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Validate thefactor from multiple logistic regression using artificial neural networks (ANNS) model: A case study of an elderly health status at receiving home care

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Abstract— This study aims to validate the factor that perhaps influences the health status of an elderly at receiving home care. This research paper, we developed the R syntax for Multilayer Perceptron Neural Network (MLPNN) which considering the logistic based selection. At first, the related factors will be determined through multiple logistics regression procedures, then the selected variable will be validate using Artificial Neural Networks (ANNS) through the Multilayer Perceptron Neural Network (MLPNN). The validation process will be emphasizing on the Mean Square Error for forecasting (MSE-F) and the accuracy value. Through this developed methodology, we hope that the significant variable which treated as input to MLPNN will lower the MSE-F.Health.Through the developed MLPNN methodology, it was found that the Mean Square Error for forecasting (MSE-F.Health) is 0.105 with an accuracy of 91.28%. In conclusion, thisshowed that the developed model can predict the outcome by more than 90%.The developed R syntax is given in this paper for a better illustration.

Keywords— Multilayer Perceptron Neural Network (MLP),Mean Square Error for forecasting (MSE-F)

1. Introduction

Obesity among the elders has been studying throughout the world. These researches are important in order to reduce the burden in the healthcare and the caregivers. The elder community is known of their ageing process which precipitate lot of chronic diseases which potential to be economic consumption of the countries. A study of obesity in Europe (Portugal) showed high obesity prevalence in elder community compared to younger age[1]. Here the male group shows higher than female obesity and it is associated with high risk of complication such as metabolic [1]. Osteosarcopenic obesity syndrome (OSO) which consists of obesity associated with osteoporosis, osteopenia and sarcopenia is one of conditions among the elderly [2]. These syndromes reflect the cycles among the elders: bone and metabolic dysfunction. The physical disability in return will further increase the obesity among the elderly [3]. In addition, this obesity and physical disability enhance the burden in the family and healthcare providers.

The obesity and elderly have been discussed among the scientist. Obesity in the elder is linked to the hippocampus atropy and dysfunction which lead to cognitive dysfunction and mental changes [4]. This brain impairment will further increase the burden to the caregivers where lot of time need tobe spent. Psychological treatment is one of the suggested treatments for this group [5]. The possible cognitive impairment are depression and anxiety disorder [5]. Furthermore, obesity is thought to link with social isolation in the elderly [6]. In order to counter these disabilities, few methods are suggested based on studies. For example, gardening is suggested as non-pharmacological method to reduce the psychological

problem in the elderly which may benefit to the healthcare team [7].

In this paper, the health status for obese elderly who stay at receiving home care has been analyzed to identify the most associated factors that contribute to the health status. Due to missing observations for many variables, we have used only some selected variables that are having most associated with the health status among obese elderly. Obesity is also growing rapidly and is now a very important global public health problem. It is therefore surprising that more consideration has not been given to the problem of obesity in the elderly [8]. Visser et al. documenting that people aged 65 and over, body fat is not only associated with mobility-related problems but also anticipates the development of complications in people with disabilities [9]. There is a lack of information on health status, influential factors, and health behaviors among obese elderly people. The identification of risk factors that cause low health status plays an important role in addressing unmet health demands and advising community efforts to guide to improve health status among the population. The main objective of this paper is to determine the factor which has the most significant relationship toward health status. Through the logistics regression modeling procedure, the potential factor will be studied, and the validation of the variable will be tested through the MLP neural network analysis. The advantage of such a proposed methodology is that we can use to identify thefactors accurately that attribute to the health factor among obese elderly.

2. Material and Methods

2.1 Study design

The study design used in this study was Computational Statistics Study Design (CSSD).This is a combination of a cross-sectional study with advanced computational statistical modeling techniques, which more focusing on the methodology development of the MLP neural network. This developed methodology was based on the MSE-F and the accuracy value of the predicted analysis.

2.2 Data

Initially, there was a total of 174 respondents who participated in this research. They are consisting of 87 elderly from RSK PengkalanChepa and 87 elderly in RSK Bedong. The source of the population comprises an elderly which age more than 60 years old and living in Rumah Seri Kenangan (RSK) in PengkalanChepa, Kelantan, and RSK Bedong, Kedah. RSK is a government-funded public sheltered home for the elderly suffering from a lack of financial and family support. The Selected variables are Health status (Y), Gender (X1) Education level (X2) Duration of stay at receiving home care (X3), and Psychological Stress (X4).

Table 1: Data Description among obese elderly

Num.	Code	Variables	Explanation of user variables
1.	Y	Health Self-Assessment	0 = Healthy 1 = Not Healthy
2.	X1	Gender	0 = Male 1= Female
3	X2	Education	0 = Not Formal Education 1 = Formal Education
4.	X3	Duration of Stay At Receiving Home Care	0 = More than 60 Months 1 = Less than 60 Months
5	X4	Psychological Stress or Acute Disease	0 = Yes 1 = No

2.3 Crosstabulation Analysis

Crosstabulation analysis was conducted for the selected variables, this is to obtain the distribution of the data and straightly emerge the special characteristic of the health status. Table 2 display the crosstabulation of gender vs. health status. The overall health status differs from gender which is female elderly 22 (43.1%) having is healthier compared to male elderly 14 (27.5%). For not healthy, the prevalence of not healthy for male 10 (19.6%) is higher than female 5 (9.8%).

Table 2: Crosstabulation of Gender vs. health status

			Health status		
			Not Healthy	Healthy	Total
Gender of an elderly	Male	Count	10	14	24
		% of Total	19.6%	27.5%	47.1%
	Female	Count	5	22	27
		% of Total	9.8%	43.1%	52.9%
Total		Count	15	36	51
		% of Total	29.4%	70.6%	100.0%

Table 3 summary the case of health and not healthy according to the duration of stay at receiving home care. The elderly who are staying more than 60 months have a good health status 25 (49.0%) compare to those staying less than 60 11 (21.6%).

Table 3: Crosstabulation Duration of stay vs. health status

			Health status		
			Not Healthy	Healthy	Total
Duration of stay	> 60 months	Count	4	25	29
		% of Total	7.8%	49.0%	56.9%
	< 60 months	Count	11	11	22
		% of Total	21.6%	21.6%	43.1%
Total		Count	15	36	51
		% of Total	29.4%	70.6%	100.0%

Education plays a very important in ensuring health status. Table 4 shows those elderly with formal education having good health, it is about 28 (54.9%). In this study, it was found that 5 (9.8%) among the elderly having no formal education and not healthy.

Table 4: Crosstabulation for the education level of stay vs. health status

			Health status		
			Not Healthy	Healthy	Total
Education	Not Formal Education	Count	5	8	13
		% of Total	9.8%	15.7%	25.5%
	Formal Education	Count	10	28	38
		% of Total	19.6%	54.9%	74.5%
Total		Count	15	36	51
		% of Total	29.4%	70.6%	100.0%

Table 5 summary the finding of Psychological stress/Acute disease vs. health status. It was reported that 10

(19.6%) of the elderly having psychological stress/acute disease and the majority is elderly healthy with no psychological stress/acute disease 28 (54.9%).

Table 5: Crosstabulation for Psychological stress/ Acute disease vs. health status

			Health status		
			Not Healthy	Healthy	Total
Psychological stress/ Acute disease vs. Health status	Yes	Count	10	8	18
		% of Total	19.6%	15.7%	35.3%
	No	Count	5	28	33
		% of Total	9.8%	54.9%	64.7%
Total		Count	15	36	51
		% of Total	29.4%	70.6%	100.0%

3. Results

3.1Logistics Regression Model for determining the health status

The logistic regression model for health status is presented here. The outcome of the variable is health status and the explanatory variables are Gender (X1) Education level (X2) Duration of stay at receiving home care (X3), and Psychological Stress(X4). The models are shown below

$Health_{ij} = 0$, if Not Healthy

$Health_{ij} = 1$, if Healthy

Then let us define the following models:

$$\sum_{i=1}^{n} y_i = \sum_{i=1}^{n} \pi(x_i)$$

$$\hat{\pi}(x_i) = \frac{e^{\beta_0+\beta_1(\text{Gender})+\beta_2(\text{Education})+\beta_3(\text{Duration})+\beta_4(\text{Psychological})}}{1+e^{\beta_0+\beta_1(\text{Gender})+\beta_2(\text{Education})+\beta_3(\text{Duration})+\beta_4(\text{Psychological})}}$$

The estimated logit is given by

$$\hat{g}(x) = \beta_0 + \beta_1(\text{Gender}) + \beta_2(\text{Education}) + \beta_3(\text{Duration}) + \beta_4(\text{Psychological}) \quad (1)$$

The estimated parameter for equation(1) is given in Table 6.

Table 6: Variables in the Equation

						95% C.I.for EXP(B)	
	B	S.E.	Wald	Sig.	Exp(B)	Lower	Upper
Gender of residents	2.050	0.984	4.340	0.037*	7.768	1.129	53.444
Education level	1.740	1.080	2.597	0.107*	5.700	0.686	47.326
Duration of stay	-2.083	0.911	5.229	0.022*	0.124	0.021	0.743
Psychological stress/ acute disease in the past 3 months?	2.730	0.963	8.034	0.005*	15.336	2.322	101.301
Constant	-1.702	1.311	1.686	.194	.182		

Significant at the level of 0.25
Log-likelihood = 37.879926; Hosmer and Lemeshow Test : $\chi^2(df): 2.356(6), p = 0.884$
Classification Table, 80.4%
Area Under the Curve (ROC) Curve, 0.890, $p< 0.05$

Table 6 shows the result of multiple logistic regression. According to the finding from the results, it was found that gender is significant, 2.050 (0.984), exp = 7.768; 95% CI (1.129;53.444); p< 0.25)] women have 7 times better health compared than men. The second factor is the education factor [1.740 (1.080), exp = 5.7; 95% CI (0.686, 47.326); p< 0.25)] which is significant. The third factor is about the duration of staying at receiving home care. Those who have stayed longer (more than 60 months) showing much healthier compared to those who are less than 60 months. About 29 (56.9%) elderly had stayed more than 60 months in this study and 25% (49%) in a good health while 4 (7.8%) is not healthy.

3.2 Artificial Neural Networks (ANNS): Multilayer Perceptron Model (MLP) for determining the health status

Artificial neural networks (ANN), also known as neural networks (NNs),is a computational model based on the structure and functions of biological neural networks [10]. A multilayer perceptron (MLP) is a class of feedforward artificial neural network (ANN) with one or more layers between the input, hidden, and output layer [11, 13]. In the MLP model, the analysis of the output node of this analysis is fixed at one since there is only one dependent variable. Figure 1 gives the MLP with N input nodes, H hidden nodes, and one output node [12]. The values of the hidden node h_j, j =1…3are given by $h_j = g_1\left(\sum_{j=1}^{3} v_{ji}x_i + E_1\right)$ where v_{ji} the output *weight*, E_1 is the bias. The values of the hidden node n_j, j =1…3are given by $n_j = g_2\left(\sum_{j=1}^{3} v_{ji}h_i + E_2\right)$ where v_{ji} the output *weight.*, E_2 is the bias. The values of the hidden node Y_j, j =1,2are given bywhere $Y_i = g_3\left(\sum_{j=1}^{3} v_{ji}n_i + E_3\right)$ v_{ji} the output *weight*, E_3 is the bias [12]. Figure 1 gives the general architecture of the MLP.

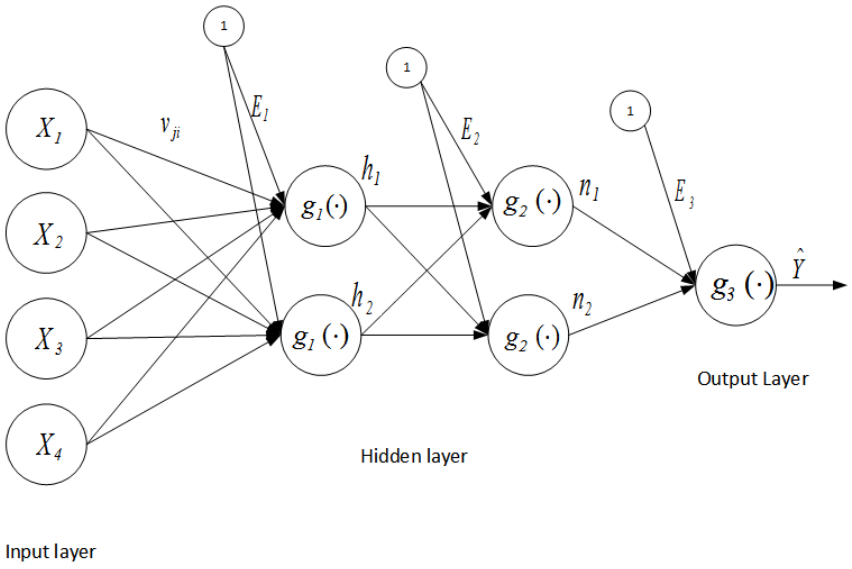

Fig. 1: The Conceptual of the general architecture of the MLP with two hidden layers, four input nodes, 2 hidden nodes, and one output node

Phase I: Fitting Multiple Logistic Regression (MLR) to determine the factor that contributing to the health status among the obese elderly.

Phase I: Fitting Multilayer Perceptron Neural Network (MLPNN) using the selected variable from Phase I.

We used both logistic regression models and the multilayer perceptron model in this study. This is to establish the methodology procedures which had been carried out and to ensure the result obtained from the analysis is clinically related to the studied factor. Below is the R Syntax for the Artificial Neural Network Models.

```
# STEP 1-Dataset for the Obese of Elderly/
Input = ("
Gender Edu Duration Health Psy
1 1 0 1 1
1 1 0 1 0
1 0 1 1 1
1 0 1 1 1
1 1 1 1 0
1 1 1 1 1
1 1 0 1 1
1 1 0 1 1
1 1 0 1 1
1 0 0 1 1
1 0 1 0 1
⋮ ⋮ ⋮
0 1 0 1 1
0 1 0 1 1
0 1 1 1 1
0 1 0 1 1
0 1 0 0 0
0 0 1 0 0
0 1 1 1 0
")
data = read.table(textConnection(Input),header=TRUE)

####################MULTILAYER PERCEPTRON MODEL#################

#STEP 2-Install the Neuralnet Package
if(!require(neuralnet)){install.packages("neuralnet")}
library("neuralnet")

#STEP 3- Checking for the Missing Values
apply(data, 2, function(x) sum(is.na(x)))

#STEP 4 - Max-Min Data Normalization
normalize <- function(x) {return ((x - min(x)) / (max(x) - min(x)))}
maxmindf<- as.data.frame(lapply(data, normalize))

#STEP 5-Determine the Training and Testing of the Dataset
#/60% for Training and 40% For Testing
Training <- maxmindf[1:39, ]
Testing <- maxmindf[40:50, ]
```

#STEP 6 -Print Dataset -Training and Testing Data set

```
print(Training)
print(Testing)
```

#STEP 7-Plotting the Architecture of MLP Neural Network/.

```
nn<- neuralnet(Health ~Gender+Edu+Duration+Psy,data=Training, hidden=c(2,2),act.fct = "logistic", linear.output = FALSE, stepmax = 1000000)

plot(nn)
options(warn=-1)
nn$result.matrix
```

####TESTING THE ACCURACY OF THE MODEL- PREDICTED MEAN SQUAREERROR######

#STEP 8-Predicted Results are Compared to The Actual Results

```
Temp_test<- subset(Testing, select = c("Gender","Edu","Duration","Psy"))
head(Temp_test)
nn.results<- compute(nn, Temp_test)
results <- data.frame(actual = Testing$Health, prediction = nn.results$net.result)
results
```

#STEP 9-Use the Predicted Mean Squared Error NN (MSE-forecasts the Network) as a #Measure of How Far the Predictions Are from The Real Data

```
predicted <- compute(nn,Testing[,1:4])
MSE.net <- sum((Testing$Health - predicted$net.result)^2)/nrow(Testing)
```

#STEP 10-Printing the Predicted Mean Square Error

```
MSE.net
```

###############NEURAL NETWORK PARAMETER OUTPUT###################

#STEP 11-Neural Network Parameter Output

```
library(neuralnet)
nn<- neuralnet(Health ~Gender+Edu+Duration+Psy,data=Training, hidden=c(2,2),act.fct = "logistic", linear.output = FALSE, stepmax = 1000000)
nn$result.matrix
```

################MODEL VALIDATION CALCULATION####################

```
#STEP 12- Model Validate
results <- data.frame(actual = Testing$Health, prediction = nn.results$net.result)
results
```

####################MODEL ACCURACY CALCULATION #################

#STEP 13- Model Accuracy

```
predicted1=results$prediction * abs(diff(range(data$Health))) + min(data$Health)
print(predicted)
actual1=results$actual*abs(diff(range(data$Health)))+min(data$Health)
print(actual1)
deviation= ((actual1-predicted1))
print(deviation)
value=abs(mean(deviation))
```

```
print(value)
accuracy_in_percent=(1-value)*100
accuracy_in_percent
```

##########################THE END OF R SYNTAX ######################

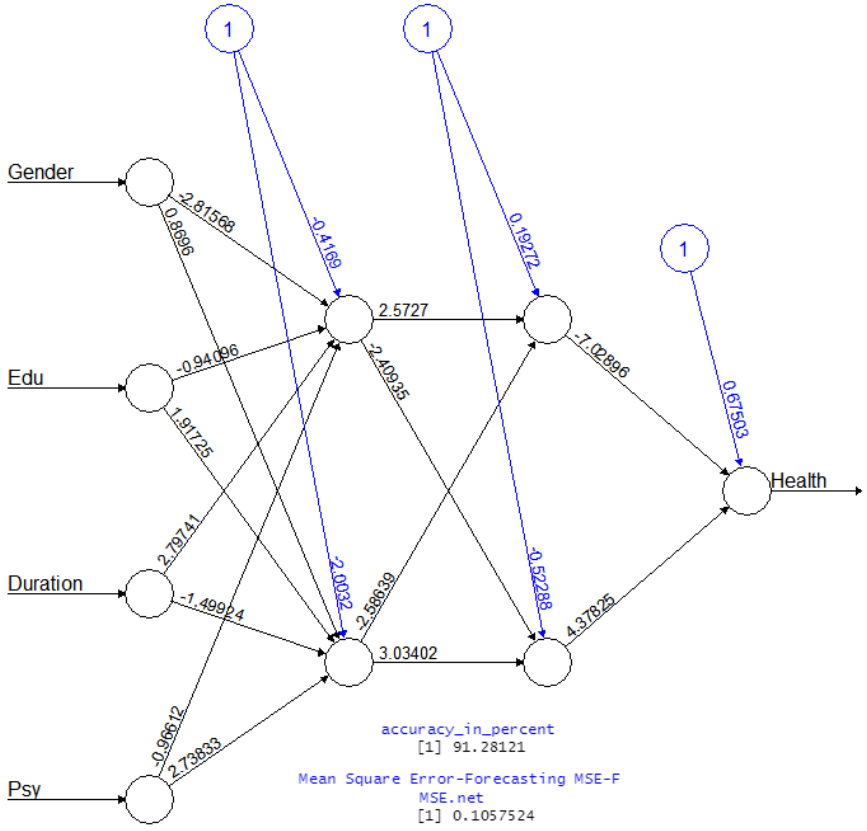

Fig. 2: The architecture of the MLP with two hidden layers, four input nodes, 2 hidden nodes, and one output node

4. Summary and Conclusion

The knowledge of obesity among the elderly is very important in our community nowadays. In Malaysia the important of obesity knowledge helps to reduce burden to the caregivers and to the country. Central body obesity is associated with cardiovascular and metabolic effect [1]. Besides cardiac disease, bone is one of the organs that cause severe immobility among the elders. The metabolic dysfunction among the elders such as bone and metabolic interrelated are known as Osteosarcopenic obesity syndrome (OSO) [2]. Bone problems such as fracture of osteoporosis can lead to more obesity of movement reduction among the elders. Additional obesity is produced more in the disable elder people [3]. The psychology of the elderly with obesity is linked to the part of the brain which impaired such as hippocampus region [4]. The combination of physical disability and brain dysfunction is adding to the elderly healthcare consumption. The psychological effect such as anxiety and depression are suggested among the obese elderly [5]. Methodology to counter the effect of these disabilities were studied such as gardening which shows some beneficial to the psychological of the elderly [7].

The finding of this study is emphasizing the development of a logistic regression model for the health status among obese elderly who living in Rumah Seri Kenangan (RSK) in PengkalanChepa, Kelantan, and RSK Bedong, Kedah. There are four variables found to be significantly related to health status. Gender, education level, duration of stay in receiving home care, and the status of having psychological stress or acute disease. Barer [4] and Miller &Cafasso [15] literature strongly indicates that women are more likely to be caregivers than men. There are a variety of factors that have contributed to the dominance of women in the care position including the fact that fewer women have a paying job and that the role of women as carers for a disabled spouse or relative is more easily assumed due to the traditional role of women in society [15]. This study also supported by Hopp [16] has shown that women are a little more cared for than men. Home care provides seniors with a choice of age at home-where most would prefer to be-and encourages family caregivers' peace of mind and well-being. It also decreases the expense of the nation's system by improving patient outcomes, increasing preventive care, and reducing hospital admissions. And home care is good for the economy of the country, generating employment in a rapidly growing industry [17].

Studies from Hank [18] indicate that increased education would contribute to improved elderly health. In short, several demographic factors, including various mattresses, differential fertility, and transfer of education across generations contribute to the relationship between education and elderly health. Strong educational gradients in health can lead rapidly to improving the health of the elderly. In South Korea, Khang et al. [19] demonstrated persistent educational disparities in elderly health and mortality. At the same time, education growth also allows the population aging due to resulting fertility declines and increased prospects for survival. Besides that, less psychological distress was separately correlated with beneficial health habits such as non-smoking and lower alcohol intake, improved health status, higher well-being, more social support, and fewer difficulties performing everyday activities. Awareness of the impact of beneficial health habits such as healthy eating concerning psychological distress offers useful insights into how society can encourage healthy lifestyles for an aging population [20].

Studying this four-factor in logistics regression brings a significant finding toward the health care management system in receiving home care. The four-factor had been validating through the MLP neural network and the result for MLP shows that the efficiency for MLP is 91.28% and the mean square error for forecasting, MSE-F is given as of 0.105. The smallest the forecasting error from the model, the better the significant result obtained for the model. This finding may provide important information for the caretaker in receiving home care for improved and upgrade their management system and understand the health status among obese elderly. This Ideas and techniques based on methodologies are coordinated with the R syntax algorithm had led to successful research and gives the best results for decision making, especially for the decision-maker.

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