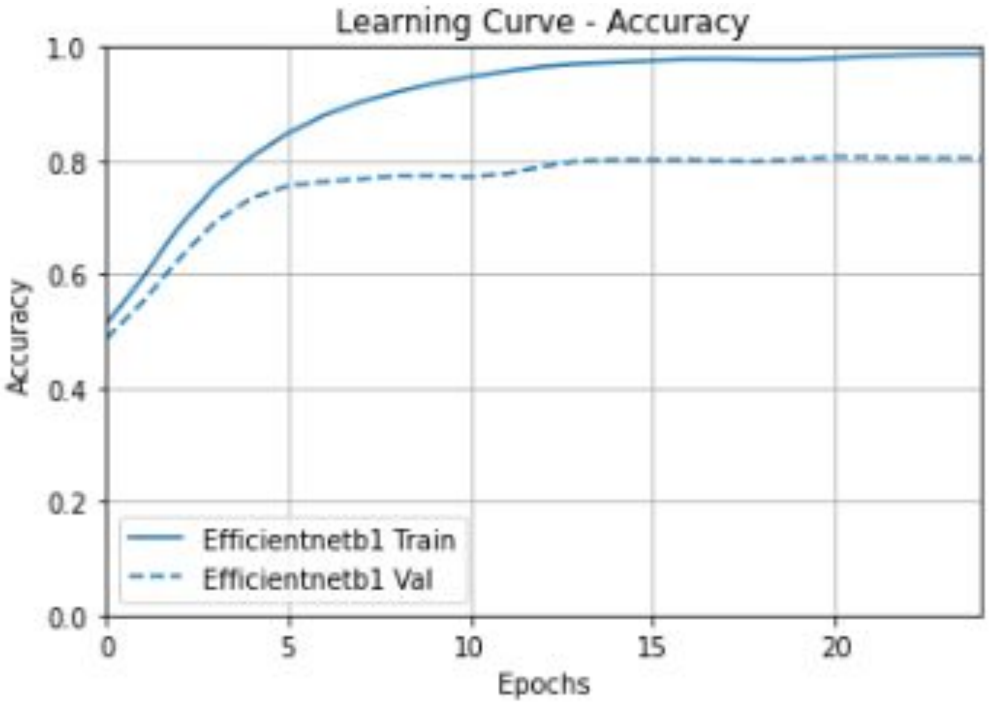
One vs Rest - Bcc



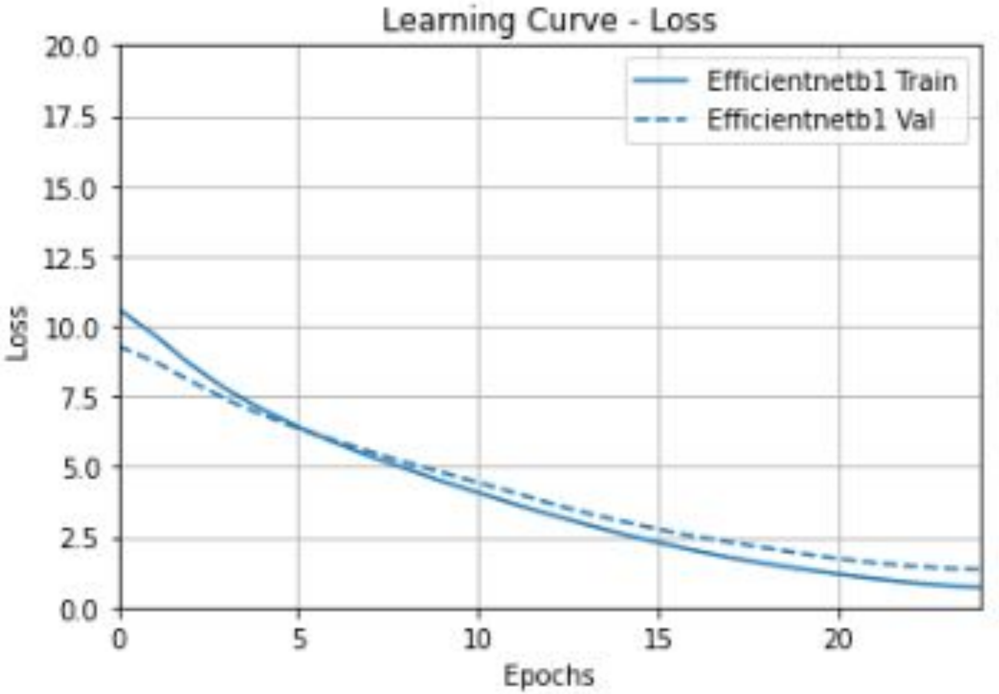
Classification Report:

	precision	recall	f1-score	support
other	0.97	0.97	0.97	643
bcc	0.76	0.75	0.75	79
accuracy			0.95	722
macro avg	0.86	0.86	0.86	722
weighted avg	0.95	0.95	0.95	722

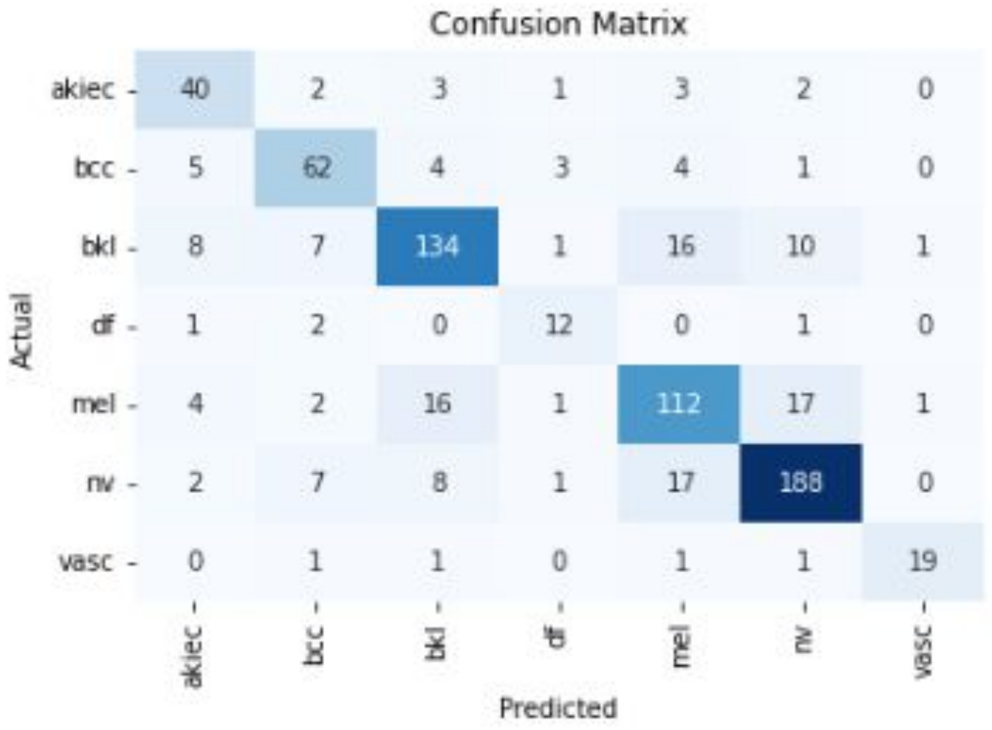
On High Resolution



On High Resolution



On High Resolution



- Mel: 122 out of 153
- Bcc: 62 out of 79

On High Resolution

Classification Report:

```
===========================================================
              precision    recall  f1-score   support

       akiec       0.67      0.78      0.72        51
         bcc       0.75      0.78      0.77        79
         bkl       0.81      0.76      0.78       177
          df       0.63      0.75      0.69        16
         mel       0.73      0.73      0.73       153
          nv       0.85      0.84      0.85       223
        vasc       0.90      0.83      0.86        23

    accuracy                           0.79       722
   macro avg       0.76      0.78      0.77       722
weighted avg       0.79      0.79      0.79       722
```

Conclusion

- Model:
    - Data preprocessing technique is effective
    - Our model is matching with human benchmark
- Findings:
    - Age and localization are very effective in model training
    - One vs Rest is effective for Bcc, but not Mel
- Limitations:
    - Dataset suffer from biases: light skins
    - More risk factor features will improve model accuracy: family history, pre-existing condition

Attribute

April 17, 2022 – May 17, 2022

Period: 1 month

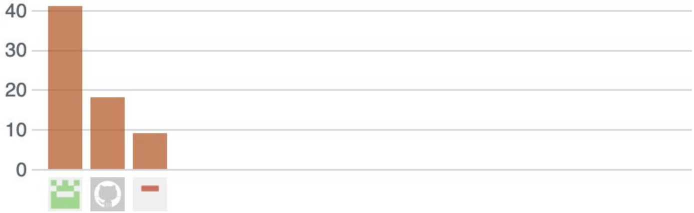
Overview

23 Active pull requests

0 Active issues

23 Merged pull requests	**0** Open pull requests	**0** Closed issues	**0** New issues

Excluding merges, **3 authors** have pushed **68 commits** to main and **68 commits** to all branches. On main, **0 files** have changed and there have been **0 additions** and **0 deletions**.



23 Pull requests merged by **2** people

Notebook List

albert6051 Add files via upload

..	
1.0-gqc-initial-EDA.ipynb	Move Notebook to Individual folders
2.0-gqc-Linear_and_Logistic_Model_test.ipynb	Move Notebook to Individual folders
2.1-gqc-Linear_and_Logistic_Model_Sklearn.ipynb	Update to Sklearn Model
3.0-gqc-DNN_and_CNN_Model_test.ipynb	Move Notebook to Individual folders
3.1-gqc-CNN_with_regularization.ipynb	Add files via upload
3.2-gqc-DNN.ipynb	Add files via upload
4.0-gqc-balanced_image_numpy_convertor.ipynb	Move Notebook to Individual folders
4.0-gqc-image_numpy_convertor.ipynb	Move Notebook to Individual folders
5.0-gqc-pretrained_models_MobileNetV2.ipynb	Move Notebook to Individual folders
5.1-gqc-pretrained_models_EfficientNetB1.ipynb	Add files via upload
5.2-gqc-pretrained_models_EfficientNetB1_Data_Augme...	Move Notebook to Individual folders
7.0-gpc-Resample_for_Balancing_Data.ipynb	Move Notebook to Individual folders
8.0-gqc-preprocessing_pipeline.ipynb	Add files via upload
9.0-gqc-Sklearn_Models.ipynb	Sklearn Models test
9.1-gqc-Sklearn_Models_pca.ipynb	PCA model test

HuiHuang Liu and **HuiHuang Liu** sklearn model update with baggingclassifier

..	
6.0 SVM.ipynb	Move Notebook to Individual folders
Initial_EDA+Descriptions.ipynb	EDA with description
Linear+Logistic_model_with_keras.ipynb	update on the previous version
SVM_tf_ Update.ipynb	updatesvm model with multicategorical classification
keras_initial.ipynb	keras models update
keras_models.ipynb	keras models update
sklearn_models.ipynb	sklearn models update
sklearn_update_with_BaggingClassifier.ipynb	sklearn model update with baggingclassifier

Reports

	HuiHuang Liu and **HuiHuang Liu** update the version	
	..	
📁	Reports before merging	merging everything to final_report and created new folder
📁	figures	Setup Cookie Cutter
🗋	.gitkeep	Setup Cookie Cutter
🗋	Final_Report.ipynb	update the version
🗋	Report_status.ipynb	updated data section with description of each categories of tumor
🗋	Status Report#1.pptx	Status Report 5/3
🗋	research interest.docx	Setup Cookie Cutter

Reference

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10. Esteva, A. et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature 542, 115–118 (2017).
11. Han, S. S. et al. Classification of the clinical images for benign and malignant cutaneous tumors using a deep learning algorithm. J Invest Dermatol, Preprint at https://doi.org/10.1016/j.jid.2018.01.028 (2018).