CW536- 2226909

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Installing and Importing Necessary Packages

```
!pip install plotly_express
!pip install tensorflow
```

```
Collecting plotly_express
  Downloading plotly_express-0.4.1-py2.py3-none-any.whl (2.9 kB)
Requirement already satisfied: pandas>=0.20.0 in /usr/local/lib/python3.10/dist-packages (from plotly_express) (2.0.3)
Requirement already satisfied: plotly>=4.1.0 in /usr/local/lib/python3.10/dist-packages (from plotly_express) (5.15.0)
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Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from patsy>=0.5->plotly_express) (1.16.0)
Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from plotly>=4.1.0->plotly_express) (8
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from plotly>=4.1.0->plotly_express) (24.0)
Installing collected packages: plotly_express
Successfully installed plotly_express-0.4.1
Requirement already satisfied: tensorflow in /usr/local/lib/python3.10/dist-packages (2.15.0)
Requirement already satisfied: absl-py>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.4.0)
Requirement already satisfied: astunparse>=1.6.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.6.3)
Requirement already satisfied: flatbuffers>=23.5.26 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (24.3.25)
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Requirement already satisfied: google-pasta>=0.1.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (0.2.0)
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Requirement already satisfied: numpy<2.0.0,>=1.23.5 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.25.2)
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Requirement already satisfied: protobuf!=4.21.0,!=4.21.1,!=4.21.2,!=4.21.3,!=4.21.4,!=4.21.5,<5.0.0dev,>=3.20.3 in /usr/local/lib/
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Requirement already satisfied: tensorboard<2.16,>=2.15 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (2.15.2)
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Requirement already satisfied: keras<2.16,>=2.15.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (2.15.0)
Requirement already satisfied: wheel<1.0,>=0.23.0 in /usr/local/lib/python3.10/dist-packages (from astunparse>=1.6.0->tensorflow)
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Requirement already satisfied: werkzeug>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from tensorboard<2.16,>=2.15->tensorflo
Requirement already satisfied: cachetools<6.0,>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from google-auth<3,>=1.6.3->tens
Requirement already satisfied: pyasn1-modules>=0.2.1 in /usr/local/lib/python3.10/dist-packages (from google-auth<3,>=1.6.3->tenso
Requirement already satisfied: rsa<5,>=3.1.4 in /usr/local/lib/python3.10/dist-packages (from google-auth<3,>=1.6.3->tensorboard<2
Requirement already satisfied: requests-oauthlib>=0.7.0 in /usr/local/lib/python3.10/dist-packages (from google-auth-oauthlib<2,>=
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests<3,>=2.21.0->tens
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests<3,>=2.21.0->tensorboard<2.16
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests<3,>=2.21.0->tensorboar
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests<3,>=2.21.0->tensorboar
Requirement already satisfied: MarkupSafe>=2.1.1 in /usr/local/lib/python3.10/dist-packages (from werkzeug>=1.0.1->tensorboard<2.1
Requirement already satisfied: pyasn1<0.7.0,>=0.4.6 in /usr/local/lib/python3.10/dist-packages (from pyasn1-modules>=0.2.1->google
Requirement already satisfied: oauthlib>=3.0.0 in /usr/local/lib/python3.10/dist-packages (from requests-oauthlib>=0.7.0->google-a
```

```
## Importing the necessary packages
import numpy as np
import pandas as pd
import seaborn as sns
import os
import random
import cv2
from skimage import feature
import matplotlib.pyplot as plt
from sklearn import preprocessing
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
import tensorflow as tf
from pandas import DataFrame
from sklearn.cluster import KMeans
```

```
from sklearn import metrics
from sklearn.model_selection import KFold
import plotly_express as px
from sklearn.svm import SVC
from mpl_toolkits.mplot3d import Axes3D
from sklearn.metrics import classification_report
from sklearn.ensemble import RandomForestClassifier
from tensorflow import keras
from keras.models import Sequential
from keras.utils import to_categorical
from keras.layers import Conv2D, MaxPooling2D, Dense, Flatten, Dropout
from sklearn.model_selection import cross_validate, cross_val_score, cross_val_predict
from sklearn.metrics import roc_auc_score
from imblearn.over_sampling import SMOTE
from sklearn.datasets import make_classification
from sklearn.decomposition import PCA
from keras.utils import to_categorical
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras import layers
from tensorflow.keras.callbacks import ReduceLROnPlateau
from sklearn.model_selection import cross_validate
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from sklearn.base import BaseEstimator, ClassifierMixin
from sklearn.model_selection import cross_val_score
from sklearn.metrics import roc_curve, auc
from tensorflow.keras import datasets, layers, models, Sequential, optimizers
```

TASK ONE

Task: To determine the better classifier.

Key processes involve initialising HOG feature extraction, loading and converting data into numpy arrays, visualising sample distribution via histograms, displaying sample contents for each class, and splitting the dataset into 80% training and 20% testing sets.

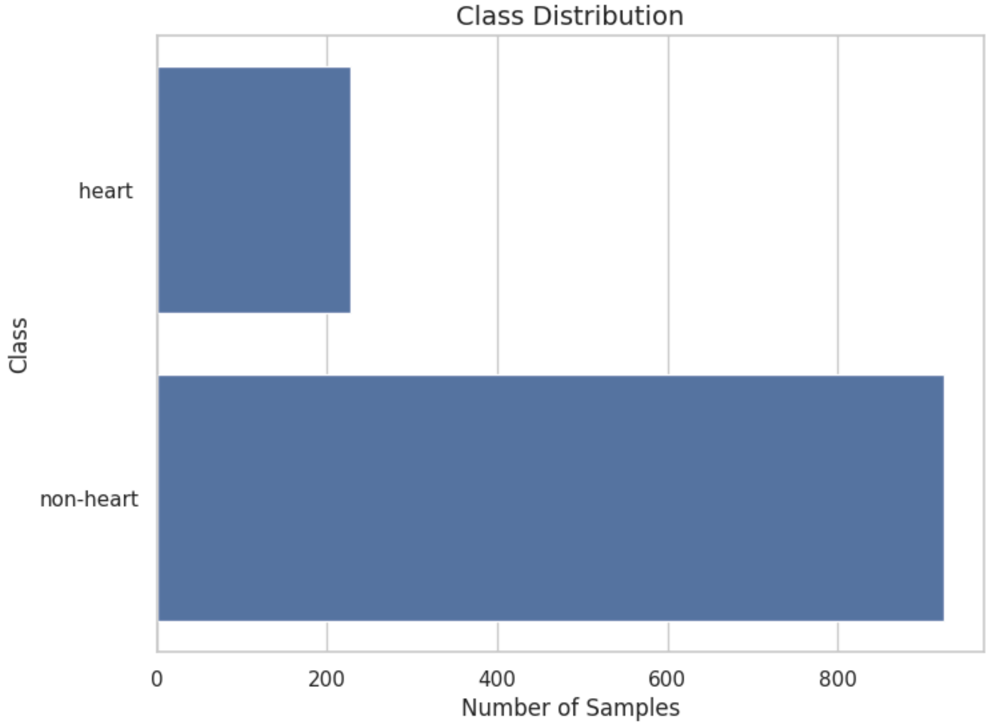
Classification experiments are conducted with SVM, CNN, K5 FOLD - SVM, and K5 FOLD - CNN, recording and comparing precision, recall, F1 scores, and accuracy. Additionally, class imbalance is addressed using HOG features and SMOTE.

LOADING THE DATA

```
#code reference {4}
################################ 1. DEFINE CLASS TO EXTRACT HOG FEATURES ################################
class HOG:
    def __init__(self, orientations = 9, pixelsPerCell = (8, 8),
        cellsPerBlock = (3, 3), transform = False):
        # store the number of orientations, pixels per cell,
        # cells per block, and whether or not power law
        # compression should be applied
        self.orientations = orientations
        self.pixelsPerCell = pixelsPerCell
        self.cellsPerBlock = cellsPerBlock
        self.transform = transform

    def describe(self, image):
        # compute HOG for the image
        hist = feature.hog(image, orientations = self.orientations,
            pixels_per_cell = self.pixelsPerCell,
            cells_per_block = self.cellsPerBlock,
            transform_sqrt = self.transform)
        ## return the HOG features
        return hist

hog = HOG(orientations = 18, pixelsPerCell = (10, 10), cellsPerBlock = (1, 1), transform = True)

########  2. LOAD IMAGES (FOR ORIGINAL REPO) and EXTRACT HOG FEATURES (FOR FEATURE REPO) ########

resize_factor = 128 # applies for both height and width

path = '/content/drive/MyDrive/Colab Notebooks/cw_data_task1/'
datarepo = [] # List to append the images as 2D numpy arrays
originalrepo = [] # Create a repo for flattened pixels
hogrepo = [] # Create a list to append the HOG features
target = [] # List to append the target/class/label
print('\nLoading images...')
for root, dirs, files in os.walk(path):
     for file in files:
        with open(os.path.join(root, file), "r") as auto:
            try:
                img = cv2.imread(root+'/'+file, 0)
                img = cv2.resize(img, (resize_factor, resize_factor))
                datarepo.append(img)
                originalrepo.append(img.flatten())
                # Extract HOG and append to HOG repo
```

```
                hogfeatures = hog.describe(img)
                hogrepo.append(hogfeatures)
                # Append the folder where the image is to the target list
                target.append(root.replace(path,'').replace('\\','').replace('/',''))
            except Exception as e:
                print("Invalid file "+file+" skipped.")

# Convert the repo lists into numpy arrays
originalrepo = np.array(originalrepo)
hogrepo = np.array(hogrepo)
target = np.array(target)

########################## 3. CALCULATE THE DISTRIBUTION AND SHOW REPOS ##########################

print('\nCalculating class distribution...')
histo = [['Class','Number of Samples']]
for i, label1 in enumerate(sorted(list(set(target)))):
    cont = 0
    for j, label2 in enumerate(target):
        if label1 == label2:
            cont+=1
    histo.append([label1,cont])
histo.append(['Total Samples', len(target)])
## Load as a panda
histo_panda = pd.DataFrame.from_records(histo[1:-1], columns=histo[0])
print(histo_panda)
print('Total images: '+str(len(target)))
## Create a histogram using seaborn
sns.set(style="whitegrid")
sns_plot = sns.barplot(y="Class", x="Number of Samples", data=histo_panda)
# Set labels and title
sns_plot.set_xlabel("Number of Samples", fontsize=12)
sns_plot.set_ylabel("Class", fontsize=12)
sns_plot.set_title("Class Distribution", fontsize=14)
sns_plot.figure.set_size_inches(8,6)
sns.set(font_scale=0.8)
print('\nShowing class distribution bar chart...')
plt.show()
print('Size of target: ', len(target))
print('Size of original repository: ', originalrepo.shape)
print('Example of the original repository: ')
print(originalrepo)
print('Size of HOG features data structure: ', hogrepo.shape)
print('Example of the HOG repository: ')
print(hogrepo)
print('Class labels', target)
```

```
Loading images...

Calculating class distribution...
       Class  Number of Samples
0      heart                228
1  non-heart                925
Total images: 1153

Showing class distribution bar chart...
```

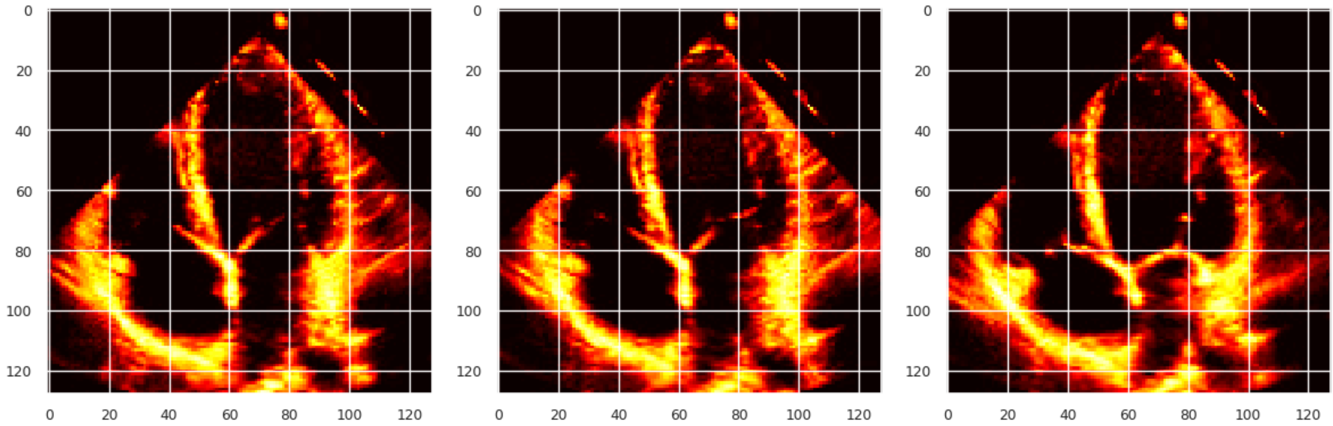



```
Size of target:  1153
Size of original repository:  (1153, 16384)
Example of the original repository:
[[10 10 10 ... 10 10 10]
 [10 10 10 ... 10 10 10]
 [10 10 10 ... 10 10 10]
 ...
 [ 0  0  0 ...  0  0  0]
 [ 0  0  0 ...  1  1  1]
 [ 0  0  0 ...  0  0  0]]
Size of HOG features data structure:  (1153, 2592)
Example of the HOG repository:
[[0.         0.         0.         ... 0.         0.         0.        ]
 [0.         0.         0.         ... 0.         0.         0.        ]
 [0.         0.         0.         ... 0.         0.         0.        ]
 ...
 [0.         0.         0.         ... 0.         0.         0.        ]
 [0.         0.         0.         ... 0.28502181 0.16723133 0.2261074 ]
 [0.         0.         0.         ... 0.2788824  0.27787874 0.26522504]]
```

DISPLAY OF HEART IMAGES

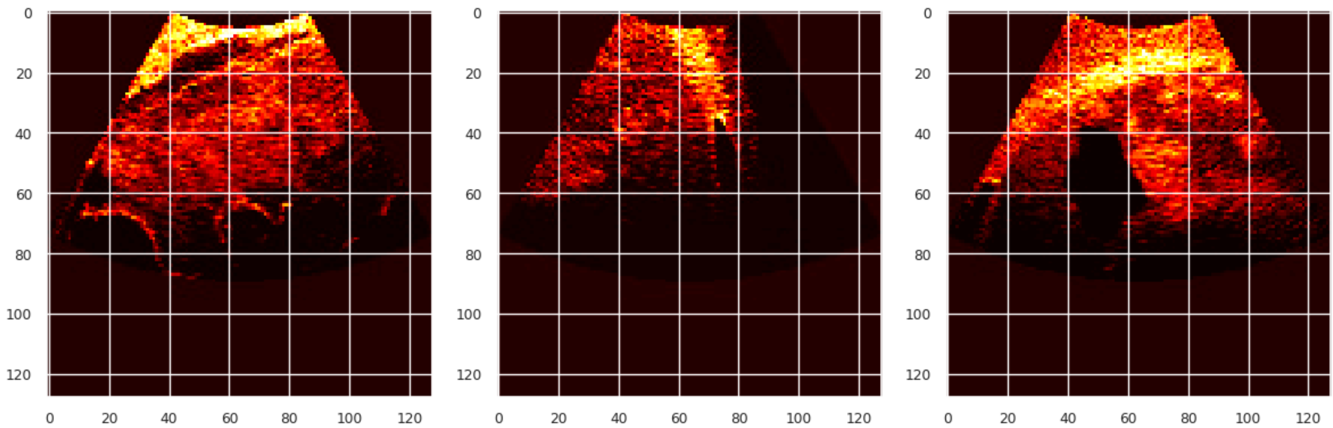
```
#Display the heart images in grey scale
heartrepo = originalrepo[np.asarray(target) == 'heart ']
heart_sample = random.sample(range(len(heartrepo)), 3)
fig,axes = plt.subplots(1,3, figsize=[12,9])

fig.tight_layout() # add spacing between subplots
for i, dat in enumerate(axes.flatten()):
    if i<len(heart_sample): # This "if" is here to avoid that, if the user specifies more subplots than data, the program crashes due to lack of d
        dat.imshow(np.asarray(heartrepo[heart_sample[i]]).reshape(128,128),
                   cmap='hot', interpolation='nearest')
print('Heart Images')
plt.show()
```

```
Heart Images
```



```
#Display the non-heart (Abdominal) images in grey scale
abdominalprepo = originalrepo[np.asarray(target) == 'non-heart']
symbols_visualise = random.sample(range(len(abdominalprepo)), 3)
fig,axes = plt.subplots(1,3, figsize=[12,9])
fig.tight_layout() # add spacing between subplots
for i, dat in enumerate(axes.flatten()):
    if i<len(symbols_visualise): # This "if" is here to avoid that, if the user specifies more subplots than data, the program crashes due to lack
        dat.imshow(np.asarray(abdominalprepo[symbols_visualise[i]]).reshape(128,128),
                   cmap='hot', interpolation='nearest')
print('Non- heart (Abdominal Images)')
plt.show()
```

```
Non- heart (Abdominal Images)
```



TRAINING THE DATA/ USING THE BINARISED TARGETS - SVM

```
#binarizing target names
target_new = [0 if i == 'heart ' else 1 for i in target]
target_new =np.array(target_new)
print(target_new,target_new.shape)
x_train, x_test, y_train, y_test = train_test_split(originalrepo,target_new, stratify=target_new, test_size=0.2)
print('Number of heart and non-heart (Abdominal) samples in the training set: ',np.count_nonzero(y_train == 0),np.count_nonzero(y_train == 1))
print('Number of heart and non-heart (Abdominal) samples in the test set: ',np.count_nonzero(y_test == 0),np.count_nonzero(y_test == 1))
```

```
[1 1 1 ... 0 0 0] (1153,)
Number of heart and non-heart (Abdominal) samples in the training set:  182 740
Number of heart and non-heart (Abdominal) samples in the test set:  46 185
```

TRAINING THE DATA/ USING THE BINARISED TARGETS - CNN

```
#binarizing target names
x_train_cn, x_test_cn, y_train_cn, y_test_cn = train_test_split(originalrepo,target_new, stratify=target_new, test_size=0.2)
print('Number of heart and non-heart (Abdominal) samples in the training set: ',np.count_nonzero(y_train_cn == 0),np.count_nonzero(y_train_cn == 1
print('Number of heart and non-heart (Abdominal) samples in the test set: ',np.count_nonzero(y_test_cn == 0),np.count_nonzero(y_test_cn == 1))
```

```
Number of heart and non-heart (Abdominal) samples in the training set:  182 740
Number of heart and non-heart (Abdominal) samples in the test set:  46 185
```

SVM CLASSIFIER / NON- NEURAL NETWORK

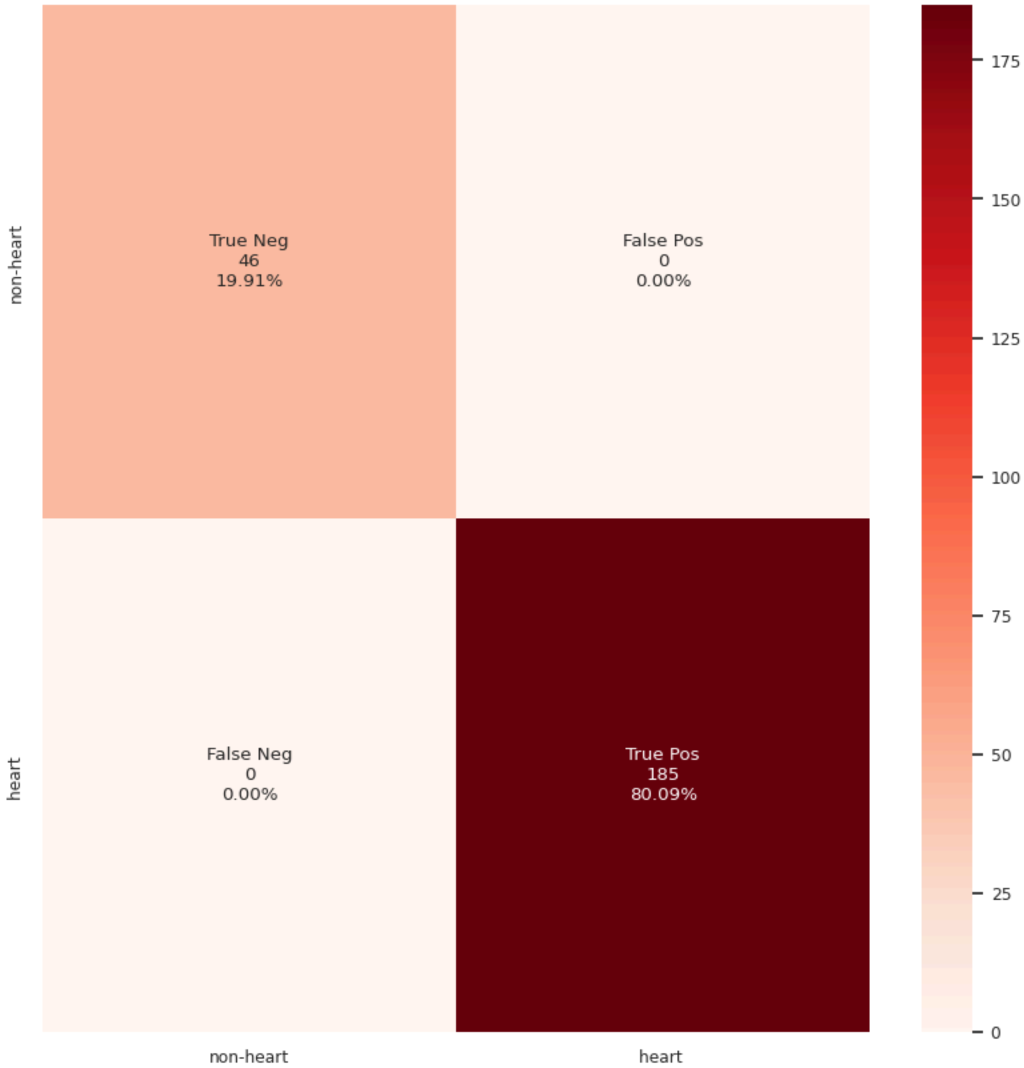
```
#Initializing the SVM Classifier
svmmodel= SVC(kernel='linear', random_state=42)
#Training the data with the classifier
binSVM = svmmodel.fit(x_train,y_train)

# Test the SVM model by predicting Y
y_predicted = binSVM.predict(x_test)

#Get accuracy to evaluate the performance of training set
svmaccuracy = binSVM.score(x_train,y_train)
print( "Binarised Training set accuracy:", svmaccuracy)

#get the confusion matrix of the SVM classifier
cm = confusion_matrix(y_test, y_predicted)
print("Binarized Confusion Matrix:" ,cm)
```

```
Binarised Training set accuracy: 1.0
Binarized Confusion Matrix: [[ 46   0]
 [  0 185]]
```

PLOT SHOWING SVM CONFUSION MATRIX

```
# Plotting the confusion matrix
plt.figure(figsize = (10,10))
labels = ['TN','FP','FN','TP']
classes = ['non-heart','heart ' ]
labels = np.asarray(labels).reshape(2,2)
group_names = ['True Neg','False Pos','False Neg','True Pos']
group_counts = ['{0:0.0f}'.format(value) for value in cm.flatten()]
group_percentages = ['{0:.2%}'.format(value) for value in cm.flatten()/np.sum(cm)]
labels = [f'{v1}\n{v2}\n{v3}' for v1, v2, v3 in zip(group_names,group_counts,group_percentages)]
labels = np.asarray(labels).reshape(2,2)
sns.heatmap(cm, annot=labels, fmt='', cmap= "Reds",xticklabels = classes,yticklabels = classes)
```

```
<Axes: >
```



from the SVM classifier , one can see that the non-hearts and hearts have been classified correctly based on the confusion matrix report with no false negative or false postive values.

SVM CLASSIFICATION REPORT

```
# imported classification_report from sklearn.metrics at the top
#Generata a classification report for each class

report_of_each_class = classification_report(y_test,y_predicted)
print('SVM CLASSIFICATION REPORT OF BINARISED DATA')
print(report_of_each_class)
```

```
SVM CLASSIFICATION REPORT OF BINARISED DATA
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        46
           1       1.00      1.00      1.00       185

    accuracy                           1.00       231
   macro avg       1.00      1.00      1.00       231
weighted avg       1.00      1.00      1.00       231
```

to support the SVM confusion matrix results, the classfier displays a 100% accuracy, precision, recall anf f-1 score

5 FOLD CROSS VALIDATION SVM

```
kf = KFold(n_splits=5)
kf.get_n_splits(originalrepo)
print(kf)
```

```
KFold(n_splits=5, random_state=None, shuffle=False)
```

```
# Initialize KFold cross-validation
kf = KFold(n_splits=5)

# Iterate over folds
i = 1
for train_index, test_index in kf.split(originalrepo):
    print('Fold', i)
    print('TRAIN INDEXES:', train_index)
    print('TEST INDEXES:', test_index)

    # Extract training and testing data using indices
    x_train, x_test = originalrepo[train_index], originalrepo[test_index]
    y_train, y_test = originalrepo[train_index], originalrepo[test_index]
    i += 1
```

```
Fold 1
TRAIN INDEXES: [ 231  232  233  234  235  236  237  238  239  240  241  242  243  244
  245  246  247  248  249  250  251  252  253  254  255  256  257  258
  259  260  261  262  263  264  265  266  267  268  269  270  271  272
  273  274  275  276  277  278  279  280  281  282  283  284  285  286
  287  288  289  290  291  292  293  294  295  296  297  298  299  300
  301  302  303  304  305  306  307  308  309  310  311  312  313  314
  315  316  317  318  319  320  321  322  323  324  325  326  327  328
  329  330  331  332  333  334  335  336  337  338  339  340  341  342
  343  344  345  346  347  348  349  350  351  352  353  354  355  356
  357  358  359  360  361  362  363  364  365  366  367  368  369  370
  371  372  373  374  375  376  377  378  379  380  381  382  383  384
  385  386  387  388  389  390  391  392  393  394  395  396  397  398
  399  400  401  402  403  404  405  406  407  408  409  410  411  412
  413  414  415  416  417  418  419  420  421  422  423  424  425  426
  427  428  429  430  431  432  433  434  435  436  437  438  439  440
  441  442  443  444  445  446  447  448  449  450  451  452  453  454
  455  456  457  458  459  460  461  462  463  464  465  466  467  468
  469  470  471  472  473  474  475  476  477  478  479  480  481  482
  483  484  485  486  487  488  489  490  491  492  493  494  495  496
  497  498  499  500  501  502  503  504  505  506  507  508  509  510
  511  512  513  514  515  516  517  518  519  520  521  522  523  524
  525  526  527  528  529  530  531  532  533  534  535  536  537  538
  539  540  541  542  543  544  545  546  547  548  549  550  551  552
  553  554  555  556  557  558  559  560  561  562  563  564  565  566
  567  568  569  570  571  572  573  574  575  576  577  578  579  580
  581  582  583  584  585  586  587  588  589  590  591  592  593  594
  595  596  597  598  599  600  601  602  603  604  605  606  607  608
  609  610  611  612  613  614  615  616  617  618  619  620  621  622
  623  624  625  626  627  628  629  630  631  632  633  634  635  636
  637  638  639  640  641  642  643  644  645  646  647  648  649  650
  651  652  653  654  655  656  657  658  659  660  661  662  663  664
  665  666  667  668  669  670  671  672  673  674  675  676  677  678
  679  680  681  682  683  684  685  686  687  688  689  690  691  692
  693  694  695  696  697  698  699  700  701  702  703  704  705  706
  707  708  709  710  711  712  713  714  715  716  717  718  719  720
  721  722  723  724  725  726  727  728  729  730  731  732  733  734
  735  736  737  738  739  740  741  742  743  744  745  746  747  748
  749  750  751  752  753  754  755  756  757  758  759  760  761  762
  763  764  765  766  767  768  769  770  771  772  773  774  775  776
  777  778  779  780  781  782  783  784  785  786  787  788  789  790
  791  792  793  794  795  796  797  798  799  800  801  802  803  804
  805  806  807  808  809  810  811  812  813  814  815  816  817  818
  819  820  821  822  823  824  825  826  827  828  829  830  831  832
  833  834  835  836  837  838  839  840  841  842  843  844  845  846
  847  848  849  850  851  852  853  854  855  856  857  858  859  860
  861  862  863  864  865  866  867  868  869  870  871  872  873  874
  875  876  877  878  879  880  881  882  883  884  885  886  887  888
  889  890  891  892  893  894  895  896  897  898  899  900  901  902
  903  904  905  906  907  908  909  910  911  912  913  914  915  916
  917  918  919  920  921  922  923  924  925  926  927  928  929  930
  931  932  933  934  935  936  937  938  939  940  941  942  943  944
  945  946  947  948  949  950  951  952  953  954  955  956  957  958
  959  960  961  962  963  964  965  966  967  968  969  970  971  972
  973  974  975  976  977  978  979  980  981  982  983  984  985  986
  987  988  989  990  991  992  993  994  995  996  997  998  999 1000
 1001 1002 1003 1004 1005 1006 1007 1008 1009 1010 1011 1012 1013 1014
 1015 1016 1017 1018 1019 1020 1021 1022 1023 1024 1025 1026 1027 1028
```

```
# Cross validating the original data of K5fold SVM
scores_svm = cross_validate(svmmodel, originalrepo, target_new, cv=5 , scoring = 'accuracy')
print('SVM cross-validated scores: ', scores_svm)
print('Precision for SVM: ',cross_validate(svmmodel, originalrepo, target_new, cv=5, scoring = 'precision'))
print('Recall for SVM: ',cross_validate(svmmodel, originalrepo, target_new, cv=5, scoring = 'recall'))
print('F1-Score for SVM: ',cross_validate(svmmodel, originalrepo, target_new, cv=5, scoring = 'f1'))
# Print the type of scores_svm
print(type(scores_svm))
```

```
SVM cross-validated scores:  {'fit_time': array([0.3431716 , 0.37828064, 0.40928674, 0.39971352, 0.37180901]), 'score_time': array(
Precision for SVM:  {'fit_time': array([0.37695551, 0.3881166 , 0.40964389, 0.37979102, 0.36366987]), 'score_time': array([0.064264
Recall for SVM:  {'fit_time': array([0.38623762, 0.35354018, 0.58872008, 0.54399204, 0.70641232]), 'score_time': array([0.04667568,
F1-Score for SVM:  {'fit_time': array([0.63094854, 0.46112442, 0.91057754, 0.61889505, 0.36266565]), 'score_time': array([0.1020441
<class 'dict'>
```

The precision, accuracy, recall and F1-score have a mean of 1.0 for SVM after being cross validated 5 times.Seems we might have a perfect classifier. However we are yet to compare this to CNN and this has made me look into the mean runtime to aid the comparison with the CNN classifier

```
# Calculate the mean fit time
mean_fit_time = np.mean(scores_svm['fit_time'])
# Calculate the mean score time
mean_score_time = np.mean(scores_svm ['score_time'])
print("Mean Fit Time:", mean_fit_time)
print("Mean Score Time:", mean_score_time)
```

```
Mean Fit Time: 0.380452299118042
Mean Score Time: 0.046641063690185544
```

CNN CLASSIFIER /NEURAL NETWORK

```
# Reshape into four dimensions.
x_train_cn = x_train_cn.reshape(x_train_cn.shape[0], 128, 128, 1)
x_test_cn = x_test_cn.reshape(x_test_cn.shape[0], 128, 128, 1)
# Convert to float 32
x_train_cn = x_train_cn.astype('float32')
x_test_cn = x_test_cn.astype('float32')
# normalise
x_train_cn /= 255
x_test_cn /= 255
```

```
#print shapes
print(x_test_cn.shape)
print(y_test_cn.shape)
print(x_train_cn.shape)
print(y_train_cn.shape)
```

```
(231, 128, 128, 1)
(231,)
(922, 128, 128, 1)
(922,)
```

```
#code reference [2]
#model architecture

cnnmodel = Sequential()


cnnmodel.add(Conv2D(32, (3, 3), activation='relu', input_shape=(128,128,1)))
cnnmodel.add(Conv2D(32, (3, 3), activation='relu'))
cnnmodel.add(MaxPooling2D(pool_size=(2,2)))
cnnmodel.add(Dropout(0.25))
cnnmodel.add(Flatten())
cnnmodel.add(Dropout(0.5))
cnnmodel.add(Dense(128, activation='relu'))
cnnmodel.add(Dense(2, activation='sigmoid'))
```

```
cnnmodel.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_4 (Conv2D)           (None, 126, 126, 32)      320

 conv2d_5 (Conv2D)           (None, 124, 124, 32)      9248

 max_pooling2d_2 (MaxPoolin  (None, 62, 62, 32)        0
 g2D)

 dropout_4 (Dropout)         (None, 62, 62, 32)        0

 flatten_2 (Flatten)         (None, 123008)            0

 dropout_5 (Dropout)         (None, 123008)            0

 dense_4 (Dense)             (None, 128)               15745152

 dense_5 (Dense)             (None, 2)                 258

=================================================================
Total params: 15754978 (60.10 MB)
Trainable params: 15754978 (60.10 MB)
Non-trainable params: 0 (0.00 Byte)
```

```
#Training the CNN Model
cnnmodel.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
history = cnnmodel.fit(x_train_cn, y_train_cn, epochs =4, batch_size=32)
```

```
Epoch 1/4
29/29 [==============================] - 49s 2s/step - loss: 0.0811 - accuracy: 0.9610
Epoch 2/4
29/29 [==============================] - 58s 2s/step - loss: 3.7223e-05 - accuracy: 1.0000
Epoch 3/4
29/29 [==============================] - 62s 2s/step - loss: 7.2578e-06 - accuracy: 1.0000
Epoch 4/4
29/29 [==============================] - 53s 2s/step - loss: 4.2886e-06 - accuracy: 1.0000
```

CNN takes longer time (more than 40s) to classify images in comparison to SVM (Fit time of 0.3s and Score time of 0.04s)

```
# Evaluate cnn model on test data
loss, accuracy = cnnmodel.evaluate(x_test_cn, y_test_cn, verbose=0)
print('Loss: ', loss,'\nAcc: ', accuracy)
```

```
Loss:  4.108771008759504e-06
Acc:  1.0
```

TESTING THE PREDICTION OF THE CNN MODEL

```
#Check the labels that have been predicted for CNN
predict_x= cnnmodel.predict(x_test_cn)
classes_x=np.argmax(predict_x,axis=1)
print(classes_x)
```

```
8/8 [==============================] - 2s 262ms/step
[1 0 0 1 1 0 1 1 1 0 1 0 1 1 1 1 1 1 1 1 0 1 0 1 1 0 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 0 1 1 1 1 1 0 1 1 1 1 1 1 1 1 0 0 1 0 1 1 1 1 1 0 1 1 1 1 1 1
 1 0 1 0 1 1 1 1 1 1 1 1 0 0 1 1 1 1 1 1 0 1 1 0 1 1 1 1 0 1 1 1 1 1 1 1 0
 1 0 1 0 1 1 0 0 1 1 1 0 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 0 1 1 1 1 1 1 0
 1 1 1 1 1 0 1 1 0 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 0 1 0 1 1 1 0
 0 1 1 1 0 1 1 1 1 0 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 0 0 1 1
 0 1 0 1 1 0 1 1 1]
```

CNN CLASSIFICATION REPORT

```
# Convert probabilities to class labels
y_pred_cnn_labels = np.argmax(predict_x, axis=1)

#print classification report for CNN
cnn_report_of_each_class = classification_report(y_test_cn, y_pred_cnn_labels)
print('CNN CLASSIFICATION REPORT OF BINARISED DATA')
print(cnn_report_of_each_class)
```

```
CNN CLASSIFICATION REPORT OF BINARISED DATA
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        46
           1       1.00      1.00      1.00       185

    accuracy                           1.00       231
   macro avg       1.00      1.00      1.00       231
weighted avg       1.00      1.00      1.00       231
```

```
# Check the label that has been predicted incorrectly for CNN
incorrect_labels = []
accuracy = 0

for i, cla in enumerate(classes_x):
    if cla != y_test_cn[i]:
        print("Sample " + str(i) + " was classified as " + str(cla) + " when it really was " + str(y_test_cn[i]))
        incorrect_labels.append(i)
    else:
        print("Sample " + str(i) + " classified correctly")
```

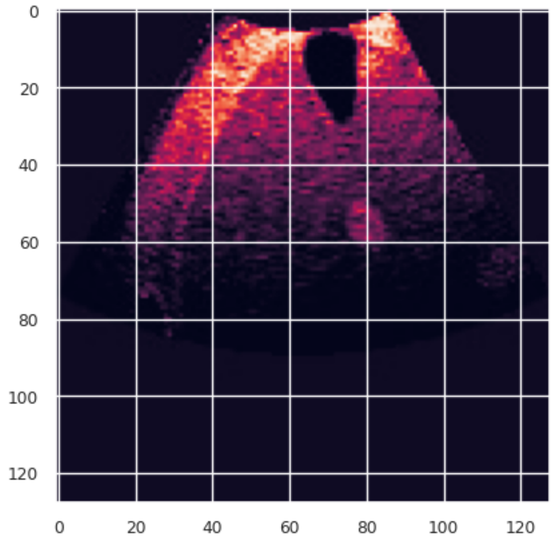
```
Sample 0 classified correctly
Sample 1 classified correctly
Sample 2 classified correctly
Sample 3 classified correctly
Sample 4 classified correctly
Sample 5 classified correctly
Sample 6 classified correctly
Sample 7 classified correctly
Sample 8 classified correctly
```

```
Sample 9 classified correctly
Sample 10 classified correctly
Sample 11 classified correctly
Sample 12 classified correctly
Sample 13 classified correctly
Sample 14 classified correctly
Sample 15 classified correctly
Sample 16 classified correctly
Sample 17 classified correctly
Sample 18 classified correctly
Sample 19 classified correctly
Sample 20 classified correctly
Sample 21 classified correctly
Sample 22 classified correctly
Sample 23 classified correctly
Sample 24 classified correctly
Sample 25 classified correctly
Sample 26 classified correctly
Sample 27 classified correctly
Sample 28 classified correctly
Sample 29 classified correctly
Sample 30 classified correctly
Sample 31 classified correctly
Sample 32 classified correctly
Sample 33 classified correctly
Sample 34 classified correctly
Sample 35 classified correctly
Sample 36 classified correctly
Sample 37 classified correctly
Sample 38 classified correctly
Sample 39 classified correctly
Sample 40 classified correctly
Sample 41 classified correctly
Sample 42 classified correctly
Sample 43 classified correctly
Sample 44 classified correctly
Sample 45 classified correctly
Sample 46 classified correctly
Sample 47 classified correctly
Sample 48 classified correctly
Sample 49 classified correctly
Sample 50 classified correctly
Sample 51 classified correctly
Sample 52 classified correctly
Sample 53 classified correctly
Sample 54 classified correctly
Sample 55 classified correctly
Sample 56 classified correctly
```

All samples are classified correctly for the CNN model , which supports the minimal loss and accuracy of 1.0 (100%)

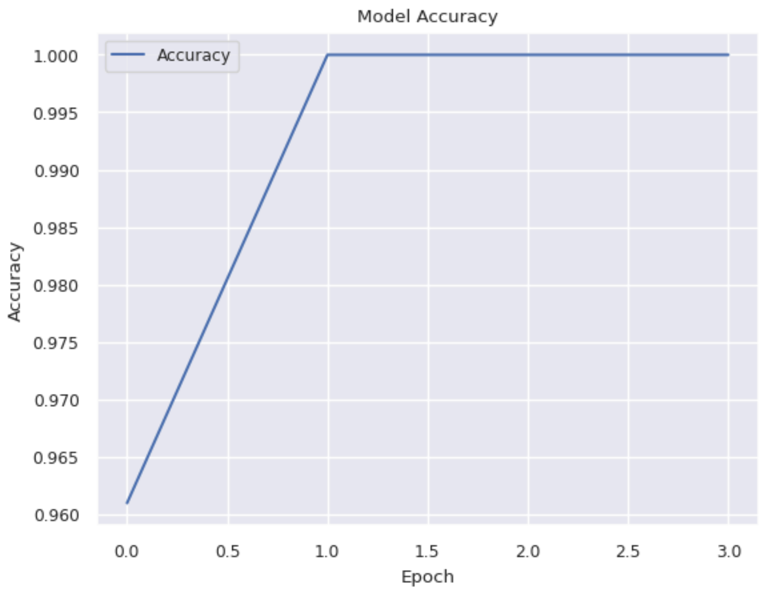
```
#Show a sample from the original dataset (correct prediction) for CNN
image_to_show = 229 # choose any random Sample since all were classified correctly
from_group = 'test' # 'train' or 'test'
if from_group == 'train':
    plt.imshow(x_train_cn[image_to_show])
    print('Ground truth label: ',y_train_cn[image_to_show])
else:
    plt.imshow(x_test_cn[image_to_show])
    print('Ground truth label: ',y_test_cn[image_to_show])
    if len(predict_x)>image_to_show:
        print('Predicted label: ',classes_x[image_to_show])
```

```
Ground truth label:  1
Predicted label:  1
```



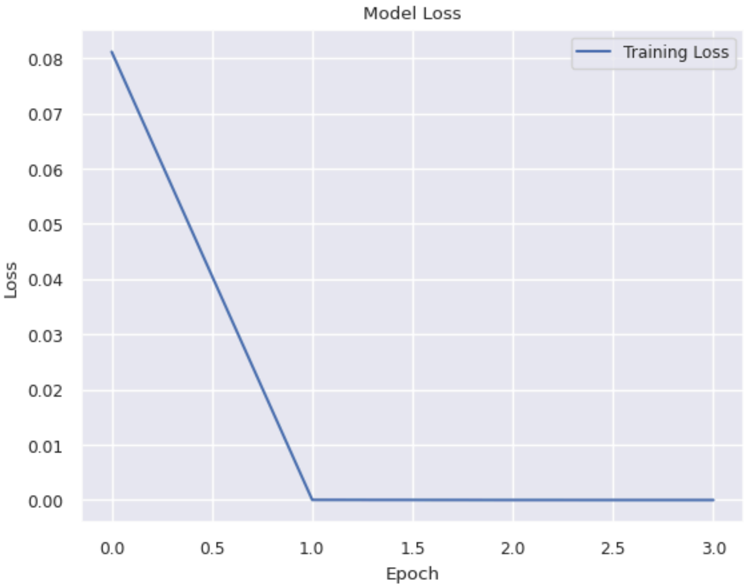
This output supports the classification as we can see all samples predicted correctly. Any sample number that is inputed in the code chunk above will produce the correct classification predictation

```
#visualise the accuracy and loss of CNN model
plt.plot(history.history['accuracy'], label='Accuracy')
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```



The accuracy is increasing across epochs when classifying the samples

```
#visualise the loss from CNN model
# Plot training loss
plt.plot(history.history['loss'], label='Training Loss')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

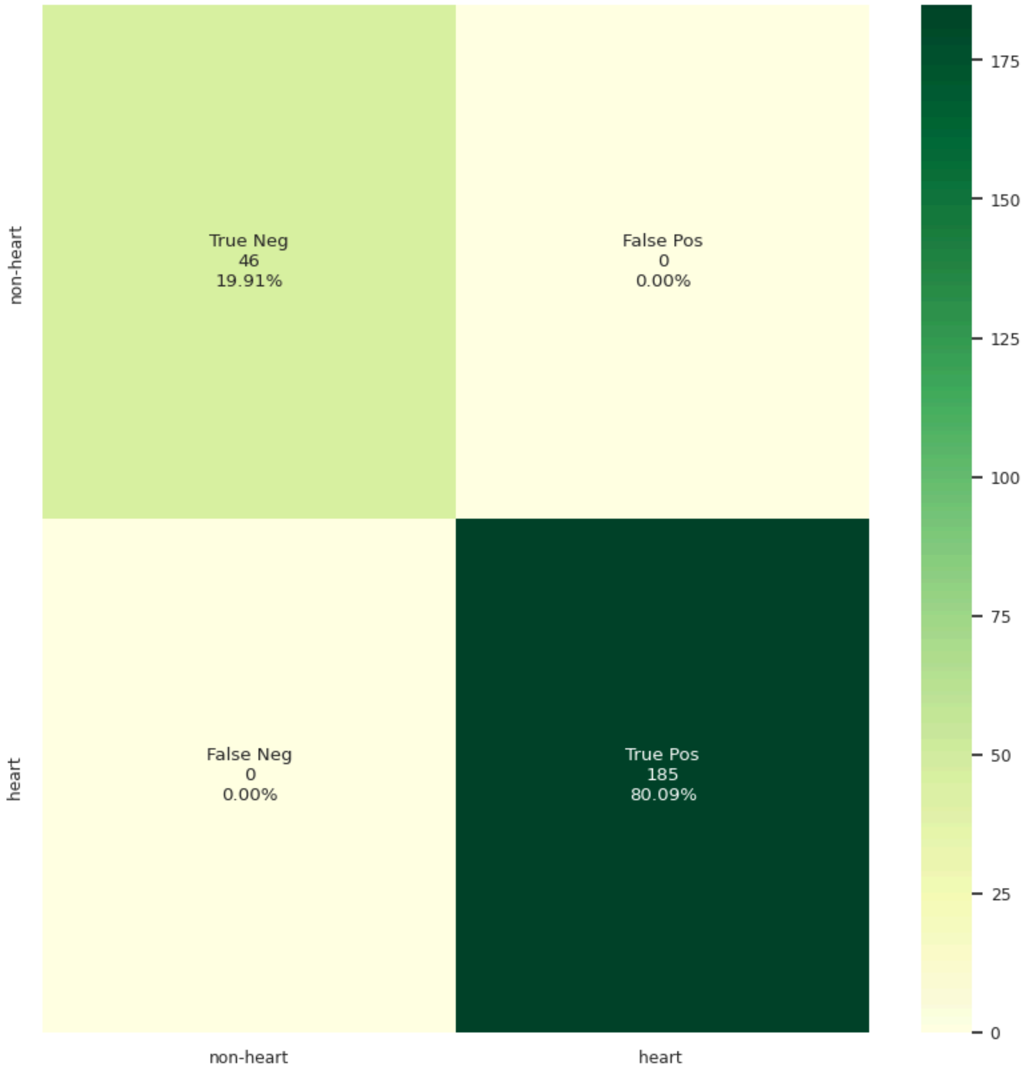


The loss reduces and the accuracy increases across epochs

CNN CONFUSION MATRIX

```
#CNN CONFUSION MATRIX

predictions = cnnmodel.predict(x_test_cn)
pred_labels= np.argmax(predictions,axis=1)
cf_matrix_cn = confusion_matrix(y_test_cn, pred_labels)
plt.figure(figsize = (10,10))

labels = ['TN','FP','FN','TP']
labels = np.asarray(labels).reshape(2,2)

group_names = ['True Neg','False Pos','False Neg','True Pos']

group_counts = ['{0:0.0f}'.format(value) for value in
                cf_matrix_cn.flatten()]
group_percentages = ['{0:.2%}'.format(value) for value in
                     cf_matrix_cn.flatten()/np.sum(cf_matrix_cn)]
labels = [f'{v1}\n{v2}\n{v3}' for v1, v2, v3 in
          zip(group_names,group_counts,group_percentages)]
labels = np.asarray(labels).reshape(2,2)
sns.heatmap(cf_matrix_cn, annot=labels, fmt='', cmap= "YlGn",
           xticklabels = classes,yticklabels = classes)
cf_matrix_cn
```

```
8/8 [==============================] - 2s 263ms/step
array([[ 46,   0],
       [  0, 185]])
```



from the confusion matrix results all samples are classified correctly with no false negatives or false positives

K5 FOLD CNN

```
# Initialize KFold cross-validation
kf = KFold(n_splits=5)

# Initialize lists to store performance metrics
accuracy_scores = []
precision_scores = []
recall_scores = []
f1_scores = []

# Iterate over folds
for fold_idx, (train_index, test_index) in enumerate(kf.split(originalrepo)):
    print('Fold', fold_idx + 1)
    x_train_cn, x_test_cn = originalrepo[train_index], originalrepo[test_index]
    y_train_cn, y_test_cn = target_new[train_index], target_new[test_index]

    # Defining the CNN model ( rebuilt the same archictecture as seen before)
    cnnmodel = Sequential()
    cnnmodel.add(Conv2D(32, (3, 3), activation='relu', input_shape=(128,128,1)))
    cnnmodel.add(Conv2D(32, (3, 3), activation='relu'))
    cnnmodel.add(MaxPooling2D(pool_size=(2,2)))
    cnnmodel.add(Dropout(0.25))
    cnnmodel.add(Flatten())
    cnnmodel.add(Dropout(0.5))
    cnnmodel.add(Dense(128, activation='relu'))
    cnnmodel.add(Dense(2, activation='sigmoid'))

    # Compile your CNN model
    cnnmodel.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])

    # Reshape input data
```

```
    x_train_cn = x_train_cn.reshape(-1, 128, 128, 1)
    x_test_cn = x_test_cn.reshape(-1, 128, 128, 1)

    # Train your model
    cnnmodel.fit(x_train_cn, y_train_cn, epochs= 4, batch_size=32, verbose=0)

    # Predict probabilities for each class
    y_pred_probabilities = cnnmodel.predict(x_test_cn)

    # Convert probabilities to predicted classes
    y_pred_cn = np.argmax(y_pred_probabilities, axis=1)

    # Calculate evaluation metrics for this fold
    accuracy = accuracy_score(y_test_cn, y_pred_cn)
    precision = precision_score(y_test_cn, y_pred_cn)
    recall = recall_score(y_test_cn, y_pred_cn)
    f1 = f1_score(y_test_cn, y_pred_cn)

    # Print evaluation metrics for each fold
    print("Accuracy:", accuracy)
    print("Precision:", precision)
    print("Recall:", recall)
    print("F1 Score:", f1)
    print()

    # Store metrics in lists
    accuracy_scores.append(accuracy)
    precision_scores.append(precision)
    recall_scores.append(recall)
    f1_scores.append(f1)
```

```
Fold 1
8/8 [==============================] - 2s 265ms/step
Accuracy: 1.0
Precision: 1.0
Recall: 1.0
F1 Score: 1.0

Fold 2
8/8 [==============================] - 2s 271ms/step
Accuracy: 1.0
Precision: 1.0
Recall: 1.0
F1 Score: 1.0

Fold 3
8/8 [==============================] - 2s 279ms/step
Accuracy: 1.0
Precision: 1.0
Recall: 1.0
F1 Score: 1.0

Fold 4
8/8 [==============================] - 3s 300ms/step
Accuracy: 1.0
Precision: 1.0
Recall: 1.0
F1 Score: 1.0

Fold 5
8/8 [==============================] - 4s 467ms/step
Accuracy: 0.008695652173913044
Precision: 0.008695652173913044
Recall: 1.0
F1 Score: 0.017241379310344827
```

```
# Report the average metrics across all folds
print('Average Accuracy:', np.mean(accuracy_scores))
print('Average Precision:', np.mean(precision_scores))
print('Average Recall:', np.mean(recall_scores))
print('Average F1-Score:', np.mean(f1_scores))
```

```
Average Accuracy: 0.8017391304347827
Average Precision: 0.8017391304347827
Average Recall: 1.0
Average F1-Score: 0.803448275862069
```

The CNN model perfomed lower than the SVM when running the k5 cross validation with Average scores of 80% and 100% for recall. The results were extemely low for the 5 fold which affects the average. It is important to note that in the initial CNNMODEL classificaton report was 100% across all metrics.

HOG FEATURES AND APPLICATION OF SMOTE

```
#splitting the HOG features of heart and non heart images into an 80/20 training split
print(target_new,target_new.shape)
x1_train, x1_test, y1_train, y1_test = train_test_split(hogrepo,target_new, stratify=target_new, test_size=0.2)
print('Number of heart and non-heart (Abdominal) samples in the training set: ',np.count_nonzero(y1_train == 0),np.count_nonzero(y1_train == 1))
print('Number of heart and non-heart (Abdominal) samples in the test set: ',np.count_nonzero(y1_test == 0),np.count_nonzero(y1_test == 1))
```

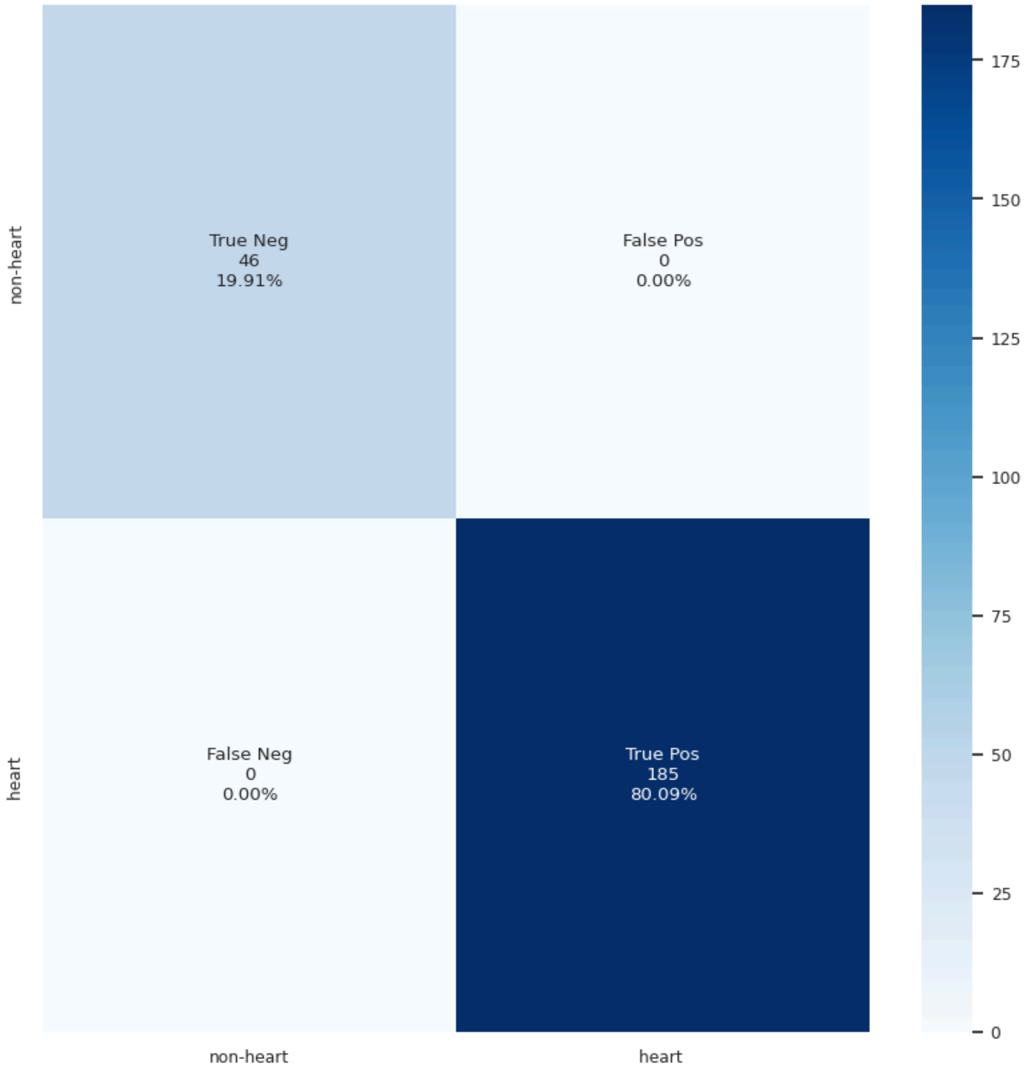
```
[1 1 1 ... 0 0 0] (1153,)
Number of heart and non-heart (Abdominal) samples in the training set:  182 740
Number of heart and non-heart (Abdominal) samples in the test set:  46 185
```

```
#Visualise the HOG- SVM Classification result
# Applying SMOTE to balance the classes
smote = SMOTE(random_state=42)
x1_train_new, y1_train_new = smote.fit_resample(x1_train, y1_train)

# Initializing the SVM Classifier
hogmodel = SVC(kernel='linear', random_state=42)

# Training the data with the classifier
hogSVM = hogmodel.fit(x1_train_new, y1_train_new)

# Test the SVM model by predicting Y
y_predicted_hog = hogSVM.predict(x1_test)

# Get accuracy to evaluate the performance of the training set
hogsvmaccuracy = hogSVM.score(x1_train_new, y1_train_new)
print("HOG Training set accuracy:", hogsvmaccuracy)

# Get the confusion matrix of the SVM classifier
hogcm = confusion_matrix(y1_test, y_predicted_hog)
print("HOG Confusion Matrix:", hogcm)
```

```
HOG Training set accuracy: 1.0
HOG Confusion Matrix: [[ 46   0]
 [  0 185]]
```

```
# Plotting the confusion matrix as a heatmap for HOG features of original data
plt.figure(figsize = (10,10))
labels = ['TN','FP','FN','TP']
classes = ['non-heart','heart ' ]
labels = np.asarray(labels).reshape(2,2)
group_names = ['True Neg','False Pos','False Neg','True Pos']
group_counts = ['{0:0.0f}'.format(value) for value in hogcm.flatten()]
group_percentages = ['{0:.2%}'.format(value) for value in hogcm.flatten()/np.sum(hogcm)]
labels = [f'{v1}\n{v2}\n{v3}' for v1, v2, v3 in zip(group_names,group_counts,group_percentages)]
labels = np.asarray(labels).reshape(2,2)
sns.heatmap(hogcm, annot=labels, fmt='', cmap= "Blues",xticklabels = classes,yticklabels = classes)
```

```
<Axes: >
```



HOG features after the application of the smote oversampling technique still exhibits proper classifcation in SVM and it is supported by the confusion matrix with no false negatives or false positives

```
#Generating a classification report for each class from the HOG extraction
hog_of_each_class = classification_report(y1_test,y_predicted_hog)
print('HOG FEATURES CLASSIFICATION REPORT')
print(hog_of_each_class)
```

```
HOG FEATURES CLASSIFICATION REPORT
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        46
           1       1.00      1.00      1.00       185

    accuracy                           1.00       231
   macro avg       1.00      1.00      1.00       231
weighted avg       1.00      1.00      1.00       231
```

SUMMARY ONE

The classification methods SVM, CNN, and HOG+SVM achieved 100% accuracy in classifying heart versus non-heart samples. SVM showed perfect scores across all metrics with no misclassifications, as confirmed by the confusion matrix. CNN also reached 100% accuracy, though it required more time for classification. The HOG features paired with SVM, plus SMOTE for balancing, exhibited the same high performance of the other methods.

Despite all techniques demonstrating perfect results, the choice of the most suitable classifier depends on specific needs, such as processing time. With both the original and HOG-enhanced data providing precise predictions, the models reliably distinguished between classes. CNN's robustness in handling imbalanced data makes it especially pertinent for medical imaging, justifying the longer processing time for complex pattern detection.

Considering the visual distinction in the dataset between heart and non-heart images, it will be expected that the accuracy and other metrics will be 100% after classification. We probe further in task 2.

TASK TWO

CNN is selected to assess its efficacy in effectively classifying these heart images with different valve positions.

For these experiments, precision, recall, F1 score, accuracy, confusion matrix, and AUC-ROC will be reported and compared to analyse the results. The focus of the experiments is solely on CNN classification.

DEFINING VARIABLES AND LOADING DATASETS

```
########  2. LOAD IMAGES (FOR ORIGINAL REPO) ########

resize_width = 128
resize_height = 128
path = '/content/drive/MyDrive/Colab Notebooks/cwdata_task2/heart'
images = [] # List to append the images as 2D numpy arrays.
target1 = [] # List to append the target
originalrepo1 = [] # Create a repo for flattened pixels

for root, dirs, files in os.walk(path):
     for file in files:
        with open(os.path.join(root, file), "r") as auto:
            try:
                img = cv2.imread(root+'/'+file, 0)
                img = cv2.resize(img, (resize_width, resize_height))
                images.append(img)
                # Append the flattened image to the pixel repo
                originalrepo1.append(img.flatten())
                # Append the folder where the image is to the target list
                target1.append(root.replace(path,'').replace('\\','').replace('/',''))
            except Exception as e:
                print("Invalid file "+file+" skipped.")
# Convert the repo list into numpy array
originalrepo1 = np.array(originalrepo1)

########################## 3. CALCULATE THE DISTRIBUTION AND SHOW REPOS ##########################

print('\nCalculating class distribution...')
histo = [['Class','Number of Samples']]
for i, label1 in enumerate(sorted(list(set(target1)))):
    cont = 0
    for j, label2 in enumerate(target1):
        if label1 == label2:
            cont+=1
    histo.append([label1,cont])
histo.append(['Total Samples', len(target1)])
## Load as a panda
histo_panda = pd.DataFrame.from_records(histo[1:-1], columns=histo[0])
print(histo_panda)
print('Total images: '+str(len(target1)))
## Create a histogram using seaborn
sns_plot = sns.barplot(y="Class", x="Number of Samples", data=histo_panda)
# Set labels and title
sns_plot.set_xlabel("Number of Samples", fontsize=12)
sns_plot.set_ylabel("Class", fontsize=12)
sns_plot.set_title("Class Distribution", fontsize=14)
sns_plot.figure.set_size_inches(8,6)
sns.set(font_scale=0.8)
print('\nShowing class distribution bar chart...')
plt.show()
print('Size of target: ', len(target1))
print('Size of original repository: ', originalrepo1.shape)
print('Example of the original repository: ')
print(originalrepo1)
print('Class Labels',target1)
```

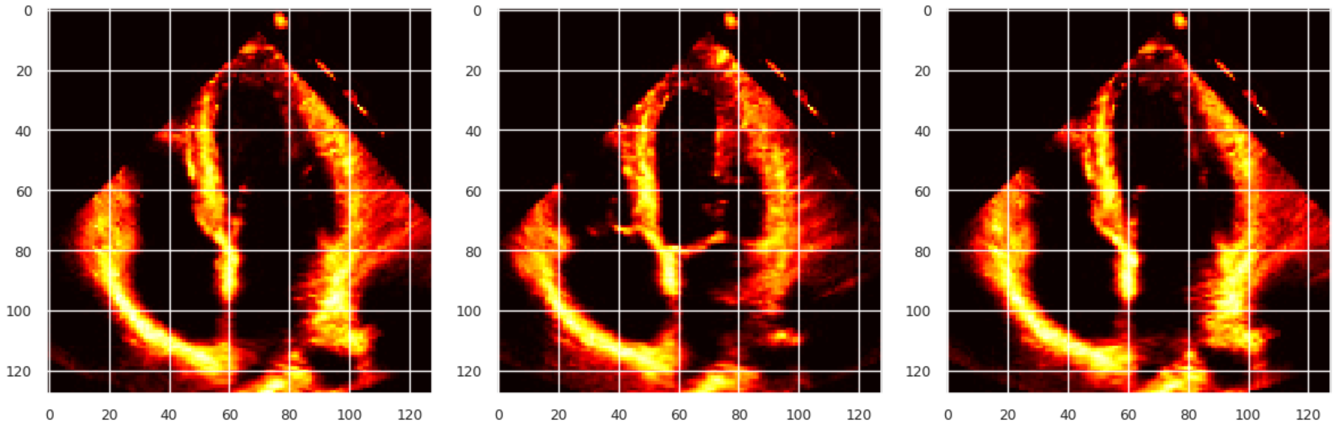
```
Calculating class distribution...
    Class  Number of Samples
0  closed                 80
1    open                138
Total images: 218

Showing class distribution bar chart...
```


```
Size of target:  218
Size of original repository:  (218, 16384)
Example of the original repository:
[[0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 ...
 [0 0 0 ... 1 1 1]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]]
Class Labels ['closed', 'closed', 'closed', 'closed', 'closed', 'closed', 'closed', 'closed', 'closed', 'closed', 'closed', 'closed
```

DISPLAYING THE OPEN HEART SAMPLES

```
#Display the open heart x ray images in hot colour scale for better visualization
openheart = originalrepo1[np.asarray(target1) == 'open']

openheart_sample = random.sample(range(len(openheart)), 3)
fig,axes = plt.subplots(1,3, figsize=[12,9])

fig.tight_layout() # add spacing between subplots
for i, dat in enumerate(axes.flatten()):
    if i<len(openheart_sample): # This "if" is here to avoid that, if the user specifies more subplots than data, the program crashes due to lack
        dat.imshow(np.asarray(openheart[openheart_sample[i]]).reshape(128,128),
                   cmap='hot', interpolation='nearest')
print(' Open Heart Images')
plt.show()
```

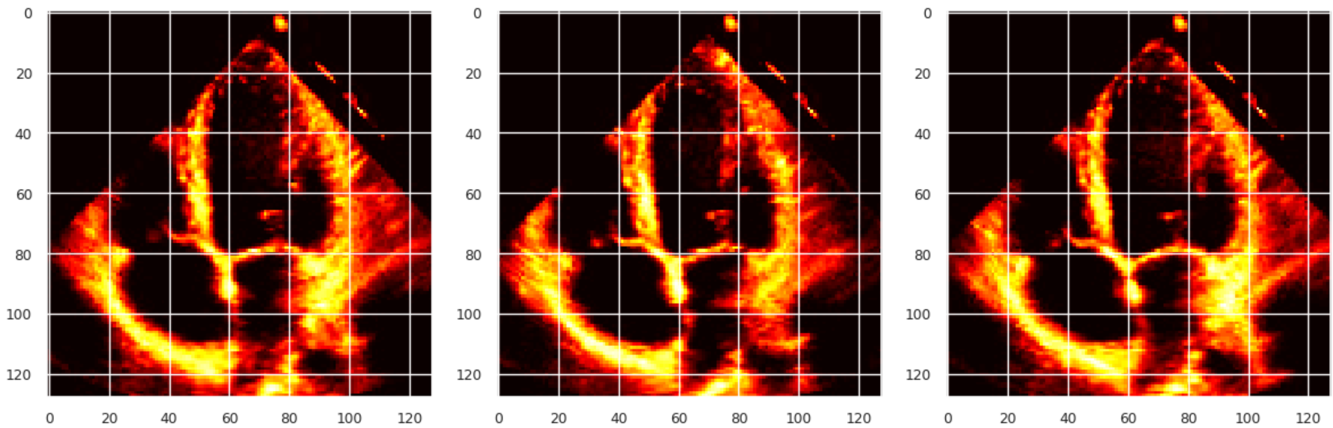
```
Open Heart Images
```



DISPLAYING THE CLOSED HEART SAMPLES

```
#Display the closed heart x ray images using hot color scale, for better visualition
closedheart = originalrepo1[np.asarray(target1) == 'closed']

closedheart_sample = random.sample(range(len(closedheart)), 3)
fig,axes = plt.subplots(1,3, figsize=[12,9])

fig.tight_layout() # add spacing between subplots
for i, dat in enumerate(axes.flatten()):
    if i<len(closedheart_sample): # This "if" is here to avoid that, if the user specifies more subplots than data, the program crashes due to lac
        dat.imshow(np.asarray(closedheart[closedheart_sample[i]]).reshape(128,128),
                   cmap='hot', interpolation='nearest')
print(' Closed Heart Images')
plt.show()
```

```
Closed Heart Images
```



TRAINING THE DATASET

Binarizing the target names Splittling the dataset 80/20

```
#binarizing target names
target_heart = [0 if i == 'closed' else 1 for i in target1]
target_heart =np.array(target_heart)
print(target_heart,target_heart.shape)
X_train, X_test, Y_train, Y_test = train_test_split(originalrepo1,target_heart, stratify=target_heart, test_size=0.2)
print('Number of closed and open heart samples in the training set: ',np.count_nonzero(Y_train == 0),np.count_nonzero(Y_train == 1))
print('Number of closed and open heart samples in the test set: ',np.count_nonzero(Y_test == 0),np.count_nonzero(Y_test == 1))
```

```
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1] (218,)
Number of closed and open heart samples in the training set:  64 110
Number of closed and open heart samples in the test set:  16 28
```

CNN CLASSIFICATION OF DATASET 2

```
# Reshape into four dimensions.
X_train = X_train.reshape(-1, 128, 128, 1)
X_test = X_test.reshape(-1, 128, 128, 1)
# Convert to float 32
X_train = X_train.astype('float32')
X_test = X_test.astype('float32')
# normalise
X_train /= 255
X_test /= 255
```

```
#print shapes
print(X_test.shape)
print(Y_test.shape)
print(X_train.shape)
print(Y_train.shape)
```

```
(44, 128, 128, 1)
(44,)
(174, 128, 128, 1)
(174,)
```

```
#training the model
cnnmodel2 = Sequential()

cnnmodel2.add(Conv2D(32, (3, 3), activation='relu', input_shape=(128,128,1)))
cnnmodel2.add(Conv2D(32, (3, 3), activation='relu'))
cnnmodel2.add(MaxPooling2D(pool_size=(2,2)))
cnnmodel2.add(Dropout(0.25))
cnnmodel2.add(Flatten())
cnnmodel2.add(Dropout(0.5))
cnnmodel2.add(Dense(128, activation='relu'))
cnnmodel2.add(Dense(2, activation='sigmoid'))
```

```
#printing out the model summary
cnnmodel2.summary()
```

```
Model: "sequential_14"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_28 (Conv2D)          (None, 126, 126, 32)      320

 conv2d_29 (Conv2D)          (None, 124, 124, 32)      9248

 max_pooling2d_14 (MaxPooli  (None, 62, 62, 32)        0
 ng2D)

 dropout_28 (Dropout)        (None, 62, 62, 32)        0

 flatten_14 (Flatten)        (None, 123008)            0

 dropout_29 (Dropout)        (None, 123008)            0

 dense_28 (Dense)            (None, 128)               15745152

 dense_29 (Dense)            (None, 2)                 258

=================================================================
Total params: 15754978 (60.10 MB)
Trainable params: 15754978 (60.10 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
#Training the CNN Model
cnnmodel2.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
history1 = cnnmodel2.fit(X_train, Y_train, epochs=10, batch_size=32)
```

```
Epoch 1/10
6/6 [==============================] - 10s 1s/step - loss: 0.9524 - accuracy: 0.5690
Epoch 2/10
6/6 [==============================] - 9s 1s/step - loss: 0.5565 - accuracy: 0.6322
Epoch 3/10
6/6 [==============================] - 10s 2s/step - loss: 0.4202 - accuracy: 0.8908
Epoch 4/10
6/6 [==============================] - 8s 1s/step - loss: 0.2462 - accuracy: 0.9483
Epoch 5/10
6/6 [==============================] - 10s 2s/step - loss: 0.1530 - accuracy: 0.9540
Epoch 6/10
6/6 [==============================] - 10s 2s/step - loss: 0.1675 - accuracy: 0.9540
Epoch 7/10
6/6 [==============================] - 8s 1s/step - loss: 0.1193 - accuracy: 0.9770
```

```
Epoch 8/10
6/6 [==============================] - 10s 2s/step - loss: 0.0980 - accuracy: 0.9770
Epoch 9/10
6/6 [==============================] - 9s 1s/step - loss: 0.0865 - accuracy: 0.9770
Epoch 10/10
6/6 [==============================] - 9s 1s/step - loss: 0.0869 - accuracy: 0.9655
```

Due to data shuffling between epochs, accuracy may fluctuate with each run. As the model trains across epochs, an increase in accuracy and a corresponding decrease in loss are typically observed.

```
# Evaluate model on test data
loss, accuracy = cnnmodel2.evaluate(X_test, Y_test, verbose=0)
print('Loss: ', loss,'\nAcc: ', accuracy)
```

```
Loss:  0.14518000185489655
Acc:  0.9772727489471436
```

```
#Check the labels that have been predicted
predict_x1= cnnmodel2.predict(X_test)
classes_x1=np.argmax(predict_x1,axis=1)
print(classes_x1)
```

```
2/2 [==============================] - 0s 101ms/step
[1 0 0 0 1 1 0 0 1 1 0 0 1 1 0 0 1 0 1 1 0 1 0 1 1 1 1 1 0 1 1 0 1 1 1 1 1
 1 0 1 0 1 0 1]
```

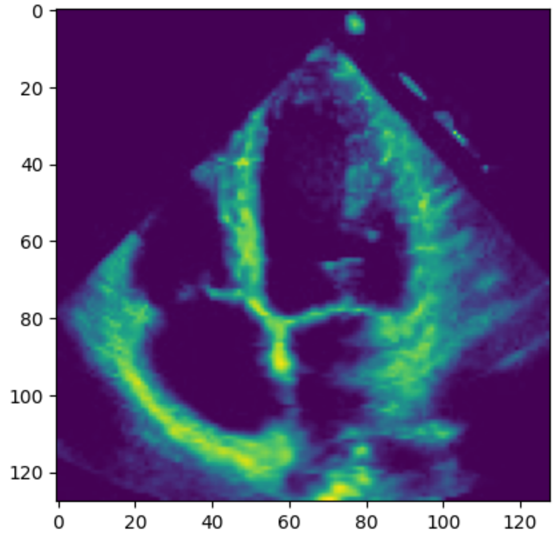
```
# Check the label that has been predicted incorrectly
incorrect_labels = []
accuracy = 0

for i, cla in enumerate(classes_x1):
    if cla != Y_test[i]:
        print("Sample " + str(i) + " was classified as " + str(cla) + " when it really was " + str(Y_test[i]))
        incorrect_labels.append(i)
    else:
        print("Sample " + str(i) + " classified correctly")
```

```
Sample 0 classified correctly
Sample 1 classified correctly
Sample 2 classified correctly
Sample 3 classified correctly
Sample 4 classified correctly
Sample 5 classified correctly
Sample 6 classified correctly
Sample 7 classified correctly
Sample 8 classified correctly
Sample 9 classified correctly
Sample 10 classified correctly
Sample 11 classified correctly
Sample 12 classified correctly
Sample 13 classified correctly
Sample 14 classified correctly
Sample 15 classified correctly
Sample 16 classified correctly
Sample 17 classified correctly
Sample 18 classified correctly
Sample 19 classified correctly
Sample 20 classified correctly
Sample 21 classified correctly
Sample 22 classified correctly
Sample 23 classified correctly
Sample 24 classified correctly
Sample 25 classified correctly
Sample 26 classified correctly
Sample 27 classified correctly
Sample 28 was classified as 0 when it really was 1
Sample 29 classified correctly
Sample 30 classified correctly
Sample 31 classified correctly
Sample 32 classified correctly
Sample 33 classified correctly
Sample 34 classified correctly
Sample 35 classified correctly
Sample 36 classified correctly
Sample 37 classified correctly
Sample 38 classified correctly
Sample 39 classified correctly
Sample 40 classified correctly
Sample 41 classified correctly
Sample 42 classified correctly
Sample 43 classified correctly
```

One sample was classified incorrectly, we an check this below

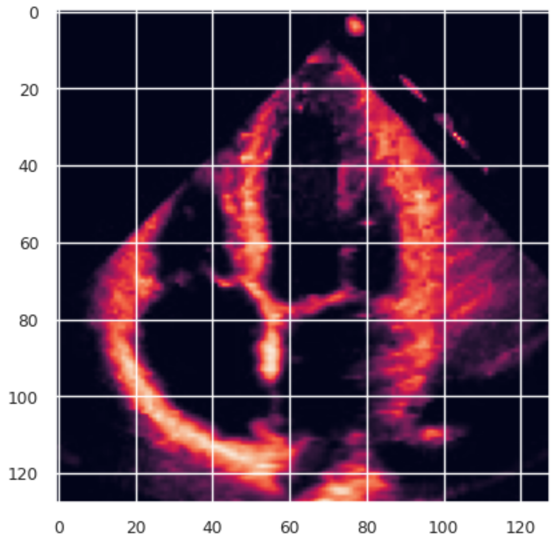
```
#Show a sample from the heart dataset (correct prediction)
image_to_show = 36  #sample number
from_group = 'test' # 'train' or 'test'
if from_group == 'train':
    plt.imshow(X_train[image_to_show])
    print('Ground truth label: ',Y_train[image_to_show])
else:
    plt.imshow(X_test[image_to_show])
    print('Ground truth label: ',Y_test[image_to_show])
    if len(predict_x1)>image_to_show:
        print('Predicted label: ',classes_x1[image_to_show])
```

```
Ground truth label:  0
Predicted label:  0
```




```
#Show a sample from the heart dataset (incorrect prediction)
image_to_show = 28 #sample number
from_group = 'test' # 'train' or 'test'
if from_group == 'train':
    plt.imshow(X_train[image_to_show])
    print('Ground truth label: ',Y_train[image_to_show])
else:
    plt.imshow(X_test[image_to_show])
    print('Ground truth label: ',Y_test[image_to_show])
    if len(predict_x1)>image_to_show:
        print('Predicted label: ',classes_x1[image_to_show])
```

```
Ground truth label:  1
Predicted label:  0
```



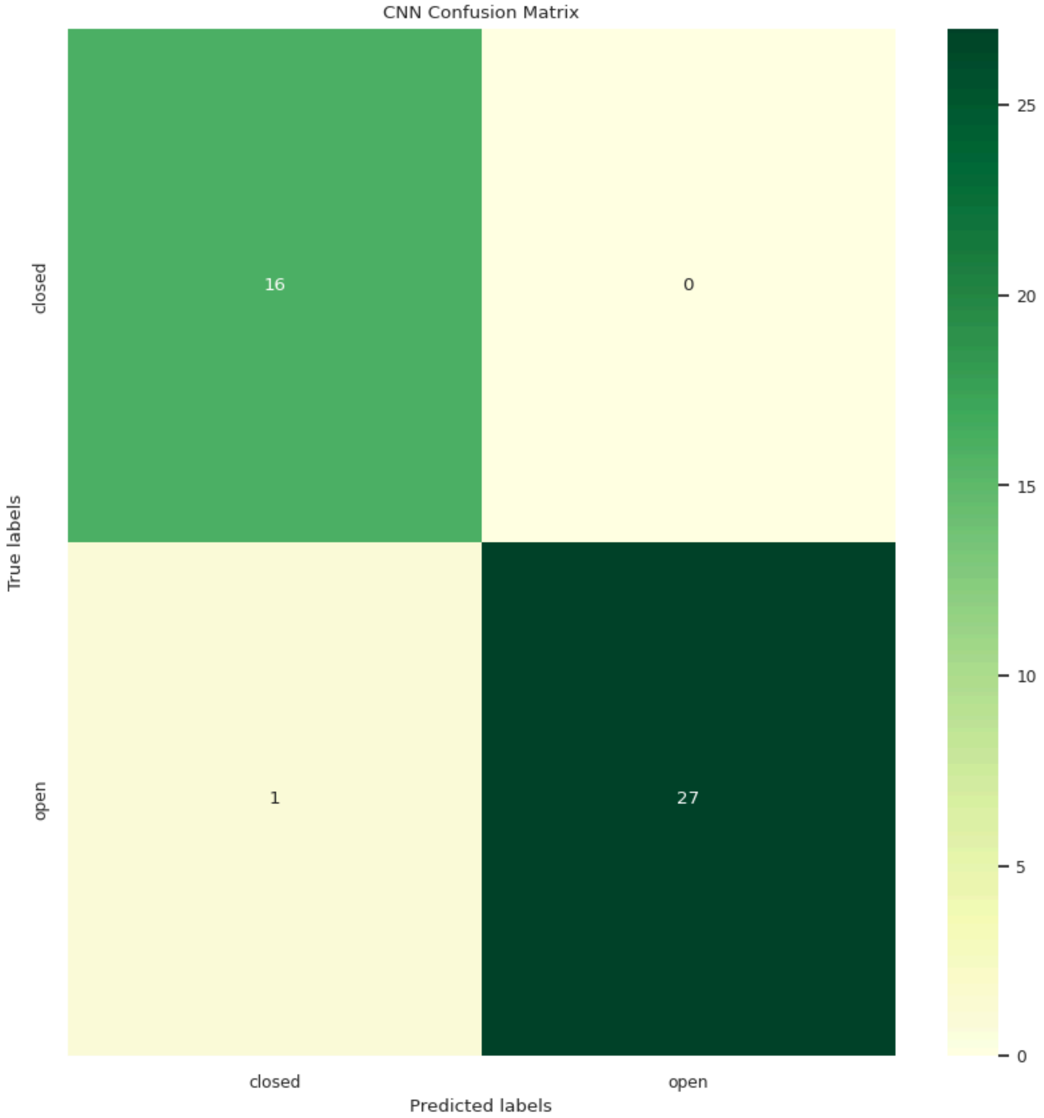
Sample 28 is the incorrectly classified sample

CONFUSION MATRIX FOR CNN

```
#CNN CONFUSION MATRIX

predictions1 = cnnmodel2.predict(X_test)
```

```
pred_labels1= np.argmax(predictions1,axis=1)
cf_matrix_cn_2 = confusion_matrix(Y_test, pred_labels1)
plt.figure(figsize = (10,10))

classes = ['closed', 'open']

# Your confusion matrix computation
cf_matrix_cn_2 = confusion_matrix(Y_test, pred_labels1)

plt.figure(figsize=(10, 10))
sns.heatmap(cf_matrix_cn_2, annot=True, fmt='d', cmap="YlGn",
            xticklabels=classes, yticklabels=classes)
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('CNN Confusion Matrix')
plt.show()
```

```
2/2 [==============================] - 1s 243ms/step
<Figure size 1000x1000 with 0 Axes>
```



The confusion matrix supports the classification results, with only one sample, number 28, being misclassified as a false negative—an open heart identified as a closed heart.

CNN CLASSIFICATION REPORT

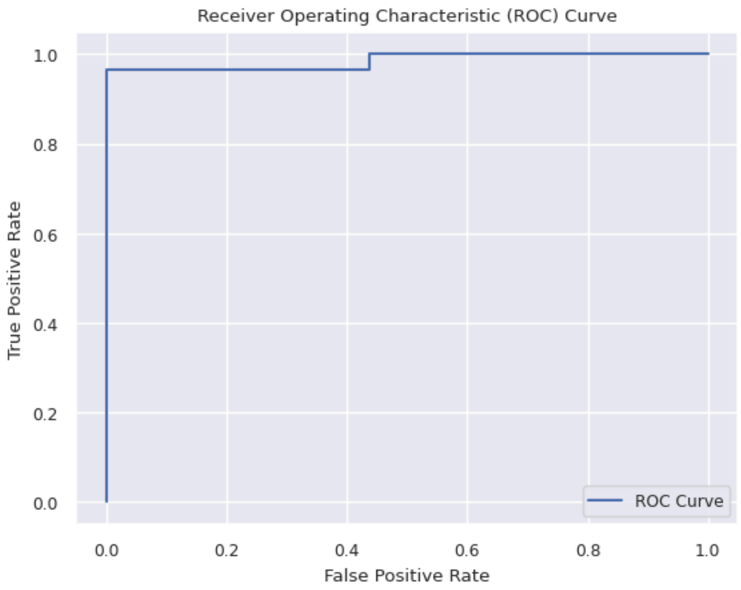
```
# Convert probabilities to class labels
y_cnn_labels = np.argmax(predict_x1, axis=1)

#print classification report for CNN
cnn_report_of_each_class = classification_report(Y_test, y_cnn_labels)
print('CNN CLASSIFICATION REPORT OF HEART IMAGES')
print(cnn_report_of_each_class)
```

```
CNN CLASSIFICATION REPORT OF HEART IMAGES
              precision    recall  f1-score   support
```

```
              0       0.94      1.00      0.97        16
              1       1.00      0.96      0.98        28

       accuracy                           0.98        44
      macro avg       0.97      0.98      0.98        44
   weighted avg       0.98      0.98      0.98        44
```

AUC-ROC EVALUATION METRIC

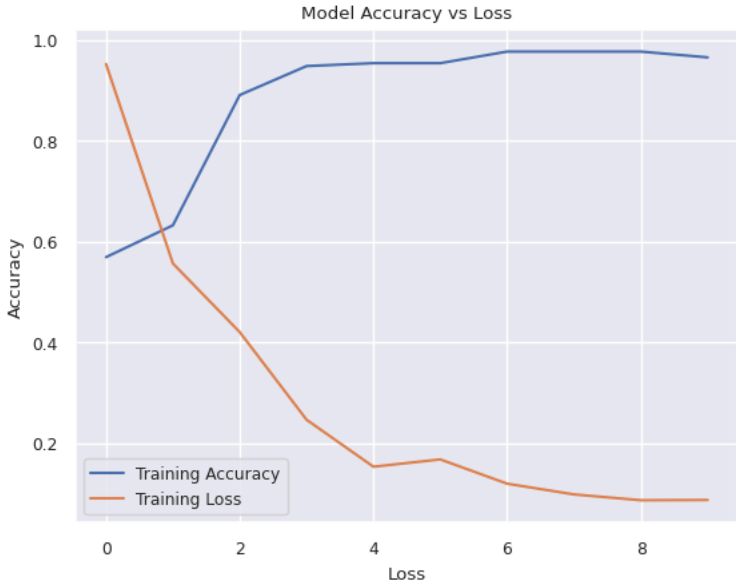
```
# Convert predictions to class labels
predicted_labels = np.argmax(predictions1, axis=1)


# Plot ROC curve
fpr, tpr, thresholds = roc_curve(Y_test, predictions1[:, 1])
plt.plot(fpr, tpr, label='ROC Curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()
plt.show()

#Print the ROC Value
roc_auc = roc_auc_score(Y_test, predictions1[:, 1])
print("ROC AUC:", roc_auc)
```




```
ROC AUC: 0.984375
```

VISUALISING THE MODEL ACCURACY AGAINST LOSS

```
#visualise the training accuracy against the loss
plt.plot(history1.history['accuracy'], label='Training Accuracy')
plt.plot(history1.history['loss'], label='Training Loss')
plt.title('Model Accuracy vs Loss')
plt.xlabel('Loss')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```



SUMMARY TWO

The CNN model's accuracy varies with each run. The model's average accuracy stands at 97.7% with a loss of 0.145, showcasing effective training with improved accuracy over time.

The confusion matrix shows predictive accuracy, with only one open heart sample misclassified as closed. High precision, recall, and F1-scores are evident in the classification report, with 98% overall accuracy and a ROC AUC of 0.984375, reflecting the model's strong discriminatory power between open and closed heart states.

CNN is a good classifier for classifying medical images or images in general

---

TASK THREE

The training set from the previous task is used to apply transfer learning and pre-trained techniques and then predicted against the test set. Also Same will applied using U-NET and performance of both models will be . CNN architecture will be used

The masks, countours and heart images will be imported for U-NET

IMAGE DATA GEN

```
#converting grayscale images to RGB format
#bringing in the training set from task 2
X_train_rgb = np.zeros((X_train.shape[0], 128, 128, 3))

# Fill the RGB channels with the grayscale values
X_train_rgb[:, :, :, 0] = X_train[:, :, :, 0]
X_train_rgb[:, :, :, 1] = X_train[:, :, :, 0]
X_train_rgb[:, :, :, 2] = X_train[:, :, :, 0]

X_test_rgb = np.zeros((X_test.shape[0], 128,128, 3))
X_test_rgb[:, :, :, 0] = X_test[:, :, :, 0]
X_test_rgb[:, :, :, 1] = X_test[:, :, :, 0]
X_test_rgb[:, :, :, 2] = X_test[:, :, :, 0]


datagen = ImageDataGenerator(

      featurewise_center=False,
      samplewise_center=False,
      featurewise_std_normalization=False,
      samplewise_std_normalization=False,
      zca_whitening=False,
      rotation_range = 30,
      zoom_range = 0.2,

      width_shift_range = 0.1,
      height_shift_range = 0.1,
      horizontal_flip = True,
      vertical_flip=False)
```

```
datagen.fit(X_train_rgb) # Adding the traing samples from task 2 to the  data gen
```

APPLICATION OF TRANSFERRED LEARNING

```
from keras.applications.vgg16 import VGG16 #(if you want to use VG16)
from keras.applications.inception_v3 import InceptionV3

# Notice 1st time this is being run, it will download the weights for the ResNet model
tf.keras.backend.clear_session()
base_model = tf.keras.applications.ResNet152V2(
    weights='imagenet',
    input_shape=(128, 128, 3),
    include_top=False)
# freeze the layers
base_model.trainable = False
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet152v2_weights_tf_dim_ordering_tf_ker
234545216/234545216 [==============================] - 6s 0us/step
```

```
#defining the pre-trained model class " get_trained"
def get_pretrained():

    #Input shape = [width, height, color channels]
    inputs = layers.Input(shape=(128,128, 3))

    x = base_model(inputs)

    # Head
    x = layers.GlobalAveragePooling2D()(x)
    x = layers.Dense(128, activation='relu')(x)
    x = layers.Dropout(0.1)(x)

    #Final Layer (Output)
    output = layers.Dense(1, activation='sigmoid')(x)

    model = tf.keras.Model(inputs=[inputs], outputs=output)

    return model
```

```
#training the model
model_pretrained = get_pretrained()
model_pretrained.compile(loss='binary_crossentropy'
              , optimizer = tf.keras.optimizers.Adam(learning_rate=0.00005), metrics='binary_accuracy')

model_pretrained.summary()
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 input_2 (InputLayer)        [(None, 128, 128, 3)]     0         
                                                                 
 resnet152v2 (Functional)    (None, 4, 4, 2048)        58331648  
                                                                 
 global_average_pooling2d (  (None, 2048)              0         
 GlobalAveragePooling2D)                                         
                                                                 
 dense (Dense)               (None, 128)               262272    
                                                                 
 dropout (Dropout)           (None, 128)               0         
                                                                 
 dense_1 (Dense)             (None, 1)                 129       
                                                                 
=================================================================
Total params: 58594049 (223.52 MB)
Trainable params: 262401 (1.00 MB)
Non-trainable params: 58331648 (222.52 MB)
_________________________________________________________________
```

Calculating the class weights

```
from sklearn.utils.class_weight import compute_class_weight
# Assuming Y_train contains label training data
# Compute class frequencies
class_labels, class_counts = np.unique(Y_train, return_counts=True)

# Compute class weights
total_samples = np.sum(class_counts)
class_weights = {class_labels[i]: total_samples / (len(class_labels) * class_counts[i]) for i in range(len(class_labels))}
```

```
# Print class weights
print("Class weights:", class_weights)
```

```
Class weights: {0: 1.359375, 1: 0.7909090909090909}
```

Calculating the learning rate reduction

```
learning_rate_reduction = ReduceLROnPlateau(monitor = 'val_accuracy', patience = 2, verbose = 1, factor = 0.3, min_lr = 0.000001)
```

```
# Split the training data into training and validation sets
X_train_partial, X_val, Y_train_partial, Y_val = train_test_split(X_train_rgb, Y_train, test_size=0.2, random_state=42)

# Train your model on the training subset
history_2 = model_pretrained.fit(
    X_train_partial, Y_train_partial,
    epochs=15,
    batch_size=32,
    validation_data=(X_val, Y_val)
)

# Evaluate the model on the validation subset
val_loss, val_accuracy = model_pretrained.evaluate(X_val, Y_val)
print("Validation accuracy:", val_accuracy)
```

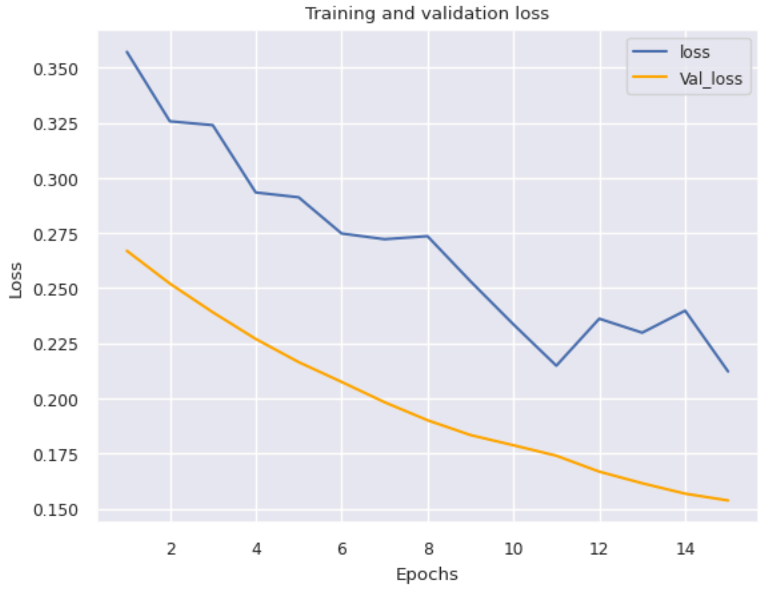
```
Epoch 1/15
5/5 [==============================] - 30s 5s/step - loss: 0.3572 - binary_accuracy: 0.8633 - val_loss: 0.2670 - val_binary_accuracy
Epoch 2/15
5/5 [==============================] - 25s 5s/step - loss: 0.3257 - binary_accuracy: 0.8921 - val_loss: 0.2521 - val_binary_accuracy
Epoch 3/15
5/5 [==============================] - 29s 6s/step - loss: 0.3239 - binary_accuracy: 0.9209 - val_loss: 0.2391 - val_binary_accuracy
Epoch 4/15
5/5 [==============================] - 33s 7s/step - loss: 0.2934 - binary_accuracy: 0.9065 - val_loss: 0.2270 - val_binary_accuracy
Epoch 5/15
5/5 [==============================] - 26s 5s/step - loss: 0.2912 - binary_accuracy: 0.9065 - val_loss: 0.2165 - val_binary_accuracy
Epoch 6/15
5/5 [==============================] - 30s 6s/step - loss: 0.2748 - binary_accuracy: 0.9353 - val_loss: 0.2075 - val_binary_accuracy
Epoch 7/15
5/5 [==============================] - 25s 5s/step - loss: 0.2722 - binary_accuracy: 0.9281 - val_loss: 0.1983 - val_binary_accuracy
Epoch 8/15
5/5 [==============================] - 28s 6s/step - loss: 0.2736 - binary_accuracy: 0.9137 - val_loss: 0.1901 - val_binary_accuracy
Epoch 9/15
5/5 [==============================] - 30s 7s/step - loss: 0.2532 - binary_accuracy: 0.9424 - val_loss: 0.1834 - val_binary_accuracy
Epoch 10/15
5/5 [==============================] - 28s 6s/step - loss: 0.2336 - binary_accuracy: 0.9424 - val_loss: 0.1788 - val_binary_accuracy
Epoch 11/15
5/5 [==============================] - 23s 5s/step - loss: 0.2149 - binary_accuracy: 0.9496 - val_loss: 0.1740 - val_binary_accuracy
Epoch 12/15
5/5 [==============================] - 23s 5s/step - loss: 0.2362 - binary_accuracy: 0.9424 - val_loss: 0.1668 - val_binary_accuracy
Epoch 13/15
5/5 [==============================] - 29s 6s/step - loss: 0.2298 - binary_accuracy: 0.9353 - val_loss: 0.1616 - val_binary_accuracy
Epoch 14/15
5/5 [==============================] - 24s 5s/step - loss: 0.2398 - binary_accuracy: 0.9424 - val_loss: 0.1568 - val_binary_accuracy
Epoch 15/15
5/5 [==============================] - 30s 6s/step - loss: 0.2122 - binary_accuracy: 0.9424 - val_loss: 0.1538 - val_binary_accuracy
2/2 [==============================] - 7s 447ms/step - loss: 0.1538 - binary_accuracy: 0.9429
Validation accuracy: 0.9428571462631226
```

```
# Evaluate model on test data from task 2
loss, accuracy = model_pretrained.evaluate(X_test_rgb, Y_test, verbose=0)
print('Loss: ', loss,'\nAcc: ', accuracy)
```

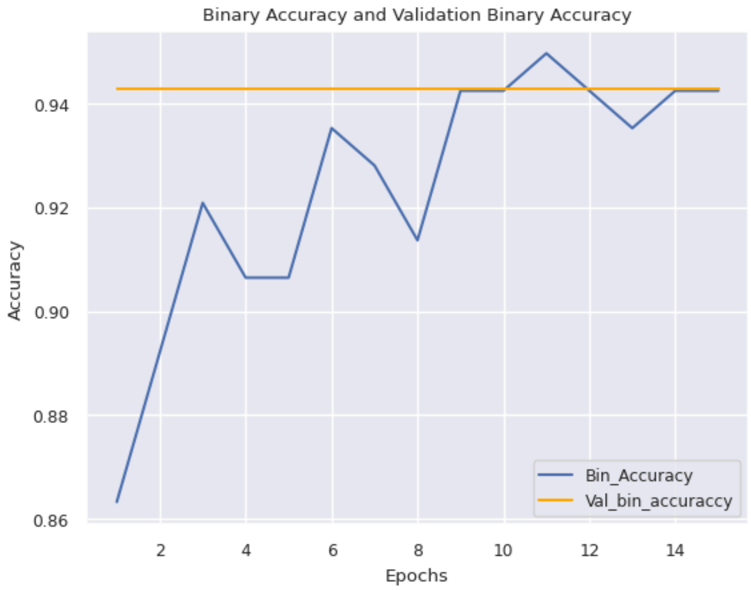
```
Loss:  0.27312496304512024
Acc:  0.9090909361839294
```

results predicted against the test shows 0.27 loss and 0.90 Accuracy

```
# Extract loss history from history_2 object
loss = history_2.history['loss']
val_loss = history_2.history['val_loss']

# Plotting the loss and validation loss
epochs = range(1, len(loss) + 1)
plt.plot(epochs, loss, 'b', label='loss')
plt.plot(epochs, val_loss, 'orange', label='Val_loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```




```
# Extract binary accuracy history from history_2 object
binary_accuracy = history_2.history['binary_accuracy']
val_binary_accuracy = history_2.history['val_binary_accuracy']

# Plotting the binary accuracy in blue and validation binary accuracy in orange
epochs = range(1, len(binary_accuracy) + 1)
plt.plot(epochs, binary_accuracy, 'b', label='Bin_Accuracy')
plt.plot(epochs, val_binary_accuracy, 'orange', label='Val_bin_accuraccy')
plt.title('Binary Accuracy and Validation Binary Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```




```
print("Loss of the model is - " , model_pretrained.evaluate(X_test_rgb,Y_test)[0])
print("Accuracy of the model is - " , model_pretrained.evaluate(X_test_rgb,Y_test)[1]*100 , "%")
```

```
2/2 [==============================] - 6s 2s/step - loss: 0.2731 - binary_accuracy: 0.9091
Loss of the model is -  0.27312496304512024
2/2 [==============================] - 7s 2s/step - loss: 0.2731 - binary_accuracy: 0.9091
Accuracy of the model is -  90.90909361839294 %
```

```
predictions = model_pretrained.predict(X_test_rgb)
pred_labels= np.where(predictions>0.5, 1, 0)
```

```
2/2 [==============================] - 11s 2s/step
```

CLASSIFICATION REPORT

```
#print classification report for CNN
cnn_report_of_each_class = classification_report(Y_test, pred_labels)
print('TRANSFER LEARNING CNN CLASSIFICATION REPORT OF HEART IMAGES')
print(cnn_report_of_each_class)
```

```
TRANSFER LEARNING CNN CLASSIFICATION REPORT OF HEART IMAGES
              precision    recall  f1-score   support

           0       0.88      0.88      0.88        16
           1       0.93      0.93      0.93        28

    accuracy                           0.91        44
   macro avg       0.90      0.90      0.90        44
weighted avg       0.91      0.91      0.91        44
```

```
cf_matrix_3 = confusion_matrix(Y_test, pred_labels)
plt.figure(figsize = (10,10))

labels = ['TN','FP','FN','TP']
labels = np.asarray(labels).reshape(2,2)

group_names = ['True Neg','False Pos','False Neg','True Pos']

group_counts = ['{0:0.0f}'.format(value) for value in
                cf_matrix_3.flatten()]
group_percentages = ['{0:.2%}'.format(value) for value in
                     cf_matrix_3.flatten()/np.sum(cf_matrix_3)]
labels = [f'{v1}\n{v2}\n{v3}' for v1, v2, v3 in
          zip(group_names,group_counts,group_percentages)]
labels = np.asarray(labels).reshape(2,2)
sns.heatmap(cf_matrix_3, annot=labels, fmt='', cmap= "YlGn",
           xticklabels = classes,yticklabels = classes)
cf_matrix_3
```

```
array([[14,  2],
       [ 2, 26]])
```

For tranfer learning the accuracy was approx 91%, meaning some samples wwould have been classified wrongly. 2 Open hearts classified has closed and 2 closed hearts classified as open.

FINE TUNING THE MODEL

Fine tuning the model with the same architecture to see if the performance will be better.

```
#Fine tunning
base_model.trainable = True

# Retrain the last 5 layers (all lower layers will be kept frozen)
for layer in base_model.layers[:-5]:
    layer.trainable = False


model_pretrained.compile(loss='binary_crossentropy'
              , optimizer = tf.keras.optimizers.Adam(learning_rate=0.000005), metrics='binary_accuracy')

model_pretrained.summary()
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_2 (InputLayer)        [(None, 128, 128, 3)]     0

 resnet152v2 (Functional)    (None, 4, 4, 2048)        58331648

 global_average_pooling2d (  (None, 2048)              0
 GlobalAveragePooling2D)

 dense (Dense)               (None, 128)               262272

 dropout (Dropout)           (None, 128)               0

 dense_1 (Dense)             (None, 1)                 129

=================================================================
Total params: 58594049 (223.52 MB)
Trainable params: 1317121 (5.02 MB)
Non-trainable params: 57276928 (218.49 MB)
_________________________________________________________________
```

```
# Train your model on the training subset
history_ft = model_pretrained.fit(
    X_train_partial, Y_train_partial,
    epochs=15,
    batch_size=32,
    validation_data=(X_val, Y_val)
)

# Evaluate the model on the validation subset
val_loss, val_accuracy = model_pretrained.evaluate(X_val, Y_val)
print("Validation accuracy:", val_accuracy)
```

```
Epoch 1/15
5/5 [==============================] - 48s 8s/step - loss: 0.3759 - binary_accuracy: 0.9496 - val_loss: 0.1597 - val_binary_accuracy
Epoch 2/15
5/5 [==============================] - 27s 6s/step - loss: 0.3604 - binary_accuracy: 0.9568 - val_loss: 0.1677 - val_binary_accuracy
Epoch 3/15
5/5 [==============================] - 34s 7s/step - loss: 0.3497 - binary_accuracy: 0.9496 - val_loss: 0.1745 - val_binary_accuracy
Epoch 4/15
5/5 [==============================] - 35s 8s/step - loss: 0.3437 - binary_accuracy: 0.9424 - val_loss: 0.1811 - val_binary_accuracy
Epoch 5/15
5/5 [==============================] - 27s 5s/step - loss: 0.3293 - binary_accuracy: 0.9424 - val_loss: 0.1873 - val_binary_accuracy
Epoch 6/15
5/5 [==============================] - 38s 8s/step - loss: 0.3157 - binary_accuracy: 0.9496 - val_loss: 0.1928 - val_binary_accuracy
Epoch 7/15
5/5 [==============================] - 31s 7s/step - loss: 0.3104 - binary_accuracy: 0.9568 - val_loss: 0.1975 - val_binary_accuracy
Epoch 8/15
5/5 [==============================] - 27s 6s/step - loss: 0.3093 - binary_accuracy: 0.9568 - val_loss: 0.2013 - val_binary_accuracy
Epoch 9/15
5/5 [==============================] - 36s 8s/step - loss: 0.2833 - binary_accuracy: 0.9568 - val_loss: 0.2036 - val_binary_accuracy
Epoch 10/15
5/5 [==============================] - 30s 6s/step - loss: 0.2909 - binary_accuracy: 0.9424 - val_loss: 0.2047 - val_binary_accuracy
Epoch 11/15
5/5 [==============================] - 33s 6s/step - loss: 0.2724 - binary_accuracy: 0.9640 - val_loss: 0.2059 - val_binary_accuracy
Epoch 12/15
5/5 [==============================] - 26s 5s/step - loss: 0.2561 - binary_accuracy: 0.9496 - val_loss: 0.2071 - val_binary_accuracy
Epoch 13/15
5/5 [==============================] - 26s 5s/step - loss: 0.2571 - binary_accuracy: 0.9496 - val_loss: 0.2072 - val_binary_accuracy
Epoch 14/15
5/5 [==============================] - 29s 6s/step - loss: 0.2500 - binary_accuracy: 0.9640 - val_loss: 0.2067 - val_binary_accuracy
Epoch 15/15
5/5 [==============================] - 29s 6s/step - loss: 0.2492 - binary_accuracy: 0.9640 - val_loss: 0.2059 - val_binary_accuracy
```

```
2/2 [==============================] - 5s 712ms/step - loss: 0.2059 - binary_accuracy: 0.9714
Validation accuracy: 0.9714285731315613
```

```
print("Loss of the model is - " , model_pretrained.evaluate(X_test_rgb,Y_test)[0])
print("Accuracy of the model is - " , model_pretrained.evaluate(X_test_rgb,Y_test)[1]*100 , "%")
```

```
2/2 [==============================] - 7s 2s/step - loss: 0.2860 - binary_accuracy: 0.9091
Loss of the model is -  0.2860245406627655
2/2 [==============================] - 5s 1s/step - loss: 0.2860 - binary_accuracy: 0.9091
Accuracy of the model is -  90.90909361839294 %
```

```
predictions2 = model_pretrained.predict(X_test_rgb)
pred_labels2= np.where(predictions>0.5, 1, 0)
```

```
2/2 [==============================] - 10s 2s/step
```

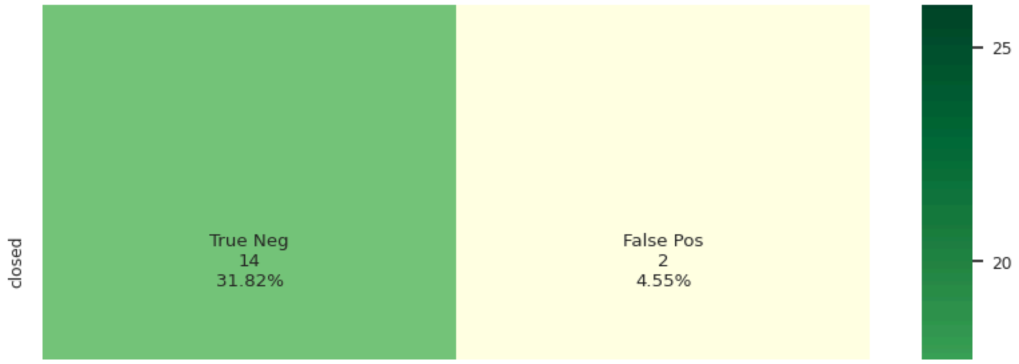
CLASSIFICATION REPORT

```
cnn_report_of_each_class1 = classification_report(Y_test, pred_labels2)
print('FINE TUNING- CNN CLASSIFICATION REPORT OF HEART IMAGES')
print(cnn_report_of_each_class1)
```

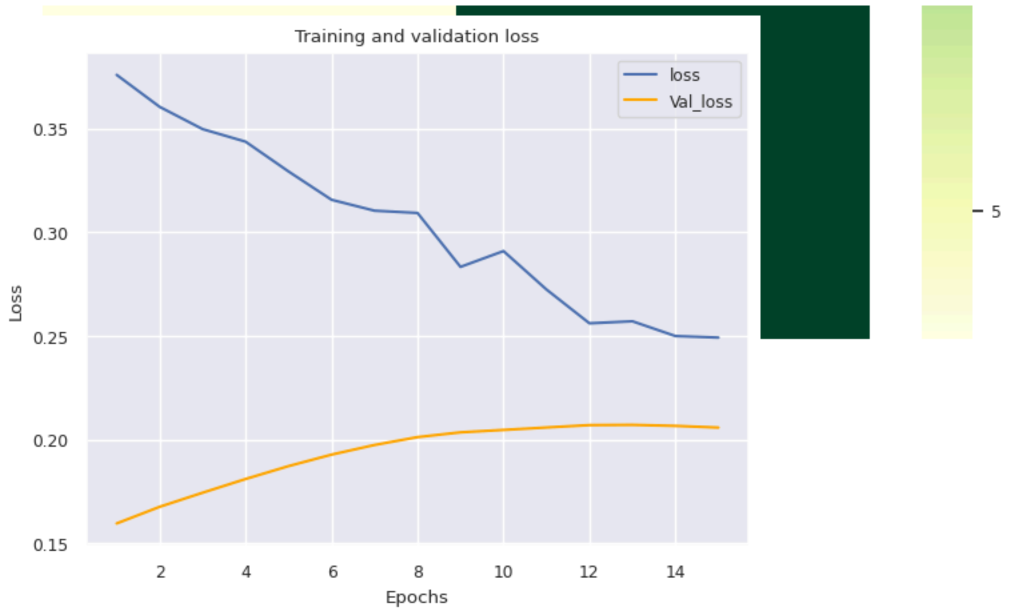
```
FINE TUNING- CNN CLASSIFICATION REPORT OF HEART IMAGES
              precision    recall  f1-score   support

           0       0.88      0.88      0.88        16
           1       0.93      0.93      0.93        28

    accuracy                           0.91        44
   macro avg       0.90      0.90      0.90        44
weighted avg       0.91      0.91      0.91        44
```

```
cf_matrix_ft = confusion_matrix(Y_test, pred_labels2)
plt.figure(figsize = (10,10))

labels = ['TN','FP','FN','TP']
labels = np.asarray(labels).reshape(2,2)

group_names = ['True Neg','False Pos','False Neg','True Pos']

group_counts = ['{0:0.0f}'.format(value) for value in
                cf_matrix_ft.flatten()]
group_percentages = ['{0:.2%}'.format(value) for value in
                     cf_matrix_ft.flatten()/np.sum(cf_matrix_3)]
labels = [f'{v1}\n{v2}\n{v3}' for v1, v2, v3 in
          zip(group_names,group_counts,group_percentages)]
labels = np.asarray(labels).reshape(2,2)
sns.heatmap(cf_matrix_ft, annot=labels, fmt='', cmap= "YlGn",
           xticklabels = classes,yticklabels = classes)
cf_matrix_ft
```

```
array([[14,  2],
       [ 2, 26]])
```




```
# Extract loss history from history_ft object
loss = history_ft.history['loss']
val_loss = history_ft.history['val_loss']

# Plotting the loss and validation loss
epochs = range(1, len(loss) + 1)
plt.plot(epochs, loss, 'b', label='loss')
plt.plot(epochs, val_loss, 'orange', label='Val_loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```




```
# Extract binary accuracy history from history_ft object
binary_accuracy = history_ft.history['binary_accuracy']
val_binary_accuracy = history_ft.history['val_binary_accuracy']

# Plotting the binary accuracy in blue and validation binary accuracy in orange
epochs = range(1, len(binary_accuracy) + 1)
```