RIESGO DE PADECER UN ATAQUE AL CORAZÓN

INTRODUCCIÓN AL CASO DE ESTUDIO

La enfermedad cardíaca es la principal causa de morbilidad y mortalidad a nivel mundial: representa más muertes al año que cualquier otra causa. Según la OMS , se estima que 17,9 millones de personas murieron por enfermedades cardíacas en 2016, lo que representa el 31% de todas las muertes mundiales. Más de las tres cuartas partes de estas muertes se produjeron en países de ingresos bajos y medianos. De todas las enfermedades cardíacas, la enfermedad coronaria (también conocida como ataque cardíaco) es, con mucho, la más común y la más fatal. En los Estados Unidos, por ejemplo, se estima que alguien tiene un ataque cardíaco cada 40 segundos y alrededor de 805,000 estadounidenses tienen un ataque cardíaco cada año (CDC 2019). El lado positivo es que los ataques cardíacos son altamente prevenibles y las modificaciones simples en el estilo de vida (como reducir el consumo de alcohol y tabaco, comer de manera saludable y hacer ejercicio) junto con un tratamiento temprano mejoran enormemente su pronóstico. Sin embargo, es difícil identificar a los pacientes de alto riesgo debido a la naturaleza multifactorial de varios factores de riesgo que contribuyen, como la diabetes, la presión arterial alta, el colesterol alto, etc. Aquí es donde el aprendizaje automático y la minería de datos vienen al rescate. Tanto los médicos como los científicos han recurrido a las técnicas de aprendizaje automático (ML) para desarrollar herramientas de detección y esto se debe a su superioridad en el reconocimiento y la clasificación de patrones en comparación con otros enfoques estadísticos tradicionales.

DESCRIPCIÓN DEL CONJUNTO DE DATOS

El conjunto de datos está disponible públicamente en el sitio web de Kaggle y proviene de un estudio cardiovascular en curso en residentes de la ciudad de Framingham, Massachusetts. El objetivo de la clasificación es predecir si el paciente tiene un riesgo de 10 años de enfermedad coronaria (CHD) en el futuro.

El conjunto de datos proporciona la información de los pacientes. Incluye más de 4000 registros y 15 atributos. Cada atributo es un factor de riesgo potencial.

Existen factores de riesgo demográficos, conductuales y médicos.

Atributos:

1. Demográfico :
   - Sexo: masculino o femenino (nominal)
   - Edad: edad del paciente
2. Educación : no se proporcionó más información
3. Comportamiento :
   - Fumador actual: si el paciente es actual fumador o no (nominal)
   - Cigs Per Day: la cantidad de cigarrillos que la persona fumó en promedio en un día (se puede considerar continuo ya que se puede fumar cualquier cantidad de cigarrillos, incluso medio cigarrillo).
4. Información sobre antecedentes médicos :
   - BP Meds: si el paciente estaba o no tomando medicación para la presión arterial (nominal)
   - Accidente cerebrovascular prevalente: si el paciente había tenido previamente un accidente cerebrovascular o no (nominal)
   - Hip prevalente: si el paciente era hipertenso o no (nominal)
   - Diabetes: si el paciente tenía diabetes o no (nominal)
5. Información sobre la condición médica actual :
   - Tot Chol: nivel de colesterol total (continuo)
   - Sys BP: presión arterial sistólica (continua)
   - Dia BP: presión arterial diastólica (continua)
   - IMC: índice de masa corporal (continuo)
   - Frecuencia cardíaca: frecuencia cardíaca (continua: en la investigación médica, variables como la frecuencia cardíaca, aunque de hecho son discretas, se consideran continuas debido a la gran cantidad de valores posibles).
   - Glucosa: nivel de glucosa en sangre (continuo)

Variable objetivo a predecir:

Riesgo de desarrollar enfermedad coronaria a 10 años vista (CHD) - (binario: "1", significa "Hay riesgo", "0" significa "No hay riesgo")

DESARROLLO DEL PROYECTO

El proyecto se ha llevado a cabo en el lenguaje de programación Python y haciendo uso de sus diferentes librerías principales para proyectos de Data Science.

A continuación se muestra una breve descripción del enfoque general del proyecto:

1. **Limpieza y preprocesamiento de datos** : se verifica y se tratan las variables faltantes y duplicadas del conjunto de datos, ya que pueden afectar enormemente el rendimiento de diferentes algoritmos de aprendizaje automático.
2. **Análisis exploratorio de datos** : el objetivo es obtener información estadística importante a partir de los datos verificando las distribuciones de los diferentes atributos, las correlaciones de los atributos entre sí y la variable objetivo y calcular probabilidades y proporciones importantes para los atributos categóricos.
3. **Selección de características** : dado que tener características irrelevantes en un conjunto de datos puede disminuir la precisión de los modelos aplicados, se utiliza la técnica de selección de características para seleccionar las características más importantes que luego se usaran para construir diferentes modelos.
4. **Desarrollo y comparación de modelos** : se realizará el modelado de cuatro modelos de clasificación diferentes, es decir, regresión logística, K-vecinos más cercanos, árboles de decisión y máquina de vectores de soporte. Ddespués se compara el desempeño de los modelos usando su precisión y su F1.

```
In [ ]: from google.colab import drive
        drive.mount("/content/drive")
```

```
Mounted at /content/drive
```

1- Limpieza y preprocesamiento de datos

```
In [ ]: import warnings
        warnings.filterwarnings('ignore')
```

```
In [ ]: # Carga de las principales librerías

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

        %matplotlib inline
```

```
In [ ]: # Carga del dataset

        data = pd.read_csv('/content/drive/MyDrive/01_Oriol/01_Machine Learning/00_PROYECTOS/04_Proyectos_Machine Lear
```

```
In [ ]: # Eliminamos la columna de 'education' ya que no aporta información relevante para el proyecto

        data.drop(['education'], axis= 1, inplace = True)
```

```
In [ ]: data.head()
```

Out[ ]:

	male	age	currentSmoker	cigsPerDay	BPMeds	prevalentStroke	prevalentHyp	diabetes	totChol	sysBP	diaBP	BMI	heartRate	glucose
0	1	39	0	0.0	0.0	0	0	0	195.0	106.0	70.0	26.97	80.0	77.0
1	0	46	0	0.0	0.0	0	0	0	250.0	121.0	81.0	28.73	95.0	76.0
2	1	48	1	20.0	0.0	0	0	0	245.0	127.5	80.0	25.34	75.0	70.0
3	0	61	1	30.0	0.0	0	1	0	225.0	150.0	95.0	28.58	65.0	103.0
4	0	46	1	23.0	0.0	0	0	0	285.0	130.0	84.0	23.10	85.0	85.0

```
In [ ]: # Datos faltantes

        missing_data = data.isnull().sum()
        total_percentage = (missing_data.sum()/data.shape[0]) * 100
        print(f'El porcentaje total de datos faltantes es del {round(total_percentage,2)}%')
```

```
El porcentaje total de datos faltantes es del 12.74%
```

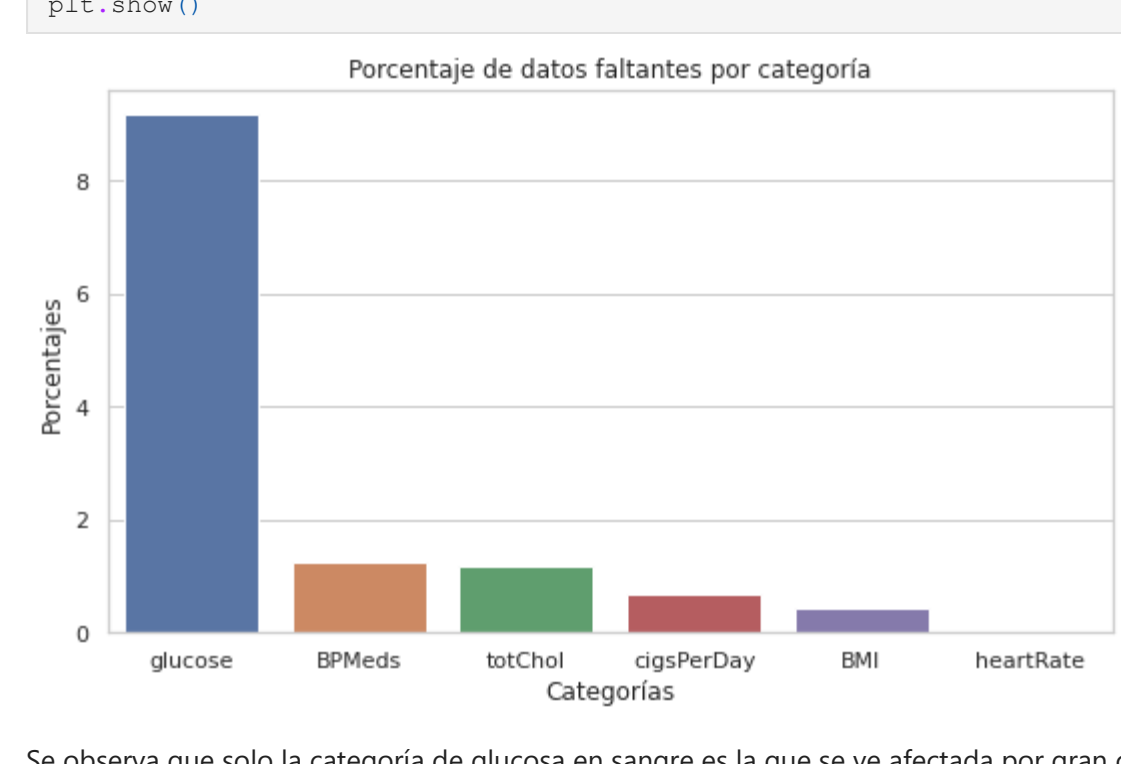
```
In [ ]: # Porcentaje de datos faltantes por categoría

        total = data.isnull().sum().sort_values(ascending=False)
        percent_total = (data.isnull().sum()/data.isnull().count()).sort_values(ascending=False)*100
        missing = pd.concat([total, percent_total], axis=1, keys=["Total", "Percentage"])
        missing_data = missing[missing['Total']>0]
        missing_data
```

Out[ ]:

	Total	Percentage
glucose	388	9.150943
BPMeds	53	1.250000
totChol	50	1.179245
cigsPerDay	29	0.683962
BMI	19	0.448113
heartRate	1	0.023585

```
In [ ]: plt.figure(figsize= (9, 5))
        sns.set(style='whitegrid')
        sns.barplot(x = missing_data.index, y = missing_data['Percentage'], data = missing_data)
        plt.title('Porcentaje de datos faltantes por categoría')
        plt.xlabel('Categorías')
        plt.ylabel('Porcentajes')
        plt.show()
```



Se observa que solo la categoría de glucosa en sangre es la que se ve afectada por gran cantidad de datos faltantes con un 9,15%.

Como los valores son inferiores al 10% podemos eliminar los datos faltantes.

```
In [ ]: data.dropna(axis=0, inplace=True)
```

```
In [ ]: data.shape
```

```
Out[ ]: (3751, 15)
```

2- Análisis exploratorio de datos

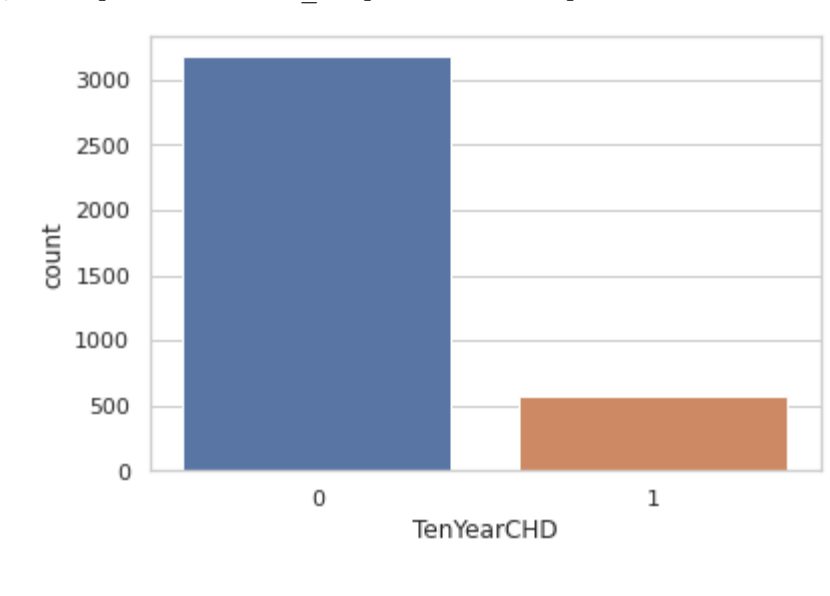
```
In [ ]: data['TenYearCHD'].value_counts()
```

```
Out[ ]: 0    3179
        1     572
        Name: TenYearCHD, dtype: int64
```

Se puede observar que disponemos de un dataset desbalanceado, ya que solo disponemos 572 casos con riesgo a padecer enfermedad coronaria en 10 años, y 3179 casos a no padecerla.

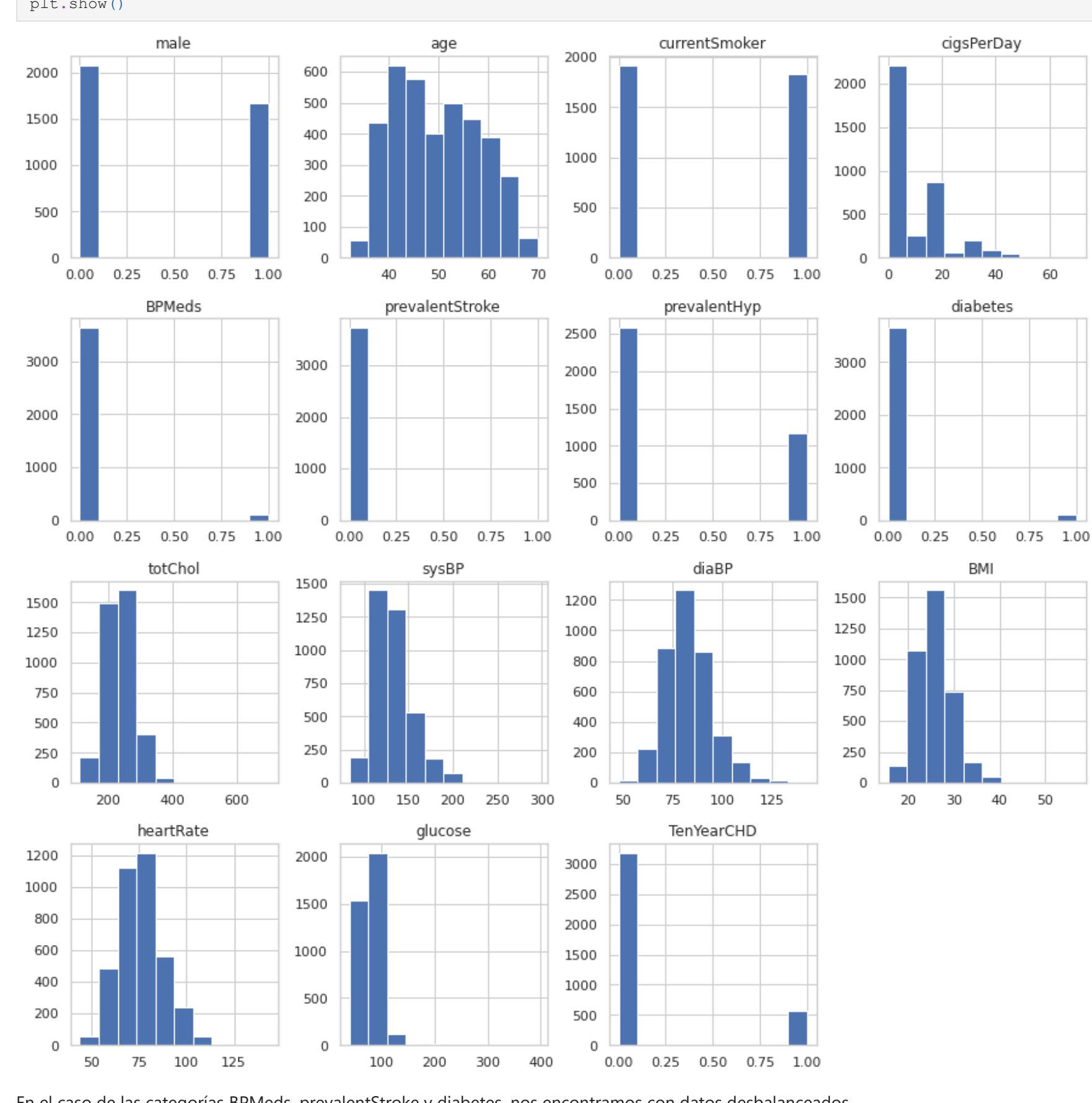
```
In [ ]: sns.countplot(data['TenYearCHD'], label= 'count')
```

```
Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fbc0c73c190>
```



Distribución de los datos

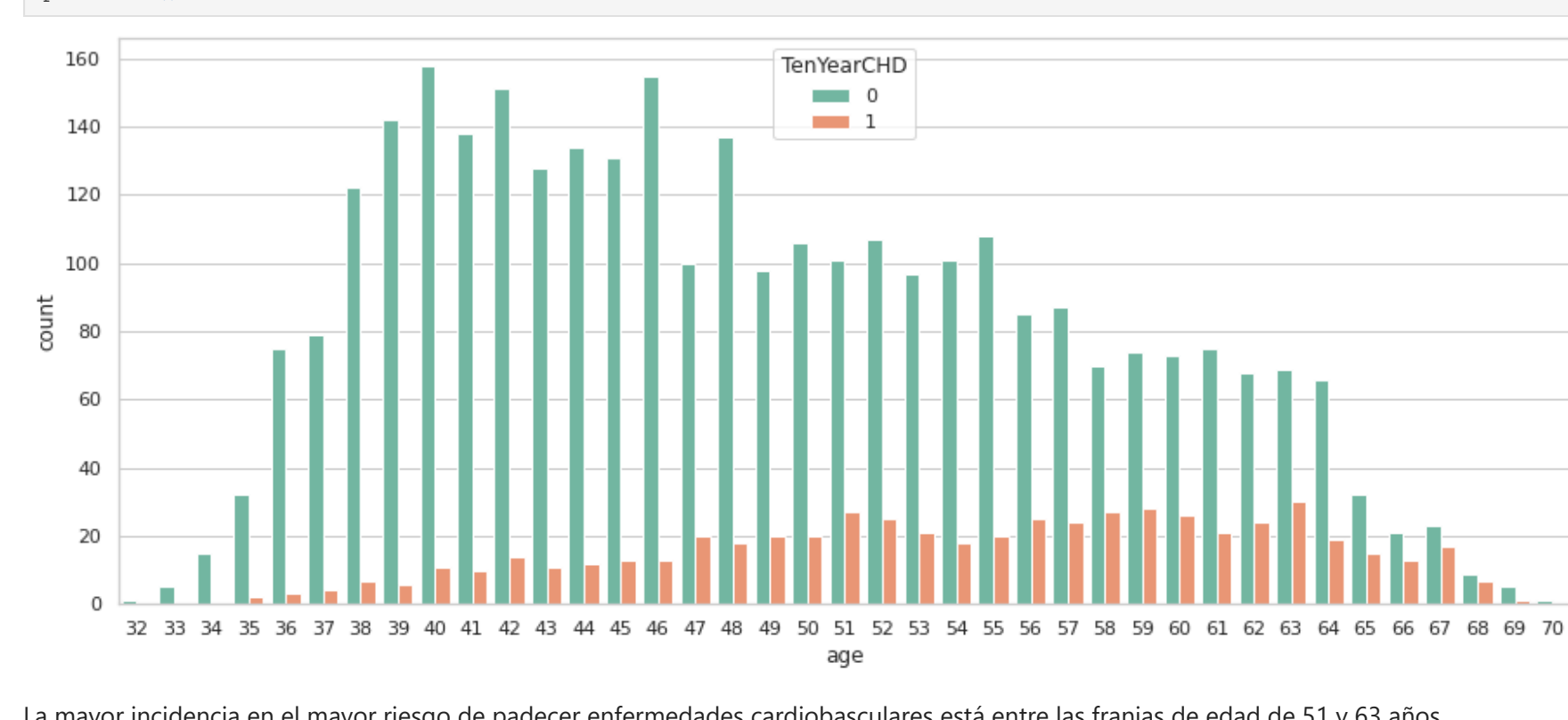
```
In [ ]: fig = plt.figure(figsize = (15, 15))
        ax = fig.gca()
        data.hist(ax = ax)
        plt.show()
```



En el caso de las categorías BPMeds, prevalentStroke y diabetes, nos encontramos con datos desbalanceados

```
In [ ]: # Distribución del riesgo por edad

        plt.figure(figsize = (15,6))
        sns.countplot(x = 'age', data = data, hue = 'TenYearCHD', palette = 'Set2')
        plt.show()
```



La mayor incidencia en el mayor riesgo de padecer enfermedades cardiobasculares está entre las franjas de edad de 51 y 63 años

Correlación de las variables

A continuación se realiza un estudio para ver la correlación de las variables

```
In [ ]: data.iloc[:, 1:15].corr()
```

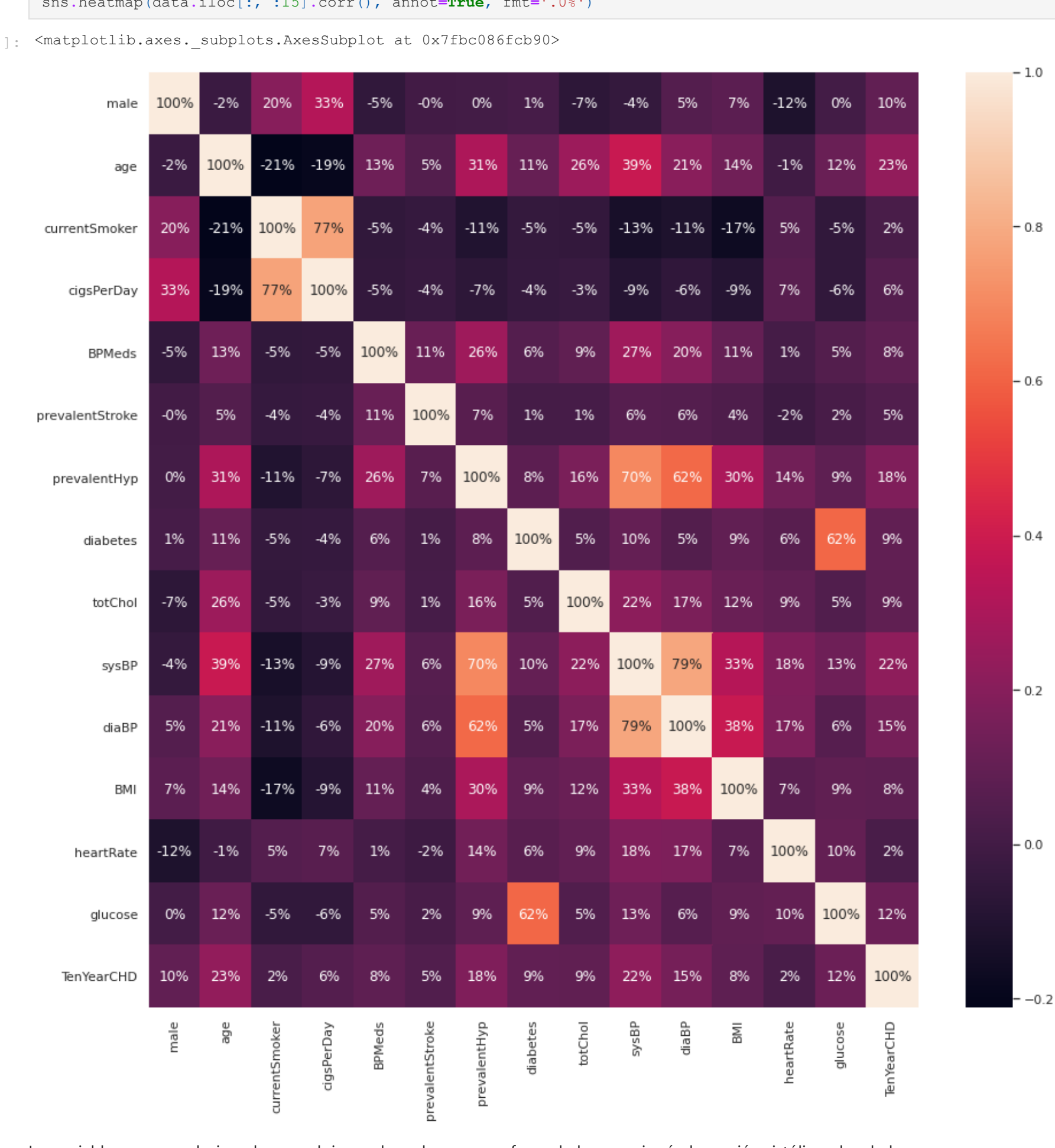
Out[ ]:

	age	currentSmoker	cigsPerDay	BPMeds	prevalentStroke	prevalentHyp	diabetes	totChol	sysBP	diaBP
age	1.000000	-0.211338	-0.188804	0.131690	0.050018	0.305292	0.109321	0.261443	0.388280	0.205191
currentSmoker	-0.211338	1.000000	0.773259	-0.051816	-0.037573	-0.105258	-0.045308	-0.049945	-0.133154	-0.114118
cigsPerDay	-0.188804	0.773259	1.000000	-0.046625	-0.035713	-0.067470	-0.039436	-0.030600	-0.092310	-0.056202
BPMeds	0.131690	-0.051816	-0.046625	1.000000	0.111601	0.262955	0.056337	0.089625	0.269479	0.199282
prevalentStroke	0.050018	-0.037573	-0.035713	0.111601	1.000000	0.065169	0.009423	0.012297	0.060421	0.055189
prevalentHyp	0.305292	-0.105258	-0.067470	0.262955	0.065169	1.000000	0.082030	0.164645	0.697849	0.616753
diabetes	0.109321	-0.045308	-0.039436	0.056337	0.009423	0.082030	1.000000	0.047453	0.104393	0.051761
totChol	0.261443	-0.049945	-0.030600	0.089625	0.012297	0.164645	0.047453	1.000000	0.216375	0.169811
sysBP	0.388280	-0.133154	-0.092310	0.269479	0.060421	0.697849	0.104393	0.216375	1.000000	0.785853
diaBP	0.205191	-0.114118	-0.056202	0.199282	0.055189	0.616753	0.051761	0.169811	0.785853	1.000000
BMI	0.136428	-0.165404	-0.090525	0.105128	0.035568	0.303411	0.093098	0.119651	0.330484	0.383907
heartRate	-0.005893	0.054924	0.067194	0.010228	-0.016673	0.142013	0.063370	0.094795	0.181381	0.174918
glucose	0.118529	-0.054078	-0.055090	0.052464	0.015789	0.085776	0.616087	0.046902	0.132878	0.061731
TenYearCHD	0.231584	0.021709	0.055920	0.084740	0.047684	0.178615	0.093222	0.089613	0.220108	0.148994

Para ver la correlación en mas detalle de forma visual se ejecuta un mapa de correlación.

```
In [ ]: plt.figure(figsize=(15,15))
        sns.heatmap(data.iloc[:, :15].corr(), annot=True, fmt='.0%')
```

```
Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fbc086fcb90>
```



Las variables mas correlacionadas con el riesgo de padecer una enfermedad coronaria són la presión sistólica y la edad.

La máxima correlación es del 23%. Esto nos indica que ninguna de las características es importante para predecir el riesgo coronario.

3- Selección de características

Aquí se utiliza el algoritmo de Boruta, que se trata de un algoritmo construido alrededor del algoritmo de clasificación de random forest. Intenta capturar todas las características importantes e interesantes de un conjunto de datos con respecto a una variable resultado.

```
In [ ]: pip install boruta
```

```
Collecting boruta
  Downloading https://files.pythonhosted.org/packages/b2/11/583f4eac99d802c79af9217e1eff56027742a69e6c866b295cc
e6a5a8fc2/Boruta-0.3-py3-none-any.whl (56kB)
     |████████████████████████████████| 61kB 3.9MB/s
Requirement already satisfied: numpy>=1.10.4 in /usr/local/lib/python3.7/dist-packages (from boruta) (1.19.5)
Requirement already satisfied: scikit-learn>=0.17.1 in /usr/local/lib/python3.7/dist-packages (from boruta) (0.
22.2.post1)
Requirement already satisfied: scipy>=0.17.0 in /usr/local/lib/python3.7/dist-packages (from boruta) (1.4.1)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (from scikit-learn>=0.17.
1->boruta) (1.0.1)
Installing collected packages: boruta
Successfully installed boruta-0.3
```

```
In [ ]: from sklearn.ensemble import RandomForestClassifier
        from boruta import BorutaPy
```

```
In [ ]: # Primero definimos las variables

        X = data.iloc[:, :-1].values
        y = data.iloc[:,-1].values

        forest = RandomForestClassifier(n_estimators= 500, n_jobs= -1, class_weight= 'balanced')

        feat_selector = BorutaPy(forest, n_estimators= 'auto', verbose= 2)

        feat_selector.fit(X, y)
```

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Iteration:      1 / 100
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Iteration:      88 / 100
Confirmed:      2
Tentative:      1
Rejected:       11
Iteration:      89 / 100
Confirmed:      2
Tentative:      1
Rejected:       11
Iteration:      90 / 100
Confirmed:      2
Tentative:      1
Rejected:       11
Iteration:      91 / 100
Confirmed:      2
Tentative:      1
Rejected:       11
Iteration:      92 / 100
Confirmed:      2
Tentative:      1
Rejected:       11
Iteration:      93 / 100
Confirmed:      2
Tentative:      1
Rejected:       11
Iteration:      94 / 100
Confirmed:      2
Tentative:      1
Rejected:       11
Iteration:      95 / 100
Confirmed:      3
Tentative:      0
Rejected:       11


BorutaPy finished running.

Iteration:      96 / 100
Confirmed:      3
Tentative:      0
Rejected:       11
```

```
Out[ ]: BorutaPy(alpha=0.05,
                 estimator=RandomForestClassifier(bootstrap=True, ccp_alpha=0.0,
                                                  class_weight='balanced',
                                                  criterion='gini', max_depth=None,
                                                  max_features='auto',
                                                  max_leaf_nodes=None, max_samples=None,
                                                  min_impurity_decrease=0.0,
                                                  min_impurity_split=None,
                                                  min_samples_leaf=1,
                                                  min_samples_split=2,
                                                  min_weight_fraction_leaf=0.0,
                                                  n_estimators=24, n_jobs=-1,
                                                  oob_score=False,
                                                  random_state=RandomState(MT19937) at 0x7FBC2CC62050,
                                                  verbose=0, warm_start=False),
                 max_iter=100, n_estimators='auto', perc=100,
                 random_state=RandomState(MT19937) at 0x7FBC2CC62050, two_step=True,
                 verbose=2)
```

```python
# Mostramos las características mas importantes

important_features = data.columns[:-1][feat_selector.support_].tolist()
important_features
```

```
['age', 'sysBP', 'BMI']
```

Tal y como se había observado en el mapa de correlación, las características con mayor correlación con el riesgo de enfermedad coronaria a 10 años son:

- Edad
- Tensión sistólica
- Añadiendo el índice de masa corporal

```python
# Buscamos las 5 caracteristicas mas importantes

most_important_features = data.columns[:-1][feat_selector.ranking_ <=4].tolist()

most_important_features
```

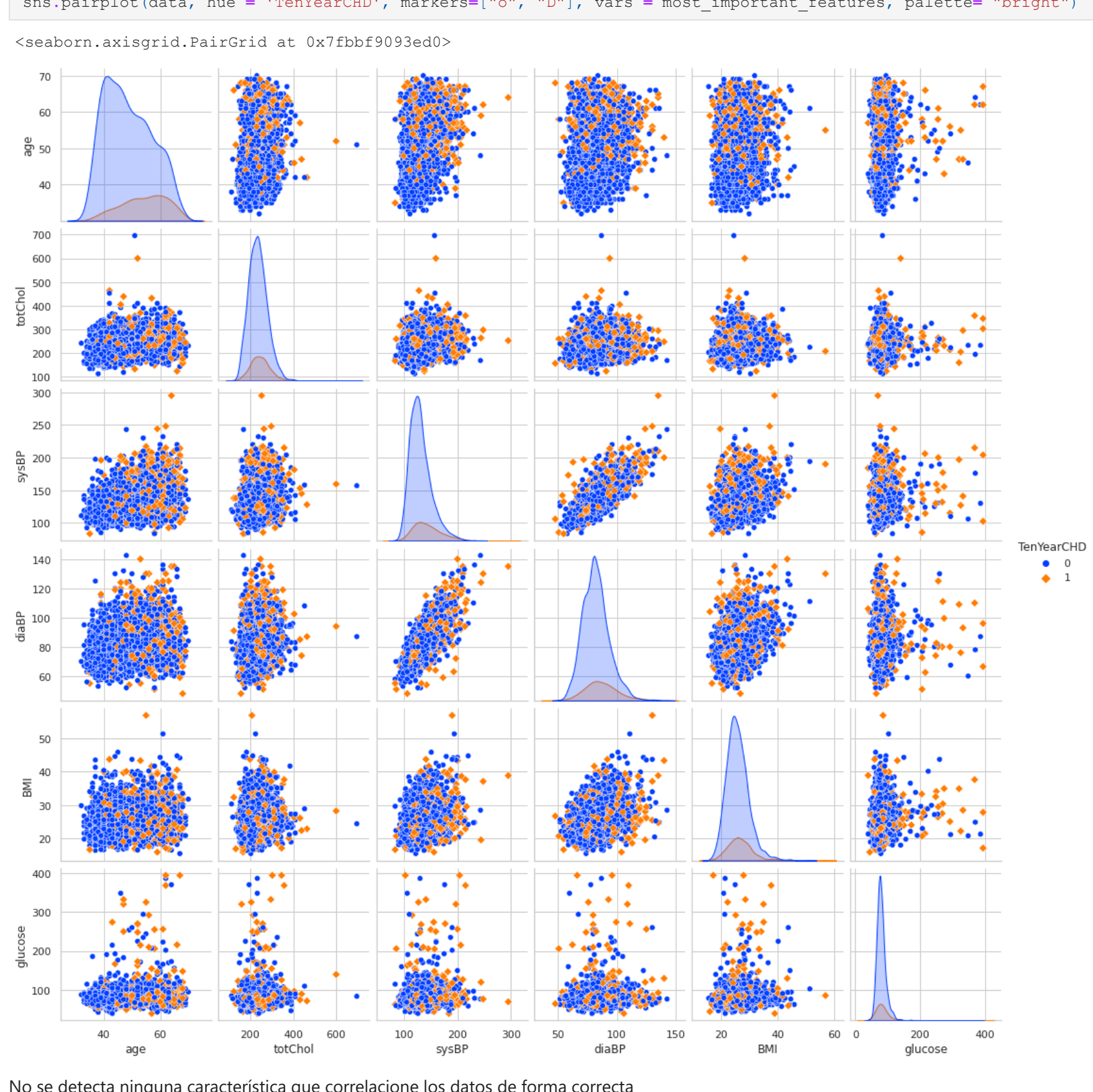
```
['age', 'totChol', 'sysBP', 'diaBP', 'BMI', 'glucose']
```

Las 5 características mas importantes y con mayor correlación con el riesgo de enfermedad coronaria a 10 años son:

- Edad
- Colesterol total
- Tensión sistólica
- Tensión diastólica
- Índice de masa corporal
- Nivel de glucosa en sangre

```python
# Observamos la correlación de las características mas importantes

sns.pairplot(data, hue ='TenYearCHD', markers=["o", "D"], vars = most_important_features, palette= "bright")
```

```
<seaborn.axisgrid.PairGrid at 0x7fbbf9093ed0>
```



No se detecta ninguna característica que correlacione los datos de forma correcta

4- Desarrollo y comparación de modelos

Balanceado del dataset

```python
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler
from imblearn.pipeline import Pipeline
from collections import Counter
```

```python
X = data[most_important_features]
y = data.iloc[:,-1]
```

```python
num_before = dict(Counter(y))

num_before
```

```
{0: 3179, 1: 572}
```

```python
# Definimos la canalización del proceso de balanceado

over = SMOTE(sampling_strategy=0.8)
under = RandomUnderSampler(sampling_strategy=0.8)
steps = [('o', over), ('u', under)]
pipeline = Pipeline(steps=steps)
```

```python
# Transformación del dataset

X_smote, y_smote = pipeline.fit_resample(X, y)
```

```python
num_after = dict(Counter(y_smote))

num_after
```

```
{0: 3178, 1: 2543}
```

Preparación de los datos para el modelado

```python
# Nuevo dataset

new_data = pd.concat([pd.DataFrame(X_smote), pd.DataFrame(y_smote)], axis=1)
new_data.columns = ['age', 'totChol', 'sysBP', 'diaBP', 'BMI', 'glucose','TenYearCHD']
new_data.head()
```

	age	totChol	sysBP	diaBP	BMI	glucose	TenYearCHD
0	61.0	238.0	119.0	78.0	25.36	75.0	0
1	45.0	291.0	125.0	82.0	21.26	72.0	0
2	44.0	232.0	125.0	86.0	23.23	80.0	0
3	46.0	233.0	108.0	74.0	23.97	82.0	0
4	45.0	240.0	141.0	89.0	25.01	76.0	0

```python
X_new = new_data[most_important_features]
y_new= new_data.iloc[:,-1]
X_new.head()
```

	age	totChol	sysBP	diaBP	BMI	glucose
0	61.0	238.0	119.0	78.0	25.36	75.0
1	45.0	291.0	125.0	82.0	21.26	72.0
2	44.0	232.0	125.0	86.0	23.23	80.0
3	46.0	233.0	108.0	74.0	23.97	82.0
4	45.0	240.0	141.0	89.0	25.01	76.0

```python
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X_new,y_new,test_size=.2,random_state=40)
```

```python
# Escalamos las características para aplicar en el modelo

from sklearn.preprocessing import StandardScaler
```

```python
scaler = StandardScaler()

X_train_scaled = scaler.fit_transform(X_train)
X_train = pd.DataFrame(X_train_scaled)

X_test_scaled = scaler.transform(X_test)
X_test = pd.DataFrame(X_test_scaled)
```

Modelos

1- Regresión logística

```python
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import f1_score
from sklearn.metrics import classification_report
from sklearn.metrics import recall_score,precision_score,classification_report,roc_auc_score,roc_curve
```

```python
params_grid = {'penalty':['l1','l2'],
               'C':[0.001 , .009 , 0.01 , .09 , 1 , 5 , 10 , 25, 100],
               'class_weight':['balanced',None]}
logistic_clf = GridSearchCV(LogisticRegression(),param_grid=params_grid,cv=10)
```

```python
logistic_clf.fit(X_train, y_train)
```

```python
logistic_clf.best_params_
```

```
{'C': 0.009, 'class_weight': 'balanced', 'penalty': 'l2'}
```

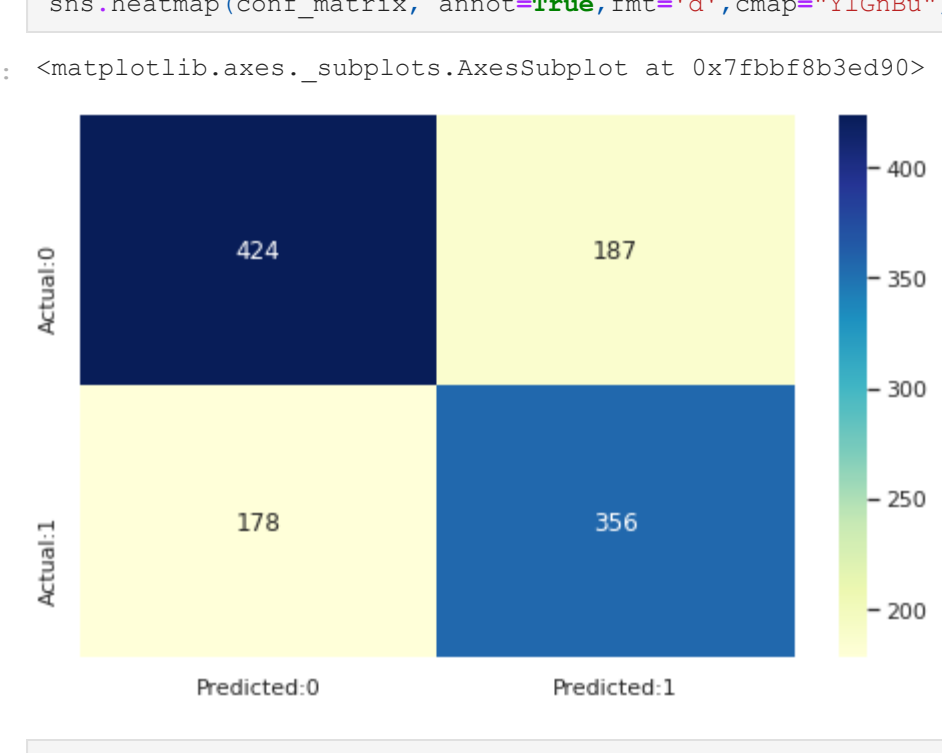
```python
logistic_predict = logistic_clf.predict(X_test)
```

```python
log_accuracy = accuracy_score(y_test,logistic_predict)
print(f"Con el modelo de Regresión logística obtenemos una precisión de {round(log_accuracy*100,2)}%")
```

```
Con el modelo de Regresión logística obtenemos una precisión de 68.12%
```

```python
# Elaboramos la matriz de confusión

cm=confusion_matrix(y_test,logistic_predict)
conf_matrix=pd.DataFrame(data=cm,columns=['Predicted:0','Predicted:1'],index=['Actual:0','Actual:1'])
plt.figure(figsize = (8,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu")
```

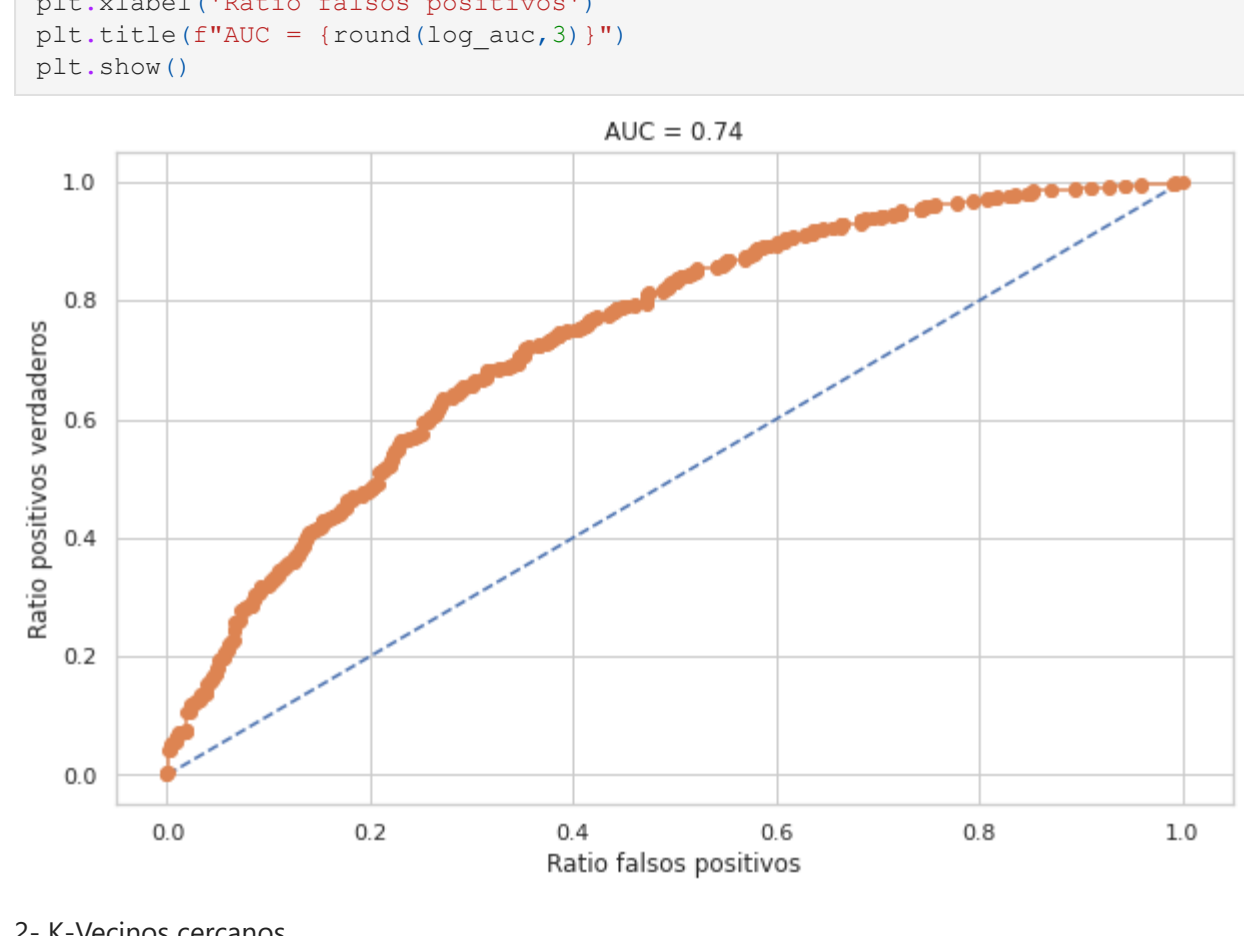
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbbf8b3ed90>
```




```python
print(classification_report(y_test,logistic_predict))
```

```
              precision    recall  f1-score   support

           0       0.70      0.69      0.70       611
           1       0.66      0.67      0.66       534

    accuracy                           0.68      1145
   macro avg       0.68      0.68      0.68      1145
weighted avg       0.68      0.68      0.68      1145
```

```python
# Curva ROC y AUC
probs = logistic_clf.predict_proba(X_test)

probs = probs[:, 1]

# calculate AUC
log_auc = roc_auc_score(y_test, probs)

# Cálculo de la curva ROC
fpr, tpr, thresholds = roc_curve(y_test, probs)

# plot curve
sns.set_style('whitegrid')
plt.figure(figsize=(10,6))
plt.plot([0, 1], [0, 1], linestyle='--')
plt.plot(fpr, tpr, marker='o')
plt.ylabel('Ratio positivos verdaderos')
plt.xlabel('Ratio falsos positivos')
plt.title(f"AUC = {round(log_auc,2)}")
plt.show()
```



2- K-Vecinos cercanos

```python
from sklearn.neighbors import KNeighborsClassifier
```

```python
params_grid= {'n_neighbors': np.arange(1, 10)}
grid_search = GridSearchCV(estimator = KNeighborsClassifier(), param_grid = params_grid,
                           scoring = 'accuracy', cv = 10, n_jobs = -1)
knn_clf = GridSearchCV(KNeighborsClassifier(),params_grid,cv=3, n_jobs=-1)
```

```python
knn_clf.fit(X_train,y_train)
knn_clf.best_params_
```

```
{'n_neighbors': 1}
```

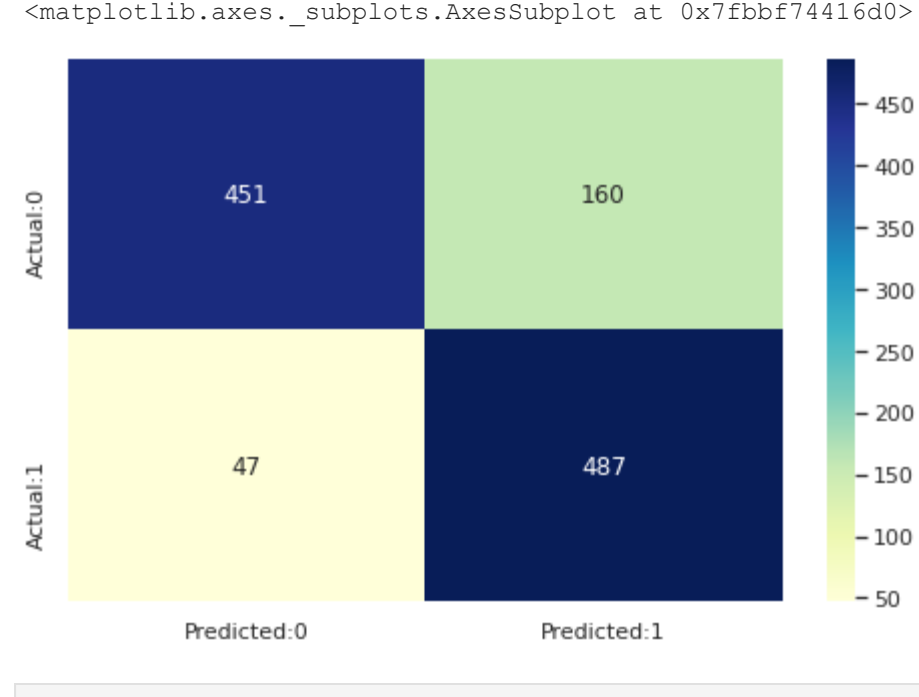
```python
knn_predict = knn_clf.predict(X_test)
```

```python
knn_accuracy = accuracy_score(y_test,knn_predict)
print(f"Con el modelo de K vecinos cercanos obtenemos una precisión de {round(knn_accuracy*100,2)}%")
```

```
Con el modelo de K vecinos cercanos obtenemos una precisión de 81.92%
```

```python
cm=confusion_matrix(y_test,knn_predict)
conf_matrix=pd.DataFrame(data=cm,columns=['Predicted:0','Predicted:1'],index=['Actual:0','Actual:1'])
plt.figure(figsize = (8,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu")
```

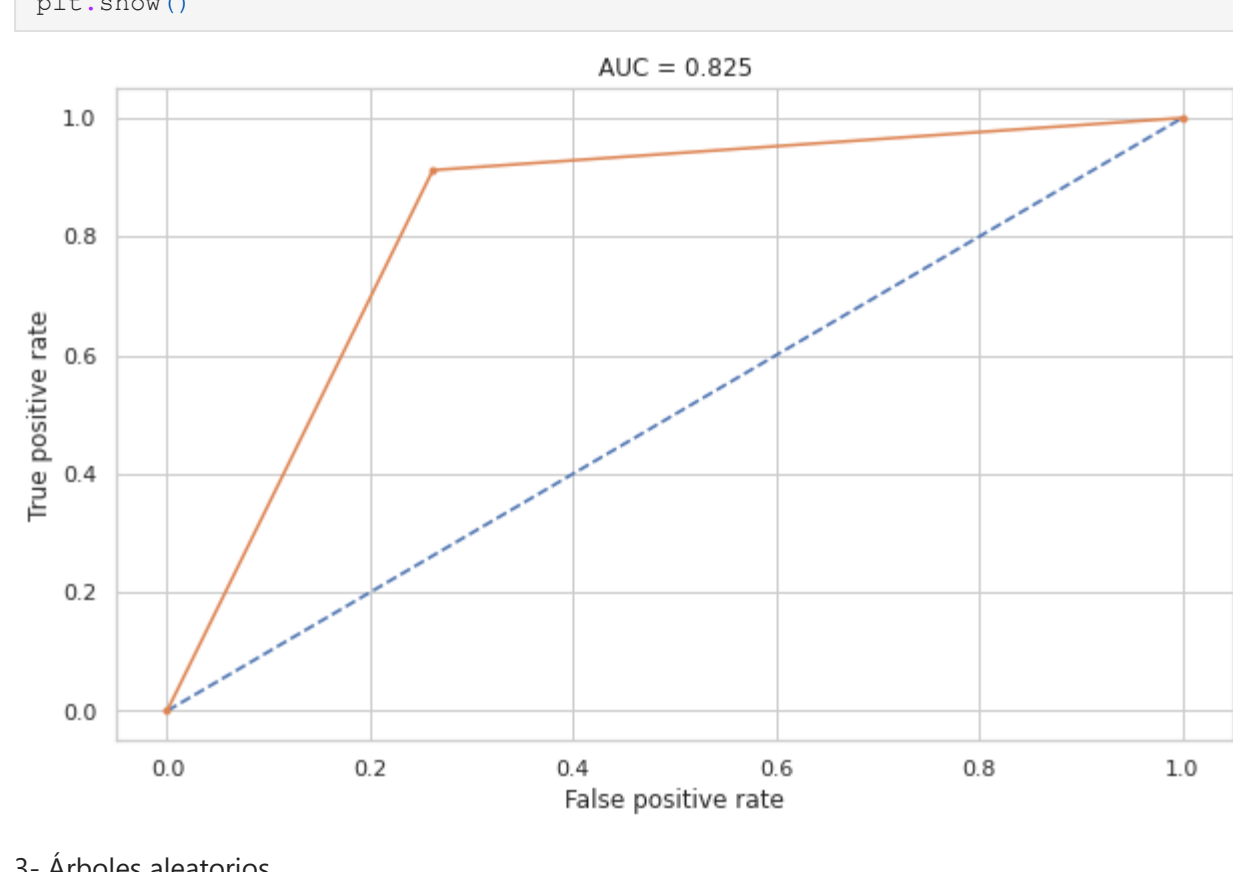
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbbf74416d0>
```




```python
print(classification_report(y_test,knn_predict))
```

```
              precision    recall  f1-score   support

           0       0.91      0.74      0.81       611
           1       0.75      0.91      0.82       534

    accuracy                           0.82      1145
   macro avg       0.83      0.83      0.82      1145
weighted avg       0.83      0.82      0.82      1145
```

```python
# Curva ROC y AUC
probs = knn_clf.predict_proba(X_test)

probs = probs[:, 1]
# cálculo AUC
knn_auc = roc_auc_score(y_test, probs)

# Cálculo ROC
fpr, tpr, thresholds = roc_curve(y_test, probs)

# plot curve
sns.set_style('whitegrid')
plt.figure(figsize=(10,6))
plt.plot([0, 1], [0, 1], linestyle='--')
plt.plot(fpr, tpr, marker='.')
plt.ylabel('True positive rate')
plt.xlabel('False positive rate')
plt.title(f"AUC = {round(knn_auc,3)}")
plt.show()
```



3- Árboles aleatorios

```python
from sklearn.tree import DecisionTreeClassifier
dtree= DecisionTreeClassifier(random_state=7)
```

```python
params = {'max_features': ['auto', 'sqrt', 'log2'],
          'min_samples_split': [2,3,4,5,6,7,8,9,10,11,12,13,14,15],
          'min_samples_leaf':[1,2,3,4,5,6,7,8,9,10,11]}
tree_clf = GridSearchCV(dtree, param_grid=params, n_jobs=-1)
```

```python
tree_clf.fit(X_train,y_train)
tree_clf.best_params_
```

```
{'max_features': 'auto', 'min_samples_leaf': 2, 'min_samples_split': 9}
```

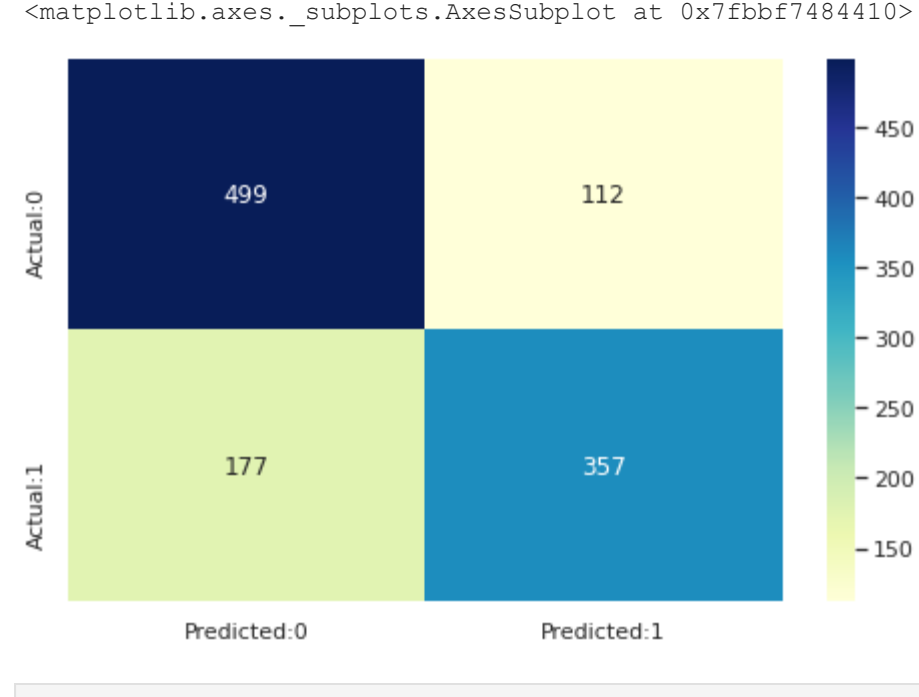
```python
tree_predict = tree_clf.predict(X_test)
```

```python
tree_accuracy = accuracy_score(y_test,tree_predict)
print(f"Con el modelo de árboles aleatorios obtenemos una precisión de {round(tree_accuracy*100,2)}%")
```

```
Con el modelo de árboles aleatorios obtenemos una precisión de 74.76%
```

```python
cm=confusion_matrix(y_test,tree_predict)
conf_matrix=pd.DataFrame(data=cm,columns=['Predicted:0','Predicted:1'],index=['Actual:0','Actual:1'])
plt.figure(figsize = (8,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu")
```

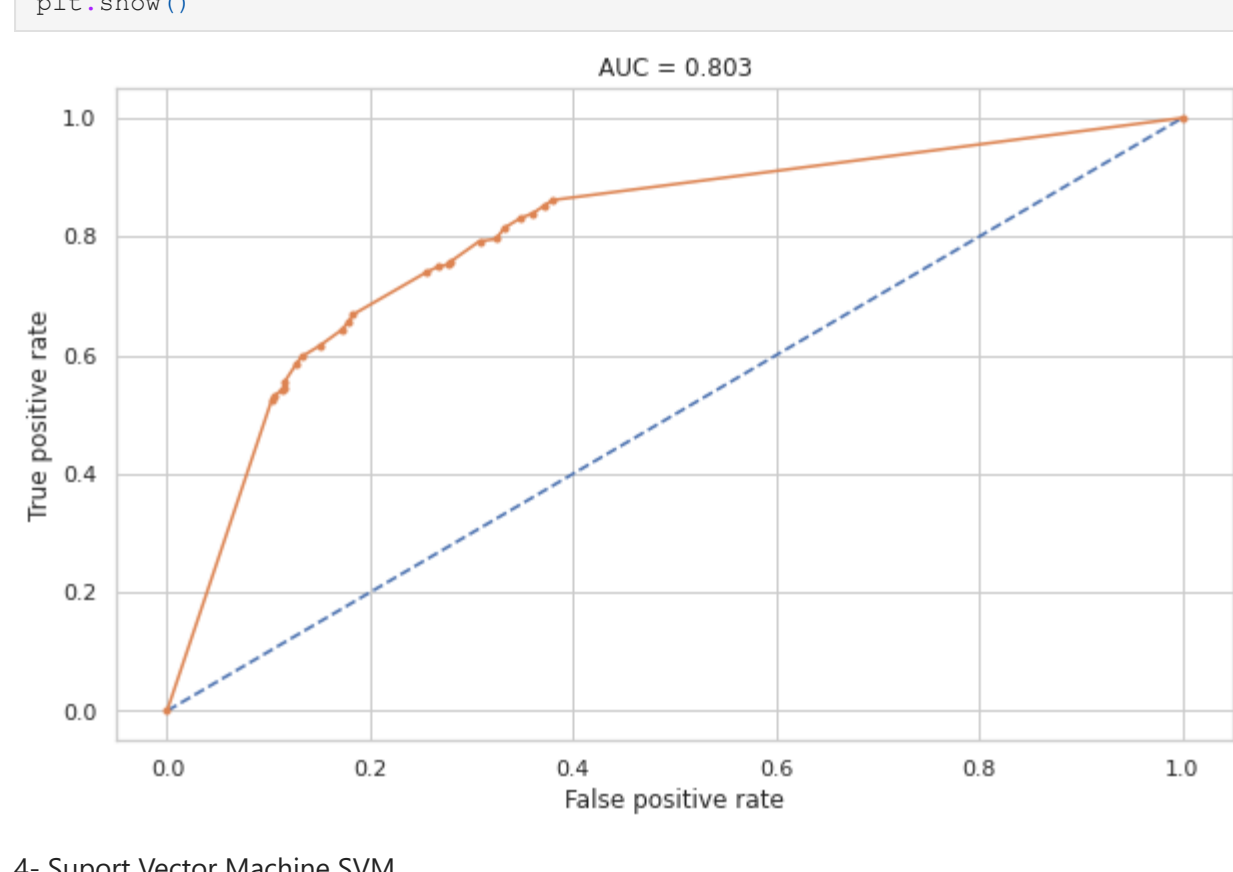
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbbf7484410>
```




```python
print(classification_report(y_test,tree_predict))
```

```
              precision    recall  f1-score   support

           0       0.74      0.82      0.78       611
           1       0.76      0.67      0.71       534

    accuracy                           0.75      1145
   macro avg       0.75      0.74      0.74      1145
weighted avg       0.75      0.75      0.75      1145
```

```python
probs = tree_clf.predict_proba(X_test)

probs = probs[:, 1]
# cálculo AUC
tree_auc = roc_auc_score(y_test, probs)

# cálculo curva ROC
fpr, tpr, thresholds = roc_curve(y_test, probs)

# plot curve
sns.set_style('whitegrid')
plt.figure(figsize=(10,6))
plt.plot([0, 1], [0, 1], linestyle='--')
plt.plot(fpr, tpr, marker='.')
plt.ylabel('True positive rate')
plt.xlabel('False positive rate')
plt.title(f"AUC = {round(tree_auc,3)}")
plt.show()
```



4- Suport Vector Machine SVM

```python
from sklearn.svm import SVC
```

```python
Cs = [0.001, 0.01, 0.1, 1, 10]
gammas = [0.001, 0.01, 0.1, 1]
param_grid = {'C': Cs, 'gamma' : gammas}
svm_clf = GridSearchCV(SVC(kernel='rbf', probability=True), param_grid, cv=10)
```

```python
svm_clf.fit(X_train,y_train)
svm_clf.best_params_
```

```
{'C': 10, 'gamma': 1}
```

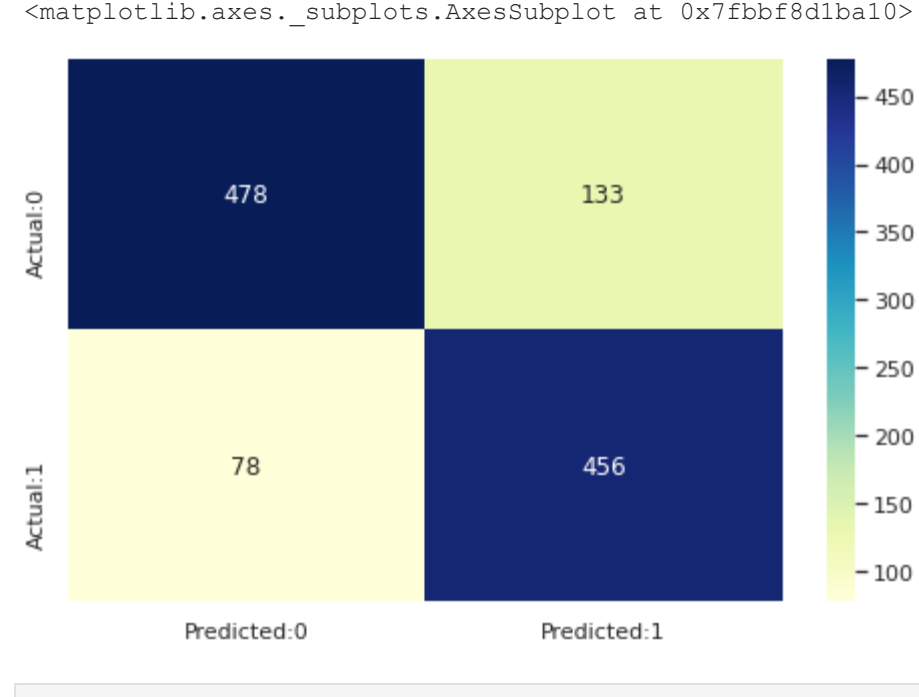
```python
svm_predict = svm_clf.predict(X_test)
```

```python
svm_accuracy = accuracy_score(y_test,svm_predict)
print(f"Con el modelo de Suport Vector Machine obtenemos una precisión de {round(svm_accuracy*100,2)}%")
```

```
Con el modelo de Suport Vector Machine obtenemos una precisión de 81.57%
```

```python
cm=confusion_matrix(y_test,svm_predict)
conf_matrix=pd.DataFrame(data=cm,columns=['Predicted:0','Predicted:1'],index=['Actual:0','Actual:1'])
plt.figure(figsize = (8,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu")
```

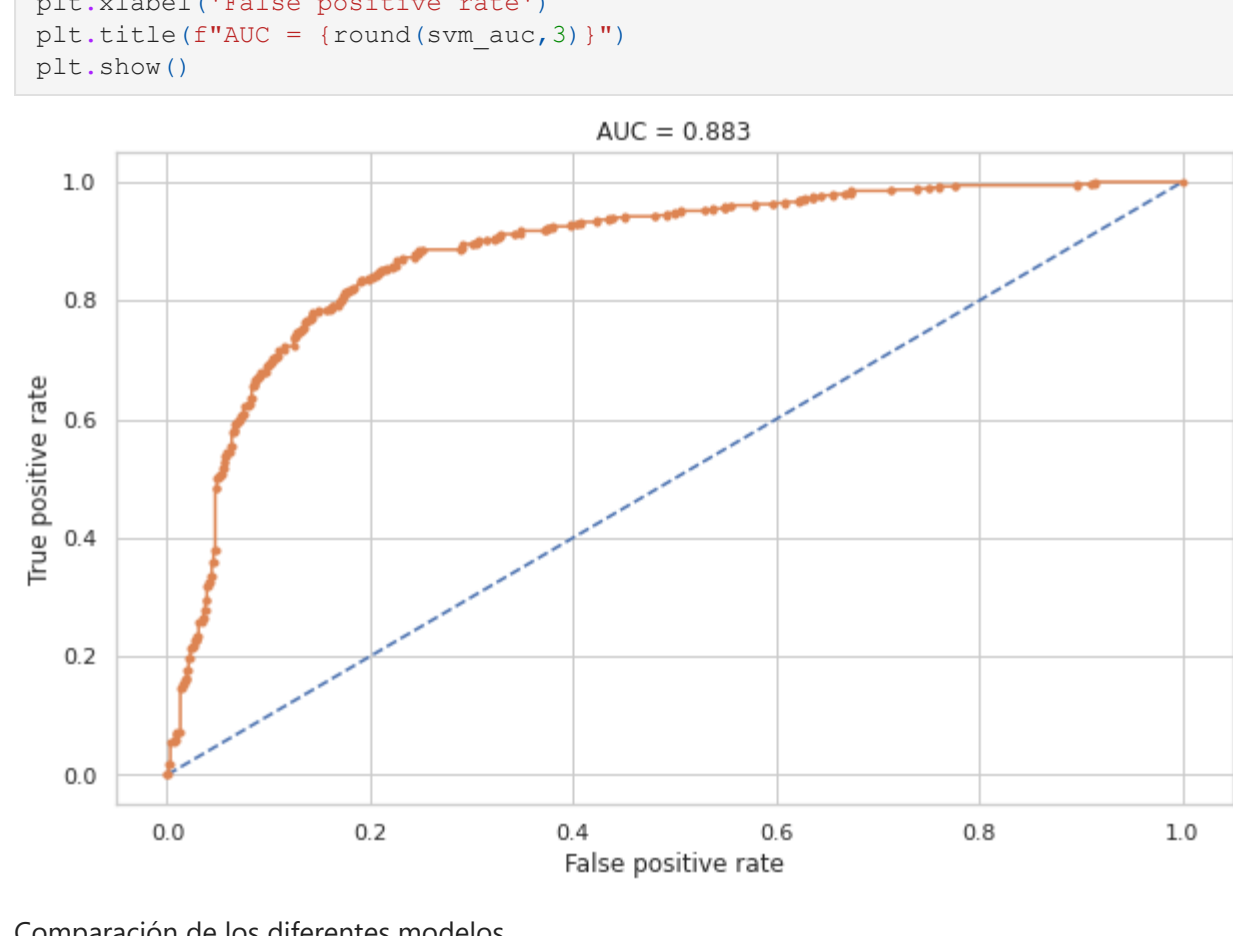
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbbf8d1ba10>
```




```python
print(classification_report(y_test,svm_predict))
```

```
              precision    recall  f1-score   support

           0       0.86      0.78      0.82       611
           1       0.77      0.85      0.81       534

    accuracy                           0.82      1145
   macro avg       0.82      0.82      0.82      1145
weighted avg       0.82      0.82      0.82      1145
```

```python
probs = svm_clf.predict_proba(X_test)

probs = probs[:, 1]
# Cálculo AUC
svm_auc = roc_auc_score(y_test, probs)

# Cálculo curva ROC
fpr, tpr, thresholds = roc_curve(y_test, probs)

# plot curve
sns.set_style('whitegrid')
plt.figure(figsize=(10,6))
plt.plot([0, 1], [0, 1], linestyle='--')
plt.plot(fpr, tpr, marker='.')
plt.ylabel('True positive rate')
plt.xlabel('False positive rate')
plt.title(f"AUC = {round(svm_auc,3)}")
plt.show()
```



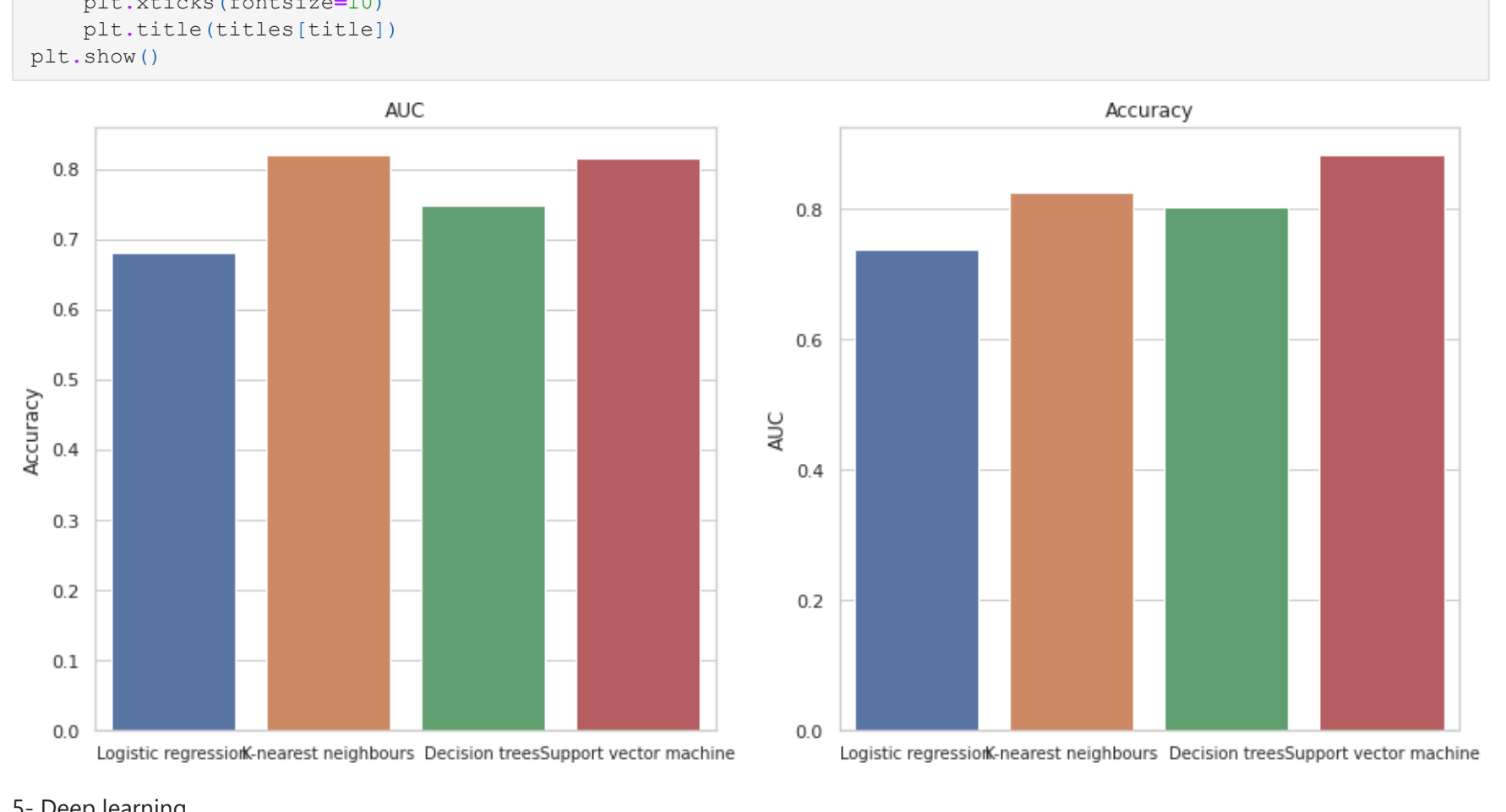
Comparación de los diferentes modelos

```python
comparison = pd.DataFrame({
    "Logistic regression":{'Accuracy':log_accuracy, 'AUC':log_auc},
    "K-nearest neighbours":{'Accuracy':knn_accuracy, 'AUC':knn_auc,},
    "Decision trees":{'Accuracy':tree_accuracy, 'AUC':tree_auc,},
    "Support vector machine":{'Accuracy':svm_accuracy, 'AUC':svm_auc,}
}).T
```

```python
comparison
```

	Accuracy	AUC
Logistic regression	0.681223	0.739526
K-nearest neighbours	0.819214	0.825060
Decision trees	0.747598	0.802600
Support vector machine	0.815721	0.882583

```python
fig = plt.gcf()
fig.set_size_inches(15, 15)
titles = ['AUC','Accuracy','F1 score']
for title,label in enumerate(comparison.columns):
    plt.subplot(2,2,title+1)
    sns.barplot(x=comparison.index, y = comparison[label], data=comparison)
    plt.xticks(fontsize=10)
    plt.title(titles[title])
plt.show()
```



5- Deep learning

```python
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
X = scaler.fit_transform(X_new)
```

```python
X
```

```
array([[0.76315789, 0.21440823, 0.1678487 , 0.31746032, 0.23800291,
        0.09887006],
       [0.34210526, 0.30531732, 0.19621749, 0.35978836, 0.13863306,
        0.09039548],
       [0.31578947, 0.20411664, 0.19621749, 0.4021164 , 0.18637906,
        0.11299435],
       ...,
       [0.58591165, 0.19601966, 0.43043355, 0.72331065, 0.23649159,
        0.14788943],
       [0.83144271, 0.2585394 , 0.33460715, 0.48191471, 0.29927631,
        0.11100964],
       [0.71841792, 0.16573782, 0.24018856, 0.37063901, 0.25836228,
        0.10621402]])
```

```python
X.shape
```

```
(5721, 6)
```

```python
y = new_data['TenYearCHD']
```

```python
y.shape
```

```
(5721,)
```

```python
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20)
```

```python
import tensorflow as tf
```

```python
model = tf.keras.models.Sequential()
model.add(tf.keras.layers.Dense(units = 500, activation='relu', input_shape=(6, )))
model.add(tf.keras.layers.Dense(units = 500, activation='relu'))
model.add(tf.keras.layers.Dense(units = 500, activation='relu'))
model.add(tf.keras.layers.Dense(units = 1, activation='sigmoid'))
```

```python
model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_9 (Dense)              (None, 500)               3500
_________________________________________________________________
dense_10 (Dense)             (None, 500)               250500
_________________________________________________________________
dense_11 (Dense)             (None, 500)               250500
_________________________________________________________________
dense_12 (Dense)             (None, 1)                 501
=================================================================
Total params: 505,001
Trainable params: 505,001
Non-trainable params: 0
_________________________________________________________________
```

```python
model.compile(optimizer= 'Adam', loss= 'binary_crossentropy', metrics=['accuracy'])
```

```python
epochs_hist = model.fit(X_new, y_new, epochs = 100, batch_size=50)
```

```
Epoch 1/100
115/115 [==============================] - 2s 8ms/step - loss: 3.8721 - accuracy: 0.5293
Epoch 2/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6549 - accuracy: 0.6216
Epoch 3/100
115/115 [==============================] - 1s 7ms/step - loss: 0.6571 - accuracy: 0.6099
Epoch 4/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6653 - accuracy: 0.6078
Epoch 5/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6587 - accuracy: 0.6156
Epoch 6/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6495 - accuracy: 0.6247
Epoch 7/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6413 - accuracy: 0.6386
Epoch 8/100
115/115 [==============================] - 1s 7ms/step - loss: 0.6469 - accuracy: 0.6295
Epoch 9/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6487 - accuracy: 0.6298
Epoch 10/100
115/115 [==============================] - 1s 7ms/step - loss: 0.6505 - accuracy: 0.6183
Epoch 11/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6399 - accuracy: 0.6433
Epoch 12/100
115/115 [==============================] - 1s 7ms/step - loss: 0.6372 - accuracy: 0.6461
Epoch 13/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6562 - accuracy: 0.6226
Epoch 14/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6513 - accuracy: 0.6370
Epoch 15/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6390 - accuracy: 0.6306
Epoch 16/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6378 - accuracy: 0.6361
Epoch 17/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6327 - accuracy: 0.6408
Epoch 18/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6244 - accuracy: 0.6554
Epoch 19/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6403 - accuracy: 0.6322
Epoch 20/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6410 - accuracy: 0.6358
Epoch 21/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6264 - accuracy: 0.6545
Epoch 22/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6293 - accuracy: 0.6452
Epoch 23/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6373 - accuracy: 0.6422
Epoch 24/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6314 - accuracy: 0.6394
Epoch 25/100
115/115 [==============================] - 1s 7ms/step - loss: 0.6364 - accuracy: 0.6373
Epoch 26/100
115/115 [==============================] - 1s 7ms/step - loss: 0.6282 - accuracy: 0.6513
Epoch 27/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6251 - accuracy: 0.6526
Epoch 28/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6314 - accuracy: 0.6430
Epoch 29/100
115/115 [==============================] - 1s 7ms/step - loss: 0.6475 - accuracy: 0.6329
Epoch 30/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6286 - accuracy: 0.6535
Epoch 31/100
115/115 [==============================] - 1s 7ms/step - loss: 0.6297 - accuracy: 0.6550
Epoch 32/100
115/115 [==============================] - 1s 7ms/step - loss: 0.6187 - accuracy: 0.6636
Epoch 33/100
115/115 [==============================] - 1s 7ms/step - loss: 0.6215 - accuracy: 0.6508
Epoch 34/100
115/115 [==============================] - 1s 7ms/step - loss: 0.6271 - accuracy: 0.6492
Epoch 35/100
115/115 [==============================] - 1s 7ms/step - loss: 0.6205 - accuracy: 0.6626
Epoch 36/100
115/115 [==============================] - 1s 7ms/step - loss: 0.6297 - accuracy: 0.6474
Epoch 37/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6213 - accuracy: 0.6666
Epoch 38/100
115/115 [==============================] - 1s 7ms/step - loss: 0.6338 - accuracy: 0.6410
Epoch 39/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6346 - accuracy: 0.6367
Epoch 40/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6209 - accuracy: 0.6503
Epoch 41/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6182 - accuracy: 0.6660
Epoch 42/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6210 - accuracy: 0.6573
Epoch 43/100
115/115 [==============================] - 1s 7ms/step - loss: 0.6171 - accuracy: 0.6619
Epoch 44/100
115/115 [==============================] - 1s 7ms/step - loss: 0.6149 - accuracy: 0.6576
Epoch 45/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6248 - accuracy: 0.6504
Epoch 46/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6164 - accuracy: 0.6643
Epoch 47/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6226 - accuracy: 0.6488
Epoch 48/100
115/115 [==============================] - 1s 7ms/step - loss: 0.6099 - accuracy: 0.6632
Epoch 49/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6155 - accuracy: 0.6554
Epoch 50/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6186 - accuracy: 0.6576
Epoch 51/100
115/115 [==============================] - 1s 7ms/step - loss: 0.6269 - accuracy: 0.6495
Epoch 52/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6135 - accuracy: 0.6634
Epoch 53/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6136 - accuracy: 0.6715
Epoch 54/100
115/115 [==============================] - 1s 7ms/step - loss: 0.6165 - accuracy: 0.6493
Epoch 55/100
115/115 [==============================] - 1s 8ms/step - loss: 0.5995 - accuracy: 0.6764
Epoch 56/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6166 - accuracy: 0.6524
Epoch 57/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6166 - accuracy: 0.6577
Epoch 58/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6172 - accuracy: 0.6640
Epoch 59/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6115 - accuracy: 0.6581
Epoch 60/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6035 - accuracy: 0.6739
Epoch 61/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6034 - accuracy: 0.6782
Epoch 62/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6194 - accuracy: 0.6558
Epoch 63/100
115/115 [==============================] - 1s 7ms/step - loss: 0.6019 - accuracy: 0.6736
Epoch 64/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6069 - accuracy: 0.6696
Epoch 65/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6090 - accuracy: 0.6589
Epoch 66/100
115/115 [==============================] - 1s 7ms/step - loss: 0.6063 - accuracy: 0.6699
Epoch 67/100
115/115 [==============================] - 1s 7ms/step - loss: 0.6167 - accuracy: 0.6496
Epoch 68/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6073 - accuracy: 0.6664
Epoch 69/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6096 - accuracy: 0.6541
Epoch 70/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6137 - accuracy: 0.6541
Epoch 71/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6229 - accuracy: 0.6488
Epoch 72/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6111 - accuracy: 0.6642
Epoch 73/100
115/115 [==============================] - 1s 7ms/step - loss: 0.6091 - accuracy: 0.6641
Epoch 74/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6092 - accuracy: 0.6632
Epoch 75/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6066 - accuracy: 0.6668
Epoch 76/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6069 - accuracy: 0.6625
Epoch 77/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6069 - accuracy: 0.6576
Epoch 78/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6061 - accuracy: 0.6660
Epoch 79/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6110 - accuracy: 0.6541
Epoch 80/100
115/115 [==============================] - 1s 7ms/step - loss: 0.5989 - accuracy: 0.6667
Epoch 81/100
115/115 [==============================] - 1s 7ms/step - loss: 0.5969 - accuracy: 0.6725
Epoch 82/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6008 - accuracy: 0.6693
Epoch 83/100
115/115 [==============================] - 1s 8ms/step - loss: 0.5914 - accuracy: 0.6872
Epoch 84/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6024 - accuracy: 0.6697
Epoch 85/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6043 - accuracy: 0.6620
Epoch 86/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6040 - accuracy: 0.6714
Epoch 87/100
115/115 [==============================] - 1s 7ms/step - loss: 0.5964 - accuracy: 0.6745
Epoch 88/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6076 - accuracy: 0.6635
Epoch 89/100
115/115 [==============================] - 1s 8ms/step - loss: 0.5920 - accuracy: 0.6752
Epoch 90/100
115/115 [==============================] - 1s 7ms/step - loss: 0.5954 - accuracy: 0.6746
Epoch 91/100
115/115 [==============================] - 1s 8ms/step - loss: 0.5968 - accuracy: 0.6794
Epoch 92/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6017 - accuracy: 0.6608
Epoch 93/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6004 - accuracy: 0.6705
Epoch 94/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6029 - accuracy: 0.6640
Epoch 95/100
115/115 [==============================] - 1s 8ms/step - loss: 0.5915 - accuracy: 0.6730
Epoch 96/100
115/115 [==============================] - 1s 8ms/step - loss: 0.5944 - accuracy: 0.6803
Epoch 97/100
115/115 [==============================] - 1s 8ms/step - loss: 0.5968 - accuracy: 0.6759
Epoch 98/100
115/115 [==============================] - 1s 7ms/step - loss: 0.5929 - accuracy: 0.6747
Epoch 99/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6004 - accuracy: 0.6756
Epoch 100/100
115/115 [==============================] - 1s 8ms/step - loss: 0.6016 - accuracy: 0.6641
```

In [ ]:

```python
y_pred = model.predict(X_test)
y_pred
```

Out[ ]:

```
array([[0.00752971],
       [0.00756618],
       [0.00760016],
       ...,
       [0.00803477],
       [0.00738287],
       [0.00738704]], dtype=float32)
```

In [ ]:

```python
y_pred = (y_pred > 0.5)
y_pred
```

Out[ ]:

```
array([[False],
       [False],
       [False],
       ...,
       [False],
       [False],
       [False]])
```

In [ ]:

```python
epochs_hist.history.keys()
```

Out[ ]:

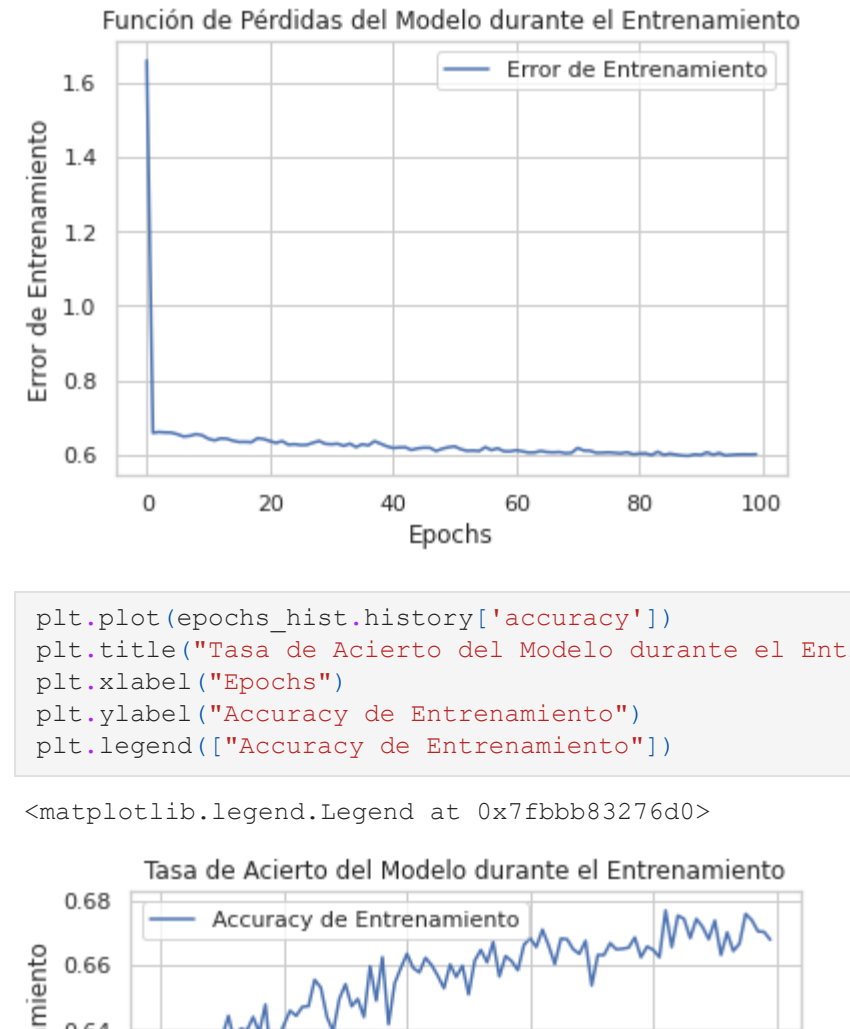
```
dict_keys(['loss', 'accuracy'])
```

In [ ]:

```python
plt.plot(epochs_hist.history['loss'])
plt.title("Función de Pérdidas del Modelo durante el Entrenamiento")
plt.xlabel("Epochs")
plt.ylabel("Error de Entrenamiento")
plt.legend(["Error de Entrenamiento"])
```

Out[ ]:

```
<matplotlib.legend.Legend at 0x7fbbb8b69f10>
```

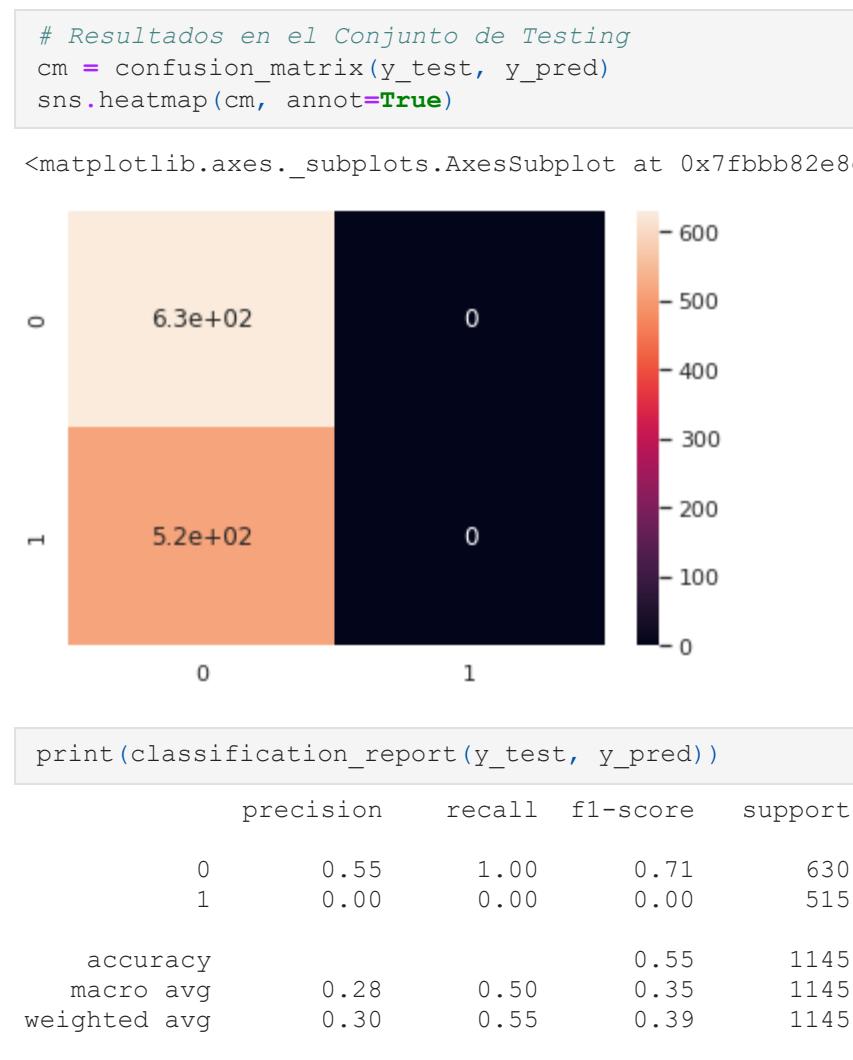


In [ ]:

```python
plt.plot(epochs_hist.history['accuracy'])
plt.title("Tasa de Acierto del Modelo durante el Entrenamiento")
plt.xlabel("Epochs")
plt.ylabel("Accuracy de Entrenamiento")
plt.legend(["Accuracy de Entrenamiento"])
```

Out[ ]:

```
<matplotlib.legend.Legend at 0x7fbbb83276d0>
```

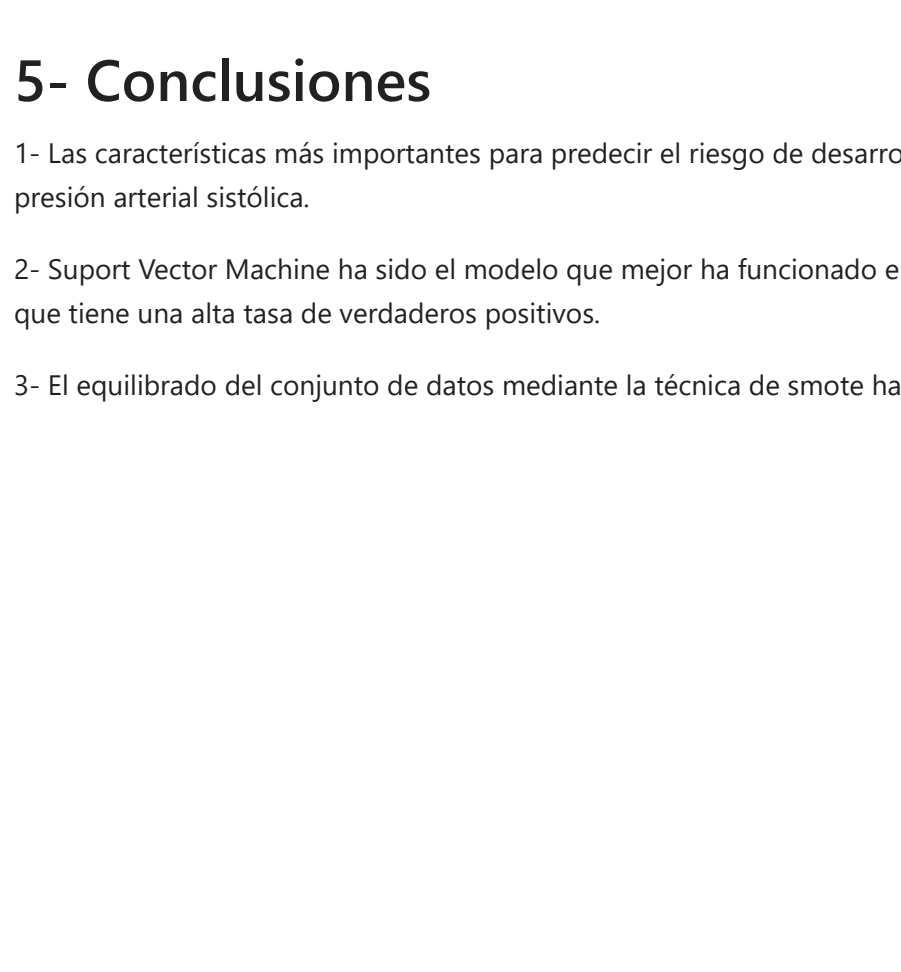


In [ ]:

```python
# Resultados en el Conjunto de Testing
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbbb82e8e10>
```



In [ ]:

```python
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.55      1.00      0.71       630
           1       0.00      0.00      0.00       515

    accuracy                           0.55      1145
   macro avg       0.28      0.50      0.35      1145
weighted avg       0.30      0.55      0.39      1145
```

5- Conclusiones

1- Las características más importantes para predecir el riesgo de desarrollar una cardiopatía isquémica a los diez años son la edad y la presión arterial sistólica.

2- Suport Vector Machine ha sido el modelo que mejor ha funcionado en términos de precisión y puntuación F1. Su alto AUC demuestra que tiene una alta tasa de verdaderos positivos.

3- El equilibrado del conjunto de datos mediante la técnica de smote ha ayudado a mejorar la sensibilidad de los modelos