HOME APPLIANCE IDENTIFICATION FOR NILM SYSTEMS BASED ON DEEP NEURAL NETWORKS

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ABSTRACT

This paper presents the proposal for the identification of residential equipment in non-intrusive load monitoring systems. The system is based on a Convolutional Neural Network to classify residential equipment. As inputs to the system, transient power signal data obtained at the time an equipment is connected in a residence is used. The methodology was developed using data from a public database (REED) that presents data collected at a low frequency (1 Hz). The results obtained in the test database indicate that the proposed system is able to carry out the identification task, and presented satisfactory results when compared with the results already presented in the literature for the problem in question.

KEYWORDS

Convolutional Neural Networks, identification of residential equipment, non-intrusive load monitoring, NILM.

1. INTRODUCTION

The reduction and rationalization of electricity consumption are increasingly becoming priorities, not only for residential consumers, but also for electric power companies and government. Considering this concern, which is worldwide, research in Non-Intrusive Load Monitoring (NILM) has been emphasizing. Research in this area began in 1992 with the presentation of the work of George W. Hart [1] and since then many works have been presented, focusing on the various stages of a NILM system.

A NILM system has as main objective to measure an aggregate load of a residence through a single sensor, placed in the central meter of the residence. From the aggregate load, measured over a period of time, it is possible, through specific software, to carry out an identification of the electric equipment in operation and obtain the individual consumption thereof, in addition to obtaining the operating hours of each equipment [1]. This information can be used by residential consumers to take actions aimed at reducing and rationalizing their consumption, thus ensuring greater energy efficiency. In addition to this main functionality of the NILM systems, it is also possible to highlight: the possibility of identifying the load profile of a residence; possibility of identifying non-standard behavior of loads; possibility of detection of power failures and thefts; possibility of the use of the information of the load disaggregated by the electric power concessionaires that can promote aid to their customers in the process of identification of waste during peak hours, thus helping to reduce consumption during these periods, offering for this incentive to consumers [2].

Currently as Deep Neural Networks have been receiving increasing attention by the academic community and is under development, with significant improvements in the area of computer vision, image recognition and signal processing. In addition to the promising results for problems involving a 2-D data application, some authors have been developing research in the

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area of application of deep neural networks in problems with 1-D data, such as time series data [3-8]. Due to this advancement in the area, some researchers have sought to apply as Deep Neural Networks to equipment identification problems in NILM systems. Some works were used in Long Short Term Units (LSTM), Auto-encoder Neural Network and Convolutional Neural Network (CNN) [9-12], with satisfactory results.

Considering the good results already presented by the academic community involving deep neural networks for the NILM problem, this paper presents the results obtained from the application of Convolutional Neural Networks for the problem of equipment identification. Here, unlike what we already have in the literature, a CNN network was developed to identify the type of equipment from the transient power signal data obtained at the moment an equipment is connected. The choice of the use of the transient power signal is due to the fact that each type of equipment presents different transient signal characteristics, depending on the generation mechanism, which is suitable for the development of classification systems. For the development and testing of the proposed system, the public database was used, and much used by researchers in the area, REDD (Reference Energy Disaggregation Dataset) [13]. This database has data of several equipments that were collected individually in 6 different residences at a frequency of 1 Hz. The system was developed to identify 6 equipments, these being classified as on / off loads, multilevel or variable.

2. Non-Intrusive Load Monitoring Systems

The non-intrusive load monitoring aims to obtain a good approximation of the various electric devices in operation in a residence, using dedicated hardware and software [14]. The monitoring and identification of loads are performed based on the analysis of measurements of a single point of current and voltage of the aggregate load obtained through a meter outside the residence. Since each electrical equipment has its own profile of energy consumption called the electric signature, the developed algorithms try to identify such signatures in the aggregate load curve, thus indicating the periods of operation of the equipment and their respective energy consumption.

NILM methods fall into two broad groups, methods based on low frequency measurements (methods based on macroscopic characteristics) and methods based on high frequency measurements (methods based on microscopic characteristics). Sampling frequencies above 1 Hz are defined here as high frequencies [14]. The methodology of a NILM system is based on four main steps, as can be seen in Figure 1, which are the signal acquisition, event detection, characteristic extraction and equipment identification.

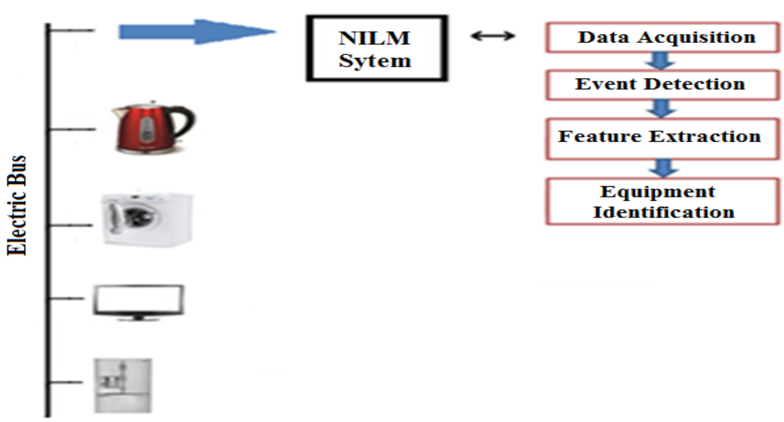

Figure 1 Residential electricity system with integrated NILM system

During the signal acquisition step, the aggregate load is measured through a single sensor on the main branch that is outside the residence. Figure 2 shows an example of the load measured over a period of 1 hour for one of the 6 equipment chosen (Refrigerator). For this stage we use the public database REDD (Reference Energy Disaggregation Data Set), being one of the most used in the field of NILM systems research.

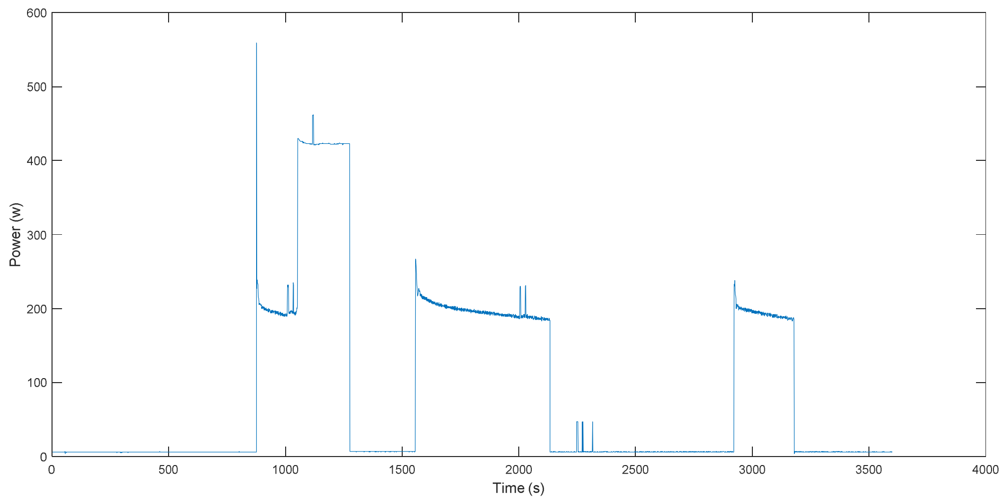

Figure 2 Load example measured over an hour

In the event detection stage, the on / off moments of equipment in a residence (event) are detected from the aggregate signal. In order to detect abrupt changes in the signal, a methodology was used based on an analysis window that scans the whole measured aggregate load, and it is possible to identify the occurrence of an event when the difference between the final average) and the initial mean (left margin mean) of the window reach a predetermined threshold value, as can be seen in Figure 3. For each detected event, the first twelve transient samples were separated to form the training database of the system. The choice of the number of samples to be used as input to the system was based on the evaluation, for all equipment, of the number of samples sufficient to characterize a complete transient.

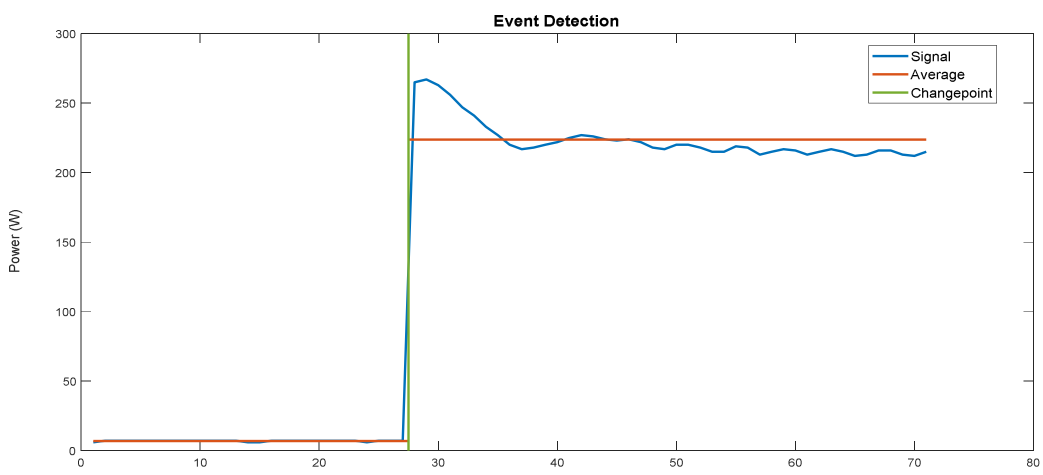

Figure 3 Event Detection Through Windowing

With the detected events, the third stage, of characteristic extraction or electric signatures, takes place. Electrical signatures represent a set of characteristics of voltage, current or power for a given equipment, and can be divided into macroscopic and microscopic. The macroscopic (low frequency) characteristics must be obtained from a sample period of up to one sample per cycle (1 Hz). The low frequencies are applied in several methods, and can be used to acquire the active power, reactive power and effective values of voltage and current [17].

The extracted characteristics can be classified into two main categories: steady state and transient state. Real and reactive power are the most commonly used steady-state characteristics in NILM systems. In works such as [18] and [14], it is assumed that the real power is used to disaggregate the devices, having results with great precision. The transient behavior of most electrical appliances is distinct, therefore, this feature becomes suitable for the identification of load [19].

In the fourth and last step, from the characteristics / signatures extracted, we have the identification of each equipment for each detected event. Methods for identifying equipment used in NILM systems may be of the supervised or unsupervised type. Supervised techniques require the use of labeled data for learning a model that can properly identify equipment, while the unsupervised model eliminates the need for labeled data.

In [20] the authors point out the main supervised techniques to solve NILM problems, such as Artificial Neural Networks (RNA), Supporting Vector Machines (SVM), Naive Bayes Classifier and K-Nearest Neighbor (KNN). Recently the researchers have turned their attention to the use of Neural Networks Deep to the problem of equipment identification. In [9] the authors apply 3 types of deep neural networks, a recurrent neural network based on Long Short Term Memory Units, a self-encoder neural network and a convolutional neural network, to predict the start and end time of an event of an equipment, as well as to predict the average demand of each device. In [10] the author sought to make an analysis of the various methods of deep learning to improve the performance of a NILM system. In [11], the authors used convolutional neural networks for the task of load disaggregation, promoting the individual identification of equipment loads based on the time series of the aggregate load. In [12], it is shown that CNN networks can also be used in the NILM context for equipment classification based on the VI path of an equipment.

3. CONVOLUTIONAL NEURAL NETWORK

A convolutional neural network (CNN) can be considered as a variant of the neural network Perceptron of Multiple Layers (MLP). Instead of using fully-connected hidden layers, such as MLP, the architecture of a CNN is based on the alternation of convolution layers - the layer that names the network; and pooling layers. Each layer will have a set of filters, also known as kernel, that will be responsible for extracting local features from an input. With this, we can create several convolution and pooling maps, containing several specific characteristics like borders, colour intensity, contours and shapes. Each feature map will have a shared set of weights, which decreases the computational complexity of the network [24]. Finally, we have the layer responsible for the classification process, which have the fully connected layer, which connects all the neurons of the layer before it to the output neurons, as shown in Figure 4.

The convolution layer consists of neurons that are responsible for extracting different sub-region resources from the input images [28]. These areas are derived from the filters used in this layer, being able to extract specific characteristics of the input. In this layer we specify the amount of filters, their sizes, in addition to the stride, which defines the size of the neighbourhood that each layer's neuron will process. [24]

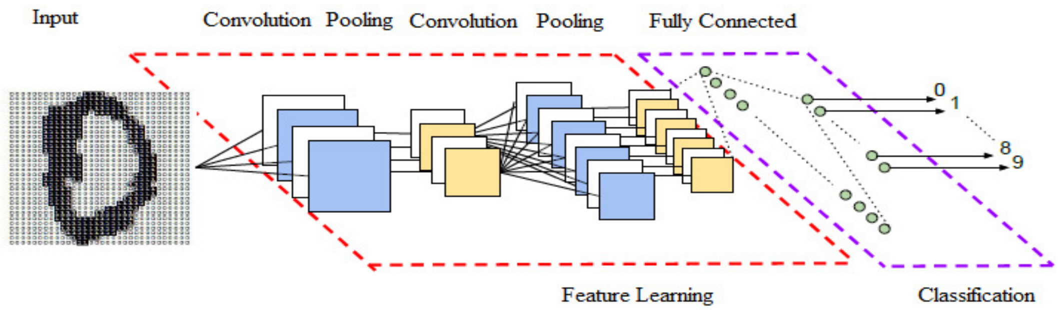

Figure 4 Illustration of the architecture of a CNN [24]

The Pooling layer follows the convolutional layer reducing the number of connections to the following layers, being Max-Pooling in our work. A Max-Pooling layer returns the maximum values obtained in its filters. This layer does not perform any learning, but reduces the number of parameters to be learned in the following layers. [28,24]

The fully connected layer connects all the neurons of the anterior layer with the output neurons, which represent the classes to be classified. This layer combines all the characteristics (local information) learned in previous layers, sweeping the input to identify the highest standards. For our classification problem, it will combine the characteristics of the transients to classify the equipment. At the output of the classification layer, the Softmax activation function is applied which is responsible for performing the multi-class classification (for example: object recognition). [28,24]

4. Proposed CNN-Based Equipment Identification System

4.1. REED Database

The REDD (Reference Energy Disaggregation Data Set) is a public database, one of the most widely used in NILM systems research. REDD consists of data collected in six households, and contains aggregated data of current and voltage collected at the 15 kHz frequency, data from 24 individual circuits collected at the 1 Hz frequency, as well as data from more than 20 equipment monitors collected in the frequency of 1/3 HZ [13]. Table 1 shows the equipment per household that was measured in REDD.

Table 1. Description of the houses and devices used in the evaluation in REDD data set [3].

House	Device Categories
1	Electronics, Lighting, Refrigerator, Disposal, Dishwasher, Furnace, Washer Dryer, Smoke Alarms, Bathroom GFI, Kitchen Outlets, Microwave
2	Lighting, Refrigerator, Dishwasher, Washer Dryer, Bathroom GFI, Kitchen Outlets, Oven, Microwave, Electric Heat, Stove
3	Electronics, Lighting, Refrigerator, Disposal, Dishwasher, Furnace, Washer Dryer, Bathroom GFI, Kitchen Outlets, Microwave, Electric Heat, Outdoor Outlets
4	Lighting, Dishwasher, Furnace, Washer Dryer, Smoke Alarms, Bathroom GFI, Kitchen Outlets, Stove, Disposal, Air Conditioning
5	Lighting, Refrigerator, Disposal, Dishwasher, Washer Dryer, Kitchen Outlets, Microwave, Stove
6	Lights, refrigerator, crazy washer, heater, clothes dryer, bathroom equipment, cooking utensils, cooker, electronic, air conditioning.

For the development of the proposed system based on a Neural Convolutional Network to identify the equipment, in an initial phase, 6 equipment were chosen: microwave, oven, dishwasher, air conditioning, washer / dryer and refrigerator. The chosen equipment can be considered the most energy consuming in a residence. According to Batra [16], it is necessary to prioritize the identification of equipment with higher energy consumption in the residences, since these devices contribute with the most significant characteristics in the aggregate load, and the other appliances, with lower consumption, can only be considered as noise in the load total aggregate.

For the development of the system were used as inputs to the CNN network the transient power signals obtained at the moment an equipment is connected in a residence. In order to create the CNN network training database, an algorithm for event detection was developed. In this algorithm, for each detected event, the first twelve transient samples were selected to form the system training database. The choice of the number of samples to be used as input to the system was based on the evaluation, for all equipment, of the number of samples sufficient to characterize a complete transient.

4.2. Evaluating NILM Algorithms

In order to evaluate the performance of the proposed system, some evaluation metrics have been used that are generally used to evaluate equipment identification systems in the context of NILM systems:

Confusion Matrix: Allows an effective measure of the classification model, presenting the number of correct classifications versus classifications predicted for each class, on a set of examples [9]. The main diagonal presents for each class the correct classification number and the percentage that this number represents within the complete number of data of the class.
Accuracy: presents the percentage of positive and negative samples correctly classified on the sum of positive and negative samples.

$$\mathrm{Acc} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}} \qquad (1)$$

Being True positive (TP), the number of times an equipment is correctly classified as ON; True Negative (TN), the number of times an equipment is correctly classified as OFF; False Positive (FP) The number of times an equipment is incorrectly classified as ON and False Negative (FN) is the number of times an equipment is incorrectly classified as OFF.

Sensitivity: percentage of positive samples correctly classified on the total of positive samples.

$$\mathrm{Sens} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} = \frac{\mathrm{TP}}{Positive} \qquad (2)$$

Precision: percentage of positive samples correctly classified on the total of samples classified as positive.

$$\mathrm{Prec} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \qquad (3)$$

F-score: It is a weighted average of precision and sensitivity

$$\text{F - score} = \frac{2\times(\mathrm{Prec}\times\mathrm{Sens})}{(\mathrm{Prec}+\mathrm{Sens})} \qquad (4)$$

4.3. CNN Training

Different from the work presented in [29], the database for development of the identification system has the same amount of standards for each equipment, reaching 600 standards, considering all 6 equipments. Another difference is the fact that each pattern presents 12 transient samples of a given equipment (improving the representation with larger transients), thus forming a 12x600 two-dimensional array. The data were divided into training, validation and test data, corresponding respectively to approximately 60%, 20% and 20% of the total standards. In addition, all equipment has the same amount of transients and is arranged in random order in the CNN training database. Table 2 presents the organization of the data in a more detailed way.

Table 2. Data Organization.

N°	Equipment	Trai	Valid	Test	Total
1	Refrigerator	60	20	20	100
2	Microwave	60	20	20	100
3	Oven	60	20	20	100
4	Dishwasher	60	20	20	100
5	Air conditioning	60	20	20	100
6	Washer / Dryer	60	20	20	100
#	Overall	360	120	120	600

The approach consists of directly using the 12 samples of the transient power signal of the equipment as input to CNN, without the need to apply techniques of transformation of the signal to images, as spectrogram [22], or binary images [23]. For this, it was necessary to only resize the training input matrix to 4D, assuming the dimension 1x12x1x360, and in this way CNN interprets the data as a 4-D numerical matrix (a cluster of colored images), where the first three dimensions refer to the height, width and channels and the last dimension should index the individual images, that is, index the transients. [29]

For this approach, which is focused on the classification of equipment through the behavior of its power transients, an architecture based on three layers of convolution followed by pooling was used. Between each convolution and pooling layer normalization is applied in the filter sets (batches), which serves to accelerate network formation and reduce sensitivity for initialization. In addition, we used the non-linear activation function (ReLU) which is simply the identity function for positive values. After the 3 layers of convolution and pooling a fully connected layer is used, followed by the Softmax function. This architecture, derived from a reduction in the convolutional network GoogLeNet [12] (that has five layers of convolution always followed by a pooling), is represented in Figure 4, containing specifications such as: the number of filters in each layer, the size of the stride and the configuration of the output layer. During the training phase, cross validation was used to control the overtraining of CNN. Cross-validation estimates the error of the learning method in unused observations in training, that is, estimates how the constructed model will behave for new data other than training data.

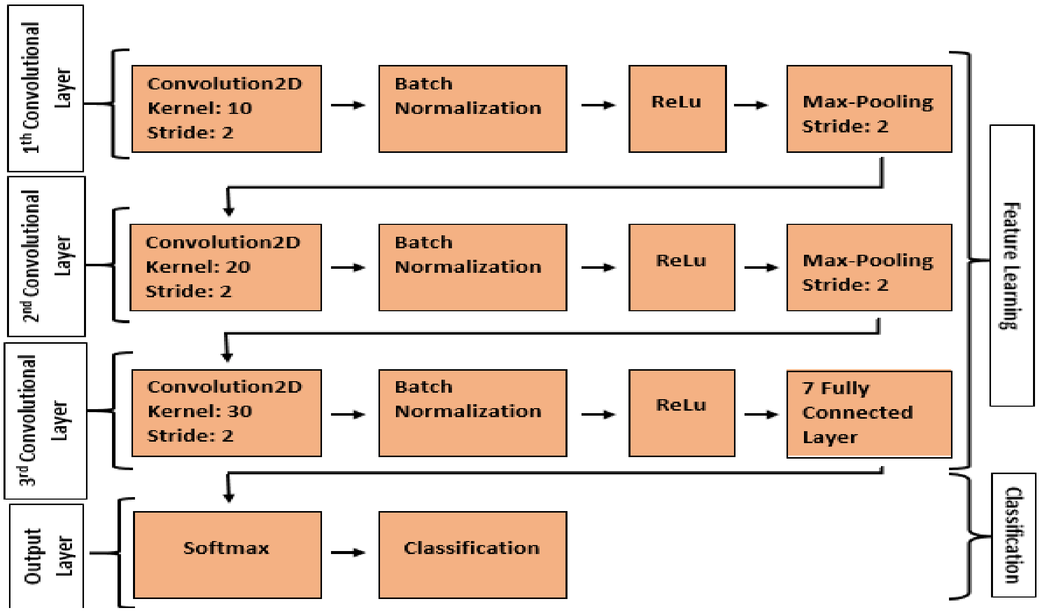

Figure 5 CNN architecture developed for the proposal

4. RESULTS

Table 3 shows the results obtained for the test data, after the training of the projected CNN network. The result are given in the form of metrics: sensitivity (Sens), precision (Prec) and F-score (F). The 3 assessment metrics used in this study can assist us in measuring the performance of the CNN from another perspective. Thus, we have as an example, the Air-conditioning and Washer, which were accurately classified, not having FP, besides presenting the same performance for the sensitivity. Then, to harmonize the two metrics of evaluation already mentioned and to bring a better comparison between the equipments, the metric F-score is used. In this way, we can analyze in column F that the equipment Air-conditioning and Oven had results of 100%, demonstrating an excellent performance for the presented model. Other equipment also had excellent F-score values, such as: dishwasher and refrigerator, in which all are above 90%.

Table 3. Results for Test Data

N	Equipment	Sens.	Prec.	F
1	Refrigerator	1.00	0.8696	0.930
2	Microwave	0.70	0.9333	0.800
3	Oven	0.95	0.8636	0.904
4	Dishwasher	0.95	0.9500	0.950
5	Air conditioning	1.00	1.0000	1.000
6	Washer / Dryer	1.00	1.0000	1.000
#	Overall	0.9333	0.9361	0.930

Figure 6 shows the confusion matrix obtained for the test data which thus allows a broader view of the performance of our algorithm, as well as providing a detailed account of the results obtained in Table 3. The 6 appliances are defined as follows: Refrigerator (1), Microwave (2), Oven (3), Dishwasher (4), Air Conditioning (5) and washer/dryer (6). Each matrix column represents the categories of appliances predicted by the CNN, while the lines represent the real categories. The number of checks for each class can be found on the main diagonal of the matrix.

	1	2	3	4	5	6	
1	**20** 16.7%	**2** 1.7%	**0** 0.0%	**1** 0.8%	**0** 0.0%	**0** 0.0%	87.0% 13.0%
2	**0** 0.0%	**14** 11.7%	**1** 0.8%	**0** 0.0%	**0** 0.0%	**0** 0.0%	93.3% 6.7%
3	**0** 0.0%	**3** 2.5%	**19** 15.8%	**0** 0.0%	**0** 0.0%	**0** 0.0%	86.4% 13.6%
4	**0** 0.0%	**1** 0.8%	**0** 0.0%	**19** 15.8%	**0** 0.0%	**0** 0.0%	95.0% 5.0%
5	**0** 0.0%	**0** 0.0%	**0** 0.0%	**0** 0.0%	**20** 16.7%	**0** 0.0%	100% 0.0%
6	**0** 0.0%	**0** 0.0%	**0** 0.0%	**0** 0.0%	**0** 0.0%	**20** 16.7%	100% 0.0%
	100% 0.0%	70.0% 30.0%	95.0% 5.0%	95.0% 5.0%	100% 0.0%	100% 0.0%	**93.3% 6.7%**

Figure 6 Confusion Matrix for Test Data

Based on these results, we can infer that the equipments that have FN values had a decrease in sensitivity, such as the Micro-Wave equipment, where 70% of the time the model predicts correctly. Refrigerators and Oven had the worst precisions, this is due to the fact that these equipments have FP values, with 3 FP values in both. The Air Conditioning and Washer-Dryer equipment did not present FP and FN values, reaching 100% accuracy and sensitivity. In comparison with results already presented in the literature, there is a classifier system of equipment with satisfactory results, considering that among the equipment used there are those with complex load behavior (loads in the multilevel or variable state), which makes the rating.

4.1. Comparison With State Of The Art

In this section, we compare our results with some state-of-the-art NALM algorithms, proposed for low sampling rates and active power measurements. Table 5 presents the results of some systems already developed to identify equipment in NILM systems using as input the power transient measurements for low frequency. A direct comparison of results should be carried out with caution since for all the presented systems one has the database used for different training, test and validation and equipment and number of equipment also identified different.

Table 5. Comparison between systems presented in the literature

Authors	Technique	Nº of Appliance categories	Sens	Prec	F	Acc
This Study	CNN	6	0.933	0.936	0.930	0.93
Deyvison [29]	CNN	7	0.82	0.84	0.82	0.82
Kelly [7]	Autoencoder	5	0.80	0.58	0.55	0.91
Kelly [7]	LSTM	5	0.69	0.39	0.39	0.68
WONG [16]	PDT	6	0.77	0.76	0.73	-----
Zhao [17]	GSP	8	0.51	0.89	0.64	0.77

[7] Uses long short-term memory; [16] Uses Particle-based Distribution Truncation (PDT) and [17] Uses Graph Signal Processing (GSP).

5. CONCLUSIONS

In this article, we describe how to apply CNNs to the recognition of technical equipment in an innovative manner. From the results obtained, the efficiency of the proposed system is clearly evident, where a weighted average of precision and sensitivity was obtained that was higher than 90%; and with an average degree of accuracy of 93%. The results obtained can be regarded as satisfactory when compared with the results of the identification systems already shown in the literature and also when account is taken of the complexity of the system put forward which was designed to identify loads in a multilevel or variable state.

One point that should be stressed with regard to the direct use of the power supply transient signal as an entry to the identification system, is that it speeds up the system. This means that it is a system that can achieve good results in classification by using data where the measured power is of a low frequency. This is beneficial since the use of low frequencies is common in available low–cost measuring devices which are currently being used for the development of NILM systems.

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