Research Article

Logistic Regression Analysis of Functional Constipation Factors in the Elderly

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Running title: LR Analysis of FC Factors in the Elderly

Abstract

Background: Machine learning software programs are of great interest at the scientific and applied levels in medical sciences today. There are various applications for these software programs in the field of diagnosis and treatment of diseases. Elderly people can benefit significantly from these software programs due to their physical limitations. The aim of this study is to develop and evaluate a supervised machine learning model for predicting functional constipation (FC) in the elderly.

Methods: The specific software in excel was designed as logistic regression supervised machine learning (LR-SML 402). This software development was based on a secondary analysis of source

data, exclusive articles, and doctoral dissertations of elderly individuals with FC who underwent colorectal evaluations using advanced laboratory equipment. The correlation between labeled data and the output data of colorectal parameters was measured using 480 datasets from published sources and research labs. Strong correlations were obtained between variables such as age, body mass index, and Wexner's questionnaire with indicators of FC.
Results: To validate the performance of LR-SML 402, the results were compared with those of a neural network in SPSS software. The model designed in Excel software demonstrated strong capability in terms of sensitivity, specificity, and area under the curve (AUC).
Conclusion: The findings show that the supervised machine learning approach using logistic regression may provide meaningful clinical predictions in determining laboratory indicators of FC in the elderly. This approach can reduce the time and cost of diagnosis.
Keywords: Chronic constipation, elderly, supervised logistic machine learning

Introduction:
Artificial intelligence (AI) is one of the most important consequences of the development of extensive software technology in applied engineering fields. Today, this technique is ready to help patients, students, professors and the treatment and health of society (1). Recently, artificial intelligence methods are being used to predict diseases and aging problems and help clinical professionals make decisions based on medical records. The improvement of artificial intelligence, as one of the latest generations of modern technologies, has made rapid progress and plays an important role in predicting and classifying problems related to the elderly. (2) Many scientists in clinical and therapeutic research widely use this method for diagnosis, treatment, prediction as well as for improving and effectiveness of health care. Important and unprecedented developments in this field, especially in the discussion of machine learning, are taking place. Despite the development of machine learning, there are still limitations in the curricula of medical and rehabilitation schools in the world, especially at the graduate level, so training and familiarization of academic staff, students and other teaching staff is essential (3). On the other hand, with the increase in the number of adults in society, which is expected to increase by 56% in the next 15 years (seniors over 60 years old) and the number of "elderly" (over 80 years old) will triple by 2050, therefore, with the increase in the number of elderly people, sphincter problems will be one of the most important problems and limitations of the elderly.
Logistic regression supervised machine learning (LR-SML) is a good interpretability and low computational cost, and it’s considered as a classification algorithm for high-dimensional data, it is a statistical method that predicts the probability of an outcome based on one or more predictor variables (4).
Various machine learning approaches have been used to identify the onset of dementia and cognitive problems. Some research has focused on the Activities of Daily Living (ADL) of the elderly to predict their cognitive level. Deep learning techniques can be useful for discovering anomalies in the normal behavior of people (5). Ju (2017) utilized deep learning with brain network data and clinically relevant information (including the subject's age, gender, and ApoE gene) to construct a targeted auto-encoder network. This network successfully distinguished normal aging from mild cognitive impairment and early-stage Alzheimer's disease. The model presented by Ju (2017) is more stable and reliable compared to traditional methods and can help predict and prevent Alzheimer's in its early stages (6). According to the review of studies conducted in this field, no research has focused on predicting indicators of functional constipation in the elderly. The purpose of this research is to design a logistic regression supervised machine learning (LR-SML) program

based on artificial intelligence to predict the rate and extent of functional constipation in the elderly without performing time-consuming, costly.

Methods:

1-Eldely subjects:

The prediction of functional constipation values was done in 480 cases in both male (240 case) and female (240 case) groups separately. The primary data (input layer) were recorded from previous population (retrospective study) of elder subjects (thesis data, clinics in Tehran town in this area). The ethical approve accepted from Theran University of Medical Sciences (IR.TUMS.MEDICINE.REC.1402.682).

A Consolidated Standards of Reporting Trials (CONSORT) flow diagram illustrates participant progression from enrolment to analysis (figure 1).

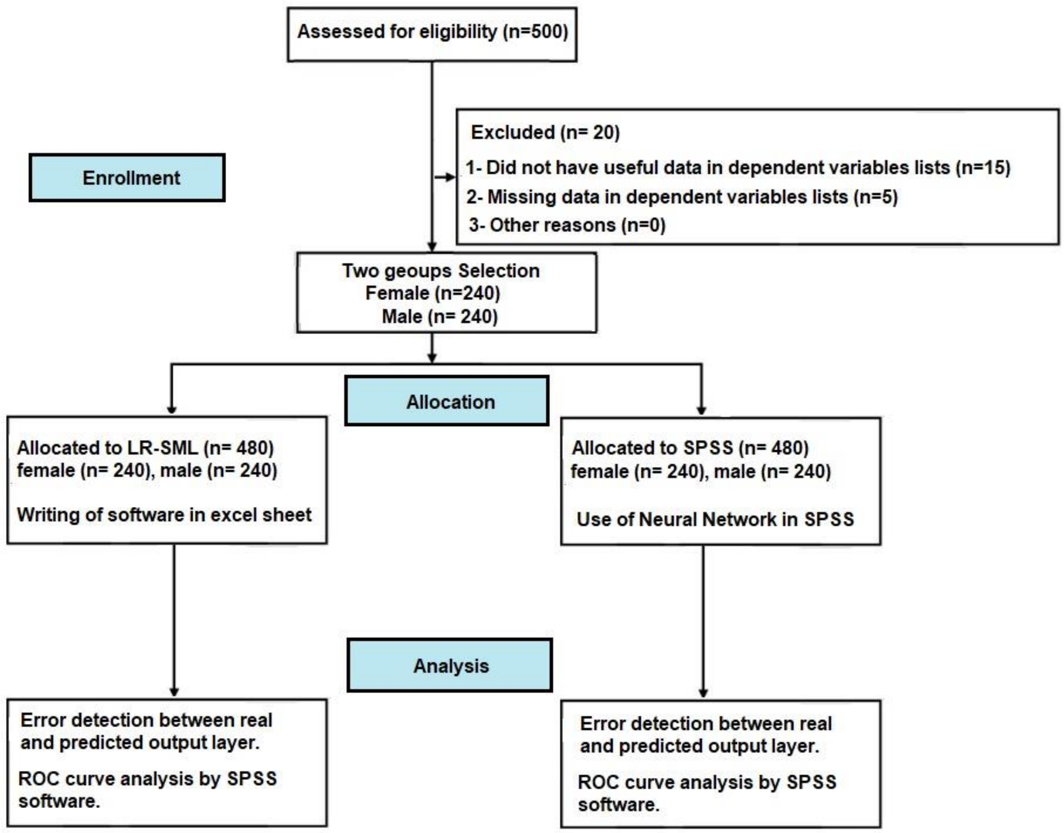


Figure 1. Consolidated Standards of Reporting of two different machine learning software analysis.

2- Logistic regression supervised machine learning:

Logistic regression supervised machine learning (LR-SML) was used for prediction of rest anal pressure, rectal pressure during coughing, anal pressure during coughing, maximum pressure during squeezing, pressure during squeezing, threshold of anorectal inhibitory reflex and defecation index as output data. These parameters changes based on age, weight, height, body mass index and Wexner questionnaire as input data, and there are moderate to good correlations between input and output data by previous sources and documents (tables 1,2).

Table 1. Correlations between of input layers and primary output layer variables in 240 cases (females)

Primary output layer	Input layer				
	Age (year)	Height (m)	Weight (Kg)	BMI (Kg/m^2)	Wexner
Rest anal pressure (mm Hg)	0.709	-0.222	0.691	0.631	0.916
Rectal pressure during coughing (mm Hg)	-0.653	0.182	-0.651	-0.579	-0.956
Anal pressure during coughing (mm Hg)	-0.664	0.192	-0.684	-0.607	-0.953
Maximum pressure during squeezing (mm Hg)	-0.648	0.181	-0.648	-0.576	-0.959
Pressure during squeezing (mm Hg)	-0.627	0.166	-0.610	-0.539	-0.945

Threshold of anorectal inhibitory reflex (cm^3)	-0.629	0.140	-0.665	-0.560	-0.923
Defecation Index (Ratio)	-0.573	0.170	-0.594	-0.531	-0.944

Table 2. Correlations between of input layers and primary output layer variables in 240 cases (males)

Primary output layer	**Input layer**				
	Age (year)	**Height (m)**	**Weight (Kg)**	**BMI (Kg/m^2)**	**Wexner**
Rest anal pressure (mm Hg)	0.661	-0.152	0.632	0.584	0.955
Rectal pressure during coughing (mm Hg)	-0.602	0.121	-0.637	-0.567	-0.914
Anal pressure during coughing (mm Hg)	-0.572	0.110	-0.597	-0.528	-0.858
Maximum pressure during squeezing (mm Hg)	-0.572	0.119	-0.611	-0.545	-0.865
Pressure during squeezing (mm Hg)	-0.553	0.137	-0.645	-0.582	-0.839
Threshold of anorectal inhibitory reflex (cm^3)	-0.616	0.121	-0.792	-0.683	-0.893
Defecation Index (Ratio)	-0.539	0.165	-0.771	-0.699	-0.878

We use two independent softwares 1- Logistic Regression Supervised Machine Learning in excel sheet, 2- SPSS (Neural Network, Multilayer Perception),
The sensitivity and specificity of LR-SML software were evaluated and compare with Neural Network, Multilayer Perception in SPSS softwares.
Dedicated Non-Negative Matrix Factorization (NMF) equations were written in excel sheet to calculate multiple regression between input variables and prediction in the Input Layer.
Nonnegative matrix factorization (NMF) is a technique where a matrix V with nonnegative entries is factored into two matrices W and H (Figure 2).

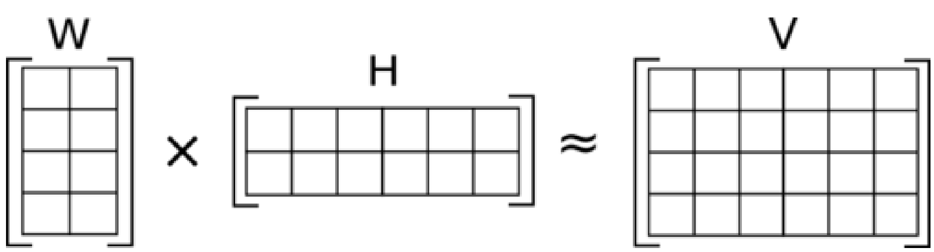
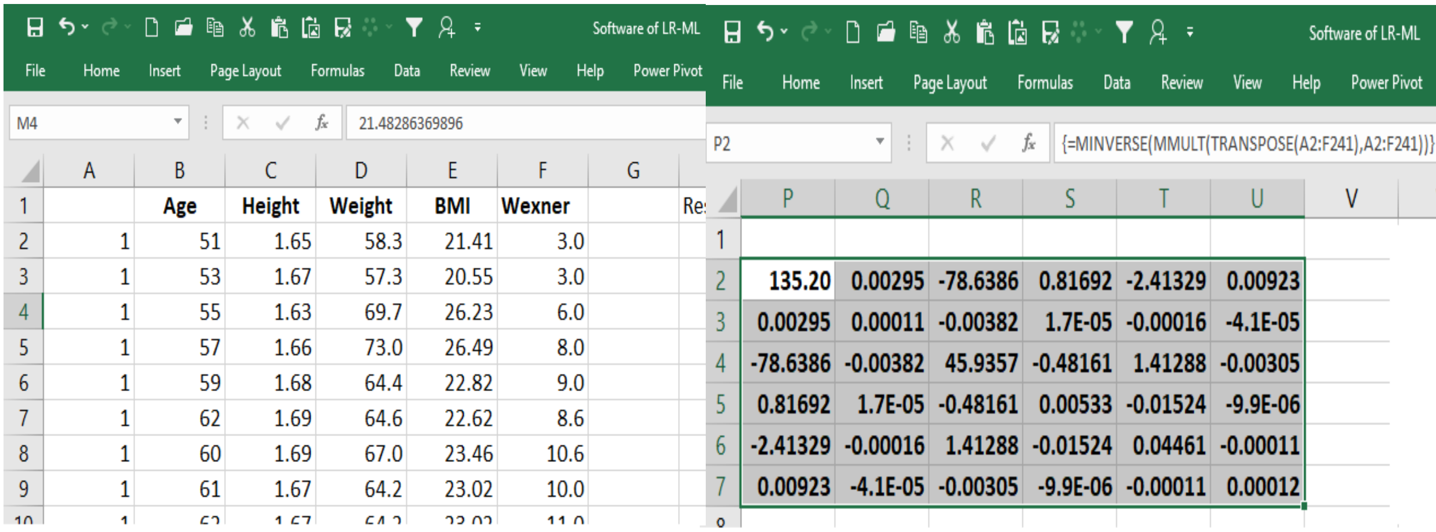


Figure 2. Nonnegative matrix factorization (NMF) diagram, Matrix multiplication can be implemented as computing the column vectors of V as linear combinations of the column vectors in W using coefficients supplied by columns of H. That is, each column of V can be computed as follows: V=W.H

The equations of NMF are:

a) MINVERSE (MMULT (TRANSPOSE (A2:F241), A2:F241))

A2:F241 is the input layer (intercept “A”, age “B”, weight “C”, height “D” MBI “E” and Wexner “F”) for 240 cases in excel sheet (Figure 3).



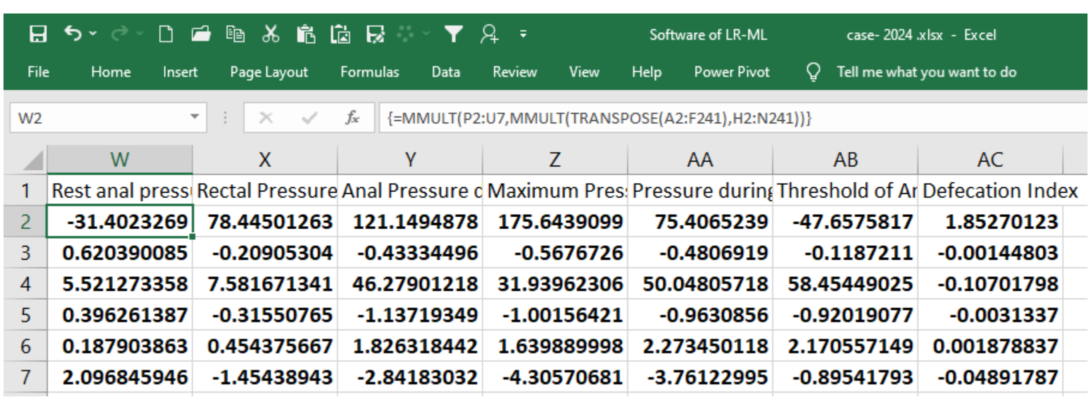
	A	B	C	D	E	F
1		Age	Height	Weight	BMI	Wexner
2	1	51	1.65	58.3	21.41	3.0
3	1	53	1.67	57.3	20.55	3.0
4	1	55	1.63	69.7	26.23	6.0
5	1	57	1.66	73.0	26.49	8.0
6	1	59	1.68	64.4	22.82	9.0
7	1	62	1.69	64.6	22.62	8.6
8	1	60	1.69	67.0	23.46	10.6
9	1	61	1.67	64.2	23.02	10.0

	P	Q	R	S	T	U
2	135.20	0.00295	-78.6386	0.81692	-2.41329	0.00923
3	0.00295	0.00011	-0.00382	1.7E-05	-0.00016	-4.1E-05
4	-78.6386	-0.00382	45.9357	-0.48161	1.41288	-0.00305
5	0.81692	1.7E-05	-0.48161	0.00533	-0.01524	-9.9E-06
6	-2.41329	-0.00016	1.41288	-0.01524	0.04461	-0.00011
7	0.00923	-4.1E-05	-0.00305	-9.9E-06	-0.00011	0.00012

Figure 3. the input layer (Age, Height, Weight, BMI, Wexner) and Non-Negative Matrix Factorization (NMF) equations (MINVERSE (MMULT (TRANSPOSE (A2:F241), A2:F241)) in excel sheet.

b) MMULT (P2:U7, MMULT (TRANSPOSE (A2:F241), H2:N241))

P2:U7 is for MINVERSE (MMULT (TRANSPOSE (intercept…)) and H2:N241 is for primary output layer (rest anal pressure “H”, rectal pressure during coughing “I”, anal pressure during coughing “J”, maximum pressure during squeezing “K”, pressure during squeezing “L”, threshold of anorectal inhibitory reflex” M” and defecation index” N” in excel sheet Figure 4).



	W	X	Y	Z	AA	AB	AC
1	Rest anal press	Rectal Pressure	Anal Pressure c	Maximum Pres	Pressure during	Threshold of Ar	Defecation Index
2	-31.4023269	78.44501263	121.1494878	175.6439099	75.4065239	-47.6575817	1.85270123
3	0.620390085	-0.20905304	-0.43334496	-0.5676726	-0.4806919	-0.1187211	-0.00144803
4	5.521273358	7.581671341	46.27901218	31.93962306	50.04805718	58.45449025	-0.10701798
5	0.396261387	-0.31550765	-1.13719349	-1.00156421	-0.9630856	-0.92019077	-0.0031337
6	0.187903863	0.454375667	1.826318442	1.639889998	2.273450118	2.170557149	0.001878837
7	2.096845946	-1.45438943	-2.84183032	-4.30570681	-3.76122995	-0.89541793	-0.04891787

Figure 4. The hidden layer measured via MMULT (P2:U7, MMULT (TRANSPOSE (A2:F241), H2:N241))

c) MMULT ($A$2: $F$241, W2:W7 …AC7)

W2:W7 is multiple regression values (Hidden layer) for detection and predict the output layers depended to number of them (w, x, y, z, aa, ab, ac). This equation can predict all of output layer at AE – AK columns in excel sheet (Figure 5).

Software of LR-ML 240 case- 2024 .xlsx - Excel

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AE2 {=(MMULT($A$2:$F$241,W2:W7))}

	AE	AF	AG	AH	AI	AJ	AK
1	Rest anal pressure	Pressure during co	Pressure during cou	m Pressure during s	essure during squeez	l of Anorectal inhibit	Defecation Index
2	42.764	67.266	139.694	163.202	114.723	32.885	1.313
3	43.556	66.920	139.305	162.282	113.751	32.852	1.310
4	56.849	60.508	124.348	143.860	100.493	28.525	1.136
5	63.805	56.484	115.904	132.190	90.919	25.774	1.022
6	63.155	55.808	116.191	129.976	87.127	25.749	0.988
7	64.274	55.684	115.899	129.787	87.044	25.719	1.001
8	68.336	52.818	109.888	121.286	80.082	23.781	0.901
9	66.396	54.014	112.617	124.748	82.557	24.655	0.939
10	69.113	52.351	109.342	119.874	78.315	23.641	0.888

Figure 5. The output layer measured by MMULT ($A$2: $F$241, W2:W7)) equation for each column AE to AK

Then, from this particular controlled matrix, an algorithm was used to determine the best estimate between inputs and outputs (Figure 6).

Input Layer

Age	80
Height	1.75
Weight	78.3
BMI	25.57
Wexner	21.0
Gender	2.0

Logistic Regression
Supervised
Machine Learning
Version 402

Hidden Layer

-31.402327	78.445013	121.14949	175.64391	75.406524	-47.65758	1.8527012
0.62039009	-0.209053	-0.433345	-0.567673	-0.480692	-0.118721	-0.001448
5.52127336	7.5816713	46.279012	31.939623	50.048057	58.45449	-0.107018
0.39626139	-0.315508	-1.137193	-1.001564	-0.963086	-0.920191	-0.003134
0.18790386	0.4543757	1.8263184	1.63989	2.2734501	2.1705571	0.0018788
2.09684595	-1.454389	-2.84183	-4.305707	-3.76123	-0.895418	-0.048918
225.10792	-101.9312	-436.3014	-489.8226	-364.5806	-123.215	0.7044106
0.24290179	-0.017075	-0.127536	-0.050362	0.1765633	0.0297533	0.0087955
-112.41786	108.57262	365.1036	426.67882	332.69412	105.44261	0.8365823
1.30604004	-1.431428	-4.485082	-5.500616	-4.711565	-1.578928	-0.0275
-4.1869278	4.0207169	12.958157	15.242002	11.097289	3.4996244	0.0217728
3.14886818	-2.223545	-4.980803	-7.23647	-5.482552	-0.936512	-0.044065

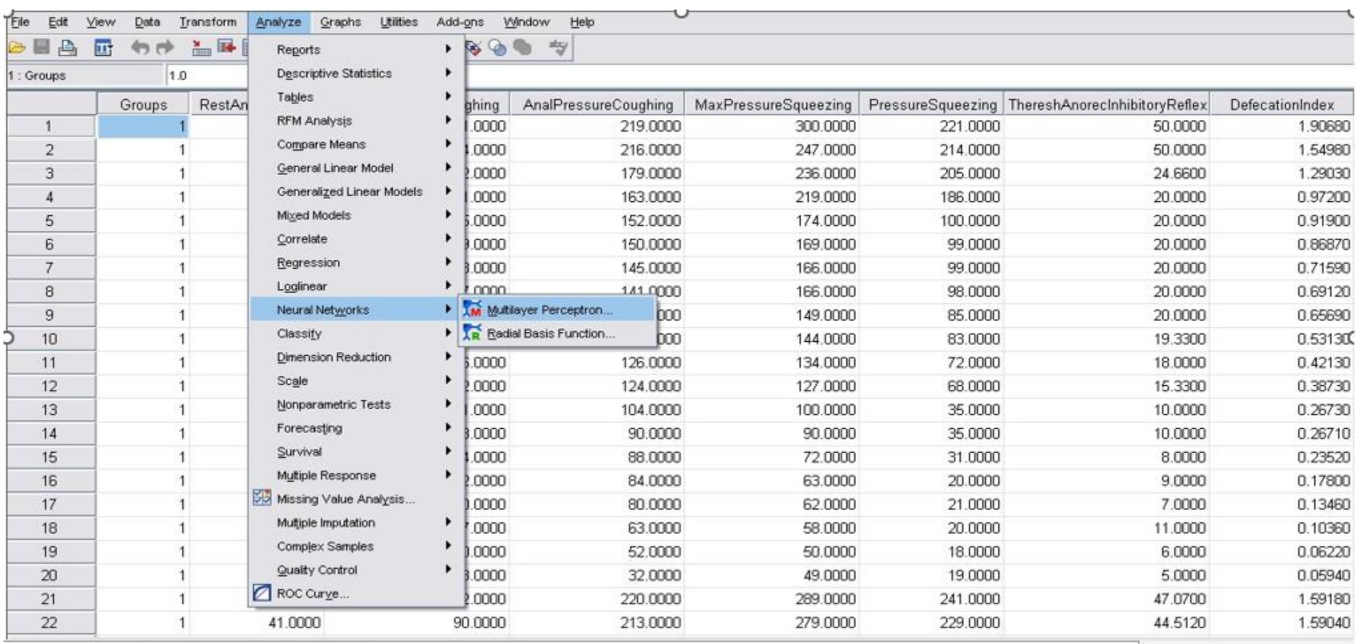
Synaptic Weigh > 0
Synaptic Weigh < 0

Output Layer		Result
Rest anal pressure	109.149	Abnormal
Rectal Pressure during coughing	30.729	Normal
Anal Pressure during coughing	67.954	Normal
Maximum Pressure during squeezing	59.870	Weakness
Pressure during squeezing	31.438	Weakness
Threshold of Anorectal inhibitory reflex	9.869	Weakness
Defecation Index	0.350	Normal

Figure 6. The software of logistic regression supervised machine learning (LR-SML).

2 - Software under SPSS environment in the Neural Networks section

In all versions of SPSS software, there is this option (Neural Networks) that by evaluating the number of input layers and initial output, it can give an estimate of the output layer along with the neural network. In this software, based on the Multilayer Perception option and in the Partitions section, by selection 70% training and 30% testing, prediction of output layer will be measured. With this ability we predicted functional constipation for comparison to software of LR-SML under excel sheet. Then the software gave an image of the hidden layers and calculation matrix with multiple regression calculations and finally stored the predicted values in new columns in the input file (Figures 7 and 8).



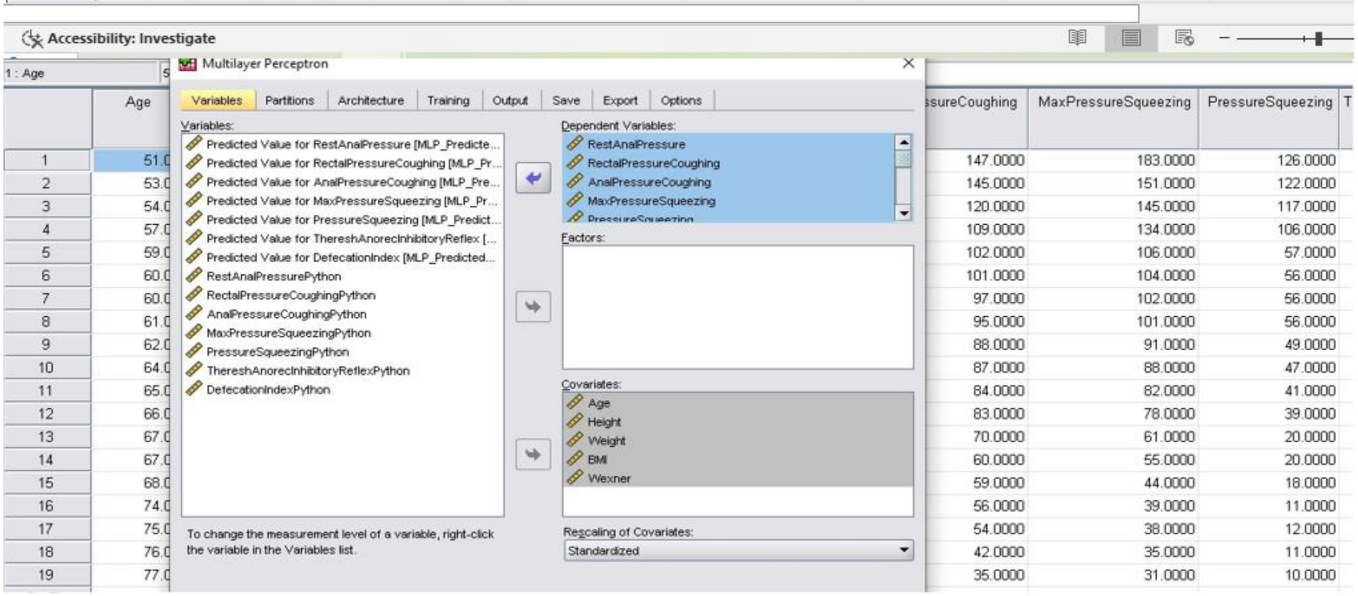


Figure 7. The software of SPSS (Neural Networks). The setting step in the SPSS softwares to estimate and predict the output layer based on the input layer and the initial output layer.

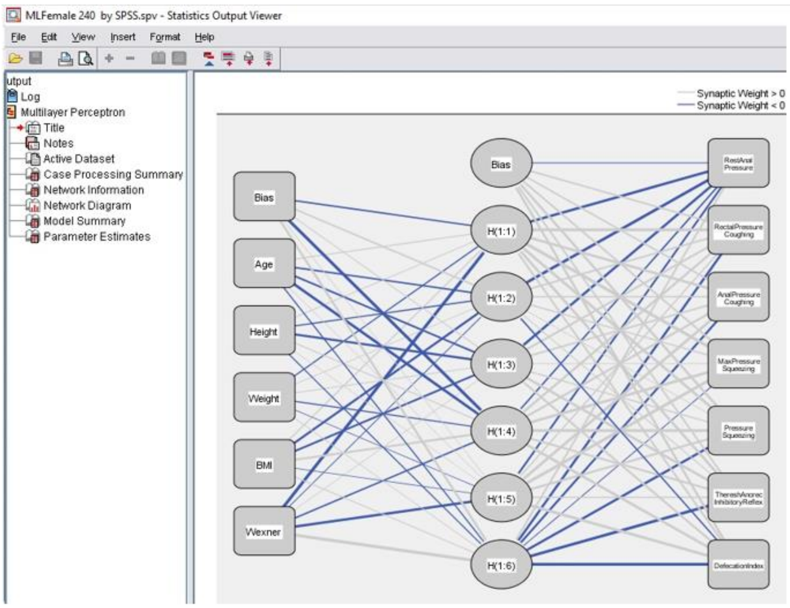


Figure 8. The output in the SPSS software along with the neural cells of the hidden layer and the inhibitory or excitatory effect on these neurons from the input layer and their effect on the predicted of output layer.

Results:

As mentioned earlier, there were moderate to good correlations between the initial inputs and outputs, then the appropriate algorithm was written using supervised machine learning methods in the Excel environment. Various criteria have been used and discussed to verify and validate this algorithm. A comparative analysis between the radial basis function network machine learning algorithm and logistic multiple regression in SPSS using labeled data for training and testing was performed (Figure 9).

The mean and standard deviations of two groups (Female -Male) measured (tables 3,4).

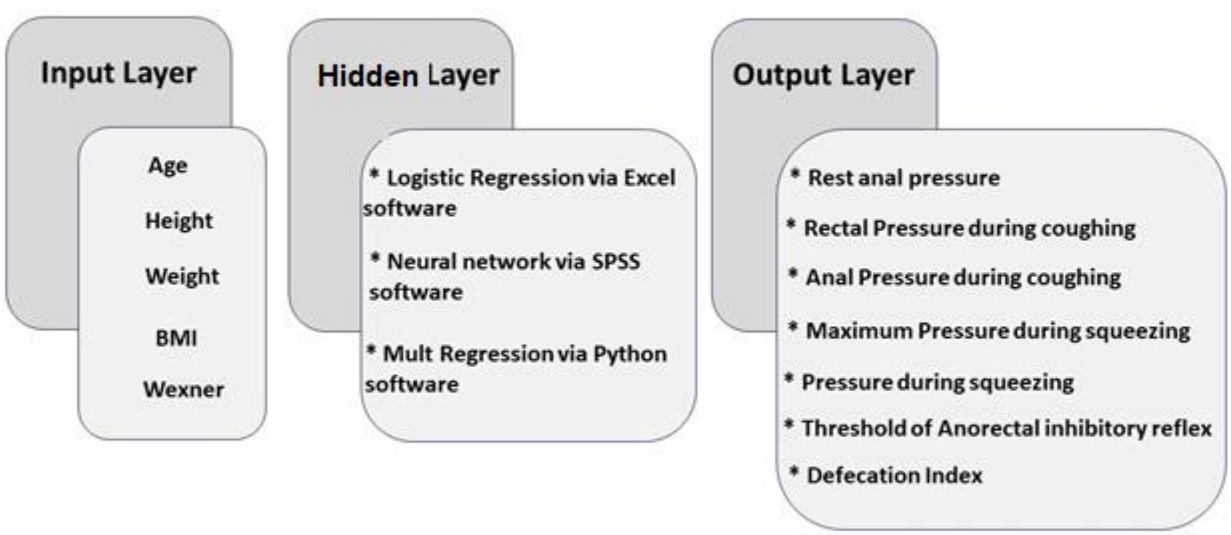


Figure 9. The Three stages for design of ML software

Table 3. Mean (SD, Max, Min) of 240 cases (female)

	Mean	SD	Maximum	Minimum
Age (year)	65.13	8.21	79.00	49.00
Height (m)	1.72	0.06	1.82	1.51
Weight (Kg)(	71.98	7.66	85.10	56.50
BMI (Kg/m2)(	24.38	3.61	36.18	17.95
Wexner questionnaire scale	17.24	7.79	30.00	2.00
Rest anal pressure (mm Hg)	87.82	23.36	176.00	43.00
Rectal pressure during coughing (mm Hg)	41.18	13.53	70.00	14.00
Anal pressure during coughing (mm Hg)	86.30	27.61	147.00	21.00
Maximum pressure during squeezing (mm Hg)	87.36	39.53	183.00	12.00
Pressure during squeezing (mm Hg)	51.55	33.96	137.00	1.00
Threshold of anorectal inhibitory reflex (cm3)	16.60	8.85	44.00	0.00
Defecation Index (Ratio)	0.55	0.42	1.70	0.00

Table 4. Mean (SD, Max, Min) of 240 cases (male)

	Mean	SD	Maximum	Minimum
Age (year)	65.13	8.20	79.00	49.00
Height (m)	1.74	0.07	1.87	1.51
Weight (Kg)(	74.93	8.36	90.00	54.50
BMI (Kg/m2)(	24.85	3.60	35.83	16.98
Wexner questionnaire scale	13.96	7.25	30.00	2.00
Rest anal pressure (mm Hg)	82.99	24.27	157.00	38.00
Rectal pressure during coughing (mm Hg)	47.61	17.84	92.00	7.00
Anal pressure during coughing (mm Hg)	107.43	42.58	220.00	18.00
Maximum pressure during squeezing (mm Hg)	115.30	62.00	300.00	0.00
Pressure during squeezing (mm Hg)	72.33	52.09	241.00	1.00
Threshold of anorectal inhibitory reflex (cm3)	17.88	9.73	50.00	0.07
Defecation Index (Ratio)	0.60	0.44	1.91	0.01

The receiver operating characteristic ROC curve (SPSS, 22) was used to measured (TP, TN, FP, FN) and evaluate the specificity and sensitivity of these two software with real variables from primary data. The area under the curve was measured by SPSS version 22 for both groups (tables 5-7) (Figures 10 and 11).

Table 5. The area under curve of two software in both groups.

	Female		Male	
	LR-SML	**SPSS**	**LR-SML**	**SPSS**
Rest anal pressure (mm Hg)	0.491	0.500	0.799	0.690
Rectal pressure during coughing (mm Hg)	0.820	0.745	0.862	0.874
Anal pressure during coughing (mm Hg)	0.839	0.755	0.860	0.902
Maximum pressure during squeezing (mm Hg)	0.867	0.867	0.884	0.922
Pressure during squeezing (mm Hg)	0.882	0.556	0.865	0.861
Threshold of anorectal inhibitory reflex (cm^3)	0.867	0.859	0.880	0.858
Defecation Index (Ratio)	0.896	0.881	0.819	0.849

Two software have good area under curve.

The accuracy percentage was calculated with the following equation (7):

$$Accuracy = \frac{\text{number of correct classification}}{\text{number of total clasification}}\ x\ 100$$

The detection performance of the model was evaluated using two metrics sensitivity and specificity which are indicative of model's ability to correctly reject negative false instances and avoiding false positive detections respectively (8).
The equations of the metrics are:

$$Sensitivity = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$Specificity = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

Where the TP (true positive) indicates the number of correct predicted event values, TN (true negative) indicates the number of correct predicted non-event values, FP (false positive) indicates incorrectly predicted event values and FN (false negative) indicates numbers of incorrect predicted non-events values.

Table 6. The ROC curve of the two software LR-SML and SPSS, (female).

LR-SML	TP	TN	FP	FN	Sensitivity	Specificity	ACC

Rest Anal Pressure	225	4	5	6	0.97	0.40	0.533
Rectal Pressure during Coughing	216	7	8	9	0.96	0.44	0.581
Anal Pressure during Coughing	215	8	7	10	0.96	0.50	0.575
Maximum Pressure during Squeezing	212	5	16	7	0.97	0.23	0.678
Pressure during Squeezing	196	8	26	10	0.95	0.23	0.799
Threshold of Anorectal Inhibitory Reflex	190	19	10	21	0.90	0.63	0.502
Defecation reflex	178	16	28	18	0.91	0.36	0.822
SPSS (Nural Network)	**TP**	**TN**	**FP**	**FN**	**Sensitivity**	**Specificity**	**ACC**
Rest Anal Pressure	228	1	8	3	0.99	0.10	0.531
Rectal Pressure during Coughing	226	2	8	4	0.98	0.18	0.573
Anal Pressure during Coughing	223	5	5	7	0.97	0.45	0.567
Maximum Pressure during Squeezing	215	7	9	9	0.96	0.41	0.670
Pressure during Squeezing	194	9	26	11	0.95	0.25	0.785
Threshold of Anorectal Inhibitory Reflex	192	15	16	17	0.92	0.47	0.671
Defecation reflex	187	16	19	18	0.91	0.44	0.824

Table 7. The ROC curve of the two software LR-SML and SPSS, (male).

LR-SML	**TP**	**TN**	**FP**	**FN**	**Sensitivity**	**Specificity**	**ACC**
Rest Anal Pressure	225	4	5	6	0.97	0.40	0.515
Rectal Pressure during Coughing	208	11	8	13	0.94	0.55	0.562
Anal Pressure during Coughing	213	9	7	11	0.95	0.53	0.563
Maximum Pressure during Squeezing	204	8	18	10	0.95	0.30	0.691
Pressure during Squeezing	199	10	19	12	0.94	0.33	0.790
Threshold of Anorectal Inhibitory Reflex	189	18	13	20	0.90	0.56	0.500
Defecation reflex	204	8	18	10	0.95	0.30	0.820
SPSS (Nural Network)	**TP**	**TN**	**FP**	**FN**	**Sensitivity**	**Specificity**	**ACC**
Rest Anal Pressure	233	0	5	2	0.99	0.00	0.519
Rectal Pressure during Coughing	221	2	13	4	0.98	0.13	0.562
Anal Pressure during Coughing	222	2	12	4	0.98	0.13	0.557
Maximum Pressure during Squeezing	201	10	17	12	0.94	0.36	0.658
Pressure during Squeezing	202	11	14	13	0.94	0.42	0.792
Threshold of Anorectal Inhibitory Reflex	182	22	12	24	0.88	0.63	0.683
Defecation reflex	197	14	13	16	0.92	0.50	0.821

As can be seen in tables 6 and 7, both softwares have high true positive with good sensitivity in the two groups, and both softwares have relatively good accuracy (Acc).
Sensitivity and specificity are inversely related, as sensitivity increases, specificity tends to decrease, and vice versa. Highly sensitive tests will lead to positive findings for patients with a disease, whereas highly specific tests will show patients without a finding having no disease.
These results suggest this two software can predict the elderly difficulty in functional constipation.

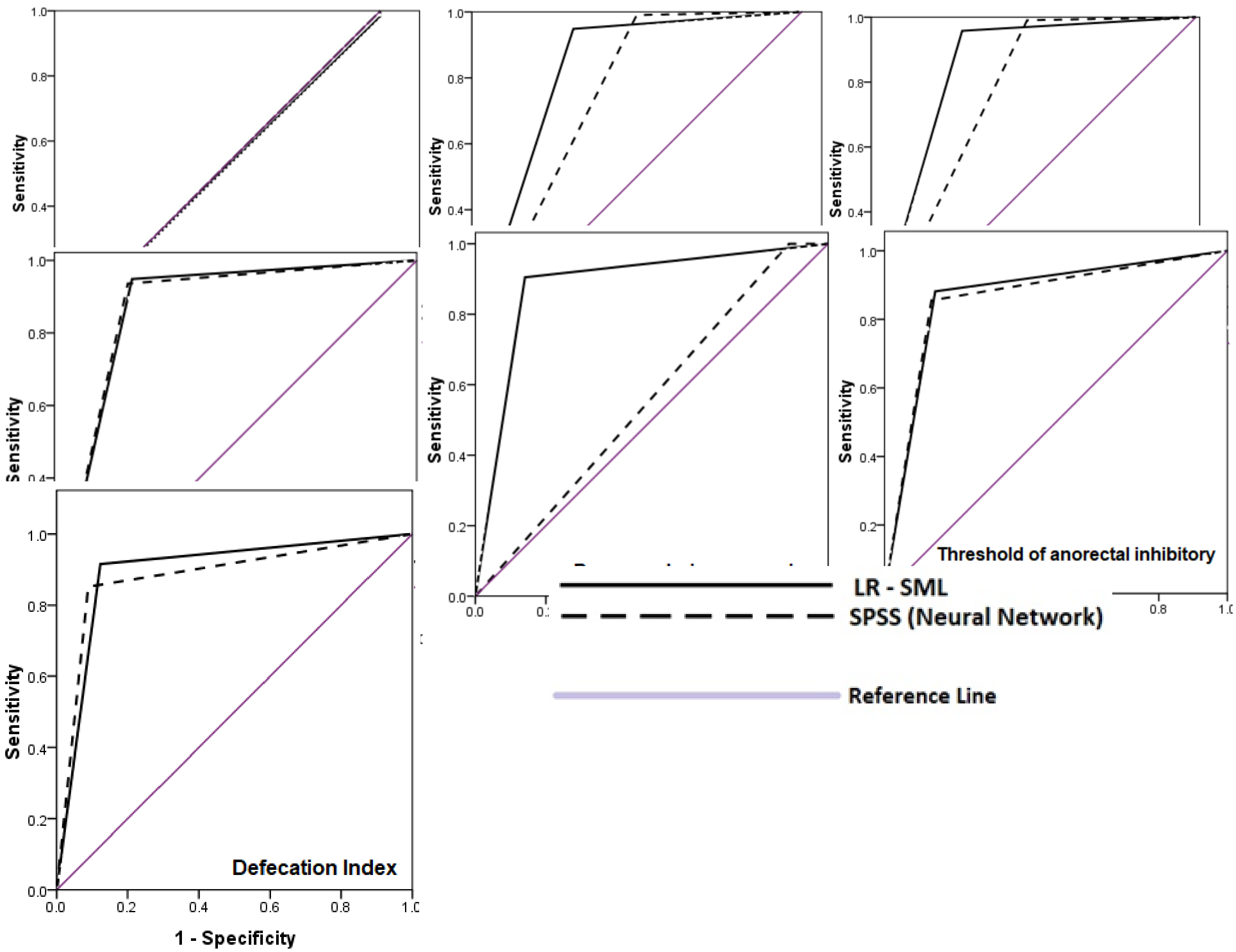


Figure 10. Comparison of changes in sensitivity and 1-specificity in two software programs for predicting the initial outcome in the *female group*.
LR-SML software performed relatively better than SPSS (Neural Network) software.

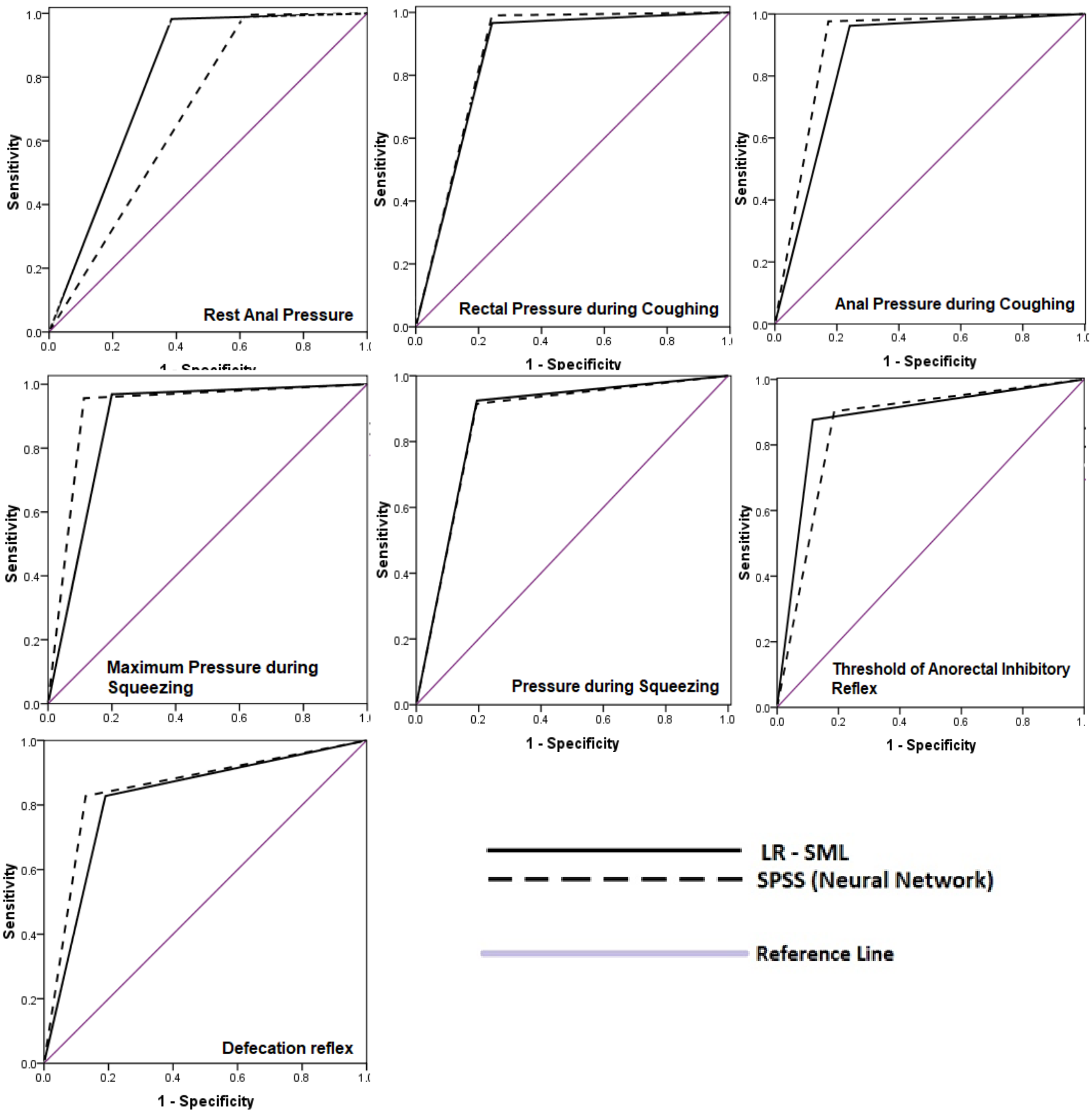


Figure 11. Comparison of changes in sensitivity and 1-specificity in two software programs for predicting the initial outcome in the *male group*.
LR-SML software performed relatively is similar to SPSS (Neural Network) software.

Discussion

In this study, a machine learning approach was used to create a prediction model. Estimation of functional constipation variables in elderly subjects using age, weight, height, BMI and Wexner questionnaire (with moderate to good correlation between them and outcome measures in functional constipation. These results showed that the LR-SML software is user friendly and simple prediction ability and is consistent with previous studies that used LR-SML for subjects with tinnitus to predict brain waves activities and non-specific back pain to estimate lumbar muscle activity (9,10). The sensitivity criteria show that this model correctly identifies the problems of the elderly in functional constipation. In this study, we had limitations to compare other machine learning software such as random forests and we suggest that it be done for future studies, also our model was very simple and designed for clinicians and medical students.
There are need new revise for external validation by several step input data at other sources (younger and elder subjects) to compare and develop this simple software.

Conclusion

Results of this study suggest that LR-SML may provide relative good clinically relevant, predictions for defining functional constipation of elderly subjects. The writing of this software in excel sheet is very easy than other softwares and in comparison, to SPSS (Neural Network) software may be have need low time to predication and it is not limitation in outcome variables.
Further studies are necessary to improve deep learning and for other disability of above population. This study was just on elder subjects with problems in FC and we suggest more research in younger group with and without FC and elder subjects without FC.

Authors contributions

Each author was involved in data analysis and contributed equally to the writing of the manuscript.

Conflict of interest

Authors declare that they have no conflicts of interest

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