Programma seconda 3

May 14, 2024

Contents

1 Puliamo il dataset

[19]:
```
import sys
import pandas as pd
import numpy as np
import sklearn
import matplotlib

print('Python: {}'.format(sys.version))
print('Pandas: {}'.format(pd.__version__))
print('Numpy: {}'.format(np.__version__))
print('Sklearn: {}'.format(sklearn.__version__))
print('Matplotlib: {}'.format(matplotlib.__version__))
```

```
Python: 3.11.9 (tags/v3.11.9:de54cf5, Apr  2 2024, 10:12:12) [MSC v.1938 64 bit
(AMD64)]
Pandas: 2.2.1
Numpy: 1.26.4
Sklearn: 1.4.1.post1
Matplotlib: 3.8.4
```

[20]:
```
import matplotlib.pyplot as plt
from pandas.plotting import scatter_matrix
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split, GridSearchCV
```

[21]:
```
cleveland = pd.read_csv(r'C:\Users\david\Documents\heart.csv')
```

[22]:
```
print( 'Shape of DataFrame: {}'.format(cleveland.shape))
print (cleveland.loc[1])
```

```
Shape of DataFrame: (303, 14)
age          37.0
sex           1.0
cp            2.0
trestbps    130.0
chol        250.0
fbs           0.0
restecg       1.0
thalach     187.0
exang         0.0
oldpeak       3.5
```

```
slope          0.0
ca             0.0
thal           2.0
target         1.0
Name: 1, dtype: float64
```

[24]:
```
#ultimi 20 valori del dataframe
print(cleveland.tail(20))
```

```
     age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
283   40    1   0       152   223    0        1      181      0      0.0
284   61    1   0       140   207    0        0      138      1      1.9
285   46    1   0       140   311    0        1      120      1      1.8
286   59    1   3       134   204    0        1      162      0      0.8
287   57    1   1       154   232    0        0      164      0      0.0
288   57    1   0       110   335    0        1      143      1      3.0
289   55    0   0       128   205    0        2      130      1      2.0
290   61    1   0       148   203    0        1      161      0      0.0
291   58    1   0       114   318    0        2      140      0      4.4
292   58    0   0       170   225    1        0      146      1      2.8
293   67    1   2       152   212    0        0      150      0      0.8
294   44    1   0       120   169    0        1      144      1      2.8
295   63    1   0       140   187    0        0      144      1      4.0
296   63    0   0       124   197    0        1      136      1      0.0
297   59    1   0       164   176    1        0       90      0      1.0
298   57    0   0       140   241    0        1      123      1      0.2
299   45    1   3       110   264    0        1      132      0      1.2
300   68    1   0       144   193    1        1      141      0      3.4
301   57    1   0       130   131    0        1      115      1      1.2
302   57    0   1       130   236    0        0      174      0      0.0

     slope  ca  thal  target
283      2   0     3       0
284      2   1     3       0
285      1   2     3       0
286      2   2     2       0
287      2   1     2       0
288      1   1     3       0
289      1   1     3       0
290      2   1     3       0
291      0   3     1       0
292      1   2     1       0
293      1   0     3       0
294      0   0     1       0
295      2   2     3       0
296      1   0     2       0
297      1   2     1       0
298      1   0     3       0
```

```
299       1    0      3        0
300       1    2      3        0
301       1    1      3        0
302       1    1      2        0
```

[37]:
```python
#rimuove i missing values indicati con "?"
data = cleveland[~cleveland.isin(['?'])]
data.loc[280:]
```

[37]:
```
     age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
280   42    1   0       136   315    0        1      125      1      1.8
281   52    1   0       128   204    1        1      156      1      1.0
282   59    1   2       126   218    1        1      134      0      2.2
283   40    1   0       152   223    0        1      181      0      0.0
284   61    1   0       140   207    0        0      138      1      1.9
285   46    1   0       140   311    0        1      120      1      1.8
286   59    1   3       134   204    0        1      162      0      0.8
287   57    1   1       154   232    0        0      164      0      0.0
288   57    1   0       110   335    0        1      143      1      3.0
289   55    0   0       128   205    0        2      130      1      2.0
290   61    1   0       148   203    0        1      161      0      0.0
291   58    1   0       114   318    0        2      140      0      4.4
292   58    0   0       170   225    1        0      146      1      2.8
293   67    1   2       152   212    0        0      150      0      0.8
294   44    1   0       120   169    0        1      144      1      2.8
295   63    1   0       140   187    0        0      144      1      4.0
296   63    0   0       124   197    0        1      136      1      0.0
297   59    1   0       164   176    1        0       90      0      1.0
298   57    0   0       140   241    0        1      123      1      0.2
299   45    1   3       110   264    0        1      132      0      1.2
300   68    1   0       144   193    1        1      141      0      3.4
301   57    1   0       130   131    0        1      115      1      1.2
302   57    0   1       130   236    0        0      174      0      0.0

     slope  ca  thal  target
280      1   0     1       0
281      1   0     0       0
282      1   1     1       0
283      2   0     3       0
284      2   1     3       0
285      1   2     3       0
286      2   2     2       0
287      2   1     2       0
288      1   1     3       0
289      1   1     3       0
290      2   1     3       0
291      0   3     1       0
```

```
292      1  2     1       0
293      1  0     3       0
294      0  0     1       0
295      2  2     3       0
296      1  0     2       0
297      1  2     1       0
298      1  0     3       0
299      1  0     3       0
300      1  2     3       0
301      1  1     3       0
302      1  1     2       0
```

[45]:
```python
#elimina le righe con valori mancanti
data = data.dropna(axis=0)
data.loc[280:]
```

[45]:
```
     age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
280   42    1   0       136   315    0        1      125      1      1.8
281   52    1   0       128   204    1        1      156      1      1.0
282   59    1   2       126   218    1        1      134      0      2.2
283   40    1   0       152   223    0        1      181      0      0.0
284   61    1   0       140   207    0        0      138      1      1.9
285   46    1   0       140   311    0        1      120      1      1.8
286   59    1   3       134   204    0        1      162      0      0.8
287   57    1   1       154   232    0        0      164      0      0.0
288   57    1   0       110   335    0        1      143      1      3.0
289   55    0   0       128   205    0        2      130      1      2.0
290   61    1   0       148   203    0        1      161      0      0.0
291   58    1   0       114   318    0        2      140      0      4.4
292   58    0   0       170   225    1        0      146      1      2.8
293   67    1   2       152   212    0        0      150      0      0.8
294   44    1   0       120   169    0        1      144      1      2.8
295   63    1   0       140   187    0        0      144      1      4.0
296   63    0   0       124   197    0        1      136      1      0.0
297   59    1   0       164   176    1        0       90      0      1.0
298   57    0   0       140   241    0        1      123      1      0.2
299   45    1   3       110   264    0        1      132      0      1.2
300   68    1   0       144   193    1        1      141      0      3.4
301   57    1   0       130   131    0        1      115      1      1.2
302   57    0   1       130   236    0        0      174      0      0.0

     slope  ca  thal  target
280      1   0     1       0
281      1   0     0       0
282      1   1     1       0
283      2   0     3       0
284      2   1     3       0
```

```
285        1   2     3       0
286        2   2     2       0
287        2   1     2       0
288        1   1     3       0
289        1   1     3       0
290        2   1     3       0
291        0   3     1       0
292        1   2     1       0
293        1   0     3       0
294        0   0     1       0
295        2   2     3       0
296        1   0     2       0
297        1   2     1       0
298        1   0     3       0
299        1   0     3       0
300        1   2     3       0
301        1   1     3       0
302        1   1     2       0
```

[28]:

```
#stampa la forma e il tipo di dati del dataframe
print(data.shape)
print(data.dtypes)
```

```
(303, 14)
age            int64
sex            int64
cp             int64
trestbps       int64
chol           int64
fbs            int64
restecg        int64
thalach        int64
exang          int64
oldpeak      float64
slope          int64
ca             int64
thal           int64
target         int64
dtype: object
```

[29]:

```
#stampa le caratteristiche data
data.describe()
```

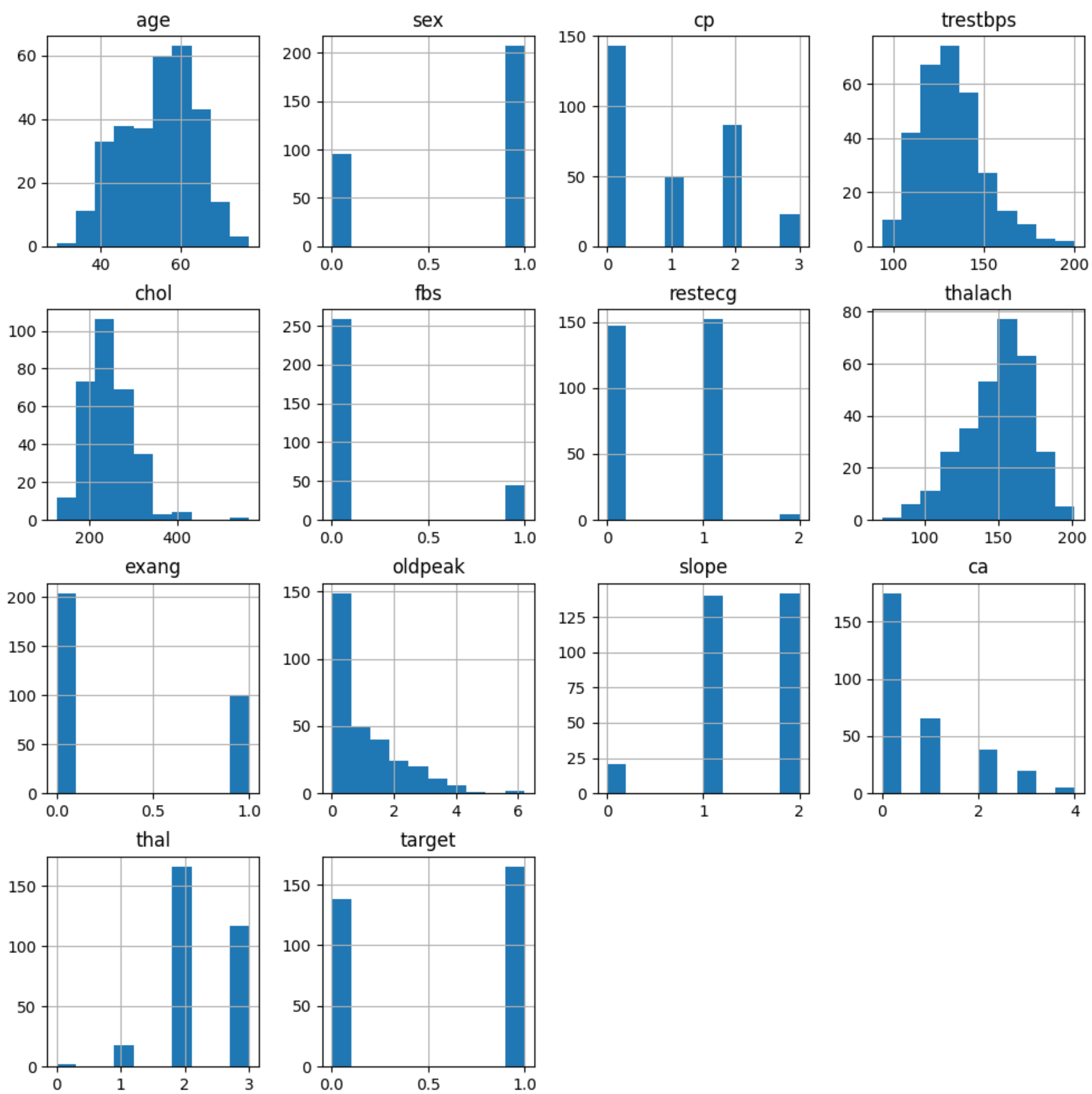
[29]:

```
              age         sex          cp    trestbps        chol         fbs  \
count  303.000000  303.000000  303.000000  303.000000  303.000000  303.000000
mean    54.366337    0.683168    0.966997  131.623762  246.264026    0.148515
std      9.082101    0.466011    1.032052   17.538143   51.830751    0.356198
min     29.000000    0.000000    0.000000   94.000000  126.000000    0.000000
```

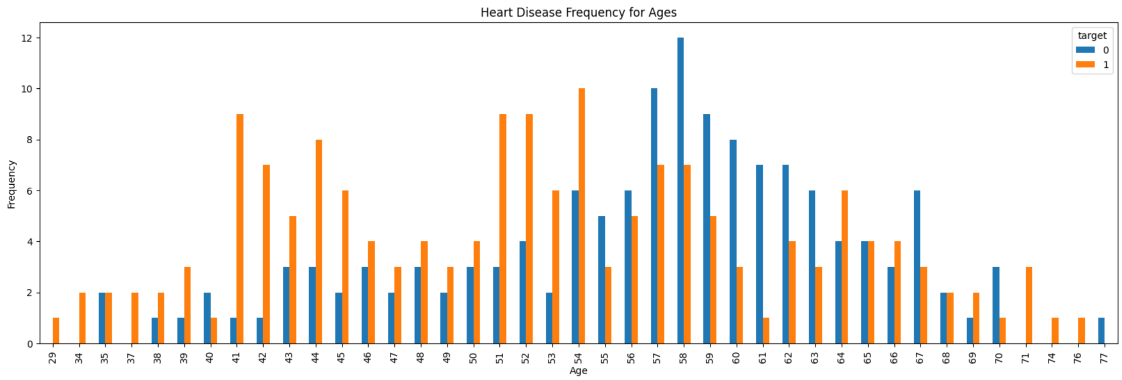
```
25%     47.500000    0.000000    0.000000  120.000000  211.000000    0.000000
50%     55.000000    1.000000    1.000000  130.000000  240.000000    0.000000
75%     61.000000    1.000000    2.000000  140.000000  274.500000    0.000000
max     77.000000    1.000000    3.000000  200.000000  564.000000    1.000000

          restecg     thalach       exang     oldpeak       slope          ca  \
count  303.000000  303.000000  303.000000  303.000000  303.000000  303.000000
mean     0.528053  149.646865    0.326733    1.039604    1.399340    0.729373
std      0.525860   22.905161    0.469794    1.161075    0.616226    1.022606
min      0.000000   71.000000    0.000000    0.000000    0.000000    0.000000
25%      0.000000  133.500000    0.000000    0.000000    1.000000    0.000000
50%      1.000000  153.000000    0.000000    0.800000    1.000000    0.000000
75%      1.000000  166.000000    1.000000    1.600000    2.000000    1.000000
max      2.000000  202.000000    1.000000    6.200000    2.000000    4.000000

             thal      target
count  303.000000  303.000000
mean     2.313531    0.544554
std      0.612277    0.498835
min      0.000000    0.000000
25%      2.000000    0.000000
50%      2.000000    1.000000
75%      3.000000    1.000000
max      3.000000    1.000000
```

2 Visualiziamo i grafici

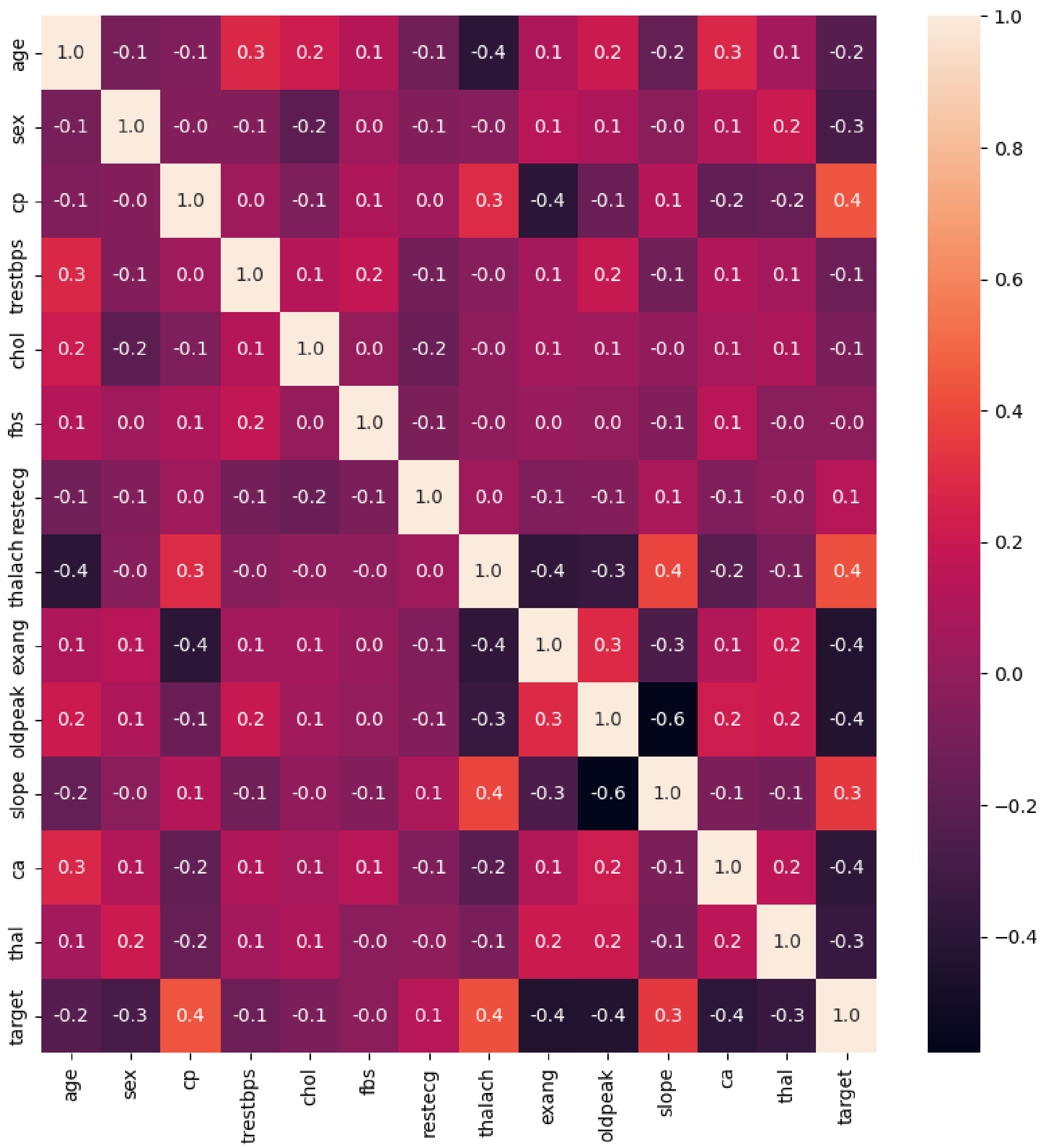
[20]:
```
#istogrammi per ogni caratteristica
data.hist(figsize = (12, 12))
plt.show()
```



[21]:
```
pd.crosstab(data.age,data.target).plot(kind="bar",figsize=(20,6))
plt.title('Heart Disease Frequency for Ages')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```



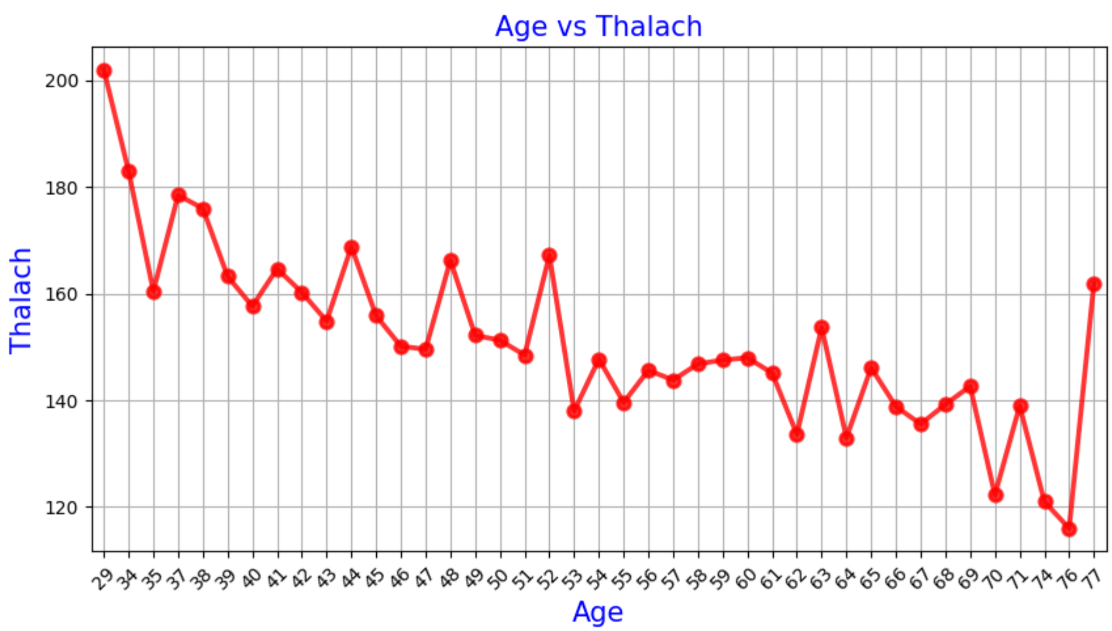
[22]:
```
plt.figure(figsize=(10,10))
sns.heatmap(data.corr(),annot=True,fmt='.1f')
plt.show()
```



3 Age vs Thalach

[23]:
```
age_unique=sorted(data.age.unique())
age_thalach_values=data.groupby('age')['thalach'].count().values
mean_thalach=[]
for i,age in enumerate(age_unique):
    mean_thalach.append(sum(data[data['age']==age].thalach)/
 ↪age_thalach_values[i])
```

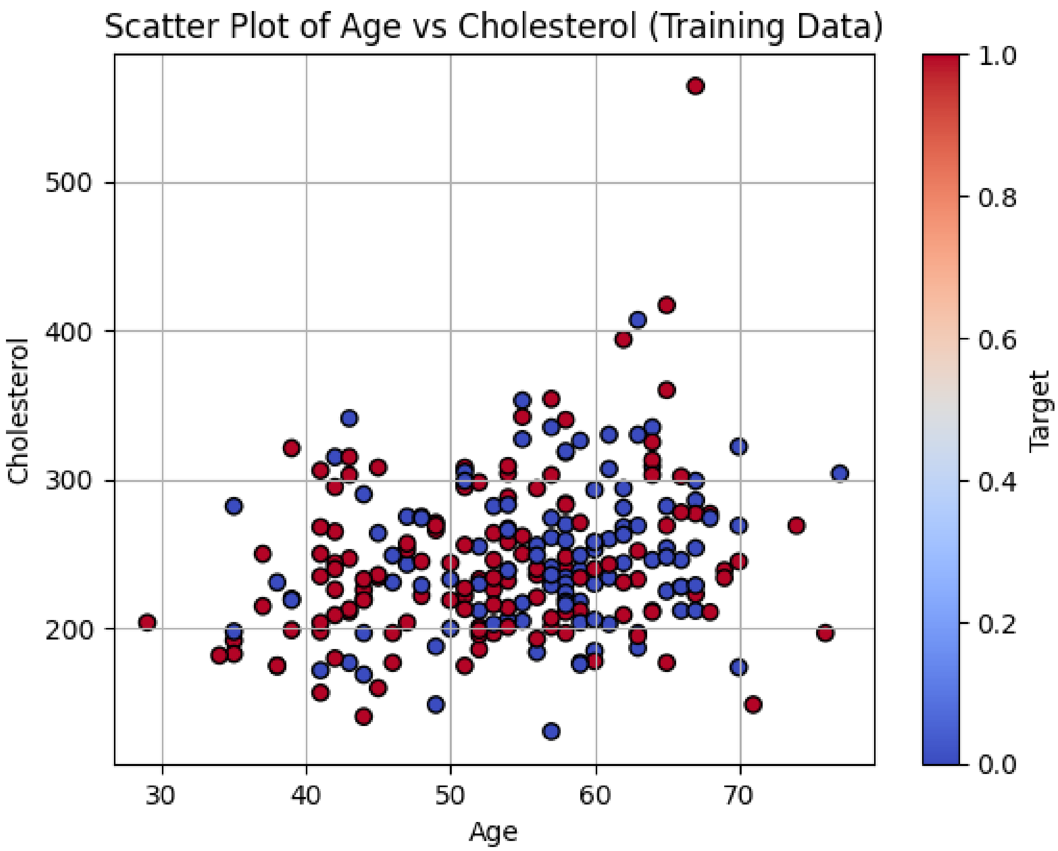
```
plt.figure(figsize=(10,5))
sns.pointplot(x=age_unique,y=mean_thalach,color='red',alpha=0.8)
plt.xlabel('Age',fontsize = 15,color='blue')
plt.xticks(rotation=45)
plt.ylabel('Thalach',fontsize = 15,color='blue')
plt.title('Age vs Thalach',fontsize = 15,color='blue')
plt.grid()
plt.show()
```



4 Test e train dataset

[4]:
```
#dividiamo il dataset in features (X) e target variable (y)
X = heart_data.drop('target', axis=1)  #features
y = heart_data['target']               #target variable

#suddividiamo il dataset in set di addestramento e di test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

#grafico per visualizzare i dati di addestramento
plt.scatter(X_train['age'], X_train['chol'], c=y_train, cmap='coolwarm',␣
↪marker='o', edgecolors='k')
plt.xlabel('Age')
plt.ylabel('Cholesterol')
plt.title('Scatter Plot of Age vs Cholesterol (Training Data)')
```

```
plt.colorbar(label='Target')
plt.grid(True)
plt.show()
```

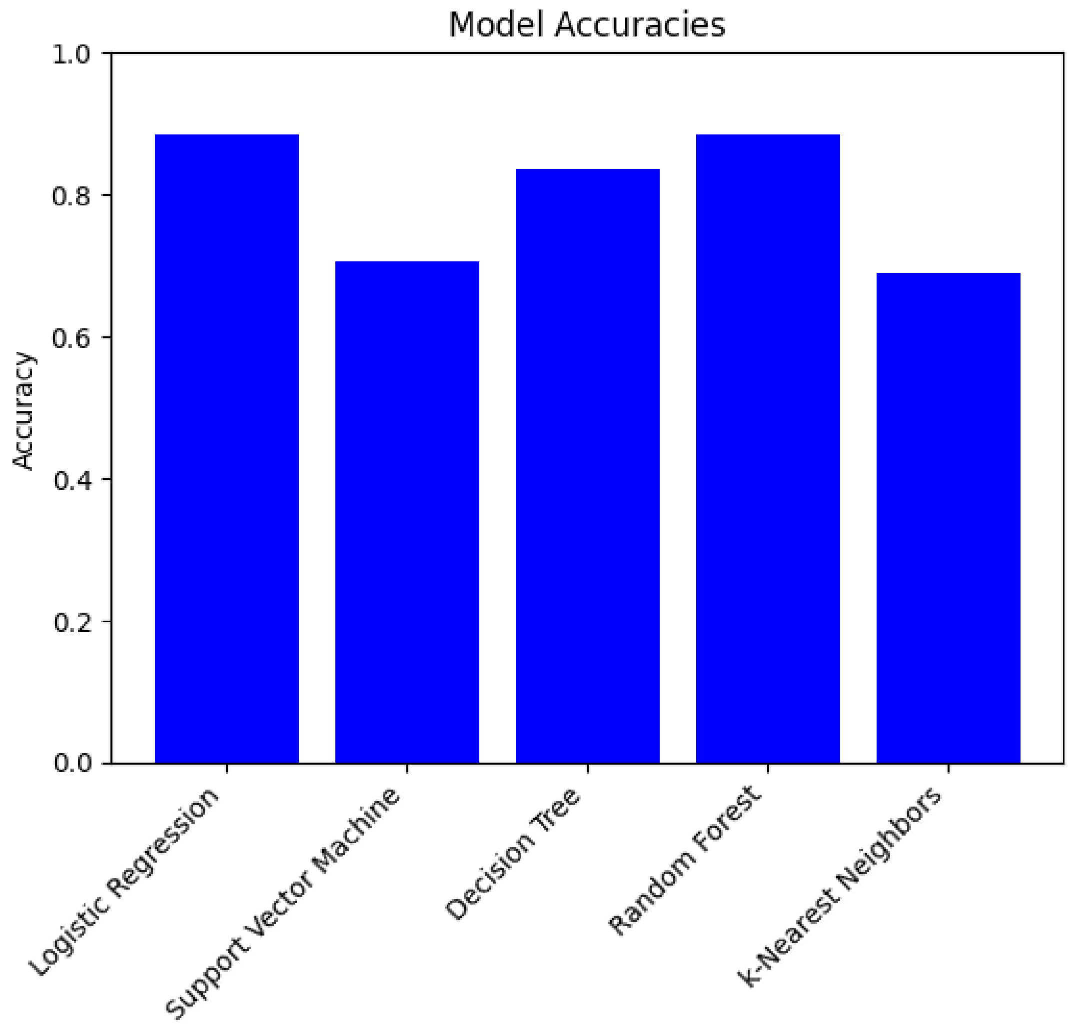


5 Accuratezza dei vari modelli

[7]:
```
#dividiamo il dataset in features (X) e target variable (y)
X = heart_data.drop('target', axis=1)  # Features
y = heart_data['target']               # Target variable

#suddividiamo il dataset in set di addestramento e di test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

#inizializziamo i modelli
models = {
    'Logistic Regression': LogisticRegression(),
    'Support Vector Machine': SVC(),
    'Decision Tree': DecisionTreeClassifier(),
```

```python
    'Random Forest': RandomForestClassifier(),
    'k-Nearest Neighbors': KNeighborsClassifier()
}

#addestramento e valutazione dei modelli
results = {}
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    results[name] = accuracy

#grafico a barre
plt.bar(results.keys(), results.values(), color='blue')
plt.ylabel('Accuracy')
plt.title('Model Accuracies')
plt.ylim(0, 1)
plt.xticks(rotation=45, ha='right')
plt.show()
```

```
C:\Users\david\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n
2kfra8p0\LocalCache\local-packages\Python311\site-
packages\sklearn\linear_model\_logistic.py:469: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```



6 Logistic Regression model

[8]:
```
#divisione del dataset in features (X) e target variable (y)
X = heart_data.drop('target', axis=1)
y = heart_data['target']

#suddivididivisione del dataset in set di addestramento e di test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

#addestramento e valutazione della regressione logistica
model = LogisticRegression().fit(X_train, y_train)

#valutazione dell'accuratezza del modello sui dati di test
```

```
accuracy = accuracy_score(y_test, model.predict(X_test))
print(f'Accuracy del modello di regressione logistica: {accuracy:.2f}')
```

```
Accuracy del modello di regressione logistica: 0.89
```

```
C:\Users\david\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n
2kfra8p0\LocalCache\local-packages\Python311\site-
packages\sklearn\linear_model\_logistic.py:469: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

7 Support Vector Machine model

[12]:
```
#divisione del dataset in features (X) e target variable (y)
X = heart_data.drop('target', axis=1)
y = heart_data['target']

#suddividivisione del dataset in set di addestramento e di test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

#definiamo i parametri della griglia da testare
param_grid = {'C': [0.1, 1, 10, 100], 'gamma': [0.1, 0.01, 0.001]}

#cerchiamo i migliori parametri con la cross-validation
grid_search = GridSearchCV(SVC(kernel='rbf'), param_grid, cv=5)
grid_search.fit(X_train, y_train)

#valutiamo l'accuratezza del modello migliore
accuracy = accuracy_score(y_test, grid_search.best_estimator_.predict(X_test))
print(f'Accuracy del modello Support Vector Machine: {accuracy:.2f}')
```

```
Accuracy del modello Support Vector Machine: 0.67
```

8 Decision Tree model

[13]:
```
#divisione del dataset in features (X) e target variable (y)
X = heart_data.drop('target', axis=1)  #features
y = heart_data['target']               #target variable
```

```
#suddividivisione del dataset in set di addestramento e di test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

#inizializziamo e addestriamo dell modello di albero decisionale
decision_tree = DecisionTreeClassifier()
decision_tree.fit(X_train, y_train)

#valutia l'accuratezza del modello sui dati di test
y_pred = decision_tree.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)

print(f'Accuracy of Decision Tree model: {accuracy:.2f}')
```

```
Accuracy of Decision Tree model: 0.80
```

9 Random Forest model

[14]:
```
#divisione del dataset in features (X) e target variable (y)
X = heart_data.drop('target', axis=1)  #features
y = heart_data['target']               #target variable

#suddividivisione del dataset in set di addestramento e di test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

#definiamo i parametri della griglia da testare
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

#inizializziamo il classificatore Random Forest
random_forest = RandomForestClassifier(random_state=42)

#utilizziamo la ricerca dei parametri tramite cross-validation per trovare i␣
↪migliori parametri
grid_search = GridSearchCV(random_forest, param_grid, cv=5)
grid_search.fit(X_train, y_train)

#otteniamo il miglior modello dalla ricerca dei parametri
best_random_forest = grid_search.best_estimator_

#valutiamo l'accuratezza del modello sui dati di test
y_pred = best_random_forest.predict(X_test)
```

```
accuracy = accuracy_score(y_test, y_pred)

print(f'Accuracy of Random Forest model: {accuracy:.2f}')
```

```
Accuracy of Random Forest model: 0.85
```

10 k-Nearest Neighbors model

[15]:
```
#divisione del dataset in features (X) e target variable (y)
X = heart_data.drop('target', axis=1)  #features
y = heart_data['target']               #target variable

#suddividivisione del dataset in set di addestramento e di test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

#definiamo i parametri della griglia da testare
param_grid = {'n_neighbors': range(1, 21)}  # Testa k da 1 a 20

#inizializziamo il classificatore k-Nearest Neighbors
knn = KNeighborsClassifier()

#utilizziamo la ricerca dei parametri tramite cross-validation per trovare il␣
 ↪miglior valore di k
grid_search = GridSearchCV(knn, param_grid, cv=5)
grid_search.fit(X_train, y_train)

#otteniamo il miglior modello dalla ricerca dei parametri
best_knn = grid_search.best_estimator_

#valutiamo l'accuratezza del modello sui dati di test
y_pred = best_knn.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)

print(f'Accuracy of k-Nearest Neighbors model: {accuracy:.2f}')
```

```
Accuracy of k-Nearest Neighbors model: 0.66
```