An application of LSTM neural networks to improve the efficiency of monitoring and warning the health status of office workers

Nguyen Chi Ngon[1*], Pham Thanh Tung[2], Le Thanh Phuong[3], Nguyen Thi Kim Nguyen[1]

[1]Can Tho University;
[2]Vinh Long University of Tenology Education;
[3]Long An College.
[*]Corresponding author: ncngon@ctu.edu.vn
Received 01 April 2022; Revised 16 May 2022; Accepted 25 May 2022; Published 26 August 2022.
DOI: https://doi.org/10.54939/1859-1043.j.mst.81.2022.3-13

ABSTRACT

This article proposes a solution to improve office chairs (referred to as IoT chairs) based on IoT technology and LSTM (Long Short – Term Memory) neural networks to monitor and promptly warn via the Internet about questions of abnormal health status of office staff. An IoT circuit with the MCU-ESP8266 module is used to collect weight and an accelerometer sensor embedded in the chair, which can communicate with a computer to monitor the searing time of the user and warn by sound for prolonged sitting. LSTM neural networks built on MATLAB is trained by deep learning techniques to track inappropriate postures of people sitting in chairs, through analyzing signals from sensors. Experiment results on many different scenarios show that the accuracy of capacity of reminding about the status of prolonged sitting is 100% and reliability of the capacity of detecting and warning abnormal health conditions is 94%. Experiments also show that the ability to complete IoT chairs for a popular application is completely feasible.

Keywords: IoT technology; Deep learning techniques; LSTM neural networks; MCU-ESP8266; Health monitoring.

1. INTRODUCTION

In modern society, people spend more time sitting without physical activities, especially the groups of office staff. Meanwhile, sitting and working for a long time without standing up will have many health risks [1, 2], such as muscle and joint diseases [3], obesity and high blood pressure [2] resulting in a high risk of stroke [4]. Studies have also shown that digestive diseases, cardiovascular diseases, and deep vein thrombosis are caused by sitting for long periods of time [5]. According to the World Health Organization, about 17 million people die by heart attacks and strokes every year [6]. The emergency of people having a stroke needs to be very urgent, especially in the first period after the stroke called the “golden hours” [7]. Therefore, monitoring to promptly detect abnormal health status of office staff, especially stroke risk, is a difficult and challenging sensitive research topic for scientists.

Many studies focus on developing office chairs with the function of monitoring the health of sitting people. For example, in the study [8], the authors developed a mechanism to automatically change the sitting posture by moving the chair frame mechanism, by controlling the servo motors. A lot of research has focused on developing health monitoring chairs that use sensors to measure the blood pressure, the heart rate, the temperature, and the weight [3, 4, 9-11]. The arrangement of many sensors on the arms and the back of the chair to directly contact the bodies of the sitting people, in order to accurately measure biological parameters like the above studies will cause psychological discomfort.

In addition, several studies to monitor abnormal health conditions without using sensors to measure directly have been implemented. For example, studies [12, 13] have used images processing techniques to monitor falling conditions. However, there are many locations where cameras cannot or should not be installed. At the same time, the user in the feeling of being followed by cameras also has a bad mentality. A form of real-time monitoring of the living behavior of the elderly in the family has been deployed in the study [14]. This study uses location sensor, combined with real-time information to identify abnormal lifestyle behavior in time frames of the day, to alert caregivers. The limitation of this study is that the monitored person can remove the location device, as this product is not suitable for use in the office. The study [15] has initially built a health monitoring chair model on an IoT platform, using contactless sensors in order to detect abnormal health status of sitting people. The basic limitation of the study [15] is using a four-layer feed-forward neural networks to identify the health status of people sitting in a chair, which has not yet achieved high reliability, only 82% due to the influence of the person's heart rate being monitored on the accelerometer.

This study aims at improving the IoT chairs in [15, 16] by long-short term memory (LSTM) neural networks [17, 18] to improve the reliability in recognizing the movement state of the sitting people and alerting the user to the prolonged sitting status, or suspicions of bad health by sending messages to one or more other trackers' phones. The LSTM neural network is trained by deep learning techniques with Adam's optimization algorithm. The LSTM neural network has many advantages in predicting factors changing over time, thanks to its mechanism of remembering past data [19, 20] and abilities of recognizing of several complex objects in real life [19-21].

The rest of this article is organized as follows: Session 2 presents IoT circuits and LSTM neural networks; Session 3 illustrates the design of the IoT chair based on deep learning algorithm; Session 4 presents experiment results and discussion; and session 5 is the conclusion.

2. IOT TECHNOLOGY AND LSTM DEEP LEARNING NEURAL NETWORKS

2.1. IoT platforms

The Internet of Things (IoT) refers to the billions of physical devices that are connected to the internet. It is an internetwork in which devices and facilities are embedded with electronics, software, sensors, actuators, and the connectivity to a computer network, making these devices able to collect and transmit data to each other [22, 23]. This study aims at integrating the popular MCU-ESP8266 module [24] with easy for internet connectivity, along with gravity and accelerometer sensors onto office chairs, to monitor inappropriate movements of sitting people. Two sensor modules are used including the accelerometer MPU6050 [25] and the load cell Mavin NA2 [26].

The sensor module MPU6050 [25] integrates accelerometer sensor and gyroscope sensor with I^2C suitable for communication with ESP8266 module. This module gives 3-axis acceleration (x, y, z) in space. The accelerometer sensor integrated in the back of the office chair can record the movement of the sitting people by reading these 3 axes (x, y, z) acceleration information. To detect the sitting people in the chair, the Mavin NA2 load cell sensor module [26] is integrated into the seat surface to measure the weight of the sitting people.

2.2. LSTM deep learning networks

LSTM is an improved Recurrent Neural Network (RNN), widely used for prediction models, thanks to its efficient deep learning techniques [18-20]. A typical LSTM network structure includes input layer, to receive data; The LSTM layer has a sufficiently large number of memory cells (hidden nodes), along with four layers followed by the fully connected and active layers. Each LSTM memory cell has a structure shown in figure 1. The main and most important feature of an LSTM network is that the cells can remember the past states of data. Each LSTM cell typically contains three types of gates, including input gate, output gate and forget gate, shown in figure 1. The gates of the LSTM cell include *sigmoid* activation functions with outputting value from 0 to 1. The sigmoid activation function described as (1), is commonly used for these gates. If the activation function gives a value of 0, the data attribute will be deleted, otherwise, when the activation function gives a value of 1, the data's attribute will be kept for the next computation layer - this is also called the memory mechanism of data attribute of the LSTM network.

Let *i(k)*, *f(k)* and *o(k)* be the output of input gate, forget gate and output gate respectively; w_m is the corresponding weight of port *m*; *h*(*k*-*1*) is the output of the LSTM cell at the previous time *k*-*1;* *x*(*k*) is the current input signal at *k* sampling time; and b_m is the corresponding activation threshold of gate *m*. Then, the output gate is (2), (3) and (4) [20]. In which, the input gate (2) helps determine the storage of new information in the cell; Output gate (4) provides the output value of the LSTM cell at sampling time *k*. While the forget gate (3) determines what information to remove from the cell.

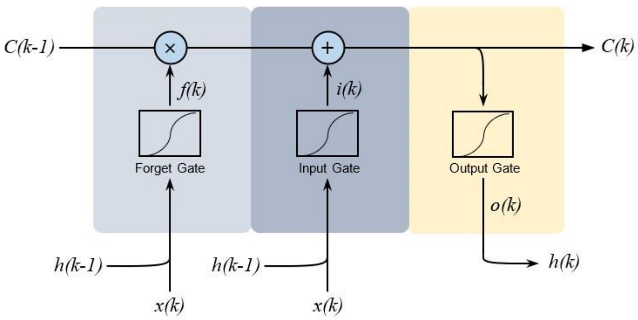


Figure 1. *Structure of an LSTM cell [18, 20].*

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{1}$$

$$i(k) = \sigma\left(w_i\left[h(k-1), x(k)\right] + b_i\right) \tag{2}$$

$$f(k) = \sigma\left(w_f\left[h(k-1), x(k)\right] + b_f\right) \tag{3}$$

$$o(k) = \sigma\left(w_o\left[h(k-1), x(k)\right] + b_o\right) \tag{4}$$

3. DESIGN OF AN IOT CHAIR WITH LSTM DEEP LEARNING NETWORKS

This study aims at improving the ability to recognize abnormal movements of people sitting in IoT chairs using the feed-forward neural networks of [15, 16] by proposing to use the LSTM neural network according to a mechanism diagram shown on figure 2.

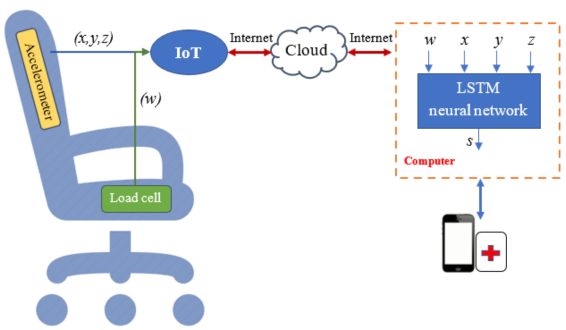


Figure 2. *IoT chair using LSTM neural network.*

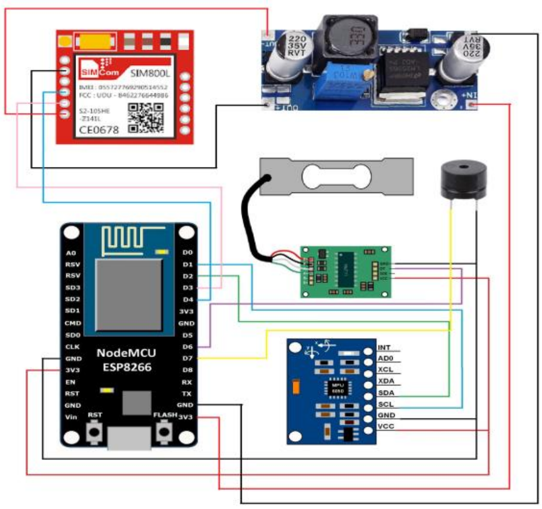


Figure 3. *IoT circuit to monitor health status.*

3.1. IoT chair model

The electronic circuit of the IoT chair as presented in figure 3 is designed including Node MCU-ESP8266, Mavin NA2 load cell sensor, MPU6050 accelerometer sensor, Loadcell HX711 24-bit ADC converter, SIM800L Module, ALP1205S Buzzer, and a removable battery. The

ESP8266 module [24] is used to read the built-in MPU6050 accelerometer sensor module [25] on the back of a common office chair and read the information from the load cell Mavin NA2 [26] through the analog-to-digital converter HX711, shown in figure 3. These modules have been completed with I^2C [27] compatibility.

When sitting people have an abnormal health condition, the Buzzer ALP1205S piezoelectric speaker will give an alarm and SIM800L Module will send a warning message to the preset phone numbers. In addition, Buzzer ALP1205S is also used to remind sitting people when working on a chair for longer than 45 minutes.

3.2. Data collection

This study arranged four types of experiments corresponding to four hypothetical cases. The data from the 3-axis accelerometer (x, y, z) and the value of the weight from load cell (w) were transmitted to Google Sheets (cloud) via Wi-Fi connection by the microcontroller. On the computer, a simple MATLAB program was built to access and read data from cloud. The data set [w, x, y, z] read from sensors do not subtract the offset value or reduce the value to ensure that the data are not affected by other factors. The goal of this study is to detect someone sitting on IoT chair and have inappropriate movements, not to determine the weight or speed of movement on the chair of that person. Depending on the state of the experiment, which simulates normal or abnormal health, the value of the state variable (s) - the desired output of the network, is assigned 1 for alerting case, and 0 for normal case. Four cases of experiment include [15, 16]:

- Case 1: No one is sitting on the IoT chair – collect (w, x, y, z) and assign $s = 0$.
- Case 2: People sitting and working normally – collect (w, x, y, z) and assign $s = 0$.
- Case 3: People sitting without movements – collect (w, x, y, z) and assign $s = 1$.
- Case 4: Put the bag on the IoT chair – collect (w, x, y, z) and assign $s = 0$.

Figures 4 and 5 illustrate corresponding experimental data for case 3 and case 4. The data set (***P***, ***T***) is used to train the neural network, where ***P*** is the input matrix and ***T*** is the desired output state vector, organized as (5) and (6). Dividing the values (w, x, y, z) by a factor is just a trick to standardize the data to the range (0, 1) for a more convergent training algorithm.

$$\boldsymbol{P} = \left[{w_i}/{100}, {x_i}/{300}, {y_i}/{300}, {z_i}/{300} \right]^T; i = 1, 2, \ldots N \tag{5}$$

$$\boldsymbol{T} = \left[s_i \right]; i = 1, 2, \ldots N \tag{6}$$

	A	B	C	D	E	F	G
1	IoT Chair data collection						
2	**Case3**: person in conscious state				**S** = 1: SMS warning		
3	**Date**	**Time**	**W**	**X**	**Y**	**Z**	**S**
4	8/8/2021	16:42:20	112.77	174.63	267.47	179.76	1.00
5	8/8/2021	16:42:23	112.97	168.93	267.02	179.42	1.00
6	8/8/2021	16:42:26	113.15	176.78	267.80	179.88	1.00
7	8/8/2021	16:42:29	113.46	168.06	267.86	179.55	1.00
8	8/8/2021	16:42:33	117.76	107.03	268.25	174.30	1.00
9	8/8/2021	16:42:36	117.34	352.21	300.95	184.69	1.00
10	8/8/2021	16:42:40	117.43	351.30	342.79	206.28	1.00
11	8/8/2021	16:42:43	115.25	20.65	318.58	156.86	1.00

... TH3 TH4

Figure 4. *Experimental data Case 3.*

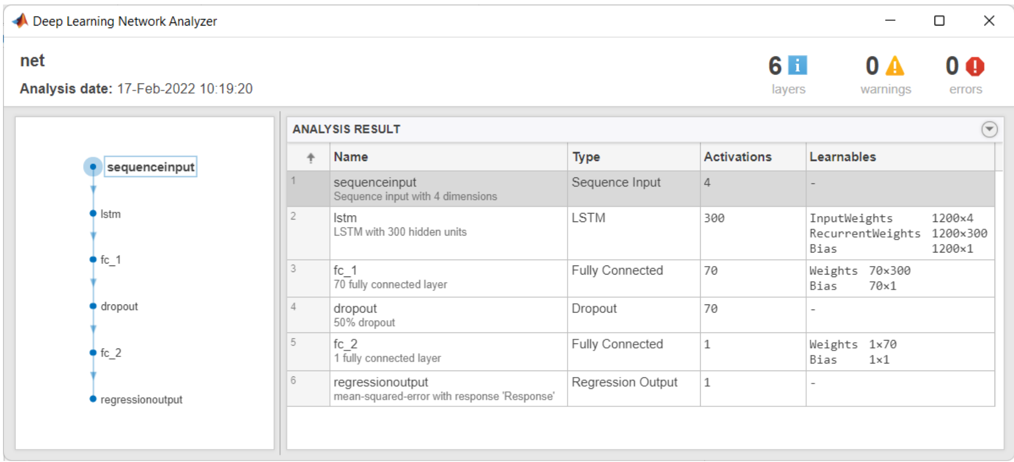
	A	B	C	D	E	F	G
1	IoT Chair data collection						
2	**Case4:** put a bag on chair			**S** = 0: No action			
3	**Date**	**Time**	**W**	**X**	**Y**	**Z**	**S**
4	8/8/2021	16:51:29	80.37	226.55	268.47	181.61	0.00
5	8/8/2021	16:51:32	80.18	229.29	269.11	181.03	0.00
6	8/8/2021	16:51:35	80.27	240.22	268.97	181.80	0.00
7	8/8/2021	16:51:39	80.11	225.98	268.36	181.70	0.00
8	8/8/2021	16:51:42	80.25	234.18	268.67	181.84	0.00
9	8/8/2021	16:51:45	80.37	228.36	268.41	181.79	0.00
10	8/8/2021	16:51:48	80.53	215.45	267.87	181.52	0.00
11	8/8/2021	16:51:51	80.52	226.15	268.22	181.85	0.00

... TH3 TH4

Figure 5. *Experimental data Case 4.*

3.3. Building the LSTM neural network to recognize health status

The LSTM deep learning networks structure in this study is implemented with 6 layers as illustrating in figure 6 and figure 7 [28]. In order to exploit the capacity to remember past information of the input data, LSTM networks will continuously gather 10 input data samples at 10 contiguous sampling times for an output state identification *s*. With contiguous sampling times, the input dataset correlates with movement behaviors of the people sitting on the IoT chair.


Deep Learning Network Analyzer

net

Analysis date: 17-Feb-2022 10:19:20

6 layers, 0 warnings, 0 errors

sequenceinput → lstm → fc_1 → dropout → fc_2 → regressionoutput

ANALYSIS RESULT

	Name	Type	Activations	Learnables
1	sequenceinput Sequence input with 4 dimensions	Sequence Input	4	-
2	lstm LSTM with 300 hidden units	LSTM	300	InputWeights 1200×4 RecurrentWeights 1200×300 Bias 1200×1
3	fc_1 70 fully connected layer	Fully Connected	70	Weights 70×300 Bias 70×1
4	dropout 50% dropout	Dropout	70	-
5	fc_2 1 fully connected layer	Fully Connected	1	Weights 1×70 Bias 1×1
6	regressionoutput mean-squared-error with response 'Response'	Regression Output	1	-

Figure 6. *LSTM deep learning network structure.*

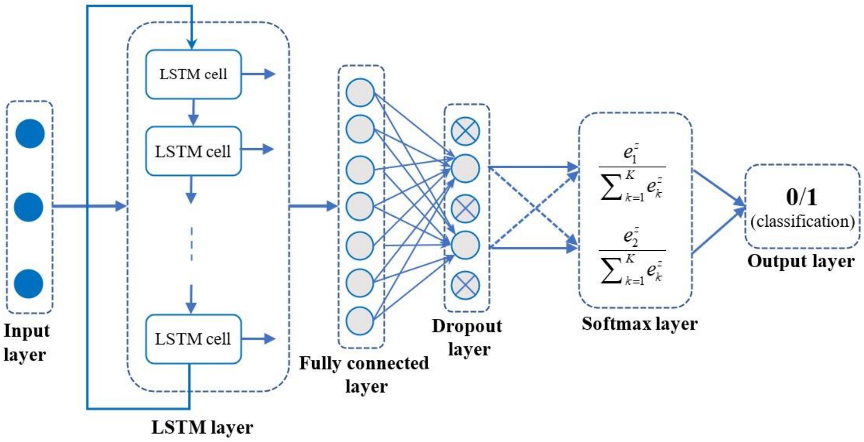


Figure 7. *Detailed structure of the LSTM neural network [28].*

The input layer that receives the input data, called ***p****(k)*, consists of 10 contiguous samples of standardized information about the weight *w* and 3-axis accelerometer (*x*, *y*, *z*) values, like (5):

$$\boldsymbol{p}(k)=\left[{}^{w_i}\!/\!_{100}, {}^{x_i}\!/\!_{300}, {}^{y_i}\!/\!_{300}, {}^{z_i}\!/\!_{300}\right]^T; i=1,2,\ldots 10 \qquad (7)$$

The standard data of the output layer ***t****(k)* is the health state of the person sitting in the IoT chair, similar to (6):

$$\boldsymbol{t}(k)=\left[s_i\right]; i=1,2,\ldots 10 \qquad (8)$$

The LSTM layer was experimentally selected based on training performance, consisting of 300 memory cells (300 cells on the LSTM layer in figure 7, which each LSTM cell is presented in figure 1). The next four layers include the full connectivity and activation layers.

The training of the LSTM networks is performed on MATLAB software with the built-in LSTM tool [17]. The Adam algorithm [29] is applied in 500 training periods (epochs) with a learning rate η = *0.01*. Training performance is evaluated by root mean square error (RMSE) according to (9).

$$RMSE = \sqrt{\frac{1}{(N-n)}\sum_{k=n}^{N}\left[t(k)-\hat{a}(k)\right]^2} \tag{9}$$

Where ***t****(k)* is the actual collected health state according to (8) and *â(k)* is the data identified by the LSTM networks for the *k* time. The training process is performed on the data collected through the experiment setup. The set of data of 3,260 samples [***p****(k)*, ***t****(k)*] was used to train and test the network. The LSTM network training performance on the Intel(R) Core (TM) i7-10700 CPU @2.90 GHz, 16 GB of RAM for more than 2 minutes, for RMSE ≅ 0.1, is presented in figure 8. At the end of the training period, the LSTM networks is saved and applied to identify the health status of people sitting on the IoT chair.

Figure 8. *LSTM network training performance.*

3.4. Monitoring and warning algorithms

The flowchart of health status monitoring for IoT chair is shown in figure 9. The computer will continuously collect 10 sets of sampled data $p_i = [w, x, y, z]$, standardize the data and feed it to the LSTM network to estimate the state s_i. The average value of s_i is estimated for decision making whether to conclude a movement reminding or support requesting when combined with the real-time factor from the system clock.

When the LSTM network determines state $s = 0$, combined with the time of sitting on the IoT chair for more than 45 minutes, the program on the computer will send the command code "712" to the IoT circuit to activate the movement prompting sound mode. When the LSTM network detects status $s = 1$ continuously for more than 3 minutes, the program will send the code "1111" to the IoT circuit to activate the alarm mode by sound alerting and SMS sending to mobile phones of support persons.

The flowchart of health status warning is presented in figure 10. The basic tasks of the software include: (i) reading data of load cell *w* and 3-axis accelerometer (*x*, *y*, *z*) arranged on IoT chair; (ii) sending sensor data to Google Sheets; (iii) putting data to MATLAB for estimating state *s* by LSTM network; (iv) transmitting command code of movement reminder "712" or support alarms "1111" from MATLAB to Google Sheets through free service ThingSpeak of the Mathworks; (v) activating the corresponding movement reminder or request support subroutine.

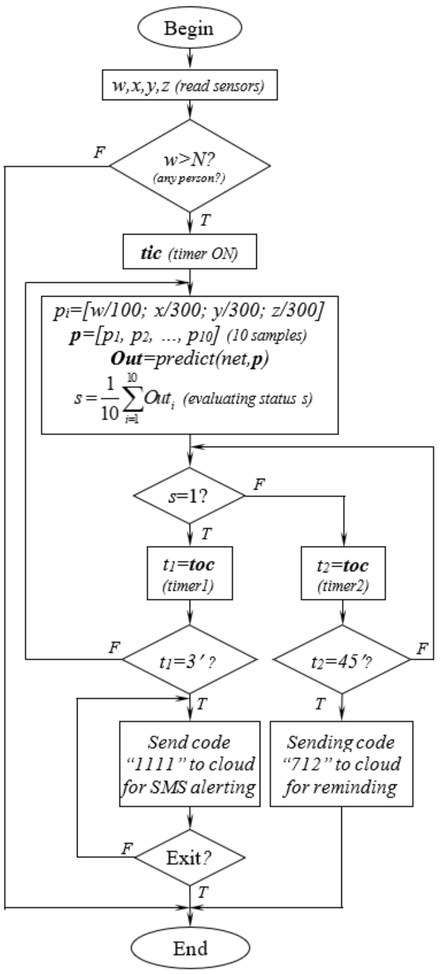


Figure 9. *IoT chair monitoring flowchart.*

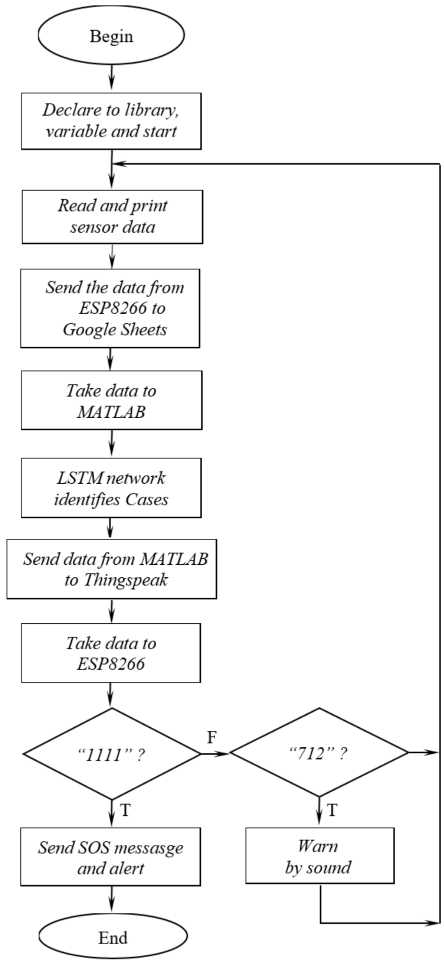


Figure 10. *IoT chair warning flowchart.*

4. RESULTS AND DISCUSSION

4.1. Experiment model

The experimental model of the IoT chair is described overly in figure 11. The IoT chair after manufacturing for testing in this study is shown in figure 12. This chair can operate with a maximum load of up to 100 kg, according to the limit of the load cell. Before conducting the test, the supporter's phone numbers, and the Wi-Fi connection need to be pre-installed on the MCU-ESP8266. The determining threshold of sitting in a chair is $w \geq N = 30$ kg. The IoT chair works properly when the testing scenarios should give correct results as described in table 1.

The experiment process is conducted many times to collect training data and evaluate the accuracy of the system. Figure 12 shows the case of placing an ordinary backpack on the IoT chair. Figure 13 illustrates an experiment in the case of normal sitting or sitting and trying not to move for more than 3 minutes to simulate oversleeping or the worst scenario of a stroke.

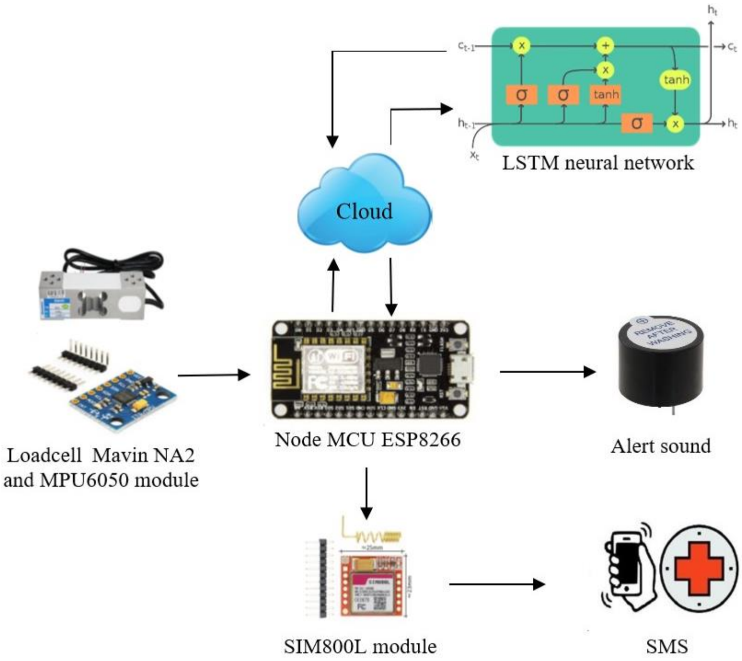


Figure 11. *The overall system of experimental model.*

Figure 12. *IoT Chair experiment with Scenario 4.*

Table 1. *Testing scenarios.*

Situation Description	Responses of the IoT chair
Scenario 1: Empty Chair	No response.
Scenario 2: Working normally	Reminding with sound when sitting longer than 45 minutes.
Scenario 3: Sitting without movements	Alerting by sound and SOS message when not moving for more than 3 minutes.
Scenario 4: Putting backpacks on the chair	No response.

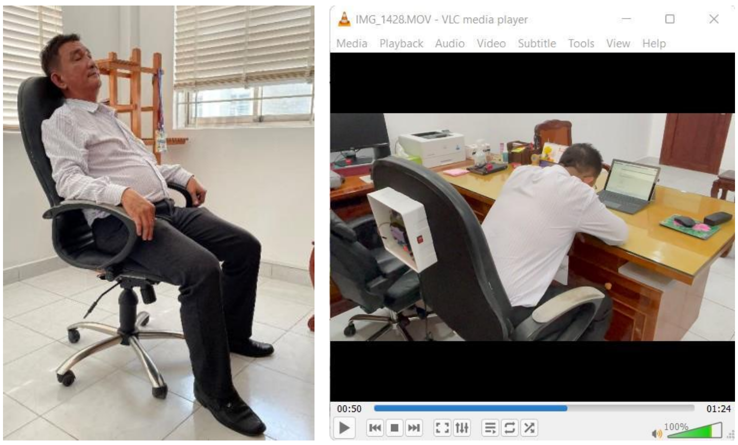


Figure 13*. Experiment simulation of a non-moving situation.*

4.2. Reliability evaluation

To evaluate the alert reliability of the IoT chair, this study conducts experiments by directly testing and simulating related situations under many different scenarios and repeating these survey cases 100 times for each scenario. The results of the IoT chair reliability survey are presented in table 2.

Table 2. *Survey results of IoT chair reliability.*

Functions	Number of experiments	Corrected times	Rate (%)
Reminding by sound to stand up for every 45 minutes	100	100	100
Warning by sound and SOS message when abnormal state exists for more than 3 minutes	100	94	94
Detecting empty IoT chair	100	100	100
Detecting bags on IoT chairs	100	100	100

The experimental results in table 2 show that this research result has improved the basic limitation of the study [15, 16] and shows the effectiveness of using LSTM deep learning networks. Experiment results also indicate that the ability to complete the IoT chair technology is feasible.

4.3. Discussion

As mentioned before, previous studies used sensors on smart chairs to measure biological parameters or camera to detect falling status of people which cause psychological discomfort. The proposed solution of this study does not use sensors to measure the body's biological parameters, but it is embedded into the seat and back of the chair. The installation is completely concealed like a regular office chair. A person sitting in the IoT chair is not under the pressure of "being tracked" as previous studies. The proposed solution can be transferable to office chairs' manufacturers for embedding IoT devices right in the production stage. Thus, the usage of IoT chairs is not only at offices but also in families, and at heart and stroke treatment centers.

Technically, the neural network used in this application is essentially a flexible tool for determining the appropriate alarm threshold. In particular, the application of the LSTM deep learning neural network to improve the reliability of multilayer feedforward network in [15, 16] is a long advance of this research. The LSTM deep learning neural network with its ability to remember past data in its memory cells is an advantage that makes it possible to solve complex problems where data is correlated and changed over time series [21, 29].

At this stage, this study has used free Google services and the LSTM neural network tool of MATLAB to evaluate the ability of proposed solution. In addition, the IoT chair plays a main role of sensor data collection only. All data processing and decision making are performed by the software. With that mechanism, a software can manage and control several IoT chairs. For further study, the LSTM network should be constructed on Python programming language and set up on our institution's severs instead of using free services of Google.

5. CONCLUSIONS

This study has designed and constructed an improved solution for office chairs with acceleration sensor to monitor the movement behavior of office workers based on IoT circuits and LSTM deep learning neural network for timely monitoring and warning via the internet on suspicion of abnormal health conditions by integrating IoT circuits hidden inside the seats. The IoT circuit does not directly measure the biological parameters of the sitting people, that it only analyzes movements such as thigh shaking, keyboard typing, backrest, etc. The LSTM deep learning neural network collects 10 sets of sampling data continuously, and then identifies the health status for once. Experimental results in many different scenarios show that the capacity of reminding people in prolonged sitting conditions has 100% accuracy and the capacity of detecting and warning abnormal health conditions has an accuracy of about 94% in 100 experiment times. The basic advantage of this method is that it takes advantage of the capacity of remembering the past signals and correlates the signals over time of the LSTM networks. Experimental results also indicate that the ability to perfect this product for a wide range of applications is completely feasible. In the future, the study can be continued to collect authentic data through coordination with health care centers related to treatment of cardiovascular and stroke, to complete the proposed solution.

REFERENCES

[1]. M. A. Huysmans, H. P. van der Ploeg, K. I. Proper, E. M. Speklé, and A. J. van der Beek, *"Is Sitting Too Much Bad for Your Health?,"* Ergonomics in Design, vol. 23, no. 3, pp. 4-8, (2015), doi: 10.1177/1064804615585410.

[2]. N. Pronk, *"The Problem With Too Much Sitting: A Workplace Conundrum,"* ACSM's Health & Fitness Journal, vol. 15, no. 1, pp. 41-43, (2011), doi: 10.1249/FIT.0b013e318201d199.

[3]. S. M. Sheikh and I. Ngebani, *"A Personal Health Care Office Chair,"* in 2019 2nd Inter. Conf. on Computer Applications & Information Security (ICCAIS), pp. 1-4, 1-3 May, (2019), doi: 10.1109/CAIS.2019.8769548.

[4]. R. Lavanya, M. Nivetha, K. Revasree, and K. Sandhiya, *"Smart Chair-A Telemedicine Based Health Monitoring System,"* in 2018 Second International Conference on Electronics, Communication and Aerospace Technology (ICECA), pp. 459-463, 29-31 March, (2018), doi: 10.1109/ICECA.2018.8474628.

[5]. R. J. Darwood and F. C. T. Smith, *"Deep vein thrombosis,"* Surgery - Oxford International Edition, vol. 31, no. 5, pp. 206-210, (2013), doi: 10.1016/j.mpsur.2013.02.001.

[6]. O. World Health, *"The atlas of heart disease and stroke / Judith Mackay and George Mensah; with Shanthi Mendis and Kurt Greenland,"* ed. Geneva: World Health Organization, (2004).

[7]. R. Advani, H. Naess, and M. W. Kurz, *"The golden hour of acute ischemic stroke,"* (in eng), Scand J Trauma Resusc Emerg Med, vol. 25, no. 1, pp. 54-54, (2017), doi: 10.1186/s13049-017-0398-5.

[8]. N. B. G. V. P. Rahul, *"Implementation of an IOT Based Smart Chair,"* Inter. J. for Research in Applied Science and Engineering Tech. (IJRASET), vol. 5, no. VI, pp. 1317-1317, (2017).

[9]. R. Febriani, A. I. Wuryandari, and T. Mardiono, *"Design interaction of smart health chair approach the usability aspect on SHESOP health care,"* in 2015 4th International Conference on Interactive Digital Media (ICIDM), pp. 1-6, 1-5 Dec., (2015), doi: 10.1109/IDM.2015.7516356.

[10]. G. R. D. Ganesh, K. Jaidurgamohan, V. Srinu, C. R. Kancharla, and S. V. S. Suresh, *"Design of a low cost smart chair for telemedicine and IoT based health monitoring: An open source technology to facilitate better healthcare,"* in 2016 11th International Conference on Industrial and Information Systems (ICIIS), pp. 89-94, 3-4 Dec., (2016), doi: 10.1109/ICIINFS.2016.8262913.

[11]. G. Jia et al., *"A Sensing Chair design for home based physiological signs monitoring,"* in 2013 IEEE International Symposium on Medical Measurements and Applications (MeMeA), pp. 261-264, 4-5 May, (2013), doi: 10.1109/MeMeA.2013.6549748.

[12]. Y. Liu, N. Wang, C. Lv, and J. Cui, *"Human body fall detection based on the Kinect sensor,"* in 2015 8th International Congress on Image and Signal Processing (CISP), pp. 367-371, 14-16 Oct., (2015), doi: 10.1109/CISP.2015.7407906.

[13]. E. E. Stone and M. Skubic, *"Fall Detection in Homes of Older Adults Using the Microsoft Kinect,"* IEEE Journal of Biomedical and Health Informatics, vol. 19, no. 1, pp. 290-301, (2015).

[14]. P. M. Hien and N. C. Ngon, *"Một giải pháp phát hiện sớm tình trạng đột quỵ của người cao tuổi,"* (in Vietnamese), Kỷ yếu Hội nghị toàn quốc lần thứ 3 về Điều khiển và Tự động hoá - VCCA-2015, pp. 35-39, 28-29 Nov, (2015), (in Vietnamese).

[15]. H. T. Tâm, *"Ứng dụng IOT để theo dõi và cảnh báo tình trạng sức khỏe bất thường của cán bộ văn phòng,"* Thạc sĩ, Bộ môn Tự động hóa, Trường Đại học Cần Thơ, Cần Thơ, (2021), (in Vietnamese).

[16]. N. C. Ngon, H. T. Tam, N. T. Hieu, N. D. Hoa, and N. C. Nghiem, *"Implementation of office chair with warning function on abnormal health using IoT technology,"* Journal of Technical Education Science, no. 69, pp. 17-25, 10/28, (2022), doi: https://doi.org/10.54644/jte.69.2022.1082.
[17]. T. M. Inc., *"Long Short-Term Memory Networks,"* in Documentations, ed, (2021).
[18]. B. Lim and S. Zohren, *"Time-series forecasting with deep learning: A survey,"* Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, vol. 379, no. 2194, (2020), doi: 10.1098/rsta.2020.0209.
[19]. N. Thai-Nghe, T. T. Hung, and N. C. Ngon, *"A Forecasting Model for Monitoring Water Quality in Aquaculture and Fisheries IoT Systems,"* in 2020 International Conference on Advanced Computing and Applications (ACOMP), pp. 165-169, 25-27 Nov., (2020), doi: 10.1109/ACOMP50827.2020.00033.
[20]. N. Thai-Nghe, N. Thanh-Hai, and N. Chi Ngon, *"Deep Learning Approach for Forecasting Water Quality in IoT Systems,"* International Journal of Advanced Computer Science and Applications, vol. 11, no. 8, pp. 686-693, (2020).
[21]. N. Duong-Trung, L.-D. Quach, M.-H. Nguyen, and C.-N. Nguyen, *"A Combination of Transfer Learning and Deep Learning for Medicinal Plant Classification,"* presented at the Proceedings of the 2019 4th International Conference on Intelligent Information Technology, Da, Nang, Viet Nam, (2019). doi: https://doi.org/10.1145/3321454.3321464.
[22]. J. Höller, V. Tsiatsis, C. E. A. Mulligan, S. Avesand, and D. Boyle, *"From Machine-to-Machine to the Internet of Things - Introduction to a New Age of Intelligence,"* (2014).
[23]. F. Xia, L. T. Yang, L. Wang, and A. Vinel, *"Internet of Things,"* International Journal of Communication Systems, vol. 25, no. 9, pp. 1101-1102, (2012), doi: https://doi.org/10.1002/dac.2417.
[24]. HTElectronics, *"Hướng dẫn sử dụng ESP8266 trong các ứng dụng internet,"* ed, (2020), (in Vietnamese).
[25]. InvenSense, *"PU-6000 and MPU-6050 Product Specification,"* in Revision 3.3, ed, (2012).
[26]. Intelligent Digital Load Cell, NTS Instrument Co. Ltd. [Online]. Available: https://www.mavin.cn/uploadfile/downloads/Mavin%20catalog.pdf.
[27]. S. Patel, P. Talati, and S. Gandhi, *"Design of I2C Protocol,"* Inter. J. of Technical Innovation in Modern Engineering & Science (IJTIMES), vol. 5, no. 3, pp. 741-744, (2019).
[28]. L. Gagliano, E. Bou Assi, D.K. Nguyen, and M. Sawan, *"Bispectrum and Recurrent Neural Networks: Improved Classification of Interictal and Preictal States,"* Scientific Reports 9, 15649, (2019). https://doi.org/10.1038/s41598-019-52152-2.
[29]. S. Hochreiter and J. Schmidhuber, *"Long Short-Term Memory,"* Neural Computation, vol. 9, no. 8, pp. 1735-1780, (1997), doi: 10.1162/neco.1997.9.8.1735.

TÓM TẮT

Ứng dụng mạng nơ-ron LSTM để cải tiến hiệu quả theo dõi và cảnh báo tình trạng sức khỏe cán bộ văn phòng

Bài báo này đề xuất giải pháp cải tiến ghế văn phòng (gọi tắt là ghế IoT) dựa trên công nghệ IoT và mạng nơ-ron LSTM (Long Short-Term Memory) để theo dõi và cảnh báo kịp thời qua mạng internet về nghi vấn tình trạng sức khỏe bất thường của cán bộ văn phòng. Một mạch IoT dùng mô-đun MCU-MSP8266 được sử dụng để thu thập dữ liệu cảm biến trọng lượng và cảm biến gia tốc tích hợp trên ghế, có thể giao tiếp với máy tính để theo dõi thời gian ngồi ghế của người sử dụng và cảnh báo bằng âm thanh nếu họ ngồi quá lâu. Một mạng nơ-ron LSTM xây dựng trên MATLAB được huấn luyện bằng kỹ thuật học sâu để theo dõi cử động bất thường của người ngồi ghế, thông qua việc phân tích tín hiệu từ các cảm biến. Kết quả thực nghiệm trên nhiều kịch bản khác nhau cho thấy khả năng nhắc nhở tình trạng ngồi lâu đạt độ chính xác 100% và khả năng phát hiện, cảnh báo tình trạng sức khỏe bất thường đạt độ tin cậy 94%. Thực nghiệm cũng cho thấy khả năng hoàn thiện ghế IoT cho mục tiêu ứng dụng rộng rãi là hoàn toàn khả thi.

Keywords: Công nghệ IoT; Kỹ thuật học sâu; Mạng nơ-ron LSTM; MCU-MSP8266; Theo dõi sức khỏe.