Data-Classifiers

December 17, 2022

1 Problem Statement

Given the MAGIC gamma telescope dataset that can be obtained using this Link. This datasetis generated to simulate registration of high energy gamma particles in a ground-based atmo-spheric Cherenkov gamma telescope using the imaging technique. The dataset consists of two classes; gammas (signal) and hadrons (background). There are 12332 gamma events and 6688 hadron events. You are required to use this dataset to apply different classification models such as Decision Trees, Naıve Bayes Classifier, Random Forests, AdaBoost and K-Nearest Neighbor (K-NN). You are also required to tune the parameters of these models, and compare the performance of models with each other.

1.1 Attribute Information:

1. fLength: continuous # major axis of ellipse [mm]
2. fWidth: continuous # minor axis of ellipse [mm]
3. fSize: continuous # 10-log of sum of content of all pixels [in #phot]
4. fConc: continuous # ratio of sum of two highest pixels over fSize [ratio]
5. fConc1: continuous # ratio of highest pixel over fSize [ratio]
6. fAsym: continuous # distance from highest pixel to center, projected onto major axis [mm]
7. fM3Long: continuous # 3rd root of third moment along major axis [mm]
8. fM3Trans: continuous # 3rd root of third moment along minor axis [mm]
9. fAlpha: continuous # angle of major axis with vector to origin [deg]
10. fDist: continuous # distance from origin to center of ellipse [mm]
11. class: g,h # gamma (signal), hadron (background)

g = gamma (signal): 12332 h = hadron (background): 6688

1.2 Importing libraries

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
```

1.3 Importing the Dataset

[2]:
```python
# Adding column names
col_names = ['fLength', 'fWidth', 'fSize', 'fConc', 'fConc1', 'fAsym', ␣
 ↪'fM3Long', 'fM3Trans', 'fAlpha', 'fDist', 'class']
# Importing the dataset
df = pd.read_csv('magic04.data',names = col_names)
#df = df.sample(frac = 1)
df.head()
```

[2]:

	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long	fM3Trans	\
0	28.7967	16.0021	2.6449	0.3918	0.1982	27.7004	22.0110	-8.2027	
1	31.6036	11.7235	2.5185	0.5303	0.3773	26.2722	23.8238	-9.9574	
2	162.0520	136.0310	4.0612	0.0374	0.0187	116.7410	-64.8580	-45.2160	
3	23.8172	9.5728	2.3385	0.6147	0.3922	27.2107	-6.4633	-7.1513	
4	75.1362	30.9205	3.1611	0.3168	0.1832	-5.5277	28.5525	21.8393	

	fAlpha	fDist	class
0	40.0920	81.8828	g
1	6.3609	205.2610	g
2	76.9600	256.7880	g
3	10.4490	116.7370	g
4	4.6480	356.4620	g

[3]:
```python
print(df['class'].value_counts())
df.describe()
```

```
g    12332
h     6688
Name: class, dtype: int64
```

[3]:

	fLength	fWidth	fSize	fConc	fConc1	\
count	19020.000000	19020.000000	19020.000000	19020.000000	19020.000000	
mean	53.250154	22.180966	2.825017	0.380327	0.214657	
std	42.364855	18.346056	0.472599	0.182813	0.110511	
min	4.283500	0.000000	1.941300	0.013100	0.000300	

```
25%     24.336000    11.863800     2.477100     0.235800     0.128475
50%     37.147700    17.139900     2.739600     0.354150     0.196500
75%     70.122175    24.739475     3.101600     0.503700     0.285225
max    334.177000   256.382000     5.323300     0.893000     0.675200

              fAsym      fM3Long     fM3Trans       fAlpha        fDist
count  19020.000000 19020.000000 19020.000000 19020.000000 19020.000000
mean      -4.331745    10.545545     0.249726    27.645707   193.818026
std       59.206062    51.000118    20.827439    26.103621    74.731787
min     -457.916100  -331.780000  -205.894700     0.000000     1.282600
25%      -20.586550   -12.842775   -10.849375     5.547925   142.492250
50%        4.013050    15.314100     0.666200    17.679500   191.851450
75%       24.063700    35.837800    10.946425    45.883550   240.563825
max      575.240700   238.321000   179.851000    90.000000   495.561000
```

1.4 Data Balancing

[4]:

```python
# Splitting dataset  by class label
df_g = df[df['class'] == 'g']
df_h = df[df['class'] == 'h']
df_g
```

[4]:

```
        fLength    fWidth   fSize   fConc  fConc1     fAsym  fM3Long  \
0       28.7967   16.0021  2.6449  0.3918  0.1982   27.7004  22.0110
1       31.6036   11.7235  2.5185  0.5303  0.3773   26.2722  23.8238
2      162.0520  136.0310  4.0612  0.0374  0.0187  116.7410 -64.8580
3       23.8172    9.5728  2.3385  0.6147  0.3922   27.2107  -6.4633
4       75.1362   30.9205  3.1611  0.3168  0.1832   -5.5277  28.5525
…           …        …       …       …       …        …        …
12327   12.8703   11.4444  2.3811  0.7360  0.3805  -15.0946   5.3032
12328   26.8595   20.5946  2.8754  0.3438  0.2152   -3.4556 -20.0014
12329   22.0913   10.8949  2.2945  0.5381  0.2919   15.2776  18.2296
12330   56.2216   18.7019  2.9297  0.2516  0.1393   96.5758 -41.2969
12331   31.5125   19.2867  2.9578  0.2975  0.1515   38.1833  21.6729

       fM3Trans   fAlpha     fDist class
0       -8.2027  40.0920   81.8828     g
1       -9.9574   6.3609  205.2610     g
2      -45.2160  76.9600  256.7880     g
3       -7.1513  10.4490  116.7370     g
4       21.8393   4.6480  356.4620     g
…           …        …        …    …
12327   11.6208  21.0120  204.0370     g
12328   -9.0535   3.9848  205.4980     g
12329    7.3975  21.0680  123.2810     g
12330   11.3764   5.9110  197.2090     g
12331  -12.0726  17.5809  171.2270     g
```

```
[12332 rows x 11 columns]
```

[5]:
```
# Balancing Data
#dfbalanced_g = df_g.sample(df_h.shape[0])
dfbalanced_g = df_g[:df_h.shape[0]]
df = pd.concat([dfbalanced_g, df_h], axis=0) # concatenate horizontally
df['class'].value_counts()
```

[5]:
```
g    6688
h    6688
Name: class, dtype: int64
```

[6]:
```
# Separating features and class
X = df.iloc[:, :-1].values
y = df.iloc[:, -1].values
y
```

[6]:
```
array(['g', 'g', 'g', …, 'h', 'h', 'h'], dtype=object)
```

1.5 Encoding class labels

[7]:
```
# Encoding the Dependent Variable(y)
from sklearn.preprocessing import LabelEncoder
le= LabelEncoder()
y = le.fit_transform(y)
print(y)
```

```
[0 0 0 … 1 1 1]
```

1.6 Splitting Dataset into Train set and Test set

[12]:
```
from sklearn.model_selection import train_test_split
from collections import Counter
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2999, random_state = 0,stratify=y)
print(f"Train set size: {X_train.shape[0]}\nTest set size: {X_test.shape[0]}")
print(Counter(y_train))
print(Counter(y_test))
```

```
Train set size: 9364
Test set size: 4012
Counter({1: 4682, 0: 4682})
Counter({0: 2006, 1: 2006})
```

1.7 Feature Scaling

[13]:
```
# for KNN as it is based upon distances
from sklearn.preprocessing import MinMaxScaler
mm = MinMaxScaler()
X_train = mm.fit_transform(X_train)
X_test = mm.transform(X_test)
print(X_train)
print(X_test)
```

```
[[0.03866115 0.05030969 0.11402557 … 0.51384336 0.61213889 0.33926103]
 [0.1060195  0.04611322 0.19295707 … 0.46895876 0.85389222 0.47096393]
 [0.18285673 0.10055191 0.41621442 … 0.52365604 0.03552222 0.34721202]
 …
 [0.0334423  0.03998955 0.11643753 … 0.46984637 0.58271778 0.44295361]
 [0.0832623  0.05837851 0.13835625 … 0.45035779 0.89218333 0.14212638]
 [0.04340349 0.02731705 0.01112518 … 0.47108938 0.25136667 0.28382466]]
[[0.18817527 0.08000094 0.27695369 … 0.45629629 0.10407333 0.30876203]
 [0.1695148  0.08601579 0.41292812 … 0.519218   0.02028444 0.42572647]
 [0.25432159 0.11695868 0.41983237 … 0.55411699 0.04223333 0.52288427]
 …
 [0.05586736 0.06523547 0.14363242 … 0.44734942 0.52550222 0.31418812]
 [0.067696   0.06311442 0.16374216 … 0.51332161 0.43543333 0.33746447]
 [0.05231504 0.0401678  0.13262783 … 0.47074563 0.02010222 0.49621104]]
```

1.8 Model Creation and Evaluation Functions

[14]:
```
# Model Creation
#from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import f1_score,␣
↪accuracy_score,recall_score,precision_score
def train_model(X_train, X_test, y_train, classifier):
    classifier.fit(X_train, y_train)
    pred = classifier.predict(X_test)
    return pred
```

[15]:
```
comparison_cols=["Classifier", "Accuracy", "F1 score", "Precision","Recall"]
comparison_df = pd.DataFrame(columns=comparison_cols)
```

[16]:
```
def evaluate(name,y_pred,y_test):
    global comparison_df
    f1 = f1_score(y_test, y_pred)
    acc = accuracy_score(y_test, y_pred)
    prec = precision_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    print(f"{name} accuracy: {acc}")
    print(f"{name} f1 score: {f1}")
```

```
    print(f"{name} precision: {prec}")
    print(f"{name} recall: {recall}")
    entry = pd.DataFrame([[name, acc*100, f1*100,prec*100,recall*100]],␣
 ↪columns=comparison_cols)
    comparison_df = comparison_df.append(entry)
    #pd.concat([comparison_df,entry])
```

1.9 Hyperparameter tuning function

[17]:
```
from sklearn.model_selection import StratifiedKFold
def cross_validation(X_train, y_train, classifier,cv=10):
    # stratified k-fold is used as the folds are made by preserving the␣
 ↪percentage of samples for each class.
    skf = StratifiedKFold(n_splits=cv)
    avg_accuracy = 0
    sum_accuracy = 0
    for train_index, test_index in skf.split(X_train, y_train):
        x_train_folds = X_train[train_index]
        y_train_folds = y_train[train_index]
        x_test_fold = X_train[test_index]
        y_test_fold = y_train[test_index]
        classifier.fit(x_train_folds,y_train_folds)
        y_pred_fold = classifier.predict(x_test_fold)
        sum_accuracy += accuracy_score(y_pred_fold,y_test_fold)
    avg_accuracy = sum_accuracy/cv
    return avg_accuracy
```

1.10 Decision Tree Classifier

Tunable parameters: None

[18]:
```
y_pred =␣
 ↪train_model(X_train,X_test,y_train,DecisionTreeClassifier(random_state=5))
evaluate("Decision Tree",y_pred,y_test)
```

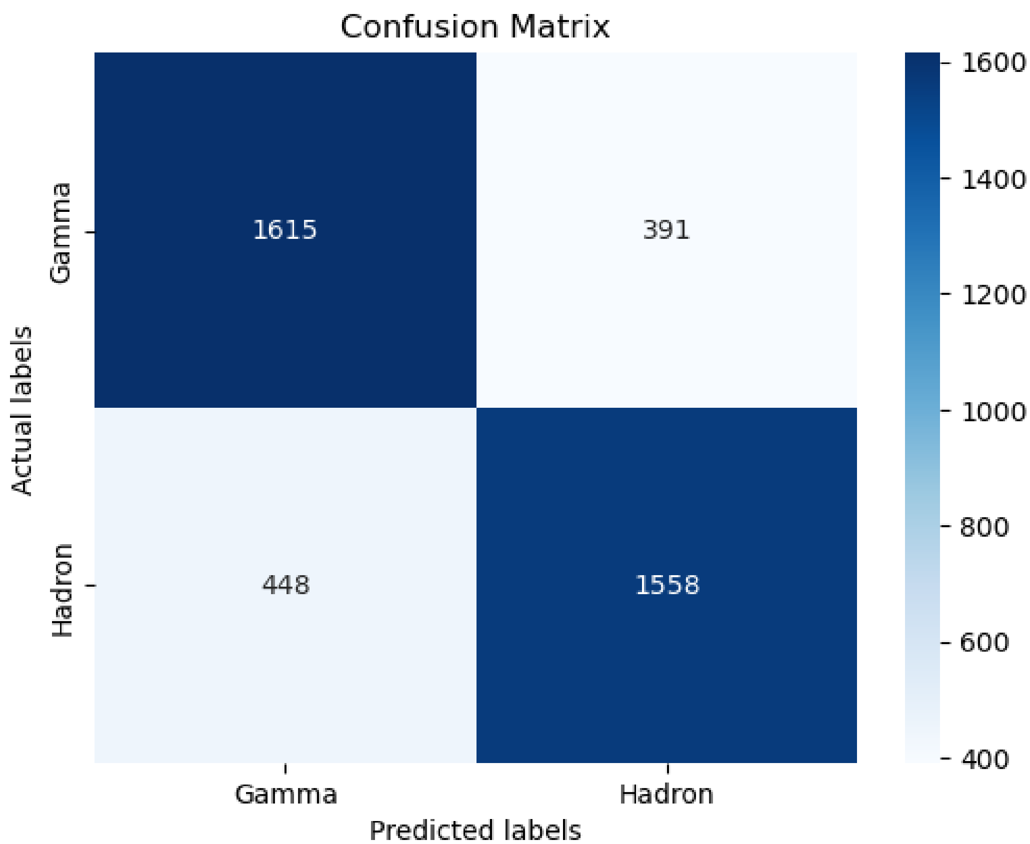
```
Decision Tree accuracy: 0.790877367896311
Decision Tree f1 score: 0.7878634639696587
Decision Tree precision: 0.7993842996408415
Decision Tree recall: 0.7766699900299102
```

```
/tmp/ipykernel_103467/1172794529.py:12: FutureWarning: The frame.append method
is deprecated and will be removed from pandas in a future version. Use
pandas.concat instead.
  comparison_df = comparison_df.append(entry)
```

[19]:
```
from sklearn.metrics import confusion_matrix
cf_matrix = confusion_matrix(y_test, y_pred)
```

```
print(cf_matrix)
ax= plt.subplot()
sns.heatmap(cf_matrix, annot=True,fmt='g',ax=ax,cmap='Blues')
ax.set_xlabel('Predicted labels');ax.set_ylabel('Actual labels');
ax.set_title('Confusion Matrix');
ax.xaxis.set_ticklabels(['Gamma', 'Hadron']); ax.yaxis.set_ticklabels(['Gamma',␣
↪'Hadron']);
```

```
[[1615  391]
 [ 448 1558]]
```



1.11 AdaBoost Classifier

An AdaBoost classifier is a meta-estimator that begins by fitting a classifier on the original dataset and then fits additional copies of the classifier on the same dataset but where the weights of incorrectly classified instances are adjusted such that subsequent classifiers focus more on difficult cases.

tunable parameters: `n_estimators`

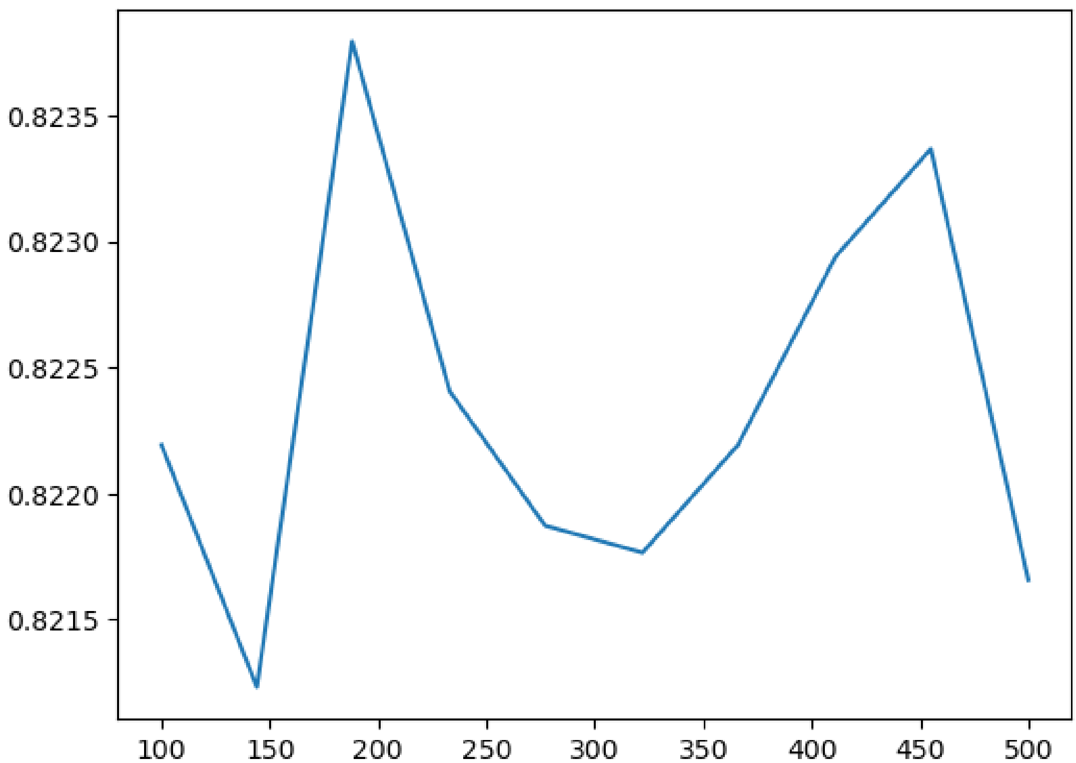
`n_estimators`: The maximum number of estimators at which boosting is terminated. In case of perfect fit, the learning procedure is stopped early.

1.12 Hyperparameter tuning

[20]:
```
import time
# possible values of n_estimators
n_trees = np.linspace(100,500,10,dtype=int)
avg_accuracies = []
for n in n_trees:
    adaboost = AdaBoostClassifier(n_estimators = n)
    t1 = time.time()
    acc_score = cross_validation(X_train,y_train,adaboost,cv=10)
    t2 = time.time() - t1
    print(f"n = {n}\taverage accuracy = {acc_score}\ttime = {t2}")
    avg_accuracies.append(acc_score)
```

```
n = 100 average accuracy = 0.8221931468863165   time = 10.614821434020996
n = 144 average accuracy = 0.8212330906968047   time = 15.230633735656738
n = 188 average accuracy = 0.8237942287168541   time = 19.895525217056274
n = 233 average accuracy = 0.8224063660162912   time = 24.690342903137207
n = 277 average accuracy = 0.8218729761285791   time = 29.395816326141357
n = 322 average accuracy = 0.8217659104798912   time = 34.204378604888916
n = 366 average accuracy = 0.8221928048235412   time = 39.30795097351074
n = 411 average accuracy = 0.8229395278621532   time = 46.42223405838013
n = 455 average accuracy = 0.823367334373204    time = 52.46410298347473
n = 500 average accuracy = 0.8216582747265779   time = 54.33817172050476
```

[22]:
```
plt.plot(n_trees,np.array(avg_accuracies))
plt.show()
```



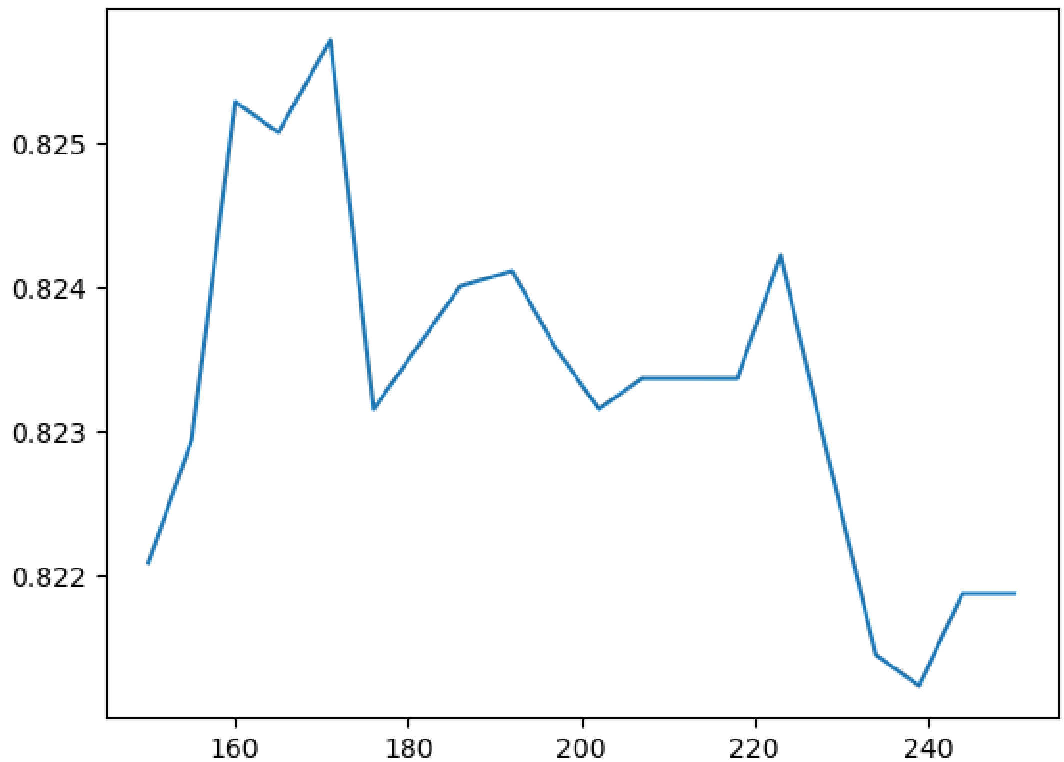
[23]:
```
n_trees = np.linspace(150,250,20,dtype=int)
avg_accuracies = []
for n in n_trees:
    adaboost = AdaBoostClassifier(n_estimators = n)
    t1 = time.time()
    acc_score = cross_validation(X_train,y_train,adaboost,cv=10)
    t2 = time.time() - t1
    print(f"n = {n}\taverage accuracy = {acc_score}\ttime = {t2}")
    avg_accuracies.append(acc_score)
```

```
n = 150 average accuracy = 0.8220874494887301   time = 16.025478839874268
n = 155 average accuracy = 0.8229414662178802   time = 16.452531814575195
n = 160 average accuracy = 0.8252899552125805   time = 17.001068592071533
n = 165 average accuracy = 0.8250765080407556   time = 17.56627869606018
n = 171 average accuracy = 0.8257176477027064   time = 18.1414852142334
n = 176 average accuracy = 0.8231535451386037   time = 18.66496992111206
n = 181 average accuracy = 0.823580667524104    time = 19.3525652885437
n = 186 average accuracy = 0.824007675888679    time = 19.782296180725098
n = 192 average accuracy = 0.8241141714327413   time = 20.394627332687378
n = 197 average accuracy = 0.8235804394822537   time = 21.102035999298096
n = 202 average accuracy = 0.8231536591595289   time = 21.463186979293823
```

```
n = 207 average accuracy = 0.8233673343732042   time = 21.96934413909912
n = 213 average accuracy = 0.8233673343732042   time = 22.6165874004364
n = 218 average accuracy = 0.8233669923104289   time = 23.104921579360962
n = 223 average accuracy = 0.8242214651232794   time = 23.70276951789856
n = 228 average accuracy = 0.8229402119877038   time = 24.56711745262146
n = 234 average accuracy = 0.8214452836384533   time = 25.188450813293457
n = 239 average accuracy = 0.8212321785294037   time = 25.73282241821289
n = 244 average accuracy = 0.8218720639611782   time = 30.268824815750122
n = 250 average accuracy = 0.8218724060239534   time = 29.331119537353516
```

[24]:

```
plt.plot(n_trees,np.array(avg_accuracies))
plt.show()
```



[35]:

```
n_trees = np.append(np.arange(160,180,2), np.arange(210,230,2))
avg_accuracies = []
for n in n_trees:
    adaboost = AdaBoostClassifier(n_estimators = n)
    t1 = time.time()
    acc_score = cross_validation(X_train,y_train,adaboost,cv=10)
    t2 = time.time() - t1
    print(f"n = {n}\taverage accuracy = {acc_score}\ttime = {t2}")
    avg_accuracies.append(acc_score)
```

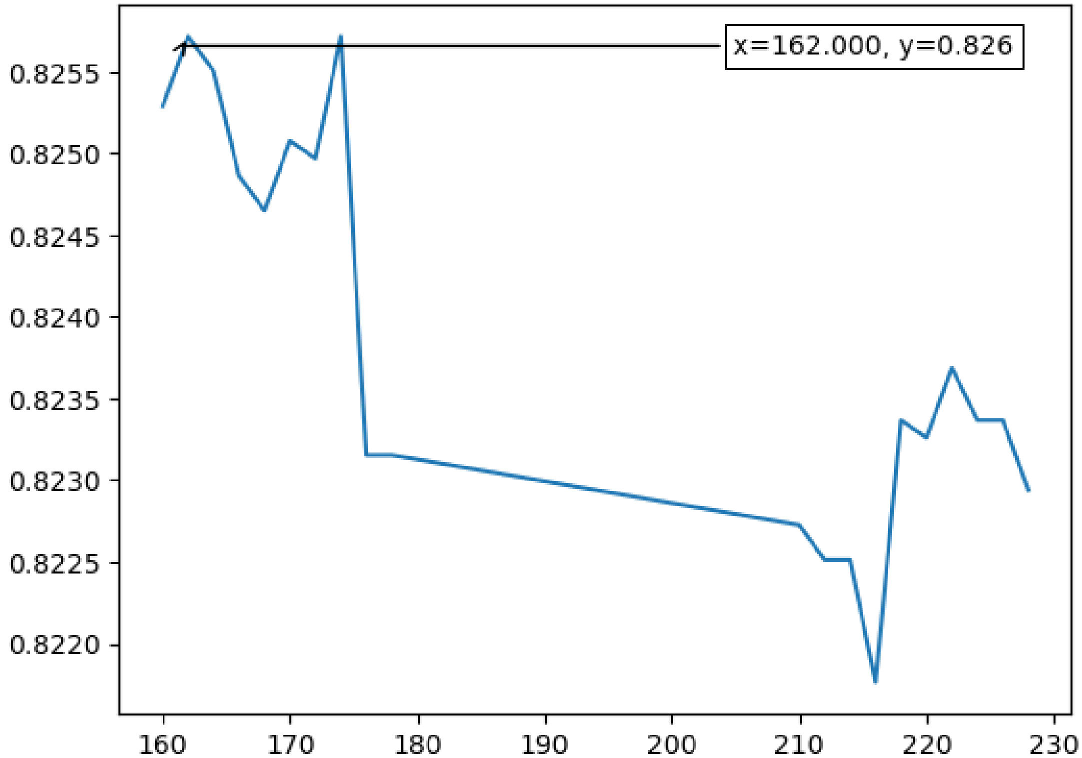
```
n = 160 average accuracy = 0.8252899552125805   time = 20.920289039611816
n = 162 average accuracy = 0.8257169635771557   time = 22.278916835784912
n = 164 average accuracy = 0.825503744447181    time = 20.267263412475586
n = 166 average accuracy = 0.8248630608689306   time = 24.5304536819458
n = 168 average accuracy = 0.8246498417389561   time = 25.378095626831055
n = 170 average accuracy = 0.8250767360826059   time = 27.45654058456421
n = 172 average accuracy = 0.8249700124966933   time = 32.40224051475525
n = 174 average accuracy = 0.8257169635771557   time = 32.43246912956238
n = 176 average accuracy = 0.8231535451386037   time = 27.431811571121216
n = 178 average accuracy = 0.8231538872013792   time = 29.31094717979431
n = 210 average accuracy = 0.8227264227531036   time = 33.8264045715332
n = 212 average accuracy = 0.8225129755812786   time = 34.81118130683899
n = 214 average accuracy = 0.8225128615603534   time = 35.082154273986816
n = 216 average accuracy = 0.8217652263543405   time = 37.366798400878906
n = 218 average accuracy = 0.8233669923104289   time = 37.05272030830383
n = 220 average accuracy = 0.8232604967663665   time = 39.5594539642334
n = 222 average accuracy = 0.8236878471937169   time = 37.14353060722351
n = 224 average accuracy = 0.8233676764359794   time = 35.75477313995361
n = 226 average accuracy = 0.8233675624150543   time = 36.94122648239136
n = 228 average accuracy = 0.8229402119877038   time = 37.269956827163696
```

[36]:

```
plt.plot(n_trees,np.array(avg_accuracies))

def annot_max(x,y, ax=None):
    xmax = x[np.argmax(y)]
    ymax = y.max()
    text= "x={:.3f}, y={:.3f}".format(xmax, ymax)
    if not ax:
        ax=plt.gca()
    bbox_props = dict(boxstyle="square,pad=0.3", fc="w", ec="k", lw=0.72)
    arrowprops=dict(arrowstyle="->",connectionstyle="angle,angleA=0,angleB=60")
    kw = dict(xycoords='data',textcoords="axes fraction",
              arrowprops=arrowprops, bbox=bbox_props, ha="right", va="top")
    ax.annotate(text, xy=(xmax, ymax), xytext=(0.94,0.96), **kw)

annot_max(n_trees,np.array(avg_accuracies))
plt.show()
```




```
Best n_estimators value: ~162
```

1.13 Hyperparameter tuning using Randomized Search

[23]:
```
'''from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.model_selection import RandomizedSearchCV
grid = dict()
grid['n_estimators'] = [100, 200, 211,300]
grid['learning_rate'] = [0.001, 0.01, 0.1, 1.0]
# define the evaluation procedure
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
# define the grid search procedure
grid_search = RandomizedSearchCV(estimator=AdaBoostClassifier(),␣
 ↪param_distributions=grid, cv=cv, scoring='accuracy')
# execute the grid search
grid_result = grid_search.fit(X_train, y_train)
# summarize the best score and configuration
print("Best: %f using %s" % (grid_result.best_score_, grid_result.
 ↪best_params_))'''
```

[23]:
```
'from sklearn.model_selection import RepeatedStratifiedKFold\nfrom
sklearn.model_selection import RandomizedSearchCV\ngrid =
```

```
dict()\ngrid[\'n_estimators\'] = [100, 200, 211,300]\ngrid[\'learning_rate\'] =
[0.001, 0.01, 0.1, 1.0]\n# define the evaluation procedure\ncv =
RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)\n# define the
grid search procedure\ngrid_search =
RandomizedSearchCV(estimator=AdaBoostClassifier(), param_distributions=grid,
cv=cv, scoring=\'accuracy\')\n# execute the grid search\ngrid_result =
grid_search.fit(X_train, y_train)\n# summarize the best score and
configuration\nprint("Best: %f using %s" % (grid_result.best_score_,
grid_result.best_params_))'
```

1.14 Testing Adaboost Classifier

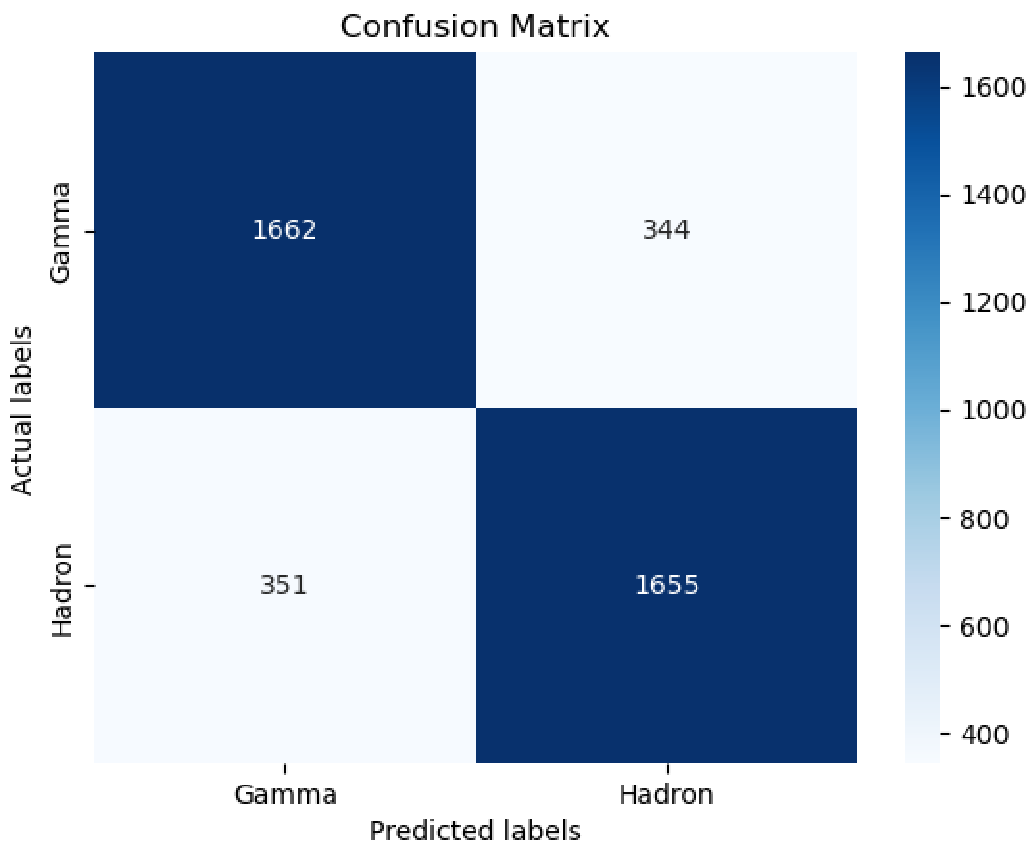
[37]:
```python
adaboost = AdaBoostClassifier(n_estimators=162)
y_pred = train_model(X_train,X_test,y_train,adaboost)
evaluate("Adaboost",y_pred,y_test)
```

```
Adaboost accuracy: 0.8267696909272183
Adaboost f1 score: 0.8264669163545567
Adaboost precision: 0.8279139569784892
Adaboost recall: 0.825024925224327
```

```
/tmp/ipykernel_103467/1172794529.py:12: FutureWarning: The frame.append method
is deprecated and will be removed from pandas in a future version. Use
pandas.concat instead.
  comparison_df = comparison_df.append(entry)
```

[38]:
```python
cf_matrix = confusion_matrix(y_test, y_pred)
print(cf_matrix)
ax= plt.subplot()
sns.heatmap(cf_matrix, annot=True,fmt='g',ax=ax,cmap='Blues')
ax.set_xlabel('Predicted labels');ax.set_ylabel('Actual labels');
ax.set_title('Confusion Matrix');
ax.xaxis.set_ticklabels(['Gamma', 'Hadron']); ax.yaxis.set_ticklabels(['Gamma',
↪'Hadron']);
```

```
[[1662  344]
 [ 351 1655]]
```



1.15 K-Nearest Neighbors (K-NN)

tunable parameters: `n_neighbors`

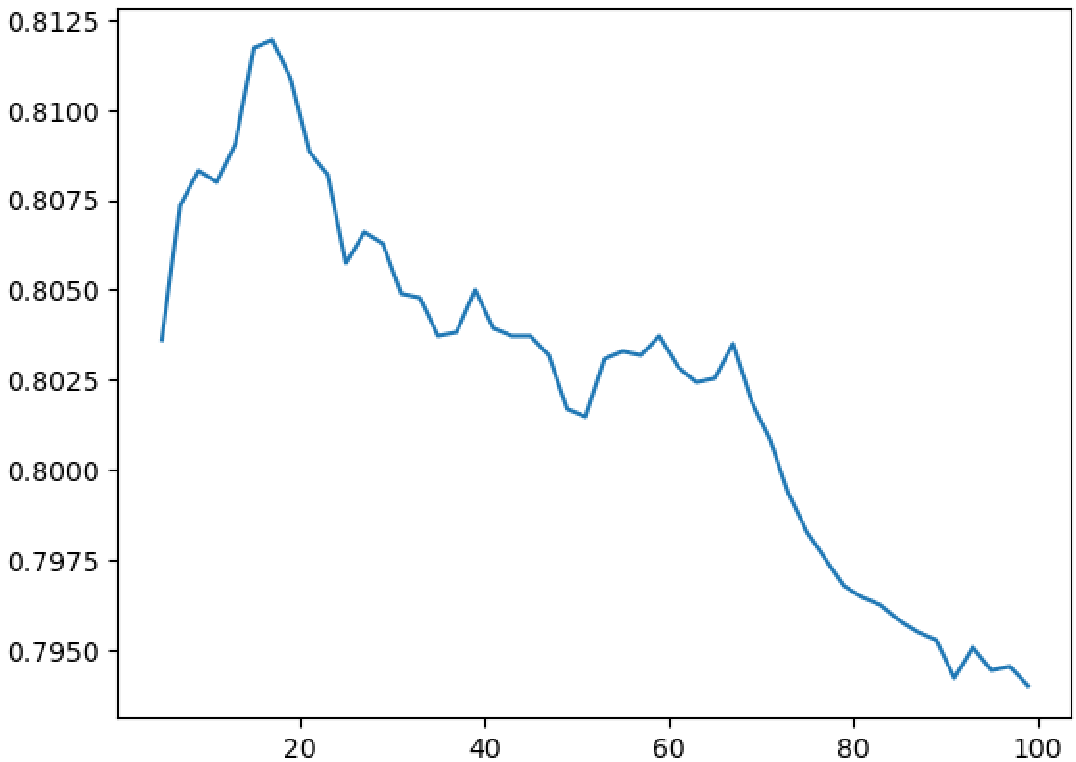
1.16 Hyperparameter tuning

[39]:
```
k_neighbors = np.arange(5,100,2)
avg_accuracies = []
for k in k_neighbors:
    knn = KNeighborsClassifier(n_neighbors=k)
    t1 = time.time()
    acc_score = cross_validation(X_train,y_train,knn,cv=10)
    t2 = time.time() - t1
    print(f"k = {k}\taverage accuracy = {acc_score}\ttime = {t2}")
    avg_accuracies.append(acc_score)
```

```
k = 5   average accuracy = 0.8036102445520802   time = 0.9275436401367188
k = 7   average accuracy = 0.8073481925402952   time = 0.8415946960449219
k = 9   average accuracy = 0.8083120114203359   time = 0.8044657707214355
```

```
k = 11  average accuracy = 0.8079916126207483   time = 0.9410521984100342
k = 13  average accuracy = 0.8090591905426484   time = 0.9799323081970215
k = 15  average accuracy = 0.8117272801904605   time = 0.9461812973022461
k = 17  average accuracy = 0.811940271278585    time = 1.0473792552947998
k = 19  average accuracy = 0.8108725793357596   time = 1.0845611095428467
k = 21  average accuracy = 0.808844375119722    time = 1.0808305740356445
k = 23  average accuracy = 0.8082022092694452   time = 1.1431636810302734
k = 25  average accuracy = 0.8057466546260569   time = 1.0238127708435059
k = 27  average accuracy = 0.8065996451668811   time = 1.022817850112915
k = 29  average accuracy = 0.8062792463672933   time = 1.0328309535980225
k = 31  average accuracy = 0.8048913836667306   time = 1.0972936153411865
k = 33  average accuracy = 0.804784546059893    time = 1.015312910079956
k = 35  average accuracy = 0.8037174242216931   time = 1.0236971378326416
k = 37  average accuracy = 0.803824489870381    time = 1.06325101852417
k = 39  average accuracy = 0.8049983352944933   time = 1.052854061126709
k = 41  average accuracy = 0.803930757372593    time = 1.0777232646942139
k = 43  average accuracy = 0.8037177662844686   time = 1.0988304615020752
k = 45  average accuracy = 0.8037176522635434   time = 1.1346666812896729
k = 47  average accuracy = 0.8031824380410292   time = 1.0866870880126953
k = 49  average accuracy = 0.8016875096917786   time = 1.1202075481414795
k = 51  average accuracy = 0.8014741765408788   time = 1.1801459789276123
k = 53  average accuracy = 0.803076740643443    time = 1.1863205432891846
k = 55  average accuracy = 0.8032906438989682   time = 1.2490835189819336
k = 57  average accuracy = 0.8031840343339809   time = 1.1462140083312988
k = 59  average accuracy = 0.8037174242216933   time = 1.2071318626403809
k = 61  average accuracy = 0.8028631794506929   time = 1.2341325283050537
k = 63  average accuracy = 0.8024348028350163   time = 1.2632079124450684
k = 65  average accuracy = 0.8025410703372284   time = 1.2628123760223389
k = 67  average accuracy = 0.8035014685895154   time = 1.2377369403839111
k = 69  average accuracy = 0.8019007288217533   time = 1.2714812755584717
k = 71  average accuracy = 0.8008325807952277   time = 1.279567003250122
k = 73  average accuracy = 0.7993382225506025   time = 1.2782516479492188
k = 75  average accuracy = 0.7982706446287023   time = 1.32497239112854
k = 77  average accuracy = 0.7975225533389888   time = 1.3332364559173584
k = 79  average accuracy = 0.7967752601957512   time = 1.287491798400879
k = 81  average accuracy = 0.7964542912915379   time = 1.3423402309417725
k = 83  average accuracy = 0.7962414142243385   time = 1.4171881675720215
k = 85  average accuracy = 0.7958137217342127   time = 1.461984634399414
k = 87  average accuracy = 0.7954934369555502   time = 1.273763656616211
k = 89  average accuracy = 0.7952803318465005   time = 1.4719879627227783
k = 91  average accuracy = 0.7942119557781244   time = 1.3731598854064941
k = 93  average accuracy = 0.7950659725072746   time = 1.5490672588348389
k = 95  average accuracy = 0.7944254029499493   time = 1.4275591373443604
k = 97  average accuracy = 0.7945320125149368   time = 1.4569587707519531
k = 99  average accuracy = 0.7939987366481497   time = 1.4227516651153564
```

[40]:
```
plt.plot(k_neighbors,np.array(avg_accuracies))
plt.show()
```



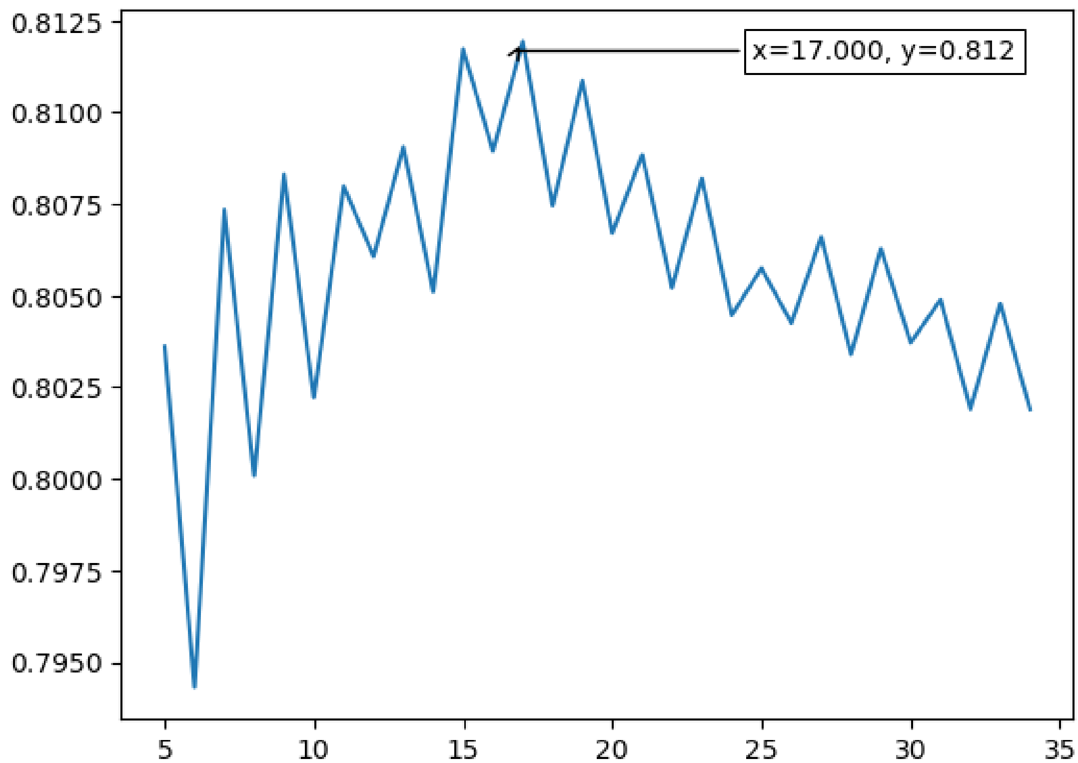
[41]:
```
k_neighbors = np.arange(5,35,1)
avg_accuracies = []
for k in k_neighbors:
    knn = KNeighborsClassifier(n_neighbors=k)
    t1 = time.time()
    acc_score = cross_validation(X_train,y_train,knn,cv=10)
    t2 = time.time() - t1
    print(f"k = {k}\taverage accuracy = {acc_score}\ttime = {t2}")
    avg_accuracies.append(acc_score)
```

```
k = 5   average accuracy = 0.8036102445520802   time = 0.8367834091186523
k = 6   average accuracy = 0.794319705552363    time = 0.9571902751922607
k = 7   average accuracy = 0.8073481925402952   time = 0.9600963592529297
k = 8   average accuracy = 0.800088252196043    time = 0.8641960620880127
k = 9   average accuracy = 0.8083120114203359   time = 0.8481636047363281
k = 10  average accuracy = 0.8022234080398436   time = 0.9617252349853516
k = 11  average accuracy = 0.8079916126207483   time = 1.0233728885650635
k = 12  average accuracy = 0.8060689917813717   time = 0.9200780391693115
```

```
k = 13  average accuracy = 0.8090591905426484   time = 1.0408422946929932
k = 14  average accuracy = 0.8051068832152076   time = 1.063035011291504
k = 15  average accuracy = 0.8117272801904605   time = 1.0479013919830322
k = 16  average accuracy = 0.8089509846847092   time = 1.0557396411895752
k = 17  average accuracy = 0.811940271278585    time = 1.012247085571289
k = 18  average accuracy = 0.8074556002517582   time = 1.1496648788452148
k = 19  average accuracy = 0.8108725793357596   time = 1.009418249130249
k = 20  average accuracy = 0.8067088772131463   time = 1.030416488647461
k = 21  average accuracy = 0.808844375119722    time = 1.0960516929626465
k = 22  average accuracy = 0.8052132647383449   time = 0.958836555480957
k = 23  average accuracy = 0.8082022092694452   time = 0.9168310165405273
k = 24  average accuracy = 0.8044656295323318   time = 0.9686422348022461
k = 25  average accuracy = 0.8057466546260569   time = 0.974470853805542
k = 26  average accuracy = 0.8042516122558812   time = 1.1010453701019287
k = 27  average accuracy = 0.8065996451668811   time = 1.2187957763671875
k = 28  average accuracy = 0.8033970254221054   time = 1.363678216934204
k = 29  average accuracy = 0.8062792463672933   time = 1.1283354759216309
k = 30  average accuracy = 0.8037167400961425   time = 0.9869060516357422
k = 31  average accuracy = 0.8048913836667306   time = 1.0695619583129883
k = 32  average accuracy = 0.8019016409891544   time = 1.156188726425171
k = 33  average accuracy = 0.804784546059893    time = 1.0777318477630615
k = 34  average accuracy = 0.8019019830519298   time = 1.0036108493804932
```

[42]:

```
plt.plot(k_neighbors,np.array(avg_accuracies))
annot_max(k_neighbors,np.array(avg_accuracies))
plt.show()
```



1.17 Testing KNN Classifier

[43]:
```
knn = KNeighborsClassifier(n_neighbors=17)
y_pred = train_model(X_train,X_test,y_train,knn)
evaluate("KNN",y_pred,y_test)
```

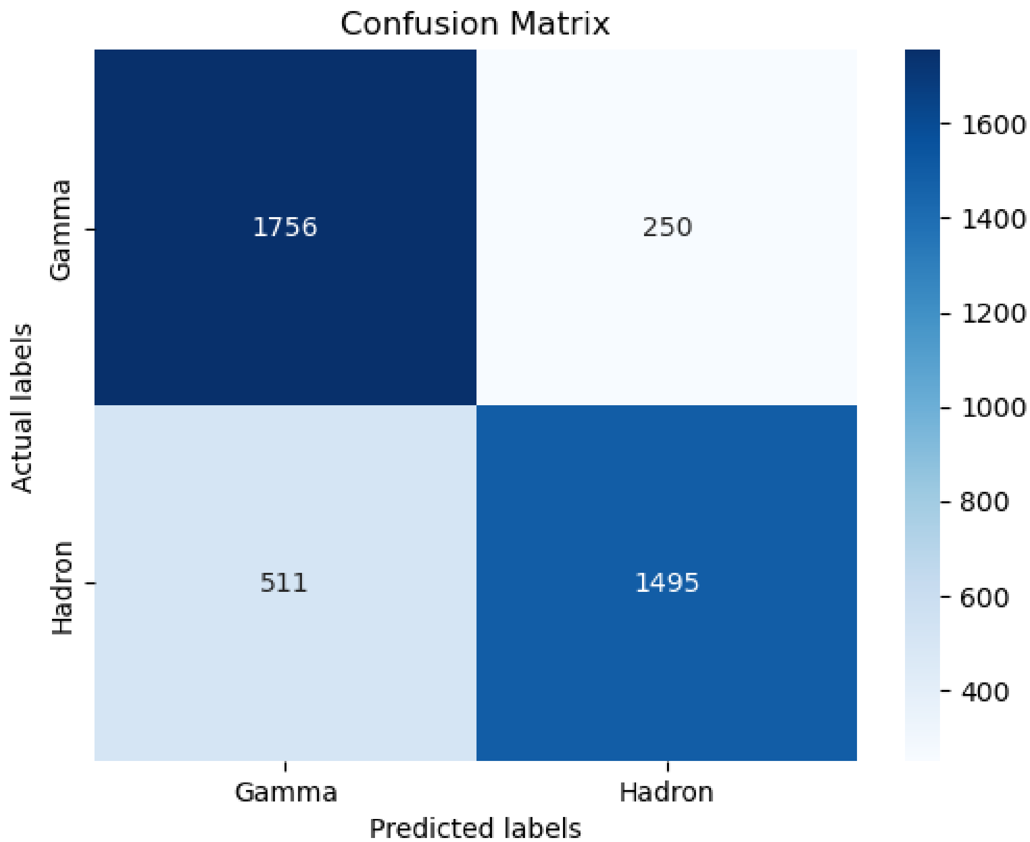
```
KNN accuracy: 0.8103190428713859
KNN f1 score: 0.7971207677952545
KNN precision: 0.8567335243553008
KNN recall: 0.7452642073778664
```

```
/tmp/ipykernel_103467/1172794529.py:12: FutureWarning: The frame.append method
is deprecated and will be removed from pandas in a future version. Use
pandas.concat instead.
  comparison_df = comparison_df.append(entry)
```

[44]:
```
cf_matrix = confusion_matrix(y_test, y_pred)
print(cf_matrix)
ax= plt.subplot()
sns.heatmap(cf_matrix, annot=True,fmt='g',ax=ax,cmap='Blues')
ax.set_xlabel('Predicted labels');ax.set_ylabel('Actual labels');
ax.set_title('Confusion Matrix');
```

```
ax.xaxis.set_ticklabels(['Gamma', 'Hadron']); ax.yaxis.set_ticklabels(['Gamma',␣
↪'Hadron']);
```

```
[[1756  250]
 [ 511 1495]]
```



1.18 Random Forest

A random forest is a meta estimator that fits a number of decision tree classifiers on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting. The sub-sample size is controlled with the max_samples parameter if bootstrap=True (default), otherwise the whole dataset is used to build each tree.

tunable parameters: `n_estimators`

`n_estimators`: The number of trees in the forest.

1.19 Hyperparameter tuning

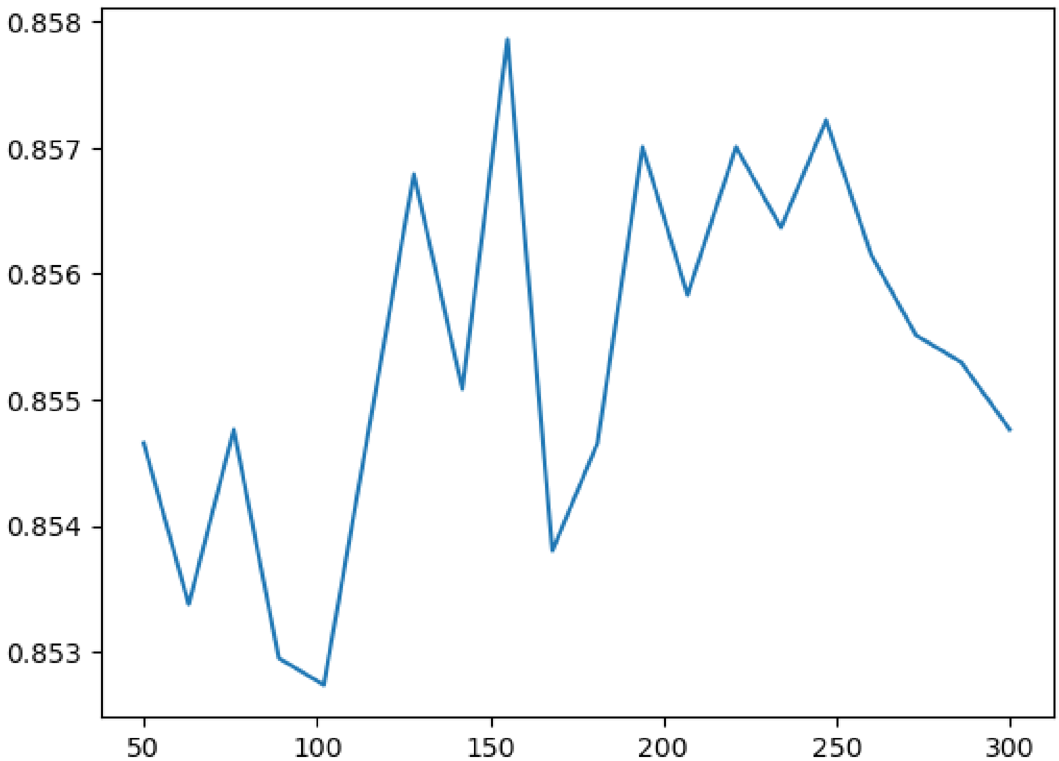
[45]:

```
n_estimators = np.linspace(50,300,20,dtype=int)
avg_accuracies = []
for n in n_estimators:
    rf = RandomForestClassifier(n_estimators=n)
    t1 = time.time()
    acc_score = cross_validation(X_train,y_train,rf,cv=10)
    t2 = time.time() - t1
    print(f"n = {n}\taverage accuracy = {acc_score}\ttime = {t2}")
    avg_accuracies.append(acc_score)
```

```
n = 50  average accuracy = 0.8546554743726569   time = 14.546619415283203
n = 63  average accuracy = 0.8533742212370814   time = 18.63932204246521
n = 76  average accuracy = 0.8547642503352215   time = 22.82245397567749
n = 89  average accuracy = 0.8529476689562067   time = 26.597578048706055
n = 102 average accuracy = 0.852735590035483    time = 29.100209712982178
n = 115 average accuracy = 0.8547636802305959   time = 30.842748403549194
n = 128 average accuracy = 0.8567916564047833   time = 34.293354511260986
n = 142 average accuracy = 0.8550833949046328   time = 38.108360052108765
n = 155 average accuracy = 0.8578606025777852   time = 41.908435583114624
n = 168 average accuracy = 0.8538020277481323   time = 45.20749306678772
n = 181 average accuracy = 0.8546560444772824   time = 48.60418939590454
n = 194 average accuracy = 0.8570068138904849   time = 52.40931987762451
n = 207 average accuracy = 0.8558319422780469   time = 59.73830986022949
n = 221 average accuracy = 0.857005673681234    time = 59.9186155796051
n = 234 average accuracy = 0.85636624433316     time = 60.4331157207489
n = 247 average accuracy = 0.8572191208530588   time = 63.94174265861511
n = 260 average accuracy = 0.8561514289102335   time = 67.44234561920166
n = 273 average accuracy = 0.8555110873947587   time = 70.46408534049988
n = 286 average accuracy = 0.855297982285709    time = 74.47242665290833
n = 300 average accuracy = 0.8547637942515209   time = 77.95634722709656
```

[46]:

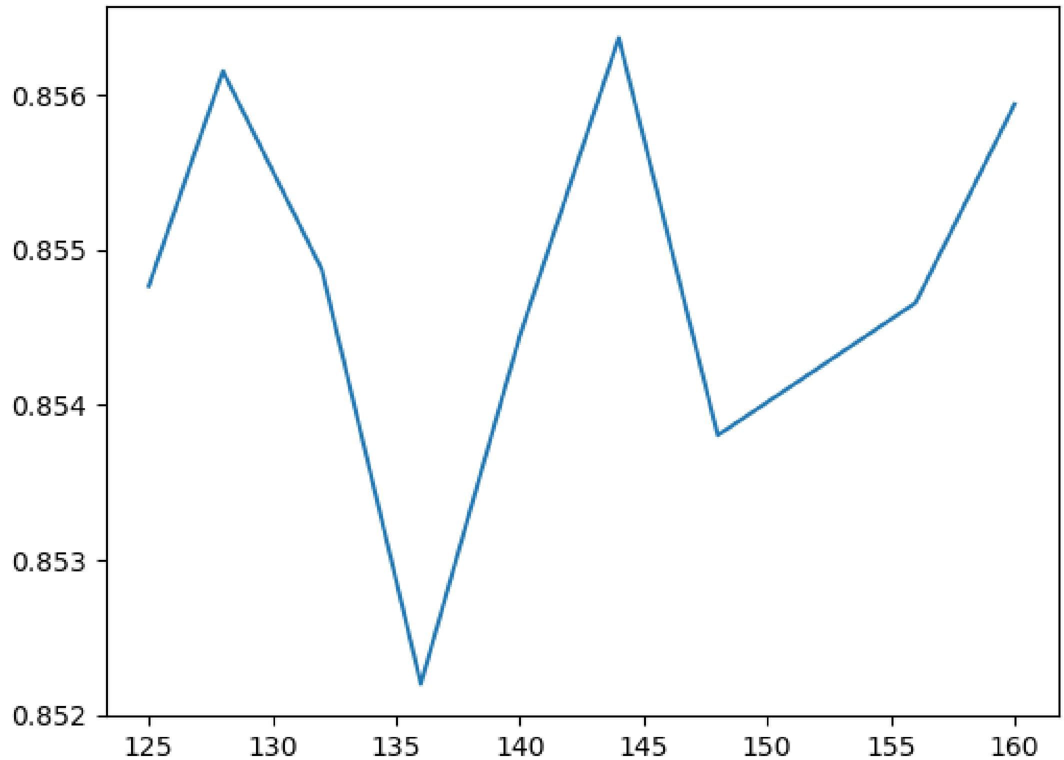
```
plt.plot(n_estimators,np.array(avg_accuracies))
plt.show()
```



[47]:
```
n_estimators = np.linspace(125,160,10,dtype=int)
avg_accuracies = []
for n in n_estimators:
    rf = RandomForestClassifier(n_estimators=n)
    t1 = time.time()
    acc_score = cross_validation(X_train,y_train,rf,cv=10)
    t2 = time.time() - t1
    print(f"n = {n}\taverage accuracy = {acc_score}\ttime = {t2}")
    avg_accuracies.append(acc_score)
```

```
n = 125 average accuracy = 0.8547644783770716   time = 32.737011432647705
n = 128 average accuracy = 0.8561508588056078   time = 32.50386452674866
n = 132 average accuracy = 0.8548707458792839   time = 34.80695652961731
n = 136 average accuracy = 0.8522000337501938   time = 35.76816487312317
n = 140 average accuracy = 0.8544441935984091   time = 38.21756052970886
n = 144 average accuracy = 0.8563655602076092   time = 42.68096613883972
n = 148 average accuracy = 0.8538029399155332   time = 44.07245111465454
n = 152 average accuracy = 0.8542298342591833   time = 41.50951528549194
n = 156 average accuracy = 0.854657640770234    time = 42.76413345336914
n = 160 average accuracy = 0.8559387798848844   time = 45.390727519989014
```

[48]:
```
plt.plot(n_estimators,np.array(avg_accuracies))
plt.show()
```

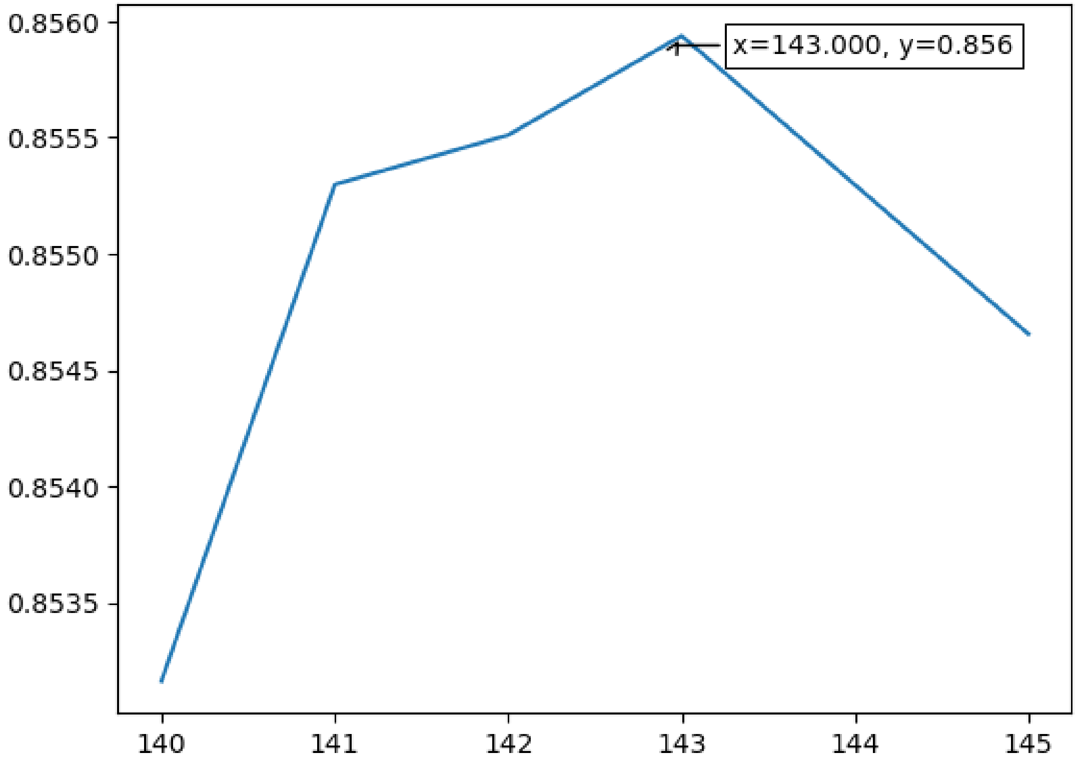


[49]:
```
n_estimators = np.linspace(140,145,5,dtype=int)
avg_accuracies = []
for n in n_estimators:
    rf = RandomForestClassifier(n_estimators=n)
    t1 = time.time()
    acc_score = cross_validation(X_train,y_train,rf,cv=10)
    t2 = time.time() - t1
    print(f"n = {n}\taverage accuracy = {acc_score}\ttime = {t2}")
    avg_accuracies.append(acc_score)
```

```
n = 140 average accuracy = 0.8531625984000583   time = 37.9939911365509
n = 141 average accuracy = 0.8552982103275593   time = 40.81869029998779
n = 142 average accuracy = 0.8555108593529083   time = 39.429386138916016
n = 143 average accuracy = 0.8559375256547082   time = 38.95640182495117
n = 145 average accuracy = 0.854655702414507    time = 40.980098724365234
```

[50]:
```
plt.plot(n_estimators,np.array(avg_accuracies))
annot_max(n_estimators,np.array(avg_accuracies))
```

```
plt.show()
```




```
best n_estimators value: ~143
```

1.20 Testing Random Forest Classifier

[51]:
```
rf = RandomForestClassifier(n_estimators=143)
y_pred = train_model(X_train,X_test,y_train,rf)
evaluate("Random Forest",y_pred,y_test)
```

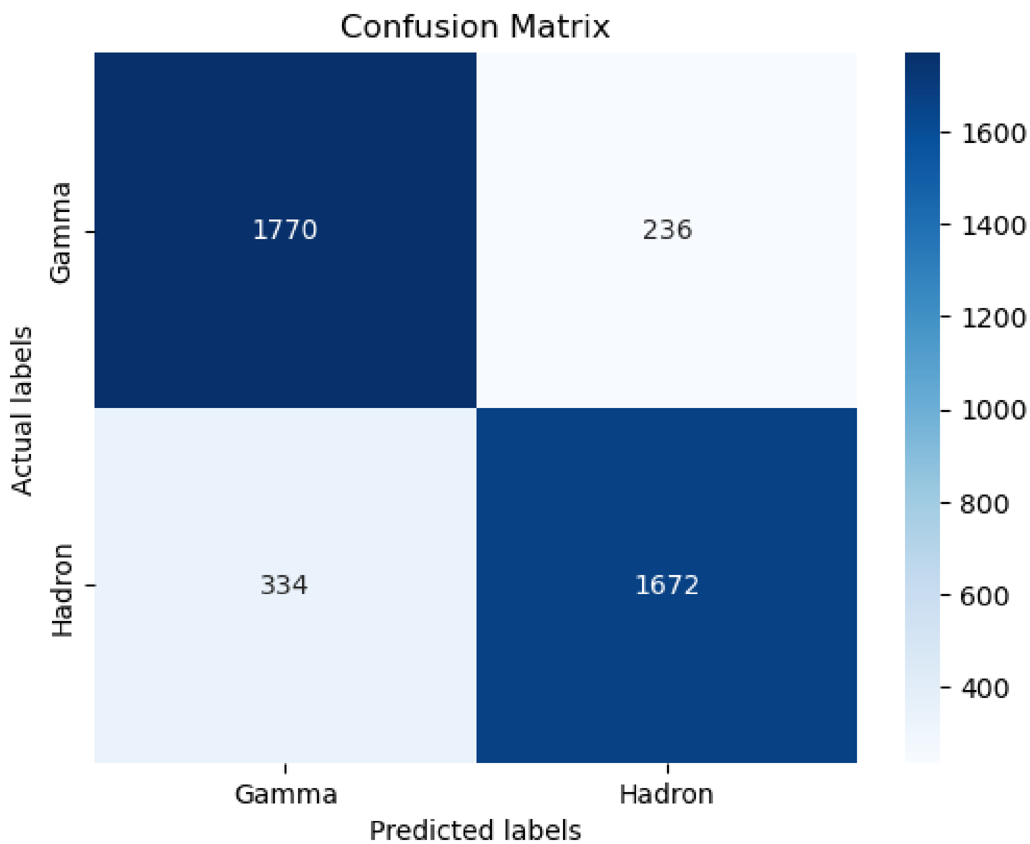
```
Random Forest accuracy: 0.8579262213359921
Random Forest f1 score: 0.854368932038835
Random Forest precision: 0.8763102725366876
Random Forest recall: 0.8334995014955134
```

```
/tmp/ipykernel_103467/1172794529.py:12: FutureWarning: The frame.append method
is deprecated and will be removed from pandas in a future version. Use
pandas.concat instead.
  comparison_df = comparison_df.append(entry)
```

[52]:
```
cf_matrix = confusion_matrix(y_test, y_pred)
print(cf_matrix)
ax= plt.subplot()
```

```
sns.heatmap(cf_matrix, annot=True,fmt='g',ax=ax,cmap='Blues')
ax.set_xlabel('Predicted labels');ax.set_ylabel('Actual labels');
ax.set_title('Confusion Matrix');
ax.xaxis.set_ticklabels(['Gamma', 'Hadron']); ax.yaxis.set_ticklabels(['Gamma',␣
↪'Hadron']);
```

```
[[1770  236]
 [ 334 1672]]
```



1.21 Naïve Bayes

Tunable parameters: None

1.22 Choosing `var_smoothing` parameter

`var_smoothing`: Portion of the largest variance of all features that is added to variances for calculation stability.

[53]:
```
var_smoothing = np.logspace(0,-9, num=10)
avg_accuracies = []
for v in var_smoothing:
```

```
    nb = GaussianNB(var_smoothing=v)
    t1 = time.time()
    acc_score = cross_validation(X_train,y_train,nb,cv=10)
    t2 = time.time() - t1
    print(f"v = {v}\taverage accuracy = {acc_score}\ttime = {t2}")
    avg_accuracies.append(acc_score)
```

```
v = 1.0 average accuracy = 0.6869899844019376   time = 0.04506111145019531
v = 0.1 average accuracy = 0.6889132893668646   time = 0.043242692947387695
v = 0.01        average accuracy = 0.6598669147761999   time =
0.040185689926147446
v = 0.001       average accuracy = 0.651217173375658    time =
0.03883981704711914
v = 0.0001      average accuracy = 0.650790279032008    time =
0.035029888153076172
v = 1e-05       average accuracy = 0.6506836694670207   time =
0.040584325790405273
v = 1e-06       average accuracy = 0.6506836694670207   time =
0.05889701843261719
v = 1e-07       average accuracy = 0.6506836694670207   time =
0.05028414726257324
v = 1e-08       average accuracy = 0.6506836694670207   time =
0.046877384185791016
v = 1e-09       average accuracy = 0.6506836694670207   time =
0.03712105751037598
```

Best `var_smoothing` value: ~0.1

1.23 Feature Selection

[54]:
```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
def feature_select(X_train,y_train):
    n_samples = X_train.shape[0]
    for i in range(1,X.shape[1]+1):
        select = SelectKBest(k=i, score_func=chi2)
        select.fit(X_train, y_train)
        X_new = select.transform(X_train)
        acc_score = cross_validation(X_new,y_train,GaussianNB(var_smoothing=0.
 ↪1),cv=10)
        print(f"no. of features= {i}\taverage accuracy = {acc_score}")
        avg_accuracies.append(acc_score)
```

[55]:
```
feature_select(X_train,y_train)
```

```
no. of features= 1      average accuracy = 0.7047201242371999
no. of features= 2      average accuracy = 0.7367549872752648
no. of features= 3      average accuracy = 0.723832083663994
no. of features= 4      average accuracy = 0.7236181804084686
no. of features= 5      average accuracy = 0.7129420591266908
no. of features= 6      average accuracy = 0.7108070173038156
no. of features= 7      average accuracy = 0.70140895657171
no. of features= 8      average accuracy = 0.6986320909613333
no. of features= 9      average accuracy = 0.6968163077287943
no. of features= 10     average accuracy = 0.6889132893668646
```

The best 2 features yield max accuracy

1.24 Testing Naive Bayes Classifier

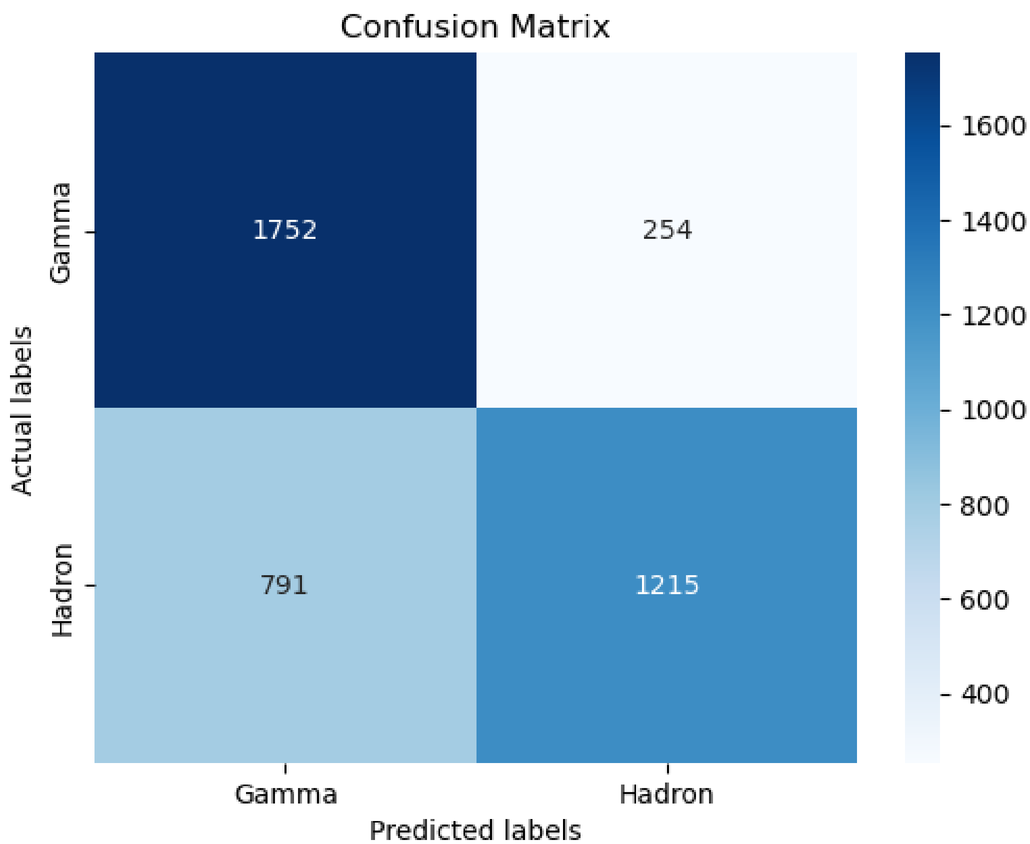
[56]:
```
select = SelectKBest(k=2, score_func=chi2)
select.fit(X_train, y_train)
X_new = select.transform(X_train)
X_test_new = select.transform(X_test)
y_pred = train_model(X_new,X_test_new,y_train,GaussianNB(var_smoothing=0.1))
evaluate("Naive Bayes",y_pred,y_test)
```

```
Naive Bayes accuracy: 0.7395314057826521
Naive Bayes f1 score: 0.6992805755395683
Naive Bayes precision: 0.8270932607215793
Naive Bayes recall: 0.6056829511465603
```

```
/tmp/ipykernel_103467/1172794529.py:12: FutureWarning: The frame.append method
is deprecated and will be removed from pandas in a future version. Use
pandas.concat instead.
  comparison_df = comparison_df.append(entry)
```

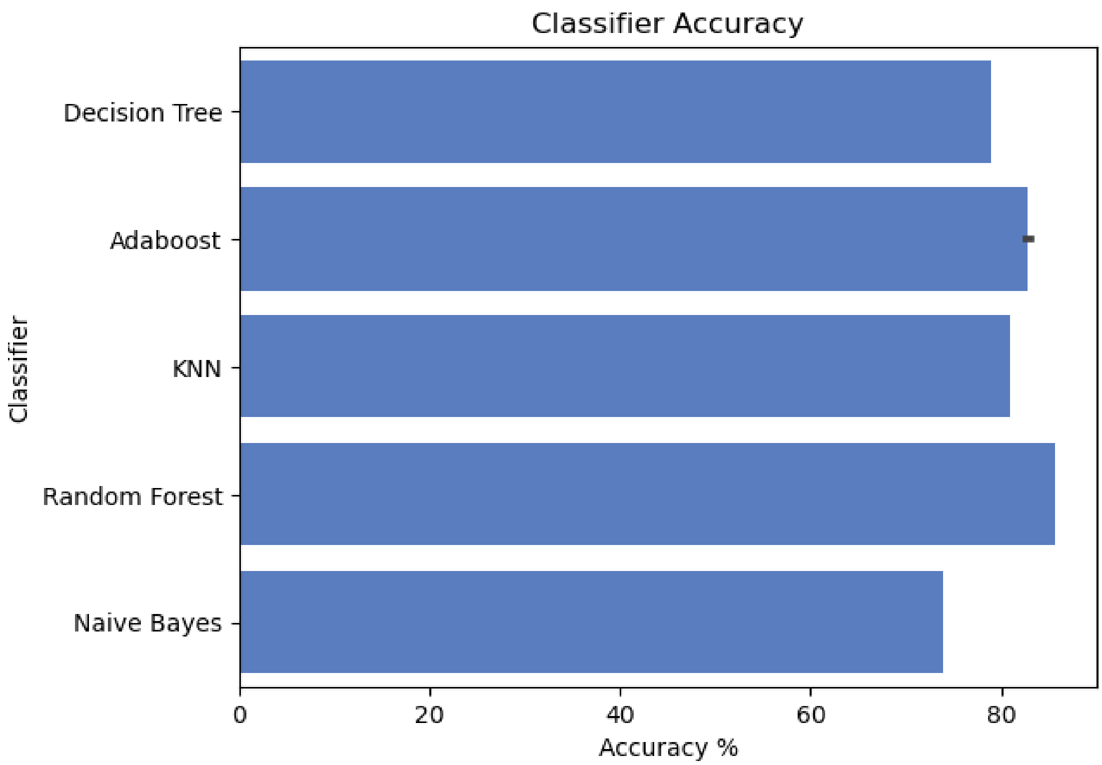
[57]:
```
cf_matrix = confusion_matrix(y_test, y_pred)
print(cf_matrix)
ax= plt.subplot()
sns.heatmap(cf_matrix, annot=True,fmt='g',ax=ax,cmap='Blues')
ax.set_xlabel('Predicted labels');ax.set_ylabel('Actual labels');
ax.set_title('Confusion Matrix');
ax.xaxis.set_ticklabels(['Gamma', 'Hadron']); ax.yaxis.set_ticklabels(['Gamma',␣
↪'Hadron']);
```

```
[[1752  254]
 [ 791 1215]]
```



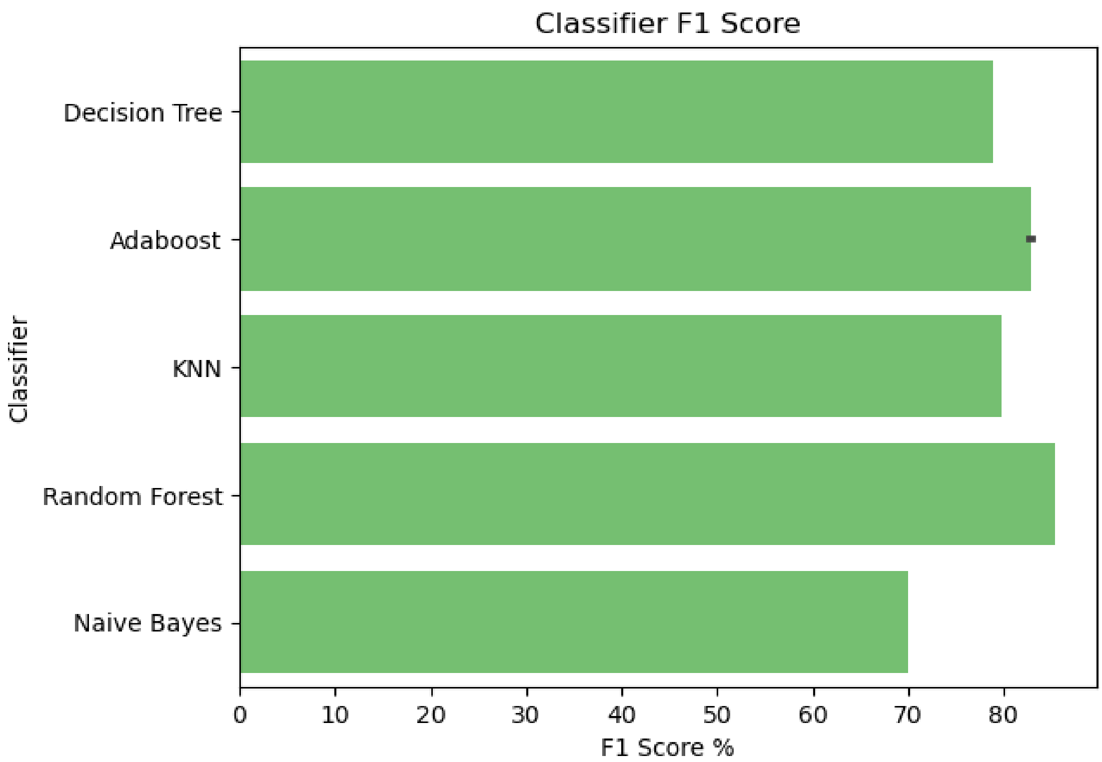
[58]:
```
sns.set_color_codes("muted")
sns.barplot(x='Accuracy', y='Classifier', data=comparison_df, color="b")

plt.xlabel('Accuracy %')
plt.title('Classifier Accuracy')
plt.show()
```



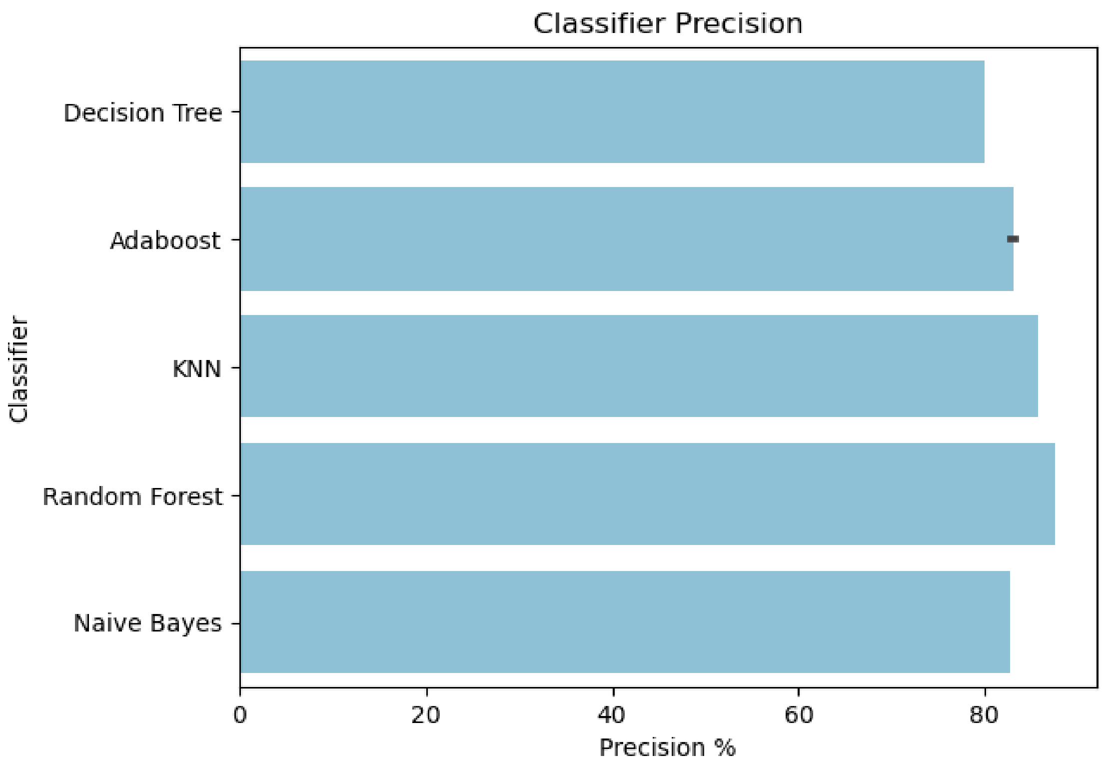
[59]:
```
sns.set_color_codes("muted")
sns.barplot(x='F1 score', y='Classifier', data=comparison_df, color="g")

plt.xlabel('F1 Score %')
plt.title('Classifier F1 Score')
plt.show()
```



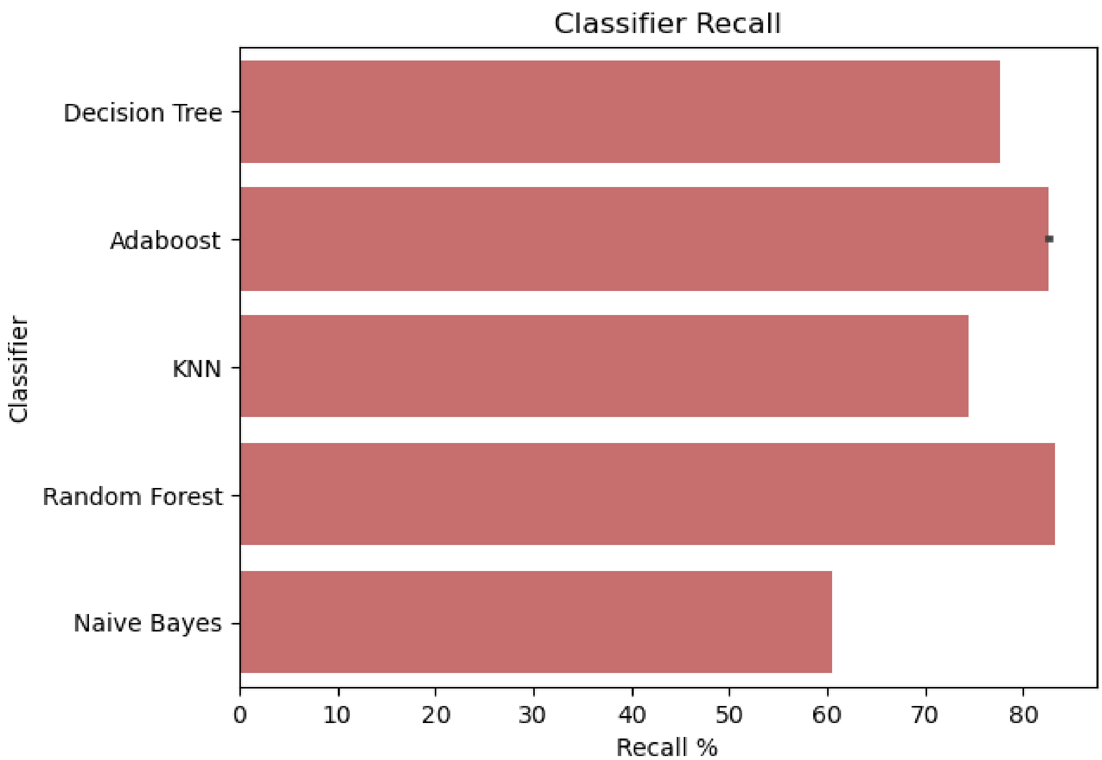
[60]:
```
sns.set_color_codes("muted")
sns.barplot(x='Precision', y='Classifier', data=comparison_df, color="c")

plt.xlabel('Precision %')
plt.title('Classifier Precision')
plt.show()
```



[61]:
```
sns.set_color_codes("muted")
sns.barplot(x='Recall', y='Classifier', data=comparison_df, color="r")

plt.xlabel('Recall %')
plt.title('Classifier Recall')
plt.show()
```


Classifier Recall
Decision Tree
Adaboost
KNN
Random Forest
Naive Bayes
Classifier
0
10
20
30
40
50
60
70
80
Recall %

```
[ ]:
```