Transfer Learning For Energy Disaggregation

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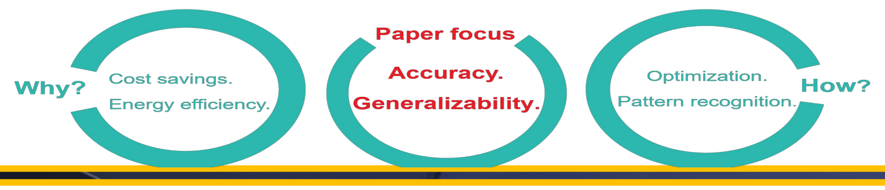
Introduction

- This research paper focuses on Non-Intrusive Load Monitoring (NILM) or energy disaggregation, a valuable technique for understanding and managing energy consumption at the individual appliance level. The paper begins by reviewing the influential work of George Hart and the concept of disaggregating total energy to identify individual appliances. It highlights the challenges faced in NILM due to limited labeled data and the complexity of distinguishing between different appliance signatures.
- To address these challenges, the paper explores the potential of deep learning techniques, particularly transfer learning. Transfer learning, a powerful method that uses pre-trained models from massive datasets like ImageNet, can be adapted to improve energy disaggregation accuracy, generalization, and training time. The paper also discusses the benefits of leveraging pre-trained models and the potential to handle limited labeled data effectively
- Overall, the research aims to optimize energy consumption and reduce waste by developing accurate and efficient energy disaggregation methods, ultimately supporting the transition towards sustainable and energy-efficient practices.



AIM and Objectives

- Understand effective NILM system frameworks and review benchmark algorithms.
- Propose a transfer learning approach for high-accuracy load disaggregation.
- Investigate domain adaptation methods for energy disaggregation to address generalizability challenges.
- Utilize load signature characteristics (statistical values) for event and device identification through supervised or unsupervised methods. Explore knowledge transfer between buildings to improve energy disaggregation across different appliance types and usage patterns.
- (Optional) Incorporate supplementary data sources like weather information, occupancy data, and appliance metadata to enhance transfer learning and disaggregation accuracy.

Methodology

The REFIT Electrical Load Measurements dataset provides cleaned electrical consumption data in Watts for 20 households, capturing both aggregate and appliance-level information. The data is time-stamped and sampled at 8-second intervals, making it valuable for research in various energy-related fields, including non-intrusive appliance load monitoring, demand response strategies, energy conservation analysis, and smart home/building automation.

- Timestamp duplicates were merged to avoid redundant data entries and ensure data consistency.
- IAM (Individual Appliance Monitor) readings exceeding 4000 Watts (the rated limit of the sensor) were set to 0 Watts to handle sensor limitations.
- Individual IAM readings were processed to display data for one appliance per IAM, enhancing data accuracy and clarity.. Missing values (NaN) were handled by forward-filling for gaps less than 2 minutes and zeroing for gaps exceeding 2 minutes, ensuring a continuous and complete dataset.

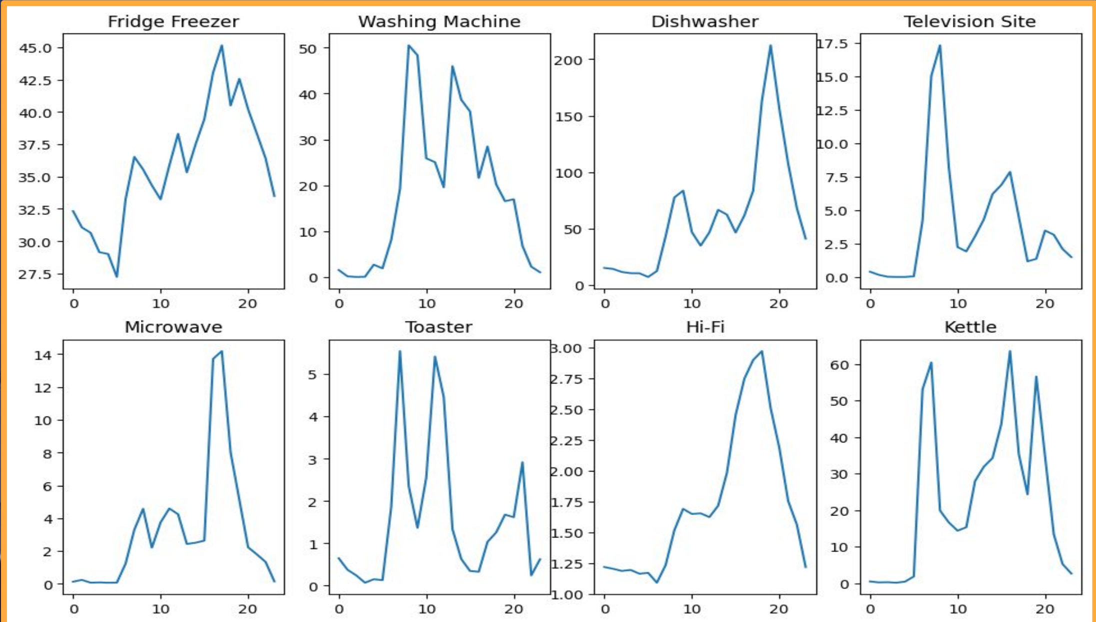


Figure 1: Energy usage of appliances with respect to aggregate power

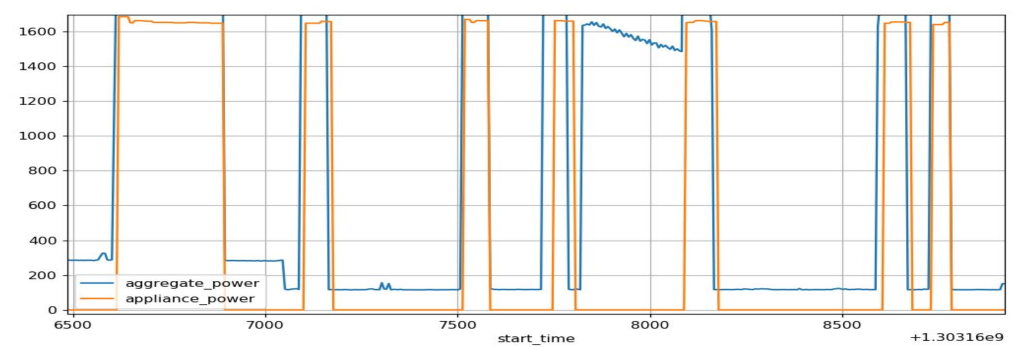


Figure 2: Appliance activation function graph zoomed in

Result and Discussion

- **Evaluation** - This study discovered that CNN layers that were trained on washing machines can also be used effectively on other appliances. This shows that different appliances have comparable energy usage profiles, making it possible to use a sizable dataset to thoroughly train the CNN layers. Once the CNN layers have been trained, they can be used to extract unique signatures from previously unexplored data from various appliances. Once fully connected, the layers can be adjusted exclusively based on hidden data, allowing for precise and effective non-intrusive load monitoring (NILM) for a variety of appliances.
- **Issues** – Data quality issues with the original data. Benchmarking and validation on the REFIT dataset, which is thought to be "noisier" than other publicly available datasets due to the concurrent operation of several labelled and unlabelled appliances.
- **Future work** – In addition to energy consumption data, further work on this project may explore the integration and use of context-rich data sources, such as weather data, occupancy data, and appliance metadata. More precise disaggregation strategies could be created by introducing these additional data sources into the transfer learning process, improving the system's overall performance. A worthwhile direction for additional research and advancement in the study would be to examine how these auxiliary data sources might be effectively used and assimilated throughout the transfer learning phase.

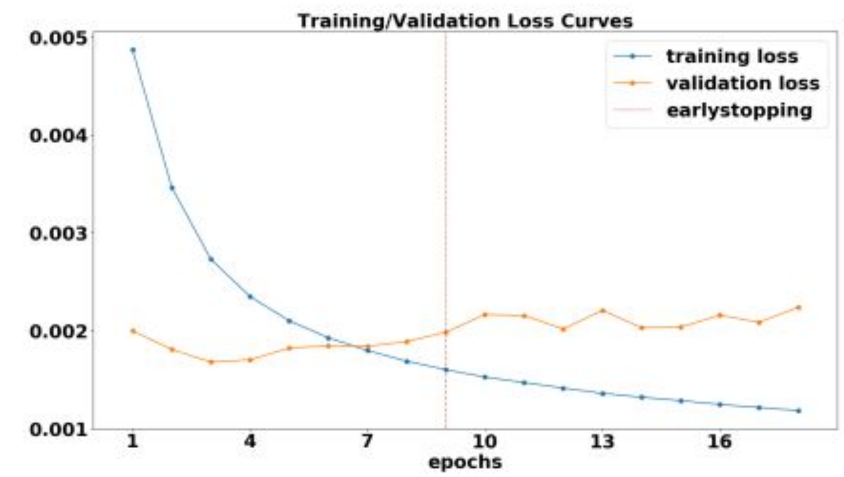


Figure 3: The training and validation losses are shown. When the patience of early halting was set to 6, the iteration ended at the 9th epoch, as seen by the vertical dashed line.

References

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