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Prediction of Stroke Risk Using the Magnetoplethysmogram Radial Artery Pulse Data

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Long periods of stress and depression can cause heart disease, brain disease, and high blood pressure. However, regardless of the advancements in modern medicine, stroke patients face difficulties without special medicines or treatments. A computer simulation is conducted to predict stroke risk factors using a magnetoplethysmogram equipped with a magnetic sensing Hall device to analyze radial artery pulses. We use logistic regression analysis to determine the vacuous pulse from the clinical data of 60 patients with deficiency syndrome and perform a computer simulation to determine stroke and early stage diseases using a TensorFlow-based open source. Additionally, computer simulations using brachycardia diagnostic cluster analysis and fuzzy inference, which are used in oriental medicine, are conducted to improve the prediction rate of stroke by more than 10%.

Keywords : stroke, magnetoplethysmogram (MPG), magnetic sensing Hall device, vacuous pulse, cluster analysis, fuzzy theory

1. Introduction

In addition to cancer and heart disease, stroke is one of the three leading causes of death [1]. A stroke that clogs or bursts the cerebrovascular system results in permanent disability or increases the mortality rate. If a stroke is suspected, it should be treated fast within 3-4 h to reduce the after-effects and avoid threats to life [1]. Arteriosclerosis, a major cause of cerebrovascular diseases, causes accumulation of cholesterol or triglycerides in blood vessels, narrowing and hardening them. Currently, there is no clear method for reducing or eliminating the risk of heart disease. Most reports focus on preventing further progression, death, or complications from arteriosclerosis if the patient already has cerebrovascular disease and arteriosclerosis [2, 3].

In particular, individuals with severe depression and high stress levels have increased heart rates and are more likely to develop irregular heartbeat disorders. Currently, MRI, carotid ultrasound, and vascular aging can be used to diagnose brain and heart diseases and identify patients with cerebrovascular diseases. However, it is difficult to detect diseases, such as stroke or brain disease, at an early stage. Accordingly, a computer simulation was conducted to predict and determine the risk to the patient health status through factor analysis and cluster analysis of the radial artery pulses of 186 patients measured using a magnetoplethysmogram (MPG) equipped with a magnetic sensing Hall device [4-6].

In this study, self-diagnosis tests of stroke patients were examined from an oriental medical scientific perspective. A computer simulation was performed to predict the risk of stroke in patients based on data mining cluster analysis and a fuzzy inference system for patients with hematoma. Finally, we explained the results of automatically identifying stroke patients based on ischemic pulse waveforms.

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2. Stroke Self-diagnosis

A research team at the University of Oxford in the UK conducted a comparative analysis of the correlation between health information and mortality rates for one million people born in Sweden between 1932 and 1995. The research team collected information on chronic respiratory disease, cardiovascular disease, diabetes, and mental illness. It was shown that people with mental illness are up to twice as likely to die from chronic diseases, such as diabetes, than people without mental illness. Additionally, 21% of people suffering from mental illness die within 5 years of being diagnosed with heart disease, diabetes, or chronic lung disease [7]. In other words, research results show that patients with mental illnesses, such as anxiety, depression, and schizophrenia, have a high risk of premature death from heart disease or diabetes.

Stroke is one of the three major causes of death along with cancer and heart disease and is a terrible disease that ranks first in the number of deaths in Korea. There are two main types of stroke: cerebral hemorrhage and cerebral infarction. Cerebral hemorrhage refers to the hardening of arteries entering the brain due to arteriosclerosis, whereas cerebral infarction refers to the complete blockage of blood vessels due to the progression of arteriosclerosis [2, 8].

In this study, we simulated a web-based depression self-diagnosis system to address this problem. Stroke has five main symptoms. Symptom-1: very severe headache. The headaches were so severe that the person sometimes vomited or passed out. Symptom-2: sudden pronunciation errors or words that do not fit the situation. Symptom-3: one arm or leg becomes heavy and cannot move. Additionally, there are cases in which people lose strength while eating and their spoons or chopsticks keep falling, resulting in serious injuries. Symptom-4: Dizziness where a person cannot sit down, and if one tries to get up and walk, one will suffer a serious injury. Symptom-5: sudden loss of vision or seeing objects overlap.

Figure 1 shows the results of a computer simulation of a self-diagnosed stroke. It consists of five questions to self-diagnose stroke. The stroke risk rate in the present study was slightly higher than 60%. If there were more than four, it was considered very dangerous by more than 80%. In addition, various causes of stroke are called "risk factors," and because stroke is a disease of the blood vessels distributed in the brain, all causes of damage to blood vessels in the brain are risk factors for stroke. High blood pressure, vascular aging, vascular speed, heart disease, diabetes, cholesterol levels, alcohol consumption, and stress are known risk factors for stroke. In this study, to determine stroke risk factors, computer simulation results were obtained to easily calculate the stroke risk by entering four risk factors, as shown in Fig. 1(b). Figure 1(b) shows the results of a computer simulation that can easily calculate stroke risk by entering the first risk factor, vascular aging, the second risk factor, vascular speed, the third risk factor, high pressure, and the fourth risk factor, cholesterol level, as the input variables.

3. Pulse Diagnosis for Deficiency Patients using MPG

Vascular diseases such as stroke and heart disease are difficult to detect early; however, they are dangerous diseases that currently have no breakthrough treatment in medical technology. In particular, many products have been developed for existing pulse waves; however, it is impossible to accurately analyze a patient's pulse wave

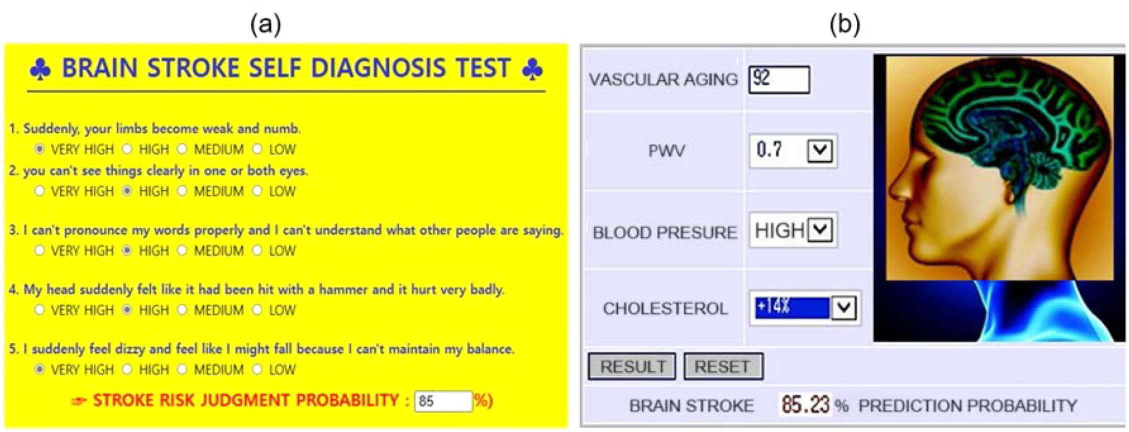


Fig. 1. (Color online) (a) Brain stroke self-diagnosis test with five symptoms. (b) Calculation of stroke risk probability.

using analog methods. This is because, the pulse wave detection sensor must be accurately located on the upper part of the patient's radial artery to accurately measure pulse waves; however, it is difficult for oriental doctors to accurately measure the pulse sensor at the same location each time in the patient's radial artery [9-11]. In addition, the patient's radial artery pulse wave must be pressurized during measurement. However, because the entire wrist is pressurized with a cuff, there is a problem that the patient's normal pulse waveform cannot be detected. In particular, the radial artery pulse waves cannot be accurately measured even if the patient's forearm is thick or thin and the elasticity of the skin is incorrect because of the thickness of the blood vessels or the patient's sex or age.

The real measurement features of the radial artery pulse using an MPG equipped with a magnetic-sensing Hall device as a pulsimeter are shown in Fig. 2(a). We focused on developing a pulsimeter that determines the pulse using a clip-type pulsimeter that can easily measure the pulse while carrying and moving in a ubiquitous era. The principle of the magnetic sensing Hall device of the MPG used in this study is related to charge moving through a current-carrying wire or another solid [6, 12]. In a magnetic field perpendicular to a current-carrying wire, the charges moving in the wire are deflected to one side. Theoretically, currents in a magnetic field are energized. The direction of the force can be determined by applying Fleming's left-hand law, whereas Lorenz's law can be used to determine the magnitude of the force received by the charge. The Hall effect occurs when the charge moving in the magnetic field generates a Hall voltage corresponding to the Lorentz force and moves in a straight line without bending; the force in the electric field due to the Hall voltage balances the Lorentz force due to the magnetic field. If the position of the magnet changes according to the vertical displacement of the radial artery by attaching a permanent magnet to the nearby skin surface to obtain the pulse generated by the radial artery, the strength of the magnetic field accepted by the sensor at a certain distance changes according to the displacement of the magnet, as shown in Fig. 2(b) [10]. The pulse indicated a maximum vertical displacement of approximately 1.13 mm per unit waveform of the radial artery. Therefore, the maximum displacement of the magnet in close contact with the skin is expected to be within 1.13 mm. For the magnet, a wide-shaped magnet with a 3 mm diameter and 1 mm thickness that is easy to obtain, easy to contact with the skin surface, and easy to attach to the measurement unit was selected.

The nine parameters of the pulse wave shown in Fig. 2(c) are listed in Table 1. In addition, the waveforms were measured for the first time. The definitions of the nine pulse-wave factors in each area are recorded. Clinical data were used to calculate the average values of the pulse wave parameters from the region in which five consecutive pulse waves were located. These average values were saved as clinical data in Microsoft Excel. A logistic regression method with normal statistics was used to determine the correlation between the nine main

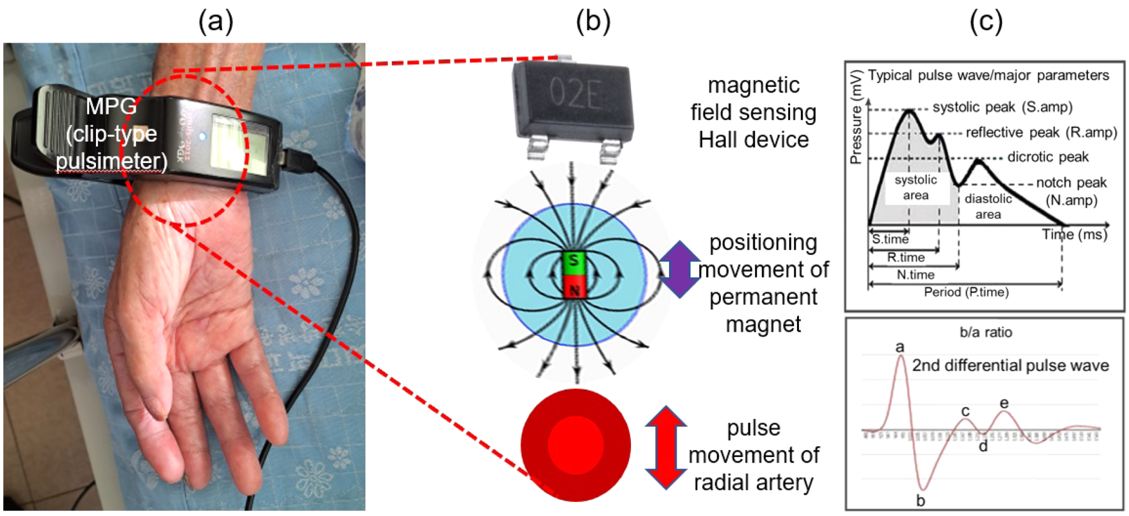


Fig. 2. (Color online) (a) Real measuring feature of the radial artery pulse using MPG equipped with a magnetic sensing Hall device as pulsimeter worn on the wrist. (b) Operating principle of MPG for measuring of pulse waveform corresponding to positioning change of permanent magnet according to the movement of the radial artery. (c) Definition of nine variables after analyzing the pulse waveform measured by MPG.

Table 1. Definitions of the nine major parameters of the pulse wave.

Parameter	Definition
S.amp	Systolic peak amplitude
R.amp	Reflective peak amplitude
N.amp	Notch peak amplitude
S.time	Systolic peak time
S.amp/S.time	Systolic peak amplitude/Systolic peak time
R.time	Reflective peak time
N.time	Reflective peak time
P.time	Period time
b/a rate	Maximum peak/minimum peak in the 2^{nd} derivative

parameters of the pulse wave and secondary variables. Sex, age, body mass index (BMI; kg/m^2), diastolic blood pressure (DBP), systolic blood pressure (SBP), and body temperature were selected as the secondary variables. The BMI was defined as weight (kg)/[height (m)]^2.

It was difficult to identify the patient's deficiency symptoms with a vacuous pulse at the beginning. Therefore, a simulation was conducted to determine the initial patient using a pulse waveform technique used in oriental medicine. In the clinical trials for this study, 60 participants were classified as having deficiency syndromes as presented in Table 2. Overall, the number of research participants was 60, consisting of 30 males and 30 females as the deficiency syndrome group. All patients were aged 40-75 years old. Their height varied from 142 to 190 cm, with an average height of 165 cm, and their weight varied from 39 to 110 kg, with an average weight of 65.2 kg. The significance probabilities (p-values) for distinctions based on age and sex were all more than 0.05; therefore, age and sex were not considered to be appropriate variables for the vacuous pulse. The average SBP for the participants in the clinical test was 130.6 mmHg (range, 90-186 mmHg), the average DBP was 82.5 mmHg (range, 55-128 mmHg), and the average body temperature was 36.7 ℃ (range, 36.0-37.5 ℃) [8, 10].

Table 2. p-value for two parameters [age, sex (male, female)] of the clinical participants (n = 60).

Clinical participants and parameters	Age (y)	Clinical participants (n)	p
		Deficiency syndrome	
Clinical participants	40	20	0.200
	50	34	
	Above 60	6	

Table 3. Comparison of the average values and p values of the parameters for the deficiency syndrome (n= 60) with standard deviations.

Parameter	Deficiency syndrome (n = 60)	p
S.amp	158.10 ± 79.68	0.106
R.amp	118.51 ± 63.64	0.127
N.amp	88.60 ± 49.69	0.130
S.time	170.68 ± 29.50	0.825
S.amp/S.time	12.06 ± 5.53	0.013
R.time	302.82 ± 32.93	0.437
N.time	354.22 ± 37.75	0.373
P.time	722.54 ± 137.03	0.105
b/a rate	-1.05 ± 0.16	0.165

Table 3 presents the average values and standard deviations of the test variables for the deficiency groups used in this study. For the variables of primary significance for the pulse, only the S.amp/S.time ratio showed a statistically significant difference with p = 0.05. The measured values for the pulse wave variables are indications of the distribution of values for the deficiency syndrome group. The logistic regression analysis of the binary clinical data from the deficiency syndrome group yielded a distinct regression equation that allowed the vacuous pulse to be assessed using the major variable of the S.amp/S.time ratio [8, 10]. Based on the above data and analyses, we expressed a logistic regression equation (1) for the probability (P) as follows:

$$P = \left(1 + \exp\left(A + 0.120 \times \frac{S.amp}{S.time}\right)\right)^{-1} \quad (1)$$

where A is the value of the secondary variables, including sex, age, BMI, and SBP.

In this study, 186 clinical data verified by oriental doctors at Sangji University Oriental Medicine Hospital were analyzed and clustered using the Weka data-mining tool [10, 11]. For the pulse machine, a clip-type pulsimeter (SPULS-2011) with a Hall device was used, as shown in Fig. 2(a). At least 60 subjects were recruited from the vacuous pulse group of men and women according to the clinical trial procedure at the Oriental Medicine Hospital affiliated with Sangji University (Table 2). After measuring the pulse wave information for each pulse group using a clip-type pulsimeter, pulse wave variables were extracted through a pulse wave analysis program, and statistical analysis of the statistical package for the social science program between biometric information and pulse wave variables was conducted [13].

Because there was an overlap between the pulse wave variables of the replete and vacuous pulse groups, significant variables were extracted using only the pulse wave variables of the two pulse groups. Consequently, significant variables were derived, such as the age, sex, SBP, DBP, and BMI, and pulse wave variables, such as S.amp, R.amp, N.amp, S.time, R.time, and N.time, as illustrated in Fig. 2(c) and Table 1. Logistic regression analysis was used to determine the probability Equation (1) for hirsutism and varicose veins from the derived variables. Based on the brachycardia classification using logistic regression equations, the final classification accuracy was 65.5% [8, 10].

As a result of factor analysis, there was no significant difference when observing the BMI and vacuous pulse in men, and when observing the same in women; the p-value was 0.068, which was close to 0.05, but there was no significant difference. When the variance analysis of the variables obtained in the circular pulse wave and the secondary differential wave was conducted according to the truth, there were four significant variables: S.amp, R.amp, N.amp, and S.amp/S.time. There were no significant differences in the variance analysis according to the ideological form of each variable. Therefore, as a result of factor analysis, it is considered appropriate to use BMI, S.amp, R.amp, N.amp, and S.amp/S.time as variables to distinguish false rooms [13-15].

4. Computer Simulation

Heart disease increases with age, as does the mortality rate. It has been a dangerous disease, especially since the 1970s, with a mortality rate of more than 80%. In 2020 in south Korea, myocardial infarction was the No. 2 disease with the number of deaths categorized after cancer patients. In other words, heart disease is a dangerous disease that causes death in one-third of the patients before they arrive at the hospital because it suddenly causes extreme pain without symptoms. Heart disease can be classified into two main categories, ischemic heart disease and other heart diseases, which can be classified as dangerous diseases, including angina, myocardial infarction, and sudden death.

Oriental medicine classifies patients with the same disease according to two opposing concepts: virtual disorder and demonstration. In the early stages of the disease, the term “weakness” refers to a state of energy deficiency owing to a sudden decrease in immunity. This means that the condition of a disease lasts for a long time, and fraud occurs when the energy of the disease is full. Stroke and heart disease are accompanied by chest pain and shortness of breath, numbness in limbs and severely reduced pulse rates or arrhythmia symptoms due to high risk levels of vascular aging, disappearance of vascular elasticity, and deformed hard-like plastic heart vessels. In particular, dangerous heart disease symptoms can occur if the peripheral blood vessels of the heart and brain become hard and oil stains accumulate in the blood vessels and become narrow. Unfortunately, there is still no specific treatment for stroke or heart disease.

If depression and stress are left unattended for an extended period, healthy individuals are more likely to develop cancer, diabetes, high blood pressure, heart disease, and cerebral infarction. In this study, using recently published risk judgment data for diabetic patients and a heart disease risk determination data set, a computer simulation was performed to determine early heart disease by adding three hypotheses, pulse data, and vascular aging. Patients with stroke and heart disease use various biometric information, such as the electrocardiogram (ECG), oxygen saturation, chest pain, blood flow rate, vascular aging, heart rate, high blood pressure, and diabetes levels, to determine the risk of heart disease. Although mid- and late-stage heart disease patients can be accurately determined using existing two-way techniques, early heart disease patients are currently difficult to identify using two-way techniques.

Therefore, to accurately determine atrial fibrillation, it is necessary to be admitted to a hospital and undergo an ECG extension test for 24-48 h. In this study, to address this problem, the basic concepts of systolic and brachycardia were inserted into the hypothesis data of 750 people, and a heart disease risk simulation was conducted using TensorFlow open-source Python. In other words, in the case of patients with brachycardia, no conditions were added to the database, and the data mining Weka tool was used to conduct an automatic cardiac disease risk analysis computer simulation so that the heart disease risk level could be somewhat low or high [15].

To diagnose stress and depression, it describes the independent variables and dependent data for the diagnosis of stroke and heart disease. The input variable comprised eight independent variable data points, one dependent data point, and nine data points. For the independent variable data, 50 were written as hypothetical data for dizziness, heart rate, chest pain, vascular aging, postprandial blood sugar, BMI, hermetic pulse, and eight veins, and 80% of the training data were used as the test data.

Figure 3 illustrates the results of automatically classifying patients with synchrony, midcardia, and ischemia when the independent variable was peak systolic blood pressure (maxpress) and the dependent variable was S.amp. Cluster analysis used in statistics is a multivariate

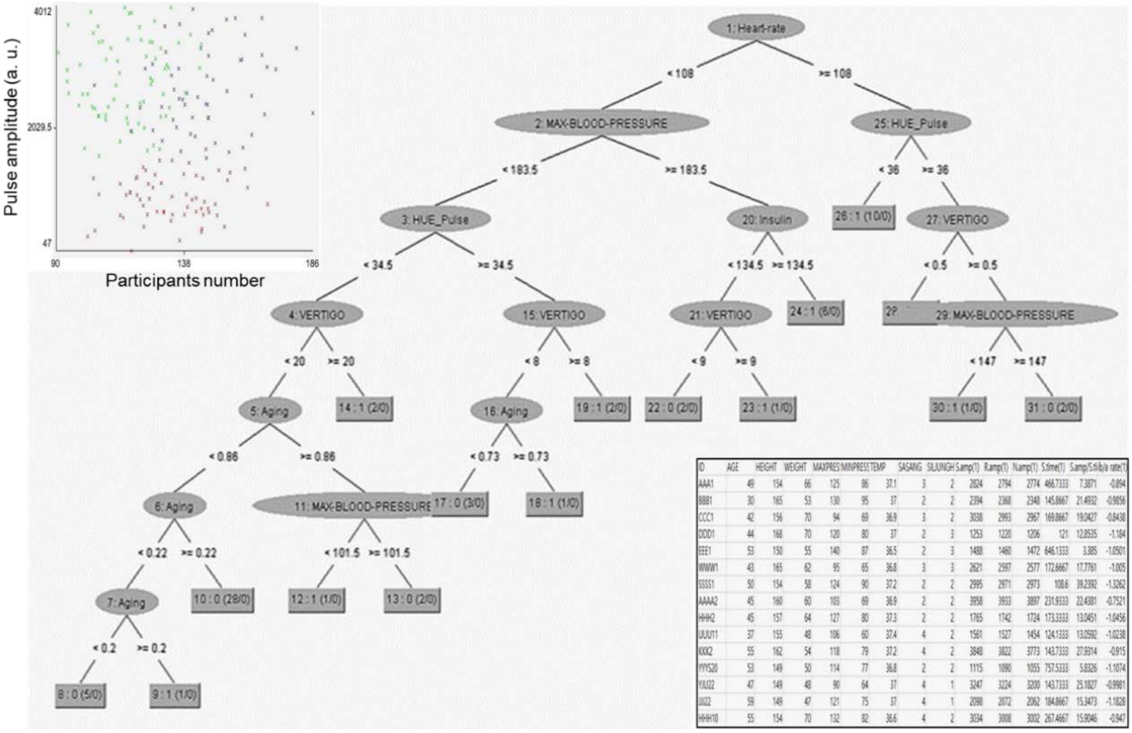


Fig. 3. (Color online) Data mining-based analysis result screen with results of cluster analysis of 186 real pulse data and 186 clinical data for determining the vacuous pulse wave and replete pulse wave (upper left inset), independent variables and dependent data for stroke and heart disease diagnosis (bottom right inset).

analysis technique that groups observations into several clusters with similar characteristics, identifies the characteristics of the clusters, and analyzes the relationships between clusters. In particular, the expectation maximization (EM) classification technique is used to estimate the parameters and weights in a mixed model, and maximum likelihood estimation (MLE) is used when the statistical model formula cannot be solved accurately. In other words, it is a classification technique that predicts unknown distribution parameters using given data and maximizes the expected value based on the given data. The most basic assumption in classifying a cluster is that each object should be classified such that the characteristics of the objects within the cluster are as homogeneous as possible, and the characteristics of the objects belonging to different clusters are heterogeneous. However, when cluster analysis is performed, data with different cluster homogeneity and heterogeneity are often mixed, making it difficult to perform cluster analysis [15, 16].

Although it is not actual clinical data but a computer simulation, as shown in Fig. 3, it was confirmed that peak blood pressure and dizziness factors are significant in determining stroke and heart disease. In addition, we analyzed the correlation between significantly reduced immunity, brain disease, heart disease, temporary decline in hypocardia, and vascular aging. Although these are hypothetical data as shown in Fig. 4(b), when the systolic blood pressure is greater than 183 mmHg, we can confirm the process of determining deficient pulse, dizziness, and vascular aging by factor analysis.

Figure 4(a) shows the MATLAB-based stroke prediction judgment fuzzy membership function and judgment fuzzy rules. With current medical technology, stroke and heart disease are very difficult to detect early; therefore, the stroke self-diagnosis test, as described in Section 2, has less than 70% confidence. Therefore, to improve the reliability of these ambiguous self-diagnostic tests, the risk of stroke in patients can be objectively assessed. The visually impaired member shelter function and language-impaired member shelter function were composed of two input conditions, and a fuzzy membership function was implemented to calculate the risk of stroke as an output condition [17].

Figure 4(b) shows the MATLAB-based stroke risk prediction fuzzy rules. This rule consists of 14 rules. As shown on the screen, the simulation results confirmed that the risk of stroke was 65% when the risk of visual impairment was 61% for vision and 62% for speech. In other words, as explained in Section 2, if a stroke self-diagnosis test results in more than three questions, the risk

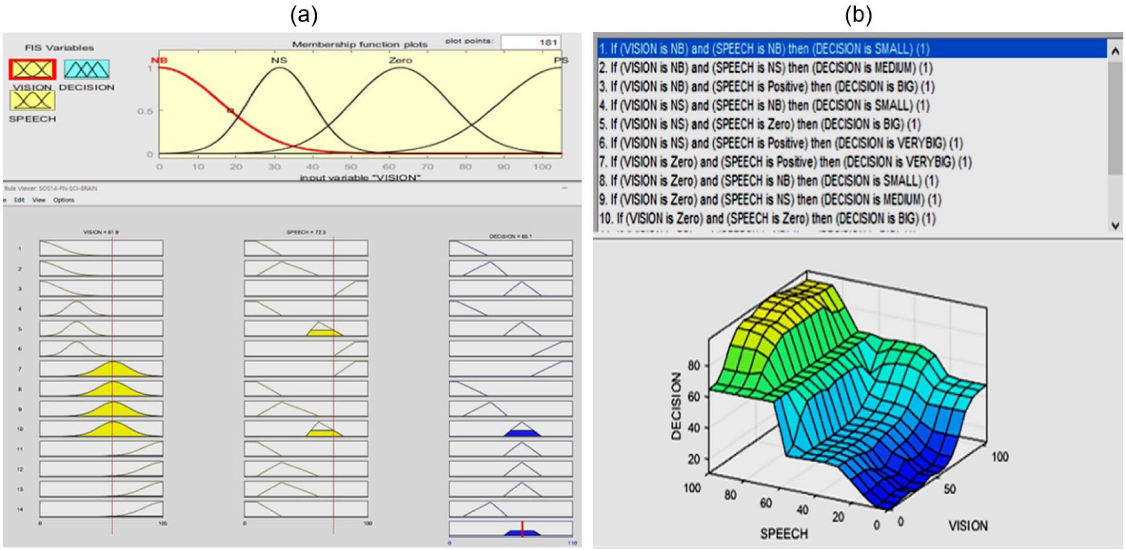


Fig. 4. (Color online) (a) MATLAB-based stroke and heart disease prediction judgment fuzzy theory execution screen. (b) MATLAB-based stroke and heart disease prediction fuzzy rules.

of stroke is predicted to be > 60%. However, although the stroke risk level is more than 60%, existing stroke prediction methods have difficulty in determining speech impairment and visual impairment phenomena, which are the most significant risk factors for stroke.

In this study, a MATLAB fuzzy inference-based stroke risk simulation was performed. This is because the fuzzy inference method is not a conventional inference method, and additional rules that can infer ambiguous stroke symptoms in stroke patients more accurately are designed using the fuzzy confidence concept as a fuzzy input membership function and an output membership function. In other words, it is possible to objectively determine speech and visual impairment symptoms that can accurately identify patients with stroke. Computer simulations have shown that the risk prediction rate for stroke patients is higher than that for conventional stroke patients. It was confirmed that the fuzzy inference method could achieve a higher accuracy than 10%.

Figure 5 shows the simulation results of the correlation analysis of stroke and heart disease prediction. Observing the class items, the correlation from VERTIGO to SiLPulse is indicated by numbers; the higher the number, the darker the color. From the independent variables, Vertigo (0.61), Maxblood Pressure (0.54), and the heart rate (0.51), the heart rate has the highest correlation in determining the dependent variable heart disease risk, and the independent variable, the BMI (0.31) has the second highest correlation in determining the dependent variable heart disease risk. Therefore, heart rate and body mass index are significant parameters for determining heart disease. However, a patient may have a variation in the number of heartbeats, high blood pressure, and pulse and pulse levels if the pulse waveform is different before and after treatment, and if the person feels good and bad. If a patient has a high heart rate at home and high blood pressure, normal levels are often observed at a hospital. In other words, even for the same patient, there are numerous differences in the number of heartbeats, hypertension levels, pulse, and hermetic levels before and after exercise, on stressful days, before and after drinking alcohol, and before and after bathing.

To accurately diagnose stroke and heart disease patients, a method of initially identifying the presence or absence of a patient's disease is being implemented by hospitalization for at least three days, performing an ECG test, and an EEG test 24 h a day. In particular, the pulse waveform when feeling fear or anxiety is not the same; in elderly, female, and young patients, the heart rate and high blood pressure levels should be corrected according to the basic metabolic rate, physical condition, age, and physiological phenomena. Regardless of the quality of the pulse wave, an accurate and reliable pulse wave can be analyzed by considering the patient's different physical and psychological conditions. In this study, to address these issues, 750 virtual data were established and computer simulations were performed for the early detection of stroke and heart disease in patients.

Figure 6(a) shows the average, standard deviation, and minimum values of the data-based variables for 750 stroke patients. Although it was a computer simulation, the average value of dizziness for stroke and heart disease

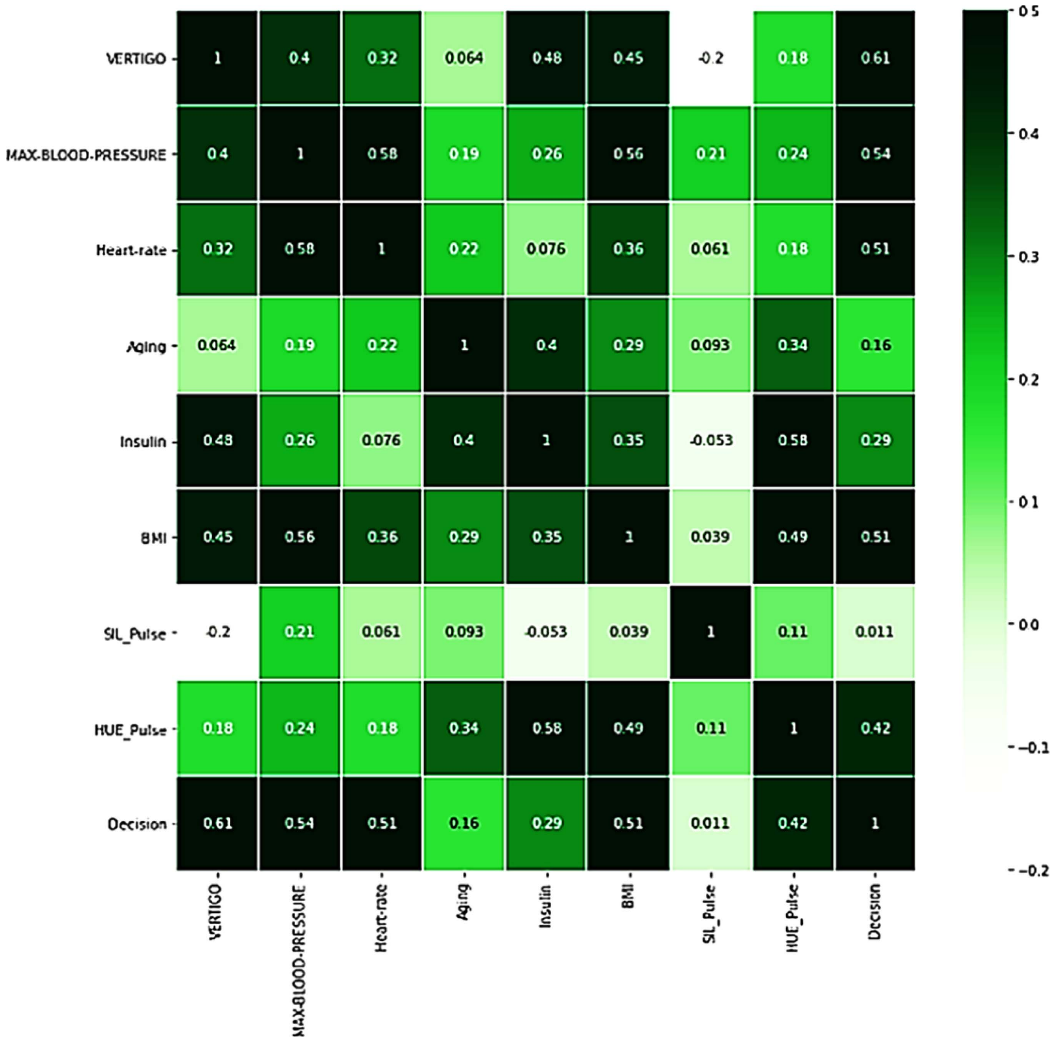
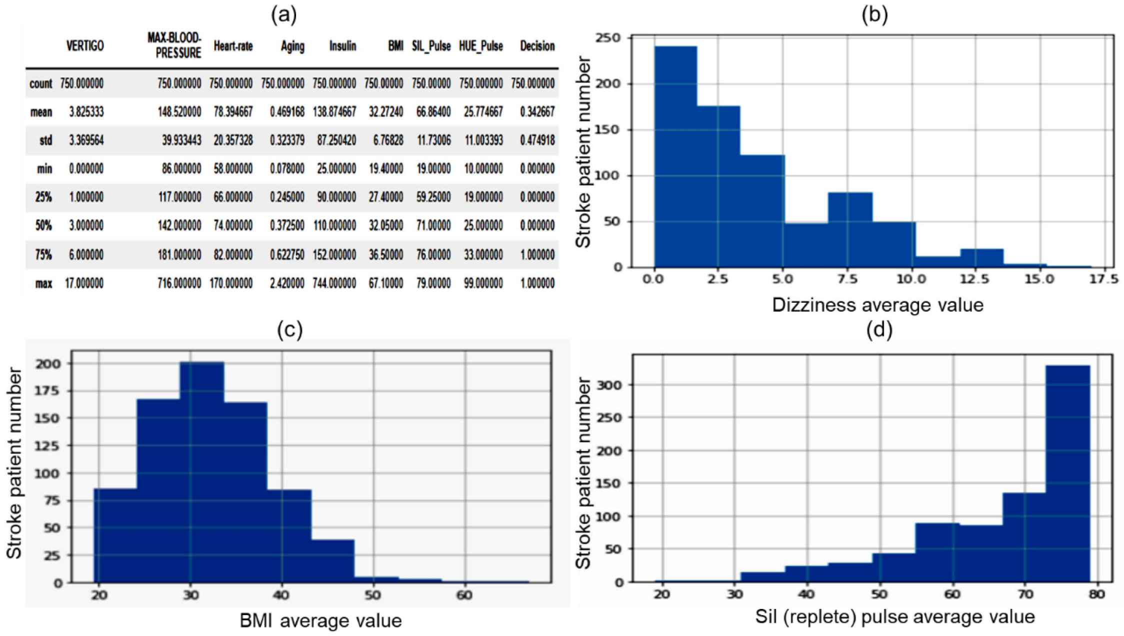


Fig. 5. (Color online) Analysis of the correlation between stroke and heart disease predictions.

patients was 3.8, the average value of maximum blood pressure was 148, the heart rate partial value was 78, and the average value of vascular aging was 0.46, assuming that they were hospitalized for 3 days to accurately detect stroke and heart disease at an early stage. In addition, the average blood sugar level was 138, the average BMI was 32, the average sil (replete) pulse value was 66, and the average hue (vacuous) pulse value was 25. Figs. 6(b), 6(c), and 6(d) show that if dizziness occurs more than 7-10 times, the BMI level is 33 or higher, and the pulse level is 67 or higher, it can be observed that the risk of stroke and heart disease is classified as high.

5. Conclusion

For the treatment of stroke and heart disease, oriental medicine hospitals predict heart disease using an oriental medicine MPG as a clip-type pulsimeter. We conducted a computer simulation experiment to predict stroke and heart disease in the early stages using the Weka data mining expectation maximization tool cluster analysis on data from 186 patients with arrhythmia. Although it is a computer simulation, based on this hypothesis, the simulation results confirmed that high blood pressure, heart rate, diabetes level, dizziness, and vacuous and replete pulse waveforms can be considered risk factors for stroke. In this study, because the hypothetical data included 60 people, it was predicted that only approximately 42-54% of the factors, such as hypertension, cadaveric beats, vacuous pulse waveform, and release pulse waveform, would affect the determination of stroke risk. If the big data from more than 750 clinical stroke patients are secured, it is expected that the early risk of stroke will be accurately determined to be over 75%, based on



(a)

	VERTIGO	MAX-BLOOD-PRESSURE	Heart-rate	Aging	Insulin	BMI	SIL_Pulse	HUE_Pulse	Decision
count	750.000000	750.000000	750.000000	750.000000	750.000000	750.00000	750.00000	750.000000	750.000000
mean	3.825333	148.520000	78.394667	0.469168	138.874667	32.27240	66.86400	25.774667	0.342667
std	3.369564	39.933443	20.357328	0.323379	87.250420	6.76828	11.73006	11.003393	0.474918
min	0.000000	86.000000	58.000000	0.078000	25.000000	19.40000	19.00000	10.000000	0.000000
25%	1.000000	117.000000	66.000000	0.245000	90.000000	27.40000	59.25000	19.000000	0.000000
50%	3.000000	142.000000	74.000000	0.372500	110.000000	32.05000	71.00000	25.000000	0.000000
75%	6.000000	181.000000	82.000000	0.622750	152.000000	36.50000	76.00000	33.000000	1.000000
max	17.000000	716.000000	170.000000	2.420000	744.000000	67.10000	79.00000	99.000000	1.000000

Fig. 6. (Color online) (a) Data-driven mean and standard deviation and minimum value results for 750 stroke patients. Data based on average measurement results of (a) dizziness, (b) BMI, (c) sil (replete) pulse for 750 stroke patients.

oriental and western medicine treatments. Additionally, to improve the prediction rate of stroke and heart disease by more than 10%, a simulation experiment using MATLAB-based fuzzy inference was performed.

Acknowledgments

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