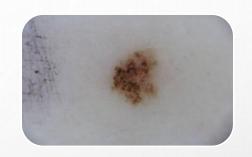
SKIN CANCER DETECTION MODELS

CLASSIFY CANCER IMAGES AS MALIGNANT OR BENIGN



- TRAINING DATAT SET: 2000 DERMOSCOPIC IMAGES
 - CLASS LABELS MALIGNANT/BENIGN (1/0) FOR MELANOMA
 - 374 MALIGNANT
 - 1626 BENIGN
- VALIDATION DATA SET: 150 DERMOSCOPIC IMAGES
 - CLASS LABELS MALIGNANT/BENIGN (1/0) FOR MELANOMA
 - 30 MALIGNANT
 - 120 BENIGN









Melanoma detection models using neural networks By Tripti Singh and Akash Singh

DATA PREPARATION

- RESIZING OF IMAGES CONVERTED TO 224 X 224 X 3
- ROTATION OF IMAGES 180 AND 90 DEGREES
- UPSCALING OF MALIGNANT IMAGES
- CONVERTED IMAGE PIXELS TO A VECTOR
- DEVELOPED TRAIN DATA (.H5 FILES) PREDICTOR MATRIX AND LABEL VECTOR
- STANDARDIZED PREDICTORS

MODELS DEVELOPED

- I. DEEP MODELS USING KERAS LIBRARIES
- II. SHALLOW NEURAL NETWORK 2 LAYERS
- III. DEEP NEURAL NETWORK 5 LAYERS

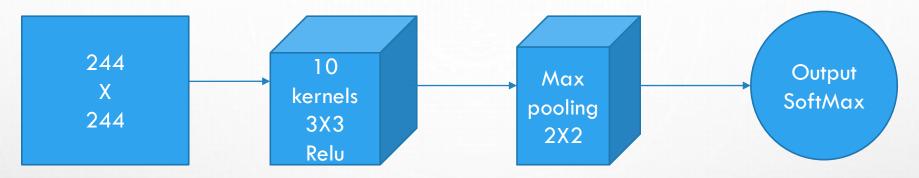
OPTIMIZER = Adam()

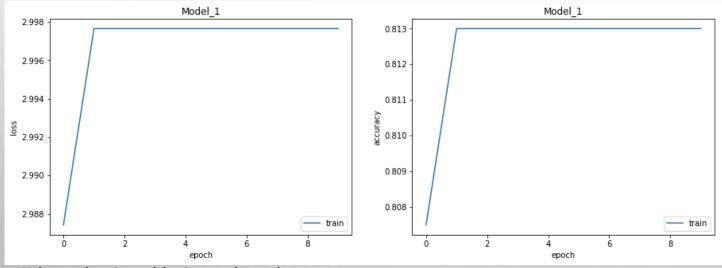
METRICS =['accuracy']

LOSS = 'binary_crossentropy'

KERNEL_INITIAL ='glorot_uniform'

CCN MODEL 1





Epoch 2/10

loss: 2.9977

acc: 0.8130

deepPredict(model1,x_test,y_test)

Test score: 3.20604784648

Test accuracy: 0.80000000795

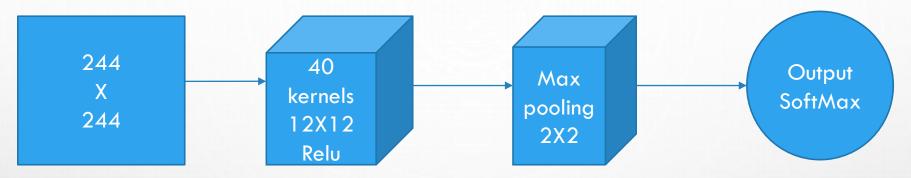
Melanoma detection models using neural networks By Tripti Singh and Akash Singh OPTIMIZER = Adam()

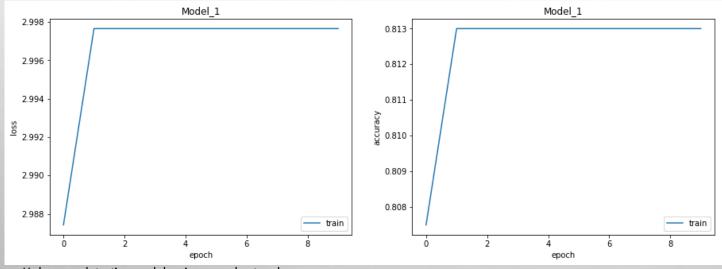
METRICS =['accuracy']

LOSS = 'binary_crossentropy'

KERNEL_INITIAL ='glorot_uniform'

CCN MODEL 2





Epoch 2/10

loss: 2.9977

acc: 0.8130

deepPredict(model1,x_test,y_test)

Test score: 3.20604784648

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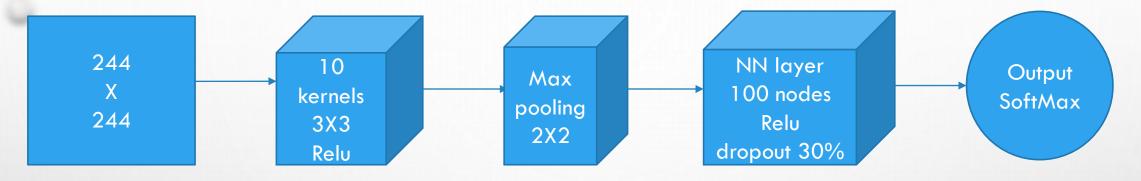
OPTIMIZER = Adam()

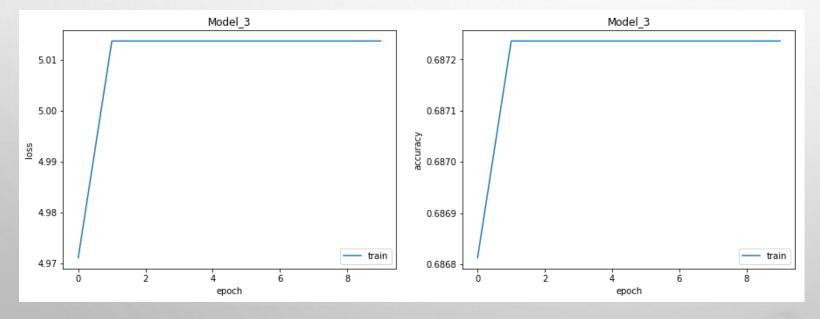
METRICS =['accuracy']

LOSS = 'binary_crossentropy'

KERNEL_INITIAL ='glorot_uniform'

CCN MODEL 3





Epoch 10/10

loss: 5.0137

acc: 0.6872

deepPredict(model1,x_test,y_test)

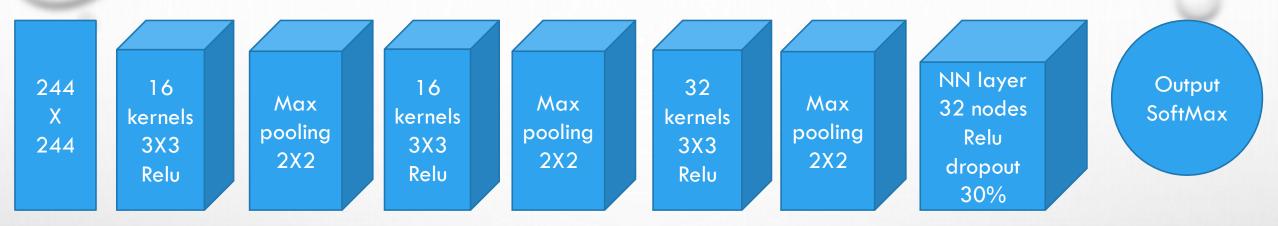
Test score: 3.20604784648

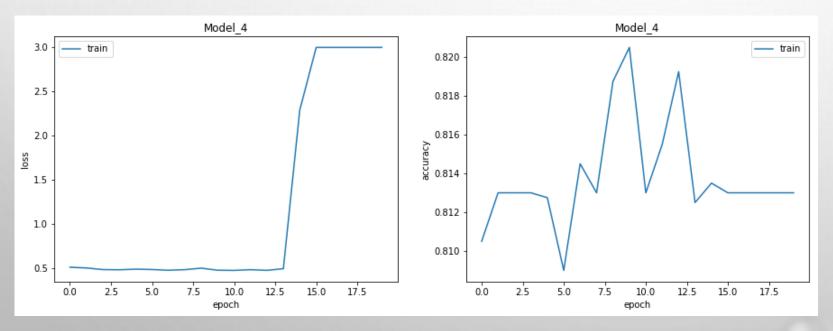
OPTIMIZER = rmsprop

METRICS =['accuracy']

LOSS = 'binary_crossentropy'

CCN MODEL 4





Epoch 10/10

loss: 0.4868

acc: 0.8183

deepPredict(model1,x_test,y_test)

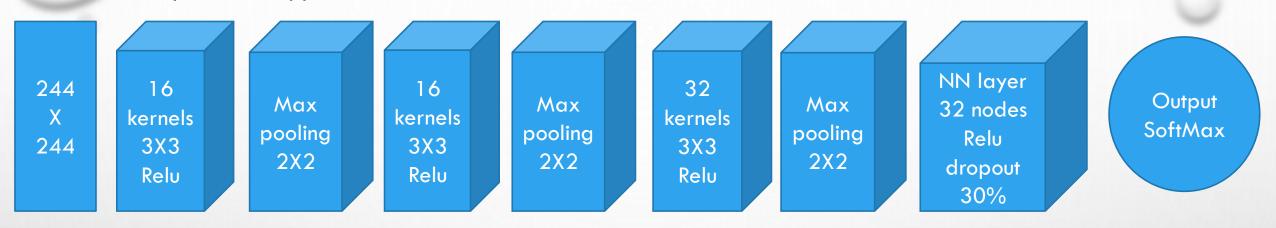
Test score: 0.488429104487

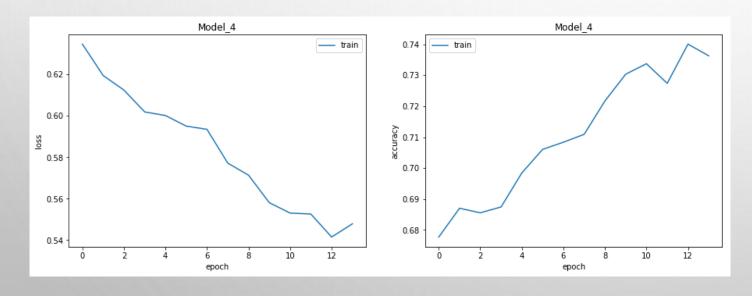
OPTIMIZER = rmsprop

METRICS =['accuracy']

LOSS = 'binary_crossentropy'

CCN MODEL 4 IMAGES ROTATED (180)





Epoch 13/14

loss: 0.5415

acc: 0.7401

deepPredict(model1,x_test,y_test)

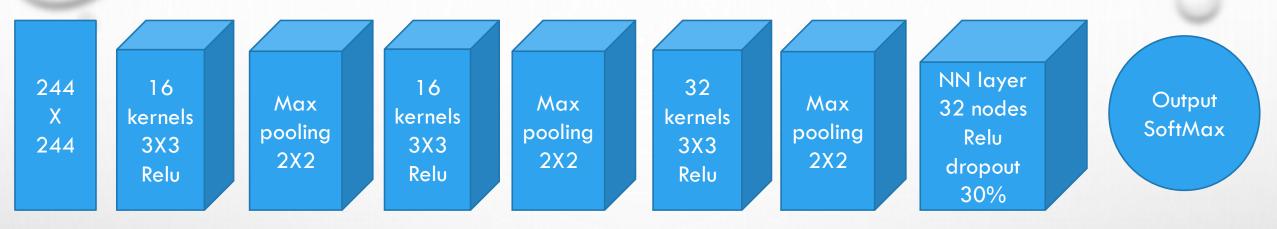
Test score: 0.5447554938

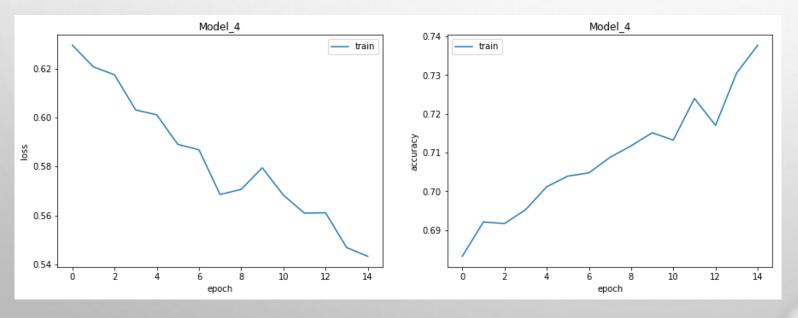
OPTIMIZER = rmsprop

METRICS =['accuracy']

LOSS = 'binary_crossentropy'

CCN MODEL 4 IMAGES ROTATED (90)





Epoch 13/14

loss: 0.5433

acc: 0.7377

deepPredict(model1,x_test,y_test)

Test score: 0.527270306746

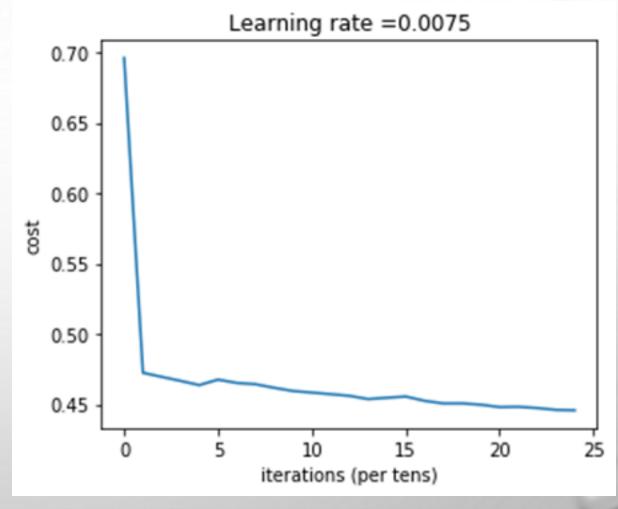
SHALLOW NEURAL NETWORK

Cost after iteration 0: 0.6960335407116954 Cost after iteration 100: 0.4724549661840295 Cost after iteration 200: 0.4695814213451869

Cost after iteration 2200: 0.44743597272294433 Cost after iteration 2300: 0.4461306727321353 Cost after iteration 2400: 0.44582365392664597

predictions_train = predict(X, Y, parameters)
Accuracy: 0.82

for shallow 2 layer model [150528, 7, 1]



DEEP NEURAL NETWORK

Cost after iteration 0: 0.653496

Cost after iteration 100: 0.473703

Cost after iteration 200: 0.465915

Cost after iteration 2200: 0.452765

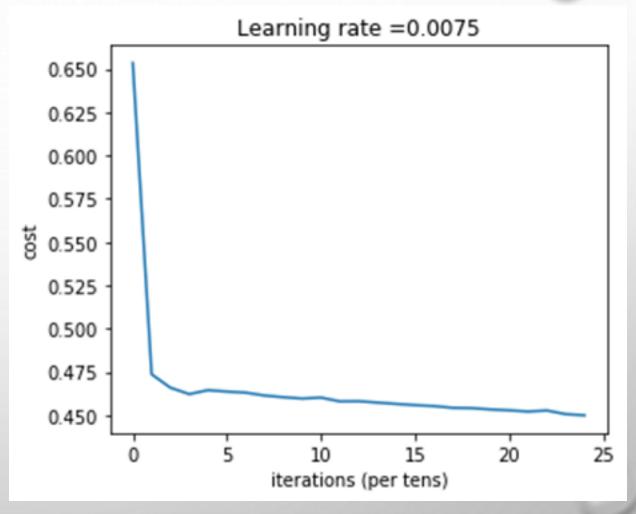
Cost after iteration 2300: 0.450670

Cost after iteration 2400: 0.450000

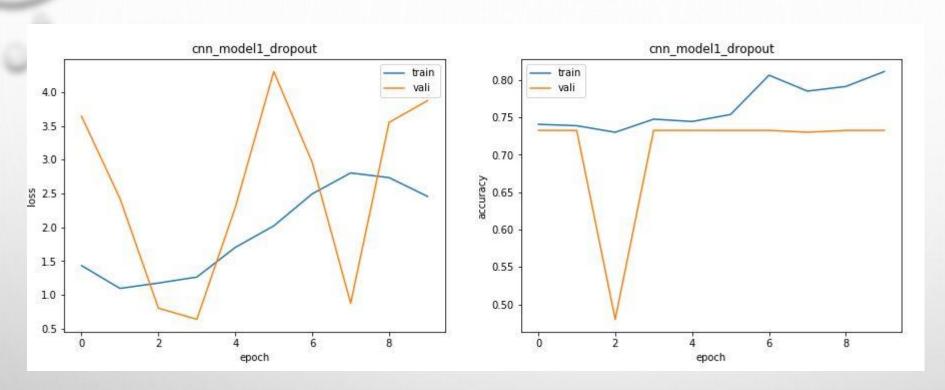
pred_train = predict(X, Y, parameters)

Accuracy: 0.8145

for [150528, 20, 7, 5, 1] 5-layer model

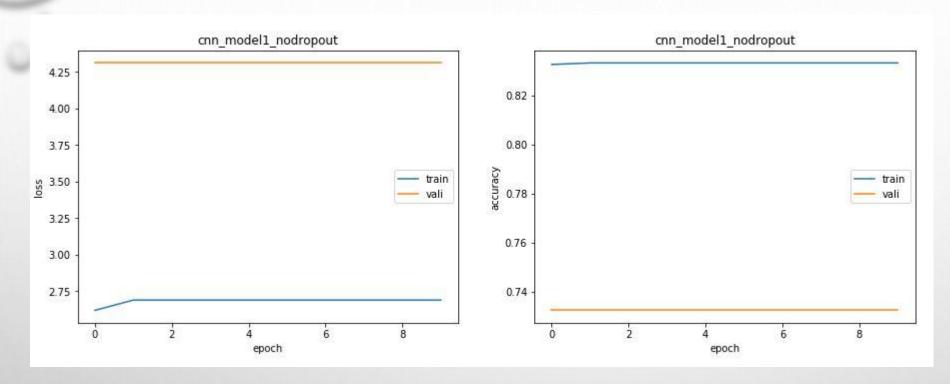


KERAS NEURAL NETWORK_1 RELU, 1 SOFTMAX



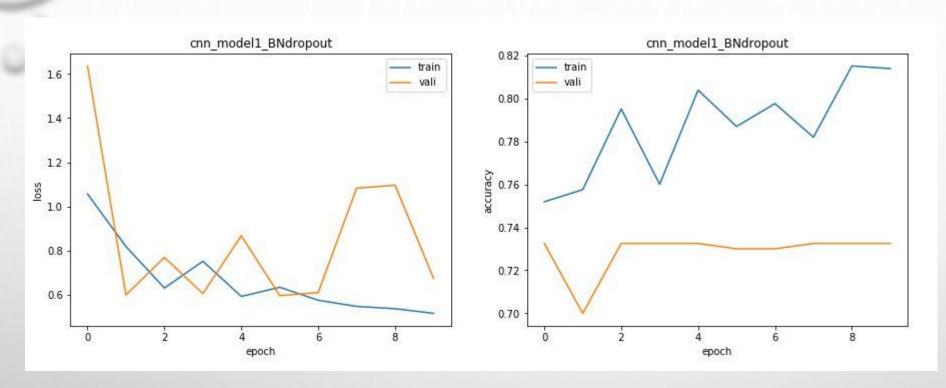
With dropout

KERAS NEURAL NETWORK_1 RELU, 1 SOFTMAX



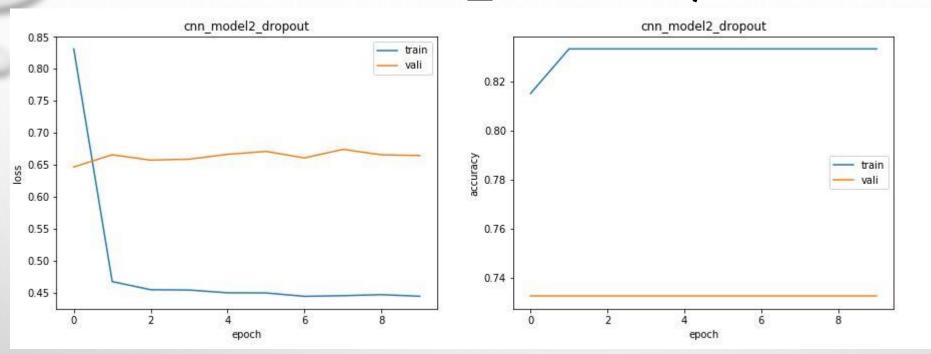
Without dropout

BATCH NORMALIZATION



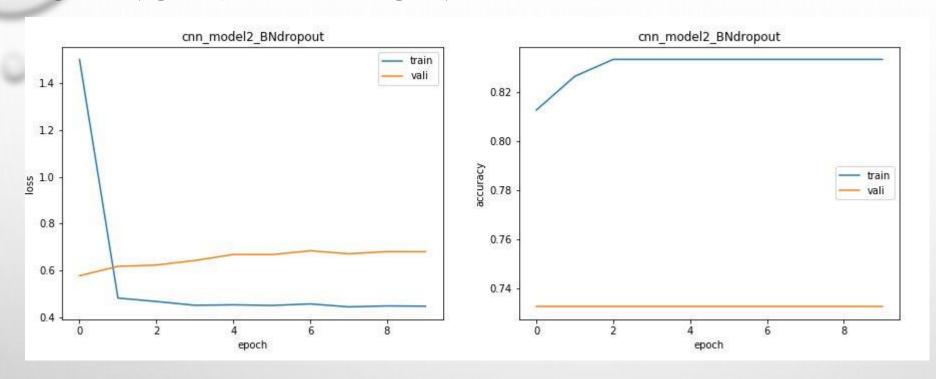
Dropout & batch normalization -

KERAS NEURAL NETWORK_3 CONVO, 1 OUTPUT



Without dropout

BATCH NORMALIZATION



Dropout and batch normalization

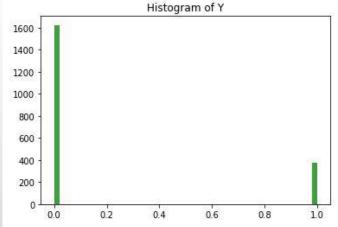
STEPS FORWARD

- 1) ADDRESS CLASS IMBALANCE ACCURACY IS IMPROVED JUST A LITTLE OVER BASELINE
- 2) DEEPER NETWORKS USUALLY LEARN BETTER NOT ABLE TO RUN DEEPER NETWORKS WITH CURRENT HARDWARE

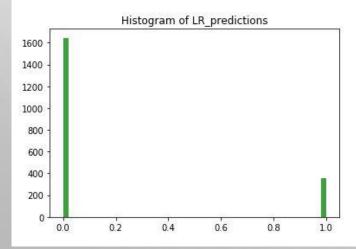
NEED BIG DATA TOO......2000 IMAGES ISN'T GOOD ENOUGH DATA FOR NEURAL

LOGISTIC

```
plt.title('Histogram of Y')
    ...: n, bins, patches = plt.hist(Y[:], 50, facecolor='green', alpha=0.75)
```



In [99]: plt.title('Histogram of LR_predictions')
...: n, bins, patches = plt.hist(LR_predictions[:], 50, facecolor='green', alpha=0.75)



Confusion Matrix: confusion_matrix(y_true, y_pred)

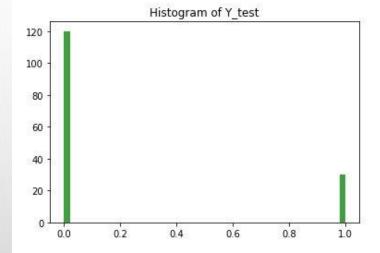
array([[1624, 2], [21, 353]], dtype=int64)

Accuracy = ((1624+353)/2000)*100 ...: print('Accuracy =' + str(Accuracy) + "%")

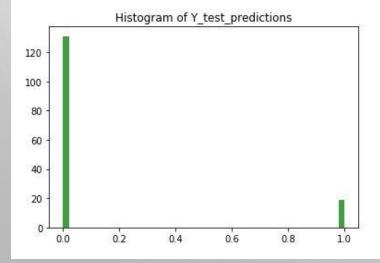
Accuracy =98.85 % on Training Data

LOGISTIC

```
In [34]: plt.title('Histogram of Y_test')
    ...: n, bins, patches = plt.hist(Y test[:], 50, facecolor='green', alpha=0.75)
```



In [35]: plt.title('Histogram of Y_test_predictions')
...: n, bins, patches = plt.hist(Y_test_predictions[:], 50, facecolor='green', alpha=0.75)



Confusion Matrix: confusion_matrix(y_true, y_pred)

array([[109, 11], [22, 8]], dtype=int64)

Accuracy = ((109+8)/150)*100...: print('Accuracy = ' + str(Accuracy) + "%")

Accuracy = 78.0 % on Test data

Upsampled the data

Original dataset shape Counter({0: 1626, 1: 374})
Resampled dataset shape Counter({0: 1626, 1: 1626})

array([[1626, 0], [0, 1626]], dtype=int64)

Accuracy on upsampled data = 100 % on Test data

array([[108, 12], [23, 7]], dtype=int64)

Accuracy of upsampled model on Test data = 76.66 %

QUESTIONS?