uActivity: A User-Specific Human Activity Recognition and Fall Detection for Elderly Care

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ABSTRACT

Falls are a major concern among the elderly, as they can cause serious injuries and even death. Therefore, the development of an effective and reliable fall detection system for the elderly is a critical area of research that can significantly improve their safety and quality of life. This paper presents a user-centric Human Activity Recognition (uHAR) model that integrates machine learning algorithms and advanced sensor technology to analyze and classify the various activities and movements. The proposed model, called uActivity, aims to significantly improve the safety and well-being of elderly people, using a uHAR model that integrates multiple sensor data streams and machine learning algorithms. In the performance analysis of daily activity and fall classification, the uActivity algorithm demonstrates satisfactory results in accurately classifying activities and detecting falls among elderly individuals, achieving an accuracy of more than 99% in detecting falls. The proposed uHAR architecture with the uActivity algorithm can significantly improve the accuracy and reliability of fall detection and daily activity classification systems for elderly people.

Keywords-human activity recognition; machine learning; LSTM; user-centric model; fall detection

I. INTRODUCTION

Falls are a significant health concern among the elderly, as they can cause severe injuries and even death [1]. Falls can lead to decreased mobility and independence, reducing quality of life [2]. For this reason, there is growing interest in developing systems to automatically detect falls and alert caregivers or emergency services [3]. However, developing an effective fall detection system for the elderly poses several challenges [4]. One of the main challenges is distinguishing between actual falls and other activities that can generate similar sensor data, such as abrupt sitting or dropping an object [5]. Another challenge is to ensure that the fall detection system is reliable and accurate in detecting falls while minimizing false alarms [6]. One promising approach is to use machine learning algorithms, such as neural networks or support vector machines, to analyze sensor data and identify fall-related patterns. These algorithms can be trained on large datasets of annotated sensor data to learn the distinguishing features between fall and non-fall events [7]. In general, developing an effective and reliable fall detection system for the elderly is a critical area of research that can have significant implications for improving their safety and quality of life.

Human Activity Recognition (HAR) uses built-in smartphone or smartwatch sensors and has shown promising results in detecting falls with high accuracy [8, 9]. Incorporating machine learning techniques on smartphones can significantly reduce the need for external hardware and thus make a system more affordable [9, 10]. HAR is a non-intrusive and convenient way to detect falls without requiring elderly people to wear additional equipment [11-14]. Many activities are directly related to falls, such as standing up from sitting or walking on uneven surfaces. By training HAR algorithms on large datasets with annotated sensor data, fall-related patterns can be accurately identified in real-time. However, there are still challenges to overcome in developing fall detection systems that utilize smartphones or other existing devices [15]. Most developments are based on general model training, which may not be suitable for older adults' unique characteristics and lifestyles. As every human has a different daily activity pattern, a user-specific approach that adapts to an individual's activity patterns and preferences may improve the accuracy of fall detection systems.

Most developments in this area use raw data or feature data. Using raw data can lead to a high computational load [9]; therefore, collecting and processing feature data from sensors is a more efficient approach. However, the accuracy and efficiency of fall detection can be improved by exploring novel sensor data integration methods, such as combining inertial sensor data with computer vision. A trajectory can be generated by integrating multiple sensor data streams, such as cameras, microphones, and inertial sensors. This can provide a more comprehensive understanding of the situational context around a potential fall event and different human activities. Trajectory analysis can help develop a user-specific HAR model, including different types of falls. Position, angular velocity, velocity, acceleration, and orientation can be extracted from the trajectory data for further analysis and classification.

II. PROPOSED UHAR MODEL

The proposed user-centric HAR (uHAR) model was developed to improve fall detection systems for the elderly by considering individual characteristics and preferences. The model integrates machine learning algorithms and advanced sensor technology to analyze and classify various activities and movements, including fall incidents. Data collection involves gathering sensor data from wearable devices and ambient sensors, such as accelerometers and gyroscopes. The raw data is transformed into a trajectory representation, and feature extraction techniques are applied to capture key features for a specific person's activities. The uActivity algorithm is then applied to develop a prediction model of activities categorized into different categories, including falls, for each user individually. The uHAR model operates within a three-tier architecture (cloud-edge-end), leveraging cloud computing resources, edge devices, and end-user devices. The edge tier plays a crucial role in real-time data collection, preprocessing, and classification of user activities, providing low-latency processing and reducing the burden on the cloud infrastructure. The end tier, including wearable devices, interacts directly with the user, providing real-time feedback and information. The integration of cloud computing, edge devices, and wearable end devices ensures efficient processing, storage, and real-time data collection for user-centric activity recognition.

III. UACTIVITY ALGORITHM FOR FALL DETECTION

The uActivity algorithm is a user-centric approach that uses wearable devices to detect falls in real time. It uses accelerometer and gyroscope data from these devices and applies a user-centric activity recognition model to classify features. The accuracy of the algorithm depends on the quality of the sensor data and the effectiveness of the model. The ActDec-SysOpt [16] algorithm enhances the efficiency and accuracy of fall detection using wearable devices.

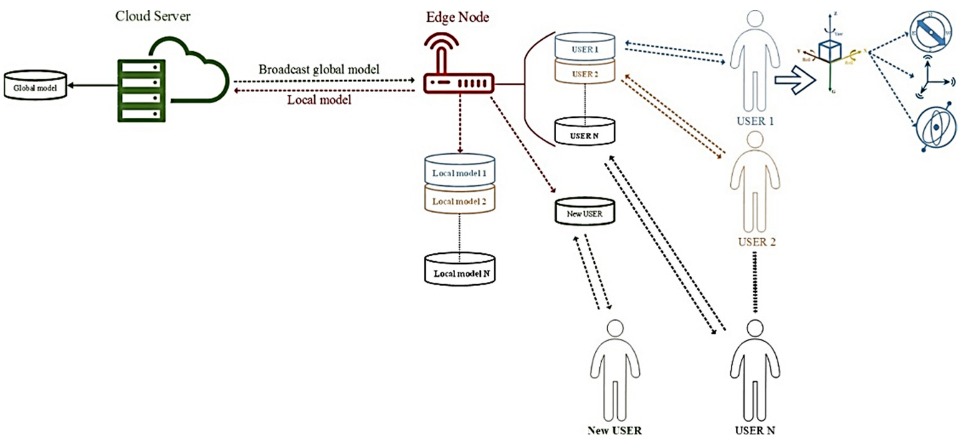

Fig. 1. User-centric HAR (uHAR) model.

A. Data Collection, Processing, and Feature Extraction

Particle kinematics studies a particle's trajectory, defining its position and trajectory in a 3D coordinate system. The particle's position vector represents its separation from the origin and direction. The frame of reference affects the position vector, with different frames resulting in different values. The uActivity algorithm collects and processes accelerometer and gyroscope data from wearable devices to convert it into a trajectory. This dataset is called uHAR.

```
Algorithm 1 Trajectory generation and
  feature extraction
Require: Accraw, Gryroraw
Ensure: P, A, V, ω
Gryroraw →ωbody
For every 1 second do
  Traj→ Viewpoint(t))
  Viewpoint(t), Viewpoint(t − 1) → P, A,
  V, ω
```

B. User Identification

The uActivity algorithm uses unique movement patterns and characteristics to identify users, creating profiles based on daily activities. The system continuously updates and refines profiles to improve accuracy, selecting a user-specific model for each individual.

```
Algorithm 2 User Identification
Require: (P, A, V, ω)unlabeled
Ensure: Userselection,
  trModelspecific ∈ trModel
Load Userrecognition Model
Repeat every 1.5 seconds
  Procedure Userselection((P, A,
    V,ω)unlabeled)
    (P, A, V, ω)unlabeled →
    Userrecognition
    Return User(n)
  Endprocedure
  Procedure trModelspecific(n)
    User(n) → trModel
    Find trModel(n)
    If trModel(n) ⊂ trModel then
      trModel(n) → trModel_specific
      Return trModelspecific
     Else
      Develop trModel_NewUser
    End if
  Endprocedure
```

C. Activity Recognition and Decision-Making

The activity recognition and decision-making phase involves analyzing the extracted features to classify the type of activity being performed based on a user-specific activity model. The algorithm uses Long-Short-Term Memory (LSTM) to classify and recognize activities accurately. The following algorithm describes the steps in this phase.

```
Algorithm 3 Activity Recognition and
Decision-making
Require: (P, A, V, ω)unlabeled,
  trModelspecific
Ensure: AUser, FUser, (P, A, V, ω)labeled
  {AUser, FUser}⊂ A Load trModelspecific
Procedure A((P, A, V, ω)unlabeled,
  trModelspecific)
  (P, A, V, ω)unlabeled → trModelspecific
  trModelspecific → Adetected
  If Adetected ⊂ A then
    Classify Adetected
    Adetected → ASpecific or Fspecific
    Return ASpecific or Fspecific
  Else
    GoTo procedure A
  Endif
Endprocedure
Procedure (P, A, V, ω)labeled((P, A, V,
  ω)unlabeled)
  (P, A, V, ω)unlabeled → (P, A, V,
  ω)labeled
  Return (P, A, V, ω)labeled
Endprocedure
```

D. System Optimization

The uActivity algorithm continuously improves activity recognition performance and accuracy through system optimization. It incorporates LSTM and BiLSTM architectures, trained using adaptive moment estimation and stochastic gradient descent. The algorithm accurately recognizes activities like walking, standing, and sitting. It also addresses limited labeled training data using Gaussian-binary restricted Boltzmann machines.

```
Algorithm 4 System Optimization
Require: (P, A, V, ω)labeled
Ensure: UserModelUpdated,
  ActivityModelUpdated
Procedure UPDATE((P, A, V, ω)labeled)
  (P, A, V, ω)labeled → Train_Data
  Train_Data → Train_Network
  Validation (NewUserModel,
  NewActivityModel)
  AccNew > AccOld
  Pass UserModelUpdated,
  ActivityModelUpdated
Endprocedure
```

IV. RESULT AND DISCUSSION

The uActivity algorithm enhances activity recognition accuracy in user-centric contexts using user-specific models, LSTM and Bi-LSTM architectures, adaptive moment estimation, and stochastic gradient descent with momentum optimization algorithms. The uActivity algorithm underwent a comparative analysis to assess its performance against other classification techniques, focusing on predictive accuracy, speed, robustness, and scalability.

Fig. 2. Body positions of the used smartphone.

A. Experimental Setup and Data Collection

The uActivity algorithm was evaluated using a comprehensive experimental setup involving seven subjects with varying ages, sex, weight, and height. The algorithm was tested on eight activities, including walking, running, jumping, and others. Data were collected from three body positions using smartphones attached to the devices (see Figure 2). The computational efficiency was determined using MATLAB-2022a on three different computing platforms. Training and execution times were based on the software and hardware used, and may vary depending on the computational resources used.

TABLE I. PERFORMANCE METRICS FOR USER RECOGNITION

Users	Activity identification and classification				
	Accuracy (%)	**Precision (%)**	**Recall (%)**	**FAR (%)**	**F1-score (%)**
User 1	99.66	99.47	99.68	0.049	99.57
User 2	99.81	99.80	99.81	0.028	99.81
User 3	99.31	99.46	99.00	0.105	99.23
User 4	98.85	98.49	98.92	0.164	98.71
User 5	99.35	99.42	99.09	0.097	99.25
User 6	99.69	99.72	99.55	0.045	99.63
User 7	99.37	99.51	99.10	0.001	99.30
Average	99.44	99.39	99.34	0.081	99.37

TABLE II. PERFORMANCE EVALUATION METRICS FOR DAILY ACTIVITY AND FALL CLASSIFICATION

Activity	User recognition				
	Accuracy	**Precision**	**Recall**	**FAR**	**F1-score**
Walk	98.90	98.96	98.80	0.187	98.88
Run	99.41	99.47	99.44	0.101	99.45
Jump	99.91	99.92	99.54	0.015	99.92
Stand to Sit	99.57	99.62	99.55	0.074	99.58
Upstrairs	99.83	99.84	99.82	0.028	99.83
Downstairs	99.49	99.50	99.49	0.083	99.49
Forward Fall	99.65	99.56	99.68	0.057	99.62
Backward Fall	99.25	99.08	99.35	0.122	99.22
Average	99.50	99.49	99.50	0.66	99.50

B. Results in User and Activity Recognition

One of the critical metrics considered was user recognition, which refers to the ability to accurately identify and distinguish different users based on their activity patterns. Table I shows the performance results of the uActivity algorithm in terms of user recognition, indicating that it performs well in successfully recognizing individual users, considering various characteristics such as age, sex, weight, and height. These results demonstrate its effectiveness and robustness in distinguishing different users based on their activity patterns and characteristics. Table II shows performance results on activity recognition.

C. Performance Analysis

The computational efficiency of the uActivity algorithm in the field of user identification was also examined. The model training time and processing time of 1-second signal windows were examined to understand the algorithm's practicality and scalability in real-time applications. For this reason, MATLAB-2022b was used on different machines. Table III shows the computational efficiency of uActivity in identifying a person. It is important to note that the computers run only the MATLAB2022b program while performing the simulation job.

TABLE III. TRAINING AND PROCESSING TIME FOR USER RECOGNITION

Performance evaluation metrics	Machine configuration		
	MacBook Air (2017) - Intel i5, 8GB RAM, 256 GB SSD	**PC - Ryzen 5700G, 64 GB RAM, 1TB SSD, NVIDIA 2060**	**PC - Intel i5 8th Gen, 24 GB RAM, 256 GB SSD, NVIDIA 1030**
Training time	5 min 32 sec	2 min 5 Sec	3 min 2 sec
Processing time for a 1-second signal window	15.92 ms	3.35 ms	4.96 ms

D. Comparison with Related Works

The classification performance of the proposed uActivity algorithm was compared with two previous works in [16, 17] that utilized LSTM-based algorithms on the UniMIB SHAR [18], MobiAct [19], UCI HAR [20], HAPT [21], SisFall [22], and Real-Life [23] datasets. Table IV shows a comparison of the uActivity algorithm with ActDec-SysOpt [17] in terms of classification performance, showing that the proposed uActivity algorithm is superior. These results indicate that the developed trajectory-based human activity and the fall-related dataset are very useful for developing a user-centric activity model that includes fall.

Table V compares the performance of uActivity and other algorithms on the uHAR dataset. The proposed uActivity algorithm outperforms the other methods across all metrics. Table VI further highlights the effectiveness of the uActivity algorithm by comparing its performance on three different datasets: SisFall [22], the Real Life [23], and uHAR. This comparison demonstrates that the uActivity algorithm performs significantly better when used with the uHAR dataset, achieving a much higher accuracy and a lower FAR compared to its performance on the other two datasets.

TABLE IV. COMPARISON OF UACTIVITY WITH SIMILAR WORKS FOR PARTICULAR DAILY ACTIVITY AND FALL RECOGNITION

Metrics	Algorithm and dataset					
	ActDect-SysOpt with UniMIB SHAR [17]	**ActDect-SysOpt with MobiAct [17]**	**Event detection algorithm with SisFall [16]**	**ActDect-SysOpt with HAPT [17]**	**ActDect- SysOpt with UCI HAR [17]**	**uActivity with uHAR (proposed)**
Accuracy (%)	89.95	59.65	89.96	92.01	91.24	**99.44**
Precision (%)	78.44	52.08	90.23	92.04	91.54	**99.39**
Recall (%)	77.18	51.35	89.86	91.87	91.14	**99.34**
FAR (%)	2.26	10.66	Not Measured	1.69	1.87	**0.081**
F1-score (%)	77.81	51.71	89.86	91.96	91.34	**99.37**

TABLE V. PERFORMANCE EVALUATION OF DIFFERENT MACHINE LEARNING MODELS AND UACTIVITY ON THE UHAR DATASET

Metrics	Algorithm and dataset				
	SVM on uHAR	**RNN on uHAR**	**NB on uHAR**	**ActDect-SysOpt on uHAR**	**uActivity on uHAR**
Accuracy (%)	36.8551	91.0348	57.936%	94.9314	**99.44**
Precision (%)	28.635	90.88	57.246	94.539	**99.39**
Recall (%)	29.958	88.899	57.936	94.649	**99.34**
FAR (%)	18.926	1.4102	6.1387	0.75635	**0.081**
F1-score (%)	29.281	89.879	57.589	94.594	**99.37**

TABLE VI. PERFORMANCE EVALUATION OF UACTIVITY ON DIFFERENT DATASETS

Metrics	Algorithm and Dataset		
	uActivity on SisFall	**uActivity on Real Life**	**uActivity on uHAR**
Accuracy (%)	63.2528	81.14207	**99.44**
Precision (%)	64.271	82.2971	**99.39**
Recall (%)	52.654	80.6799	**99.34**
FAR (%)	6.3827	4.16598	**0.081**
F1-score (%)	57.856	81.47	**99.37**

V. DISCUSSION

The uActivity algorithm is a reliable tool for identifying daily activities and falls in elderly people, exhibiting excellent accuracy, precision, recall, and F1-score, with more than 99% accuracy in most cases. Its processing time is 3.35 ms for classifying activities and falls, and 3.75 ms for selecting a user-centric model. The algorithm's low computational resources impact its processing time, with the desktop PC having the lowest processing time.

The uActivity algorithm demonstrates effectiveness in daily activity and fall classification for the elderly. This performance is a result of its user-centric design, which leverages trajectory-based modeling to accurately recognize and classify activities and falls, and its ability to select appropriate user-specific activity models. The algorithm's effectiveness is further highlighted by its superior performance compared to other machine learning techniques, such as SVM, RNN, Naive Bayes, and ActDec-SysOpt. The proposed algorithm performs best with the uHAR dataset, indicating that this specific user-centric dataset is highly suitable for developing accurate and reliable fall detection systems.

VI. CONCLUSION

This study focused on daily activities and fall detection. The uActivity algorithm significantly outperforms other machine learning techniques, including SVM, RNN, Naive Bayes, and ActDec-SysOpt, on the uHAR dataset. The uActivity algorithm achieves an exceptional accuracy of 99.44%, coupled with a very low False Alarm Rate (FAR) of 0.081%. Furthermore, Table VI highlights the critical role of the dataset in the algorithm's performance. Although uActivity excels with the uHAR dataset, its accuracy drops considerably on other public datasets, underscoring the importance of a purpose-built, user-centric dataset for achieving high-accuracy results in personalized fall detection systems. In essence, the results confirm that the uActivity algorithm, when combined with the tailored uHAR dataset, represents a significant improvement in the accuracy and reliability of fall detection and daily activity classification for elderly people.

The proposed architecture can significantly improve the accuracy and reliability of fall detection and daily activity classification systems for elderly people. Future research should focus on enhancing the computing performance, investigating parallel computing implementation, and reducing the memory footprint of these algorithms. Since this study considers a cloud-edge-end-based architecture, another major direction is to examine wireless communication to support the latency requirement of fall detection. In addition, the handling of new users should be addressed.

In conclusion, the uActivity algorithm has shown satisfactory results in accurately classifying different activities and detecting falls among elderly people, which encourages us to dig further in this direction.

DATA AVAILABILITY STATEMENT

The supporting data and code are available in [24].

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