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Health care Monitoring System and Analytics Based on Internet of Things Framework

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ABSTRACT

The Internet of things (IoT) has been a controversial domain of inquiry in engineering applications since the term was first introduced in 2000. The emergence of IoT also promotes the advancement of health care monitoring from face-to-face consultation to telemedicine or eHealth system. This paper presents the prototyping of an embedded health care monitoring system based on the IoT paradigm. The proposed system architecture consists of three sensors for the measurement of three basic vital signs, i.e. body temperature, pulse rate, and blood pressure. The integrated sensors are interfaced with the Intel Edison platform, and the output readings are transferred to IBM Bluemix for cloud storage and display. Taking advantage of IoT, the condition of the physical body can be monitored remotely and diagnosed with anomalies by doctors. The paper also presents the health care analytical framework related to diabetes and kidney disease. The prediction results from the analytics show the potential of the classification model to be integrated into the proposed system to identify the potential risk of certain diseases at early stages of early treatment. In the preliminary investigation, the accuracy of the developed model to differentiate between a healthy person and patients with diabetes and kidney disease is 90.54% and 87.88%, respectively. Concerning the functionality of the proposed system architecture, the sensors' measurement accuracy is above 90% compared to conventional medical equipment.

KEYWORDS

Artificial neural network; Data analytic; Embedded monitoring system; Health care; IoT; Sensor

1. INTRODUCTION

A 2015 report from the World Health Organisation revealed that 44% of the member states have less than one physician per 1000 population [1]. The shortage of workforce in the health care industry is not only in rural areas, but also critical in urban areas due to population density. In addition, the growth of chronic diseases and the inadequate growth of expertise in the past decade have accentuated the gravity of the problem. In fact, simply educating and training more physicians falls short of addressing the shortage problem. To tackle the issues, a growing number of research related to telemedicine and eHealth has been recorded in the past decade.

Telecommunications play a vital role in the health care industry [2]. In fact, telemedicine or eHealth system is introduced for remote patient monitoring, home health care, and disease management. In 2015, a computer-based information system for health administration was developed and reported to greatly enhance the effective utilisation of available health care data and further streamline the data collection and reporting machinery [3]. Historically, such systems have not been widely adopted because of the cost constraints, immaturity, and the limitations of technologies. However, the emergence of the cloud computing and the Internet of things (IoT) paradigm promotes the advancement of eHealth applications. Instead of hardwired machine-to-machine (M2M) configuration with its many wired connections that take up vital space, IoT builds on cloud computing and acts as a network to collect data from sensors. In other words, IoT connects specific devices to the Internet, processes the data on the cloud and is capable of displaying the obtained information on any smart phone, tablet, or computer with network access. The communication in IoT is mobile, virtual, and instant, and it stands to dramatically change people's lives, workspace productivity, and consumption [4]. Thus, incorporating IoT into the current health care system is beneficial for patients, doctors, and the society. In fact, the use of IoT not only strengthens the ability of a doctor to examine, diagnose, and treat disease remotely, but also reduces the infrastructure cost and expense on both hospital and patient [5].

A typical example of IoT solutions in health care is measuring vital signs via remote sensors and presenting the continuous and real-time data to the respected specialist through cloud services. Through IoT implementation, nurses and doctors no longer need to walk around the wards to track the conditions of patients. Instead, the information or any abnormal sign detected from the patients can be tracked immediately. Besides that, the devices with health monitoring and activity tracking functions are experiencing increased popularity, as they allow users to become more aware of their health-related behaviour [6].

A study of using a wireless body sensor network to perform remote health care monitoring in hospitals was reported in 2013 [7]. By attaching a few wireless sensors on patients, the body conditions of the patient such as their heart rate and blood pressure are identified and sent to its base station, i.e. hospital. The system can alert the patient and send a short message service or email to physicians if an abnormal condition is detected. In 2016, a self-aware early warning score system for IoT-based personalised health care was reported [8]. The system monitored the vital sign of patients and is capable to detect and predict patient deterioration. Another IoT-based health care system specifically for elderly people is proposed in 2016 [9]. The system captures brain and body movement signal for the detection of strokes and produces an alarm in the case of a stroke. In early 2017, a remote mobile health care platform to monitor cardiovascular and respiratory variables was proposed [10]. The system employs IEEE 802.15.4 (low-rate wireless personal area networks) and IEEE 802.11 (wireless local area network) to transmit the real-time measured heart rate, respiration rate, body temperature, and fall detection to the server.

From the technical viewpoint, there is still room to improve the current IoT implementation despite several health care monitoring systems having been proposed and reported. This paper highlights two issues. First, there is a lack of integration of health care data analytics into the IoT framework. Specifically, the lack of semantic data descriptions increases the difficulty of modelling the relationship between the physiological data and the diseases even though they are known to be related to each other. Second, the majority of current health care systems do not consider two-way communication between the patients and doctors. In this case, both doctor and patient can access and view the data, but the patient is unable to question or consult the doctor virtually.

This paper presents the prototyping of a new wireless embedded health care monitoring system which utilises Intel Edison as the IoT gateway. To address the lack of health care analytic in the current monitoring system, the paper also presents several health care analytic model for the early prediction diabetes and kidney disease that have potential to be integrated into the proposed monitoring system architecture in this study.

The remainder of the paper is organised as follows. Section 2 details the system architecture of the proposed health care monitoring system followed by the analytical framework in Section 3. The results are discussed in Section 4 before drawing to a conclusion.

2. SYSTEM ARCHITECTURE

The system architecture of health care monitoring systems has to meet the requirements of measuring vital signs of patients, processing and converting sensor signals to readable output and displaying the monitoring results on web applications. In general, the system architecture of the proposed health care system is divided into front-end (presentation layer) and back-end (data access layer). In the front-end layer, the system integrates microcontroller-enabled sensors to measure vital signs of a user and utilises Arduino Nano and Intel Edison to convert the detected signals as readable outputs. Besides sensors, the front-end layer includes a graphical user interface (GUI) or web application which allows both patients and doctors to access and view the obtained data and information. In the back-end layer, the output from the data acquisition system is stored on the cloud database and analysed prior to data visualisation.

The system architecture for the proposed health care system is illustrated in Figure 1. This study considers three types of vital signs measured from patients, i.e. body temperature, pulse rate, and blood pressure. These are the vital signs that are often included in the clinical study.

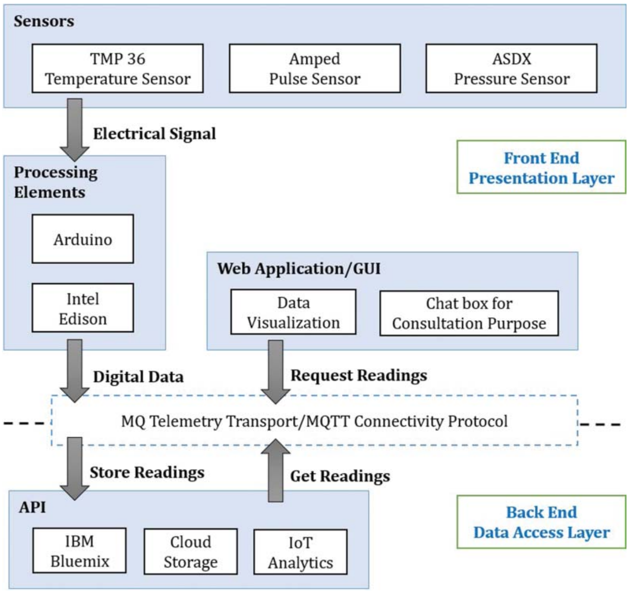

Figure 1: System architecture of IoT health care system

Sensor TMP 36 is used to measure body temperature. It is an analogue sensor which converts the temperature to a proportional analogue voltage. The output of the sensor is interfaced to one of the input channels of Arduino which has a built-in 10-bit analogue-to-digital converter (ADC) module. In this study, the voltage to be measured by the ADC channel ranges from 0.5 to 1.0 V, which corresponds to the temperature range from 0 to 50 °C. Thus, the reference voltage of the ADC is configured using the microcontroller internal built-in reference voltage, i.e. 1.1 V, instead of the default value of 5 V. The configuration of the reference voltage at lower level results in better resolution, where 1 bit represents 0.1 °C, compared to set 5 V as the reference voltage (1 bit represents 0.4 °C). Given that the output voltage is directly proportional (linear) to the temperature, and the scale factor is 10 mV/°C, the equivalent temperature from the converted ADC signal is calculated using the equation as follows:

$$\text{Temperature in }^\circ\text{C} = \frac{(V_{\text{out}} \text{ in mV}) - 500}{10} \tag{1}$$

To measure the pulse rate, the proposed system utilises an Amped sensor which operates based on the photoplethysmography (PPG) technique. The PPG is a non-invasive method that measures the variation of blood volumes in tissues using light detector. The sensor gives the output in a fluctuation of voltage relative to the changes of light intensity detected. The little variation of the light intensity is synchronous with the changes of blood volume and heartbeat. The sampling rate of the pulse sensor configured in this study is 500 Hz, meaning that the raw pulse signal is read every 2 ms. Once the signal is read, the executed program checks on the peak and trough value of the PPG waveform, and the inter-beat interval (IBI) is calculated based on the time interval between two peaks of the waveform. To achieve more accurate results and avoid signal fluctuation, the pulse rate in beats per minute (BPM) is derived from the average of 10 IBI obtained using the equation as follows:

$$\text{Pulse rate in BPM} = \frac{60000}{\text{average of 10 IBI}} \tag{2}$$

In this study, the data collection of blood pressure is represented by the value of mean arterial pressure (MAP) instead of the diastolic and systolic readings. MAP describes a person's average blood pressure for a complete single cardiac cycle. The relationship between MAP and diastolic/systolic blood pressure (D.Bp/S.Bp) readings is stated as follows:

$$\text{MAP} = \frac{\text{S.Bp} + 2 \times \text{D.Bp}}{3} \tag{3}$$

In the prototyping system, the measurement of blood pressure system employs a blood pressure cuff, motor, valve, and pressure transducer. The motor is powered and controlled by the microcontroller to inflate the inflatable cuffs. At the same time, the pressure transducer linked to the cuff through a tube is able to return the value of MAP based on the detected oscillations that have the maximum amplitude from the cuff. On the interfacing side with the microcontroller, the pressure transducer produces an analogue output voltage proportional to the applied differential input pressure in psi. Referring to the conversion formulas, the measured blood pressure in the system is represented in mmHg using the following equation:

$$\text{Pressure (in mmHg)} = \frac{15 \times (V_{\text{out}} - 0.5)}{4 \times 51.7} \tag{4}$$

where

$$V_{\text{out}} = \frac{(\text{ADC value} \times 5)}{1024} \tag{5}$$

As for the processing element, the proposed study utilises the Edison platform to act as a sink node which gathers all sensor readings from the Arduino and wraps the collected data into JavaScript object notation format (JSON) prior to transmitting the data to the server. The Edison platform has a built-in Wi-Fi radio that can connect to the Internet without the need of wiring additional hardware modules. Due to the small packet data size, the proposed system employs the ISO standard publish-subscribe-based messaging protocol (MQTT) to transmit data between the processing elements and server.

In the IoT framework, application programming interface (API) acts as a component that controls and manages the transferred data to the server from the processing elements. In this study, Node-Red from IBM Bluemix is used as the API to control and process the received data. The received packet data in JSON is flowed into two different paths. The first path directs the data to the cloud database for storing. The data flows through the second path and processed for the visualisation at GUI.

In order to resolve the lack of communication between patients and doctors in the current health care monitoring system, a chat box is also included in the GUI of the proposed system. The chat box is created using the websocket protocol in Node-Red and can provide a duplex communication channel for users to consult with doctors or vice versa.

3. HEALTH CARE ANALYTICS

The emergence of IoT has promoted the growth of digital data at an exponential rate. Without further analyses, the data is meaningless if used solely for storing and display purposes. In health care applications, the vital signs are usually used to predict and detect certain potential diseases. For example, a fever is an illness indicated by high body temperature (>37.5°C), and the level of obesity can be indicted by the body mass index (BMI). However, analysing all the raw data from sensors or database manually is beyond human limits. The highlighted issues promote the advancement of health care analytics. By using analytical tools or machine learning, some useful information is automatically extracted and can be used as a pre-screening model for the early detection of certain diseases.

In general, the health condition of a patient could be monitored or assessed by considering certain physiological indices. However, for complex chronic diseases, e.g. diabetes and kidney diseases, relying on a single physiological parameter is insufficient to predict or detect the presence of the disease. Figure 2 shows the relationships between the two specified diseases and physiological parameters summarised from two databases. Even though they are related to each other, it hardly models the relationship because of the lack of semantic data descriptions.

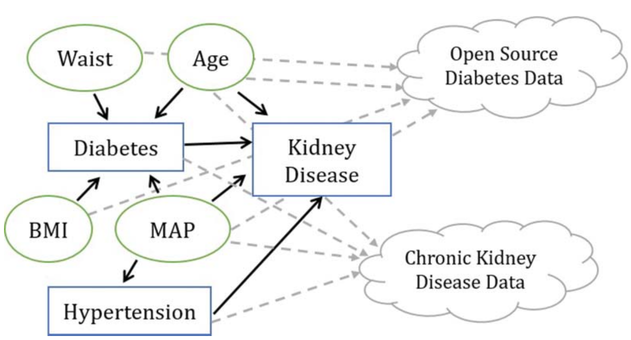

Figure 2: Relation of health data extracted from open data

In this study, the analytics for diabetes and chronic kidney disease are demonstrated using statistical test and machine learning algorithms. The analyses are performed offline, to discover the hidden pattern and the domain knowledge from the historic diagnoses provided by the open sources data. The knowledge is then used to support and develop the prediction model for the detection of complex diseases.

The analytical framework presented in this study involves feature selection and machine learning. The vital signs or other human body parameters that could be used as biomarkers for specified diseases are identified. Next, the computation model capable of relating the selected features and the presence of illness is developed to predict the outcomes. The typical flow of the analytical framework presented in this study is illustrated in Figure 3.

In this study, the data-set used to analyse the risk factors and characteristics related to diabetes are courtesy of John Schorling [11]. The data-set consists of the potential indicators of Type 2 diabetes, such as cholesterol, age, waist, diastolic pressure, systolic pressure, etc. for 403 subjects. By removing the missing data in the data-set, the actual count of respondents is 372. Among the 372 respondents, 286 are treated as the control group (healthy population), and the remaining 86 are categorised as the treatment group (diabetes population). The details of the respondents are tabulated in Table 1.

Table 1: Tabulation of respondents

Population	Number of respondents
Healthy	286
Diabetic	86
Total	372

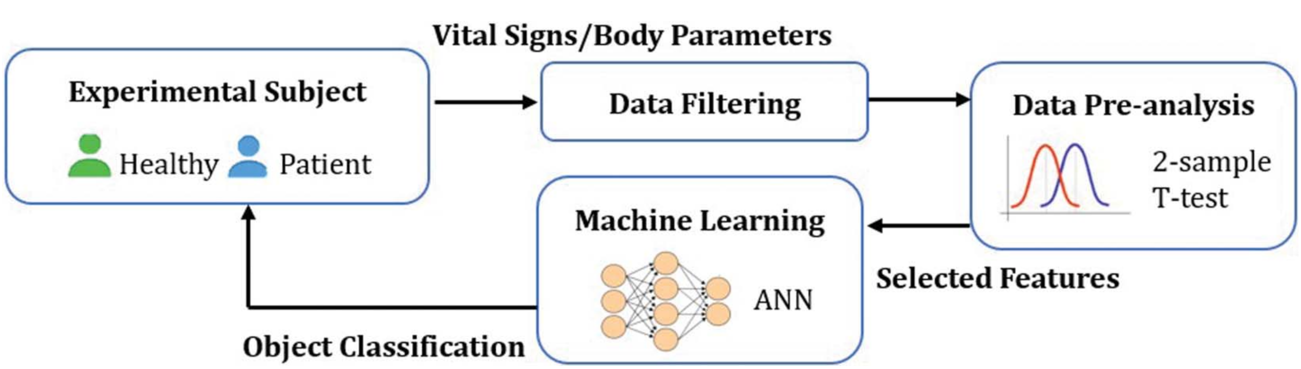

Figure 3: Framework of health care analytics

Four potential indicators are selected from the data-set to study the risk factors of diabetes, i.e. age, BMI, MAP, and waist circumference (in inches). The BMIs are derived from the height and weight recorded in the data-set, whereas the MAP is calculated from the diastolic and systolic blood pressure.

In general, diabetic patients have a higher value of age, waist, BMI, and MAP regardless of gender. To strengthen the evidence and support the practicality of the selected features to be used in the classification model, a two-sample *T*-test was carried out to test and identify the magnitude of differences for each indicator between diabetic patients (treatment group) and the control group.

The hypotheses of interest for analysing the significance between the two populations are formulated below. A significant difference means that the presence of diabetes shows different values or levels on the specified features. These features are selected to develop the classification model due to its discriminatory power. On the other hand, a non-significant difference means that both population groups produce the same effect on the investigated features.

The null hypothesis, H_o: $\mu_d = 0$, where μ_d = the mean difference of each feature (age, waist, BMI, and MAP) between two populations (diabetic patients and non-diabetic), is not statistically significant.

The alternate hypothesis, H_o: $\mu_d \neq 0$, is significant.

The calculated *p*-values for each potential feature are summarised in Table 2. The *p*-value for all investigated cases resulting from the *T*-test is < 0.05. Hence, at 95% confidence interval, the null hypotheses for all four cases are rejected, where the mean differences of all investigated features between diabetic patient and non-diabetic are statistically significant. The confidence interval stated in the table indicates the value of the mean difference, e.g. the mean age value for diabetic patients is between 11 and 17 and is higher than non-diabetic cases.

Table 2: Exploratory analyses between diabetic and non-diabetic

	Mean		StdDev		*T*-test result	
Criteria	Diabetic	Non-diabetic	Diabetic	Non-diabetic	*p*-Value	95 % CI
Age	57.4	43.4	1.40	0.92	0.00	(10.67, 17.43)
Waist	40.66	37.05	5.72	5.60	0.00	(2.23, 5.00)
BMI	30.17	28.29	7.15	6.68	0.00	(0.17, 3.60)
MAP	104.6	100.2	15.0	14.90	0.02	(0.73, 8.02)

From the pre-analyses, the classification model concerning the selected features and the output (either diabetic: 1 or non-diabetic: 0) is developed using the classic artificial neural network (ANN) trained with the resilient backpropagation algorithm. Out of 372 data, 298 (80%) is used as training data, and the remaining 74 sets of data served as testing data. In the training stage, the ANN is evaluated using 10-fold validation technique to produce an optimal classification model. In the 10-fold validation process, the entire training data is randomly divided into 10 groups of subset data. For each training iteration, one of the subset data is treated as validation data, and this process repeats for 10 iterations. The training results and the prediction accuracy of the developed model on the testing data are presented in the next section.

The data-set used for the analysis of kidney disease is sourced from UCI machine learning repository [12]. The data was collected from the hospital over a period of nearly two months by Dr P. Soundarapandian to be used in the prediction of chronic kidney disease. Typically, the majority of patients may not have severe symptoms until their kidney disease is advanced. Although some studies reveal the risk factors for the disease, the supporting evidence is inconclusive for some potential risks, and the casual relationship is not clearly established. The present study aims to provide sufficient details to support the study of potential indicators for chronic kidney disease and develop a prediction model to be included in the proposed health care monitoring system for the early diagnosis of chronic kidney disease based on the identified markers.

The analytical works are similar to the prediction of diabetes discussed in the previous section. In this case, the selected potential indicators to study the risk factors for chronic kidney disease are: (a) age, (b) MAP, (c) diabetes and (d) hypertension. The features (a) and (b) are numerical data while (c) and (d) belong to categorical data.

To further identify the discriminatory power of the specified features, two sample *T*-tests are used to determine the magnitude of differences in features (a) and (b) between kidney disease and non-kidney disease. For the features involving categorical data, i.e. (c) and (d), Chi-squared test is conducted. The null hypothesis of Chi-squared test states that the chronic kidney disease is independent of other diseases, i.e. diabetes and hypertension. The results of the conducted tests are summarised in Table 3.

Table 3: Exploratory analyses between CKD and non-CKD

	Mean		StdDev		*T*-test result	
Criteria	CKD	Non-CKD	CKD	Non-CKD	*p*-Value	95 % CI
Age	57.5	46.0	14.00	15.3	0.00	(8.23, 14.74)
Waist	79.6	71.67	15.60	8.59	0.00	(5.58, 10.88)
Chi-squared test					*p*-Value	X-squared
Diabetes					0.00	123.42
Hypertension					0.00	135.57

4. RESULTS AND DISCUSSIONS

pThe sensor responses of the proposed health care monitoring system are tested on 10 students aged between 20 and 24 years. The readings produced from the sensor are inspected by comparing them with conventional medical devices, Medisana BU510. The obtained results support the capability of the proposed health care monitoring system to perform the measurement of three vital signs, i.e. temperature, pulse rate, and blood pressure with an average accuracy above 90% (98.90%, 98.49%, and 94.28%, respectively). Regarding data transmission delay, the data successfully transferred from the processing unit to the cloud in between 1 and 9 s even at low internet speeds (64 kbps). At high internet speeds (10 Mbps), the transmission delay is less than 3 s.

For the development of the ANN classification model to predict the presence of diabetes and kidney disease, the best training accuracy achieved in this study is 92.5% and 93.2%, respectively. The optimised ANN model for diabetes classification is a 5-7-1 multilayer perceptron with seven hidden neurons and the activation function of each neuron is sigmoid transfer function. On the other hand, the optimised ANN model for the prediction of chronic kidney disease is 4-5-1 model with five hidden neurons and sigmoid activation function.

The optimised ANN model obtained from the training stage is evaluated using the specified testing data. The testing data consists of the remaining 20% of the data in the data-set. Thus, it is different from the training data. Tables 4 and 5 present the confusion matrix for 2-class classification, showing the actual and predicted classification by the adopted ANN model. The performance of the ANN is evaluated for sensitivity, specificity, and overall accuracy. The evaluation scheme is calculated using the following equations:

$$\text{Sensitivity} = \frac{\text{True} +}{(\text{True} +) + (\text{False} -)} \tag{6}$$

$$\text{Specificity} = \frac{\text{True} -}{(\text{False} +) + (\text{True} -)} \tag{7}$$

$$\text{Accuracy} = \frac{(\text{True} +) + (\text{True} -)}{(\text{True} + \text{ and } -) + (\text{False} + \text{ and } -)} \tag{8}$$

In this study, the accuracy obtained for the prediction of diabetes and kidney disease using the specified data-set is 90.54% and 87.88%, respectively. It is difficult to discuss and compare the obtained findings with other scholars since the included features, classification algorithm, and data-set are different. However, there are results concerning using vital signs as features combined with the ANN for the prediction of disease. In 2011, a study used blood pressure, creatinine, urine pH, and fasting glucose as classification features [13]. The best prediction accuracy achieved was 88.8% using ANN trained with Bayesian regulation. Another research obtained accuracy of 81.48% using probabilistic neural network on the features specified in the Pima Indian Diabetes Data-set in 2016 [14]. The satisfactory results achieved from the developed prediction model support further integration of the model to the proposed health care monitoring system framework. The web application developed in the present study is illustrated in Figure 4. The GUI can display the analysed health status of the user besides the three basic vital signs measured by the integrated sensors in the proposed system. Moreover, the information can be viewed at any place and anytime with network connectivity.

Table 4: Confusion matrix of classification performance on diabetes

	Predicted as					
Actual	Diabetic	Non-diabetic	Total	Sensitivity	Specificity	Accuracy
Diabetic	16	1	17	94.12 %	89.47 %	90.54 %
Non-diabetic	6	51	57			

Table 5: Confusion matrix of classification performance on chronic kidney disease

	Predicted as					
Actual	CKD	Non-CKD	Total	Sensitivity	Specificity	Accuracy
CKD	35	3	38	92.11 %	82.14%	87.88 %
Non-CKD	5	23	28			

5. CONCLUSION

In summary, an innovative framework based on IoT technology for health care monitoring applications was successfully developed. The system can perform measurements of three basic vital signs, i.e. body temperature, pulse rate, and

Figure 4: Web application GUI for (a) healthy subject and (b) unhealthy subject

blood pressure with high accuracy. The data is available for doctors to view and monitor in real time even if the patients perform the tests outside the hospital. Also, the study presents the machine learning framework to automatically predict the potential risks such as diabetes and kidney disease. The prediction results support further integration of the prediction model into the proposed system in next stage of works. However, the presented analytics are a preliminary investigation requiring further clinical test and real-time data to further validate the machine learning model prior to system integration. Nevertheless, due to the coupling of remote monitoring and fast analytical techniques to process the received data, it is possible to apply the described solution for health care monitoring and chronic disease control.

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DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

REFERENCES

1. World Health Organization, “Global Health Observatory Data,” 2015. [Online]. Available: http://www.who.int/gho/en/
2. “Telecommunications and Health,” *IETE J. Res.*, Vol. 27, no. 3, pp. 96–9, Jul. 2015. doi:10.1080/03772063.1981.11452330
3. K. Ravindra, “A computer-based information system for health administration,” *IETE J. Res.*, Vol. 22, no. 5, pp. 281–6, Jul. 2015.
4. D. Shin and Y. Park, “Understanding the Internet of things ecosystem: Multi-level analysis of users, society, and ecology,” *Digit. Policy, Regul. Gov.*, Vol. 19, no. 1, pp. 77–100, 2017.
5. B. Xu, L. Xu, H. Cai, L. Jiang, Y. Luo, and Y. Gu, “The design of an M-health monitoring system based on a cloud computing platform,” *Enterprise Inform. Syst.*, Vol. 11, no. 1, pp. 17–36, Jun. 2017.
6. D. Shin, S. Lee, and Y. Hwang, “How do credibility and utility affect the user experience of health informatic services?” *Comput. Hum. Behav.*, Vol. 67, pp. 292–302, 2016.
7. M. Aminian and H. R. Naji, “A hospital healthcare monitoring system using wireless sensor networks,” *J. Heal. Med. Inform.*, Vol. 4, no. 2, p. 121, Feb. 2013.
8. I. Azimi, A. Anzanpour, A. M. Rahmani, P. Liljeberg, and H. Tenhunen, “Self-aware early warning score system for iot-based personalized healthcare,” in *eHealth 360°*, Springer, Cham, Dec. 2016, pp. 49–55.
9. S. J. Park, M. Subramaniya, S. E. Kim, S. Hong, J. H. Lee, C. M. Jo, and Y. Seo, “Development of the elderly healthcare monitoring system with IoT,” *Adv. Hum. Factors Ergon. Healthc.*, Vol. 482, pp. 309–15, Jul. 2016.
10. R. Miramontes, R. Aquino, A. Flores, G. Rodriguez, R. Anguiano, A. Rios, and A. Edwards, “PlaIMoS: A remote mobile healthcare platform to monitor cardiovascular and respiratory variables,” *Sensors*, Vol. 17, no. 1, Jan. 2017.
11. J. Schorling, “Diabetes sata,” 2015. [Online]. Available: staff.pubhealth.ku.dk/tag/Teaching/share/data/Diabetes.html.
12. M. Lichman, “UCI machine learning repository,” 2013. [Online]. Available: http://archieve.ics.uci.edu/ml.
13. M. A. Sapon, K. Ismail and S. Zainudin, “Prediction of diabetes by using artificial neural network,” in *Proceedings*

of the 2011 International Conference on Circuits, System and Simulation, Singapore, Vol. 2829, 2011, pp. 299–303.

14. Z. Soltani and A. Jafarian, "A new artificial neural networks approach for diagnosing diabetes disease type II," *Int. J. Adv. Comput. Sci. Appl.*, Vol. 7, no. 6, Jun. 2016.

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