Assignment Trees_sense_time

April 23, 2024

1 Assignment on Decision Trees for Heart Failure data

The variables of this dataset are as follows

- `age`: age of the patient (years)
- `anaemia`: decrease of red blood cells or - hemoglobin (boolean)
- `cpk`: level of the CPK enzyme in the blood (mcg/L)
- `diabetes`: if the patient has diabetes (boolean)
- `ef`: ejection fraction: percentage of blood leaving the heart at each contraction
- `hbp`: if the - patient has hypertension (boolean)
- `platelets`: platelets in the blood (kiloplatelets/mL)
- `sc`: level of serum creatinine in the blood (mg/dL)
- `ss`: level of serum sodium in the blood (mEq/L)
- `sex`: female/male (binary)
- `smoking`: if the patient smokes or not (boolean)
- `fup`: follow-up period (days) -> WE REMOVE IT
- `death_event`: the patient deceased during the follow-up period (boolean)

[36]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
import keras
import sklearn
import seaborn as sns
from keras.datasets import mnist
from keras.models import Sequential, Model
from keras.layers import Dense, Input
from keras.optimizers import RMSprop, Adam
from scipy.interpolate import interp1d
from sklearn.metrics import confusion_matrix, classification_report,␣
↪ConfusionMatrixDisplay
from sklearn.manifold import TSNE
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
```

```
import io
import tensorflow as tf
import keras
from keras.wrappers.scikit_learn import KerasClassifier, KerasRegressor
from keras.callbacks import EarlyStopping
from datetime import datetime
from sklearn.model_selection import GridSearchCV, cross_val_score
from sklearn.metrics import accuracy_score, mean_squared_error
from keras.layers import Dense, Dropout, Input
from keras.optimizers import RMSprop
from keras import initializers
from sklearn.metrics import confusion_matrix, classification_report,␣
↪ConfusionMatrixDisplay
from matplotlib.colors import ListedColormap
import missingno as msno
import random
```

[37]:
```
data = pd.read_csv("HFCRD.csv")
data.shape
```

[37]:
```
(299, 13)
```

[38]:
```
data.head()
```

[38]:

	age	anaemia	creatinine_phosphokinase	diabetes	ejection_fraction	high_blood_pressure	platelets	serum_creatinine	serum_sodium	sex	smoking	time	DEATH_EVENT
0	75.0	0	582	0	20	1	265000.00	1.9	130	1	0	4	1
1	55.0	0	7861	0	38	0	263358.03	1.1	136	1	0	6	1
2	65.0	0	146	0	20	0	162000.00	1.3	129	1	1	7	1
3	50.0	1	111	0	20	0	210000.00	1.9	137	1	0	7	1
4	65.0	1	160	1	20	0	327000.00	2.7	116	0	0	8	1

[39]:
```
df = data.drop('time', axis=1)
print(df.shape)
```

```
df.head()
```

```
(299, 12)
```

[39]:

	age	anaemia	creatinine_phosphokinase	diabetes	ejection_fraction	high_blood_pressure	platelets	serum_creatinine	serum_sodium	sex	smoking	DEATH_EVENT
0	75.0	0	582	0	20	1	265000.00	1.9	130	1	0	1
1	55.0	0	7861	0	38	0	263358.03	1.1	136	1	0	1
2	65.0	0	146	0	20	0	162000.00	1.3	129	1	1	1
3	50.0	1	111	0	20	0	210000.00	1.9	137	1	0	1
4	65.0	1	160	1	20	0	327000.00	2.7	116	0	0	1

1.0.1 1. Exploratory Data Analysis

Notice we have 12 variables on 299 entries and there are no missing values.

[40]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 299 entries, 0 to 298
Data columns (total 12 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   age                       299 non-null    float64
 1   anaemia                   299 non-null    int64
 2   creatinine_phosphokinase  299 non-null    int64
 3   diabetes                  299 non-null    int64
 4   ejection_fraction         299 non-null    int64
 5   high_blood_pressure       299 non-null    int64
 6   platelets                 299 non-null    float64
 7   serum_creatinine          299 non-null    float64
 8   serum_sodium              299 non-null    int64
 9   sex                       299 non-null    int64
 10  smoking                   299 non-null    int64
 11  DEATH_EVENT               299 non-null    int64
dtypes: float64(3), int64(9)
```

```
memory usage: 28.2 KB
```

[41]:
```
df.describe()
```

[41]:

	age	anaemia	creatinine_phosphokinase	diabetes	\
count	299.000000	299.000000	299.000000	299.000000	
mean	60.833893	0.431438	581.839465	0.418060	
std	11.894809	0.496107	970.287881	0.494067	
min	40.000000	0.000000	23.000000	0.000000	
25%	51.000000	0.000000	116.500000	0.000000	
50%	60.000000	0.000000	250.000000	0.000000	
75%	70.000000	1.000000	582.000000	1.000000	
max	95.000000	1.000000	7861.000000	1.000000	

	ejection_fraction	high_blood_pressure	platelets	\
count	299.000000	299.000000	299.000000	
mean	38.083612	0.351171	263358.029264	
std	11.834841	0.478136	97804.236869	
min	14.000000	0.000000	25100.000000	
25%	30.000000	0.000000	212500.000000	
50%	38.000000	0.000000	262000.000000	
75%	45.000000	1.000000	303500.000000	
max	80.000000	1.000000	850000.000000	

	serum_creatinine	serum_sodium	sex	smoking	DEATH_EVENT
count	299.00000	299.000000	299.000000	299.00000	299.00000
mean	1.39388	136.625418	0.648829	0.32107	0.32107
std	1.03451	4.412477	0.478136	0.46767	0.46767
min	0.50000	113.000000	0.000000	0.00000	0.00000
25%	0.90000	134.000000	0.000000	0.00000	0.00000
50%	1.10000	137.000000	1.000000	0.00000	0.00000
75%	1.40000	140.000000	1.000000	1.00000	1.00000
max	9.40000	148.000000	1.000000	1.00000	1.00000

[42]:
```
X = df.iloc[:,:-1]
y = df['DEATH_EVENT']
```

1.1 2. Train-Test Partition

[43]:
```
np.random.seed(1234)
X_train, X_test, y_train, y_test = sklearn.model_selection.train_test_split(np.
  ↪array(X), np.array(y), test_size = 1/3, random_state = 8)
print(X_train.shape); print(X_test.shape);
print((X_test.shape[0]/(X_test.shape[0] + X_train.shape[0])))
print((y_test.shape[0]/(y_test.shape[0] + y_train.shape[0])))
```

```
(199, 11)
(100, 11)
```

```
0.33444816053511706
0.33444816053511706
```

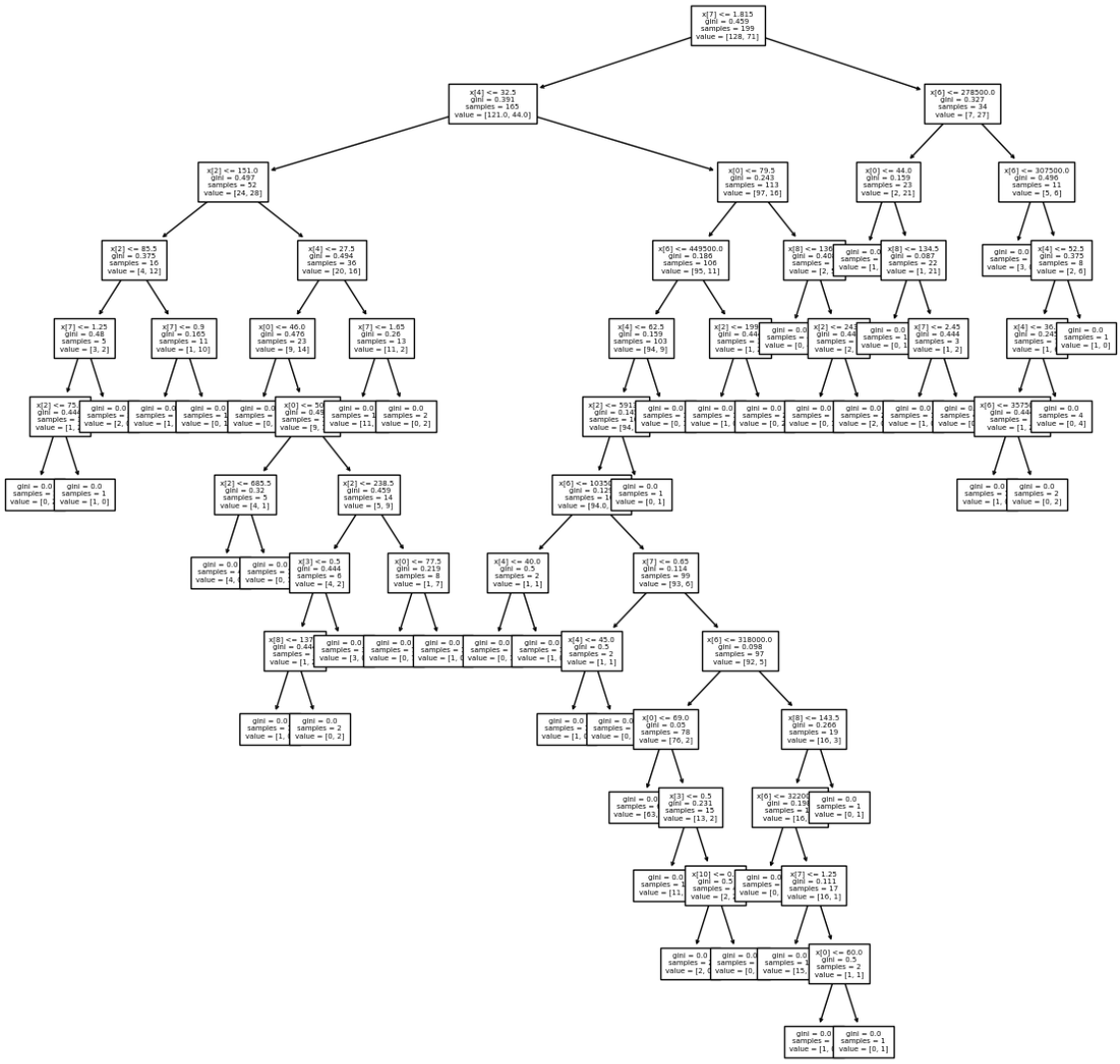
[44]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

1.2 3. Fitting Statistical Models

We will now be fitting the available data using three different statistical models - A *decision tree* to predcit survival (encoded in `death_event`) - A *logistic* classifier to predict survival - (To be decided by us)

[45]:
```
from sklearn import tree
```

[46]:
```
# Naive classification tree
clf_0 = tree.DecisionTreeClassifier()
clf_0 = clf_0.fit(X_train, y_train)

plt.figure(figsize=(14,14))
tree.plot_tree(clf_0, fontsize = 5)
plt.show()
```



[47]:
```
from sklearn.metrics import accuracy_score
y_test_pred = clf_0.predict(X_test)
accuracy_score(y_test, y_test_pred)
```

[47]: 0.66

[48]:
```
aux = 0
for criterion in ['gini', 'entropy']:
    for splitter in ['best', 'random']:
        for max_depth in [1, 2, 3, 4, 5, 6]:
            # print(criterion, splitter, max_depth)
            clf = tree.DecisionTreeClassifier(criterion = criterion, splitter =␣
 ↪splitter, max_depth = max_depth, random_state = 321)
```

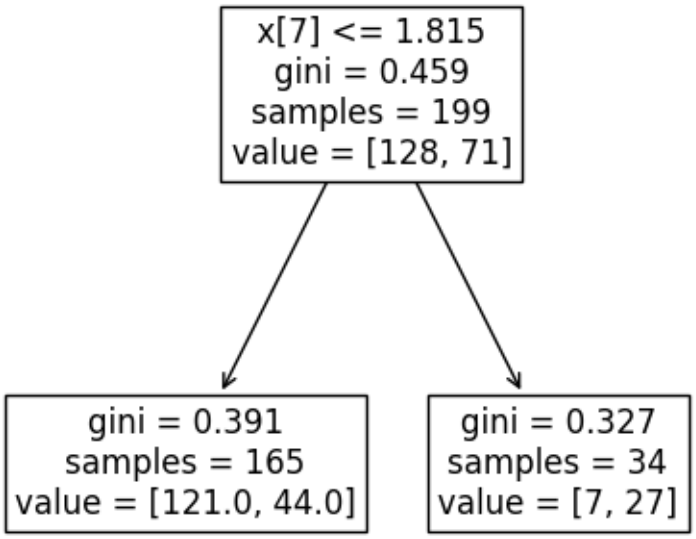
```
            clf = clf.fit(X_train, y_train)
            y_train_pred = clf.predict(X_train)
            y_test_pred = clf.predict(X_test)
            train_acc = accuracy_score(y_train, y_train_pred); ␣
 ↪#print(train_acc)
            test_acc = accuracy_score(y_test, y_test_pred);  #print(test_acc)
            if test_acc > aux:
                aux = test_acc
                combination = [criterion, splitter, max_depth]

print(aux)
print(combination)
```

```
0.77
['gini', 'best', 1]
```

[49]:
```
X.columns
```

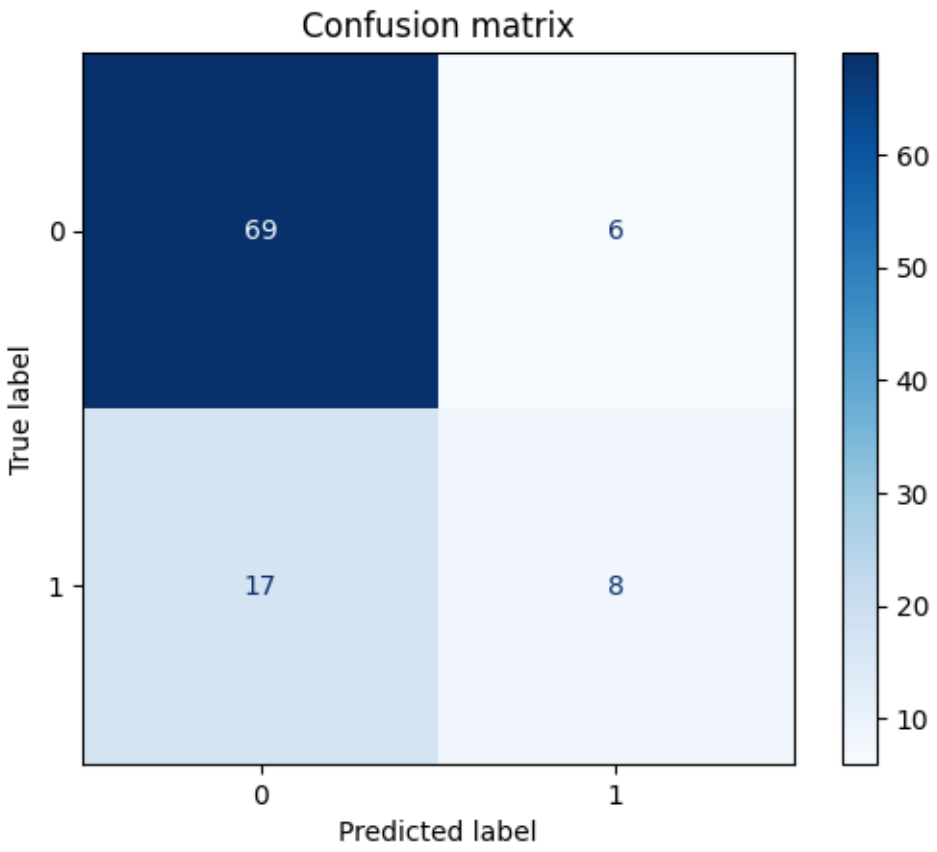
[49]:
```
Index(['age', 'anaemia', 'creatinine_phosphokinase', 'diabetes',
       'ejection_fraction', 'high_blood_pressure', 'platelets',
       'serum_creatinine', 'serum_sodium', 'sex', 'smoking'],
      dtype='object')
```

[50]:
```
clf = tree.DecisionTreeClassifier(criterion = combination[0], splitter =␣
 ↪combination[1], max_depth = combination[2], random_state = 321)
clf = clf.fit(X_train, y_train)
plt.figure(figsize=(5,5))
tree.plot_tree(clf, fontsize = 12)
plt.show()
y_train_pred = clf.predict(X_train)
y_test_pred = clf.predict(X_test)
train_acc = accuracy_score(y_train, y_train_pred); print(train_acc)
test_acc = accuracy_score(y_test, y_test_pred); print(test_acc)

# x[7] is serum_creatinine
```




```
0.7437185929648241
0.77
```

[51]:
```
confusion_mtx = confusion_matrix(y_test, y_test_pred)

disp = ConfusionMatrixDisplay(confusion_matrix= confusion_mtx, display_labels=␣
 ↪None)
disp.plot(cmap= plt.cm.Blues)
plt.title("Confusion matrix")
plt.show()

print("\nClassification Report:\n", classification_report(y_test, y_test_pred))
```




```
Classification Report:
              precision    recall  f1-score   support

           0       0.80      0.92      0.86        75
           1       0.57      0.32      0.41        25

    accuracy                           0.77       100
   macro avg       0.69      0.62      0.63       100
weighted avg       0.74      0.77      0.75       100
```

[52]:
```
from sklearn.linear_model import LogisticRegression
```

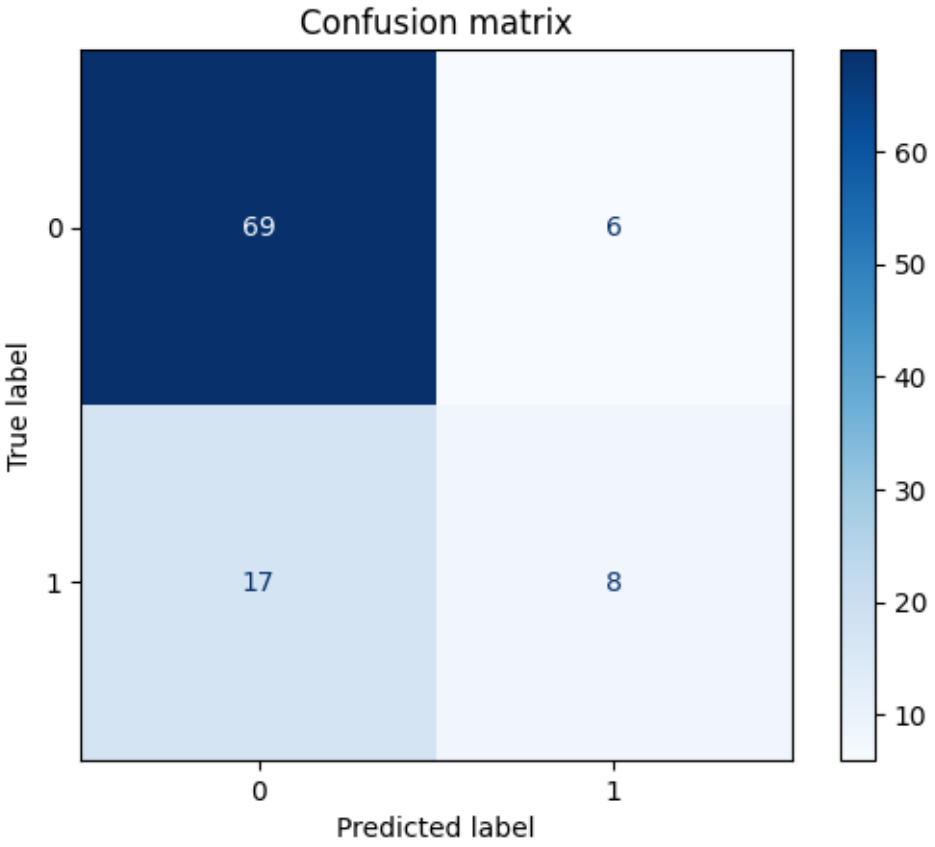
[18]:
```
# X_train_scaled
```

[53]:
```
lg_model = LogisticRegression()
lg_model = lg_model.fit(X_train_scaled, y_train)
y_pred_lg = lg_model.predict(X_test_scaled)
```

[54]:
```
print(X_train_scaled.shape); print(y_train.shape);
print(X_test_scaled.shape); print(y_test.shape);
print(y_pred_lg.shape)
```

```
(199, 11)
(199,)
(100, 11)
(100,)
(100,)
```

[55]:
```
confusion_mtx = confusion_matrix(y_test, y_pred_lg)

disp = ConfusionMatrixDisplay(confusion_matrix= confusion_mtx, display_labels=␣
 ↪None)
disp.plot(cmap= plt.cm.Blues)
plt.title("Confusion matrix")
plt.show()

print("\nClassification Report:\n", classification_report(y_test, y_pred_lg))
```



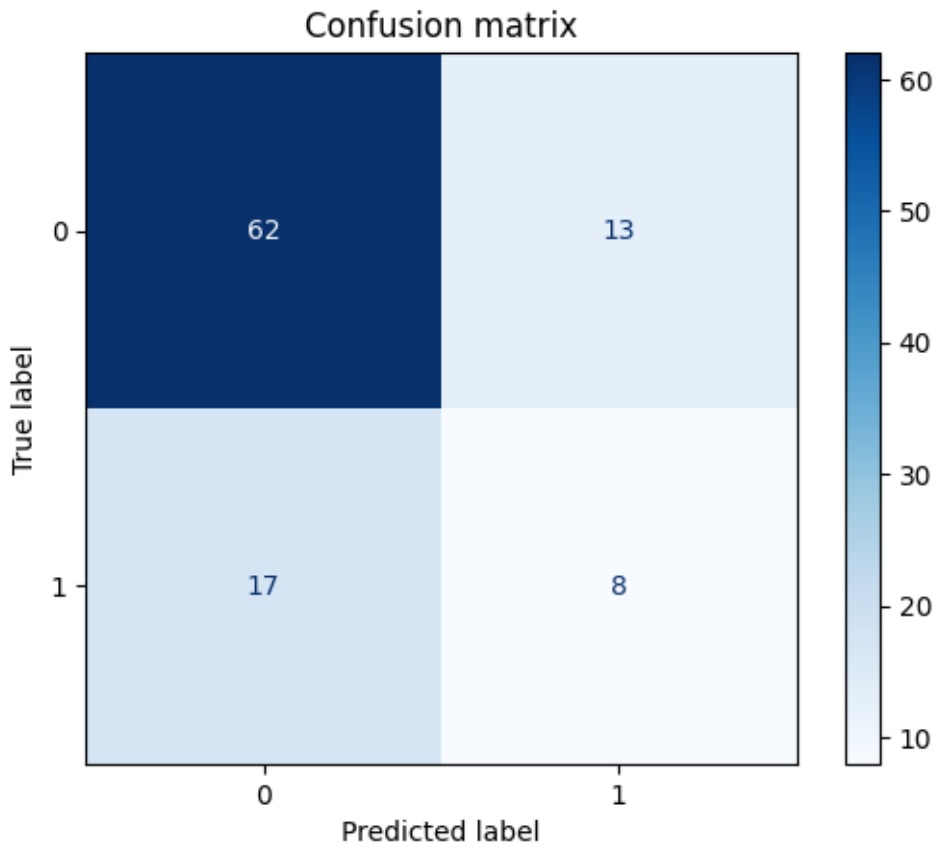
```
Classification Report:
              precision    recall  f1-score   support

           0       0.80      0.92      0.86        75
           1       0.57      0.32      0.41        25

    accuracy                           0.77       100
   macro avg       0.69      0.62      0.63       100
weighted avg       0.74      0.77      0.75       100
```

1.3 Support Vector Machine

[56]:
```
from sklearn.svm import SVC
```

[57]:
```
svm_model = SVC()
svm_model = svm_model.fit(X_train_scaled, y_train)
y_pred_svm = svm_model.predict(X_test_scaled)
```

[58]:
```
confusion_mtx = confusion_matrix(y_test, y_pred_svm)

disp = ConfusionMatrixDisplay(confusion_matrix= confusion_mtx, display_labels=␣
 ↪None)
disp.plot(cmap= plt.cm.Blues)
plt.title("Confusion matrix")
plt.show()

print("\nClassification Report:\n", classification_report(y_test, y_pred_svm))
```




```
Classification Report:
              precision    recall  f1-score   support

           0       0.78      0.83      0.81        75
           1       0.38      0.32      0.35        25

    accuracy                           0.70       100
   macro avg       0.58      0.57      0.58       100
weighted avg       0.68      0.70      0.69       100
```

1.4 Neural network

[59]:
```
input_layer = Input(shape=(X_train_scaled.shape[1],))
```

[27]:
```
# # Grid search
# aux = 0;
# for neurons in [5, 10, 16, 32, 64]:
#     for dropout_rate in [0, 0.1, 0.2, 0.3]:
```

```
#         for batch_size in [16, 32]:

#             combination = [neurons, dropout_rate, batch_size]
#             print(combination)
#             keras.utils.set_random_seed(1)

#             model = Sequential()
#             model.add(Dense(neurons, input_shape=(X_train_scaled.shape[1],),␣
 ↪activation='relu'))
#             model.add(Dropout(rate=dropout_rate))
#             model.add(Dense(2,activation='softmax'))
#             model.compile(optimizer='adam', loss='binary_crossentropy',␣
 ↪metrics = 'accuracy')

#             history = model.fit(X_train_scaled, pd.get_dummies(y_train).
 ↪values,
#             batch_size=batch_size,
#             epochs=200,
#             validation_split=0.3,
#             verbose=0)

#             score = model.evaluate(X_test_scaled,pd.get_dummies(y_test).
 ↪values)
#             if score[1] > aux:
#                 aux = score[1]

# print(combination)
# print(aux)
```

```
[5, 0, 16]
4/4 [==============================] - 0s 2ms/step - loss: 0.6961 - accuracy:
0.7900
[5, 0, 32]
4/4 [==============================] - 0s 2ms/step - loss: 0.6233 - accuracy:
0.7700
[5, 0.1, 16]
4/4 [==============================] - 0s 2ms/step - loss: 0.6711 - accuracy:
0.7800
[5, 0.1, 32]
4/4 [==============================] - 0s 1ms/step - loss: 0.5994 - accuracy:
0.7700
[5, 0.2, 16]
4/4 [==============================] - 0s 2ms/step - loss: 0.6322 - accuracy:
0.7600
[5, 0.2, 32]
4/4 [==============================] - 0s 2ms/step - loss: 0.5817 - accuracy:
0.7500
```

```
[5, 0.3, 16]
4/4 [==============================] - 0s 2ms/step - loss: 0.6121 - accuracy:
0.7500
[5, 0.3, 32]
4/4 [==============================] - 0s 2ms/step - loss: 0.5698 - accuracy:
0.7500
[10, 0, 16]
4/4 [==============================] - 0s 2ms/step - loss: 0.8464 - accuracy:
0.7300
[10, 0, 32]
4/4 [==============================] - 0s 2ms/step - loss: 0.7032 - accuracy:
0.7600
[10, 0.1, 16]
4/4 [==============================] - 0s 2ms/step - loss: 0.8014 - accuracy:
0.7300
[10, 0.1, 32]
4/4 [==============================] - 0s 2ms/step - loss: 0.6804 - accuracy:
0.7600
[10, 0.2, 16]
4/4 [==============================] - 0s 2ms/step - loss: 0.7669 - accuracy:
0.7400
[10, 0.2, 32]
4/4 [==============================] - 0s 2ms/step - loss: 0.6581 - accuracy:
0.7600
[10, 0.3, 16]
4/4 [==============================] - 0s 2ms/step - loss: 0.7458 - accuracy:
0.7500
[10, 0.3, 32]
4/4 [==============================] - 0s 2ms/step - loss: 0.6407 - accuracy:
0.7600
[16, 0, 16]
4/4 [==============================] - 0s 1ms/step - loss: 0.9397 - accuracy:
0.7700
[16, 0, 32]
4/4 [==============================] - 0s 2ms/step - loss: 0.7964 - accuracy:
0.7700
[16, 0.1, 16]
4/4 [==============================] - 0s 2ms/step - loss: 0.8925 - accuracy:
0.7600
[16, 0.1, 32]
4/4 [==============================] - 0s 2ms/step - loss: 0.7671 - accuracy:
0.7700
[16, 0.2, 16]
4/4 [==============================] - 0s 2ms/step - loss: 0.8598 - accuracy:
0.7600
[16, 0.2, 32]
4/4 [==============================] - 0s 2ms/step - loss: 0.7343 - accuracy:
0.7700
```

```
[16, 0.3, 16]
4/4 [==============================] - 0s 2ms/step - loss: 0.8171 - accuracy:
0.7800
[16, 0.3, 32]
4/4 [==============================] - 0s 2ms/step - loss: 0.7076 - accuracy:
0.7900
[32, 0, 16]
4/4 [==============================] - 0s 1ms/step - loss: 1.0190 - accuracy:
0.7700
[32, 0, 32]
4/4 [==============================] - 0s 1ms/step - loss: 0.8531 - accuracy:
0.7800
[32, 0.1, 16]
4/4 [==============================] - 0s 2ms/step - loss: 0.9683 - accuracy:
0.7800
[32, 0.1, 32]
4/4 [==============================] - 0s 2ms/step - loss: 0.8202 - accuracy:
0.7800
[32, 0.2, 16]
4/4 [==============================] - 0s 1ms/step - loss: 0.9192 - accuracy:
0.7700
[32, 0.2, 32]
4/4 [==============================] - 0s 2ms/step - loss: 0.7881 - accuracy:
0.7900
[32, 0.3, 16]
4/4 [==============================] - 0s 2ms/step - loss: 0.8816 - accuracy:
0.7700
[32, 0.3, 32]
4/4 [==============================] - 0s 1ms/step - loss: 0.7652 - accuracy:
0.7900
[64, 0, 16]
4/4 [==============================] - 0s 2ms/step - loss: 1.1972 - accuracy:
0.7200
[64, 0, 32]
4/4 [==============================] - 0s 2ms/step - loss: 0.9857 - accuracy:
0.7300
[64, 0.1, 16]
4/4 [==============================] - 0s 2ms/step - loss: 1.1265 - accuracy:
0.7200
[64, 0.1, 32]
4/4 [==============================] - 0s 2ms/step - loss: 0.9522 - accuracy:
0.7300
[64, 0.2, 16]
4/4 [==============================] - 0s 2ms/step - loss: 1.0886 - accuracy:
0.7200
[64, 0.2, 32]
4/4 [==============================] - 0s 2ms/step - loss: 0.9214 - accuracy:
0.7400
```

```
[64, 0.3, 16]
4/4 [==============================] - 0s 2ms/step - loss: 1.0399 - accuracy:
0.7300
[64, 0.3, 32]
4/4 [==============================] - 0s 1ms/step - loss: 0.8996 - accuracy:
0.7400
[64, 0.3, 32]
0.7900000214576721
```

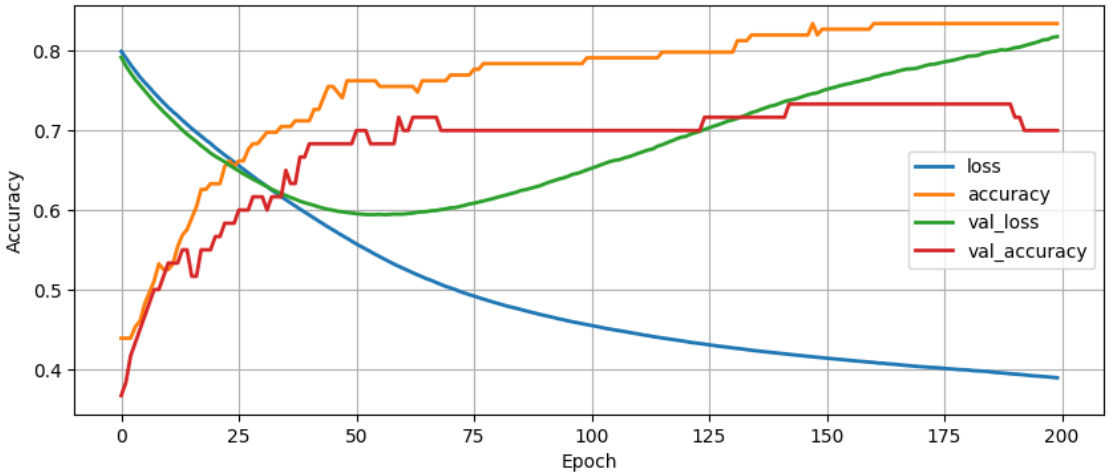
Best combination is 'neurons' = 5, 'dropout_rate' = 0, 'batch_size' = 16.

[62]:
```
keras.utils.set_random_seed(1)

model = Sequential()
model.add(Dense(5, input_shape=(X_train_scaled.shape[1],), activation='relu'))
model.add(Dropout(rate=0))
model.add(Dense(2,activation='softmax'))

model.compile(optimizer='adam', loss='binary_crossentropy', metrics =␣
 ↪'accuracy')


history = model.fit(X_train_scaled, pd.get_dummies(y_train).values,
    batch_size=16,
    epochs=200,
    validation_split=0.3,
    verbose=0)

score = model.evaluate(X_test_scaled,pd.get_dummies(y_test).values)

if score[1] > aux:
    aux = score[1]
    print(aux)
```

```
4/4 [==============================] - 0s 2ms/step - loss: 0.6961 - accuracy:
0.7900
```

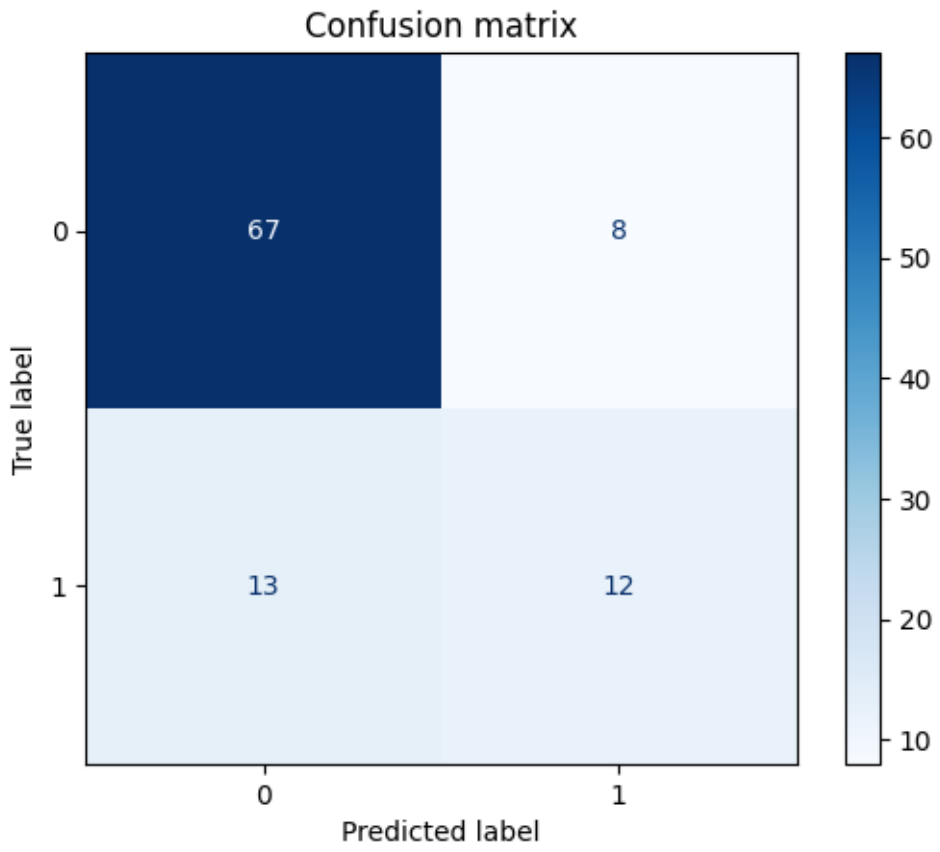
[63]:
```
pd.DataFrame(history.history).plot(figsize=(10, 4), linewidth=2)
plt.grid(); plt.xlabel('Epoch'); plt.ylabel('Accuracy')
```

[63]:
```
Text(0, 0.5, 'Accuracy')
```



[64]:
```
yhat = model.predict(X_test_scaled);

y_pred_labels = np.argmax(yhat, axis=1)

confusion_mtx = confusion_matrix(y_test, y_pred_labels)

disp = ConfusionMatrixDisplay(confusion_matrix= confusion_mtx, display_labels=␣
 ↪None)
disp.plot(cmap= plt.cm.Blues)
plt.title("Confusion matrix")
plt.show()

print("\nClassification Report:\n", classification_report(y_test,␣
 ↪y_pred_labels))
```

```
4/4 [==============================] - 0s 1ms/step
```




```
Classification Report:
              precision    recall  f1-score   support

           0       0.84      0.89      0.86        75
           1       0.60      0.48      0.53        25

    accuracy                           0.79       100
   macro avg       0.72      0.69      0.70       100
weighted avg       0.78      0.79      0.78       100
```