Improving the Generalizability of Deep Learning NILM Algorithms using One-Shot Transfer Learning

Can one-shot transfer learning be leveraged to enhance the performance of a CNN-based NILM algorithm on unseen data?

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Abstract

Non-Intrusive Load Monitoring (NILM) is a technique used to disaggregate household power consumption data into individual appliance components without the need for dedicated meters for each appliance. This paper focuses on improving the generalizability of NILM algorithms to unseen households using Convolutional Neural Networks (CNNs) and one-shot transfer learning. The research investigates the effectiveness of one-shot transfer learning in fine-tuning a CNN model to accurately detect the ON/OFF state of appliances in households not seen during the training phase of the CNN. The study utilizes the Pecan Street dataset for training and evaluation, which includes detailed energy consumption records from various locations in the United States. The results suggest that one-shot transfer learning could enhance the performance of the NILM algorithm, particularly when multiple data samples are used for fine-tuning. However, the effectiveness of one-shot transfer learning varies strongly depending on the number of samples and the characteristics of the target household.

Introduction

- Non-intrusive load monitoring (NILM) refers to the process of disaggregating a power time-series into individual components that constitute the aggregate signal (figure 1).
- NILM was initially introduced by G. Hart [1]
- Current issues [2]:
  - **Limited generalizability of the algorithm to unseen households during training.**
  - Inadequate detection of low-energy consuming appliances.
  - Inability to identify appliances that switch on\off simultaneously
  - High computational complexity
  - Challenges associated with automatic detection of new appliances without necessitating algorithm retraining.
- This study attempts to enhance the generalizability.

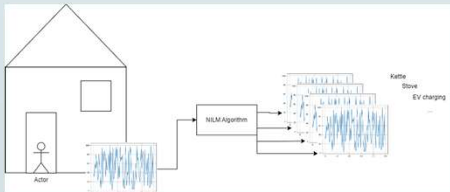

Figure 1: Graphical illustration of Non-Intrusive Load monitoring (NILM)

Methodology (figure 2)

- Using a Convolutional Neural Network (CNN) as NILM algorithm
  - deep learning model designed to automatically learn and extract meaningful features from the data
- Attempt to improve the generalizability to unseen households during training using one-shot transfer learning.
  - technique that allows a pre-trained model to quickly adapt and perform well on a new task with very limited labeled data [3]
- Using the Pecan Street New York dataset to train the CNN
- Freeze the existing layers from the CNN
- Extend the CNN with layers used for transfer learning
- Apply one-shot transfer learning to fine-tune the model to an unseen household during the training phase.

Results

- The measurements suggest an improvement after applying one-shot transfer learning (Table 1, Figure 3)
- Improvement is seen at n = 1 but improves if using more samples (n≥2)
- High standard deviation
  - Consequence of wide distribution of improvement scores
  - Improvement is very much dependent on the household, i.e. the appliance set.

household id	n=0	n=1	n=2	n=3	n=4	n=5
661	0.0	16.8	41.7	33.7	41.7	33.7
1642	0.0	2.0	1.9	5.2	8.1	7.9
2335	0.7	16.4	25.3	21.6	34.3	29.4
2818	0.9	7.3	14.4	18.0	18.0	18.0
3039	0.0	0.7	19.1	19.0	18.6	18.6
3456	0.0	12.2	15.7	18.3	20.9	13.2
3538	3.2	11.8	7.5	12.7	18.9	16.6
4031	2.3	22.3	32.4	38.2	30.3	29.8
4373	3.3	2.8	14.1	10.2	12.6	15.0
4767	0.3	5.4	9.4	11.5	11.5	11.5
5746	0.0	7.6	20.3	17.3	19.2	20.4
6139	0.5	0.4	1.6	1.3	0.2	0.2
7536	0.9	2.5	17.7	9.1	18.2	20.9
7719	2.1	10.4	12.9	12.7	21.0	18.6
7800	0.0	8.7	9.8	10.0	9.7	9.7
7901	0.9	8.9	8.7	9.2	2.2	6.2
7951	1.5	6.6	12.0	7.2	11.1	10.5
8565	0.1	18.9	35.1	32.7	18.3	18.3
9019	0.3	5.6	4.7	5.3	5.6	5.3
9278	4.6	23.5	24.5	20.4	38.5	33.9
8156	0.7	0.5	1.4	2.1	0.6	0.6
8386	0.0	8.4	8.6	11.3	8.3	10.1
2361	0.7	10.3	27.7	42.5	42.5	42.5
9922	0.0	0.0	0.0	0.1	0.0	0.0
9160	0.0	0.0	0.0	10.7	13.6	20.4
mean	0.9	8.4	14.7	15.2	17.0	16.5

Table 1: The accuracy score in % on an Austin household after feeding n samples to the transfer learning layer.

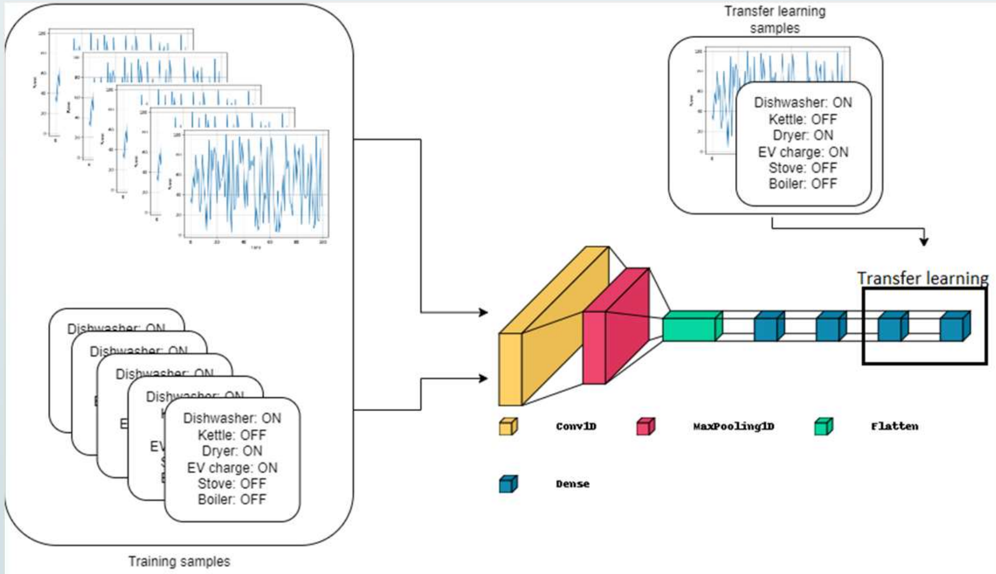

Figure 2: Graphical representation of how the Convolutional Neural Network (CNN) is extended to be used for one shot transfer learning.

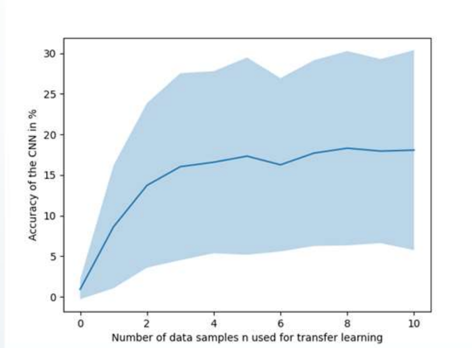

Figure 3: The mean accuracy values across all households, with standard deviation, extended to visualize 10 samples for transfer learning.

Conclusion

- This study highlights the potential of one-shot transfer learning to enhance the generalizability of deep-learning NILM algorithms.
- Further research should be conducted to investigate the relationship between the data used for one-shot transfer learning, the appliance set, and the improvement score.

Acknowledgements

[1] G.W. Hart, "Nonintrusive Appliance Load Monitoring," Proceedings of the IEEE, vol. 80, no. 12, pp. 1870–1891, 1992.

[2] S. Dash and N. C. Sahoo, "Electric energy disaggregation via non-intrusive load monitoring: A state-ofthe-art systematic review," Electric Power Systems Research, vol. 213, 12 2022.

[3] N. O' Mahony, S. Campbell, A. Carvalho, L. Krpalkova, G. V. Hernandez, S. Harapanahalli, D. Riordan, and J. Walsh, "One-shot learning for custom identification tasks; a review," in Procedia Manufacturing, vol. 38. Elsevier B.V., 2019, pp. 186–193.