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A Hybrid Deep Learning Model for Human Activity Recognition Using Multimodal Body Sensing Data

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ABSTRACT Human activity recognition from multimodal body sensor data has proven to be an effective approach for the care of elderly or physically impaired people in a smart healthcare environment. However, traditional machine learning techniques are mostly focused on a single sensing modality, which is not practical for robust healthcare applications. Therefore, recently increasing attention is being given by the researchers on the development of robust machine learning techniques that can exploit multimodal body sensor data and provide important decision making in Smart healthcare. In this paper, we propose an effective multi-sensors-based framework for human activity recognition using a hybrid deep learning model, which combines the simple recurrent units (SRUs) with the gated recurrent units (GRUs) of neural networks. We use the deep SRUs to process the sequences of multimodal input data by using the capability of their internal memory states. Moreover, we use the deep GRUs to store and learn how much of the past information is passed to the future state for solving fluctuations or instability in accuracy and vanishing gradient problems. The system has been compared against the conventional approaches on a publicly available standard dataset. The experimental results show that the proposed approach outperforms the available state-of-the-art methods.

INDEX TERMS Multi-modal body sensor data, activity recognition, deep recurrent neural networks (RNNs), simple recurrent unit (SRU), gated recurrent unit (GRU), robust healthcare.

I. INTRODUCTION

In recent years, human activity recognition (HAR) from wearable body sensor network is becoming popular due to its immense potential in many application areas such as smart healthcare, transportation, security, robotics and smart home [1]–[8]. HAR systems usually convert specific body movements sensed by various wearable body sensors to some sensor signal patterns, and can be classified using machine learning techniques [9]–[12]. For example, various machine learning algorithms can be used to identify complex activity patterns such as sitting and relaxing, lying down, walking, climbing stairs, etc.. Thus, recognition of everyday activities is essential for keeping up healthy lifestyle among the elderly residents for monitoring and preventing serious illness.

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However, HAR is challenging due to the large variability in body movements of users in various situations. In particular, it is not easy to identify an activity from multimodal body sensors data [13]–[15]. Traditional machine learning techniques are mostly focused on a single sensing modality, which is not practical for robust healthcare applications. In multimodal sensor data case, it is difficult to increase recognition accuracy while using fewer numbers of features. HAR from multimodal sensor data relies upon combinations of sensors, such as accelerometer sensors or gyroscope sensors [16]–[18].

To identify human activity properly from multimodal sensor data, robust ML algorithms need to be used. There are many ML algorithms that could be utilized such as hidden Markov models (HMM), support vector machine etc. [19]. Now-a-days, deep learning methods have been controlling over other ML algorithms for a tremendous scope of utilizations [20]–[28]. DL is a king of neural network that uses many non-linear information-processing layers for feature extraction and classification. Among the deep learning methods, Deep Belief Network (DBN) [23]–[25] and Convolutional Neural Network (CNN) network are popular [26], [27]. DBN uses confined Boltzmann machines that make the preparation procedure exceptionally quicker than run of the mill enormous neural system. CNN is mostly used in image feature extraction scenario.

However, these methods do not take into account the sequences of patterns or do not remember the changes in the sequences of patterns through the length of intervals between these sequences. To solve these issues, recurrent neural networks (RNNs) are used in many applications to achieve promise results due to its internal memory capability [28].

Deep learning based on RNNs achieved high accuracies in many time-series applications for prediction and classification. Based on the type of recurrent units used to build the RNNs, there are three architectures of RNNs. The first architecture of RNNs is based on the simple recurrent units (SRUs), which is simple and fast. However, it suffers from the vanishing gradient problem [29]. The second architecture of RNNs depends on the gated recurrent units (GRUs), which solve the instability in accuracy and gradient vanishing problems by using two gates (update and forget gates) [30]. The third architecture is based on long short-term memory (LSTM) units, which also reduce the vanishing gradient problem by using three gates (update, forget, and output gates). Among these different architectures of RNNs, the last two architectures achieve excellent accuracy results at the expense of computational cost due to these additional gates.

In this paper, we propose a framework for human activity recognition based on a hybrid deep learning model and using multimodal body sensing data. The hybrid deep learning model contains a set of neural network layers, combining two types of recurrent units, which are simple recurrent units (SRUs) and gated recurrent units (GRUs), called a deep SRUs-GRUs neural network model. We exploit the advantage of SRUs, which are simple and fast, and GRUs, which are effective and more accurate. The main contributions of this study are summarized in the following points:

- We propose an effective multi-sensors-based framework for human activity recognition using a hybrid deep learning model that combines simple and gated recurrent neural network units.
- We use the deep-simple recurrent units to process the sequences of multi-sensors input data by using the capability of their internal memory states and exploit their speed advantage.
- We use the deep-gated recurrent units to store and learn how much of the past information is passed to the future state for solving fluctuations or instability in accuracy and vanishing gradient problems.
- We use a dropout method to reduce the overfitting problem by setting off randomly some neurons during training phase.
- We optimize the model's hyper-parameters based on manual and grid search methods.
- We evaluate the proposed framework using a public MHEALTH dataset of multi-sensors data and compare with the state-of-the-art work on the same dataset.

The rest of the paper is organized as follows: proposed approach is given in Section II, experiments and discussions are reported in Section III, and finally a conclusion is summarized in Section IV.

II. METHODOLOGY

This section explains the methodology adopted in this study. The main goal of our methodology is to develop an accurate hybrid deep learning model for recognizing human activities using multimodal body sensing data. The input of the model is a sequence of raw data coming from multiple sensors and the output is the activity name or activity code. In the following, we describe the dataset used and the proposed model.

A. MHEALTH DATASET

The dataset used in our study is a mobile health (MHEALTH) benchmarked dataset [31]. It was collected from ten subjects by using body motion and vital signs recordings of SHIMMER2 wearable sensors. These sensors were attached by using elastic straps and placed on right wrist, left ankle, and chest of each subject as shown in Figure 1. All participants were asked to perform 12 physical activities listed in Table 1. By using multiple sensors, mobile health system captures the body dynamics and measures the diversity resulted from the motion of body parts, such as the acceleration and orientation of magnetic field.

The sensors placed on chest provide two measurements of lead ECG. Such dataset collected multimodal body

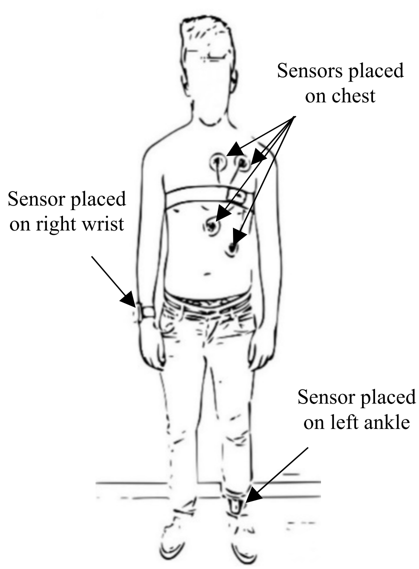


FIGURE 1. A setup of sensor deployment for gathering the multimodal sensing data.

TABLE 1. The Number of Instances for each Activity in the dataset.

ACTIVITY Code	ACTIVITY Name with (repetitions) or (duration)	Number of instances
L1	Standing still (1 min)	3072
L2	Sitting and relaxing (1 min)	3072
L3	Lying down (1 min)	3072
L4	Walking (1 min)	3072
L5	Climbing stairs (1 min)	3072
L6	Waist bends forward (20x)	3072
L7	Frontal elevation of arms (20x)	3072
L8	Knees bending (crouching) (20x)	3379
L9	Cycling (1 min)	3072
L10	Jogging (1 min)	3072
L11	Running (1 min)	3072
L12	Jump front & back (20x)	1075
Total		**35174**

NOTE: In brackets are the number of repetitions (Nx) or the duration of the exercises (min).

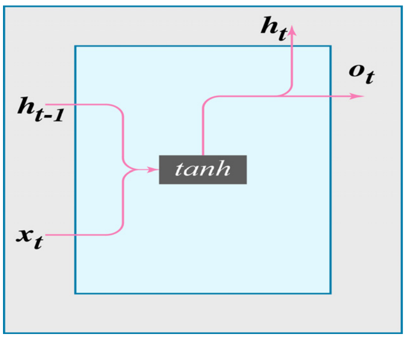


FIGURE 2. A typical structure of SRU.

sensing can be utilized for various arrhythmias checking, heart monitoring, or even analyzing the effects of exercise on the ECG.

The sampling rate of this dataset was 50 Hz, which is sufficient for representing the simulated human activities. By using video camera, all performed sessions were recorded to label the data and verify against anomalous in the signals. The distribution of data points in each activity is shown in Table 1.

B. METHODS

In this subsection, we explain the methods used to build the hybrid deep learning model. The hybrid model consists of a set of neural network layers, which combines SRUs and GRUs to form the deep SRUs-GRUs neural network model. Through the explanation, the mathematical equations and basic structures of the methods are first introduced, then, the proposed framework of multi-sensors-based human activity recognition will be explained in more detail.

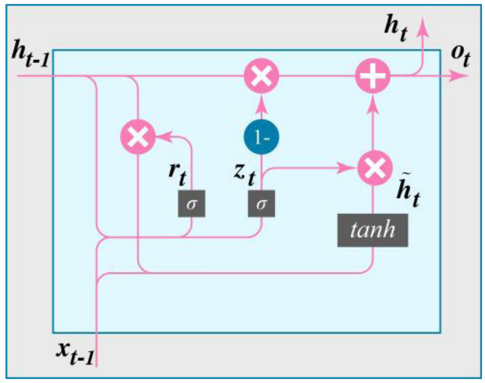


FIGURE 3. A typical structure of GRU.

C. SIMPLE RECURRENT UNIT (SRU)

Simple recurrent unit (SRU) is the simplest type of recurrent units that can be used to build simple recurrent neural networks (RNNs). It achieves a great promise results in many time series applications due to its internal memory capability. The simplicity of SRU makes it fast and suitable for real-time applications [30]. It has no gates and works by multiplying the input vector x_t by the weight matrix W_h and multiplying the previous output vector h_{t-1}, which holds information from previous units by the weight matrix U_h. Then, both are added together and passed through the *tanh* activation function to give up an output value between 1 and -1. A typical structure of SRU is shown in Figure 2. The following equations show the basic computations behind SRU.

$$h_t = \sigma_h(W_h x_t + U_h h_{t-1} + b_h) \tag{1}$$

$$o_t = \sigma_o(W_o h_t + b_o) \tag{2}$$

where x_t denotes the input vector, h_t represents the hidden layer vector, o_t represents the output vector, both b_h and b_o are the bias vectors of hidden and output layers, W_h and W_o represent the weight matrices of hidden and output layers, and σ_h and σ_o represent the activation function of hidden and output layers that can be computed as:

$$\sigma(x) = \tanh(x) = \frac{2}{1 + e^{-2x}} - 1 \tag{3}$$

D. GATED RECURRENT UNIT (GRU)

In order to solve the vanishing gradient problem, Gated Recurrent Unit (GRU) was proposed by Cho, et al. [31]. GRU can be considered as an LSTM unite but with no output gate. Both GRU and LSTM have a similar architecture and achieve excellent accuracies.

In this type of architecture, GRU has an update and rest gates. Both gates enable GRU to pass the information forward over many time windows for a better predication or classification. More specifically, data and weights are stored in memory to be used with a given state to update the values for future as needed [31]. A typical structure of GRU is shown in Figure 3.

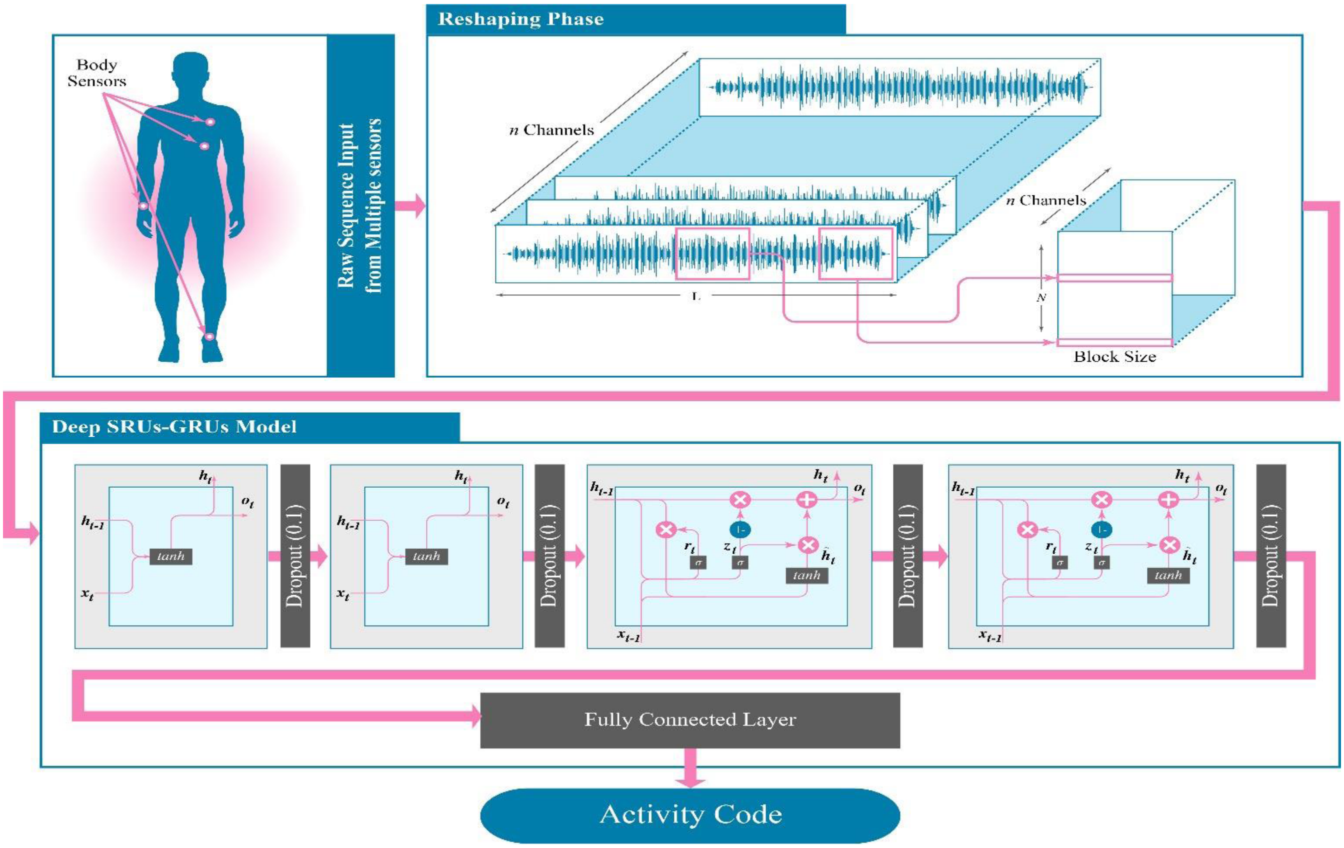


FIGURE 4. An architecture of proposed hybrid deep SRUs-GRUs model.

In order to understand how GRU works, we explain its main components in the following lines. As mentioned before, the GRU consists of two gates, which are the update gate and the reset gate (current and final memory content). In update gate, GRU calculates z_t at a given time t in order to solve vanishing gradient problem using the following calculation:

$$z_t = \sigma\left(W_z\left[h_{t-1}, x_t\right] + b_z\right) \tag{4}$$

Whereas, in the reset gate, GRU computes z_t at a given time t in order to indicate how much of the past information to forget. This gate performs the following equation:

$$r_t = \sigma\left(W_r\left[h_{t-1}, x_t\right] + b_r\right) \tag{5}$$

Current memory content stage is calculated based on the following equation:

$$\tilde{h}_t = tanh(W_h\left[r_t h_{t-1}, x_t\right]) \tag{6}$$

Lastly, final memory at current time step calculates h_t to store the current unit information for computing the output vector o_t the as following:

$$h_t = (1 - z_t)\, h_{t-1} + z_t \tilde{h}_t \tag{7}$$

$$o_t = \sigma_o(W_o h_t + b_o) \tag{8}$$

where the bias vector of the output layer is b_o and the weight matrix of the output layer is W_o.

E. PROPOSED FRAMEWORK

Figure 4 illustrates a high-level architecture of the proposed framework and its functions for multi-sensors-based human activity recognition. The framework consists of several components. For capturing the input data to the framework, a set of wearable body sensors are placed on the patients to record the multimodal raw data of their activities' signals. The first component contains the reshaping phase, which processes the signals as channels; every channel represents a class of activity. In this phase, the raw data signals of L length are divided into a number of time-series blocks of w length, producing N blocks in order to simplify the classification process. In our model, the block size is selected to be 100 because it is sufficient to analyze the activities from multi-sensors data.

The second component is the deep SRUs-GRUs neural network model, which consists of four hidden layers as well as the input and output layers. The input layer has n-input dimensions (23 input dimensions for the MHEALTH dataset). The first two hidden layers contain 64 units of SRUs and the second two hidden layers have 32 units of GRUs. We chose 64 units for the first two hidden layers because they are sufficiently enough to process and remember the changes in the activity signals and we selected 32 units for the second two hidden layers to make the accuracy stable and make the model fast. The hidden layers of deep SRUs-GRUs model are separated by dropout regularization method. The goal for

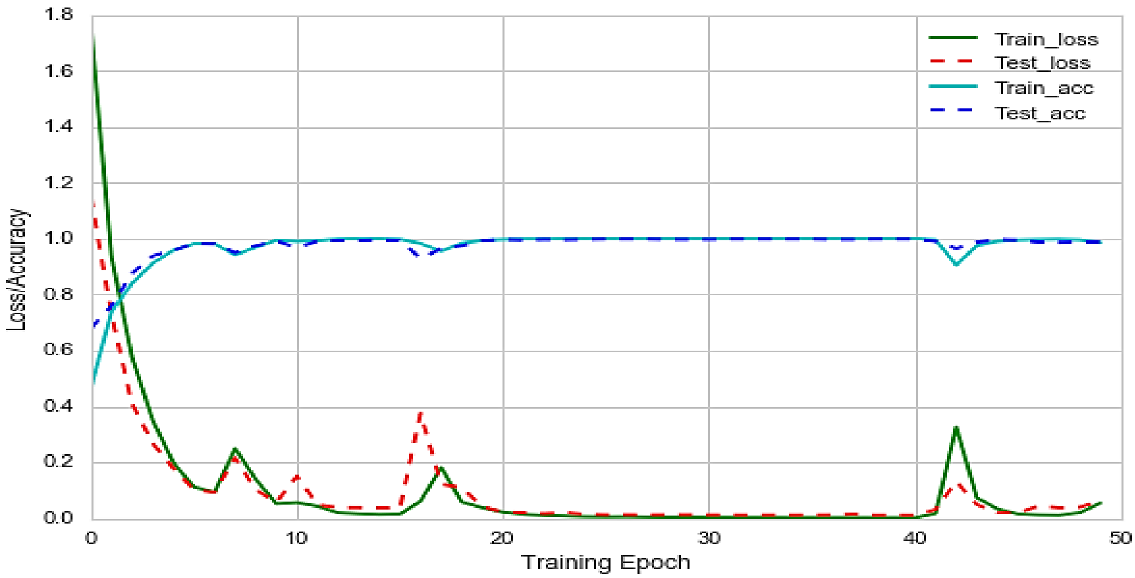


FIGURE 5. Loss and accuracy values of deep SRUs-GRUs model during the training progress of first experiment.

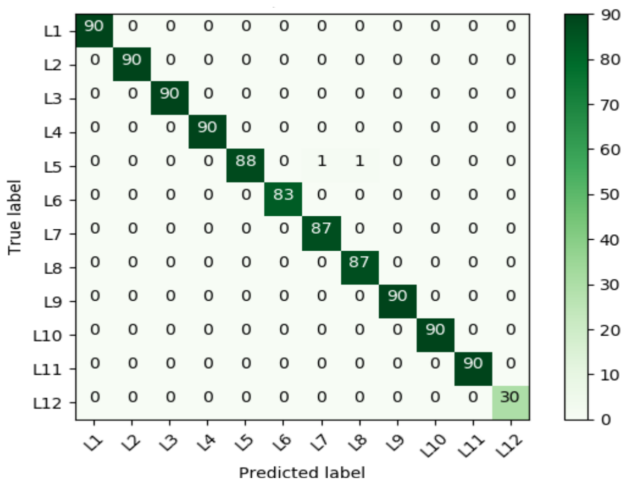


FIGURE 6. Confusion matrix of human activities classified of the first experiment.

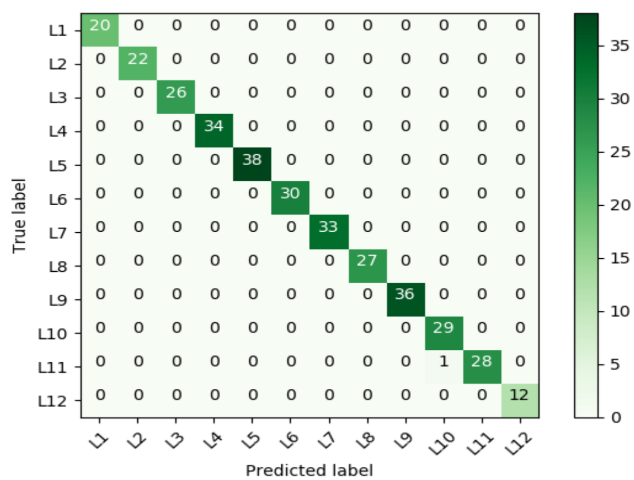


FIGURE 7. Confusion matrix of human activities classified of the second experiment.

dropout here is to avoid the overfitting issue by ignoring some random neurons in the training phase (10% in our model). The output layer in the deep SRUs-GRUs model is a fully connected layer with a softmax activation function, which represents the final of classification, resulting in the activity code output. The output layer has m activity codes (12 activity codes for the MHEALTH dataset).

III. EXPERIMENTS AND DISCUSSIONS

A. EXPERIMENT SETUP AND EVALUATION METRICS

All experiments are implemented on a laptop computer i7-4510U 2.0GHz CPU and 8GB RAM with operating system windows (x64) version 10, and using python programming language tool. To evaluate the performance of the proposed model, four evaluation metrics are used as well as the recognition time. These four evaluation metrics are computed as follows:

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{9}$$

$$Precision = \frac{TP}{TP + FP} \tag{10}$$

$$Recall(Sensitivity) = \frac{TP}{TP + FN} \tag{11}$$

$$F1 - score = \frac{2 \times (Recall \times Precision)}{(Recall + Precision)} \tag{12}$$

where TP and TN are true positive and true negative rates, FP and FN are false positive and false negative rates.

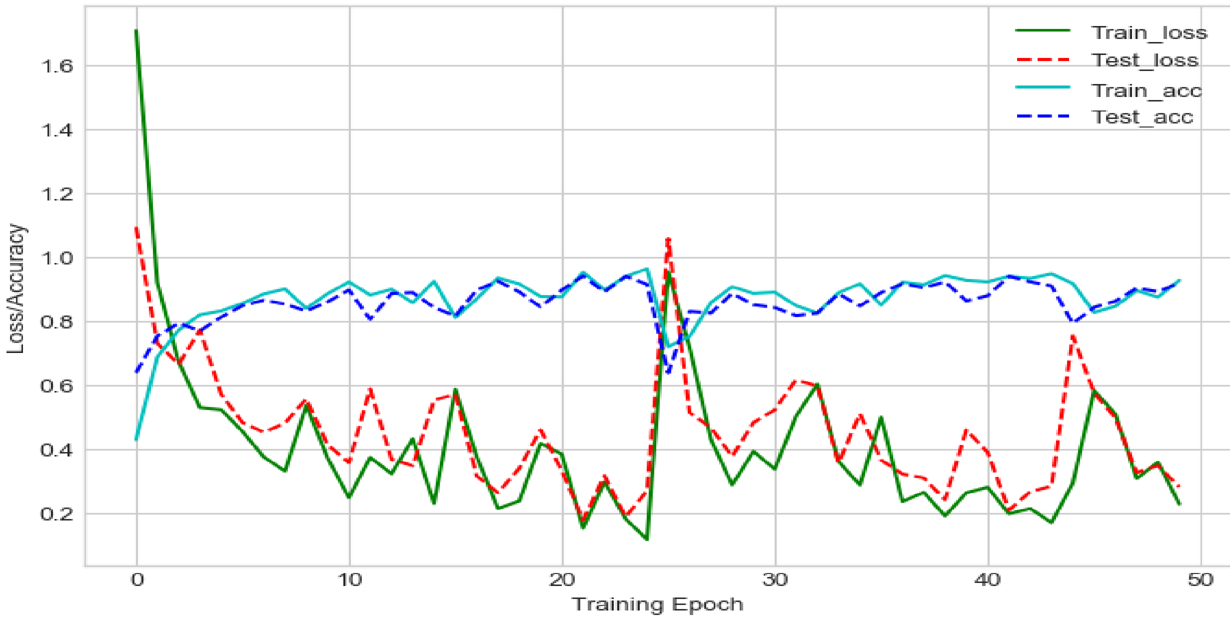


FIGURE 8. Loss and accuracy values of deep SRUs model during the training progress of first experiment.

For more detail, F1-score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account. On the other hand, the accuracy is used to measure the ratio of correctly classified activities from the total activities in the testing dataset. Whereas, the precision is used to measure the ratio of correctly classified true positive activities to the total classified activities of true positive and false positive. The recall metric is the ratio of true positive activities to the true positive and false negative of activities. For F1-score, the weighted average result of recall and precision is computed.

In the following, the hyper-parameters settings and experimental results will be explained with more discussions.

B. HYPER-PARAMETERS SETTINGS

For developing deep learning models, a rigorous effort is necessary for settings the models' hyper-parameters. This is done by choosing the best values for these hyper-parameters that achieves high results. In machine learning field, there are commonly three methods for tuning the hyper-parameters of the models. These methods are manual-based method using the results of validation set and the experience in the domain, random-based method using a random set of values, and grid search-based method using an exhaustive set of values. In our model, an effective method based on manual and grid search-methods is used. This method starts with an initial range of coarse values, after that, we narrow this range based on the results of validation set and our experience in the field. Based on the results of tuning process, the value of learning rate is set to be 0.001. The number of epochs is set to be 50. The number of SRUs in the first and second hidden layers is 64 units. In addition, the number of GRUs in the third and fourth hidden layers is 32 units. We selected these numbers of units because they are sufficient to process the raw data of activities.

C. EXPERIMENTAL RESULTS

The experimental results are obtained based on two experiments. The first experiment is conducted using holdout technique. While, the second experiment is performed using 10-folds cross validation technique. In the first experiment, the dataset is divided into two data subsets: training dataset that contains 70% (2348 instances), and testing dataset that contains 30% (1007 instances). For validation, a subset of 40% (940 instances) from the training dataset is taken as a validation dataset. On the other hand, in the second experiment, the dataset is divided into ten subsets or folds; each fold has 336 instances. Each time of ten times, one fold is used for testing and the remaining nine folds are used for training, as well as 20% (604 instances) of training set is taken as a validation dataset. Figure 5 shows the training progress of the model in the first experiment. In the training progress, the loss and accuracy values are monitored among the number of training epochs.

We can see the stability of the model after the epoch number 20 and we can notice that the gap between training and validation sets is small, which means that there is no any overfitting in the training phase.

Figure 6 demonstrates the confusion matrix of classified activities of the first experiment. It can be seen that the model

TABLE 2. Results of evaluation metrics (in percentage) obtained from the first experiment.

Activity	Precision	Recall	F1-score
L1	100	100	100
L2	100	100	100
L3	100	100	100
L4	100	100	1.00
L5	100	98	99
L6	100	100	100
L7	99	100	99
L8	99	100	99
L9	100	100	100
L10	100	100	100
L11	100	100	100
L12	100	100	100
Weighted avg.	100	100	100

TABLE 3. Results of evaluation metrics (in percentage) obtained from the second experiment.

Activity	Precision	Recall	F1-score
L1	100	100	100
L2	100	100	100
L3	100	100	100
L4	100	100	100
L5	100	100	100
L6	100	100	100
L7	100	100	100
L8	100	100	100
L9	97	100	98
L10	100	97	98
L11	100	100	100
L12	100	100	100
Weighted avg.	100	100	100

is able to recognize almost all activities in the testing dataset. From the confusion matrix of the first experiment, the model achieves 99.80% of accuracy for recognizing the activities.

The results of other evaluation metrics are listed in Table 2, in which the model attains a weighted average of 100% for the F1-score.

In Table 2, we can notice that the model can able to classify all activities with high results in terms of precision and recall (sensitivity). The high results of recall and precision of the first experiment demonstrate that the model has a high ability to reduce the false positives and false negatives problem in human activity recognition application that uses multimodal sensing data. During the experiments, we found that the average classification time of 1007 samples of the model is 2.4 seconds, making it efficient for real-time human activity recognition applications. Figure 7 shows the confusion matrix of classified activities, obtained from the average of 10-folds test sets amongst the second experiment.

From the confusion matrix of the second experiment, the average accuracy for the 10-folds is approximately 99.70%. The results of other evaluation metrics are also listed in Table 3. The weighted average of precision, recall, F1-score is 100%, which proves the effectiveness of the developed model.

TABLE 4. Results of accuracy and average classification time of deep SRUs-GRUs and deep SRUs models.

Model	Accuracy	Average Classification Time of 1007 samples in Seconds
Deep SRUs-GRUs	**99.80%**	2.4
Deep SRUs	94.14%	**1.7**

TABLE 5. Comparison results of sensitivity and F1-score for the proposed framework against the mHealthDroid framework.

Activity	mHealthDroid framework [1]		Proposed framework	
	Sensitivity	F1-score	Sensitivity	F1-score
L1	1.00	1.00	1.00	1.00
L2	1.00	1.00	1.00	1.00
L3	1.00	1.00	1.00	1.00
L4	1.00	1.00	1.00	1.00
L5	0.99	0.99	1.00	1.00
L6	0.97	0.97	1.00	1.00
L7	1.00	0.99	1.00	1.00
L8	0.95	0.96	1.00	1.00
L9	1.00	1.00	0.97	0.98
L10	0.96	0.95	1.00	0.98
L11	0.94	0.95	1.00	1.00
L12	0.99	0.99	1.00	1.00
Average	0.982	0.982	**0.997**	**0.996**

To show the effectiveness of the hybrid deep SRUs-GRUs model, we conducted the first experiment on the deep SRUs model that contains 64 simple units and compared it with the hybrid deep model. Figure 8 shows the loss and accuracy values of deep SRUs model during the training progress of first experiment. Table 4 demonstrates the accuracy and average classification time of 1007 samples by using deep SRUs-GRUs and deep SRUs models.

As shown in Table 4, the accuracy of deep SRUs-GRUs is higher than the accuracy of deep SRUs with a slight increase in average classification time, which highlighted in a bold font face. This proves the effectiveness of adding the deep GRUs to the model. Moreover, the Figure 8 demonstrates how the hybrid deep SRUs-GRUs solves the problem of fluctuations or instability in accuracy.

To compare the proposed framework with a recent related work of activity recognition using multimodal sensing data, we selected the work published in [30] that used the 10-folds cross validation technique on the same dataset. The authors in this work used statistical functions and time/frequency transformations for feature extraction. In addition, they used the sallow classification techniques to build a framework, called mHealthDroid. Table 5 shows the results of comparison in terms of sensitivity and F1-score.

We can see that the sensitivity and F1-score results of deep SRUs-GRUs model are higher than the results of mHealthDroid framework. The reason for this improvement is due to the ability of the proposed framework to process and remember the signals' patterns for recognizing human activities from multimodal body sensing data.

IV. CONCLUSIONS AND FUTURE WORK

Sensor-based user behavior and health status monitoring is getting more and more interest in the huge amount of pattern recognition researchers, with the promise of improving people's wellness, health, and lifetime. Given such goals, smart environments support application which very often demand. Hence, the user care applications in smart environments very often demands continuous observation of the users' activities with the help of an event-driven system. In this work, we proposed a deep SRUs-GRUs based activity recognition system based on the wearable body multi-sensors data. The novelty of the work is the application of the proposed deep learning model, which is a hybrid of SRUs and GRUs, for recognizing effectively the human activities using a multimodal body sensing data. We use the deep SRUs networks to process the sequences of multi-sensors input data by using the capability of their internal memory states and exploit their speed advantage. We then use a dropout technique to ignore randomly some neurons during the training phase, reducing the overfitting problem. Next, we use the deep GRUs networks to store and learn how much of the past information is passed to the future state for solving fluctuations or instability in accuracy and vanishing gradient problems. Finally, we optimized the model's hyper-parameters based on manual and grid search methods. The experimental results have showed good performance by achieving 0.99 precision, recall, F1-score, and accuracies on the big datasets.

In the future, the proposed deep SRUs-GRUs based human activity recognition system can be more analyzed on complex and bigger datasets with more complex activities to get a real-time human behavior monitoring system. Moreover, we aim to conduct another study investigating the consumption of computational resources for SRUs-GRUs model on constrained mobile devices with limited resources.

REFERENCES

[1] P. Castillejo, J.-F. Martínez, J. Rodríguez-Molina, and A. Cuerva, "Integration of wearable devices in a wireless sensor network for an E-health application," *IEEE Wireless Commun.*, vol. 20, no. 4, pp. 38–49, Aug. 2013.

[2] R. Chatterjee, T. Moitra, S. H. Islam, M. M. Hassan, A. Alamri, and G. Fortino, "A novel machine learning based feature selection for motor imagery EEG signal classification in Internet of medical things environment," *Future Gener. Comput. Syst.*, vol. 98, pp. 419–434, Sep. 2019.

[3] R. Gravina, P. Alinia, H. Ghasemzadeh, and G. Fortino, "Multi-sensor fusion in body sensor networks: State-of-the-art and research challenges," *Inf. Fusion*, vol. 35, pp. 68–80, May 2017.

[4] M. Z. Uddin and M. M. Hassan, "Activity recognition for cognitive assistance using body sensors data and deep convolutional neural network," *IEEE Sensors J.*, to be published.

[5] G. Fortino, S. Galzarano, R. Gravina, and W. Li, "A framework for collaborative computing and multi-sensor data fusion in body sensor networks," *Inf. Fusion*, vol. 22, pp. 50–70, Mar. 2015.

[6] G. Fortino, A. Guerrieri, F. L. Bellifemine, and R. Giannantonio, "SPINE2: Developing BSN applications on heterogeneous sensor nodes," in *Proc. SIES*, 2009, pp. 128–131.

[7] G. Fortino, R. Giannantonio, R. Gravina, P. Kuryloski, and R. Jafari, "Enabling effective programming and flexible management of efficient body sensor network applications," *IEEE Trans. Human-Mach. Syst.*, vol. 43, no. 1, pp. 115–133, Jan. 2013.

[8] R. Gravina and G. Fortino, "Automatic methods for the detection of accelerative cardiac defense response," *IEEE Trans. Affect. Comput.*, vol. 7, no. 3, pp. 286–298, Jul./Sep. 2016.

[9] S. Iyengar, F. T. Bonda, R. Gravina, A. Guerrieri, G. Fortino, and A. Sangiovanni-Vincentelli, "A framework for creating healthcare monitoring applications using wireless body sensor networks," in *Proc. ICST 3rd Int. Conf. Body Area Netw.*, 2008, Art. no. 8.

[10] H. Ghasemzadeh, P. Panuccio, S. Trovato, G. Fortino, and R. Jafari, "Power-aware activity monitoring using distributed wearable sensors," *IEEE Trans. Human-Mach. Syst.*, vol. 44, no. 4, pp. 537–544, Apr. 2014.

[11] P. C. Roy, A. Bouzouane, S. Giroux, and B. Bouchard, "Possibilistic activity recognition in smart homes for cognitively impaired people," *Appl. Artif. Intell.*, vol. 25, no. 10, pp. 883–926, Nov. 2011.

[12] K. Sim, C. Phua, G.-E. Yap, J. Biswas, and M. Mokhtari, "Activity recognition using correlated pattern mining for people with dementia," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Aug./Sep. 2011, pp. 7593–7597.

[13] M. Tolkiehn, L. Atallah, B. Lo, and G.-Z. Yang, "Direction sensitive fall detection using a triaxial accelerometer and a barometric pressure sensor," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.* , Aug. 2011, pp. 369–372.

[14] L. Chen, J. Hoey, C. D. Nugent, D. J. Cook, and Z. Yu, "Sensor-based activity recognition," *IEEE Trans. Syst., Man, Cybern. C, Appl. Rev.*, vol. 42, no. 6, pp. 790–808, Nov. 2012.

[15] W. Ugulino, D. Cardador, K. Vega, E. Velloso, R. Milidiú, and H. Fuks, "Wearable computing: Accelerometers' data classification of body postures and movements," in *Advances in Artificial Intelligence—SBIA*. Berlin, Germany: Springer, 2012, pp. 52–61.

[16] O. D. Lara and M. A. Labrador, "A survey on human activity recognition using wearable sensors," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 3, pp. 1192–1209, 3rd Quart., 2013.

[17] P. Dohnálek, P. Gajdoš, P. Moravec, T. Peterek, and V. Snášel, "Application and comparison of modified classifiers for human activity recognition," *Przeglad Elektrotechniczny*, vol. 89, pp. 55–58, Jan. 2013.

[18] N. Ravi, N. Dandekar, P. Mysore, and M. L. Littman, "Activity recognition from accelerometer data," in *Proc. 17th Conf. Innov. Appl. Artif. Intell. (IAAI)*, Pittsburgh, PA, USA, vol. 3, Jul. 2005, pp. 1541–1546.

[19] A. Mannini and A. M. Sabatini, "Machine learning methods for classifying human physical activity from on-body accelerometers," *Sensors*, vol. 10, pp. 1154–1175, Feb. 2010.

[20] J. Wang, Y. Chen, S. Hao, X. Peng, and L. Hu, "Deep learning for sensor-based activity recognition: A survey," *Pattern Recognit. Lett.*, vol. 119, pp. 3–11, Mar. 2019.

[21] H. F. Nweke, Y. W. Teh, M. A. Al-Garadi, and U. R. Alo, "Deep learning algorithms for human activity recognition using mobile and wearable sensor networks: State of the art and research challenges," *Expert Syst. Appl.*, vol. 105, pp. 233–261, Sep. 2018.

[22] L. Cohen, N. Sebe, A. Garg, L. S. Chen, and T. S. Huang, "Facial expression recognition from video sequences: Temporal and static modeling," *Comput. Vis. Image Understand.*, vol. 91, pp. 160–187, Jul. 2003.

[23] G. E. Hinton, S. Osindero, and Y.-W. Teh, "A fast learning algorithm for deep belief nets," *Neural Comput.*, vol. 18, no. 7, pp. 1527–1554, 2006.

[24] M. M. Hassan, S. Huda, M. Z. Uddin, A. Almogren, and A. Alrubaian, "Human activity recognition from body sensor data using deep learning," *J. Med. Syst.*, vol. 42, no. 6, p. 99, 2018.

[25] M. M. Hassan, M. G. R. Alam, M. Z. Uddin, S. Huda, A. Almogren, and G. Fortino, "Human emotion recognition using deep belief network architecture," *Inf. Fusion*, vol. 51, pp. 10–18, Nov. 2019.

[26] S. Kiranyaz, T. Ince, and M. Gabbouj, "Real-time patient-specific ECG classification by 1-D convolutional neural networks," *IEEE Trans. Biomed. Eng.*, vol. 63, no. 3, pp. 664–675, Mar. 2016.

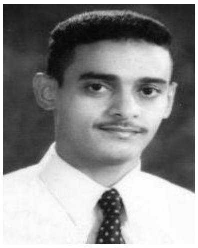
[27] F. J. Ordóñez and D. Roggen, "Deep convolutional and LSTM recurrent neural networks for multimodal wearable activity recognition," *Sensors*, vol. 16, no. 1, p. 115, 2016.

[28] S.-W. Lee and H.-H. Song, "A new recurrent neural-network architecture for visual pattern recognition," *IEEE Trans. Neural Netw.*, vol. 8, no. 2, pp. 331–340, Mar. 1997.

[29] T. Lei, Y. Zhang, S. I. Wang, H. Dai, and Y. Artzi, "Simple recurrent units for highly parallelizable recurrence," in *Proc. Conf. Empirical Methods Natural Lang. Process.*, 2018, pp. 4470–4481.

[30] J. Liu, C. Wu, and J. Wang, "Gated recurrent units based neural network for time heterogeneous feedback recommendation," *Inf. Sci.*, vol. 423, pp. 50–65, Jan. 2018.

[31] O. Banos, C. Villalonga, R. Garcia, A. Saez, M. Damas, J. A. Holgado-Terriza, S. Lee, H. Pomares, and I. Rojas, "Design, implementation and validation of a novel open framework for agile development of mobile health applications," *Biomed. Eng. Online*, vol. 14, no. 2, p. S6, 2015.



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