This code loads a dataset, visualizes correlations, distributions, and pairwise relationships between features,

trains a linear regression model for diabetes prediction, and evaluates model performance using accuracy, confusion matrix, and classification report.

Here a more concise version:

1.Load Data: Import dataset.

2.Visualizations: Show correlations, target distribution, and pairwise relationships.

3.Train Model: Fit a linear regression model.

4Evaluate: Calculate accuracy, confusion matrix, and classification report.

In [80]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [81]:
```
from sklearn.datasets import load_diabetes
```

In [82]:
```
diabetes = load_diabetes()
```

In [83]:
```
diabetes
```

Out[83]:

```
{'data': array([[ 0.03807591,  0.05068012,  0.06169621, ..., -0.00259226,
          0.01990749, -0.01764613],
        [-0.00188202, -0.04464164, -0.05147406, ..., -0.03949338,
         -0.06833155, -0.09220405],
        [ 0.08529891,  0.05068012,  0.04445121, ..., -0.00259226,
          0.00286131, -0.02593034],
        ...,
        [ 0.04170844,  0.05068012, -0.01590626, ..., -0.01107952,
         -0.04688253,  0.01549073],
        [-0.04547248, -0.04464164,  0.03906215, ...,  0.02655962,
          0.04452873, -0.02593034],
        [-0.04547248, -0.04464164, -0.0730303 , ..., -0.03949338,
         -0.00422151,  0.00306441]]),
 'target': array([151.,  75., 141., 206., 135.,  97., 138.,  63., 110., 310., 101.,
         69., 179., 185., 118., 171., 166., 144.,  97., 168.,  68.,  49.,
         68., 245., 184., 202., 137.,  85., 131., 283., 129.,  59., 341.,
         87.,  65., 102., 265., 276., 252.,  90., 100.,  55.,  61.,  92.,
        259.,  53., 190., 142.,  75., 142., 155., 225.,  59., 104., 182.,
        128.,  52.,  37., 170., 170.,  61., 144.,  52., 128.,  71., 163.,
        150.,  97., 160., 178.,  48., 270., 202., 111.,  85.,  42., 170.,
        200., 252., 113., 143.,  51.,  52., 210.,  65., 141.,  55., 134.,
         42., 111.,  98., 164.,  48.,  96.,  90., 162., 150., 279.,  92.,
         83., 128., 102., 302., 198.,  95.,  53., 134., 144., 232.,  81.,
        104.,  59., 246., 297., 258., 229., 275., 281., 179., 200., 200.,
        173., 180.,  84., 121., 161.,  99., 109., 115., 268., 274., 158.,
        107.,  83., 103., 272.,  85., 280., 336., 281., 118., 317., 235.,
         60., 174., 259., 178., 128.,  96., 126., 288.,  88., 292.,  71.,
        197., 186.,  25.,  84.,  96., 195.,  53., 217., 172., 131., 214.,
         59.,  70., 220., 268., 152.,  47.,  74., 295., 101., 151., 127.,
        237., 225.,  81., 151., 107.,  64., 138., 185., 265., 101., 137.,
        143., 141.,  79., 292., 178.,  91., 116.,  86., 122.,  72., 129.,
        142.,  90., 158.,  39., 196., 222., 277.,  99., 196., 202., 155.,
         77., 191.,  70.,  73.,  49.,  65., 263., 248., 296., 214., 185.,
         78.,  93., 252., 150.,  77., 208.,  77., 108., 160.,  53., 220.,
        154., 259.,  90., 246., 124.,  67.,  72., 257., 262., 275., 177.,
         71.,  47., 187., 125.,  78.,  51., 258., 215., 303., 243.,  91.,
        150., 310., 153., 346.,  63.,  89.,  50.,  39., 103., 308., 116.,
        145.,  74.,  45., 115., 264.,  87., 202., 127., 182., 241.,  66.,
         94., 283.,  64., 102., 200., 265.,  94., 230., 181., 156., 233.,
         60., 219.,  80.,  68., 332., 248.,  84., 200.,  55.,  85.,  89.,
         31., 129.,  83., 275.,  65., 198., 236., 253., 124.,  44., 172.,
        114., 142., 109., 180., 144., 163., 147.,  97., 220., 190., 109.,
        191., 122., 230., 242., 248., 249., 192., 131., 237.,  78., 135.,
        244., 199., 270., 164.,  72.,  96., 306.,  91., 214.,  95., 216.,
        263., 178., 113., 200., 139., 139.,  88., 148.,  88., 243.,  71.,
         77., 109., 272.,  60.,  54., 221.,  90., 311., 281., 182., 321.,
         58., 262., 206., 233., 242., 123., 167.,  63., 197.,  71., 168.,
        140., 217., 121., 235., 245.,  40.,  52., 104., 132.,  88.,  69.,
        219.,  72., 201., 110.,  51., 277.,  63., 118.,  69., 273., 258.,
         43., 198., 242., 232., 175.,  93., 168., 275., 293., 281.,  72.,
        140., 189., 181., 209., 136., 261., 113., 131., 174., 257.,  55.,
         84.,  42., 146., 212., 233.,  91., 111., 152., 120.,  67., 310.,
         94., 183.,  66., 173.,  72.,  49.,  64.,  48., 178., 104., 132.,
        220.,  57.]),
 'frame': None,
 'DESCR': '.. _diabetes_dataset:\n\nDiabetes dataset\n----------------\n\nTen baseline variables, age, sex, body mass index, average blood\npressure, and six blood serum measurements were obtained for each of n =\n442 diabetes patients, as well as the response of interest, a\nquantitative measure of disease progression one year after baseline.\n\n**Data Set Characteristics:**\n\n:Number of Instances: 442\n\n:Number of Attributes: First 10 columns are numeric predictive values\n\n:Target: Column 11 is a quantitative measure of disease progression one year after baseline\n\n:Attribute Information:\n    - age     age in years\n    - sex\n    - bmi     body mass index\n    - bp      average blood pressure\n    - s1      tc, total serum cholesterol\n    - s2      ldl, low-density lipoproteins\n    - s3      hdl, high-density lipoproteins\n    - s4      tch, total cholesterol / HDL\n    - s5      ltg, possibly log of serum triglycerides level\n    - s6      glu, blood sugar level\n\nNote: Each of these 10 feature variables have been mean centered and scaled by the standard deviation times the square root of `n_samples` (i.e. the sum of squares of each column totals 1).\n\nSource URL:\nhttps://www4.stat.ncsu.edu/~boos/var.select/diabetes.html\n\nFor more information see:\nBradley Efron, Trevor Hastie, Iain Johnstone and Robert Tibshirani (2004) "Least Angle Regression," Annals of Statistics (with discussion), 407-499.\n(https://web.stanford.edu/~hastie/Papers/LARS/LeastAngle_2002.pdf)\n',
 'feature_names': ['age',
  'sex',
  'bmi',
  'bp',
  's1',
  's2',
  's3',
  's4',
  's5',
  's6'],
 'data_filename': 'diabetes_data_raw.csv.gz',
 'target_filename': 'diabetes_target.csv.gz',
 'data_module': 'sklearn.datasets.data'}
```

In [84]:
```
print(diabetes.DESCR)
```

```
.. _diabetes_dataset:

Diabetes dataset
----------------

Ten baseline variables, age, sex, body mass index, average blood
pressure, and six blood serum measurements were obtained for each of n =
442 diabetes patients, as well as the response of interest, a
quantitative measure of disease progression one year after baseline.

**Data Set Characteristics:**

:Number of Instances: 442

:Number of Attributes: First 10 columns are numeric predictive values

:Target: Column 11 is a quantitative measure of disease progression one year after baseline

:Attribute Information:
    - age     age in years
    - sex
    - bmi     body mass index
    - bp      average blood pressure
    - s1      tc, total serum cholesterol
    - s2      ldl, low-density lipoproteins
    - s3      hdl, high-density lipoproteins
    - s4      tch, total cholesterol / HDL
    - s5      ltg, possibly log of serum triglycerides level
    - s6      glu, blood sugar level

Note: Each of these 10 feature variables have been mean centered and scaled by the standard deviation times the
square root of `n_samples` (i.e. the sum of squares of each column totals 1).

Source URL:
https://www4.stat.ncsu.edu/~boos/var.select/diabetes.html

For more information see:
Bradley Efron, Trevor Hastie, Iain Johnstone and Robert Tibshirani (2004) "Least Angle Regression," Annals of St
atistics (with discussion), 407-499.
(https://web.stanford.edu/~hastie/Papers/LARS/LeastAngle_2002.pdf)
```

In [85]:
```
 # problem statement
# A quantitative measure of disease progression one year after baseline.
```

In [86]:
```
diabetes.data
```

Out[86]:
```
array([[ 0.03807591,  0.05068012,  0.06169621, ..., -0.00259226,
         0.01990749, -0.01764613],
       [-0.00188202, -0.04464164, -0.05147406, ..., -0.03949338,
        -0.06833155, -0.09220405],
       [ 0.08529891,  0.05068012,  0.04445121, ..., -0.00259226,
         0.00286131, -0.02593034],
       ...,
       [ 0.04170844,  0.05068012, -0.01590626, ..., -0.01107952,
        -0.04688253,  0.01549073],
       [-0.04547248, -0.04464164,  0.03906215, ...,  0.02655962,
         0.04452873, -0.02593034],
       [-0.04547248, -0.04464164, -0.0730303 , ..., -0.03949338,
        -0.00422151,  0.00306441]])
```

In [87]:
```
diabetes.target
```

Out[87]:
```
array([151.,  75., 141., 206., 135.,  97., 138.,  63., 110., 310., 101.,
        69., 179., 185., 118., 171., 166., 144.,  97., 168.,  68.,  49.,
        68., 245., 184., 202., 137.,  85., 131., 283., 129.,  59., 341.,
        87.,  65., 102., 265., 276., 252.,  90., 100.,  55.,  61.,  92.,
       259.,  53., 190., 142.,  75., 142., 155., 225.,  59., 104., 182.,
       128.,  52.,  37., 170., 170.,  61., 144.,  52., 128.,  71., 163.,
       150.,  97., 160., 178.,  48., 270., 202., 111.,  85.,  42., 170.,
       200., 252., 113., 143.,  51.,  52., 210.,  65., 141.,  55., 134.,
        42., 111.,  98., 164.,  48.,  96.,  90., 162., 150., 279.,  92.,
        83., 128., 102., 302., 198.,  95.,  53., 134., 144., 232.,  81.,
       104.,  59., 246., 297., 258., 229., 275., 281., 179., 200., 200.,
       173., 180.,  84., 121., 161.,  99., 109., 115., 268., 274., 158.,
       107.,  83., 103., 272.,  85., 280., 336., 281., 118., 317., 235.,
        60., 174., 259., 178., 128.,  96., 126., 288.,  88., 292.,  71.,
       197., 186.,  25.,  84.,  96., 195.,  53., 217., 172., 131., 214.,
        59.,  70., 220., 268., 152.,  47.,  74., 295., 101., 151., 127.,
       237., 225.,  81., 151., 107.,  64., 138., 185., 265., 101., 137.,
       143., 141.,  79., 292., 178.,  91., 116.,  86., 122.,  72., 129.,
       142.,  90., 158.,  39., 196., 222., 277.,  99., 196., 202., 155.,
        77., 191.,  70.,  73.,  49.,  65., 263., 248., 296., 214., 185.,
        78.,  93., 252., 150.,  77., 208.,  77., 108., 160.,  53., 220.,
       154., 259.,  90., 246., 124.,  67.,  72., 257., 262., 275., 177.,
        71.,  47., 187., 125.,  78.,  51., 258., 215., 303., 243.,  91.,
       150., 310., 153., 346.,  63.,  89.,  50.,  39., 103., 308., 116.,
       145.,  74.,  45., 115., 264.,  87., 202., 127., 182., 241.,  66.,
        94., 283.,  64., 102., 200., 265.,  94., 230., 181., 156., 233.,
        60., 219.,  80.,  68., 332., 248.,  84., 200.,  55.,  85.,  89.,
        31., 129.,  83., 275.,  65., 198., 236., 253., 124.,  44., 172.,
       114., 142., 109., 180., 144., 163., 147.,  97., 220., 190., 109.,
       191., 122., 230., 242., 248., 249., 192., 131., 237.,  78., 135.,
       244., 199., 270., 164.,  72.,  96., 306.,  91., 214.,  95., 216.,
       263., 178., 113., 200., 139., 139.,  88., 148.,  88., 243.,  71.,
        77., 109., 272.,  60.,  54., 221.,  90., 311., 281., 182., 321.,
        58., 262., 206., 233., 242., 123., 167.,  63., 197.,  71., 168.,
       140., 217., 121., 235., 245.,  40.,  52., 104., 132.,  88.,  69.,
       219.,  72., 201., 110.,  51., 277.,  63., 118.,  69., 273., 258.,
        43., 198., 242., 232., 175.,  93., 168., 275., 293., 281.,  72.,
       140., 189., 181., 209., 136., 261., 113., 131., 174., 257.,  55.,
        84.,  42., 146., 212., 233.,  91., 111., 152., 120.,  67., 310.,
        94., 183.,  66., 173.,  72.,  49.,  64.,  48., 178., 104., 132.,
       220.,  57.])
```

In [88]:
```
diabetes.feature_names
```

Out[88]:
```
['age', 'sex', 'bmi', 'bp', 's1', 's2', 's3', 's4', 's5', 's6']
```

In [89]:
```
data = pd.DataFrame(diabetes.data,columns = diabetes.feature_names)
data
```

Out[89]:

	age	sex	bmi	bp	s1	s2	s3	s4	s5	s6
0	0.038076	0.050680	0.061696	0.021872	-0.044223	-0.034821	-0.043401	-0.002592	0.019907	-0.017646
1	-0.001882	-0.044642	-0.051474	-0.026328	-0.008449	-0.019163	0.074412	-0.039493	-0.068332	-0.092204
2	0.085299	0.050680	0.044451	-0.005670	-0.045599	-0.034194	-0.032356	-0.002592	0.002861	-0.025930
3	-0.089063	-0.044642	-0.011595	-0.036656	0.012191	0.024991	-0.036038	0.034309	0.022688	-0.009362
4	0.005383	-0.044642	-0.036385	0.021872	0.003935	0.015596	0.008142	-0.002592	-0.031988	-0.046641
...	...	...	...	...	...	...	...	...	...	...
437	0.041708	0.050680	0.019662	0.059744	-0.005697	-0.002566	-0.028674	-0.002592	0.031193	0.007207
438	-0.005515	0.050680	-0.015906	-0.067642	0.049341	0.079165	-0.028674	0.034309	-0.018114	0.044485
439	0.041708	0.050680	-0.015906	0.017293	-0.037344	-0.013840	-0.024993	-0.011080	-0.046883	0.015491
440	-0.045472	-0.044642	0.039062	0.001215	0.016318	0.015283	-0.028674	0.026560	0.044529	-0.025930
441	-0.045472	-0.044642	-0.073030	-0.081413	0.083740	0.027809	0.173816	-0.039493	-0.004222	0.003064

442 rows × 10 columns

In [90]:
```
data['target'] = diabetes.target
```

In [91]:
```
data
```

Out[91]:

	age	sex	bmi	bp	s1	s2	s3	s4	s5	s6	target
0	0.038076	0.050680	0.061696	0.021872	-0.044223	-0.034821	-0.043401	-0.002592	0.019907	-0.017646	151.0
1	-0.001882	-0.044642	-0.051474	-0.026328	-0.008449	-0.019163	0.074412	-0.039493	-0.068332	-0.092204	75.0
2	0.085299	0.050680	0.044451	-0.005670	-0.045599	-0.034194	-0.032356	-0.002592	0.002861	-0.025930	141.0
3	-0.089063	-0.044642	-0.011595	-0.036656	0.012191	0.024991	-0.036038	0.034309	0.022688	-0.009362	206.0
4	0.005383	-0.044642	-0.036385	0.021872	0.003935	0.015596	0.008142	-0.002592	-0.031988	-0.046641	135.0
...	...	...	...	...	...	...	...	...	...	...	...
437	0.041708	0.050680	0.019662	0.059744	-0.005697	-0.002566	-0.028674	-0.002592	0.031193	0.007207	178.0
438	-0.005515	0.050680	-0.015906	-0.067642	0.049341	0.079165	-0.028674	0.034309	-0.018114	0.044485	104.0
439	0.041708	0.050680	-0.015906	0.017293	-0.037344	-0.013840	-0.024993	-0.011080	-0.046883	0.015491	132.0
440	-0.045472	-0.044642	0.039062	0.001215	0.016318	0.015283	-0.028674	0.026560	0.044529	-0.025930	220.0
441	-0.045472	-0.044642	-0.073030	-0.081413	0.083740	0.027809	0.173816	-0.039493	-0.004222	0.003064	57.0

442 rows × 11 columns

In [92]:
```
data.head()
```

Out[92]:

	age	sex	bmi	bp	s1	s2	s3	s4	s5	s6	target
0	0.038076	0.050680	0.061696	0.021872	-0.044223	-0.034821	-0.043401	-0.002592	0.019907	-0.017646	151.0
1	-0.001882	-0.044642	-0.051474	-0.026328	-0.008449	-0.019163	0.074412	-0.039493	-0.068332	-0.092204	75.0
2	0.085299	0.050680	0.044451	-0.005670	-0.045599	-0.034194	-0.032356	-0.002592	0.002861	-0.025930	141.0
3	-0.089063	-0.044642	-0.011595	-0.036656	0.012191	0.024991	-0.036038	0.034309	0.022688	-0.009362	206.0
4	0.005383	-0.044642	-0.036385	0.021872	0.003935	0.015596	0.008142	-0.002592	-0.031988	-0.046641	135.0

In [93]:
```
data.tail()
```

Out[93]:

	age	sex	bmi	bp	s1	s2	s3	s4	s5	s6	target
437	0.041708	0.050680	0.019662	0.059744	-0.005697	-0.002566	-0.028674	-0.002592	0.031193	0.007207	178.0
438	-0.005515	0.050680	-0.015906	-0.067642	0.049341	0.079165	-0.028674	0.034309	-0.018114	0.044485	104.0
439	0.041708	0.050680	-0.015906	0.017293	-0.037344	-0.013840	-0.024993	-0.011080	-0.046883	0.015491	132.0
440	-0.045472	-0.044642	0.039062	0.001215	0.016318	0.015283	-0.028674	0.026560	0.044529	-0.025930	220.0
441	-0.045472	-0.044642	-0.073030	-0.081413	0.083740	0.027809	0.173816	-0.039493	-0.004222	0.003064	57.0

In [94]:
```
data.isnull().sum()
```

Out[94]:
```
age       0
sex       0
bmi       0
bp        0
s1        0
s2        0
s3        0
s4        0
s5        0
s6        0
target    0
dtype: int64
```

In [95]:
```
data.describe
```

Out[95]:
```
<bound method NDFrame.describe of            age       sex       bmi        bp        s1        s2        s3  \
0    0.038076  0.050680  0.061696  0.021872 -0.044223 -0.034821 -0.043401
1   -0.001882 -0.044642 -0.051474 -0.026328 -0.008449 -0.019163  0.074412
2    0.085299  0.050680  0.044451 -0.005670 -0.045599 -0.034194 -0.032356
3   -0.089063 -0.044642 -0.011595 -0.036656  0.012191  0.024991 -0.036038
4    0.005383 -0.044642 -0.036385  0.021872  0.003935  0.015596  0.008142
..        ...       ...       ...       ...       ...       ...       ...
437  0.041708  0.050680  0.019662  0.059744 -0.005697 -0.002566 -0.028674
438 -0.005515  0.050680 -0.015906 -0.067642  0.049341  0.079165 -0.028674
439  0.041708  0.050680 -0.015906  0.017293 -0.037344 -0.013840 -0.024993
440 -0.045472 -0.044642  0.039062  0.001215  0.016318  0.015283 -0.028674
441 -0.045472 -0.044642 -0.073030 -0.081413  0.083740  0.027809  0.173816

           s4        s5        s6  target
0   -0.002592  0.019907 -0.017646   151.0
1   -0.039493 -0.068332 -0.092204    75.0
2   -0.002592  0.002861 -0.025930   141.0
3    0.034309  0.022688 -0.009362   206.0
4   -0.002592 -0.031988 -0.046641   135.0
..        ...       ...       ...     ...
437 -0.002592  0.031193  0.007207   178.0
438  0.034309 -0.018114  0.044485   104.0
439 -0.011080 -0.046883  0.015491   132.0
440  0.026560  0.044529 -0.025930   220.0
441 -0.039493 -0.004222  0.003064    57.0

[442 rows x 11 columns]>
```

In [96]:
```
data.shape
```

Out[96]:
```
(442, 11)
```

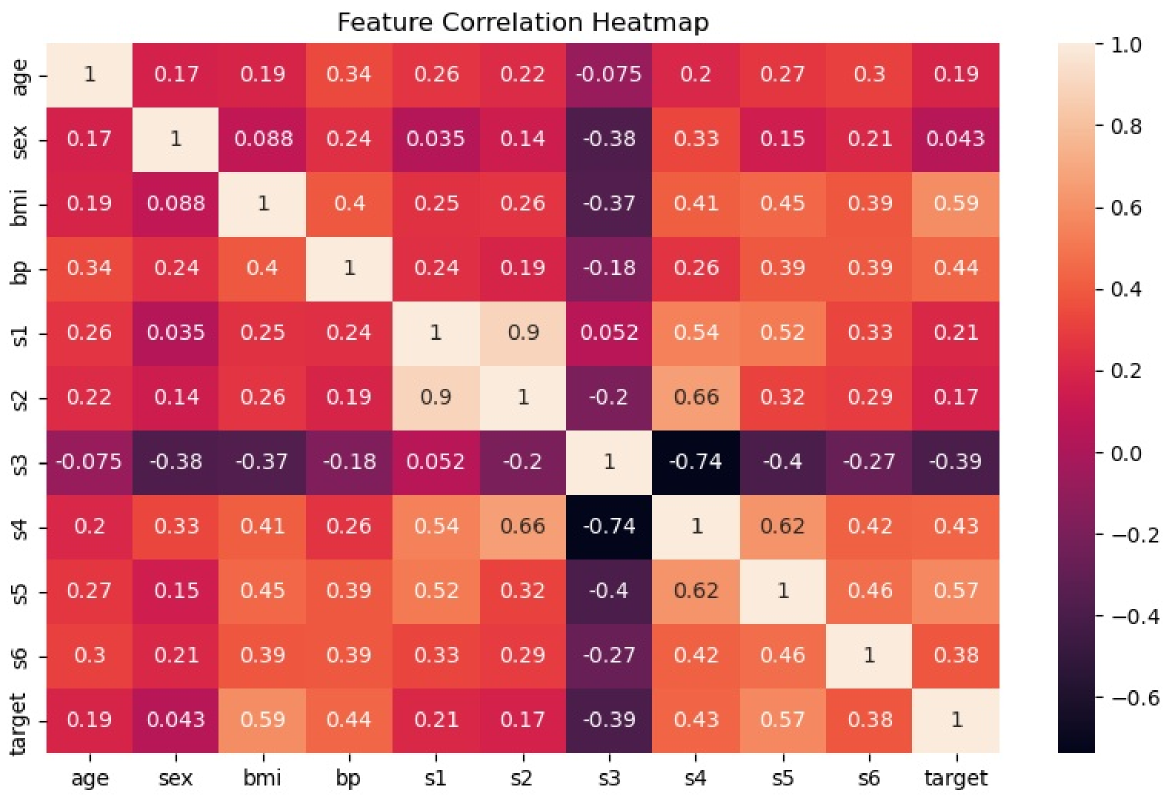
In [97]:
```
data.corr
```

Out[97]:
```
<bound method DataFrame.corr of            age       sex       bmi        bp        s1        s2        s3  \
0    0.038076  0.050680  0.061696  0.021872 -0.044223 -0.034821 -0.043401
1   -0.001882 -0.044642 -0.051474 -0.026328 -0.008449 -0.019163  0.074412
2    0.085299  0.050680  0.044451 -0.005670 -0.045599 -0.034194 -0.032356
3   -0.089063 -0.044642 -0.011595 -0.036656  0.012191  0.024991 -0.036038
4    0.005383 -0.044642 -0.036385  0.021872  0.003935  0.015596  0.008142
..        ...       ...       ...       ...       ...       ...       ...
437  0.041708  0.050680  0.019662  0.059744 -0.005697 -0.002566 -0.028674
438 -0.005515  0.050680 -0.015906 -0.067642  0.049341  0.079165 -0.028674
439  0.041708  0.050680 -0.015906  0.017293 -0.037344 -0.013840 -0.024993
440 -0.045472 -0.044642  0.039062  0.001215  0.016318  0.015283 -0.028674
441 -0.045472 -0.044642 -0.073030 -0.081413  0.083740  0.027809  0.173816

           s4        s5        s6  target
0   -0.002592  0.019907 -0.017646   151.0
1   -0.039493 -0.068332 -0.092204    75.0
2   -0.002592  0.002861 -0.025930   141.0
3    0.034309  0.022688 -0.009362   206.0
4   -0.002592 -0.031988 -0.046641   135.0
..        ...       ...       ...     ...
437 -0.002592  0.031193  0.007207   178.0
438  0.034309 -0.018114  0.044485   104.0
439 -0.011080 -0.046883  0.015491   132.0
440  0.026560  0.044529 -0.025930   220.0
441 -0.039493 -0.004222  0.003064    57.0

[442 rows x 11 columns]>
```

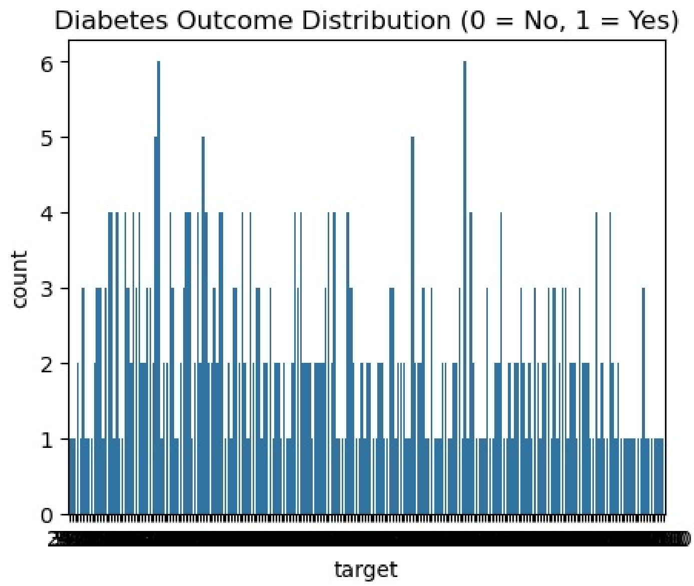
In [98]:
```
# 1. Correlation heatmap
plt.figure(figsize=(10, 6))
sns.heatmap(data.corr(),annot= True)
plt.title("Feature Correlation Heatmap")
plt.show()
```



In [99]:
```
print(data.columns)
```

```
Index(['age', 'sex', 'bmi', 'bp', 's1', 's2', 's3', 's4', 's5', 's6',
       'target'],
      dtype='object')
```

In [100…
```
# 2. Outcome distribution
plt.figure(figsize=(5, 4))
sns.countplot(x='target', data=diabetes)
plt.title("Diabetes Outcome Distribution (0 = No, 1 = Yes)")
plt.show()
```



In [101…
```
# 3. Pairplot for key features
sns.pairplot(data[['age', 'sex', 'bmi', 'bp', 's1', 's2', 's3', 's4', 's5', 's6','target']], hue='target')
plt.suptitle("Pairwise Relationships", y=1.02)
plt.show()
```

In [102…

```
#2.EDA DATA CLEANING ,DATA PREPARING,FEATURE ENGINEERING
#3.DIVIDE THE DATA INTO X AND Y

x = data[["bmi"]]
y = data["target"]
```

In [103…

```
x
```

Out[103…

	bmi
0	0.061696
1	-0.051474
2	0.044451
3	-0.011595
4	-0.036385
...	...
437	0.019662
438	-0.015906
439	-0.015906
440	0.039062
441	-0.073030

442 rows × 1 columns

In [104…
```
y
```
Out[104…
```
0      151.0
1       75.0
2      141.0
3      206.0
4      135.0
       ...
437    178.0
438    104.0
439    132.0
440    220.0
441     57.0
Name: target, Length: 442, dtype: float64
```
In [105…
```
from sklearn.model_selection import train_test_split
```
In [106…
```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.2,random_state = 1)
```
In [107…
```
x_train
```
Out[107…

	bmi
438	-0.015906
232	0.000261
80	0.012117
46	-0.011595
381	-0.089197
...	...
255	-0.065486
72	-0.004050
396	-0.030996
235	-0.014828
37	0.011039

353 rows × 1 columns

In [108…
```
x_test
```
Out[108…

	bmi
246	-0.032073
425	-0.040696
293	0.092953
31	-0.065486
359	0.005650
...	...
277	-0.059019
132	-0.021295
213	-0.070875
286	-0.054707
256	0.160855

89 rows × 1 columns

In [109…
```
y_train
```

Out[109…
```
438    104.0
232    259.0
80     143.0
46     190.0
381    104.0
       ...
255    153.0
72     202.0
396     43.0
235    124.0
37     276.0
Name: target, Length: 353, dtype: float64
```

y_test

In [110…
```
#scaling
#model training
```

In [111…
```
from sklearn.linear_model import LinearRegression
```

In [112…
```
 model = LinearRegression()
 model.fit(x_train,y_train)
```

Out[112…
```
▾ LinearRegression
LinearRegression()
```

In [113…
```
model.coef_
```

Out[113…
```
array([977.74040067])
```

In [114…
```
model.intercept_
```

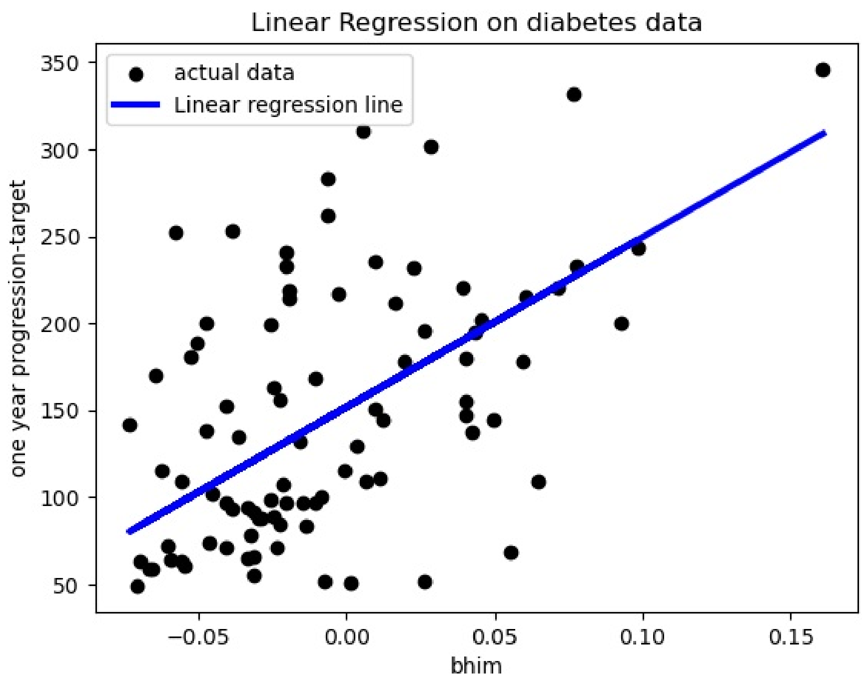
Out[114…
```
151.66780594915235
```

In [115…
```
y_pred = model.predict(x_test)
```

In [116…
```
y_pred
```

Out[116…
```
array([120.30830405, 111.87774078, 242.55147149,  87.63987137,
       157.19201836, 170.89168368, 226.74416536, 136.11561019,
       129.79268773, 116.09302241, 189.86045104, 131.90032855,
       121.36212446, 152.97673673, 194.07573268, 215.15214086,
       148.76145509, 119.25448364, 127.68504691, 162.46112041,
       155.08437755, 100.28571628, 141.38471223, 111.87774078,
        90.8013326 , 196.1833735 , 129.79268773, 190.91427145,
       113.9853816 , 163.51494082, 145.59999387, 150.86909591,
       205.66775718, 119.25448364,  95.01661424, 167.73022245,
        80.26312851, 210.93685922, 190.91427145, 127.68504691,
       161.4073    , 145.59999387, 121.36212446, 138.223251  ,
       132.95414896, 102.3933571 , 179.32224695, 113.9853816 ,
       209.88303881, 131.90032855, 144.54617346, 200.39865513,
       107.66245914, 105.55481833, 174.05314491, 137.16943059,
       158.24583877, 121.36212446,  83.42458974, 126.6312265 ,
       122.41594487, 227.79798576, 161.4073    , 131.90032855,
       247.82057354,  86.58605096, 105.55481833, 221.47506331,
       193.02191227,  92.90897342,  97.12425505, 128.73886732,
       106.60863873, 132.95414896, 177.21460613,  88.69369178,
       126.6312265 , 111.87774078, 190.91427145, 177.21460613,
        97.12425505, 123.46976528, 141.38471223, 143.49235305,
        93.96279383, 130.84650814,  82.37076933,  98.17807546,
       308.94215725])
```

In [117…
```
#visualize the result
plt.scatter(x_test,y_test,color = 'black',label = 'actual data')
plt.plot(x_test,y_pred,color = 'blue',linewidth = 3,label = "Linear regression line")
plt.xlabel("bhim")
plt.ylabel("one year progression-target")
plt.title("Linear Regression on diabetes data")
plt.legend()
plt.show()
```




```
In [118…: # Convert to binary prediction using threshold (0.5)
y_pred_binary = [1 if pred >= 0.5 else 0 for pred in y_pred]
```

```
In [119…: y_pred_binary
```

```
Out[119…: [1,
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```

In [120…
```python
from sklearn.metrics import mean_squared_error
```

In [121…
```python
mean_squared_error(y_test,y_pred)
```

Out[121… 3989.8289727609317

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

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