Step 1 : Import Libraries

```
import numpy as np
import pandas as pd
import matplotlib.pylab as plt
import seaborn as sns
from sklearn.model_selection import KFold, cross_val_score

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
from sklearn import preprocessing
from sklearn.metrics import classification_report, confusion_matrix , precision_score,  recall_score, auc,roc_curve,accuracy_score,f1_score
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
from sklearn.ensemble import RandomForestClassifier
from tabulate import tabulate

import warnings as warn
from warnings import filterwarnings

filterwarnings("ignore")
```

Step 2 : Read Dataset

```
data = pd.read_csv("IRIS.csv")
df = pd.DataFrame(data)
```

```
df["species"].replace({"Iris-setosa":0 , "Iris-versicolor":1 , "Iris-virginica":2} , inplace = True)
df
```

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	0
1	4.9	3.0	1.4	0.2	0
2	4.7	3.2	1.3	0.2	0
3	4.6	3.1	1.5	0.2	0
4	5.0	3.6	1.4	0.2	0
...	...	...	...	...	...
145	6.7	3.0	5.2	2.3	2
146	6.3	2.5	5.0	1.9	2
147	6.5	3.0	5.2	2.0	2
148	6.2	3.4	5.4	2.3	2
149	5.9	3.0	5.1	1.8	2

150 rows × 5 columns

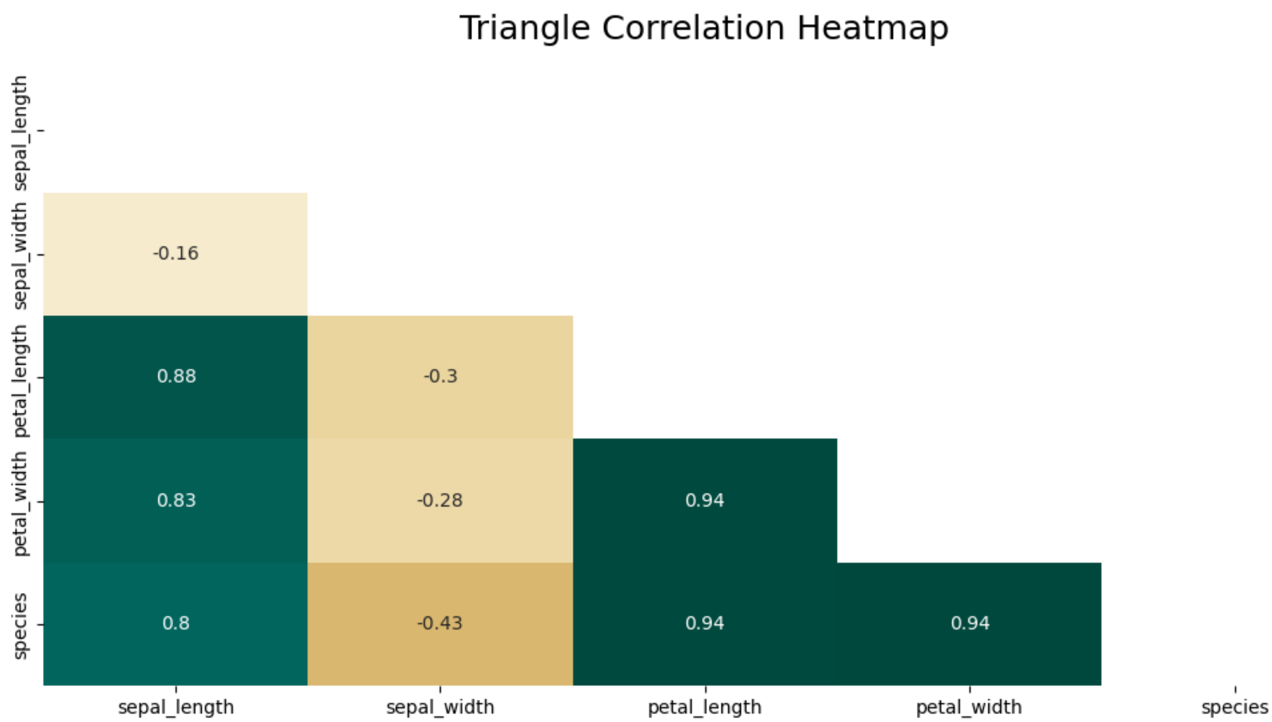
Step 3 : Dataset Overview

```
df.describe(include = 'all')
```

	sepal_length	sepal_width	petal_length	petal_width	species
count	150.000000	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.054000	3.758667	1.198667	1.000000
std	0.828066	0.433594	1.764420	0.763161	0.819232
min	4.300000	2.000000	1.000000	0.100000	0.000000
25%	5.100000	2.800000	1.600000	0.300000	0.000000
50%	5.800000	3.000000	4.350000	1.300000	1.000000

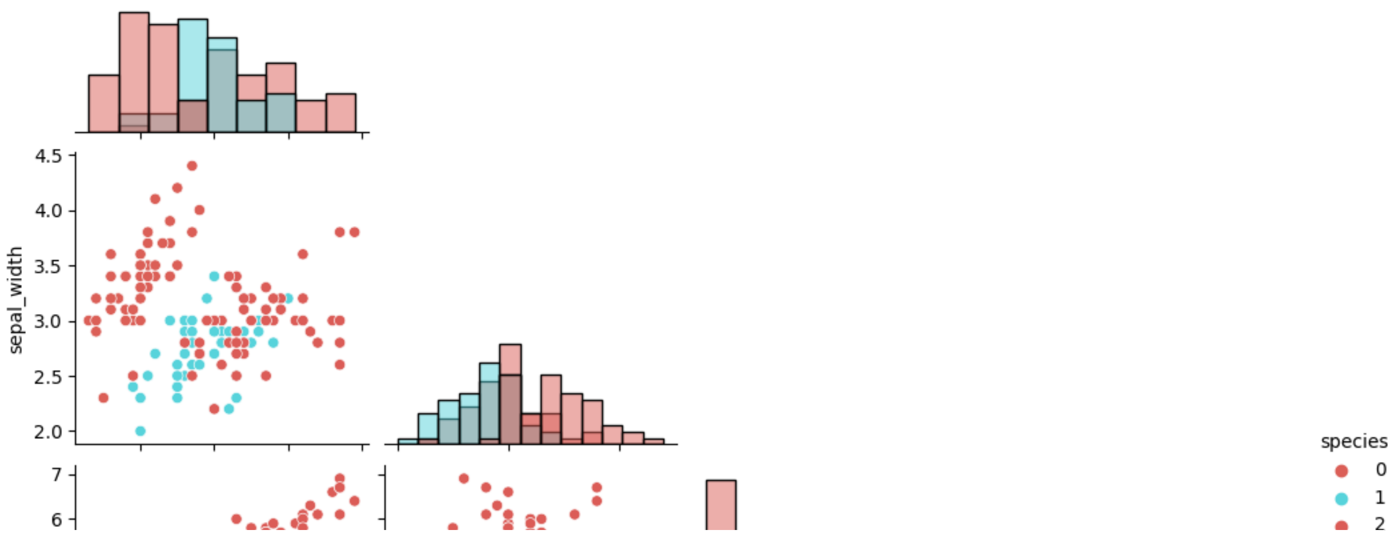
```
plt.figure (figsize = (16 , 6))

mask = np.triu(np.ones_like(df.corr(method = "spearman") , dtype = bool))
heatmap = sns.heatmap(df.corr(method = "spearman") , mask = mask , vmin = -1 , vmax = 1 ,
                      annot = True , cmap="BrBG")
heatmap.set_title("Triangle Correlation Heatmap" , fontdict = {'fontsize': 18} , pad =16 )
```

```
Text(0.5, 1.0, 'Triangle Correlation Heatmap')
```



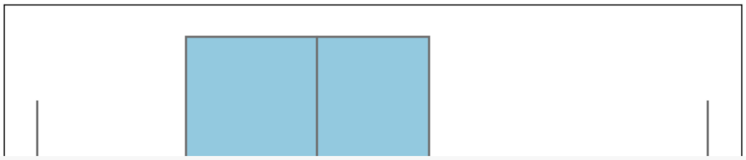

```
sns.pairplot(df , hue='species' , diag_kind="hist" , corner=True , palette = 'hls')
```

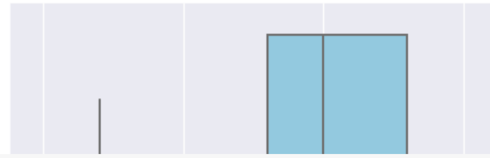
```
<seaborn.axisgrid.PairGrid at 0x79d69b9914e0>
```



Step 4 : Data science & Visualization

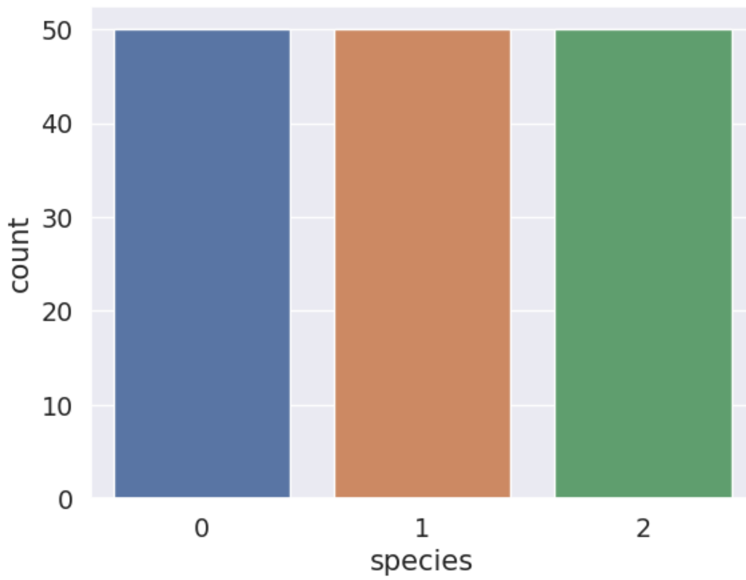
```
Num = ['sepal_length' , 'sepal_width' , 'petal_length' , 'petal_width']

j = 0
while j < 5:
    fig = plt.figure (figsize = [20 , 4])
    plt.subplot(1, 2, 1)
    sns.boxplot (x = Num[j] , data = df , color='skyblue')
    sns.set(font_scale=1.25)
    j += 1
    plt.subplot(1, 2, 2)
    sns.boxplot (x = Num[j] , data = df , color='skyblue')
    sns.set(font_scale=1.25)
    j += 1
    if j == 4:
        break
    plt.show()
```





```
sns.countplot(x = df['species'] , data = df)
```

```
<Axes: xlabel='species', ylabel='count'>
```



Step 5 : Models

```
X = pd.DataFrame(df , columns = ["sepal_length" , "sepal_width" , "petal_length" , "petal_width"])
y = df["species"].values.reshape(-1,1)
```

```
Scaler = preprocessing.MinMaxScaler(feature_range = (0,1))
Norm1 = Scaler.fit_transform(df)
Norm1_df=pd.DataFrame (Norm1 , columns = ["species" , "sepal_length" , "sepal_width" , "petal_length" , "petal_width"])
Norm1_df.head()
```

	species	sepal_length	sepal_width	petal_length	petal_width
0	0.222222	0.625000	0.067797	0.041667	0.0
1	0.166667	0.416667	0.067797	0.041667	0.0
2	0.111111	0.500000	0.050847	0.041667	0.0
3	0.083333	0.458333	0.084746	0.041667	0.0
4	0.194444	0.666667	0.067797	0.041667	0.0

```
X_train, X_test, y_train, y_test = train_test_split(X,y , test_size=0.5 , random_state = 0)
```

```
def Evaluate_Performance(Model, Xtrain, Xtest, Ytrain, Ytest) :
    Model.fit(Xtrain,Ytrain)
    overall_score = cross_val_score(Model, Xtrain,Ytrain, cv=10)
    model_score = np.average(overall_score)
    Ypredicted = Model.predict(Xtest)
    avg = 'weighted'
    print("\n • Training Accuracy Score : ", round(Model.score(Xtrain, Ytrain) * 100,2))
    print(f" • Cross Validation Score : {round(model_score * 100,2)}")
    print(f" • Testing Accuracy Score :{round(accuracy_score(Ytest, Ypredicted) * 100,2)}")
    print(f" • Precision Score is : {np.round(precision_score(Ytest, Ypredicted , average=avg) * 100,2)}")
    print(f" • Recall Score is : {np.round(recall_score(Ytest, Ypredicted , average=avg) * 100,2)}")
    print(f" • F1-Score Score is : {np.round(f1_score(Ytest, Ypredicted , average=avg) * 100,2)}")
```

Logestic Regression

```
LogReg = LogisticRegression(solver = "liblinear" , C=50)
LogReg.fit(X_train , y_train.ravel())
y_pred_LR = LogReg.predict(X_test)
print("Logistic Regression : ")
Evaluate_Performance(LogReg, X_train, X_test, y_train, y_test)
```

```
Logistic Regression :
```

- Training Accuracy Score : 98.67
- Cross Validation Score : 97.32
- Testing Accuracy Score :94.67
- Precision Score is : 94.67
- Recall Score is : 94.67
- F1-Score Score is : 94.67

```
kfold = KFold(37)
LR_r = cross_val_score (LogReg, X, y, cv = kfold)
print(np.std(LR_r))
```

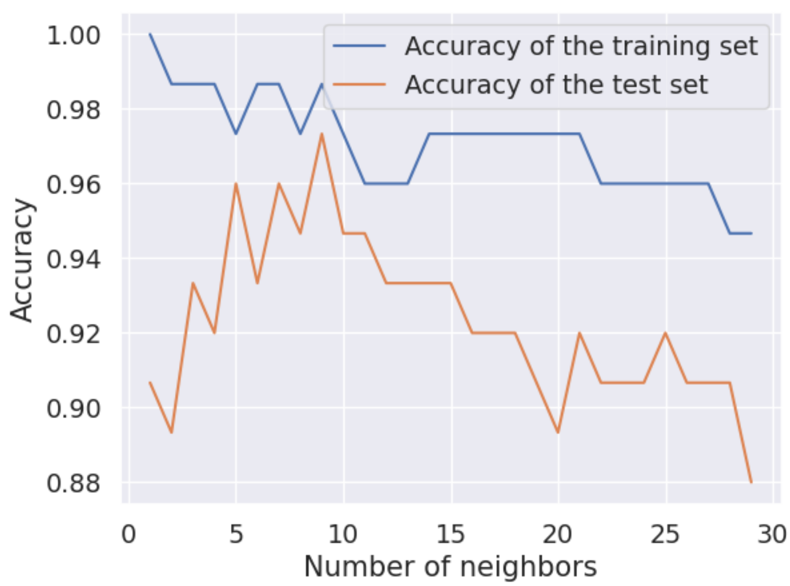
```
0.10335850365390781
```

```
cm = confusion_matrix (y , LogReg.predict(X))

fig, ax = plt.subplots (figsize = (8, 8))
ax.imshow(cm)
ax.grid(False)
ax.set_xlabel('Predicted outputs', fontsize= 14 , color='black')
ax.set_ylabel('Actual outputs', fontsize= 14 , color='black')
ax.xaxis.set(ticks=range(3))
ax.yaxis.set(ticks=range(3))
ax.set_ylim(2.5 , -0.5)

for i in range(3):
    for j in range(3):
        ax.text(j, i, cm[i, j], ha = 'center' , va = 'center' , color = 'red')

plt.show()
```

K Nearest Neighbors

```
training_acc = []
test_acc = []

neighbors_setting = range(1,30)

for n_neighbors in neighbors_setting:
    KNN = KNeighborsClassifier(n_neighbors = n_neighbors)
    KNN.fit(X_train , y_train.ravel())
    training_acc.append(KNN.score(X_train , y_train))
    test_acc.append(KNN.score(X_test , y_test))

plt.plot(neighbors_setting , training_acc , label = "Accuracy of the training set")
plt.plot(neighbors_setting , test_acc , label = "Accuracy of the test set")
plt.xlabel("Number of neighbors")
plt.ylabel("Accuracy")
plt.grid(linestyle='-')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x79d6989e2b90>
```




```
parameters = {"n_neighbors" : range(1,50)}
grid_kn = GridSearchCV(estimator = KNN , param_grid = parameters , scoring = "accuracy" , cv = 5 , verbose = 1 , n_jobs = -1)

grid_kn.fit(X_train , y_train.ravel())
grid_kn.best_params_
```

```
Fitting 5 folds for each of 49 candidates, totalling 245 fits
{'n_neighbors': 3}
```

```
K = 3
KNN = KNeighborsClassifier(K)
KNN.fit(X_train , y_train.ravel())
y_pred_KNN = KNN.predict(X_test)
print("K-Nearest Neighbors : ")
Evaluate_Performance(KNN, X_train, X_test, y_train, y_test)
```

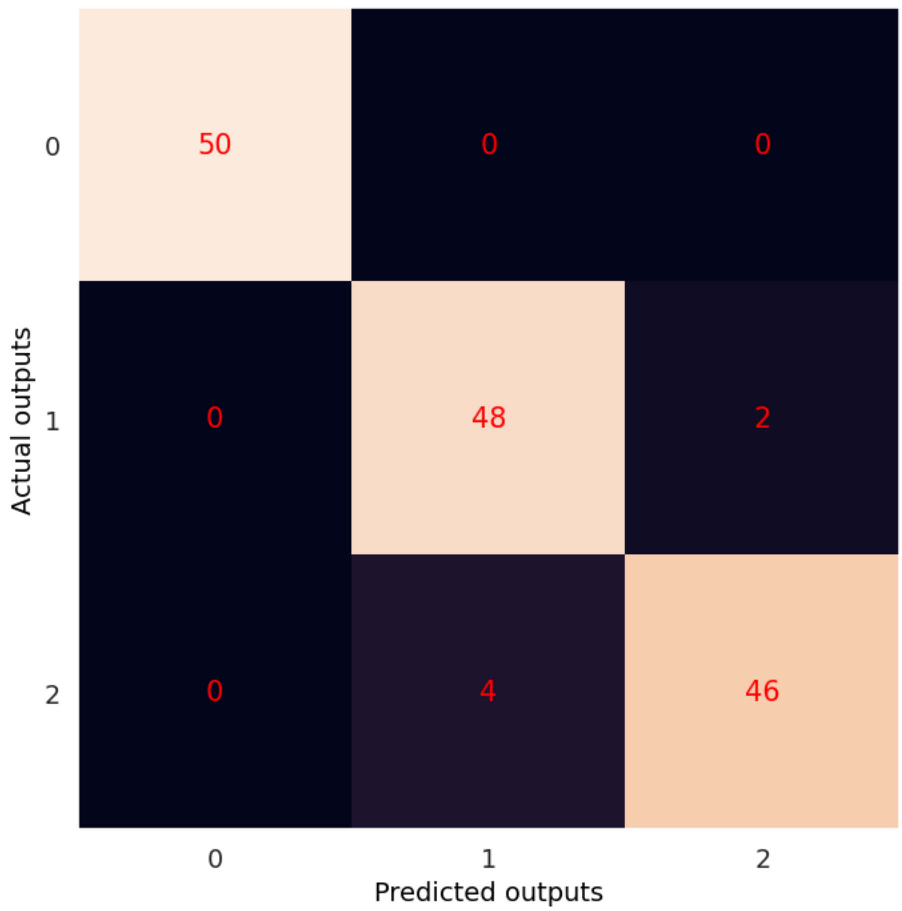
K-Nearest Neighbors :

- Training Accuracy Score : 98.67
- Cross Validation Score : 97.14
- Testing Accuracy Score :93.33
- Precision Score is : 93.63
- Recall Score is : 93.33
- F1-Score Score is : 93.27

```
KNN_r = cross_val_score (KNN, X, y, cv = 10)
K = np.std(KNN_r)
print(K)
```

```
0.04472135954999579
```

```
cm = confusion_matrix (y , KNN.predict(X))

fig, ax = plt.subplots (figsize = (8, 8))
ax.imshow(cm)
ax.grid(False)
ax.set_xlabel('Predicted outputs', fontsize= 14 , color='black')
ax.set_ylabel('Actual outputs', fontsize= 14 , color='black')
ax.xaxis.set(ticks=range(3))
ax.yaxis.set(ticks=range(3))
ax.set_ylim(2.5 , -0.5)

for i in range(3):
    for j in range(3):
        ax.text(j, i, cm[i, j], ha = 'center' , va = 'center' , color = 'red')

plt.show()
```



Naive Bayes

```
NB = GaussianNB()
NB.fit(X_train , y_train.ravel())
y_pred_NB = NB.predict(X_test)
print("Naive Bayes : ")
Evaluate_Performance(NB, X_train, X_test, y_train, y_test)
```

Naive Bayes :

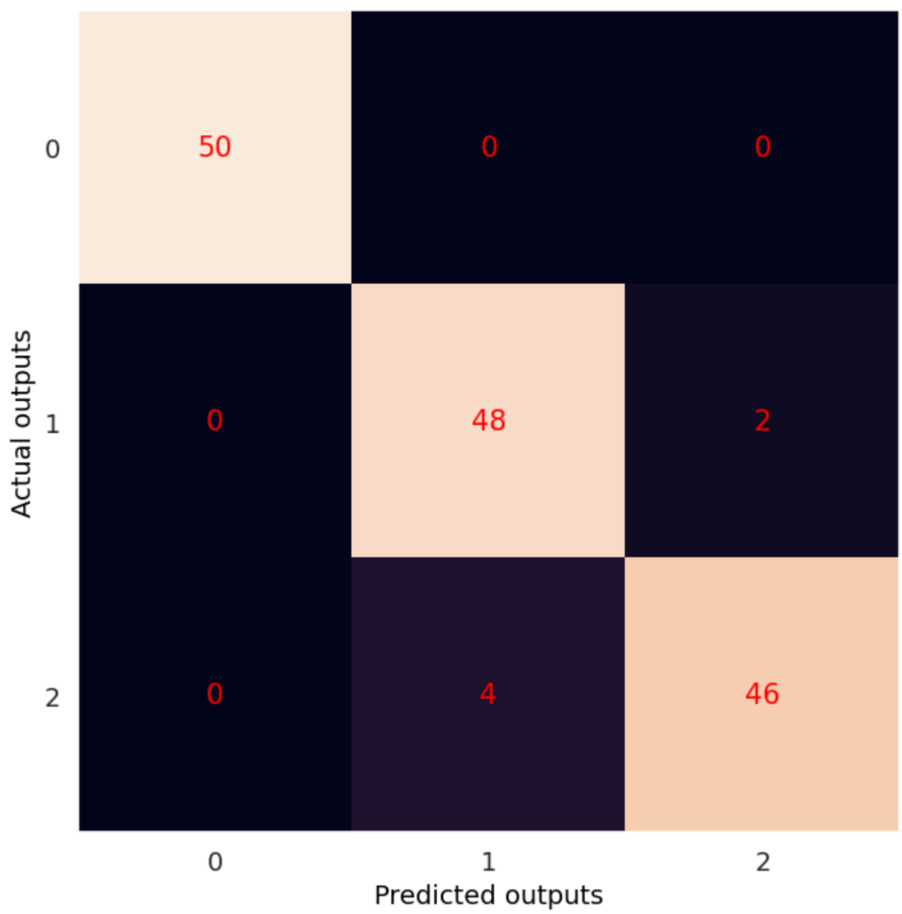
- Training Accuracy Score : 97.33
- Cross Validation Score : 97.14

- Testing Accuracy Score :94.67
- Precision Score is : 95.29
- Recall Score is : 94.67
- F1-Score Score is : 94.59

```
NB_r = cross_val_score (NB, X, y, cv = 10)
N = np.std(NB_r)
print(N)
```

```
0.04268749491621898
```

```
cm = confusion_matrix (y , NB.predict(X))

fig, ax = plt.subplots (figsize = (8, 8))
ax.imshow(cm)
ax.grid(False)
ax.set_xlabel('Predicted outputs', fontsize= 14 , color='black')
ax.set_ylabel('Actual outputs', fontsize= 14 , color='black')
ax.xaxis.set(ticks=range(3))
ax.yaxis.set(ticks=range(3))
ax.set_ylim(2.5 , -0.5)

for i in range(3):
    for j in range(3):
        ax.text(j, i, cm[i, j], ha = 'center' , va = 'center' , color = 'red')

plt.show()
```



Support Vector Machine

```
SVM = SVC()
SVM.fit(X_train , y_train)
y_pred_SVM = SVM.predict(X_test)
print("SVM : ")
Evaluate_Performance(SVM, X_train, X_test, y_train, y_test)
```

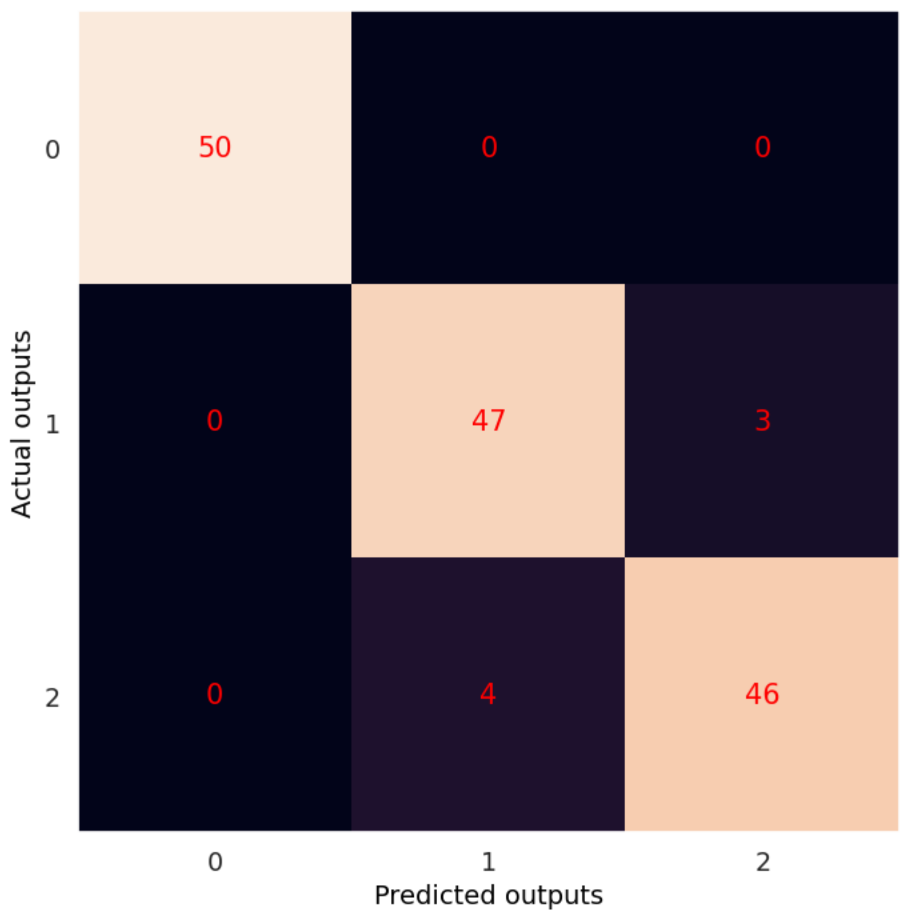
SVM :

- Training Accuracy Score : 96.0
- Cross Validation Score : 95.71
- Testing Accuracy Score :94.67
- Precision Score is : 94.8
- Recall Score is : 94.67
- F1-Score Score is : 94.64

```
SVM_r = cross_val_score (SVM, X, y, cv = 10)
S = np.std(SVM_r)
print(S)
```

```
0.03265986323710904
```

```
cm = confusion_matrix (y , SVM.predict(X))

fig, ax = plt.subplots (figsize = (8, 8))
ax.imshow(cm)
ax.grid(False)
ax.set_xlabel('Predicted outputs', fontsize= 14 , color='black')
ax.set_ylabel('Actual outputs', fontsize= 14 , color='black')
ax.xaxis.set(ticks=range(3))
ax.yaxis.set(ticks=range(3))
ax.set_ylim(2.5 , -0.5)

for i in range(3):
    for j in range(3):
        ax.text(j, i, cm[i, j], ha = 'center' , va = 'center' , color = 'red')

plt.show()
```



Decision Tree

```
DT = DecisionTreeClassifier(max_depth = 3)
DT = DT.fit(X_train , y_train)
```

```
y_pred_DT = DT.predict(X_test)
print("Decision Tree : ")
Evaluate_Performance(DT, X_train, X_test, y_train, y_test)
```

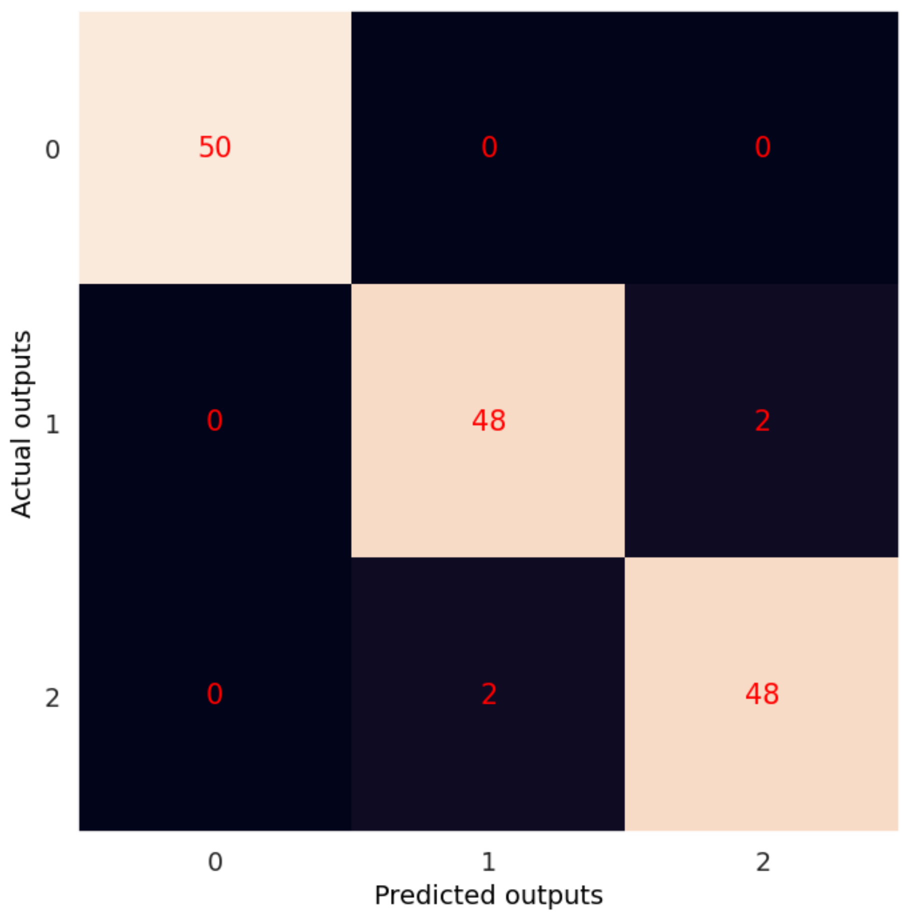
Decision Tree :

- Training Accuracy Score : 98.67
- Cross Validation Score : 94.46
- Testing Accuracy Score :96.0
- Precision Score is : 96.03
- Recall Score is : 96.0
- F1-Score Score is : 95.99

```
DT_r = cross_val_score (DT, X, y, cv = 10)
D = np.std(DT_r)
print(D)
```

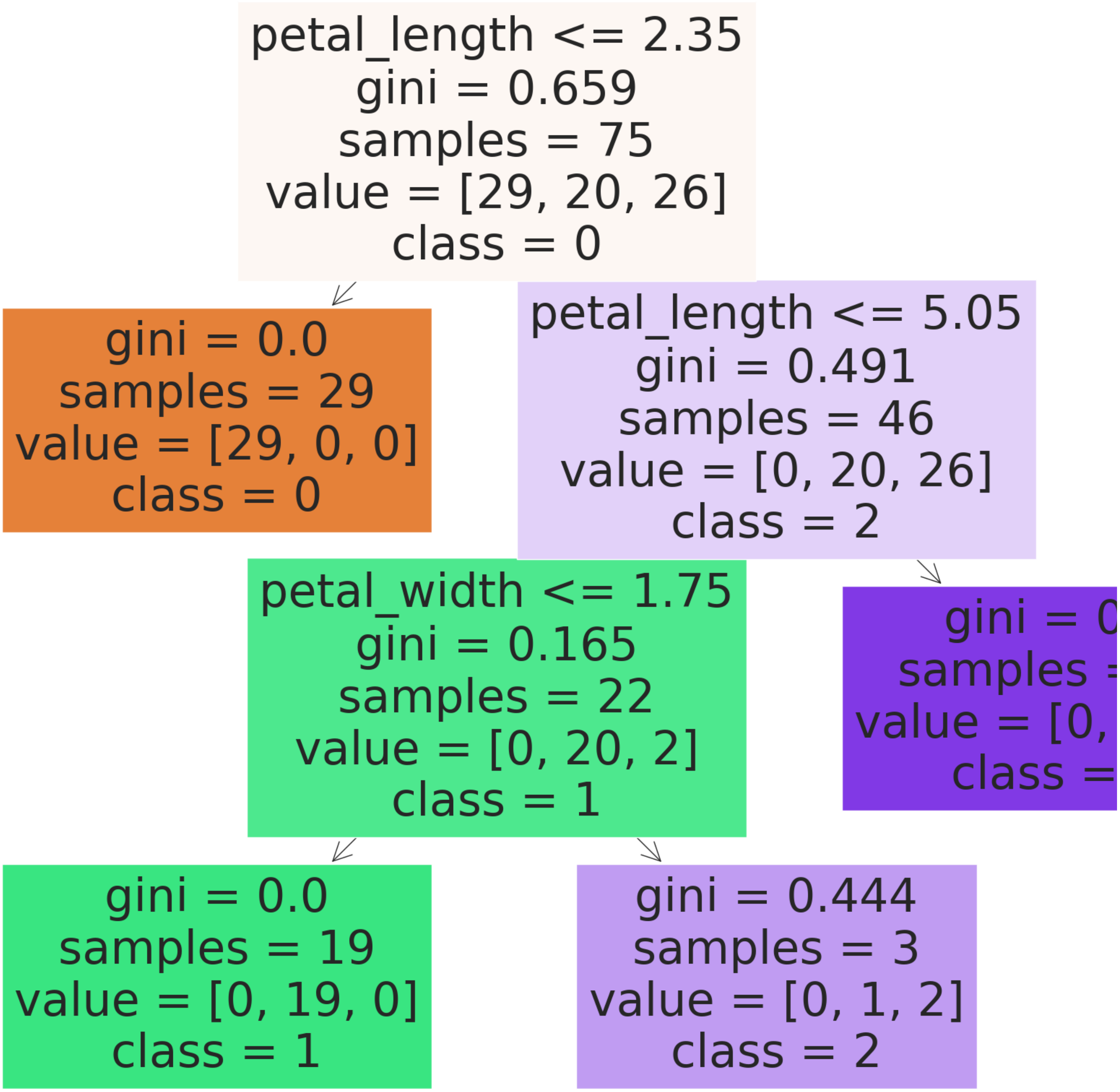
0.03265986323710903

```
cm = confusion_matrix (y , DT.predict(X))

fig, ax = plt.subplots (figsize = (8, 8))
ax.imshow(cm)
ax.grid(False)
ax.set_xlabel('Predicted outputs', fontsize= 14 , color='black')
ax.set_ylabel('Actual outputs', fontsize= 14 , color='black')
ax.xaxis.set(ticks=range(3))
ax.yaxis.set(ticks=range(3))
ax.set_ylim(2.5 , -0.5)

for i in range(3):
    for j in range(3):
        ax.text(j, i, cm[i, j], ha = 'center' , va = 'center' , color = 'red')

plt.show()
```




```
#white box one
F = ["sepal_length" , "sepal_width" , "petal_length" , "petal_width"]
```

```
T = ['0' , '1' , '2']
fig = plt.figure(figsize = (25 , 20))
plot = tree.plot_tree (DT , feature_names = F , class_names = T , filled = True)
```



Random Forest

```
RF = RandomForestClassifier(n_estimators = 400, max_depth = 3)
RF = RF.fit(X_train , y_train)
y_pred_RF = RF.predict(X_test)
print("Random Forest : ")
Evaluate_Performance(RF, X_train, X_test, y_train, y_test)
```

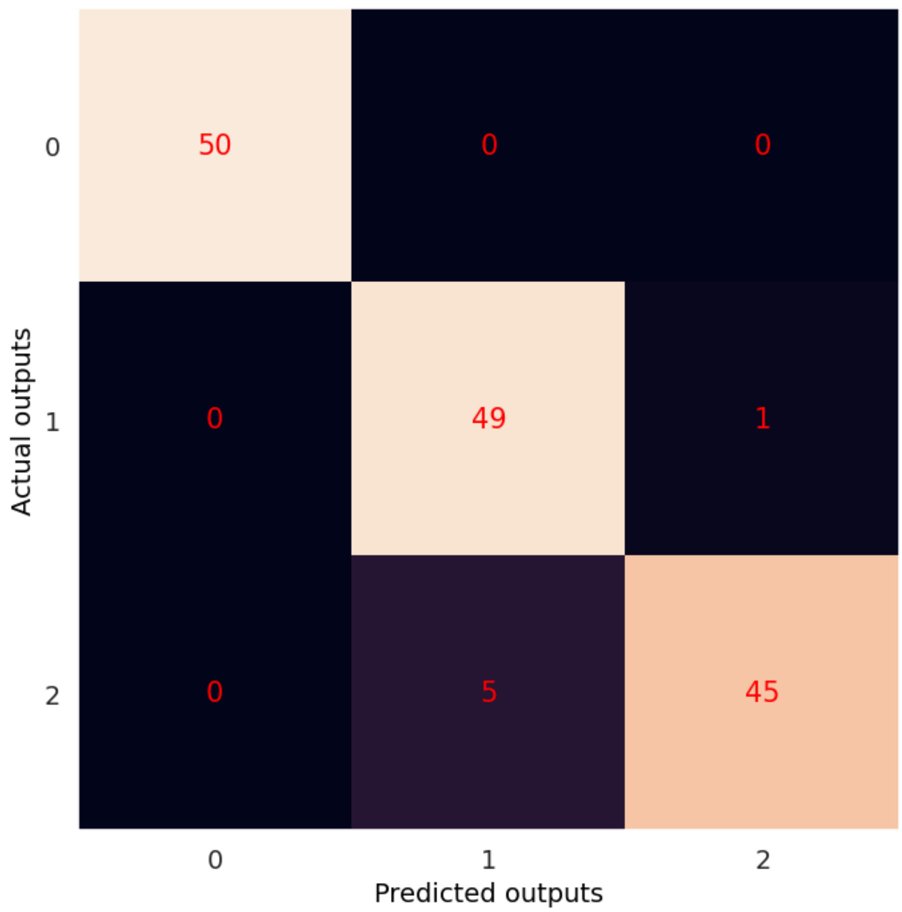
Random Forest :

- Training Accuracy Score : 98.67
- Cross Validation Score : 95.71
- Testing Accuracy Score :93.33
- Precision Score is : 93.63
- Recall Score is : 93.33
- F1-Score Score is : 93.27

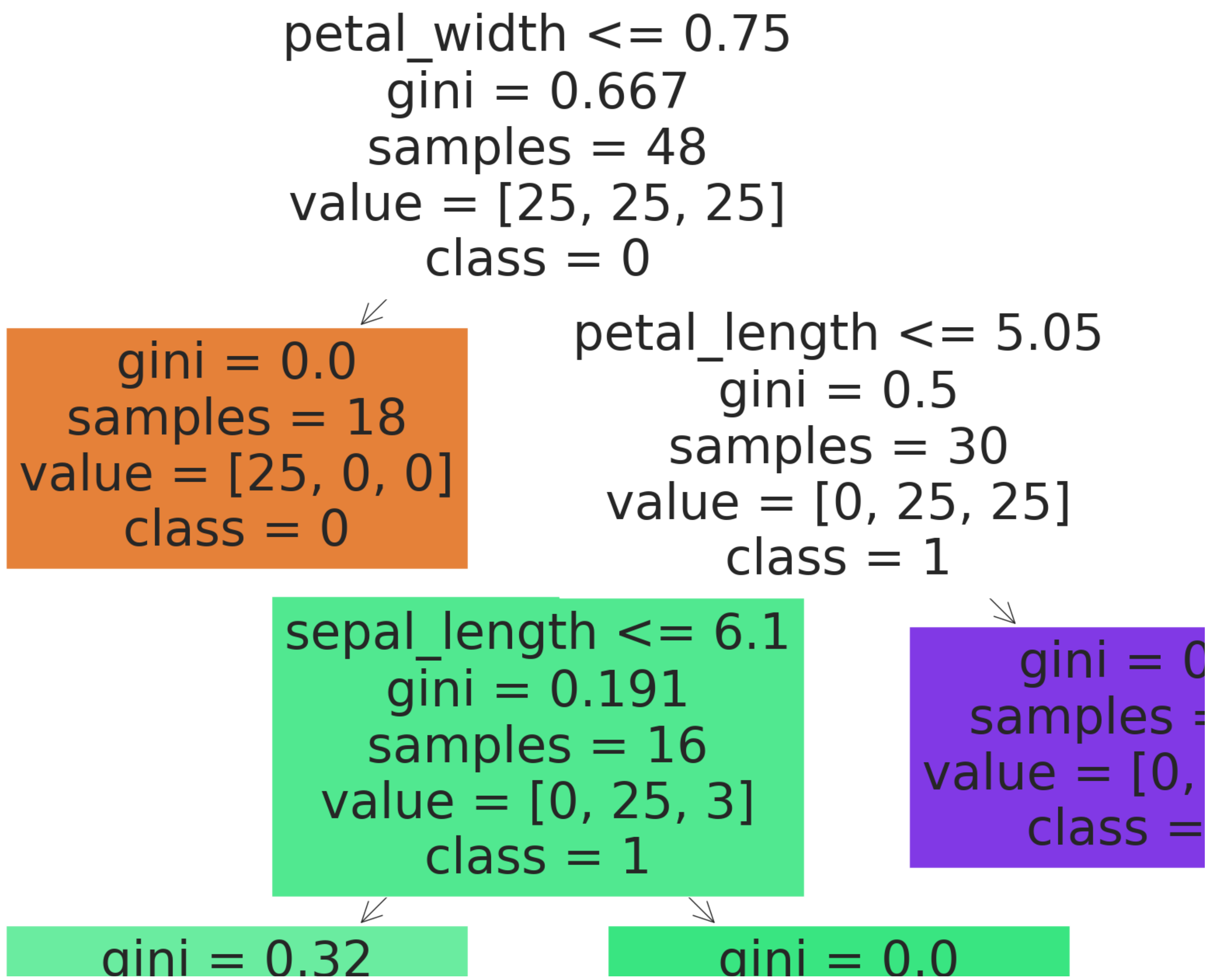
```
RF_r = cross_val_score (RF, X, y, cv = 10)
R = np.std(RF_r)
print(R)
```

    0.059999999999999984

```
cm = confusion_matrix (y , RF.predict(X))

fig, ax = plt.subplots (figsize = (8, 8))
ax.imshow(cm)
ax.grid(False)
ax.set_xlabel('Predicted outputs', fontsize= 14 , color='black')
ax.set_ylabel('Actual outputs', fontsize= 14 , color='black')
ax.xaxis.set(ticks=range(3))
ax.yaxis.set(ticks=range(3))
ax.set_ylim(2.5 , -0.5)

for i in range(3):
    for j in range(3):
        ax.text(j, i, cm[i, j], ha = 'center' , va = 'center' , color = 'red')

plt.show()
```




```
#white box one
F = ["sepal_length" , "sepal_width" , "petal_length" , "petal_width"]
T = ['0' , '1' , '2']
fig = plt.figure(figsize = (25 , 20))
plot = tree.plot_tree (RF.estimators_[5] , feature_names = F , class_names = T , filled = True)
```



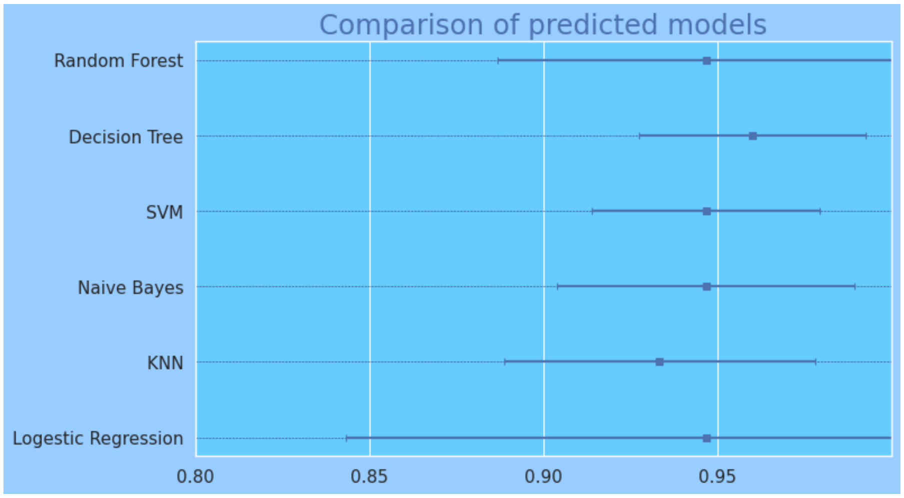
Step 6 : Conclusion

```
models = pd.DataFrame ({'Model' : ['Logestic Regression' , ' KNN' , 'Naive Bayes' , 'SVM' , 'Decision Tree' , 'Random Forest'] ,
                        'Precision' : [precision_score(y_test, y_pred_LR, average='weighted') , precision_score(y_test, y_pred_KNN, average='
                        'Recall' : [recall_score(y_test, y_pred_LR, average='weighted') , recall_score(y_test, y_pred_KNN, average='weighted'
                        'F1-score' : [f1_score(y_test, y_pred_LR, average='weighted') , f1_score(y_test, y_pred_KNN, average='weighted') , f1
                        'Accuracy' : [accuracy_score(y_test, y_pred_LR) , accuracy_score(y_test, y_pred_KNN) , accuracy_score(y_test, y_pred_
                        'Err' : [np.std(LR_r) , np.std(KNN_r) , np.std(NB_r) , np.std(SVM_r) , np.std(DT_r) , np.std(RF_r)]})

print(tabulate(models, headers='keys', tablefmt='rst'))
```

```
====  ===================  ===========  ========  ==========  ==========  =========
  ..  Model                  Precision    Recall    F1-score    Accuracy        Err
====  ===================  ===========  ========  ==========  ==========  =========
   0  Logestic Regression     0.946667  0.946667    0.946667    0.946667  0.103359
   1  KNN                     0.936277  0.933333    0.932698    0.933333  0.0447214
   2  Naive Bayes             0.952941  0.946667    0.945909    0.946667  0.0426875
   3  SVM                     0.947955  0.946667    0.946367    0.946667  0.0326599
   4  Decision Tree           0.960281  0.96        0.959902    0.96      0.0326599
   5  Random Forest           0.947955  0.946667    0.946367    0.946667  0.06
====  ===================  ===========  ========  ==========  ==========  =========
```

```
fig, ax = plt.subplots(figsize=(10, 6), dpi= 80, facecolor='#99ccff')

ax.set_facecolor('#66ccff')

ax.set_title('Comparison of predicted models', fontdict={'size':22} , color='b')

ax.errorbar(models['Accuracy'], models['Model'], xerr = models['Err'] , fmt='o', marker='s', color='b'
            , linewidth=2, capsize=3)
```

```
ax.set(xlim=(0.8, 1), xticks=np.arange(0.8, 1, step = 0.05))

plt.grid(color = '#333366', axis = 'y', linestyle = '--', linewidth = 0.5)

plt.show()
```



All the models have good results in all four parameters (Recall, F1_score, Precision, Accuracy), but the Decision Tree Algorithm predicted slightly better than the rest of the models