ISSN 2089-8673 (Print) | ISSN 2548-4265 (Online)
Volume 13, Issue 1, March 2024

ADAPTIVE THRESHOLD FILTERING TO REDUCE NOISE IN ELDERLY ACTIVITY CLASSIFICATION USING BI-LSTM

Endang Sri Rahayu[1,2], Eko Mulyanto Yuniarno[1], I Ketut Eddy Purnama[1], Mauridhi Hery Purnomo[1]

[1] Department of Electrical Engineering, Institut Teknologi Sepuluh Nopember, Surabaya
[2]Department of Electrical Engineering, Universitas Jayabaya, Jakarta

email: 7022201010@student.its.ac.id[1], ekomulyanto@ee.its.ac.id[2], ketut@te.its.ac.id[3], hery@ee.its.ac.id[4]

Abstract

As the global population ages, there is an increasing need to provide better care and support for older individuals. Deep learning support to accurately predict elderly activities is very important to develop. This research discusses a new model integrating filtering techniques using adaptive thresholds with Bidirectional - Long Short-Term Memory (Bi-LSTM) networks. The problem of activity prediction accuracy, mainly due to noise or irrational measurements in the dataset, is solved with adaptive thresholds. Adaptive characteristics at the threshold are needed because each individual has different activity patterns. Experiments using the HAR70+ dataset describe the activity patterns of 15 elderly subjects and the gesture patterns of 7 activities. Based on body movement patterns, the elderly can be classified as using walking aids. The proposed model design obtains an accuracy of 94.71% with a loss of 0.1984.

Keywords : Adaptive threshold, accelerometer sensor, elderly daily activity, deep learning

Received: 29-02-2024 | **Revised:** 18-03-2024 | **Accepted:** 19-03-2024
DOI: https://doi.org/10.23887/janapati.v13i1.76064

INTRODUCTION

Accurate predictions of the daily life activities of the elderly as a vulnerable group are significant, including trends in dangerous activities that must be anticipated for their safety and comfort. It also has broader implications for healthcare systems, resource allocation, and technological progress. Health services with the Cloud-Digital Twin Healthcare (DTH) concept were researched by Liu et al. [1] to solve the problem of interaction and convergence between physical and virtual space in the health sector. Hussain builds real-time monitoring and interaction of health services with an Internet of Things (IoT) platform for the elderly and people with disabilities.

Phyo et al. [3] designed a monitoring model for older people who live alone to analyze the normal and abnormal daily activities of older people. Meanwhile, Baek et al. [4] designed an IoT-based remote monitoring system for the condition of diapers for lying patients. Prediction of elderly activity for fall detection was carried out by Garcia et al. [5] and Juraev et al. [6] using CNN-LSTM, while Yu et al. [7] used Federated Learning and Extreme Learning Machine. The dataset is a video sourced from a depth sensor camera by Msaad et al. [8] to monitor and detect changes in routine activities. Sun et al. [9] analyze gait recognition using the gait template construction method. With the Random Forest algorithm, Xu et al. [10] recognize elderly activities, and after being correlated with location and time, it will be corrected with an activity similarity matrix. Arifoglu et al. [11] use RNN to detect abnormal behaviour.

Technological advances used for elderly care, such as wearable sensors studied by [12-18], increasingly enable data collection to predict the daily activities of older people in real time and can provide significant benefits for the individual.

Our challenge is getting accurate activity movement predictions from time series datasets, as done by Wen et al. [19], who used an LSTM-attention-LSTM prediction model solution using 3D accelerometer sensor data as researched by [20 – 22].

A dataset that contains noise will affect the level of prediction accuracy, so the dataset must be prepared to avoid noise. If Yue *et al.* [23] use adjustment of the binarization threshold in image preprocessing to improve the data quality, then an adaptive threshold is used in this research.

Table 1. Related studies that support our contribution

Research	Gap Analysis	Related with our study
Arifoglu *et al.* [11]	Detecting abnormal movements in elderly with dementia by paying attention to deviations from the usual pattern.	We differentiated the movements of walking aid users based on gesture patterns.
Ustad *et al.* [26]	The shuffling activity is replaced by standing, and the activity of going up/down stairs is replaced by walking.	In our study, all activities, whether shuffling or ascending/descending stairs, are still identified as activities according to the annotation as long as they do not include irrational measurements.
Yue *et al.* [23]	Improving performance by adjustment of the binarization threshold in image preprocessing and parameters optimization of each traditional model.	Improve performance by reducing data noise with a filtering principle that uses an adaptive threshold according to the activity characteristics of each individual.
Shrestha *et al.* [22]	Human Activity Classification from FMCW Radar with Bi-LSTM Networks.	Feeding filtering results from accelerometer signal data into the Bi-LSTM model.

Khalid et al. [24] researched deep learning models for time series data by demonstrating using the Doppler domain to collect and group continuous activity sourced from radar data using Bi-LSTM networks and CNN-LSTM. Meanwhile, Multimodal Bi-LSTM in Ogawa et al. [25] is used to classify favourite videos. Table 1 summarizes research related to contributions to this study. By addressing these issues, researchers and health professionals can take significant steps to improve the lives of older adults.

This research aims to develop a robust model by combining adaptive filtering and a bidirectional deep learning Bi-LSTM to increase the accuracy of activity predictions by reducing noise. The experiment was initiated by observing the activity patterns of older adults and movement patterns from the experimental results of accelerometer data so that activity patterns could be observed, including observing the patterns of subjects who used walking aids. The main contributions are as follows:

1. The activity patterns and movement patterns of the elderly in the 15 subjects were observed, and the patterns of subjects who use walking aids were tested compared to subjects who do not use walking aids.
2. Apply adaptive threshold filtering as a valuable technique to reduce noise.
3. Combining adaptive threshold with Bi-LSTM networks as the network chosen for activity datasets with frames arranged based on time sequence to improve performance.

This research follows a well-structured and coherent writing sequence. The first part covers the introductory aspect, which includes the background and research objectives and explores related works, providing a comprehensive review of existing literature in the field. The second section presents the proposed methodology, detailing the approach to address the research problem. Next, the third section discusses the experiments conducted to validate and evaluate the methodology. Results and discussion continue in the fourth section. Finally, the fifth section serves as a conclusion, summarizing the main findings and suggesting potential areas for future research and improvement. This coherent structure allows readers to follow the research process smoothly and gain a comprehensive understanding of its contributions

METHODS

The steps taken to predict activity in this research are as follows:

1. Investigate the dataset to observe the subject's activity patterns and gesture patterns;
2. Eliminate irrational measurements by applying filtering using thresholds;
3. Preprocessing uses sliding windows and separate validation data: training, testing;

ISSN 2089-8673 (Print) | ISSN 2548-4265 (Online)
Volume 13, Issue 1, March 2024

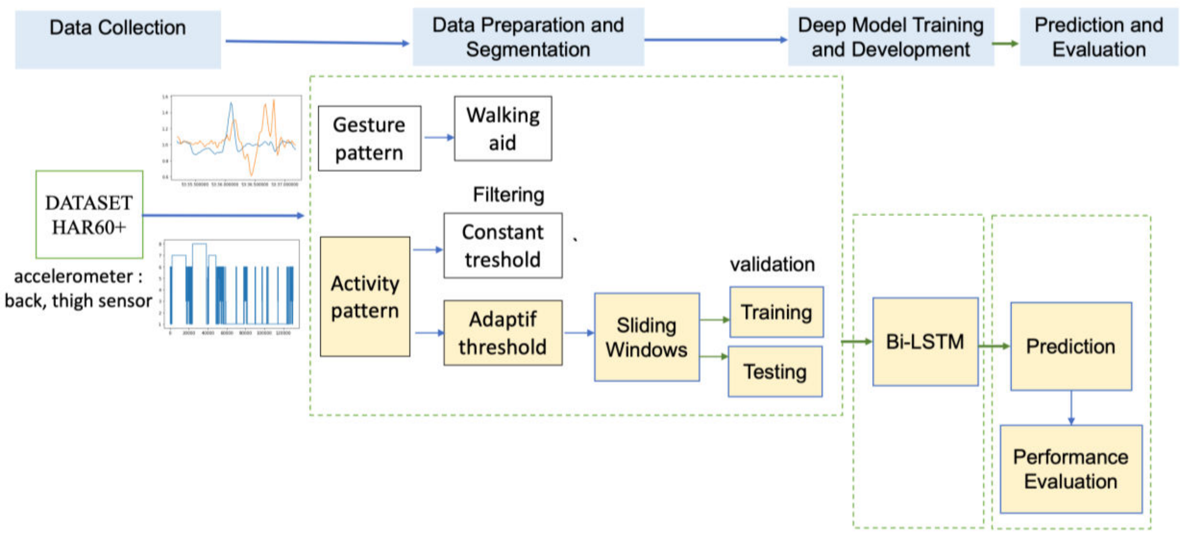


Figure 1. Flow diagram of adaptive threshold filtering for elderly activity classification using Bi-LSTM

Table 2. Description of 7 activities with labels: 1, 3, 4, 5, 6, 7, 8.

Label	Activity	Description
1	walking	Move toward a goal by one or more steps. Walking can occur in any direction. Walking can be done using a walking aid.
3	shuffling (standing with leg movement)	Stepping in place with undirected foot movements. Including turning around.
4 / 5	stairs (up/down)	Start: Lift the heel of the foot that will land on the first step. End: When the heel of the foot is placed on a flat surface
6	standing	Upright, legs supporting body weight, without any leg movement. Upper body and arm movements are permitted. The position of the feet is the same before and after the upper body movement.
7	sitting	When the person's buttocks are on the seat of a chair, bed, or floor. Sitting can include some movement of the upper body and legs. Adjustment of sitting position is permitted
8	lying	The person lies on his stomach, back, or resting on his right/left shoulder. Arm, leg, and head movements are permitted

4. Feed the filtered data into the Bi-LSTM model
5. Evaluation of model performance: loss and accuracy.

In the proposed method, we carry out a series of experimental stages, as depicted in the flow diagram in Figure 1. We use different colours to describe the main flow of the proposed model. In another part of the model series above, we also observe the activity movement patterns of each subject. Through walking activities, we found differences in the patterns of subjects who used walking aids.

Dataset: HAR70+

The HAR70+ dataset contains recordings of 18 older adult participants wearing two Axivity AX3 3-axial accelerometers, one sensor mounted on the right front thigh and one on the lower back. Eighteen subjects were instructed to conduct eight activities in approximately 40 minutes in a semi-structured free living environment. A description of each activity is shown in Table 2. Participants' ages were between 70 and 95 years. Five of the 18 subjects used walking aids when recording data. The sampling rate provided is 50Hz. Video recording from a chest-worn camera annotates the activity performed frame by frame. The dataset contains the following annotated activities with corresponding coding schemes: 1: walking; 3: shuffling; 4: stairs (up) 5: stairs (down) 6: standing; 7: sitting; 8: lying. Activity identification based on body movements at the position of the sensor worn by the participant is recorded into a video file with a resolution of 1920×1080 pixels at a speed of 60 frames per second (fps) and saved in MP4 format.

Activity and Gesture Patterns

Each subject has activity characteristics with gesture movement speeds and different frame lengths, so each subject forms a different pattern.

The first experiment was to observe the activity patterns of older adults originating from the HAR70+ dataset. In the dataset, 15 subjects carried out 7 activity labels (walking, shuffling, stairs-up, stairs-down, standing, sitting, lying). Each subject carried out regulated activities for about 40 minutes. Algorithm 1 shows the steps taken to observe activity patterns and gesture patterns.

Algorithm 1: Observation of activity and gesture patterns

1. Read dataset (15 subjects): times-dates; thigh_x, thigh_y, thigh_z; back_x, back_y, back_z; label_act
2. For Subject ⇐ 1 to 15
3. For time ⇐ 1 to 40 (minutes)
4. **{Activity Patterns}**
5. Recognize label.act
6. Plot Activity/subject
7. **{Gesture Patterns}**
8. For label_act ⇐ 1 to 8
9. $back = \sqrt{back\_x^2 + back\_y^2 + back\_z^2}$
10. $thigh = \sqrt{thigh\_x^2 + thigh\_y^2 + thigh\_z^2}$
11. Plot Gesture/activity

Filtering

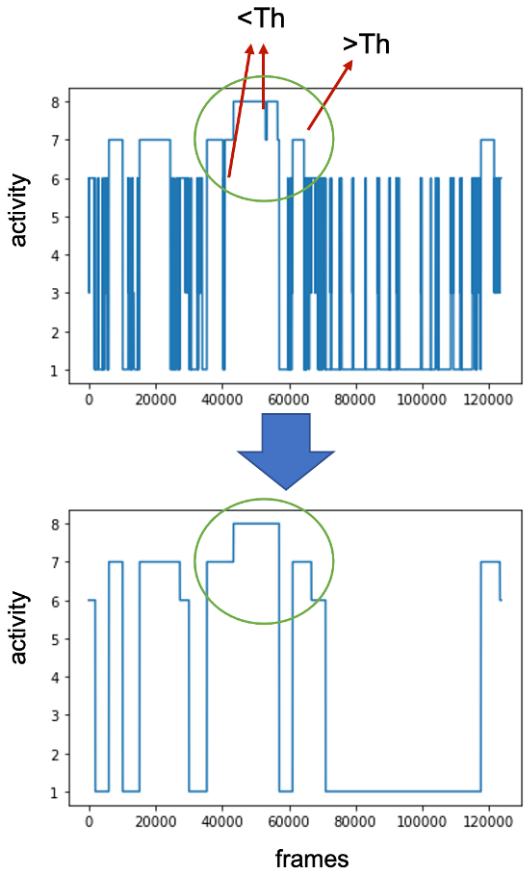


Figure 2. Implementation of threshold (th) in activity sequences

In the HAR70+ dataset, as can be seen from the results of observations made on the dataset, several activities are carried out in a series of short frames. This short activity results from measurements we consider irrational, which we call noise, and we will reduce them using a threshold value filtering method. We determine a threshold to distinguish between natural movement and noise. The threshold is used to eliminate activity that is less than the threshold (*Th*), considered noise. The assumption used is that the subject is considered to continue carrying out activities according to the activity before encountering noise activity. Figure 2 shows the threshold (*Th*) implementation in the activity sequence.

The constant threshold value is determined directly. We experimented to see the application of a constant threshold across activities and subjects. The results obtained ignore the characteristics of each subject when carrying out activities.

Determining the threshold is adaptive because each individual has different movement characteristics. So, each individual's threshold should be different. Therefore, we set a threshold calculation formula based on the characteristics of each individual. We pay attention to the number of frames used to carry out the activity and the number of activities, so we get an average value for each movement. In determining the threshold, we calculate the average of all activities performed in the range according to the dataset, according to (1).

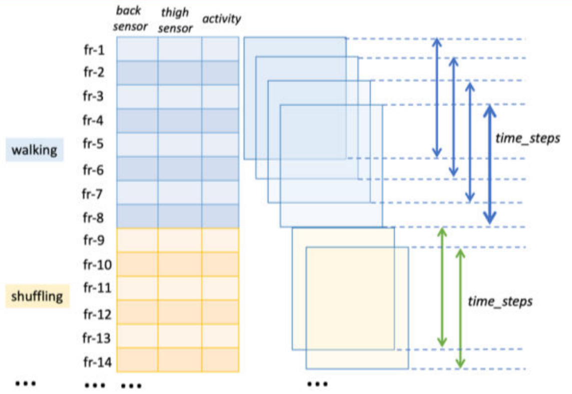


Figure 3. Sliding windows on time series data

$$Th = \frac{\left(\sum_{i=1}^{7} \frac{Max_i - Min_i}{Act_i}\right)}{7} \quad (1)$$

where *Max* is the highest number of frames, *Min* is the smallest number of frames and *Act* is the number of activities.

Sliding Windows

An activity is described as a series of frames in times series data. Timesteps frames slice each activity, thus forming three dimensions, namely timesteps, number of attributes, and number of windows resulting from the slicing process.

In the Bi-LSTM prediction model, the input is a sequence of windows whose shifts are illustrated in Figure 3. We separate training and testing data using random split validation 80%:20%.

Bi-LSTM Model

Next, we evaluate the model performance using Bi-LSTM on time series datasets. Figure 4 shows the use of two layers (left to right and right to left) in Bi-LSTM to capture patterns and relationships in data that may not be visible if only one direction is used.

Our proposed model uses LSTM, which runs both ways. The input data sequence will be processed from start to end and from end to end. So, information from both sequence directions will improve the results of our classification model. In the LSTM layer, we use 64 unit cells (neurons). The model receives input sequences with timesteps of 100, and the feature dimension for each timestep is 128. The next layer is the Dense layer, which contains 64 fully connected neurons. The activation function used is ReLU (Rectified Linear Activation Unit), which is defined as *f(x)=max(0,x)*. The output layer in our model is the Dense layer, which has 8 neurons, which refers to the number of activities to be classified. The output's activation function is SoftMax, which is commonly used for multiclass classification. Meanwhile, we use sparse categorical cross-entropy as the loss function because the target label is an integer. We use the' Adam' optimizer to adjust the model parameters during the training process.

We implement our proposed model with the Bi-LSTM architecture as in Table 3, which is integrated with filtering using an adaptive threshold to improve and evaluate the model performance.

RESULT AND DISCUSSION

In experimental validation, we used macOS Monterey version 12.0.1, 1.6 GHz Dual-Core Intel Core i5 processor, 8 GB 2133 MHz LPDDR3 memory, with Python 3.11.3 64-bit encoding.

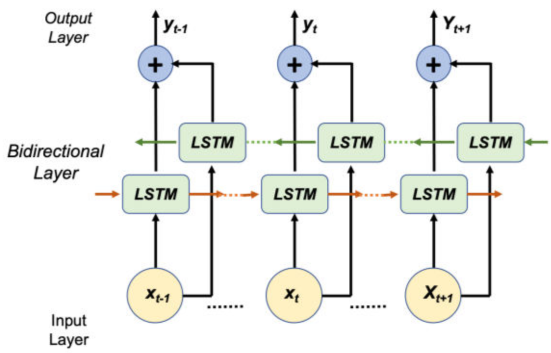


Figure 4. Bi-LSTM Network

Table 3. Bi-LSTM model architecture

Layer (type)	Output Shape	Param #
Bidirectional	(None, 100, 128)	36352
Bidirectional	(None, 128)	98816
Dense	(None, 64)	8256

ISSN 2089-8673 (Print) | ISSN 2548-4265 (Online)
Volume 13, Issue 1, March 2024

Dense	(None, 8)	520

Investigation of the HAR70+ dataset to obtain gesture patterns for 7 activities from 15 subjects as initial experimental results are presented in Figure 5.

Data sourced from 2 3-axial accelerometer sensors installed on the front thighs and lower back is the data that will be processed to obtain gesture patterns from activities such as walking, shuffling, stairs-ascending, stairs-descending, standing, sitting and lying. In the walking pattern, the sensor's resultant speed shows apparent movement differences at several marked values. As the experimental results shown in Table 4, in subject 1, in 200 frames, there were four relatively fast movements; it is assumed that the right thigh moves with more significant acceleration (assumed stepping movements) 4 times. Meanwhile, the second subject made two stepping movements in the same period. These results confirm that pattern detection can differentiate subjects who do not use walking aids from those who use walking aids. A study by Argaflo et al. [11] shows that LSTMs can encode activity sequences. The results of this research support the results of our experiments in detecting walking aid users, so the use of Bi-LSTM successfully detected this anomalous activity.

In the next experiment, we observe the characteristics of the dataset. Each subject carried out activities within around 40 minutes. In this range, we detect the number of activities and the shortest and longest activity frames for each individual. The first subject who carried out activities for 40 minutes was detected walking 30 times, with 75 frames as the shortest walking time and 9693 frames as the longest. Five people should have carried out activities going upstairs: the third, fifth, thirteenth, fourteenth and fifteenth subjects. All subjects' longest average activity time was when sitting, while the fastest average activity detected occurred during shuffling activities.

The results of this second experiment are shown in Table 5. It can be observed that activity is carried out with a relatively small number of frames. We classify this as an irrational measurement, which we consider noise to reduce. Filtering using adaptive thresholding will be used to reduce noise. The following experimental result is Figure 6, which depicts activity patterns that have gone through filtering using an adaptive threshold as proposed in the designed model.

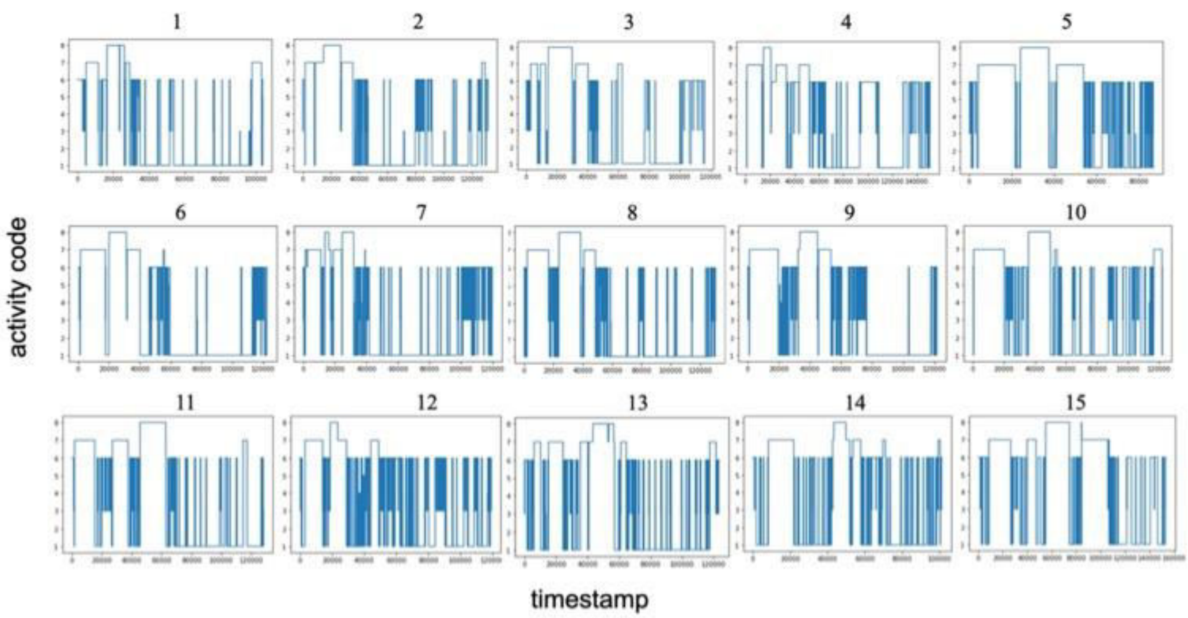


Figure 5. Activity patterns in about 40 minutes from 15 subjects

Table 4. Comparison of movement patterns between Subject 1 who does not use a walking aid and Subject 3 who uses a walking aid

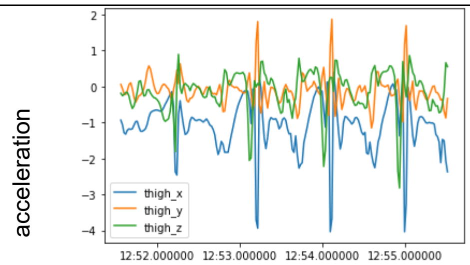
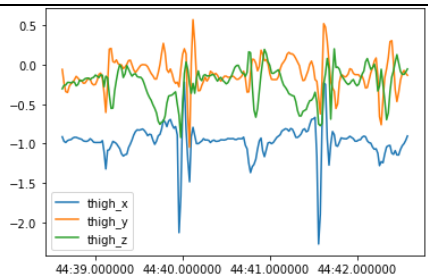
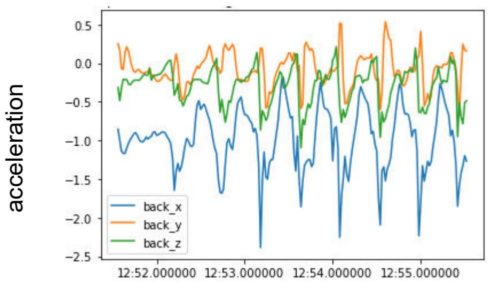
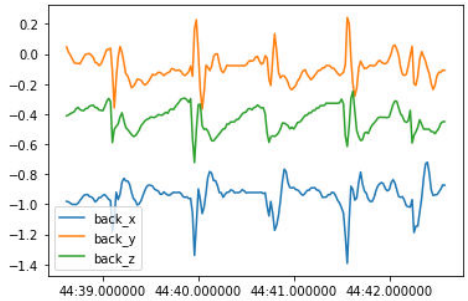
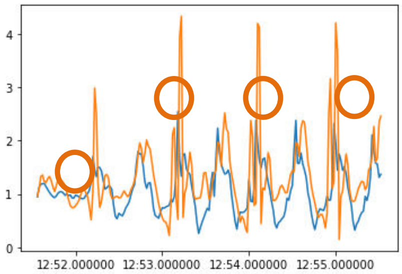
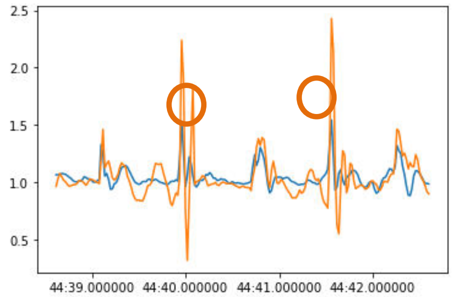
<table>
<tr><th></th><th>Subject 1 (frames: 91280-91479)</th><th>Subject 3 (frames: 7338-7537)</th></tr>
<tr><td>Thigh sensor</td><td>
</td><td>
</td></tr>
<tr><td>Back sensor</td><td>
</td><td>
</td></tr>
<tr><td>Resultant (Thigh sensor; Back sensor)</td><td>
</td><td>
</td></tr>
<tr><td></td><td>timestamp</td><td>timestamp</td></tr>
</table>

Table 5. Observation results on the characteristics of the HAR70+ dataset

ISSN 2089-8673 (Print) | ISSN 2548-4265 (Online)
Volume 13, Issue 1, March 2024

Subject	1 - walking			3 - shuffling			4 - stairs A			5 - stairs - D			6 - standing			7 - Sitting			8 - lying		
	Act	Min	Max	Act	Min	Max	Act	Min	Max	Act	Min	Max	Act	Min	Max	Act	Min	Max	Act	Min	Max
1	30	75	9693	25	15	263	1	91	91	3	85	327	41	13	2911	3	2327	6829	2	2625	6951
2	26	65	11325	51	11	503	0	0	0	1	155	155	60	5	1421	4	2282	8159	1	12211	12211
3	23	85	100119	42	7	659	0	0	0	0	0	0	48	21	3401	4	2923	8083	1	15613	15613
4	34	59	20153	52	9	531	1	201	201	1	183	183	74	7	12289	3	8203	12433	1	6029	6029
5	40	67	3671	53	7	199	0	0	0	0	0	0	80	11	1015	3	73	17491	1	13379	13379
6	23	115	22129	42	11	311	1	143	143	1	129	129	59	5	3397	4	63	16179	1	11229	11229
7	50	51	12323	48	5	109	2	103	153	3	167	213	91	9	1641	5	17	8639	2	2511	7281
8	51	55	10835	52	7	159	2	199	471	6	11	475	93	7	885	2	7831	14661	1	14743	14743
9	40	73	26923	46	13	233	3	83	503	2	173	429	82	7	1335	3	1091	18585	1	11425	11425
10	40	61	9527	66	13	395	1	199	199	1	171	171	96	14	2003	4	227	19665	1	13999	13999
11	39	53	9381	55	11	1313	2	69	81	3	69	171	87	9	1309	4	181	13591	1	17185	17185
12	65	53	4279	98	5	339	3	173	561	3	161	505	134	17	1911	3	4945	10985	1	4749	4749
13	55	39	6445	69	5	319	0	0	0	0	0	0	117	7	1697	8	431	9203	2	3195	9607
14	58	43	5479	24	9	67	0	0	0	0	0	0	88	15	2185	6	637	13573	1	6509	6509
15	55	57	7045	28	7	145	0	0	0	0	0	0	79	17	3721	4	719	21621	2	13	19489

Act: number of activity, *Min*: shortest frame, *Max*: longest frame

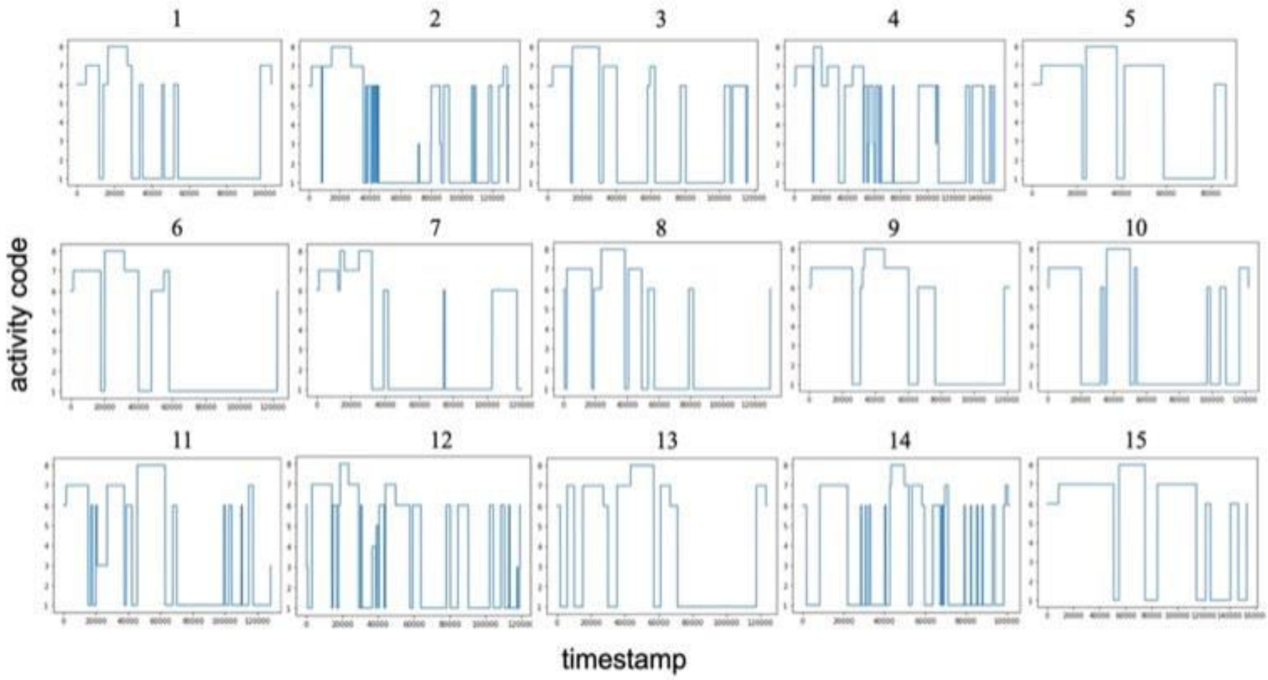
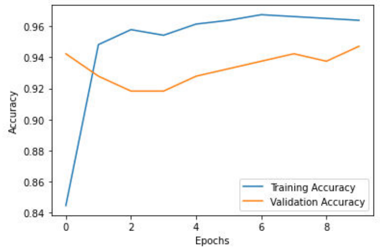
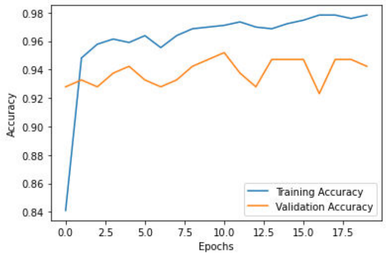


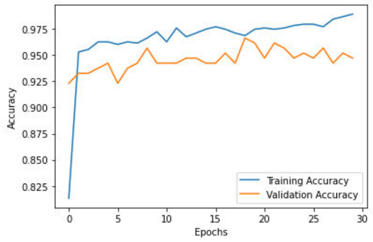
Figure 6. Results of applying adaptive thresholds to activity patterns in around 40 minutes from 15 subjects

Table 6. Model performance test results at epochs (10, 20, 30)

Epochs=10	Epochs=20	Epoch3 = 30







Loss of 0.1984 Accuracy of 0.9471	Loss of 0.2175 Accuracy of 0.9423	Loss of 0.2257 Accuracy of 0.9471

Finally, we conduct experiments to measure the model performance. From Table 6, accuracy and loss do not change significantly with increasing the number of epochs. Using only 10 epochs, the model achieved an accuracy of 94.71% with a loss of 0.1984. These results show that the model can learn patterns effectively during training. A robust model architecture, good training techniques, sufficient quality of data, and a large amount of data support this capability. A good relationship between input features and output labels can illustrate the model's high performance. A pre-processing strategy on the same dataset, namely HAR70+, was also carried out by Yue et al. [23], who used the binarization threshold adjustment method and parameter optimization with an accuracy of 92.86%. This accuracy value is slightly lower than the proposed model. However, Yue et al.'s model also shows that the chosen strategy contributes quite well to the model in capturing relevant information.

CONCLUSION

Adaptive filtering is a valuable technique to improve the accuracy of activity predictions, especially in scenarios involving noise-containing sensor data from elderly individuals. A filter with an adaptive threshold was chosen because each individual has different activity characteristics, so it is necessary to apply a threshold obtained from the activity patterns of each subject.

The combination of adaptive filtering with Bi-LSTM for time series data such as human activity data has proven effective in reducing noise, so data fed to the Bi-LSTM model can improve model performance.

The implications of the research results show that the ability to recognize elderly activities accurately can improve elderly care and well-being, so we are considering further research on assistance service systems that can respond quickly to elderly needs based on monitoring through identifying elderly activities.

ACKNOWLEDGMENT

The authors would like to thank the Ministry of Education, Culture, Research and Technology of the Republic of Indonesia for providing funding support through the PDUPT scheme for this research.

REFERENCES

[1] Liu, Y., Zhang, L., Yang, Y., Zhou, L., Ren, L., Wang, F., Liu, R., Pang, Z., & Deen, M. J. A Novel Cloud-Based Framework for the Elderly Healthcare Services Using Digital Twin. *IEEE Access*. 2019; 7:49088–49101.

[2] Hussain, A., Wenbi, R., da Silva, A. L., Nadher, M., & Mudhish, M. Health and emergency-care platform for the elderly and disabled people in the Smart City. *Journal of Systems and Software*, 2015; 110: 253–263.

[3] Phyo, C. N., Zin, T. T., & Tin, P. Deep learning for recognizing human activities using motions of skeletal joints. *IEEE Transactions on Consumer Electronics*, 2019; 65(2): 243–252.

[4] Baek, J. Smart predictive analytics care monitoring model based on multi sensor IoT system: Management of diaper and attitude for the bedridden elderly. *Sensors International*, 2023; 4.

[5] García, E., Villar, M., Fáñez, M., Villar, J. R., de la Cal, E., & Cho, S. B. Towards effective detection of elderly falls with CNN-LSTM neural networks. *Neurocomputing*, 2022; 500:231–240.

[6] Juraev, S., Ghimire, A., Alikhanov, J., Kakani, V., & Kim, H. Exploring Human Pose Estimation and the Usage of Synthetic Data for Elderly Fall Detection in Real-World Surveillance. *IEEE Access*, 2022; 10: 94249–94261.
[7] Yu, Z., Liu, J., Yang, M., Cheng, Y., Hu, J., & Li, X. An Elderly Fall Detection Method Based on Federated Learning and Extreme Learning Machine (Fed-ELM). *IEEE Access*, 2022; 10:130816–130824
[8] Msaad, S., Zoetgnandé, Y. W. K., Dillenseger, J. L., & Carrault, G. Detecting change in the routine of the elderly. *Measurement: Sensors*, 2022; 24.
[9] Sun, F., Zang, W., Gravina, R., Fortino, G., & Li, Y. Gait-based identification for elderly users in wearable healthcare systems. *Information Fusion*, 2022; 53:134–144.
[10] Xu, H., Pan, Y., Li, J., Nie, L., & Xu, X. Activity Recognition Method for Home-Based Elderly Care Service Based on Random Forest and Activity Similarity. *IEEE Access*, 2019; 7:16217–16225.
[11] Arifoglu, D., & Bouchachia, A. Activity Recognition and Abnormal Behaviour Detection with Recurrent Neural Networks. *Procedia Computer Science*, 2017; 110: 86–93.
[12] Halim, N. Stochastic recognition of human daily activities via hybrid descriptors and random forest using wearable sensors. *Array*. 2022; 15.
[13] Park, J., Lim, W. S., Kim, D. W., & Lee, J. GTSNet: Flexible architecture under budget constraint for real-time human activity recognition from wearable sensor. *Engineering Applications of Artificial Intelligence*, 2023; 124.
[14] Gupta, S. Deep learning based human activity recognition (HAR) using wearable sensor data. *International Journal of Information Management Data Insights*, 2021; 1(2).
[15] Athota, R. K., & Sumathi, D. Human activity recognition based on hybrid learning algorithm for wearable sensor data. *Measurement: Sensors*, 2022; 24.
[16] Hsu, Y. L., Yang, S. C., Chang, H. C., & Lai, H. C. Human Daily and Sport Activity Recognition Using a Wearable Inertial Sensor Network. *IEEE Access*, 2018; 6: 31715–31728.
[17] Yen, C. T., Liao, J. X., & Huang, Y. K. Human daily activity recognition performed using wearable inertial sensors combined with deep learning algorithms. *IEEE Access*, 2020; 8: 174105–174114.
[18] Bianchi, V., Bassoli, M., Lombardo, G., Fornacciari, P., Mordonini, M., & de Munari, I. IoT Wearable Sensor and Deep Learning: An Integrated Approach for Personalized Human Activity Recognition in a Smart Home Environment. *IEEE Internet of Things Journa*l, 2019; 6(5): 8553–8562.
[19] Wen, X., & Li, W. Time Series Prediction Based on LSTM-Attention-LSTM Model. *IEEE Access*, 2023; 11: 48322–48331.
[20] Siirtola, P., & Röning, J. Revisiting "Recognizing Human Activities User-Independently on Smartphones Based on Accelerometer Data" – What Has Happened Since 2012? *International Journal of Interactive Multimedia and Artificial Intelligence*, 2018; 5(3): 17.
[21] Ferrari, A., Micucci, D., Mobilio, M., & Napoletano, P. On the Personalization of Classification Models for Human Activity Recognition. *IEEE Access*, 2020; 8: 32066–32079.
[22] Shrestha, A., Li, H., le Kernec, J., & Fioranelli, F. Continuous Human Activity Classification from FMCW Radar with Bi-LSTM Networks. *IEEE Sensors Journal*, 2020; 20(22): 13607–13619.
[23] Yue, X., Li, H., Saho, K., Uemura, K., C V, A., & Meng, L. Machine Learning based Apathy Classification on Doppler Radar Image for the Elderly Person. *Procedia Computer Science*, 2021; 187: 146–151.
[24] Khalid, H. U. R., Gorji, A., Bourdoux, A., Pollin, S., & Sahli, H. Multi-View CNN-LSTM Architecture for Radar-Based Human Activity Recognition. *IEEE Access*, 2022; 10: 24509–24519.
[25] Ogawa, T., Sasaka, Y., Maeda, K., & Haseyama, M. Favorite video classification based on multimodal bidirectional LSTM. *IEEE Access*, 2018; 6: 61401–61409.
[26] Ustad, A., Logacjov, A., Trollebø, S. Ø., Thingstad, P., Vereijken, B., Bach, K., & Maroni, N. S. Validation of an Activity Type Recognition Model Classifying Daily Physical Behavior in Older Adults: The HAR70+ Model. *Sensors*, 2023; 23(5).