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BRAIN-INSPIRED SPIKING NEURAL NETWORKS FOR WI-FI BASED HUMAN ACTIVITY RECOGNITION

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ABSTRACT

Human activities can be recognized through reflections of wireless signals which solve the problem of privacy concerns and restriction of the application environment in vision-based recognition. Spiking Neural Networks (SNNs) for human activity recognition (HAR) using Wi-Fi signals have been proposed in this work. SNNs are inspired by information processing in biology and processed in a massively parallel fashion. The proposed method reduces processing resources while still maintaining accuracy through using frail but robust to noise spiking signals information transfer. The performance of HAR by SNNs is compared with other machine learning (ML) networks, such as LSTM, Bi-LSTM and GRU models. Significant reduction in memory usage while still having accuracy that is on a par with other ML networks has been observed. More than 70% saving in memory usage has been achieved in SNNs compared with the other existing ML networks, making SNNs a potential solution for edge computing in industrial revolution 4.0.

KEYWORDS

Human activity recognition, Wi-Fi signals, Spiking neural network.

1. INTRODUCTION

The area of human activity recognition (HAR) has become one of the most popular study fields due to the increment in computer vision technology and the availability of sensors at cheap prices and small sizes. With the help of technology, the data can be collected easily through wearable sensors, images or video frames [1]. However, there have been some problems in image processing using data collected from video or images. Firstly, privacy is a big concern and secondly, there are line of sight issues where the object needs to be inside the camera capturing area for a model to learn.

Indoor HAR using Wi-Fi has its benefits compared to the traditional technique where no extra wearable device is needed and there is no line of sight limitation. Received Signal Strength (RSS) has been used in human movement tracking due to its simplicity and easiness of measurement [2]. However, RSS-based algorithms have several limitations, due to the multipath and random noise in the enclosed environment havings a significant impact on RSS [3]. Therefore, a modified Wi-Fi system called channel state information (CSI) is used, which enables more information to be extracted from the signal captured. There will be a reflection in the wireless signal which will cause variation in CSI when detecting the movement of the human body. Unlike RSS, CSI consists of two types of information which are amplitude and phase information. Authors in [4] state that there have been some sources, such as carrier frequency offset (CFO) and sampling frequency offset (SFO), which often exacerbate the phase information. However, the amplitude information of CSI is more stable and has commonly been used for HAR. There have been several types of machine learning (ML) methods, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). Both CNNs and RNNs are famous image-processing methods that result in high accuracy and had been used in many areas, such as functional magnetic resonance imaging (MRI) for autism spectrum disorder detection [5]-[6], racing bib number recognition [7] and HAR [8]. However, more hardware resources are needed for these ML methods. To solve this, a new type of neural network called Spiking Neural Networks (SNNs) can be applied to this Wi-Fi CSI-based HAR.

2. RELATED WORK IN HUMAN ACTIVITY RECOGNITION (HAR) USING CSI

The Wi-Fi system can be built up with a transmitter and a receiver. The router sends out the signal with a certain frequency and the frequency is received by a laptop with a CSI reader, such as NIC

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5300 chips to record the CSI readings on the other side in the line-of-sight (LOS), as shown in Figure 1. When there is a movement of a human in the LOS of the Wi-Fi system, it can cause a variation in the Wi-Fi signal which is recorded as amplitude and phase information in CSI. The dataset will have 30 subcarriers for each receiver or 30 packets received by each receiver. There are three receivers in NIC 5300 chip, thus 90 subcarriers for each amplitude and phase information will be gathered. The movement of humans will cause different signal reflections and this means that the signals can be used for recognizing human activities through the ML method.

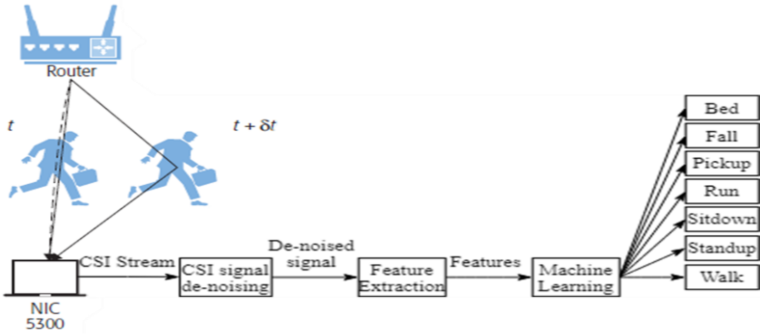
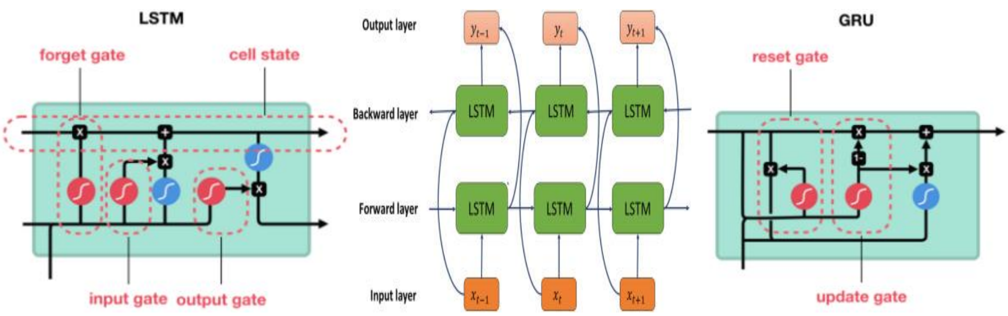


Figure 1. Human activity recognition using channel state information extracted from Wi-Fi.

2.1 Existing Machine Learning (ML) Models

CSI data has been used for location-oriented HAR using the moving variance thresholding method in E-eyes [9]. CARM [10] is a model that uses the relationship between Wi-Fi signal dynamics theory and human activities in activities classification. Beside these non-neural network methods, RNN has also been used for HAR. Several famous RNN methods have been proposed by other researchers to solve HAR using CSI data, such as Long Short-Term Memory (LSTM) [11], Bidirectional LSTM (Bi-LSTM) [4] and Gated Recurrent Units (GRU) [12] model. The structure of these models is shown in Figure 2. LSTM is a kind of RNN that is capable of learning long-term relationships, notably in sequence prediction issues. LSTM has two different states called cell state and hidden state which carry long- and short-term memory, respectively, between the cells. Bi-LSTM is an upgraded version of LSTM, where each training sequence will go through the model in both forward and reverse orders within two hidden layers, but with the same output layer. GRU model is a model that is significantly less complicated than an LSTM, since it has only two gates (update gate and reset gate), while LSTM has three gates (forget, input and output gates) in each cell. GRU can perform similarly to LSTM with a shorter training time. However, when having a bigger size of datasets, LSTM is said to have a better result than GRU. Since these three models are a kind of RNN model, they can extract the features of the datasets during training with all the CSI datasets inserted into the model.



a) b) c)

Figure 2. Machine learning models: a) LSTM, b) Bi-LSTM and c) GRU.

When compared with the Random Forest (RF) and Hidden Markov model (HMM), LSTM in [11] had obtained a high accuracy in classification. Authors in [4] proposed an attention-based Bi-LSTM model, which has a higher accuracy, but the time consumed is twice that of the LSTM model. The deep GRU algorithm in [12] achieves a high average accuracy of 98.12% when compared with RF and LSTM algorithms.

Although RNN-based models can achieve a high accuracy, they need a high memory bandwidth on demand to ensure that the classification can take place with the required low latency in edge computing. Memory bandwidth and latency are critical concerns in edge computing. The quantity of data that may be transferred to or from a particular destination is referred to as bandwidth, while latency is the time for an operation to complete. Edge computing is the science of allowing data to be processed at the edge of the network without having to send it to a central server. Therefore, low bandwidth and latency are the keys that enable edge devices to analyze the data in near real-time. Spiking Neural Networks (SNNs), a novel type of neural network, can be used to overcome this problem.

2.2 Spiking Neural Networks (SNNs)

SNNs represent the third generation of neural network models if neural network models are classified based on their computational units [13]-[14]. SNNs use spikes for information encoding and use spiking neurons or integrate-and-fire neurons as computational units. The computational units of the first generation are based on McCulloch-Pitts neurons or in other words, perceptron and threshold gates. For the second generation of the neural network models, an activation function, such as sigmoid and linear saturated functions, is applied to the output of every possible output value.

SNNs are a type of promising artificial neural network (ANN). Their outputs were presented in trains of spikes, having three new dimensions in the structure and the functionality of ANNs which are time, phase and frequency [15]. Not like ANNs, SNNs can be considered time-dependent during computation since the single-bit impulses or the so-called spikes will be sent out by neurons to synapses, potentially in a non-zero traveling time. SNNs are highly inspired by natural brain computation and recent developments in neuroscience [16]. With the involvement of spike firing timing, the strength and interest of SNNs are gained from the precise modeling of neuronal synaptic connections. Hence, the computational power of the 1st and 2nd generations was overcome by SNNs.

SNNs have been said to be the artificial neural network type that is closest to human neurons, because it transfers the data information in spike, having timing characteristics. In a human neuron, the postsynaptic neuron receives the pulse (spike) from other presynaptic neurons and action potential is produced when the membrane potential accumulated reached the threshold voltage. The action potential produced will be the input pulse for the next postsynaptic neuron. The spiking neuron model has also been called as biological neuron model, because it can simulate the motion of activation function in the human neurons.

There have been several existing spiking models such as Hodgkin-Huxley model, the earliest model that was introduced in the year 1952 by Alan Hodgkin and Andrew Huxley, Integrate-and-Fire (IF) model, a model that uses a basic mathematical equation to explain the motion of activation function in the neurons and also the Izhikevich model, a model having the characteristics of both Hodgkin-Huxley and IF models. Figure 3 shows the motion of an action potential, where a spike is emitted when the voltage has reached the threshold.

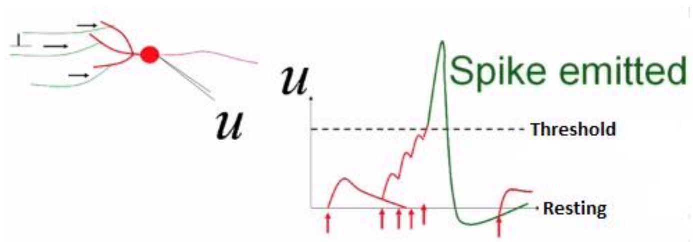


Figure 3. Spike generated with the motion of action potential exceeding the threshold in the neuron.

SNNs had shown their flexibility in image processing works and great work in energy saving, since they are promising high importance to biological systems. The energy-saving of the spiking model has been achieved by more than 90%, where energy consumption is reduced from 1.69W-28W to 0.136W compared to the Support Vector Machine and CNN model in [17]. In [18], 95% of energy saving has been achieved, where energy is reduced from 657.5µJ to 31.5µJ compared with the fully connected deep neural network model. Several types of SNNs are proposed by other researchers, such as fuzzy SNNs [19], artificial SNNs [20] and reservoir-based convolution SNNs [21], in their works. Along with that, there have also been learning rules proposed by other researchers, such as synaptic weight association training (SWAT) [22], Synaptic Efficacy Function-based leaky-integrate-and-fire neuRON (SEFRON) [23] and spike-timing-dependent-plasticity (STDP) with dynamic threshold neurons [24].

3. METHODOLOGY

In this paper, a spiking model based on Synaptic Efficacy Function-based leaky-integrate-and-fire neuRON (SEFRON) [23] has been used to classify human activities from the CSI dataset. The SNN model trains to classify the data with seven different human activities, which are ‘Bed’, ‘Fall’, ‘Pickup’, ‘Run’, ‘Sitdown’, ‘Standup’ and ‘Walk’ on MATLAB software.

3.1 Data Pre-processing

The dataset used is based on the Kazuki dataset having three receivers (30 subcarriers for each receiver) with a 50 Hz sampling frequency for 19.8s (990 data for each subcarrier) [25]. Since SNN is a time-dependent neural network, only the data of the first receiver and the first subcarrier is used in this paper for the classification method. MATLAB smooth function is used as the denoise method to remove noise from data. With the default setting, the function smooths the response data using a moving average low-pass filter with the filter coefficient equal to the reciprocal of the span. Span is the number of data points used for calculating the smoothed value and the number is 5 in default. An overview of data selection and pre-processing is shown in Figure 4. For the LSTM, Bi-LSTM and GRU models with a total of 90 input neurons, all the 90 subcarriers are used, where each subcarrier inserts to each input neuron for a time range of 990 data without any data pre-processing.

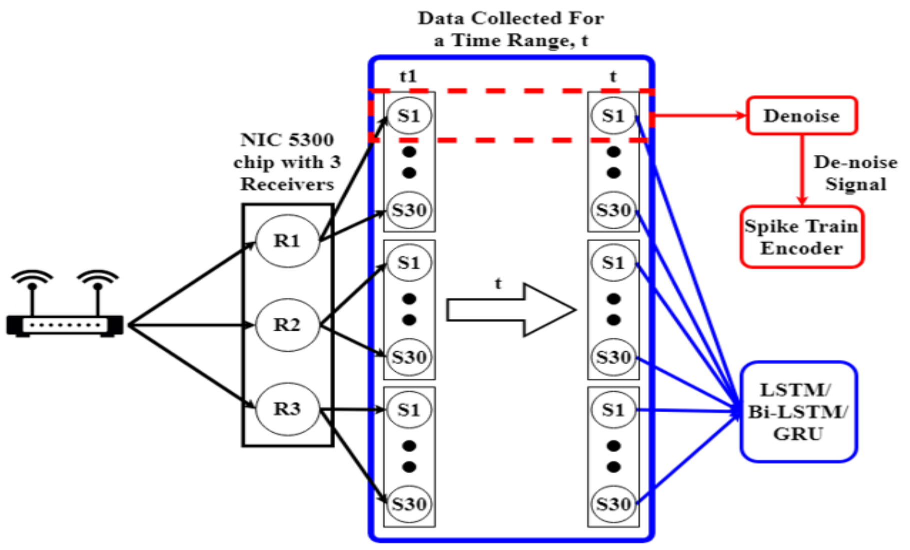


Figure 4. Overview of data pre-processing and data selection for Spike Train Encoder, LSTM, Bi-LSTM and GRU.

3.2 Spike Train Encoder

The data consists of analogue values and needs to be converted into the spike train pattern that is needed by the Spiking Neuron Model. The population encoding method is useed to convert the analogue CSI data into the spike train needed by SNNs. By setting the number of receptive field neurons, each real value converts the presynaptic spike along with the presynaptic spike time interval. In this paper, each spike train is designed to have a presynaptic spike along with the time interval of [0,2.5] ms. Since the precision of the time step is set as 0.01, the time step interval is [0.250]. An overview of the spike train encoder is shown in Figure 5.

3.3 SNN Model

In this paper, each analogue value in the spike train pattern is the input synapse for the SNN model. Input presynaptic neurons are multiplied with their time-varying weight and summed up at the output postsynaptic neuron. There are 7 layers of time-varying synaptic weight and output postsynaptic

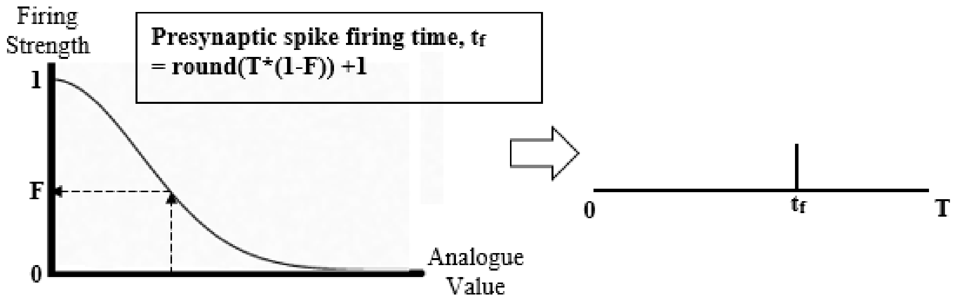


Figure 5. Overview of Spike Train Encoder.

Neurons, since there are 7 classes of activities. The synaptic weight in this model can be either positive or negative along with the time interval. At the output postsynaptic neuron, a postsynaptic spike is fired when the voltage reaches its threshold at time t. The postsynaptic spike time interval is set to [0,4] ms with time step interval of [0,400] to allow the model to capture the postsynaptic spike after time T.

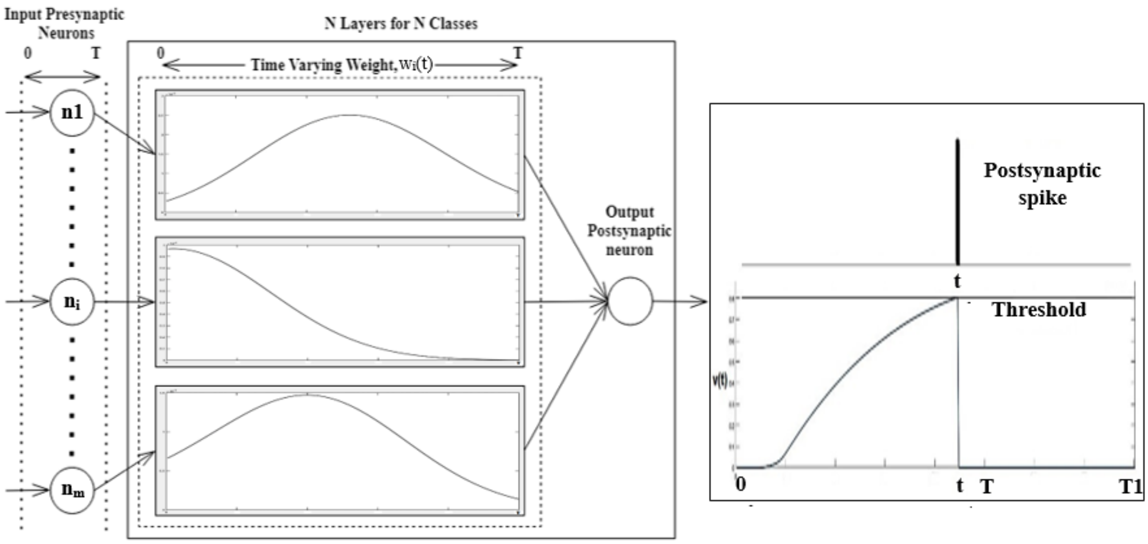


Figure 6. A model with m number of input presynaptic neurons. Spike train input pattern in a time interval of [0, T] and postsynaptic output spike time interval of [0, T1].

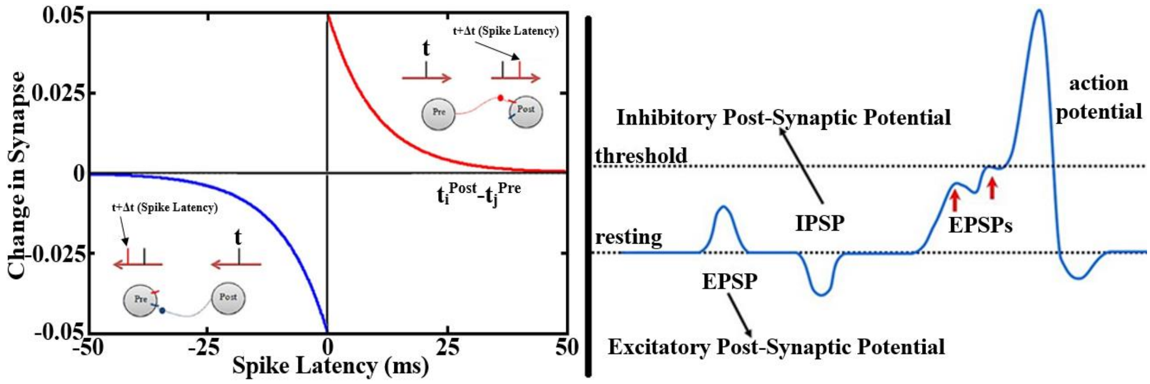
3.4 Model Training

In training, only the first actual postsynaptic spike is important and is used for the classification method. If the postsynaptic spike does not fire, the firing time is taken as the end of the simulation time. Since only the first postsynaptic spike is used by the SNN model, the membrane potential, or the postsynaptic spikes after the first postsynaptic spike, is not considered. The target class postsynaptic neuron is designed to fire a postsynaptic spike at the desired postsynaptic firing time of 2ms. Weight update with a 0.5 learning rate occurs when the target class postsynaptic neuron is fired outside the firing time or another class fires in the desired postsynaptic firing time range of 2±0.05 ms. The output postsynaptic neuron that is fired first is the output class for the data.

Normalized STDP learning rule, with a learning window size of 1.5 ms, computes the results of postsynaptic potential due to fractional contribution ($V_{STDP}(t)$) in both actual and desired postsynaptic spike firing times. Then, by minimizing an error function in the ratio of threshold and $V_{STDP}(t)$, it calculates the change in the time-varying weight on both actual and desired postsynaptic spike firing times. Finally, the learning rule uses a Gaussian distribution function centred at the current presynaptic spike timing to regulate the change in synaptic time-varying weight.

3.5 Spike-Timing-Dependent-Plasticity (STDP) Learning Rules

SNNs can be trained for solving pattern classification problems, using normalized STDP supervised learning rules to reduce the error by computing the changes in the weight. STDP is a neuron's rule strengthening or weakening the connections between neurons based on the degree of synchronous firing. When the postsynaptic spike timing is after the presynaptic spike timing, the synaptic weight will be strengthened in a positive value if the spike latency is near zero. On the other hand, for the postsynaptic spike that spikes before the presynaptic spike, the synaptic weight will be strengthened in a negative value for the spike latency that is near to zero as shown in Figure 7 a). The effect of these positive and negative weight values is shown in Figure 7 b), where a positive weight value will cause an excitatory postsynaptic potential (EPSP) and a negative weight value will cause an inhibitory postsynaptic potential (IPSP) in the postsynaptic neurons.



a) b)

Figure 7. a) STDP learning rule and b) Excitatory and inhibitory Postsynaptic potential.

4. RESULTS

By adjusting the desired postsynaptic firing time parameter, the threshold value for each class to fire is influenced. A lower threshold indicates that it is easier to have a postsynaptic spike, while a higher threshold indicates that more presynaptic spikes are needed to fire a spike on the postsynaptic neuron. Table 1 shows the threshold values for each class with different desired postsynaptic firing time values. The effect of low and high thresholds in training spike time is shown in Figure 8. It seems that the model is firing earlier with a lower firing threshold than the model with a higher firing threshold. The classes which do not fire are considered fired at the end of the simulation time.

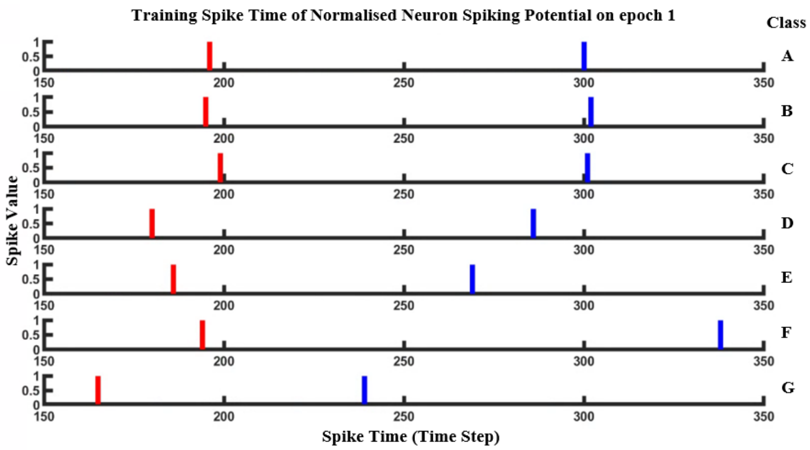


Figure 8. Effect of threshold in training postsynaptic spike time with a lower threshold (red colour) and a higher threshold (red colour).

Table 1. Threshold values for postsynaptic in different classes.

PARAMETER	CLASS						
Desired postsynaptic firing time step	A-Bed	B-Fall	C-Pickup	D-Run	E-Sitdown	F-Standup	G-Walk
150	0.6044	0.5822	0.6965	0.4908	0.6058	0.6485	0.6085
220	0.8500	0.8374	0.8967	0.7884	0.8480	0.8728	0.8516

Figure 9 shows the example increase of membrane potential due to a spike in the spike train fired as a postsynaptic spike at a time of 263ms when reaching the threshold. Since only the first postsynaptic spike is used by the SNN model, the membrane potential, or the postsynaptic spikes after the first postsynaptic spike, was not considered. The postsynaptic spike firing output for class G from both training and testing datasets for all epochs is shown in Figure 10.

Table 2 shows the comparison of the results of SNNs with other ML models, such as the Bi-LSTM, LSTM and GRU models with 100 hidden neurons each. SNN model achieves 85% classification accuracy on the testing data which is higher than that of the Bi-LSTM model. Figure 11 shows the memory profiling summary graph for all the models in Table 2, with the stacks representing the functions that are running in that period. Comparing the memory needed by the model, SNNs only need 13620kb of memory size to run; however, the Bi-LSTM model needs the largest memory size which is 108520kb. In this case, the SNNs model shows a saving in the memory usage which saved 74%, 87% and 72% of memory when compared with the LSTM, Bi-LSTM and GRU models, respectively.

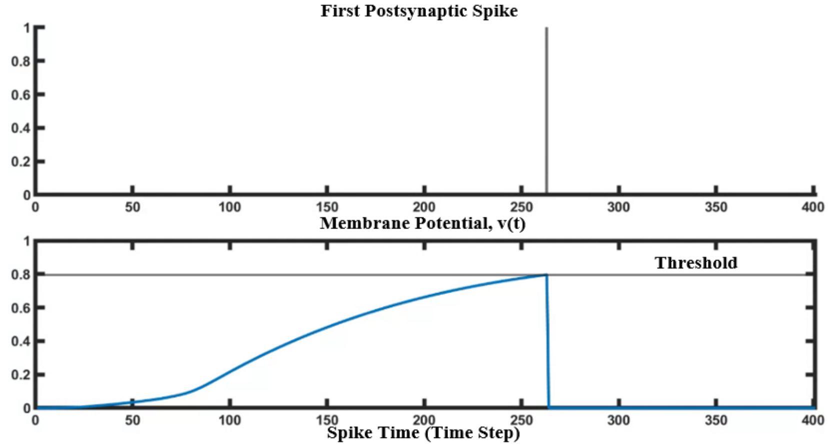


Figure 9 . Postsynaptic spike caused by membrane potential.

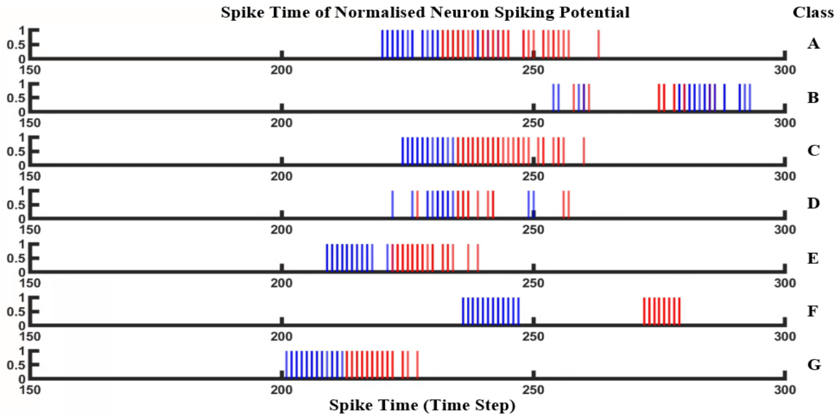


Figure 10. Example of firing output for one of the class G training (blue colour) and testing datasets (red colour) for all epochs.

Table 2. Results of SNN model and other ML models.

Model	SNNs	LSTM	Bi-LSTM	GRU
Number of inputs	990	90	90	90
Number of hidden neurons	-	100	100	100
Overall training accuracy (%)	100	100	100	100
Overall testing accuracy (%)	84.8073	85.71	80.00	88.57
Learning rate	0.5	0.001 (Adam optimizer)		
Time for training and testing all dataset (s)	71	84	184	73
Peak memory (kb)	13620	54252	108520	49100

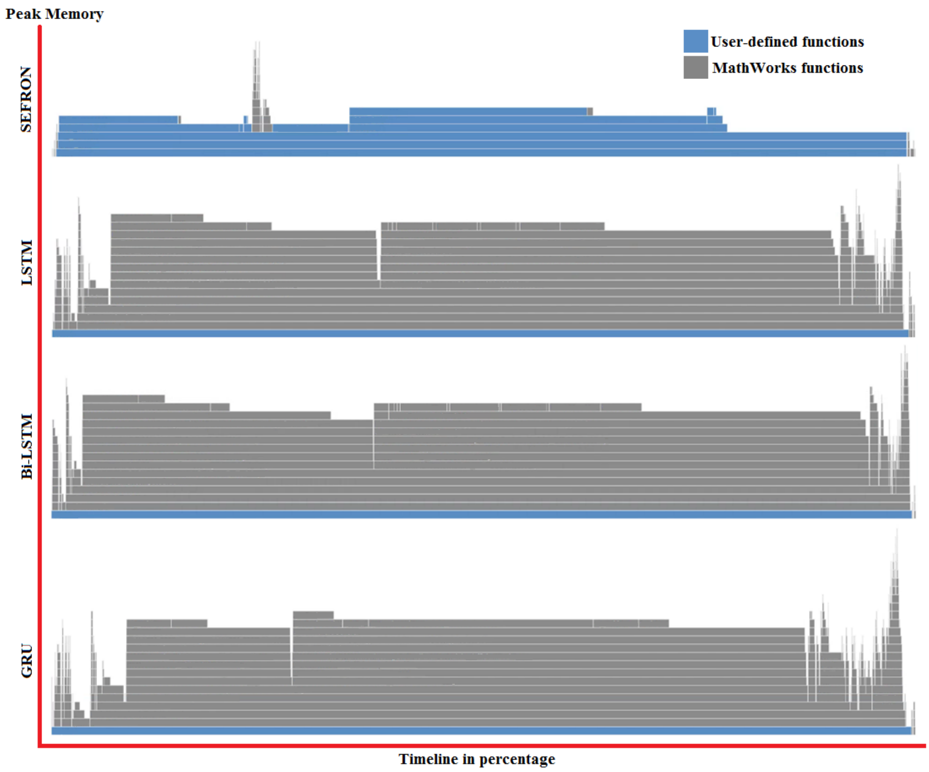


Figure 11. Graph of memory profiling summary.

Table 3 shows the confusion table of testing data for the SNN model and the other compared models. All the test data for activities ‘A-Bed’, ‘B-Fall’, ‘C-Pickup’ and ‘D-Run’ has been predicted correctly by the SNN model. On the other hand, the accuracy to predict activities of ‘E-Sitdown’ and ‘F-Standup’ is very low. This may be due to the threshold for these activities that are very close to each other and have a miss-postsynaptic spike at wrong classes. Besides that, similar or less clear features among the datasets of different classes may cause a decrease in the classification accuracy.

Table 3. Confusion table for testing data where activity A to activity G refer to ‘Bed’, ‘Fall’, ‘Pickup’, ‘Run’, ‘Sitdown’, ‘Standup’ and ‘Walk’.

SNNs							
Actual	Predicted						
	A	B	C	D	E	F	G
A	1.0	0	0	0	0	0	0
B	0	1.0	0	0	0	0	0
C	0	0	1.0	0	0	0	0
D	0	0	0	1.0	0	0	0
E	0.4	0.2	0.2	0	0.2	0	0
F	0.4	0	0.2	0	0	0.4	0
G	0	0	0	0.2	0	0	0.8

LSTM							
Actual	Predicted						
	A	B	C	D	E	F	G
A	0.6	0.2	0	0.2	0	0	0
B	0	1.0	0	0	0	0	0
C	0	0	1.0	0	0	0	0
D	0	0	0	1.0	0	0	0
E	0	0	0	0.6	0.4	0	0
F	0	0	0	0	0	1.0	0
G	0	0	0	0	0	0	1.0

Bi-LSTM							
Actual	Predicted						
	A	B	C	D	E	F	G
A	1.0	0	0	0	0	0	0
B	0.4	0.6	0	0	0	0	0
C	0	0	1.0	0	0	0	0
D	0	0	0	1.0	0	0	0
E	0.6	0	0	0	0.4	0	0
F	0.4	0	0	0	0	0.6	0
G	0	0	0	0	0	0	1.0

GRU							
Actual	Predicted						
	A	B	C	D	E	F	G
A	0.6	0.2	0	0.2	0	0	0
B	0	1.0	0	0	0	0	0
C	0	0	1.0	0	0	0	0
D	0	0	0	1.0	0	0	0
E	0.4	0	0	0	0.6	0	0
F	0	0	0	0	0	1.0	0
G	0	0	0	0	0	0	1.0

5. CONCLUSIONS

HAR using Wi-Fi signals is very useful in many areas, such as keeping track of elderly people and creating a smart home environment. The existing ML models require a high demand on hardware resources, which is less advantageous for mobile edge computing applications. As a result, an SNN method is proposed and this is the first CSI-based Wi-Fi signal HAR using SNNs. In this paper, the SNN model has achieved lower memory usage while maintaining high overall accuracy of 84.8073%. The proposed SNN model has saved 87% memory when compared with the Bi-LSTM model. The memory needed by the SNN model is as low as 13620kb, while the Bi-LSTM model needed 108520kb of memory. More than 70% of memory saving running in SNNs compared to other models demonstrates that the SNN model is the preferred computational model to exploit machine intelligence while keeping computational accuracy, thereby avoiding expensive memory access operations.

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ملخص البحث:

فـــي هـــذا البحـــث تـــمّ اقتـــراح شـــبكات عصـــبيّة ناتئـــة (SNNs) لتمييـــز الأنشـــطة البشـــرية باســـتخدام إشـــارات (واي-فـــاي). وتجـــدر الإشـــارة الـــى أن الشـــبكات العصـــبية النّاتئـــة مســـتوحاة مـــن معالجـــة المعلومـــات فـــي علـــم الأحيـــاء التـــي تجـــري معالجتهـــا بطريقـــة متوازيـــة الـــى حـــدّ كبيـــر. وتعمـــل الطريقـــة المقترحـــة علـــى تقليـــل المـــوارد الخاصـــة بالمعالجـــة فـــي الوقـــت الـــذي تحـــافظ فيـــه علـــى الدّقّـــة مـــن خـــلال اســـتخدام نقـــل المعلومـــات بطريقـــةٍ ســـهلة لكنهـــا متينـــة بالنســـبة الـــى الضّـــجيج النّـــاجم عـــن الإشـــارات النّاتئـــة. كـــذلك تمـــت مقارنـــة أداء تمييـــز الأنشـــطة البشـــرية باســـتخدام الشّـــبكات العصـــبية النّاتئـــة بـــأداء شـــبكات أخـــرى مـــن شـــبكات تعلّـــم الآلـــة (ML)، مثـــل نمـــاذج LSTM و Bi-LSTM و GRU. وقـــد اتّضـــح تحقيـــق وَفْـــرٍ فـــي اســـتخدام الـــذاكرة مـــع الحفـــاظ علـــى الدّقّـــة علـــى نحـــوٍ متقـــارب لشـــبكات تعلّـــم الآلـــة الأخـــرى. فقـــد تـــمّ تحقيـــق وَفْـــرٍ نســـبته 70% فـــي اســـتخدام الـــذّاكرة فـــي الشّـــبكات العصـــبية النّاتئـــة. وهـــذا مـــن شـــأنه أن يجعـــل مـــن الشّـــبكات العصـــبية النّاتئة حلاً محتملاً لحساب الحواف في الثّورة الصناعية الرابعة.