Long Short-Term Memory Fuzzy Finite State Machine for Human Activity Modelling

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ABSTRACT

A challenging key aspect of recognising and modelling human activity is to design a model that can deal with the uncertainty in human behaviour. Several machine learning and deep learning techniques are employed to model the Activity of Daily Living (ADL). This paper provides a new method based on Fuzzy Finite State Machine (FFSM) and Long Short-Term Memory (LSTM) neural network for modelling and recognising human activities. The learning capability in the LSTM allows the system to learn the relations in the temporal data to identify the parameters of the rule-based system through time steps in the learning mode. The learned parameters are then used for generating the fuzzy rules that govern the transitions between the system's states. Experimental results are presented to demonstrate the effectiveness of the proposed approach.

CCS CONCEPTS

• **Computing methodologies** → **Activity recognition and understanding**; Vagueness and fuzzy logic; • **Computer systems organization** → *Neural networks.*

KEYWORDS

Human activity modelling; Activity of Daily Living; ADL; fuzzy finite state machine; deep learning; Long Short-Term Memory; LSTM

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1 INTRODUCTION

Monitoring and recognising human activities in an indoor environment have become an attractive research field within the general topic of Ambient Intelligence (AmI) [6, 9, 18]. Several methods can be used to gather the information that represents the Activity of Daily Living (ADL) and Activity of Daily Working (ADW) for the monitored user. This information is commonly gathered from the signals that are collected from sensory devices such as ambient and/or wearable sensors [13]. The information can also be extracted from images or videos streams using cameras [11], although, for privacy concerns, attention has predominantly focused on data collected by ambient sensors, which are more acceptable to users [1]. The gathered information is then processed and analysed, to be used in many different applications including energy consumption optimisation, addressing health and safety concerns, or leading to an improved level of comfort and quality of life [16].

Different techniques are employed for recognising and modelling human activities based on the gathered sensory information. One of the promising techniques used to model dynamic processes is Finite State Machine (FSM). The classic FSM contains a number of states representing different actions and the functionality of transitions between them. Since humans behave with some unpredictability in their living/working places, a sense of fuzziness is integrated within the FSM, thereby creating a more powerful tool to model dynamic processes that may change over time [4, 16, 18, 19, 26]. Fuzzy Finite State Machine (FFSM) is a suitable technique to deal with a large amount of uncertain data gathered from low-level sensory devices in AmI environments. In this case, the system can assign a degree of truth to the occurrence of each activity. The transitions between the system's states in the FFSM are triggered by fuzzy values, instead of crisp values as they are in FSM. This provides an accurate model supported by a fuzzy reasoning mechanism, represented by a degree of truth related to each state transition. Therefore, more than one state can be in an active mode at any time based on the membership values of each state [4, 16]. Readers are referred to [27] for a detailed definition of the FFSM with some recent developments reported in [3, 8, 20].

To represent human activities in a numerical or analytical model, it is essential to use the correct tools to represent the activities and the links between them. The activities of an occupant in a home or office environment are a collection of tasks and events which are represented in a temporally sequential manner. One of the effective techniques used with temporal sequential data is Recurrent Neural Networks (RNNs) [14, 18, 23], which is used in deep learning models to enhance the performance of learning ability. More recently within the machine learning community, attention has predominantly been focused on Long Short-Term Memory (LSTM) neural networks. LSTM has internal memory cells that can remember previous information from the inputs and outputs, and the output of the LSTM network is modulated by the state of these memory cells. Once the data that represents human activities is sequential temporal data, it is essential to modulate the output depending on the historical context of inputs, rather than only on the very last input.

In this research, FFSM is introduced as a means of defining activities and the transition between activities or states. There are many unknown parameters, however, and the main task of this research is to identify the parameters which produce an accurate representation of real activities. In this contribution, the concept of FFSM is integrated with the LSTM to enhance the learning capability of the model, based on the numerical and temporal information gathered from the sensory data.

The rest of this paper is organised as follows: Section 2 presents relevant literature in the field of recognising and modelling human activities. The proposed approach is explained in Section 3. This is followed by Section 4 which illustrates the recognition and modelling of human activities using the proposed approach. In Section 5, the experimental results are shown and analysed, and finally Section 6, where pertinent conclusions are drawn.

2 RELATED WORK

Many research works are conducted to monitor and analyse the activities of people using different machine learning techniques, including genetic-FFSM [5], dynamic Bayesian network modelling [29], echo-state neural networks [17], Neuro-FFSM [20], LSTM classifier [18] and regression models [2]. Most of these studies are employed to enhance the quality of life by supporting independent living, especially for the elderly and disabled people. Human activities within an indoor environment, such as house or office, can be sensed based on data collected by either wearable sensors or ambient sensors. These can include obtrusive images and videos that are captured using a camera to extract the necessary features, and then used as inputs to their systems [11, 25]. Attention has predominantly been focused on data collected by ambient sensory devices because of security and privacy purposes with intrusive methods [1], but the observation of activities in an AmI environment can still use many different methods to identify the human activity.

Most of the research related to human activity recognition are carried out using statistical techniques, which are used to find the relationship between the action (activity) and the temporal data gathered from sensors, and ultimately identify the activity of the user. Several graphical probability-based techniques are involved to recognise and model human activities, for example, the Hidden Markov Module (HMM) can represent random variables, actions and temporal variation within the collected data [10, 15, 21]. Relatively new research [1] has presented a new model based on the Markov Modulated Poisson Process (MMPP), which promises to come up with a model to represent multi-visitor recognition with more accuracy. The only issue with this approach is the difficulty in processing a large amount of low-level data.

In [12, 16], the authors used a traditional FSM for locating and modelling the activity of a single user in an apartment. FSM is a powerful technique for modelling dynamic events, that is, the events that change over time such as human activity. The fuzzy system is used to increase the efficiency of the classical FSM by proposing FFSM, where transitions between the states are triggered by the sense of fuzzy instead of using crisp values. This has the advantage of smooth modelling and reasoning with a degree of truth, which proves to be more accurate. Thus, the system can be in more than one state at a time, based on the membership value for each state [4][16]. The main advantage of using the fuzzy sense is that it can deal with uncertain data and can represent it in more than one state at a same time as membership degrees. In [16], it is shown that the ADW in an AmI environment can be modelled using the FFSM technique using sequential events based on a dataset collected from a real smart office environment.

Computational intelligence techniques are also widely used to recognise and model human activities, as an alternative or in combination with other statistical methods. Neural Networks (NNs) are used to deal with and process pattern recognition based on numerical information data that is gathered from sensors in an AmI environment [7, 22]. Recurrent Neural Networks (RNNs) are proven to be a powerful tool to solve the difficulties of the temporal relationships of inputs and outputs at different time steps [14, 18, 23]. In [18], authors created fuzzy temporal windows for the collated binary data representing the human activities, and then applied them to an ensemble classifier based on LSTM. LSTM is used in [14] with fuzzy ground truth for annotating historical documents. Fuzzy ground truth is used to provide all possible annotations for each input variable, instead of just one, before they trained using the LSTM. Therefore, based on the literature review conducted for this research, LSTM could be integrated with the FFSM for the learning process and controlling the states (activities) transitions.

3 METHODOLOGIES

The overall architecture of the proposed method is shown in Figure 1, that consists of three stages: data collection, data processing, and the fuzzy finite state machine module. In the data collection stage, the binary data is gathered from a real-world environment representing ADL for a single user. The data processing stage is designed to transform the data into meaningful features and they are used as inputs to the FFSM module. The extracted features will be fuzzified before they are applied to the learning phase using the LSTM.

In this section, FFSM and the LSTM are briefly introduced, then the proposed enhancement version of the FFSM with the LSTM is presented.

3.1 Fuzzy Finite State Machine

Fuzzy Finite State Machine (FFSM) is an extended version of the classical FSM. The FSM can be presented as a model made of two or more states, each state represents one event from a sequence of events in a dynamic process [20]. Only one single state of this model can be active at a time. The model is moved from one state

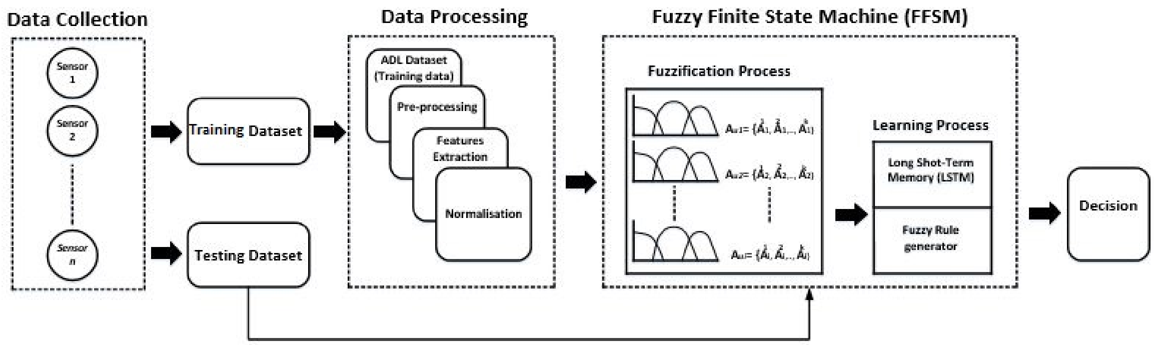

Figure 1: Architecture of the proposed Long Short-Term Fuzzy Finite State Machine.

to another by triggering fixed values. Once the fuzziness aspect is added to the state transitions, the transitions are not triggered based on fixed values, but by means of fuzzy variables [5, 16, 24]. That means the current *activated* state of the model is not necessarily one state, but it could be more than one state at any given time with a fuzzy belonging degree [24].

The states in FFSM are represented as a set of linguistic labels $S = \{s_1, s_2, ..., s_n\}$ where n is the number of states. For a non-sequential system at time t, the FFSM state is represented as a state vector $S(t)$. When the system evolves over time, the next state is represented as a vector $S(t+1)$.

The main components of the FFSM is defined as:

$$\big(S(t), U(t), f, Y(t), g\big)$$

where $S(t) = [s_1(t), s_2(t), ..., s_n(t)]$ is the state vector, $U(t) = [u_1(t), u_2(t), ..., u_k(t)]$ is the input vector to the system, with k being the number of input variables, $Y(t) = [y_1(t), y_2(t), ..., y_p(t)]$ is the vector of output variables with p being the number of output variables, f is the function that calculates the next state at time t, and g is the function that calculate the output vector Y at time t [4, 5, 16]. Considering the complexity of identifying the functions f and g, it is difficult to use the FFSM for the modelling in our case.
Generally, the states and outputs of the time-invariant FFSM are expressed [16] as:

$$S(t+1) = f\big(S(t), U(t)\big) \tag{1}$$

$$Y(t) = g\big(S(t), U(t)\big) \tag{2}$$

The transition mechanism from state s_i to state s_j is represented by the following general fuzzy rule:

R_{ij}**: IF** ($S(t)$ **is** s_i) **AND** H_{ij} **THEN** $S(t+1)$ **is** s_j

where, ($S(t)$ is s_i) is used to determine if the state s_i is an *activated* state in time instant t. H_{ij} which represents all constraints imposed on the input variables that are required to either remain in state s_i. $S(t+1)$ is s_j, determines the next value of the state vector $S(t+1)$ for being in state s_j.

More details about each of these elements readers are referred to our previous publications [19, 20].

3.2 Long Short-Term Memory

A Long Short-Term Memory (LSTM) is a particular kind of RNNs designed to solve vanishing and gradients problems in the classical RNNs [14, 28]. LSTM is a powerful tool for sequential learning tasks that are represented as temporal data. It can also remember previous information for long periods. These characteristics make LSTM especially useful for temporary data classification problems. LSTM cell consists of three gating mechanisms to provide the ability to remove or add information to the memory cell. These three gates are used to regulate the impact of the input through the input gate, the previous cell state through the forget gate and the output through the output gate. The essential gate in the LSTM cell is the forget gate as it decides the information that is going to be remembered or forgotten from the previous states.

The state equations for each LSTM cell as they defined in [14, 28] are formulated as follows:

$$f_t = \sigma(w_{xf}.x_t + w_{hf}.h_{t-1} + b_f) \tag{3}$$

$$i_t = \sigma(w_{xi}.x_t + w_{hi}.h_{t-1} + b_i) \tag{4}$$

$$v_t = tanh(w_{xv}.x_t + w_{hv}.h_{t-1} + b_v) \tag{5}$$

$$o_t = \sigma(w_{xo}.x_t + w_{ho}.h_{t-1} + b_o) \tag{6}$$

$$C_t = f_t.C_{t-1} + i_t.v_t \tag{7}$$

$$y_t = o_t.tanh(C_t) \tag{8}$$

where, f, i and o denote the forget, input and output gates. C and y are the cell state and output respectively at time t. $b_j, j \in \{f, i, o, v\}$ are the bias units for the forget, input and output gates and the remembering inputs. w_{ij} is the weight connection between i and j. σ is a logistic sigmoid function and $tanh$ is the tangent hyperbolic function.

LSTM learns the temporal relations in the given data by storing the information through multiple time steps. The next section introduces the proposed approach, which integrates the learning abilities of the LSTM in the temporal data with the sequential events modelling in the FFSM.

3.3 Long Short-Term Memory Fuzzy Finite State Machine

In this section, FFSM is introduced as a means of defining the states and the transition between them. There are many unknown parameters, however, and the primary task of this research is to identify the parameters which will produce an accurate representation of the real data. In our previous publication [20], the FFSM was integrated with standard NNs. The integration was used to add the learning capability of the machine learning algorithms with the FFSM to identify the unknown parameters that govern the states' transitions and the output of each state. In order to improve the learning capability of the FFSM for enhanced modelling of the time sequential data, integration of Long Short-Term Memory Fuzzy and Finite State Machine (LSTM-FFSM) is proposed. The LSTM-FFSM is an enhancement of FFSM allowing the system to learn the temporal relations in the data by storing the information through the time sequential steps. The learned relations are then used to formulate the fuzzy rules that control the transitions between the system's states, and identify the current activated states at any given time t.

In this approach, the experts are also allowed to introduce their own knowledge over the whole system by defining the following aspects:

- Defining the system states.
- Specifying the general structure of the fuzzy rules that represent the state transitions.
- Specifying the number of linguistic labels that are associated with each input variable.

In a typical FFSM, a rule to identify the transition between state i and state j is presented as R_{ij}. This demonstrates the relation between the system's current state $S(t)$ and the input variables, represented as H_{ij} to identify the next state $S(t+1)$. Each input variable involved in the term H_{ij} is fuzzified to convert the numerical data into their relevant linguistic labels. These associated labels with input u_i are represented as $A_{u_i} = \{A^1_{u_i}, A^2_{u_i}, ..., A^{k_i}_{u_i}\}$, where k_i is the number of associated linguistic labels. At this point, LSTM is employed to learn the temporal relations in the data by storing the previous information in a time-sequential manner. Thus the term H_{ij} will be represented as:

$$H_{ij} = \begin{cases} \sum_{u=1}^{i}(u_{i(t)} \quad \textbf{is} \quad \{A^1_{ui}, A^2_{ui}, ..., A^k_{ui}\} & k \neq 0 \\ y_t = o_t.tanh(C_t) \end{cases} \tag{9}$$

where u_i is the input at time t, k is the number of linguistic labels that are associated with the input u_i, C and y are the LSTM cell state and output at time t.

Based on the explanation introduced in the proceeding sections, LSTM-FFSM is proposed to generate the fuzzy rules representing the transition based on learning the relations in the temporal sequential data.

4 HUMAN ACTIVITIES MODELLING

In this section, a dataset representing ADL for a single user is used for modelling and recognising the user's activities. The dataset was gathered using low-level sensory devices. The proposed LSTM-FFSM is applied to the gathered data from smart home environment for modelling the human activities.

4.1 Data Collection

An important factor in designing a smart environment to collect the dataset for recognising and modelling human activities is that the technology should not interfere with the normal daily activities of the user. Thus, all the employed devices should operate autonomously. To achieve that, the environment is supplied with sensors to detect movement once any item or object is moved, and record this information. Examples of these sensors are: PIR sensors to capture the movements; electrical sensors to measure the usage of electrical devices; temperature sensors to measure the ambient temperature; mat pressure sensors to measure bed occupancy; light sensors to monitor ambient light; and on/off switch sensors to monitor doors opening and closing. The data in this research is collected from a real home environment showing the ADL of a single user, represented as binary sensory data. The experiment was conducted at the Smart Home facilities within Nottingham Trent University. A floor plan of the house is shown in Figure 3. The sensors used in this experiment are:

- 6 Passive Infrared Red (PIR) sensors for detecting the movements.
- 2 on/off door switches to detect when doors are opened.
- 2 Electricity usage plugs to measure electricity consumption in the microwave and kettle.
- 1 Mat pressure sensor to identify bed occupancy.

The information recorded from each sensor consists of (t, a_{on}, a_{off}, l), where t is the timestamp for the sensor triggered on a_{on} or triggered off a_{off} and l is the sensor location. The challenge here is to understand and identify the human activities from the low-level sensory data. This could be achieved using common-sense knowledge or using computational intelligence integrated with the sensory data. Once the activities are identified, the next step is to extract the numerical features.

4.2 Features Extraction

Extraction of the numerical information from acquired raw sensor data is crucial to any learning system as raw data does not provide adequate information that can be used as inputs to the model. Therefore, the acquired raw sensor data is used for identifying the ADL activities as shown in Figure 2. The numerical features are then extracted from the identified activities. Four different features are extracted for use as the inputs to the proposed system. The input variable vector is $U = [u_1, u_2, u_3, u_4]$. where u_1 and u_2 represent the activity start and end times respectively, u_3 denotes the duration of each activity which is represented in minutes, and u_4 is the activity count, which defines the number of each activity per day. Each input variable is fuzzified to translate the numerical data to the associated linguistic labels. These values are represented as fuzzy Membership Functions (MFs). The associated linguistic labels with each input are then used as fuzzified inputs to the LSTM-FFSM model.

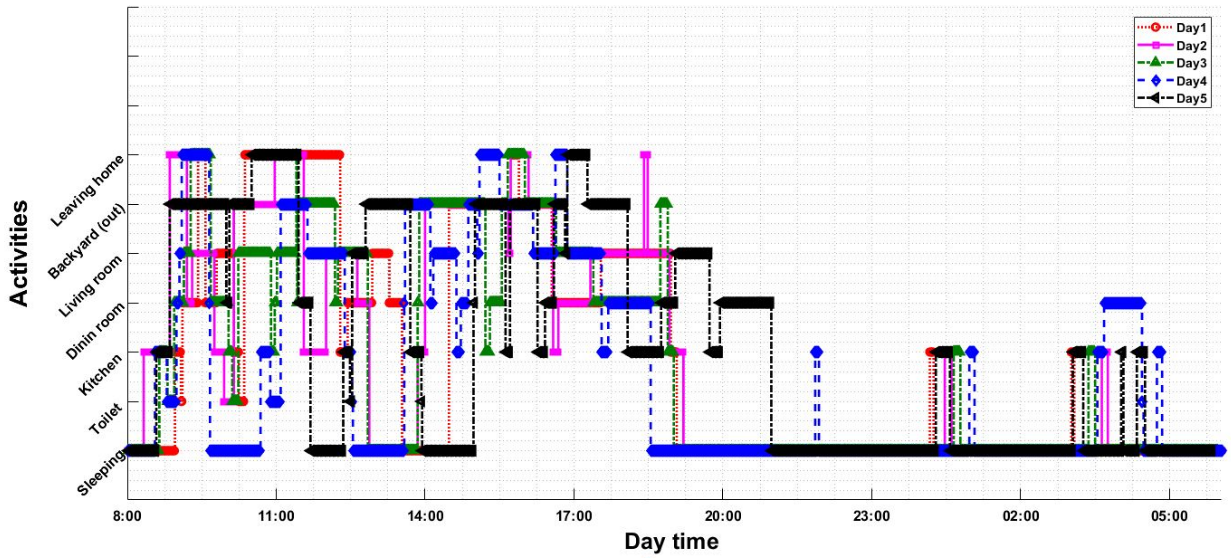

Figure 2: An illustration of multilevel activities over five days.

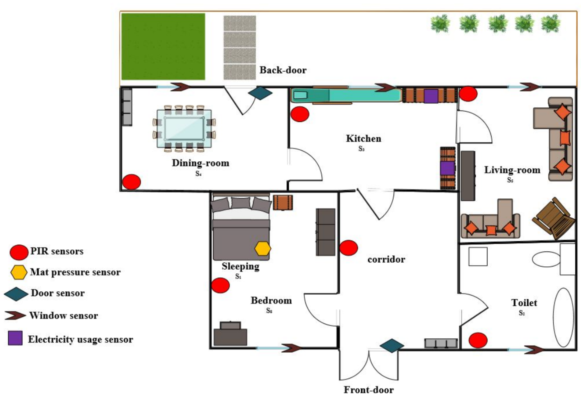

Figure 3: Floor plan layout and location of installed sensors.

4.3 System Definition

The collected dataset represents seven different activities. Each activity is represented as one state in the FFSM model. These states are defined based on the experts' knowledge. These states are:

- s_1 $\longrightarrow$ The sleeping state represents the sleeping activity, either night sleeping or daytime napping.
- s_2 $\longrightarrow$ The grooming state represents the time when the user is using the toilet.
- s_3 $\longrightarrow$ The kitchen state represents when the user is using the kitchen for preparing food or cleaning e.g., dishwashing.
- s_4 $\longrightarrow$ The dining state, which usually comes after kitchen state, represents the time when the user is in the dining room to eat the prepared meal.
- s_5 $\longrightarrow$ The living room state represents the time spent in the living room for either relaxing or watching TV.
- s_6 $\longrightarrow$ The garden state represents the time when the user is leaving to go to the garden through the back door.
- s_7 $\longrightarrow$ The leaving the home state represents when the user is leaving home through the front door.

Table 1: Recall, precision, Accuracy and F-score for each activity obtained from the proposed LSTM-FFSM approach.

Activities	Recall	Precision	Accuracy	F-score
Sleeping	92.85	92.86	91.99	92.90
Toilet	100	98.69	100	98.98
Kitchen	92.30	100	92.77	96.00
Dining room	100	98.8	100	100
Living room	92.76	85.71	92.52	88.89
Garden	100	100	100	100
Leaving home	100	100	100	100

Once the system states are created, the numerical features are extracted from the collected data. Four features are used in this experiment, representing the start time u_1, end time u_2, activity duration u_3 and activity count u_4. The extracted features are then fuzzified using Gaussian MFs. Six different linguistic labels are used with start and end time features, five linguistic labels are used with the activity duration, and three linguistic labels with the activity count feature. Thus, every single value from these features is represented with the relevant number of belonging degrees to each MF. The linguistic labels associated with each input are represented as MFs. These MFs are illustrated in Figure 4 and explained as follows:

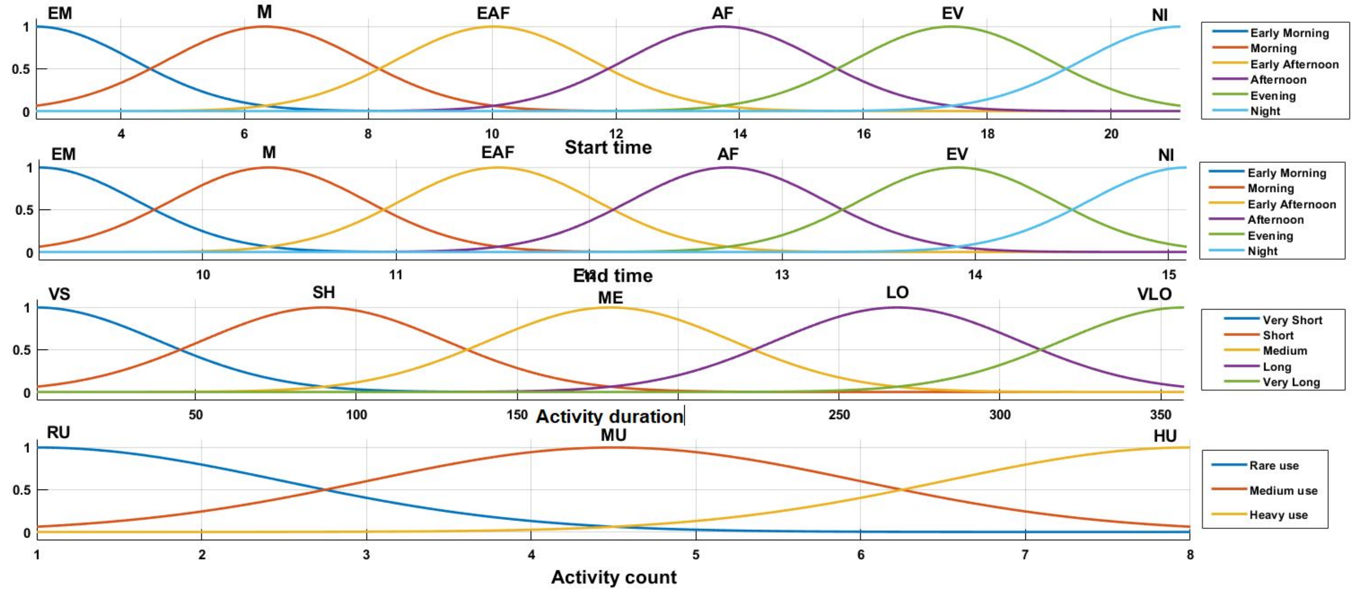

Figure 4: Linguistic labels associated with input variables.

$$U(t) = \begin{cases} u_1(x) \rightarrow \{EM_{u_1}, M_{u_1}, EAF_{u_1}, AF_{u_1}, EV_{u_1}, NI_{u_1}\} \\ u_2(x) \rightarrow \{EM_{u_2}, M_{u_2}, EAF_{u_2}, AF_{u_2}, EV_{u_2}, NI_{u_2}\} \\ u_3(x) \rightarrow \{VS_{u_3}, SH_{u_3}, ME_{u_3}, LO_{u_3}, VLO_{u_3}\} \\ u_4(x) \rightarrow \{RU_{u_4}, MU_{u_4}, HU_{u_4}\} \end{cases} \tag{10}$$

where $U(t)$ is the input vector to the system, x denotes the single value from each input variable $\{u_1, u_2, u_3, u_4\}$. A set of fuzzy rules are required to control the transition between the system's states. In the standard FFSM, these rules are defined based on the experts' knowledge. In this contribution, as the generated data is temporal data, LSTM is employed to learn the relations in the data through the time steps. The learned relations are used to generate the fuzzy rules in the system. The final output for this model, Y, is represented as the degree of belonging to each state in the system.

5 EXPERIMENTAL RESULTS

The proposed LSTM-FFSM is implemented to model ADL for a single user based on a low-level sensory data gathered from smart home environment. In this section, the results obtained from the conducted experiment is presented. A sample of the generated ADL data is illustrated in Figure 2 as a multilevel graph which demonstrates the seven different activities. As humans behave with some unpredictability in their environment, datasets representing the human activities are usually imbalanced, where some activities appear more dominant than the other activities. In that case, if the dominant activities are identified with a high degree of accuracy, the performance over the whole system will be high even if the other activities are not well identified. Therefore, each activity will be evaluated separately and then the performance over the whole system will be calculated. Table 1 illustrates the recall, precision, accuracy and F-score for the results obtained by using LSTM-FFSM for each activity.

The overall performance for the whole system based on the obtained results is 96.94%, 96.78%, 96.81% and 96.93% for the recall, precision, accuracy and f-score respectively.

6 CONCLUSION

The work presented in this paper has proposed a new method for recognising and modelling human activities using data gathered from low-level sensory devices, representing the ADL for a single user within a smart home environment. Considering the results obtained from the conducted experiment, the results illustrated in Table 1 show that the LSTM-FFSM model exhibits a high score for accuracy, recall, precision and f-score when its performance is tested for each activity separately. Also, the overall activity recognition performance, when it is over the whole system, demonstrates the effectiveness of the proposed approach. The essential feature of the proposed approach is that it integrates the available expert's knowledge with the learned information from the deep learning technique. The LSTM-FFSM model is considerably better for ADL recognition based on data gathered from low-level ambient sensors. In addition, it can be seen how the LSTM-FFSM model is able to follow the proper sequence of states with the correct state activation degree.

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