

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

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

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 accident [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, sitting, 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 consumes 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 followings. 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 figure 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.

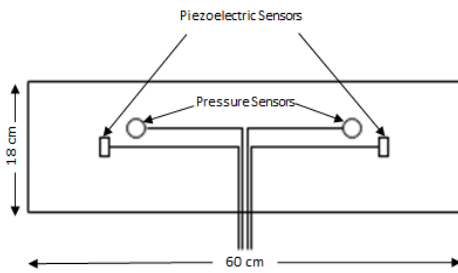


Fig. 1. Sensor Panel

2.2 Data Collection

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

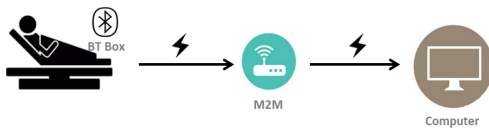


Fig. 2. Data Collection Flow

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 (2.1).

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

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 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 x 4 sensors =120 data points as described in figure 3.

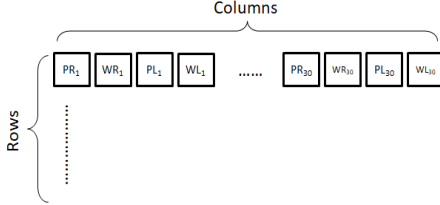


Fig. 3. Data Accumulation Structure

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 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 (2.2) [15].

$$x_{norm} \equiv \frac{x_t - min}{max - min} \quad (2.2)$$

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.

Figure 4(A) shows the normal one second window size that strides one second each to fit the signal into the model.

Figure 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.

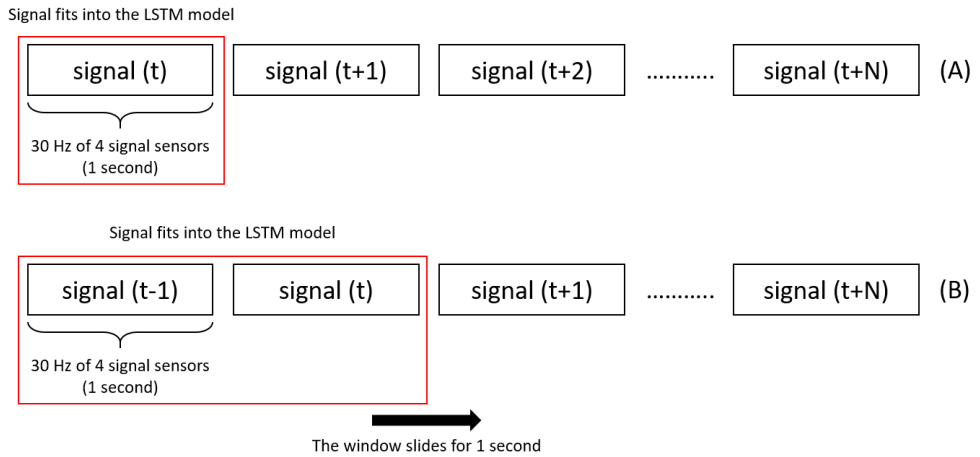


Fig. 4. (A) Data before Preprocessing (B) Data after Preprocessing

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 backpropagated 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, and
- (3) The output gate is used to decide the value that the unit is going to output.

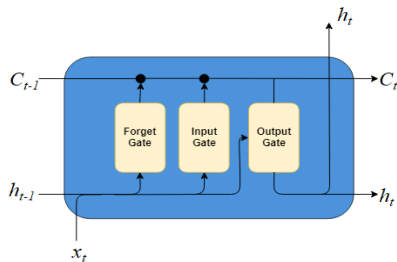


Fig. 5. LSTM Unit

Figure 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.

3.3 Stacked LSTM (2-Layers)

Stacked LSTM or 2-Layers LSTM is 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]. Figure 6 illustrates the architecture of Stacked LSTM.

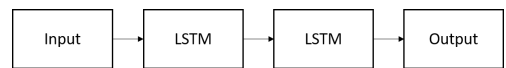


Fig. 6. Stacked LSTM Architecture [11]

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 Figure 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.

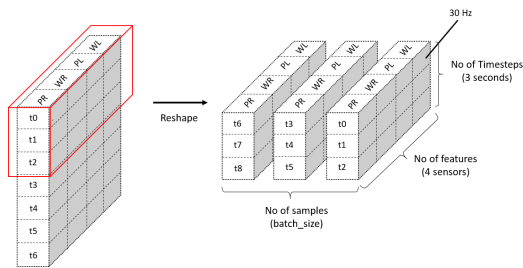


Fig. 7. Input Data Shape for LSTM

In this research, we choose the number of 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. Figure 8 shows the process flow of the experiment.

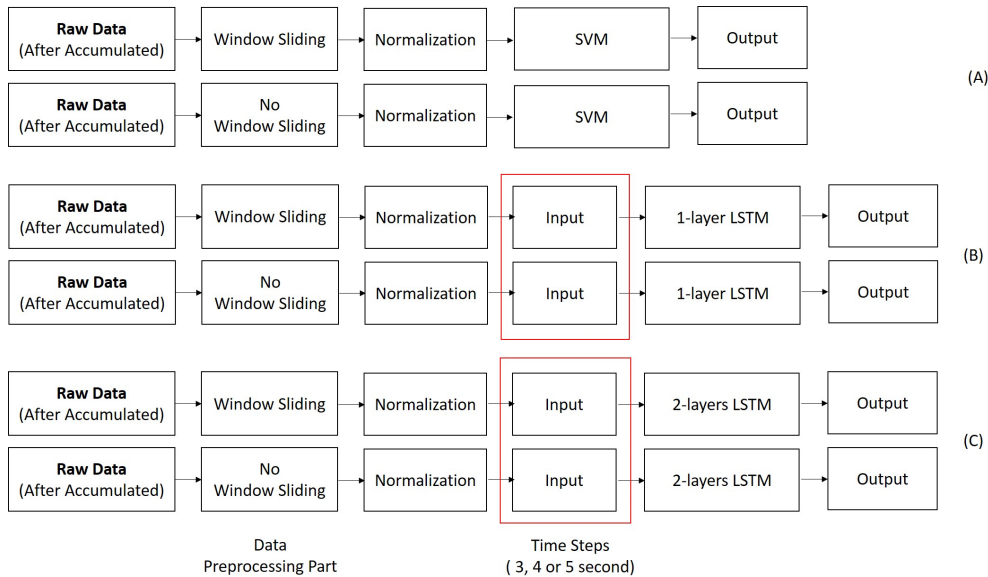


Fig. 8. Experimental Flow (A) SVM (B) 1-Layer LSTM (C) 2-Layers LSTM

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 Layer)	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	-	-

4. Experiment Result

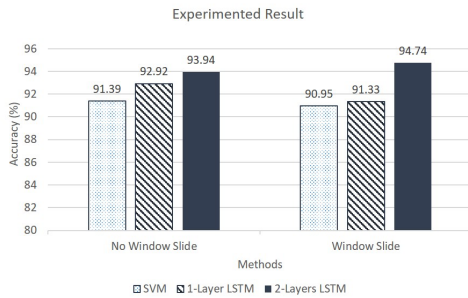


Fig. 9. Experiment Result

Figure 9 illustrates the comparison of the accuracy of the approaches. Without the 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 Figure 10, the prediction 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.

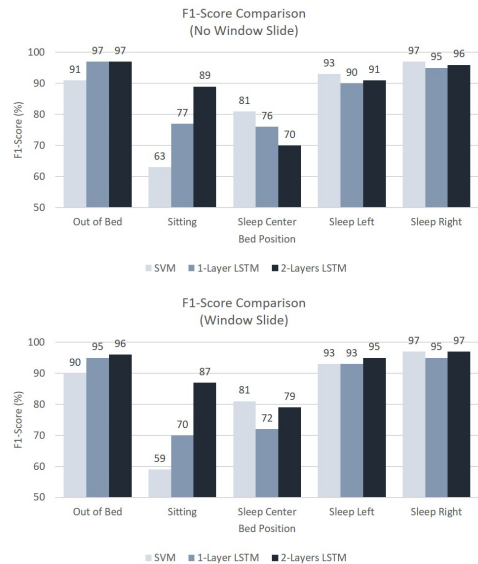


Fig. 10. F1-Score Comparison

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.

SVM (No Window Slide)

Target	Predicted					
	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

As shown in Figure 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.

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%
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

LSTM 1 Layer (No Window Slide)

Target	Predicted				
	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

For the second approach, we work with Long Short Term Memory (LSTM) 1 layer for the expectation to see some improvement 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 (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%
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 Window Sliding

The LSTM (1 layer) model without window sliding, as shown in figure 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 the result from LSTM shows some improvement from the SVM model but the individual predicted position is still not good enough.

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.

		LSTM 2 Layer (No Window Slide)				
		Predicted				
Target		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

Figure 15 and Figure 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 predictions 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].

		LSTM 2 Layer (Window Slide)				
		Predicted				
Target		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

According to the previous study result, as shown in Figure 17, the total accuracy is 91.5% for classification by combining Neural Network and Bayesian Network. 2 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 prediction for sleep right position while other position prediction still remains high.

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. The comparison of experimented

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 increase 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 result 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, systematically designing the experiment parameters, as well as the new approaches to enhance the prediction.

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Appendix

Table 3. 1 Layer of Experimental Result

Preprocess 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
	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. 2 Layers of Experimental Result

Preprocess 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	91.7	94	82	68	94	95
		5	93.93	99	88	65	90	95
Window Slide	128	3	93.5	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