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Deep Learning-Based Prediction of Obesity Levels According to Eating Habits and Physical Condition

Mehmet Kivrak

Inonu University, Faculty of Medicine Dept. of Biostatistics and Medical Informatics,Malatya, Turkey. (e-mail: mehmetkivrak83@gmail.com).

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Corresponding author: Mehmet Kivrak
✉ mehmetkivrak83@gmail.com
☎ +90 533 5113432

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ABSTRACT

Obesity occurs as a result of excessive fat storage in the body and brings along physical and mental problems [1]. The physical function has been associated with impaired quality of life in various areas such as distress in society, sexual function, self-esteem, and work-related quality of life [2]. The prevalence of obesity has been steadily increasing over the past few decades and is now unprecedented. This increase has occurred in almost all ages, genders, and races. These data show that the segments of individuals in the highest weight categories i.e. (BMI> 40 kg / m2) increased proportionally more than those in the lower BMI categories (BMI <35 kg / m2) [3]. Given the numerous and important health consequences associated with obesity, there is an urgent need to develop highly effective interventions aimed at reversing these “obesogenic” drivers, including both government policies and health education and development programs. It is important to implement measures to be taken, including both government policies and health education and development programs, especially during the COVID-19 pandemic process we are in. In this study, the data set on the open-source access website was used for the prediction of obesity levels and consists of patient records of 17 variables created by the deep learning repository. In addition, the performance of deep learning methods in the prediction of obesity levels was examined and determined. Performance evaluation of models is compared in terms of accuracy, Fleiss's kappa, classification error, and absolute error.

1. INTRODUCTION

THE international incidence of obesity and weight problems has doubled because 1980 to an extent that virtually a third of the arena populace is now categorized as obese or chubby [4]. Weight problems adversely impact nearly all physiological functions of the physique and include a huge public health threat [5]. The World Health Organization (WHO) defines obese and obesity as irregular or immoderate fat accumulation that offers a hazard to wellness. Obesity occurs as a result of excessive fat storage in the body and brings along physical and mental problems [1]. The physical function has been associated with impaired quality of life in various areas such as distress in society, sexual function, self-esteem, and work-related quality of life [2]. The prevalence of obesity has been steadily increasing over the past few decades and is now unprecedented. This increase has occurred in almost all ages, genders, and races. These data show that the segments of individuals in the highest weight categories i.e. (BMI> 40 kg/ m2) increased proportionally more than those in the lower BMI categories (BMI <35 kg / m2) [3]. Given the numerous and important health consequences associated with obesity, there is an urgent need to develop highly effective interventions aimed at reversing these “obesogenic” drivers, including both government policies and health education and development programs. It is important to implement measures to be taken, including both government policies and health education and development programs, especially during the COVID-19 pandemic process we are in.

In this study, the data set on the open-source access website was used for the prediction of obesity levels and consists of patient records of 17 variables created by the deep learning repository. In addition, the performance of deep learning methods in the prediction of obesity levels was examined and determined. Performance evaluation of models is compared in terms of accuracy, Fleiss's kappa, classification error, and absolute error.

2. MATERIAL AND METHOD

1.1.2.1. Data Set

The dataset used for the analysis was obtained from https://archive.ics.uci.edu/ml/datasets[6]. The dataset includes data for estimating obesity levels in people between the ages of 14 and 61 years with various eating habits and physical conditions in Mexico, Peru, and Colombia countries and consists of patient records of 17 variables. After all, the calculation was made to obtain the mass body index (BMI) for each individual, the results were compared with the data provided by WHO and the Mexican Normativity [6]. A detailed explanation of the variables is given in Table I.

TABLE 1
THE DETAIL EXPLANATION OF THE VARIABLES

Variables	*Explanation*
Obesity Level	Target (1:Insufficient Weight (BMI<18.5), 2:Normal Weight (18.5 to 24.9), 3:Overweight (25 to 29.9), 4:Obesity Type I (30 to 34.9), 5: Obesity Type II (35 to 39.9), 6: Obesity Type III (BMI>40)
Age	Age
Gender	Gender (1:male, 0:female)
Height	Height
Weight	Weight
History	Family History have overweight (1:Yes, 0: No)
FAVC	Eat High Caloric Food Frequently (1:Yes, 0: No)
FCVC	Frequency Eating Vegetables (1:Never, 2:Sometimes, 3:Always)
NCP	Number of main meals (Between 1 y 2, Three, More than three
CAEC	Consumption of food between meals (0:No, 1:Sometimes, 2:Frequently, 3:Always)
Smoke	Smoking (1:Yes, 0: No)
CH2O	Consumption of water daily (Less than a liter, between 1and 2 Lt, More than 2 Lt
SCC	The attributes related to the physical condition are: Calories consumption monitoring (1:Yes, 0: No)
FAF	Physical activity frequency (Not have, 1 or 2 days, 2 or 4 days, 4 or 5 days)
TUE	Time using technology devices (0-2 hours, 3-5 hours, More than 5 hours)
CALC	Consumption of alcohol (0:No, 1:Sometimes, 2:Frequently, 3:Always)
MTRANS	Transportation used (1:Automobile, 2:Motorbike, 3:Bike, 4: Public Transportation, 5:Walking)

2.2. Knowledge Discovery in Databases (KDD)

In the process of KDD; data selection (obesity dataset), data preprocessing (extreme and missing value analyses), data transformation (normalization, etc.), data mining and evaluation, and interpretation of the results were performed.

2.3. Deep Learning

Deep Learning can mechanically extract function representation from raw data, which is a new method of desktop finding out derived from artificial neural networks [7]. DL learns characteristic hierarchies with better hierarchy elements with a blend of low-degree aspects. Therefore, DL effectually solves problematic and extreme dimensional problems It's used. Convolutional Neural network (CNN) is one of the most positive deep studying units [8].

$$Z^l_{i,j,k} = \; w^{l^T}_k x^l_{i,j} + b^l_k \tag{1}$$

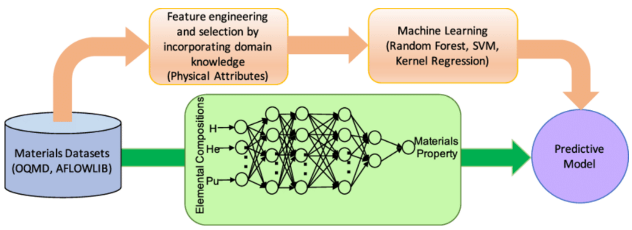

Fig.1. Comparison of Deep Learning Approach With Conventional NN.

The worth of the region of the layer l and its place within the *k* characteristic map (i, j),$Z^l_{i,j,k}$ can be estimated as shown in equation 1.
The place w^l_k and b^l_k are l^{th}, lth layers within the k property map are the weight vector and the bias. The activation value $a^l_{i,j,k}$ for the convolution feature $Z^l_{i,j,k}$ can be expressed, as shown in equation 2 [8].

$$a^l_{i,j,k} = \mathrm{a}(Z^l_{i,j,k}) \tag{2}$$

Hyperparameters of the deep learning model are epsilon, rho, L1, L2, max w2, and dropout, which are tuned by using a grid search optimization algorithm.

2.5. Performance Metrics

Accuracy (AC) is outlined because the division of values incompatible eyes via the whole number of observations and is indicated via equation 3.

$$AC = \frac{TP+TN}{TP+TN+FN+FP} \tag{3}$$

Fleiss's kappa coefficient is a generalization of Scott's pi coefficient, which examines the problem of matching two valuers [9]. Similarly, it is related to Cohen's kappa coefficient [10]. However, while Scott's pi coefficient and Cohen's kappa coefficient require two valuers, Fleiss's kappa coefficient can be applied to any number of values greater than two. Just like them, it is expressed numerically between the values of 0 and 1 how much the match between a fixed number of values is not a matter of randomness and therefore how reliable it is [11].

Absolute Error is the amount of error in your measurements. It is the difference between the measured value and the “true” value [12].

3. RESULTS

3.1. Statistical Analysis

Quantitative data were summarized as the arithmetic means with standard deviation, median with min and max values, and qualitative data as numbers by percentage. After the suitability of the data to multiple normal distributions, the difference between the groups in normally distributed groups was examined by t-test in independent samples and the Kruskal Wallis H-test for variables that did not show normal distribution. When significant differences in categorical data were determined among the groups ($p<0.05$), pairwise comparisons were performed by the Bonferroni-adjusted Pearson chi-square test. Upon seeing significant differences ($p<0.001$) in the Kruskal Wallis H test, pairwise comparisons of the groups with significant differences were identified using the post-hoc Conover multiple comparison test. For statistical analysis, IBM SPSS version 22 [13], RStudio version 1.1.463 [14], and Rapid Miner Studio version 8.1.001 [15] were used.

1.2. 3.2. Data Mining

In this study, the performance of deep learning methods in the prediction of obesity levels was examined and determined. Performance evaluation of models is compared in terms of accuracy, Fleiss's kappa, classification error, and absolute error.

1.3. 3.3. Model Development

The 10-fold cross-validation method was used in the performance evaluation of all classifier methods to verify the quality of the models. Cross-validation is the re-sampling procedure used to evaluate machine learning models in a data sample. The procedure has a single parameter named k that expresses the number of groups to split a given data sample. In 10-fold cross-validation, the models are trained and tested ten different times, and then, mean performance metrics (i.e., accuracy, precision, and so on) are estimated at the end of the process [16].

1.4. 3.4. Evaluation of the Models

Hyperparameters of the deep learning model were 1.0E-8 for epsilon, 0.99 for rho, 1.0E-5 for L1, 0.0 for L2, 10.0 for max w2, and 0.15 for dropout, respectively. Figure 2 depicts the pseudo-codes of CNN in the deep learning algorithm.

Algorithm 2 Training process of wCNN (wCNN=wCPNN+FCNN)

Input:
train_x, *train_y*, *test_x* and *test_y* are set same as the pseudocode of CNN
Output:
$wc_{ij}^l, bc_j^l, ac_j^l$: weights and bias of wCPNN ($l = 2, 4$, wCPNN have 5 layers)
w_{jk}, b_k : weights and bias of FCNN (FCNN have 2 layers)
Required parameters:
max_time and *target_error* are set same as the pseudocode of CNN
η_wCPNN,: learning rate of wCPNN
Initialization work:
t=1 and $loss(1) = 1$ are set same as the pseudocode of CNN
$wc_{ij}^l, ac_j^l, bc_j^l, w_{jk}, b_k$: weights and bias of wCNN are set as random number.
Begin:
Set the required parameters and complete the initialization work
while *t* < *max_time* and *loss(t)* > *target_error*
  for all *trainingSet*:
    train_p (prediction of label) is calculated according to *train_x* and forward calculation formula 29-31 and 4-9.
  end for
  $loss(t)$ is re-calculated as $loss(t) = \frac{1}{2}\sum_{n=1}^{N}(train\_p(n) - train\_y(n))^2$, *N* is the total number of *trainingSet*.
  $\Delta w_{ij}^{-1}, \Delta b_j^{-1}$ and Δw^l , Δac^l , Δbc^l are calculated according to the formula 22-23 and 34-36
  $w_{ij}^{-1}(t), b_j^{-1}(t)$ and w^l $(t), ac^l$ $(t), bc^l$ (t) are adjusted according to the formula 37-41
  t++
end while
End

Fig.5. Pseudo Code of CNN

Which variable is more important in the deep learning algorithm is calculated and presented in table II.

TABLE II:
VARIABLE IMPORTANCE OF DEEP LEARNING

Variable	Relative İmportance
Weight	0.75
FCVC	0.36
Gender	0.29
Family His.	0.21
Age	0.21
CAEC	0.18
NCP	0.14
FAF	0.11
CALC	0.10
Height	0.10
TUE	0.10
FAVC	0.08
CH2O	0.07
MTRANS	0.07
SCC	0.04
SMOKE	0.01

Table II and figure 2. tabulates the importance levels of variables in obesity levels in the deep learning modeling. Weight (0.75), FCVC (0.36), Gender (0.29), Family His. (0.21), Age (0.21), and CAEC (0.18) were calculated from deep learning. In comparison, the lowest relative significance was estimated for Smoke (0.01) from deep learning.

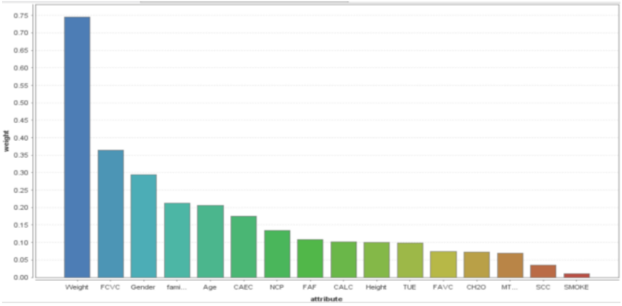

Fig.2. Variable Importance of Deep Learning

1.5. 3.5. General Assessment

According to the general assessment, the deep learning method provided the 0.82 accuracy value, 0.78 Kappa value, 0.18 classification error value, and 0.28 absolute error value. The performance metrics of the deep learning method presented in Table 3.

TABLE 3
MODEL PERFORMANCE METRICS

	Accuracy (%)	**F.Kappa** (%)	Clas.Error (%)	A. Error (%)
Deep Learning	**82.0**	**0.78**	**18.0**	**28.1**

Figure 3. shows that in the classification process performed with deep learning approaches the correct positive, and negative rates in the deep learning algorithm, according to the confusion matrix.

	true 2	true 3	true 4	true 1	true 5	true 6	class preci
pred. 2	116	39	0	5	0	0	72.50%
pred. 3	30	466	40	0	3	0	86.46%
pred. 4	0	67	270	0	9	2	77.59%
pred. 1	141	7	0	267	0	0	64.34%
pred. 5	0	1	40	0	285	1	87.16%
pred. 6	0	0	1	0	0	321	99.69%
class recall	40.42%	80.34%	76.92%	98.16%	95.96%	99.07%	

Fig.3. Confusion Matrix for the Model

4. CONCLUSION

Obesity is increasing all over the world due to urbanization, economic development, and lifestyle changes and is considered an epidemic health problem. In addition to the life-threatening diseases it has caused, it is understood how serious a public health problem it is when the negative effects of obesity on COVID 19 are seen in these extraordinary days that our world is going through. Individuals with asthma, chronic lung disease, diabetes, heart, and chronic kidney disease are at higher risk for COVID 19. Obesity plays a key role in the development of these chronic diseases (diabetes, heart diseases, asthma, etc.). These features of obesity suggest that it is one of the important factors for the increased risk of death in COVID-19 patients. In this study, using methods based on deep learning, eating habits and physical condition values and obesity levels were tried to be accurately predicted and the most important variables affecting the obesity risk level were determined. In the next period, studies on the relationship between obesity and COVID 19 in terms of risk factors are recommended.

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BIOGRAPHIES

Mehmet Kıvrak obtained his BSc degree in statistics from Dokuz Eylul University (DEU) in 2001. He received the BSc. and MSc. diploma in Statistics from Dokuz Eylul University in 2001 and 2006 respectively, and Ph.D. degrees in the Graduate Department of Biostatistics and Medical Informatics of Inonu University in 2017. He was accepted as an expert statisticianTurkish Statistical Institute in 2009. His research interests are data mining, cognitive systems, reliability and genetics and bioengineering, and signal processing. His current research interests are genetics and bioengineering and data mining.