



# ApplianceNet: a neural network based framework to recognize daily life activities and behavior in smart home using smart plugs

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Received: 9 July 2021 / Accepted: 24 February 2022 / Published online: 21 March 2022  
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## Abstract

A smart plug can transform the typical electrical appliance into a smart multi-functional device, which can communicate over the Internet. It has the ability to report the energy consumption pattern of the attached appliance which offer the further analysis. Inside the home, smart plugs can be utilized to recognize daily life activities and behavior. These are the key elements to provide human-centered applications including healthcare services, power consumption footprints, and household appliance identification. In this research, we propose a novel framework *ApplianceNet* that is based on energy consumption patterns of home appliances attached to smart plugs. Our framework can process the collected univariate time-series data intelligently and classifies them using a multi-layer, feed-forward neural network. The performance of this approach is evaluated on publicly available real homes collected dataset. The experimental results have shown the *ApplianceNet* as an effective and practical solution for recognizing daily life activities and behavior. We measure the performance in terms of precision, recall, and F1-score, and the obtained score is 87%, 88%, 88%, respectively, which is 11% higher than the existing method in terms of F1-score. Furthermore, our scheme is simple and easy to adopt in the existing home infrastructure.

**Keywords** Daily activities · Home appliances · Healthcare applications · Intelligent data processing · Time-series analysis

## 1 Introduction

Electricity is an integral part of our communities and its demand is increasing globally with the electrification of the automobile, growing digital connected devices, and Heating, Ventilation, and Air Conditioning (HVAC) of the building. There is a clear need for a detailed understanding of the usage of electricity to efficiently manage the smart

grids and do spatial load forecasting. From a consumer perspective, electricity usage information has useful applications [1, 2]. These include (i) to reduce the utility bills and contribute at an individual level to reduce global warming [3] (ii) monitoring of daily living activities and behavior [4] (iii) non-intrusive monitoring of the aging population to provide remote healthcare services [5].

The activities of daily living and behavior can be recognized intrusively using video camera [6] and embedded sensors over the home appliances [7, 8]. However, several problems are associated with these approaches; for instance, video cameras are not practical due to privacy reasons. Similarly, home appliances are not designed to share their interaction patterns and usage. To make them a smart appliance, sensors are placed over the appliances, which put an extra layer of tiny sensors that may complicate interaction with them. An alternative solution is Non-Intrusive Appliance Load Monitoring (NIALM) that is based on a smart meter to disaggregate the load to recognize the individual appliances [9]. However, energy disaggregation is an extremely challenging problem [5] when

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various appliances are working simultaneously. Similarly, such a solution has adoption limitations because instalment of the smart meter is related to service providers not the residents of the house.

In this paper, we consider a unique perspective to recognize the daily living activities by considering a smart plug as an Individual Appliance Monitor (IAM) to collect the energy consumption data of home appliances [10]. It is considered as Intrusive Load Monitoring (ILM) because smart plug is attached to each device [11]. The ILM is the preferred approach for the situations when the consumer is interested to monitor daily life activities without adding an extra layer of sensors inside the home or involvement of smart meter. The trivial solution for recognizing the electrical appliance is to statically map the smart plugs for specific appliances. The potential problem with this approach can reduce the applicability of provided services. For instance, a smart plug is specified for the oven and if households use it for TV or any other device then the service model will lead to false-positive results. The oven smart plug used for TV can point to some emergency at home in a scenario of 3 hours usage. It can consider stove is ON for 3 hours while in home setting smart plug is attached with TV. The goal of our research is to make the smart plug intelligent which can tell which device is connected to it. Consequently, it will allow the consumer to use the smart plug freely with any appliance. Furthermore, it provides the freedom to residents by specifying which devices are allowed to be monitored and accessed by smart hand-held devices to control its states. Intelligent data processing of smart plugs' may helps to avoid unseen problems in daily activities as well as emergency situations at home. For example, excessive watching of the television leads to sedentary activity, which may not suitable for the resident health conditions. Similarly, keeping the microwave 'ON' after finishing the cooking activity may lead to an emergency.

In our research, IAM-based solution is considered as an effective and seamless way to monitor the activities of daily living and behavior. With the help of smart plugs, we monitor basic household appliances, such as toaster, microwave, fridge, washing machine, etc. To distinguish the type of meal (i.e., breakfast, lunch, or dinner), the time information is available in collected data streams. The data stream of smart plugs contains two columns; one is a timestamp and the second is electric power consumption in watts. The task of recognizing home appliances is very challenging because most energy consumption patterns of appliances overlap with other appliances. It makes an unnoticeable difference in readings. The proposed ApplianceNet framework (see block diagram in Fig. 1) processes time-series data by extracting features to a representable form and recognizes non-linearly separable home

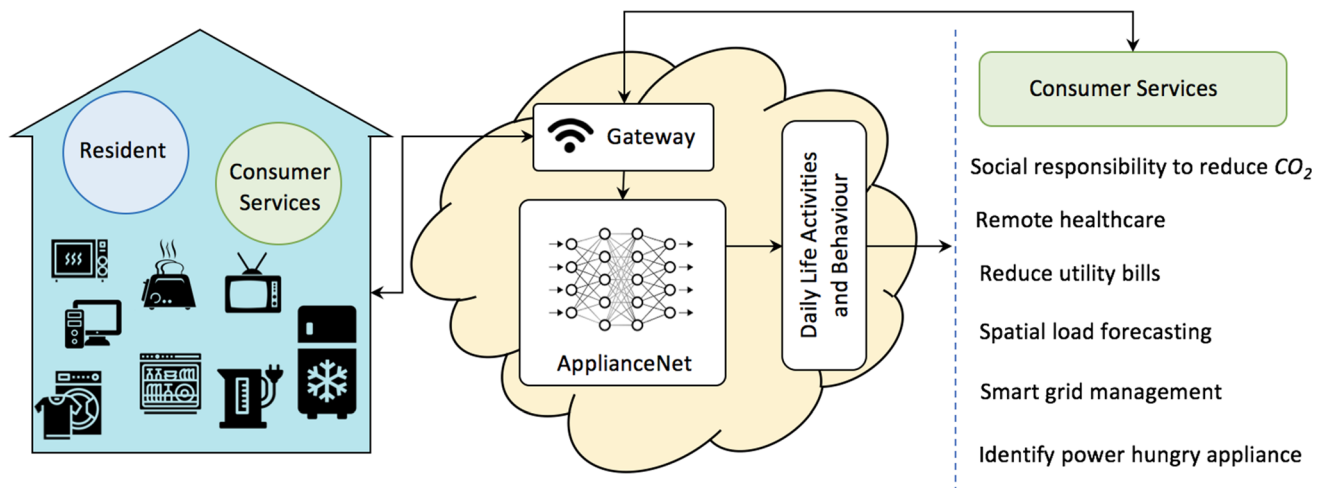
appliances by a feed-forward neural network. Our contributions in this research are as follows.

- The proposed model is based on a data-driven approach that does not require domain expert knowledge.
- The proposed solution is integrated easily with existing home infrastructure without disturbing residents' privacy and additional sensors that may affect home aesthetics or complicate the resident interaction.
- The home appliances usage differ from one another in terms of duration. For instance, the duration of watching television is longer than the toaster or dishwasher. In such scenarios, small usage of home appliances produces few data samples. Consequently, it degrades the performance of the machine learning model. This problem is known as an imbalance dataset. We solve this issue by data augmentation and validate performance empirically.
- The usage pattern of home appliances can provide information on behavioral changes, which can be captured by our framework and may assist the family to understand the occupant's behavior.

The rest of the research paper is organized as follows. We briefly describe related research work and their limitations in Sect. 2. In Sect. 3, we introduce ApplianceNet and its implementation for recognizing home appliances. In Sect. 4, experimental setting and hyper-parameter details. In Sect. 5, we present the results and comparison with the state-of-the-art techniques. Finally, we conclude our paper in Sect. 6.

## 2 Related work

Smart homes are designed to monitor vital signs, daily life activities, and possibly avoid emergencies [12, 13]. In this section, we briefly explain different kinds of sensor technologies and developed models used for activity recognition in the home environment. The advancement of neural network-based approaches has made significant improvements in recognition tasks [14]. Mehr et al. [15] proposed a Convolutional Neural Network (CNN) to recognize human action using multiple cameras inside the home environment. The experiments were performed on a publicly available dataset, collected using three static cameras to recognize the ambulatory activities including walking, table cleaning, drinking, etc. They achieved 82% of accuracy for twelve actions available in the dataset. Chen et al. [16] also proposed a novel CNN architecture to recognize the fridge, dishwasher, microwave, washing machine, and kettle. Their model confirms the applicability of neural network architecture for non intrusive load monitoring. Similarly, Junfeng et al. [17] proposed temporal and



**Fig. 1** Block diagram of the proposed ApplianceNet framework

spectral features learning with two-stream CNN. They fused both temporal and spectral feature to recognize the appliances. They obtained more than 90% accurate results based on the fusion of temporal and spectral features.

Another possible way to recognize daily life activities is embedded sensors for household objects. Karvigh et al. [7] proposed a framework for real-time activity recognition for energy efficiency in building. Their approach is capable to detect action, activity recognition, and waste estimation. Particularly, for activity recognition tap sensors we used over the objects to sense the ON/OFF states. Their activity recognition algorithm is based on ontology and data-driven solutions. A number of sophisticated algorithms were developed by the research community to monitor home activities [8, 18]. These algorithms are based on data-driven to knowledge-driven approaches. Most of the developed models were mature enough to achieve more than 90% accuracy and successfully deployed in different application scenarios [19].

Smart plugs were utilized to monitor the energy usage in home environments and the developed techniques found in [20]. Gajowniczek et al. [3] considered the appliances' status either ON/OFF to detect usage patterns using hierarchical and c-means clustering. The goal of their study was to contribute in energy consumption awareness and energy-saving recommendations. Yan et al. [20] used smart meter data to extract the characteristics of occupant behavior and energy consumption of home appliances. Seven home appliances, such as refrigerator, electric cooker, air conditioner, television, laptop computer, washing machine, and water dispenser were analyzed in Beijing, China. They developed a Bayes classification based approach to recognize the appliances.

Yassine et al. [9] introduced a mining algorithm to recognize the daily life activities using smart meter data for

health care systems. They performed experiments on a large-scale publicly available dataset collected for five houses in southern England. They learned the activities patterns from appliance usage inside the home by mapping back to energy consumption data from the smart meter. This technology adoption in a setting where legacy meters are used is a challenge to keep the track of energy usage. Similarly, Delvin et al. [5] classify the activities of daily living using smart meter data. Their approach is based on neural networks to identify home appliances. They consider seven common home appliances and achieved acceptable (i.e., 77% F1-score) results.

France et al. [21] developed an intrusive load monitoring approach over the layer architecture and Internet of things (IoT) for load monitoring and activity recognition in smart homes. They consider 5 activities (i.e., dishwasher, hairdryer, iron, oven, and washing machine). The approach is based on hand-crafted features and neural networks as a classifier. They reported high accuracy (i.e., 91% F1-score) for considered activities. Similarly, Paganelli et al. [22] also propose a neural network-based approach for appliance recognition from smart plugs. The designed approach is developed for home energy management systems in Italy. Their approach is also based on hand-crafted features. In future work, they also emphasized the need for complex event processing techniques.

The above-discussed approaches did not consider the appliances level usage patterns as well as automatic feature extraction for daily life activities which can be monitored through smart plugs. Our framework is based on appliance level monitoring and automatic feature extraction scheme to recognize the daily life activities and behavior inside the home environment depending on the intended appliance's usage.

### 3 Proposed model

In our proposed model, we consider a set of smart plugs denoted by  $\mathcal{P}$  attached with each home appliance, where each smart plug  $p \in \mathcal{P}$  sends univariate time-series measurement  $v_p$  at each time instant  $t$ . Note that this measurement is continuously repeated after an interval of length  $\Delta t$ . Then, the time series sample for a smart plug  $p$  is represented as a sequence of length  $N$  as follows:

$$\mathcal{V}_p = (v_p(t_1), v_p(t_2), \dots, v_p(t_N))^T, \forall p \in \mathcal{P}, \quad (1)$$

where  $t_{i+1} = t_i + \Delta t$  and  $\mathcal{V}_p = (\cdot)^T$  represents the transpose of  $p^{th}$  smart plug sample. In this work, it is assumed that each smart plug  $p$  is identically independent with other, then, we can analyze for a single smart plug  $p$  and apply the analysis for the whole system. Thus, we simplify by stating  $v_p = v$  and sequence length  $t_1 = t$ , where  $t \in \{1, 2, \dots, N\}$ .

$$\mathcal{V} = \{v_t\}_{t=1}^N \quad (2)$$

The design of our proposed framework is based on the standard layered architecture used in a smart home. The inspired architecture of *ApplianceNet* alongside the standard architecture of a smart home is illustrated in Fig. 2.

The architecture consists of four layers and these are described in the following subsections.

#### 3.1 Physical layer

Home appliances are plugged into smart plugs for monitoring daily energy usage. Smart plugs fits between the socket and the home appliance. It seamlessly collects time-series data about their energy consumption and track how much attached appliance consumes electricity. For instance, a microwave oven or any other home appliance can be monitored for energy usage connected to the smart plug. Figure 3 presents a smart plug “current cost” as an Individual Appliance Monitor (IAM) to accurately measure power consumption in watts.

The smart plug has the characteristics to connect over the home Internet and send energy consumption reading to

**Fig. 3** Current cost smart plug [23]



the server database for storage and further processing. This server can reside inside the home or a cloud service platform. The cloud computing could provide a cost-effective solution as well as zero-level management at the user end.

#### 3.2 Communication layer

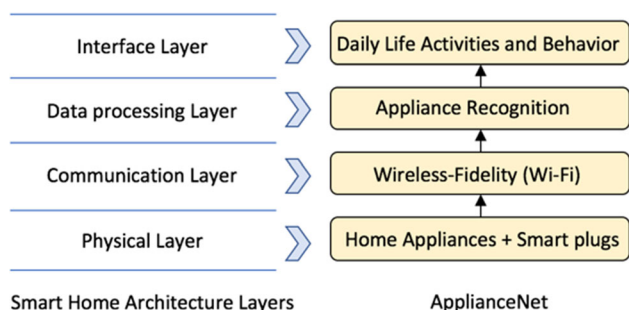
The communication layer in smart home connects the physical layer object to low-powered wireless networks or ZigBee. The ZigBee provides connectivity using radio signals for seamless communication in home settings as well as it does not interfere with Wi-Fi, Bluetooth, or phone networks. Smart plugs are connected over the Wi-Fi access point, while few smart plugs have ZigBee to communicate with the gateway. It establishes communication to send the energy consumption data stream continuously to the server for storage and further processing. The secure communication is essential for home appliances [24]. The security and network protocol is not the part of this research. We assume that it is available from smart plug providers for secure communication over the Internet.

#### 3.3 Data processing layer

This layer is a central part of our proposed framework. It is responsible to process the collected data stream from each appliance. It consists of three major components, (1) *Data preprocessing*, (2) *Feature extraction and selection*, and (3) *Classifier*. The detailed description and working of these sub-components are as follows.

##### 3.3.1 Data preprocessing

The energy consumption data is sent to the server from smart plugs periodically. In the case of the current cost smart plug, it sends data after every 6 ~ 8 seconds. Figure 4 presents one-week data stream for ‘Microwave’, ‘Toaster’, and ‘Kettle’.



**Fig. 2** The layered architecture of ApplianceNet

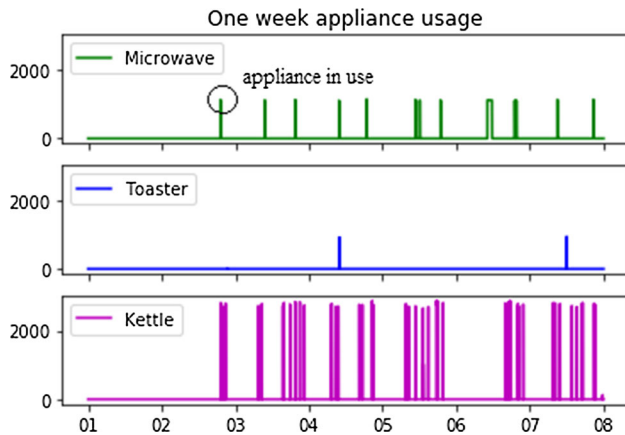


Fig. 4 One week data stream of three home appliances

In Fig. 4, it is clear that home appliances' working patterns vary from one appliance to another appliance. The x-axis shows the days of the week while the y-axis presents the energy consumption. For example, in the case of a toaster, its usage is during 4<sup>th</sup> and 7<sup>th</sup> day of the week. The appliance data becomes more complicated when the number of individual appliance monitor increase in a home environment. In order to recognize the device at a unit time, the collected data requires further processing in the form of feature extraction.

### 3.3.2 Feature extraction and selection

The time-series measurement  $v_t$  of smart plug  $p$  contains just one attribute of energy consumption. The temporal features are extracted over the window of  $t$  minutes, periodically. We mapped time series data  $v_t$  to a well-defined feature space with a dimension of  $M$  and the feature vector is defined as:

$$\mathbf{v}_t = (v_{t,1}, v_{t,2}, \dots, v_{t,M}) \quad (3)$$

The feature extraction is a process to transform the data into a meaningful representation, where the machine learning model can distinguish between different home appliances. These features can be obtained by handcrafted

methods with the support of domain knowledge or automatic feature extraction over the given time-series. The automatic feature extraction methods relax the domain expert constrain to extract the features. In the case of automatically extracted features, the number of obtained features is huge as compared to handcrafted features, which is further refined by the feature selection mechanism. The required  $\mathbf{v}_t$  can be extracted by applying time series characterization methods  $f_j : v_t \rightarrow v_{t,j}$ .

Then, we can obtained the required feature vector  $\mathbf{v}_t$ :

$$\mathbf{v}_t = (f_1(v_t), f_2(v_t), \dots, f_M(v_t)), \forall t \in N \quad (4)$$

We used TSFRESH (Time Series FeatuRe Extraction on basis of Scalable Hypothesis tests) library [25] to extract a large number of time series characteristics (i.e., 63 characteristics resulting in  $M = 794$  features) as features. The extracted temporal features describe the basic and complex characteristics of given time series, which are listed in Table 1.

Table 1 represent the subset of extracted features which are used in feature selection to reduce the noise, redundancies or irrelevant information. The feature selection is also helpful in reducing the computational cost of the proposed scheme. The feature selection is based on automatically configuration of feature significance hypothesis tests [26]. A feature vector  $\mathbf{V}_\phi$  is defined as meaningful features for the classification of home appliances. A hypothesis test is applied to extract the relevant features:

$$\mathbf{v}_t \sim \mathbf{v}_\phi \quad (5)$$

In a hypothesis test, each feature vector  $\mathbf{v}_t$  is evaluated individually and independently with respect to its significance for the classification of home appliances. The result of these tests is a vector of p-values, computing the implications of each feature for predicting the home appliance. In order to decide which features to keep, this vector is evaluated on basis of the Benjamini-Yekutieli (BY) procedure [27]. The BY is a statistical procedure that facilitates to avoid false-positive rate. The procedure pseudo code is presented in the following algorithm 1



**Algorithm 1** Feature selection-based on BY procedure**Require:** feature vector  $\vec{v}_t$ 

- 1: Calculate and ordered  $p$ -values ( $p_1, \dots, p_\nu$ ) for  $\vec{v}_t$
- 2: Multiply each  $p_i$  with its adjustment factor  $\alpha_i, i = 1, 2, 3, \dots, m$ , given by :

$$\alpha_i = \frac{lm}{i}, \text{ where } l = \sum_{k=1}^m \frac{1}{k}$$

- 3: If step 3 violated the existing order, then:

$$\tilde{p}_{(i)} = \min_{j=1, \dots, m} \alpha_j P_j$$

- 4: Set  $\tilde{p}_{(i)} = \min(\tilde{p}_{(i)}, 1)$  for all  $i$ .

- 5: **return**  $\vec{V}_\phi$  based on  $\tilde{p}_{(i)}$

**Table 1** A subset of extracted primary features

Characteristics	Measures
Energy	Absolute energy, energy ratio, FFT coefficients
Statistical	Auto-correlation, entropy, mean absolute change
Linear trend intercept	Standard deviation, max, min, mean and variance
Wavelet	Continuous wavelet coefficients and peaks
Spectral	Spectral density estimation, signal symmetry
Miscellaneous	Number of crossings, number of peaks

We extract the selected feature vector  $\mathbf{v}_\phi$  for each smart plug  $p$  and supplied it to the classifier for recognizing home appliances.

**3.3.3 Classifier**

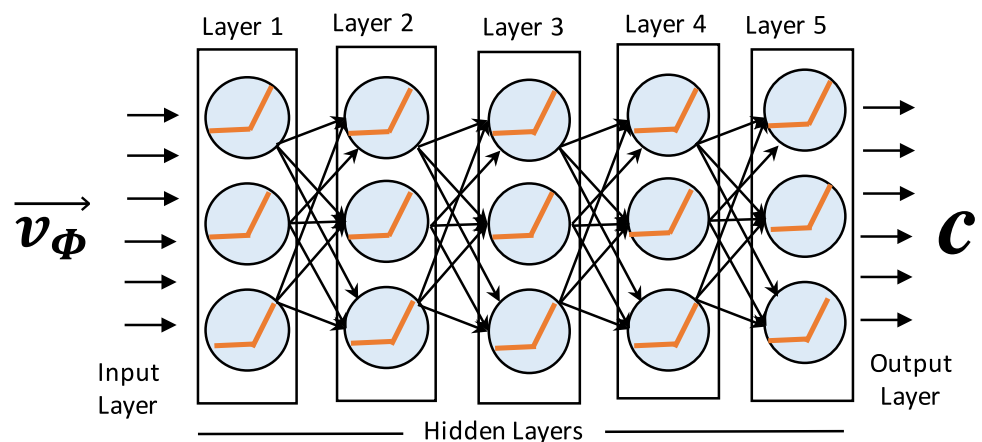
A non-linear classifier is designed to recognize home appliances. The classification network is based on a multi-layered feed-forward neural network using a back-propagation learning mechanism. The designed and implemented architecture is presented in Fig. 5.

In Fig. 5, architecture contains input and output layer with five hidden layers. The feature vector  $\mathbf{v}_\phi$  is connected

to every neuron in first layer  $l_i$  and every subsequent layer is fully connected to  $l_{i+1}$  with  $i \in [1, L]$ . A weighted sum is calculated over each neuron and non-linearity is applied to squash the strengths.

$$y = \phi \left[ f \left( \sum_{k=0}^m w^k f^k + b \right) \right] \quad (6)$$

where  $\phi$  is the activation function,  $b$  is the bias and  $m$  is the number of neurons in each  $l_i$  and considered as hyper-parameters. The model is trained to minimize the cross-entropy loss (i.e., presented in “(7)”) over the extracted feature vectors to recognize home appliances.

**Fig. 5** The architectural designed of feed-forward neural network

$$L(\Theta) = - \sum_{i=1}^c y_i \log(\hat{y}_i) \quad (7)$$

where  $c$  is the class labels,  $y_i$  is the original label, and  $\hat{y}$  is the predicted label for home appliances. The details on the training procedure and optimal parameters are discussed in Sect. 4.

### 3.4 Interface layer

At this layer of smart home, the interface connects the residents, family members, and caregivers in case of healthcare consumer service. Based on the service, it can facilitate the user to reduce the utility bills, identify power-hungry devices, power consumption patterns, and awareness to reduce the  $CO_2$  as a social responsibility for contributing towards the reduction of global warming. In the case of caregivers, it should integrate with the individual physician to check the performed activities, frequency, or skipping of daily activities. In the case of residents to send reminders for the completion of tasks in case of dementia. In case of cardiovascular complications, alerts can be generated to perform some tasks and discontinue sedentary activities like excessive watching of television. Furthermore, information about the duration of the activities can be determined and shared with personal doctors via secure communication.

## 4 Experimental setup and details

This section explains the dataset, experimental setup, and hyper-parameter setting with neural network convergence.

### 4.1 Dataset

In our experiments, we used a publicly available REFIT dataset [28]. It contains information on the individual appliance usage by utilizing the smart plug “current cost”. By default, all of the installed load monitoring devices had the voltage pre-set to 240 V, suitable for the UK where the main voltage is rated at 230 V +10 to −6% [28]. The dataset was collected continuously from 20 houses over a

**Table 3** The number of common home appliances across the five houses

No.	Appliances
1.	Microwave
2.	Kettle
3.	Toaster
4.	Fridge
5.	Dishwasher
6.	Washing machine
7.	Television
8.	Desktop PC

period of 2 years. The dataset consists of whole house aggregate loads logged by smart meter as well as nine appliances inside the house which are connected with the “current cost” smart plug. We processed only one-month data from five houses to get a sufficient footprint of attached home appliances with these smart plugs. The one-month appliance data signature is sufficient to train the ApplianceNet and learn the pattern to recognize the appliance. The detail about the houses description is presented in Table 2.

In Table 2, the house numbers are kept the same as appeared in the dataset for compatibility reasons. The house 2 construction year is missing in the dataset while the number of occupants, appliances, house type, and size information is provided. The selection of the houses depends on the number of maximum common electrical appliances that were attached with smart plugs to report the energy values. The considered common home appliances are listed in Table 3. In Table 3, all the home appliances are essential for daily life activities including meal preparation (breakfast, lunch, dinner), sedentary behavior while watching television, and doing laundry which is considered as an ambulatory activity. The relationship between the recognized home appliances and daily life activities is presented in Fig. 6.

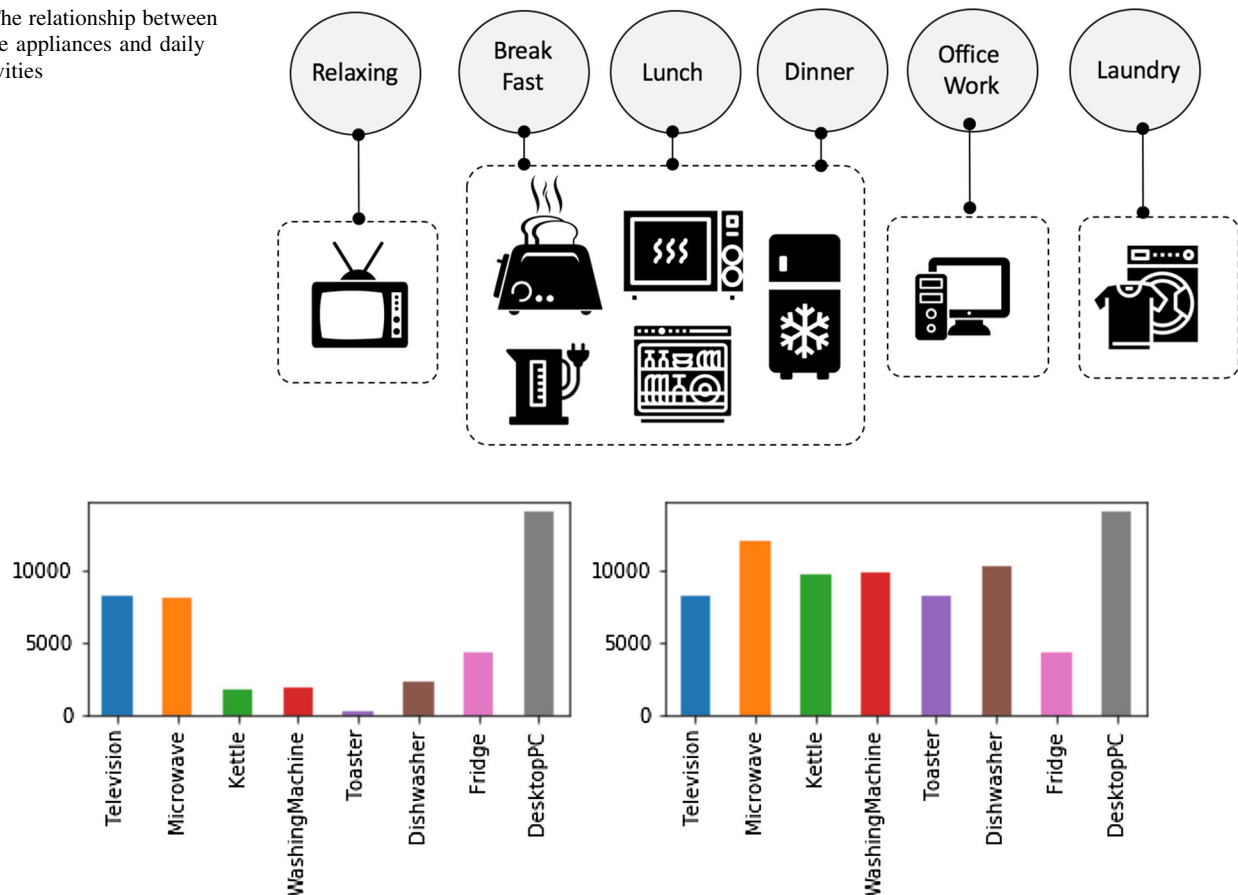
### 4.2 Data augmentation

The classifier requires a sufficient amount of data to train the feed-forward neural network. In the case of appliance

**Table 2** Detailed description of the houses including occupancy, construction year, appliances owned, type and size in terms of bedrooms

House	Occupancy	Construction year	Appliances	Type	Size
2	4	—	15	Semi-detached	3 bed
3	2	1988	27	Detached	3 bed
4	2	1850–1899	33	Detached	4 bed
5	4	1878	44	Mid-terrace	4 bed
6	2	2005	49	Detached	4 bed

**Fig. 6** The relationship between the home appliances and daily life activities



**Fig. 7** The number of training samples before and after data augmentation

recognition, some appliance generates an insufficient amount of data due to less resident interaction or daily usage. In this case, a data augmentation strategy is applied to up-sample the minor classes using scikit learn library [29]. The number of synthetic examples is added to the minor classes with the objective to increase the recognition of electrical appliances during the training phase of the model. It is based on bootstrapping procedure to re-sample the minor classes. The bootstrap is a statistical method to perform data augmentation. It resamples the data instances to create synthetic instances with similar properties to the original instances. This property is quantified by mean and histogram. Furthermore, it calculates the standard error, confidence interval, and performs hypothesis testing to include the generated sample into the minor classes. Consequently, it increases the performance of the proposed model. Some of the appliance usages are for short time like 'Toaster' while 'Desktop PC' and 'Television' usage is high as compared to other appliances. Figure 7 (left) presents the number of instances for each appliance usage and Fig. 7 (right) presents the data samples after augmentation.

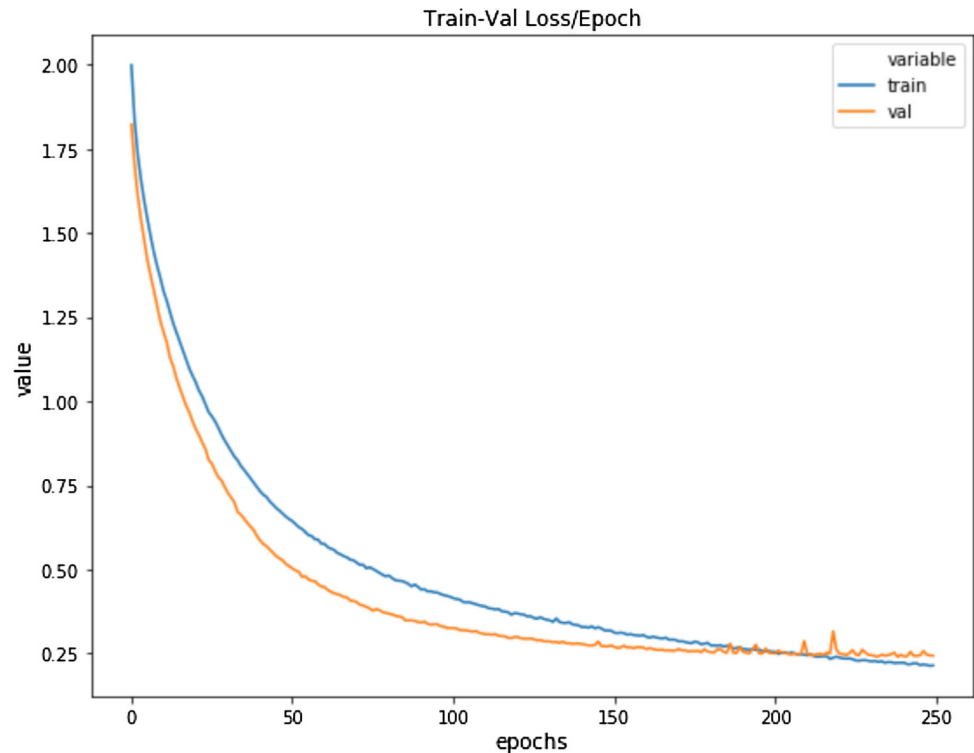
In Fig. 7, it is visible that appliance 'Toaster', 'Kettle' and 'Dishwasher', and 'Washing Machine' are the minor activities which are dominated by 'Desktop PC', 'Microwave' and 'Television' activity during the learning phase of the model. By augmentation, we up-sampled the minor classes with synthetic samples to make the class balance as shown in Fig. 7 (right). It contributes to improve the performance of the model.

### 4.3 Training parameters

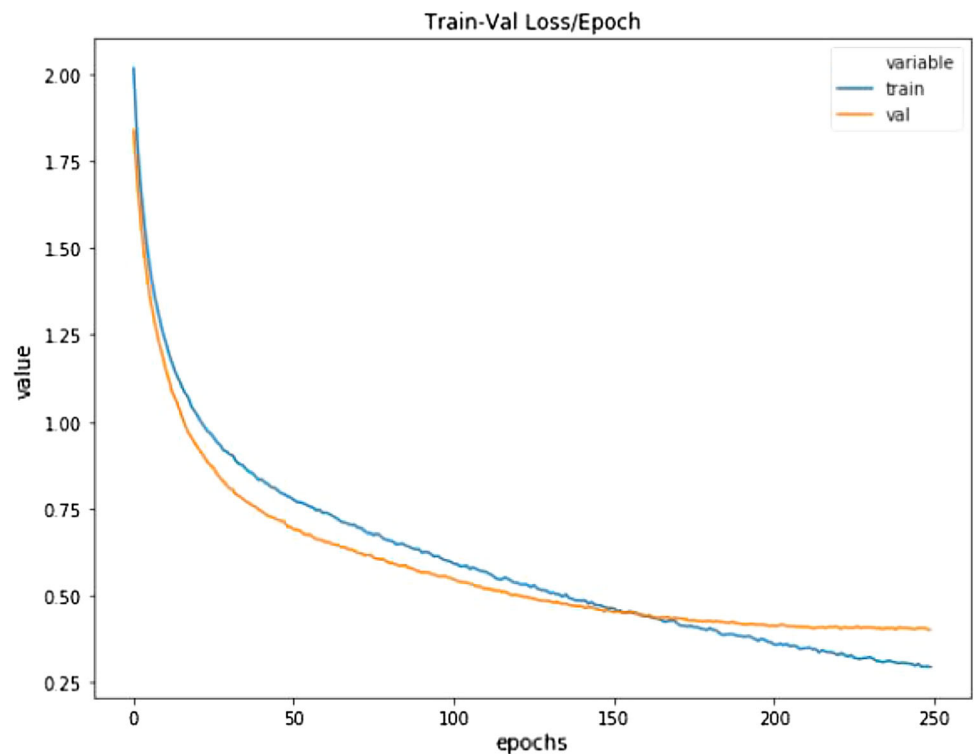
Our proposed model has nine nobs (i.e., hyperparameters) to tune for obtaining the best performance. The number of hidden layers plays an important role to understand the feature spaces of the provided data, while a number of neurons in each layer accommodate the information in terms of weights. One of the best practices is to reduce the number of neurons in each layer when moving from input to output. The loss function for ApplianceNet is cross-entropy which aligns well in the case of a classification problem. The role of the loss function is to guide the network to optimize the weights. We also included the batch processing which stochastic gradient descent (SGD)



**Fig. 8** The network convergence over the training and validation set (with data augmentation)



**Fig. 9** The network convergence over the training and validation set (without data augmentation)



optimizer to update the weights of connection between the neurons after each batch. Consequently, it helps reduce the memory utilization because few examples were used in the batch to update the weights. All the training

hyperparameters setting and experimental arrangements can be analyzed by plotting the network convergence graph. This graph explains how the learning of the network is going on with respect to reduce the loss. The curve

**Table 4** The optimal hyper-parameter to train the classifier

Parameters	Values/settings
Hidden layers	5
Each layer neurons	[512, 256, 128, 64, 32]
Loss function	Cross-entropy
Batch size	100
Batch normalization	All 5 layers
Optimizer	Stochastic Gradient Descent (SGD)
Learning rate	0.001
Epochs	250

smoothness also explains the right learning rate and batch setting as proceeded by the number of epochs. The following convergence graphs with data augmentation and without data augmentation is presented in Figs. 8 and 9. These graphs explain that the choice of our hyperparameters is correct.

In Fig. 8, after two hundred epochs, ApplianceNet converges and loss reached to an optimal position. The network is saved to recognize the unknown data stream during the test time. Fig. 9 presents the convergence of the model around one hundred and sixty epochs without data augmentation. After this point, we stop the training to cease the over-fitting. The model parameters are fined tuned until we obtain the above convergence graph. The optimal parameters are presented in Table 4. These parameters are optimal parameter which is selected using a trial and error method.

#### 4.4 Performance measures

We have evaluated the proposed model performance using standard metrics, such as precision, recall, and F1-score and accuracy. They are calculated using values of the confusion matrix and computed as:

**Table 5** The obtained results of ApplianceNet

Appliance	Precision ( <i>p</i> )	Recall ( <i>r</i> )	F1-score	Accuracy
Television	0.84	0.85	0.85	0.85
Microwave	0.94	0.95	0.94	0.95
Kettle	0.75	0.81	0.78	0.81
Washing machine	0.82	0.86	0.84	0.86
Toaster	0.93	0.95	0.94	0.95
Dish washer	0.91	0.83	0.87	0.83
Desktop PC	0.92	0.93	0.93	0.93
Fridge	0.89	0.83	0.86	0.82

**Table 6** The obtained results of ApplianceNet without data augmentation

Appliance	Precision ( <i>p</i> )	Recall ( <i>r</i> )	F1-score	Accuracy
Television	0.80	0.86	0.83	0.85
Microwave	0.93	0.96	0.94	0.96
Kettle	0.79	0.73	0.76	0.73
Washing machine	0.86	0.76	0.81	0.76
Toaster	0.00	0.00	0.00	0.00
Dish washer	0.91	0.75	0.83	0.75
Desktop PC	0.91	0.92	0.91	0.92
Fridge	0.88	0.83	0.86	0.83

$$\text{Precision}(p) = \frac{TP}{(TP + FP)} \quad (8)$$

$$\text{Recall}(r) = \frac{TP}{(TP + FN)} \quad (9)$$

$$\text{F1 - Score} = \frac{2 * p * r}{(p + r)} \quad (10)$$

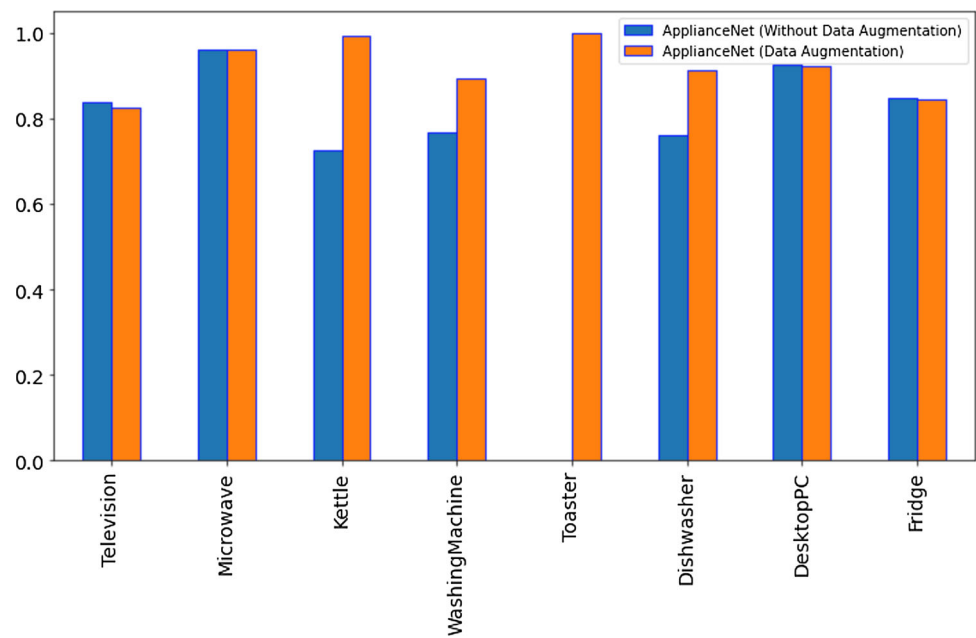
where TP is true positive, FP is false positive and FN is false negative.

## 5 Results and discussion

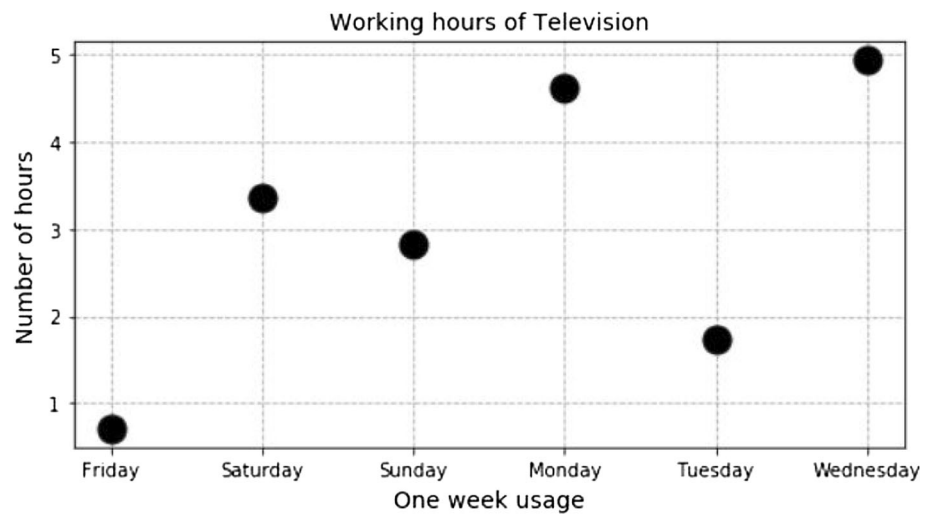
The experiments are performed in open-source python environment using SciKit learn [29] and PyTorch [30] libraries. Each appliance precision, recall, F1-score and Accuracy are presented in Table 5.

In Table 5, the appliance ‘Microwave’, ‘Toaster’, and ‘Desktop PC’ usage is recognized more than 90%. The less precise appliance recognition is ‘Kettle’ as compared to the other appliances. However, it is recognized 81% correctly as shown in Table 5. The signature of appliances was complex and even difficult to learn the minor classes (i.e., kettle, toaster, dish washer, and washing machine). The data augmentation helps to learn the signatures and the reported model presents the better result as compared to the baseline model (i.e., without data augmentation). Similarly, Table 6 presents the results of our model without data augmentation. It can be seen that the accuracy of recognized appliances decreased in the case of minor activities. For instance, in the case of ‘Toaster’, model did not learn any pattern and no instance is recognized during the model evaluation. While in the case of data augmentation ‘Toaster’ is recognized 95% correctly.

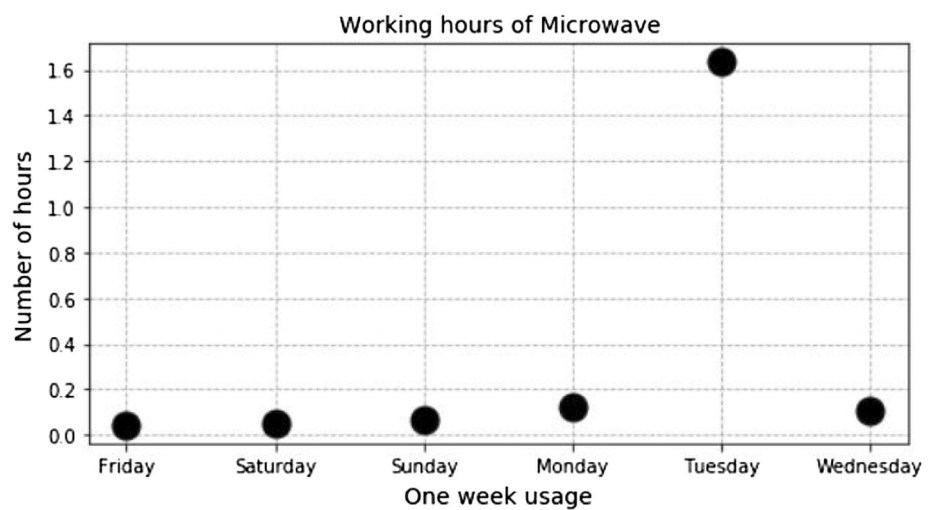
**Fig. 10** The obtained results using data augmentation and without data augmentation



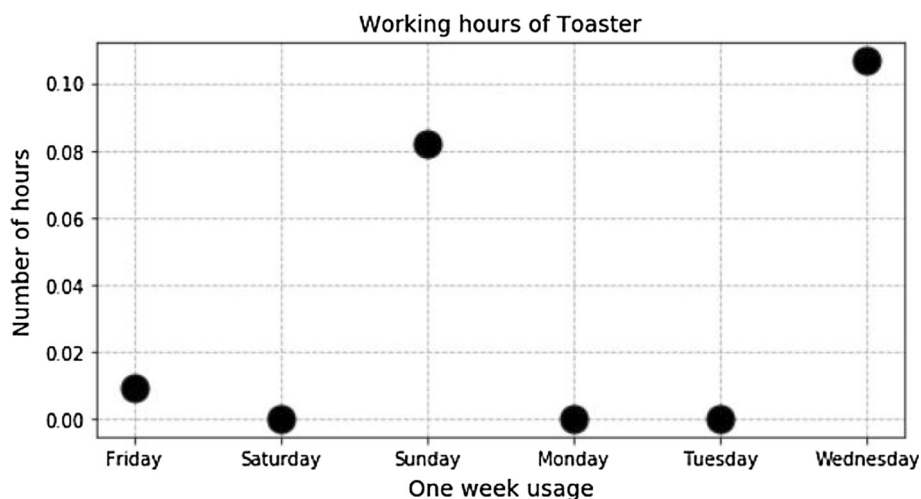
**Fig. 11** One week behavior pattern of watching television usage



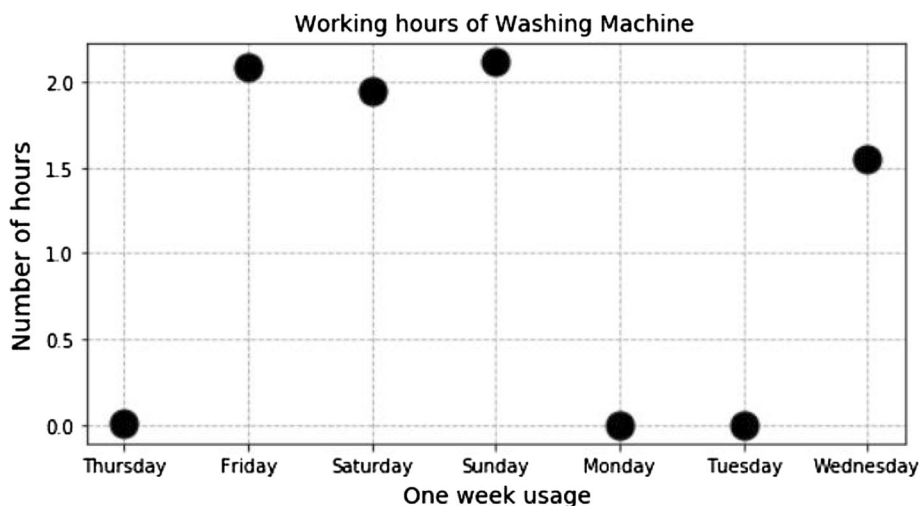
**Fig. 12** One week behavior pattern of microwave usage



**Fig. 13** One week behavior pattern of toaster usage



**Fig. 14** One week behavior pattern of washing machine usage



## 5.1 Sensitivity analysis

A sensitivity analysis is performed to analyze the impact of the data augmentation. The performance metrics (i.e., precision, recall, and F1-score) are reported in Table 6.

Furthermore, Fig. 10 presents the accuracy of the proposed model with and without data augmentation.

Figure 10 presents the obtained individual appliance accuracy. It confirms data augmentation produces accurate results for minor classes. In the case of ‘Toaster’, it does not recognize any usage, while in the case of data augmentation, it is fully recognized. The augmentation assists the model to learn the signature of the appliance.

## 5.2 Behavioural recognition

We also presented the weekly usage of home appliances, which can be related to resident behavior. In Fig. 11, the number of hours is presented to watch the television. This pattern can be extended to months. It may have an indicator

**Table 7** The comparison with existing work

Comparison	Precision ( <i>p</i> )	Recall ( <i>r</i> )	F1-score
Devlin et al. [5]	0.76	0.85	0.77
ApplianceNet (Our model)	0.87	0.88	0.88

to see the sedentary pattern of the resident. The one-week behavior has two peaks more than four houses to watch the television, while Friday has the least time to watch it. In Fig. 12, we can observe on Friday there is no usage of the microwave. This pattern is the same for Saturday as well. It may possible to dine out or skip the meal. To extend this work, we can confirm with the user about such situations. However, ‘Toaster’ is recognized on Friday as shown in Fig. 13. This home appliance can provide the eating pattern of the resident that may help the individual or practitioner to analyze the daily routines of the resident. In Fig. 14, the usage pattern is found on Friday, Saturday,

**Table 8** The overall ApplianceNet accuracy as compared to the state-of-the-art techniques

Model	Precision ( <i>p</i> )	Recall ( <i>r</i> )	F1-score	Accuracy
ApplianceNet	0.87	0.88	0.88	0.89
k-nearest neighbor	0.78	0.73	0.73	0.83
Decision tree	0.68	0.62	0.62	0.80
Naive bayes	0.55	0.48	0.48	0.53

Sunday, and Wednesday. This washing machine usage pattern is frequent and may help to diagnose complications by practitioners or healthcare givers. Such information can also be useful for energy providers as well as residents to use the washing machine in an optimal way. Consequently, it can help to reduce energy consumption.

### 5.3 Comparative analysis

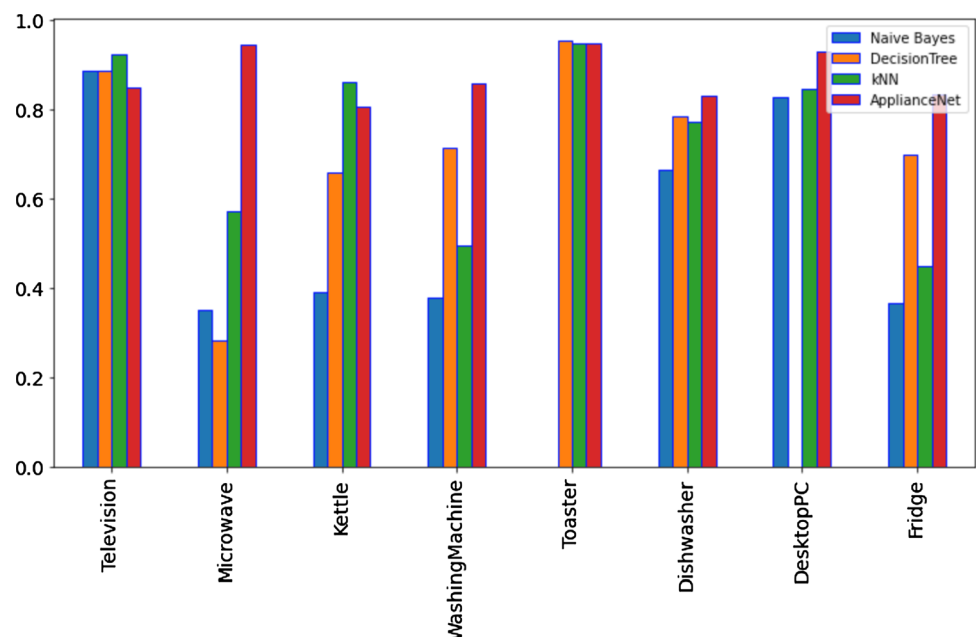
The direct comparison of presented ApplianceNet with existing models is difficult, since the different datasets have been used with different set of appliances. However, a recent study Devlin et al. [5] classify the activities of daily living using residential smart meter data were identified that is similar to our work in terms of recognizing the appliances. To recognize daily living activities they consider seven appliances—hair dryer, vacuum cleaner, iron, microwave, kettle, toaster, oven. In comparison to our framework, we recognized eight appliances—television, microwave, kettle, washing machine, toaster, dish washer, microwave, kettle, washing machine, toaster, dish washer,

desktop PC, and Fridge. The average of performance measures are reported in Table 7.

In Table 7, the ApplianceNet has better performance as compared to the existing method. The common appliances in both models are ‘Microwave’, ‘Kettle’ and ‘Toaster’, where our framework is superior by 14%, 7% and 11% respectively in terms of F1-score. Furthermore, we also compare the performance of our classifier in ApplianceNet with three state-of-the-art machine learning algorithms. These methods are decision tree, Naive Bayes classifier, and k-nearest neighbours with default parameters. The selection of these algorithms is based on the most frequently used models for the classification task. The Naive Bayes classifier is probability based model, which is consider as gold standard for making comparison, decision tree is well known method based on information theory to calculate the information gain, and k nearest neighbour is the non-parametric approach that is ranked in top 10 methods in data mining algorithm. Table 8 presents the improvement obtained by ApplianceNet.

Table 8 shows that our model provides better results as compared to the state-of-the-art methods. Furthermore, we also presented the individual accuracy of each appliance to analyze the improvement.

In Fig. 15, it is clear that the proposed ApplianceNet performs better in most of the cases. Our model obtained the best results in the case of ‘Microwave’, ‘Kettle’, ‘Toaster’, and ‘Dishwasher’ where state-of-the-art models have more confusion to recognize these appliances.

**Fig. 15** The ApplianceNet individual appliance recognition accuracy as compared to the state-of-the-art techniques



## 6 Conclusion

The advancement in technology has enabled the research community to recognize daily life activities in the home environment which can be used in multiple services. In this research, we present ApplianceNet to identify the home appliances using smart plugs to recognize daily life activities in the home environment. Our model processed the temporal energy consumption data to extract basic and complex characteristics in the form of features. These features are further processed by a multi-layer, feed-forward neural network to classify the home appliances which are non-linear separable after the feature extraction technique. This approach has the potential to be adopted in existing homes as a low-cost and sustainable solution with superior recognition as compared to the existing solutions.

In future work, the research community can develop consumer applications based on the daily living activities for diverse applications.

## Declarations

**Conflicts of interest** The authors declare that they have no conflict of interest.

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