In [3]:

```
!pip list
```

```
Package                         Version

WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\minicon
da3\lib\site-packages)
WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\minicon
da3\lib\site-packages)
WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\minicon
da3\lib\site-packages)
WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\minicon
da3\lib\site-packages)


------------------------------- -----------
absl-py                         1.4.0
aiobotocore                     2.5.0
aiohttp                         3.8.4
aioitertools                    0.11.0
aiosignal                       1.3.1
anyio                           3.6.2
argon2-cffi                     21.3.0
```

In [168]:

```
import pandas as pd
```

In [169]:

```
masses_data = pd.read_csv('C:/Users/Amrita/Downloads/mammographic_masses.data.txt')
```

In [170]:

```

masses_data.head()
```

Out[170]:

	5	67	3	5.1	3.1	1
0	4	43	1	1	?	1
1	5	58	4	5	3	1
2	4	28	1	1	3	0
3	5	74	1	5	?	1
4	4	65	1	?	3	0

In [171]:

```
masses_data.describe()
```

Out[171]:

	1
count	960.000000
mean	0.462500
std	0.498852
min	0.000000
25%	0.000000
50%	0.000000
75%	1.000000
max	1.000000

In [172]:

```
#using the optional parmaters in read_csv to convert missing data  into NaN, and to add
```

In [173]:

```
masses_data = pd.read_csv('mammographic_masses.data.txt', na_values=['?'], names = ['BI-
masses_data.head()
```

Out[173]:

	BI-RADS	age	shape	margin	density	severity
0	5.0	67.0	3.0	5.0	3.0	1
1	4.0	43.0	1.0	1.0	NaN	1
2	5.0	58.0	4.0	5.0	3.0	1
3	4.0	28.0	1.0	1.0	3.0	0
4	5.0	74.0	1.0	5.0	NaN	1

In [174]:

```
masses_data.describe()
```

Out[174]:

	BI-RADS	age	shape	margin	density	severity
count	959.000000	956.000000	930.000000	913.000000	885.000000	961.000000
mean	4.348279	55.487448	2.721505	2.796276	2.910734	0.463059
std	1.783031	14.480131	1.242792	1.566546	0.380444	0.498893
min	0.000000	18.000000	1.000000	1.000000	1.000000	0.000000
25%	4.000000	45.000000	2.000000	1.000000	3.000000	0.000000
50%	4.000000	57.000000	3.000000	3.000000	3.000000	0.000000
75%	5.000000	66.000000	4.000000	4.000000	3.000000	1.000000
max	55.000000	96.000000	4.000000	5.000000	4.000000	1.000000

In [175]:

```
#before droping rows with missing value need to check that no bias in data in present an
```

In [176]:

```
masses_data.loc[(masses_data['age'].isnull()) |
              (masses_data['shape'].isnull()) |
              (masses_data['margin'].isnull()) |
              (masses_data['density'].isnull())]
```

Out[176]:

	BI-RADS	age	shape	margin	density	severity
1	4.0	43.0	1.0	1.0	NaN	1
4	5.0	74.0	1.0	5.0	NaN	1
5	4.0	65.0	1.0	NaN	3.0	0
6	4.0	70.0	NaN	NaN	3.0	0
7	5.0	42.0	1.0	NaN	3.0	0
...	...	...	...	...	...	...
778	4.0	60.0	NaN	4.0	3.0	0
819	4.0	35.0	3.0	NaN	2.0	0
824	6.0	40.0	NaN	3.0	4.0	1
884	5.0	NaN	4.0	4.0	3.0	1
923	5.0	NaN	4.0	3.0	3.0	1

130 rows × 6 columns

In [177]:

```
#above we can see missing data is in random format. no correlation is observed. hence , 
```

In [178]:

```
masses_data.dropna(inplace=True)
masses_data.describe()
```

Out[178]:

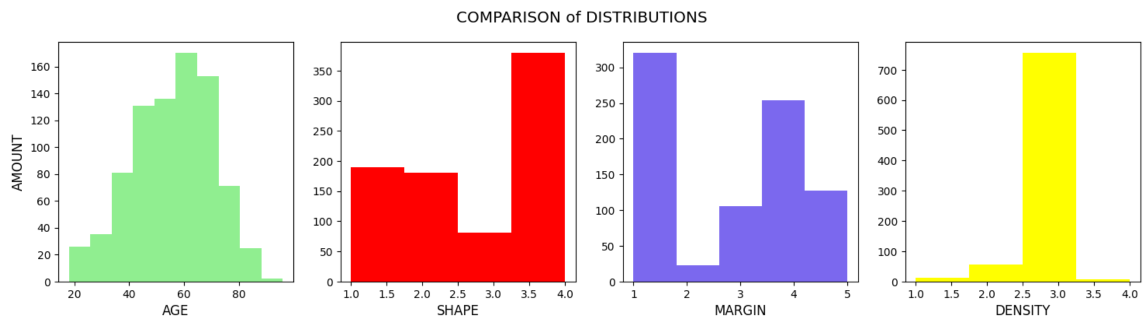
	BI-RADS	age	shape	margin	density	severity
count	830.000000	830.000000	830.000000	830.000000	830.000000	830.000000
mean	4.393976	55.781928	2.781928	2.813253	2.915663	0.485542
std	1.888371	14.671782	1.242361	1.567175	0.350936	0.500092
min	0.000000	18.000000	1.000000	1.000000	1.000000	0.000000
25%	4.000000	46.000000	2.000000	1.000000	3.000000	0.000000
50%	4.000000	57.000000	3.000000	3.000000	3.000000	0.000000
75%	5.000000	66.000000	4.000000	4.000000	3.000000	1.000000
max	55.000000	96.000000	4.000000	5.000000	4.000000	1.000000

In [180]:

```
%matplotlib inline
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
fig, axes = plt.subplots(1,4, sharey=False, figsize=(18,4))
ax1, ax2, ax3, ax4 = axes.flatten()

ax1.hist(masses_data['age'], bins=10, color="lightgreen")
ax2.hist(masses_data['shape'], bins=4, color="red")
ax3.hist(masses_data['margin'], bins=5, color="mediumslateblue")
ax4.hist(masses_data['density'], bins=4, color="yellow")
ax1.set_xlabel('AGE', fontsize="large")
ax2.set_xlabel('SHAPE', fontsize="large")
ax3.set_xlabel('MARGIN', fontsize="large")
ax4.set_xlabel('DENSITY', fontsize="large")
ax1.set_ylabel("AMOUNT", fontsize="large")

plt.suptitle('COMPARISON of DISTRIBUTIONS', ha='center', fontsize='x-large')
plt.show()
```



#now need to convert the Pandas dataframes into numpy arrays that can be used by scikit_learn. Creating an array that extracts only the feature data we want to work with (age, shape, margin, and density) and another array that contains the classes (severity).also one more array of the feature name labels.

In [16]:

```
all_features = masses_data[['age', 'shape',
                             'margin', 'density']].values


all_classes = masses_data['severity'].values

feature_names = ['age', 'shape', 'margin', 'density']

all_features
```

Out[16]:

```
array([[67.,  3.,  5.,  3.],
       [58.,  4.,  5.,  3.],
       [28.,  1.,  1.,  3.],
       ...,
       [64.,  4.,  5.,  3.],
       [66.,  4.,  5.,  3.],
       [62.,  3.,  3.,  3.]])
```

In [17]:

```
#as Some of the models require the input data to be normalized, hence using preprocessin
```

In [18]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [19]:

```
!pip install scikit-learn
```

```
Requirement already satisfied: scikit-learn in c:\users\amrita\miniconda3
\lib\site-packages (1.2.2)
Requirement already satisfied: scipy>=1.3.2 in c:\users\amrita\miniconda3
\lib\site-packages (from scikit-learn) (1.10.1)
Requirement already satisfied: joblib>=1.1.1 in c:\users\amrita\miniconda3
\lib\site-packages (from scikit-learn) (1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\amrita\min
iconda3\lib\site-packages (from scikit-learn) (3.1.0)
Requirement already satisfied: numpy>=1.17.3 in c:\users\amrita\miniconda3
\lib\site-packages (from scikit-learn) (1.24.2)

WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\miniconda3
\lib\site-packages)
WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\miniconda3
\lib\site-packages)
WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\miniconda3
\lib\site-packages)
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\lib\site-packages)
WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\miniconda3
\lib\site-packages)
WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\miniconda3
\lib\site-packages)
```

In [20]:

```
from sklearn import preprocessing

scaler = preprocessing.StandardScaler()
all_features_scaled = scaler.fit_transform(all_features)
all_features_scaled
```

Out[20]:

```
array([[ 0.7650629 ,  0.17563638,  1.39618483,  0.24046607],
       [ 0.15127063,  0.98104077,  1.39618483,  0.24046607],
       [-1.89470363, -1.43517241, -1.157718  ,  0.24046607],
       ...,
       [ 0.56046548,  0.98104077,  1.39618483,  0.24046607],
       [ 0.69686376,  0.98104077,  1.39618483,  0.24046607],
       [ 0.42406719,  0.17563638,  0.11923341,  0.24046607]])
```

In [21]:

```
from sklearn import tree
from sklearn import svm
from sklearn import linear_model
from sklearn import model_selection
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import confusion_matrix
from sklearn.metrics import f1_score
from sklearn.metrics import accuracy_score
```

In [22]:

```
#creating a single train/test split of our data. Set aside 75% for training, and 25% for
```

In [23]:

```
import numpy
from sklearn.model_selection import train_test_split

numpy.random.seed(1234)

(training_inputs,
 testing_inputs,
 training_classes,
 testing_classes) = train_test_split(all_features_scaled, all_classes, train_size=0.75,
```

In [24]:

```
# using DecisionTreeClassifier to fit training data
```

In [25]:

```
from sklearn.tree import DecisionTreeClassifier

clf= DecisionTreeClassifier(random_state=1)

# Train the classifier on the training set
clf.fit(training_inputs, training_classes)
```

Out[25]:

```
▾ DecisionTreeClassifier
DecisionTreeClassifier(random_state=1)
```

In [26]:

```
y_pred = clf.predict(testing_inputs)
print(y_pred)
```

```
[0 0 0 0 0 0 0 0 0 1 0 1 1 1 0 0 0 1 0 1 0 1 1 0 1 0 1 1 0 0 1 0 0 0 1 1 0
 1 1 1 1 1 0 0 1 1 0 1 0 1 0 0 0 0 0 1 1 0 1 0 0 1 0 1 1 0 0 0 1 0 1 1 1 0
 0 0 0 1 0 0 1 0 0 1 1 0 1 0 0 1 0 1 1 0 1 1 0 0 0 0 1 1 0 0 0 0 0 1 1 0 1
 0 1 1 0 0 1 1 0 1 0 1 1 1 0 0 1 1 0 0 1 1 1 1 1 0 1 0 0 0 1 1 1 1 0 0 0 0
 1 1 1 0 0 0 0 1 0 0 1 0 0 1 0 1 1 0 0 0 0 0 1 1 1 0 1 1 0 0 0 1 1 1 1 0 0
 0 0 0 0 0 1 1 1 1 0 1 1 0 0 0 1 0 1 1 0 1 1 0]
```

In [27]:

```
print(clf.score(testing_inputs, testing_classes))
```

```
0.7355769230769231
```

In [28]:

```
confusion_matrix(testing_classes,y_pred)
```

Out[28]:

```
array([[88, 31],
       [24, 65]], dtype=int64)
```

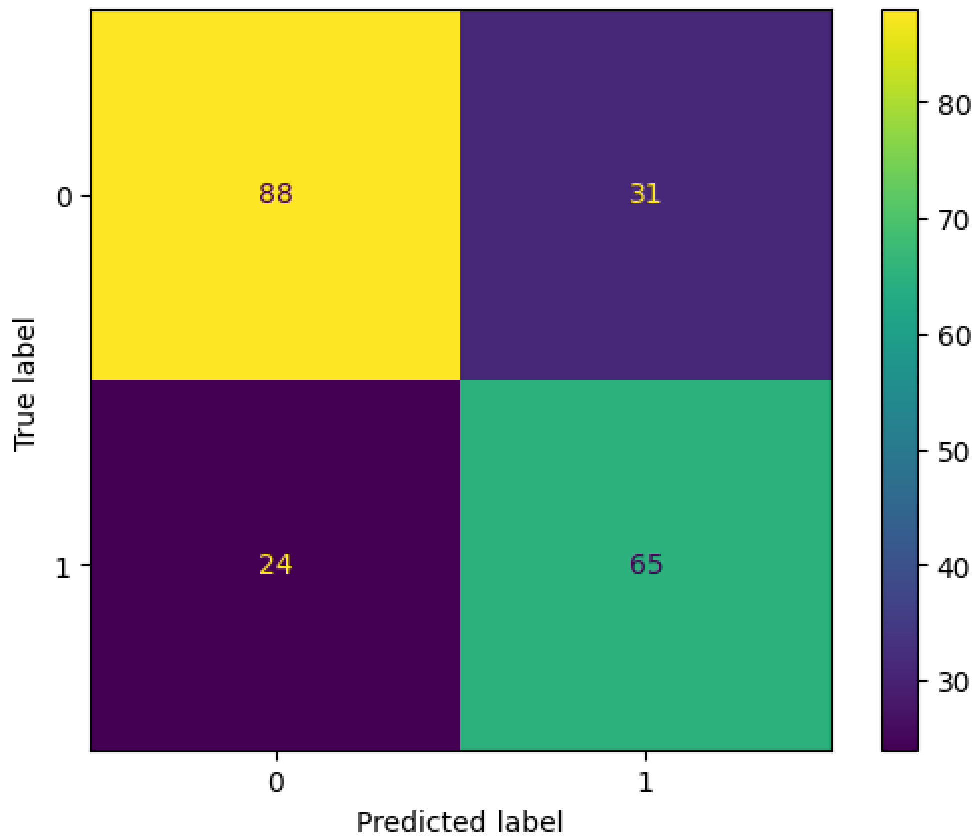
In [29]:

```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
```

In [30]:

```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import ConfusionMatrixDisplay
y_pred = clf.predict(testing_inputs)
cm = confusion_matrix(testing_classes,y_pred)

cm_display = ConfusionMatrixDisplay(cm).plot()
```



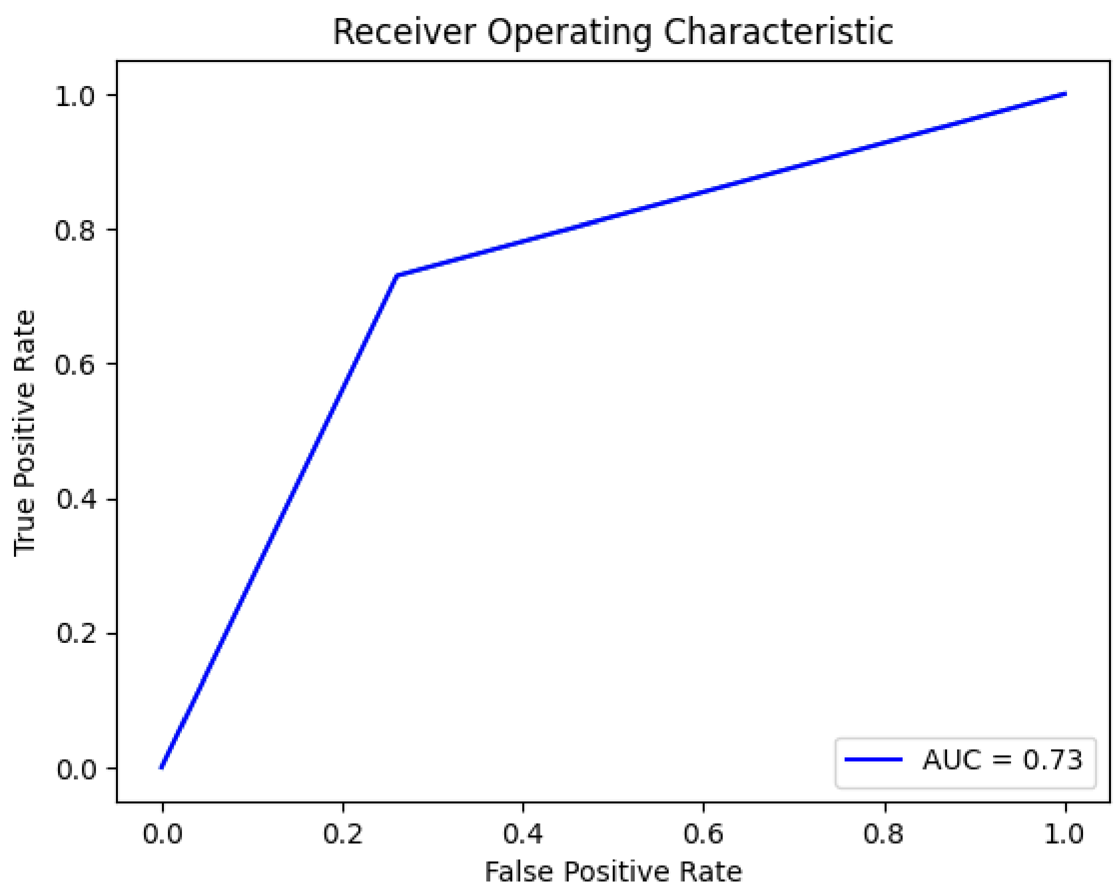
In [31]:

```
from sklearn.metrics import roc_curve
from sklearn.metrics import RocCurveDisplay
import matplotlib.pyplot as plt
from sklearn import metrics


fpr, tpr, _ = roc_curve(testing_classes, y_pred, pos_label=clf.classes_[1])
roc_display = RocCurveDisplay(fpr=fpr, tpr=tpr).plot()
roc_auc = metrics.auc(fpr,tpr)
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b',label='AUC = %0.2f'% roc_auc)
plt.legend(loc='lower right')
```

Out[31]:

```
<matplotlib.legend.Legend at 0x1fc8f1957f0>
```



In [32]:

```
!pip install six
```

```
Requirement already satisfied: six in c:\users\amrita\miniconda3\lib\site-
packages (1.16.0)

WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\miniconda3
\lib\site-packages)
WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\miniconda3
\lib\site-packages)
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\lib\site-packages)
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\lib\site-packages)
WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\miniconda3
\lib\site-packages)
WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\miniconda3
\lib\site-packages)
```

In [33]:

```


!pip install pydotplus
```

```
Requirement already satisfied: pydotplus in c:\users\amrita\miniconda3\lib
\site-packages (2.0.2)
Requirement already satisfied: pyparsing>=2.0.1 in c:\users\amrita\minicon
da3\lib\site-packages (from pydotplus) (3.0.9)

WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\miniconda3
\lib\site-packages)
WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\miniconda3
\lib\site-packages)
WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\miniconda3
\lib\site-packages)
WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\miniconda3
\lib\site-packages)
WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\miniconda3
\lib\site-packages)
WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\miniconda3
\lib\site-packages)
```

In [34]:

```
!pip install graphviz
```

```
Requirement already satisfied: graphviz in c:\users\amrita\miniconda3\lib
\site-packages (0.20.1)

WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\miniconda3
\lib\site-packages)
WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\miniconda3
\lib\site-packages)
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\lib\site-packages)
WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\miniconda3
\lib\site-packages)
WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\miniconda3
\lib\site-packages)
WARNING: Ignoring invalid distribution -ymongo (c:\users\amrita\miniconda3
\lib\site-packages)
```

In [35]:

```
conda install graphviz
```

```
Retrieving notices: ...working... done
Collecting package metadata (current_repodata.json): ...working... done
Solving environment: ...working... done

## Package Plan ##

  environment location: C:\Users\Amrita\miniconda3

  added / updated specs:
    - graphviz


The following packages will be downloaded:

    package                    |            build
    ---------------------------|-----------------
    openssl-1.1.1u             |       h2bbff1b_0         5.5 MB
    ------------------------------------------------------------
                                           Total:         5.5 MB
```

In [36]:

```
from six import StringIO
from IPython.display import Image
from sklearn.tree import export_graphviz
import pydotplus
import graphviz
```

In [ ]:

```

```

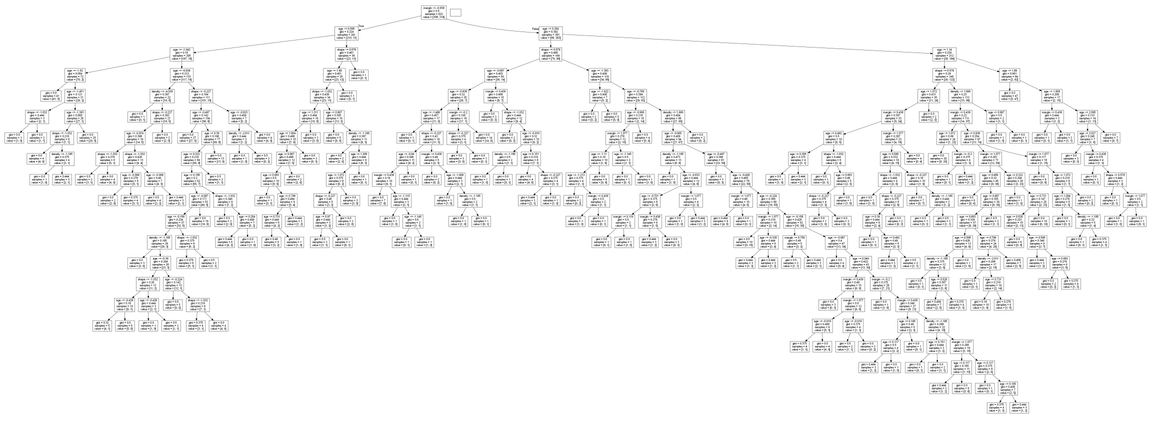
In [37]:

```
import six
import sys
sys.modules['sklearn.externals.six'] = six
```

In [38]:

```
from IPython.display import Image
from sklearn.externals.six import StringIO
from sklearn.externals.six import StringIO
from sklearn import tree
from pydotplus import graph_from_dot_data

dot_data = StringIO()
tree.export_graphviz(clf, out_file=dot_data,
                         feature_names=feature_names)
graph = graph_from_dot_data(dot_data.getvalue())
Image(graph.create_png())
```

Out[38]:



In [39]:

```
clf.score(testing_inputs, testing_classes)
```

Out[39]:

0.7355769230769231

In [40]:

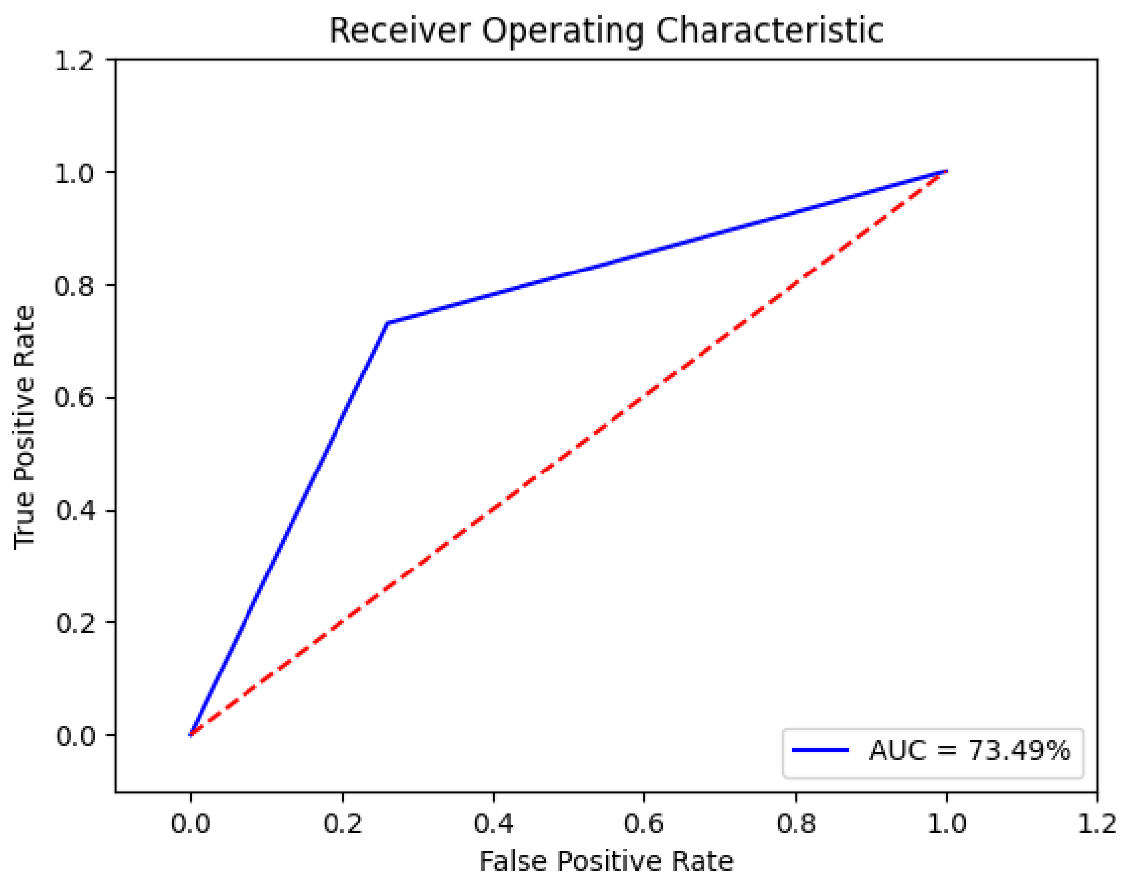
```
import matplotlib.pyplot as plt
```

In [41]:

```
from sklearn import metrics

# ROC curve
# we use Receiver Operating Characteristic (ROC) metric to evaluate classifier output qu

def createROC(testing_classes, y_pred):


    fpr, tpr, thresholds = metrics.roc_curve(testing_classes, y_pred)
    roc_auc = metrics.auc(fpr, tpr)

    plt.title('Receiver Operating Characteristic')

    plt.plot(fpr, tpr, 'b', label='AUC = %0.2f%%'% (roc_auc*100))
    plt.legend(loc='lower right')
    plt.plot([0,1], [0,1], 'r--')

    plt.xlim([-0.1,1.2])
    plt.ylim([-0.1,1.2])

    plt.ylabel('True Positive Rate')
    plt.xlabel('False Positive Rate')

    plt.show()
```

In [42]:

```
createROC(testing_classes, y_pred)
```



In [43]:

```
#Now instead of a single train/test split, using K-Fold cross validation to get a better
```

In [125]:

```
from sklearn.model_selection import cross_val_score

clf = DecisionTreeClassifier(random_state=1)

cv_scores = cross_val_score(clf, all_features_scaled, all_classes, cv=10)

cv_scores.mean()
```

Out[125]:

```
0.7373493975903613
```

In [126]:

```
#RandomForestClassifier
```

In [127]:

```
from sklearn.ensemble import RandomForestClassifier

clf = RandomForestClassifier(n_estimators=10, random_state=1)
cv_scores = cross_val_score(clf, all_features_scaled, all_classes, cv=10)

cv_scores.mean()
```

Out[127]:

```
0.7421686746987952
```

In [128]:

```
print("Accuracy: %0.2f (+/- %0.2f)" % (cv_scores.mean(), cv_scores.std() * 2))
```

```
Accuracy: 0.74 (+/- 0.08)
```

KNN-using neighbors.KNeighborsClassifier - Starting with a K of 10. K is an example of a hyperparameter - a parameter on the model itself which may need to be tuned for best results on a particular data set.

In [129]:

```
from sklearn import neighbors

clf = neighbors.KNeighborsClassifier(n_neighbors=10)
cv_scores = cross_val_score(clf, all_features_scaled, all_classes, cv=10)

cv_scores.mean()
```

Out[129]:

```
0.7927710843373494
```

As choosing K is a bit tricky, so trying different values of K. Writing a for loop to run KNN with K values ranging from 1 to 50 and see if K makes a substantial difference.

In [130]:

```
for n in range(1, 50):
    clf = neighbors.KNeighborsClassifier(n_neighbors=n)
    cv_scores = cross_val_score(clf, all_features_scaled, all_classes, cv=10)
    print (n, cv_scores.mean())
```

```
1 0.7228915662650601
2 0.6855421686746987
3 0.7530120481927711
4 0.7385542168674699
5 0.7783132530120482
6 0.7650602409638554
7 0.7975903614457832
8 0.7819277108433734
9 0.7927710843373493
10 0.7927710843373494
11 0.7951807228915662
12 0.7843373493975905
13 0.7843373493975904
14 0.7855421686746988
15 0.7855421686746988
16 0.7831325301204819
17 0.7867469879518072
18 0.7783132530120482
19 0.7855421686746988
20 0.7843373493975904
21 0.7867469879518072
22 0.783132530120482
23 0.7795180722891566
24 0.7771084337349399
25 0.7855421686746988
26 0.7831325301204819
27 0.7843373493975904
28 0.7843373493975904
29 0.7867469879518072
30 0.7843373493975904
31 0.7867469879518072
32 0.789156626506024
33 0.7867469879518072
34 0.789156626506024
35 0.7843373493975904
36 0.7867469879518072
37 0.7831325301204819
38 0.7867469879518072
39 0.7819277108433734
40 0.7843373493975904
41 0.7819277108433734
42 0.7831325301204819
43 0.7831325301204819
44 0.7843373493975904
45 0.7831325301204819
46 0.7831325301204819
47 0.7879518072289157
48 0.7903614457831325
49 0.7903614457831325
```

In [131]:

```
print("Accuracy: %0.2f (+/- %0.2f)" % (cv_scores.mean(), cv_scores.std() * 2))
```

```
Accuracy: 0.79 (+/- 0.07)
```

Naive Bayes Now trying naive_bayes.MultinomialNB.

In [132]:

```
from sklearn.naive_bayes import MultinomialNB

scaler = preprocessing.MinMaxScaler()
all_features_minmax = scaler.fit_transform(all_features)

clf = MultinomialNB()
cv_scores = cross_val_score(clf, all_features_minmax, all_classes, cv=10)

cv_scores.mean()
```

Out[132]:

```
0.7855421686746988
```

SVM using svm.SVC with a linear kernel.

In [133]:

```
from sklearn import svm

C = 1.0
svc = svm.SVC(kernel='linear', C=C)
```

In [134]:

```
cv_scores = cross_val_score(svc, all_features_scaled, all_classes, cv=10)

cv_scores.mean()
```

Out[134]:

```
0.7975903614457832
```

svm.SVC may perform differently with different kernels. The choice of kernel is an example of a "hyperparamter." Trying the rbf, sigmoid, and poly kernels and see what the best-performing kernel is.

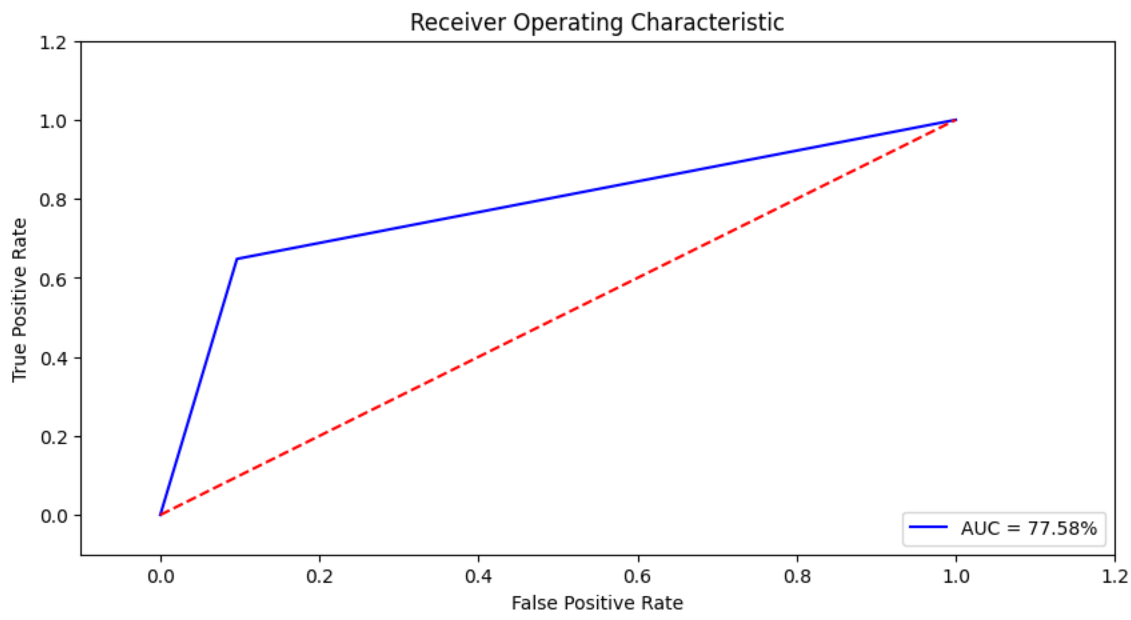
In [135]:

```
# Build the model SVM-Poly kernel
svc = svm.SVC(kernel='poly', C=1, gamma='scale')

# Fit the model
svc = svc.fit(training_inputs,training_classes)

# Predict the results
y_pred = svc.predict(testing_inputs)

# Evaluates the accuracy of our prediction on the test set
scores = model_selection.cross_val_score(svc,all_features_scaled, all_classes, cv=10)
print(scores)
# The mean score and the 95% confidence interval of the score estimate
print("Accuracy: %0.2f (+/- %0.2f)" % (scores.mean(), scores.std() * 2))

## Adding the results to a new dictionary to compare at the end
models=[]
model = {}
model['label'] = 'SVM - Poly Kernel'
model['pred'] = y_pred
model['acc'] = accuracy_score(testing_classes, y_pred)
models.append(model)
```

```
[0.75903614 0.79518072 0.84337349 0.80722892 0.8313253  0.73493976
 0.74698795 0.79518072 0.84337349 0.74698795]
Accuracy: 0.79 (+/- 0.08)
```

In [136]:

```
createROC(y_pred, testing_classes)
```



In [137]:

```
C = 1.0
svc = svm.SVC(kernel='rbf', C=C)
cv_scores = cross_val_score(svc, all_features_scaled, all_classes, cv=10)
cv_scores.mean()
```

Out[137]:

```
0.8012048192771084
```

In [138]:

```


# Fit the model
svc = svc.fit(training_inputs,training_classes)

# Predict the results
y_pred = svc.predict(testing_inputs)


# The mean score and the 95% confidence interval of the score estimate
print("Accuracy: %0.2f (+/- %0.2f)" % (cv_scores.mean(), cv_scores.std() * 2))

## Adding the results to a new dictionary to compare at the end
models=[]
model = {}
model['label'] = 'SVM - Sigmoid Kernel'
model['pred'] = y_pred
model['acc'] = accuracy_score( testing_classes, y_pred)
models.append(model)
```

```
Accuracy: 0.80 (+/- 0.08)
```

In [139]:

```
C = 1.0
svc = svm.SVC(kernel='sigmoid', C=C)
cv_scores = cross_val_score(svc, all_features_scaled, all_classes, cv=10)
cv_scores.mean()
```

Out[139]:

```
0.7457831325301204
```

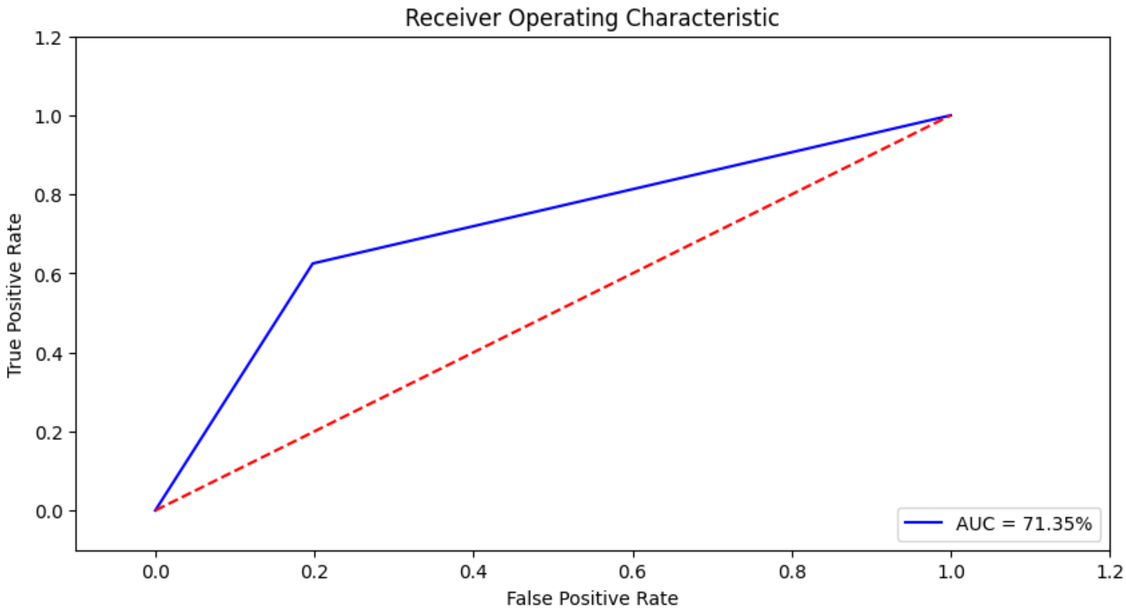
In [140]:

```
# Fit the model
svc = svc.fit(training_inputs,training_classes)

# Predict the results
y_pred = svc.predict(testing_inputs)


# The mean score and the 95% confidence interval of the score estimate
print("Accuracy: %0.2f (+/- %0.2f)" % (cv_scores.mean(), cv_scores.std() * 2))

## Adding the results to a new dictionary to compare at the end
models=[]
model = {}
model['label'] = 'SVM - Sigmoid Kernel'
model['pred'] = y_pred
model['acc'] = accuracy_score( testing_classes, y_pred)

models.append(model)
#print(models)
```

```
Accuracy: 0.75 (+/- 0.08)
```

In [141]:

```
createROC(y_pred,testing_classes)
```



In [142]:

```
C = 1.0
svc = svm.SVC(kernel='poly', C=C)
cv_scores = cross_val_score(svc, all_features_scaled, all_classes, cv=10)
cv_scores.mean()
```

Out[142]:

```
0.7903614457831326
```

In [143]:

```
#Logistic Regression
```

In [144]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression()
cv_scores = cross_val_score(clf, all_features_scaled, all_classes, cv=10)
cv_scores.mean()
```

Out[144]:

```
0.8072289156626505
```

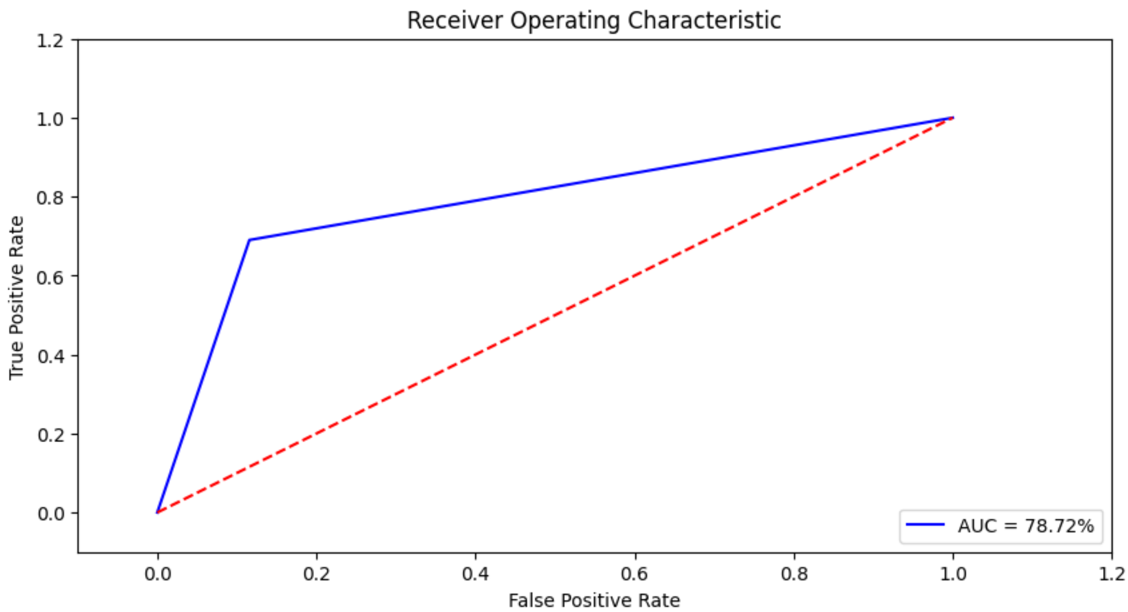
In [157]:

```

# The mean score and the 95% confidence interval of the score estimate
print("Accuracy: %0.2f (+/- %0.2f)" % (cv_scores.mean(), cv_scores.std() * 2))

## Adding the results to a new dictionary to compare at the end

model = {}
model['label'] = 'Logistic Regression'
model['pred'] = y_pred
model['acc'] = accuracy_score(testing_classes, y_pred)
models.append(model)
```

```
Accuracy: 0.80 (+/- 0.11)
```

In [158]:

```
createROC(y_pred, testing_classes)
```



Neural Networks trying artificial neural network atlast.. using Keras to set up a neural network with 1 binary output neuron and see how it performs

In [159]:

```
from tensorflow.keras.layers import Dense
from tensorflow.keras.models import Sequential

def create_model():
    model = Sequential()
    #4 feature inputs going into an 6-unit layer (more does not seem to help - in fact yo
    model.add(Dense(6, input_dim=4, kernel_initializer='normal', activation='relu'))
    # "Deep learning" turns out to be unnecessary - this additional hidden layer doesn't
    #model.add(Dense(4, kernel_initializer='normal', activation='relu'))
    # Output layer with a binary classification (benign or malignant)
    model.add(Dense(1, kernel_initializer='normal', activation='sigmoid'))
    # Compile model; adam seemed to work best
    model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model
```

In [160]:

```
from tensorflow.keras.wrappers.scikit_learn import KerasClassifier

# Wrap our Keras model in an estimator compatible with scikit_learn
estimator = KerasClassifier(build_fn=create_model, epochs=100, verbose=0)
# Now we can use scikit_learn's cross_val_score to evaluate this model identically to th
cv_scores = cross_val_score(estimator, all_features_scaled, all_classes, cv=10)
cv_scores.mean()
```

```
C:\Users\Amrita\AppData\Local\Temp\ipykernel_14832\2792759154.py:4: Deprec
ationWarning: KerasClassifier is deprecated, use Sci-Keras (https://githu
b.com/adriangb/scikeras) instead. See https://www.adriangb.com/scikeras/st
able/migration.html (https://www.adriangb.com/scikeras/stable/migration.ht
ml) for help migrating.
  estimator = KerasClassifier(build_fn=create_model, epochs=100, verbose=
0)
```

Out[160]:

```
0.8024096369743348
```

In [161]:

```
import keras
from keras.models import Sequential
from keras.layers import Dense, Dropout
from keras.optimizers import RMSprop
from keras.wrappers.scikit_learn import KerasClassifier
ann = Sequential()

ann.add(Dense(128, input_dim=4, kernel_initializer='normal', activation='relu'))
ann.add(Dropout(0.2))

ann.add(Dense(64, kernel_initializer='normal', activation='relu'))
ann.add(Dropout(0.2))

ann.add(Dense(32, kernel_initializer='normal', activation='relu'))
ann.add(Dropout(0.2))

ann.add(Dense(16, kernel_initializer='normal', activation='relu'))
ann.add(Dense(1, kernel_initializer='normal', activation='sigmoid'))

ann.compile(loss='binary_crossentropy', optimizer='rmsprop', metrics=['accuracy'])
history = ann.fit(training_inputs, training_classes, batch_size=10, epochs=100, verbose=
```

```
Epoch 1/100
63/63 - 1s - loss: 0.6850 - accuracy: 0.6833 - 1s/epoch - 17ms/step
Epoch 2/100
63/63 - 0s - loss: 0.5180 - accuracy: 0.8055 - 140ms/epoch - 2ms/step
Epoch 3/100
63/63 - 0s - loss: 0.4532 - accuracy: 0.8103 - 138ms/epoch - 2ms/step
Epoch 4/100
63/63 - 0s - loss: 0.4467 - accuracy: 0.8135 - 142ms/epoch - 2ms/step
Epoch 5/100
63/63 - 0s - loss: 0.4513 - accuracy: 0.8087 - 140ms/epoch - 2ms/step
Epoch 6/100
63/63 - 0s - loss: 0.4497 - accuracy: 0.8183 - 139ms/epoch - 2ms/step
Epoch 7/100
63/63 - 0s - loss: 0.4346 - accuracy: 0.8167 - 140ms/epoch - 2ms/step
Epoch 8/100
63/63 - 0s - loss: 0.4429 - accuracy: 0.8183 - 141ms/epoch - 2ms/step
Epoch 9/100
63/63 - 0s - loss: 0.4416 - accuracy: 0.8199 - 157ms/epoch - 2ms/step
Epoch 10/100
```

In [163]:

```
# Evaluates the accuracy of our prediction on the test set
score = ann.evaluate(testing_inputs, testing_classes, verbose=0)
print('Test Loss:', score[0])
print('Test Accuracy:', score[1])

# Predict the results
y_pred = ann.predict(testing_inputs)

## Adding the results to a new dictionary to compare at the end

model = {}
model['label'] = 'ANN - Artificial Neural Network'
model['pred'] = y_pred
model['acc'] = metrics.roc_auc_score(testing_classes, y_pred)#accuracy_score(y_test, y_p

models.append(model)
#print(models)
```

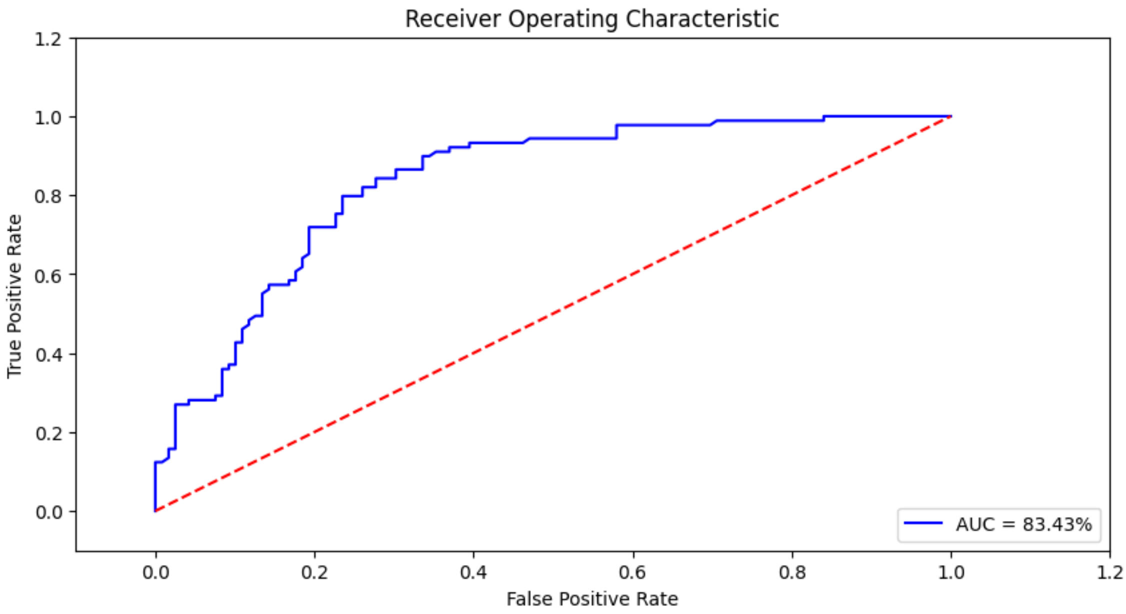
```
Test Loss: 0.5056726336479187
Test Accuracy: 0.7692307829856873
7/7 [==============================] - 0s 3ms/step
```

BEST MODEL in terms of accuracy....

except decision trees , other algorithms could be tuned to produce comparable results with 79-80% accuracy. Additional hyperparameter tuning, or different topologies of the multi-level perceptron might make a difference.will continue to work on it.

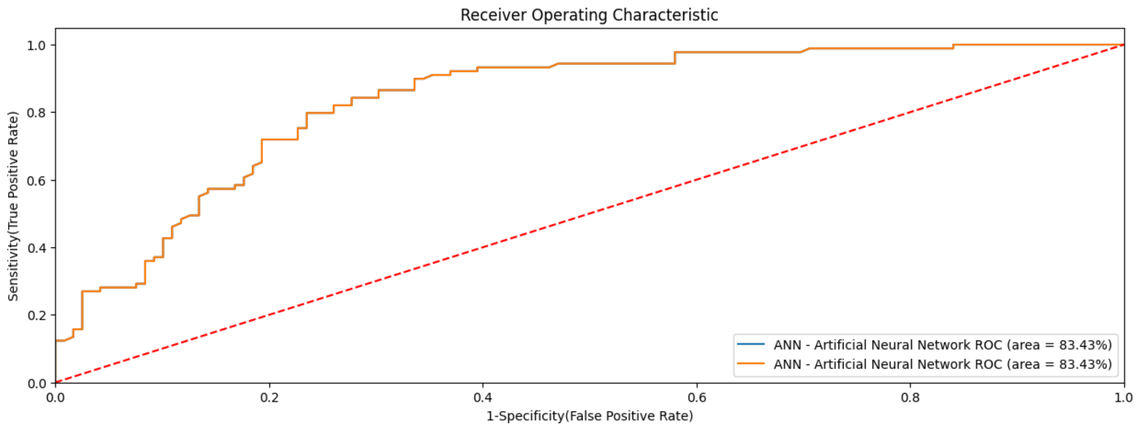
In [164]:

```
createROC(testing_classes, y_pred)
```



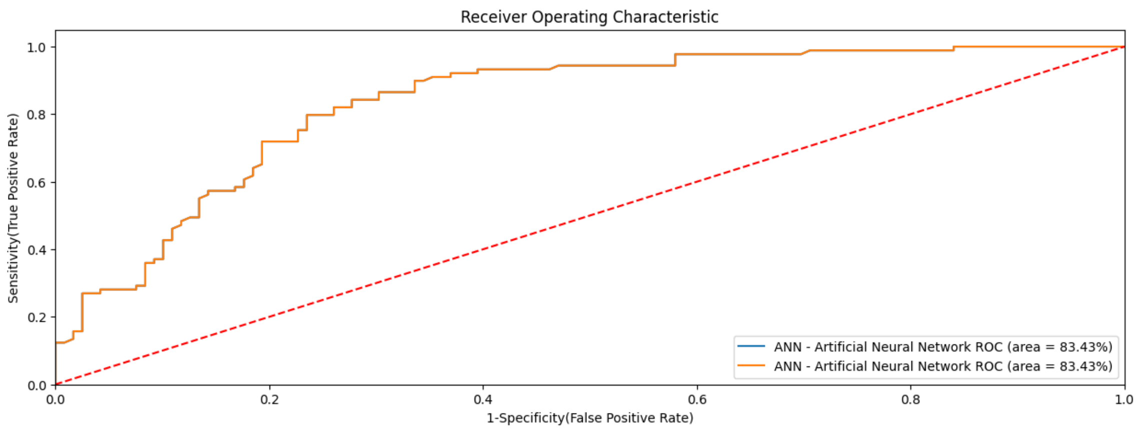
In [165]:

```
## CReate graph comparaison between classifiers

## ROC curves for all classifiers

plt.figure(figsize = (15, 5))

for m in models:
    mod = m['label']
    y_pred = m['pred']
    # Compute False postive rate, and True positive rate
    fpr, tpr, thresholds = metrics.roc_curve(testing_classes, y_pred)
    # Calculate Accuracy of the curve to display on the plot
    auc = metrics.auc(fpr, tpr)#metrics.roc_auc_score(y_test, y_pred)
    # Now, plot the computed values
    plt.plot(fpr, tpr, label='%s ROC (area = %0.2f%%)' % (m['label'], auc*100))
# Custom settings for the plot
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('1-Specificity(False Positive Rate)')
plt.ylabel('Sensitivity(True Positive Rate)')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
# Display
plt.show()
```



In [166]:

```
## CReate graph comparaison between classifiers

## ROC curves for all classifiers

plt.figure(figsize = (15, 5))

for m in models:
    mod = m['label']
    y_pred = m['pred']
    # Compute False postive rate, and True positive rate
    fpr, tpr, thresholds = metrics.roc_curve(testing_classes, y_pred)
    # Calculate Accuracy of the curve to display on the plot
    auc = metrics.auc(fpr, tpr)#metrics.roc_auc_score(testing_classes, y_pred)
    # Now, plot the computed values
    plt.plot(fpr, tpr, label='%s ROC (area = %0.2f%%)' % (m['label'], auc*100))
# Custom settings for the plot
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('1-Specificity(False Positive Rate)')
plt.ylabel('Sensitivity(True Positive Rate)')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
# Display
plt.show()
```



In [121]:

```
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score

dicti={SVC(kernel="rbf", C=1, gamma=1000, probability=True):"svc",
    LogisticRegression(solver="liblinear", random_state=0):"lr",
    KNeighborsClassifier(n_neighbors=10):'knn',
    RandomForestClassifier(max_depth=3, n_estimators=100, random_state=0):'rfc',
    DecisionTreeClassifier(random_state=0):'dtc'}
for model in dicti:
    model.fit(training_inputs,training_classes)
    pred_c=model.predict(testing_inputs)
    accc=accuracy_score(testing_classes, pred_c)
    print("Accuracy score for ", dicti[model], " is ", accc.round(2))
```

```
Accuracy score for  svc  is  0.62
Accuracy score for  lr  is  0.78
Accuracy score for  knn  is  0.77
Accuracy score for  rfc  is  0.76
Accuracy score for  dtc  is  0.73
```

In [122]:

```
from sklearn.model_selection import cross_val_score
for model in dicti:
    score=cross_val_score(model,all_features_scaled,all_classes, cv=10)
    print("Accuracy score for ", dicti[model], "with cros. val. is ",'{:3.2f}'.format(sc
```

```
Accuracy score for  svc with cros. val. is  0.71
Accuracy score for  lr with cros. val. is  0.81
Accuracy score for  knn with cros. val. is  0.79
Accuracy score for  rfc with cros. val. is  0.80
Accuracy score for  dtc with cros. val. is  0.73
```

In [123]:

```
#again LR is winner with cross-validation
```

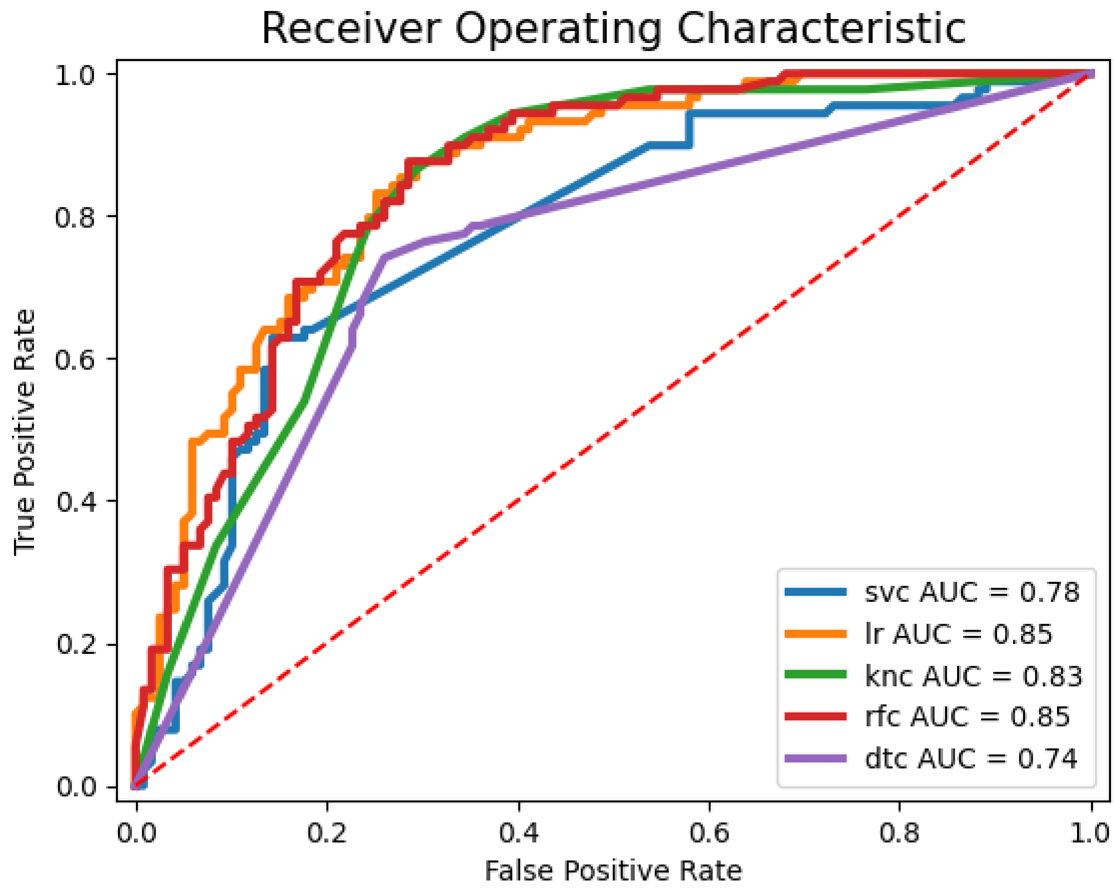
In [97]:

```
from sklearn.neighbors import KNeighborsClassifier
for n in range(1,11):
    model=KNeighborsClassifier(n_neighbors=n)
    model.fit(training_inputs,training_classes)
    pred_c=model.predict(testing_inputs)
    acc=accuracy_score(testing_classes, pred_c)
    print(n,"neighbor(s):")
    print("Accuracy score for KNN is :", acc.round(2))
    score=cross_val_score(model,training_inputs,training_classes, cv=10)
    print("Accuracy score for KNN with cros. val. is ",'{:3.2f}'.format(score.mean()),"\
```

```
1 neighbor(s):
Accuracy score for KNN is : 0.73
Accuracy score for KNN with cros. val. is  0.69

2 neighbor(s):
Accuracy score for KNN is : 0.75
Accuracy score for KNN with cros. val. is  0.66

3 neighbor(s):
Accuracy score for KNN is : 0.75
Accuracy score for KNN with cros. val. is  0.76

4 neighbor(s):
Accuracy score for KNN is : 0.74
Accuracy score for KNN with cros. val. is  0.74

5 neighbor(s):
Accuracy score for KNN is : 0.77
Accuracy score for KNN with cros. val. is  0.78

6 neighbor(s):
Accuracy score for KNN is : 0.76
Accuracy score for KNN with cros. val. is  0.78

7 neighbor(s):
Accuracy score for KNN is : 0.78
Accuracy score for KNN with cros. val. is  0.79

8 neighbor(s):
Accuracy score for KNN is : 0.77
Accuracy score for KNN with cros. val. is  0.80

9 neighbor(s):
Accuracy score for KNN is : 0.78
Accuracy score for KNN with cros. val. is  0.80

10 neighbor(s):
Accuracy score for KNN is : 0.77
Accuracy score for KNN with cros. val. is  0.80
```

In [124]:

```
from sklearn.metrics import roc_curve, auc
dicti={SVC(kernel="rbf", C=1, gamma=1000, probability=True):"svc",
    LogisticRegression(solver="liblinear", random_state=0):"lr",
    KNeighborsClassifier(n_neighbors=10):'knc',
    RandomForestClassifier(max_depth=3, n_estimators=100):'rfc',
    DecisionTreeClassifier():'dtc'}
for model in dicti:
    model.fit(training_inputs,training_classes)
    prob=model.predict_proba(testing_inputs)
    fpr, tpr, thresholds=roc_curve(testing_classes, prob[:,1])
    roc_auc=auc(fpr, tpr)
    plt.plot(fpr, tpr, lw=3, label=dicti[model]+' AUC = %0.2f' % roc_auc)
    plt.legend(loc='lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.title('Receiver Operating Characteristic', fontsize=15)

plt.xlim([-0.02, 1.02])
plt.ylim([-0.02, 1.02])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.rcParams["figure.figsize"] = (10,5)
plt.show()
```



In [ ]: