CS 634 Data Mining Final term Project

Option 1: Supervised Data Mining (Classification)

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Programming Language: Python

Classification Algorithms Implemented:

i) Random Forest

ii) Naïve Bayes

iii) KNN, K-Nearest Neighbor

Dataset used: Bank Marketing Data Set

Source of Data:

https://archive.ics.uci.edu/ml/datasets/Bank+Marketing

Code:

Detailed implementation of the classifiers process

Steps to Implement the process:

1. Preprocess the data

Supervised Data Mining (Classification) ¶

In [287]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
```

In [288]:
```
data = pd.read_csv('bank.csv', header=0)
data = data.dropna()
print(data.shape)
print(list(data.columns))
```

```
(4521, 17)
['age', 'job', 'marital', 'education', 'default', 'balance', 'housing', 'loan', 'contact', 'day', 'month', 'duration', 'campaig
n', 'pdays', 'previous', 'poutcome', 'y']
```

In [289]:
```
dataset.head()
```

Out[289]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
0	30	unemployed	married	primary	no	1787	no	no	cellular	19	oct	79	1	-1	0	unknown	no
1	33	services	married	secondary	no	4789	yes	yes	cellular	11	may	220	1	339	4	failure	no
2	35	management	single	tertiary	no	1350	yes	no	cellular	16	apr	185	1	330	1	failure	no
3	30	management	married	tertiary	no	1476	yes	yes	unknown	3	jun	199	4	-1	0	unknown	no
4	59	blue-collar	married	secondary	no	0	yes	no	unknown	5	may	226	1	-1	0	unknown	no

In [292]:
```
#checking for missing values in dataset
data.isnull().sum()
```

Out[292]:
```
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
y            0
dtype: int64
```

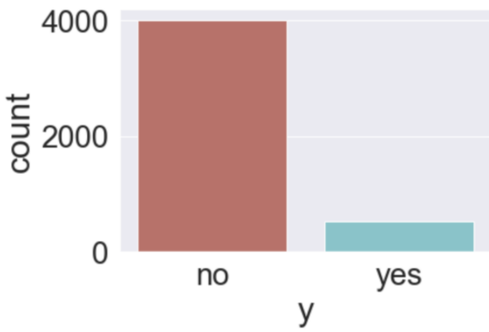
In [293]:
```
data['job'].unique()
```

Out[293]:
```
array(['unemployed', 'services', 'management', 'blue-collar',
       'self-employed', 'technician', 'entrepreneur', 'admin.', 'student',
       'housemaid', 'retired', 'unknown'], dtype=object)
```

In [294]:
```
#Frequency of 'subscribed'
data['y'].value_counts()
```

Out[294]:
```
no     4000
yes     521
Name: y, dtype: int64
```

In [295]:
```
sns.countplot(x='y', data=data, palette='hls')
plt.show()
plt.savefig('count_plot')
```




```
<Figure size 432x288 with 0 Axes>
```

In [296]:
```
#Normalizing the frequency table of 'Subscribed' variable
data['y'].value_counts(normalize=True)
```

Out[296]:
```
no     0.88476
yes    0.11524
Name: y, dtype: float64
```

From the above analysis we can see that only 3,715 people out of 31,647 have subscribed which is roughly 12%.

In [297]:
```
data.groupby('y').mean()
```

Out[297]:

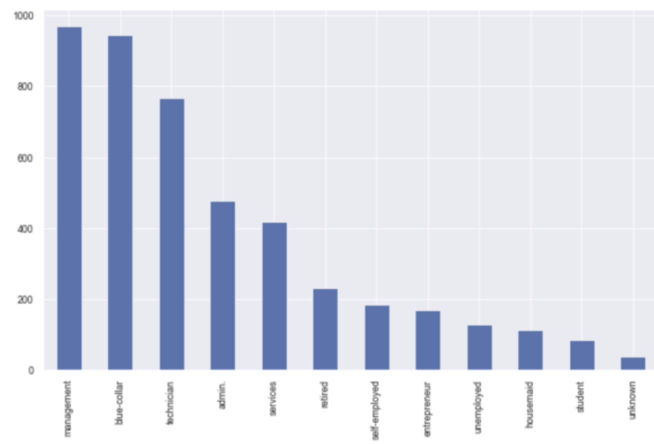
	age	balance	day	duration	campaign	pdays	previous
y							
no	40.998000	1403.211750	15.948750	226.347500	2.862250	36.006000	0.471250
yes	42.491363	1571.955854	15.658349	552.742802	2.266795	68.639155	1.090211

Analyzed the data for all attributes:

In [298]:
```
#Analysis 'job'
#Frequency table
data['job'].value_counts()
```

Out[298]:
```
management       969
blue-collar      946
technician       768
admin.           478
services         417
retired          230
self-employed    183
entrepreneur     168
unemployed       128
housemaid        112
student           84
unknown           38
Name: job, dtype: int64
```

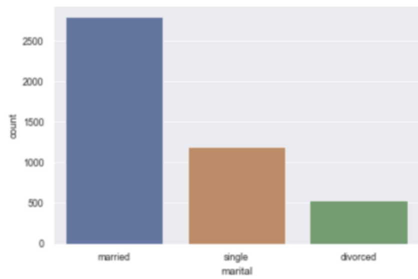
In [299]:
```
# Plotting the job frequency table
sns.set_context('paper')
data['job'].value_counts().plot(kind='bar', figsize=(10,6));
```



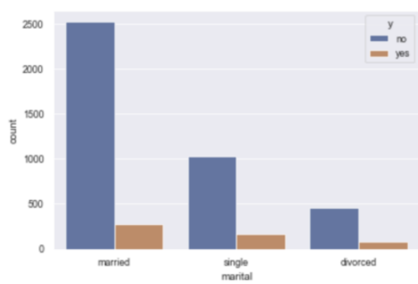
In [300]:
```
# Analysing 'marital'
data['marital'].value_counts()
```

Out[300]:
```
married     2797
single      1196
divorced     528
Name: marital, dtype: int64
```

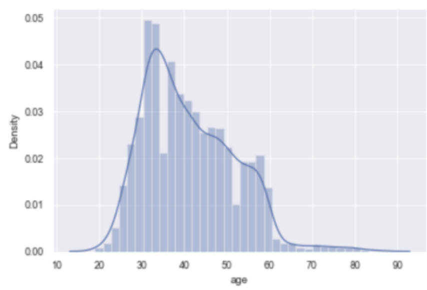
In [301]:
```
sns.countplot(data=data, x='marital');
```



In [302]:
```
sns.countplot(data=data, x='marital', hue='y');
```



In [303]:
```
# Analysing 'age'
sns.distplot(data['age']);
```



In [304]:
```
#default vs subscription
pd.crosstab(data['default'], data['y'])
```

Out[304]:

y	no	yes
default		
no	3933	512
yes	67	9

Correlation matrix:

In [307]:
```
# Converting the target variables into 0s and 1s
data['y'].replace('no', 0,inplace=True)
data['y'].replace('yes', 1,inplace=True)
data['y']
```

Out[307]:
```
0       0
1       0
2       0
3       0
4       0
       ..
4516    0
4517    0
4518    0
4519    0
4520    0
Name: y, Length: 4521, dtype: int64
```

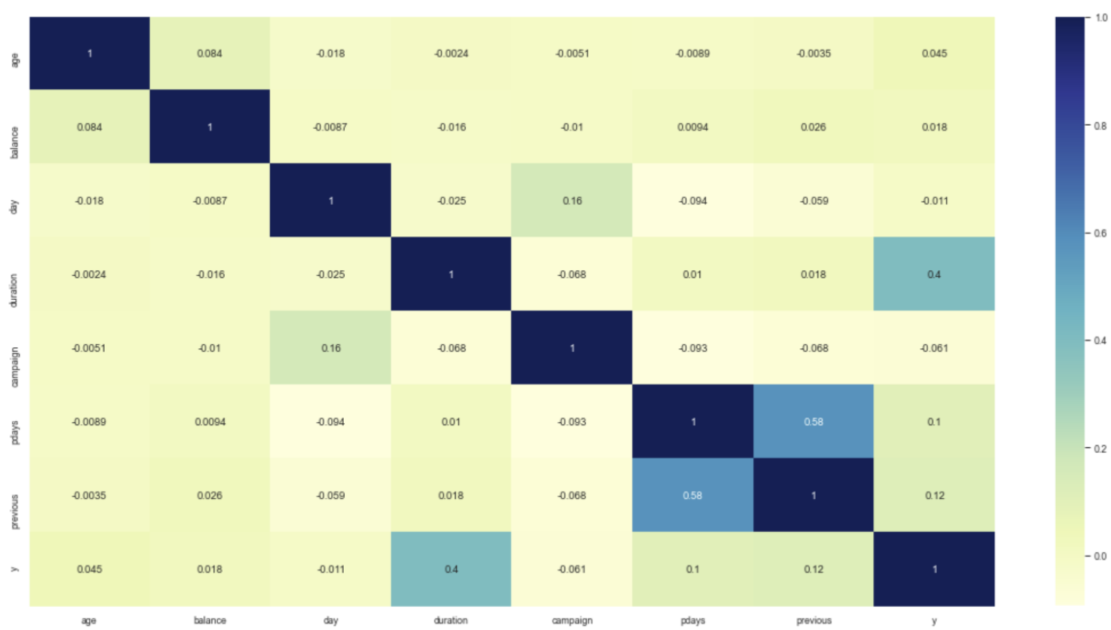
In [308]:
```
#Correlation matrix
dc = data.corr()
dc
```

Out[308]:

	age	balance	day	duration	campaign	pdays	previous	y
age	1.000000	0.083820	-0.017853	-0.002367	-0.005148	-0.008894	-0.003511	0.045092
balance	0.083820	1.000000	-0.008677	-0.015950	-0.009976	0.009437	0.026196	0.017905
day	-0.017853	-0.008677	1.000000	-0.024629	0.160706	-0.094352	-0.059114	-0.011244
duration	-0.002367	-0.015950	-0.024629	1.000000	-0.068382	0.010380	0.018080	0.401118
campaign	-0.005148	-0.009976	0.160706	-0.068382	1.000000	-0.093137	-0.067833	-0.061147
pdays	-0.008894	0.009437	-0.094352	0.010380	-0.093137	1.000000	0.577562	0.104087
previous	-0.003511	0.026196	-0.059114	0.018080	-0.067833	0.577562	1.000000	0.116714
y	0.045092	0.017905	-0.011244	0.401118	-0.061147	0.104087	0.116714	1.000000

In [309]:
```
fig,ax= plt.subplots()
fig.set_size_inches(20,10)
sns.heatmap(dc, annot=True, cmap='YlGnBu')
```

Out[309]: <AxesSubplot:>



2. Split the dataset with the help of train_test_split function

In [310]:
```python
target = data['y']
data = data.drop('y', axis=1)
```

In [311]:
```python
#generating dummy values on the dataset
data = pd.get_dummies(data)
data.head()
```

Out[311]:

	age	balance	day	duration	campaign	pdays	previous	job_admin.	job_blue-collar	job_entrepreneur	...	month_jun	month_mar	month_may	month_nov	mor
0	30	1787	19	79	1	-1	0	0	0	0	...	0	0	0	0	
1	33	4789	11	220	1	339	4	0	0	0	...	0	0	1	0	
2	35	1350	16	185	1	330	1	0	0	0	...	0	0	0	0	
3	30	1476	3	199	4	-1	0	0	0	0	...	1	0	0	0	
4	59	0	5	226	1	-1	0	0	1	0	...	0	0	1	0	

5 rows × 51 columns

In [312]:
```python
from sklearn.model_selection import train_test_split
X_train, X_val, y_train, y_val = train_test_split(data, target, test_size=0.2, random_state=12)
```

Random Forest Classifier:

Import classifier using sklearn and used confusion matrix and classification report

Random Forest Classifier

In [313]:
```python
from sklearn.ensemble import RandomForestClassifier
```

In [314]:
```python
#creating an object of random forest classifier
rfclf = RandomForestClassifier()
rfclf.fit(X_train,y_train)
```

Out[314]:
```
RandomForestClassifier()
```

In [315]:
```python
#Making predictions and Accuracy
y_pred = rfclf.predict(X_val)

print("Accuracy of Random forest classifier on dataset:",metrics.accuracy_score(y_val, y_pred))
```

```
Accuracy of Random forest classifier on dataset: 0.8983425414364641
```

In [316]:
```python
from sklearn.metrics import classification_report
```

In [317]:
```python
print(classification_report(y_val, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.91      0.99      0.94       792
           1       0.76      0.27      0.40       113

    accuracy                           0.90       905
   macro avg       0.83      0.63      0.67       905
weighted avg       0.89      0.90      0.88       905
```

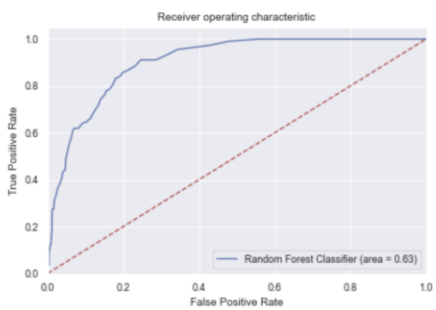
In [318]:
```
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(y_val, y_pred)
print(confusion_matrix)
```

```
[[782  10]
 [ 82  31]]
```

The result is telling us that we have 775+17 correct predictions and 85+28 incorrect predictions.

Roc for Random Forest classifier

In [320]:
```
rf_roc_auc = roc_auc_score(y_val, rfclf.predict(X_val))
fpr, tpr, thresholds = roc_curve(y_val, rfclf.predict_proba(X_val)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='Random Forest Classifier (area = %0.2f)' % rf_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.savefig('RF_ROC')
plt.show()
```



Naive Bayes Classifier:

Import classifier using sklearn and used confusion matrix and classification report

Naive Bayes Classifier

In [321]:
```
#Import Gaussian Naive Bayes model
from sklearn.naive_bayes import GaussianNB
```

In [322]:
```
#creating an object of Naive Bayes classifier
nbclf = GaussianNB()
nbclf.fit(X_train,y_train)
```

Out[322]:
```
GaussianNB()
```

In [323]:
```
#Predict the response for dataset
y_pred = nbclf.predict(X_val)
print("Accuracy of Naive Bayes classifier on dataset:",metrics.accuracy_score(y_val, y_pred))
```

```
Accuracy of Naive Bayes classifier on dataset: 0.8232044198895028
```

In [324]:
```
from sklearn.metrics import classification_report
print(classification_report(y_val, y_pred))
```

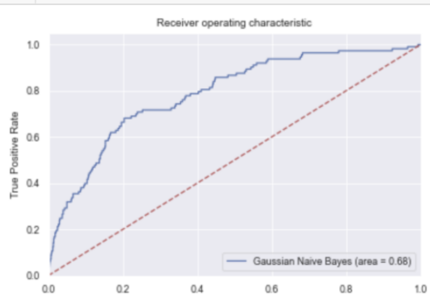
```
              precision    recall  f1-score   support

           0       0.92      0.87      0.90       792
           1       0.35      0.48      0.40       113

    accuracy                           0.82       905
   macro avg       0.63      0.68      0.65       905
weighted avg       0.85      0.82      0.83       905
```

Roc for Naive Bayes Classifier

In [325]:
```
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(y_val, y_pred)
print(confusion_matrix)
```

```
[[691 101]
 [ 59  54]]
```

In [326]:
```
rf_roc_auc = roc_auc_score(y_val, nbclf.predict(X_val))
fpr, tpr, thresholds = roc_curve(y_val, nbclf.predict_proba(X_val)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='Gaussian Naive Bayes (area = %0.2f)' % rf_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.savefig('NB_ROC')
plt.show()
```



KNN, K-Nearest Neighbor Classifier:

KNN, K-Nearest Neighbor Classifier

In [327]:
```python
from sklearn.neighbors import KNeighborsClassifier
```

In [328]:
```python
knclf = KNeighborsClassifier(n_neighbors=3)
knclf.fit(X_train,y_train)
```

Out[328]:
```
KNeighborsClassifier(n_neighbors=3)
```

In [329]:
```python
#Predict the response for dataset
y_pred = knclf.predict(X_val)
print("Accuracy of K-Nearest Neighbor classifier on dataset:",metrics.accuracy_score(y_val, y_pred))
```

```
Accuracy of K-Nearest Neighbor classifier on dataset: 0.8574585635359117
```

In [330]:
```python
from sklearn.metrics import classification_report
print(classification_report(y_val, y_pred))
```

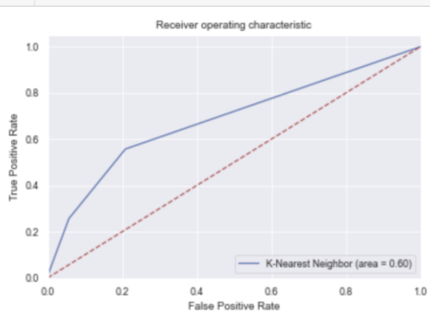
```
              precision    recall  f1-score   support

           0       0.90      0.94      0.92       792
           1       0.39      0.26      0.31       113

    accuracy                           0.86       905
   macro avg       0.65      0.60      0.62       905
weighted avg       0.84      0.86      0.84       905
```

In [331]:
```python
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(y_val, y_pred)
print(confusion_matrix)
```

```
[[747  45]
 [ 84  29]]
```

Roc for KNN Classifier

In [332]:
```python
rf_roc_auc = roc_auc_score(y_val, knclf.predict(X_val))
fpr, tpr, thresholds = roc_curve(y_val, knclf.predict_proba(X_val)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='K-Nearest Neighbor (area = %0.2f)' % rf_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.savefig('KNN_ROC')
plt.show()
```



comparison of classification accuracies between the classification algorithms:

In [333]:
```
from sklearn.model_selection import train_test_split
from sklearn import model_selection
from sklearn.utils import class_weight
from sklearn.svm import SVC
X_train, X_val, y_train, y_val = train_test_split(data, target, test_size=0.25, random_state=8675309)
```

In [334]:
```
def run_exps(X_train: pd.DataFrame , y_train: pd.DataFrame, X_test: pd.DataFrame, y_test: pd.DataFrame) -> pd.DataFrame:

    dfs = []
models = [
          ('RF', RandomForestClassifier()),
          ('KNN', KNeighborsClassifier()),
          ('GNB', GaussianNB())
        ]
results = []
names = []
scoring = ['accuracy', 'precision_weighted', 'recall_weighted', 'f1_weighted', 'roc_auc']
target_names = ['malignant', 'benign']
for name, model in models:
        kfold = model_selection.KFold(n_splits=5, shuffle=True, random_state=90210)
        cv_results = model_selection.cross_validate(model, X_train, y_train, cv=kfold, scoring=scoring)
        clf = model.fit(X_train, y_train)
        y_pred = clf.predict(X_val)
        print(name)
        print(classification_report(y_val, y_pred, target_names=target_names))
results.append(cv_results)
names.append(name)
this_df = pd.DataFrame(cv_results)
this_df['model'] = name
dfs.append(this_df)
final = pd.concat(dfs, ignore_index=True)

#return final

```

```
RF
              precision    recall  f1-score   support

   malignant       0.91      0.99      0.95      1001
      benign       0.73      0.25      0.38       130

    accuracy                           0.90      1131
   macro avg       0.82      0.62      0.66      1131
weighted avg       0.89      0.90      0.88      1131

KNN
              precision    recall  f1-score   support

   malignant       0.90      0.97      0.93      1001
      benign       0.42      0.15      0.22       130

    accuracy                           0.88      1131
   macro avg       0.66      0.56      0.58      1131
weighted avg       0.84      0.88      0.85      1131

GNB
              precision    recall  f1-score   support

   malignant       0.93      0.86      0.90      1001
      benign       0.33      0.52      0.40       130

    accuracy                           0.82      1131
   macro avg       0.63      0.69      0.65      1131
weighted avg       0.86      0.82      0.84      1131
```

In [335]:

```python
seed = 10
models = []
models.append(('RF', RandomForestClassifier()))
models.append(('NB', GaussianNB()))
models.append(('KNN', KNeighborsClassifier()))


results = []
names = []
scoring = 'accuracy'
for name, model in models:
    kfold = model_selection.KFold(n_splits=10, random_state=seed)
    cv_results = model_selection.cross_val_score(model, X_train, y_train, cv=kfold, scoring=scoring)
    results.append(cv_results)
    names.append(name)
    msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
    print(msg)
```

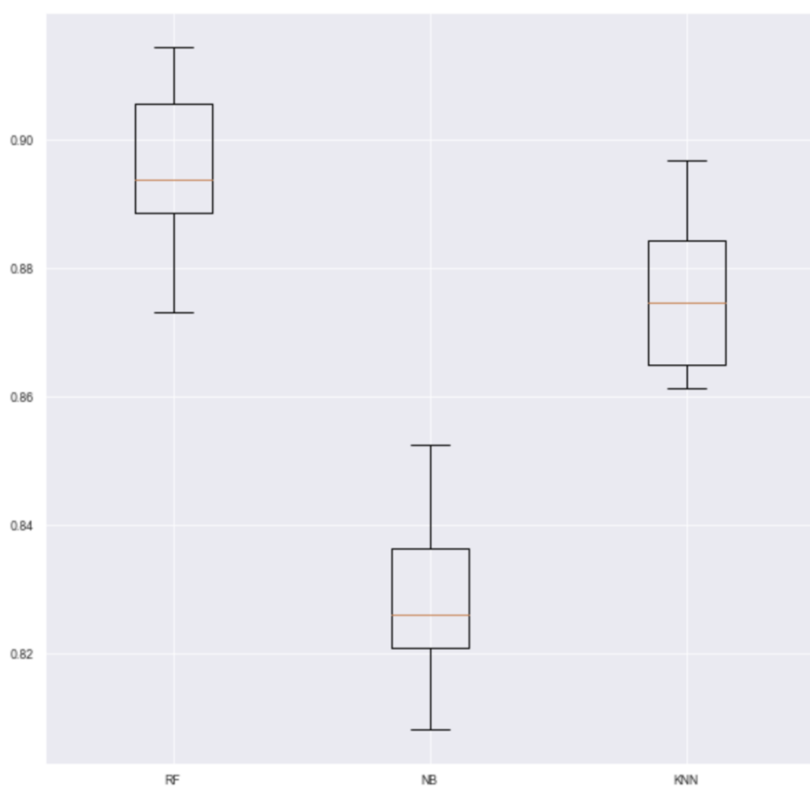
```
RF: 0.895280 (0.011818)
NB: 0.828614 (0.013222)
KNN: 0.875221 (0.011275)
```

In [336]:

```python
# boxplot algorithm comparison
fig = plt.figure(figsize=(10,10))
fig.suptitle('comparison of classification accuracies')
ax = fig.add_subplot(111)
plt.boxplot(results)
ax.set_xticklabels(names)
plt.show()
```

comparison of classification accuracies

comparison of classification accuracies



comparison of classification accuracies between the classification algorithms: Random Forest, KNN and Naïve Bayes:

RF

	precision	recall	f1-score	support
malignant	0.91	0.99	0.95	1001
benign	0.73	0.25	0.38	130
accuracy			0.90	1131
macro avg	0.82	0.62	0.66	1131
weighted avg	0.89	0.90	0.88	1131

KNN

	precision	recall	f1-score	support
malignant	0.90	0.97	0.93	1001
benign	0.42	0.15	0.22	130
accuracy			0.88	1131
macro avg	0.66	0.56	0.58	1131
weighted avg	0.84	0.88	0.85	1131

GNB

	precision	recall	f1-score	support
malignant	0.93	0.86	0.90	1001
benign	0.33	0.52	0.40	130
accuracy			0.82	1131
macro avg	0.63	0.69	0.65	1131
weighted avg	0.86	0.82	0.84	1131