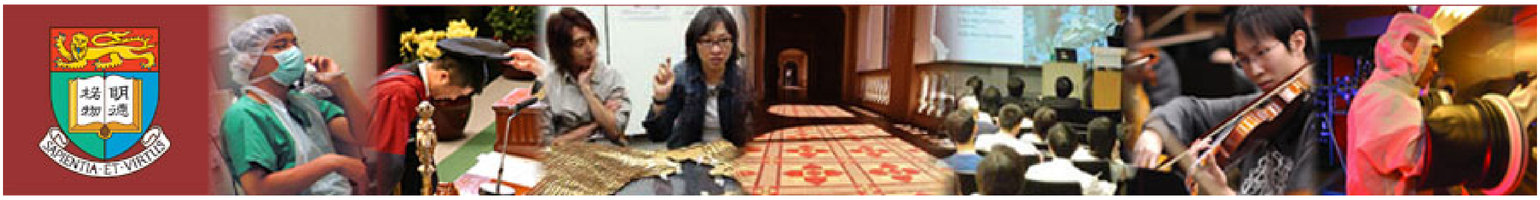

Predicting Systolic Blood Pressure Using Machine Learning

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***Abstract*— In this paper, a new study based on machine learning technique, specifically artificial neural network, is investigated to predict the systolic blood pressure by correlated variables (BMI, age, exercise, alcohol, smoke level etc.). The raw data are split into two parts, 80% for training the machine and the remaining 20% for testing the performance. Two neural network algorithms, back-propagation neural network and radial basis function network, are used to construct and validate the prediction system. Based on a database with 498 people, the probabilities of the absolute difference between the measured and predicted value of systolic blood pressure under 10mm Hg are 51.9% for men and 52.5% for women using the back-propagation neural network. With the same input variables and network status, the corresponding results based on the radial basis function network are 51.8% and 49.9% for men and women respectively. This novel method of predicting systolic blood pressure contributes to giving early warnings to young and middle-aged people who may not take regular blood pressure measurements. Also, as it is known an isolated blood pressure measurement is sometimes not very accurate due to the daily fluctuation, our predictor can provide another reference value to the medical staff. Our experimental result shows that artificial neural networks are suitable for modeling and predicting systolic blood pressure.**

Keywords*— *Systolic blood pressure; artificial neural network; prediction; hypertension.

I. INTRODUCTION

Hypertension, or high blood pressure, indicates that the force of blood flow in the arteries is higher than normal, and this condition may cause many serious consequences. Recent studies have shown that hypertension relates to many diseases including stroke, loss of consciousness, memory loss, heart attack and damage to eyes and kidneys [1-5]. Monitoring of the blood pressure levels is usually a routine for elderly citizens. However, for many adults, measurement of blood pressure is not regularly carried out. Yet, early detection will help them to get rid of the cardiovascular risk for heart disease later in life.

For most people with hypertension, there are often no signs or symptoms even if their blood pressure readings have already reached an emergent level. Early detection or prediction is highly desirable for uncontrolled high blood pressure increases the risk of serious health problems such as heart attack and stroke. It is well-known that the blood pressure measured in a clinic may fluctuate and vary a lot within a day. Fig. 1 shows the measurement readings of blood pressure of an adult woman over a 24-hour period without any medication [6]. Another reference [7] also states that the blood pressures are usually lower when asleep, and it rises during the day and reaches a peak value in mid-afternoon. Then, blood pressure begins to drop again. It is interesting to note that blood pressure during sleep could be 20% lower than during the day.

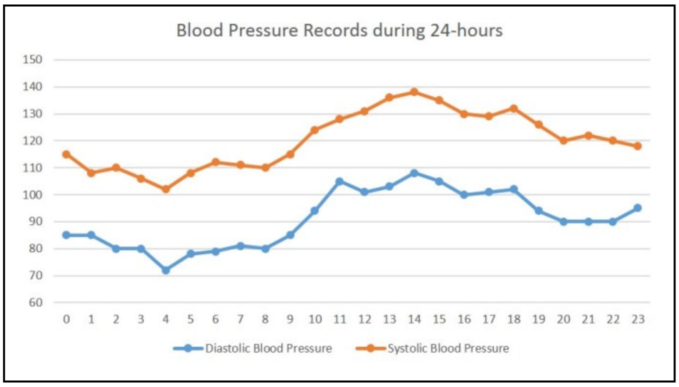

Fig. 1. Blood pressure measurement over a 24-hour period

This paper aims to develop a method for predicting the systolic blood pressure of a person given some health measurements and lifestyle of the person. Fig. 2 shows that an artificial neural network can be used to predict the systolic blood pressure when the input variables (e.g. age, gender, height, weight, stress and exercise levels) are provided.

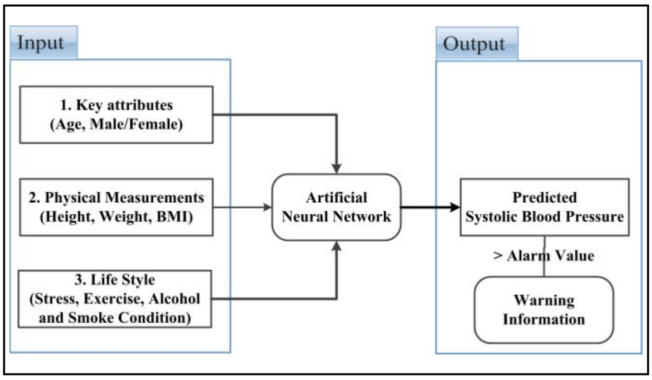

Fig. 2. Predicting method without taking blood pressure measurement

Assuming that the predicted value is larger than the hypertension alarm value (e.g. more than 140 mmHg for a

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person of aged 54), warming information will be provided to the user. It must be noted that a normal blood pressure range would depend on the age group of a person.

Another scenario on the usefulness of the blood pressure predictor is as follows. Suppose the person provides all the relevant information for the neural-network-based blood pressure predictor, and his blood pressure measurement is also taken (Fig. 3). Suppose the measured value seems normal, but the predicted value is at an alarming value, the person would be recommended to double check on his blood pressure. For example, the measured value is 134mmHg for a person of aged 54, but the predictor gives a value of 150mmHg. The relatively low value of his systolic blood pressure measurement could be inaccurate due to the daily frustration or an unknown reason. In such a situation, the person should double check and is advised to have further measurements of his blood pressure.

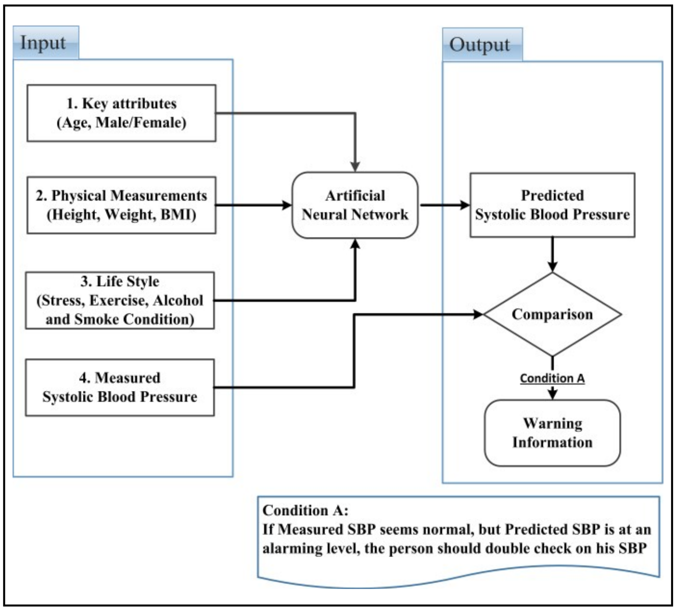

Fig. 3. Predicting method with blood pressure measurement

In this paper, the machine learning method of artificial neural network is used to learn the relationship between the correlated variables (BMI, age, exercise, alcohol, smoke level etc.) and the systolic blood pressure value. It is then used to predict the systolic blood pressure when the input variables are provided.

II. CORRELATION OF BLOOD PRESSURE AND OTHER VARIABLES

According to the World Health Organization [8], there are many variables/factors that would relate to the blood pressure values of a person. These include age, gender, body mass index, alcohol level, level of exercise, stress level, salt intake, smoking status, cholesterol and blood glucose.

A. Age

Age has a strong relationship with blood pressure, especially the systolic blood pressure, and is considered as the most interdependent cause of hypertension. Sparrow et al. [9] used the multiple linear regression analyses to indicate that the systolic blood pressure (SBP) of a person aged over 50 years old would increase more rapidly than the SBP of those whose age was between 20 and 39.

B. Male/ Female

According to a survey [10], blood pressure of male is usually higher than that of the female at the same age. In fact, men are in higher risk for hypertension and cardiovascular disease than premenopausal women of the same age. It also shows that blood pressure goes up with age for both male and female. In addition, men have higher daily mean blood pressure than women until the age has reached 80.

C. BMI

Obesity, indicated by body mass index (BMI), has become a serious public health issue all over the world. Fat people, with BMI exceeding 30 kg/mm^2, have higher probability in gaining high blood pressure (hypertension) because their hearts need to provide more nutrients and oxygen to body tissues. Golino et al. [11] carried out a study to predict the blood pressure by machine learning method and gave a conclusion that body mass index, waist circumference, and waist-hip ratio have the correlated relationship with the heart diseases, such as hypertension and cardiovascular diseases.

D. Alcohol consumption

According to Michael et al. [12], alcohol consumption seems to be significantly related to the systolic and diastolic blood pressure both for men and women. They have found that blood pressure would be slightly higher with more alcohol intake. Also, cardiovascular disease is more likely to occur on a heavy drinker. Hartung et al. [13] also obtained a similar result and concluded that blood pressure readings are related to the alcohol consumption significantly in both male and female. They also found that the blood pressure of a regular medium alcohol person is much lower than one who overdrinks daily, which shows that the relationship between blood pressure and alcohol intake quantity is not linear.

E. Exercise level

Many studies [13] have shown that blood pressure of a person would drop in response to strengthened physical activity. Lack of physical activity also increases the risk of overweight and leads to the higher probability of hypertension.

F. Stress level

American Heart Association (AHA) points out that although stress is not a confirmed risk factor for high blood pressure, many studies are being carried out. In a stressful situation, people's bodies react by releasing stress hormones into the blood, which would raise blood pressure [14].

G. Salt intake level

High level of salt intake may lead to high blood pressure and hypertension, which suggests that too much sodium in the diet can cause a person's body to hold fluid, and finally increases blood pressure. A study by Denton et al. [15] showed that additional salt intake within the dietetic contributes to a significant rise in both systolic and diastolic blood pressure.

H. Smoke status

Tobacco and exposure to secondhand smoke have a significant effect on the blood pressure. Experiments have shown that blood pressure will be temporarily increased a few minutes after smoking [16]. Many cases show the evidences that smoking is one of the primary causes of heart disease, such as shock and other heart attacks. It must be noted [17] that blood pressure will increase after smoking cessation.

I. Cholesterol and blood glucose

Cholesterol [18] and blood glucose [19] are well-known to be related to blood pressure. Yet, the database used for study in this paper does not contain these two items. The purpose of this paper is to predict on the systolic blood pressure of a person based on the value of the variables or factors discussed in this section.

III. ARTIFICIAL NEURAL NETWORK

Artificial neural network (ANN) is based on intelligent computational model, and uses the computer network system to simulate the biological neural network. It consists of an input layer of source, at least one middle or hidden layer of computational neurons, and an output layer of computational neurons [20, 21, 22]. The ability of an ANN is to discover the nonlinear relationship between its inputs and outputs. It has played a major role in many scientific and industrial applications, such as time series prediction, pattern recognition, decision making, load forecasting, event prediction etc. [23, 24]. In this paper, we aim to use neural network to learn the correlation between the input variables (such as BMI, age, exercise level etc.) and the output, which is the systolic blood pressure. Essentially, we would like to use the neural network as a tool to predict the value of the blood pressure of a person, given some health-related measurements and data of a person. For example, Fig. 4 shows an ANN which gives a prediction of systolic blood pressure based on four input variables.

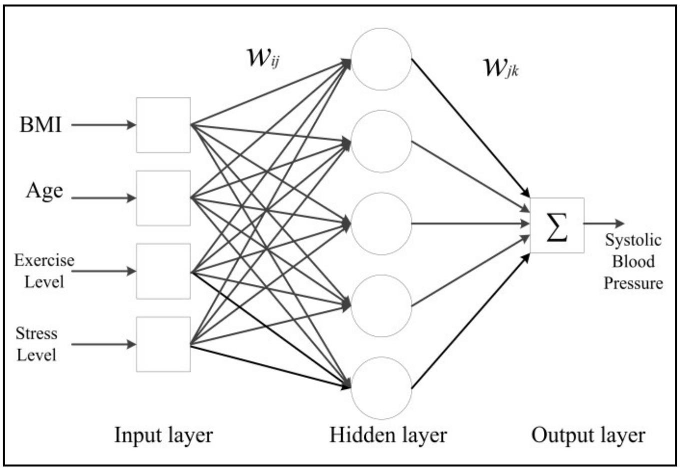

Fig 4. Structure of Artificial Neural Network

The strength of a neural network is on its learning capability. It can solve the problem by first training the neural network using some training examples or instances of input-output pairs. Two types of well-known algorithms for the training of neural networks are back-propagation (BP) algorithm, and the radial basis function (RBF) network with one hidden layer. The interconnection weights between the different layers in an ANN will be obtained at the end of the training.

A. Back-propagation Neural Network [20, 21, 25, 26]

The back-propagation (BP) neural network is a typical architecture of multi-layered feed-forward neural network. It is probably the most popular type of ANN being used in many industrial applications and has been found to perform well on a wide variety of problems. A typical BP neural network is usually consisted of layers of neurons, and the objective is to train the network weights so as to minimize the mean-square error of the network output. It is widely recognized that the performance of the BP algorithm could be sensitive to the initial conditions. Hence, the training of the ANN is usually repeated a number of times so as to obtain a fair comparison of its performance. Fig. 4 shows the architecture of a typical BP neural network with four inputs, one hidden layer with five hidden nodes, and one output value.

B. Radial Basis Function Neural Network [27, 28]

Although the multilayer feed-forward ANN based on the BP training algorithm is very popular, some researchers have found that the training of such ANN is slow and inefficient [26]. Very often, an optimal neural network architecture may not be achieved. Therefore, in this paper, we have examined the development of an alternate neural network architecture, which is the radial basis function network.

Similar to the BP neural network, our radial basis function (RBF) neural network is composed of one hidden layer. In a RBF network, the hidden layer can implement a better nonlinear mapping from the data space to the feature space. The most common basis function chosen is a Gaussian function, which means that the closer the input to the center of the Gaussian, the larger the response of the node. In stage one of the training of the RBF network, the self-organizing feature map (SOFM) is used as a clustering algorithm to determine the weights between the input and the hidden layer. At each hidden node, the basis function used is a Gaussian function. In the second stage, the weights between the hidden and output layer are determined by a least-mean-square algorithm. The convergence of the weights is found to be quick and efficient.

IV. DESCRIPTION OF THE DATABASE

The data were collected from the health and body conditions of 498 people, and the data include systolic blood pressure (SBP), age, BMI, exercise level, smoking status, alcohol use level, stress level and salt intake level [29]. These variables are believed to be correlated with the blood pressure reading of a person. Table I provides some details on its data.

TABLE I. VARIABLE IN THIS STUDY

Variable	Description
Systolic Blood Pressure (SBP)	Continuous Variable (in mm Hg)
Age	Continuous Variable (in year)
Body Mass Index (BMI)	Continuous Variable (in kg/m^2)
Smoking Status	Binary Variable (Yes, No)
Exercise Level	Categorical Variable (Low, Medium, High)
Stress Level	Categorical Variable (Low, Medium, High)
Alcohol Level	Categorical Variable (Low, Medium, High)
Salt Intake Level	Categorical Variable (Low, Medium, High)

Among the 498 cases, 236 of them were male accounting for 47% of the data while the remaining 262 cases were female. Due to the obvious influence of gender difference, the author split the data into male and female sets respectively.

V. EXPERIMENTAL RESULTS

A. Back-propagation ANN

The BP algorithm is used for the training of the ANN. The output is the predicted value of the systolic blood pressure. The number of inputs is the factors used for the prediction. The number of hidden nodes varies from around 3 to 6, which would affect the number of parameters used in the training, and hence would affect the degree of freedoms. Given the data from a database, a percentage (80%, 85% or 90%) is used for training, and the rest will be used for testing the performance of the ANN. For the systolic blood pressure data in the database, only the values in the range from 80 to 160 (in mmHg) are used for the training of the ANN. The predicted value of the systolic blood pressure from the neural network will be compared with the value in the database. The absolute difference (error) between the two values will be recorded, and the result is shown in a table. Each result shown in the table is based on the averages of twenty-five cases of training and testing.

<u>*Male*</u>

Different percentages of the database have been used for the training of the BP ANN. It is found that the best result is obtained when 80% is used for training, and the remaining 20% used for testing the performance of the ANN (Table II).

TABLE II. COMPARISON OF PERFORMANCE BASED ON DIFFERENT PERCENTAGE OF DATA FOR TRAINING

	80% for training	**85% for training**	**90% for training**
error less than 5	**30.5%**	28.5%	30.2%
error less than 10	**51.9%**	49.7%	46.1%
error less than 15	**67.6%**	64.7%	63.0%
error less than 20	**79.8%**	77.4%	80.7%
error less than 25	**87.8%**	88.6%	87.4%
error less than 30	**93.4%**	93.7%	92.4%

Number of hidden nodes = 5, Inputs are BMI, Age, Exercise Level, Stress Level

TABLE III. COMPARISON OF PERFORMANCE BASED ON DIFFERENT NUMBER OF HIDDEN NODES

	3 hidden nodes	**4 hidden nodes**	**5 hidden nodes**	**6 hidden nodes**	**10hidden nodes**
error less than 5	29.0%	25.1%	**30.5%**	25.0%	17.5%
error less than 10	48.3%	51.4%	**51.9%**	46.6%	35.0%
error less than 15	62.9%	65.7%	**67.6%**	63.6%	48.8%
error less than 20	76.8%	80.9%	**79.8%**	73.3%	61.2%
error less than 25	87.9%	88.2%	**87.8%**	82.0%	71.9%
error less than 30	92.7%	92.8%	93.4%	89.2%	80.1%

80% of data for training, Inputs are BMI, Age, Exercise Level, Stress Level

TABLE IV. COMPARISON OF PERFORMANCE BASED ON DIFFERENT NUMBER OF INPUTS

Inputs / Error	**BMI, Age, Exercise, Stress**	**BMI, Age, Exercise, Stress, Smoke**	**BMI, Age, Exercise, Stress, Alcohol**	**BMI, Age, Exercise, Stress, Salt**	**BMI, Age, Exercise, Stress, Salt, Smoke, Alcohol**
< 5	**30.5%**	30.0%	28.2%	25.5%	27.1%
< 10	**51.9%**	49.4%	50.5%	46.7%	48.1%
< 15	**67.6%**	67.1%	63.8%	61.8%	59.3%
< 20	**79.8%**	78.8%	75.0%	75.1%	70.3%
< 25	**87.8%**	86.1%	82.0%	84.2%	80.0%
< 30	**93.4%**	89.9%	87.4%	90.9%	86.6%

80% of data for training, Number of hidden nodes = 5

It seems that the use of 5 hidden nodes (Table III), with 80% of data for training is the "best" result. From Table IV, the use of additional inputs does not help with the prediction. However, this may only due to insufficient information or insufficient number of cases in the database. In addition, the factors like stress and salt intake are very subjective. Further study should be carried out in the future based on a larger database.

<u>*Female*</u>

TABLE V. COMPARISON OF PERFORMANCE BASED ON DIFFERENT PERCENTAGE OF DATA FOR TRAINING

	80% for training	**85% for training**	**90% for training**
error less than 5	**30.5%**	26.3%	32.7%
error less than 10	**54.3%**	50.0%	54.0%
error less than 15	**67.3%**	67.3%	67.5%
error less than 20	**76.3%**	77.4%	78.1%
error less than 25	**85.9%**	86.5%	87.3%
error less than 30	**90.6%**	92.8%	92.1%

Number of hidden nodes = 4, Inputs are BMI, Age, Exercise Level, Stress Level

TABLE VI. COMPARISON OF PERFORMANCE BASED ON DIFFERENT NUMBER OF HIDDEN NODES

	3 hidden nodes	**4 hidden nodes**	**5 hidden nodes**	**6 hidden nodes**	**10 hidden nodes**
error less than 5	29.2%	**30.5%**	28.2%	28.2%	22.4%
error less than 10	53.2%	**54.3%**	53.6%	51.5%	42.6%
error less than 15	69.9%	**67.3%**	68.3%	67.5%	56.2%
error less than 20	79.1%	**76.3%**	79.1%	80.0%	69.4%
error less than 25	87.4%	**85.9%**	86.0%	87.7%	79.5%
error less than 30	93.2%	**90.6%**	92.5%	92.7%	84.6%

80% of data for training, Inputs are BMI, Age, Exercise Level, Stress Level

TABLE VII. COMPARISON OF PERFORMANCE BASED ON DIFFERENT NUMBER OF INPUTS

Inputs / Error	BMI, Age, Exercise, Stress	BMI, Age, Exercise, Stress, Smoke	BMI, Age, Exercise, Stress, Alcohol	BMI, Age, Exercise, Stress, Salt	BMI, Age, Exercise, Stress, Salt, Smoke, Alcohol
< 5	**29.2%**	29.0%	26.9%	26.4%	23.6%
< 10	**52.6%**	48.7%	51.6%	47.9%	45.2%
< 15	**69.4%**	63.7%	65.7%	64.5%	59.3%
< 20	**80.0%**	73.0%	77.4%	75.8%	70.1%
< 25	**88.8%**	83.0%	85.3%	84.4%	78.8%
< 30	**94.5%**	90.0%	90.7%	90.1%	86.0%

80% of data for training, Number of hidden nodes = 4

For the female case, it seems that the use of 4 hidden nodes (Table VI), with 80% of data for training (Table V) is giving the "best" result. From Table VII, the use of additional inputs does not help with the prediction. Again, this may only due to insufficient information or insufficient number of cases in the database. Also, the factors like stress and salt intake are very subjective. Further study should be carried out in the future based on a larger database.

B. Radial-Basis Function (RBF) Network

The RBF algorithm is used for the training of ANN. The output is the predicted value of the systolic blood pressure. The number of inputs is the factors used for the prediction. The number of clusters naturally formed is determined first, which would provide the weights between the input and middle layer. In the second stage, the weights are determined by an iterative least-mean-square (LMS) algorithm.

Given the data from a database, a percentage (80%, 85% or 90%) is used for training, and the rest will be used for testing the performance of the ANN. For the systolic blood pressure data in the database, only the values in the range from 80 to 160 (in mmHg) are used for the training of the neural network.

The predicted value of the systolic blood pressure from the neural network will be compared with the value in the database. The absolute difference (error) between the two values will be recorded, and the result is shown in a table. Again, each result shown in the table is the based on the averages of twenty-five cases of training and testing. Summary of observations for the database for both the Male and Female cases are given below.

<u>Male</u>

An example of one training case of RBF is shown below. Based on the training cases, the clustering algorithm is naturally forming five clusters, with centers shown below:

TABLE VIII. THE CENTER OF FIVE CLUSTERS

Exercise	BMI	Age	Stress
0.9996	34.014	27.984	2.8089
0.9945	21.738	48.76	1.0971
2.2029	26.262	52.424	2.9466
2.694	26.976	31.968	2.454
2.5023	28.614	37.376	1.1016

TABLE IX. COMPARISON OF PERFORMANCE BASED ON DIFFERENT PERCENTAGE OF DATA FOR TRAINING

	80% for training	85% for training	90% for training
error less than 5	**27.7%**	27.9%	26.6%
error less than 10	**51.8%**	50.6%	50.5%
error less than 15	**70.9%**	68.5%	67.8%
error less than 20	**82.8%**	83.6%	77.6%
error less than 25	**92.7%**	90.2%	89.6%
error less than 30	**96.5%**	95.5%	97.3%

Number of RBF nodes = 5, Inputs are BMI, Age, Exercise Level, Stress Level

TABLE X. COMPARISON OF PERFORMANCE BASED ON DIFFERENT INPUTS

Inputs / Error	BMI, Age, Exercise, Stress	BMI, Age, Exercise, Stress, Smoke	BMI, Age, Exercise, Stress, Alcohol	BMI, Age, Exercise, Stress, Salt	BMI, Age, Exercise, Stress, Salt, Smoke, Alcohol
< 5	27.7%	27.5%	26.6%	**33.0%**	28.1%
< 10	51.8%	52.0%	51.4%	**55.9%**	49.6%
< 15	70.9%	71.4%	68.8%	**70.9%**	65.5%
< 20	82.8%	82.4%	82.0%	**83.6%**	79.6%
< 25	92.7%	88.2%	91.2%	**90.7%**	88.5%
< 30	96.5%	94.5%	94.7%	**93.9%**	93.7%

80% of data for training, Number of RBF nodes = 5

236 male cases are selected from the database for this experiment. Table VIII shows that only five clusters are generated and the centers are listed. Then, as shown in Table IX, by the use of different percentages (80%, 85%, 90%) of data for training the system, the percentage of 80% for training seems to be the best choice. Lastly, based on Table X, more variables/factors (smoke and salt intake) seem to improve on the prediction. However, further studies using a larger database should be carried out to examine the results on the use of different input variables for the neural network.

<u>Female</u>

The RBF is naturally forming five clusters, with centers at:

TABLE XI. THE CENTER OF FIVE CLUSTERS

Exercise	BMI	Age	Stress
1.011	28.722	32.568	2.2293
2.6229	26.808	38.072	3
1.524	21.15	26.656	0.9891
2.3739	22.944	46.96	1.9368
0.9999	22.356	52.168	1.3923

TABLE XII. COMPARISON OF PERFORMANCE BASED ON DIFFERENT PERCENTAGE OF DATA FOR TRAINING

	80% for training	85% for training	90% for training
error less than 5	**28.4%**	23.5%	28.8%
error less than 10	**49.9%**	49.2%	47.5%
error less than 15	**69.5%**	67.9%	59.5%
error less than 20	**83.2%**	77.0%	68.1%
error less than 25	**89.6%**	87.4%	80.6%
error less than 30	**93.7%**	92.5%	88.7%

Number of RBF nodes = 5, Inputs are BMI, Age, Exercise Level, Stress Level

TABLE XIII. COMPARISON OF PERFORMANCE BASED ON DIFFERENT INPUTS

Inputs / Error	BMI, Age, Exercise, Stress	BMI, Age, Exercise, Stress, Smoke	BMI, Age, Exercise, Stress, Alcohol	BMI, Age, Exercise, Stress, Salt	BMI, Age, Exercise, Stress, Salt, Smoke, Alcohol
< 5	28.4%	**29.0%**	25.7%	22.3%	25.4%
< 10	49.9%	**50.2%**	42.1%	44.5%	48.6%
< 15	69.5%	**69.4%**	59.4%	61.1%	67.4%
< 20	83.2%	**79.5%**	74.6%	69.8%	79.1%
< 25	89.6%	**90.5%**	84.4%	80.1%	86.5%
< 30	93.7%	**94.8%**	92.5%	87.9%	91.4%

80% of data for training, Number of RBF nodes = 5

262 female cases are selected from the database for this experiment. Table XI shows that only five clusters are generated and the centers are listed. Then, by different percentage (80%, 85%, 90%) of data for training the system, the percentage (80% for training, 20% for testing) seems to be the best choice (Table XII). From Table XIII, the use of an additional input (Smoke) seems to provide a slightly better result. Further studies with the use of a larger database should be carried out to examine the results on the use of different input variables for the neural network.

VI. CONCLUSIONS

This paper proposes a machine learning method to predict the systolic blood pressure (SBP) of a person using the back-propagation (BP) neural network and the radial basis function (RBF) network.

The average prediction errors (absolute difference between the predicted value and measured value) for the relationship between SBP and input attributes (BMI, age, exercise and stress level) are at an acceptable level. The results obtained from the BP neural network and RBF network are in agreement. Generally speaking, with the database used in the experiment, the use of 80% of data for training, and use of four or five hidden nodes in both neural networks, are giving reasonably good results.

Our results indicate that the machine learning technique can be an efficient tool for analyzing the relationship between the lifestyle condition (BMI, age, stress and exercise level) and the systolic blood pressure of a person. It contributes to the development of a SBP predictor, which can provide early warning to hypertension and cardiovascular disease risks.

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