AN IOT BASED SMART MONITORING SYSTEM DETECTING PATIENT FALLS

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ABSTRACT

Fall detection systems are important instruments for senior citizens whether they are in a hospital, at home, or in a senior living facility. Existing fall detection systems are often passive and require pushbutton to alarm care providers. The delay can cause significant consequences and damages to the patients. Early detection is vital for quick recovery and prevention of post injuries. Recent sensory detections often use pre-settings to predict fall, hence can cause false alarms. Further, they often cannot furnish vital information for treatment. A smart fall detection system can alleviate those concerns and pinpoint what happened and transfers vital data. We propose an active detection system using IoT in patient's surroundings environment detecting falls, which immediately alarms the care providers and transmits vital information for treatment. The system integrates advanced ICT technologies to monitor, detect, and react to the falls. The system uses ANN to improve fall detections.

Keywords: IoT (Internet of Things), Wireless Network, Smart Healthcare, Artificial Neural Network

1 INTRODUCTION

Aging is a worldwide hot topic in our modern society. Advances in medical technology, increasing awareness of health issues and wellness, and prolonging of life expectancy has led to an increasing population of senior citizens around the world. Most senior citizens are often alone at home, where unattended care can cause numerous issues and risks. Senior falls are among serious concerns, whether the person is at home, in a nursing home, or in a hospital. Once the fall occurs, if the patient is not taken care of immediately, multiple life-threatening consequences can occur according to the healthcare professionals' reports (Kisella et al 2005, Imran et al 2021, Hsieh et al2017, Al-Okby et al 2020). The facts sheets from the World Health Organization (WHO) on falls give an estimate of over 680,000 deaths worldwide due to falls (WHO 2022) where adults over 60 years of age suffers most. Further, the fact sheets indicate that over 37 million falls require medical care. And finally, it suggests education, safer environment, and fall related research to reduce the risk (WHO 2022). To emphasize the importance of the issue beyond the fact sheets, the following quotation is selected verbatim from Gill Wayne, a Registered Nurse, in (Wayne 2017):

> *Falls put a person, especially adults and older adults, at risk of serious injury. Fall prevention may not seem like a favorite topic but plays a very important role in health care. Based on statistics evaluated by the Centers for Disease Control and Prevention (CDC), about one in three community-dwelling adults older than age 65 fall every year, and women fall more frequently than men in this*

> *age-group. …. In fact, falls are a leading cause of injury and accidental death among individuals older than 65 years." (Wayne 2017)*

Some statistics reported in (Kinsella et al 2005, Demura et al 2013) estimated that by the year 2025, 20% of the population in developed countries would be elderly people aged 65 and over. The WHO's fact sheets (WHO 2022) confirm the projection by reflecting that between 2015 to 2050, the proportion would be from 12% to 22%. In a nutshell, the elderly population is growing rapidly. It is also a common occurrence for the elderly to be alone at home. Further, the elderly may have many unexpected risky situations while at home alone, especially falls. According to the US demographic data, between 2003 and 2006, the elderly fall accidents during the four years, resulted in rapid increases in the number of deaths from 13,700 to 15,802. According to CDC's fact sheets (CDC 2022), fall death rate in the US increased 30% from 2007 to 2016 for older adults, and the rate will continue to grow by 2030 by 7 fall death every hour.

Elderly falls can lead to numerous serious diseases, such as skin abrasions, calf fractures, and muscle tissue contusions. When they live alone, accidental falls becomes highly likely. In such cases, it can be difficult to get timely assistance to prevent future serious consequences. As a result, it is critical to have an intelligent solution that can automatically detect the fall situation in real-time, react immediately, alarm the care providers, and assist them with vital information for proper needed care. Further, the intelligent data should assist remote monitoring to determine whether the patient is in immediate danger and transfer data such as body temperature, heart pulse, etc. to the caregiver.

The aftermath complex challenges of falls could be mitigated with an intelligent fall-detection care device (Imran et al 2021, Al-Namhian et al 2021, Hsieh et al 2017, Al-Okby et al 2020, Ramanujam et al 2019, Bated et al 2021, Al-Hababi 2020). These intelligent systems can use Internet of Things (IoT) (Borgia 2014) with integrated advanced Information and Communication Technologies (ICT) such as wearable devices and other wireless sensors. In general, IoT-based intelligence systems may provide multiple automated and ubiquitous services for our senior citizens to assist them with their daily life. This paper, however, focuses on the elderly falls. We propose an intelligent system to monitor senior citizens, detect eventual falls quickly, alarm the caregivers with vital timely information, and prevent further damages and consequences. The proposed system is referred to as the Smart Elderly Monitoring System (SEMS).

SEMS uses ubiquitous devices such as motion detectors, wearable smart wristbands, and wireless components like ZigBee and Bluetooth for fall detections. The IoT sensory part is integrated with an intelligent monitoring system connected to quickly connect to an edge datacenter as well as the designated help providers. We discuss how integration of artificial intelligence and IoT could improve senior cares and monitor detecting the falls. A future continuation of this research can extend to a fall prevention.

The rest of this paper is as follows: Section 2 presents related works. Sections 3 describes an intelligent healthcare system, whereas Section 4 explains details and the architecture of SEMS. Section 5 presents performance analysis case studies. Section 6 gives conclusion and future work.

2 RELATED WORK

IoT-based innovative works are hot topics of research and development, especially in the healthcare with focused on elderly care as well as patient falls. Several methods propose structural frameworks based on IoT, while others include theoretically analysis and feasibility performance of the frameworks. Several approaches use IoT as a foundation and add Artificial Neural Networks (ANN) (Misiunas 2016) to identify abnormal behaviors of patients. While most solutions have been either theoretically proven or yielded good results, it appears that the actual deployment for smart elderly care systems need more developing times and improvements.

Artificial Intelligence (AI) related work for healthcare and patient falls are available in the literature. Ramanujan and Padmavathi (2019) suggested a vision-based fall detection intelligent technique to monitor elderly. They set up sensors in the ambient added with infrared camera. They tested the system with 10 cases with 94% accuracy. Bates et al (2021) describes potential of AI to improve the safely of the patients. While their work is general use such as surgery etc., it provides example of the case for falls as well. Al-Habibi et al (2020) developed a testbed for post-surgery monitoring using AI. Santos et al (2016) developed an AI based monitoring system called AMBRO to assist patients with personal. The system uses a mobile platform architecture added with IoT, AI, and other assisted software. While the system seems to help assist patients, it is not focused on falls. An IoT and AI based health monitoring system for elderly called E-PHMS is proposed by Imran et al (2021). The authors suggest that their system is suitable for most cases of elderly people including falls.

Al-Nahiam et al (2021) described an intelligent fall monitoring system using IoT. Their system is focused on patients with neurological disorder. They suggest their system can deal with emotion recognition in real-time. Yi-Zeng and Yu-Lin (2017) developed an AI and IoT based fall detection system to assist elderly at home. They simulated a real-home and suggested achieving 82.7% and 98% separately. A new approach for fall detections for elderly based on embedded technology was suggested by Al-Okby and Al-Barrak in (2020). Their system uses wearable waist device to detect fall.

Earlier examples of elderly care can include the Human Activity Recognition system monitors the indoor activities of the elderly people proposed by Jalal et al (2014). It uses IoT technology as the core to collect patient body information to identify abnormalities. Meanwhile, Foroughi et al (2008), Do et al (2018), and Lotfi et al (2011) proposed the elderly abnormality detection system based on an MLP neural network, Bayesian classification, and a circulating neural network. Although the accuracy and performance of these systems have been confirmed experimentally, the accuracy can be further improved. Each system uses AI technology to analyze abnormalities in the elderly care, but in the analysis process, the input information is not complete. A single input message leads that the accuracy of the anomaly detection could still increase. The system proposed in the paper collects environmental information and physiological parameters of the patients, analyses the information affecting the health to improve accuracy of detection and reduce the false positive rate. Wang et al (2014) and Ray (2014) proposed the wearable device-based IoT systems to detect the daily life of elderly people. Ransing and Rajput (2015) proposed an environment-based elderly abnormal state detection system. Separate wearable devices and separate environmental monitoring cannot guarantee that all abnormalities in the independent life of the elderly people are accurately identified. The system combines sensors deployed in the living environment of elderly people and wearable devices to obtain health data. In (Hussain et al 2015, Alba and Antonio 2017, Catarinucci et al 2015), IoT based solutions for healthcare are explored for availability and reliability of IoT-based solutions. Although the proposed approach by (Hussain et al 2015) can improve the availability of the system, these usability-enhancing features do not affect the monitoring of the health of the elderly people. The system proposed in the paper contains a fault-tolerant algorithm, which improves the reliability of the system.

3 INTELLIGENT HEALTHCARE

Application of IoT in healthcare may cover most aspects of the field including prescriptions, remote monitoring, medical information, medical emergency, and medical equipment just to name a few. It is hoped that the technological advances will improve patients care as well as minimize the cost of diagnostic treatments. In this section, we focus on monitoring systems with artificial intelligence.

3.1 Homecare and Remote Monitoring

Remote monitoring and homecare can display physiological parameters of the observed subjects to interject emergency assistance in the event of an accident. These systems often use Wireless Sensors Network (WSN) (Liang et al 2008), wearable devices, body area network, biomedical sensors, and/or biosensors transplanted into the human body. Remote monitoring and homecare based on IoT has numerous applications such as infant monitoring, home monitoring for senior citizen, monitoring of Parkinson's patients, rehabilitation monitoring, and postoperative patients monitoring. These applications can follow three general architectures of IoT; Data Collection Layer, Data Transport Layer, and Application & Data Processing Layer using Edge Computing. These three layers often can follow two additional analytical and monitoring layers: Data Analytics and Response using AI & Machine Learning.

Data Collection Layer (also called perception layer): The physical signals and the background information on the nursing object is taken through the sensor nodes. Based on the position of the sensor nodes in the human body, it can be divided into three types: (a) sensor nodes implanted in the human body, (b) sensor nodes worn on the body, (c) surrounding environment sensor nodes for recognizing human activities or behaviors close to the body. The human body signals to be monitored by the sensor nodes are also divided into continuous time-varying physiological signals, discrete time-varying physiological signals (such as body temperature, blood pressure), and human body activity and motion signals (such as the human body).

Data Transport Layer: Responsible for communication of external networks and temporarily storing data collected from the sensory layer, while also receiving and analyzing these perceptual data and executing specified user programs. The transport layer can be connected by short-distance network Bluetooth, Zigbee, Wi-Fi, or remote networks such as LTE or 5G.

Application and Data Processing Layer: This mainly refers to remote servers and their external networks that provide various application services, such as storage of physiological parameters or medical data of the monitoring object, analysis, and prediction of the patient's condition by the expert, and remote access of the medical data of the monitoring object by the medical staff. These include medical database servers, medical transaction management servers, various specialized telemedicine analysis devices, various mobile communication terminals including mobile phones and PDAs, and doctors and experts. What differentiate IoT with traditional Internet services is the ability to apply the principles of artificial intelligence (Aletan 1992) and analytics to the vast collected data in order to add augmented intelligence to the use of the collected data. Machine Learning and Deep Learning are among the technologies predicted to help users to better understand the numerous complexities surrounding our daily life.

3.2 What AI Can Do for Patients

Artificial Intelligence is often used in clinical diagnosis of medical expert systems (Shibuya 2015). Clinical AI uses mainly computer system principles and methods to simulate medical skills for diagnostics and treatments. It can help doctors to solve complex medical problems and ease diagnostics. As an auxiliary tool for diagnosis, it can inherit and forward valuable techniques to enrich clinical experience focused medical experts. In general, Artificial Intelligence has the following effects in the medical field:

a) Offering doctors and health providers with comprehensive and effective information to deliver a systematic and trustworthy diagnosis of the illness and suggest treatment.

b) Significantly improve and automate the measurements, analysis of the data, reduce the intensity of manual work done, and thus lower subjective uncertainties.

c) Concentrate on the knowledge and expertise to assist the doctors to make more reliable and correct diagnoses. As the number of cases increases, the knowledge of the system can be enriched. The knowledge accumulation and analysis can be carried out automatically or under manual intervention to improve the level of medical care.

Human fall detections can be achieved in different ways, while most commonly used being in the following two categories (Shibuya et al 2015): The first method uses sensors to collect motion data, detect the fall, and alarm the fall. The second approach acquires moving images to monitor the human body via a camera or motion detection device to detect and analyze a stream of images (Khan and Hoey 2017).

The first method obtains the corresponding samples through the actual fall and trains the samples with the support vector machine algorithm to obtain the data model. It collects data from the accelerometer and gyroscope to monitor if the threshold is exceeded. When the collected data exceeds the threshold, the collected acceleration and angular acceleration data are continuously calculated by the support vector machine algorithm. Finally, the result is determined based on the support vector machine model obtained through the training to determine whether a fall has occurred.

In the second method, after the depth camera or other motion detection device captures human body, the background of the image is removed, the foreground information is intercepted, and the contour information of the foreground is obtained. A contour image is mapped to a curvature scale space to form a curvature scale space (CSS) image. Peak points at different scales constitute a video word package based on curvature scale features. The extreme learning machine classifier is trained using the obtained video word package. By extracting the object feature variables from the target area, the extracted variables are sent to two offline trained classifiers for fall detection.

The first method deploys the sensors on clothes or the body of the patient and has the advantages of small size, portability, and low cost. The latter approach accurately distinguishes the posture of walking, squatting and falling. It meets the requirements for real-time processing on lower performance hardware platforms. However, this method requires a large amount of infrastructure, and can invade the privacy of the patient. It can be debated here whether safety is a prime concern or privacy.

The method of detecting whether or not a fall occurs can be roughly classified into a threshold judgment and a pattern recognition. The threshold value determining method is to obtain acceleration data from an acceleration sensor worn on a human body, and then compare it with a predetermined threshold value. When the data is greater than the present threshold value, the system can determine that the human body has fallen. Afterwards and for further review of the system, the data can be analyzed to increase the correctness of the judgment and increase performance of the detection process.

A monitoring fall detection method can use pattern recognition, screens shots, and signals to integrate a vector machine algorithm for self-learning purposes. The data is then used to improve accuracy of the fall detection. This approach can require large processing power and high-end hardware to achieve the desired accuracy.

3.3 Artificial Neural Network for Monitoring Abnormalities

One of the dreams of computer science researchers has long been to mimic human neurons and its networks to design and build artificial intelligence computer systems for diverse purposes. ANN (Aletan 1992, Misinunas et al 2016) helps targeting that dream by illustrating and studying of the human brain connection mechanism. ANN can improve the reasoning ability of knowledge and self-organization and self-learning ability, thus accelerating the application and development of neural network in medical expert systems. ANN belongs to the field of artificial intelligence but is different from other artificial intelligence methods. It is a branch of artificial intelligence. Traditional artificial intelligence is used to realize the intelligence of the human brain and logical thinking through symbols, whereas ANN realizes its intelligence through learning or training. An ANN module can learn itself based the collected monitoring data that is streaming to it. In medical practice, the judgment of disorders and the corresponding treatments are often based on experiences. Therefore, the learning, memory and induction functions of ANN has attracted numerous scientist and researcher in medical field to help detecting abnormalities including patient falls.

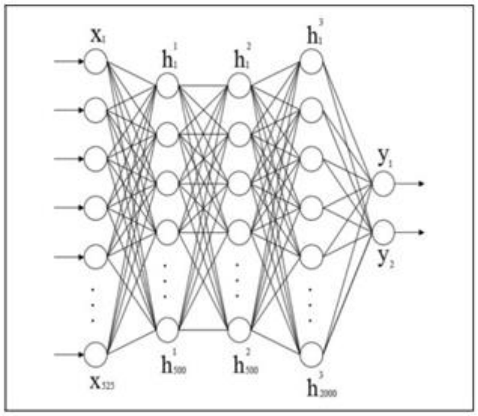

Figure 1: Typical structure of an ANN module connected with multiple input sensors to detect abnormality or controlled situation.

The abnormalities that senior citizen may confront at home, while modest compared to their other medical conditions, can have crucial consequences on their overall health. Figure 1 shows the structure of an ANN. Integrating an ANN module with the information of a patient collected by the sensors, the system can quickly and accurately identify whether the person is subject to any abnormal behaviors. As the self-learning process improves, so does the accuracy of the ANN. Even for the first-time users, ANN can provide sufficient high accuracy to start working with the patient.

4 A SMART ELDERLY MONITORING SYSTEM

4.1 ANN and Sensing Components

The fall detection system is composed of sensor segments, wireless sensor networks, a data processing center, and a client module. The latter includes both the heath provider as well as the patients and other human (e.g., paramedics, relatives, etc.) who could be involved in the fall case. The sensors section while focused on the fall detection measures, includes movement and acceleration of the body, floor pressure, distance measuring, and additional measurements as needed. Other comfortable and diagnostic components such as temperature, a humidity, gas leaks, and smokes and fire detections can easily be integrated.

In addition, wearable device and body-area-networks are used to collect various vital data such as heart rate, blood pressure, body temperature, and the like. The main component of the wireless sensor network is ZigBee. The data package is sent to the processing center via Wi-Fi. A daisy-chain-based fault-tolerant algorithm is applied to the gateway to provide fault recovery. The data cleaning, data storage, data analysis and data representation are processed in data center

In the datacenter, the collected data from the sensors feeds to the ANN module to analyze and send further to the client segment, where a real-time display and monitoring system, saves, recaps, and visualize the data about the patient. The remote caregiver could send the health report to the user via the Internet, phone, display device, and/or any messaging system. When an emergency abnormality occurs, the caregiver will directly dispatch the ambulance and paramedics and notify patient's contact-person about the case.

The system collects environmental information through sensors deployed in the home. The information can be used to identify anomalies such as fires, gas leaks, and other hazardous items in patient's environment. The physiological parameter sensor on the wearable device monitors vital information of the elderly and can detect abnormalities such as fever and heart disease. Acceleration sensors, floor pressure sensors, ultrasonic distance sensors deployed in the environment, and heart rate sensors collected on wearable devices, all collect data to identify the fall of the elderly person.

The fall detection module is implemented in the datacenter using the algorithm shown in Figure 2b integrated with ANN module. The data collected by the sensors are streamed to the inputs to the neural network, whereas the output is only two types: abnormal or non-anomalous (i.e., normal behavior). Through the ANN module, the datacenter can accurately identify whether the state of the senior citizen is a fall case or less life threating situation. This cycle is repeated in real-time.

4.2 Architecture and Infrastructure

SEMS deploys large numbers of sensors in the residential environment of the designated person, which often rank into two main categories: environmental anomalies detection and monitoring abnormal conditions. Environmental monitoring provides information gathering and other living assistance of the patient such as fires, gas leaks, floods, etc. Wearable devices are integrated in the system to collect the physiological parameters of the elderly people and to detect abnormalities in the body, such as fever, heart disease, high blood pressure, and such.

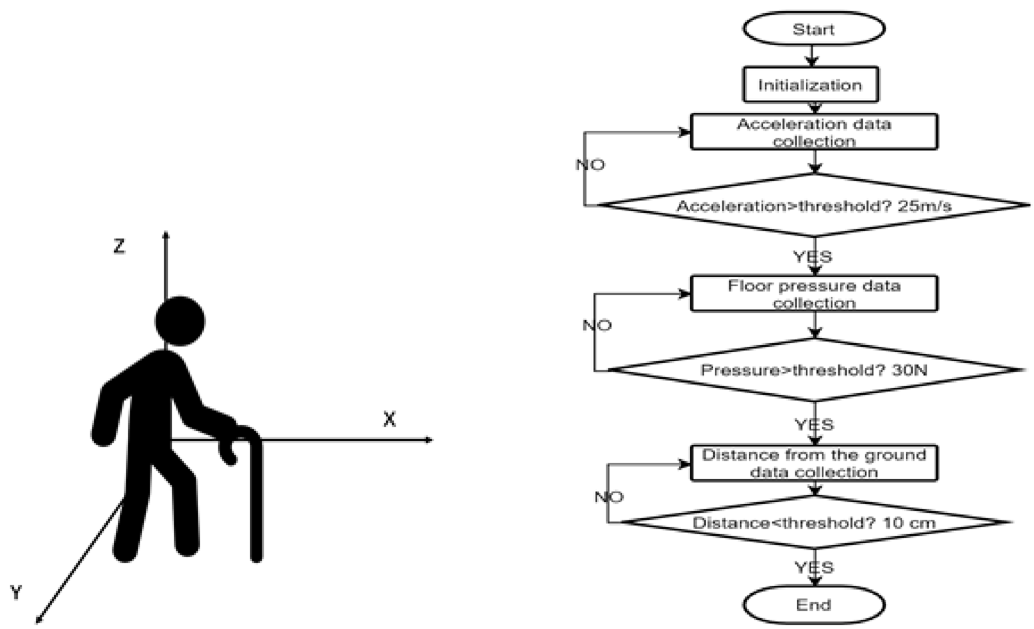

Figure 2: SEMS Fall detections: a) 3D axis movement of the person; b) the Fall Detection Algorithm using flowchart.

Fall detection: major components include floor pressure sensors, ultrasonic distance measuring sensors, and acceleration sensors. We construct a three-dimensional axis model of the human body. Figure 2a represents an example of 3D-axis model that the collected data by ultrasonic distance measuring and acceleration sensor can provide the image. Through this module, we can get the distance from the human body to the ground, the tilt angle of the human body, and the tilt acceleration of the human body. Combining this data with the data collected by the floor pressure sensor and the heart rate as inputs to the ANN module, monitoring system we can accurately identify whether a fall is imminent, has occurred, or the situation is under control. Figure 2b describes the detection algorithm where the provided data feeds in through the algorithm in the ANN module in the Data Center.

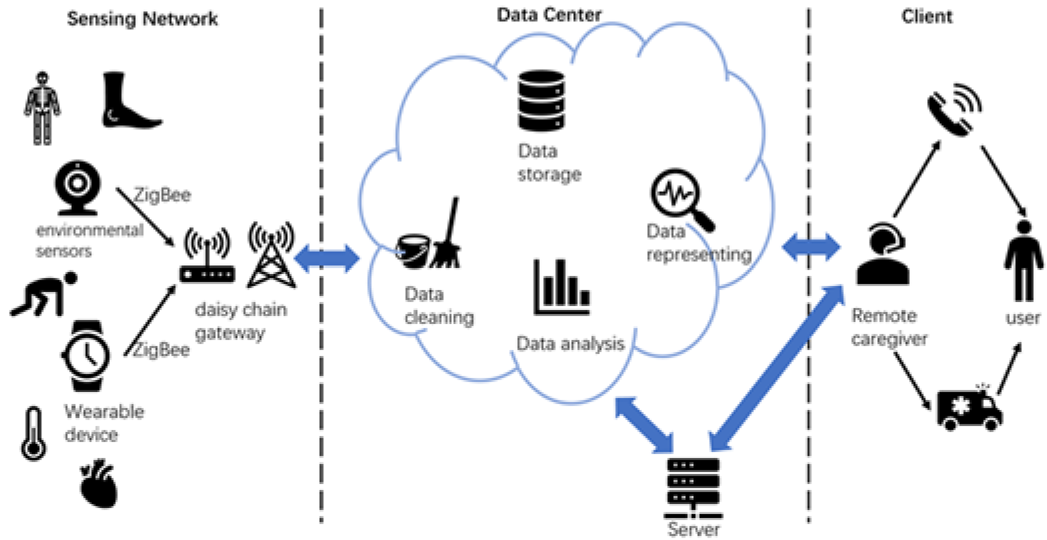

Figure 3: Overview of SEMS with 3 main components: Sensing, Computing, Monitoring.

The infrastructure and the architecture of SEMS is presented in Figure 3. The collected data by the sensors are amplified and filtered by signal a processing module to obtain meaningful information to detect any abnormal state. This information is transmitted to the cloud-based data processing center through a wireless network. The data processing center sends the processed information to the client module over their internal network. The details of the SEMS and its integrated monitoring systems are still as part of the ongoing research work.

5 PERFORMANCE ANALYSIS STUDIES

Performance study of the proposed smart fall detection system is crucial to pinpoint potential bottlenecks of the system to improve and correct if need it. In this regard, we have long way to go. Nevertheless, to show the roadmap, we present rudimentary simulation models as a concept in this section. We utilize three conceptual models for performance simulation; base, intermediate, and improved models.

5.1 Base Model

Figure 4a shows the basic model of the elderly care system. In this model, the sensors used to collect data are abstracted as a Home module while interacts and transmits the collected information to the datacenter module named as Data Center. After the information is processed in the Data-Center module, it is sent to the Server and the Client modules. The basic model includes only the four essential components of the elderly monitoring system. Through the analysis of the basic model, we can get a general understanding of the performance of the system and thus move towards the improved model. Figure 4b shows potential implementation of the basic model using OMNeT++ simulation tool and a client-server module. The data transmission between home and datacenter has a delay of 1 us (microsecond) with a data transmission rate of 512 Mbps. We need to vary these parameters for fine-tuning the system.

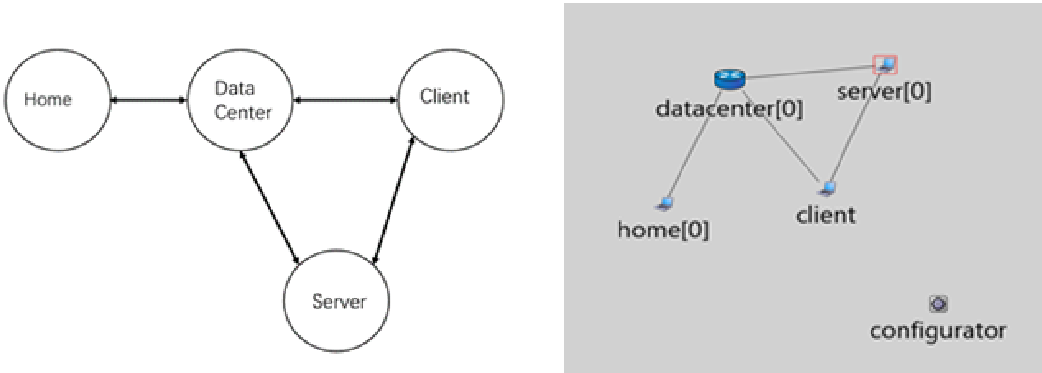

Figure 4: Base Model; a) Conceptual Model, b) Potential Implementation Model.

5.2 Intermediate Model

Extension of the base model is shown in Figure 5. The sensor is divided into environment-based sensors deployed at home and the wearable devices. Data is collected through the sensors and wearable devices. All factors that cause the abnormity are collected and sent to the Datacenter. The Data-Center module processes the information and sends it to the Server and Client models. The caregiver can monitor the health status through the client module and generate a health report to send to the user module. When the patient has an emergency or abnormality, the system dispatches the Emergency module over-sending vital data.

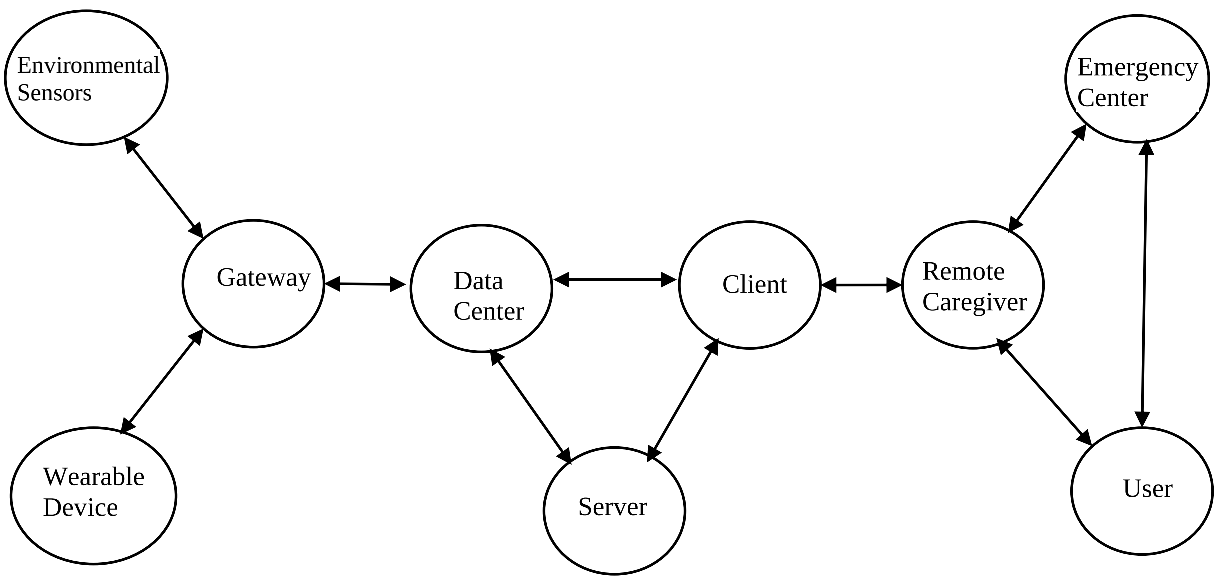

Figure 5: Conceptual Intermediate Model.

5.3 The Improved Model

Figure 6 shows an overview of the Improved Model expresses full functionality of SEMS, the IoT-based fall detection system. In the sensor section, the sensors associated with the fall detection form a new sensor module which works with the environmental sensor module and the wearable device unit to create a sensor network. The collected information is wrapped and sent to the Datacenter model through the ZigBee network. The gateway uses a daisy-chain-based fault-tolerant algorithm. In the Datacenter model, the data flows through by data cleaning, data analysis, data storage, and data presentation units. The data analysis unit is performed by the ANN module.

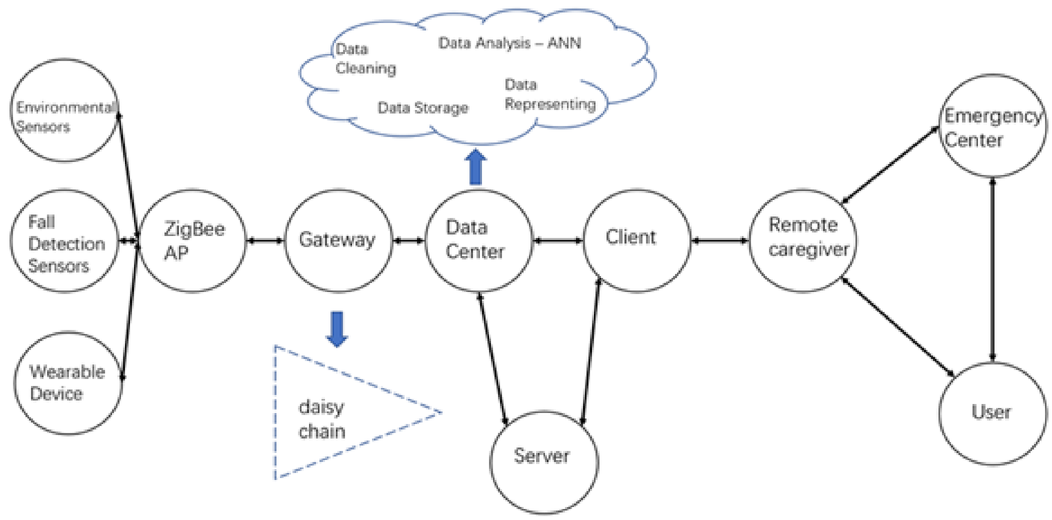

Figure 6: An overview of an Improved Model for simulation studies

Fall detection monitoring system of SEMS using in the algorithm of Figure 2b, is modelled in the datacenter with the ANN module represented in Figure 6. When the data collected by the fall detection module exceeds certain threshold, the system triggers a fall detection case. The threshold of acceleration is set to 25m/s, the threshold of floor pressure is 30N (the pressure unit as Newton), and the threshold of distance from human body to ground is 10cm. When the acceleration is greater than 25m/s, the floor pressure is greater than 30N, and the distance from the human body to the ground is less than 10cm, then it is determined that the elderly has an abnormal case trigged as falling.

6 CONCLUDING REMARKS AND FUTURE WORK

Falls are among major dilemmas affecting our senior citizens around the world. Further, falls can trigger several health associated risks especially when the persons are living alone. A smart surveillance system for to detect falls is designed and described in this paper. With a reliable and high-performance monitoring system, elderly can live better life without worrying about sudden abnormalities. This paper presented an IoT-based fall detection and monitoring system that quickly reacts to the situation and inform the caregivers with vital information for treatment options. The system uses a fault-tolerant and an AI-based fall detection algorithm. An ANN module is integrated in the data analysis unit to improve accuracy of detected anomalies, as well as self-learning purposes. The presented ANN module is an overview and thus needs detail studies to make the system workable. Further work will enrich how the system could become viable.

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