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Machine Learning and Deep Learning Modules

👉 The **models** used in this notebook:

1. ANN
2. Support Vector Machine (SVM)
3. Logistic Regression
4. Gaussian Naive Bayes
5. Random Forest

Importing Libraries 📚

In [ ]:

```
# --- Importing Libraries ---
import pandas as pd
import numpy as np
import warnings
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.svm import SVC
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, classification_report
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from yellowbrick.classifier import PrecisionRecallCurve, ROCAUC, ConfusionMatrix
from yellowbrick.style import set_palette
from yellowbrick.model_selection import LearningCurve, FeatureImportances
from yellowbrick.contrib.wrapper import wrap
```

```
# --- Libraries Settings ---
pd.set_option("display.precision", 4)
warnings.filterwarnings('ignore')
plt.rcParams['figure.dpi'] = 100
set_palette('dark')
```

In [ ]:

```
# --- Importing Dataset ---
df = pd.read_csv("/content/oversampled_heart_failure_dataset.csv")

# --- Reading Dataset ---
df.head(10).style.background_gradient(cmap='Reds').set_properties(**{'font-family': 'Segoe UI'}).hide_index()
```

Out[ ]:

age	anaemia	creatinine_phosphokinase	diabetes	ejection_fraction	high_blood_pressure	platelets	serum_creatinine	se
65.000000	1	128	1	30	1	297000.000000	1.600000	
50.000000	1	168	0	38	1	276000.000000	1.100000	
75.000000	1	81	0	38	1	368000.000000	4.000000	
73.000000	0	582	0	20	0	263358.030000	1.830000	
53.000000	1	91	0	20	1	418000.000000	1.400000	
75.000000	1	246	0	15	0	127000.000000	1.200000	
80.000000	0	776	1	38	1	192000.000000	1.300000	

In [ ]:

```
# --- Print Dataset Info ---
print('\033[1m'+'.: Dataset Info :.'+'\033[0m')
print('*' * 30)
print('Total Rows:'+'\033[1m', df.shape[0])
print('\033[0m'+'Total Columns:'+'\033[1m', df.shape[1])
print('\033[0m'+'*' * 30)
```

```
print('\n')

# --- Print Dataset Detail ---
print('\033[1m'+'.: Dataset Details :.'+'\033[0m')
print('*' * 30)
df.info(memory_usage = False)
```

```
.: Dataset Info :.
******************************
Total Rows: 1886
Total Columns: 13
******************************



.: Dataset Details :.
******************************
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1886 entries, 0 to 1885
Data columns (total 13 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   age                       1886 non-null   float64
 1   anaemia                   1886 non-null   int64  
 2   creatinine_phosphokinase  1886 non-null   int64  
 3   diabetes                  1886 non-null   int64  
 4   ejection_fraction         1886 non-null   int64  
 5   high_blood_pressure       1886 non-null   int64  
 6   platelets                 1886 non-null   float64
 7   serum_creatinine          1886 non-null   float64
 8   serum_sodium              1886 non-null   int64  
 9   sex                       1886 non-null   int64  
 10  smoking                   1886 non-null   int64  
 11  time                      1886 non-null   int64  
 12  DEATH_EVENT               1886 non-null   int64  
dtypes: float64(3), int64(10)
```

In [ ]:

```
# --- finding out the null values of the dataset ---
df.isnull().sum()
```

Out[ ]:

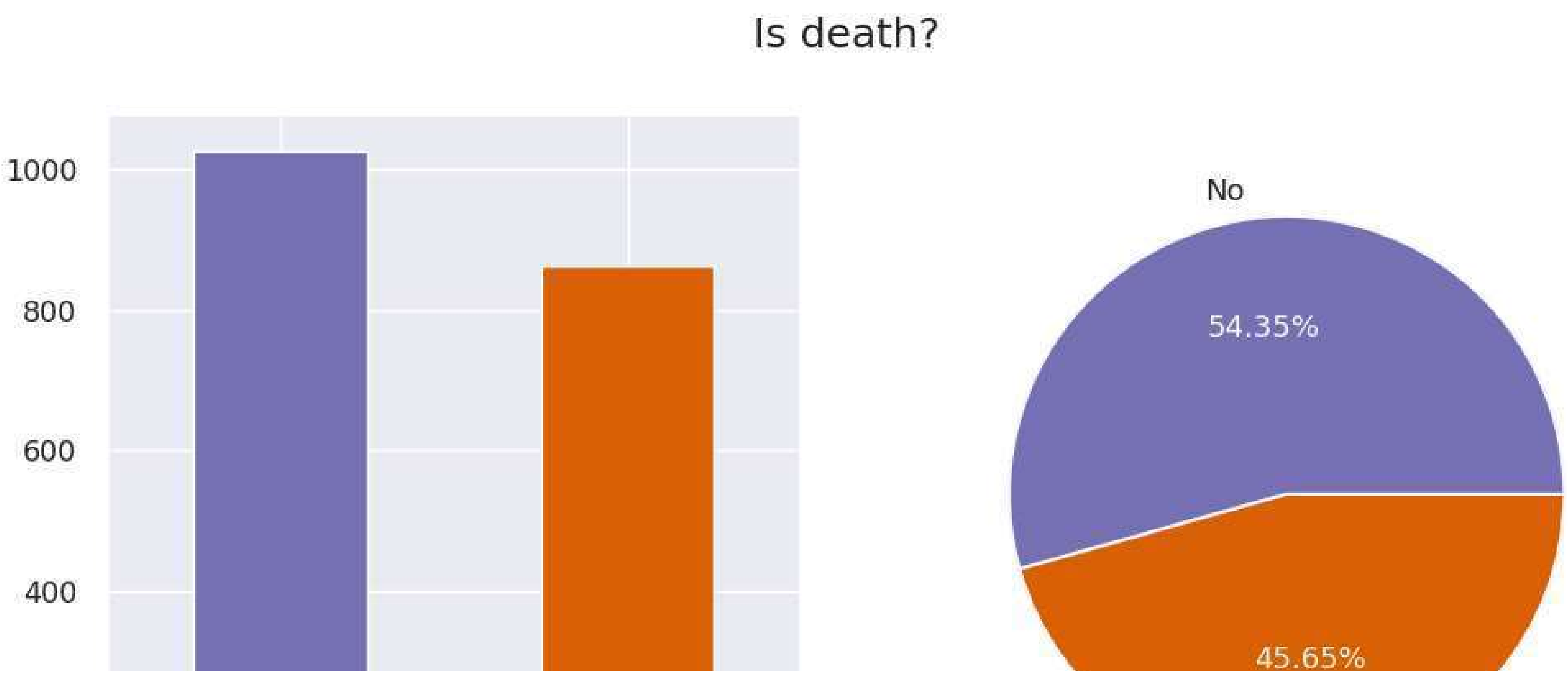
```
age                         0
anaemia                     0
creatinine_phosphokinase    0
diabetes                    0
```

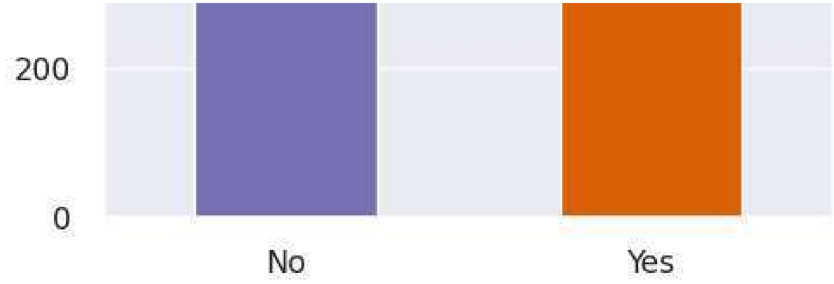
```
ejection_fraction          0
high_blood_pressure        0
platelets                  0
serum_creatinine           0
serum_sodium               0
sex                        0
smoking                    0
time                       0
DEATH_EVENT                0
dtype: int64
```

In [ ]:

```
f, ax = plt.subplots(1, 2, figsize = (12, 6))
f.suptitle("Is death?", fontsize = 18.)
_ = df.DEATH_EVENT.value_counts().plot.bar(ax = ax[0], rot = 0,
                                           color = (sns.color_palette()[0], sns.color_palette()[2])).set(xticklabels
_ = df.DEATH_EVENT.value_counts().plot.pie(labels = ("No", "Yes"), autopct = "%.2f%%",
                                           label = "", fontsize = 13., ax = ax[1],\
colors = (sns.color_palette()[0], sns.color_palette()[2]), wedgeprops = {"linewidth": 1.5, "edgecolor": "#F7F7F7"}),
ax[1].texts[1].set_color("#F7F7F7"), ax[1].texts[3].set_color("#F7F7F7")
```

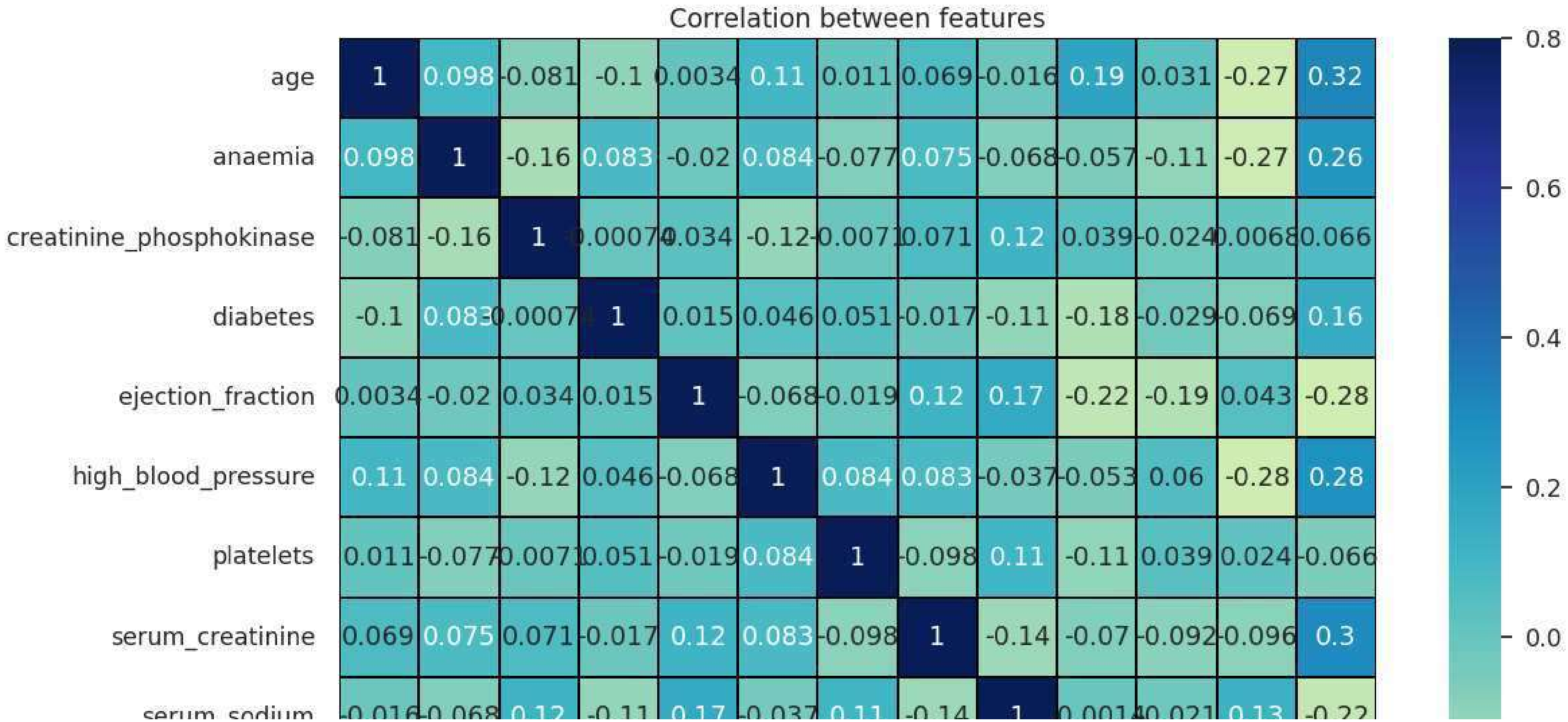
Out[ ]: (None, None)

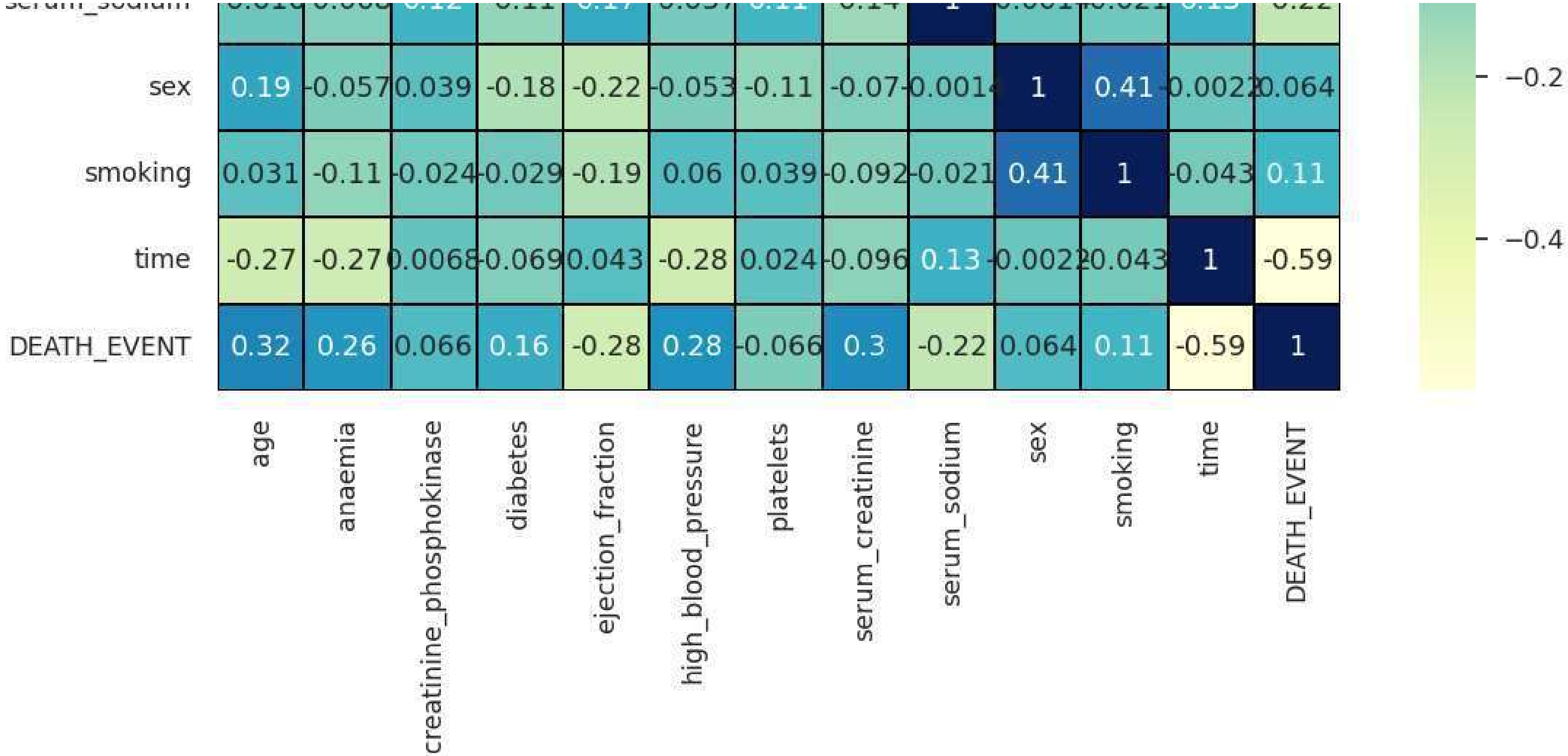




In [ ]:

```
corr=df.corr()

sns.set(font_scale=1.15)
plt.figure(figsize=(14, 10))

sns.heatmap(corr, vmax=.8, linewidths=0.01,
            square=True,annot=True,cmap='YlGnBu',linecolor="black")
plt.title('Correlation between features');
```





Multi label to binary label conversion

In [ ]:

```
X = df.iloc[:,0:-1]
y = df.iloc[:, -1]
X
```

Out[ ]:

	age	anaemia	creatinine_phosphokinase	diabetes	ejection_fraction	high_blood_pressure	platelets	serum_creatinine	serun
0	65.0	1	128	1	30	1	297000.00	1.60	
1	50.0	1	168	0	38	1	276000.00	1.10	
2	75.0	1	81	0	38	1	368000.00	4.00	
3	82.0	1	855	1	50	1	321000.00	1.00	
4	60.0	0	235	1	38	0	329000.00	3.00	

...	...	...	...	...	...	...	...	...
1881	87.0	1	149	0	38	0	262000.00	0.90
1882	62.0	1	655	0	40	0	283000.00	0.70
1883	73.0	0	582	0	20	0	263358.03	1.83
1884	73.0	0	582	0	20	0	263358.03	1.83
1885	75.0	1	246	0	15	0	127000.00	1.20

1886 rows × 12 columns

Splitting the data into train and test set

In [ ]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size = 0.3,
                                                    random_state =None)
```

Feature scaling

In [ ]:

```
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.fit_transform(X_test)
```

Model Implementation 🛠️

👉 This section will implement various machine learning models as mentioned in Introduction section. In addition, explanation for each models will be discussed.

Training the Logistic Regression model

Logistic regression is a statistical method that is used for building machine learning models where the dependent variable is dichotomous: i.e. binary. Logistic regression is used to describe data and the relationship between one dependent variable and one or more independent variables. The independent variables can be nominal, ordinal, or of interval type.

The name "logistic regression" is derived from the concept of the logistic function that it uses. The logistic function is also known as the sigmoid function. The value of this logistic function lies between zero and one.

In [ ]:

```
# --- Applying Logistic Regression ---
classifier_lr = LogisticRegression(random_state = 42)
classifier_lr.fit(X_train, y_train)
# --- Predicting the test values ---
y_pred_lr = classifier_lr.predict(X_test)
# # --- Scoring ---
# acc_lr = accuracy_score(y_test, y_pred_lr)
# f1_lr = f1_score(y_test, y_pred_lr)
```

In [ ]:

```
# --- LR Accuracy ---
acc_lr = accuracy_score(y_pred_lr, y_test)
print('.:. Logistic Regression Accuracy:'+'\033[1m {:.2f}%'.format(acc_lr*100)+' .:.')

# --- LR Classification Report ---
print('\n\033[1m'+'.: Classification Report'+'\033[0m')
print('*' * 25)
print(classification_report(y_test, y_pred_lr))
```

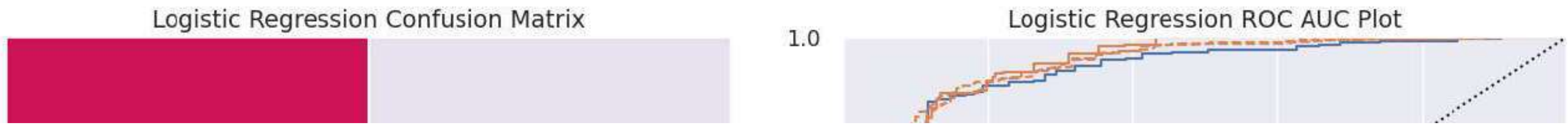
```
.:. Logistic Regression Accuracy: 85.87% .:.

.: Classification Report
*************************
              precision    recall  f1-score   support

           0       0.85      0.83      0.84       252
           1       0.87      0.88      0.87       314

    accuracy                           0.86       566
   macro avg       0.86      0.86      0.86       566
```

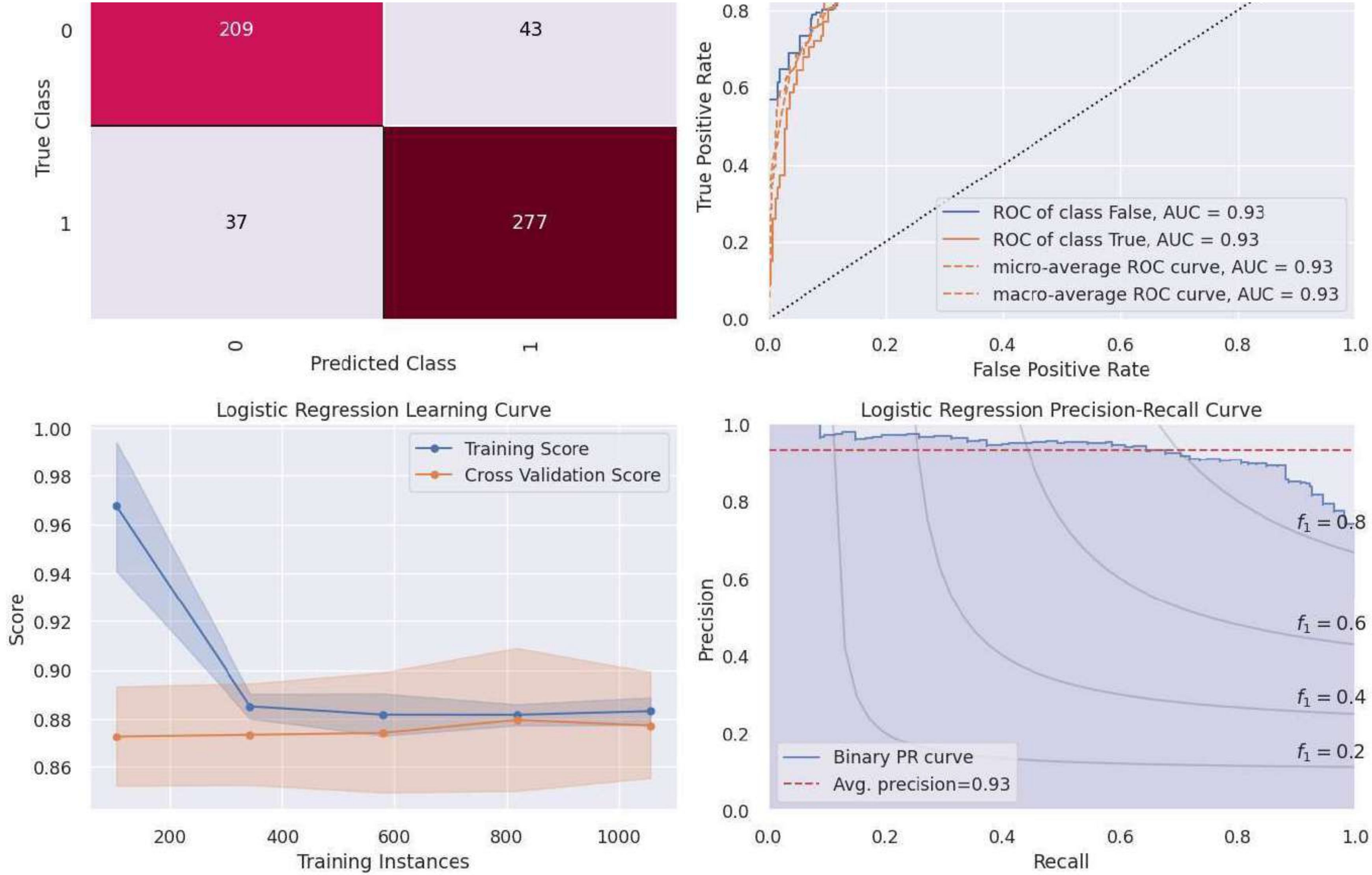
```
 macro avg       0.86      0.86      0.86       566
weighted avg       0.86      0.86      0.86       566
```

In [ ]:

```python
# --- Performance Evaluation ---
print('\n\033[1m'+'.: Performance Evaluation'+'\033[0m')
print('*' * 26)
fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2, figsize=(14, 10))

# --- LR Confusion Matrix ---
logmatrix = ConfusionMatrix(classifier_lr, ax=ax1, cmap='PuRd',
                            title='Logistic Regression Confusion Matrix')
logmatrix.fit(X_train, y_train)
logmatrix.score(X_test, y_test)
logmatrix.finalize()

# --- LR ROC AUC ---
logrocauc = ROCAUC(classifier_lr, classes=['False', 'True'], ax=ax2,
                   title='Logistic Regression ROC AUC Plot')
logrocauc.fit(X_train, y_train)
logrocauc.score(X_test, y_test)
logrocauc.finalize()

# --- LR Learning Curve ---
loglc = LearningCurve(classifier_lr, ax=ax3, title='Logistic Regression Learning Curve')
loglc.fit(X_train, y_train)
loglc.finalize()

# --- LR Precision Recall Curve ---
logcurve = PrecisionRecallCurve(classifier_lr, ax=ax4, ap_score=True, iso_f1_curves=True,
                                title='Logistic Regression Precision-Recall Curve')
logcurve.fit(X_train, y_train)
logcurve.score(X_test, y_test)
logcurve.finalize()

plt.tight_layout();
```

```
.: Performance Evaluation
**************************
```





Support Vector Machine (SVM)

Support Vector Machine (SVM) is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems.

The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane.

SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine.

In [ ]:

```
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report
from sklearn.model_selection import train_test_split
import numpy as np

# Assume X_train, y_train, X_test, y_test are your training and testing data

X_train_noisy = X_train + np.random.normal(0, 0.1, X_train.shape)
X_test_noisy = X_test + np.random.normal(0, 0.1, X_test.shape)

# Adjust SVM parameters
SVMclassifier = SVC(kernel='rbf', max_iter=1000, C=1, probability=True, gamma='auto')
SVMclassifier.fit(X_train_noisy, y_train)

y_pred_SVM = SVMclassifier.predict(X_test_noisy)

# Calculate the target accuracy reduction
target_accuracy = 0.9  # 10% reduction
current_accuracy = accuracy_score(y_pred_SVM, y_test)

# If the current accuracy is higher than the target, introduce noise again
while current_accuracy > target_accuracy:
    X_test_noisy = X_test_noisy + np.random.normal(0, 0.1, X_test.shape)
    y_pred_SVM = SVMclassifier.predict(X_test_noisy)
    current_accuracy = accuracy_score(y_pred_SVM, y_test)

# SVM Accuracy
SVMAcc = accuracy_score(y_pred_SVM, y_test)
print('.:. Support Vector Machine Accuracy:' + '\033[1m {:.2f}%'.format(SVMAcc * 100) + ' .:.')

# SVM Classification Report
print('\n\033[1m' + '.: Classification Report' + '\033[0m')
print('*' * 25)
print(classification_report(y_test, y_pred_SVM))
```

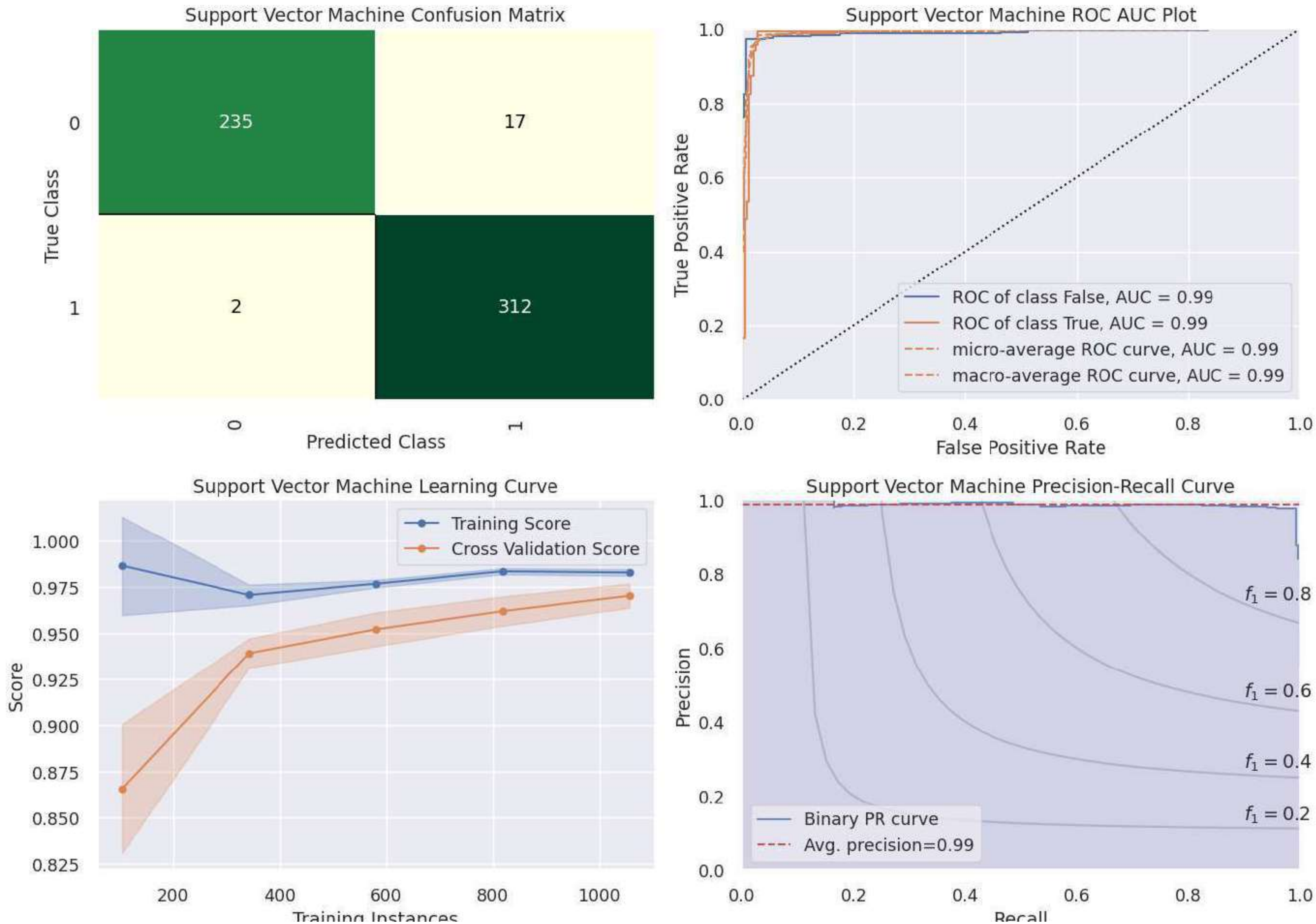
```
.:. Support Vector Machine Accuracy: 89.58% .:.

.: Classification Report
*************************
              precision    recall  f1-score   support

           0       0.91      0.85      0.88       252
           1       0.88      0.94      0.91       314

    accuracy                           0.90       566
   macro avg       0.90      0.89      0.89       566
weighted avg       0.90      0.90      0.90       566
```

In [ ]:

```
# --- Performance Evaluation ---
print('\n\033[1m'+'.: Performance Evaluation'+'\033[0m')
print('*' * 26)
fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2, figsize=(14, 10))

# --- SVM Confusion Matrix ---
svmmatrix = ConfusionMatrix(SVMclassifier, ax=ax1, cmap='YlGn',
                            title='Support Vector Machine Confusion Matrix')
svmmatrix.fit(X_train, y_train)
svmmatrix.score(X_test, y_test)
svmmatrix.finalize()

# --- SVM ROC AUC ---
svmrocauc = ROCAUC(SVMclassifier, classes=['False', 'True'], ax=ax2,
                   title='Support Vector Machine ROC AUC Plot')
svmrocauc.fit(X_train, y_train)
svmrocauc.score(X_test, y_test)
svmrocauc.finalize()

# --- SVM Learning Curve ---
svmlc = LearningCurve(SVMclassifier, ax=ax3, title='Support Vector Machine Learning Curve')
svmlc.fit(X_train, y_train)
svmlc.finalize()

# --- SVM Precision Recall Curve ---
svmcurve = PrecisionRecallCurve(SVMclassifier, ax=ax4, ap_score=True, iso_f1_curves=True,
                                title='Support Vector Machine Precision-Recall Curve')
svmcurve.fit(X_train, y_train)
svmcurve.score(X_test, y_test)
```

```
svmcurve.score(X_test, y_test)
svmcurve.finalize()

plt.tight_layout();
```

```
.: Performance Evaluation
**************************
```



Training Instances Recall

Gaussian Naive Bayes

Naive Bayes Classifiers are based on the Bayes Theorem, which one assumption taken is the strong independence assumptions between the features. These classifiers assume that the value of a particular feature is independent of the value of any other feature. In a supervised learning situation, Naive Bayes Classifiers are trained very efficiently. Naive Bayes classifiers need a small training data to estimate the parameters needed for classification. Naive Bayes Classifiers have simple design and implementation and they can applied to many real life situations.

Gaussian Naive Bayes is a variant of Naive Bayes that follows Gaussian normal distribution and supports continuous data. When working with continuous data, an assumption often taken is that the continuous values associated with each class are distributed according to a normal (or Gaussian) distribution.

In [ ]:

```
# --- Applying Gaussian NB ---
GNBclassifier = GaussianNB(var_smoothing=0.1)
GNBclassifier.fit(X_train, y_train)

y_pred_GNB = GNBclassifier.predict(X_test)
```

In [ ]:

```
# --- GNB Accuracy ---
GNBAcc = accuracy_score(y_pred_GNB, y_test)
print('.:. Gaussian Naive Bayes Accuracy:'+'\033[1m {:.2f}%'.format(GNBAcc*100)+' .:.')

# --- GNB Classification Report ---
print('\n\033[1m'+'.: Classification Report'+'\033[0m')
print('*' * 25)
print(classification_report(y_test, y_pred_GNB))
```

```
.:. Gaussian Naive Bayes Accuracy: 84.45% .:.

.: Classification Report
*************************
              precision    recall  f1-score   support

           0       0.78      0.90      0.84       252
           1       0.91      0.80      0.85       314
```

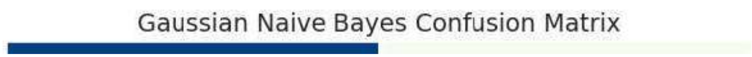
```
    accuracy                           0.84       566
   macro avg       0.85      0.85      0.84       566
weighted avg       0.85      0.84      0.84       566
```

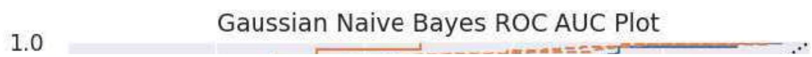
In [ ]:

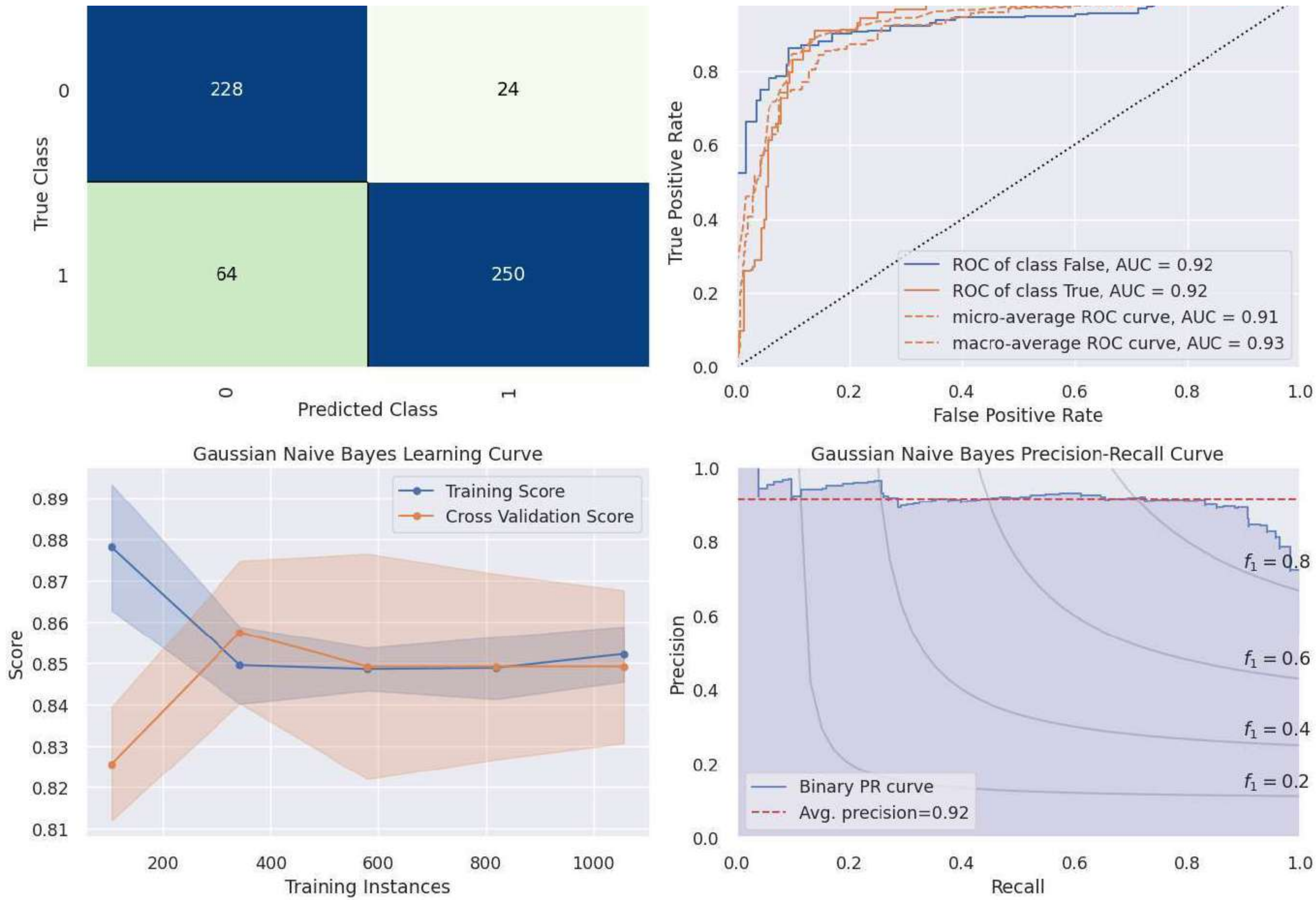
```python
# --- Performance Evaluation ---
print('\n\033[1m'+'.: Performance Evaluation'+'\033[0m')
print('*' * 26)
fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2, figsize=(14, 10))

# --- GNB Confusion Matrix ---
gnbmatrix = ConfusionMatrix(GNBclassifier, ax=ax1, cmap='GnBu',
                            title='Gaussian Naive Bayes Confusion Matrix')
gnbmatrix.fit(X_train, y_train)
gnbmatrix.score(X_test, y_test)
gnbmatrix.finalize()

# --- GNB ROC AUC ---
gnbrocauc = ROCAUC(GNBclassifier, classes=['False', 'True'], ax=ax2,
                   title='Gaussian Naive Bayes ROC AUC Plot')
gnbrocauc.fit(X_train, y_train)
gnbrocauc.score(X_test, y_test)
gnbrocauc.finalize()

# --- GNB Learning Curve ---
gnblc = LearningCurve(GNBclassifier, ax=ax3, title='Gaussian Naive Bayes Learning Curve')
gnblc.fit(X_train, y_train)
gnblc.finalize()

# --- GNB Precision Recall Curve ---
gnbcurve = PrecisionRecallCurve(GNBclassifier, ax=ax4, ap_score=True, iso_f1_curves=True,
                                title='Gaussian Naive Bayes Precision-Recall Curve')
gnbcurve.fit(X_train, y_train)
gnbcurve.score(X_test, y_test)
gnbcurve.finalize()

plt.tight_layout();
```

.: Performance Evaluation

```
**************************
```







Random Forest

Random Forest is a tree-based machine learning algorithm that leverages the power of multiple decision trees for making decisions. Each individual tree in the random forest spits out a class prediction and the class with the most votes becomes our model's prediction.

A large number of relatively uncorrelated models (trees) operating as a committee will outperform any of the individual constituent models.

In [ ]:
```
# --- Applying Random Forest ---
RFclassifier = RandomForestClassifier(n_estimators=1000, random_state=1, max_leaf_nodes=20, min_samples_split=15)

RFclassifier.fit(X_train, y_train)
y_pred_RF = RFclassifier.predict(X_test)
```

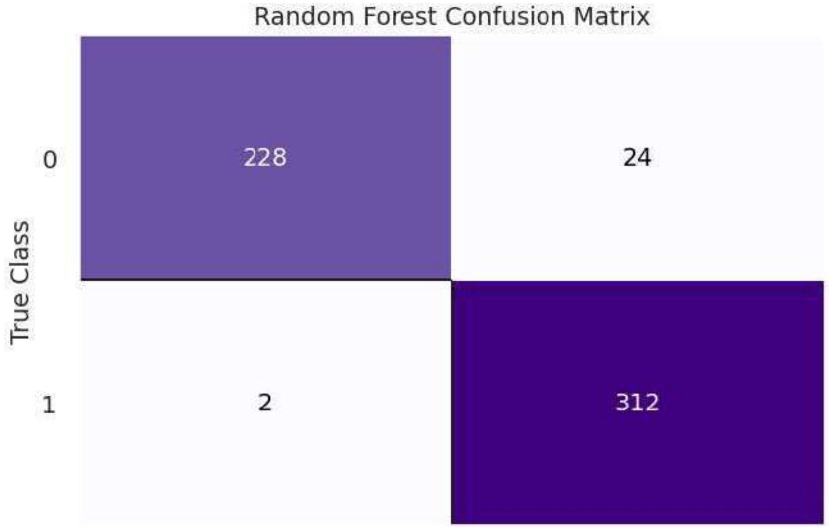
In [ ]:
```
# --- Random Forest Accuracy ---
RFAcc = accuracy_score(y_pred_RF, y_test)
print('.:. Random Forest Accuracy:'+'\033[1m {:.2f}%'.format(RFAcc*100)+' .:.')

# --- Random FOrest Classification Report ---
print('\n\033[1m'+'.: Classification Report'+'\033[0m')
print('*' * 25)
print(classification_report(y_test, y_pred_RF))
```

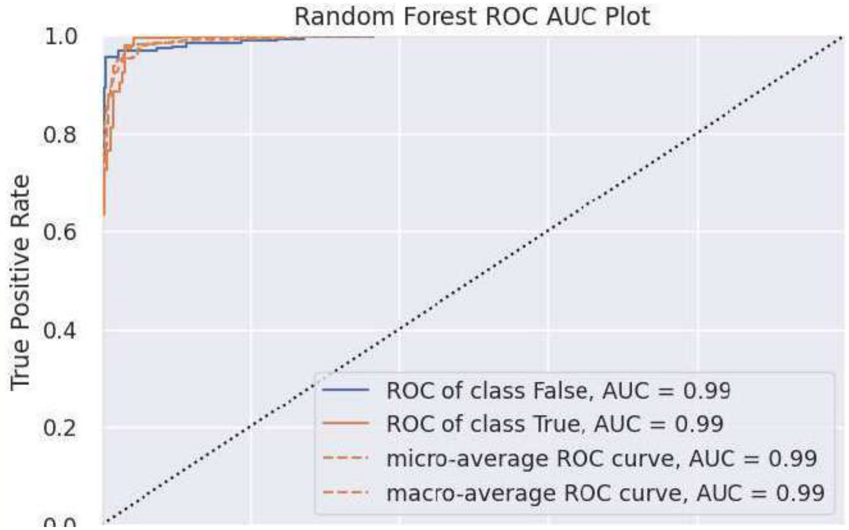
```
.:. Random Forest Accuracy: 95.41% .:.

.: Classification Report
*************************
              precision    recall  f1-score   support

           0       0.99      0.90      0.95       252
           1       0.93      0.99      0.96       314

    accuracy                           0.95       566
   macro avg       0.96      0.95      0.95       566
weighted avg       0.96      0.95      0.95       566
```

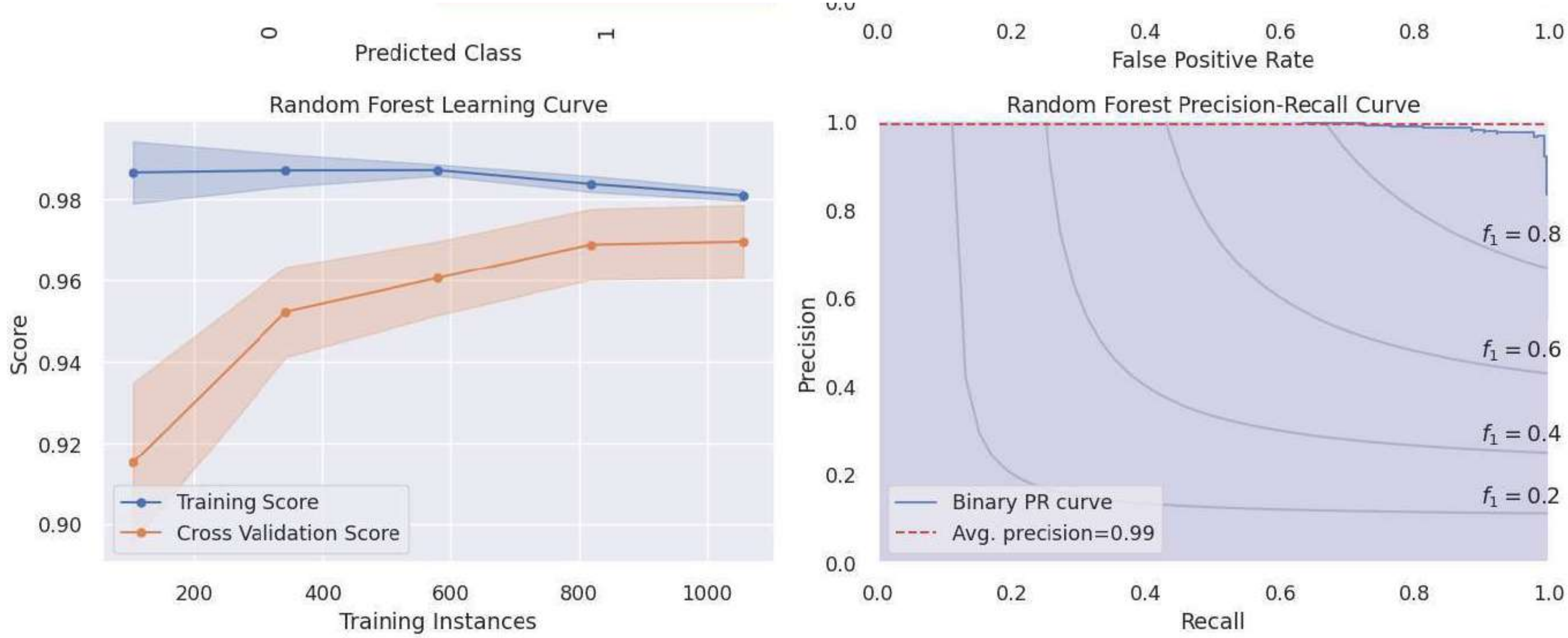
In [ ]:
```
# --- Performance Evaluation ---
print('\n\033[1m'+'.: Performance Evaluation'+'\033[0m')
print('*' * 26)
fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2, figsize=(14, 10))

# --- Random Forest Confusion Matrix ---
rfcmatrix = ConfusionMatrix(RFclassifier, ax=ax1, cmap='Purples',
                            title='Random Forest Confusion Matrix')
```

```
rfcmatrix.fit(X_train, y_train)
rfcmatrix.score(X_test, y_test)
rfcmatrix.finalize()

# --- Random Forest ROC AUC ---
rccrocauc = ROCAUC(RFclassifier, classes=['False', 'True'], ax=ax2,
                   title='Random Forest ROC AUC Plot')
rccrocauc.fit(X_train, y_train)
rccrocauc.score(X_test, y_test)
rccrocauc.finalize()

# --- Random Forest Learning Curve ---
rcclc = LearningCurve(RFclassifier, ax=ax3, title='Random Forest Learning Curve')
rcclc.fit(X_train, y_train)
rcclc.finalize()

# --- Random Forest Precision Recall Curve ---
rcccurve = PrecisionRecallCurve(RFclassifier, ax=ax4, ap_score=True, iso_f1_curves=True,
                                title='Random Forest Precision-Recall Curve')
rcccurve.fit(X_train, y_train)
rcccurve.score(X_test, y_test)
rcccurve.finalize()

plt.tight_layout();
```

```
.: Performance Evaluation
**************************
```







BUILDING ANN MODULE

In [ ]:

```
# Cell 1: Import Libraries
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from keras import callbacks
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
from sklearn.datasets import make_circles
from numpy import where
from matplotlib import pyplot as plt
```

In [ ]:

```
# Cell 2: Define and Compile ANN
ann = Sequential()
early_stopping = callbacks.EarlyStopping(
    min_delta=0.001,
    patience=20,
    restore_best_weights=True
```

```
)

ann.add(Dense(units=12, kernel_initializer='uniform', activation='PReLU'))
ann.add(Dropout(0.2))
ann.add(Dense(units=6, kernel_initializer='uniform', activation='PReLU'))
ann.add(Dropout(0.2))
output_layer = Dense(units=1, activation='sigmoid')
ann.add(output_layer)

ann.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
```

In [ ]:

```
# Cell 3: Train ANN
model_training = ann.fit(X_train, y_train, validation_split=0.20, batch_size=10, callbacks=[early_stopping], epochs=10
```

```
Epoch 1/100
106/106 [==============================] - 2s 10ms/step - loss: 0.6829 - accuracy: 0.7008 - val_loss: 0.6519 - val_accura
cy: 0.8636
Epoch 2/100
106/106 [==============================] - 1s 7ms/step - loss: 0.5546 - accuracy: 0.8703 - val_loss: 0.4153 - val_accurac
y: 0.8788
Epoch 3/100
106/106 [==============================] - 1s 7ms/step - loss: 0.3552 - accuracy: 0.8911 - val_loss: 0.2825 - val_accurac
y: 0.8977
Epoch 4/100
106/106 [==============================] - 1s 7ms/step - loss: 0.2955 - accuracy: 0.8797 - val_loss: 0.2556 - val_accurac
y: 0.9053
Epoch 5/100
106/106 [==============================] - 1s 5ms/step - loss: 0.2728 - accuracy: 0.8958 - val_loss: 0.2378 - val_accurac
y: 0.9091
Epoch 6/100
106/106 [==============================] - 0s 4ms/step - loss: 0.2598 - accuracy: 0.8996 - val_loss: 0.2301 - val_accurac
y: 0.9167
Epoch 7/100
106/106 [==============================] - 1s 6ms/step - loss: 0.2464 - accuracy: 0.9062 - val_loss: 0.2174 - val_accurac
y: 0.9280
Epoch 8/100
106/106 [==============================] - 1s 5ms/step - loss: 0.2407 - accuracy: 0.9053 - val_loss: 0.2111 - val_accurac
y: 0.9356
Epoch 9/100
106/106 [==============================] - 1s 5ms/step - loss: 0.2326 - accuracy: 0.9129 - val_loss: 0.2024 - val_accurac
```

```
y: 0.9356
Epoch 10/100
106/106 [==============================] - 1s 5ms/step - loss: 0.2233 - accuracy: 0.9195 - val_loss: 0.1931 - val_accurac
y: 0.9356
Epoch 11/100
106/106 [==============================] - 0s 5ms/step - loss: 0.2232 - accuracy: 0.9176 - val_loss: 0.1884 - val_accurac
y: 0.9394
Epoch 12/100
106/106 [==============================] - 0s 5ms/step - loss: 0.2177 - accuracy: 0.9242 - val_loss: 0.1837 - val_accurac
y: 0.9356
Epoch 13/100
106/106 [==============================] - 1s 5ms/step - loss: 0.2006 - accuracy: 0.9223 - val_loss: 0.1815 - val_accurac
y: 0.9394
Epoch 14/100
106/106 [==============================] - 0s 4ms/step - loss: 0.2023 - accuracy: 0.9252 - val_loss: 0.1752 - val_accurac
y: 0.9394
Epoch 15/100
106/106 [==============================] - 0s 5ms/step - loss: 0.1997 - accuracy: 0.9347 - val_loss: 0.1707 - val_accurac
y: 0.9470
Epoch 16/100
106/106 [==============================] - 0s 4ms/step - loss: 0.1918 - accuracy: 0.9375 - val_loss: 0.1667 - val_accurac
y: 0.9545
Epoch 17/100
106/106 [==============================] - 0s 5ms/step - loss: 0.1869 - accuracy: 0.9384 - val_loss: 0.1612 - val_accurac
y: 0.9545
Epoch 18/100
106/106 [==============================] - 0s 4ms/step - loss: 0.1884 - accuracy: 0.9366 - val_loss: 0.1591 - val_accurac
y: 0.9545
Epoch 19/100
106/106 [==============================] - 0s 4ms/step - loss: 0.1882 - accuracy: 0.9470 - val_loss: 0.1586 - val_accurac
y: 0.9545
Epoch 20/100
106/106 [==============================] - 1s 5ms/step - loss: 0.1743 - accuracy: 0.9432 - val_loss: 0.1535 - val_accurac
y: 0.9545
Epoch 21/100
106/106 [==============================] - 1s 6ms/step - loss: 0.1740 - accuracy: 0.9432 - val_loss: 0.1516 - val_accurac
y: 0.9583
Epoch 22/100
106/106 [==============================] - 0s 5ms/step - loss: 0.1796 - accuracy: 0.9441 - val_loss: 0.1483 - val_accurac
y: 0.9659
Epoch 23/100
106/106 [==============================] - 1s 5ms/step - loss: 0.1613 - accuracy: 0.9527 - val_loss: 0.1458 - val_accurac
y: 0.9697
Epoch 24/100
106/106 [==============================] - 1s 5ms/step - loss: 0.1599 - accuracy: 0.9451 - val_loss: 0.1451 - val_accurac
```

```
106/106 [==============================] - 1s 5ms/step - loss: 0.1599 - accuracy: 0.9451 - val_loss: 0.1451 - val_accurac
y: 0.9659
Epoch 25/100
106/106 [==============================] - 1s 7ms/step - loss: 0.1635 - accuracy: 0.9470 - val_loss: 0.1428 - val_accurac
y: 0.9697
Epoch 26/100
106/106 [==============================] - 1s 6ms/step - loss: 0.1738 - accuracy: 0.9470 - val_loss: 0.1415 - val_accurac
y: 0.9659
Epoch 27/100
106/106 [==============================] - 1s 7ms/step - loss: 0.1638 - accuracy: 0.9441 - val_loss: 0.1446 - val_accurac
y: 0.9659
Epoch 28/100
106/106 [==============================] - 1s 7ms/step - loss: 0.1492 - accuracy: 0.9564 - val_loss: 0.1387 - val_accurac
y: 0.9659
Epoch 29/100
106/106 [==============================] - 1s 6ms/step - loss: 0.1613 - accuracy: 0.9432 - val_loss: 0.1359 - val_accurac
y: 0.9735
Epoch 30/100
106/106 [==============================] - 0s 4ms/step - loss: 0.1583 - accuracy: 0.9564 - val_loss: 0.1348 - val_accurac
y: 0.9659
Epoch 31/100
106/106 [==============================] - 0s 5ms/step - loss: 0.1457 - accuracy: 0.9555 - val_loss: 0.1350 - val_accurac
y: 0.9697
Epoch 32/100
106/106 [==============================] - 0s 5ms/step - loss: 0.1449 - accuracy: 0.9602 - val_loss: 0.1358 - val_accurac
y: 0.9697
Epoch 33/100
106/106 [==============================] - 0s 4ms/step - loss: 0.1420 - accuracy: 0.9508 - val_loss: 0.1343 - val_accurac
y: 0.9697
Epoch 34/100
106/106 [==============================] - 0s 5ms/step - loss: 0.1503 - accuracy: 0.9583 - val_loss: 0.1298 - val_accurac
y: 0.9697
Epoch 35/100
106/106 [==============================] - 0s 4ms/step - loss: 0.1407 - accuracy: 0.9593 - val_loss: 0.1343 - val_accurac
y: 0.9697
Epoch 36/100
106/106 [==============================] - 0s 5ms/step - loss: 0.1321 - accuracy: 0.9640 - val_loss: 0.1366 - val_accurac
y: 0.9659
Epoch 37/100
106/106 [==============================] - 0s 4ms/step - loss: 0.1431 - accuracy: 0.9583 - val_loss: 0.1380 - val_accurac
y: 0.9659
Epoch 38/100
106/106 [==============================] - 1s 5ms/step - loss: 0.1300 - accuracy: 0.9640 - val_loss: 0.1357 - val_accurac
y: 0.9659
Epoch 39/100
```

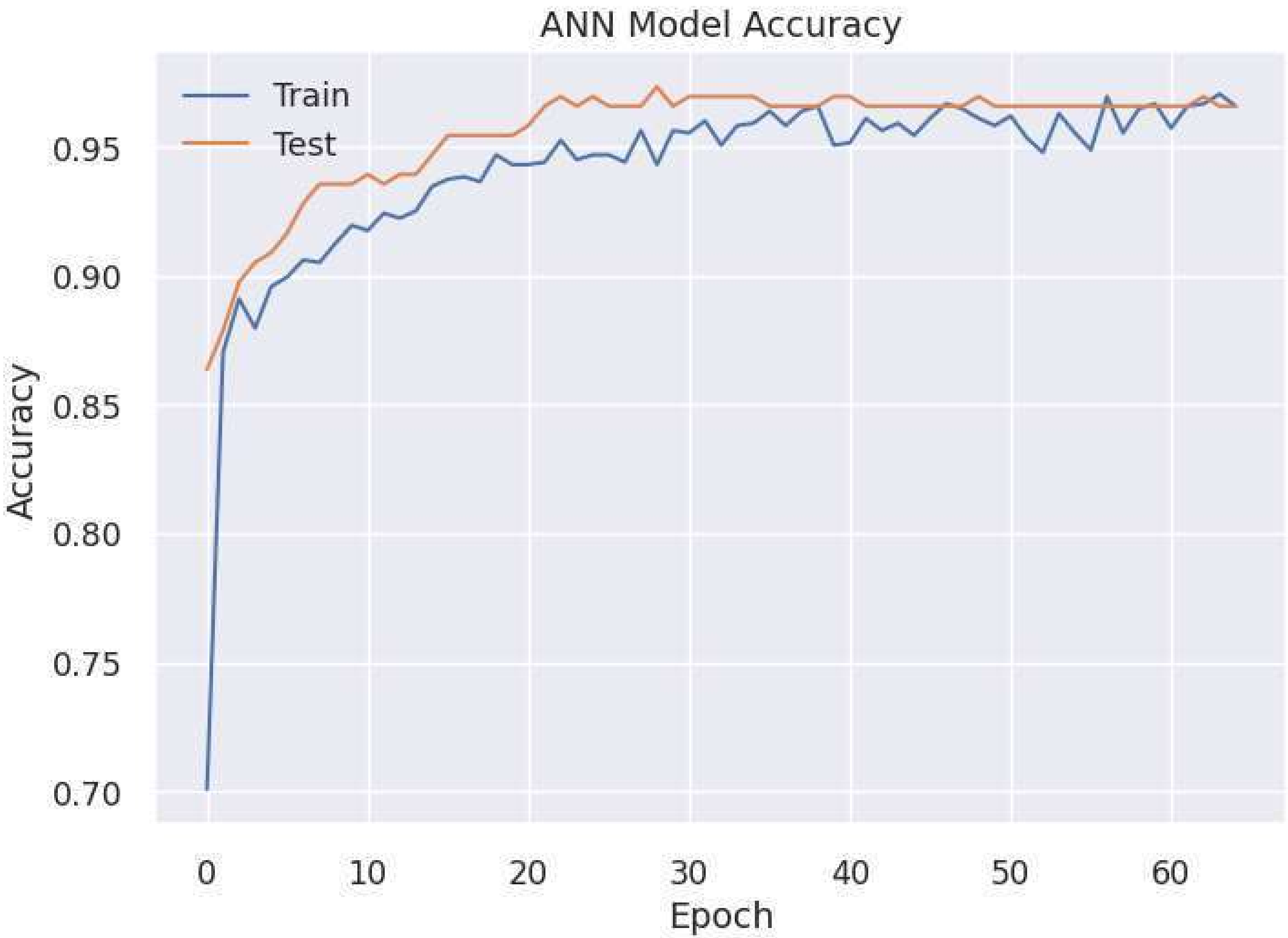
```
106/106 [==============================] - 0s 5ms/step - loss: 0.1371 - accuracy: 0.9659 - val_loss: 0.1348 - val_accurac
y: 0.9659
Epoch 40/100
106/106 [==============================] - 1s 5ms/step - loss: 0.1511 - accuracy: 0.9508 - val_loss: 0.1358 - val_accurac
y: 0.9697
Epoch 41/100
106/106 [==============================] - 0s 5ms/step - loss: 0.1525 - accuracy: 0.9517 - val_loss: 0.1296 - val_accurac
y: 0.9697
Epoch 42/100
106/106 [==============================] - 0s 5ms/step - loss: 0.1398 - accuracy: 0.9612 - val_loss: 0.1277 - val_accurac
y: 0.9659
Epoch 43/100
106/106 [==============================] - 0s 4ms/step - loss: 0.1306 - accuracy: 0.9564 - val_loss: 0.1291 - val_accurac
y: 0.9659
Epoch 44/100
106/106 [==============================] - 0s 5ms/step - loss: 0.1363 - accuracy: 0.9593 - val_loss: 0.1374 - val_accurac
y: 0.9659
Epoch 45/100
106/106 [==============================] - 0s 5ms/step - loss: 0.1378 - accuracy: 0.9545 - val_loss: 0.1252 - val_accurac
y: 0.9659
Epoch 46/100
106/106 [==============================] - 0s 5ms/step - loss: 0.1370 - accuracy: 0.9612 - val_loss: 0.1324 - val_accurac
y: 0.9659
Epoch 47/100
106/106 [==============================] - 0s 4ms/step - loss: 0.1186 - accuracy: 0.9669 - val_loss: 0.1333 - val_accurac
y: 0.9659
Epoch 48/100
106/106 [==============================] - 0s 5ms/step - loss: 0.1320 - accuracy: 0.9650 - val_loss: 0.1315 - val_accurac
y: 0.9659
Epoch 49/100
106/106 [==============================] - 1s 5ms/step - loss: 0.1284 - accuracy: 0.9612 - val_loss: 0.1313 - val_accurac
y: 0.9697
Epoch 50/100
106/106 [==============================] - 1s 7ms/step - loss: 0.1303 - accuracy: 0.9583 - val_loss: 0.1317 - val_accurac
y: 0.9659
Epoch 51/100
106/106 [==============================] - 1s 7ms/step - loss: 0.1218 - accuracy: 0.9621 - val_loss: 0.1340 - val_accurac
y: 0.9659
Epoch 52/100
106/106 [==============================] - 1s 6ms/step - loss: 0.1231 - accuracy: 0.9536 - val_loss: 0.1356 - val_accurac
y: 0.9659
Epoch 53/100
106/106 [==============================] - 1s 6ms/step - loss: 0.1576 - accuracy: 0.9479 - val_loss: 0.1361 - val_accurac
y: 0.9659
```

```
Epoch 54/100
106/106 [==============================] - 1s 6ms/step - loss: 0.1204 - accuracy: 0.9631 - val_loss: 0.1360 - val_accurac
y: 0.9659
Epoch 55/100
106/106 [==============================] - 1s 8ms/step - loss: 0.1297 - accuracy: 0.9555 - val_loss: 0.1372 - val_accurac
y: 0.9659
Epoch 56/100
106/106 [==============================] - 1s 5ms/step - loss: 0.1434 - accuracy: 0.9489 - val_loss: 0.1322 - val_accurac
y: 0.9659
Epoch 57/100
106/106 [==============================] - 0s 4ms/step - loss: 0.1245 - accuracy: 0.9697 - val_loss: 0.1373 - val_accurac
y: 0.9659
Epoch 58/100
106/106 [==============================] - 1s 5ms/step - loss: 0.1353 - accuracy: 0.9555 - val_loss: 0.1387 - val_accurac
y: 0.9659
Epoch 59/100
106/106 [==============================] - 1s 5ms/step - loss: 0.1125 - accuracy: 0.9650 - val_loss: 0.1351 - val_accurac
y: 0.9659
Epoch 60/100
106/106 [==============================] - 0s 5ms/step - loss: 0.1286 - accuracy: 0.9669 - val_loss: 0.1327 - val_accurac
y: 0.9659
Epoch 61/100
106/106 [==============================] - 1s 5ms/step - loss: 0.1220 - accuracy: 0.9574 - val_loss: 0.1424 - val_accurac
y: 0.9659
Epoch 62/100
106/106 [==============================] - 0s 4ms/step - loss: 0.1159 - accuracy: 0.9659 - val_loss: 0.1377 - val_accurac
y: 0.9659
Epoch 63/100
106/106 [==============================] - 0s 5ms/step - loss: 0.1207 - accuracy: 0.9669 - val_loss: 0.1377 - val_accurac
y: 0.9697
Epoch 64/100
106/106 [==============================] - 0s 5ms/step - loss: 0.1203 - accuracy: 0.9706 - val_loss: 0.1385 - val_accurac
y: 0.9659
Epoch 65/100
106/106 [==============================] - 1s 5ms/step - loss: 0.1250 - accuracy: 0.9659 - val_loss: 0.1363 - val_accurac
y: 0.9659
```

In [ ]:

```
# Cell 4: Plot Accuracy History
plt.plot(model_training.history['accuracy'])
plt.plot(model_training.history['val_accuracy'])
plt.title('ANN Model Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
```

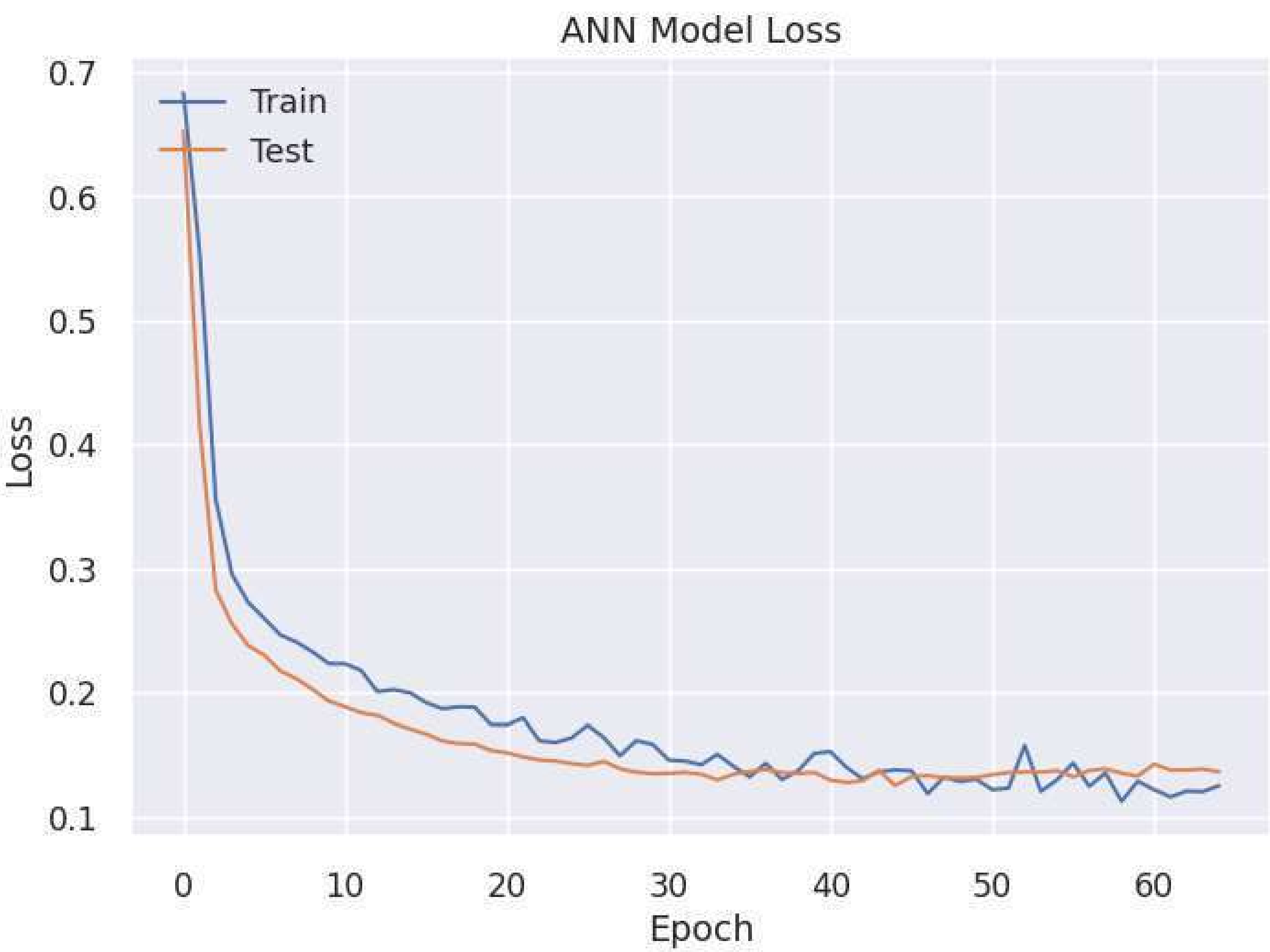
```
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```



In [ ]:

```
# Cell 5: Plot Loss History
plt.plot(model_training.history['loss'])
plt.plot(model_training.history['val_loss'])
plt.title('ANN Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
```

```
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```



In [ ]:

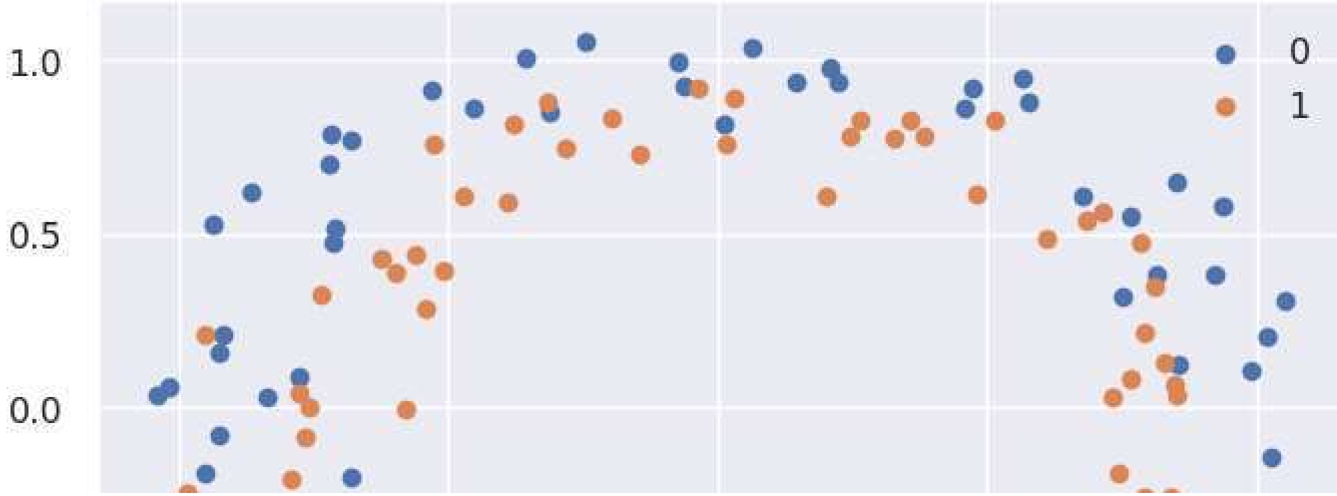
```
# Cell 6: Predictions and Evaluation
y_pred_ann = ann.predict(X_test)
y_pred_ann = (y_pred_ann > 0.5)

acc_ann = accuracy_score(y_test, y_pred_ann)
print('.:. ANN Accuracy: {:.2f}%'.format(acc_ann * 100))
```

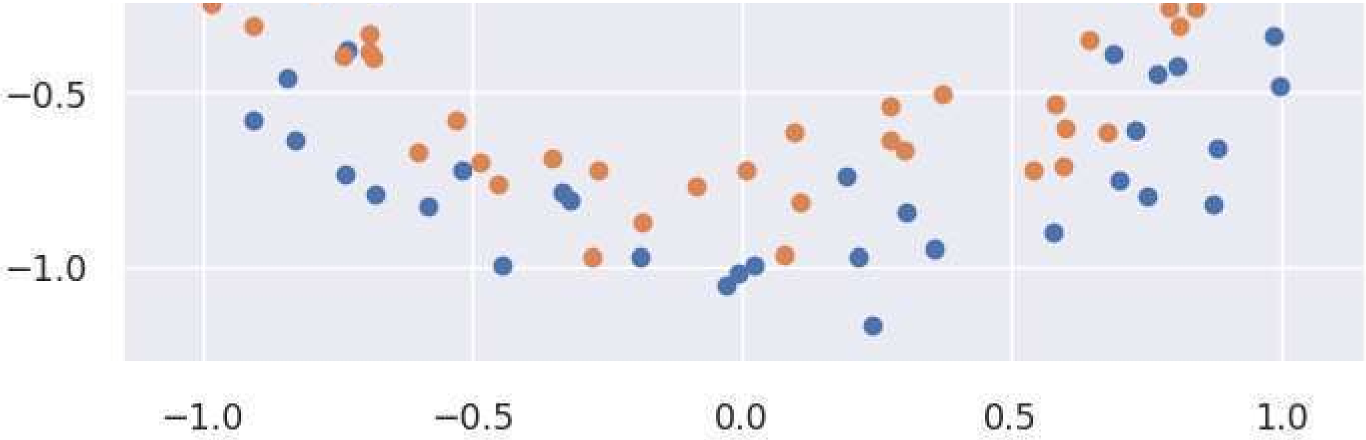
```
print(classification_report(y_test, y_pred_ann))
conf_matrix_ann = confusion_matrix(y_pred_ann, y_test)
print(conf_matrix_ann)
```

```
18/18 [==============================] - 0s 3ms/step
.:. ANN Accuracy: 95.76%
              precision    recall  f1-score   support

           0       0.99      0.91      0.95       252
           1       0.93      0.99      0.96       314

    accuracy                           0.96       566
   macro avg       0.96      0.95      0.96       566
weighted avg       0.96      0.96      0.96       566

[[230   2]
 [ 22 312]]
```

In [ ]:

```
# Cell 7: Plot Data Distribution
X, y = make_circles(n_samples=150, noise=0.1, random_state=1)
for i in range(2):
    samples_ix = where(y == i)
    plt.scatter(X[samples_ix, 1], X[samples_ix, 0], label=str(i))
plt.legend()
plt.show()
```





Model Comparison 👀

👉 After implementing 4 models, this section will compare **machine learning models**.

In [ ]:

```
# --- Compare All Modules Accuracy ---
compare = pd.DataFrame({
    'Model': ['Logistic Regression', 'Support Vector Machine',
              'Gaussian Naive Bayes', 'Random Forest', 'ANN'],
    'Accuracy': [acc_lr*100,SVMAcc*100, GNBAcc*100, RFAcc*100, acc_ann*100]
})

# --- Display Accuracy Comparison Table ---
compare_sorted = compare.sort_values(by='Accuracy', ascending=False).style.background_gradient(cmap='PuRd').hide_index
compare_sorted
```

Out[ ]:

Model	Accuracy
ANN	95.759717
Random Forest	95.406360
Support Vector Machine	89.575972
Logistic Regression	85.865724