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Non-Invasive Diabetes Prediction Method Based on Metabolic Heat Conformation Theory and Machine Learning

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Abstract. Existing blood glucose meters use needles, which causes problems such as pain and infection. To solve these problems, it is necessary to realize a non-invasive blood glucose meter. One of the non-invasive blood glucose meters is the Metabolic Heat Conformation (MHC) theory. However, this theory is based on body temperature, and the prediction accuracy of conventional methods is not very high. In this study, we propose a method for determining the presence or absence of diabetes using machine learning and MHC theory. The proposed method uses machine learning to classify the presence or absence of diabetes based on skin and ambient temperature. In our experiments, we evaluated whether the proposed method can classify actual diabetics from healthy people. As a result, we were able to classify diabetic and non-diabetic data with about 80% accuracy. These results can be used for the early detection of diabetes in daily life.

1. Introduction

Diabetes is one of the top 10 causes of death in the world; the World Health Organization (WHO) states that 422 million adults worldwide have diabetes, making it a familiar disease [1]. The global epidemic of diabetes is also said to be a rapid increase in obesity and lack of physical activity, and is expected to continue to grow. Currently, blood glucose self-monitoring devices are commercially available to measure blood glucose levels at home. These allow people to check their blood glucose levels. However, with current self-monitoring devices, a blood sample is pulled out of the fingertip with a needle to measure blood glucose. This causes various problems [2]. First, the measurement is performed with a needle, which is painful and causes stress to the patient during each measurement [3]. In addition, the needles and test paper are disposable, which is costly and can cause infections when collecting blood [4]. In diabetic patients, blood is drawn for blood glucose control, but people who have never been diagnosed with diabetes may be very reluctant to have their blood drawn to check their blood glucose levels. For this reason, it would be very convenient if people could easily predict diabetes on their own, instead of having to be diagnosed by a medical institution or have their blood drawn. In addition, making it easier for people to measure themselves on a daily basis would lead to the early detection of diabetes.

Tools already exist to determine the likelihood of diabetes without measuring blood sugar levels. For example, the National Center for Global Health and Medicine (NCGHM) in Japan has published a diabetes risk prediction tool. It uses parameters such as age, weight, and blood pressure to predict the likelihood of developing diabetes in three years. However, it covers ages 30 to 64 years old and does not cover all ages. In addition to the NCGHM, there are other organizations that have released diabetes prediction tools, but they are all based on the NCGHM theory and have age requirements. If you do not use this diabetes prediction tool, you must make a diagnosis in a hospital. Currently, diabetes is determined by calculating a value called Hemoglobin A1c based on blood glucose levels measured with an invasive blood glucose meter over a period of one to two months. This requires continuously measuring blood glucose levels with a painful instrument, making it difficult for diabetics and healthy individuals to receive an accurate diabetes diagnosis. Thus, because diabetes is a familiar disease that requires blood glucose measurement with blood draws, there are few easy predictive measures until the onset of the disease, and it often goes unnoticed until diagnosed in the hospital after the onset.

The best way to achieve these is through noninvasive blood glucose assays. Examples of noninvasive blood glucose assays are shown in Table 1. Non-invasive blood glucose testing is a measurement method that does not involve blood sampling or skin penetration through solids [6]. The realization of this study allows for easy diabetes diagnosis at home and improves the problems of age limitation and prediction accuracy, which are problems with existing diabetes diagnostic tools. Previous studies have attempted to measure blood glucose by optical methods [7] and temperature-based methods [8]. In the case of the optical method, the size of the device is 20 x 10 x 5 cm, even without the power supply [5]. On the other hand, temperature-based methods can be used to develop a small measurement device that can be mounted on a wearable device. This method is called the MHC method, a theory based on the correlation between the concentration of glucose in the body and the amount of heat released from the human body [8]. However, the MHC theory is based on temperature, which makes the predictions of traditional methods less accurate [9].

Table.1 Comparison of noninvasive blood glucose measurement method [5]

	Optical method	MHC technology
Invasiveness	Noninvasive	Noninvasive
Measurement object	Blood glucose	Metabolic fever
Measurement accuracy	High	Low
Medical waste	None	None
Productization	Production of prototype	Difficult as medical equipment
Size	20×10×5cm	Hand size

On the other hand, research on the application of artificial intelligence technology in medicine has been conducted for a long time, such as the Antimicrobial Propulsion System (NYCIN) and the internal medicine diagnostic support system INTERNIST-I [10]. These and other applications of statistical machine learning methods using artificial intelligence have been actively researched until now. Machine learning can be broadly classified into supervised, unsupervised, and reinforcement learning, but supervised learning is most commonly used for medical applications [11]. It is a method of optimizing a mathematical model to represent the relationship between input and output data by preparing input data and an output data set that is the correct answer.

Therefore, in this study, we investigated a simple method for predicting the likelihood of diabetes in an average household. MHC technology and machine learning are used to predict diabetes. As shown in Table 1, the MHC theory is one of the non-invasive blood glucose measures and is based on the correlation between blood glucose and body temperature. In this study, we decided to use the MHC technology, which is advantageous due to the miniaturization of the sensor, as we aim to create a measurement device that can be used at home. We aimed to propose and validate a non-invasive and simple blood glucose measurement using MHC and machine learning.

2. Proposed Method

Figure 1 shows the flow from measurement to prediction of the proposed method presented in this paper. In this method, air temperature and hand surface temperature are measured using a sensor. Based on the data, thermal radiation (hr) and thermal convection (hc) are calculated using a calculator. In a study based on the MHC theory conducted by Hillson et al. they injected glucose into the body of a subject and saw a change in temperature in the cheek within 2 minutes [12]. This study is considered the basis for non-invasive blood glucose measurement, and studies by Zhang et al. [13, 14] have demonstrated that glucose concentration has a direct effect on body temperature. These studies confirmed that the MHC theory can predict blood glucose levels by thermal radiation and thermal convection. Thermal radiation can be measured by the Stefan-Boltzmann law and is obtained as follows:

$$hr = \rho\ \sigma\ (Ts^4 - To^4) \tag{1}$$

In this case, hr (W/m^2) is the thermal radiation, ρ is the reflection coefficient of the skin surface, σ is the Stefan-Boltzmann constant, Ts(°C) is the surface temperature and To(°C) is the ambient temperature.

The thermal convection is also calculated as follows:

$$hc = h\ (Ts - To) \tag{2}$$

In this case, hc (W/m^2) is the heat convection and h is the heat transfer coefficient.

The measurements of these Eq. (1), Eq. (2) are sensitive to disturbances caused by sudden changes in ambient temperature, so they must be measured while the patient is resting in a room with the same temperature for a certain time. Finally, these two values are used as features and machine learning is used to perform a binary classification of diabetic patients and healthy individuals.

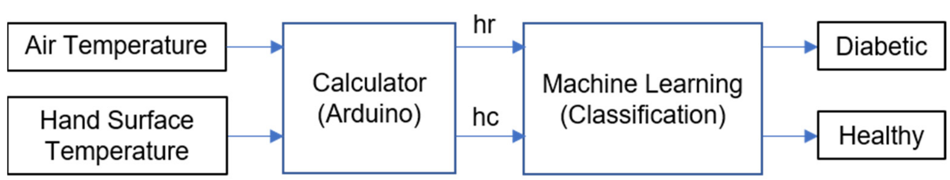

Fig. 1. Block Diagram of Proposed Method

3. Experiment

In this experiment, we tested whether the proposed method is capable of predicting diabetes. Three middle-aged men and women, totaling 195 samples, were obtained. Two of the subjects were identified as diabetic by their reports. The samples were obtained simultaneously using the instrument shown in Fig. 2 at the same time that they were being measured with an invasive blood glucose meter.

The experimental instrument is shown in Fig. 2, and the details are given in Table 2. The instrument measures the surface temperature and air temperature of the fingertips and calculates thermal radiation and convection using Eq. (1), Eq. (2).

First, based on the data (195 samples) from the subjects (3), we check if the measurements of diabetics and healthy subjects can be classified. Five classification methods were tried to find the best algorithm: support vector machine (SVM), neural network (NN), decision tree, naïve Bayesian and logistic. The true value of the classification was confirmed verbally whether the patient was diagnosed with diabetes at the hospital or not.

This experiment was conducted with the approval of the 10th Shikoku Regional College of Technology Bioethics Committee in 2018.

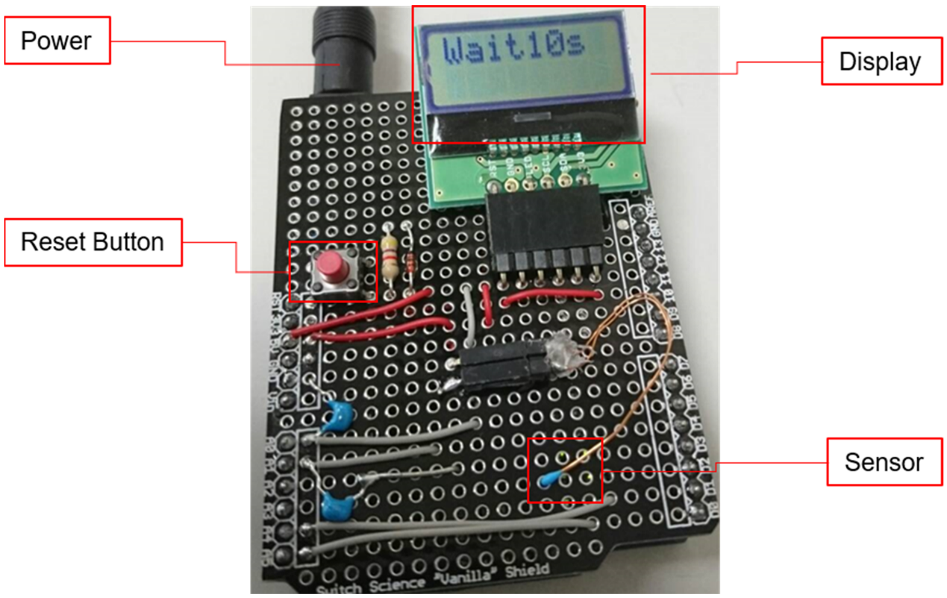

Fig. 2. Measuring Instruments

Table 2. Using Machines

Equipment name	Model number
Microcomputer	Arduino UNO
Display	LCD
Temperature sensor	NTC thermistor

5. Result and Discussion

Box plots of hr and hc obtained from the subjects are shown in Fig. 3 and 4. As shown in Fig. 3 and 4, differences can be seen in the measurements of both thermal radiation and thermal convection between diabetic and healthy subjects. Because healthy people have changes in their blood glucose levels in their daily lives, both hr and hc have broad values, with hr centered at 40 (W/m2) and hc centered at 35 (W/m2). On the other hand, since diabetic patients tend not to lower their blood glucose levels, the observed values are limited, and both hr and hc are mainly 15 (W/m2). These differences may be predictive by classification.

Table 3 shows the results of the binary classification of diabetic patients and healthy subjects using these values. Table 3 shows that all of the methods are accurate in about 80% of the cases, and almost all of them are able to classify with high accuracy. This result suggests that the proposed method is effective in predicting diabetes. A breakdown of the results of each classification is shown in Tables 4 to 8. With SVM (Table 4), the probability of correctly classifying diabetes was 75.4% and 90.3% for non-diabetes. Using NN (Table 5), the probability of correctly classifying diabetes was 72.1% and 93.1% for non-diabetes. Using the decision tree (Table 6), the probability of correctly classifying diabetes was 76.2% and 95.8% for non-diabetes. Using Naive Bayes (Table 7), the probability of correctly classifying diabetes was 79.5% and 72.2.8% for non-diabetes. Using logistic regression (Table 8), the probability of correctly classifying diabetes was 79.5% for nondiabetic patients and 90.3% for nondiabetic patients. In all of the results, the accuracy of the prediction of the healthy population is particularly high, while the diabetic population is incorrectly identified as diabetic about 20% of the time. Because this classification is based on the results of a single measurement, we believe that a new trend can be observed by confirming the results by taking into account the results of multiple measurements. Our results confirm from Table 3 that the decision tree and the logistic are the most accurate. The decision tree (Table 6) showed the highest predictive accuracy for non-diabetes, and the logistic regression (Table 8) showed the highest predictive accuracy for diabetes. The data used in this study are relatively clearly separated in terms of values, as shown in Fig. 3, so a simple separation model is better for prediction. Therefore, the prediction accuracy of the decision tree and the logistic is likely to be higher.

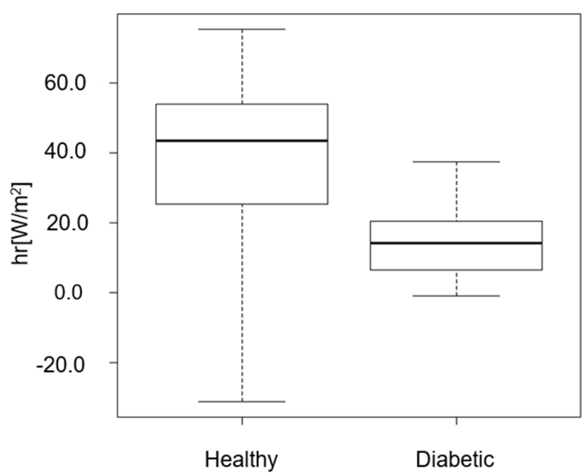

Fig.3.hr Between Healthy and Diabetic

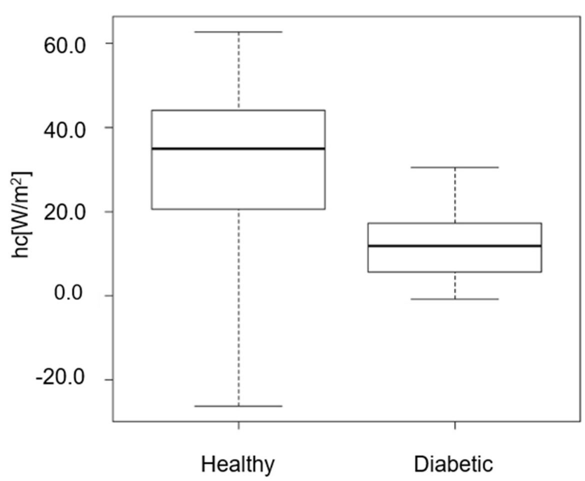

Fig.4. hc Between Healthy and Diabetic

Decision tree and logistic classification can be created with simple models and can be easily implemented. They are also computationally fast and can be classified with high accuracy in this study, as shown in Table 5. The diabetes prediction system should be easy to use at home. Therefore, these models, which are easy to implement and capable of high-speed processing, are also favorable for future development. In summary, the use of decision trees or logistic based on MHC theory to predict the likelihood of diabetes seems to be the best way to do so.

Table 3. Classification Results

	SVM	NN	Decision Tree	Naive Bays	Logistic
Correctly Classified	80.9%	79.9%	83.5%	76.8%	83.5%
Incorrectly Classified	19.1%	20.1%	16.5%	23.2%	16.5%

Table 4. Confusion Matrix (SVM)

Predict			
Diabetic	Healthy		
92	30	Diabetic	Actual
7	65	Healthy	

Table 5. Confusion Matrix (NN)

Predict			
Diabetic	Healthy		
88	34	Diabetic	Actual
5	67	Healthy	

Table 6. Confusion Matrix (Decision Tree)

Predict			
Diabetic	Healthy		
93	29	Diabetic	Actual
3	69	Healthy	

Table 7. Confusion Matrix (Naive Bays)

Predict			
Diabetic	Healthy		
97	25	Diabetic	Actual
20	52	Healthy	

Table 8. Confusion Matrix (Logistic)

Predict			
Diabetic	Healthy		
97	25	Diabetic	Actual
7	65	Healthy	

6. CONCLUSION

In this paper, we utilized the MHC theory of non-invasive blood glucose measurement and machine learning to attempt to predict the likelihood of diabetes. The results showed that diabetics and healthy subjects differed in thermal radiation and convection, and that the classification by decision trees and logistics could predict the likelihood of diabetes with an accuracy of 83.5%. These classification models have very high accuracy in predicting the likelihood of diabetes in healthy subjects, which may be sufficient for use as an indicator of the likelihood of diabetes.

7. ACKNOWLEDGMENT

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