Cat vs Dod Audio Claaification using Mfccs

- 1: Extracting data into Dataframe (Train/Test)
- 2: Feature Extraction using MFccs and librosa module
- 3: Train test data creation
- 4: Modle building and training
- 5: Visualisations

```
import pandas as pd
import numpy as np
import os
import tensorflow as tf
import librosa.display
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder,OneHotEncoder
import tensorflow.keras.layers as layers
from sklearn.metrics import confusion_matrix,classification_report,accuracy_s
In [6]: pud
```

pwd

Out [6]: pwd

'/home/honey/Desktop/Vidyashilp-Assignment/Taskl'

Out[6]: /nome/noney/besktop/vidyashitp-Assignment/raski

1: Extracting data into Dataframe (Train/Test)

```
In [17]:
          #Function to generate the train data
          def generate_Train_data(directory):
              names = []
              label names = []
              for folder in os.listdir(directory):
                  #for each folder in cat and dog get the respective files
                  for filename in os.listdir(directory + '/' + str(folder)):
                      #for each file
                      f = os.path.join(directory + '/' + str(folder), filename)
                      names.append(f.split('/')[-1])
                      label_names.append(f.split('/')[-2])
              return names, label_names
          def generate_Test_data(directory):
              #test data creator
              names=[]
              label names=[]
              for folder in os.listdir(directory):
                  #print("folder = ", folder)
                  for filename in os.listdir(directory + '/' + str(folder)):
                      f = os.path.join(directory + '/' + str(folder), filename)
                      names.append(f.split('/')[-1])
                      label names.append(f.split('/')[-2])
```

```
for i in range(len(label)):
    if(label[i]=='test'):
        label[i]='dogs'

    return names, label_names
In [18]: #calling the above function to generate train and test data
```

```
#calling the above function to generate train and test data
name, label = generate_Train_data('input/cats_dogs/train')
Tname, Tlabel = generate_Test_data('input/cats_dogs/test')
train_data = pd.DataFrame({'name': name, 'label': label})
test_data = pd.DataFrame({'name': Tname, 'label': Tlabel})
```

2: Feature Extraction using MFccs and librosa module

```
In [24]:
          def get_features(directory):
              features=[]
              names=[]
              #loop through the folder
              for folder in os.listdir(directory):
                  #print("folder = ", folder)
                  for filename in os.listdir(directory+ '/' + str(folder)):
                      f = os.path.join(directory + '/' + str(folder), filename)
                      #useing librosa we get the required audio format
                      x,sr = librosa.load(f,sr=None)
                      #extracted x is used to get mfccs as using librosa's feature.mfcd
                      mfccs= np.mean(librosa.feature.mfcc(x,sr=sr,n mfcc=100).T,axis=0)
                      features.append(mfccs)
                      names.append(f.split('/')[-1])
              return [names, features]
In [47]:
          names, train features = get features('input/cats dogs/train')
          T names, test features = get features('input/cats dogs/test')
In [31]:
          print("train_features = ", len(train_features))
         train features = 210
```

3: Train test data creation

```
In [32]: #creating trainig and testing dataset using the feature extracted
    X_train =np.array(train_features)
    X_test =np.array(test_features)
    Y_train=train_data.label
    Y_test=test_data.label

In [33]: Y_train=LabelEncoder().fit_transform(Y_train).reshape(-1,1)
    Y_test =LabelEncoder().fit_transform(Y_test).reshape(-1,1)

print("Y_train_shape = ", Y_train.shape)
    print("Y_test_shape = ", Y_train.shape)
    print("X_train_shape = ", X_train.shape)
    print("Y_test_shape = ", X_train.shape)
    print("Y_test_shape = ", X_train.shape)
```

```
Y_train shape = (210, 1)
Y_test shape = (67, 1)
X_train shape = (210, 100)
Y_test shape = (67, 100)
```

```
4: Modle building and training
In [51]:
         def build model():
             model=tf.keras.Sequential()
             model.add(layers.Dense(input shape=(100,), units= 200,activation='relu'))
             model.add(layers.Dense(150,activation='relu'))
             model.add(layers.Dense(200,activation='relu'))
             model.add(layers.Dense(1,activation='sigmoid'))
             return model
         def build model2():
             model=tf.keras.Sequential()
             model.add(layers.Dense(input shape=(100,), units= 200,activation='relu'))
             model.add(layers.Dense(25,activation='relu'))
             model.add(layers.Dense(25,activation='relu'))
             model.add(layers.Dense(1,activation='sigmoid'))
             return model
In [53]:
         model = build model()
         model2 = build model2()
         model.summary()
         model.compile(optimizer='sqd',loss='binary crossentropy',metrics=['accuracy']
         hist=model.fit(X train,Y train,epochs=100,validation data = (X test,Y test))
         Model: "sequential 4"
         Layer (type)
                                    Output Shape
                                                             Param #
         dense 16 (Dense)
                                    (None, 200)
                                                             20200
         dense 17 (Dense)
                                    (None, 150)
                                                             30150
                                    (None, 200)
         dense 18 (Dense)
                                                             30200
                                                             201
        dense_19 (Dense)
                                    (None, 1)
         Total params: 80,751
        Trainable params: 80,751
        Non-trainable params: 0
         Epoch 1/100
         7/7 [======
                                 =======] - 1s 143ms/step - loss: 29.3328 - accura
         cy: 0.6143 - val loss: 2.3882 - val accuracy: 0.4179
         Epoch 2/100
```

0.6286 - val_loss: 0.5220 - val_accuracy: 0.7612

0.8000 - val_loss: 0.4511 - val_accuracy: 0.8209

0.7571 - val_loss: 0.5065 - val_accuracy: 0.7164

```
localhost:8888/lab/tree/Task1/Main-Copy1.ipynb
```

Epoch 3/100

Epoch 4/100

Epoch 5/100

```
7/7 [==========] - 0s 4ms/step - loss: 0.4478 - accuracy:
0.8190 - val loss: 0.5619 - val accuracy: 0.6119
Epoch 6/100
0.7524 - val loss: 0.3780 - val accuracy: 0.8358
Epoch 7/100
0.8714 - val loss: 0.3920 - val accuracy: 0.8358
Epoch 8/100
0.8048 - val loss: 0.3714 - val accuracy: 0.8657
Epoch 9/100
0.8714 - val_loss: 0.3236 - val_accuracy: 0.8657
Epoch 10/100
0.8619 - val loss: 0.3233 - val accuracy: 0.8806
Epoch 11/100
0.8857 - val loss: 0.4864 - val accuracy: 0.7313
Epoch 12/100
0.8476 - val loss: 0.2897 - val accuracy: 0.9104
Epoch 13/100
0.8762 - val loss: 0.6202 - val accuracy: 0.7612
Epoch 14/100
0.8524 - val loss: 0.3341 - val accuracy: 0.8657
Epoch 15/100
0.8810 - val loss: 0.4378 - val accuracy: 0.8209
Epoch 16/100
0.8333 - val loss: 0.3134 - val accuracy: 0.8806
Epoch 17/100
0.9000 - val loss: 0.3266 - val accuracy: 0.8657
Epoch 18/100
0.8333 - val loss: 0.3177 - val accuracy: 0.8955
Epoch 19/100
0.8857 - val_loss: 0.4002 - val_accuracy: 0.8358
Epoch 20/100
0.9048 - val loss: 0.2937 - val accuracy: 0.8955
Epoch 21/100
0.7952 - val_loss: 0.3258 - val_accuracy: 0.8955
Epoch 22/100
0.8952 - val loss: 0.3015 - val accuracy: 0.8806
Epoch 23/100
0.9095 - val loss: 0.2973 - val accuracy: 0.9254
Epoch 24/100
0.9190 - val loss: 0.4888 - val accuracy: 0.7015
Epoch 25/100
0.9190 - val_loss: 0.2789 - val_accuracy: 0.8955
Epoch 26/100
0.8667 - val_loss: 0.3113 - val_accuracy: 0.8657
```

```
Epoch 27/100
0.8667 - val loss: 0.4107 - val accuracy: 0.8209
Epoch 28/100
0.9095 - val loss: 0.5170 - val accuracy: 0.6866
Epoch 29/100
0.8810 - val loss: 0.2804 - val_accuracy: 0.9104
Epoch 30/100
0.9429 - val loss: 0.3024 - val accuracy: 0.8657
Epoch 31/100
0.9429 - val loss: 0.3331 - val accuracy: 0.8507
Epoch 32/100
0.8810 - val loss: 0.2928 - val accuracy: 0.8955
Epoch 33/100
0.9381 - val loss: 0.4645 - val accuracy: 0.8060
Epoch 34/100
0.9000 - val loss: 0.2895 - val accuracy: 0.8955
Epoch 35/100
0.9286 - val loss: 0.2785 - val accuracy: 0.8657
Epoch 36/100
0.9524 - val loss: 0.2231 - val accuracy: 0.9254
Epoch 37/100
7/7 [=========================== ] - 0s 4ms/step - loss: 0.1926 - accuracy:
0.9190 - val loss: 1.1845 - val accuracy: 0.6567
Epoch 38/100
0.9048 - val loss: 0.3504 - val accuracy: 0.8507
Epoch 39/100
0.8905 - val loss: 0.3556 - val accuracy: 0.8358
Epoch 40/100
0.9571 - val_loss: 0.2720 - val_accuracy: 0.9104
Epoch 41/100
0.9619 - val_loss: 0.2577 - val_accuracy: 0.9254
Epoch 42/100
0.8857 - val loss: 0.2926 - val accuracy: 0.8806
Epoch 43/100
0.8905 - val_loss: 0.3883 - val_accuracy: 0.8358
Epoch 44/100
0.9333 - val_loss: 0.3409 - val_accuracy: 0.8507
Epoch 45/100
0.9476 - val_loss: 0.3084 - val_accuracy: 0.8657
Epoch 46/100
0.9667 - val loss: 0.2818 - val accuracy: 0.9104
Epoch 47/100
0.9667 - val loss: 0.2647 - val accuracy: 0.9104
Epoch 48/100
```

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0.9571 - val_loss: 0.3107 - val_accuracy: 0.8657
Epoch 49/100
0.8952 - val loss: 0.3925 - val accuracy: 0.8060
Epoch 50/100
0.9476 - val loss: 0.2462 - val accuracy: 0.9104
Epoch 51/100
0.9667 - val loss: 0.2274 - val accuracy: 0.8955
Epoch 52/100
0.9667 - val loss: 0.2860 - val accuracy: 0.8806
Epoch 53/100
0.9429 - val loss: 0.2409 - val accuracy: 0.9104
Epoch 54/100
0.9095 - val loss: 0.2901 - val accuracy: 0.9104
Epoch 55/100
0.9333 - val loss: 0.2793 - val accuracy: 0.8657
Epoch 56/100
0.9762 - val loss: 0.2360 - val accuracy: 0.8955
Epoch 57/100
0.9095 - val loss: 0.4769 - val accuracy: 0.7612
Epoch 58/100
0.8571 - val loss: 0.2978 - val accuracy: 0.9104
Epoch 59/100
0.9476 - val loss: 0.2534 - val accuracy: 0.9104
Epoch 60/100
0.9333 - val loss: 0.2307 - val accuracy: 0.9104
Epoch 61/100
0.9429 - val loss: 0.4208 - val accuracy: 0.8209
Epoch 62/100
0.9333 - val_loss: 0.2262 - val_accuracy: 0.9104
Epoch 63/100
0.9667 - val loss: 0.2264 - val accuracy: 0.9254
Epoch 64/100
7/7 [=============== ] - 0s 4ms/step - loss: 0.0972 - accuracy:
0.9762 - val loss: 0.5093 - val accuracy: 0.7612
Epoch 65/100
0.8810 - val_loss: 0.3179 - val_accuracy: 0.8955
Epoch 66/100
0.9476 - val_loss: 0.3413 - val_accuracy: 0.8507
Epoch 67/100
0.9714 - val_loss: 0.2732 - val_accuracy: 0.8955
Epoch 68/100
0.9667 - val loss: 0.2276 - val accuracy: 0.9254
Epoch 69/100
0.9571 - val_loss: 0.2312 - val_accuracy: 0.9104
Epoch 70/100
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0.9714 - val loss: 0.2465 - val accuracy: 0.9104
Epoch 71/100
0.9857 - val loss: 0.2221 - val accuracy: 0.9254
Epoch 72/100
0.9857 - val loss: 0.3288 - val accuracy: 0.8806
Epoch 73/100
0.9619 - val loss: 0.2801 - val accuracy: 0.9104
Epoch 74/100
0.9190 - val_loss: 0.3365 - val_accuracy: 0.8657
Epoch 75/100
0.9238 - val loss: 0.2433 - val accuracy: 0.9104
Epoch 76/100
0.9810 - val loss: 0.3222 - val accuracy: 0.8358
Epoch 77/100
0.9762 - val loss: 0.2314 - val accuracy: 0.9254
Epoch 78/100
0.9429 - val loss: 0.2790 - val accuracy: 0.8955
Epoch 79/100
0.9714 - val loss: 0.2248 - val accuracy: 0.9254
Epoch 80/100
0.9762 - val loss: 0.7340 - val accuracy: 0.8060
Epoch 81/100
0.9095 - val loss: 0.4483 - val accuracy: 0.8060
Epoch 82/100
0.9762 - val loss: 0.2551 - val accuracy: 0.9254
Epoch 83/100
0.9619 - val loss: 0.2805 - val accuracy: 0.8955
Epoch 84/100
0.9857 - val_loss: 0.2901 - val_accuracy: 0.9104
Epoch 85/100
0.9905 - val loss: 0.3039 - val accuracy: 0.8806
Epoch 86/100
0.9619 - val loss: 0.2969 - val accuracy: 0.9104
Epoch 87/100
0.9952 - val loss: 0.2868 - val accuracy: 0.9104
Epoch 88/100
0.9524 - val loss: 0.2760 - val accuracy: 0.9104
Epoch 89/100
0.9810 - val loss: 0.3516 - val accuracy: 0.8209
Epoch 90/100
0.9429 - val_loss: 0.2806 - val_accuracy: 0.9104
Epoch 91/100
0.9667 - val_loss: 0.2635 - val_accuracy: 0.9254
```

```
Epoch 92/100
    0.9857 - val loss: 0.2550 - val accuracy: 0.9104
    Epoch 93/100
    0.9857 - val loss: 0.2568 - val accuracy: 0.9403
    Epoch 94/100
    0.9857 - val loss: 0.3107 - val accuracy: 0.8358
    Epoch 95/100
    0.9286 - val loss: 0.2956 - val accuracy: 0.9254
    Epoch 96/100
    0.9810 - val loss: 0.2915 - val accuracy: 0.9104
    Epoch 97/100
    7/7 [=============== ] - 0s 4ms/step - loss: 0.1022 - accuracy:
    0.9667 - val loss: 0.2221 - val accuracy: 0.9403
    Epoch 98/100
    0.9857 - val_loss: 0.2791 - val accuracy: 0.9104
    Epoch 99/100
    0.9905 - val loss: 0.2343 - val accuracy: 0.9254
    Epoch 100/100
    0.9905 - val loss: 0.2955 - val accuracy: 0.8507
In [54]:
     model2.compile(optimizer='adam',loss='binary_crossentropy',metrics=['accuracy
     hist2=model.fit(X train,Y train,epochs=100,validation data = (X test,Y test))
    Epoch 1/100
    0.9714 - val loss: 0.4927 - val accuracy: 0.7761
    Epoch 2/100
    0.9952 - val loss: 0.2975 - val accuracy: 0.8955
    Epoch 3/100
    0.9667 - val loss: 0.3203 - val accuracy: 0.8806
    Epoch 4/100
    0.9857 - val loss: 0.2508 - val accuracy: 0.9254
    Epoch 5/100
    0.9905 - val_loss: 0.3387 - val_accuracy: 0.8507
    Epoch 6/100
    0.9905 - val loss: 0.2850 - val accuracy: 0.9254
    Epoch 7/100
                  =======] - Os 4ms/step - loss: 0.0432 - accuracy:
    7/7 [=========
    0.9952 - val loss: 0.3027 - val accuracy: 0.8507
    Epoch 8/100
    0.9333 - val loss: 0.3764 - val_accuracy: 0.8358
    Epoch 9/100
    0.9571 - val_loss: 0.3132 - val_accuracy: 0.8806
    Epoch 10/100
    0.9714 - val_loss: 0.2487 - val_accuracy: 0.9254
    Epoch 11/100
    0.9952 - val loss: 0.2623 - val accuracy: 0.9104
```

```
Epoch 12/100
0.9810 - val loss: 0.2826 - val accuracy: 0.9254
Epoch 13/100
0.9714 - val loss: 0.3058 - val accuracy: 0.9254
Epoch 14/100
0.9905 - val loss: 1.1377 - val_accuracy: 0.6119
Epoch 15/100
0.9000 - val loss: 0.3372 - val accuracy: 0.8657
Epoch 16/100
0.9810 - val loss: 0.3736 - val accuracy: 0.8806
Epoch 17/100
0.8905 - val loss: 0.3380 - val accuracy: 0.8657
Epoch 18/100
0.9810 - val loss: 0.2620 - val accuracy: 0.9104
Epoch 19/100
0.9667 - val loss: 0.3538 - val accuracy: 0.8657
Epoch 20/100
7/7 [============== ] - Os 3ms/step - loss: 0.0620 - accuracy:
0.9857 - val loss: 0.2788 - val accuracy: 0.9104
Epoch 21/100
0.9762 - val loss: 0.2839 - val accuracy: 0.9104
Epoch 22/100
0.9952 - val loss: 0.2996 - val accuracy: 0.9104
Epoch 23/100
0.9810 - val loss: 0.2809 - val accuracy: 0.8955
Epoch 24/100
0.9857 - val loss: 0.3154 - val accuracy: 0.8806
Epoch 25/100
0.9857 - val_loss: 0.3112 - val_accuracy: 0.8806
Epoch 26/100
0.9905 - val_loss: 0.3117 - val_accuracy: 0.8955
Epoch 27/100
0.9810 - val loss: 0.2966 - val accuracy: 0.9104
Epoch 28/100
0.9905 - val_loss: 0.3096 - val_accuracy: 0.9104
Epoch 29/100
0.9905 - val_loss: 0.3307 - val_accuracy: 0.9104
Epoch 30/100
0.9952 - val_loss: 0.3016 - val_accuracy: 0.8955
Epoch 31/100
0.9952 - val loss: 0.2812 - val accuracy: 0.9104
Epoch 32/100
0.9619 - val loss: 0.3555 - val accuracy: 0.8955
Epoch 33/100
```

```
0.9524 - val_loss: 0.2482 - val_accuracy: 0.9254
Epoch 34/100
0.9714 - val loss: 0.2781 - val accuracy: 0.9254
Epoch 35/100
0.9905 - val loss: 0.2884 - val accuracy: 0.8955
Epoch 36/100
0.9952 - val loss: 0.3285 - val_accuracy: 0.8806
Epoch 37/100
0.9952 - val loss: 0.2942 - val accuracy: 0.9254
Epoch 38/100
0.9857 - val loss: 0.7950 - val accuracy: 0.7164
Epoch 39/100
0.9429 - val loss: 0.3103 - val accuracy: 0.9104
Epoch 40/100
0.9905 - val loss: 0.4597 - val accuracy: 0.8358
Epoch 41/100
0.9619 - val loss: 0.3254 - val accuracy: 0.8955
Epoch 42/100
0.9905 - val loss: 0.3007 - val accuracy: 0.9104
Epoch 43/100
1.0000 - val loss: 0.3226 - val accuracy: 0.9104
Epoch 44/100
0.9952 - val loss: 0.3243 - val accuracy: 0.9104
Epoch 45/100
0.9952 - val loss: 0.2911 - val accuracy: 0.8955
Epoch 46/100
0.9952 - val loss: 0.3272 - val accuracy: 0.9104
Epoch 47/100
0.9952 - val_loss: 0.3151 - val_accuracy: 0.9254
Epoch 48/100
7/7 [=============== ] - 0s 5ms/step - loss: 0.0407 - accuracy:
0.9810 - val loss: 0.3993 - val accuracy: 0.8955
Epoch 49/100
0.9905 - val loss: 0.3300 - val accuracy: 0.9104
Epoch 50/100
0.9905 - val_loss: 0.3662 - val_accuracy: 0.8806
Epoch 51/100
0.9762 - val_loss: 0.9515 - val_accuracy: 0.7015
Epoch 52/100
0.8952 - val_loss: 0.2424 - val_accuracy: 0.9552
Epoch 53/100
0.9619 - val loss: 0.2826 - val accuracy: 0.9104
Epoch 54/100
0.9810 - val loss: 0.2760 - val accuracy: 0.9104
Epoch 55/100
```

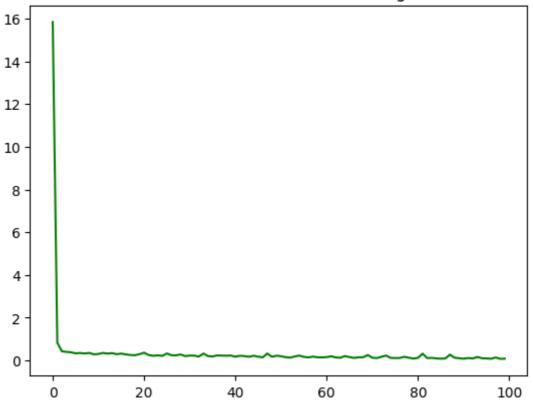
```
0.9952 - val loss: 0.2913 - val accuracy: 0.9104
Epoch 56/100
0.9952 - val loss: 0.3319 - val accuracy: 0.8657
Epoch 57/100
0.9905 - val loss: 0.4461 - val accuracy: 0.7910
Epoch 58/100
0.9762 - val loss: 0.2887 - val accuracy: 0.8955
Epoch 59/100
0.9905 - val_loss: 0.3894 - val_accuracy: 0.8657
Epoch 60/100
7/7 [=============== ] - 0s 5ms/step - loss: 0.0239 - accuracy:
1.0000 - val loss: 0.3274 - val accuracy: 0.9104
Epoch 61/100
0.9810 - val loss: 0.3839 - val accuracy: 0.8507
Epoch 62/100
0.9762 - val loss: 0.2876 - val accuracy: 0.9104
Epoch 63/100
0.9952 - val loss: 0.3314 - val accuracy: 0.8358
Epoch 64/100
0.9905 - val loss: 0.3580 - val accuracy: 0.9254
Epoch 65/100
0.9857 - val loss: 0.3287 - val accuracy: 0.9104
Epoch 66/100
0.9952 - val loss: 0.3264 - val accuracy: 0.9104
Epoch 67/100
0.9905 - val loss: 0.3387 - val accuracy: 0.8955
Epoch 68/100
0.9905 - val loss: 0.4784 - val accuracy: 0.8358
Epoch 69/100
0.9714 - val_loss: 0.3411 - val_accuracy: 0.9104
Epoch 70/100
0.9952 - val loss: 0.3523 - val accuracy: 0.9104
Epoch 71/100
1.0000 - val_loss: 0.3521 - val_accuracy: 0.8955
Epoch 72/100
0.9857 - val loss: 0.3918 - val accuracy: 0.8806
Epoch 73/100
0.9905 - val loss: 0.3447 - val accuracy: 0.8955
Epoch 74/100
0.9857 - val loss: 0.3899 - val accuracy: 0.8358
Epoch 75/100
1.0000 - val_loss: 0.3333 - val_accuracy: 0.9104
Epoch 76/100
0.9857 - val_loss: 0.3347 - val_accuracy: 0.9104
```

```
Epoch 77/100
0.9952 - val loss: 0.3223 - val accuracy: 0.9104
Epoch 78/100
1.0000 - val loss: 0.3413 - val accuracy: 0.9104
Epoch 79/100
0.9952 - val loss: 0.2920 - val_accuracy: 0.9104
Epoch 80/100
0.9952 - val loss: 0.3533 - val accuracy: 0.9104
Epoch 81/100
1.0000 - val loss: 0.3403 - val accuracy: 0.9104
Epoch 82/100
1.0000 - val loss: 0.3586 - val accuracy: 0.9104
Epoch 83/100
0.9952 - val loss: 0.3538 - val accuracy: 0.9104
Epoch 84/100
1.0000 - val loss: 0.3530 - val accuracy: 0.9104
Epoch 85/100
1.0000 - val loss: 0.3652 - val accuracy: 0.8955
Epoch 86/100
1.0000 - val loss: 0.3664 - val accuracy: 0.9104
Epoch 87/100
1.0000 - val loss: 0.3556 - val accuracy: 0.8955
Epoch 88/100
1.0000 - val loss: 0.3583 - val accuracy: 0.9104
Epoch 89/100
1.0000 - val loss: 0.3635 - val accuracy: 0.9104
Epoch 90/100
1.0000 - val_loss: 0.3388 - val_accuracy: 0.9104
Epoch 91/100
1.0000 - val_loss: 0.3618 - val_accuracy: 0.9104
Epoch 92/100
7/7 [=============== ] - 0s 5ms/step - loss: 0.0113 - accuracy:
1.0000 - val loss: 0.3415 - val accuracy: 0.9104
Epoch 93/100
1.0000 - val_loss: 0.3650 - val_accuracy: 0.9104
Epoch 94/100
1.0000 - val_loss: 0.3654 - val_accuracy: 0.9104
Epoch 95/100
1.0000 - val_loss: 0.3655 - val_accuracy: 0.9104
Epoch 96/100
1.0000 - val loss: 0.3618 - val accuracy: 0.9104
Epoch 97/100
1.0000 - val loss: 0.3925 - val accuracy: 0.8955
Epoch 98/100
```

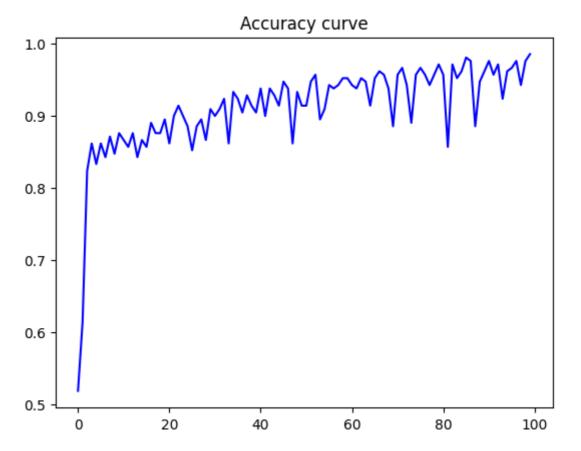
5: Visualisations

```
plt.title('loss function curve for training')
plt.plot(hist.history['loss'],color='green')
plt.show()
```

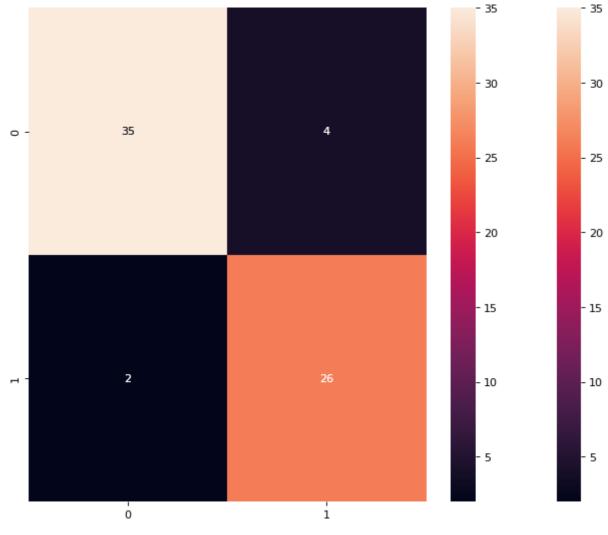
loss function curve for training



```
plt.title('Accuracy curve')
plt.plot(hist.history['accuracy'],color='blue')
plt.show()
```



```
In [46]:
    Y_predicted =model.predict(X_test)
    #masking if greater than 0.5
    Y_predicted =(Y_predicted>0.5)*1
    sns.heatmap(confusion_matrix(Y_test,Y_predicted),annot=True,)
    plt.show()
```



In []:	
In []:	

19/11/2021, 03:30 Main-Copy1 In []: In [42]: plt.figure(figsize=(10,8),dpi=80) sns.heatmap(confusion_matrix(Y_test,Y_pred),annot=True,cmap='Blues') plt.title('1 signifies dog sounds and 0 signifies cat sounds \n'+'Accuracy:'+ plt.show() NameError Traceback (most recent call last) <ipython-input-42-38fb401baffb> in <module> 1 plt.figure(figsize=(10,8),dpi=80) -> 2 sns.heatmap(confusion_matrix(Y_test,Y_pred),annot=True,cmap='Blues') 3 plt.title('1 signifies dog sounds and 0 signifies cat sounds \n'+'Acc uracy: '+str(accuracy_score(Y_test,Y_pred))) 4 plt.show() NameError: name 'Y_pred' is not defined In []: