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EdgeFall: a promising cloud-edge-end architecture for elderly fall care

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ABSTRACT

Elder citizens face sudden fall, which can lead to injuries of both destructive and non-virulent. These sudden falls are later more precarious than diseases like heart attack, blood sugar, blood pressure because these can be untreated for a lengthy time which can lead to death. Elder citizen who experiences a precipitous fall, carry out their communal life narrowed. Therefore, a shrewd and adequate anti-fallen system is required for aiding elderly health care, specifically to those who live individually. So, it can identify and anticipate a precipitous fall through appropriate human activity recognition. In this study, we have suggested an end-edge-cloud based wearable EdgeFall architecture for elderly care. We have performed simulation setups to clarify the query of why we need such a strategy, and its validity. We have achieved maximum 91.87% accuracy with 1.6% false alarm rate (FAR). These empirical results indicate the superiority of using tightly couple multiple information for recognizing human activity. We can accomplish a low FAR with an enhanced accuracy. We can observe that our proposed end-edge-cloud based architecture can reduce the execution time to millisecond range (ms) of 14.16 to 15.74. This work serves as the starting mark for future related research activities.

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1. INTRODUCTION

Any abnormality in everyday human activity brings an unusual fall. An adequate routine human activity recognition can identify, anticipate and inhibit many diseases. Walking, running (jogging), jumping, walking stairs, sitting, standing, and laying are closely related to elderly fall-related service [1]–[3]. Besides, human activity recognition is an elemental part of most explorations concerned to fall detection and prediction [3]. That is why we choose to lead our investigation with human activity recognition from the context of fall detection and prediction.

We can express the interpretation of fall as the sudden change of state from a higher post ion like standing to a lower position like laying or sitting [4]. People over 65 years of age are at significant risk of falling, corresponding to many published articles. A survey from the World Health Organization (WHO) shows that there are around 650 thousand injuries occur that are linked to falls every year [1], [5]–[7]. These falls induce curable or incurable injuries from flesh cramping, fractured extremities, posterior damage, and brain injury to life expiry. Every inmate has to put in an abundance of payment in medicine, therapy, and treatment [4], [8]–[10]. The after-effects of falls are likewise severe as they lead to falls, depression, restraint of regular living movements, fewer personal tasks, and poorer conditions of life, specifically for independent elderly citizens [8]. A surprisingly striking factor is the aged populations will explode in the upcoming 20 years [11]. A survey was done on people equal to and over 65 years to answer the requirement of a fall-related service in [12]. The number of participants was 125. The analysis shows that falling on the floor for more than an hour leads to death within a six months period [12]. Over eight hundred thousand old individuals, 65 years or above, are using medical alert systems like MobileHelp, Bay alarm medical, LifeFone, Philips Lifeline, and QMedic, with the lowest cost of USD 19.99 [13]. These services offer wearable or mobile devices to bring mobility to the users. Besides the subscription fees, these devices still require user aid for pressing the SOS button during an accident. This is the communal demand to promote a dynamic solution that can predict and detect a precipitous fall. We crave to build up such a structure that can be self-employed in a necessary and affordable.

Now, we recommend the interpretation of a wearable smart anti-fall from the point of its performance and the opportunity of fitting into the smart environment. We can suggest the definition as a wearable device capable of predicting and detecting an abrupt fall. For example, the system designed and developed in [14] which can detect and predict a sudden fall while Mauldin *et al.* [15], Naihan *et al.* [16], [17] illustrate the opportunity of enforcing end-edge-cloud approach for fall detection. So, we should develop the architecture with various sensors like wearable cameras, accelerometers, gyroscopes, global positioning system (GPS), and alarms. The functions of such architecture should not restrict to predicting and detecting falls but continuing the auxiliary functions like position detection and sending alarms and messages to the involved parties. Comfortable to carry, small battery utilization and significant reliability are the elementary properties of such a system. Any wearable platform like spectacles on the eyes, helmet on the head, and gear around the waist can build up an anti-fall system. This system should be transparent to fuse with a smart environment like smart health care and smart home system [18], [19]. This intelligent system can be an integral part of information and communications technology (ICT)-based healthcare solutions for elderly people in the smart home concept similar to [20]. It is significant to define two more terms which are:

- Fall prediction: A process that forecasts a sudden fall and tries to restrain it. It provides a clue to the user about an abrupt fall in progress so that the user can become alert and escape the fall for further emotional and health consequences.
- Fall detection: A process that identifies a fall and gives alarms to the corresponding third parties. The third parties include the relative of the sufferers, caretakers and near medical amenities so that the effect of falls can be diminished and the medication can be set up as promptly as possible.

So, a robust prediction process is required before falling down, and a detection process is after a fall occurs. In [7], the authors reviewed sensors, algorithms, and performance on the 20 most authoritative and often cited papers among 6,830 papers with keywords linked to falling detection. The report reveals that an accelerometer is usually employed for data collection, machine learning-based algorithms have become mainstream in this area, and accuracy is the key performance evaluation factor. There is a positive suggestion of applying camera and accelerometer for data collection i,e, data fusion. This study shows nothing about the impact of false alarm rate (FAR) on fall detection or prediction. While the review on fall detection in [21], we see that wearable-based development is more suitable for real-world implementation. Researches like Saadeh *et al.* [14], Mualdin *et al.* [15], Rachakonda *et al.* [17], Ozcan *et al.* [22], Micucci *et al.* [23], George *et al.* [24], Davide *et al.* [25], Reyes-Ortiz *et al.* [26], Li *et al.* [27], Howcroft [28], Engel and Ding [29], Wang *et al.* [30], and others have developed fall detection systems with a wearable camera, kinit camera sensors, accelerometer, gyroscope, internal measurement unit (IMU), Wi-Fi system with either machine-learning interfaced or simply threshold-based techniques. Almost all instances apply experimental setup to classify a binary type grouping, i,e, defining fall or not fall. Classical machine learning techniques like support vector machine (SVM), k- neighbor nearest (k-NN), and artificial neural network (ANN), are not up to the level for defining different human activities of daily living (ADL) [23]. We have noticed that threshold-based algorithms can lead to a false alarm in recognizing multiclass human activity through our own empirical results [31]. In the case of fall prediction, a few researches like Li *et al.* [27], Engel and Ding [29], Otanasap [32], Tong *et al.* [33] have developed methods using wearable and ambient devices with both dynamic threshold and machine learning techniques. These algorithms can maintain adequate lead time to the users before falling down so they can be aware. Therefore the algorithms developed strategies for such kind of employment should recognize human activities to separate them from falls.

One of the dominant concerns regarding these developments is the on-chip or on-board system, which have defined power sources and computational capacity. It is worthwhile to investigate end-edge-cloud-based architecture for prediction. Because this architecture can hold larger and perpetual power sources and computational capacity. Therefore, our technical interest in this work is to reinforce the accuracy, lower the FAR, and raise the performance of the classification network so it can realize different human activities, lower latency in classifying tasks, less power utilization, and adequate lead time prediction. In this paper, we are mainly focusing on the classification process. We crave to estimate the usefulness of end-edge-cloud architecture using data fusion and modern machine learning approaches in ADLs recognition. Because this recognition is the initial stride toward fall detection and prediction. Thus, we propose EdgeFall, an end-edge-cloud-based architecture where different data sources are fused, and a recurrent neural network (RNN) approach will analyze human activity. We have set up our simulation through four datasets which are UniMIB SHAR [23], MobiAct [24], UCI HAR [25] and HAPT [26] for demonstrating the potency of data fusion in human activity recognition (summary is given in Table 1). We can reproduce various daily activities of a group of volunteers with these datasets. We have further studied the classic machine learning-based activity recognition model with recurrent neural network (RNN) based model on these datasets. The performance evaluating metrics will help us design human activity relevant to the real world.

Table 1. Characteristics of considered public datasets

Dataset	UniMIB SHAR [23]	MobiAct [24]	UCI HAR [25]	HAPT [26]
Size of original data	255 MB	1.24 GB	241 MB	7.54 KB
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
Device 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 (the number of female and male is) not specified)	17 (the 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
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

These results likewise indicate how adequately EdgeFall architecture can analyze different human activities. We observe from the assessment that the model developed by ActDec-SysOpt outperforms classical-based recognition models. So, our significant contributions are:

– Designing and resembling the end-edge-cloud-based EdgeFall architecture to figure out the usefulness in human activity detection.

– Spot the challenges like FAR, accuracy, precision, and recall in loosely coupled data fusion for recognizing human activities.
– Performance improvement in classifying and realizing human daily activity through tightly coupled multiple information sources and ActDec-SysOpt algorithm.

The remaining paper dwells on four more sections. The next section will present the proposed EdgeFall paradigm for activity recognition. Algorithms used for this application are depicted in section 4 with respective flowcharts. The EdgeFall is simulated using the ActDec-SysOpt algorithm for human activity detection and described there. Then, the empirical setups for evaluating EdgeFall architecture with data fusion are analyzed in section 5. The performance evaluating metrics are also enlisted in this section. Research findings and highlights on prospective research directions are mentioned in the conclusion.

2. EdgeFall: THE PROPOSED ARCHITECTURE

The proposed EdgeFall system is a three-tiered system as depicted in Figure 1 which are the artificial intelligence (AI)-aware medical cloud for model development, the mobile edge for human activity recognition, user identification, fall detection, prediction, and the body area network (BAN) for smart sensing and command execution. The proposed architecture makes the fall detection and prediction system into three distributed subsystems connected to each other by the wireless network. We expect this architecture to be efficient regarding computational capacity and energy management. BAN is indeed a platform consists sensors like wearable cameras, gyroscopes, accelerometers, GPS sensors, and other related sensors and is pictured as a wearable glass, but we can accept any platform like a watch, wearable around the waist, helmet on the head, smartphone on the pocket or similar. This layer performs data collection, feature extraction, communication to the edge node, and decision execution. The mobile edge layer consists of a rational edge node and contrasting processing units. 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. The last tier is the cloud, the intellect of this technique. Deep learning, special machine learning approach, and human intervention (HI) are used to implement this tier. It develops a user identification model and activity classification model. It should update the mobile edge node with updated reformed system parameters in a frequent cycle. This architecture can again refer to diverse areas related to health care.

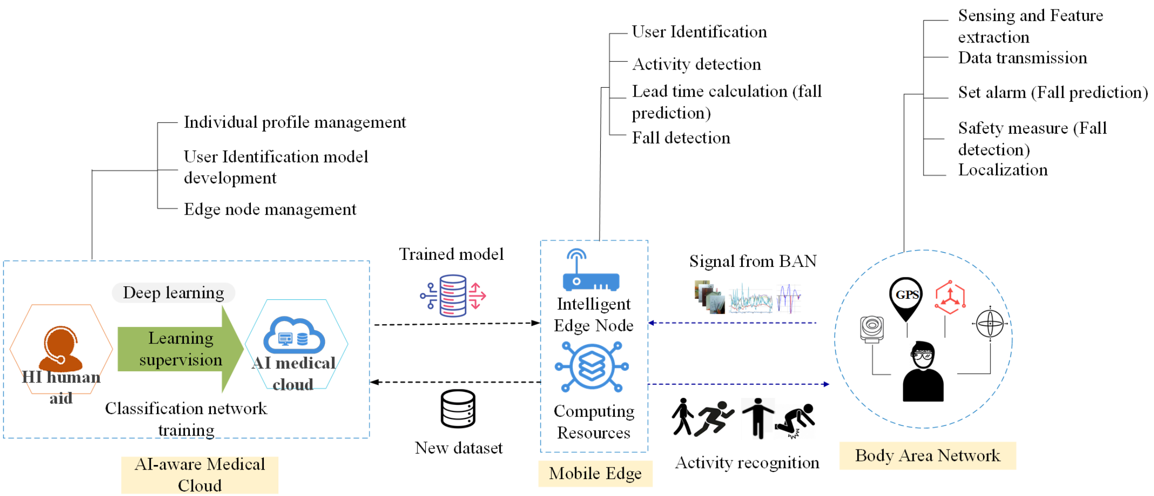


Figure 1. Proposed architecture of EdgeFall architecture

In this script, we will present the essence of this recommended architecture by breaking up the computational capacity among mobile edge nodes and the cloud. Here, we have simply focused on various human activity recognition. Because it will contribute to strong fall detection and prediction.

3. PROPOPSED ALGORITHM

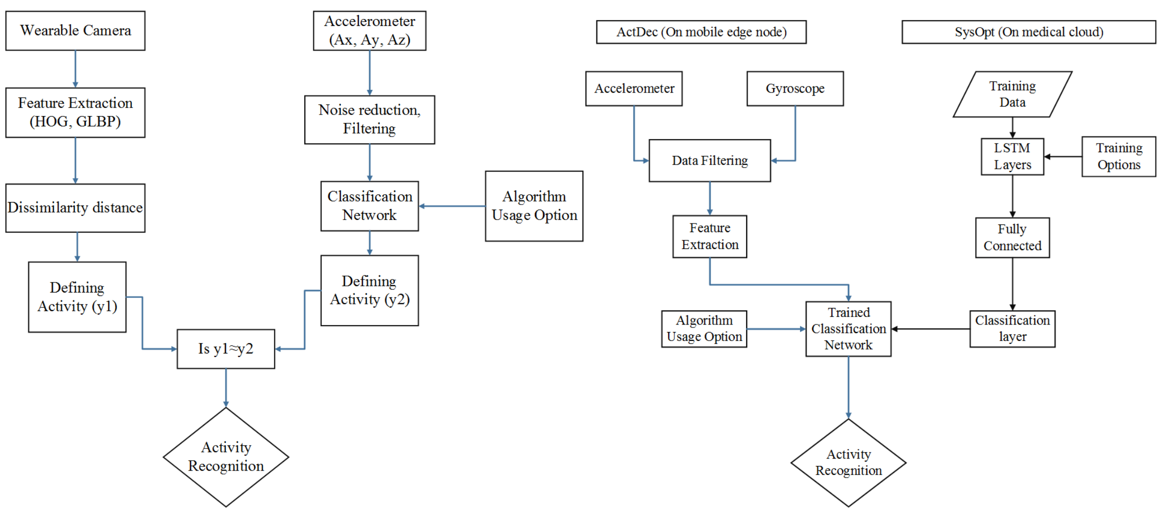
This section will discuss the methodologies named FuseFall and ActDec-SysOpt algorithm. These two approaches will demonstrate the validity of data fusion, cloud-edge-end type architecture, and the classification algorithm based on recurrent neural networks. This section will help the readers to visualize the approaches used in this paper.

3.1. FuseFall algorithm

Fall detection takes advantage of two sources (a wearable camera and a tri-axial accelerometer) of information. Two different sources detect human activity and fall separately. The block diagram in Figure 2(a) explains the FuseFall algorithm. In this algorithm, the information sources are loosely coupled and analyzed separately. We can observe that both sources use a different suitable algorithm to define the same activity separately and compare it to the final decision from the block diagram, as shown in Figure 2(a). This algorithm is explained in [31]. Two separate processes are used for two data types to reduce the complexity. Both processes run simultaneously but on two different platforms. We assume that the resource required to analyze inertia sensors data is lesser than image processing. So, the inertia sensor's data processing process will run in the edge node, while image processing will occur in the cloud. An optimization algorithm will be necessary to enhance the efficiency of the system. In the detection phase, inertia data will be analyzed to detect a fall using SVM machine learning technique. The reason behind using SVM technique is to perform binary classification between AD and fall. A signal window of 3 seconds is considered to determine an event. In the case of 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 verify the fall event determined in the detection phase. The overall fall detection algorithm is shown in algorithm 1. Finally, another process will be used to optimize the system presented in algorithm 2. This process automatically selects the optimal trained model and system parameters to overwrite the old network.

3.2. ActDec-SysOpt algorithm

Figure 2(b) displays the block diagram of ActDec-SysOpt. We train the classification model with long short term memory network (LSTM). This algorithm includes two parts. We adopt ActDec to recognize the human activity, whereas SysOpt is for training classification networks. These two parts also depict mobile edge nodes and medical cloud appropriately. We explain the details in [34].



(a) (b)

Figure 2. Block diagram of proposed algorithms (a) block diagram of FuseFall algorithm for fall detection and (b) simple block diagram of ActDec-SysOpt algorithm

Now the information sources are tightly coupled. This algorithm represents a centralized trained model of human activity recognition for all users. SysOpt generates the trained classification model (ActDec) on the cloud server and pushes it to the edge server. A multivariate time series signal is fed to the bi-directional LSTM. A signal window of 1.5 seconds is used here. A softmax layer matches the best probability fit for a certain human activity. With a fully connected network, each human activity model is trained in the cloud layer. The point should be mentioned that the SysOpt algorithm optimizes the parameters like learning rate, epoch, and number of layers. According to the incoming data and the patient's nature of performing the activities. This trained network is then passed to the edge layer, where the incoming pre-processed raw data from the edge layer will be analyzed to determine the particular activities and types of falls. The overall activity detection algorithm is shown in algorithm 3. Finally, another algorithm will be used to initialize and optimize the system presented in algorithm 4. The test data will be labelled 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. The fall detection and verification algorithm runs in an intelligent access point, whereas the optimization algorithm and process data will be stored in the cloud.

Algorithm 1: Detection process of FuseFall algorithm

```
Detection Phase
Data: Inertia Sensor's Data
Result: Detection of an activity
Load SVM 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
        end
    end
end
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 feature I(dissimilarity)
    if I(dissimilarity) ~ Fall then
        Fall verified
    else
        Consider as ADL
    end
end
```

Algorithm 2: FuseFall optimization process

```
Data: Test Data
Result: Optimization of the System
begin
    Test data ⟶ Training Data
    Evaluate Both trained model
    if Result_New > Result_Old then
        Pass Para_new to Detection process
        Modify Both Phase
    else
        Keep previous State
        Remove Test data
    end
end
```

Algorithm 3: ActDect algorithm

Data: Inertia sensor's data
Result: Event Detection
Load Trained LSTM Classification Model
initialization
while *Unless detecting an event* **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
    end
  end
end

Algorithm 4: SysOpt algorithm

Data: Test Data
Result: Optimization of detection system
begin
  Test data $\longrightarrow$ Training Data
  Run LSTM with $TrainingData_{New}$
  if $Validation_{New} > Validation_{Old}$ **then**
    Modify Classification Network
    Pass $Para_{new}$ to Event Detection Algorithm
  else
    Keep previous State
    Remove Test data
  end
end

4. EVALUATION

This section presents our experiments and results using FuseFall and ActDec-SysFall architecture. The findings will justify our claims outlined in 1. First, the performance evaluating metrics will be deliberated, and results and findings from studied algorithms will be later.

4.1. Metrics

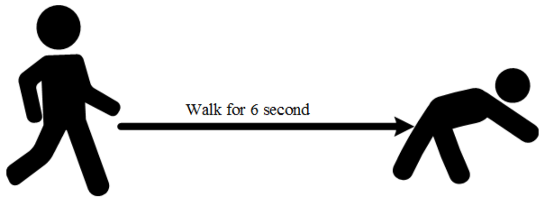
Accuracy, recall, precision, F1-score, FAR, training time, and execution time are the performance evaluation metrics. The definitions are given below:
– Accuracy is stated precisely the percentage of correctly detected activities from the tested one.
– Recall is interpreted as the percentage of proper activities that are exactly verified. It provides information about the accuracy row-wise of the confusion matrix.
– Precision is elucidating as the segment of equitable classified activities i,e, accuracy along column wise of the confusion matrix.
– F1 score is the harmonic mean of precision and recall, which measures the accuracy of the test.
– False alarm rate (FAR) acquaints with how the system gets confused between any activity and other considered activities.
– Training-time is the time required by the cloud to generate a global classification network with the proposed algorithm.
– Execution time is the time the global classifier recognizes human activities at the mobile edge node.

4.2. Experiments with FuseFall

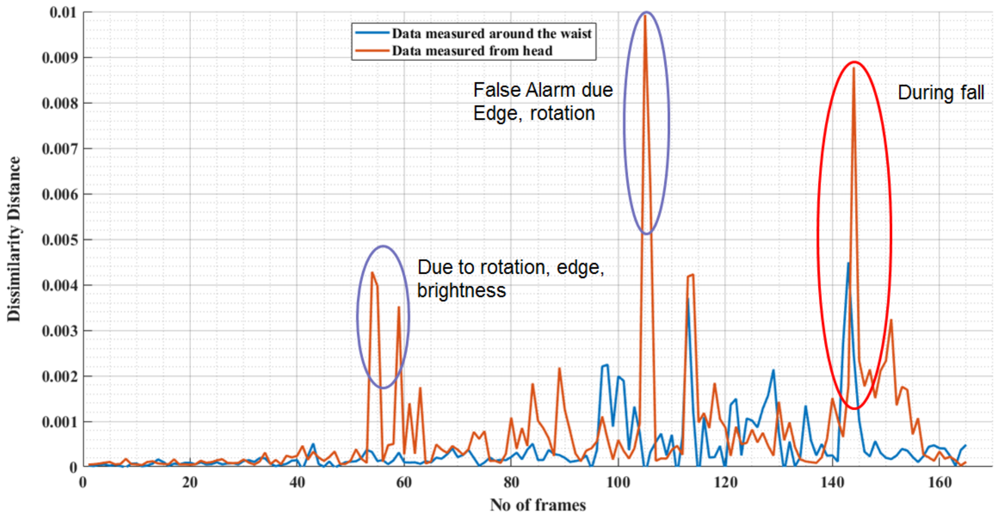
We have simulated and tested loosely coupled two different data in this experiment. The results are generated by the wearable camera $y1$ and the raw accelerometer data $y2$ separately at this stage, as shown in Figure 3(a). This experiment demonstrates the real-life daily human activities and falls related to elderly people.

4.2.1. Experimental setup and results

Figure 3(a) presents the simulation scheme. A forward fall will take place from the walking position. We present the details about how to evaluate it in [31]. We calculate the accuracy, precision, recall, F1-score, and execution time of $y2$ from 4.1. We consider the k-NN method for comparison. The results are presented in Table 2. We have utilized the frontal camera of Xiaomi S2 around the head height to perform the same activities by taking video, similarly to [34]. As illustrated in Figure 3(b), the dissimilarity distance for the video frames during the fall is considerably larger than other frames, marked by two red circles. From the binary classification between falls and daily human activity, we can determine the effectiveness of FuseFall. Nevertheless, the challenge persists in performing this FuseFall with multi-class classification to recognize the daily human activity. Please point out to [34] what we mean by multi-class activity. Table 3 gives the performance of the FuseFall algorithm for accelerometer data with k-NN. During video processing, we have observed high picks like Figure 3(b), which can cause fall alarms. Table 3 and Figure 3(b) show that a loosely coupled information source with the FuseFall algorithm is unsuitable for multi-class activity detection. That is why we hold our experiments with $y1$ and $y2$. Besides, the time involved in generating results with video processing is large in our experiments. The challenges ascribed to the multi-class activity classification are managed more accurately by the ActDec-SysOpt algorithm [34], which will be demonstrated in the next part.



(a)



(b)

Figure 3. Experimental outcome of FuseFall (a) experimental setup to evaluate FuseFall algorithm and (b) FAR during multiclass activity detection with FuseFall (video processing part)

Table 2. 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
FAR	0.033	0.10
Execution time (sec)	2.282	1.043

Table 3. 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

4.3. Experiments with ActDec-SysOpt

As we have previously noticed, that single source of information and classical machine learning-based models are not up to the adequate standard for realizing different human activities. Here we will adopt ActDec-SysOpt [34] algorithm and data fusion technique to justify some remarkable objectives, i) demand of proposed EdgeFall as shown in Figure 1, ii) the performance of multiple sources, use of features and LSTM, and iii) the prerequisite of tight coupling.

4.3.1. Experimental setup

For the experimental setup we have utilized four original data sources, named, UniMIB SHAR [23], MobiAct [24], UCI HAR [25] and HAPT [26] to simulate BAN of the EdgeFall. These sources consist of diverse human activities for several volunteers. We have transformed the original datasets in such a manner that it mirrors the BAN of the proposed architecture which relays data to the edge node regularly in time windows. The preliminary results will confirm the potency of tightly coupled data fusion. ActDec represents the mobile edge node while SysOpt is for the medical cloud. Here, we want to assess how dramatically this algorithm can recognize different human activities i,e, the classification process.

4.3.2. Results

First, we will present the operation of EdgeFall through ActDec-SysOpt algorithm. The supporting chart (Table 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 indicate that ActDec-SysOpt outperforms the other two machines learning-based classification models (where one of them is FuseFall). Accordingly, we will weigh the performance of ActDec-SysOpt on different datasets. These different datasets represent BAN of the recommended EdgeFall architecture (i,e, several users with unfamiliar weights, heights, ages, and gender).

Table 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

To conduct the simulation further sensibly, we have considered a 50-50 approach for training and test data to appraise the validity of data fusion. Figure 4 displays the simulation results and reveals that data fusion from numerous sources with proposed ActDec-SysOpt have stronger achievement than information from a single source and loosely coupled multiple information sources. We can observe that feature extraction can develop a far better result than raw data fusion. The accuracy of raw data fusion is remarkably unsatisfactory around 59.65% with a considerable FAR 10.66%. Whereas the feature extraction (tightly coupled) from multiple information sources forms a sharp accuracy of 92.01% with FAR of 1.69%.

We present the expected training time and classification execution time in Table 5. The time of training classification network and execution time to realize an activity is higher for tightly coupled multiple information sources. As we have divided the classification model development and execution process into cloud and edge, the execution time may not be a perturbing factor. This time can be boosted by adopting a hardware/software co-design concept.

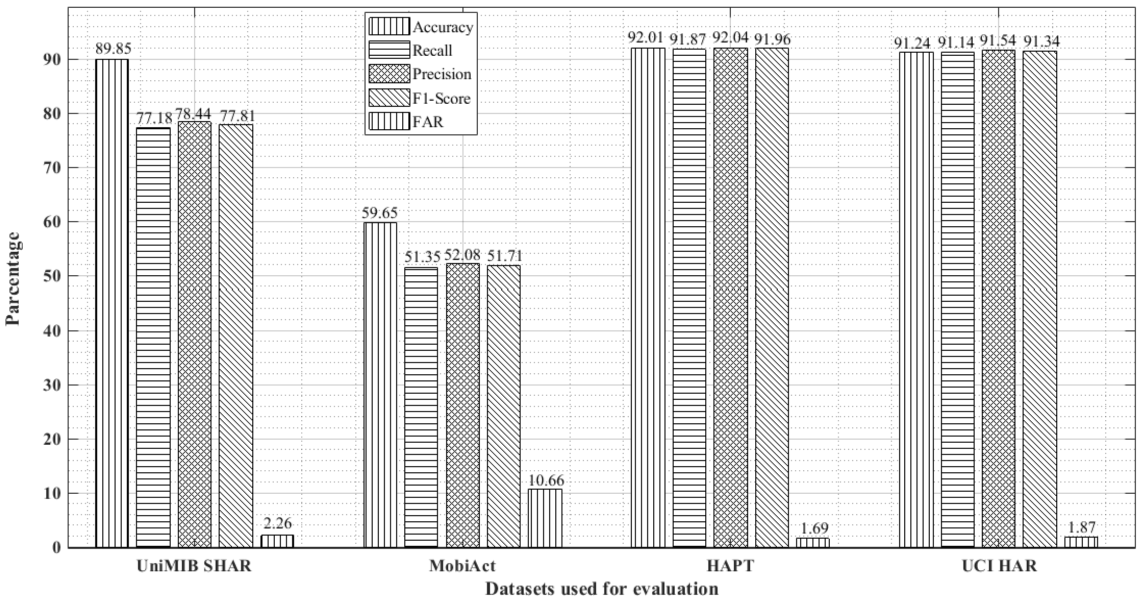


Figure 4. Advantages of data fusion from multiple information sources

From Tables 4 and 5, Figure 4 we come up with the following decisions:

- Tightly coupled information sources with an LSTM-based classification model are more adequate. The accuracy is around 92% with FAR being 1.6%. The high value of recall, precision, and F1-score confirm that the classification model is competent in recognizing human activity precisely.
- The execution time compelled to recognize activity from one window of information is noticeably less, around 15 ms with data fusion from multiple sources (check execution time of Table 4.
- RNN type machine learning-based algorithms are better applicable to recognizing human daily activities.
- Features are better reasonable as they can decrease the FAR. 1.69% with HAPT and 1.87% with UCI HAR.
- However, we can learn that training the classification model requires a lot of time, 1,094 minutes for HAPT and 691 minutes for UCI HAR. Medical cloud is good enough to deal with the training process because there are no issues with the computational capability and cache.
- The train network later can be passed to the edge node which can execute activity recognition.
- Data collection and feature extraction can be managed conveniently in BAN.

Table 5. Effectiveness of EdgeFall architecture in computation

Methods	UniMIB SHAR	Mobi Act	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

So far, ActDec-SysOpt is a definite stride toward fall prediction and detection using EdgeFall. Nevertheless, there are some challenges that need to figure out. For example, accuracy, FAR, a simple algorithm for fall prediction and detection, and user identification. Though, we are a little behind in accomplishing the coveted accuracy of over 95%.

5. CONCLUSION

In this study, we have recommended a cloud-edge-end architecture, EdgeFall, which can distribute the full function of a single board structure to three tiers. A particular contribution of this script is that we can uphold our claims through proper simulation results. We have sought to figure out challenges related to establishing this system through appropriate experimental results. The ActDec-SysOpt algorithm represents not only the EdgeFall architecture but also validates the potency of such architecture. The ActDec-SysOpt algorithm also opens up the opportunity for exploiting data fusion for this system for further enhancements in a term of accuracy and FAR for human activity recognition. We are able to obtain 92% accuracy while lowering the FAR to 1.69%. Therefore, this EdgeFall architecture can be regarded as being beneficial for reducing computational capacity and power utilization on BAN, reinforcing the classification performance by specific recognition of an activity. This architecture can also be useful in the management of mobile edge nodes, user-profile management (patient-specific), and quality of service (QoS) which are our future research directions. A suitable single algorithm requires to promote which can predict and detect falls. Visual inertial odometry-based algorithms may have the capacity because they can produce trajectory. User identification is another issue that opens a possible research trend. We can develop a modern machine learning-based algorithm to solve it with privacy protection measures. Another prospective future task for the smart anti-fall system is to build up a secure, reliable, low latency-based network. Software-defined network (SDN) can be the most practical solution for not only meeting the QoS requirements but also providing security to the network. Speeding up the execution time is another demand in implementing this EdgeFall architecture into a prototype device. Hardware-software co-design approach can overcome this challenge. This paper not only reviews but also evaluates different approaches toward developing smart anti-fall systems. Concepts, algorithms, experimental setups, results and decisions, provide comprehensive guidance for deeper investigation, particularly in this emerging area.

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