

PREDICTION OF CHRONIC KIDNEY DISORDER

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Predicting Chronic Kidney Disease based on health records using Logistic Regression and Decision Tree algorithms

Given 24 health related attributes taken in 2-month period of 400 patients, using the information of the 158 patients with complete records to predict the outcome (i.e. whether one has chronic kidney disease) of the remaining 242 patients (with missing values in their records).

This project is based on Data-mining and Machine Learning technique using Python and Scikit-learn. It is used to predict Chronic Kidney Disease of Patients.

Number of Instances: 400 (250 CKD, 150 notckd) Number of Attributes: 24 + class = 25 (11 numeric ,14 nominal)

1.Age(numerical)age in years 2.Blood Pressure(numerical) bp in mm/Hg 3.Specific Gravity(nominal) sg - (1.005,1.010,1.015,1.020,1.025) 4.Albumin(nominal) al - (0,1,2,3,4,5) 5.Sugar(nominal) su - (0,1,2,3,4,5) 6.Red Blood Cells(nominal) rbc - (normal,abnormal) 7.Pus Cell (nominal) pc - (normal,abnormal) 8.Pus Cell clumps(nominal) pcc - (present,notpresent) 9.Bacteria(nominal) ba - (present,notpresent) 10.Blood Glucose Random(numerical) bgr in mgs/dl 11.Blood Urea(numerical) bu in mgs/dl 12.Serum Creatinine(numerical) sc in mgs/dl 13.Sodium(numerical) sod in mEq/L 14.Potassium(numerical) pot in mEq/L 15.Hemoglobin(numerical) hemo in gms 16.Packed Cell Volume(numerical) 17.White Blood Cell Count(numerical) wc in cells/cumm 18.Red Blood Cell Count(numerical) rc in millions/cmm 19.Hypertension(nominal) htn - (yes,no) 20.Diabetes Mellitus(nominal) dm - (yes,no) 21.Coronary Artery Disease(nominal) cad - (yes,no) 22.Appetite(nominal)appet - (good,poor) 23.Pedal Edema(nominal) pe - (yes,no) 24.Anemia(nominal) ane - (yes,no) 25.Class (nominal) class - (ckd,notckd)

Step 1: Importing libraries

In [65]:

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

Step 2: Importing Dataset

In [66]:

```
dataset = pd.read_csv(r"C:\Users\admin\Desktop\ckd3.csv",header=0, na_values="?")
dataset.isnull()
```

Out[66]:

	Age	Bp	Sg	Al	Su	Rbc	Pc	Pcc	Ba	Bgr	...	Pcv	Wbcc	Rbcc
0	False	False	False	False	False	True	False	False	False	False	...	False	False	False
1	False	False	False	False	False	True	False	False	False	True	...	False	False	True
2	False	...	False	False	True									
3	False	...	False	False	False									
4	False	...	False	False	False									
5	False	False	False	False	False	True	True	False	False	False	...	False	False	False
6	False	False	False	False	False	True	False	False	False	False	...	False	True	True
7	False	True	False	...	False	False	False							
8	False	...	False	False	False									
9	False	...	False	False	False									
10	False	False	False	False	False	True	False	False	False	False	...	False	True	True
11	False	...	False	False	False									
12	False	False	False	False	False	True	False	False	False	False	...	False	False	False
13	False	False	True	True	True	True	True	False	False	False	...	True	True	True
14	False	...	False	False	False									
15	False	False	False	False	False	True	False	False	False	False	...	False	False	False
16	False	False	False	False	False	True	False	False	False	False	...	True	True	True
17	False	False	True	True	True	True	True	False	False	False	...	True	True	True
18	False	False	False	False	False	True	False	False	False	False	...	False	False	False
19	False	False	False	False	False	True	False	False	False	False	...	False	False	False
20	False	...	False	False	False									
21	False	False	True	True	True	True	True	False	False	True	...	False	False	False
22	False	...	False	False	False									
23	False	False	False	False	False	True	False	False	False	True	...	True	True	True
24	False	True	...	False	False	False								
25	False	False	False	False	False	True	False	False	False	False	...	False	False	False
26	False	False	False	False	False	True	False	False	False	False	...	False	False	False
27	False	...	False	False	False									
28	False	False	True	False	False	True	True	False	False	False	...	True	True	True
29	False	True	...	False	True	True								
...
370	False	...	False	False	False									
371	False	...	False	False	False									
372	False	...	False	False	False									

	Age	Bp	Sg	Al	Su	Rbc	Pc	Pcc	Ba	Bgr	...	Pcv	Wbcc	Rbcc
373	False	...	False	False	False									
374	False	...	False	False	False									
375	False	...	False	False	False									
376	False	...	False	False	False									
377	False	...	False	False	False									
378	False	True	...	False	False	False								
379	False	...	False	False	False									
380	False	...	False	False	False									
381	False	False	False	False	False	True	True	False	False	False	...	False	False	False
382	False	...	False	False	False									
383	False	...	False	False	False									
384	False	...	False	False	False									
385	False	...	False	False	False									
386	False	...	False	False	False									
387	False	...	False	False	False									
388	False	...	False	False	False									
389	False	...	False	False	False									
390	False	...	False	False	False									
391	False	...	False	False	False									
392	False	...	False	False	False									
393	False	...	False	False	False									
394	False	...	False	False	False									
395	False	...	False	False	False									
396	False	...	False	False	False									
397	False	...	False	False	False									
398	False	...	False	False	False									
399	False	...	False	False	False									

400 rows × 25 columns



In [67]:

```
dataset.isnull().sum()
```

Out[67]:

```
Age      9
Bp      12
Sg      47
Al      46
Su      49
Rbc    152
Pc       65
Pcc       4
Ba       4
Bgr     44
Bu      19
Sc      17
Sod     87
Pot     88
Hemo    52
Pcv     71
Wbcc   106
Rbcc   131
Htn      2
Dm       0
Cad      2
Appet    1
pe       1
Ane      1
Class     0
dtype: int64
```

Step 3: Data preprocessing

In [68]:

```
# Convert nominal values to binary values
cleanup = {"Rbc": {"normal": 1, "abnormal": 0},
           "Pc": {"normal": 1, "abnormal": 0},
           "Pcc": {"present": 1, "notpresent": 0},
           "Ba": {"present": 1, "notpresent": 0},
           "Htn": {"yes": 1, "no": 0},
           "Dm": {"yes": 1, "no": 0},
           "Cad": {"yes": 1, "no": 0},
           "Appet": {"good": 1, "poor": 0},
           "pe": {"yes": 1, "no": 0},
           "Ane": {"yes": 1, "no": 0},
           "Class": {"ckd": 1, "notckd": 0}}
```

In [69]:

```
# Replace binary values into dataset
dataset.replace(cleanup, inplace=True)
```

In [70]:

```
# Fill null values with mean value of the respective column  
  
dataset.fillna(round(dataset.mean(),2), inplace=True)
```

In [71]:

```
print(dataset)
```

	Age	Bp	Sg	Al	Su	Rbc	Pc	Pcc	Ba	Bgr	...	\
0	48.0	80.00	1.020	1.00	0.00	0.81	1.00	0.0	0.0	121.00	...	
1	7.0	50.00	1.020	4.00	0.00	0.81	1.00	0.0	0.0	148.04	...	
2	62.0	80.00	1.010	2.00	3.00	1.00	1.00	0.0	0.0	423.00	...	
3	48.0	70.00	1.005	4.00	0.00	1.00	0.00	1.0	0.0	117.00	...	
4	51.0	80.00	1.010	2.00	0.00	1.00	1.00	0.0	0.0	106.00	...	
5	60.0	90.00	1.015	3.00	0.00	0.81	0.77	0.0	0.0	74.00	...	
6	68.0	70.00	1.010	0.00	0.00	0.81	1.00	0.0	0.0	100.00	...	
7	24.0	76.47	1.015	2.00	4.00	1.00	0.00	0.0	0.0	410.00	...	
8	52.0	100.00	1.015	3.00	0.00	1.00	0.00	1.0	0.0	138.00	...	
9	53.0	90.00	1.020	2.00	0.00	0.00	0.00	1.0	0.0	70.00	...	
10	50.0	60.00	1.010	2.00	4.00	0.81	0.00	1.0	0.0	490.00	...	
11	63.0	70.00	1.010	3.00	0.00	0.00	0.00	1.0	0.0	380.00	...	
12	68.0	70.00	1.015	3.00	1.00	0.81	1.00	1.0	0.0	208.00	...	
13	68.0	70.00	1.020	1.02	0.45	0.81	0.77	0.0	0.0	98.00	...	
14	68.0	80.00	1.010	3.00	2.00	1.00	0.00	1.0	1.0	157.00	...	
15	40.0	80.00	1.015	3.00	0.00	0.81	1.00	0.0	0.0	76.00	...	
16	47.0	70.00	1.015	2.00	0.00	0.81	1.00	0.0	0.0	99.00	...	
17	47.0	80.00	1.020	1.02	0.45	0.81	0.77	0.0	0.0	114.00	...	
18	

In [72]:

```

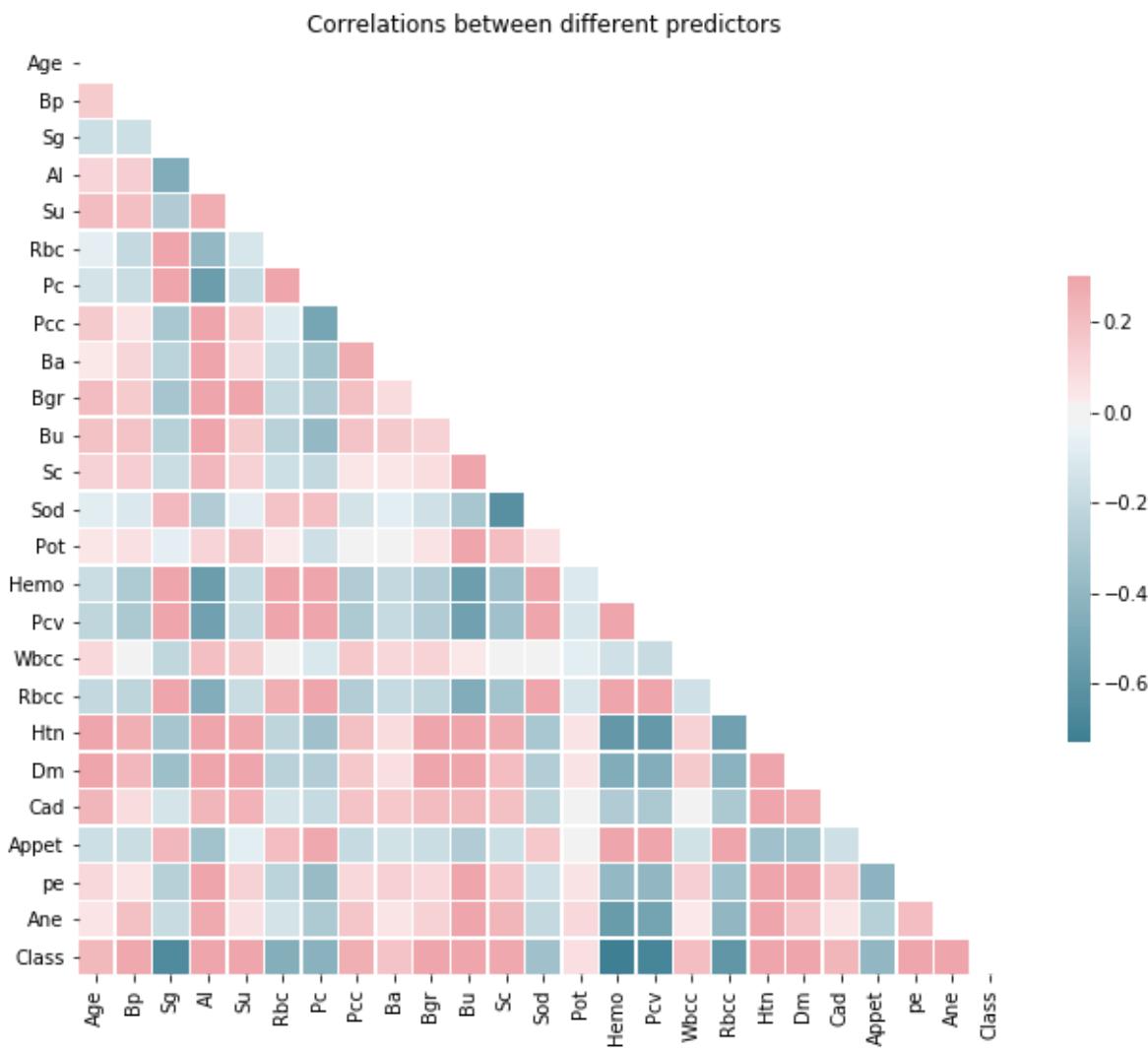
corr_df = dataset.corr()
# Generate a mask for the upper triangle
mask = np.zeros_like(corr_df, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(11, 9))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr_df, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
plt.title('Correlations between different predictors')
plt.show()

```



In [73]:

```

# Save this dataset as final.csv for further prediction
dataset.to_csv("final.csv", sep=',', index=False)

```

Step 5: Defining feature matrix and target vector

In [74]:

```
X = dataset.values[:, 0:24]  
Y = dataset.values[:, -1]
```

Step 6: Splitting the dataset

In [75]:

```
from sklearn.model_selection import train_test_split  
X_train, X_test, y_train, y_test = train_test_split( X, Y, test_size = 0.3, random_state =
```

Step 7: Model building (USING LOGISTIC REGRESSION)

In [76]:

```
from sklearn.linear_model import LogisticRegression  
logmodel=LogisticRegression()  
logmodel.fit(X_train,y_train)  
predictions=logmodel.predict(X_test)
```

```
C:\Users\admin\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.  
FutureWarning)
```

In [77]:

predictions

Out[77]:

Step 8: Evaluating the model

In [78]:

```
from sklearn.metrics import confusion_matrix  
confusion_matrix(y_test,predictions)  
from sklearn.metrics import accuracy_score  
accuracy_score(y_test,predictions)
```

Out[78]:

0.9833333333333333

