International Journal of MC Square Scientific Research Vol.10, No.4, 2019

Multilayer Neural Network Based Fall Alert System Using IOT

Shareefa Ahmad Abu Shahada[1]   Suzan Mohammed Hreiji[1]   Saleh Ibrahim Atudu[1]   Shermin Shamsudheen[2]

[1]Student, Department of Computer Science, Jazan University, Saudi Arabia

[2]Faculty of Computer Science and Information systems, Jazan University, Saudi Arabia

[2]E-mail:sherminshamsu@gmail.com

ABSTRACT

Fall in elderly people staying alone is a health concern which draws the attention of researchers in past years. In this research, we develop an elderly monitoring system using advanced technology based on sensors and the Internet of Things. In this system, older people can avoid any interaction with healthcare institutions like nursing home and hospitals. We present this challenge by establishing a smart setup to monitor human behavior through accelerometer, pulse sensor and GSM. To implement this concept, we used an alert system to the personal care assistant, to monitor the data using different learning methods. Based on Multi-layer Neural Network technique data are collected from the sensors, then processed and passed to the server in the form of an alert through the buzzer, SMS, email or voice message. The result obtained show an accuracy level of 96% compared to other classifiers.

***Keyword* –** Fall**,** *IoT, neural network , sensors, accelerometer, GSM*

1. INTRODUCTION

Remote health monitoring paves way to monitor numerous age related issues in elderly and patients. The increase in number of people living alone lead to focus on care giving services. Fall is one of the major threat elderly people face. Many studies focus on monitoring health conditions like blood glucose level, ECG, high blood pressure through the sensors attached to the body. Many existing studies focus on the values collected by the sensors. The values are varied according to sensors and mainly depends on environment factors. The accuracy of the observed values is not precise. An experimental set up reads the values from sensors and process the data using a multilayer neural network using IoT .

Artificial neural network (ANN) is a similar to a biological neural network. It is used in various fields that require pattern recognition, data classification, and result prediction because learning is possible through given data. Multilayer neural network model consist of an input layer, an output layer, and a hidden layer and back propagates until it reaches global minimum.

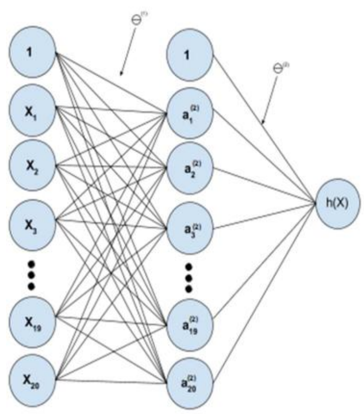

Fig:1 Multilayer Neural Network[16]

The integration of Internet of Things (IoT) in health care improves remote monitoring of patients. IoT wearable platforms collect the health data and communicate the information wirelessly, and store in cloud, where it is processed or stored for tracking the history of the user. Cloud data can store data sent from a different board for example, it is possible to store values .This information can be visualized using a graph or analyzed with other tools.

Fig 2: Internet of Things

Fall means change from the normal human posture. Fall detection algorithms can be classified as a wearable device, ambience based and vision based methods. Based on the types of sensors used vision based, accelerometer based and RF sensors. For data processing methods like rule based, shape based or threshold based, Signal processing and feature extraction ,SVM (Support Vector Machines),Kinetic Sensors, Hidden Markov based, Threshold based algorithms and Machine learning algorithm. The data collected by the sensors are trained using Multilayer neural network approach and generate accurate value about the user.

2. RELATED WORKS

A deep learning model uses single dimensional CNN [5] to extract data from a fall. The data are stored in fog device like Raspberry Pi and the sample data set are trained using the data augmentation method. This study uses real time data through smart watch and notch data sets. The study focused on solving different dimensionality issues and improve the performance of the system.

Another study implemented a care system that can detect and localize the fall of a human. The system architecture detects fall and alert to nursing care using Zigbee[10]. This approach used REST architecture web service which is easy to use and use simple HTTP protocol. The sensors are deployed in the residents of the patients and periodically data is analyzed. Based on the rule in Jess library, alert will be send to nursing homes. The performance is evaluated on the response time and rules can be added accordingly for various diseases. The accuracy of the data is precise and battery has efficient power consumption.

A wearable sensor device embedded in LowPAN [12] collect movements of elder persons and uses big data analytics and cloud computing features. Data are stored for further analysis of the patient in case of health issues. The error rate is less compared to many other studies in literature. To improve the efficiency the data are processed based on decision trees learning method.

The patient ECG variations are found using a SQAW-IoT-ECG method [7] which estimates ECG values are acceptable or not with a three module method. Available data sets and real time values are read to identify unacceptable ECG. This work compares the result obtained with RR intervals and machine learning methods thus reducing the error, determine accuracy, improved battery life and acceptability factor.

A prototype is developed considering different fall events and daily activities to predict and detect fall. The fall events are concentrated on two main assumptions: fast mode and slow mode prediction [11]. The data from accelerometer are processed using high pass filter to reduce noise. NLSVM is used to extract the features collected in fast mode considering time interval 300-700ms. The researchers focused on three conditions to detect fall: pre-fall, a fall impact and post fall. Depending on the conditions falls are detected and alert is sent .To reduce false alarm three consecutive pre-fall case values are evaluated and achieved 97.8% sensitivity and 99% specificity. In this paper, we built a prototype that reads patient values and process the data using multilayer neural network and shows the variations in values.

3. PROPOSED SYSTEM

The block depicted in Figure.3 shows the overall working of the prototype. The following components are used:

- Arduino microcontroller with 14 digital input /output pins and 6 analog input pin.

- Pulse Sensor is a well-designed plug-and-play heart-rate sensor for Arduino.

- GSM/GPRS module is used to establish communication between a computer and a GSM-GPRS system. Global System for Mobile communication (GSM) is an architecture used for mobile communication in most of the countries. Global Packet Radio Service (GPRS) is an extension of GSM that enables higher data transmission rate. GSM/GPRS module consists of a GSM/GPRS modem assembled together with power supply circuit and communication interfaces (like RS-232, USB etc.) for a computer.

- Arduino IDE is a special hardware integrating software to write sketches for Arduino Boards.

- Pulse Rate Visualizer is a processing IDE to display the BPM(Beats per Minute)
- 3 axis accelerometer for falling position & gyroscope for fall orientation
- LCD Display

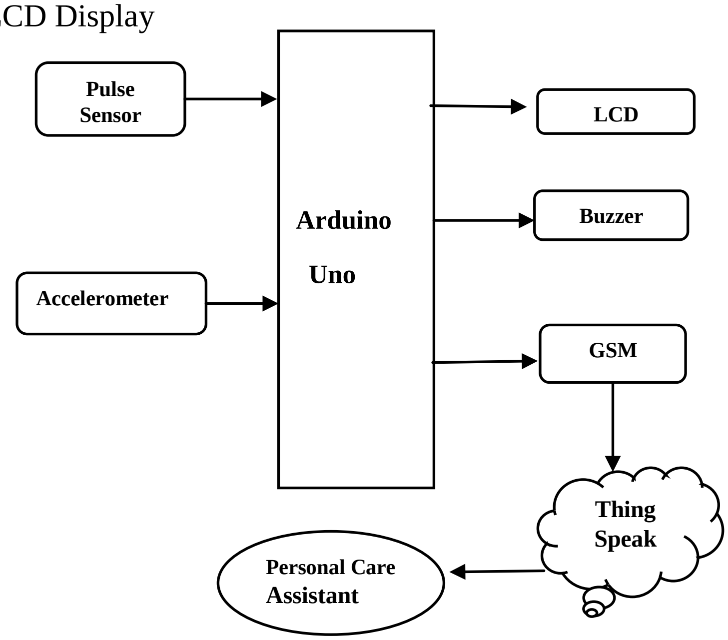

Fig: 3 Block Diagram

The experimental set up is done with 3-axis accelerometer, gyroscope for fall orientation, LCD display to display the BPM, Buzzer and pulse sensor connected into Arduino. The programming language used is a processing language like C. When IDE starts, the Arduino board is on and all connections are UP, the sensors starts reading according to the user input. The sensor values are read from the board using the processing IDE. These values can be stored in a text file or database or cloud. The pseudocode in Table. I illustrates the working of prototype.

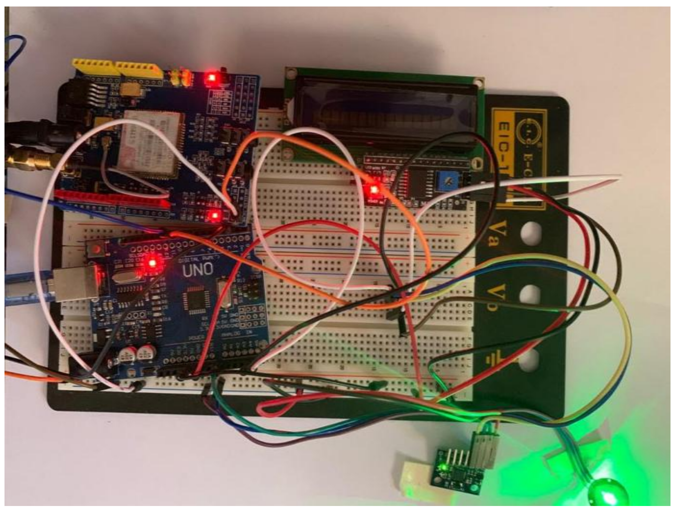

Fig.4 Demonstration

Table 1. *Pseudocode*

Step 1	Initially the connected devices are IDLE and when a sensor starts to read the device's 3-axis acceleration and velocity or heart beat depending on the behavior.
Step 2	If the detected acceleration/heartbeat is less than the pre-defined THRESHOLD function then it is identified as FALL and timer starts to read.
Step 3	If the value remains low for 60s and there is not any False Alarm then confirm it's a FALL.
Step 4	If within 30s ,the person press the false alarm then,go to IDLE state and start again

Step 5 Otherwise, a fall was detected and a SMS/buzzer/voice message is sent to family or hospital

---

Multilayer neural network with input set of data derived the results related to non-linear parameter increasing the number of hidden layers. The more hidden layers we have the less mean square error we obtain. Precisely by increasing the number of hidden layers we can successfully train neural network and an accurate prediction about classification is possible. After retrieving the data, usually there is a minimum of 100 per each of the x, y and z axes. So the last 50 data taken as raw data will be normalized.

After assigning values for x, y, and z axes of the sensors on a scale of 0-1. It aims to normalize the data by using the formula as follows:

$$Normalized(x) = \frac{x - minValue}{maxValue - minValue}$$

To decrease the errors the weight of the nodes are predicted based on trained data and actual data. The network will calculate output value, if there is error between the trained and actual data, then the weight in the network will be updated. The value of input and output range from 0-1

DISCUSSION

From the accelerometer and gyroscope data obtained from falling motion and daily activities, if any of the conditions prevail, then feature value is extracted. The assumptions in this study are defined in Table.I . The values are further analyzed using Backpropagation Neural Network.

Table I: Fall Assumption

Scenario	Explanation
Forward Fall	Fall front side and then to ground
Backward Fall	Fall backside and to ground
Lateral Fall	Fall to either left or the right

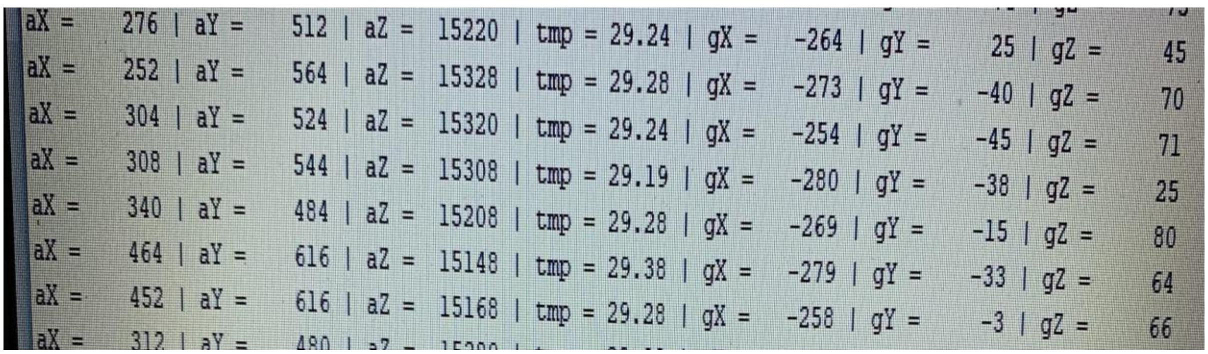
aX = 276 | aY = 512 | aZ = 15220 | tmp = 29.24 | gX = -264 | gY = 25 | gZ = 45
aX = 252 | aY = 564 | aZ = 15328 | tmp = 29.28 | gX = -273 | gY = -40 | gZ = 70
aX = 304 | aY = 524 | aZ = 15320 | tmp = 29.24 | gX = -254 | gY = -45 | gZ = 71
aX = 308 | aY = 544 | aZ = 15308 | tmp = 29.19 | gX = -280 | gY = -38 | gZ = 25
aX = 340 | aY = 484 | aZ = 15208 | tmp = 29.28 | gX = -269 | gY = -15 | gZ = 80
aX = 464 | aY = 616 | aZ = 15148 | tmp = 29.38 | gX = -279 | gY = -33 | gZ = 64
aX = 452 | aY = 616 | aZ = 15168 | tmp = 29.28 | gX = -258 | gY = -3 | gZ = 66

Fig:5 Accelerometer Data

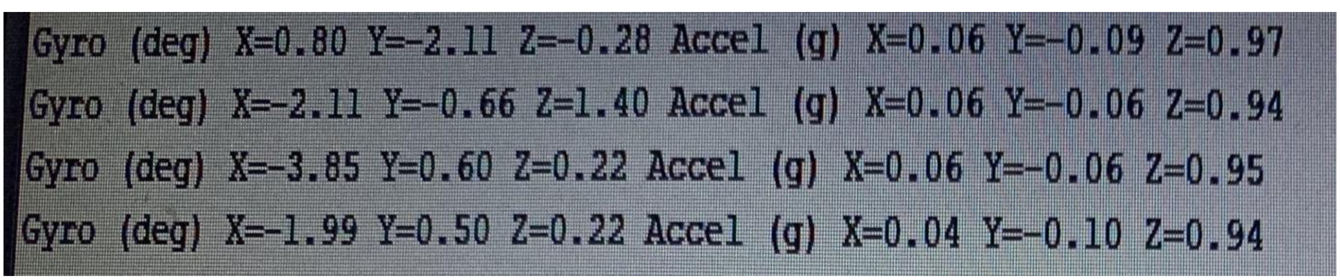
Gyro (deg) X=0.80 Y=-2.11 Z=-0.28 Accel (g) X=0.06 Y=-0.09 Z=0.97
Gyro (deg) X=-2.11 Y=-0.66 Z=1.40 Accel (g) X=0.06 Y=-0.06 Z=0.94
Gyro (deg) X=-3.85 Y=0.60 Z=0.22 Accel (g) X=0.06 Y=-0.06 Z=0.95
Gyro (deg) X=-1.99 Y=0.50 Z=0.22 Accel (g) X=0.04 Y=-0.10 Z=0.94

Fig: 6 Gyroscope Data

This study uses two models called sensitivity and specificity . The conditions are as follows:

- TP specifies the number of positive instance(Fall) that were classified as positive

- TN indicates the number of negative instances(not fall) that were classified as negative
- FP indicates number of negative instance(likely fall) that were classified as a positive
- FN specifies number of instances that are classified as negative

The sensitivity and specificity are calculated as follows:

$$\text{Sensitivity} = \frac{TP}{TP+FN}$$

$$\text{Specificity} = \frac{TN}{TN+FP}$$

Table II. Experimental Results

FALL	True Positive(TP)	False Negative(FN)	True Negative(TN)	False Positive(FP)	Sensitivity= TP/(TP+FN)	Specificity = TN/(FP+TN)
1	0.02	.0.01	0.103	0.08	90.3%	100%
2	0.05	0.04	0.01	0.1	81.8%	97.9%
3	0.008	0.104	0.0021	0.0015	89.28%	93%
4	0.0013	0.001	0.018	0.046	95.74%	100%
5	0.004	0.024	0.085	0.071	76.47%	90%
6	0.152	0.006	0.006	0.001	85.29%	92.4%
7	0.0025	0.008	0.0004	0.005	93.75%	100%
8	0.058	0.0044	0.032	0.007	84.61%	91.5%
9	0.0024	0.005	0.0065	0.0023	78.12%	88%
10	0.0047	0.0745	0.0052	6	86.66%	95.9.%

By considering the range of 10 values, each classifier is trained with the input of 10 features. The back propagation neural network achieved 100% using SVM. Support Vector machine (SVM) algorithm is used to calculate the accuracy of the data. The support vector machine is the inner product kernel between a support vector x_i and vector x drawn from input space.

Table III: Normal and Fall Accuracy

	+1	**-1**	**Total**
+1	20 95.8%	1 4.8%	95.2% 4.8%
-1	0 0.0%	28 100%	100% 0.0%

Considering the training sample $\{(x_i,d_i)\}_{i=1}$ to N,where x_i is the sample input pattern and i_{th} example and d_i is the desired response of target output. The pattern represents the classes by d_i=+1 and patterning the subset of d_i=-1 as class -1

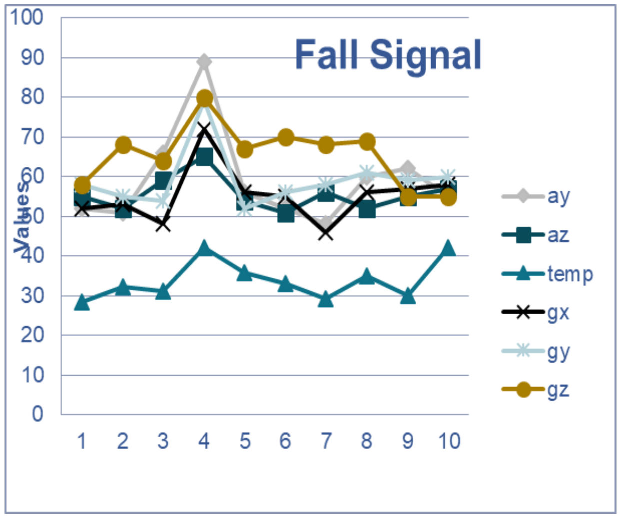

Fig:7 Fall Motion

The value of error that can be calculated with formula SSE is 0.1818 with accuracy in sensitivity of 95.74%. The BPM generated using processing IDE is obtained as below:

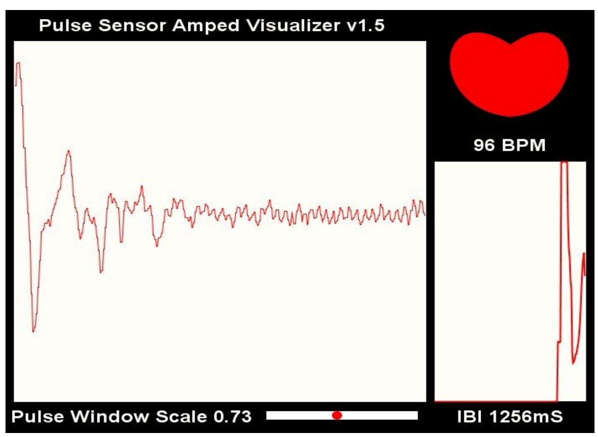

Fig. 8 BPM using Pulse Rate Visualization

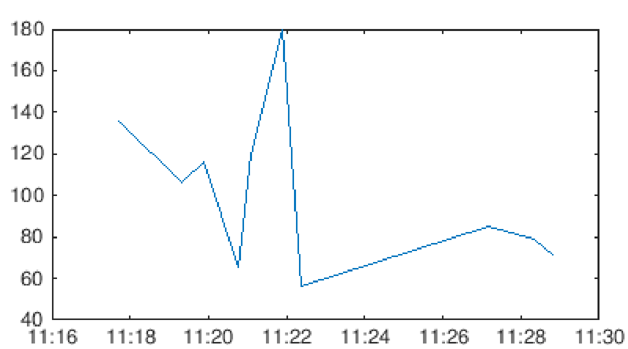

Fig:9 Results of heart beat variations

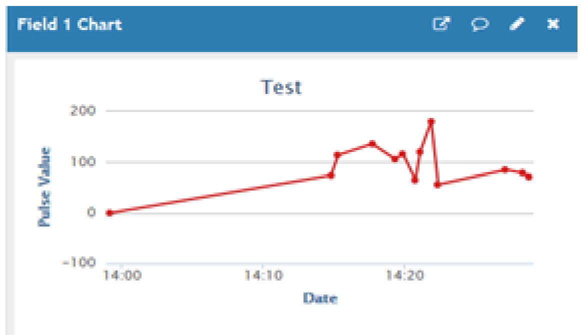

Fig.10 ThingSpeak Pulse rate Value

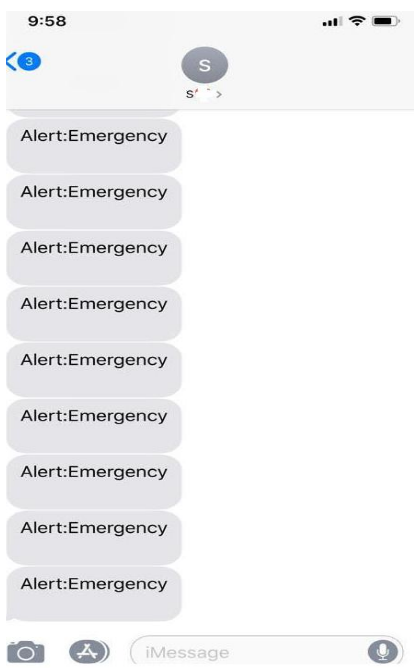

Fig 11: Sample Alert to Personal Care

The main aim of this study is to demonstrate the patient monitoring system and to analyze the accelerometer data and analyze the values using back propagation. The results of this study are compared with SVM[15] classifier to differentiate the type of fall.The accuracy of the results vary from 97% to 100%.

Table IV: Comparison

Classifier	Sensitivity	Specificity	Accuracy
SVM	95.2%	100%	97.6%
ML-NN	100%	100%	100%

CONCLUSION

In this system elderly people can avoid any interaction with healthcare institutions like nursing home and hospitals. We present this challenge by establishing in smart environment by monitoring human behavior through accelerometer and pulse sensor and record the values to cloud. We used an artificial neural network technique to analyze the data. The data was used for training the model, and various learning and optimization techniques were applied and tested. The accuracy rate depends on input data's size ,selected training data and chosen parameters for input data. The result obtained using back propagation is compared with SVM classifier and achieved accuracy of 97- 100%.In future, the results obtained pave way to further analysis by integrating WiFi module and test the accuracy of the result by analytical methods.

ACKNOWLEDGMENT

The authors are grateful to the Deanship of Scientific Research (DSR), Jazan University for providing the financial support (FR6-121) and College of Computer Science & Information Technology for the constant support and encouragement.

REFERENCES

[1]Yoo, SunGil, and Dongik Oh. “An Artificial Neural Network–Based Fall Detection.” *International Journal of Engineering Business Management*, vol. 10, 2018, p. 184797901878790, doi:10.1177/1847979018787905.

[2] Xu, Tao, et al. “New Advances and Challenges of Fall Detection Systems: A Survey.” *Applied Sciences*, vol. 8, no. 3, 2018, p. 418, doi:10.3390/app8030418.

[3] Yi, Won-Jae, and Jafar Saniie. “Patient Centered Real-Time Mobile Health Monitoring System.” *E-Health Telecommunication Systems and Networks*, vol. 05, no. 04, 2016, pp. 75–94, doi:10.4236/etsn.2016.54007.

[4] Yi, Won-Jae, et al. “Design Flow of Neural Network Application for IoT Based Fall Detection System.” *2018 IEEE International Conference on Electro/Information Technology (EIT)*, 2018, pp. 0578–82, doi:10.1109/EIT.2018.8500179.

[5] Santos, Guto, et al. “Accelerometer-Based Human Fall Detection Using Convolutional Neural Networks.” *Sensors*, vol. 19, no. 7, 2019, p. 1644, doi:10.3390/s19071644.

[6] Ajerla, Dharmitha, et al. “A Real-Time Patient Monitoring Framework for Fall Detection.” *Wireless Communications and Mobile Computing*, vol. 2019, 2019, pp. 1–13, doi:10.1155/2019/9507938.

[7] Satija, Udit, et al. “Real-Time Signal Quality-Aware ECG Telemetry System for IoT-Based Health Care Monitoring.” *IEEE Internet of Things Journal*, vol. 4, no. 3, 2017, pp. 815–23, doi:10.1109/JIOT.2017.2670022.

[8] Muhammad, Ghulam, et al. “Smart Health Solution Integrating IoT and Cloud: A Case Study of Voice Pathology Monitoring.” *IEEE Communications Magazine*, vol. 55, no. 1, 2017, pp. 69–73, doi:10.1109/MCOM.2017.1600425CM.

[9] Delahoz, Yueng, and Miguel Labrador. “Survey on Fall Detection and Fall Prevention Using Wearable and External Sensors.” *Sensors*, vol. 14, no. 10, 2014, pp. 19806–42, doi:10.3390/s141019806.

[10]Boudra, Hasna, et al. “An Intelligent Medical Monitoring System Based on Sensors and Wireless Sensor Network.” *2014 International Conference on Advances in Computing, Communications and Informatics (ICACCI)*, 2014, pp. 1650–56, doi:10.1109/ICACCI.2014.6968205.

[11] Saadeh, Wala, et al. “A Patient-Specific Single Sensor IoT-Based Wearable Fall Prediction and Detection System.” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 5, 2019, pp. 995–1003, doi:10.1109/TNSRE.2019.2911602.

[12]Gia, Tuan Nguyen, et al. “Customizing 6LoWPAN Networks towards Internet-of-Things Based Ubiquitous Healthcare Systems.” *2014 NORCHIP*, 2014, pp. 1–6, doi:10.1109/NORCHIP.2014.7004716.

[13] Baker, Stephanie B., et al. “Internet of Things for Smart Healthcare: Technologies, Challenges, and Opportunities.” *IEEE Access*, vol. 5, 2017, pp. 26521–44, doi:10.1109/ACCESS.2017.2775180.

[14] Jefiza, Adlian, et al. "Fall Detection Based on Accelerometer and Gyroscope Using Back Propagation." *2017 4th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI)*, 2017, pp. 1–6, doi:10.1109/EECSI.2017.8239149.

[15] Nukala, Bhargava, et al. "Real-Time Classification of Patients with Balance Disorders vs. Normal Subjects Using a Low-Cost Small Wireless Wearable Gait Sensor." *Biosensors*, vol. 6, no. 4, 2016, p. 58, doi:10.3390/bios6040058.

[16] Engel, William, and Wei Ding. "Reliable and Practical Fall Prediction Using Artificial Neural Network." *2017 13th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD)*, 2017, pp.1867–71, doi:10.1109/FSKD.2017.8393052.