Jatiya Kabi Kazi Nazrul Islam University

Research Report

Title: Human Activity Recognition using MATLAB and Android Joint Platform with Machine Learning Approaches

Name Kazi Md Shahiduzzaman

Designation Associate Professor

Department Electrical and Electronic Engineering

Research and Extension Center

Jatiya Kabi Kazi Nazrul Islam University

Note

1. This report is applicable to researchers from Jatiya Kabi Kazi Nazrul Islam University, who have been granted funds from the Research and Extension Center of the university.
2. This form should be filled with correct grammar, clear text, and neat handwriting.
3. All contents and results in this research work will be used for Mr. Kazi Md Shahiduzzaman's Ph.D. dissertation.
4. All research outputs (Both published journal and conference papers) will be used to fulfill the qualification criteria of Mr. Kazi Md Shahiduzzaman's Ph.D. requirements.
5. This research project report may not be distributed without Mr. Kazi Md Shahiduzzaman's concern.

Abstract

Fall or sudden fall down is such a word to elder people when they talk about it among themselves, makes them terrified with the consequences after a simple fall occurs, for example, fall while walking, fall while trying to sit down on chair, fall caused by slipping inside toilet or slippery floor. Now the question may come why the consequences of a sudden simple fall become so important because it can create fatal and non-fatal injuries. People with an age of 65 or elder are in more risk with random and sudden fall. That's why sometime it is considered more dangerous than other old-age diseases which may lead to heart-attack, brain-stroke etc. Therefore, more often it is seen that elder people limit their social life and normal daily activities inside their own apartment and keep living a poor quality of life. As mentioned above a sudden fall may occur during any activities related to daily living (ADL), so, fall detection and prediction is closely related to human activity recognition. The probability of sudden fall compared to ADL is very less. In this thesis human activity recognition is considered so that fall related service can be ensured to the user.

Research in fall related service has two directions, named fall detection and prediction, which are being an interest to the research community since 2000. Early researches are belongs to single sensors with static threshold methods and classical machine learning techniques which only classify fall and non-fall, while ADL can causes false alarm. Recently, researchers show more interest with multiple sensors and modern machine learning techniques on a single chip on-board device. This single chip on-board devices have issues with computational power, battery consumption, memory which makes them unease to users. Current available products in fall related service are mainly provide fall detection service and are also a single chip on-board device either in form of smart watch, smart phone or smart pendent. But these product are costly, generate false alarm, less accurate, perform binary classification only and are not fully automatic. Human participation is needed for pressing SOS button in emergency. Therefore, a end-edge-cloud based human activity recognition platform which can be used to predict and detect a sudden fall with a single algorithm, is introduced in this thesis work. This research work solely focus on wearable type multiple sensors where they are fused together. Signal from these different sensors are fused together and considered as the input for the human activity recognition algorithm. The algorithm will be developed with recurrent neural network (RNN), broad learning system and federated learning. The proposed method will successfully recognize daily activities as well as predict and detect a sudden fall. As the functionality of the on-board system is distributed into three tiers, this thesis work will also investigate total latency, overall accuracy, user specific model development, raw data security etc. A series of simulation setups in MATLAB and Python environment will evaluate this research work.

Key words: Elderly health-care; Human activity recognition; Fall detection and prediction; LSTM; Broad learning system (BLS); Federated learning; Wearable Camera; Accelerometer; Gyroscope; Data Fusion.

Contents

List of Figures

List of Tables

Chapter 1 Introduction

Elderly health care becomes a global issue nowadays. With the increasing number of old people around the world, the number of caregivers becomes less. According to published statistics in Statista[1], detailed elderly population distribution all over the world is shown by the following Fig. 1-1. We can see that around 9% population in the world belongs to the elderly

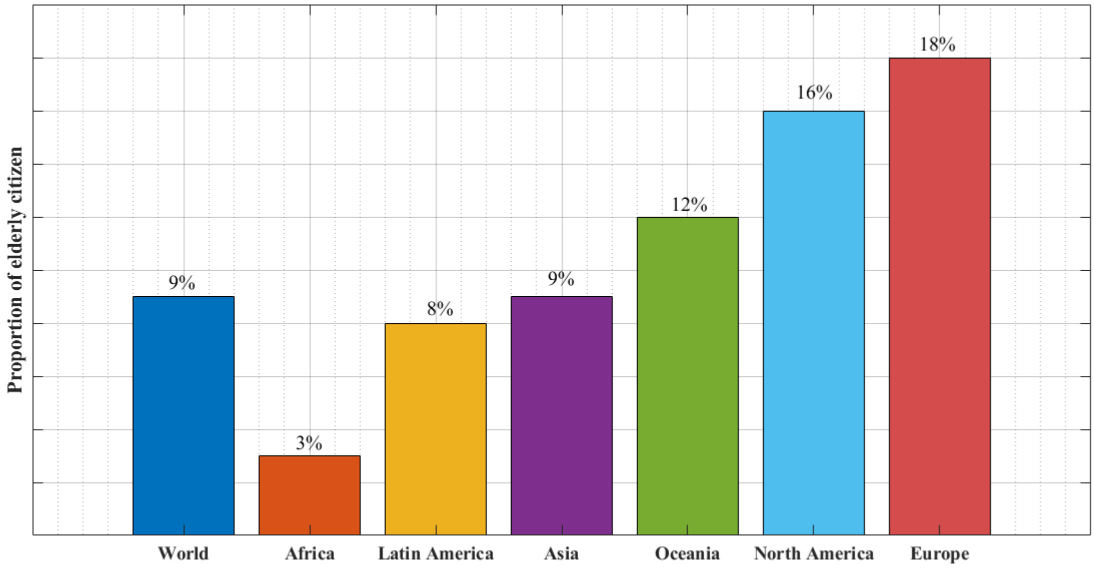


Figure 1-1 Proportion of elderly citizens globally in 2019 (Original data source in[1]).

citizen class. It is a clear identification for Europe that in upcoming years services related to elderly citizens will become an important issue to handle. Before going further the definition of elderly citizen is as the people over 65 years old are considered as old people[1,3–5]. The number of the elder citizen is also growing at a fast rate. For example, the USA is expecting an increment of 19% of elder citizens in 2030 compared with 2010, while the ratio of the working class citizen to elderly citizens will drop down from 4.3% to 2.3%[6]. Statista published that the elder citizen in the United Kingdom will be around 24.7% by the year 2046[7]. China, the largest populated country in the world, is also facing a similar increasing trend in the case of elderly citizens. From the demographic report published in Statista, there are around 167 million elderly citizens by 2018 which shows upward incremental slop[8]. The China National Committee on Aging (CNCA) has projected that by the year 2050, the elderly citizen will reach 35% of the total population[9]. The number of people aged 65 or over grows so rapidly that will be around 1.5 billion by 2050[10,11]. Due to the fact of social security provided by the governments in developed and some developing countries along with other social factors like trends of young people moving towards the city, unwilling to be burdened on grown-up children, elder citizens like to live independently, regardless of complicated medical conditions e,g, heart attack, brain stock, sudden sugar fall, dementia, frailty, urinary tract infections (UTI) or risk of falling[6,12,13]. However, untreated health conditions can cause death[6,14]. Similarly, delay in assessing health can be very dangerous due to the fear of hospitalization, wrong physician's assessment, self-impression of such changes are normal at this age, the social reluctance of admitting health issues, etc[12]. To support this increasing aging issue number of social welfare and medical supports is increasing, but the manpower is limited. Therefore, it is worth taking advantage of modern information and communication technologies like LTE-M, deep learning, IoT, wireless sensors network, modern machine learning techniques, etc. To handle the unreported health problem, sudden fall down an automatic health monitoring system can be the solution. Such a monitoring system can be a smart home that monitors human activities regularly. Examples of such systems are[15–18]. There are various techniques wearable, non-wearable, ambient, or fusion, used for this daily activity monitoring. This human activity recognition (HAR) system can be used for preventing, predicting, and detecting both chronic diseases and any sudden fall[19,20]. Researchers all around the world are making an effort on deploying ubiquitous wireless sensor networks to monitor the health of older adults. As it is a vast area to explore, in this research we are only considering human activity recognition techniques that can be used for fall detection and prediction. The following Fig. 1-2 shows the exact research area that we want to explore. As indicated in Fig. 1-2, this research work mainly focuses on developing a wearable fall prediction and detection system through human activity recognition (daily activities like walking, sitting, standing, lying down, etc) by using multiple sources of information and deep learning. The term multiple sources of information presents information fusion of wearable cameras, accelerometers, gyroscopes, and/or other wearable sensors.

1.1 Motivation

The following Fig. 1-3 shows the common fall scenarios like falling during walking stairs, falling during walking, slipping on the floor or bathroom, falling while sitting on the chair, etc. happen to elderly citizen[21,22]. The common consequences of a sudden fall are a violent blow, loss of consciousness, sudden onset of paralysis as in a stroke or an epileptic seizure. A sudden fall can occur both indoors and outdoors while performing any daily activities.

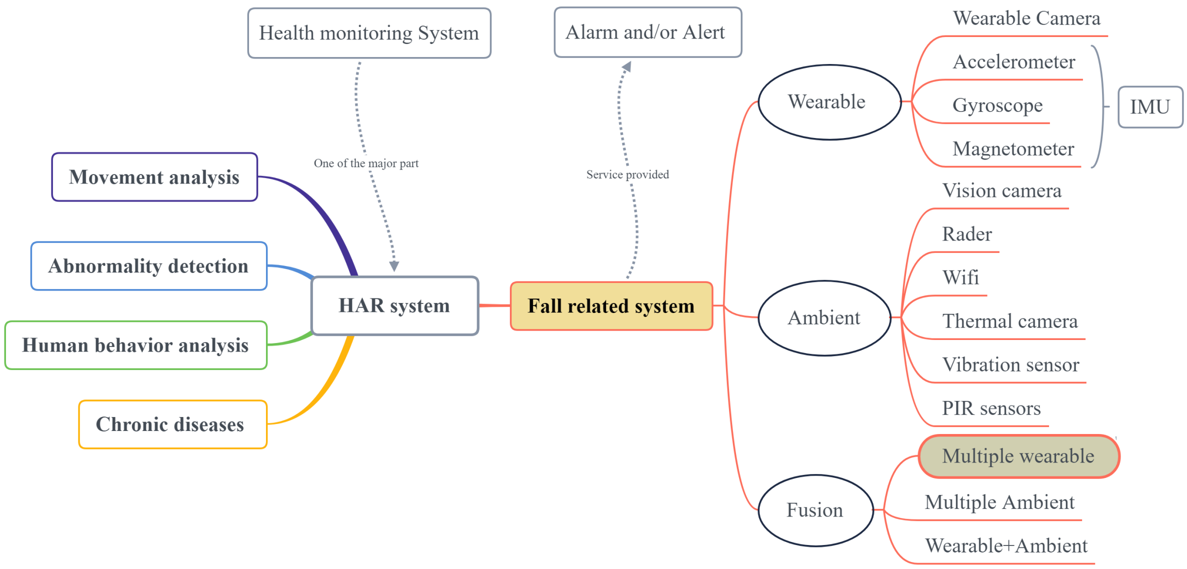


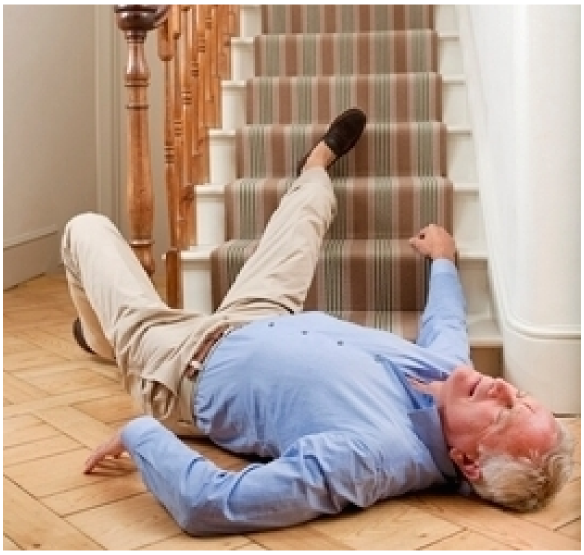
Figure 1-2 Research area covered with this research.

The definition of fall can be given as the sudden change of state from standing to either lying down, sitting, or any lower positions[26]. Elderly people described in the introductory part are at high risk of getting a sudden fall. Every year there are around 650 thousand injuries occur that are related to falls according to World Health Organization (WHO)[3],[27]. These falls can cause fatal or non-fatal injuries from pain in the muscle, broken limbs, hip fractures, and head trauma to death. Each patient has to spend a lot of money on treatment[26,28–30] as well as personal costs. The after-effects of falls are also very serious as they contribute to fear of falls, depression, avoidance of daily activities, less physical activity, and lower quality of life, especially in individuals who live independently[29]. An elderly citizen faces a sudden fall and enters into the fall cycle (see Fig. 1-4). This is a vicious cycle that causes an elderly person to fall phobic after experiencing a fall, therefore avoiding certain activities and becoming less physically active with a low-quality lifestyle. These fewer physical activities, make muscle mass, balance, and bone density lose, which eventually makes them fall again.

A survey on 125 people over and equal 65 years old people shows that falling on the floor and staying there over an hour causes death to half of the number within six months[14]. More than eight hundred thousand elderly people who are 65 or above, are using medical alert systems like MobileHelp, Bay Alarm Medical, LifeFone, Philips Lifeline, QMedic, etc with the lowest monthly cost of USD 19.99[2]. The following Fig. 1-5 shows different types of available fall detection products.

These services provide wearable or mobile devices to provide mobility to the users. Be-

(a) Fall down on floor[23].



(b) Backward fall from walking upstairs[24].

(c) Forward fall from walking[25].

Figure 1-3 Typical fall down scenarios.

sides the subscription fees, these systems also require user participation for pressing the SOS button during an emergency (see Fig. 1-5a, 1-5c and 1-5d). Similar to Medical Guardian's Freedom, the Apple watch of series 4 and 5 is capable of detecting falls using an accelerometer and gyroscope. But the Apple watch for fall detection has mixed reviews and the Apple watch itself is very costly and required an additional subscription fee for medical alerts. All these products are only capable of detecting a fall not predicting[2,29]. Therefore, this is a need of developing an effective solution that can predict and detect a sudden fall. We want to develop such a system that can be self-engaged in the emergency situation and economically cheaper.

Similarly, technical challenges in the recent developmental works in fall detection and prediction are also the motivation of this research work. Some of these technical challenges are as

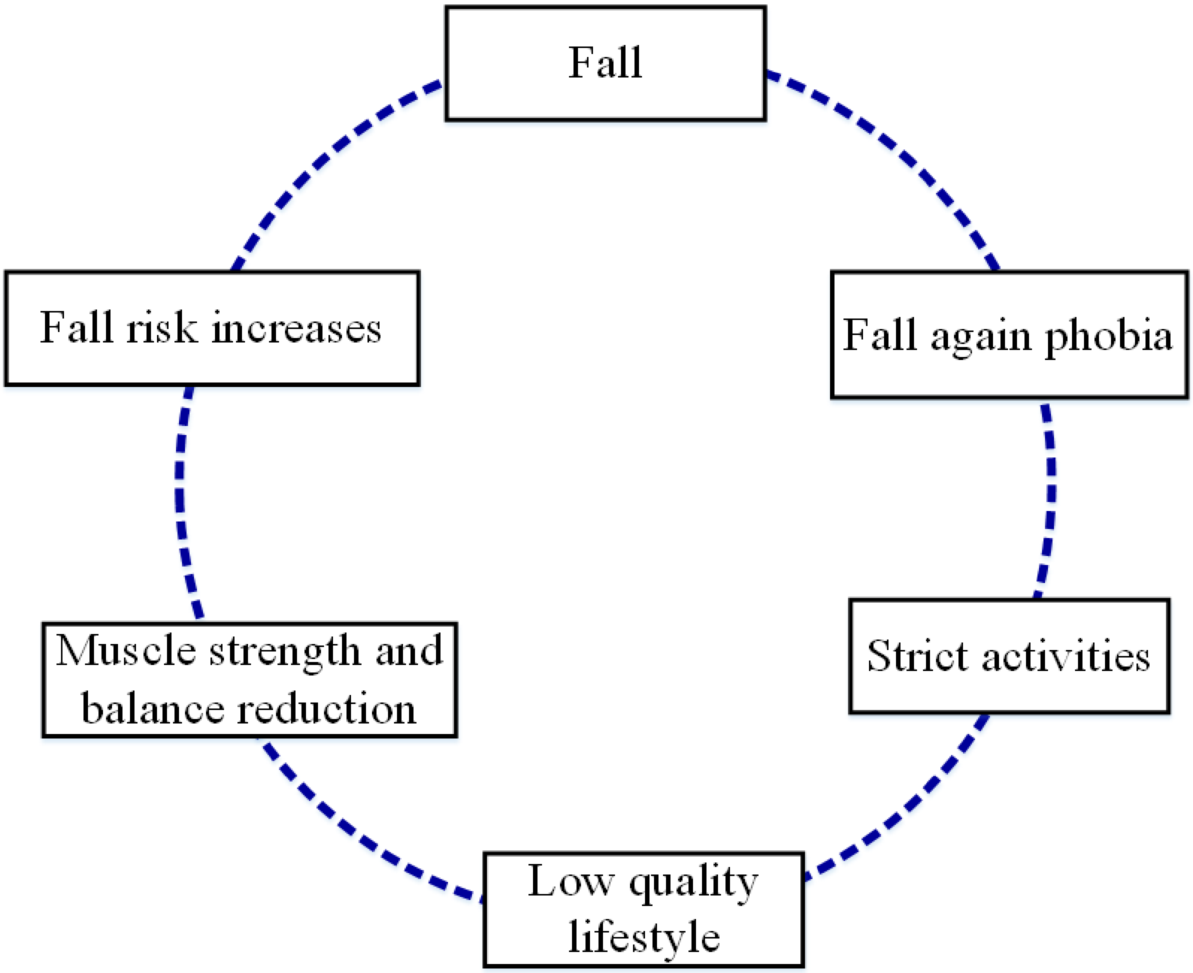


Figure 1-4 The fall cycle.

follows:

1. Most of the developments are either for fall detection[31],[32] or prediction[33],[34], so a complete system which can provide both service like[35] with more efficiency need to developed.
2. By developing a user-specific system in[35], authors are able to reach high efficiency. It will be difficult to maintain such high efficiency when we consider an end-edge-cloud type architecture.
3. Most review papers[29],[28] are only based on the published papers, so it is needed to make an alternative review based on simulation or experimental data.
4. Accuracy, sensitivity or recall, specificity, precision are the evaluating parameters in most of the research papers, for example, Ozcan[36], UniMIB SHAR[32], MobiAct[37], UCI HAR[38], HAPT[39], Li[40], Howcroft[41], Engel[33], Wang[42], Saadeh[35], Mualdin[43].

(a) Bay alarm medical in the home service.

(b) Medical guardian's Freedom.

(c) Philip's Homesafe.

(d) MobileHelp's Duo.

Figure 1-5 Some fall detection products available in market[2].

Meanwhile, false alarm rate (FAR), training time, and execution time are also very important performance-evaluating metrics to check the reliability and the latency of the developed system.

5. The advancement in distributed systems can be applied to make this system a more reliable and low latency-based system. So, we want to develop a smart system with end-edge-cloud architecture with data fusion and modern machine learning techniques.
6. Battery lifetime is also an issue, e,g, in Ozcan's research work, the smartphone dies in 4.6 hr when the APP runs[31].

Both these social and technical aspects of the need for an effective fall-related system that can make both prediction and detection, low cost, provide mobility to the user, user-specific trained model, and provide data security. In spite of proposing a single on-board system, an end-edge-cloud-based architecture is considered.

1.2 Problem statement

In this research, we are going to propose an end-edge-cloud-based three-tiered architecture for human activity recognition so that a fall detection and prediction system can be designed. This research work has four distinct but interconnected branches, feasibility analysis, new algorithm development, signal processing, and wireless network design, which are shown in Fig 1-6. This figure is also useful to state the problem statement. The problem statements of this

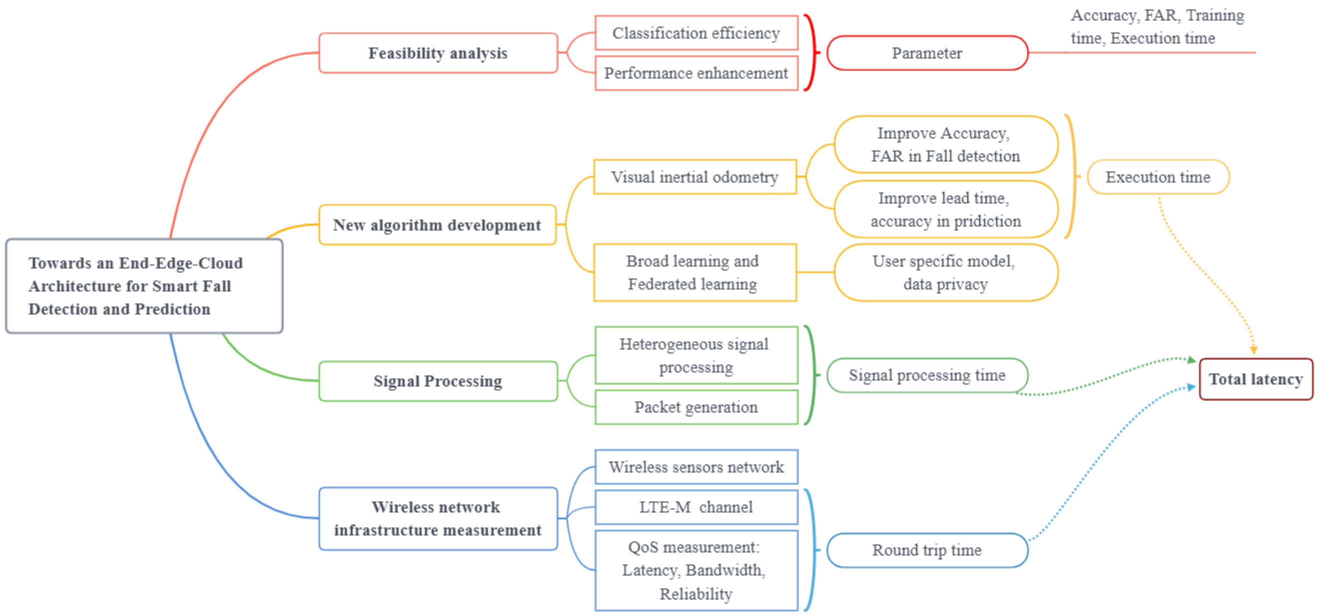


Figure 1-6 The research map of the research.

research work are very specific which is

1. Proposing and simulating the end-edge-cloud-based architecture to figure out its feasibility in human activity detection. How much performance enhancement can be achieved in classifying and recognizing human daily activity through tightly coupled multiple information sources and modern recurrent neural network-based algorithms?
2. A suitable single algorithm needs to develop which can predict and detect falls.
3. Speeding up the execution time is another challenge in implementing the end-edge-cloud-based architecture. Broad learning[44] can system can be a useful tool to speed up the

training time.

1.3 Research objectives

The main research objective of this research work is to develop an end-edge-cloud-based human activity recognition system for fall detection and prediction. Accuracy, false alarm rate (FAR), precision, recall, training time, execution time, total latency including round trip time from end to edge, signal processing time and execution time, reliability, and lead time to predict are the performance evaluating metrics for this research work. Therefore, this research work will answer the following research question to reach its final goal:

1. Is it really necessary to have an end-edge-cloud-based architecture to solve fall detection and prediction? How does this architecture improve classification efficiency?
2. There is a challenge in machine learning techniques especially in convolution neural networks (CNN), and recurrent neural networks (RNN) where the training time is large compared with classical machine learning techniques. CNN and RNN also provide a centralized model to all users. Therefore, the next research question will be how to develop a lightweight algorithm that can detect falls.
3. One of the major challenges of this architecture is to determine the total latency including end-to-end delay between end and edge, signal processing time, and execution time. Therefore, the next question to answer is how to design a protocol and measure wireless channels which can provide low end-to-end delay and reliability. Along with this question, there is another relevant question how to process signals in the end tier of the architecture?

These research questions will also serve as the core research objectives for this research.

1.3.1 Challenges

The major part of this research will be simulation-based work. In that case, we have used MATLAB 2022b, a Python platform for performing simulation. The major challenge is with the data collection. The data collection required a prototype hardware development and the contribution of volunteers. In the case of participating volunteers, most of them are willing to take part in performing daily activities but feel fear to perform fall. Another challenge is the APP and the infrastructure development for data collection. The APP requires an amount of time for trials before start making real data collection with it.

Chapter 2 Background

The background chapter will cover a brief about falls and the factors influencing falls, the current research on human activity recognition for fall detection and prediction using wearable sensors, and how and the concept of end-edge-cloud based distributed architecture and its scope for fall-related service through human activity recognition.

2.1 Factors influencing a sudden fall

There are near about 400 risk factors leading to Fall[26]. These factors related to Falls can be categorized into two ways, named, intrinsic factors and extrinsic factors[45],[29],[46],[22] in a broad sense. The intrinsic factors are mostly behavioral and biological risk factors including balance problems, low vision, side effects of medicine, chronic health conditions, sensation loss in feet, inactivity, alcohol usage, etc. While the extrinsic factors include poor light, slippery roads, clutter, and tripping hazards, holes in road, lack of stair railing, lack of grab bars, and other environmental factors. Usually, two or more risk factors interact to cause a fall (such as poor balance and low vision). The more risk factors a person has, the greater their chances of falling[30]. Fig. 2-1 depicts the factors influencing fall. The controllable factors are more related to human activity recognition. As posture is directly related to fall, the tilt transition of

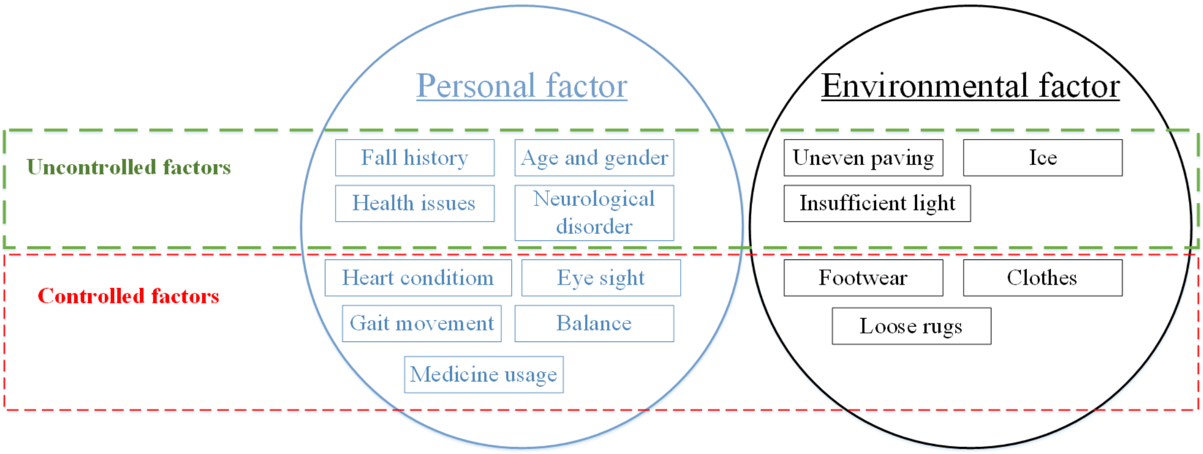


Figure 2-1 Factors which lead to a sudden fall for the elderly.

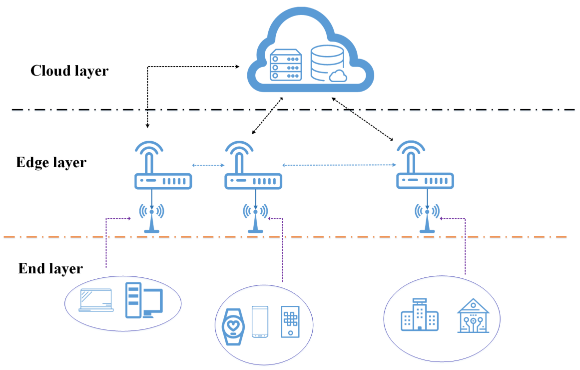
trunk and legs can be used to determine the posture which in return decides a fall or not[22]. The parameters that can separate a faller from a non-faller are gait speed, step duration, gait variability, activity level, multi-scale entropy (MSE), local dynamic stability, harmonic ratio[46], gravitational acceleration measurement during different activities[47]. That's why human activity recognition is closely related to fall detection and prediction.

2.2 Fall detection

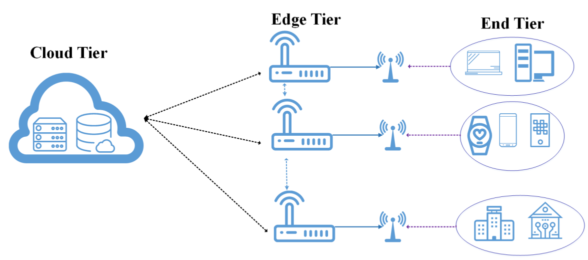
Fall detection is a process that detects a fall and provides alarms to the corresponding third party. It provides notification after recognizing and detecting a fall event occurs. The third party includes the relative of the victims, caregivers, and nearby medical facilities so that the effect of falls can be minimized and the treatment can start as soon as possible. Using different types and multiple sensors in different locales in the body can generate better results than a singular sensor in a single location[41]. A wearable camera with a single accelerometer-based system has been developed for fall detection on smartphones using data fusion techniques and pre-determined thresholds. In this case, accelerometer data and features between odd images are fused together. For fall detection the smartphone is worn around the user's waist. The dissimilarity distance between frames is calculated and summed with the accelerometer value at that particular instance. If the value crosses the pre-determined threshold, the system generates an alarm. The sensitivity of this algorithm for detecting falls is 91%[31]. The application scenario considered is to differentiate fall from ADL, in this case walking and falling down. They didn't consider the effect of other activities. Again, the energy consumption is quite high. If this application runs on the smartphone the battery may drain in a few hours[31]. Due to the fact of having low supplied power both in on-board systems and smartphones, the computational capacity is compromised. So it can be assumed that a considerable amount of time is required to execute the action of classification. There is another example of data fusion between accelerometer and gyroscope data presented in[39] using a support vector machine (SVM). UniMIB SHAR is a dataset for different human activities and falls[32] defined by raw accelerometer data. The purpose of this dataset is to find out the possibilities of machine learning techniques for human fall detection. There are four types of machine learning techniques (SVM, k-nearest neighbor (k-NN), artificial neural network (ANN), and random forest (RF)) are performed and the performance of SVM outperforms other methods in detecting falls or daily activities and classifying them. With a completely different test dataset from the trained dataset, the performance of multi-class classification is not up to the mark. Maximum accuracy is 73% with the RF method while the minimum accuracy is 63.32 % with SVM technique[32]. In[21], it is analyzed that k-NN achieved 96.26% accuracy in fall detection in a binary type classification between ADL and fall. They didn't present the challenge of classifying various activities and different types of falls. MobiAct[37], UCI HAR[38], and HAPT[39] also developed datasets for human activity recognition (briefs about these datasets are summarized in Table table:dataset). Different machine-learning techniques are applied to these datasets for performance evaluation. Another very recent work related to fall detection using deep learning and WiFi channel state information (CSI) showed that the performance of the gated recurrent neural network (GRU) and Long Term Short Memory (LSTM) to detect falls including six types of daily activity in[48]. The usage of WiFi, made this system restrict the mobility of the user to indoor only. Another use of LSTM-based technologies used in[49] with ultra-wideband radar signal. The experimental setup and results show that LSTM-based proposed algorithm enhanced accuracy, precision, and sensitivity with other considered methods. While the achieved accuracy is still below 90 %[49]. But these developmental works are restricted to indoor usage only. Another related recent work in[43], shows that Deep learning outperforms traditional machine learning techniques with both simulated and real-time measurement data in achieving high accuracy which is almost 100 %. The authors have introduced an IoT-based system architecture where a smartwatch communicates with a smartphone for fall detection. Smart-watch collects data while smart-phone performs the classification. Heavy-duty computational platforms run in the lower layer in order to develop classification models, provide privacy, and save user-specific data. This work can be a benchmark for researchers who want to develop a distributed system for fall detection and prediction. One of the drawbacks of this project is the use of two smart devices by a single user i,e, a smartwatch, and a smartphone. If any user will forget to wear one of these devices the system will not work. There is no information about the time required to develop the classification model and classify different activities.

2.3 End-Edge-Cloud architecture

An end-edge-cloud-based architecture is a distributed three layers or tiers system, where the cloud will be on the top, the edge will be in the middle, and the end devices will be at the bottom layer[50]. Typical end-edge-cloud architectures are shown in Fig. 2-2. The end-edge-cloud architecture can be considered as the role of family members in taking financial decisions for a child or dependent. Let's assume that the child or dependent is the end which needs money for some purpose. The mother is allowed to give him money up for some matters like daily expenses, school fees, books, and related materials, or a small amount of pocket money. While for bigger financial issues like buying cycles, new clothes, investing in sports, educational materials or others the father has to think of the necessity and the logical explanation for the spending before allocating the fund. In this way, the father acts as the cloud, the mother as the edge, and the child as an end device. So in reality, in spite of letting the end devices take all computation and data saving, the end devices only perform signal processing and ask for service from the nearest edge devices or nodes. In case of updating edge nodes and new service scenarios the edge contacts the cloud. Cloud servers have more computational power and storage capacity.



(a) Layered type end-edge-cloud architecture.



(b) Tiered based end-edge-cloud architecture.

Figure 2-2 Typical end-edge-cloud representation.

Before going into further details about the application area we should start this section with the brief concept of cloud and edge computing, after that the application area. The point should be mentioned here that when we describe our own end-edge-cloud-based architecture for human daily activity recognition for fall detection and prediction, the tiered-based representation will be considered like Fig. 2-2b.

2.3.1 Cloud computing

The national institute of Standard and Technology provides the definition of cloud computing as "*a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction*"[51,52]. The concept of the cloud in computer and information engineering is the on-demand support of computational resources and storage without active user management. Based on the definition cloud computing can be categorized into three service models and four developmental models. The following Fig. 2-3 visualize them clearly.

For our research work, we are going to use the cloud as infrastructure as a service(IaaS) and deployed it as a private cloud. In the IaaS service model, the cloud provides infrastruc-

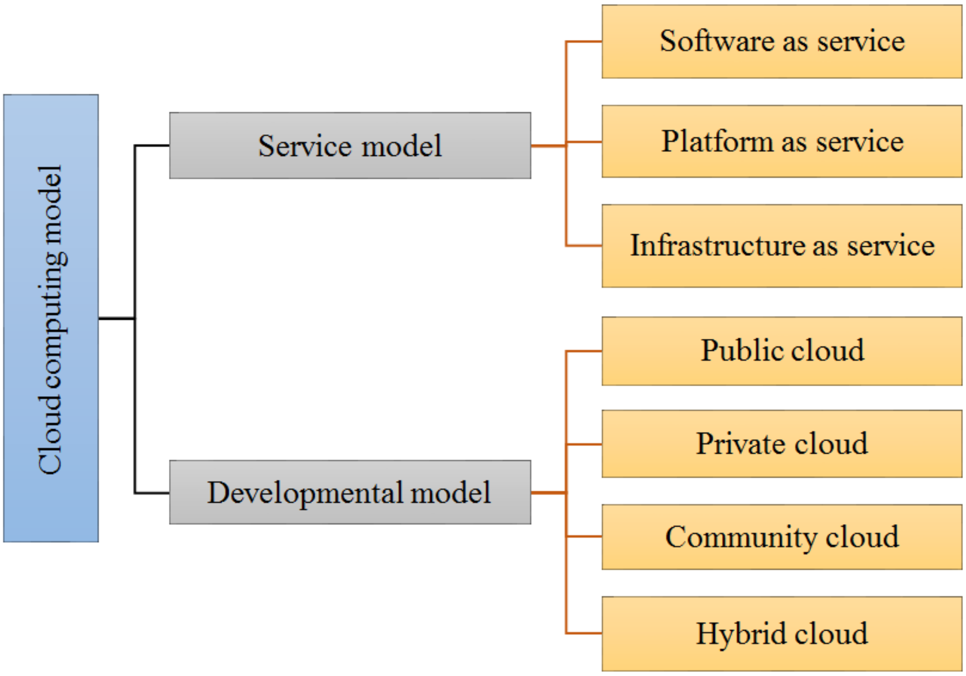


Figure 2-3 Cloud computing model from the point of application.

ture resources like computational power, storage, and networks based on demand. Without any investment in the servers and other related equipment, the consumers can start the implementations [52]. Similarly, a private cloud is used exclusively for a particular purpose with a specific organization, institute, enterprise, or government body [52]. It provides a high degree of performance, reliability, and security to the service. In this theses work, the cloud layer will be used to provide computational resources, large data storage, private networks, data security, and privacy.

2.3.2 Edge computing

Edge computing is another concept we are going to apply in this research work. We can define edge computing as such platform which provides small computational power and storage to the end devices (e,g, IoT) as up-link data from IoT side and down-link data from the cloud side [53,54]. Location-wise edge nodes or devices will be situated at the edge of the network as shown in Fig. 2-3. See the middle part of the figure marked 'Edge layer of tier'. The edge computing implementations are two types [54–56]. The following diagram, Fig 2-4 shows the brief about these two implementations.

In this research work, we are going to consider edge as MEC. According to [50], MEC will bring the limited version of cloud computing to the edge of the network i,e, more closer to the

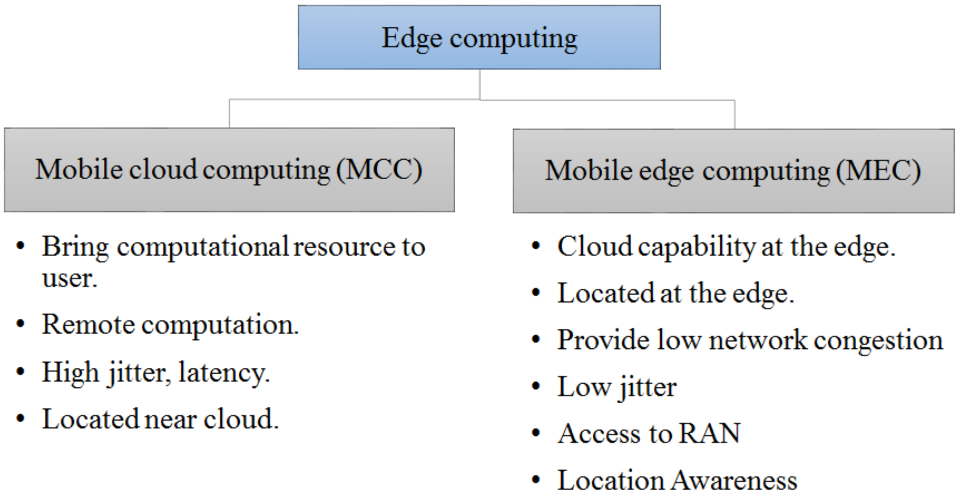


Figure 2-4 Edge implementation scenarios.

user. MEC has both computational capability and storage capacity. The deployment of MEC will be at a macro or micro base station near the end devices. In this way, the end-to-end delay can be minimized.

2.3.3 Application scenarios of end-edge-cloud architecture

The application scenario of end-edge-cloud-based architecture is quite large. Therefore, a brief discussion will be presented here.

1. *Smart health-care*[35,57–61]
2. *Smart cities/home*[62–65].
3. *Computational offloading*[66–69].
4. *Edge video caching*[70,71].
5. *Smart grid*[72–75].
6. *Indoor and outdoor navigation.*[76,77]
7. *Content delivery*[58].
8. *Mobile big data analytic*[63,78].
9. *Load balancing*[67,79,80].

In this application scenario, the cloud is deployed as a private cloud and provides IaaS service to the consumers. The edge nodes are implemented as MEC, located near the edge of the cellular network. These application scenarios provide low latency, small computational power, and data storage capacity. In this way, quality of service (QoS) enhancement is achieved. Therefore, we can consider that the end-edge-cloud-based distributed system will be beneficial for human daily activity recognition for fall detection and prediction purpose.

Chapter 3 Methodology

In this chapter, the considered methods for simulating end-edge-cloud-based architecture for fall detection and prediction will be discussed. The main idea of this research is to use and apply currently developed machine learning techniques like Long Short Term Memory (LSTM) type Recurrent Neural Network (RNN) to develop human activity recognition model for fall detection. The Internet of Things (IoT) and long-term evaluation (LTE) will be used for wireless communication. Besides, this chapter will also present the performance evaluation metrics.

3.1 Proposed EdgeFall architecture

In this research, a new end-edge-cloud-based three-tiered architecture will be presented to recognize daily activity so that a sudden fall can be predicted and eventually detected. In the proposed architecture the cloud will provide IaaS service and be deployed as private cloud due to ensuring the data privacy issues of the users. The edge will act as a MEC node or device which brings some computational power and temporary data storage capacity. Different sensors like wearable cameras, accelerometers, gyroscope,s etc. will form the end tier of the architecture.

The proposed architecture is called ”EdgeFall” which is shown in the following Fig. 3-1. We have already presented similar distributed architecture in[60,61]. The proposed architecture makes the daily activity recognition for fall detection and prediction system into three distributed sub-systems connected to each other by wireless networks like LTE-M. We are expecting that this architecture will be efficient in terms of computational capacity and energy management.

The end tier is a platform for supporting sensors like wearable cameras, gyroscopes, accelerometers, GPS sensors, and other related sensors. This end tier can be implemented with IoT technology. The purpose of this tier is to collect data, extract features from raw data, send them to the edge node for computation, and execute decisions based on the data received from the edge node. The next tier is the mobile edge layer which is composed of intelligent edge nodes and heterogeneous computing resources. User identification, activity recognition, lead time calculation for fall prediction, and fall detection are major responsibilities of this tier. It will adapt protocols, classification networks, and users' daily human activity patterns from the cloud in order to perform its own functions. The last tier is the cloud which is considered the brain of the system. It is designed with deep learning, different machine learning technique, human intervention (HI), etc. The purpose of this tier is to develop a user identification model and

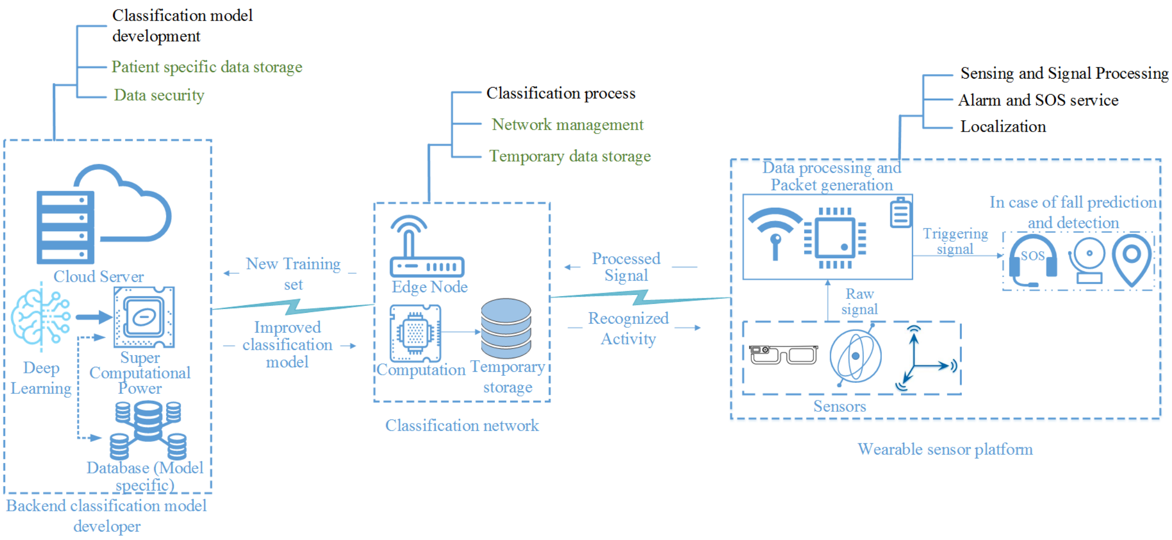


Figure 3-1 Proposed architecture of EdgeFall system.

activity classification model. It should update the mobile edge tier with new improved system parameters at regular intervals. This architecture can also be applicable to other areas related to health care.

We have already simulated a recurrent neural network-based algorithm called ActDec-SysOpt[61] using long short-term memory (LSTM). The performance is promising but needs to modify for better accuracy and lower false alarm rate in fall detection. The training time is also an issue (see the result part of[61]).

3.2 Comparison between the proposed work with other related work

This section compares the proposed research with two recently published works to show its effectiveness. Two research works named Ozcan16:IESL[31] and Saadeh19:ITNRE[35]. In Ozca16:IESL, the authors used wearable cameras and accelerometers as sensors. They fused these data with loose coupling and used a static threshold-based based algorithm for fall detection. They published their work in 2016. The reason behind considering this work is they use wearable cameras and accelerometers. A recent work is presented by Saadeh19:ITNRE which is published in 2019. This work demonstrated both fall detection and prediction with a single device by using two algorithms. The authors claimed to have a patient-specific system while the classification model is developed outside and pushed into the device. The high accuracy achieved by them is due to the fact of considering only binary classification of fall and non-fall.

There is not much information about the offline training model in their paper whereas the model is a centralized model or user-specific model. The following Table 3.1 shows the comparison between our work with these considered published works.

3.3 Dataset definition

As our primary goal is to recognize activities of daily living (ADL) and predict and detect a sudden fall, so we have to consider all ADLs and all possible falls which can occur to elderly people. There are various kinds of daily activities like walking, sitting, laying, stepping into or from the car, bending, jumping, going up and down stairs, running, swimming, etc. But only daily activities which can cause falls are included in this research. There are 7 activities which are described in the following Table 3.2.

While performing these activities, anybody can face a sudden fall. In a broad sense, this fall can be categorized into four types which are Fall backward, Fall forward, Fall side-ward, and Specific fall. The following TABLE 3.3 provides more details about these falls.

3.4 Data collection

For the data collection, we have developed an APP using for collecting IMU (accelerometer and gyroscope) data using a smartphone. Using this technique we can develop the trajectory of human daily activity. For the data collection, we are going to use the following protocols as described in Table 3.4.

3.5 Performance evaluation metrics

We are considering accuracy, recall, precision, F1-Score, training time, and execution time as the performance evaluation metrics. The definitions are given below:

1. **Accuracy** is defined as the percentage of falls correctly detected from the dataset which is given by
$$Accuracy = \frac{\sum True\ positive}{Total\ no.\ of\ Samples}. \tag{3.1}$$
2. **Recall** is defined as the proportion of actual falls that are correctly identified. It provides information about the accuracy row-wise of the confusion matrix.
$$Recall = \frac{\sum True\ positive}{True\ positive + False\ negetive}. \tag{3.2}$$

Table 3.1 Comparison between our works with other

Metrics	**proposed research**	**Ozcan16:IESL**[31]	**Saadeh19:ITNRE**[35]
System	end-edge-cloud	on-board	onboard and offline training
Activity recognition	multi-class	binary type	multi-class
Service	Human activity recognition, fall detection, and prediction	Fall detection	Fall detection and prediction
The algorithm used	LSTM, BLS, Federated learning and semi-supervised learning	Static Threshold	Machine learning for prediction and threshold for detection
No. of Algorithms	1 for activity recognition, fall detection and prediction	1 for detection	1 for detection and 1 for prediction
Used sensors	Wearable camera, Accelerometer and Gyroscope	Accelerometer and wearable camera	Accelerometer
Information type	Features (Tightly coupled)	Raw data (Loosely coupled)	Raw data (Loosely coupled
Latency	expected less than 100 ms	not specified	1 sec
Trained model	User specific	centralized	centralized
Performance evaluation	As mentioned in answer to question 5	FD sensitivity or Recall, FD Specificity	FD sensitivity or Recall, FD Specificity, FP sensitivity or Recall, FP

Table 3.2 Considered ADL for the proposed system

Name of The ADL	Description	Label
Walking	Normal walking movement	ADL_walk
Sitting Down	From standing position to sit on chair or some lower platform	ADL_sit
Running	Slow and moderate running (like Jogging)	ADL_run
Laying Down	From Stand up position to sit on the bed to lay down (in normal speed)	ADL_laying
Jumping	Continuous Jumping (like playing with rope)	ADL_jump
Stair climbing up	Climbing stairs from lower floor to upper floor	ADL_climbUp
Stair climbing down	Climbing stairs from upper floor to lower floor	ADL_climbDown

Table 3.3 Type of Falls for the proposed system

Categories of The Fall	Description	Label
Fall in forward direction	Forward fall from standing, walking, sitting to stand up, stair climbing down, jumping position with protection	Fall_Forward
Fall in backward direction	Backward fall from sitting to standing up, sitting, jumping position with proper protection	Fall_Backward
Fall in sideway direction	Fall right and left side from standing position	Fall_Sideward
Specific Fall	Fall caused by hitting with object, sudden unconscious, any other means that causes a fall	Fall_specific

3. **Precision** is defined as the portion of actual identified fall i,e, accuracy along column

Table 3.4 Experimental protocols for training dataset acquisition and validating algorithm

Procedure	**Task**	**Repetition**
Movement procedure (Walking, running and jumping)	Open APP Register with name, activity, and trail number Walking for 9 sec Stop Register with name, activity, and trail number Running in Normal Speed for 9 sec Stop Register with name, activity, and trail number Jumping for 6 sec Leave the APP and prepare for the next activities	3 times 3 times 3 times
Stationary Procedure (Stand up position to sitting and laying down)	Open APP Register with name, activity, and trail number Standing to Sit on Chair at normal speed Register with name, activity, and trail number Standing to Lay down on the floor at normal speed Leave the APP and prepare for the next activities	9 times 9 times
Climbing Procedure (Stair Climbing)	Open APP Register with name, activity, and trail number Climbing Up and down for 9 sec (each activity) Leave the APP and prepare for the next activities	3 times
Fall Procedure	Start Registration APP and Camera Register with name, activity, and trail number Repeat each type of fall describe in Table 3.3 Leave the APP and prepare for the next activities	3 times

wise of the confusion matrix.

$$Precision = \frac{\sum True\ positive}{True\ positive + True\ negetive}. \tag{3.3}$$

4. **F1 score** is the harmonic mean of precision and recall, which measures the accuracy of the test.

$$F1 - score = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}. \tag{3.4}$$

5. **FAR** FAR is the False alarm rate of the classification network. This factor enlightens how the system gets confused between any activity and other considered activities. The following equation is used to describe FAR

$$FAR = \frac{\sum False\ negetive}{False\ negetive + True\ nagetive}. \tag{3.5}$$

6. **Training-time** is the time required to train the classification network with the considered method.
7. **Execution time**, τ_{cls} is the time required for the trained classifier to recognize human activities
8. **Bandwidth** is defined as the maximum data rate of uplink and downlink channel to support this system in bit/s.
9. **Network Latency**,τ_{net} means the round trip time required for end-to-edge tier.
10. **Maximum packet size** describes the largest packet which can be sent from end to edge and edge to cloud with high reliability.
11. **Reliability** measures the packet drop rate. There are two types of reliability considered in this work, i) end-to-edge reliability and i) edge-to-cloud reliability.
12. **Packet generation time**, τ_{sig} includes signal processing and packet generation time.
13. **Total latency**, τ gives the total time required from generation of signal to reception of the recognized daily activity by end tier. The following simplified equation will be used:

$$\tau = \tau_{sig} + \tau_{net} + \tau_{cls}. \tag{3.6}$$

Chapter 4 Feasibility Analysis of the Proposed Cloud-Edge-End-based Fall Detection System

In this chapter, the results and findings related to the feasibility analysis of end-edge-cloud architecture, deep learning, and data fusion from multiple sensors. Partial results are published in two conferences, named, 'Generating a Visual-Inertial Odometry Dataset based on a Helmet Prototype for Recognizing Human Activities' [81] in International Conference on Advancement in Electrical and Electronic Engineering (ICAEEE), 2022 and 'Performance Enhancement of Human Activity Recognition and Fall Related System using Multi-modal Broad Learning System (mBLS)' [82] in Third International Conference on Advances in Physical Sciences and Materials (ICAPSM), 2022. A journal paper 'EdgeFall: A Promising Cloud-Edge-End Architecture for Elderly Fall Care' [83] is published in the International Journal of Electrical and Computer Engineering (IJECE). All this information is presented in chapter **??**. The research map presented by Fig. 1-6 in **??** shows one of the tasks of this thesis work is feasibility analysis. We have proposed EdgeFall, an end-edge-cloud-based architecture where data fusion and deep learning-based algorithms will be used to classify human activity. We have set up our simulation through four datasets which are UniMIB SHAR [32], MobiAct [37], UCI HAR [38] and HAPT [39] for proving the effectiveness of data fusion in human activity recognition. Different daily activities of a group of volunteers can be simulated with these datasets. We have also investigated the classical machine learning-based activity recognition model with the deep learning-based model on these datasets. The performance evaluating metrics will help us to model human activity suitable for the real world. These results also indicate how effectively EdgeFall architecture can classify different types of human activities. It is seen from the evaluation that the model developed by ActDec-SysOpt outperforms classical-based recognition models. So, our major contributions are:

1. Proposing and simulating the cloud-edge-end-based EdgeFall architecture to figure out the feasibility in human activity detection.
2. Finding out the challenges like FAR, accuracy, precision, and recall in loosely coupled data fusion for recognizing human activities.
3. Performance enhancement in classifying and recognizing human daily activity through tightly coupled multiple information sources and ActDec-SysOpt algorithm.

4.1 Adupted Algorithms

In this section, we are going to discuss the methodologies, named, FuseFall and ActDec-SysOpt algorithms. These two methods will be used to prove the effectiveness of data fusion, cloud-edge-end type architecture, and the classification algorithm based on recurrent neural networks.

4.1.1 FuseFall algorithm

There are two sources (a wearable camera and a tri-axial accelerometer) of information used for fall recognition. The block diagram of the FuseFall algorithm is shown in Fig. 4-1

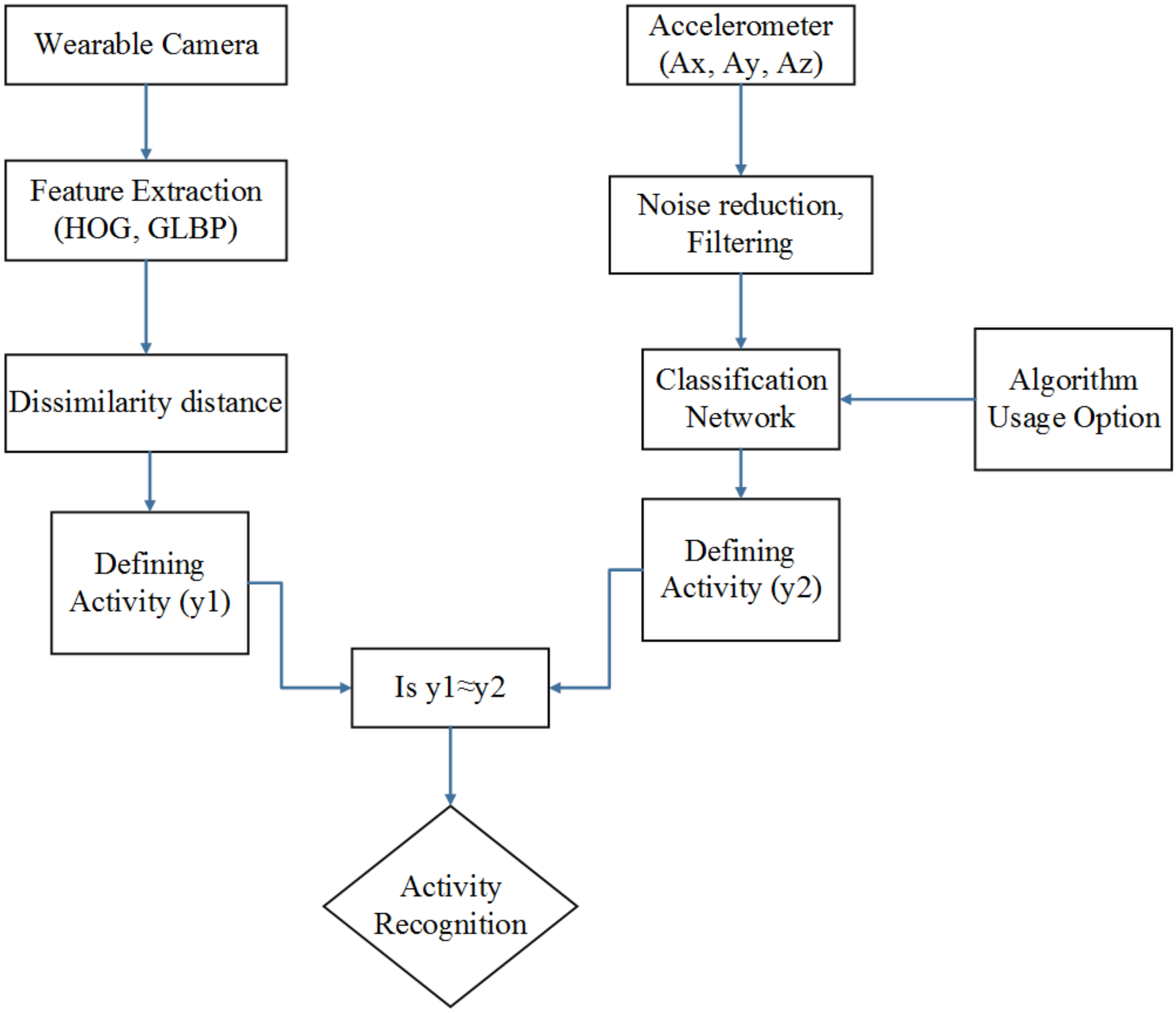


Figure 4-1 Block diagram of FuseFall algorithm for fall detection.

In this algorithm, the information sources are loosely coupled and analyzed separately.

From the block diagram (Fig. 4-1), it can be seen that both sources use different suitable algorithms to define the same activity separately and compared to come up to the final decision. This algorithm is explained in[60]. We assume that the resource required to analyze IMU data is lesser than image processing. Another algorithm will be necessary to optimize the system which will be run in a cloud node. So we can design two separate algorithms for fall detection and system optimization. Part of the FuseFall algorithm used for IMU data to detect a fall is designed with SVM machine learning technique. A signal window of 3 seconds is considered to determine an event. As we are not much interested in the specific type of ADL, the event detection has only two classes, named, ADL class and Fall class. In the case of fall detection, image processing techniques are used to determine the feature (i,e, dissimilarity distance between odd frames) from the captured images between 1.5 seconds backward and 1.5 seconds forward from the instant of fall occurrence. This dissimilarity distance will be used to verify the fall event determined in the detection phase. The overall fall detection algorithm is shown in algorithm 4.1.

Finally, another algorithm will be used to optimize the system which is presented in algorithm 4.2. In this case, the test data are added to the training data to train both phases of the FuseFall algorithm. If the result of the newly trained system is better than the old one, the parameter e,g, threshold value used in the verification phase will be changed. Otherwise, the old parameters are kept.

4.1.2 ActDec-SysOpt algorithm

The block diagram of ActDec-SysOpt is shown in Fig. 4-2. The classification model is trained with LSTM. This algorithm has two parts, ActDec is used for recognizing human activity and SysOpt is for generating a trained classification network. These two parts are also the representation of mobile edge node and medical cloud respectively. The details are discussed in[61]. Now the information sources are tightly coupled.

There are two separate algorithms will be used in the cloud and edge nodes to reduce the complexity, computational power, and battery consumption. Both Algorithms will be presented here but we will only evaluate the event detection algorithm. The trained classification network explained in the previous section will run in the edge node, while initial network training and optimization will take place in the cloud. So we can name these two algorithms event detection and system optimization algorithm. A signal window of 1.5 seconds is considered to determine an event (i,e, any type of daily activity or fall). The overall event detection algorithm is shown in Algorithm 4.3.

Algorithm 4.1: FuseFall algorithm for fall detection.

```
Detection phase;
Data: IMU Data
Result: Detection of a sudden fall
Load FuseFall trained model;
initialization;
while Unless detecting a fall do
    Extract feature F(accl) from signal window;
    %3 sec data;
    if F(accl) ~ ADL then
        go to initialization;
    else
        if F(accl) ~ Fall then
            Verification phase
Verification phase;
Data: Image data
Result: Verification of fall
while Fall detected do
    Load images between t-1.5 to t+1.5;
    %Images correspond to 3 sec;
    Extract features I(dissimilarity);
    if I(dissimilarity) ~ Fall then
        Fall verified;
    else
        Consider as ADL;
```

Algorithm 4.2: System optimization Algorithm

Data: New label data

Result: Optimization of the FuseFall trained model

begin
  New label data $\longrightarrow$ Training data;
  Evaluate both algorithms ;
  if $Result_{New} > Result_{Old}$ **then**
    Pass $Para_{new}$ to FuseFall algorithm;
    Modify both phase;
  else
    Keep previous State;
    Remove New label data;

Algorithm 4.3: ActDect algorithm for activity recognition and fall detection

Data: IMU data

Result: Human activity recognition and fall detection

Load trained ActDec classification model;
initialization;
while *Unless detecting an activity or a fall* **do**
  Extract feature **F(accl & gyro)** from signal window;
  %1.5 sec data;
  if ***F(accl & gyro)*** $\sim$ *Daily activity* **then**
    go to initialization;
  else
    if ***F(accl & gyro)*** $\sim$ *Fall* **then**
      Alarm, Protection

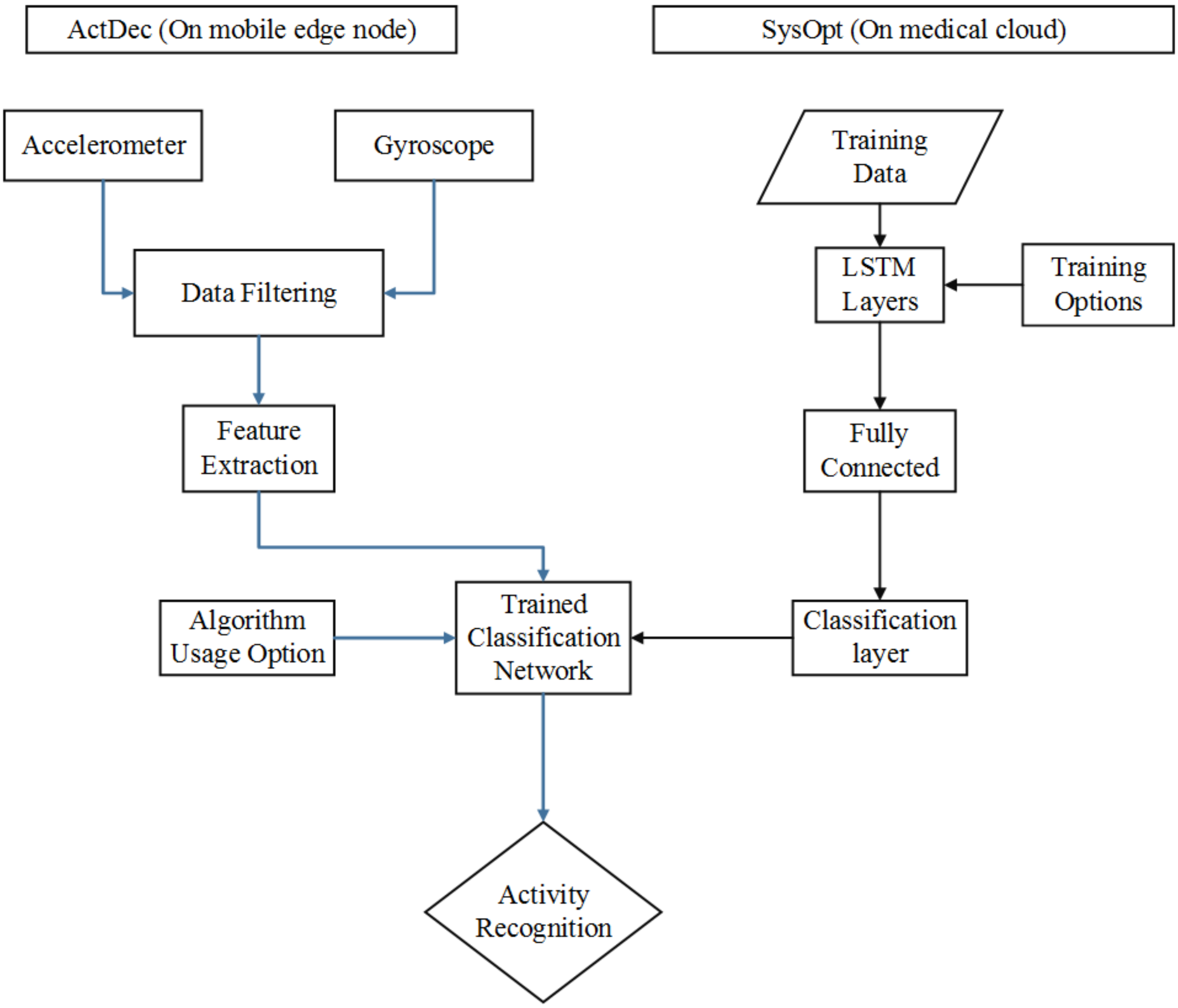


Figure 4-2 Simple block diagram of ActDec-SysOpt algorithm.

Finally, another algorithm will be used to initialize and optimize the system which is presented in Algorithm 4.4. In this case, the test data will be labeled and added to the training data to train the Even detection network. If the result of the newly trained system is better than the old one, the parameter e,g, threshold value used in the verification phase will be changed. Otherwise, the old parameters are kept.

This algorithm represents a centralized trained model of human activity recognition for all users. SysOpt generates the trained classification model (ActDec) on a cloud server and pushes it to the edge server.

Algorithm 4.4: SysOpt Algorithm.

Data: New label Data

Result: Optimization of ActDec algorithm

begin
  New label data $\longrightarrow$ Training Data;
  Run LSTM with $TrainingData_{New}$;
  if $Validation_{New} > Validation_{Old}$ **then**
    Modify ActDec classification model;
    Pass $Para_{new}$ to ActDec Algorithm;
  else
    Keep previous State;
    Remove New label data;

4.2 Results and Evaluation

In this section, we present experiments and findings using FuseFall and ActDec-SysFall architecture. The performance evaluating metrics are described in .

4.2.1 Experiments with FuseFall

We have only simulated and evaluated the results produced by the wearable camera $y1$ and by the raw accelerometer data $y2$ separately at this stage (see Fig. 4-1).

4.2.1.1 Experimental Setup and results

Fig. 4-3 provides the simulation scenario. A forward fall will occur from the walking position. The details about how we evaluate it is given in[60]. A workstation with Intel core i5 (7th generation) with 12 GB RAM is used. For analyzing and simulating purposes we have used MATLAB 2019a.

We calculate the accuracy, precision, recall, F1-score, and run time of $y2$ from **??**. We consider the k-NN method for comparison. The results are presented in the following Table 4.1.

We have performed the same activities wearing Xiaomi S2 mobile around the head height. The front camera is used for capturing video. As shown in Fig. 4-4b, the dissimilarity distance for the video frames during the fall is much higher than other frames, marked by two red circles.

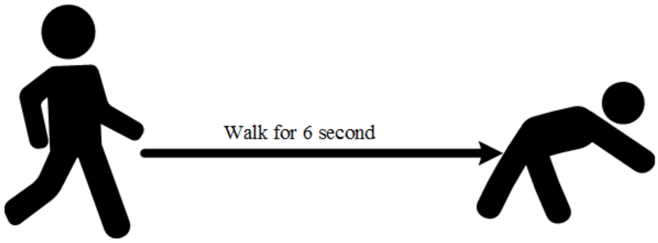


Figure 4-3 Experimental setup to evaluate FuseFall algorithm.

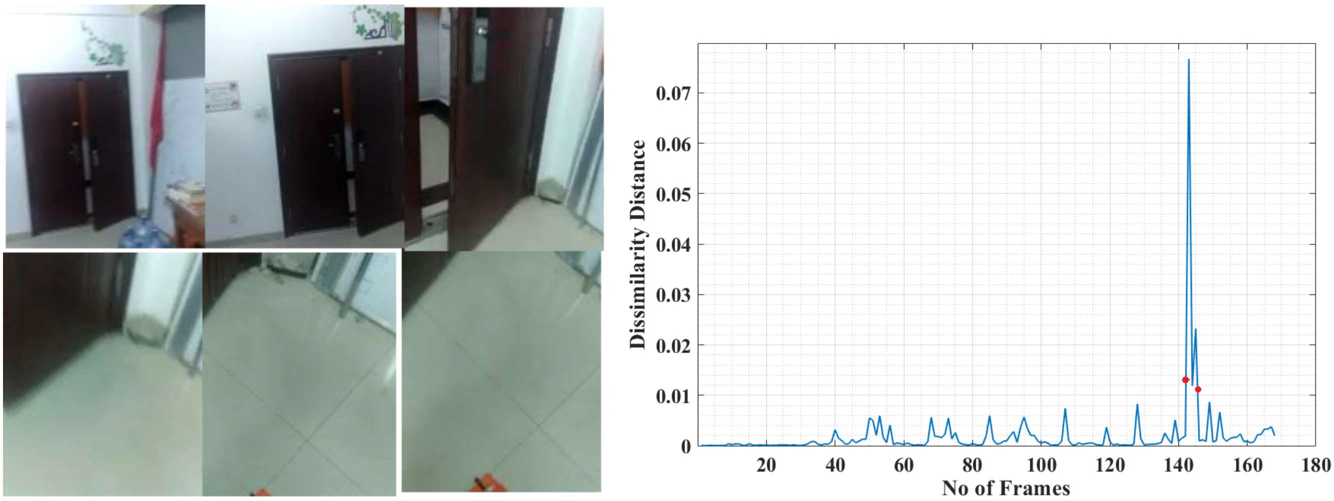
Table 4.1 Partial evaluation performance of FuseFall to differentiate fall from daily activities.

Metrics	**FuseFall for $y2$**	**k-NN**
Accuracy	0.9667	0.900
Recall	0.9667	0.900
Precision	0.9839	0.9545
F1-score	0.9752	0.9265
Run-time(sec)	2.282	1.043

From the binary type of classification between fall and human daily activity, we can see the capability of FuseFall. Still, the question remains about the performance of this FuseFall with multi-class type classification to recognize human daily activity. Please refer to[61] for what we mean by multi-class activity. Table 4.2 presents the performance of the FuseFall algorithm for accelerometer data with k-NN.

During video processing, we have observed high picks like Fig. 4-5, which can cause a fall alarm.

From Table 4.2 and Fig. 4-5, it can be easily observed that loosely coupled information source with FuseFall algorithm is not suitable for multi-class type activity detection. That is why we stop our experiments with $y1$ and $y2$. Besides, the time required to produce results with video processing is high in our experiments. The challenges related to the multi-class activity classification are handled more efficiently by the ActDec-SysOpt algorithm[61] which will be explained in the next section.



(a) Example frames of the captured video during the test.

(b) Resultant dissimilarity between frames to differentiate fall from walking.

Figure 4-4 Fall detection using wearable camera and FuseFall algorithm(test to generate $y1$).

Table 4.2 Performance of FuseFall for multi-class type human activity recognition.

Metrics	**FuseFall for $y2$**	**k-NN**
Accuracy	0.8468	0.8022
Recall	0.8198	0.8222
Precision	0.8518	0.8595
F1-score	0.8355	0.8405
False alarm rate (FAR)	0.0396	0.0547

4.2.2 Experiments with ActDec-SysOpt

As we have already observed that single sources of information and classical machine learning-based models are not up to a satisfactory level for recognizing different human activities. Here we are going to use ActDec-SysOpt[61] algorithm and data fusion technique to prove some important points like i) the need for proposed EdgeFall (see Fig. **??**), ii) the effectiveness of multiple sources, use of features and LSTM and iii) the necessity of tight coupling.

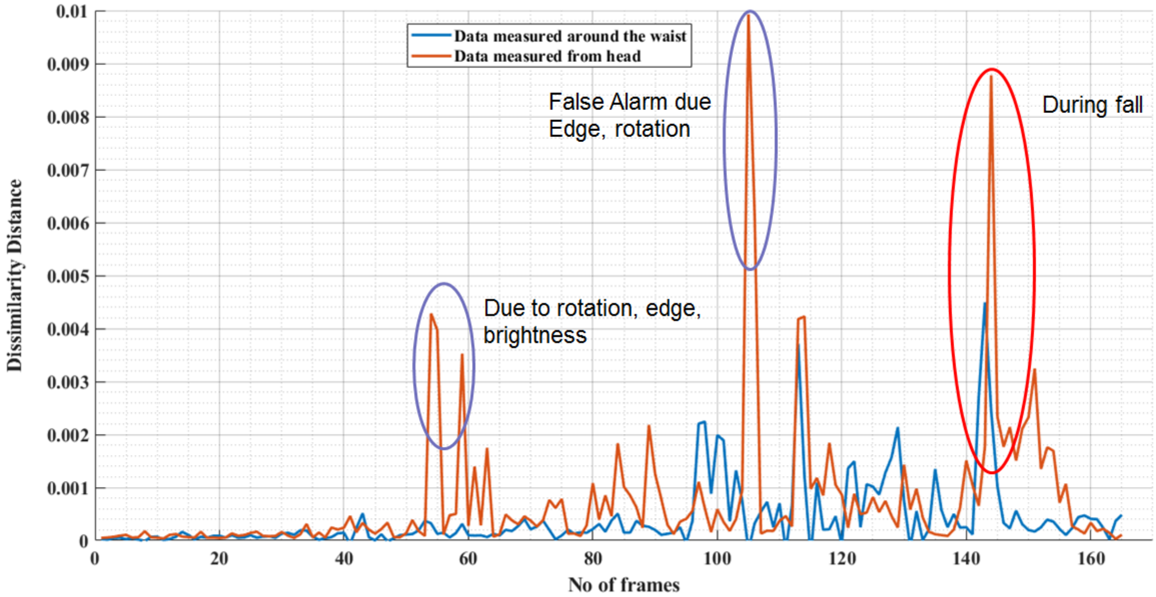


Figure 4-5 FAR during multiclass activity detection with FuseFall (video processing part).

4.2.2.1 Experimental setup

For the experimental setup we have used four different data sources, named, UniMIB SHAR[32], MobiAct[37], UCI HAR[38] and HAPT[39] to simulate BAN of the EdgeFall. These sources contain different types of human activities for a number of volunteers. The modification process of these considered datasets is described in brief with Table 4.3. UniMIB SHAR represents raw single source, MobiAct depicts loosely coupled multiple sources while HAPT and UCI HAR illustrate tightly coupled multiple information sources. We have modified the original datasets in such a way so that it represents the BAN of the proposed architecture sending data to the edge node continuously in time windows. The experimental results will prove the effectiveness of tightly coupled data fusion. The term tightly coupling mean the features extracted through signal processing. Details about the features can be found in[38] and[39].

Table 4.3 Considered datasets for performance evaluation.

Dataset	UniMIB SHAR	MobiAct	UCI HAR	HAPT
Size of original data	255 MB	1.24 GB	241 MB	7.54 KB
				Continued on next page

Table 4.3 – continued from previous page

Dataset	UniMIB SHAR	MobiAct	UCI HAR	HAPT
Representation	Both ADL and fall	Both ADL and fall	Daily Human activities	Daily Human activities
No. of sensors	1	3	2	2
Sensors used	Accelerometer	Accelerometer, Gyroscope and Orientation sensor	Accelerometer and Gyroscope	Accelerometer and Gyroscope
Devices used to collect data	Samsung Galaxy Nexus I9250 with Bosh BMA220	Samsung Galaxy S3 with LSM330DLC module	Samsung Galaxy S II	Samsung Galaxy S II with HARApp
Position of the device	Trouser front pocket (half of the time in the left one and the remaining time in the right one)	Not Specified	Waist-mounted	Different body parts (trunk, upper and lower extremities)
No of Subjects	30 (24 Females, 6 males)	57 (15 Females, 42 males)	30 (number of female and male is not specified)	17 (number of female and male is not specified)
Physical information about the subjects	Age: 18-60, Height: 160-190, Weight: 50-82	Age: 20-47, Height: 160-189, Weight: 50-120	Age: 19-48	Not specified
No. of activities	9 types of ADL and 8 type of fall	9 types of ADL and 4 type of fall	6 type of daily activities	12 type of daily activities
Nature of data	Raw accelerometer data	Raw accelerometer, gyroscope and orientation data	Extracted feature accelerometer and gyroscope data	Feature from accelerometer and gyroscope data
Sampling frequency in original dataset	50 Hz	20 Hz	50 Hz	50 Hz

Continued on next page

Table 4.3 – continued from previous page

Dataset	UniMIB SHAR	MobiAct	UCI HAR	HAPT
Sampling frequency in original dataset	50 Hz	20 Hz	50 Hz	50 Hz
Samples in modified dataset	4,632	67,348	10,299	10,411
Depicted activities	walk, walk up-stair, walk down-stair, sitting, standing, laying down	walk, walk down-stair, sitting, standing, jogging	walk, walk up-stair, walk down-stair, sitting, standing, laying down	walk, walk up-stair, walk down-stair, sitting, standing, laying down
Signal window	3 second	1 second	1.5 second	1.5 second
Original Data Source	[32]	[37]	[38]	[39]

ActDec represents the mobile edge node while SysOpt is for the medical cloud. Here, we want to evaluate how effectively this algorithm can recognize different human activities i,e, the classification process.

4.2.2.2 Results

First, we will present the performance of EdgeFall through the ActDec-SysOpt algorithm. The following table (Table 4.4 accumulates the simulation result which outperforms classical machine learning type algorithm. We have considered a traditional data split (70-30) between training and test data. Results show that ActDec-SysOpt outperforms the other two machine learning-based classification models (where one of them is FuseFall). Therefore, we will evaluate the performance of ActDec-SysOpt on different datasets. These different datasets represent the BAN of the proposed EdgeFall architecture (i,e, number of users with different weights, heights, ages, and gender). Details about these considered datasets are given in TABLE 4.3.

To make the simulation more realistic we have considered 50-50 approach for training and test data to evaluate the effectiveness of data fusion. The following Fig. 4-6 presents the simulation results and shows that data fusion from multiple sources with proposed ActDec-SysOpt has better performance than information from a single source and loosely coupled multiple in-

Table 4.4 Performance of ActDec-SysOpt over FuseFALL and k-NN algorithm.

Methods	FuseFALL	k-NN (k=2)	ActDec-SysOpt
Accuracy	0.8468	0.8022	0.9187
Recall	0.8198	0.8222	0.8303
Precision	0.8518	0.8595	0.8511
F1-score	0.8355	0.8405	0.8406
FAR	0.0396	0.0547	0.025
Training-time (minute)	2.282	1.043	112

formation sources. It can be seen that feature extraction can produce far better results than raw data fusion. The accuracy of raw data fusion is very poor around 59.65% with a large FAR of 10.66%. Whereas the feature extraction (tightly coupled) from multiple information sources produces high accuracy of 92.01 % with FAR of 1.69%.

The required training time and classification execution time are given in TABLE 4.5. The time of training classification network and execution time to recognize an activity is more for tightly coupled multiple information sources. As we have separated the classification model development process and execution process into cloud and edge, the execution time may not be a concerning factor. This time can be sped up by using a hardware/software co-design approach.

Table 4.5 Advantages of data fusion with ActDec-SysOpt algorithm.

Methods	UniMIB SHAR	MobiAct	HAPT	UCI HAR
Training-time (minute)	84	161	1094	691
Execution time (ms)	$\sim$ 4.52 - 7.065	$\sim$ 0.6 - 0.73	$\sim$ 14.16 - 15.74	$\sim$ 15.20 - 16.71

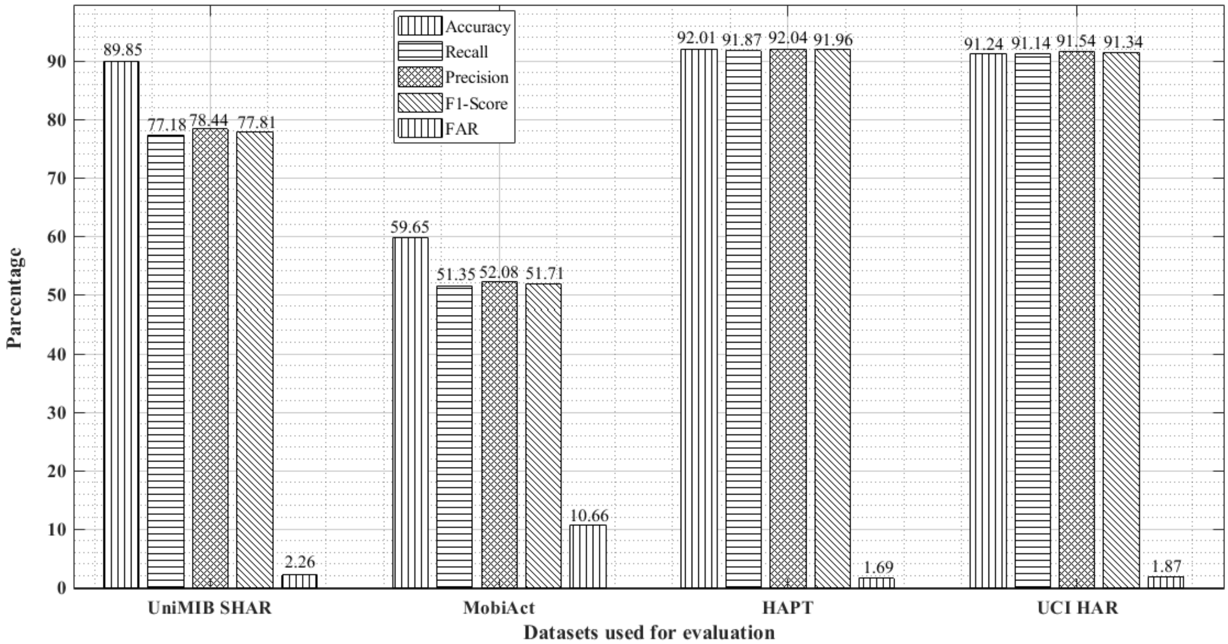


Figure 4-6 Advantages of data fusion from multiple information sources.

From these two tables (TABLE 4.4 and 4.5) and Fig. 4-6 we come up with the following decisions:

1. Tightly coupled information sources with LSTM-based classification model, are more effective. The accuracy is around 92% with FAR being 1.6 %. The high value of recall, precision, and F1-score prove that the classification model is capable of recognizing human activity correctly.
2. The execution time required to recognize activity from one window of information is very less, around 15 ms with data fusion from multiple sources (check execution time of TABLE 4.5).
3. RNN-type machine learning-based algorithms are more suitable for recognizing human daily activities.
4. Features are more suitable as they can lower the FAR. 1.69 % with HAPT and 1.87 % with UCI HAR.
5. However, we can see that training the classification model takes a lot of time, 1094 minutes for HAPT and 691 minutes for UCI HAR. The medical cloud is suitable to handle the training process because there are no issues with computational power and storage.
6. The train network then can be passed to the edge node which can execute activity recognition.

7. Data collection and feature extraction can be handled efficiently in BAN.

So far ActDec-SysOpt is a bold step toward fall detection using EdgeFall. Still, there are some challenges that need to solve. For example accuracy, FAR, single algorithm for fall prediction and detection, and user identification. Still, we are a little behind to achieve the desired accuracy of over 95%.

Chapter 5 Research Schedule

5.1 Milestones

There are few milestones of my thesis which are presented in the following Table 5.1. These milestones are important points which help me to finish this thesis work.

Table 5.1 Milestones of the thesis

Task ID	Task	Current Status
1	Literature review and feasibility analysis	Completed.
2	New algorithm development	Finished: LSTM based ActDec-SysOpt algorithm; On going: a lightweight algorithm using federated learning, broad learing system and semi-supervise learning.
3	New dataset using trajectory analysis	Finished: APP and infrastructure development; Data collection related to human daily activities and different type of fall.
4	Documentation	Finished: Report writing.

5.2 Schedule

Based on the milestones, Table 5.2 below shows the research schedule.

Table 5.2 Research Schedule

Phase	Time	Task
1	June 2021 - August, 2021	Theoretical literature review and related learning
2	September 2021 - July 2022	Simulation implementation
3	January 2022 - August 2022	Conference paper publication
5	September 2022 - June 2023	Journal paper writing and publication
6	October 2022	Research Work Presentation
7	July 2023 - August 2023	Research report writing and submission

Chapter 6 Overall Progress

This chapter focuses on the progress I have made in this research work. I started my literature review works at the beginning of June 2021. I have surveyed papers related to fall detection and prediction to understand the techniques, research scopes, and research demand. The overall progress is as follows

1. **Kazi2023:IJECE**: K. M. Shahiduzzaman and M. S. Uddin Yusuf, ”Edgefall: A promising cloud-edge-end architecture for elderly fall care,” International Journal of Electrical and Computer Engineering (IJECE), vol. 13, no. 4, pp. 4721–4733, August 2023.
2. **Kazi2022:ICAPSM**: K. M. Shahiduzzaman and M. S. Uddin Yusuf, “Performance enhancement of human activity recognition and fall related system using multi-modal broad learning system (mbls),” in 2022 Third International Conference on Advances in Physical Sciences and Materials (ICAPSM), 2022.
3. **Kazi2022:ICAEEE**: K. M. Shahiduzzaman and M. S. Uddin Yusuf, “Generating a visual-inertial odometry dataset based on a helmet prototype for recognizing human activities,” in 2022 International Conference on Advancement in Electrical and Electronic Engineering (ICAEEE), 2022, pp. 1–6.

Chapter 7 Summary

This research will propose the next-generation fall detection and prediction technique using cloud-edge-end-based architecture. From this research, it is expected to publish at least three journal papers along with a number of conference papers. The trajectory-based dataset will be a new contribution to this research community.

So far all results, published in[81–83], show that the proposed loud-edge-end-based distributed architecture with multiple information source fusion and modern learning technique can provide a next-generation fall detection and prediction system through recognizing daily human activities. This proposed solution provides both indoor and outdoor mobility facilities. One of the major contributions of this research work is to develop a model which is lightweight, and efficient in terms of accuracy and false alarm rate. As mentioned, one of the challenges of this work is to collect datasets through the developed APP and helmet infrastructure and most of the volunteers are willing to participate in tasks related to human activities but fear fall-related activities due to the possibilities of suffering injuries.

This proposed architecture can be also applicable to other application scenarios like remote ultrasound treatment, ECG measurements, and relevant cooperative use. Therefore, this research work can be a bold step towards the implementation of a smart, mobile, distance healthcare system.

Bibliography

[1] E. Duffin, "Proportion of selected age groups of world population in 2019, by region ," Available in https://www.statista.com/statistics/265759/world-population-by-age-and-region/, September 2019, [Online: accessed 20-October-2019].

[2] A. Clark, "The Best Medical Alert Systems 2019," Available in https://www.theseniorlist.com/best-medical-alert-systems/, September 2019, [Online: accessed 21-September-2018].

[3] "WHO:Fall," Available in http://www.who.int/news-room/fact-sheets/detail/falls, January 2018, [Online: accessed 20-August-2018].

[4] "OECD,Elderly population (indicator)," Available in https://data.oecd.org/pop/elderly-population.htm/, 2019, [Online: accessed 20-November-2019].

[5] "Ageing," Available in https://www.un.org/en/sections/issues-depth/ageing/index.html, 2019, [Online: accessed 20-November-2019].

[6] Z. Hajihashemi and M. Popescu, "A Multidimensional Time-series Similarity Measure With Applications to Eldercare Monitoring," *IEEE Journal of Biomedical and Health Informatics*, vol. 20, no. 3, pp. 953–962, May 2016.

[7] D. Clark, "Distribution of elderly population (aged 65 and over) as a share of population in the United Kingdom (UK) from 1976 to 2046," Available in https://www.statista.com/statistics/743332/elderly-population-of-united-kingdom-uk/, August 2019, [Online: accessed 20-November-2019].

[8] S. Han, "Number of people in China by age group 2008-2018," Available in https://www.statista.com/statistics/250753/number-of-people-in-china-by-age-group/, November 2019, [Online: accessed 20-November-2019].

[9] C. Dehua, "China's elderly population continues to rise, with 241 million now 60 or over," Available in https://gbtimes.com/chinas-elderly-population-continues-to-rise, February 2018, [Online: accessed 25-September-2019].

[10] P. Maresova, E. Javanmardi, S. Barakovic, J. B. Husic, S. Tomsone, O. Krejcar, and K. Kuca, "Consequences of chronic diseases and other limitations associated with old age – a scoping review," *BMC Public Health*, vol. 19, no. 1431, 2019.

[11] "Global Ageing," Available in https://www.ageinternational.org.uk/policy-research/statistics/global-ageing/, 2018, [Online: accessed 22-November-2018].

[12] M. Popescu, G. Chronis, R. Ohol, M. Skubic, and M. Rantz, "An eldercare electronic health record system for predictive health assessment," in *2011 IEEE 13th International Conference on e-Health Networking, Applications and Services*, June 2011, pp. 193–196.

[13] O. A. Ibrahim, J. Shao, J. M. Keller, and M. Popescu, "A temporal analysis system for early detection of health changes," in *2016 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, July 2016, pp. 186–193.

[14] L. Montanini, A. D. Campo, D. Perla, S. Spinsante, and E. Gambi, "A Footwear-Based Methodology for Fall Detection," *IEEE Sensors Journal*, vol. 18, no. 3, pp. 1233–1242, Feb 2018.

[15] Fabian Riquelme and Cristina Espinoza and Tomas Rodenas and Jean-Gabriel Minonzio and Carla Taramasco, "ehomeseniors dataset: An infrared thermal sensor dataset for automatic fall detection research," *Sensors*, vol. 19, no. 4565, October 2019.

[16] A. Benmansour, A. Bouchachia, and M. Feham, "Human activity recognition in pervasive single resident smart homes: State of art," in *2015 12th International Symposium on Programming and Systems (ISPS)*, April 2015, pp. 1–9.

[17] H. Tan and A. Zhang, "Real-world large-scale IoT systems for community eldercare: A comparative study on system dependability," in *2018 International Conference on Information Networking (ICOIN)*, Jan 2018, pp. 880–885.

[18] K. Nisar, A. A. A. Ibrahim, L. Wu, A. Adamov, and M. J. Deen, "Smart home for elderly living using Wireless Sensor Networks and an Android application," in *2016 IEEE 10th International Conference on Application of Information and Communication Technologies (AICT)*, Oct 2016, pp. 1–8.

[19] E. C. Dinarevic, J. B. Husic, and S. Barakovic, "Issues of Human Activity Recognition in Healthcare," in *2019 18th International Symposium INFOTEH-JAHORINA (INFOTEH)*, March 2019, pp. 1–6.

[20] J. A. Alvarez-García, L. M. S. Morillo, M. A. A. de La Concepción, A. Fernandez-Montes, and J. A. O. Ramirez, "Evaluating Wearable Activity Recognition and Fall Detection Systems," in *6th European Conference of the International Federation for Medical and Biological Engineering,IFMBE Proceedings*, vol. 45, 2015, pp. 653–656.

[21] C. Hsieh, C. Huang, K. Liu, W. Chu, and C. Chan, "A machine learning approach to fall detection algorithm using wearable sensor," in *2016 International Conference on Advanced Materials for Science and Engineering (ICAMSE)*, Nov 2016, pp. 707–710.

[22] S. Abbate, M. Avvenuti, P. Corsini, J. Light, and A. Vecchio, *Wireless Sensor Networks*, 1st ed. IntechOpen, December 2010, ch. Monitoring of Human Movements for Fall Detection and Activities Recognition in Elderly Care Using Wireless Sensor Network: a Survey, pp. 1–22.

[23] D. Gumaer, "Falls in the Elderly: Statistics," Available in https://www.griswoldhomecare.com/blog/falls-elderly-statistics/, June 2019, [Online: accessed 25-September-2019].

[24] "When Elderly Are Afraid to Walk," Available in https://medical-alert-systems.bestreviews.net/elderly-afraid-walk/, [Online: accessed 25-November-2019].

[25] "How to Prevent Seniors from Falling Down," Available in https://www.seniorsafetyapp.com/how-to-prevent-seniors-from-falling-down/, November 2019, [Online: accessed 25-November-2019].

[26] K. Chaccour, R. Darazi, A. H. E. Hassani, and E. Andrès, "From Fall Detection to Fall Prevention: A Generic Classification of Fall-Related Systems," *IEEE Sensors Journal*, vol. 17, no. 3, pp. 812–822, Feb 2017.

[27] T. Xu, Y. Zhou, and J. Zhu, "New Advances and Challenges of Fall Detection Systems: A survey," *Applied Science*, vol. 8(11), no. 418, p. 11, March 2018.

[28] J. Hamm, A. G.Money, A. Atwal, and I. Paraskevopoulos, "Fall prevention intervention technologies: A conceptual framework and survey of the state of the art," *Journal of Biomedical Informatics*, vol. 59, pp. 319–345, January 2016.

[29] R. Rajagopalan, I. Litvan, and T.-P. Jung, "Fall Prediction and Prevention Systems: Recent Trends, Challenges, and Future Research Directions," *Sensors*, vol. 17(11), no. 2509, p. 17, November 2017.

[30] T. R. Frieden, D. Houry, G. Baldwin, A. Dellinger, and R. Lee, "Preventing Falls: A Guide to Implementing Effective Community-Based Fall Prevention Programs," p. 64, 2015.

[31] K. Ozcan and S. Velipasalar, "Wearable Camera- and Accelerometer-Based Fall Detection on Portable Devices," *IEEE Embedded Systems Letters*, vol. 8, no. 1, pp. 6–9, March 2016.

[32] D. Micucci, M. Mobilio, and P. Napoletano, "UniMiB SHAR: A Dataset for Human Activity Recognition Using Acceleration Data from Smartphones," *Applied Sciences*, vol. 7, no. 10, 2017. [Online]. Available: http://www.mdpi.com/2076-3417/7/10/1101

[33] W. Engel and W. Ding, "Reliable and practical fall prediction using artificial neural network," in *2017 13th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD)*, July 2017, pp. 1867–1871.

[34] N. Otanasap, "Pre-Impact Fall Detection Based on Wearable Device Using Dynamic Threshold Model," in *2016 17th International Conference on Parallel and Distributed Computing, Applications and Technologies (PDCAT)*, Dec 2016, pp. 362–365.

[35] W. Saadeh, S. A. Butt, and M. A. B. Altaf, "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, pp. 995–1003, May 2019.

[36] K. Ozcan, S. Velipasalar, and P. K. Varshney, "Autonomous Fall Detection With Wearable Cameras by Using Relative Entropy Distance Measure," *IEEE Transactions on Human-Machine Systems*, vol. 47, no. 1, pp. 31–39, Feb 2017.

[37] V. George, C. Chariklei, M. Thodoris, P. Matthew, and T. Manolis, "The MobiAct Dataset: Recognition of Activities of Daily Living using Smartphones." in *International Conference on Information and Communication Technologies for Ageing Well and e-Health (ICT4AWE 2016)*, April 2016, pp. 143–151.

[38] A. Davide, G. Alessandro, O. Luca, P. Xavier, and L. R.-O. Jorge, "A Public Domain Dataset for Human Activity Recognition Using Smartphones," in *21th European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, ESANN 2013*, April 2013.

[39] R.-O. Jorge-L., O. Luca, S. Albert, P. Xavier, and A. Davide, "Transition-Aware Human Activity Recognition Using Smartphones," *Neurocomputing*, vol. 171, pp. 754–767, January 2016. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0925231215010930

[40] M. Li, G. Xu, B. He, X. Ma, and J. Xie, "Pre-Impact Fall Detection Based on a Modified Zero Moment Point Criterion Using Data From Kinect Sensors," *IEEE Sensors Journal*, vol. 18, no. 13, pp. 5522–5531, July 2018.

[41] J. Howcroft, J. Kofman, and E. D. Lemaire, "Prospective Fall-Risk Prediction Models for Older Adults Based on Wearable Sensors," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 10, pp. 1812–1820, Oct 2017.

[42] Y. Wang, K. Wu, and L. M. Ni, "WiFall: Device-Free Fall Detection by Wireless Networks," *IEEE Transactions on Mobile Computing*, vol. 16, no. 2, pp. 581–594, Feb 2017.

[43] T. R. Mauldin, M. E. Canby, V. Metsis, A. H. H. Ngu, and C. C. Rivera, "SmartFall: A Smartwatch-Based Fall Detection System Using Deep Learning," *Sensors*, vol. 18, no. 3363, October 2018.

[44] C. L. P. Chen and Z. Liu, "Broad Learning System: An Effective and Efficient Incremental Learning System Without the Need for Deep Architecture," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 29, no. 1, pp. 10–24, Jan 2018.

[45] M. Alwan, "Fall Prevention and Detection: How Can Technology Help," 2007.

[46] A. Danielsen, H. Olofsen, and B. A. Bremdal, "Fall prevention intervention technologies: A conceptual framework and survey of the state of the art," *Journal of Biomedical Informatics*, vol. 63, pp. 184–194, August 2016.

[47] L. Kau and C. Chen, "A Smart Phone-Based Pocket Fall Accident Detection, Positioning, and Rescue System," *IEEE Journal of Biomedical and Health Informatics*, vol. 19, no. 1, pp. 44–56, Jan 2015.

[48] H. Cheng, J. Zhang, Y. Gao, and X. Hei, "Deep Learning Wi-Fi Channel State Information for Fall Detection," in *IEEE INTERNATIONAL CONFERENCE ON CONSUMER ELECTRONICS - TAIWAN (IEEE 2019 ICCE-TW)*, May 2019.

[49] H. Sadreazami, M. Bolic, and S. Rajan, "On the Use of Ultra Wideband Radar and Stacked LSTM-RNN

for at Home Fall Detection," in *2018 IEEE Life Sciences Conference (LSC)*, Oct 2018, pp. 255–258.

[50] J. Ren, D. Zhang, S. He, Y. Zhang, and T. Li, "A Survey on End-Edge-Cloud Orchestrated Network Computing Paradigms: Transparent Computing, Mobile Edge Computing, Fog Computing, and Cloudlet," *ACM Comput. Surv.*, vol. 52, no. 6, pp. 125:1–125:36, Oct. 2019. [Online]. Available: http://doi.acm.org/10.1145/3362031

[51] P. Mell and T. Grance, "The NIST Definition of Cloud Computing," Available in https://csrc.nist.gov/publications/detail/sp/800-145/final, Setember 2011, [Online: accessed 25-November-2019].

[52] L. Wang, J. Yan, and Y. Ma, *Cloud Computing in Remote Sensing*, 1st ed. CRC press, June 2019, ch. Remote Sensing and Cloud Computing, pp. 1–14.

[53] W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, "Edge Computing: Vision and Challenges," *IEEE Internet of Things Journal*, vol. 3, no. 5, pp. 637–646, Oct 2016.

[54] M. De Donno, K. Tange, and N. Dragoni, "Foundations and Evolution of Modern Computing Paradigms: Cloud, IoT, Edge, and Fog," *IEEE Access*, vol. 7, pp. 150 936–150 948, 2019.

[55] P. Mach and Z. Becvar, "Mobile Edge Computing: A Survey on Architecture and Computation Offloading," *IEEE Communications Surveys Tutorials*, vol. 19, no. 3, pp. 1628–1656, thirdquarter 2017.

[56] R. Romana, J. Lopeza, and M. Mambo, "Mobile edge computing, Fog et al.: A survey and analysis of security threats and challenges," *Future Generation Computer Systems*, vol. 78, no. 2, pp. 680–698, January 2018.

[57] S. Oueida, Y. Kotb, M. Aloqaily, Y. Jararweh, and T. Baker, "An Edge Computing Based Smart Healthcare Framework for Resource Management," *Sensors (Basel)*, vol. 18(12), no. 4307, pp. 680–698, December 2018.

[58] N. Abbas, Y. Zhang, A. Taherkordi, and T. Skeie, "Mobile Edge Computing: A Survey," *IEEE Internet of Things Journal*, vol. 5, no. 1, pp. 450–465, Feb 2018.

[59] Y. Zhang, M. Qiu, C. Tsai, M. M. Hassan, and A. Alamri, "Health-CPS: Healthcare Cyber-Physical System Assisted by Cloud and Big Data," *IEEE Systems Journal*, vol. 11, no. 1, pp. 88–95, March 2017.

[60] K. M. Shahiduzzaman, X. Hei, C. Guo, and W. Cheng, "Enhancing Fall Detection for Elderly with Smart Helmet in a Cloud-Network-Edge Architecture," in *IEEE INTERNATIONAL CONFERENCE ON CONSUMER ELECTRONICS - TAIWAN (IEEE 2019 ICCE-TW)*, May 2019.

[61] K. M. Shahiduzzaman, J. Peng, Y. Gao, X. Hei, and W. Cheng, "Towards Accurate and Robust Fall Detection for the Elderly in a Hybrid Cloud-Edge Architecture," in *The 5th IEEE Smart World Congress (SmartWorld 2019)*, August 2019.

[62] H. Bangui, S. Rakrak, S. Raghay, and B. Buhnova, "Moving towards Smart Cities: A Selection of Middleware for Fog-to-Cloud Services," *Applied Science*, vol. 8(11), no. 2220, p. 20, November 2018.

[63] J. Chen and X. Ran, "Deep Learning With Edge Computing: A Review," *Proceedings of the IEEE*, vol. 107, no. 8, pp. 1655–1674, Aug 2019.

[64] S. Liu, L. Guo, H. Webb, X. Ya, and X. Chang, "Internet of Things Monitoring System of Modern Eco-Agriculture Based on Cloud Computing," *IEEE Access*, vol. 7, pp. 37 050–37 058, 2019.

[65] P. Silapasuphakornwong and K. Sookhanaphibarn, "A conceptual framework for an elder-supported smart home," in *2017 IEEE 6th Global Conference on Consumer Electronics (GCCE)*, Oct 2017, pp. 1–5.

[66] X. Ma, Y. Zhao, L. Zhang, H. Wang, and L. Peng, "When mobile terminals meet the cloud: computation offloading as the bridge," *IEEE Network*, vol. 27, no. 5, pp. 28–33, Sep. 2013.

[67] F. Wei, S. Chen, and W. Zou, "A greedy algorithm for task offloading in mobile edge computing system,"

China Communications, vol. 15, no. 11, pp. 149–157, Nov 2018.

[68] X. Wang, X. Wei, and L. Wang, "A deep learning based energy-efficient computational offloading method in Internet of vehicles," *China Communications*, vol. 16, no. 3, pp. 81–91, March 2019.

[69] H. Jeong, "Lightweight Offloading System for Mobile Edge Computing," in *2019 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*, March 2019, pp. 451–452.

[70] C. Li, L. Toni, J. Zou, H. Xiong, and P. Frossard, "QoE-Driven Mobile Edge Caching Placement for Adaptive Video Streaming," *IEEE Transactions on Multimedia*, vol. 20, no. 4, pp. 965–984, April 2018.

[71] C. Zhang, H. Pang, J. Liu, S. Tang, R. Zhang, D. Wang, and L. Sun, "Toward Edge-Assisted Video Content Intelligent Caching With Long Short-Term Memory Learning," *IEEE Access*, vol. 7, pp. 152 832–152 846, 2019.

[72] R. Mahmud, R. Vallakati, A. Mukherjee, P. Ranganathan, and A. Nejadpak, "A survey on smart grid metering infrastructures: Threats and solutions," in *2015 IEEE International Conference on Electro/Information Technology (EIT)*, May 2015, pp. 386–391.

[73] J. Yao, Z. Li, Y. Li, J. Bai, J. Wang, and P. Lin, "Cost-Efficient Tasks Scheduling for Smart Grid Communication Network with Edge Computing System," in *2019 15th International Wireless Communications Mobile Computing Conference (IWCMC)*, June 2019, pp. 272–277.

[74] K. Gai, Y. Wu, L. Zhu, L. Xu, and Y. Zhang, "Permissioned Blockchain and Edge Computing Empowered Privacy-Preserving Smart Grid Networks," *IEEE Internet of Things Journal*, vol. 6, no. 5, pp. 7992–8004, Oct 2019.

[75] S. Chen, H. Wen, J. Wu, W. Lei, W. Hou, W. Liu, A. Xu, and Y. Jiang, "Internet of Things Based Smart Grids Supported by Intelligent Edge Computing," *IEEE Access*, vol. 7, pp. 74 089–74 102, 2019.

[76] A. Hoffmann and R. Möller, "Cloud-Edge Suppression for Visual Outdoor Navigation," *Robotics*, vol. 6(4), no. 38, p. 23, December 2017.

[77] J. Santa, P. J. Fernández, R. Sanchez-Iborra, J. Ortiz, and A. F. Skarmeta, "Offloading Positioning onto Network Edge," *Wireless Communications and Mobile Computing*, vol. 2018, no. 7868796, p. 13, December 2018.

[78] S. K. Sharma and X. Wang, "Live Data Analytics With Collaborative Edge and Cloud Processing in Wireless IoT Networks," *IEEE Access*, vol. 5, pp. 4621–4635, 2017.

[79] S. Manzoor, X. Hei, and W. Cheng, "Towards Dynamic Two-tier Load Balancing for Software Defined WiFi Networks," in *Proceedings of the 2017 2Nd International Conference on Communication and Information Systems*, ser. ICCIS 2017. New York, NY, USA: ACM, 2017, pp. 63–67. [Online]. Available: http://doi.acm.org/10.1145/3158233.3159351

[80] E. El Haber, T. M. Nguyen, and C. Assi, "Joint Optimization of Computational Cost and Devices Energy for Task Offloading in Multi-Tier Edge-Clouds," *IEEE Transactions on Communications*, vol. 67, no. 5, pp. 3407–3421, May 2019.

[81] K. M. Shahiduzzaman and M. S. Uddin Yusuf, "Generating a visual-inertial odometry dataset based on a helmet prototype for recognizing human activities," in *2022 International Conference on Advancement in Electrical and Electronic Engineering (ICAEEE)*, 2022, pp. 1–6.

[82] ——, "Performance enhancement of human activity recognition and fall related system using multimodal broad learning system (mbls)," in *2022 Third International Conference on Advances in Physical Sciences and Materials (ICAPSM)*, 2022.

[83] ——, "Edgefall: A promising cloud-edge-end architecture for elderly fall care," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 13, no. 4, pp. 4721–4733, August 2023.

Researcher Seal and Signature ______________________

Date: