P-ISSN 2586-9000
E-ISSN 2586-9027
Homepage : *https://tci-thaijo.org/index.php/SciTechAsia* Science & Technology Asia
Vol.27 No.3 July - September 2022 Page: [137-151]
Original research article

Sliding Window Input on Long Short-Term Memory Networks for Bed Position Classification

Sakada Sao[1], Virach Sornlertlamvanich[1,2,*]

[1] *School of Information, Computer and Communication Technology, Sirindhorn International Institute of Technology, Thammasat University, Pathum Thani 12120, Thailand*
[2] *Asia AI Institute, Department of Data Science, Faculty of Data Science, Musashino University, Tokyo 135-8181, Japan*

Received 22 February 2020; Received in revised form 2 December 2021
Accepted 28 December 2021; Available online 29 September 2022

ABSTRACT

The research paper specifies an approach for bed position classification by using two-layer of the Long Short Term Memory approach. The two types of sensor data from pressure and piezoelectric sensors are collected and classified into 5 classes, namely out of bed, sitting, sleep center, sleep left, and sleep right. In the preprocessing process, the sensor data are normalized by min-max scaling normalization within a set range of 0 to 1 to avoid the scale bias in the training process. The 30Hz sensor sampling rate of data is accumulated to fit a one-second interval. The model has been experimentally evaluated by preprocessing the dataset and varying the number of hidden nodes of the model in 128, 80, and 50 nodes. As a result, 94.74% of the accuracy has been improved comparing to the prior result.

Keywords: Bed position classification; Elderly care; LSTM; Piezoelectric sensor; Pressure sensor

1. Introduction

As people age, their daily activities and capabilities drop slowly over time. Sleeping disorder is one of the major problems that easily happens to the elderly leading to bed fall accidence [1, 2]. Many approaches are proposed to solve the problem with unobtrusive devices, such as sensor mats or panels due to the concern over the privacy of the elderly that can be violated easily with the camera technology [3–5].

Bennett, et al. [6] employ the Kinotex fiber-optic pressure sensor mats by applying the support vector machines (SVMs) and linear classification to monitor the three types of in-bed positions, such as lying, sit-

***Corresponding author:** virach@musashino-u.ac.jp **doi:** 10.14456/scitechasia.2022.52

ting, and standing. The approach achieves a good result, however, a large number of pressure sensors are required to predict the body positions. Ostadabbas, et al. [4] utilize a pressure sensor mat to reduce the risk of pressure ulceration and to reposition the patient according to pre-defined schedule. R. Yousefi, et al. use the commercial Smart Bed Fabric pressure sensor created by VistaMedical for their research to improve the health care system for the elderly [7, 8]. In their research, the 2D Gaussian Mixture Model is used for limb detection and classification of in-bed posture images generated from pressure units inside the mat. Though they can achieve a good result, the approach still requires many pressure sensor units.

Minehura, et al. [1] use Neural Network (NN), Naïve Bayes, SVM, and Random Forest combined with a pressure-sensitive sensor mat to classify nine sleeping positions. The problem of their low accuracy rate is caused by the arm postures in some sleeping positions. Foubert, et al. [9] use a pressure sensor array for lying and sitting positions classification. They report a comparison of applying SVM, Neural Network, and k-nearest neighbor approaches with the results by 5 out of 8 selected postures.

In the rollover detection task, Townsend, et al. [2] employ five pressure sensor arrays and place those devices in a row under the bed mattress. In their approach, they apply the decision-tree technique to the data generated from each pressure-sensor unit, which is considered to be the center of gravity of the body. There is a limited number of recorded data of both non-rollover and rollover positions. The experiment is performed by a healthy volunteer in a non-sleep condition. Therefore, their result is not diverse enough to cover the possible cases. Viriyavit, et al. [10] work with Neural Network and Bayesian Network for bed posture classification using a sensor panel with just four sensor units and achieve a good result.

From the literature review, we notice that some researchers use a large number of sensors to complete their techniques. In practice, it is not affordable for a large group of people who have limited budget, and it requires much care and maintenance of the devices. In this research, we propose to use of the Long Short-Term Memory (LSTM) approach which has the potential to include the sequential information for improvement in prediction [11].

The paper is organized in the following manner. Section 2 outlines the equipment and structure of the data collected from the sensor units. In Section 3, we discuss the architecture of LSTM and the dataset. Section 4 analyses the result comparing to SVM, and previously proposed Neural Network with Bayesian Network approaches. Section 5 concludes the results.

2. Equipment and Data Preparation

2.1 Equipment

The sensor panel is equipped with two kinds of sensors, i.e. pressure and piezoelectric sensors, which are sandwiched in between two plastic panels. Each sensor type is placed symmetrically on the left-side and right-side of the panel, as shown in Fig. 1. The size of the panel is 18 cm in width and 60 cm in length. In use, the sensor panel is placed under the mattress at the thorax area of the patient. The data is collected from sensors with 30 Hz of the sampling rate. The signal ranges from -127 to 128 for the piezoelectric sensor, and 0 to 255 for the pressure sensor.

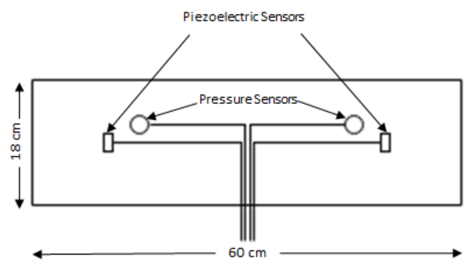

Fig. 1. Sensor Panel.

2.2 Data collection

The collected data are sent via the Bluetooth box to the M2M box as shown in Fig. 2. The M2M box wirelessly transmits those data to the computer which stores the signal data in the comma-separated value (CSV) format.

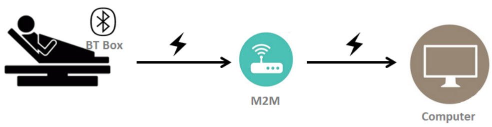

Fig. 2. Data Collection Flow.

2.3 Organized signal data

The collected data are arranged in columns. It is represented by PR: Piezo-Right, WR: Weight-Right, PL: Piezo-Left, WL: Weight-Left for each sensor. The last column is the annotated label (Label) of the bed position as shown in Eq. (2.1).

$$D = [PR, WR, PL, WL, Label]. \quad (2.1)$$

For the data annotation, we install a camera to record the patient's activities on the bed. Since it is in concern of the patient's privacy, in the experiment process, we obtain the consent from the target patient with a formal agreement for maintaining the patient's personal privacy.

The data from signal and video footage are recorded for 120 hours from a patient, whose age is more than 60. The video and recorded signal are reviewed synchronously before applying the annotated label of bed position. The five classes of bed position are predefined and represented by a number as shown in Table 1 [12].

Table 1. Five classes of bed position.

Bed Position	Tagging Label
Out of Bed	1
Sitting	2
Sleep Center	3
Sleep Left	4
Sleep Right	5

The types of bed position have unique characteristics which can be used to classify the position of the subject on the bed by the observed data of around 390,000 samples for the experiment. The data consists of out of bed, sitting, sleep at the center, sleep left side, and sleep right side of the samples around 44,000, 32,000, 90,000, 4,800, and 220,000 respectively. This dataset is shared from the previous research [13,14], and divided into training for 80% and testing for 20%.

2.4 Data accumulation

We accumulate the data to match the 30 Hz sampling before using in our model for annotating and analyzing purposes. We transform the 30 data points into a single row and consider it as one second which is equal to 30×4 sensors =120 data points as described in Fig. 3.

2.5 Data normalization

Before passing the data to the model, we normalized the signals from both pressure and piezoelectric sensors to avoid the bias of the different ranges and additional factors. For pressure sensors, the patient's weight, mattress weight, and panel's weight

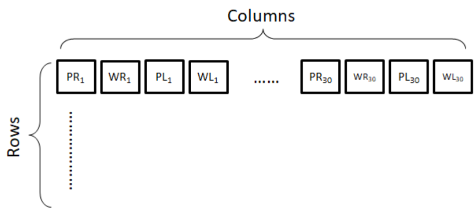

Fig. 3. Data Accumulation Structure.

are calibrated to mitigate the affected pressure. In addition, we apply the min-max scaling normalization to put the piezoelectric value into the range from 0 to 1 as shown in Eq. (2.2) [15].

$$X_{norm} = \frac{X_t - min}{max - min}. \tag{2.2}$$

X_t is the signal point at time t^{th}, X_{norm} is the normalized value, *min* is the minimum offset value and *max* is the maximum offset value.

3. Methodology

3.1 Data preprocessing

There are some studies about the movement of the elderly during sleeping. They report that older people spend less time than an adult on movement shifts during their sleep [16, 17]. The study shows that people, aged 65-75 prefer to sleep on a side position for 77% of their sleeping time. We can also observe the sort of behavior in our collected data. This situation may cause a problem to our model that learns from the previous information but it cannot be maintained long enough as the context for learning. Therefore, we apply the window sliding technique which combines the previous signal and current signal before the data will be fit into the model. The signal is segmented into a unit of one second. The window size is a span of two seconds which covers the previous one second signal and the current one second signal. By doing this, the considering signal window can capture the previous information of the signal, and it strides one second each. Fig. 4(A) shows the normal one second window size that strides one second each to fit the signal into the model. Fig. 4(B) shows how we apply the concept of window sliding. The window size is two seconds long which is the concatenation of one previous second signal and the current one second signal. The window strides one second each.

3.2 Long short-term memory

The Long Short-Term Memory or LSTM is one of the Recurrent Neural Networks (RNN) with the capability to handle long-term dependency [18,19], and to solve the gradient explosion during the long back-propagated learning process of RNN [20]. The time-series classification is commonly used by LSTM [21]. The mechanism of LSTM is described as a unit that allows the data to pass through with little modification [22]. Each unit has 3 gates:

1. Forget gate is used to decide the value that needs to remember or to forget inside the unit.

2. Input gate is used to decide the value that needs to update inside the unit.

3. The output gate is used to decide the value that the unit is going to output.

Fig. 5 is the representation of the LSTM unit, where x_t is the input data, h_{t-1} is the hidden value from the previous unit, C_{t-1} is the memory cell from the previous unit, h_t is the hidden output value, and C_t is the output memory cell.

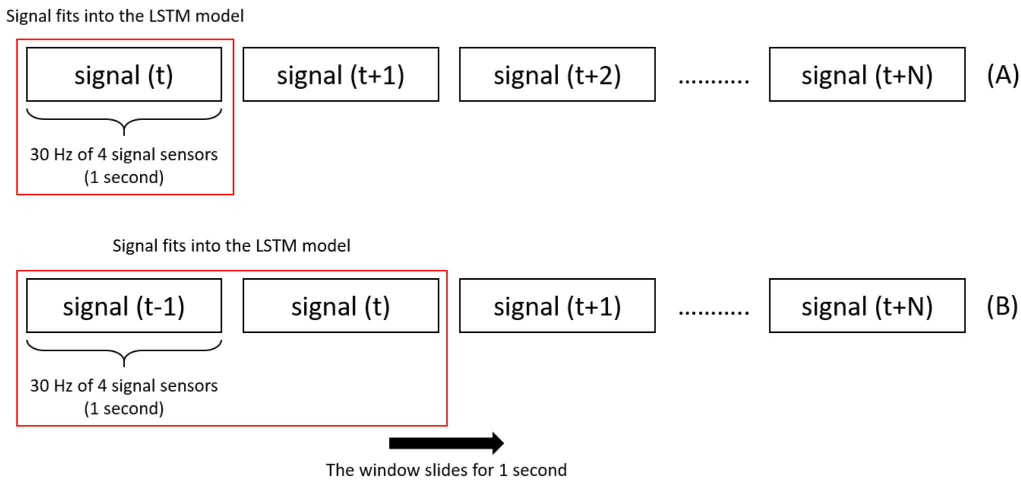

Fig. 4. (A) Data before Preprocessing. (B) Data after Preprocessing.

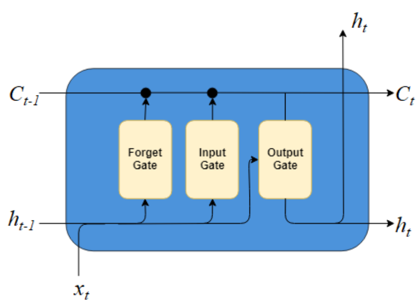

Fig. 5. LSTM Unit.

3.3 Stacked LSTM (2-Layers)

Stacked LSTM or 2-Layers LSTM was introduced by Graves, et al. in 2013 [23]. This technique is preferred as the stable approach for solving the sequence prediction problem and is used to solve some problems, such as speech recognition, fraudulent transaction, and temporal dependence in EEG [11,23–26]. Fig. 6 illustrates the architecture of Stacked LSTM.

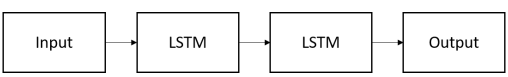

Fig. 6. Stacked LSTM Architecture [11].

There is a crucial part of how the data can be used as the input with the right shape in the LSTM model, as shown in Fig. 7. The input is required in a three dimensional (3D) shape of the data, whose three components are:

1. Batch Sizes: it is the number of samples in one batch that need to fit into the model. The number of samples can be ranged from one or more samples.

2. Time Steps: it is the point of observation in the batch.

3. Features: it is the factor that is used for the observation.

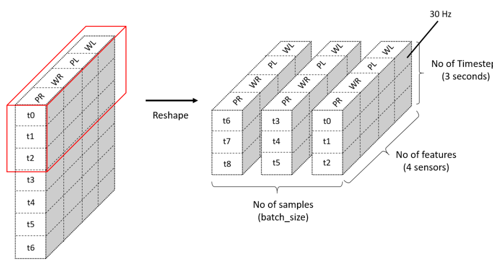

Fig. 7. Input Data Shape for LSTM.

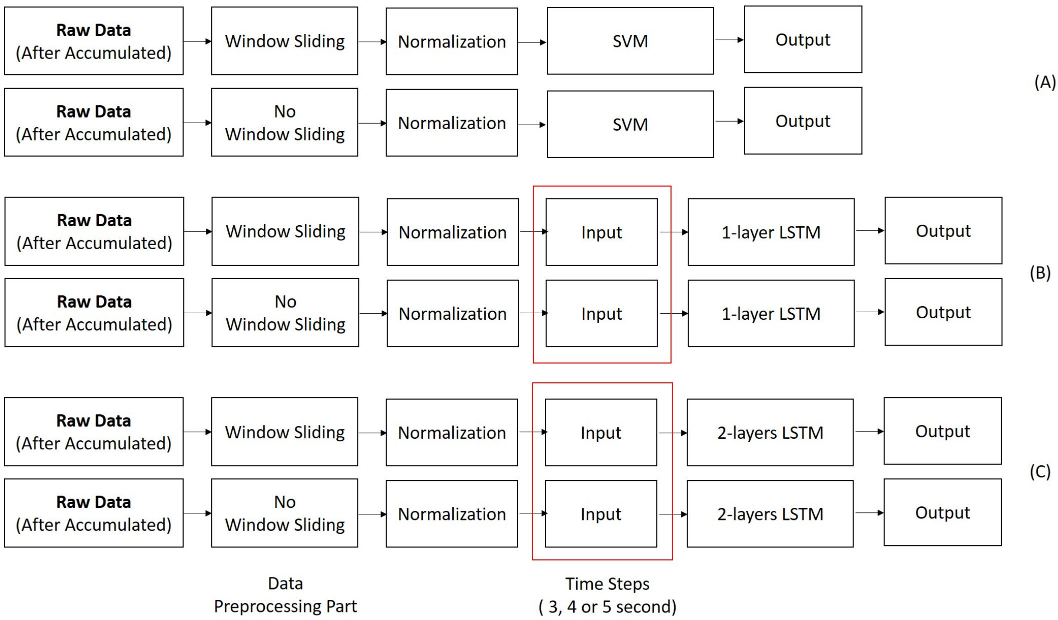

Fig. 8. Experimental Flow (A) SVM. (B) 1-Layer LSTM. (C) 2-Layers LSTM.

In this research, we choose the duration which ranges from three to five seconds for each time step. In the experiment, due to a typical movement duration of people, it happens to be around two to six seconds [27].

3.4 Experimental scheme

Some factors need to be set for the experiment. As described in Table 2, we employ three classification techniques, namely SVM, 1-layer of LSTM, and 2-layers of LSTM. Furthermore, those models are tested using window sliding and without using window sliding technique.

The first approach is the SVM model with the RBF kernel as the default configuration. It is considered to be a base model for comparison in this experiment. The second approach is 1-layer LSTM. The last approach for the experiment is 2-layers of LSTM. Since there is no rule of thumb for testing with the LSTM model, both approaches use the same configuration with three different time steps and three different hidden nodes. As the body position normally occurs in a sequence, and can be defined as a classification problem, the Softmax activation function is used in this scenario. We choose to run on the test set for 300 epochs. Fig. 8 shows the process flow of the experiment.

4. Experimental Result

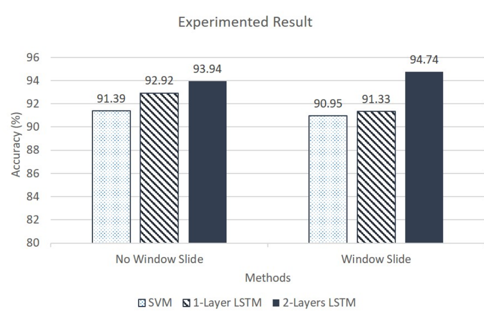

Fig. 9. Experiment Result.

Fig. 9 illustrates the comparison of the accuracy of the approaches. Without the

Table 2. Summary of the experiment parameters.

Approach	Preprocessing	Time Step (second)	Hidden Nodes
LSTM (2 Layers)	Yes	3	128,80,50
		4	128,80,50
		5	128,80,50
	No	3	128,80,50
		4	128,80,50
		5	128,80,50
LSTM (1 Layers)	Yes	3	128,80,50
		4	128,80,50
		5	128,80,50
	No	3	128,80,50
		4	128,80,50
		5	128,80,50
SVM	Yes	-	-
	No	-	-

input from window-slide, 2-layers LSTM outperforms the other two methods with 93.94% accuracy. On the right side, combining 2-layers LSTM with the window-slide technique can increase its accuracy to 94.74%. However, the accuracy is not the only factor to be considered when working with classification problems. F1-Score is another important factor that has to be considered because it appropriately shows the harmonic mean of recall and precision that can provide a better measure of the performance of the approaches.

In Fig. 10, the predictions of each approach for out of bed, sitting, sleep left, and sleep right positions are almost the same for either applying window-sliding or not. Interestingly, there is a significant improvement in the sleep center position prediction in case of using 2-layers LSTM with window sliding technique.

For the sleep center position, 2-layers LSTM can only get up to 70% while the other methods get more than 75%. But, when combining the window sliding with 2-layers LSTM, its F1-Score increase up to

9% from 70% to 79%. However, the accuracy and F1-Score cannot tell which position is confused with others. In the further analysis, we introduce the confusion matrix to measure the overall performance, and compare the result among the approaches.

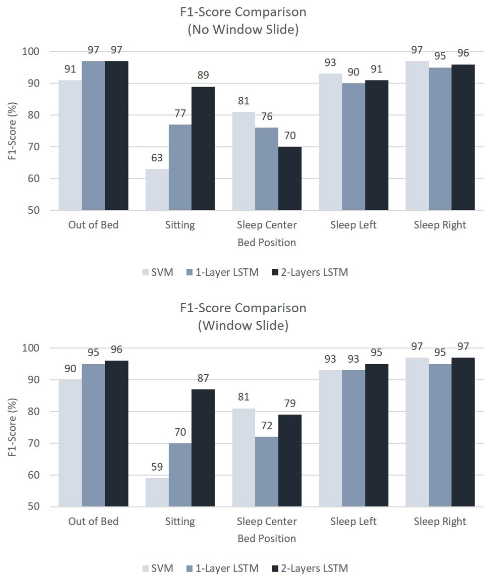

Fig. 10. F1-Score Comparison.

For the first approach, we apply Support Vector Machine (SVM) for testing with both types of datasets. Since the SVM does not require a 3D data shape, we do not need to transform the data shape. With SVM, we can achieve a total accuracy of 91.39% without window-slide and 90.95% with window-slide.

As shown in Figs. 11 and 12, the accuracy of the testing with and without window slide can reach around 91%. However, the prediction of the sitting position is extremely low comparing to other position prediction. The above confusion matrix in both figures shows the sitting position cannot reach 50%, and it has false prediction over the out of bed and sleep right positions.

For the second approach, we work with Long Short Term Memory (LSTM) 1 layer for the expectation to see some im-

SVM (No Window Slide)

Predicted

Target	Out of Bed	Sitting	Sleep Center	Sleep Left	Sleep Right
Out of Bed	100%	0%	0%	0%	0%
Sitting	41%	46%	0%	0%	13%
Sleep Center	0%	0%	91%	1%	8%
Sleep Left	0%	6%	4%	90%	0%
Sleep Right	0%	0%	2%	0%	98%
Precision	83%	100%	73%	95%	96%
Recall	100%	46%	91%	90%	98%
F1-Score	91%	63%	81%	93%	97%
Accuracy	91.39 %				

Fig. 11. SVM with no window sliding.

SVM (Window Slide)

Predicted

Target	Out of Bed	Sitting	Sleep Center	Sleep Left	Sleep Right
Out of Bed	100%	0%	0%	0%	0%
Sitting	46%	42%	0%	0%	12%
Sleep Center	0%	0%	91%	1%	8%
Sleep Left	0%	6%	4%	90%	0%
Sleep Right	0%	0%	2%	0%	98%
Precision	82%	98%	74%	96%	97%
Recall	100%	42%	91%	90%	98%
F1-Score	90%	59%	81%	93%	97%
Accuracy	90.95 %				

Fig. 12. SVM with window sliding.

provement from the SVM model. Table 3 in the appendix shows the summary results of the full experiment. Testing without window sliding technique, we choose the 80 hidden nodes model with three second-time-step that achieves the total accuracy of 92.92% in the prediction over five positions. For the window sliding part, we choose the 128 hidden nodes with three second-time-step. The total accuracy is 91.33%, which is lower than the former result on the without window sliding data.

LSTM 1 Layer (No Window Slide)

Predicted

Target	Out of Bed	Sitting	Sleep Center	Sleep Left	Sleep Right
Out of Bed	100%	0%	0%	0%	0%
Sitting	13%	62%	0%	0%	25%
Sleep Center	0%	0%	87%	0%	13%
Sleep Left	0%	2%	15%	84%	0%
Sleep Right	0%	0%	3%	0%	97%
Precision	94%	100%	67%	98%	94%
Recall	100%	62%	87%	84%	97%
F1-Score	97%	77%	76%	90%	95%
Accuracy	92.92 %				

Fig. 13. LSTM 1 Layer with no Window Sliding.

The LSTM (1 layer) model without window sliding, as shown in Fig. 13, can predict the sitting position with 62% whereas 54% of the same position can be predicted by the model with window sliding. We can observe that these two selected models are not good enough to improve on sitting position prediction but we can see the improvement in the sleep left position. The first model predicts two positions as false-negative, namely sitting becomes out of bed and sleep left becomes sleep center. The second model can help improve the prediction over the sleep left position from 84% to 96%. Even though the result from LSTM shows some improvement from the SVM model the individual predicted position is still not good enough.

LSTM 1 Layer (Window Slide)

Predicted

Target	Out of Bed	Sitting	Sleep Center	Sleep Left	Sleep Right
Out of Bed	100%	0%	0%	0%	0%
Sitting	20%	54%	0%	0%	26%
Sleep Center	0%	0%	86%	3%	10%
Sleep Left	0%	2%	2%	96%	0%
Sleep Right	0%	0%	4%	0%	96%
Precision	97%	99%	61%	89%	94%
Recall	100%	54%	86%	96%	96%
F1-Score	95%	70%	72%	93%	95%
Accuracy	91.33 %				

Fig. 14. LSTM 1 Layer with no Window Sliding.

For the third approach, we work on 2 layers of LSTM within the same parameters as the second experiment above. Table 4 in the appendix shows the summary results of the experiment.

Without window sliding, the most reliable model is the five second-time-step with 128 hidden nodes with 93.94% accuracy while the model with window sliding has 94.74% accuracy.

Figs. 15 and 16 describe the confusion matrix for both with and without window sliding on the dataset. As we can see that both models have quite good predic-

LSTM 2 Layer (No Window Slide)

Target \ Predicted	Out of Bed	Sitting	Sleep Center	Sleep Left	Sleep Right
Out of Bed	96%	4%	0%	0%	0%
Sitting	3%	87%	0%	0%	10%
Sleep Center	0%	0%	92%	1%	7%
Sleep Left	0%	6%	7%	87%	0%
Sleep Right	0%	0%	5%	0%	95%
Precision	98%	90%	57%	96%	97%
Recall	96%	87%	92%	87%	95%
F1-Score	97%	89%	70%	91%	96%
Accuracy	93.94 %				

Fig. 15. LSTM 2 layers with no Window Sliding.

LSTM 2 Layer (Window Slide)

Target \ Predicted	Out of Bed	Sitting	Sleep Center	Sleep Left	Sleep Right
Out of Bed	93%	7%	0%	0%	0%
Sitting	0%	89%	0%	0%	11%
Sleep Center	0%	0%	92%	1%	7%
Sleep Left	0%	0%	8%	92%	0%
Sleep Right	0%	0%	3%	0%	97%
Precision	100%	85%	69%	98%	97%
Recall	93%	89%	92%	92%	97%
F1-Score	96%	87%	79%	95%	97%
Accuracy	94.74 %				

Fig. 16. LSTM 2 layers with Window Sliding.

tions over five positions. However, sleep left and sitting positions have only 87% of the model without window sliding, while the model with window sliding increases to 89% and 92% respectively. We admit that there is a reduction of 3% for the out-of-bed position.

After the three different experiments, we choose some of those results to make a comparison with the previous work reported in [10].

According to the previous study result, as shown in Fig. 17, the total accuracy is 91.5% for classification by combining Neural Network and Bayesian Network. Two layers of the LSTM approach can increase the overall accuracy to 94.74%. As mentioned from the previous research, the sleep right position has only 75% in prediction due to the patient getting out and returning back to the bed usually occurs on the right side of the bed which caused the error in prediction in other positions instead. However, our proposed 2 layers of LSTM method combined with the window sliding can make an improvement up to 97% in predictions for sleep right position while other position prediction still remains high.

5. Conclusion

This research has shown a significant improvement in bed position classification. By using the proposed 2 layers of LSTM method combined with the window sliding for preprocessing dataset, we can observe the significant improvement in the prediction of sleep right position. Furthermore, this method also slightly increases the overall accuracy to 94.74% without sacrificing too much accuracy of other position prediction. We notice that this experiment is not robust to prove that the window slide technique combined with 2 layers LSTM is the major contribution in the bed position prediction. However, it yields a promising re-

Neural Network + Bayesian Network

Target \ Predicted	Out of Bed	Sitting	Sleep Center	Sleep Left	Sleep Right
Out of Bed	94.1%	5.9%	0%	0%	0%
Sitting	4.3%	93.7%	0.2%	1.7%	0.1%
Sleep Center	0%	0.9%	95.4%	1.1%	2.7%
Sleep Left	0%	0.1%	0.5%	99.3%	0.1%
Sleep Right	0%	11.1%	13.9%	0%	75.0%
Accuracy	91.50 %				

SVM (Window Slide)

Target \ Predicted	Out of Bed	Sitting	Sleep Center	Sleep Left	Sleep Right
Out of Bed	100%	0%	0%	0%	0%
Sitting	46%	42%	0%	0%	12%
Sleep Center	0%	0%	91%	1%	8%
Sleep Left	0%	6%	4%	90%	0%
Sleep Right	0%	0%	2%	0%	98%
Accuracy	90.95 %				

LSTM 1 Layer (Window Slide)

Target \ Predicted	Out of Bed	Sitting	Sleep Center	Sleep Left	Sleep Right
Out of Bed	100%	0%	0%	0%	0%
Sitting	20%	54%	0%	0%	26%
Sleep Center	0%	0%	86%	3%	10%
Sleep Left	0%	2%	2%	96%	0%
Sleep Right	0%	0%	4%	0%	96%
Accuracy	91.33 %				

LSTM 2 Layer (Window Slide)

Target \ Predicted	Out of Bed	Sitting	Sleep Center	Sleep Left	Sleep Right
Out of Bed	93%	7%	0%	0%	0%
Sitting	0%	89%	0%	0%	11%
Sleep Center	0%	0%	92%	1%	7%
Sleep Left	0%	0%	8%	92%	0%
Sleep Right	0%	0%	3%	0%	97%
Accuracy	94.74 %				

Fig. 17. Comparison of experimental results.

sult for further improvement in its robustness of the prediction model. For future research, we are looking forward to work on the improvement of equipment, collecting more data and systematically designing the experiment parameters, as well as the new approaches to enhance the prediction.

Acknowledgments

The authors gratefully acknowledge the financial support provided by Thammasat University Research fund under the TSRI, Contract No. TUFF19/2564, for the project of "AI Ready City Networking in RUN", based on the RUN Digital Cluster collaboration scheme. We are very thankful to Mr. Shunichi Yoshitake, chairman of AIVS, for his strong support in the equipment utilization under the Japanese International Cooperation Agency (JICA) grant for SME development support, and Dr. Surapong Boonprasert, Dr. Phonthep Pongthawikorn, together with the staffs of Banphaeo General Hospital for overall supports in data collection and evaluation.

References

[1] Mineharu A, Kuwahara N, Morimoto K. A study of automatic classification of sleeping position by a pressure-sensitive sensor. In: 2015 International Conference on Informatics, Electronics & Vision (ICIEV). IEEE; 2015. p. 1–5.

[2] Townsend DI, Goubran R, Frize M, Knoefel F. Preliminary results on the effect of sensor position on unobtrusive rollover detection for sleep monitoring in smart homes. In: 2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE; 2009. p. 6135–8.

[3] Steele R, Secombe C, Brookes W. Using wireless sensor networks for aged care: The patient's perspective. In: 2006 Pervasive Health Conference and Workshops. IEEE; 2006. p. 1–10.

[4] Ostadabbas S, Pouyan MB, Nourani M, Kehtarnavaz N. In-bed posture classification and limb identification. In: 2014 IEEE Biomedical Circuits and Systems Conference (BioCAS) Proceedings. IEEE; 2014. p. 133–6.

[5] Chaccour K, Darazi R, El Hassani AH, Andres E. From fall detection to fall prevention: A generic classification of fall-related systems. IEEE Sensors Journal. 2016;17(3):812–22.

[6] Bennett S, Ren Z, Goubran R, Rockwood K, Knoefel F. In-bed mobility monitoring using pressure sensors. IEEE Transactions on Instrumentation and Measurement. 2015;64(8):2110–20.

[7] Yousefi R, Ostadabbas S, Faezipour M, Farshbaf M, Nourani M, Tamil L, et al. Bed posture classification for pressure ulcer prevention. In: 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE; 2011. p. 7175–8.

[8] LTD VM. BodiTrak2 Smart Bed Sensor Pressure; 2018. Last accessed 26 November 2021.

[9] Foubert N, McKee AM, Goubran RA, Knoefel F. Lying and sitting posture recognition and transition detection using a pressure sensor array. In: 2012 IEEE International Symposium on Medical Measurements and Applications Proceedings. IEEE; 2012. p. 1–6.

[10] Viriyavit W, Sornlertlamvanich V, Kongprawechnon W, Pongpaibool P, Isshiki T. Neural network based bed posture classification enhanced by Bayesian approach. In: 2017 8th International Conference of Information and Communication Technology for Embedded Systems (IC-ICTES). IEEE; 2017. p. 1–5.

[11] Brownlee J. Stacked long short-term memory networks; 2017. Last accessed 15 May 2019.

[12] Viriyavit W, Sornlertlamvanich V. Data Labeling Scheme for Bed Position Classification. In: Information Modelling and Knowledge Bases XXXI. IOS Press; 2020. p. 222–37.

[13] Viriyavit W, Sornlertlamvanich V. Bed position classification by a neural network and Bayesian network using noninvasive sensors for fall prevention. Journal of Sensors. 2020;2020.

[14] Viriyavit W, Sornlertlamvanich V, Kongprawechnon W, Pongpaibool P. Bed Posture Classification Using Noninvasive Bed Sensors for Elderly Care. Information Modelling and Knowledge Bases XXIX. 2018;301:383.

[15] Raschka S. About feature scaling and normalization and the effect of standardization for machine learning algorithms; 2014. Last accessed 15 May 2019.

[16] Gori S, Ficca G, Giganti F, Di Nasso I, Murri L, Salzarulo P. Body movements during night sleep in healthy elderly subjects and their relationships with sleep stages. Brain research bulletin. 2004;63(5):393–7.

[17] Giganti F, Ficca G, Gori S, Salzarulo P. Body movements during night sleep and their relationship with sleep stages

are further modified in very old subjects. Brain research bulletin. 2008;75(1):66–9.

[18] Hochreiter S, Schmidhuber J. Long short-term memory. Neural computation. 1997;9(8):1735–80.

[19] Olah C. Understing LSTM networks; 2015. Last accessed 15 May 2019.

[20] Hochreiter S, Bengio Y, Frasconi P, Schmidhuber J, et al.. Gradient flow in recurrent nets: the difficulty of learning long-term dependencies. A field guide to dynamical recurrent neural networks. IEEE Press; 2001.

[21] Patterson J, Gibson A. Major Architectures of Deep Networks. In: Deep Learning A Practitioner's Approach. O'Reilly Media, Inc.; 2017. p. 117–64.

[22] Ramsundar B, Bosagh Zadeh R. Long Short-Term Memory (LSTM). In: Tensorflow for Deep Learning. O'Reilly Media, Inc.; 2018. p. 152–3.

[23] Graves A, Mohamed Ar, Hinton G. Speech recognition with deep recurrent neural networks. In: 2013 IEEE international conference on acoustics, speech and signal processing. Ieee; 2013. p. 6645–9.

[24] Heryadi Y, Warnars HLHS. Learning temporal representation of transaction amount for fraudulent transaction recognition using CNN, Stacked LSTM, and CNN-LSTM. In: 2017 IEEE International Conference on Cybernetics and Computational Intelligence (CyberneticsCom). IEEE; 2017. p. 84–9.

[25] Hefron RG, Borghetti BJ, Christensen JC, Kabban CMS. Deep long short-term memory structures model temporal dependencies improving cognitive workload estimation. Pattern Recognition Letters. 2017;94:96–104.

[26] Pascanu R, Gulcehre C, Cho K, Bengio Y. How to construct deep recurrent neural networks. arXiv preprint arXiv:13126026. 2013.

[27] Hoque E, Dickerson RF, Stankovic JA. Monitoring body positions and movements during sleep using wisps. In: Wireless Health 2010; 2010. p. 44–53.

Appendices

Table 3. Experimental Result of 1 Layer LSTM.

Preprocessing Data	Hidden Nodes	Time Step (second)	Accuracy (%)	F1-Score (%)				
				Out Of Bed	Sitting	Sleep Center	Sleep Left	Sleep Right
No Window Slide	128	3	91.79	97	78	68	94	94
		4	91.53	99	79	65	93	93
		5	92.2	95	70	80	91	96
	80	3	92.92	97	77	76	90	95
		4	91.13	98	91	54	92	93
		5	90.41	95	83	58	88	94
	50	3	92.7	99	84	66	89	94
		4	90.13	93	60	73	93	95
		5	92.23	96	82	67	97	95
Window Slide	128	3	91.33	95	70	72	93	95
		4	91.12	97	82	57	82	94
		5	92.37	100	93	52	82	94
	80	3	92.03	98	90	58	93	94
		4	92.15	95	82	66	91	96
		5	91.12	98	93	45	82	93
	50	3	92.82	96	84	67	91	96
		4	92.67	100	87	62	88	94
		5	92.54	99	87	61	89	94

Table 4. Experimental Result of 2 Layers LSTM.

Preprocessing Data	Hidden Nodes	Time Step (second)	Accuracy (%)	F1-Score (%)				
				Out Of Bed	Sitting	Sleep Center	Sleep Left	Sleep Right
No Window Slide	128	3	92.87	98	84	68	94	95
		4	92.73	97	83	70	90	95
		5	93.94	97	89	70	91	96
	80	3	91.42	98	89	56	89	93
		4	92.43	97	78	73	95	95
		5	91.21	98	90	56	95	93
	50	3	93.02	99	91	62	94	94
		4	91.70	94	82	68	94	95
		5	92.93	99	88	65	90	95
Window Slide	128	3	93.50	99	87	66	88	95
		4	95.19	97	87	78	90	97
		5	89.73	98	83	53	86	92
	80	3	91.95	99	92	54	82	93
		4	94.56	95	83	78	90	98
		5	92.14	99	92	57	88	94
	50	3	96.05	98	92	79	82	98
		4	91.06	100	88	53	85	92
		5	94.74	96	87	79	95	97