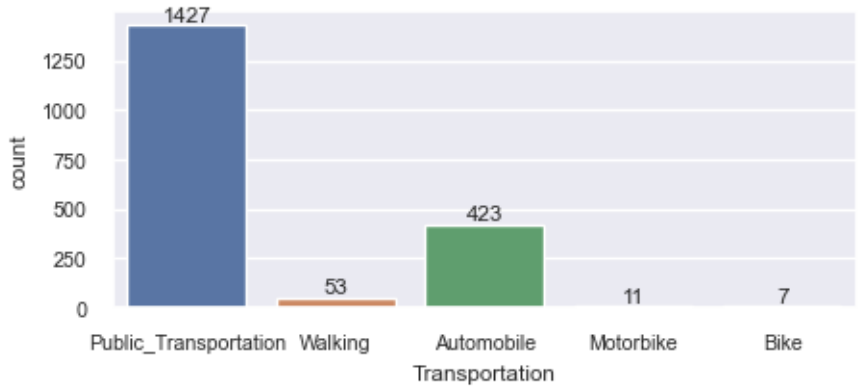
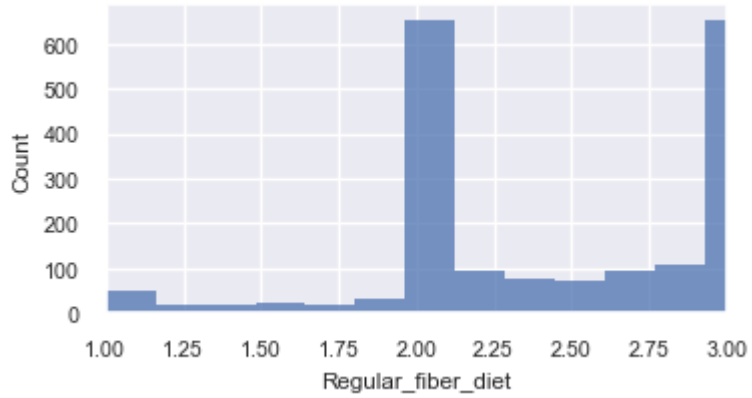
Tema ML

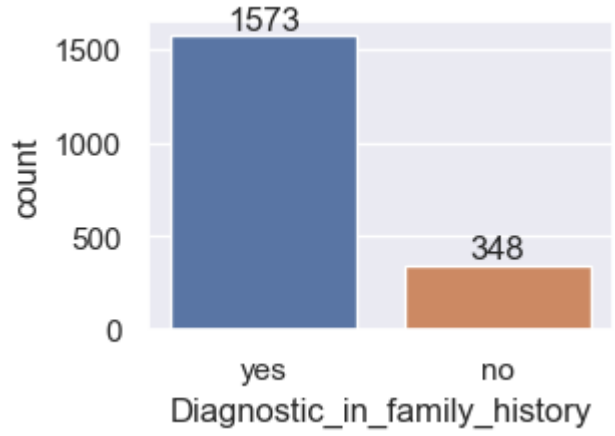
Veliscu Robert-Valentin

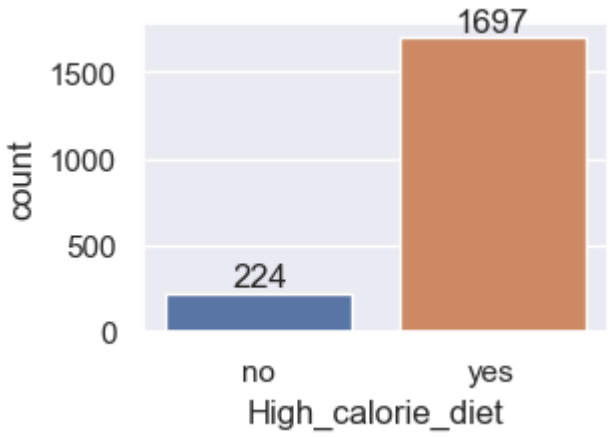
341C4

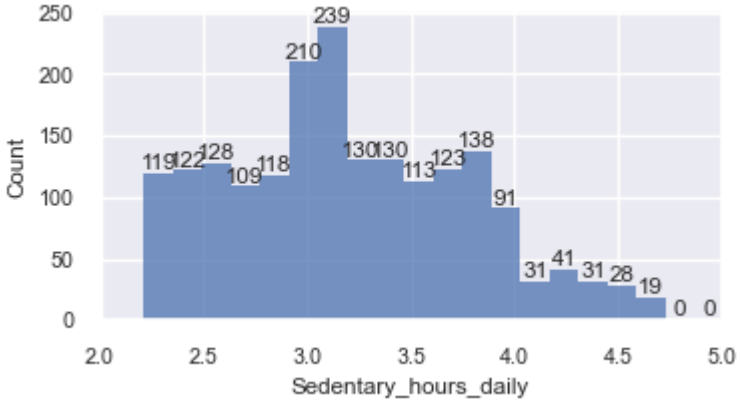
3.1.1 Diagrame count / histograme pentru fiecare atribut:



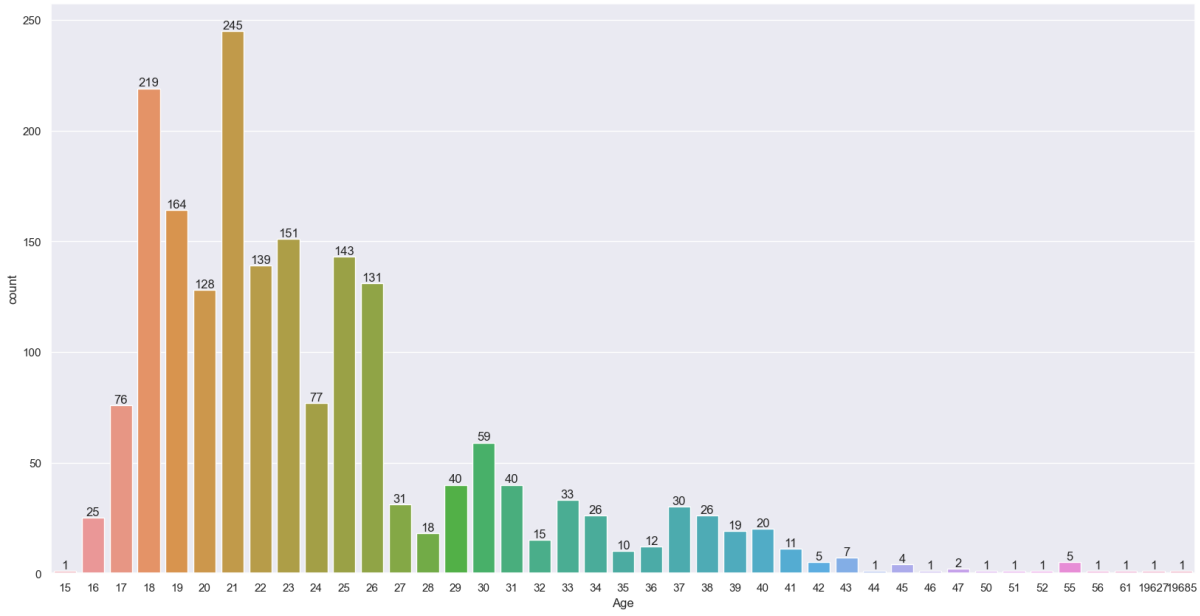




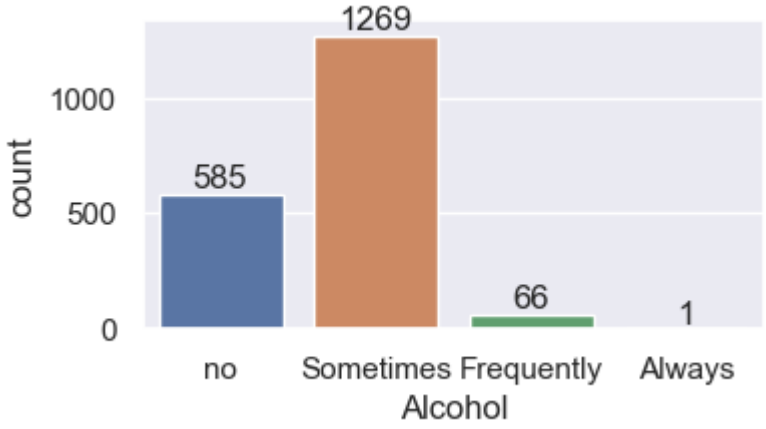


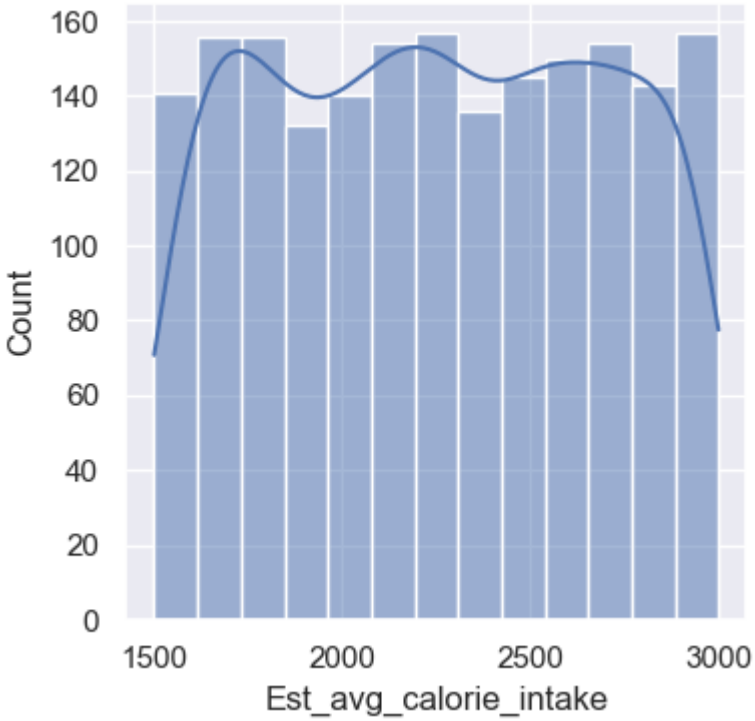


Pentru sedentary_hours_daily am setat limitele pe axa x intre 2 si 5, unde se aflau majoritatea pentru a putea viualiza histograma, deoarece era un outlier (greseala) cu o valoare foarte mare.

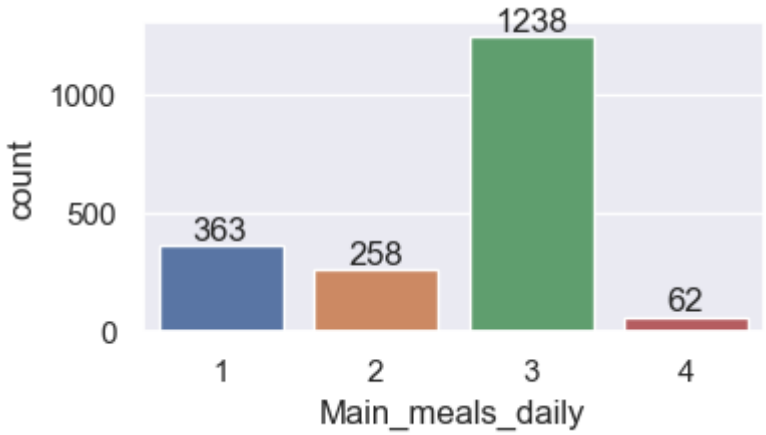


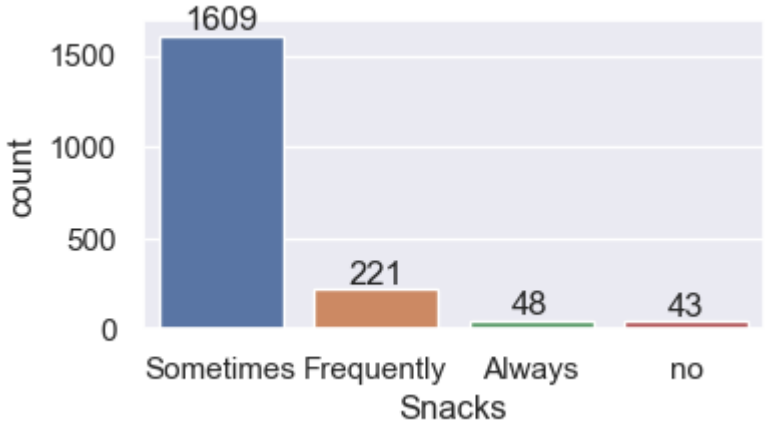
Pentru Age am rotunjit valorile la partea intreaga pentru a putea vizualiza mai bine si pentru a avea o relevanta mai mare.

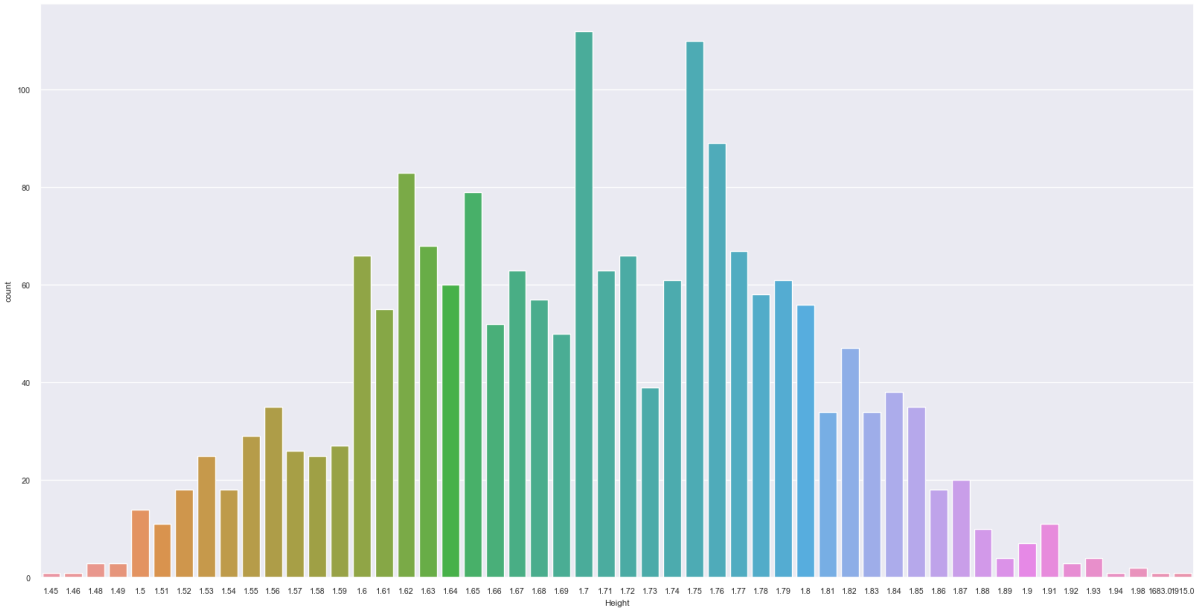


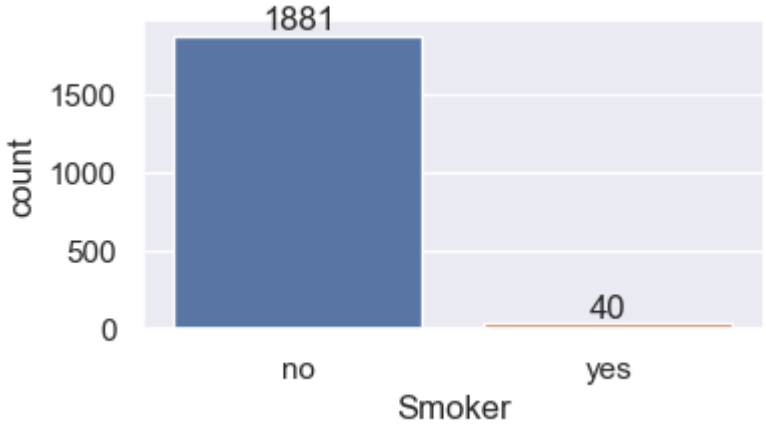


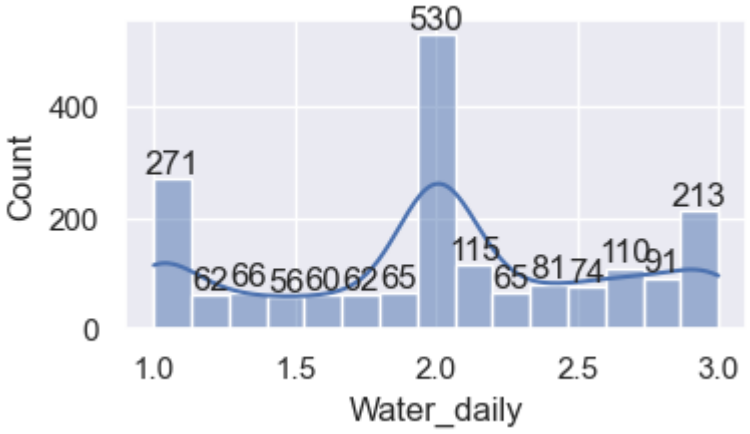
Pentru main meals daily am rotunjit din nou (fie iei masa fie nu)

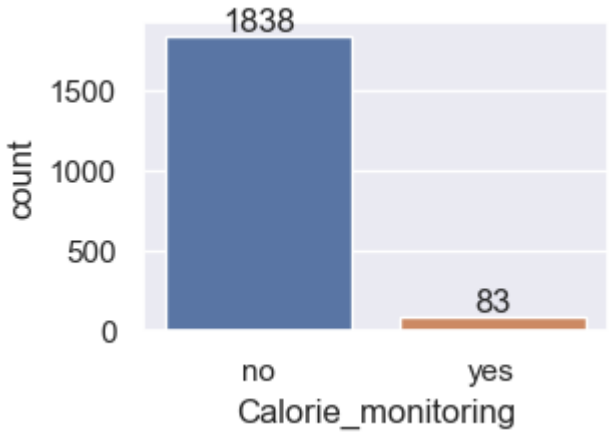


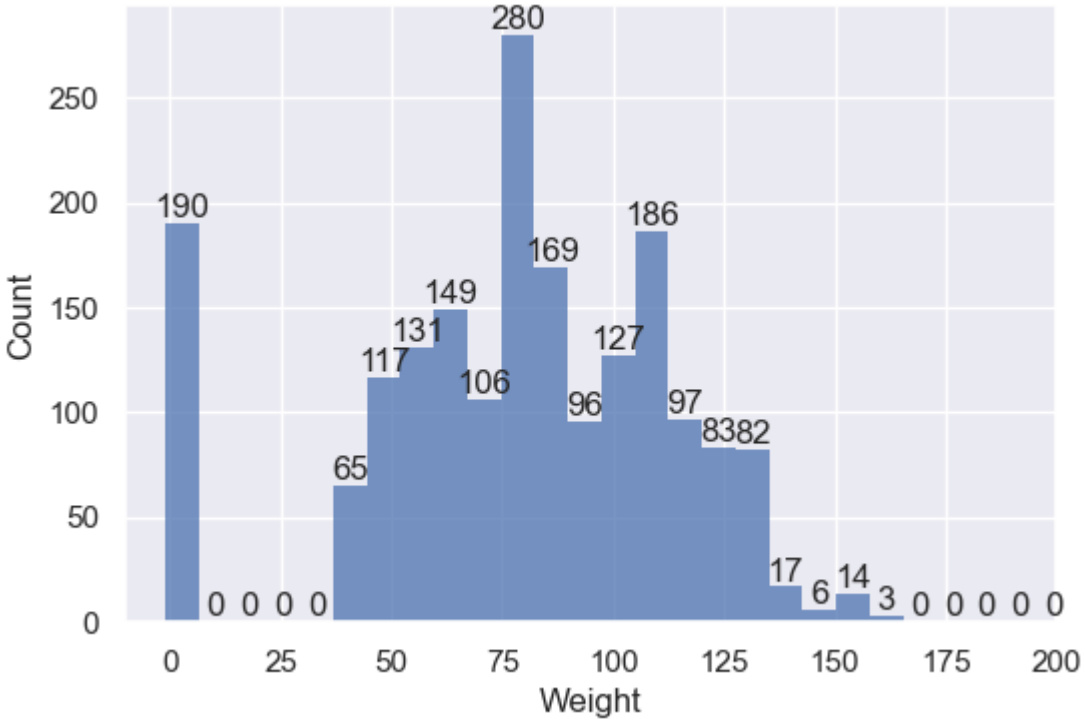

1609
221
48
43
count
1500
1000
500
0
Sometimes
Frequently
Always
no
Snacks

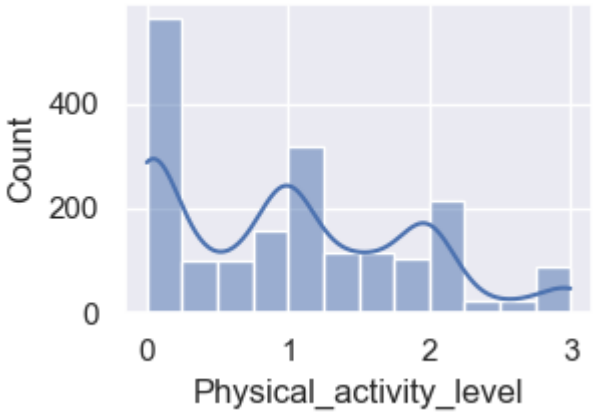

count
Height


1881
40
count
1500
1000
500
0
no
yes
Smoker

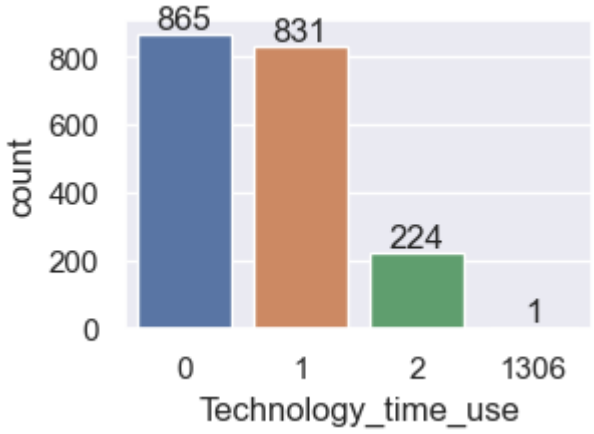

530
400
271
213
200
115
62 66 56 60 62 65 65 81 74 110 91
0
Count
1.0
1.5
2.0
2.5
3.0
Water_daily

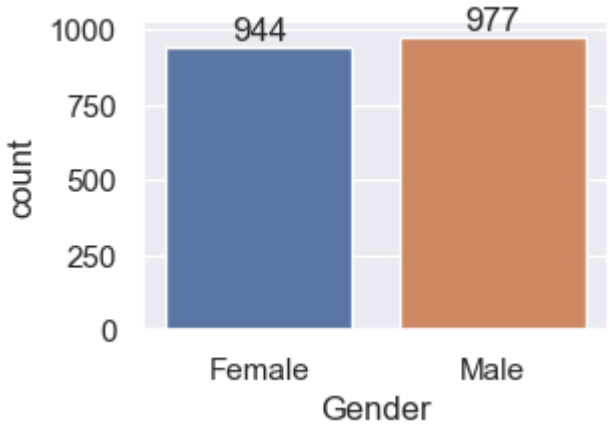

1838
1500
1000
500
0
count
83
no
yes
Calorie_monitoring

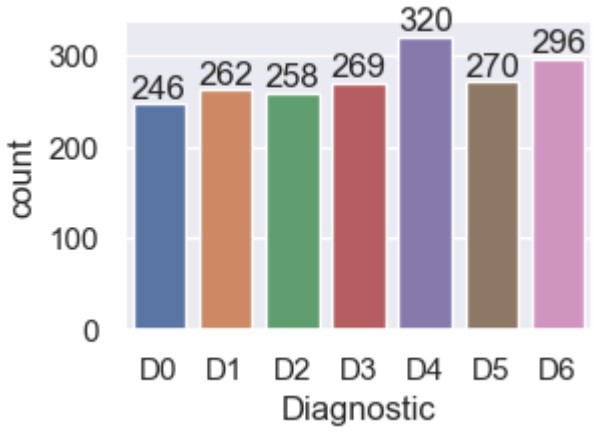

280
250
200
190
186
169
150
149
131
127
117
106
100
96
97
8382
65
50
17
6
14
3
0 0 0 0 0
0 0 0 0 0 0
0
Count
0
25
50
75
100
125
150
175
200
Weight



Putem observa un outlier la tech_time_use







3.1.2

	Regular_fiber_diet	Sedentary_hours_daily	Age	Est_avg_calorie_intake	Main_meals_daily	Height	Water_daily	Weight	Physical_activity_level	Technology_time_use
count	1921	1921	1921	1921	1921	1921	1921	1921	1921	1921
mean	3.844937	3.693571	44.79251	2253.688	2.683472	3.573488	2.010367	205.6373	1.01264	1.345653
std	62.439617	21.75984	633.3118	434.0758	0.779179	58.09816	0.611034	3225.654	0.855526	29.78993
min	1	2.21	15	1500	1	1.45	1	-1	0	0
25%	2	2.77	19.97166	1871	2.658639	1.63	1.606076	58.83071	0.115974	0
50%	2.387426	3.13	22.82975	2253	3	1.7	2	80.38608	1	1
75%	3	3.64	26	2628	3	1.77	2.480555	105.0361	1.683497	1
max	2739	956.58	19685	3000	4	1915	3	82628	3	1306
min_max_diff	2738	954.37	19670	1500	3	1913.55	2	82629	3	1306
mad	2.847637	1.133885	40.94689	375.3623	0.59542	3.738525	0.470801	254.6477	0.70216	1.510909

Din valorile statistice extrase pentru atributele numerice putem observa:

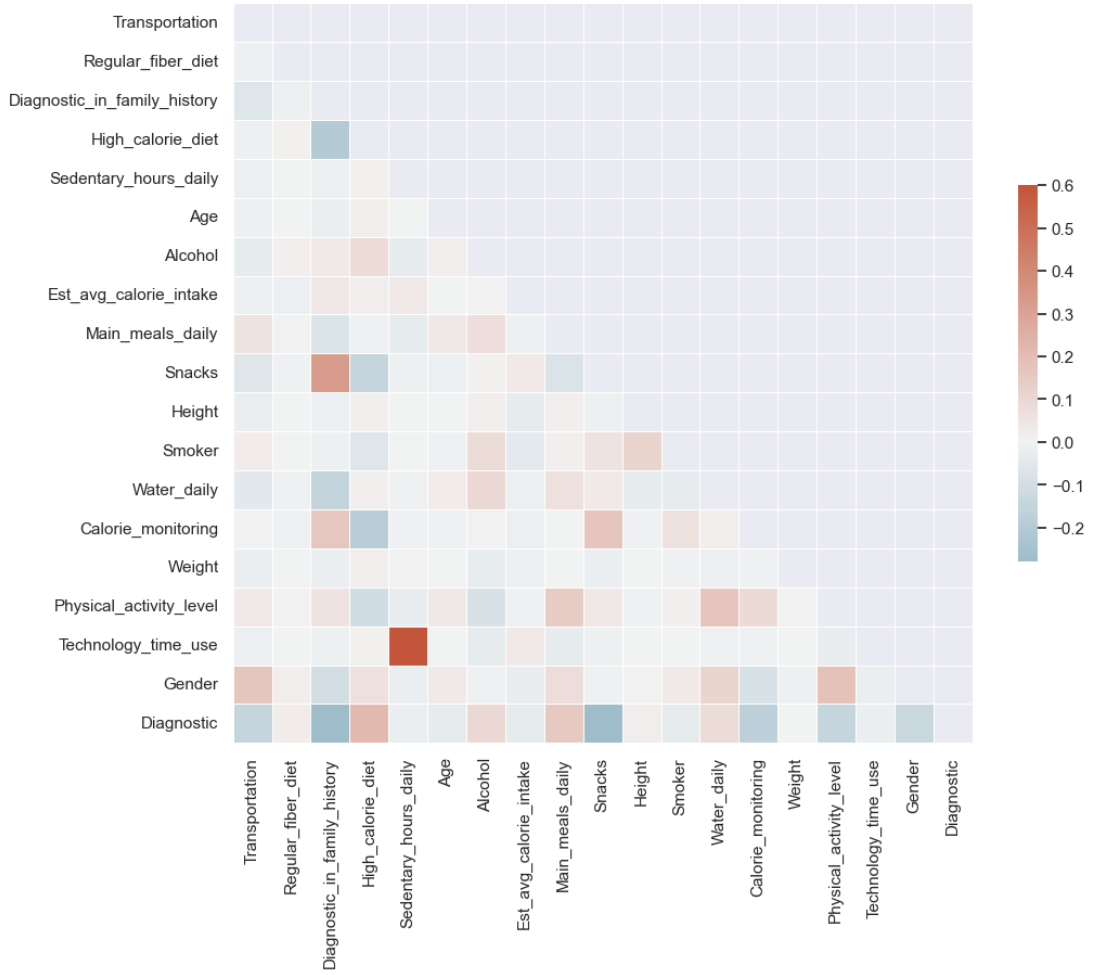
Multe dintre atribute au outlieri care influenteaza mult abaterea standard

Atributele au valori cu ordine de marimi diferite => necesita standardizare

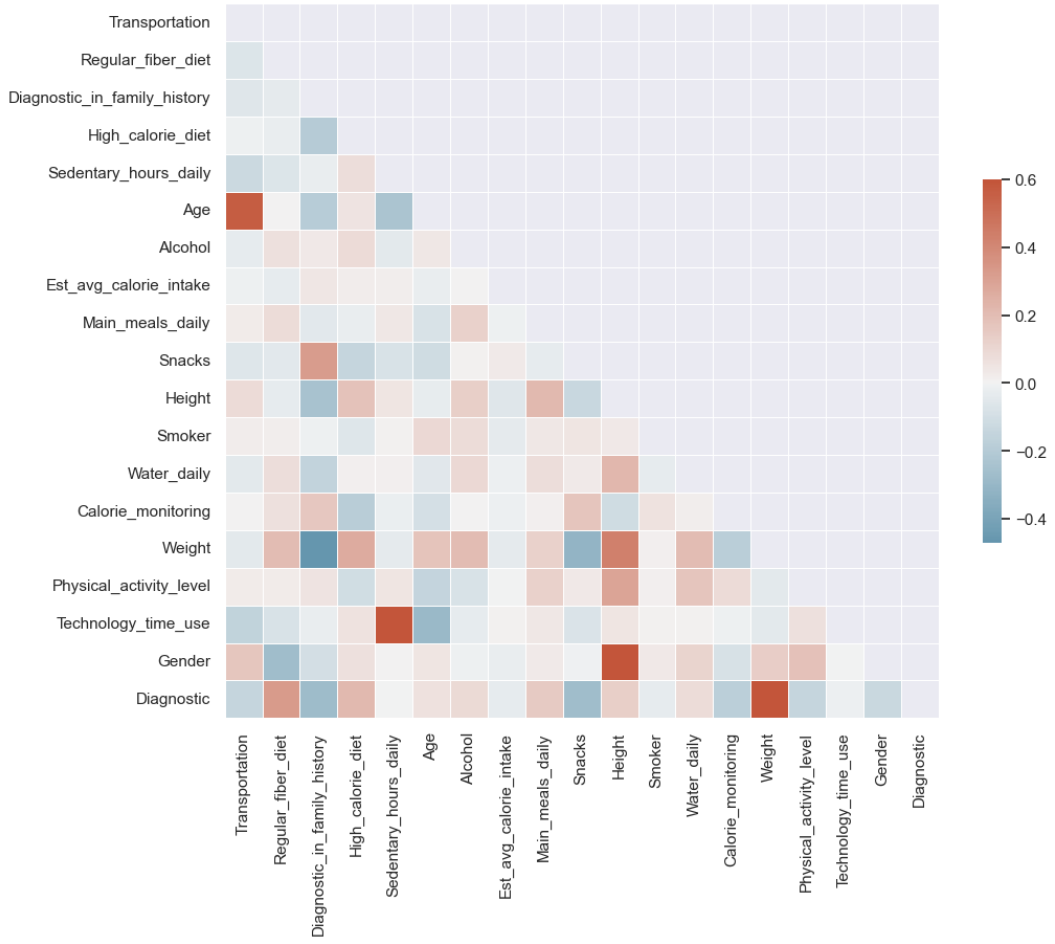
	Transportation	Diagnostic_in_family_history	High_calorie_diet	Alcohol	Snacks	Smoker	Calorie_monitoring	Gender	Diagnostic
count	1921	1921	1921	1921	1921	1921	1921	1921	1921
unique	5	2	2	4	4	2	2	2	7
top	Public_Transportation	yes	yes	Sometimes	Sometimes	no	no	Male	D4
freq	1427	1573	1697	1269	1609	1881	1838	977	320

Valori unice:

- Transportation: [Public_Transportation, Walking, Automobile, Motorbike,Bike],
- Diagnostic_in_family_history: [yes, no],
- High_calorie_diet: [no, yes],
- Alcohol: [no, Sometimes, Frequently, Always],
- Snacks: [Sometimes, Frequently, Always, no],
- Smoker: [no, yes],
- Calorie_monitoring: [no, yes],
- Gender: [Female, Male],
- Diagnostic: [D1, D2, D3, D4, D0, D5, D6]



Matricea de corelatie dupa tratarea valorilor lipsa si tratarea outlierilor:



Pentru tratarea valorilor lipsa am folosit SimpleImputer cu strategia mean.

Outlierii i-am scalat la ordinul de marime correct (am considerat ca a fost un typo / formatare automata a excel-ului), cu exceptia sedentary_hours_daily unde l-am inlocuit cu cea mai mare valoare (dintre celelalte valori) si technology_time_use unde l-am inlocuit cu 1.

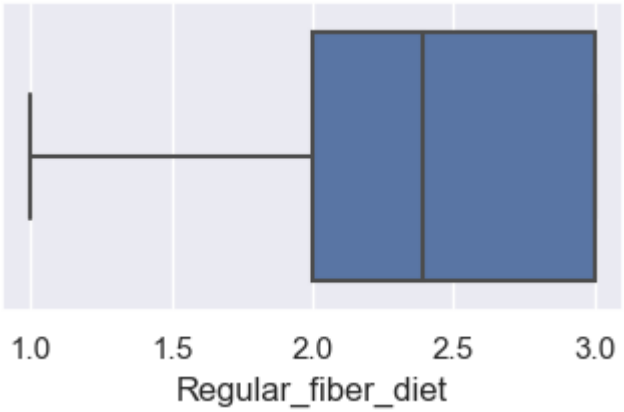
Valorile din matricea de corelatie pentru Diagnostic sortate crescator in functie de valoarea absoluta:

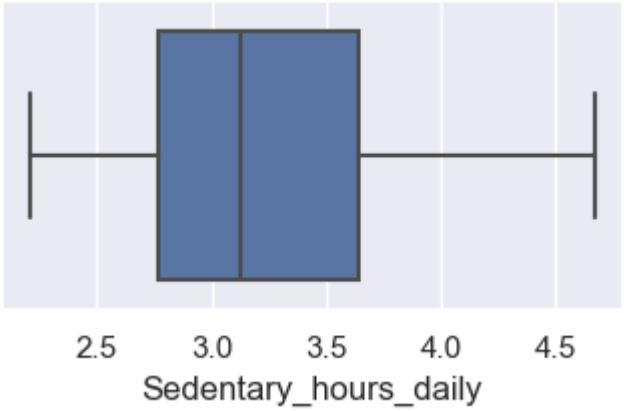
```
Sedentary_hours_daily          -0.002829
Technology_time_use            -0.015710
Est_avg_calorie_intake         -0.036043
Smoker                         -0.038645
Age                             0.061441
Water_daily                     0.081613
Alcohol                         0.094033
Gender                         -0.132271
Height                          0.134737
Physical_activity_level        -0.144771
Transportation                 -0.146906
Main_meals_daily                0.151026
Calorie_monitoring             -0.177705
High_calorie_diet               0.218737
Snacks                         -0.274317
Diagnostic_in_family_history   -0.277579
Regular_fiber_diet              0.329348
Weight                          0.598639
Diagnostic                      1.000000
```

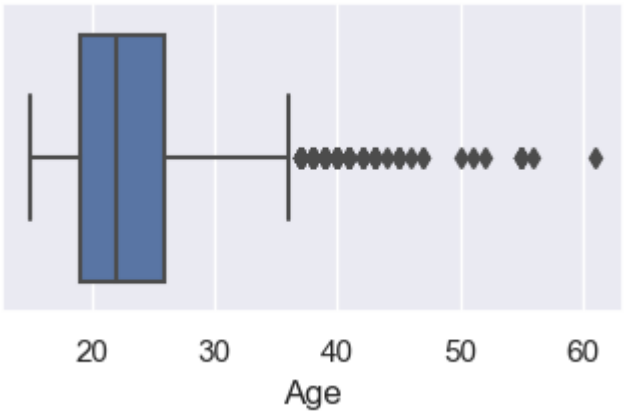
Valorile din matricea de covarianta pentru Diagnostic sortate crescator in functie de valoarea absoluta:

```
Sedentary_hours_daily          -0.003254
Smoker                         -0.011013
Technology_time_use            -0.021162
Height                          0.025091
Calorie_monitoring             -0.072110
Alcohol                         0.097250
Water_daily                     0.099499
Gender                         -0.131971
High_calorie_diet               0.140110
Diagnostic_in_family_history   -0.213364
Physical_activity_level        -0.247120
Main_meals_daily                0.250748
Transportation                 -0.257017
Snacks                         -0.329642
Regular_fiber_diet              0.350327
Age                             0.780691
Diagnostic                      3.980978
Weight                         29.727358
Est_avg_calorie_intake        -31.216057
```

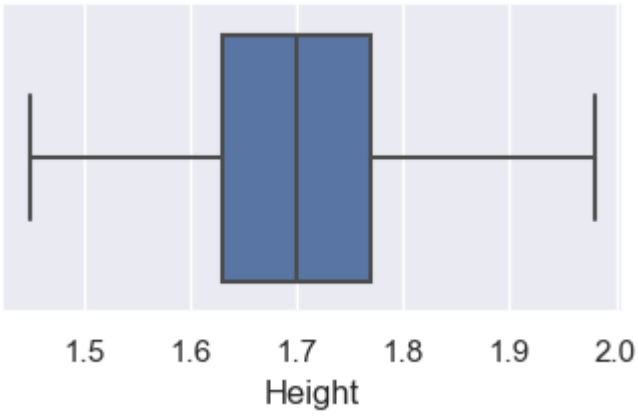
Boxplot-uri pentru fiecare atribut dupa tratarea valorilor lipsa si outlierilor (majori):

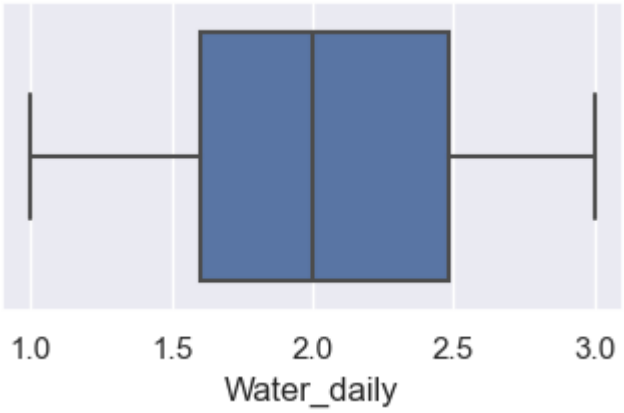


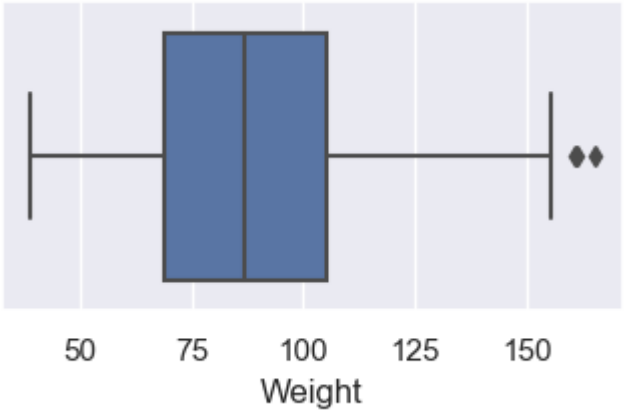


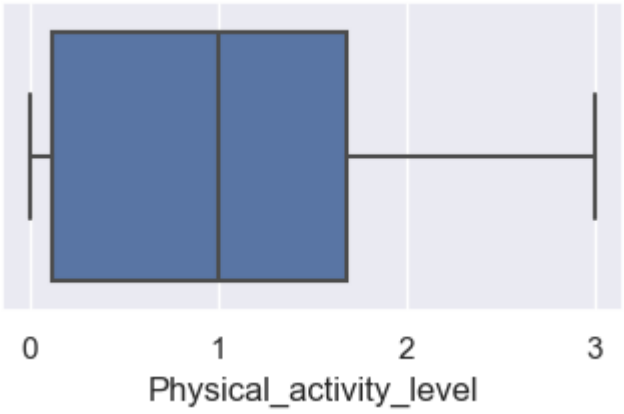


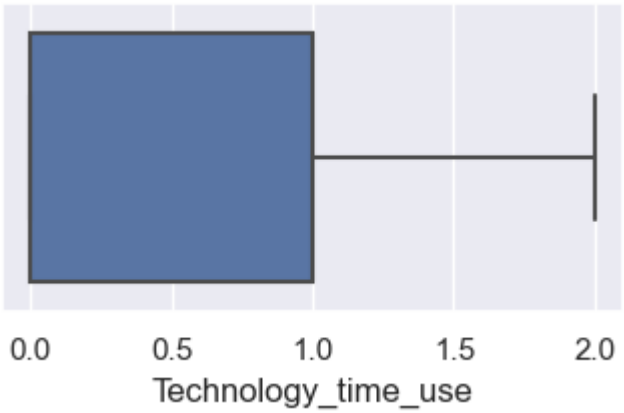

1
2
3
4
Main_meals_daily


1.5
1.6
1.7
1.8
1.9
2.0
Height


1.0
1.5
2.0
2.5
3.0
Water_daily


50
75
100
125
150
Weight





3.2

Pentru tratarea valorilor lipsa am folosit SimpleImputer cu strategia mean.

Pentru scalarea datelor am folosit RobustScaler deoarece la Age si Weight inca am cativa outlieri

Pentru partea de feature selection am folosit VarianceThreshold si SelectPercentile cu functia de scor mutual information si f_classif.

- Pentru VarianceThreshold am folosit un threshold de 50% (am eliminat atributele care in 50% din cazuri aveau aceeasi valore => nu ofereau insight). Astfel am redus datasetul la urmatoarele attribute:

```
['Transportation', 'Regular_fiber_diet', 'Sedentary_hours_daily', 'Age',
       'Alcohol', 'Est_avg_calorie_intake', 'Main_meals_daily', 'Snacks',
       'Height', 'Water_daily', 'Weight', 'Physical_activity_level',
       'Technology_time_use']
```

- Pentru SelectPercentile cu functia de scor f_classif am folostit un procent de 50% (am luat doar atributele cu cele mai bune 50% scoruri) si am redus dataset-ul la urmatoarele attribute:

```
['Regular_fiber_diet', 'Diagnostic_in_family_history',
       'High_calorie_diet', 'Age', 'Main_meals_daily', 'Snacks', 'Height',
       'Weight', 'Gender']
```

- Pentru SelectPercentile cu functia de scor mutual information am folostit un procent de 50% (am luat doar atributele cu cele mai bune 50% scoruri) si am redus dataset-ul la urmatoarele attribute:

['Regular_fiber_diet', 'Age', 'Main_meals_daily', 'Snacks', 'Height', 'Water_daily', 'Weight', 'Physical_activity_level', 'Gender']

In variance threshold doar elimin atributele care au in majoritate aceeasi valoare, fara a tine cont de relatia acestora cu target-ul. Spre exemplu Sedentary_hours_daily se afla in atributele mentinute de variance threshold dar nu in celelalte 2 cazuri deoarece, desi are o variatie de valori, aceasta nu are o relevanta ridicata pentru clasificare (asa cum se vede si din matricea de corelatie).

Diferenta intre f_classif si mutual information este functia care determina impactul atributelor asupra target-ului, iar pe baza valorilor date de aceasta functie putem alege atributele ramase. Astfel putem observa cateva diferente intre atributele ramase.

Algoritmi

SVM:

Best scores:

Selected using variance threshold: 0.845697787554465 {'C': 10, 'kernel': 'rbf'}

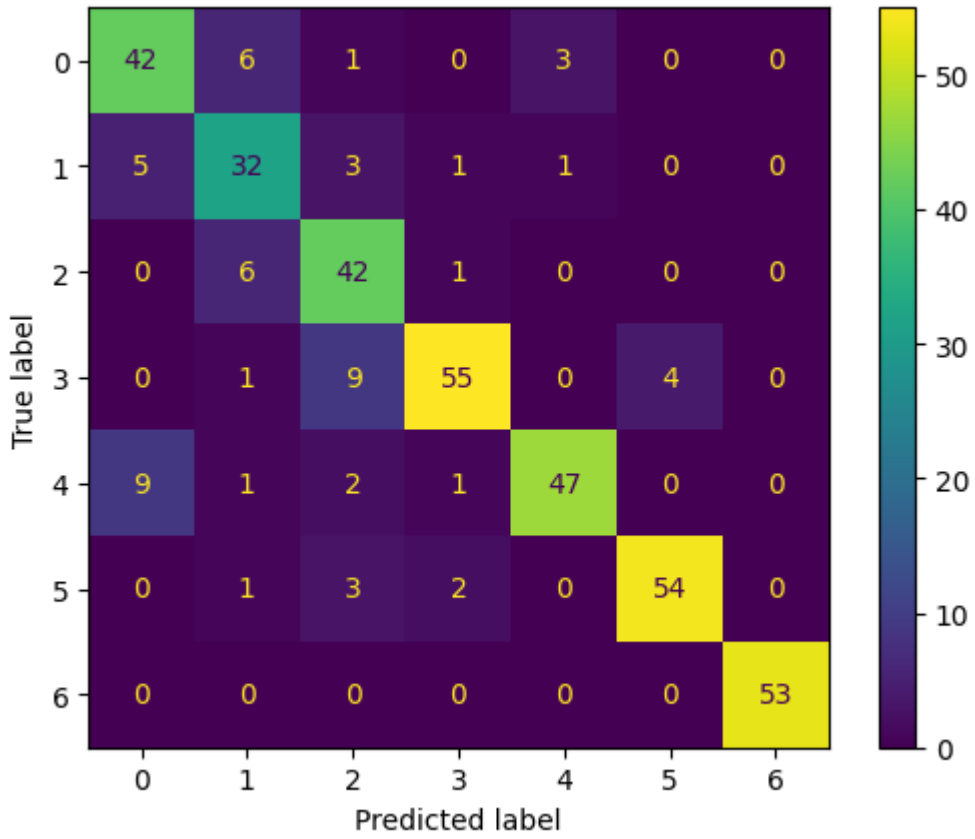
Selected using mutual information: 0.8593785693134226 {'C': 10, 'kernel': 'rbf'}

Selected using f-classif: 0.8626295528575658 {'C': 10, 'kernel': 'rbf'}

No selection: 0.8632746732095267 {'C': 10, 'kernel': 'rbf'}

	clasa	precision	recall	f1
variance threshold	0	0.653061	0.615385	0.633663
	1	0.634615	0.785714	0.702128
	2	0.72	0.734694	0.727273
	3	0.8	0.753623	0.776119
	4	0.862745	0.733333	0.792793
	5	0.857143	0.9	0.878049
	6	0.945455	0.981132	0.962963
mutual information	0	0.744681	0.673077	0.707071
	1	0.644444	0.690476	0.666667
	2	0.725806	0.918367	0.810811
	3	0.949153	0.811594	0.875
	4	0.839286	0.783333	0.810345
	5	0.933333	0.933333	0.933333
	6	0.946429	1	0.972477
f-classif	0	0.75	0.807692	0.777778
	1	0.680851	0.761905	0.719101
	2	0.7	0.857143	0.770642
	3	0.916667	0.797101	0.852713
	4	0.921569	0.783333	0.846847
	5	0.931034	0.9	0.915254
	6	1	1	1
no feature selection	0	0.6	0.692308	0.642857
	1	0.659574	0.738095	0.696629
	2	0.781818	0.877551	0.826923
	3	0.913793	0.768116	0.834646
	4	0.897959	0.733333	0.807339
	5	0.887097	0.916667	0.901639
	6	0.962963	0.981132	0.971963

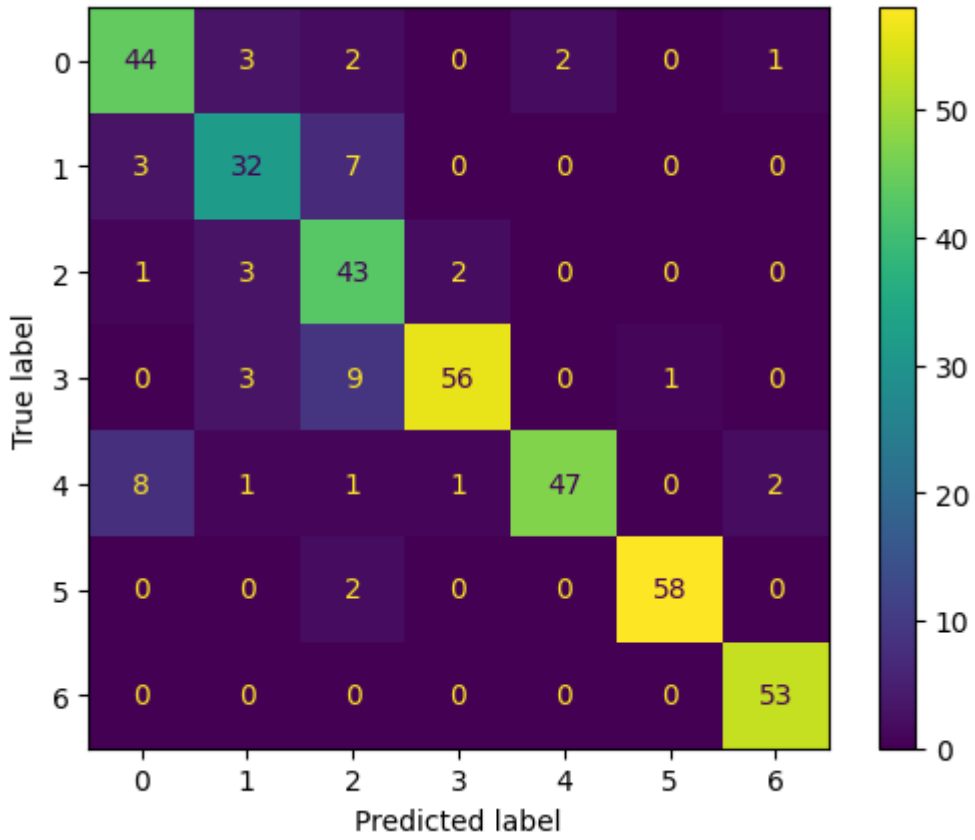
Matricea de confuzie pentru f-classif:



```
Random Forest:
Selected using variance threshold:  0.8867337873852531 {'criterion': 'entropy',
'max_depth': 8, 'max_features': 'sqrt', 'n_estimators': 500}
Selected using mutual information:  0.8899720800372265 {'criterion': 'entropy',
'max_depth': 8, 'max_features': 'sqrt', 'n_estimators': 500}
Selected using f-classif:  0.8893100384957062 {'criterion': 'entropy', 'max_depth':
8, 'max_features': 'sqrt', 'n_estimators': 500}
No selection:  0.9016921189559625 {'criterion': 'entropy', 'max_depth': 8,
'max_features': 'sqrt', 'n_estimators': 500}
```

Random Forest	clasa	precision	recall	f1
variance threshold	0	0.75	0.807692	0.777778
	1	0.744186	0.761905	0.752941
	2	0.727273	0.816327	0.769231
	3	0.904762	0.826087	0.863636
	4	0.96	0.8	0.872727
	5	0.95	0.95	0.95
	6	0.896552	0.981132	0.936937
mutual information	0	0.785714	0.846154	0.814815
	1	0.761905	0.761905	0.761905
	2	0.671875	0.877551	0.761062
	3	0.949153	0.811594	0.875
	4	0.959184	0.783333	0.862385
	5	0.983051	0.966667	0.97479
	6	0.946429	1	0.972477
f-classif	0	0.754098	0.884615	0.814159
	1	0.842105	0.761905	0.8
	2	0.692308	0.918367	0.789474
	3	0.90625	0.84058	0.87218
	4	0.957447	0.75	0.841121
	5	1	0.933333	0.965517
	6	0.981481	1	0.990654
no feature selection	0	0.733333	0.846154	0.785714
	1	0.785714	0.785714	0.785714
	2	0.688525	0.857143	0.763636
	3	0.933333	0.811594	0.868217
	4	0.979167	0.783333	0.87037
	5	0.966102	0.95	0.957983
	6	0.963636	1	0.981481

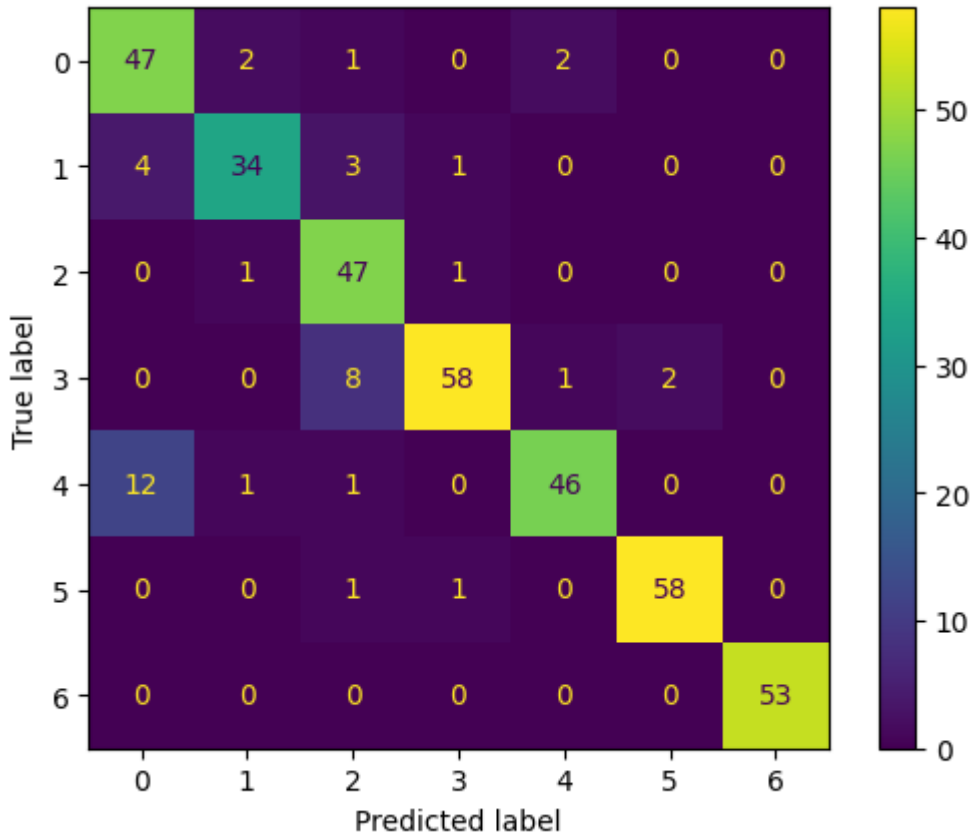
Matricea de confuzie pentru mutual information:



```
Extra trees:
Selected using variance threshold:  0.8906341215787471 {'criterion': 'gini',
'max_depth': 30, 'max_samples': 0.8, 'n_estimators': 500}
Selected using mutual information:  0.8964909683150726 {'criterion': 'entropy',
'max_depth': 20, 'max_samples': 0.8, 'n_estimators': 100}
Selected using f-classif:  0.8971318583696434 {'criterion': 'gini', 'max_depth': 20,
'max_samples': 0.8, 'n_estimators': 100}
No selection:  0.9010343077118321 {'criterion': 'entropy', 'max_depth': 20,
'max_samples': 0.8, 'n_estimators': 300}
```

Extra trees	clasa	precision	recall	f1
variance threshold	0	0.716981	0.730769	0.72381
	1	0.755556	0.809524	0.781609
	2	0.788462	0.836735	0.811881
	3	0.919355	0.826087	0.870229
	4	0.924528	0.816667	0.867257
	5	0.935484	0.966667	0.95082
	6	0.896552	0.981132	0.936937
mutual information	0	0.777778	0.807692	0.792453
	1	0.837209	0.857143	0.847059
	2	0.775862	0.918367	0.841121
	3	0.967742	0.869565	0.916031
	4	0.923077	0.8	0.857143
	5	0.983333	0.983333	0.983333
	6	0.946429	1	0.972477
f-classif	0	0.746032	0.903846	0.817391
	1	0.894737	0.809524	0.85
	2	0.770492	0.959184	0.854545
	3	0.95082	0.84058	0.892308
	4	0.938776	0.766667	0.844037
	5	0.966667	0.966667	0.966667
	6	1	1	1
no feature selection	0	0.709091	0.75	0.728972
	1	0.777778	0.833333	0.804598
	2	0.77193	0.897959	0.830189
	3	0.95	0.826087	0.883721
	4	0.903846	0.783333	0.839286
	5	0.935484	0.966667	0.95082
	6	0.962963	0.981132	0.971963

Matricea de confuzie pentru f-classif:

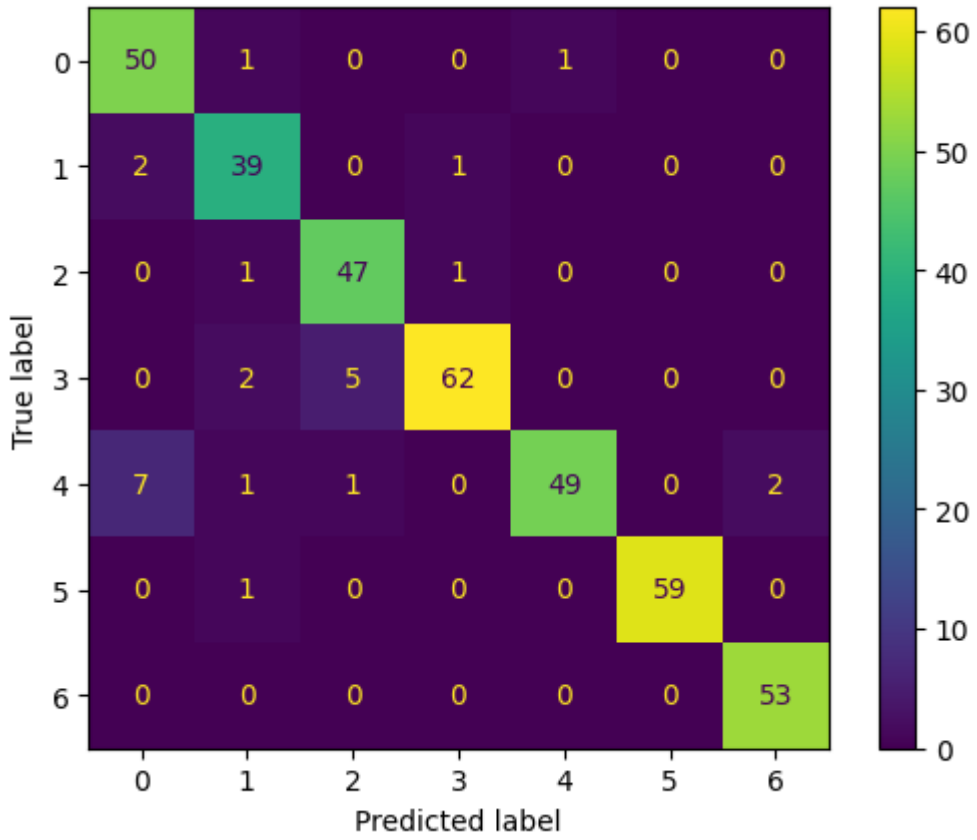


GradientBoostedTrees:

```
Selected using variance threshold:  0.9075595414357629 {'learning_rate': 0.3,
'max_depth': 7, 'n_estimators': 300}
Selected using mutual information:  0.9121155717246922 {'learning_rate': 0.1,
'max_depth': 5, 'n_estimators': 400}
Selected using f-classif:  0.9238271500486483 {'learning_rate': 0.2, 'max_depth': 5,
'n_estimators': 300}
No selection:  0.9186217691103685 {'learning_rate': 0.2, 'max_depth': 7,
'n_estimators': 500}
```

XGB	clasa	precision	recall	f1
variance threshold	0	0.87234	0.788462	0.828283
	1	0.770833	0.880952	0.822222
	2	0.821429	0.938776	0.87619
	3	0.936508	0.855072	0.893939
	4	0.980392	0.833333	0.900901
	5	0.966667	0.966667	0.966667
	6	0.866667	0.981132	0.920354
mutual information	0	0.833333	0.865385	0.849057
	1	0.770833	0.880952	0.822222
	2	0.811321	0.877551	0.843137
	3	0.967742	0.869565	0.916031
	4	0.942308	0.816667	0.875
	5	0.983051	0.966667	0.97479
	6	0.929825	1	0.963636
f-classif	0	0.847458	0.961538	0.900901
	1	0.866667	0.928571	0.896552
	2	0.886792	0.959184	0.921569
	3	0.96875	0.898551	0.932331
	4	0.98	0.816667	0.890909
	5	1	0.983333	0.991597
	6	0.963636	1	0.981481
no feature selection	0	0.849057	0.865385	0.857143
	1	0.880952	0.880952	0.880952
	2	0.87037	0.959184	0.912621
	3	0.938462	0.884058	0.910448
	4	0.961538	0.833333	0.892857
	5	0.983333	0.983333	0.983333
	6	0.898305	1	0.946429

Matricea de confuzie pentru f-classif:



Putem observa ca in majoritatea cazurilor, feature selection-ul cu SelectPercentile cu functia de scor f-classif a fost cea mai avantajoasa.
Clasele cu cele mai bune predictii au fost clasa 3 si clasa 5.
Cel mai performant model a fost GradientBoostedTrees cu hiperparametrii: 'learning_rate': 0.2, 'max_depth': 5, 'n_estimators': 300 si feature selection folosind f-classif