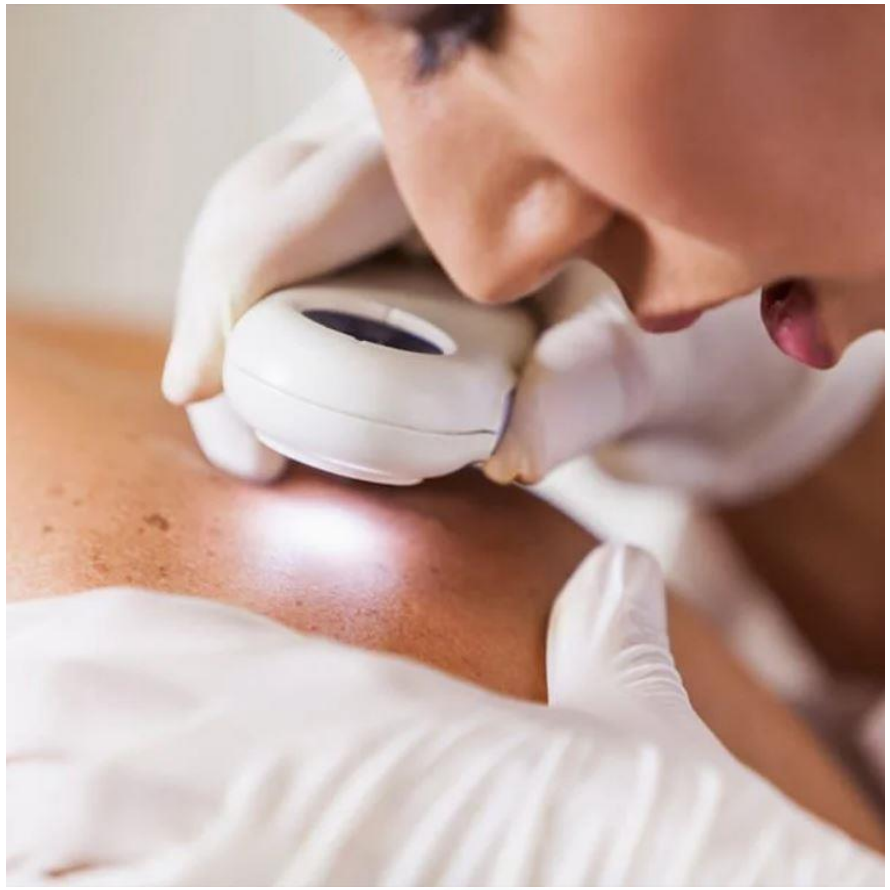
Computer Aided Pigmented Skin Lesion Classification

Ananalysis by Christopher Liedel

Use Case: Multi-Class Classification

Skin cancer is the most common human malignancy

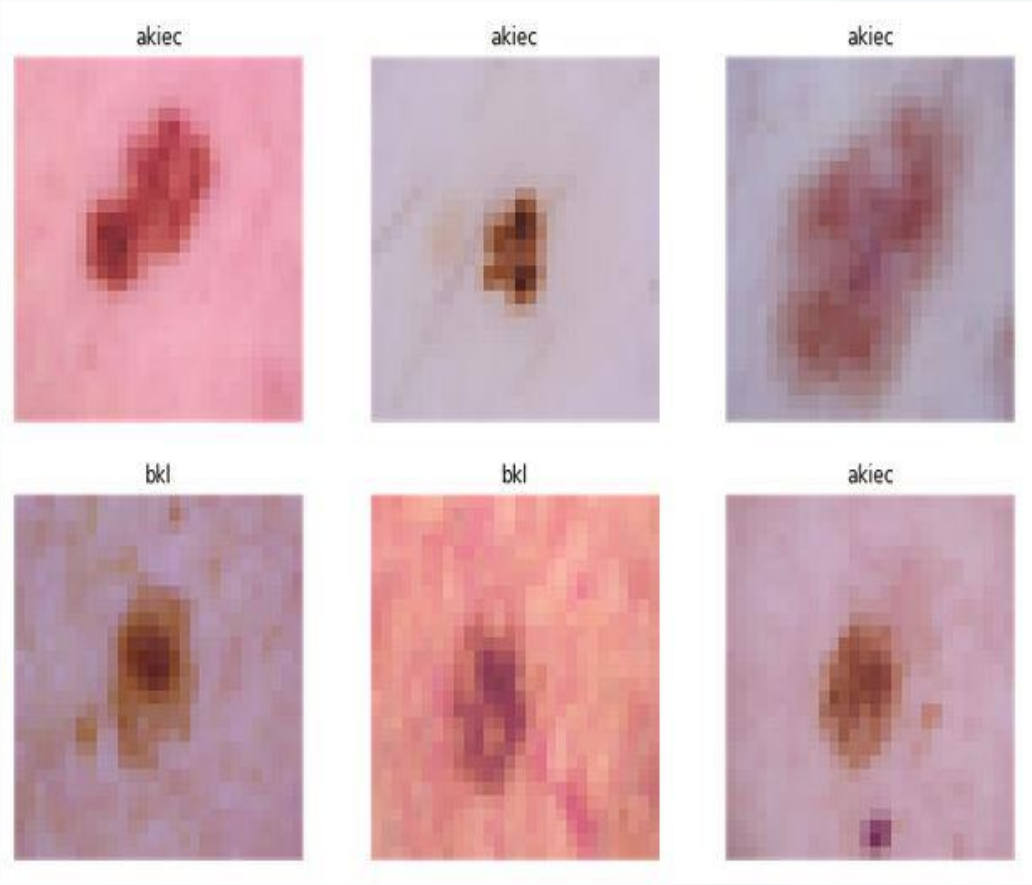
- Early detection of skin cancer allows for a more successful and simpler cure.
- Initial Diagnosis is performed in a clinical setting limiting access to medical care for some.
- Automating skin lesion classification can be used as diagnostic aid in a clinical setting.
- Automation of skin lesion classification through mobile devices can potentially expand needed low-cost medical care outside the clinic.



Data Used

Dataset: HAM_10000 (hmnist_28_28_RGB.csv) for pigmented skin lesion diagnosis.

- Contains 10,000 images of skin lesions, both benign and malignant.
- A labels column.



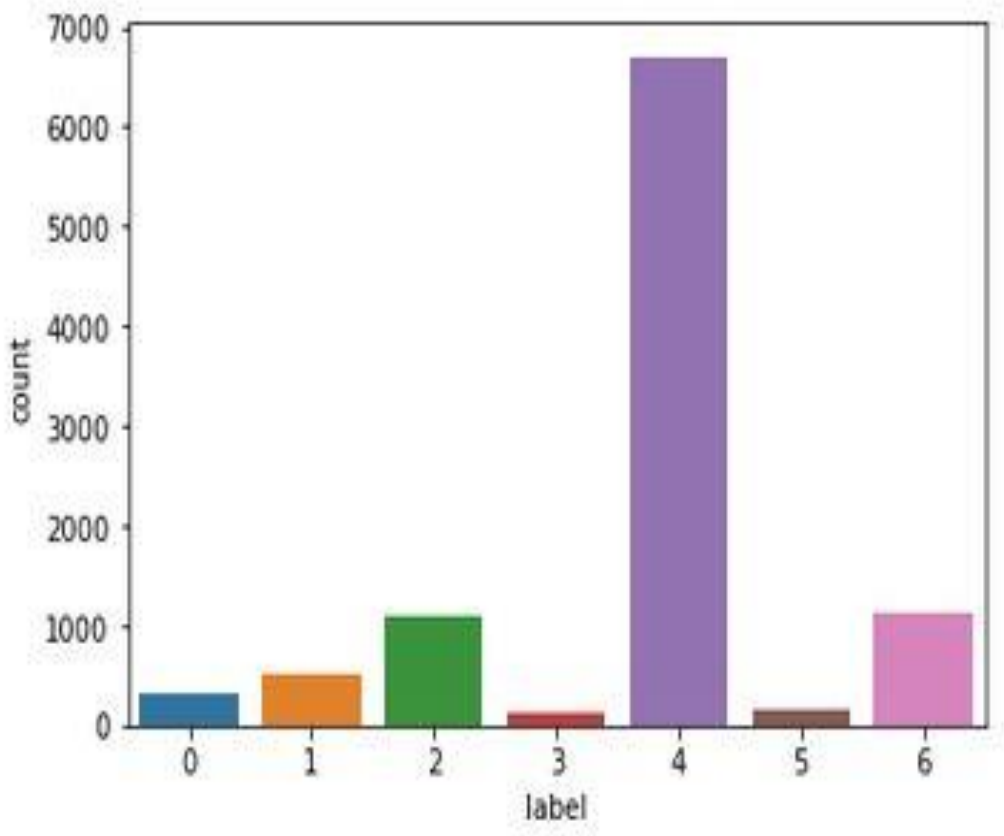
Metadata includes additional patient information including patient age, patient sex, and lesion location

HAM_10000_metadata.csv file

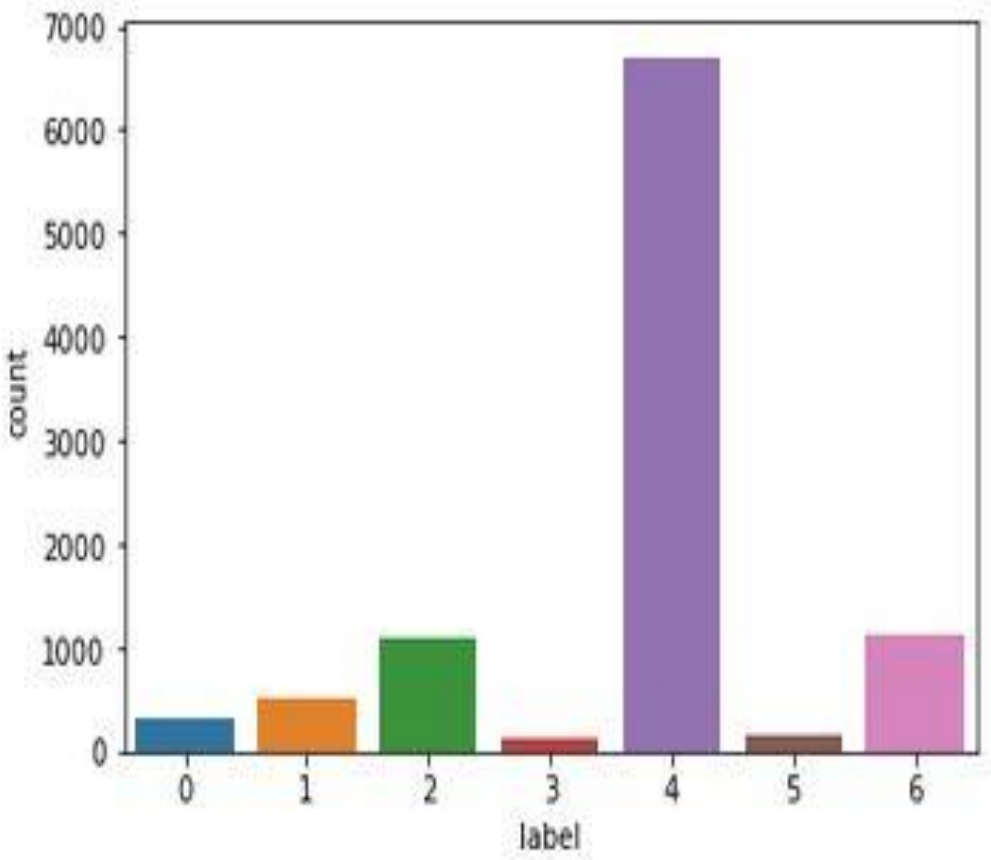
Dataset has 7 possible diagnoses:

- 0: nv - Melanocytic nevi
- 1: mel - Melanoma
- 2: bkl - Benign keratosis-like lesions
- 3: bcc - Basal cell carcinoma
- 4: akiec - Actinic keratoses
- 5: vasc - Vascular lesions
- 6: df – Dermatofibroma

Also includes image/lesion ID, dx_type, sex, age and location of lesion.

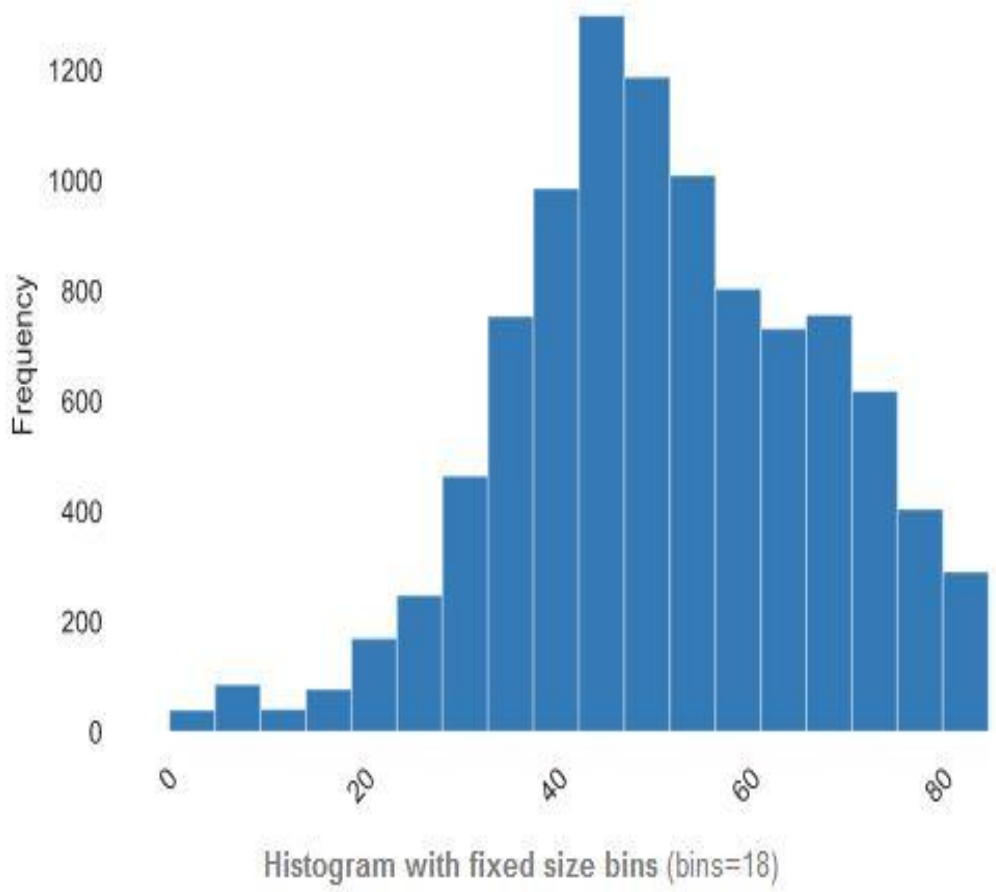


Melanocytic nevi are the most frequent lesion: 66.9%
Followed by melanoma: 11.1%



Value	Count	Frequency (%)
nv	6705	66.9%
mel	1113	11.1%
bkl	1099	11.0%
bcc	514	5.1%
akiec	327	3.3%
vasc	142	1.4%
df	115	1.1%

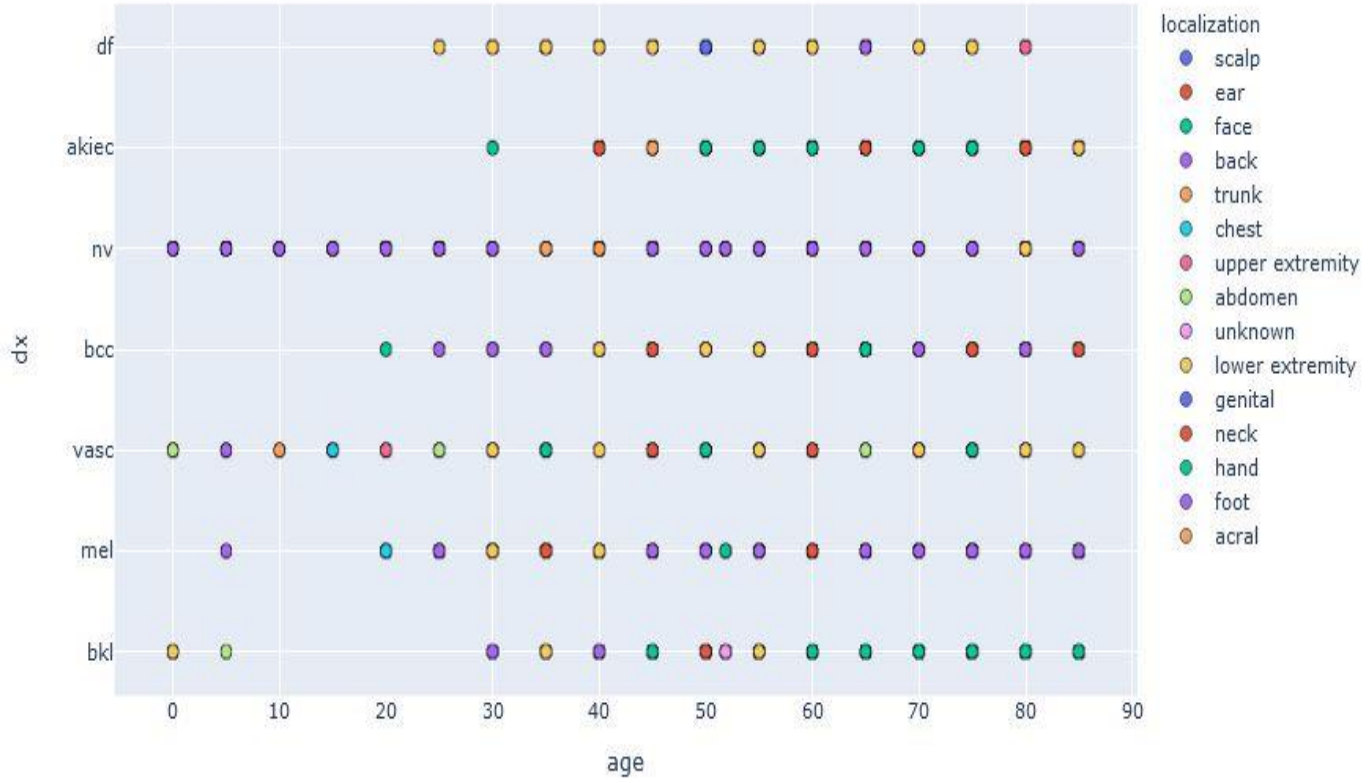
Most lesions diagnosed at age 45
Value:13%



Value	Count	Frequency (%)
45	1299	13.0%
50	1187	11.9%
55	1009	10.1%
40	985	9.8%
60	803	8.0%
70	756	7.5%
35	753	7.5%
65	731	7.3%
75	618	6.2%
30	464	4.6%
Other values (8)	1353	13.5%

Most lesions are found on an extremity: 24.2%

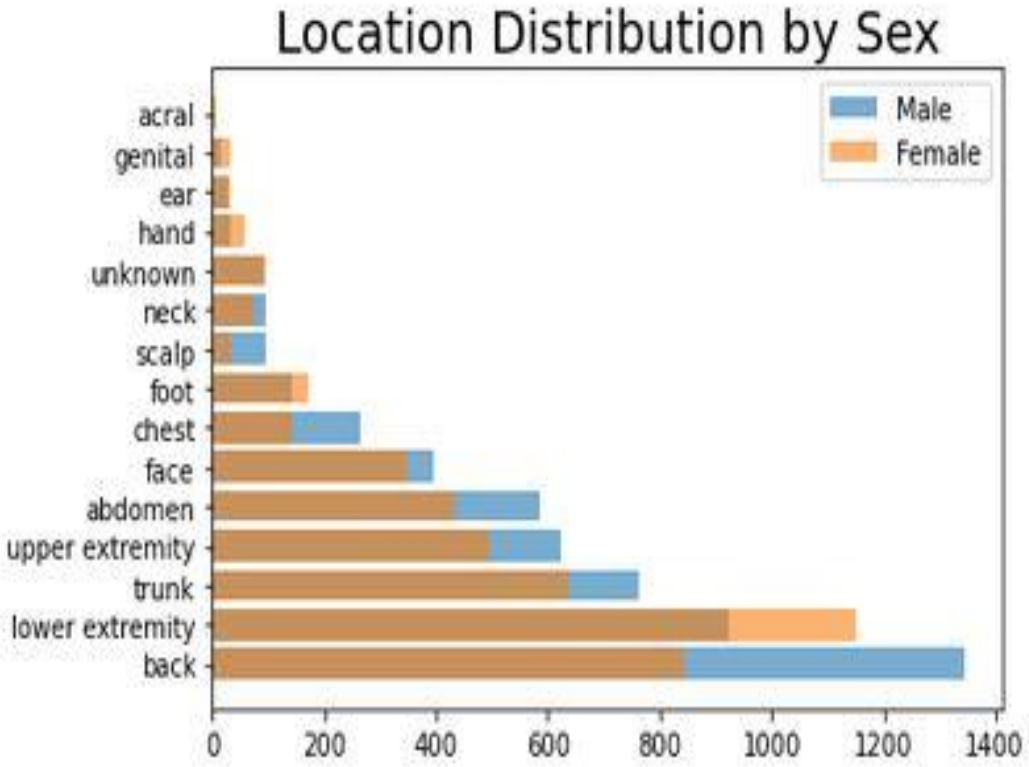
Age/Diagnosis/Location

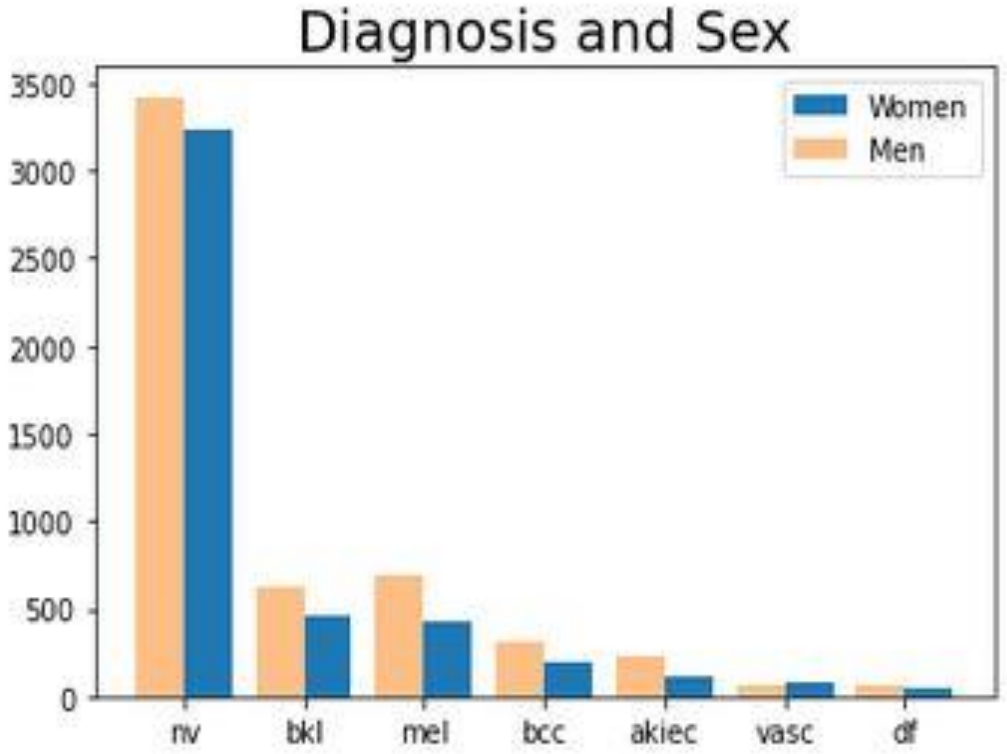


Value	Count	Frequency (%)
extremity	3195	24.2%
back	2192	16.6%
lower	2077	15.7%
trunk	1404	10.6%
upper	1118	8.5%
abdomen	1022	7.7%
face	745	5.6%
chest	407	3.1%
foot	319	2.4%
unknown	234	1.8%
Other values (6)	497	3.8%

Men have higher lesion counts than women

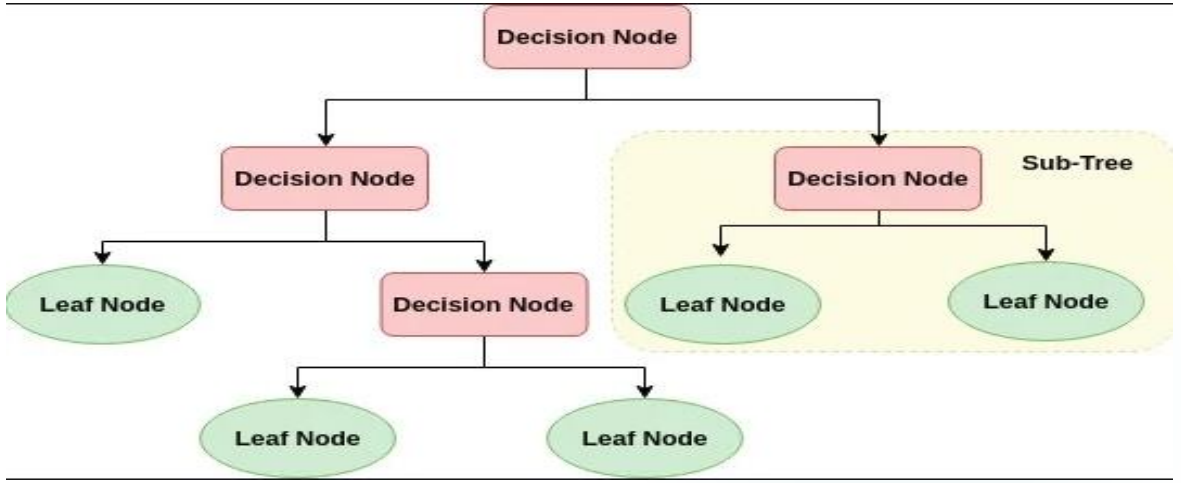
Sex/Diagnosis/Location



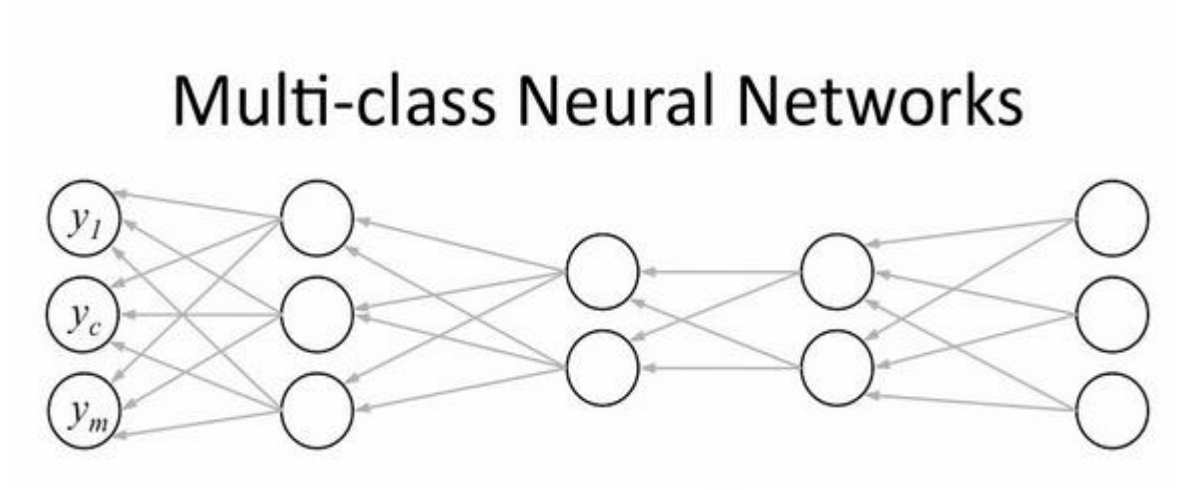


Machine Learning for Lesion Classification

- Predicting seven types of skin lesions is a multiclass classification problem



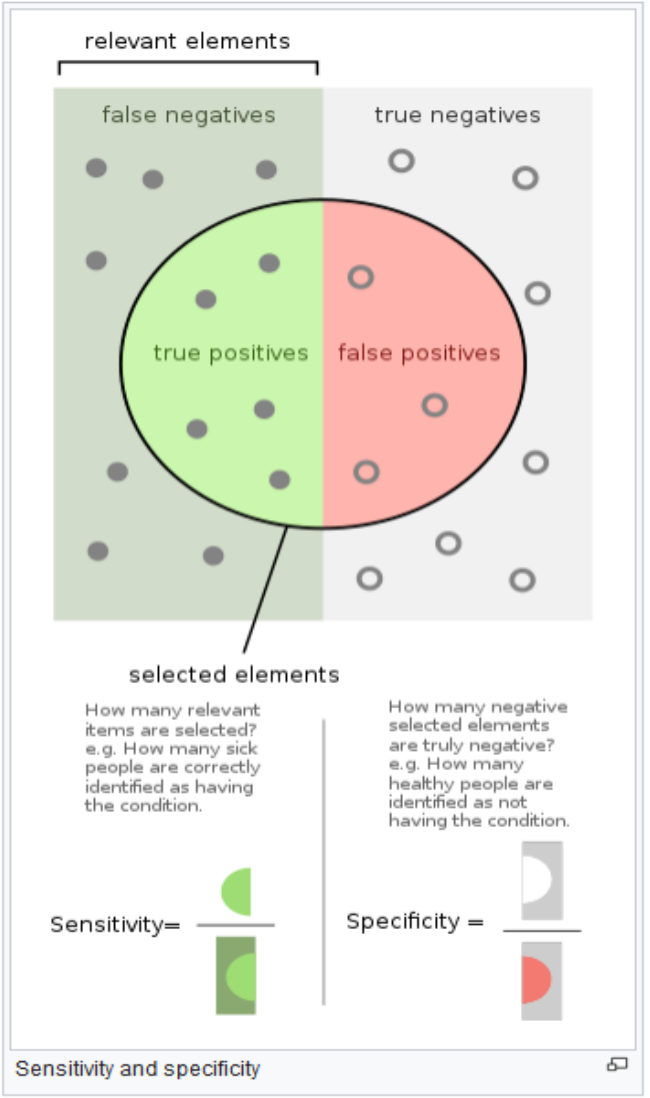
- Tree based algorithms and neural networks are evaluated for effectiveness with the use case



Evaluating Algorithm Performance

- Since we have multiple classes to predict, Accuracy along with Precision, Sensitivity (Recall), and Specificity are used to evaluate the models

- Accuracy: How often is the model correct?
- Precision: Positive predictive value
- Sensitivity (Recall): True positive rate
- Specificity: True negative rate



Best Model: Neural Network

Summary

Tuned, Fully Connected **Neural Network**

Accuracy, **Precision** and **Recall** of **0.98**

Specificity of **0.996**

Epochs: 100

Batch size: 850

1st hidden layer: 512 neurons

2nd hidden layer: 64 neurons

1st activation: relu

2nd activation: relu

Dropout: 0.2

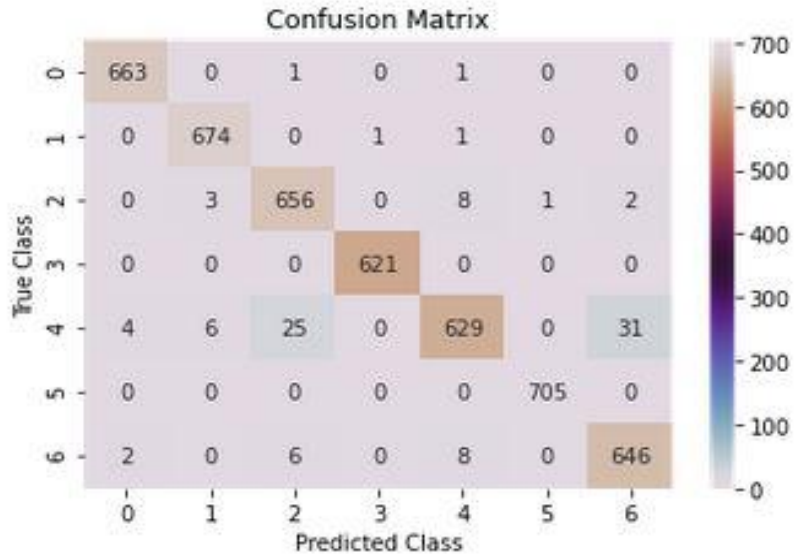
Output layer activation: softmax

Optimizer: adam

Loss: sparse_categorical_crossentropy

Classification Report

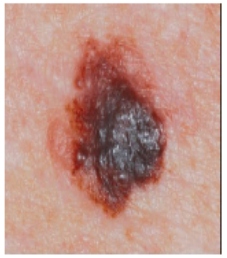
	precision	recall	f1-score	support
0	0.99	1.00	0.99	665
1	0.99	1.00	0.99	676
2	0.95	0.98	0.97	670
3	1.00	1.00	1.00	621
4	0.97	0.91	0.94	695
5	1.00	1.00	1.00	705
6	0.95	0.98	0.96	662
accuracy			0.98	4694
macro avg	0.98	0.98	0.98	4694
weighted avg	0.98	0.98	0.98	4694



Example of a prediction made using our best model

- The image used was selected from an external source and not taken from the dataset used to train and evaluate the model
- Model predicted melanoma: class 1. This is the label given from the source as well.

```
from keras.preprocessing import image

img_path = ('./Desktop/mel2.jpg')
img = image.load_img(img_path, target_size=(158,158))
img
```

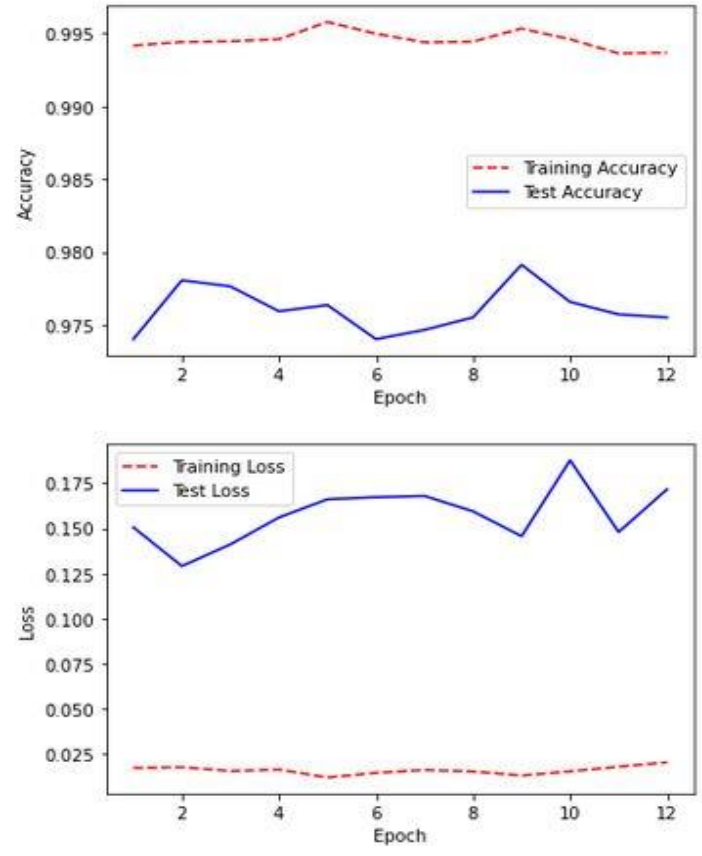


```
# Classify image not in the dataset
import cv2
img = cv2.imread('./Desktop/mel2.jpg',0)


img = cv2.resize(img,(58,58))
cv2.waitKey(0)
cv2.destroyAllWindows()

print(class_label)

prediction_cplx = tuned_model.predict_classes(img)

print('The predicted class of the lesion is:', prediction_cplx[1])
```

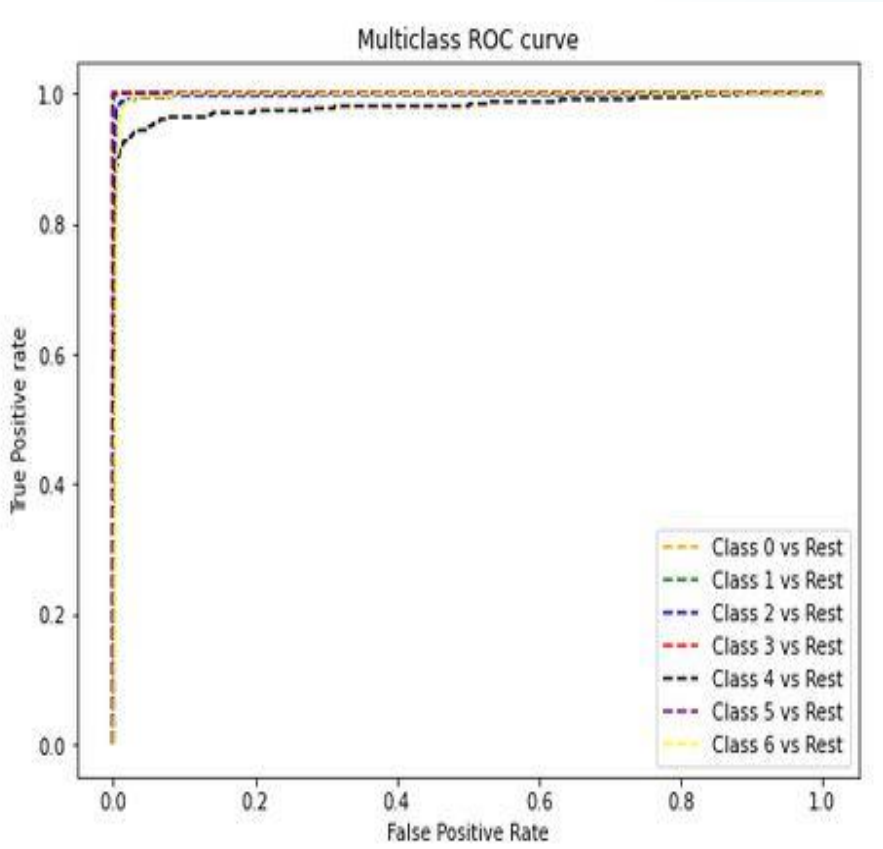
```
{0: 'nv: melanocytic nevi', 1: 'mel: melanoma', 2: 'bkl: benign keratosis-like lesion', 3: 'bcc: basal_cell_carcinoma', 4:
'akiec: actinic_keratoses', 5: 'vasc: vascular lesion', 6: 'df: dermatofibroma'}
The predicted class of the lesion is: 1
```

Performance Charts

Train and Test Performance



Probability Curves



XGBoost

Summary

Second best performing model is **XGBoost** with **accuracy**, **precision** and **recall** of **0.95**; **Specificity** of **0.991**

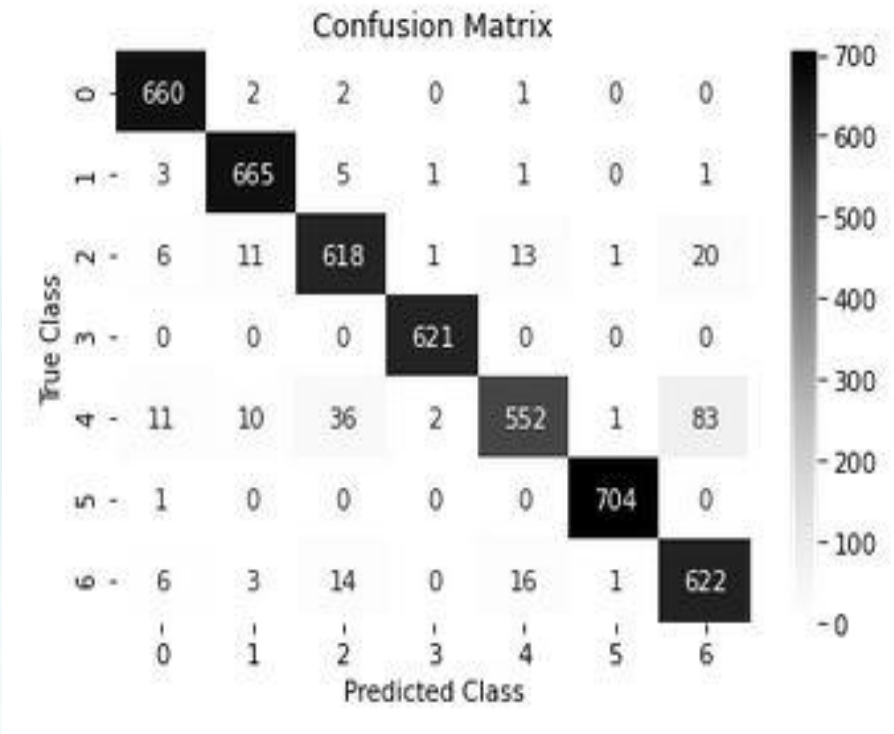
- max_depth : 7
- booster: "gbtree"
- num_classes: 7
- eval_metric: "mlogloss"
- objective: "multi:softprob"

Classification Report

xgb:	precision	recall	f1-score	support
0	0.96	0.99	0.98	665
1	0.96	0.98	0.97	676
2	0.92	0.92	0.92	670
3	0.99	1.00	1.00	621
4	0.95	0.79	0.86	695
5	1.00	1.00	1.00	705
6	0.86	0.94	0.90	662
accuracy			0.95	4694
macro avg	0.95	0.95	0.95	4694
weighted avg	0.95	0.95	0.95	4694

XGBoost Performance

Prediction Results



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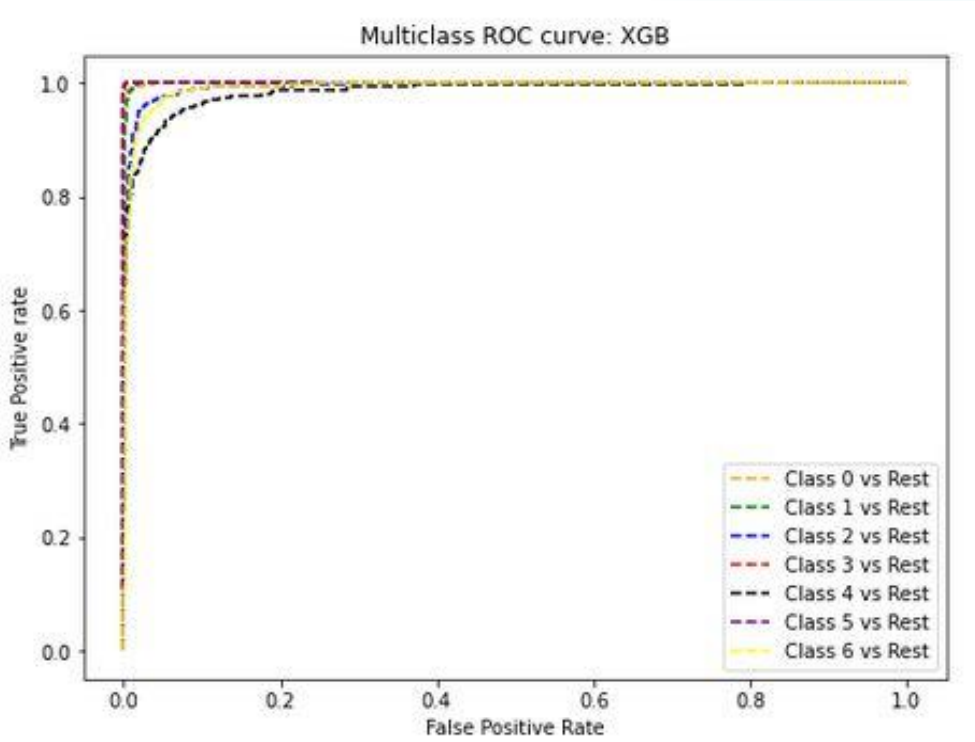

Using the model

Trained model can be used in an application placed on a tablet device or smart-phone.

- A digital image is taken of the lesion in question.
- Image enters the transformation pipeline.
- The prepared image is fed into the pre-trained model.
- Model predicts the lesion class.
- The model prediction can be used as and aid to diagnosis.

Can be used outside of a clinical setting expanding access to needed low-cost medical care, even where internet access is sparce or non-existent.

Thank you!