Sensors and Materials, Vol. 37, No. 1 (2025) 135–140
MYU Tokyo

S & M 3896

Sensing Effective Healthcare through Artificial Intelligence: Analysis of the Hypertension Topic

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(Received August 22, 2024; accepted January 6, 2025)

Keywords: machine learning, edge computing, Internet of Things, dynamic demolding comparison, APP

Owing to Taiwan's aging population, many patients suffer from chronic diseases. The number of people seeking medical treatment for chronic diseases in 2023 was roughly 12.86 million. Approximately one in two people suffered from a chronic disease. The incidence of chronic comorbidities is more than 7 million people living with more chronic conditions. Prevention can be achieved through healthcare. In order to find the beyond-compare healthcare model, a healthcare system that can collect and analyze long-term data through three core variables (daily exercise, diet, and body fat) should be developed. We applied linear regression as the basis of machine learning, a machine learning modeling approach built into the front-end sensing and conversion units (with edge computing). Dynamic disassembly and comparison results are transmitted to personal mobile phones through the Internet of Things and Line APP. This allows users to understand the best individual healthcare model and simplify tedious procedures to achieve precise healthcare goals.

1. Introduction

There is an increasing number of patients with hypertension, a chronic disease, in various countries. To improve the suffering of patients with hypertension, we analyze the causes of hypertension in many patients. The machine learning modeling method is applied to establish an exclusive healthcare model. We collect the patient's diet, exercise, and body fat data for correlation analysis (cause analysis method). Ultimately, the highly correlated pairwise parameters are used to perform linear regression to determine the regression equation for lowering an individual's blood pressure and use it to control the blood pressure. In this way, a reduction in the number of chronic patients with hypertension has been achieved.

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https://doi.org/10.18494/SAM5326

ISSN 0914-4935 © MYU K.K.
https://myukk.org/

2. Research Methods

We apply the home AI precision healthcare platform to improve the condition of patients with hypertension,[1] which enables patients to slowly return to and maintain their health, as shown in Fig. 1.[1] The healthcare platform integrates a physiological data sensing and wireless transmission unit[2,3] made by us, a home-type wireless charging unit,[1,4,5] a big data collection unit, an extensive data analysis unit, and a machine learning[6–11] modeling unit. The platform architecture is designed such that patients with hypertension wear blood oxygen detection bracelets that wirelessly charge and transmit data to the extensive data collection unit. The big data analysis unit performs data analysis (multiparameter correlation analysis), and then machine learning modeling is carried out. Specific modeling methods and linear regression analysis are used to tailor specific ways to improve the hypertension condition of the individual. Advocates of the equation (exclusive mode) guide patients to adjust their diet and exercise in accordance with the instructions and observe whether the relationship between body fat and high blood pressure[12,13] changes positively (toward the alleviation of high blood pressure).[1,14]

The sensing unit has composite sensors that collect dynamic blood pressure and heart rate data from hypertensive patients during daily home life. Data are transmitted to the home data center through a wireless network for the next step of data analysis, as shown in Fig. 2. As shown, the composite sensors use blood pressure and heart rate detection chips to match the RF communication module for the synchronous wireless transmission of dynamic data. Therefore, as long as the sensor is worn on the wrist of a patient with high blood pressure, it can collect information in real time. The patient's blood pressure and heart rhythm data are sent to the big data collection unit of the home healthcare platform.

Fig. 1. (Color online) Home AI precision healthcare platform architecture.

Fig. 2. (Color online) Physiological data sensing unit.

The big data collection unit, as shown in Fig. 2, receives the big data of blood pressure, heart rate, and heartbeat through wireless communication, and conducts multiparameter (blood pressure, heart rate, heartbeat, diet, and exercise) correlation analysis to determine the high-correlation pairs. Consequently, the parameters are combined and an exclusive machine learning model is constructed for the next unit.

In this study, we propose a home-based, long-distance wireless charging technology to address the inconvenience of traditional electrical connections for sensors. Long-distance wireless charging methods can be classified into various approaches, including electromagnetic wave wireless charging, magnetic coupling resonance, electromagnetic induction, microwave conversion, and laser-based induction. Among these, we specifically employ electromagnetic wave wireless charging technology to enable wireless power delivery to the sensor. As illustrated in Fig. 3, the technology utilizes radio frequency to wirelessly transmit power from the supply unit to the sensor, thereby significantly improving the convenience of wearing and using the sensor without the need for physical charging connections.

The linear regression method establishes the data regression equation after the multiparameter correlation analysis of the big data to determine the combination of parameters with high pairwise correlation. For example, a linear regression analysis of body fat and blood pressure will be performed using data on body fat and blood pressure (blood pressure data can be divided into systolic blood pressure and diastolic blood pressure). The regression equations belonging to the two groups can be found as Eqs. (1) and (2),[1,14] which can then be integrated into Eq. (3)[1,14] and used to find the body fat number at the optimal blood pressure distribution. After we have the corresponding reference data of the optimal body fat and blood pressure, we can use the linear regression method to analyze and determine the effect of body fat on diet [Eq. (4)],[1,14] and obtain exclusive optimal pairing parameters to keep hypertensive patients in the best condition and allow hypertensive patients to enter a healthy mode.

3. Sample System Simulations

3.1 Body fat corresponds to blood pressure

The first step involves synthesizing a comprehensive blood pressure prediction equation that relates body fat to blood pressure. This equation is derived by combining the equations for body

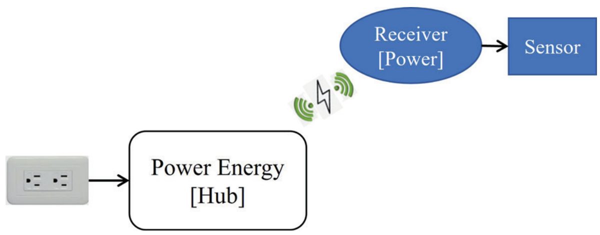

Fig. 3. (Color online) RF wireless charging unit.

fat[15,16] corresponding to diastolic blood pressure and body fat corresponding to systolic blood pressure, as illustrated in Figs. 4(a) and 4(b).[1,14] Specifically, Eqs. (1) and (2)[1,14] are integrated to form Eq. (3).[1,14] To optimize blood pressure levels, the blood pressure predicted using Eq. (3)[1,14] can be used to determine the corresponding body fat amount for individual adjustments.

$$f(z1\_1) = 0.7916 * f(y1) + 71.705 \tag{1}$$

$$f(z1\_2) = -0.3415 * f(y1) + 145.55 \tag{2}$$

$$f(z1) = f(z1\_1) + f(z1\_2) \tag{3}$$

3.2 Diet corresponds to body fat

Step 2: Collect relevant data on dietary patterns corresponding to body fat and use linear regression to establish the correlation equation [Eq. (1)] between “optimal diet” and “body fat.” The linear correlation diagram is shown in Fig. 5.[1,14]

As shown in Fig. 5,[1,14] the body fat prediction equation (the optimal amount of body fat predicted for the given type of diet) is shown as Eq. (4).[1,14] The predictive equation can be used

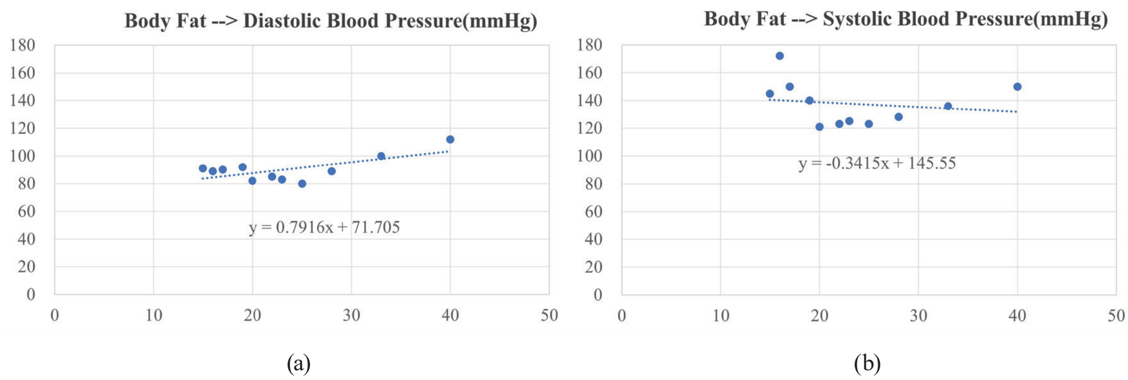

Fig. 4. (Color online) (a) Body fat versus diastolic blood pressure. (b) Body fat versus systolic blood pressure.

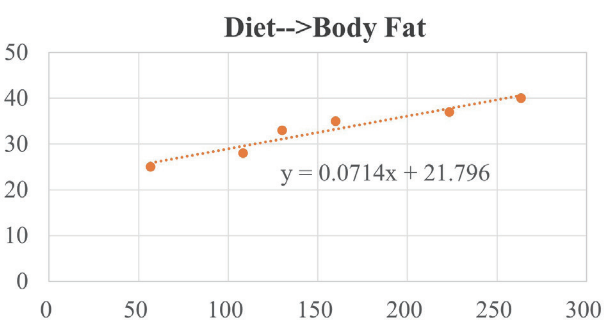

Fig. 5. (Color online) Linear correlation plot of diet versus body fat.

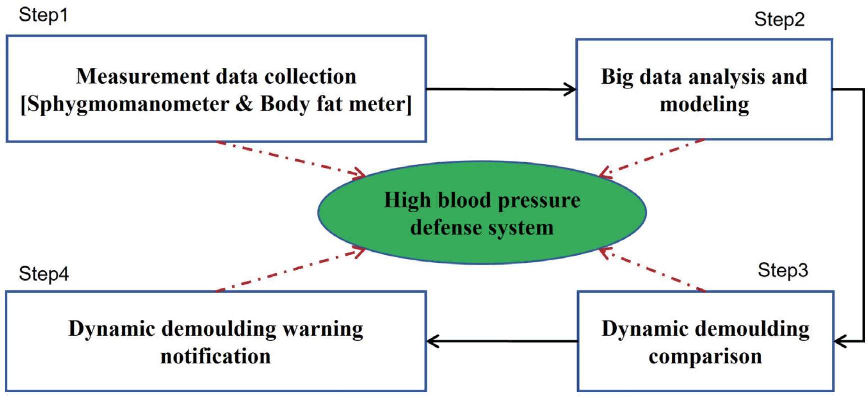

Fig. 6. (Color online) Body fat versus diastolic blood pressure.

to calculate how much of what food should be eaten for the optimal amount of body fat to maintain the body.

$$f(y1) = 0.0714 * f(Fint) + 21.796 \tag{4}$$

3.3 Simulation results

Through simulation examples, it has been determined that there is a direct positive relationship between diet and body fat and there is an indirect positive relationship between body fat and blood pressure. We can mention insights into diet through the above two relationships. The defense equation that indirectly corresponds to blood pressure due to body fat is as shown in Eq. (5).[1,14] This hypertension defense system includes four steps, which are shown in Fig. 6.[1] In Step 3, a dynamic demolding comparison of the hypertension status is performed.[17] The demolding comparison equation is shown as Eq. (6).[1] If demolding is detected in Step 4, exclusive experimental subjects receive instant SMS notifications to achieve the purpose of immediate hypertension prevention.

$$f(z1) = f(z1\_1) + f(z1\_2) = f(a1 * f(y1) + b1) + f(a2 * f(y1) + b2) \tag{5}$$

$$|\text{Predicted} - \text{Actual}| > \text{Root Mean Squared Error} \tag{6}$$

4. Conclusions

In this study, we applied linear regression methods for machine learning to analyze and model human physiological data in order to identify individual-specific correlation equations. By investigating system simulation cases, it was determined that body fat and blood pressure are strongly correlated. Consequently, body fat was found to be an intermediary, revealing a positive correlation between hypertension and diet. This finding offers significant benefits for individuals with chronic hypertension and represents a valuable contribution of this study to alleviating the burden of hypertension-related conditions.

Acknowledgments

The authors wish to extend their profound gratitude to the National Science and Technology Council (NSTC) of Taiwan for its invaluable support provided under Grant No. 113-2635-E-992-001, which has been instrumental in facilitating this research.

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