



BREAST CANCER DETECTION



Aim

Performing data preprocessing and preliminary analysis on Breast Cancer Diagnostic Dataset and getting inferences from the data using Machine Learning Classification techniques - whether or not a given tumor is malignant or benign.

Introduction

Breast cancer is one among the foremost common cancers among women worldwide, representing the bulk of latest cancer cases and cancer-related deaths consistent with global statistics, making it a big public health concern in today's society. The early diagnosis of Breast Cancer can improve the prognosis and chance of survival significantly, because it can promote timely clinical treatment to patients. Accurate classification of benign tumors can prevent patients from undergoing unnecessary treatments. Thus, the right diagnosis of Breast Cancer and therefore the classification of patients into malignant or benign groups is such a crucial topic of dialogue. I will be using Machine Learning to predict whether a tumor is Benign (non-cancerous) or Malign (cancerous).

Specification of dataset



Breast Cancer Wisconsin (Diagnostic)

Donated on 10/31/1995

Diagnostic Wisconsin Breast Cancer Database.

Dataset Characteristics

Multivariate

Subject Area

Health and Medicine

Associated Tasks

Classification

Feature Type

Real

Instances

569

Features

30

The dataset was imported from the UCI Machine Learning repository, the dataset contains 30 features and 569 instances of different kinds of samples.

Understanding and Preprocessing Data

Finding dimensions

```
df.shape

(569, 32)
```

Thus, we can see that the dataset has 32 columns (indicating 32 features) and 569 tuples(indicating 569 datapoints).

```
[ ] df.head()
```

The output of the following is as follows:

	0	1	2	3	4	5	6	7	8	9	...	22	23	24	25	26	27	28	29	30	31
0	842302	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	...	25.38	17.33	184.60	2019.0	0.1622	0.6656	0.7119	0.2654	0.4601	0.11890
1	842517	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	...	24.99	23.41	158.80	1956.0	0.1238	0.1866	0.2416	0.1860	0.2750	0.08902
2	84300903	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	...	23.57	25.53	152.50	1709.0	0.1444	0.4245	0.4504	0.2430	0.3613	0.08758
3	84348301	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	...	14.91	26.50	98.87	567.7	0.2098	0.8663	0.6869	0.2575	0.6638	0.17300
4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	...	22.54	16.67	152.20	1575.0	0.1374	0.2050	0.4000	0.1625	0.2364	0.07678

5 rows × 32 columns

Looking for missing/duplicate/unique values

We use three handy functions:

1. `df.duplicated().sum()`: Counts the number of duplicated rows in a DataFrame.
2. `df.isna().sum()`: Counts the number of missing (NaN) values in each column of a DataFrame.
3. `df.nunique()`: Returns the number of unique values in each column of a DataFrame.

```
# Check Duplication  
df.duplicated().sum()
```

```
0
```

There aren't duplicate values

```
# check Missing value  
df.isna().sum()
```

```
--      -  
27      0  
28      0  
29      0  
30      0  
31      0  
dtype: int64
```

- No Missing Value is available

```
# Check the number of unique values of each column  
df.nunique()
```

```
--      +---+  
27      529  
28      539  
29      492  
30      500  
31      535  
dtype: int64
```

Dropping useless columns/features

As a part of data preprocessing, we need to drop/remove the features from the dataset that do not provide us any insights for the classification algorithms/ data analysis algorithms to work. Here the column dropped is id.

```
[ ] df = df.drop([0], axis= 1)
```

After removing the useless column(id in this case) the dataset looks like this:

df.head()

	1	2	3	4	5	6	7	8	9	10	...	22	23	24	25	26	27	28	29	30	31
0	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	0.2419	...	25.38	17.33	184.60	2019.0	0.1622	0.6656	0.7119	0.2654	0.4601	0.11890
1	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	0.1812	...	24.99	23.41	158.80	1956.0	0.1238	0.1866	0.2416	0.1860	0.2750	0.08902
2	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	0.2069	...	23.57	25.53	152.50	1709.0	0.1444	0.4245	0.4504	0.2430	0.3613	0.08758
3	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	0.2597	...	14.91	26.50	98.87	567.7	0.2098	0.8663	0.6869	0.2575	0.6638	0.17300
4	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	0.1809	...	22.54	16.67	152.20	1575.0	0.1374	0.2050	0.4000	0.1625	0.2364	0.07678

5 rows x 31 columns

Finally, our data preprocessing step comes to an end. We can use various functions like `.describe()`, `.info()`, `.head()` to go through the dataset on a superficial level as well as in depth.

This is what the final dataset looks like:

	target	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	...	worst radius	worst texture	worst perimeter	worst area	worst smoothness	worst compactness	worst concavity	worst concave points	worst symmetry	worst fractal dimension
0	1	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	0.2419	...	25.38	17.33	184.60	2019.0	0.1622	0.6656	0.7119	0.2654	0.4601	0.11890
1	1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	0.1812	...	24.99	23.41	158.80	1956.0	0.1238	0.1866	0.2416	0.1860	0.2750	0.08902
2	1	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	0.2069	...	23.57	25.53	152.50	1709.0	0.1444	0.4245	0.4504	0.2430	0.3613	0.08758
3	1	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	0.2597	...	14.91	26.50	98.87	567.7	0.2098	0.8663	0.6869	0.2575	0.6638	0.17300
4	1	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	0.1809	...	22.54	16.67	152.20	1575.0	0.1374	0.2050	0.4000	0.1625	0.2364	0.07678

5 rows x 31 columns

Exploratory Data Analysis

1. Visualisation : Data visualization plays a pivotal role in conveying insights from the dataset. Data visualization is the presentation of data in a graphical or pictorial format to help people understand patterns, trends, and insights in the data more easily. Instead of relying solely on raw numbers or textual information, data visualization leverages visual elements such as charts, graphs, maps, and other visual representations to convey complex information in a more accessible and understandable way.

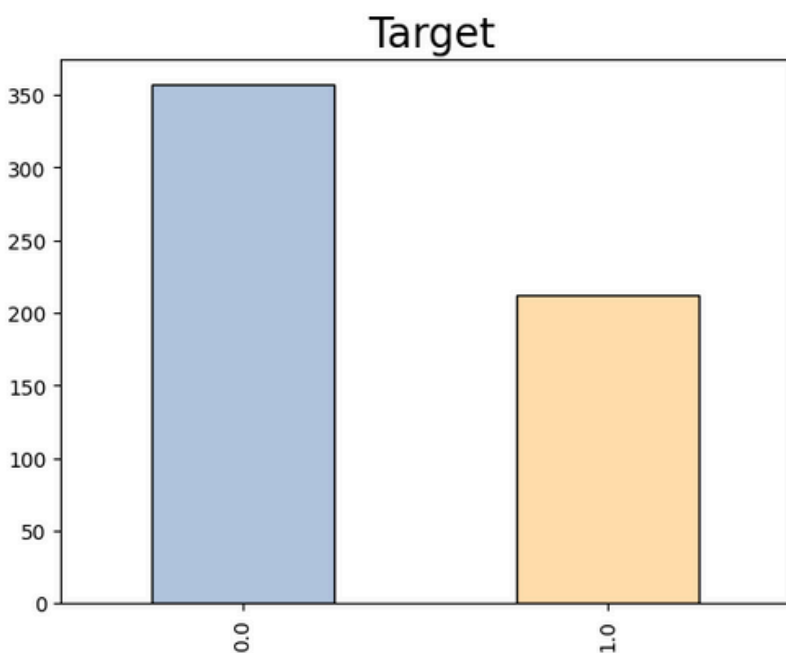
Numerical insights related to how many malignant and benign yields are there in the dataset.

```
df.target.value_counts()
```

```
0.0    357  
1.0    212  
Name: target, dtype: int64
```

Visualised target data in the dataset (we used bar chart)

```
df['target'].value_counts().plot(kind='bar', edgecolor='black', color=['lightsteelblue', 'navajowhite'])  
plt.title(" Target", fontsize=20)  
plt.show()
```



1-->Malignant

0-->Benign

2.Correlation Analysis: Correlation analysis is a statistical method used to evaluate the strength and direction of the linear relationship between two quantitative variables. The result of a correlation analysis is expressed as a correlation coefficient, which indicates the degree to which changes in one variable are associated with changes in another. The most common correlation coefficient is the Pearson correlation coefficient, denoted by r . The Pearson correlation coefficient ranges from -1 to 1.

Correlation plays a significant role in feature selection as it helps identify relationships between different features in a dataset.

High correlation between features means they are more linearly dependent and hence have almost the same effect on the dependent variable. So, we can leave one of the two features when two they have high correlation.

Now, we generate the **Correlation matrix**:

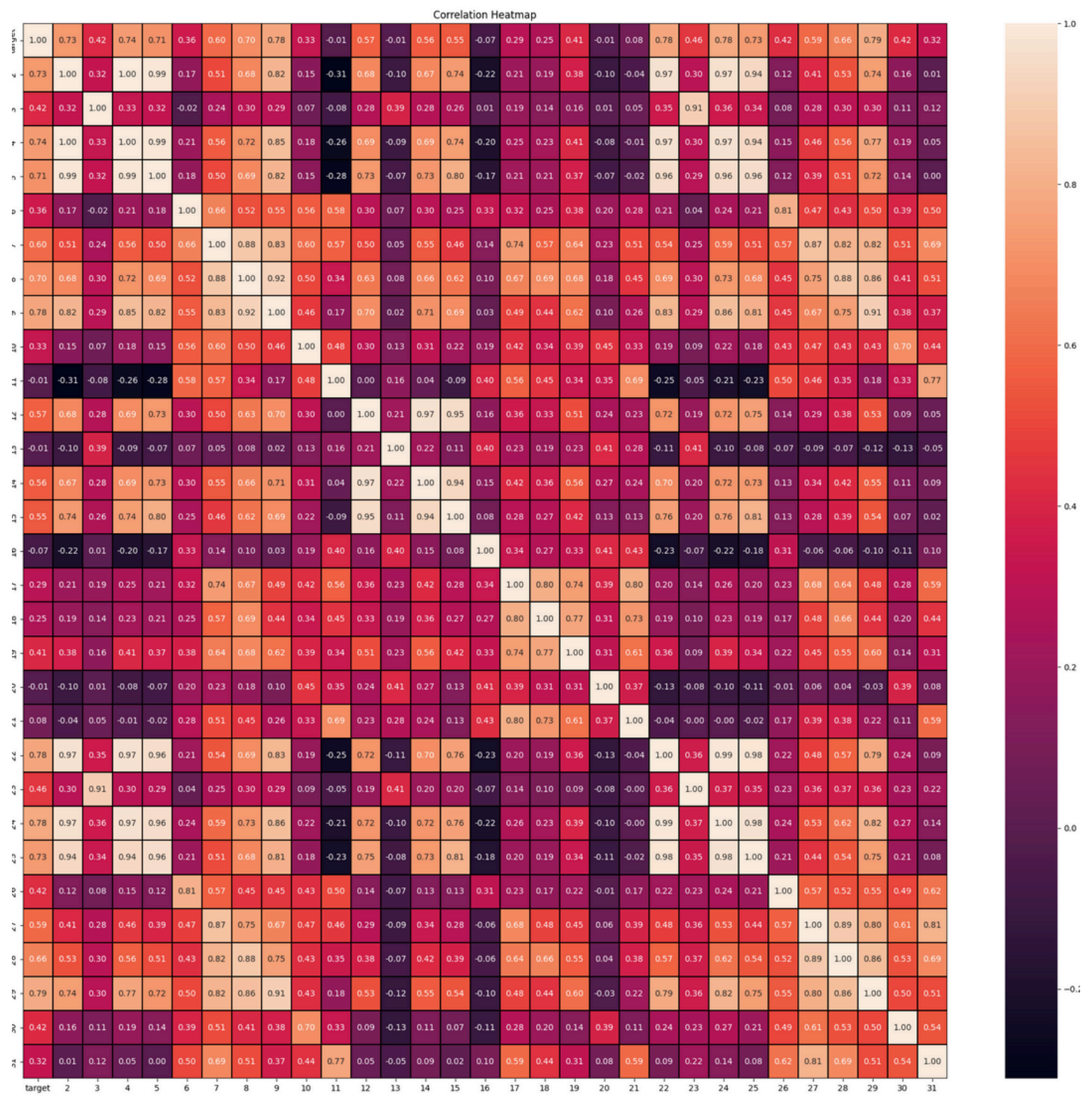
```
cor = df.corr()
```

	target	2	3	4	5	6	7	8	9	10	...	22	23	24	25	26	27	28	29	30	31
target	1.000000	0.730029	0.415185	0.742636	0.708984	0.358560	0.596534	0.696360	0.776614	0.330499	...	0.776454	0.456903	0.782914	0.733825	0.421465	0.590998	0.659610	0.793566	0.416294	0.323872
2	0.730029	1.000000	0.323782	0.997855	0.987357	0.170581	0.506124	0.676764	0.822529	0.147741	...	0.969539	0.297008	0.965137	0.941082	0.119616	0.413463	0.526911	0.744214	0.163953	0.007066
3	0.415185	0.323782	1.000000	0.329533	0.321086	-0.023389	0.236702	0.302418	0.293464	0.071401	...	0.352573	0.912045	0.358040	0.343546	0.077503	0.277830	0.301025	0.295316	0.105008	0.119205
4	0.742636	0.997855	0.329533	1.000000	0.986507	0.207278	0.556936	0.716136	0.850977	0.183027	...	0.969476	0.303038	0.970387	0.941550	0.150549	0.455774	0.563879	0.771241	0.189115	0.051019
5	0.708984	0.987357	0.321086	0.986507	1.000000	0.177028	0.498502	0.685983	0.823269	0.151293	...	0.962746	0.287489	0.959120	0.959213	0.123523	0.390410	0.512606	0.722017	0.143570	0.003738
6	0.358560	0.170581	-0.023389	0.207278	0.177028	1.000000	0.659123	0.521984	0.553695	0.557775	...	0.213120	0.036072	0.238853	0.206718	0.805324	0.472468	0.434926	0.503053	0.394309	0.499316
7	0.596534	0.506124	0.236702	0.556936	0.498502	0.659123	1.000000	0.883121	0.831135	0.602641	...	0.535315	0.248133	0.590210	0.509604	0.565541	0.865809	0.816275	0.815573	0.510223	0.687382
8	0.696360	0.676764	0.302418	0.716136	0.685983	0.521984	0.883121	1.000000	0.921391	0.500667	...	0.688236	0.299879	0.729565	0.675987	0.448822	0.754968	0.884103	0.861323	0.409464	0.514930
9	0.776614	0.822529	0.293464	0.850977	0.823269	0.553695	0.831135	0.921391	1.000000	0.462497	...	0.830318	0.292752	0.855923	0.809630	0.452753	0.667454	0.752399	0.910155	0.375744	0.368661
10	0.330499	0.147741	0.071401	0.183027	0.151293	0.557775	0.602641	0.500667	0.462497	1.000000	...	0.185728	0.090651	0.219169	0.177193	0.426675	0.473200	0.433721	0.430297	0.699826	0.438413
11	-0.012838	-0.311631	-0.076437	-0.261477	-0.283110	0.584792	0.565369	0.336783	0.166917	0.479921	...	-0.253691	-0.051269	-0.205151	-0.231854	0.504942	0.458798	0.346234	0.175325	0.334019	0.767297
12	0.567134	0.679090	0.275869	0.691765	0.732562	0.301467	0.497473	0.631925	0.698050	0.303379	...	0.715065	0.194799	0.719684	0.751548	0.141919	0.287103	0.380585	0.531062	0.094543	0.049559
13	-0.008303	-0.097317	0.386358	-0.086761	-0.066280	0.068406	0.046205	0.076218	0.021480	0.128053	...	-0.111690	0.409003	-0.102242	-0.083195	-0.073658	-0.092439	-0.068956	-0.119638	-0.128215	-0.045655
14	0.556141	0.674172	0.281673	0.693135	0.726628	0.296092	0.548905	0.660391	0.710650	0.313893	...	0.697201	0.200371	0.721031	0.730713	0.130054	0.341919	0.418899	0.554897	0.109930	0.085433
15	0.548236	0.735864	0.259845	0.744983	0.800086	0.246552	0.455653	0.617427	0.690299	0.223970	...	0.757373	0.196497	0.761213	0.811408	0.125389	0.283257	0.385100	0.538166	0.074126	0.017539
16	-0.067016	-0.222600	0.006614	-0.202694	-0.166777	0.332375	0.135299	0.098564	0.027653	0.187321	...	-0.230691	-0.074743	-0.217304	-0.182195	0.314457	-0.055558	-0.058298	-0.102007	-0.107342	0.101480
17	0.292999	0.206000	0.191975	0.250744	0.212583	0.318943	0.738722	0.670279	0.490424	0.421659	...	0.204607	0.143003	0.260516	0.199371	0.227394	0.678780	0.639147	0.483208	0.277878	0.590973
18	0.253730	0.194204	0.143293	0.228082	0.207660	0.248396	0.570517	0.691270	0.439167	0.342627	...	0.186904	0.100241	0.226680	0.188353	0.168481	0.484858	0.662564	0.440472	0.197788	0.439329
19	0.408042	0.376169	0.163851	0.407217	0.372320	0.380676	0.642262	0.683260	0.615634	0.393298	...	0.358127	0.086741	0.394999	0.342271	0.215351	0.452888	0.549592	0.602450	0.143116	0.310655
20	-0.006522	-0.104321	0.009127	-0.081629	-0.072497	0.200774	0.229977	0.178009	0.095351	0.449137	...	-0.128121	-0.077473	-0.103753	-0.110343	-0.012662	0.060255	0.037119	-0.030413	0.389402	0.078079
21	0.077972	-0.042641	0.054458	-0.005523	-0.019887	0.283607	0.507318	0.449301	0.257584	0.331786	...	-0.037488	-0.003195	-0.001000	-0.022736	0.170568	0.390159	0.379975	0.215204	0.111094	0.591328

31x31

Now, we generate the **Correlation heatmap**:

```
plt.figure(figsize=(25,23))
sns.heatmap(cor, annot= True, linewidths= 0.3 ,linecolor = "black", fmt = ".2f")
plt.title('Correlation Heatmap')
plt.show()
```



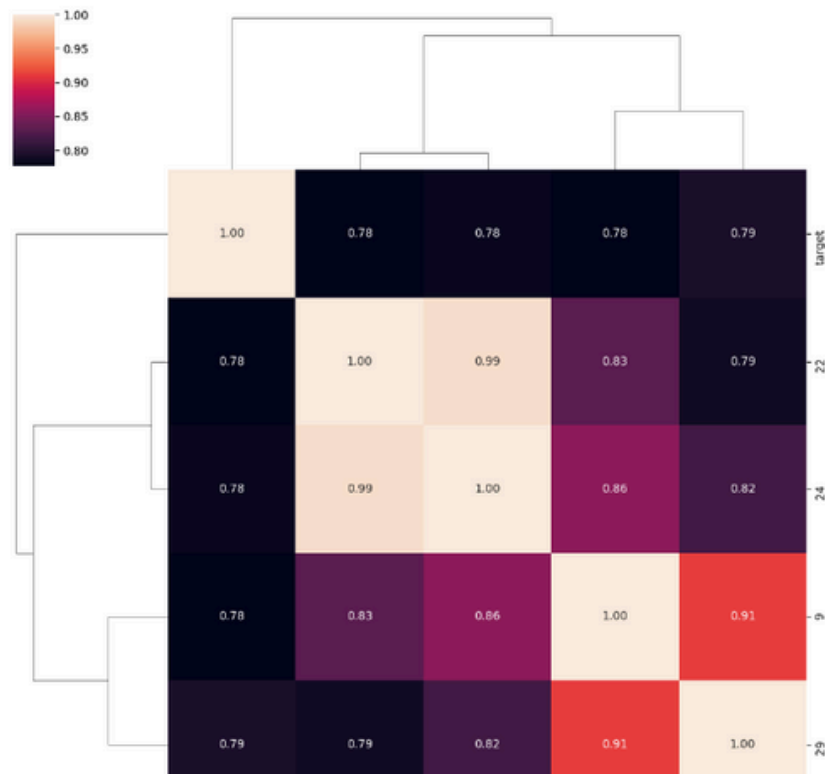
Thresholding:

Setting a correlation threshold, such as 0.75, in feature selection helps identify and eliminate highly uncorrelated features. This process reduces redundancy, improves model **interpretability**, and enhances **generalization performance**, preventing multicollinearity issues and ensuring that selected features contribute unique information to the model.

Data with a correlation greater than 0.75.

```
threshold = 0.75
filtre = np.abs(cor["target"] > threshold)
corr_features = cor.columns[filtre].tolist()
plt.figure(figsize=(10,8))
sns.clustermap(df[corr_features].corr(), annot = True, fmt = ".2f")
plt.title("\nCorrelation Between Features with Cor Threshold [0.75]\n",fontsize=20)
plt.show()
```

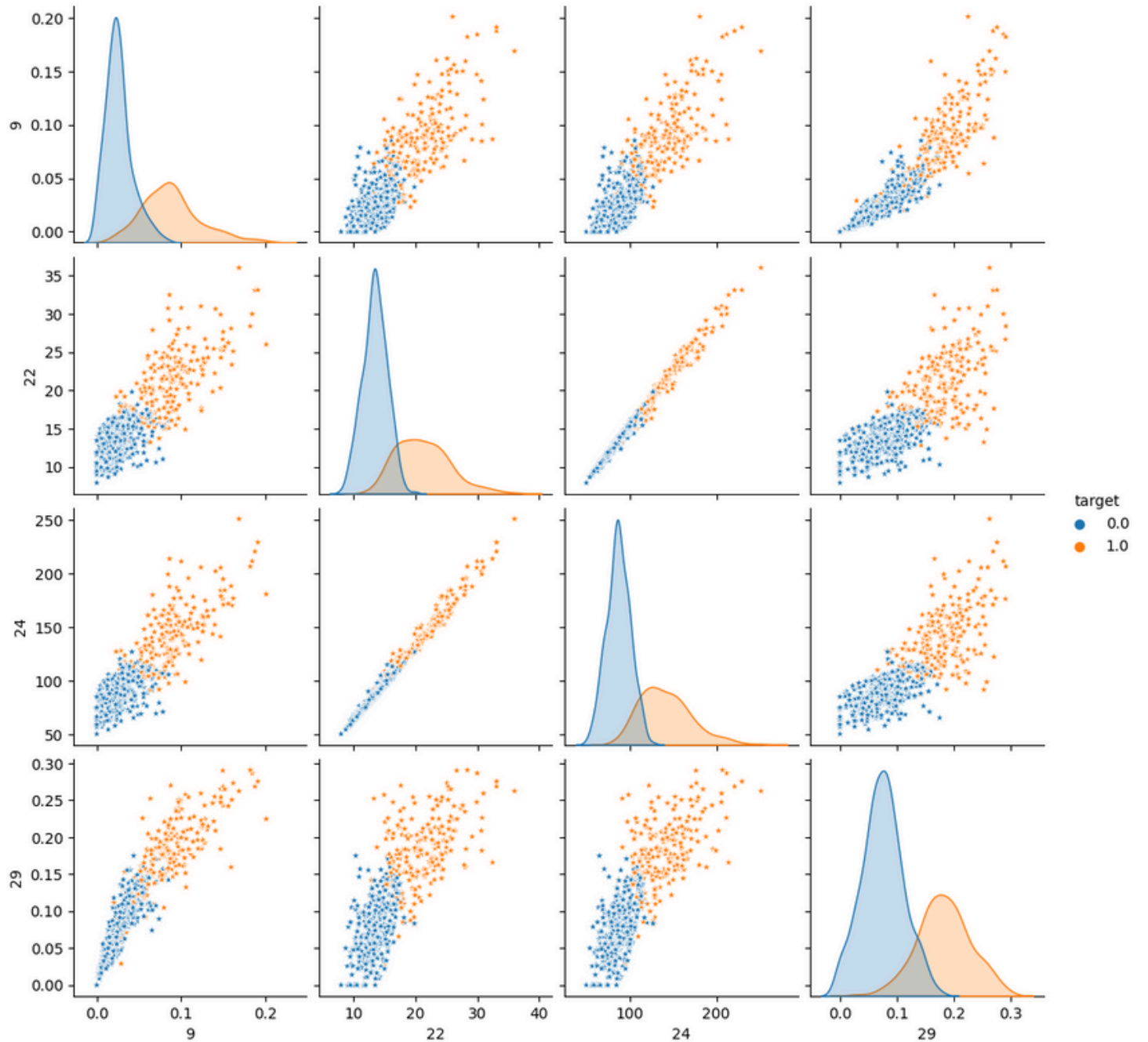
Correlation Between Features with Cor Threshold [0.75]



visualized the data with a correlation greater than 0.75

3. Pairplot : Each scatterplot in the pair plot represents the relationship between two specific features, providing insights into potential patterns or distinctions between the two classes. The diagonal plots display kernel density estimates for individual features, showing their distributions.

```
[ ] sns.pairplot(df[corr_features], diag_kind = "kde" , markers = "*", hue="target")  
plt.show()
```




Classification Algorithms

After carrying out basic data pre-processing and cleaning we can now move on to running the classifier models namely - K nearest neighbours, Random Forest, Decision Trees, Naive Bayes, Support Vector Machines and Logistic Regression. After the execution of all the above mentioned classifiers we can then compare the classifier evaluation metrics such as accuracy , precision, recall and F-scores to determine the best classification algorithm. Below is the step by step procedure so as to how we implemented the model:

Step 1 - Splitting and Standardising Data:

The code snippets provided below splits the dataset into features “x” and target variable “y”.

```
 # Splitting data  
x= df.drop('target',axis=1)  
y= df['target']
```

```
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.30,random_state=101)
```

```
[ ] s= StandardScaler()  
x_train = s.fit_transform(x_train)  
x_test = s.fit_transform(x_test)
```


This code snippet creates a list called “algorithm” containing the names of various machine learning classifiers such as KNeighborsClassifier, RandomForestClassifier, DecisionTreeClassifier, GaussianNB, LogisticRegression, and SVC. Additionally, an empty list named “Accuracy” is initialised, intended to store accuracy values related to these classifiers.

```
algorithm = ['KNeighborsClassifier', 'RandomForestClassifier', 'DecisionTreeClassifier', 'GaussianNB', 'LogisticRegression', 'SVC']  
Accuracy=[]
```

Step 2 - Model Evaluation:

This code snippet defines a function named “all” that takes a learning model as an argument. Inside the function, the model is trained on the training data (x_train and y_train), and predictions are made on the testing data (x_test). The accuracy of the model is then calculated and appended to a list named Accuracy.

Subsequently, the code generates and displays two confusion matrices: one without normalization and one with normalization. It also prints the confusion matrix, a classification report, and the accuracy score. This function is designed to provide a comprehensive evaluation of a machine learning model's performance on a given dataset.

The confusion matrix without normalisation provides raw counts of true positive, true negative, false positive, and false negative predictions, offering an absolute view of model performance. In contrast, the normalized confusion matrix presents these counts as proportions, offering a relative perspective by considering the distribution of true class instances. Both matrices contribute to a comprehensive evaluation of a machine learning model's classification accuracy and errors. We then use Matplotlib Library functions to print the various evaluation metrics which helps in better visualisation of the results.

```

def all(model):
    model.fit(x_train,y_train)
    pred = model.predict(x_test)

    acc=accuracy_score(y_test,pred)
    Accuracy.append(acc)

    # confusion matrix without Normalization
    print('confusion matrix')
    # Calculate confusion matrix
    cm = confusion_matrix(y_test,pred)
    # Plot the confusion matrix
    sns.heatmap(cm, annot=True, fmt='d', cmap=['lightsteelblue', 'navajowhite'])
    plt.title('Confusion matrix')
    plt.xlabel('Predcted label')
    plt.ylabel('True label')
    plt.show()

    # confusion matrix without Normalization
    print('Normalized confusion matrix')
    # Calculate confusion matrix
    cm1 = confusion_matrix(y_test,pred, normalize='true')
    # Plot the confusion matrix
    sns.heatmap(cm1, annot=True, cmap=['lightsteelblue', 'navajowhite'])
    plt.title('Normalized Confusion matrix')
    plt.xlabel('Predcted label')
    plt.ylabel('True label')
    plt.show()

```

```

# print Confusion matrix, Classification report and accuracy report
print(cm)
print(classification_report(y_test,pred))
print('accuracy_score : ', acc)

```

Hence the above snippets of code help us in setting up the dataset for classification algorithms to be executed on it by splitting it into training and testing splits. To ensure proper visualisation of the results we use several matplotlib library functions. We now can move on to individually running the classification algorithms as shown below.

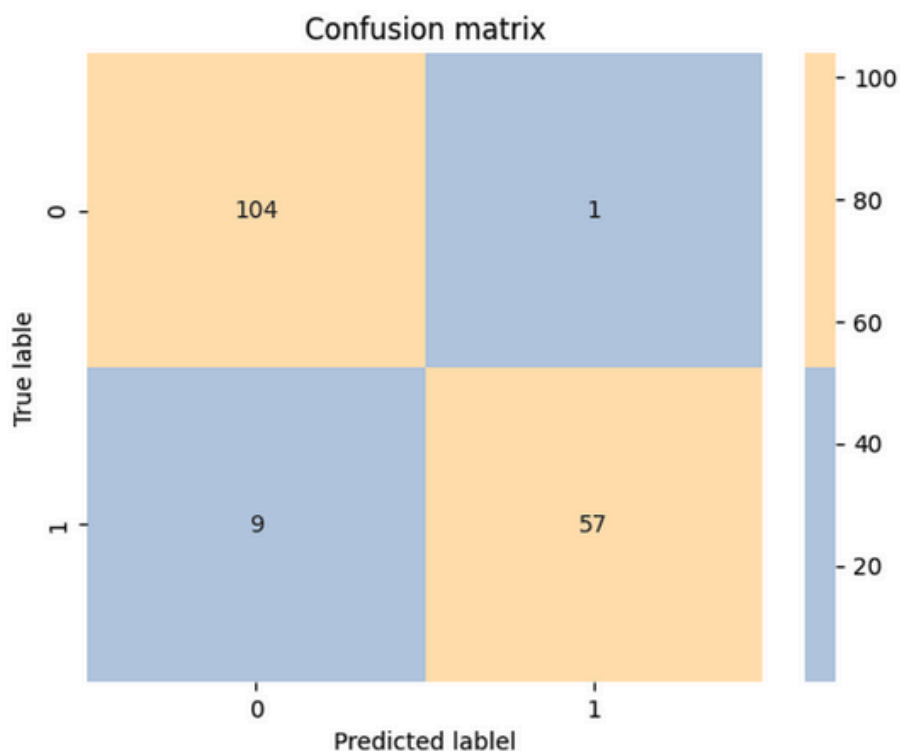
KNN

K-Nearest Neighbors (KNN) is a simple yet powerful machine learning algorithm used for classification and regression tasks. It relies on the principle of proximity, assigning a data point's label based on the majority class of its nearest neighbors. KNN is non-parametric and adaptable to various types of data.

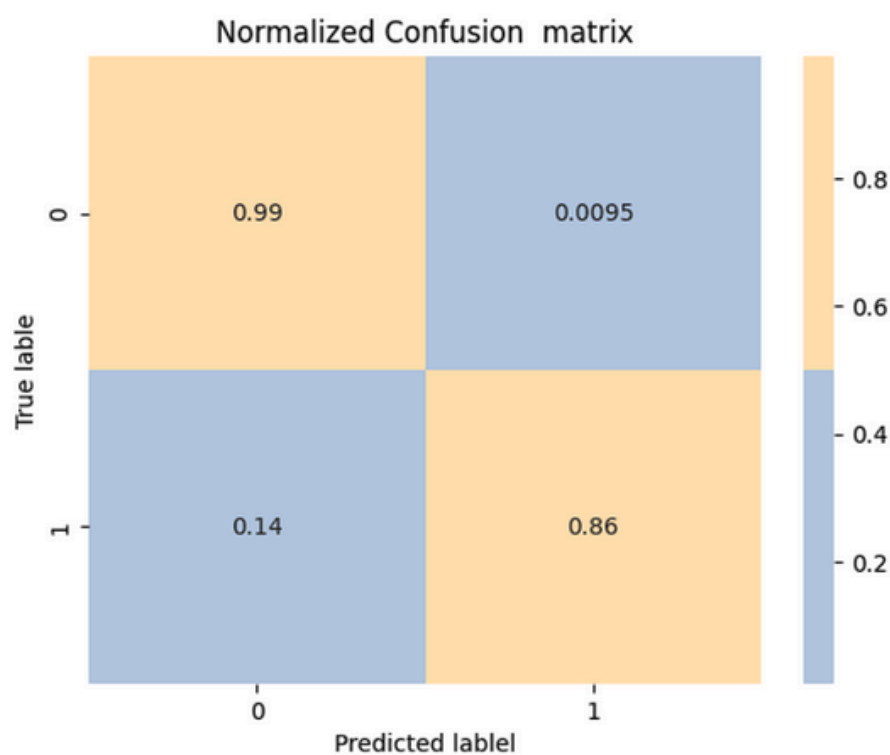
Implementation in Code :

```
[ ] model_1 =KNeighborsClassifier(n_neighbors=2)
    all(model_1)
```

Confusion Matrix:



Normalized Confusion Matrix:



Evaluation Matrix:

[[104 1] [9 57]]		precision	recall	f1-score	support
0.0	0.92	0.99	0.95	105	
1.0	0.98	0.86	0.92	66	
accuracy				0.94	171
macro avg		0.95	0.93	0.94	171
weighted avg		0.94	0.94	0.94	171
accuracy_score : 0.9415204678362573					

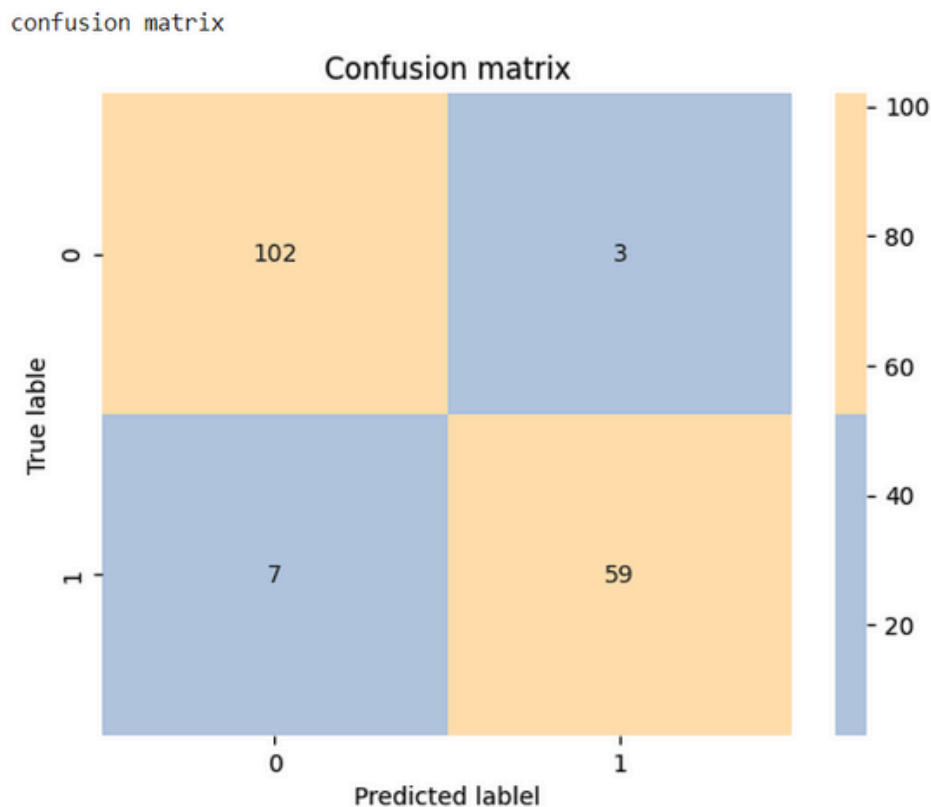
RandomForest

Random Forest is an ensemble learning algorithm widely used for classification and regression. It constructs multiple decision trees during training and merges their outputs to enhance accuracy and mitigate overfitting. By introducing randomness in tree building, Random Forest improves robustness and generalization, making it a popular choice in machine learning

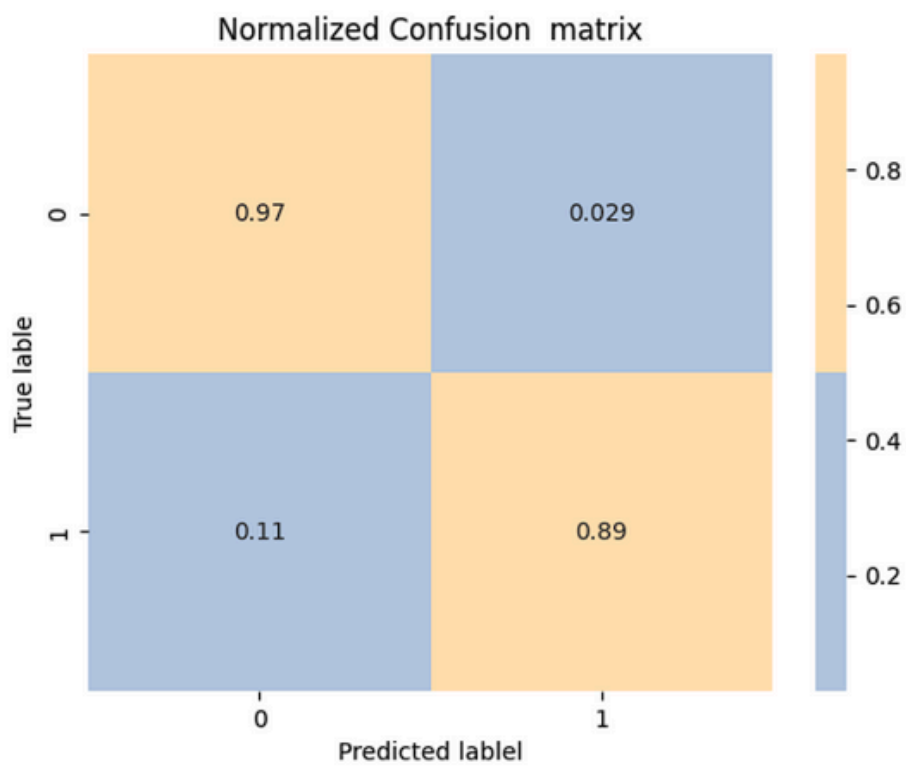
Implementation in Code :

```
▶ model_2= RandomForestClassifier(n_estimators=100,random_state=0)  
all(model_2)
```

Confusion Matrix:



Normalized Confusion Matrix:



Evaluation Matrix:

[[102 3] [7 59]]		precision	recall	f1-score	support
0.0	0.94	0.97	0.95	105	
1.0	0.95	0.89	0.92	66	
accuracy			0.94	171	
macro avg	0.94	0.93	0.94	171	
weighted avg	0.94	0.94	0.94	171	
accuracy_score : 0.9415204678362573					

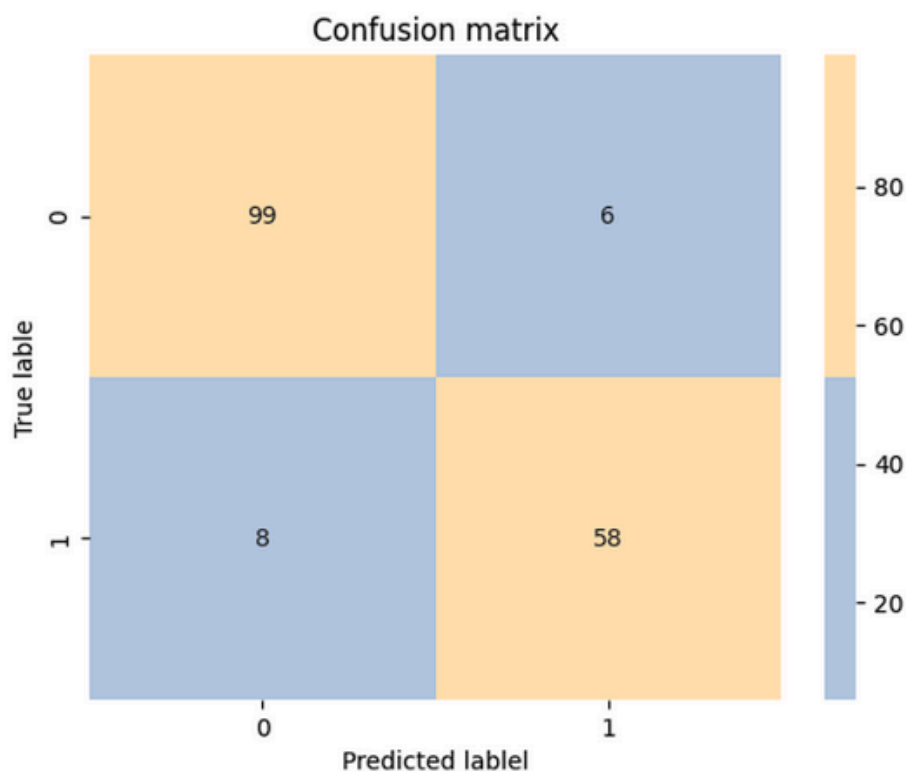
Decision Tree

Decision Trees are versatile machine learning models that make decisions by recursively partitioning data based on features. They're used for classification and regression tasks, visualizing complex decision-making processes. Decision Trees are interpretable, efficient, and handle non-linear relationships well, making them valuable in various domains like finance, healthcare, and marketing.

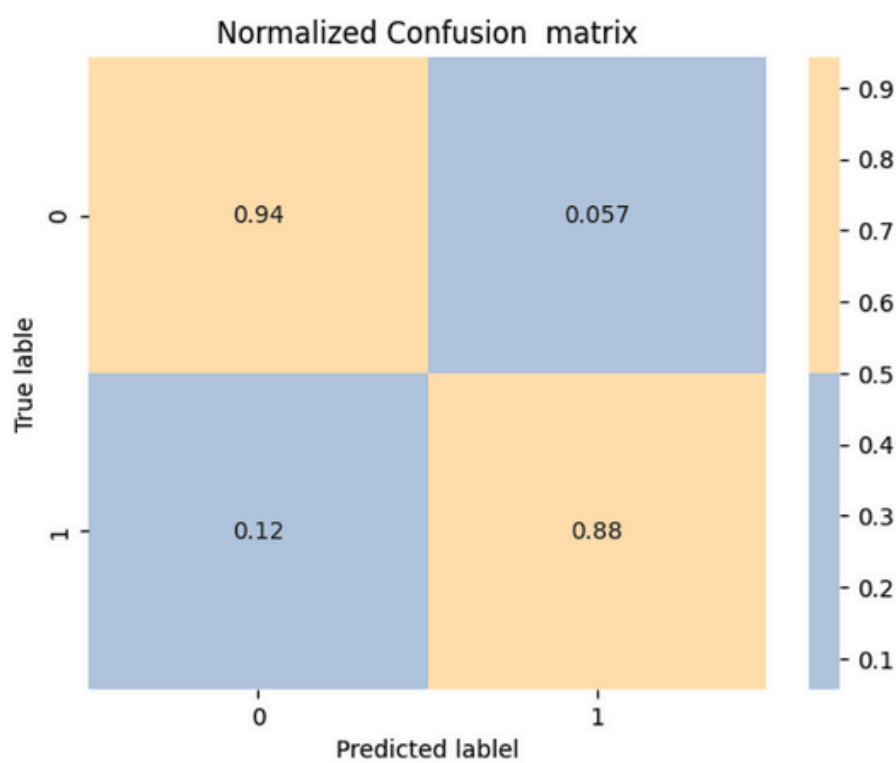
Implementation in Code :

```
[ ] model_3 = DecisionTreeClassifier(random_state=42)
    all(model_3)
```

Confusion Matrix:



Normalized Confusion Matrix:



Evaluation Matrix:

[[99 6] [8 58]]		precision	recall	f1-score	support
0.0	0.93	0.94	0.93	105	
1.0	0.91	0.88	0.89	66	
accuracy			0.92	171	
macro avg	0.92	0.91	0.91	171	
weighted avg	0.92	0.92	0.92	171	
accuracy_score : 0.9181286549707602					

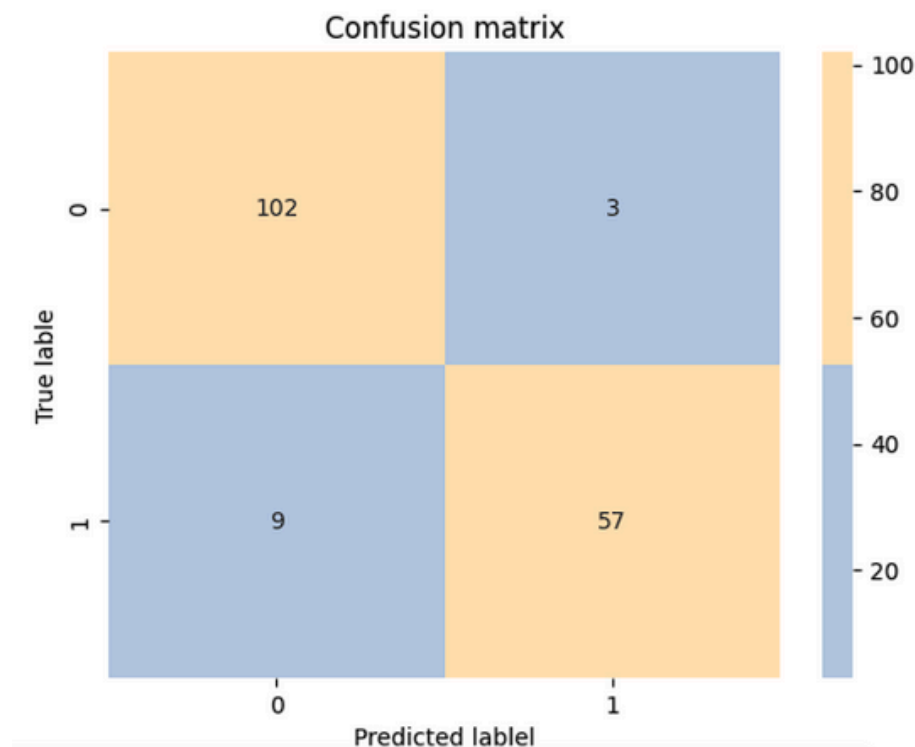
Naive Bayes

Naive Bayes, a probabilistic machine learning algorithm, is particularly suited for classification tasks. It relies on Bayes' theorem and assumes independence between features, simplifying computations. Despite its "naive" assumption, Naive Bayes often performs well in text categorization, spam filtering, and sentiment analysis, showcasing its efficiency and simplicity in diverse applications.

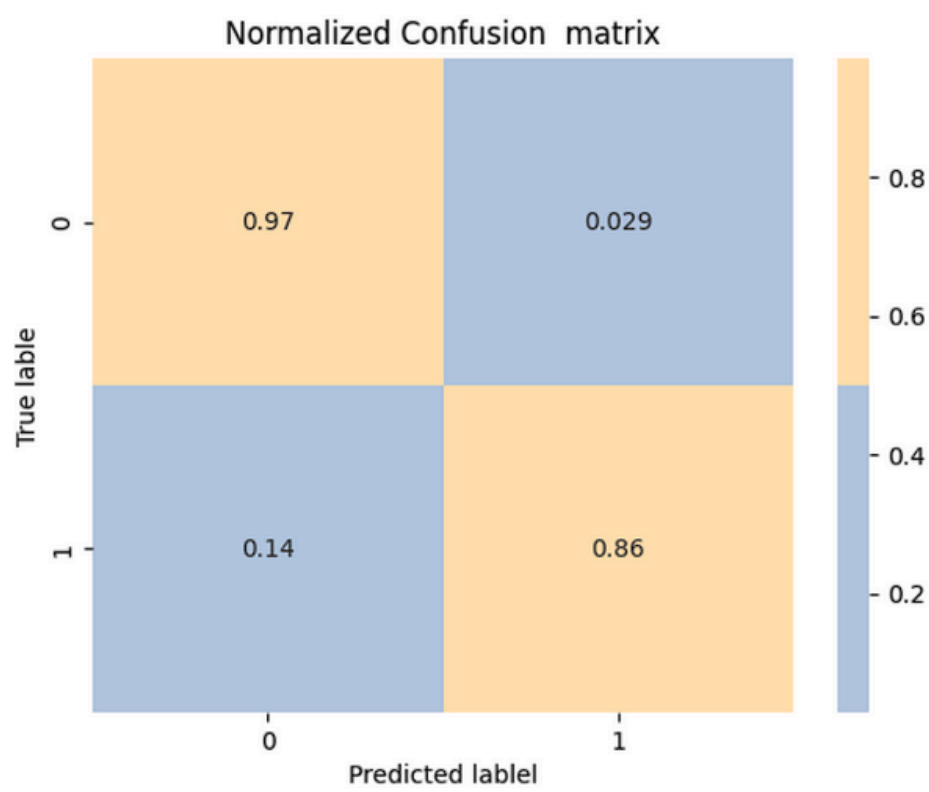
Implementation in Code :

```
model_4 = GaussianNB()  
all(model_4)
```

Confusion Matrix:



Normalized Confusion Matrix:



Evaluation Matrix:

[[102 3] [9 57]]					
	precision	recall	f1-score	support	
0.0	0.92	0.97	0.94	105	
1.0	0.95	0.86	0.90	66	
accuracy			0.93	171	
macro avg	0.93	0.92	0.92	171	
weighted avg	0.93	0.93	0.93	171	
accuracy_score : 0.9298245614035088					

Logistic Regression

Logistic Regression is a fundamental and widely employed algorithm in data science for binary and multi-class classification tasks. Despite its name, it is used for classification rather than regression. The algorithm models the probability that an instance belongs to a particular class, employing the logistic function to constrain the output between 0 and 1.

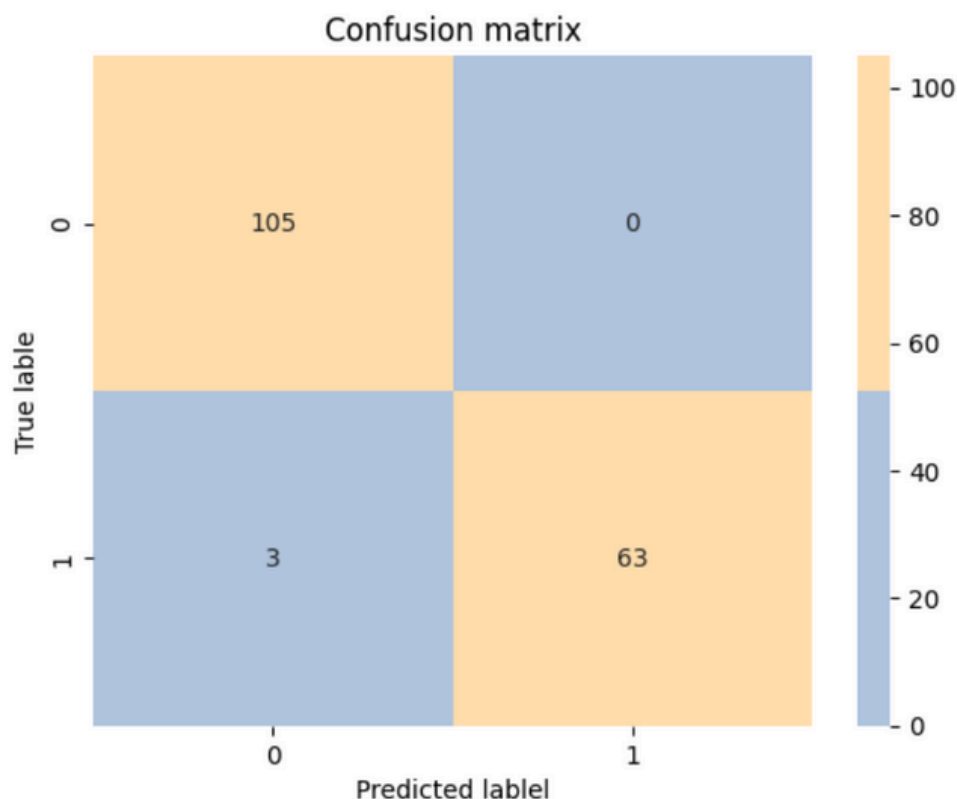
In data science applications, Logistic Regression is favored for its simplicity, interpretability, and efficiency.

Implementation in Code :

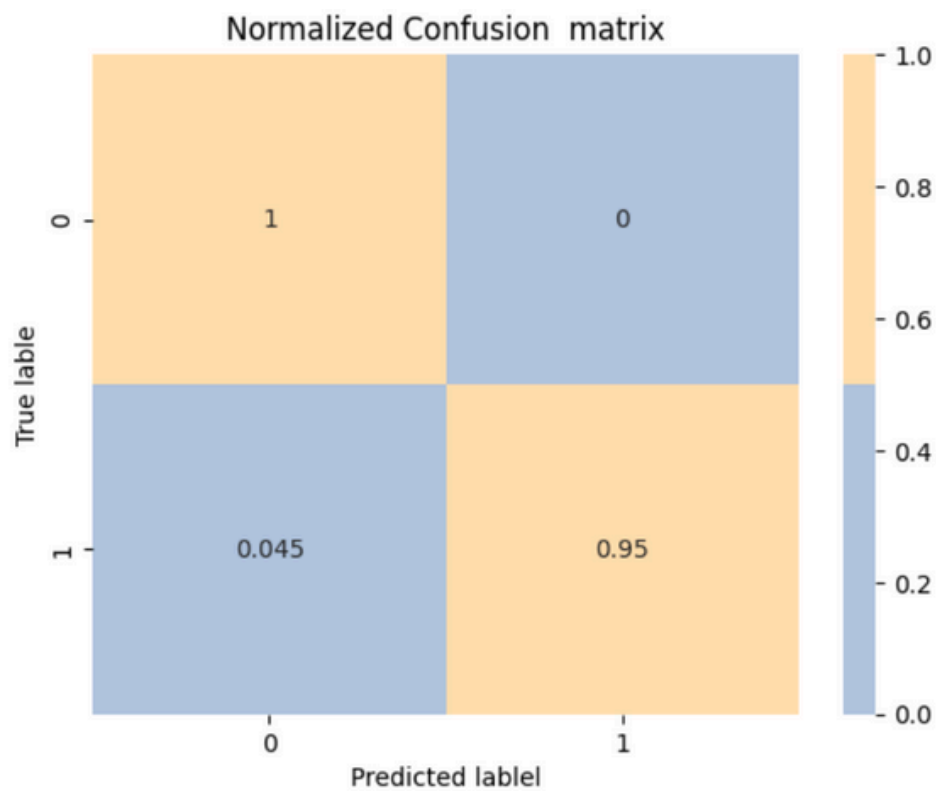


```
model_5 = LogisticRegression()  
all(model_5)
```

Confusion Matrix:



Normalized Confusion Matrix:



Evaluation Matrix:

[[105 0] [3 63]]					
		precision	recall	f1-score	support
	0.0	0.97	1.00	0.99	105
	1.0	1.00	0.95	0.98	66
	accuracy			0.98	171
	macro avg	0.99	0.98	0.98	171
	weighted avg	0.98	0.98	0.98	171
	accuracy_score :	0.9824561403508771			

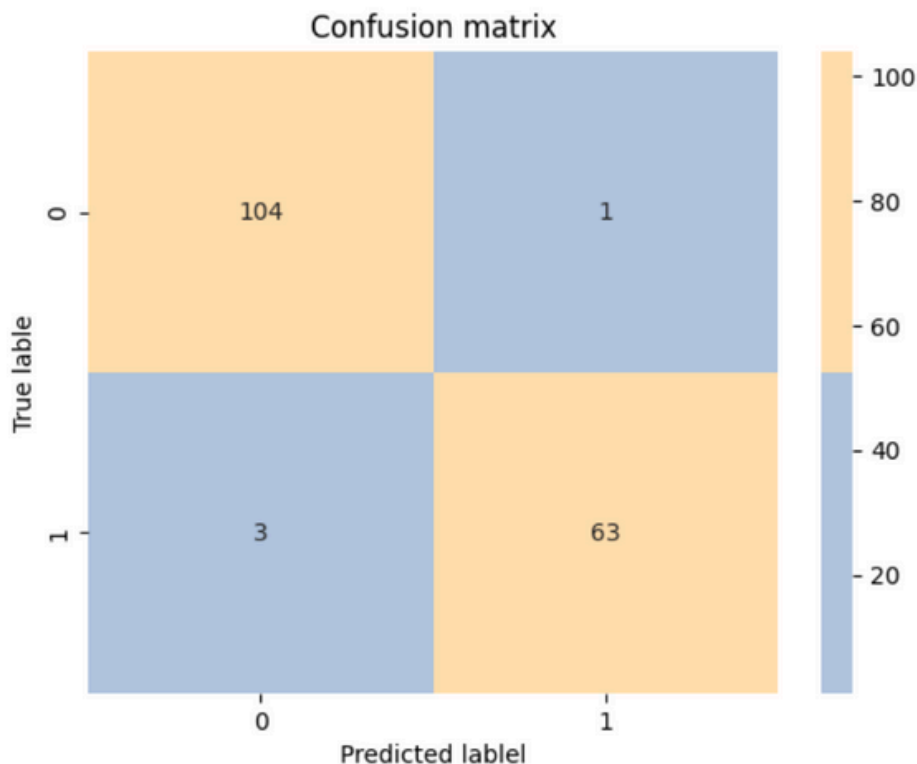
SVC

Support Vector Machines (SVM), including its variant Support Vector Classification (SVC), is a powerful algorithm in data science used for classification and regression tasks. SVC is particularly valuable in scenarios where the decision boundary between classes is complex or not easily linearly separable. SVC works by finding the hyperplane that best separates different classes while maximizing the margin between them

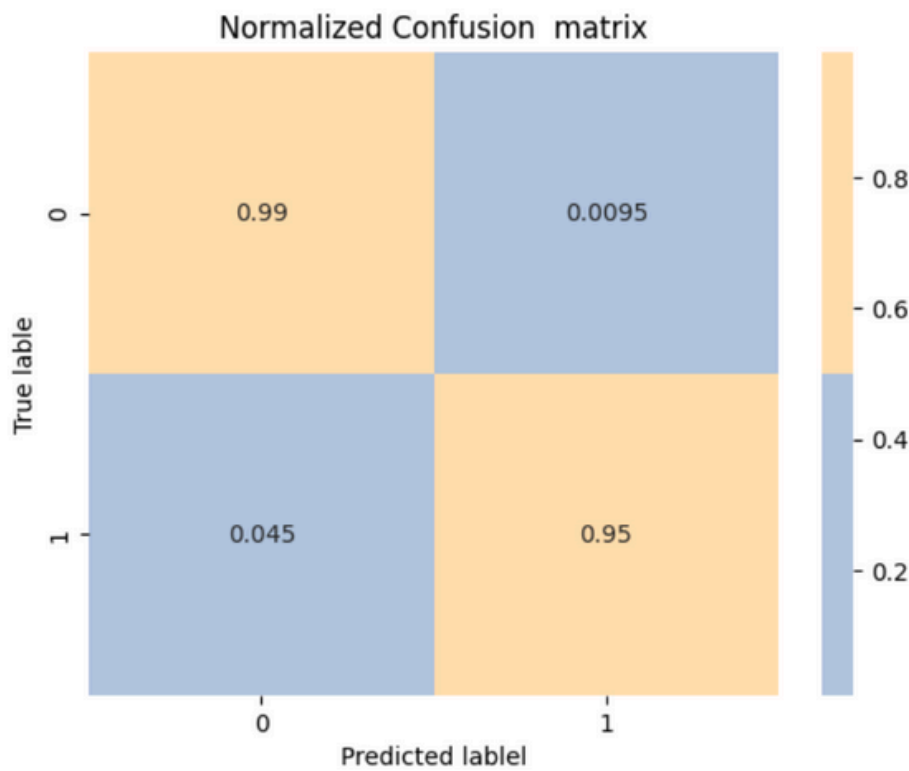
Implementation in Code :

```
[ ] model_6 = SVC(kernel = 'linear')  
    all(model_6)  
    model_6.fit(x_train, y_train)
```

Confusion Matrix:



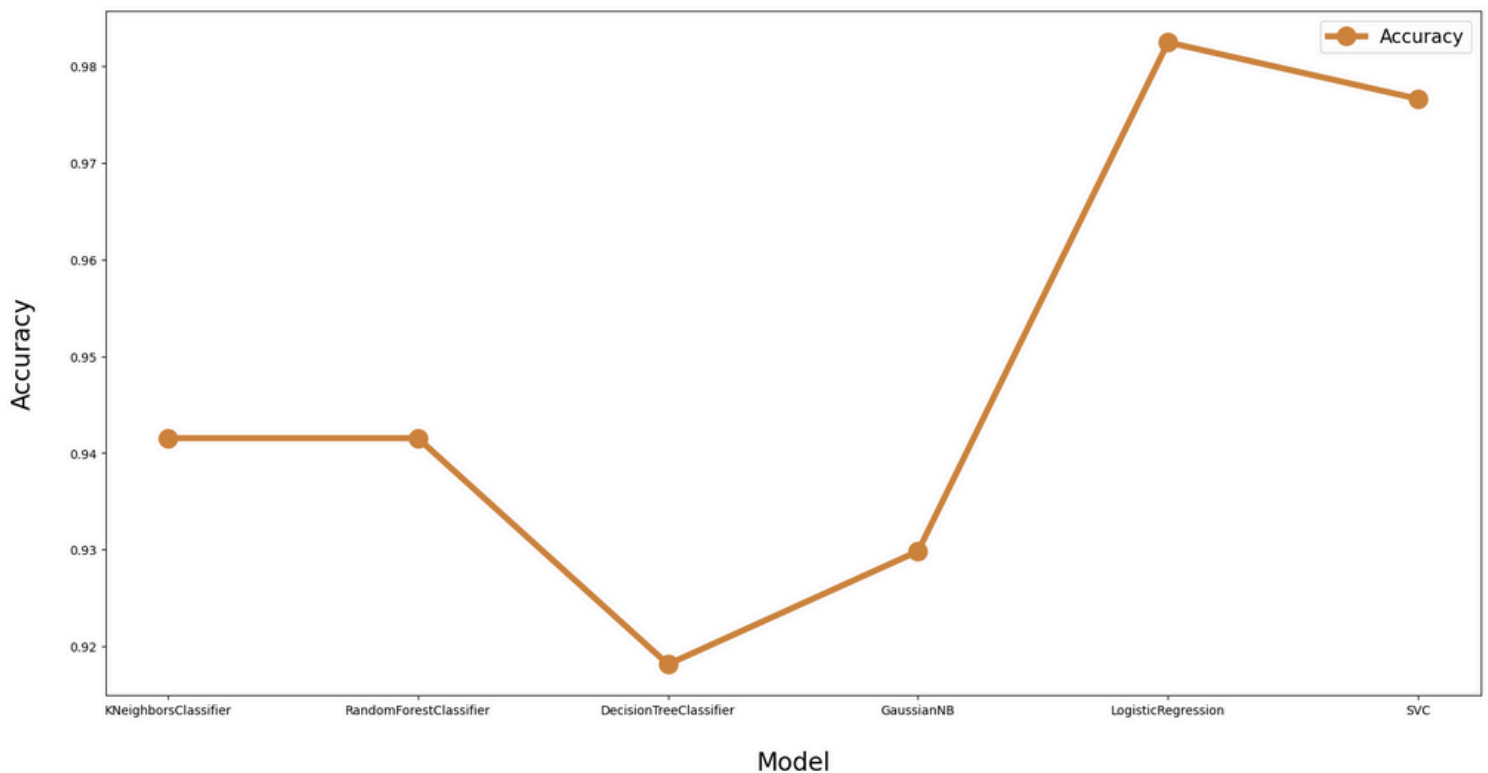
Normalized Confusion Matrix:



Evaluation Matrix:

[[104 1] [3 63]]					
		precision	recall	f1-score	support
0.0		0.97	0.99	0.98	105
1.0		0.98	0.95	0.97	66
accuracy				0.98	171
macro avg		0.98	0.97	0.98	171
weighted avg		0.98	0.98	0.98	171
accuracy_score : 0.9766081871345029					

Final Results



Highest Accuracy: Logistic Regression

Logistic Regression stands out with the highest accuracy score (close to 0.982), showcasing its effectiveness in this particular context. Its predictive capability surpasses other algorithms, making it a promising choice for this classification task.

Noteworthy Performers:

KNeighbour Classifier and Random Forest Classifier both achieve a commendable accuracy (close to 0.941), reflecting robust predictive capabilities.

Support Vector Classifier (SVC) follows closely with an accuracy of 0.977, indicating strong performance in classifying instances.