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Using Neural Network to predict the Hypertension

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***Abstract*—Development of tools to facilitate diagnosis of some disease such as cancer, cardiovascular, hypertension, diabetes, is of great relevance in the medical field.In this paper, we will present a method based on neural network to detect the hypertension based on some risk factors including obesity, stress, systolic and diastolic blood pressure, physical activities, tobacco consumption and diet lifestyle. Data represents a group of students from the Lebanese universities. A descriptive statistical analysis is performed then a neural network predicting systolic and diastolic blood pressure is designed and implemented. Descriptive statistics show some difference between male and female groups. Tobacco consumption is mostly present in the male group more than female. In the other hand, the neural network consists often inputs and two outputs. The outcomes of the network are diastolic and systolic blood pressure. Accurate results have been obtained which proves the effectiveness of the proposed neural networks can be effective tools for preliminary detection of hypertension.**

***IndexTerms*—Neural Network, Hypertension, Medical Diagnosis, Artificial Intelligence.**

I. Introduction

The cardiovascular diseases constitute an important problem in public health. Hypertension is caused by blood pressure and it is considered as a major risk factor of cardiovascular disease. Hypertension can cause stroke, heart failure, heart attack, and vision problems. The earlier diagnosis of hypertension saves enormous lives. In some cases, the use of computer based diagnoses can be more accurate than the clinical decision. The neural network, firstly developed in 1943, is a part of artificial intelligence developed to predict a model outcome. When the output of the network is discrete, then this is a classification and when the output has continuous values it is performing prediction.

This method is widely used in science and technology with applications in various branches in biology, chemistry, and economy. In particular in the medical field and medical diagnoses such as diagnosis of tuberculosis [1], diabetes [2], breast cancer [3] and predicting cardiovascular risk [4] and pre-diagnoses of hypertension [5,6]. Neural networks model can implement the complex medical processes by software. Software systems are more effective and efficient in various medical fields including predict, diagnose, treatment and help to the clinicians and physicians and the general population. This is a suitable and powerful tool to help doctors in the medical field with several advantages such as the ability to deal with a great amount of data and reduce the time of the diagnoses. The ability of neural networks to produce good prediction results in classification and regression problems has motivated its use on data related to health outcomes such as death or illness diagnosis [7,8,9]. In such studies, the dependent variable of interest is a class label, and the set of possible explanatory predictor variables which are the inputs to the neural networks may be binary or continuous. An overview of the use of the neural network in the medical diagnoses is given in [10].

In this paper, we use the neural network in order to predict the hypertension. The network contains ten inputs and three layers with two output diastolic and systolic blood pressure.

The rest of this paper is organized as follows. Section 2 describesstudy materials and methods and presents neural network architecture. Section 3 presents the results of the study. Finally a discussion and a conclusion are given in Section 4.

II. Materials and Methods

The population consists of Lebanese students in 9 universities in Lebanon. A group of more than 3000 students aged between 17 and 35 yearsis selected and students respond to a set of questions including general information, anthropometric measurements, cardiovascular history, genetic background, diet lifestyle, alcohol consumption, tobacco consumption, physical activities, stress and environment.Developing high blood pressure varies between men and women and among various groups. Several approaches are used to select or extract the most important variables called features in a study. The best known are powerful mathematical means of data mining such as genetic algorithm, artificial neural network, and principal component analysis[11,12]. In this paper,the most relevant hypertension risk factors to be used:Gender (male or female), Heart rate, BMI (Body Mass Index obtained from height and weight), BF (Body Fat), Waist, Hip, PhysAct (representing the physical activities and taking the value yes if the student exercises some physical activity or no otherwise), SMOKE (taking the value yes if the student smoke or no otherwise), SALT denoting the diet lifestyle (taking the value yes if the student adds salt before tasting and no otherwise) and STRESS (a numerical value obtained with respect to Cohen's Test indicating the stress level of a student). These variables will be considered as input for the model detailed after. Moreover, two features SBP (systolic blood pressure) and DBP (diastolic blood pressure) are measured for all students;SBP and DBP will form the outcome of the model. After the collection, the data are preprocessed. In addition, the cases for which some data are missing are removed from the database to avoid the decreasing of the performance of the network. The data were analyzed using R software and the significance level used is 0.05. Continuous variables are given as mean with standard deviations and discrete variables are given as frequency distribution with percentage for groups of male and female students. Chi-squared test was used for categorical data to find whether a significant difference exists for each risk factor between males and females. However T-tests were used to compare population groups for continuous data. All statistical tests are significant at 0.05. A neural network is finally used where parameters SBP and DBP are considered as outputs and all others parametersare considered as inputs in the network. Note that the sample used to perform the neural network is divided into two sets: train and validation.70% of the database will be used as trained set and the neural network should be verified by means of the rest of the database which is a dataset different from that one used for training. A neural network is detailed here after.

Neural Networks Architecture

Neural Networks (NN) are quantitative models, part of Artificial Intelligence with the purpose to imitate the behavior of the human brain; first developed by McCulloch and Pitts (1943) who proposed the first notion of the simple neuron model [13]. This aims to create artificial systems able to do difficult and complicated computations analogous to those performed by the human brain, such as pattern recognition. Using a training set, the network connects inputs with outputs through estimated parameters, creating some generalization beyond the training data. Networks are distinguished by their architecture, level of complexity, number of layers, presence of feedback loops, the activation or transfer function. Neural network is the connection of elementary objects the simple neuron consisting of inputs, weights, biases, an activation function and outputs, where the inputs are the explanatory variables used and the outputs are the outcomes. Weights and biases are set randomly then optimized in order to minimize the error. The activation function defines the output of the neuron. The three common functions are sigmoid, linear and hyperbolic. Out of these sigmoid function is most common form of activation function used in the construction of neural network.

The Multilayer Feedforward Perceptron

The Multilayer feedforward perceptron is a network of consecutive layers: the input layer, one or more hidden layer and an output layer. A layer is a set of neurons, with no connection between them.Each layer transfers the input to the next one. An input layer reads the incoming signals, and the output layer provides the system's response. A neuron in a hidden layer is connected at input to each of the neurons in the preceding layer and output to each neuron in the next layer. The neurons in the same layer are not connected, they only receive inputs from previous layers, there is no feedback loop and connections are unidirectional.

Back propagation algorithm

This learning algorithm is commonly used. It uses supervised learning in which the network is trained using data for which inputs as well as desired outputs are known. In order to train a neural network to perform some task, the weight of each unit must be adjusted, in such a way that the error between the desired output and the actual output is reduced [14,15]. Four stages are included in the back propagation algorithm: Initialize the weight, feed forward, back propagation of errors and updating of the weights and biases.Here in this work, we are using the resilient back propagation algorithm. The main idea behind this is to reduce the impact of the partial derivative of the activation function on the adjustment of the weights [16]. Only the sign of the derivative is taking into account to determine the direction of weights update. Actually, the feed-forward computation, generating an output using the activation function and the weights initialized randomly. Thus, the computed output is compared to the expected one, creating an error signal that takes into consideration the derivative of the activation function. Here, the activation function of the network should be differentiable. The error signal is then propagated back into the network layer by layer using the weights. Finally the weights are adjusted in a way to minimize the error.

III. RESULTS

More than 3000 students participated to the study. After data preprocessing, some cases were removed for the performance of the network. A total of 2954 cases are kept in the database. They are divided into 1406 males (48 %) and 1548 females (52 %). Table 1 shows the continuous variablesas total (males and females) and divided by gender.Results of continuous variables are given in terms of means and standard deviations. Significant difference was observed between males and females forall continuous parameters.Table 2 shows the percentage distribution of each categorical variablefor the whole students group and divided by gender. The mostly present risk factor is the smoking habit where around 50% of males students in the young Lebanese population are smokers as well as physical exercises for the female since a high percentage is observed. Significant difference was observed between males and females in SMOKE and Physical exercises and no significant difference is observed for the parameter SALT. Moreover, Chi-squared tests for all categorical variables show a significant difference between male and female students groups.

Table 1Mean and standard deviation for continuous variables divided by gender

	Total	Males	Females
SBP	115.73±14.21	123.34±12.77	108.83±11.71
DBP	72.50±9.31	71.99±9.96	72.95±8.65
HeartRate	80.69±13.02	76.65±12.60	84.37±12.28
BMI	23.59±3.82	25.08±3.87	22.23±3.21
BF	27.84±8.80	22.18±7.21	32.98±6.71
Waist	81.12±10.98	87.34±10.35	75.48±8.12
Hip	96.04±9.41	98.97±9.27	93.37±8.73
STRESS	18.23±6.59	16.7±6.32	19.62±6.52

Table 2 Percentages of qualitative variables with respect to the gender

Males						Females					
SMOKE		SALT		PhysAct		SMOKE		SALT		PhysAct	
No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
50.43	49.57	70.41	29.59	22.62	77.38	74.22	25.78	66.21	33.79	46.45	53.55

For the neural network, a multilayer feed-forward network was adapted with 10 input nodes including the gender. These input nodes represent the risk factors of the hypertension. The network contains one hidden layer of 3 nodes and two output nodes representing systolic and diastolic blood pressure in order to detect the hypertension. The training set was used to optimize the weights, with a resilient back-propagation algorithm, which requires a differentiable activation function, and since the desired outputs are positive, the logistic function was the one used as activation function. The network inputs are the following: Gender, HR, BMI, BF, Hip, Waist, SALT, SMOKE, PhysAct and STRESS. The network's output is between 0 and 1, thus the inputs were normalized using the min-max scale (subtracting the minimum value of the input variable and dividing it by maximum-minimum), and then the predicted values were denormalized.

The neural networks results were computed and evaluated using the "neuralnet" package in R. Fig. 1 gives the resulting neural network. Inputs are fed to the network in the first layer, and then each input is multiplied by a specific weight and transferred to each node of the hidden layer. The logistic function is then applied to the summation of all weighted inputs together and the bias and the resulting answers are transferred to the output node with other weights.

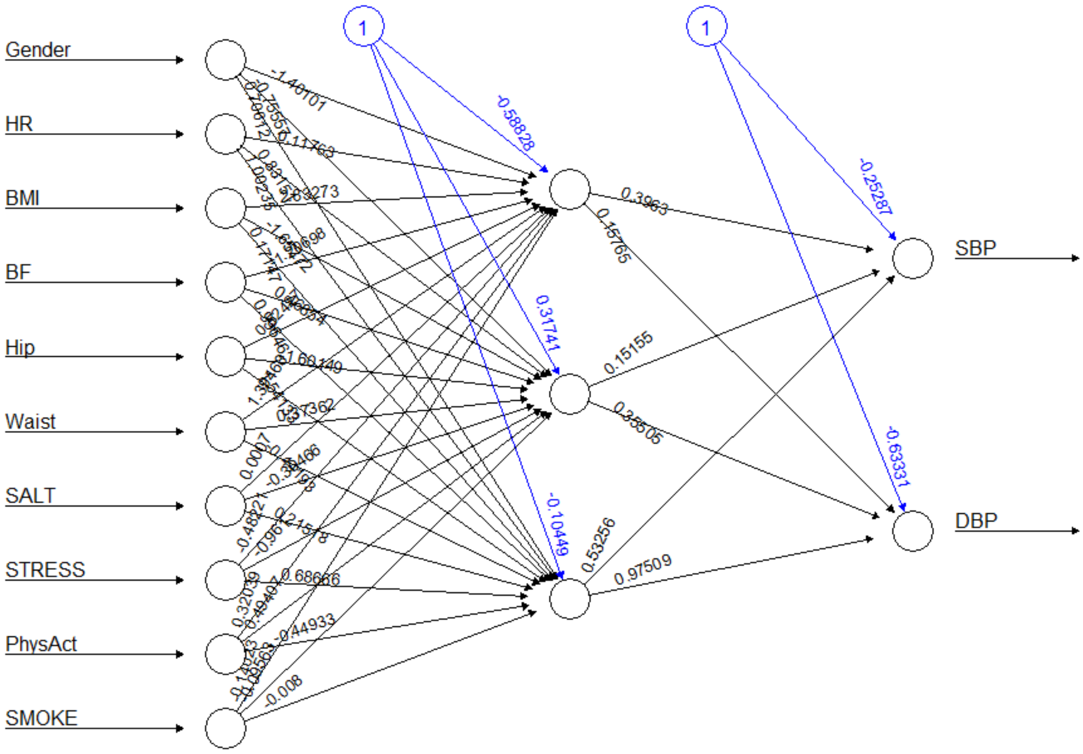

Figure 1 Neural Network for the diagnosis of hypertension

The results achieve more than 85% prediction accuracy acceptable in the diagnosis of systolic and diastolic blood pressure. Percentage error measures are often used, they are easy to interpret and have the advantage of being scale-independent. The commonly used percentage performance metric is known as Mean Absolute Percentage Error (MAPE) defined as:

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|A_i - F_i|}{A_i} \times 100$$

Where F_i is the predicted value (output of NN) of either SBP or DBP, A_i is the actual value, and n is the dimension of the test set. The NN was able to predict the value of SBP with 7.54%, and DBP with 9.84% error.

These results are remarkable, the complexity of the neural networks allowed the model to catch the relation between the risk factors and their effect on the blood pressure through sophisticated algorithms rather than the abstract character of traditional mathematical approaches. It relies on the detailed values of the risk factors of each student alone, rather than generalizing them with unconvincing mathematical assumptions.

IV. Conclusion

In this paper, we present a neural network based method to predict the blood pressure. After a preprocessing of data, statistical analysis showed some difference between male and female group for tobacco consumption and physical activities. Neural Network is a suitable and powerful tool to help doctors in the medical field with several advantages such as the ability to deal with a great amount of data and reduce the time of the diagnoses. In this paper, we outline the importance of this method to predict the hypertension using the features if the hypertension diagnoses. The neural network was able to predict the value of SBP with 7.54%, and DBP with 9.84% error. Its use makes the diagnoses more reliable and gives more satisfaction for the patient. Results show that the complexity of the neural networks allowed the model to catch the relation between the risk factors and their effect on the blood pressure through sophisticated algorithms rather than the abstract character of traditional mathematical approaches. Neural networks model can implement the complex medical processes by software. Software systems are more effective and efficient in various medical fields including predict, diagnose, treatment and help to the clinicians and physicians and the general population.

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