Introduction

Breast cancer is a disease in which cells in the breast grow out of control. There are different kinds of breast cancer. The kind of breast cancer depends on which cells in the breast turn into cancer. source information: https://www.cdc.gov/cancer/breast/basic_info/what-is-breast-cancer.htm

we will predict Breast Cancer using 6 different algorithm:

1.Logistic regression classification 2.SVM (Support Vector Machine) classification 3.Naive bayes classification 4.Decision tree classification 5.Random forest classification 6.K-Nearest Neighbor classification

Import Library

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

from sklearn import preprocessing
from sklearn.preprocessing import MinMaxScaler
```

Import the Dataset

```
data = pd.read_csv('/content/Breast_cancer_data.csv')
print('Dataset :',data.shape)
x = data.iloc[:, [0, 1, 2, 3]].values
data.info()
data[0:10]
```

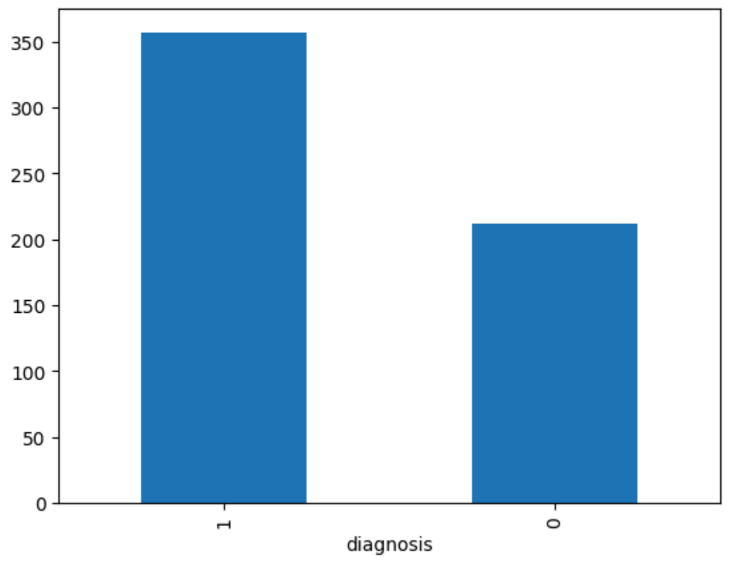
```
Dataset : (569, 6)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   mean_radius      569 non-null    float64
 1   mean_texture     569 non-null    float64
 2   mean_perimeter   569 non-null    float64
 3   mean_area        569 non-null    float64
 4   mean_smoothness  569 non-null    float64
 5   diagnosis        569 non-null    int64  
dtypes: float64(5), int64(1)
memory usage: 26.8 KB
```

	mean_radius	mean_texture	mean_perimeter	mean_area	mean_smoothness	diagnosis
0	17.99	10.38	122.80	1001.0	0.11840	0
1	20.57	17.77	132.90	1326.0	0.08474	0
2	19.69	21.25	130.00	1203.0	0.10960	0
3	11.42	20.38	77.58	386.1	0.14250	0
4	20.29	14.34	135.10	1297.0	0.10030	0
5	12.45	15.70	82.57	477.1	0.12780	0
6	18.25	19.98	119.60	1040.0	0.09463	0
7	13.71	20.83	90.20	577.9	0.11890	0
8	13.00	21.82	87.50	519.8	0.12730	0
9	12.46	24.04	83.97	475.9	0.11860	0

Visualizing the Data

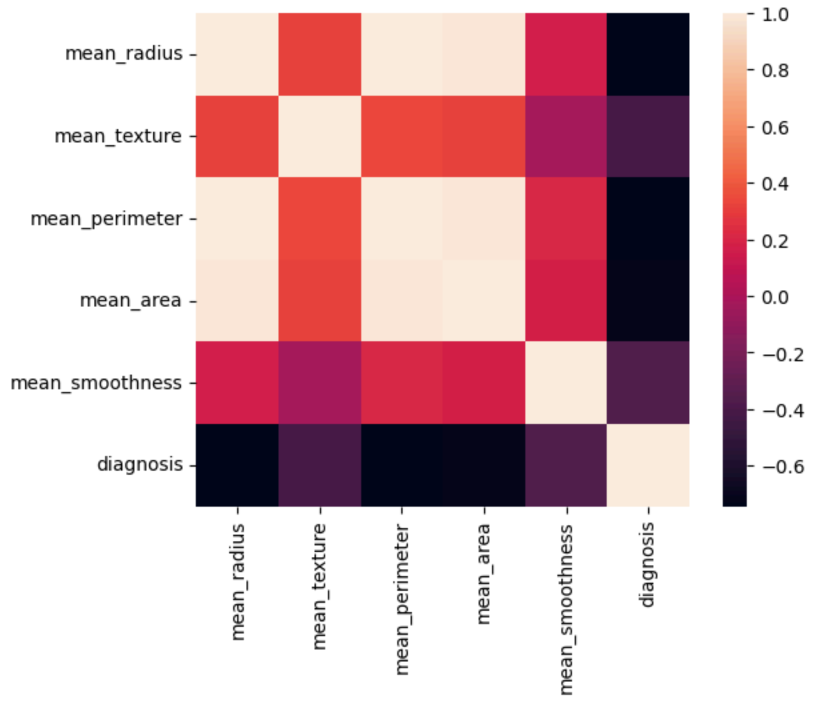
Distribution of diagnosis 357 benign, 212 malignant

```
data.diagnosis.value_counts()[0:30].plot(kind='bar')
plt.show()
```



```
data = data[['mean_radius','mean_texture','mean_perimeter','mean_area', 'mean_smoothness','diagnosis']] #Subsetting the data
cor = data.corr() #Calculate the correlation of the above variables
sns.heatmap(cor, square = True) #Plot the correlation as heat map
```

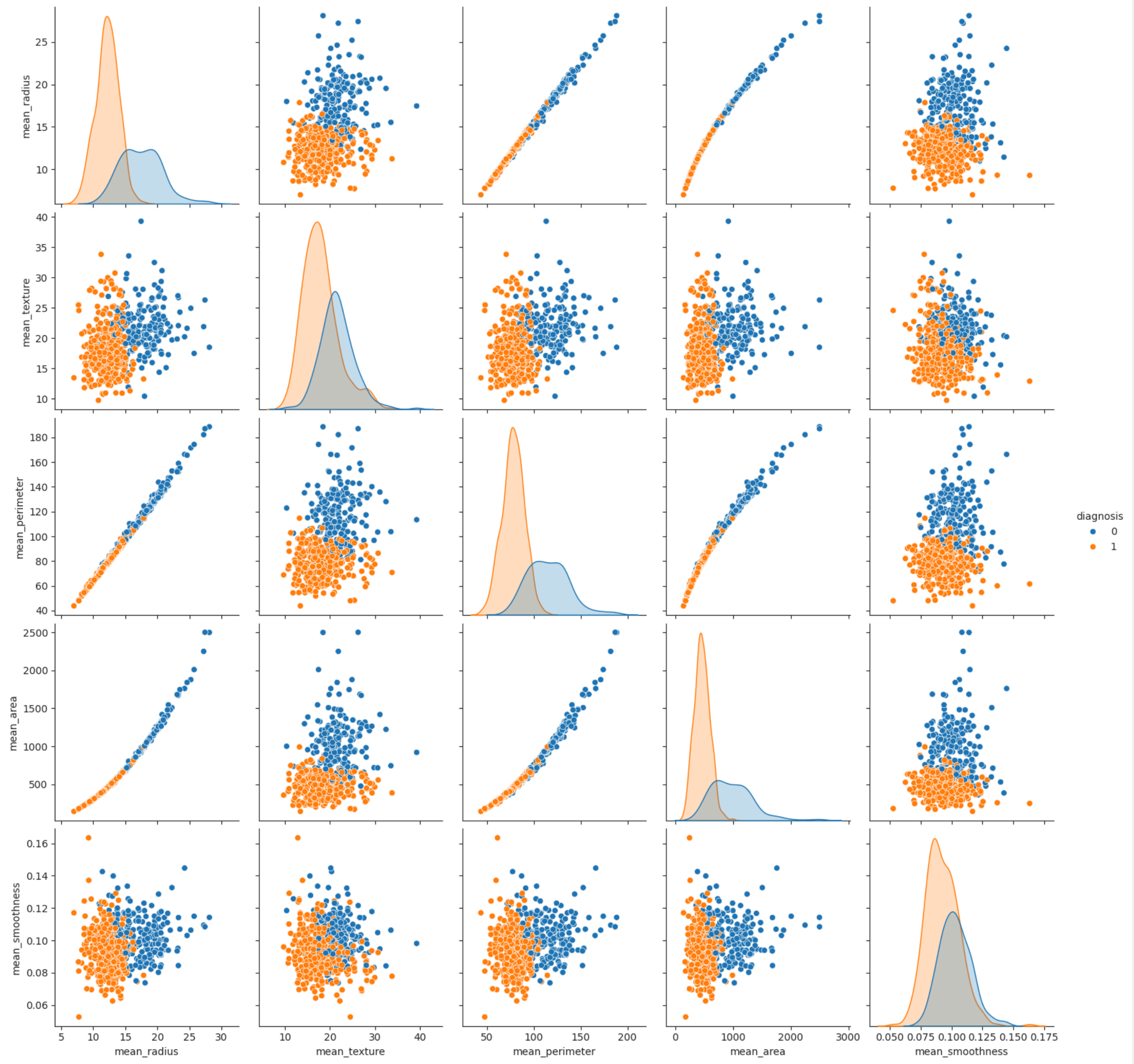
```
<Axes: >
```



We can see above, we obtain the heatmap of correlation among the variables. The color palette in the side represents the amount of correlation among the variables. The lighter shade represents a high correlation.

```
sns.set_style("ticks")
sns.pairplot(data,hue="diagnosis",size=3);
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/seaborn/axisgrid.py:2100: UserWarning: The `size` parameter has been renamed to `height`;
  warnings.warn(msg, UserWarning)
```



Data for training and testing To select a set of training data that will be input in the Machine Learning algorithm, to ensure that the classification algorithm training can be generalized well to new data. For this study using a sample size of 20%, assumed it ideal ratio between training and testing

```
from sklearn.model_selection import train_test_split
Y = data['diagnosis']
X = data.drop(columns=['diagnosis'])
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=9)
```

```
print('X train shape: ', X_train.shape)
print('Y train shape: ', Y_train.shape)
print('X test shape: ', X_test.shape)
print('Y test shape: ', Y_test.shape)
```

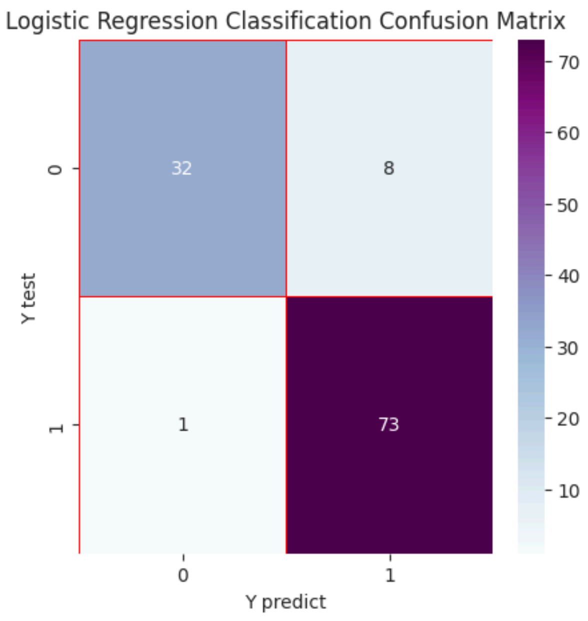
```
X train shape:  (455, 5)
Y train shape:  (455,)
X test shape:  (114, 5)
Y test shape:  (114,)
```

1. Logistic regression classification

Logistic regression is a technique that can be applied to binary classification problems. This technique uses the logistic function or sigmoid function, which is an S-shaped curve that can assume any real value number and assign it to a value between 0 and 1, but never exactly in those limits

```
from sklearn.linear_model import LogisticRegression

# We defining the model
logreg = LogisticRegression(C=10)

# We train the model
logreg.fit(X_train, Y_train)

# We predict target values
Y_predict1 = logreg.predict(X_test)
```

```
# The confusion matrix
from sklearn.metrics import confusion_matrix
import seaborn as sns

logreg_cm = confusion_matrix(Y_test, Y_predict1)
f, ax = plt.subplots(figsize=(5,5))
sns.heatmap(logreg_cm, annot=True, linewidth=0.7, linecolor='red', fmt='g', ax=ax, cmap="BuPu")
plt.title('Logistic Regression Classification Confusion Matrix')
plt.xlabel('Y predict')
plt.ylabel('Y test')
plt.show()
```



```
# Test score
score_logreg = logreg.score(X_test, Y_test)
print(score_logreg)
```

```
0.9210526315789473
```

```
#precision and recall
from sklearn.metrics import average_precision_score
average_precision = average_precision_score(Y_test, Y_predict1)

print('Average precision-recall score: {0:0.2f}'.format(
      average_precision))
```

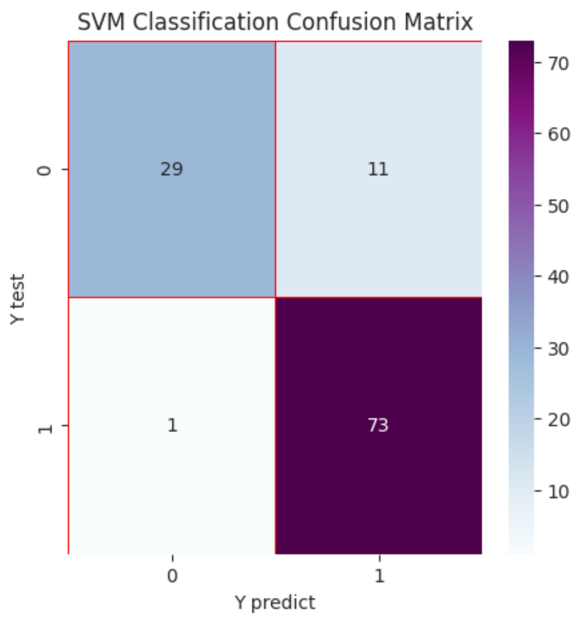
```
Average precision-recall score: 0.90
```

2. SVM (Support Vector Machine) classification

SVMs (Support Vector Machine) have shown a rapid proliferation during the last years. The learning problem setting for SVMs corresponds to a some unknown and nonlinear dependency (mapping, function) y=f(x) between some high-dimensional input vector x and scalar output y . It is noteworthy that there is no information on the joint probability functions, therefore, a free distribution learning must be carried out.

```
from sklearn.ensemble import BaggingClassifier
from sklearn.multiclass import OneVsRestClassifier
from sklearn.svm import SVC

# We define the SVM model
svmcla = OneVsRestClassifier(BaggingClassifier(SVC(C=10,kernel='rbf',random_state=9, probability=True),
                                               n_jobs=-1))

# We train model
svmcla.fit(X_train, Y_train)

# We predict target values
Y_predict2 = svmcla.predict(X_test)
```

```
# The confusion matrix
svmcla_cm = confusion_matrix(Y_test, Y_predict2)
f, ax = plt.subplots(figsize=(5,5))
sns.heatmap(svmcla_cm, annot=True, linewidth=0.7, linecolor='red', fmt='g', ax=ax, cmap="BuPu")
plt.title('SVM Classification Confusion Matrix')
plt.xlabel('Y predict')
plt.ylabel('Y test')
plt.show()
```



```
# Test score
score_svmcla = svmcla.score(X_test, Y_test)
print(score_svmcla)
```

```
0.8947368421052632
```

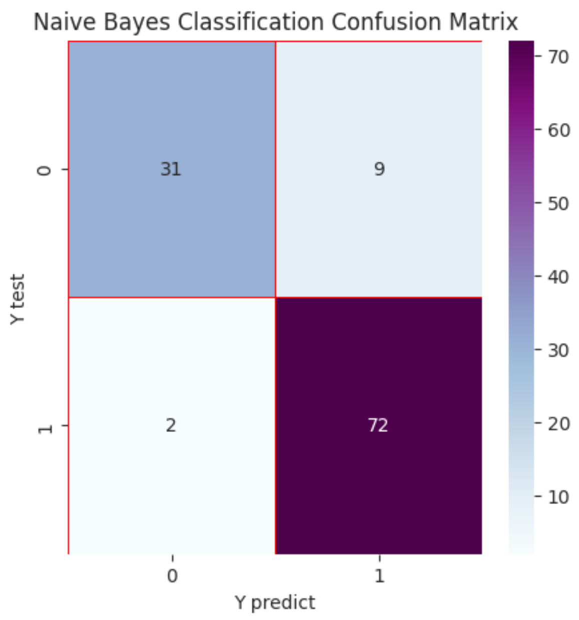
```
#precision and recall
from sklearn.metrics import average_precision_score
average_precision = average_precision_score(Y_test, Y_predict2)

print('Average precision-recall score: {0:0.2f}'.format(
      average_precision))
```

```
Average precision-recall score: 0.87
```

3. Naive bayes classification

The naive Bayesian classifier is a probabilistic classifier based on Bayes' theorem with strong independence assumptions between the features. Thus, using Bayes theorem (P(X|Y)=P(Y|X)P(X)P(Y)) , we can find the probability of X happening, given that Y has occurred.

```
from sklearn.naive_bayes import GaussianNB

# We define the model
nbcla = GaussianNB()

# We train model
nbcla.fit(X_train, Y_train)

# We predict target values
Y_predict3 = nbcla.predict(X_test)


# The confusion matrix
nbcla_cm = confusion_matrix(Y_test, Y_predict3)
f, ax = plt.subplots(figsize=(5,5))
sns.heatmap(nbcla_cm, annot=True, linewidth=0.7, linecolor='red', fmt='g', ax=ax, cmap="BuPu")
plt.title('Naive Bayes Classification Confusion Matrix')
plt.xlabel('Y predict')
plt.ylabel('Y test')
plt.show()
```



```
# Test score
score_nbcla = nbcla.score(X_test, Y_test)
print(score_nbcla)
```

```
0.9035087719298246
```

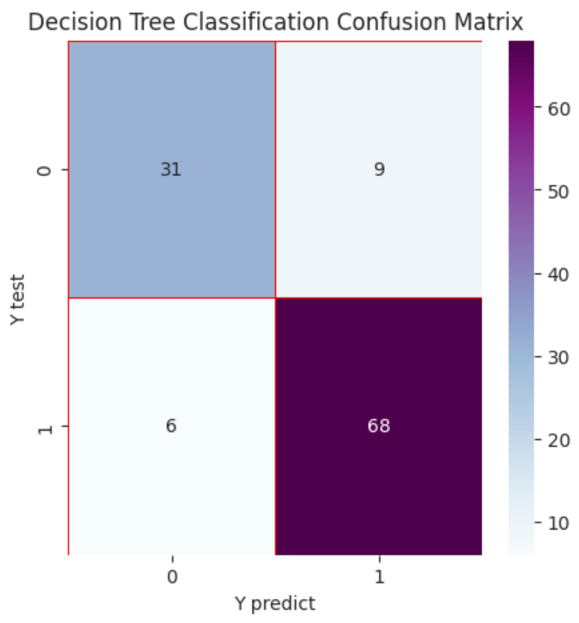
```
#precision and recall
from sklearn.metrics import average_precision_score
average_precision = average_precision_score(Y_test, Y_predict3)

print('Average precision-recall score: {0:0.2f}'.format(
      average_precision))
```

```
Average precision-recall score: 0.88
```

4. Decision tree classification

A decision tree is a flowchart-like tree structure where an internal node represents feature, the branch represents a decision rule, and each leaf node represents the outcome. The decision tree analyzes a set of data to construct a set of rules or questions, which are used to predict a class, i.e., the goal of decision tree is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features

```
from sklearn.tree import DecisionTreeClassifier

# We define the model
dtcla = DecisionTreeClassifier(random_state=9)

# We train model
dtcla.fit(X_train, Y_train)

# We predict target values
Y_predict4 = dtcla.predict(X_test)


# The confusion matrix
dtcla_cm = confusion_matrix(Y_test, Y_predict4)
f, ax = plt.subplots(figsize=(5,5))
sns.heatmap(dtcla_cm, annot=True, linewidth=0.7, linecolor='red', fmt='g', ax=ax, cmap="BuPu")
plt.title('Decision Tree Classification Confusion Matrix')
plt.xlabel('Y predict')
plt.ylabel('Y test')
plt.show()
```



```
# Test score
score_dtcla = dtcla.score(X_test, Y_test)
print(score_dtcla)
```

```
0.868421052631579
```

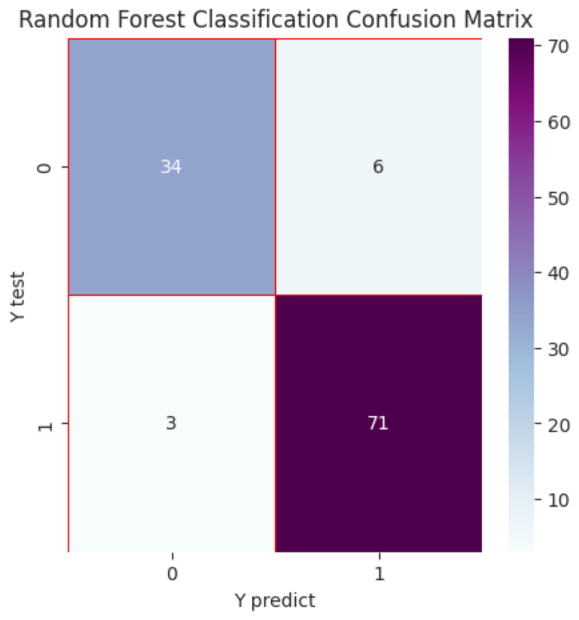
```
#precision and recall
from sklearn.metrics import average_precision_score
average_precision = average_precision_score(Y_test, Y_predict4)

print('Average precision-recall score: {0:0.2f}'.format(
      average_precision))
```

```
Average precision-recall score: 0.86
```

5. Random forest classification

Based on the previous classification method, random forest is a supervised learning algorithm that creates a forest randomly. This forest, is a set of decision trees, most of the times trained with the bagging method. The essential idea of bagging is to average many noisy but approximately impartial models, and therefore reduce the variation.

```
from sklearn.ensemble import RandomForestClassifier

# We define the model
rfcla = RandomForestClassifier(n_estimators=100,random_state=9,n_jobs=-1)

# We train model
rfcla.fit(X_train, Y_train)

# We predict target values
Y_predict5 = rfcla.predict(X_test)


# The confusion matrix
rfcla_cm = confusion_matrix(Y_test, Y_predict5)
f, ax = plt.subplots(figsize=(5,5))
sns.heatmap(rfcla_cm, annot=True, linewidth=0.7, linecolor='red', fmt='g', ax=ax, cmap="BuPu")
plt.title('Random Forest Classification Confusion Matrix')
plt.xlabel('Y predict')
plt.ylabel('Y test')
plt.show()
```



```
# Test score
score_rfcla = rfcla.score(X_test, Y_test)
print(score_rfcla)
```

```
0.9210526315789473
```

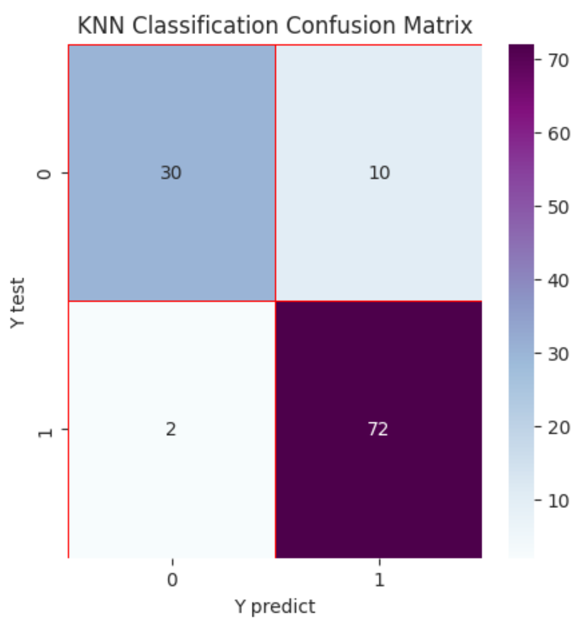
```
#precision and recall
from sklearn.metrics import average_precision_score
average_precision = average_precision_score(Y_test, Y_predict5)

print('Average precision-recall score: {0:0.2f}'.format(
      average_precision))
```

```
Average precision-recall score: 0.91
```

6. K-Nearest Neighbor classification

K-Nearest neighbors is a technique that stores all available cases and classifies new cases based on a similarity measure (e.g., distance functions). This technique is non-parametric since there are no assumptions for the distribution of underlying data and it is lazy since it does not need any training data point model generation

```
from sklearn.neighbors import KNeighborsClassifier

# We define the model
knncla = KNeighborsClassifier(n_neighbors=5,n_jobs=-1)

# We train model
knncla.fit(X_train, Y_train)

# We predict target values
Y_predict6 = knncla.predict(X_test)


# The confusion matrix
knncla_cm = confusion_matrix(Y_test, Y_predict6)
f, ax = plt.subplots(figsize=(5,5))
sns.heatmap(knncla_cm, annot=True, linewidth=0.7, linecolor='red', fmt='g', ax=ax, cmap="BuPu")
plt.title('KNN Classification Confusion Matrix')
plt.xlabel('Y predict')
plt.ylabel('Y test')
plt.show()
```



```
# Test score
score_knncla= knncla.score(X_test, Y_test)
print(score_knncla)
```

```
0.8947368421052632
```

```
#precision and recall
from sklearn.metrics import average_precision_score
average_precision = average_precision_score(Y_test, Y_predict6)

print('Average precision-recall score: {0:0.2f}'.format(
      average_precision))
```

```
Average precision-recall score: 0.87
```

Comparison of classification techniques

### Test scores

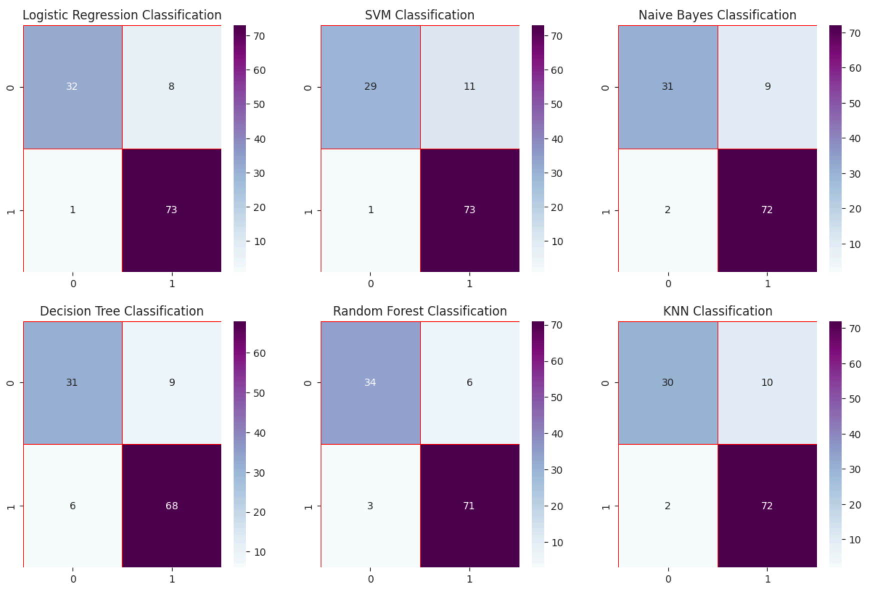
```
Testscores = pd.Series([score_logreg, score_svmcla, score_nbcla, score_dtcla, score_rfcla, score_knncla],
                        index=['Logistic Regression Score', 'Support Vector Machine Score', 'Naive Bayes Score', 'Decision Tree Score',
print(Testscores)
```

```
Logistic Regression Score       0.921053
Support Vector Machine Score    0.894737
Naive Bayes Score               0.903509
Decision Tree Score             0.868421
Random Forest Score             0.921053
K-Nearest Neighbour Score       0.894737
dtype: float64
```

The confusion matrix

Confusion matrix is a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one

```
fig = plt.figure(figsize=(15,15))
ax1 = fig.add_subplot(3, 3, 1)
ax1.set_title('Logistic Regression Classification')
ax2 = fig.add_subplot(3, 3, 2)
ax2.set_title('SVM Classification')
ax3 = fig.add_subplot(3, 3, 3)
ax3.set_title('Naive Bayes Classification')
ax4 = fig.add_subplot(3, 3, 4)
ax4.set_title('Decision Tree Classification')
ax5 = fig.add_subplot(3, 3, 5)
ax5.set_title('Random Forest Classification')
ax6 = fig.add_subplot(3, 3, 6)
ax6.set_title('KNN Classification')
sns.heatmap(data=logreg_cm, annot=True, linewidth=0.7, linecolor='red',cmap="BuPu" ,fmt='g', ax=ax1)
sns.heatmap(data=svmcla_cm, annot=True, linewidth=0.7, linecolor='red',cmap="BuPu" ,fmt='g', ax=ax2)
sns.heatmap(data=nbcla_cm, annot=True, linewidth=0.7, linecolor='red',cmap="BuPu" ,fmt='g', ax=ax3)
sns.heatmap(data=dtcla_cm, annot=True, linewidth=0.7, linecolor='red',cmap="BuPu" ,fmt='g', ax=ax4)
sns.heatmap(data=rfcla_cm, annot=True, linewidth=0.7, linecolor='red',cmap="BuPu" ,fmt='g', ax=ax5)
sns.heatmap(data=knncla_cm, annot=True, linewidth=0.7, linecolor='red',cmap="BuPu" ,fmt='g', ax=ax6)
plt.show()
```

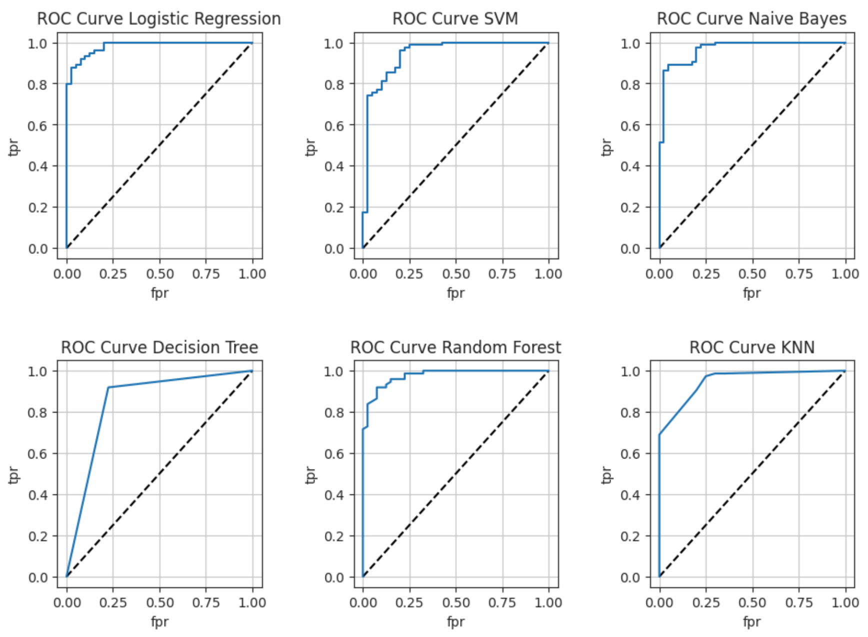


As you can see above, a Comparison of classification techniques, we can evaluate that here Logistic Regression Classification and Random Forest have the most optimal result of the accuracy.

ROC curve

From a Comparison of classification techniques, we plotting ROC to illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied.

```
from sklearn.metrics import roc_curve

# Logistic Regression Classification
Y_predict1_proba = logreg.predict_proba(X_test)
Y_predict1_proba = Y_predict1_proba[:, 1]
fpr, tpr, thresholds = roc_curve(Y_test, Y_predict1_proba)
plt.subplot(331)
plt.plot([0,1],[0,1],'k--')
plt.plot(fpr,tpr, label='ANN')
plt.xlabel('fpr')
plt.ylabel('tpr')
plt.title('ROC Curve Logistic Regression')
plt.grid(True)

# SVM Classification
Y_predict2_proba = svmcla.predict_proba(X_test)
Y_predict2_proba = Y_predict2_proba[:, 1]
fpr, tpr, thresholds = roc_curve(Y_test, Y_predict2_proba)
plt.subplot(332)
plt.plot([0,1],[0,1],'k--')
plt.plot(fpr,tpr, label='ANN')
plt.xlabel('fpr')
plt.ylabel('tpr')
plt.title('ROC Curve SVM')
plt.grid(True)

# Naive Bayes Classification
Y_predict3_proba = nbcla.predict_proba(X_test)
Y_predict3_proba = Y_predict3_proba[:, 1]
fpr, tpr, thresholds = roc_curve(Y_test, Y_predict3_proba)
plt.subplot(333)
plt.plot([0,1],[0,1],'k--')
plt.plot(fpr,tpr, label='ANN')
plt.xlabel('fpr')
plt.ylabel('tpr')
plt.title('ROC Curve Naive Bayes')
plt.grid(True)

# Decision Tree Classification
Y_predict4_proba = dtcla.predict_proba(X_test)
Y_predict4_proba = Y_predict4_proba[:, 1]
fpr, tpr, thresholds = roc_curve(Y_test, Y_predict4_proba)
plt.subplot(334)
plt.plot([0,1],[0,1],'k--')
plt.plot(fpr,tpr, label='ANN')
plt.xlabel('fpr')
plt.ylabel('tpr')
plt.title('ROC Curve Decision Tree')
plt.grid(True)

# Random Forest Classification
Y_predict5_proba = rfcla.predict_proba(X_test)
Y_predict5_proba = Y_predict5_proba[:, 1]
fpr, tpr, thresholds = roc_curve(Y_test, Y_predict5_proba)
plt.subplot(335)
plt.plot([0,1],[0,1],'k--')
plt.plot(fpr,tpr, label='ANN')
plt.xlabel('fpr')
plt.ylabel('tpr')
plt.title('ROC Curve Random Forest')
plt.grid(True)

# KNN Classification
Y_predict6_proba = knncla.predict_proba(X_test)
Y_predict6_proba = Y_predict6_proba[:, 1]
fpr, tpr, thresholds = roc_curve(Y_test, Y_predict6_proba)
plt.subplot(336)
plt.plot([0,1],[0,1],'k--')
plt.plot(fpr,tpr, label='ANN')
plt.xlabel('fpr')
plt.ylabel('tpr')
plt.title('ROC Curve KNN')
plt.grid(True)
plt.subplots_adjust(top=2, bottom=0.08, left=0.10, right=1.4, hspace=0.45, wspace=0.45)
plt.show()
```


ROC Curve Logistic Regression
ROC Curve SVM
ROC Curve Naive Bayes
ROC Curve Decision Tree
ROC Curve Random Forest
ROC Curve KNN
tpr
fpr
0.0
0.2
0.4
0.6
0.8
1.0
0.00
0.25
0.50
0.75
1.00