In [1]:
```python
from sklearn.preprocessing import LabelEncoder
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
```

In [2]:
```python
df = pd.read_csv('diabetes.csv')
df.head()
```

Out[2]:

	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunct
0	148	72	35	0	33.6	0.
1	85	66	29	0	26.6	0.
2	183	64	0	0	23.3	0.
3	89	66	23	94	28.1	0.
4	137	40	35	168	43.1	2.

In [3]:
```python
df.isnull().sum()
```

Out[3]:
```
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

In [4]:
```python
df.duplicated().sum()
```

Out[4]:
```
0
```

In [5]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 8 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Glucose                   768 non-null    int64  
 1   BloodPressure             768 non-null    int64  
 2   SkinThickness             768 non-null    int64  
 3   Insulin                   768 non-null    int64  
 4   BMI                       768 non-null    float64
 5   DiabetesPedigreeFunction  768 non-null    float64
 6   Age                       768 non-null    int64  
 7   Outcome                   768 non-null    int64  
dtypes: float64(2), int64(6)
memory usage: 48.1 KB
```

In [6]:
```
df.describe()
```

Out[6]:

	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Diabe
count	768.000000	768.000000	768.000000	768.000000	768.000000	
mean	120.894531	69.105469	20.536458	79.799479	31.992578	
std	31.972618	19.355807	15.952218	115.244002	7.884160	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	99.000000	62.000000	0.000000	0.000000	27.300000	
50%	117.000000	72.000000	23.000000	30.500000	32.000000	
75%	140.250000	80.000000	32.000000	127.250000	36.600000	
max	199.000000	122.000000	99.000000	846.000000	67.100000	

In [7]:
```
df.shape
```

Out[7]: (768, 8)

In [8]:
```
for column in df.columns:
    distinct_values = df[column].unique()
    print(f"{column}: {len(distinct_values)} values")
    print(distinct_values)
    print("-" * 50)
```

```
Glucose: 136 values
[148  85 183  89 137 116  78 115 197 125 110 168 139 189 166 100 118 107
 103 126  99 196 119 143 147  97 145 117 109 158  88  92 122 138 102  90
 111 180 133 106 171 159 146  71 105 101 176 150  73 187  84  44 141 114
  95 129  79   0  62 131 112 113  74  83 136  80 123  81 134 142 144  93
 163 151  96 155  76 160 124 162 132 120 173 170 128 108 154  57 156 153
 188 152 104  87  75 179 130 194 181 135 184 140 177 164  91 165  86 193
 191 161 167  77 182 157 178  61  98 127  82  72 172  94 175 195  68 186
 198 121  67 174 199  56 169 149  65 190]
--------------------------------------------------
BloodPressure: 47 values
[ 72  66  64  40  74  50   0  70  96  92  80  60  84  30  88  90  94  76
  82  75  58  78  68 110  56  62  85  86  48  44  65 108  55 122  54  52
  98 104  95  46 102 100  61  24  38 106 114]
--------------------------------------------------
SkinThickness: 51 values
[35 29  0 23 32 45 19 47 38 30 41 33 26 15 36 11 31 37 42 25 18 24 39 27
 21 34 10 60 13 20 22 28 54 40 51 56 14 17 50 44 12 46 16  7 52 43 48  8
 49 63 99]
--------------------------------------------------
Insulin: 186 values
[  0  94 168  88 543 846 175 230  83  96 235 146 115 140 110 245  54 192
 207  70 240  82  36  23 300 342 304 142 128  38 100  90 270  71 125 176
  48  64 228  76 220  40 152  18 135 495  37  51  99 145 225  49  50  92
 325  63 284 119 204 155 485  53 114 105 285 156  78 130  55  58 160 210
 318  44 190 280  87 271 129 120 478  56  32 744 370  45 194 680 402 258
 375 150  67  57 116 278 122 545  75  74 182 360 215 184  42 132 148 180
 205  85 231  29  68  52 255 171  73 108  43 167 249 293  66 465  89 158
  84  72  59  81 196 415 275 165 579 310  61 474 170 277  60  14  95 237
 191 328 250 480 265 193  79  86 326 188 106  65 166 274  77 126 330 600
 185  25  41 272 321 144  15 183  91  46 440 159 540 200 335 387  22 291
 392 178 127 510  16 112]
--------------------------------------------------
BMI: 248 values
[33.6 26.6 23.3 28.1 43.1 25.6 31.  35.3 30.5  0.  37.6 38.  27.1 30.1
 25.8 30.  45.8 29.6 43.3 34.6 39.3 35.4 39.8 29.  36.6 31.1 39.4 23.2
 22.2 34.1 36.  31.6 24.8 19.9 27.6 24.  33.2 32.9 38.2 37.1 34.  40.2
 22.7 45.4 27.4 42.  29.7 28.  39.1 19.4 24.2 24.4 33.7 34.7 23.  37.7
 46.8 40.5 41.5 25.  25.4 32.8 32.5 42.7 19.6 28.9 28.6 43.4 35.1 32.
 24.7 32.6 43.2 22.4 29.3 24.6 48.8 32.4 38.5 26.5 19.1 46.7 23.8 33.9
 20.4 28.7 49.7 39.  26.1 22.5 39.6 29.5 34.3 37.4 33.3 31.2 28.2 53.2
 34.2 26.8 55.  42.9 34.5 27.9 38.3 21.1 33.8 30.8 36.9 39.5 27.3 21.9
 40.6 47.9 50.  25.2 40.9 37.2 44.2 29.9 31.9 28.4 43.5 32.7 67.1 45.
 34.9 27.7 35.9 22.6 33.1 30.4 52.3 24.3 22.9 34.8 30.9 40.1 23.9 37.5
 35.5 42.8 42.6 41.8 35.8 37.8 28.8 23.6 35.7 36.7 45.2 44.  46.2 35.
 43.6 44.1 18.4 29.2 25.9 32.1 36.3 40.  25.1 27.5 45.6 27.8 24.9 25.3
 37.9 27.  26.  38.7 20.8 36.1 30.7 32.3 52.9 21.  39.7 25.5 26.2 19.3
 38.1 23.5 45.5 23.1 39.9 36.8 21.8 41.  42.2 34.4 27.2 36.5 29.8 39.2
 38.4 36.2 48.3 20.  22.3 45.7 23.7 22.1 42.1 42.4 18.2 26.4 45.3 37.
 24.5 32.2 59.4 21.2 26.7 30.2 46.1 41.3 38.8 35.2 42.3 40.7 46.5 33.5
 37.3 30.3 26.3 21.7 36.4 28.5 26.9 38.6 31.3 19.5 20.1 40.8 23.4 28.3
 38.9 57.3 35.6 49.6 44.6 24.1 44.5 41.2 49.3 46.3]
--------------------------------------------------
DiabetesPedigreeFunction: 517 values
[0.627 0.351 0.672 0.167 2.288 0.201 0.248 0.134 0.158 0.232 0.191 0.537
 1.441 0.398 0.587 0.484 0.551 0.254 0.183 0.529 0.704 0.388 0.451 0.263
```

```
 0.205 0.257 0.487 0.245 0.337 0.546 0.851 0.267 0.188 0.512 0.966 0.42
 0.665 0.503 1.39  0.271 0.696 0.235 0.721 0.294 1.893 0.564 0.586 0.344
 0.305 0.491 0.526 0.342 0.467 0.718 0.962 1.781 0.173 0.304 0.27  0.699
 0.258 0.203 0.855 0.845 0.334 0.189 0.867 0.411 0.583 0.231 0.396 0.14
 0.391 0.37  0.307 0.102 0.767 0.237 0.227 0.698 0.178 0.324 0.153 0.165
 0.443 0.261 0.277 0.761 0.255 0.13  0.323 0.356 0.325 1.222 0.179 0.262
 0.283 0.93  0.801 0.207 0.287 0.336 0.247 0.199 0.543 0.192 0.588 0.539
 0.22  0.654 0.223 0.759 0.26  0.404 0.186 0.278 0.496 0.452 0.403 0.741
 0.361 1.114 0.457 0.647 0.088 0.597 0.532 0.703 0.159 0.268 0.286 0.318
 0.272 0.572 0.096 1.4   0.218 0.085 0.399 0.432 1.189 0.687 0.137 0.637
 0.833 0.229 0.817 0.204 0.368 0.743 0.722 0.256 0.709 0.471 0.495 0.18
 0.542 0.773 0.678 0.719 0.382 0.319 0.19  0.956 0.084 0.725 0.299 0.244
 0.745 0.615 1.321 0.64  0.142 0.374 0.383 0.578 0.136 0.395 0.187 0.905
 0.15  0.874 0.236 0.787 0.407 0.605 0.151 0.289 0.355 0.29  0.375 0.164
 0.431 0.742 0.514 0.464 1.224 1.072 0.805 0.209 0.666 0.101 0.198 0.652
 2.329 0.089 0.645 0.238 0.394 0.293 0.479 0.686 0.831 0.582 0.446 0.402
 1.318 0.329 1.213 0.427 0.282 0.143 0.38  0.284 0.249 0.926 0.557 0.092
 0.655 1.353 0.612 0.2   0.226 0.997 0.933 1.101 0.078 0.24  1.136 0.128
 0.422 0.251 0.677 0.296 0.454 0.744 0.881 0.28  0.259 0.619 0.808 0.34
 0.434 0.757 0.613 0.692 0.52  0.412 0.84  0.839 0.156 0.215 0.326 1.391
 0.875 0.313 0.433 0.626 1.127 0.315 0.345 0.129 0.527 0.197 0.731 0.148
 0.123 0.127 0.122 1.476 0.166 0.932 0.343 0.893 0.331 0.472 0.673 0.389
 0.485 0.349 0.279 0.346 0.252 0.243 0.58  0.559 0.302 0.569 0.378 0.385
 0.499 0.306 0.234 2.137 1.731 0.545 0.225 0.816 0.528 0.509 1.021 0.821
 0.947 1.268 0.221 0.66  0.239 0.949 0.444 0.463 0.803 1.6   0.944 0.196
 0.241 0.161 0.135 0.376 1.191 0.702 0.674 1.076 0.534 1.095 0.554 0.624
 0.219 0.507 0.561 0.421 0.516 0.264 0.328 0.233 0.108 1.138 0.147 0.727
 0.435 0.497 0.23  0.955 2.42  0.658 0.33  0.51  0.285 0.415 0.381 0.832
 0.498 0.212 0.364 1.001 0.46  0.733 0.416 0.705 1.022 0.269 0.6   0.571
 0.607 0.17  0.21  0.126 0.711 0.466 0.162 0.419 0.63  0.365 0.536 1.159
 0.629 0.292 0.145 1.144 0.174 0.547 0.163 0.738 0.314 0.968 0.409 0.297
 0.525 0.154 0.771 0.107 0.493 0.717 0.917 0.501 1.251 0.735 0.804 0.661
 0.549 0.825 0.423 1.034 0.16  0.341 0.68  0.591 0.3   0.121 0.502 0.401
 0.601 0.748 0.338 0.43  0.892 0.813 0.693 0.575 0.371 0.206 0.417 1.154
 0.925 0.175 1.699 0.682 0.194 0.4   0.1   1.258 0.482 0.138 0.593 0.878
 0.157 1.282 0.141 0.246 1.698 1.461 0.347 0.362 0.393 0.144 0.732 0.115
 0.465 0.649 0.871 0.149 0.695 0.303 0.61  0.73  0.447 0.455 0.133 0.155
 1.162 1.292 0.182 1.394 0.217 0.631 0.88  0.614 0.332 0.366 0.181 0.828
 0.335 0.856 0.886 0.439 0.253 0.598 0.904 0.483 0.565 0.118 0.177 0.176
 0.295 0.441 0.352 0.826 0.97  0.595 0.317 0.265 0.646 0.426 0.56  0.515
 0.453 0.785 0.734 1.174 0.488 0.358 1.096 0.408 1.182 0.222 1.057 0.766
 0.171]
--------------------------------------------------
Age: 52 values
[50 31 32 21 33 30 26 29 53 54 34 57 59 51 27 41 43 22 38 60 28 45 35 46
 56 37 48 40 25 24 58 42 44 39 36 23 61 69 62 55 65 47 52 66 49 63 67 72
 81 64 70 68]
--------------------------------------------------
Outcome: 2 values
[1 0]
--------------------------------------------------
```

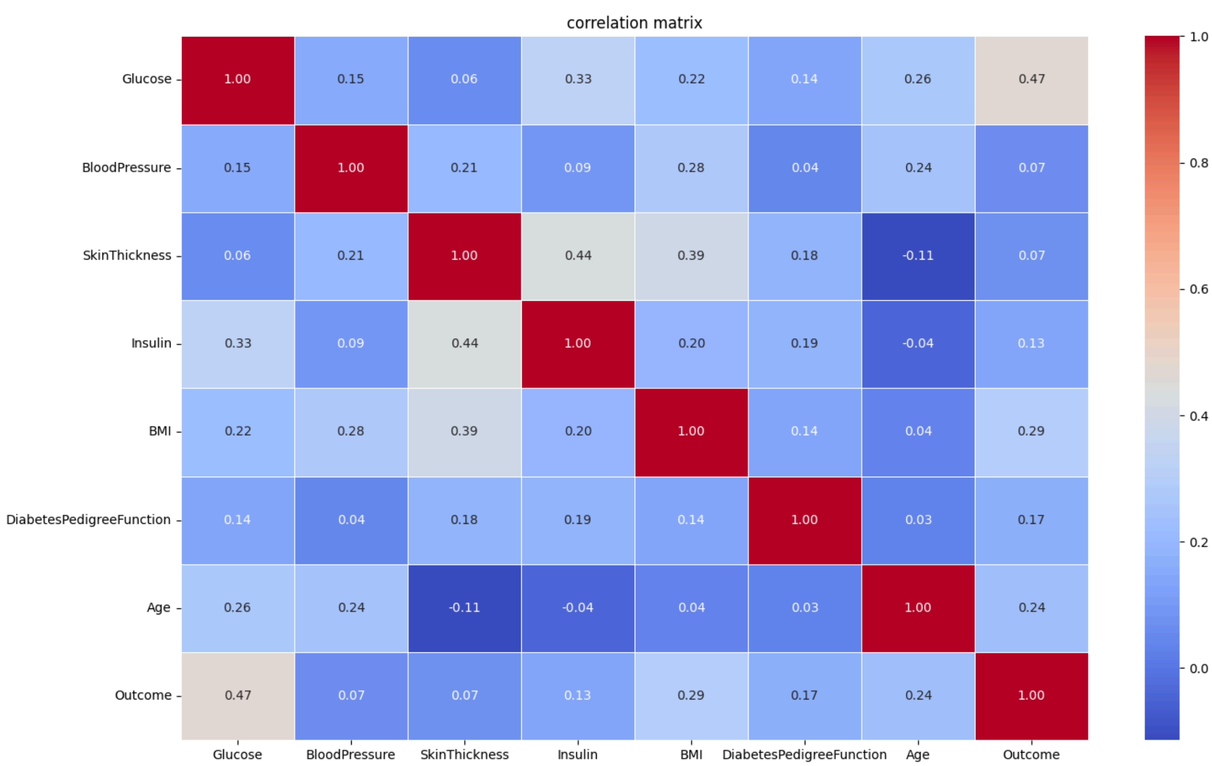
the correlation matrix

In [9]:
```python
correlation_matrix = df.corr()
correlation_matrix
```

Out[9]:

	Glucose	BloodPressure	SkinThickness	Insulin
Glucose	1.000000	0.152590	0.057328	0.331357
BloodPressure	0.152590	1.000000	0.207371	0.088933
SkinThickness	0.057328	0.207371	1.000000	0.436783
Insulin	0.331357	0.088933	0.436783	1.000000
BMI	0.221071	0.281805	0.392573	0.197859
DiabetesPedigreeFunction	0.137337	0.041265	0.183928	0.185071
Age	0.263514	0.239528	-0.113970	-0.042163
Outcome	0.466581	0.065068	0.074752	0.130548

In [10]:
```python
plt.figure(figsize=(16, 10))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", line
plt.title("correlation matrix")
plt.show()
```



covariance matrix

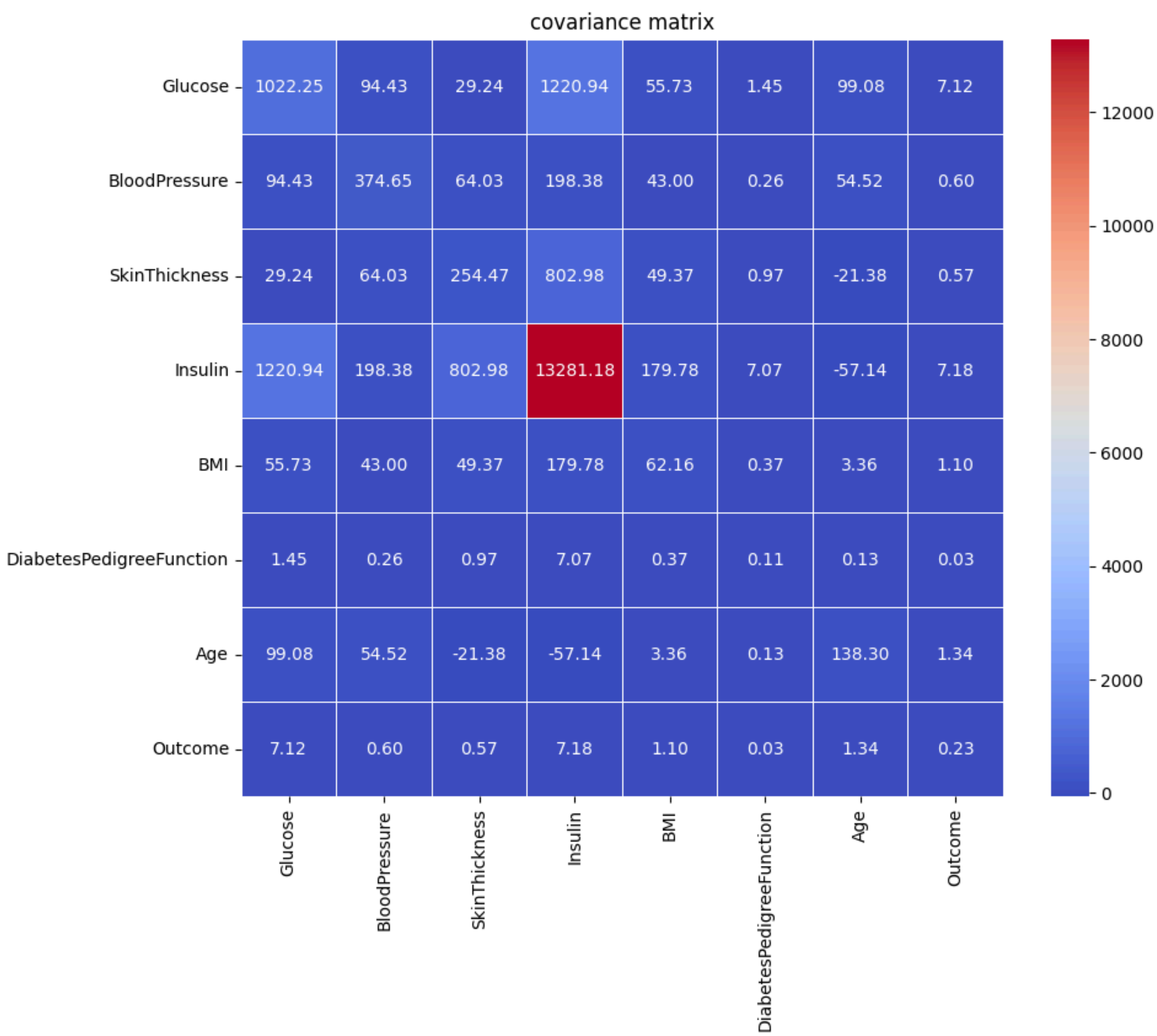
In [24]:
```python
covariance_matrix = df.cov()
covariance_matrix
```

Out[24]:

	Glucose	BloodPressure	SkinThickness	Ins
Glucose	1022.248314	94.430956	29.239183	1220.93
BloodPressure	94.430956	374.647271	64.029396	198.37
SkinThickness	29.239183	64.029396	254.473245	802.97
Insulin	1220.935799	198.378412	802.979941	13281.18
BMI	55.726987	43.004695	49.373869	179.77
DiabetesPedigreeFunction	1.454875	0.264638	0.972136	7.06
Age	99.082805	54.523453	-21.381023	-57.14
Outcome	7.115079	0.600697	0.568747	7.17

In [25]:

```
plt.figure(figsize=(10, 8))
sns.heatmap(covariance_matrix, annot=True, cmap="coolwarm", fmt=".2f", linew
plt.title("covariance matrix")
plt.show()
```



eigen values, percentage of inertia, commulative percentage

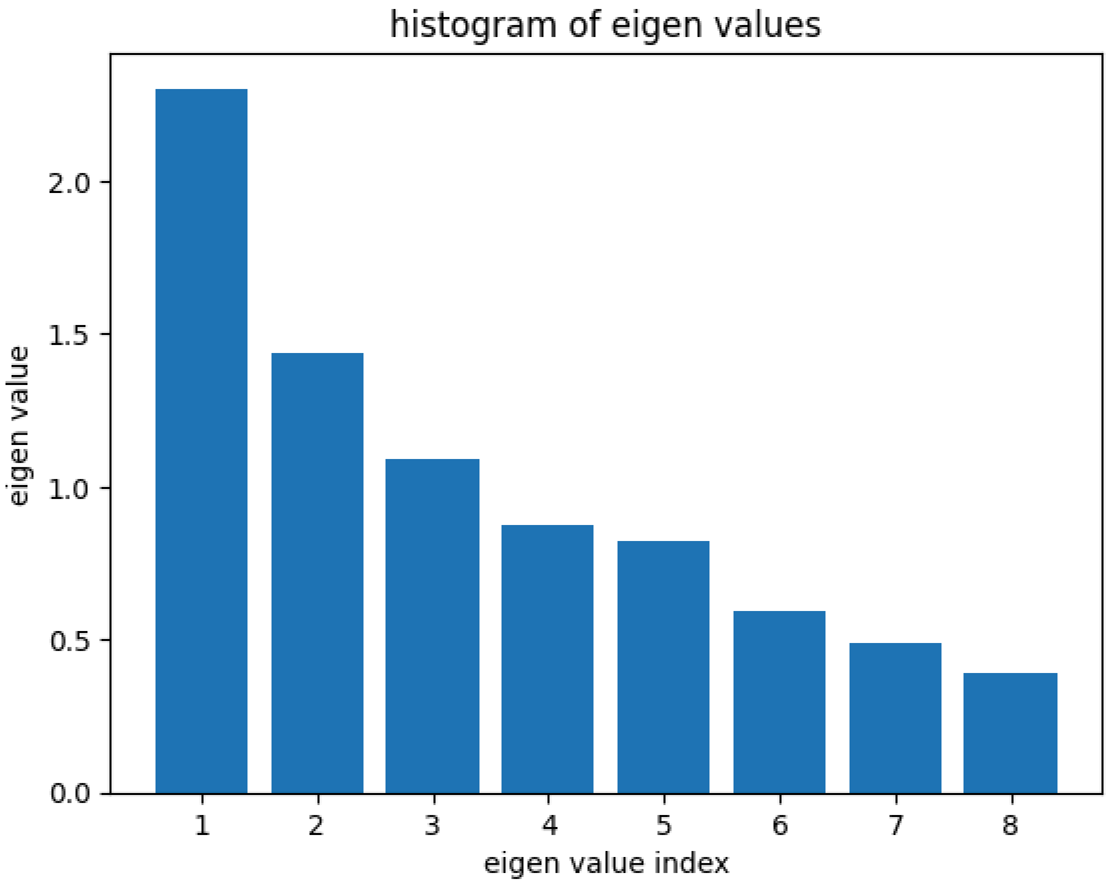
In [11]:
```
eigen_values = np.linalg.eigvals(correlation_matrix)
eigen_values_sorted = np.sort(eigen_values)[::-1]
inertia_percentage = (eigen_values_sorted / eigen_values_sorted.sum()) * 100
cumulative_percentage = np.cumsum(inertia_percentage)

result_df = pd.DataFrame({
    'eigen values': eigen_values_sorted,
    'percentage of inertia': inertia_percentage,
    'cumulative percentage': cumulative_percentage
}, index=range(1, len(eigen_values_sorted) + 1))

result_df.index.name = 'component'

result_df.round(2)
```

Out[11]:

component	eigen values	percentage of inertia	cumulative percentage
1	2.30	28.78	28.78
2	1.43	17.93	46.70
3	1.09	13.66	60.36
4	0.87	10.93	71.29
5	0.83	10.32	81.61
6	0.59	7.42	89.03
7	0.49	6.08	95.11
8	0.39	4.89	100.00

histogram of eigen values

In [12]:
```
plt.bar(range(1, len(eigen_values_sorted) + 1), eigen_values_sorted)
plt.xlabel('eigen value index')
plt.ylabel('eigen value')
plt.title('histogram of eigen values')
plt.show()
```



compute the principal components, contributions, representational qualities of individuals

In [13]:
```
pca = PCA()
pca.fit(df)

principal_components = pd.DataFrame(pca.components_, columns=df.columns)
contributions = pd.DataFrame(np.abs(principal_components), columns=df.column
representational_qualities = np.square(contributions)
```

In [14]:
```
print("principal components:")
print(principal_components)
```

```
principal components:
    Glucose  BloodPressure  SkinThickness   Insulin       BMI  \
0  0.097815       0.016095       0.060756  0.993112  0.014011
1  0.972553       0.141633      -0.057843 -0.094713  0.046982
2 -0.142387       0.922829       0.307662 -0.021181  0.132685
3  0.118136      -0.267279       0.887085 -0.065352  0.192929
4 -0.087851      -0.225609       0.249774  0.000118  0.018969
5 -0.050873      -0.075665      -0.221342  0.006133  0.970677
6 -0.006078       0.002419      -0.001054  0.000107 -0.013973
7  0.000509       0.000013      -0.002379 -0.000309  0.000380

   DiabetesPedigreeFunction       Age   Outcome
0                  0.000537 -0.003561  0.000585
1                  0.000818  0.139670  0.007007
2                  0.000644  0.124107 -0.000317
3                  0.002703 -0.293562  0.002711
4                  0.001687  0.937335  0.005965
5                  0.002039  0.016270  0.013175
6                  0.217248 -0.006026  0.975975
7                  0.976108  0.000303 -0.217270
```

In [15]:
```python
print("contributions:")
print(contributions)
```

```
contributions:
    Glucose  BloodPressure  SkinThickness   Insulin       BMI  \
0  0.097815       0.016095       0.060756  0.993112  0.014011
1  0.972553       0.141633       0.057843  0.094713  0.046982
2  0.142387       0.922829       0.307662  0.021181  0.132685
3  0.118136       0.267279       0.887085  0.065352  0.192929
4  0.087851       0.225609       0.249774  0.000118  0.018969
5  0.050873       0.075665       0.221342  0.006133  0.970677
6  0.006078       0.002419       0.001054  0.000107  0.013973
7  0.000509       0.000013       0.002379  0.000309  0.000380

   DiabetesPedigreeFunction       Age   Outcome
0                  0.000537  0.003561  0.000585
1                  0.000818  0.139670  0.007007
2                  0.000644  0.124107  0.000317
3                  0.002703  0.293562  0.002711
4                  0.001687  0.937335  0.005965
5                  0.002039  0.016270  0.013175
6                  0.217248  0.006026  0.975975
7                  0.976108  0.000303  0.217270
```

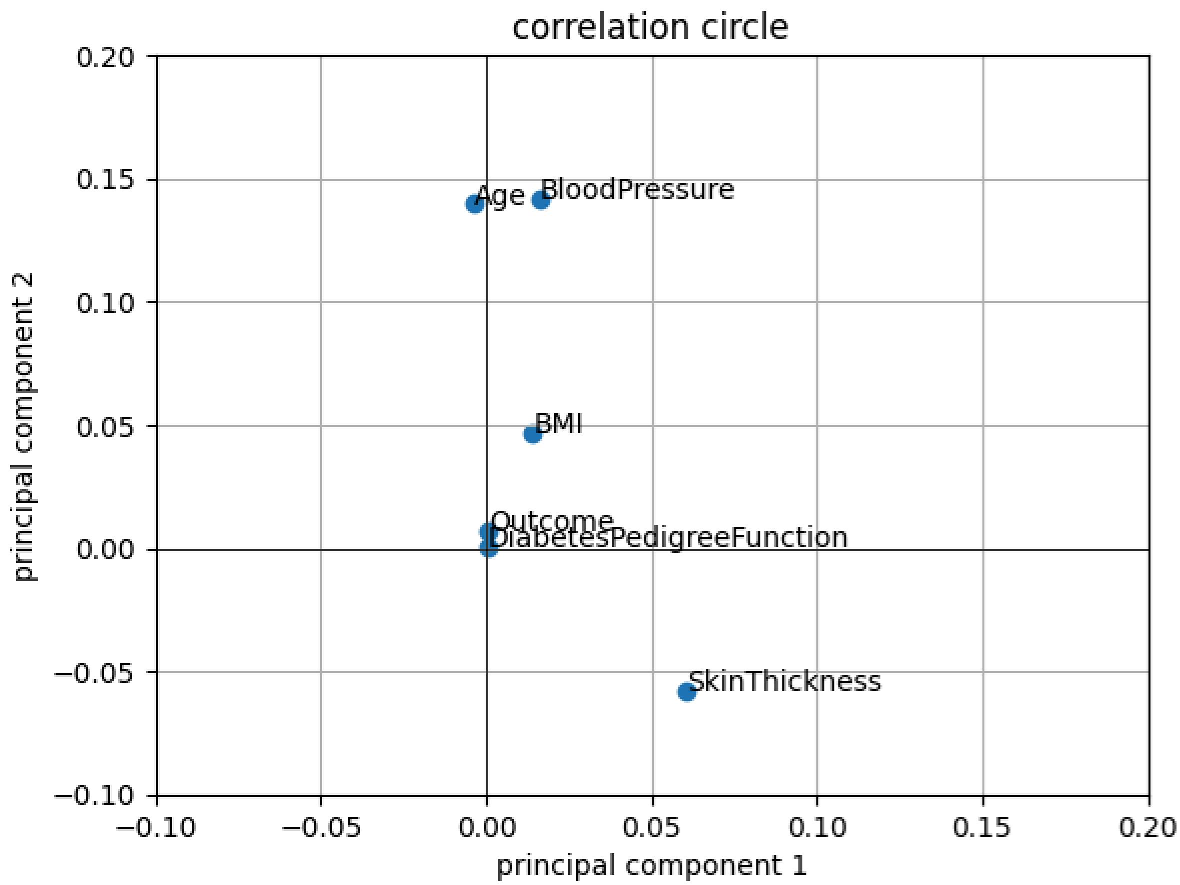
In [16]:
```python
print("representational qualities:")
print(representational_qualities)
```

```
representational qualities:
        Glucose  BloodPressure  SkinThickness       Insulin           BMI  \
0  9.567729e-03   2.590369e-04       0.003691  9.862723e-01  1.963087e-04
1  9.458592e-01   2.005985e-02       0.003346  8.970552e-03  2.207333e-03
2  2.027411e-02   8.516128e-01       0.094656  4.486158e-04  1.760537e-02
3  1.395605e-02   7.143782e-02       0.786921  4.270824e-03  3.722147e-02
4  7.717711e-03   5.089948e-02       0.062387  1.384397e-08  3.598251e-04
5  2.588034e-03   5.725203e-03       0.048992  3.761441e-05  9.422143e-01
6  3.694366e-05   5.853217e-06       0.000001  1.137727e-08  1.952416e-04
7  2.588843e-07   1.722455e-10       0.000006  9.543914e-08  1.445423e-07

   DiabetesPedigreeFunction           Age       Outcome
0              2.885481e-07  1.268357e-05  3.426749e-07
1              6.692062e-07  1.950759e-02  4.909116e-05
2              4.150814e-07  1.540261e-02  1.006460e-07
3              7.308077e-06  8.617860e-02  7.351372e-06
4              2.846191e-06  8.785974e-01  3.558533e-05
5              4.158663e-06  2.646999e-04  1.735693e-04
6              4.719683e-02  3.631234e-05  9.525277e-01
7              9.527875e-01  9.189848e-08  4.720626e-02
```

the individuals in the first factorial

In [17]:

```
fig, ax = plt.subplots()
ax.scatter(pca.components_[0, :], pca.components_[1, :])
for i, txt in enumerate(df.columns):
    ax.annotate(txt, (pca.components_[0, i], pca.components_[1, i]))
ax.set_xlim(-0.1, 0.2)
ax.set_ylim(-0.1, 0.2)
ax.axhline(0, color='black', linewidth=0.5)
ax.axvline(0, color='black', linewidth=0.5)
plt.xlabel('principal component 1')
plt.ylabel('principal component 2')
plt.title('correlation circle')
plt.grid()
plt.show()
```



compute the principal components, contributions, representational qualities of the variables.

In [18]:
```
pca_var = PCA()
pca_var.fit(df)
principal_components_var = pd.DataFrame(pca_var.components_, columns=df.colu
contributions_var = pd.DataFrame(np.abs(principal_components_var), columns=c
representational_qualities_var = np.square(contributions_var)
```

In [19]:
```
print("principal components:")
print(principal_components_var)
```

```
principal components:
    Glucose  BloodPressure  SkinThickness   Insulin       BMI  \
0  0.097815       0.016095       0.060756  0.993112  0.014011
1  0.972553       0.141633      -0.057843 -0.094713  0.046982
2 -0.142387       0.922829       0.307662 -0.021181  0.132685
3  0.118136      -0.267279       0.887085 -0.065352  0.192929
4 -0.087851      -0.225609       0.249774  0.000118  0.018969
5 -0.050873      -0.075665      -0.221342  0.006133  0.970677
6 -0.006078       0.002419      -0.001054  0.000107 -0.013973
7  0.000509       0.000013      -0.002379 -0.000309  0.000380

   DiabetesPedigreeFunction       Age   Outcome
0                  0.000537 -0.003561  0.000585
1                  0.000818  0.139670  0.007007
2                  0.000644  0.124107 -0.000317
3                  0.002703 -0.293562  0.002711
4                  0.001687  0.937335  0.005965
5                  0.002039  0.016270  0.013175
6                  0.217248 -0.006026  0.975975
7                  0.976108  0.000303 -0.217270
```

In [20]:
```python
print("contributions:")
print(contributions_var)
```

```
contributions:
    Glucose  BloodPressure  SkinThickness   Insulin       BMI  \
0  0.097815       0.016095       0.060756  0.993112  0.014011
1  0.972553       0.141633       0.057843  0.094713  0.046982
2  0.142387       0.922829       0.307662  0.021181  0.132685
3  0.118136       0.267279       0.887085  0.065352  0.192929
4  0.087851       0.225609       0.249774  0.000118  0.018969
5  0.050873       0.075665       0.221342  0.006133  0.970677
6  0.006078       0.002419       0.001054  0.000107  0.013973
7  0.000509       0.000013       0.002379  0.000309  0.000380

   DiabetesPedigreeFunction       Age   Outcome
0                  0.000537  0.003561  0.000585
1                  0.000818  0.139670  0.007007
2                  0.000644  0.124107  0.000317
3                  0.002703  0.293562  0.002711
4                  0.001687  0.937335  0.005965
5                  0.002039  0.016270  0.013175
6                  0.217248  0.006026  0.975975
7                  0.976108  0.000303  0.217270
```

In [21]:
```python
print("representational Qualities:")
print(representational_qualities_var)
```

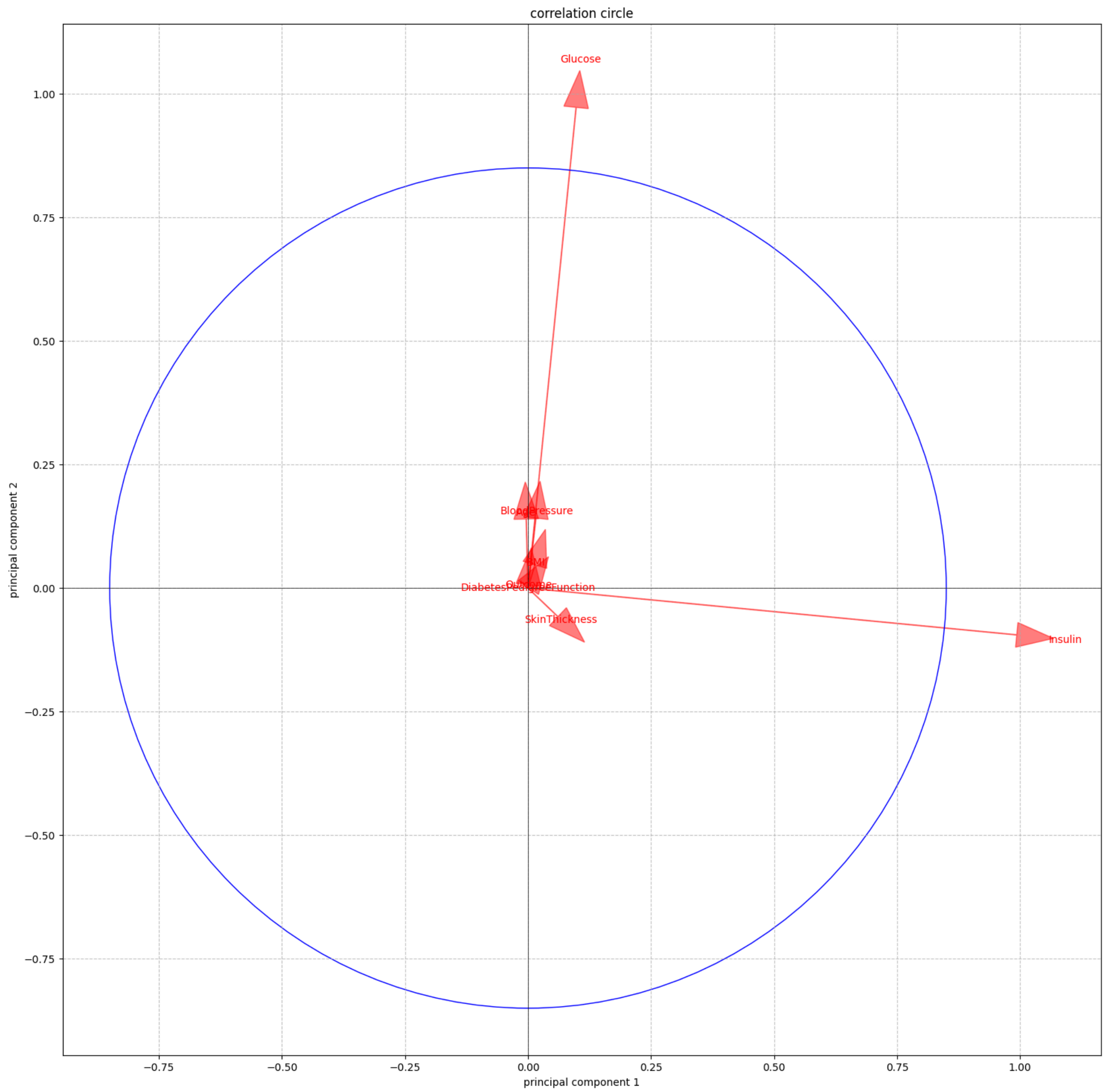
```
representational Qualities:
        Glucose  BloodPressure  SkinThickness       Insulin           BMI  \
0  9.567729e-03   2.590369e-04       0.003691  9.862723e-01  1.963087e-04
1  9.458592e-01   2.005985e-02       0.003346  8.970552e-03  2.207333e-03
2  2.027411e-02   8.516128e-01       0.094656  4.486158e-04  1.760537e-02
3  1.395605e-02   7.143782e-02       0.786921  4.270824e-03  3.722147e-02
4  7.717711e-03   5.089948e-02       0.062387  1.384397e-08  3.598251e-04
5  2.588034e-03   5.725203e-03       0.048992  3.761441e-05  9.422143e-01
6  3.694366e-05   5.853217e-06       0.000001  1.137727e-08  1.952416e-04
7  2.588843e-07   1.722455e-10       0.000006  9.543914e-08  1.445423e-07

   DiabetesPedigreeFunction           Age       Outcome
0              2.885481e-07  1.268357e-05  3.426749e-07
1              6.692062e-07  1.950759e-02  4.909116e-05
2              4.150814e-07  1.540261e-02  1.006460e-07
3              7.308077e-06  8.617860e-02  7.351372e-06
4              2.846191e-06  8.785974e-01  3.558533e-05
5              4.158663e-06  2.646999e-04  1.735693e-04
6              4.719683e-02  3.631234e-05  9.525277e-01
7              9.527875e-01  9.189848e-08  4.720626e-02
```

Question 8:

Plot the correlation circle.

In [22]:

```python
fig, ax = plt.subplots(figsize=(18, 18))
for i, var in enumerate(df.columns):
    ax.arrow(0, 0, principal_components[var][0], principal_components[var][1
             color='r', alpha=0.5, head_width=0.05)
    ax.text(principal_components[var][0] * 1.1, principal_components[var][1]
            color='r', ha='center', va='center')

circle = plt.Circle((0, 0), radius=0.85, color='b', fill=False)
ax.add_patch(circle)

plt.xlabel('principal component 1')
plt.ylabel('principal component 2')
plt.title('correlation circle')
plt.axhline(0, color='black', lw=0.5)
plt.axvline(0, color='black', lw=0.5)
plt.grid(True, linestyle='--', alpha=0.7)
plt.show()
```


correlation circle
Glucose
BloodPressure
BMI
Outcome
DiabetesPedigreeFunction
SkinThickness
Insulin
principal component 1
principal component 2
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75