Convolutional Neural Network Classifier with Fuzzy Feature Representation for Human Activity Modelling

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***Abstract*—Human activity recognition is concerned with identifying the specific movement of a person based on sensor data. In recent years, many different techniques have been proposed for modelling and recognising human activities, with a specific focus on the development of approaches to classifying human activities using deep learning techniques. The research presented in this paper proposes a fuzzy feature representation approach to represent occupancy sensor data, along with a Convolutional Neural Network Classifier (CNNC) for human activity modelling and recognition. Sensory data gathered from a home environment are converted into occupancy data representing human activities and then fuzzified before being fed as inputs into the CNNC. The learning capability of CNNC allows the model to learn the relationship between the fuzzified inputs and their corresponding output activities during training mode. The relations learned in the trained CNNC model are then used to identify human activity patterns and classify these when the testing dataset is applied. The proposed method is evaluated using a dataset representing activities of daily living for a single user gathered from a real-home environment.**

***Index Terms*—Human activity modelling, fuzzy feature representation, convolutional neural network classifier, CNNC, activities of daily living.**

I. Introduction

Human activity modelling and recognition based on gathering data from smart environments has recently attracted much research interest within the ambient intelligence research community [1]. Human behaviour is naturally associated with high amounts of uncertainty and unpredictability, therefore, modelling and recognising human activities is considered a challenging task [2], [3]. Information representing human activity can be obtained from ambient sensory devices such as motion sensors [4], [5], wearable sensors, smart phone sensors [6] and visual sensors [7], [8]. However, a robust model is required to be able to understand the relationships between the gathered datasets in order to accurately model and recognise human activities. By nature, data representing human activities that are gathered over a long time period from various sensors may contain unpredictable and noisy patterns. In this case, the challenge is in developing a human activity model that is capable of efficient activity classification and/or prediction using such data.

To handle the embedded uncertainties in human activities, several statistical and dynamic approaches are used to extract and represent human activity features, such as fuzzy feature representation [9]–[12]. Comparing the fuzzy feature representation method with other existing feature representation approaches (such as time-dependent and sequential-based feature representation, which can learn features from given data), the fuzzy features can be constructed more flexibly to capture the underlying uncertainties in the collected data. On the other hand, the Convolutional Neural Network (CNN) is widely used as a deep learning technique for classifying human activities, due to its ability to extract and learn meaningful representations and to capture local dependency from the input information [13]. Since it can handle position and scale-invariant structures in sequential input data, CNN can learn sequential relationships in human activity data over a long-term period. This motivates the use of fuzzy feature representation in combination with the Convolutional Neural Network Classifier (CNNC) in this paper.

In this paper a hybrid solution for modelling and recognising human activities is presented in which the raw data sets are initially processed within a fuzzy feature representation method, and then the fuzzified data and their associated activity labels are used to train a CNNC and to consequently classify the activities. The results of the experiments reported in this paper support the applicability of the proposed hybrid architecture.

The rest of this paper is organised as follows: a review of related work in literature is presented in Section II. Section III describes the proposed method, including the fuzzy feature representation approach and CNNC architecture. In Section IV the experiments employing the proposed CNNC model with the collected dataset are explained. The final results obtained from the experiments conducted are discussed in Section V followed by a conclusion in VI.

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II. Related Work

Representations of human activity based on data gathered from ambient sensory devices are in most cases influenced by the process of feature extraction. This is because of the limitations in terms of features that can be extracted from such data [4], [14]. Several computational intelligence techniques have been developed for modelling and classifying human activities. However, the process of extracting and representing features from the gathered dataset can be more challenging when these represent human activity than other forms of activity [11].

Many different approaches have been investigated to extract and represent the features of human activities data. Researchers in [11] proposed a Spectrogram-based technique for representing human activity data collected by inertial measurement units. The extracted features were tested with a deep Long Short-Term Memory (LSTM) neural network to evaluate the performance of this approach for feature representation in recognition of human activities. In [15]. The authors investigated methods that could be used for feature representation by creating a binary image based on data collected from Passive Infrared (PIR) sensors. To this end, they proposed a novel technique called Episode Image to generate a binary image based on binary signals from the PIR sensors. Once the binary images had been generated, they were fed into a Deep Convolutional Neural Network (DCNN) classifier where eight features were extracted from each episode to classify the activity travel pattern. The same authors, in [16], report their use of the same feature representation approach with the DCNN classifier for human posture recognition.

In the area of human activity recognition, CNN is one of the recently-used algorithms, selected due to its ability to learn fruitful features and capture local dependency and spatial information from the given data. In some recent works on human activity recognition [5], [13], researchers have focused on employing the CNN with binary datasets in order to recognise human activities and to detect any abnormal activities in the users' behavioural patterns, based on trained CNN. In [13], the Aruba test-bed data, produced by the Centre for Advanced Studies in Adaptive Systems (CASAS), representing Activities of Daily Living (ADL), were used to recognise human activities and to detect abnormalities in behavioural patterns. Since the test-bed used contain binary data, the authors used a sliding window approach of 60 seconds' length to chunk a time-series matrix containing the length t of 60 seconds and the sensor's information f. This matrix is mapped into a last-fired representation of which sensor is fired last. The mapped data is fed into a CNN classifier enhanced with LSTM to recognise the human activities and learn patterns of behavioural abnormalities.

A widely used method for feature representation is the fuzzy feature representation approach [3], [17]. In [18], the authors proposed a fuzzy computational approach to extract features from one-dimensional input vectors, and employed a deep neural network with the extracted features to classify the given data. A fuzzy temporal windows approach is proposed in [9], [19] to define temporal-sequence representations to aggregate information from binary sensors for real-time recognition of human activities. The methods in [9], [18] have been successful in capturing features which improve task classification performance for human activity recognition.

In this paper, a fuzzy feature representation method is applied to represent the occupancy data obtained from ambient sensory devices. The fuzzified features obtained are used to train a CNNC for modelling and classifying human activities. In the next section, a detailed description of the methodology used is presented.

III. Methodology

The overall framework of the proposed CNNC for human activity modelling is shown in Fig 1. The proposed framework consists of two stages; a data collection and presentation stage, and the Convolutional Neural Network Classifier. In the data collection and presentation stage, binary data is gathered from a real-world environment, representing ADL, is a represented in suitable format for classification. This is achieved by converting the the gathered binary sensor data into occupancy data represented as fuzzy features. The fuzzy set thus generated will be used as input to train the proposed CNNC in the second stage of the proposed framework.

In this section, the fuzzy feature representation approach is briefly introduced, and then the proposed convolutional neural network classifier is explained.

A. Fuzzy Feature Representation

In applying a feature representation process to a collected dataset in order to identify unique characteristics, a fuzzy feature representation approach may be selected. This approach is widely used to determine the number of degrees of membership associated with each input variable [19], [20]. By representing each value in the input data with its degrees of membership, each value is represented as a fuzzy set obtained from Membership Functions (MFs) as:

$$X_{uj} = [\mu_{A^1_{uj}}, \mu_{A^2_{uj}}, ..., \mu_{A^M_{uj}}] \qquad j = 1, ..., P \tag{1}$$

where X_{uj} is the fuzzy set of the input variable u_j. P is the total number of input variable u_j, and μ_A is the degree of MF associated with each linguistic label A. The process of fuzzy feature representation can be summarised as listed below:

1) Apply a fuzzifier algorithm which consists of M number of MFs that are presented as linguistic labels to the input data.
2) Define the degree of belonging μ_A that corresponds to the applied MFs for each value in the input variable u_j.
3) Create a matrix $q = r \times i$ to store the degree of MFs for each variable u_j, Where r is the total number of activity instances in the input data u_j, and i is the number of the fuzzy set for the variable u_j.
4) Update the matrix q after each iteration with the new fuzzy set values that correspond with the next input value.

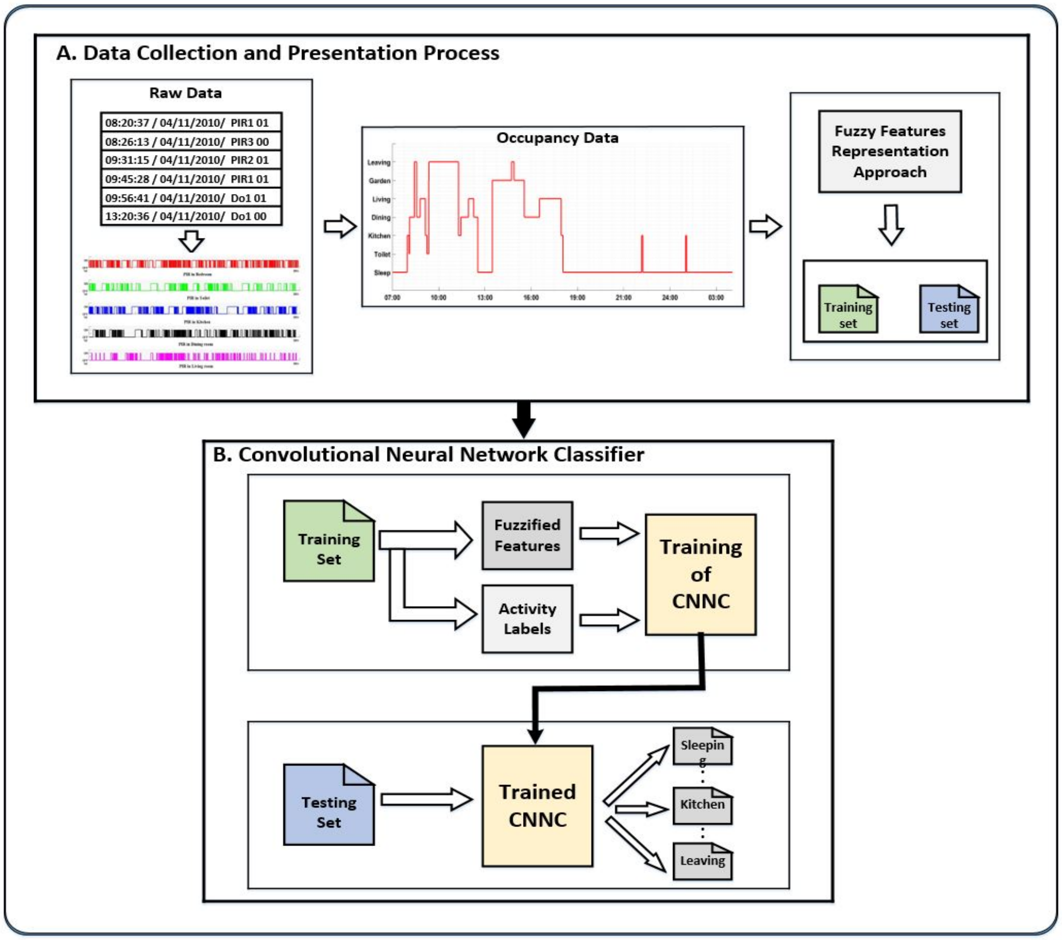

Fig. 1. Architecture framework of the proposed Convolutional Neural Network Classifier for human activity modelling.

The generated set of the fuzzified features, X_{uj}, will be used as inputs to train the proposed model, to learn the relations between input and output data. This will be elaborated on when the the process of fuzzy feature representation is explained in Section IV based on the experimental dataset representing ADL.

B. Convolutional Neural Network Classifier

The input data for a CNNC is formulated as a matrix c in dimensions $h \times w \times d$, where h is the matrix height, which will be represented as the total number of activity. w is the matrix width, which is the number of fuzzy set for each input variable. d is thenumber of channels in the input matrix q [5]. In cases where the input window has only one class, the number of channels d is 1.

A commonly used CNNC architecture containing two conventional layers or more, dependent on the complexity of the input data, and one fully-connected layer, is shown in Fig 2. Each one of these convolutional layers has multiple feature filters for accurately optimising values during the training phase. Additionally, each convolutional layer is followed by a max-pooling layer that has a window of a specific size to ensure that the outputs from each conventional layer are smaller than the inputs. The fully-connected layer in this architecture is a traditional Multi-Layer Perceptron (MLP) that contains a softmax activation function for the output layer. By operating the softmax activation function in the output layer, the CNNC can be used to classify the input features into various classes based on relations learned during the training stage [13]. In a scenario where complex input data is expected, the CNNC architecture may be modified to contain more than two of the convolutional and max-pooling layers with different sizes of border filters to process such data [16]. Also, more than one fully-connected layer could be considered after the top convolutional layer. In the training process of the CNNC, the standard forward and backward propagation algorithms are employed to select the values of the CNNC parameters. The selected features are mapped by the convolutional operator as follows [13]:

$$V_t = \frac{1}{1 + exp(d_\eta + \sum_\iota \kappa_{\iota\eta} \vartheta x_\iota)} \tag{2}$$

where ϑ is the convolutional operator, $\kappa_{\iota\eta}$ is the convolutional filter for the ι-th input, V_t is the generated η-th output feature

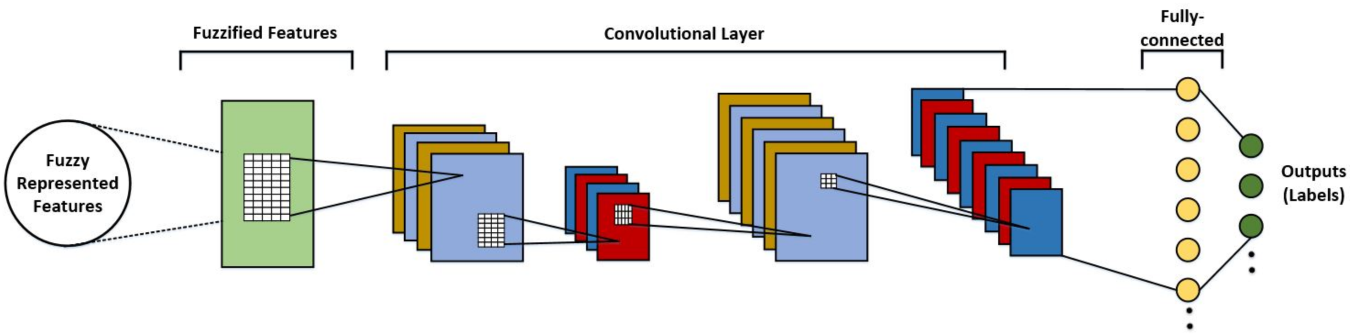

Fig. 2. The architecture of the proposed Convolutional Neural Network Classifier.

map, which is achieved by selecting the most effective features over the non-overlapping pooling regions from the input data x_ι, and d_η denotes the bias.

IV. Experimental Setup

In this section, an experiment for modelling and classifying a single user's activities is conducted using a dataset representing ADL.

A. Data Collection

The dataset in this experiment is gathered from the Smart Home Facilities within the Nottingham Trent University, representing the ADL of a single user. The low-level sensors used for collecting this dataset are listed in Table I. The collected set of the sensor readings is saved in the format of time-stamped binary data. In a data collection process using such sensors, it is essential to design a data collection system that should not interfere with the normal daily activities of the user. Sensors are installed around the home environment to detect object movement and save the captured information are transferred to a database through a communication hub.

As the dataset used was collected using low-level sensors to represent the ADL of a single user, it may contain a large volume of low-level binary data. The challenge here is to understand the actual human activities from these low-level sensory data, before they are classified into different activities.

TABLE I
List of the sensors used for collecting the dataset and measuring different conditions and activities (* denotes the unused sensors in this study).

Sensor	Purpose of use
Passive Infrared (PIR)	to detect movement
Door on/off switches	to detect when doors open and close
Mat pressure sensor	to measure bed occupancy
Electricity consumption plugs	to measure electricity usage
* Indoor temperature sensor	measuring ambient temperature
* Outdoor temperature sensor	measuring outdoor temperature
* humidity sensor	measuring ambient Humidity
* Light intensity sensor	measuring ambient light intensity

B. Sensor Data Representation and Visualisation

Before any data processing occurs, it is important to transform and visualise the collected sensor readings in an appropriate and useful format. This could be achieved using practical knowledge-based techniques such as an ontology [21], [22], or using a computational intelligence technique integrated with the collected sensory data. This process is used to visualise the collected sensor readings as occupancy data containing the user's daily activity patterns. In this experiment, a form of Finite State Machine (FSM) is used to represent and visualise the collected sensor readings as occupancy data to identify the user's activities [23].

Considering the gathered time sequence information $z(t)$ integrated with the recorded binary readings representing the occupancy in a specific area z at time t: this signal has two values of either 1 or 0, representing the presence and absence from that area; $z(t) \in [0, 1]$. To represent such data in an efficient format, a time-slice chunks approach [24] with a length of 60 seconds is applied to the binary sequence. Then, these time chunks are mapped into $last - fired$ sensor representation using FSM, considering the $Start$ and End time for each activity, as illustrated in Fig 3. The $last - fired$ sensor representation format is used to indicate which sensor is fired last. The sensor that changed its state last continues to give 1, and this changes to 0 when another sensor gives 1 during the specified time slice [24]. The generated occupancy data representing the user's daily activity pattern is shown in Fig 4, where a sample of three days' activities representing the ADL for a single user is presented as an occupancy data.

C. Convolutional Neural Network Classifier for Human Activity Modelling

Once a set of activity data is extracted from the occupancy data generated for each activity, they are fuzzified and represented as fuzzy sets, which are used as inputs for the proposed CNNC. This CNNC is applied to the fuzzy set in order to learn the relations between the input data (fuzzy sets) and their corresponding labels (activities), and ultimately for modelling the user's activities.

The fuzzy feature representation approach is applied to the activity data to represent the unique features in the user's daily

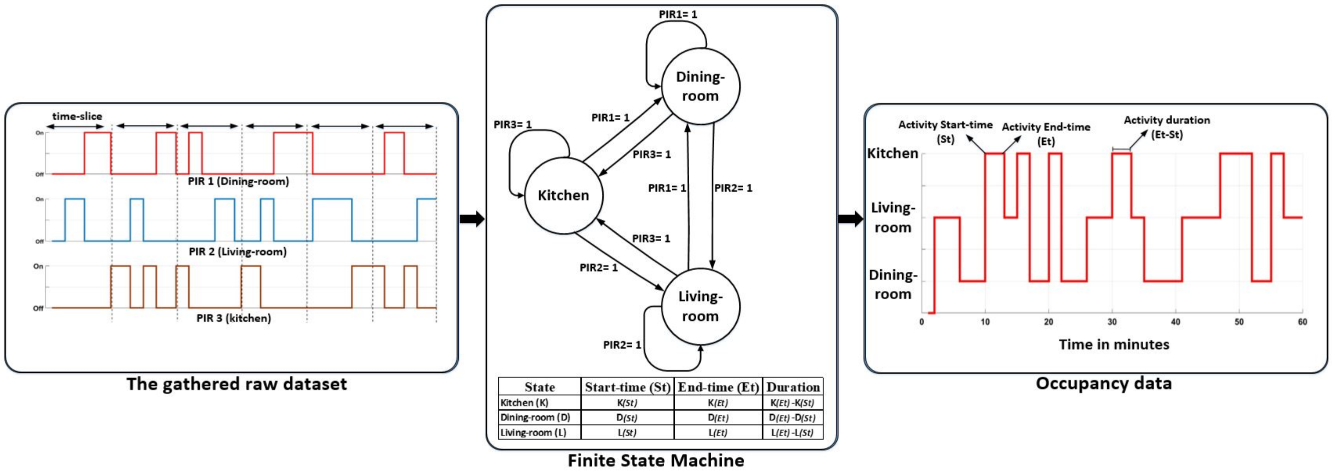

Fig. 3. An illustrative example of conversion of the time-slice windows of the gathered raw data into occupancy data using Finite State Machine.

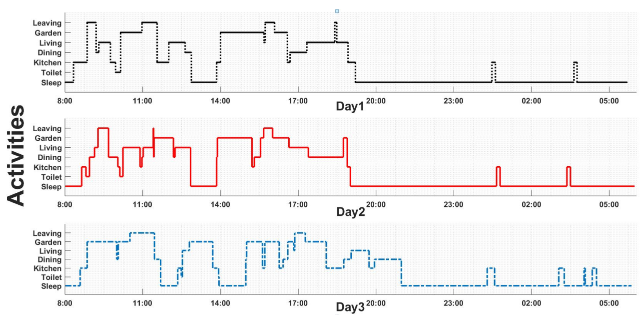

Fig. 4. A multi-level graph showing the daily activities of a single user for three days, represented as occupancy data.

activities. Three different unique features are extracted from each activity window (W) in the occupancy data. These three features are: *Start-time (St)*, which represents the time when the current activity starts; *End-time (Et)*, which identifies the ending time for the current activity; and *Duration (Du)*, which represents the duration undertaking for a specific activity and is calculated as $Du = Et - St$. Therefore, the extracted activity data vector for each activity window is expressed as:

$$U_x = \{St_x, Et_x, Du_x\} \tag{3}$$

where U is the activity data vector extracted from the activity x, and St, Et and Du are the start time, end time and duration variables for the activity x respectively. Each value in these three variables is represented with their relevant membership values for each fuzzy set, as illustrated in Fig 5. The generated set of fuzzified features for each input variable uj is expressed as:

$$X_{uj} = [\mu A^1_{uj}, \mu A^2_{uj}, \ldots, \mu A^M_{uj}] \tag{4}$$

In this contribution, as the data used is temporal data representing human activities for a single user, a sequential order is employed with the generated fuzzy sets to learn the relations in the data through the time steps using the proposed CNNC. The learned relations are then used for modelling and recognising the user's activities.

V. Results

The proposed method of using the fuzzified feature with a CNNC was implemented to model ADL for a single user based on low-level sensory data gathered from a smart home environment. A binary dataset containing seven different activities are used to test and evaluate the proposed method. Three full days' sensor readings are used for testing and evaluating the proposed method and the remaining four days' data is used for the training process. Also, each activity is evaluated separately and then the performance over the whole system is calculated. As humans behave in imbalanced and unpredictable ways during their daily life, datasets representing human activities are usually imbalanced, wherein some activities are more dominant than other activities. In this particular scenario, if the dominant activities are identified with a high degree of accuracy, the overall performance of the whole system will be high even if some activities are not well identified. Fig 6 illustrates the recall and precision for each activity, as well as the performance accuracy over the whole model.

The overall performance accuracy for the whole system based on the obtained results is 97.8%. The information given in the confusion matrix represented in Fig 6 is explained as follows:

- The rows and columns represent the output activities and target activities respectively. The activities are identified as $1, 2, ..., 7$ for Sleeping, Toilet, Meal-preparation, Dining, Relaxing, Garden and Leaving home respectively.
- The diagonal cells from the upper left to the lower right indicate the activities that are correctly recognised.
- The off-diagonal cells represent the incorrectly recognised activities.
- The right-most column shows the accuracy for each activity.

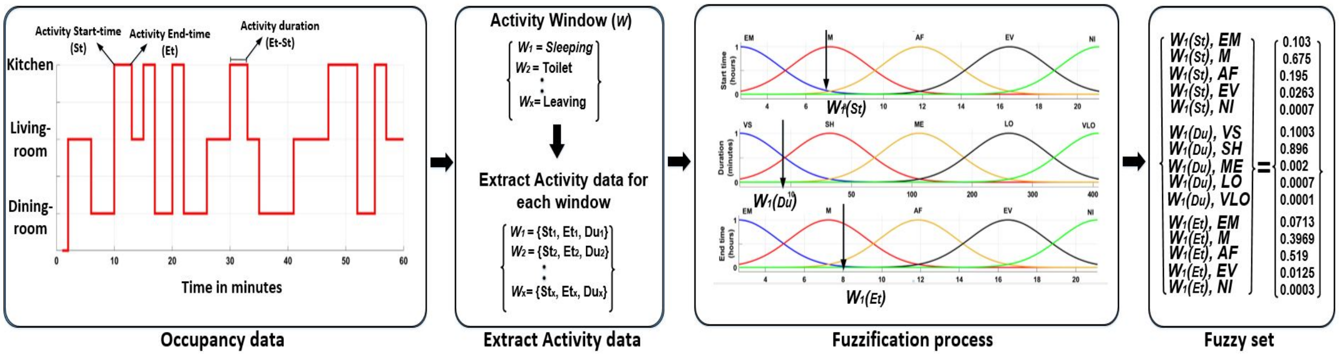

Fig. 5. An illustration of extracting activity data from the generated occupancy data and the fuzzification algorithm.

	1	2	3	4	5	6	7	
1	14 14.9%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
2	0 0.0%	26 27.7%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
3	0 0.0%	0 0.0%	12 12.8%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
4	0 0.0%	0 0.0%	0 0.0%	19 20.2%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
5	0 0.0%	0 0.0%	1 1.1%	0 0.0%	13 13.8%	1 1.1%	0 0.0%	86.7% 13.3%
6	0 0.0%	0 0.0%	0 0.0%	1 1.1%	0 0.0%	4 4.3%	0 0.0%	80.0% 20.0%
7	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	3 3.2%	100% 0.0%
	100% 0.0%	100% 0.0%	92.3% 7.7%	95.0% 5.0%	100% 0.0%	80.0% 20.0%	100% 0.0%	97.8% 2.2%

Fig. 6. Confusion matrix for ADL modelling and recognition results using fuzzy feature representation and the CNNC.

- The last row at the bottom shows the precision for each activity.
- The bottom right cell represents the accuracy over the whole model.

VI. Conclusion

This paper has introduced a sensor-based method for modelling and recognising human activities for a single user within a smart home environment. The gathered binary data was visualised first as occupancy data using FSM, and then activity data was extracted for each activity window. A fuzzy feature representation approach was applied to the extracted activity data, representing them as membership values and generating fuzzy sets. These sets were used along with the CNNC in modelling and recognising the user's activity. The proposed model was tested and evaluated using a "leave one day" approach, where one full day of sensor readings was used to test the proposed method and the remaining days were used for training the model. The fuzzy feature representation approach makes it possible to extract unique features from activity data representing ADL, and to capture underlying uncertainties in such data. For future work, different datasets will be explored using the proposed method in order to evaluate its performance robustness in human activity modelling and recognition. Furthermore, the model will be compared with state-of-the-art methods for human activity modelling and recognition.

The proposed CNNC model shows a more robust and reliable performance compared with the existing approaches once it is applied to a larger dataset (e.g., dataset representing ADL for a longer period). In particular, when this dataset contains some activities that could be happening at the same place (such as *Washing Dishes activity* and *Meal Preparation activity* in the kitchen). In real-life scenarios, it is hard to know which activity is the current activity based on the data collected from the PIR sensory devices. Therefore, by using a fuzzy feature representation approach with CNNC will be used to deal with such cases as it can detect the changes in the fuzzy feature patterns.

References

[1] A. N. Aicha, G. Englebienne, and B. Kröse, "Unsupervised visit detection in smart homes," *Pervasive and Mobile Computing*, vol. 34, pp. 157–167, 2017.

[2] G. Mohmed, A. Lotfi, and A. Pourabdollah, "Human activities recognition based on neuro-fuzzy finite state machine," *Technologies*, vol. 6, no. 4, p. 110, 2018.

[3] J. A. Iglesias, P. Angelov, A. Ledezma, and A. Sanchis, "Human activity recognition based on evolving fuzzy systems," *International journal of neural systems*, vol. 20, no. 05, pp. 355–364, 2010.

[4] T.-H. Tan, M. Gochoo, F.-R. Jean, S.-C. Huang, and S.-Y. Kuo, "Front-door event classification algorithm for elderly people living alone in smart house using wireless binary sensors," *IEEE Access*, 2017.

[5] M. Gochoo, T.-H. Tan, S.-H. Liu, F.-R. Jean, F. S. Alnajjar, and S.-C. Huang, "Unobtrusive activity recognition of elderly people living alone using anonymous binary sensors and dcnn," *IEEE journal of biomedical and health informatics*, vol. 23, no. 2, pp. 693–702, 2019.

[6] Y. Zhao, R. Yang, G. Chevalier, X. Xu, and Z. Zhang, "Deep residual bidir-lstm for human activity recognition using wearable sensors," *Mathematical Problems in Engineering*, vol. 2018, no. 7316954, p. 13, 2018.

[7] D. A. Adama, A. Lotfi, C. Langensiepen, K. Lee, and P. Trindade, "Human activity learning for assistive robotics using a classifier ensemble," *Soft Computing*, vol. 22, no. 21, pp. 7027–7039, 2018.

[8] A. Jordao, L. A. B. Torres, and W. R. Schwartz, "Novel approaches to human activity recognition based on accelerometer data," *Signal, Image and Video Processing*, pp. 1–8, 2018.

[9] J. Medina-Quero, S. Zhang, C. Nugent, and M. Espinilla, "Ensemble classifier of long short-term memory with fuzzy temporal windows on binary sensors for activity recognition," *Expert Systems with Applications*, vol. 114, pp. 441–453, 2018.

[10] M. Jenckel, S. S. Parkala, S. S. Bukhari, and A. Dengel, "Impact of training lstm-rnn with fuzzy ground truth," in *ICPRAM*. IEEE, 2018, pp. 388–393.

[11] O. Steven Eyobu and D. Han, "Feature representation and data augmentation for human activity classification based on wearable imu sensor data using a deep lstm neural network," *Sensors*, vol. 18, no. 9, Aug 2018.

[12] G. Acampora, D. J. Cook, P. Rashidi, and A. V. Vasilakos, "A survey on ambient intelligence in healthcare," *Proceedings of the IEEE*, vol. 101, no. 12, pp. 2470–2494, 2013.

[13] D. Arifoglu and A. Bouchachia, "Detection of abnormal behaviour for dementia sufferers using convolutional neural networks," *Artificial intelligence in medicine*, vol. 94, pp. 88–95, 2019.

[14] Z. Wang, M. Jiang, Y. Hu, and H. Li, "An incremental learning method based on probabilistic neural networks and adjustable fuzzy clustering for human activity recognition by using wearable sensors," *IEEE Transactions on Information Technology in Biomedicine*, vol. 16, no. 4, pp. 691–699, 2012.

[15] M. Gochoo, S.-H. Liu, D. Bayanduuren, T.-H. Tan, V. Velusamy, and T.-Y. Liu, "Deep convolutional neural network classifier for travel patterns using binary sensors," in *2017 IEEE 8th International Conference on Awareness Science and Technology (iCAST)*. IEEE, 2017, pp. 132–137.

[16] M. Gochoo, T.-H. Tan, F.-R. Jean, S.-C. Huang, and S.-Y. Kuo, "Device-free non-invasive front-door event classification algorithm for forget event detection using binary sensors in the smart house," in *IEEE International Conference on Systems, Man, and Cybernetics*, 2017, pp. 405–409.

[17] G. Mohmed, A. Lotfi, , and A. Pourabdollah, "Long short-term memory fuzzy finite state machine for human activity modelling," in *PETRA '19*, 2019.

[18] Y. Deng, Z. Ren, Y. Kong, F. Bao, and Q. Dai, "A hierarchical fused fuzzy deep neural network for data classification," *IEEE Transactions on Fuzzy Systems*, vol. 25, no. 4, pp. 1006–1012, 2017.

[19] I. N. Yulita, M. I. Fanany, and A. M. Arymurthy, "Fuzzy clustering and bidirectional long short-term memory for sleep stages classification," in *International Conference on Soft Computing, Intelligent System and Information Technology (ICSIIT)*, 2017, pp. 11–16.

[20] G. Acampora, P. Foggia, A. Saggese, and M. Vento, "A hierarchical neuro-fuzzy architecture for human behavior analysis," *Information Sciences*, vol. 310, pp. 130–148, 2015.

[21] K. Wongpatikaseree, M. Ikeda, M. Buranarach, T. Supnithi, A. O. Lim, and Y. Tan, "Activity recognition using context-aware infrastructure ontology in smart home domain," in *2012 Seventh International Conference on Knowledge, Information and Creativity Support Systems*. IEEE, 2012, pp. 50–57.

[22] S. Ali, S. Khusro, I. Ullah, A. Khan, and I. Khan, "Smartontosensor: ontology for semantic interpretation of smartphone sensors data for context-aware applications," *Journal of Sensors*, vol. 2017, 2017.

[23] C. Langensiepen, A. Lotfi, and S. Puteh, "Activities recognition and worker profiling in the intelligent office environment using a fuzzy finite state machine," in *IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, 2014, pp. 873–880.

[24] T. L. van Kasteren, G. Englebienne, and B. J. Kröse, "Human activity recognition from wireless sensor network data: Benchmark and software," in *Activity recognition in pervasive intelligent environments*. Springer, 2011, pp. 165–186.