An Aggregated Approach Towards NILM on ACS-F2 Using Machine Learning

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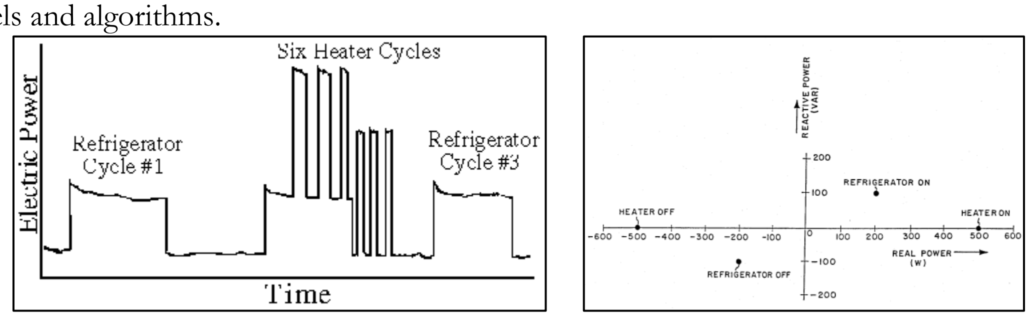
The Energy Sector across the globe is experiencing rapid growth, driven by Internet of Things (IoT) integration technologies and advanced algorithms. This evolution is particularly evident in the ongoing competition among tech companies in the development of smart metering solutions. Despite these advancements, a critical challenge persists— the lack of definitive technical protocols for monitoring the total usage or power signatures of individual appliances, referred to as non-intrusive load monitoring (NILM) in aggregate. While intrusive load monitoring (ILM) provides very accurate and thorough insights, non-intrusive methods are essential to address losses specially in residential areas. In this research a groundbreaking approach is proposed towards handling NILM problems by analyzing and aggregating the load patterns of four key appliances of daily use, namely the Coffee Machine, Fridge, Kettle, and Laptop from the ACS-F2 dataset. The generated aggregated dataset, is systematically combined using electrical formulations to yield the desired data which reflects the simultaneous operation of multiple appliances, this has been explored for the first time in the known literature. The proposed dataset contains around 6750 aggregated appliance load patterns for both training and testing. Furthermore, multiple Time Series Classifiers (TSC) were gauged using a suite of evaluation metrics, on the proposed dataset and an accuracy of 92.1% was achieved by the CATCH22 classifier.

Keywords: Non-Intrusive Load Monitoring (NILM); Intrusive Load Monitoring (ILM); Appliance Identification; Load Patterns; AEON toolkit; Energy Disaggregation.

Introduction:

Complex algorithms used in digital devices are becoming popular in the context of global digital advancements. Smart energy metering, these days, is an important topic worldwide owing to its growing demand. According to the Federal Energy Regulatory Commission US, the annual smart metering and demand response study shows an yearly growth of approximately 8 million additional smart meters. The annual report, mandated by regulations, includes 2021 smart meter data sourced from the EIA and the Institute for Electric Innovation. The figures from these sources indicate 111.2 million and 115.3 million smart meters, reflecting penetrations of 68.3% and 70.8%, respectively, among a total of 162.8 million metering endpoints in the United States. Additionally, it's noteworthy that the year 2021 marked the sixth consecutive year with an increase of nearly 8 million advanced meters [1]. IoT has seen a surge in its popularity which has increased the interest of many developers to quickly incorporate it in energy metering [2]. The commercial energy metering is advancing relatively slowly as compared to other areas of digital innovation. The absence of comprehensive data on individual appliance energy usage is a significant problem with commercial energy metering nowadays [3]. To prevent energy theft or loss, one must be aware of the energy consumption of their appliances. George Hart came up with the concept in the beginning and had a patent for it in the 1980s [4]. His research demonstrates the analysis of both single-state and multistate appliances, as shown in Figure 1, including freezers and many more [5].

With technological advancements, the nature of load has evolved significantly. It's a challenge not only for the energy disaggregation problem but also for a low maximum demand. In the past, energy disaggregation was simpler because of the less complex energy patterns unlike the modern appliances. Fortunately, sophisticated machine learning models simplify the energy disaggregation problem [6]. Researchers' work in feature engineering equips us with powerful tools to enable the available models to classify more complex patterns. As stated by the famous No Free Lunch Theorem, there is no single exclusive ML strategy that can handle all possible problems better than any other machine learning algorithm [7]. In ML, the most time-consuming process is algorithm and model selection. Machine learning has seen a growth in recent years, resulting in the creation of very effective categorization techniques that help in the selection of models and algorithms.



(a) **(b)**

Figure 1: Classification of Appliances (a) Total Load vs Time graph approach by G. Hart for NILM [5] (b) Segregate appliances by mapping them on Real vs Reactive Plot. Source: G. Hart Patent [4]

The ACS-F2 dataset was selected for this work because of its low sampling rate which is similar to the commercial energy meters and could be easily deployed after the parameters are finalized [8]. This dataset, an improved version of the previously developed ACS-F1 dataset [9] comprises 15 classes, each representing a different appliance, and 15 subclasses for each class representing different manufacturing brands, totaling approximately 225 load signatures of appliances. This dataset consists of two distinct instances: A1 and A2 used for training and testing respectively. The subclasses represent the load signatures of appliances from various manufacturers, allowing for comparisons. The ACS-F2 dataset's appliance signatures are presegregated, and the pre-processed data is then fed into the proposed algorithm, which combines the data into an aggregated dataset, for this study to be implementable [10]. AEON is a toolkit for learning tasks that is specially being used here for TSC [11]. It is compatible with scikit-learn and offers the ability to access the latest algorithms for time series machine learning, and additionally offers an abundance of conventional methods for learning tasks including classification and forecasting [12]. This research focuses on utilizing the models included in AEON toolkit.

Related Work:

Researchers have recently concentrated on categorizing appliances according to their electrical properties, using two main approaches: ILM and NILM. NILM uses larger electrical patterns for categorization, whereas intrusive load monitoring requires direct access to specific appliances for in-depth study [5]. A pivotal figure in the evolution of intelligent load classification is George Hart, who introduced the concept in the 1980s and patented his work in 1989. Hart's approach incorporated a cluster analysis unit to differentiate between various appliances operating simultaneously as illustrated in Figure 2. This marked a significant advancement in load monitoring methodologies, particularly for intrusive approaches [4].

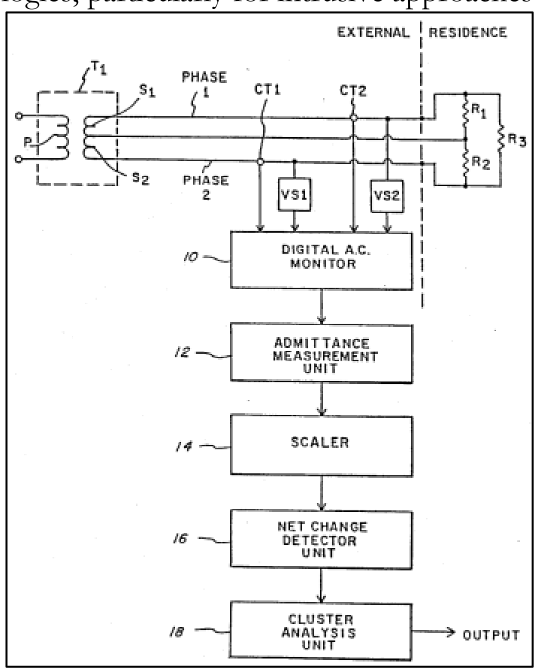


Figure 2: Patented NILM hardware design by George Hart [4]

It's noteworthy that non-intrusive load monitoring technique predates its intrusive counterpart. This method typically involves installing an energy meter at a household's primary supplying point and disaggregating energy consumption through a thorough examination of electrical patterns. The advantages of NILM lie in its holistic approach to understanding energy usage without direct appliance access. NILM has undergone a radical change in the modern environment due to the widespread implementation of smart energy metering and IoT. By leveraging these technologies, aggregated data can be seamlessly transmitted to online servers, where sophisticated algorithms can be applied with minimal difficulty as Ruano, A., et al. [13] presented in their research. This integration enhances the efficiency and accessibility of energy analysis, opening new possibilities for optimizing consumption patterns and enhancing overall energy management strategies. According to Yu, L., et al. [14], A better knowledge of electricity consumption and appliance safety is anticipated from smart home systems, which are anticipated to meet the increasing need for intelligent and energy-saving services. Home appliance power consumption must be measured and tracked in the context of a smart grid, since comprehensive data on power loads becomes essential for demand management and optimization.

NILM's optimization is difficult because of the multiple states of each appliance, erratic consumption patterns, and the difficulties in detecting concurrent appliance consumption. Furthermore, appliances frequently generate distinct waveforms. This complexity and the management of aggregated information create exponential hurdles, as Kelly describes [15]. Furthermore, NILM could be categorized as a pattern recognition problem, employing techniques based on event detection to classify and recognize appliance properties, as shown in Figure 1(b). Algorithmic strategies centered around event detection aim to determine the distinguishing characteristics of particular appliances after identifying important events, hence aiding differentiation and identification [13]. Salihagiü, Kevric, et al. [10] studied the use of sophisticated feature extraction approaches to improve the comprehension of household energy consumption patterns in the context of load categorization using the ACS-F2 dataset of Appliance Consumption Signatures. The study addresses the challenge of predicting appliance states based on historical data and suggests utilizing machine learning algorithms implemented in the WEKA software for effective categorization.

Puente, C., et al. [16] provide a comprehensive overview of techniques for NILM, showcasing their growing importance in energy disaggregation amid the increasing deployment of smart meters employing the well-known UK-DALE dataset [17] and a public dataset of a single house from France [18]. It emphasizes the uses of NILM in Ambient Assisted Living (AAL) and Home Energy Management Systems (HEMS), with a focus on new approaches, emphasizing the significance of determining appliance status for informed decision-making. Additionally, it offers insights into future research directions in these areas, complementing existing NILM reviews. Angelis, G.-F., et al. [19], discussed the distinct energy consumption behavior of electrical appliances, referred to as "load signatures," allowing for four classifications. Lamps and toasters are examples of Type I appliances, which have binary ON/OFF states. Type II equipment, which includes washing machines, has many finite states with distinct patterns. Type-III equipment, such as dimmer lights, have continually fluctuating usage, which makes disaggregation challenging. Finally, Type-IV equipment, such as television receivers, is constantly operating, resulting in specific consumption characteristics. These categories help to understand energy use without requiring further equipment deployment.

Moreover, Kelly, J et.al. [17][20], focused on using deep neural networks to energy disaggregation using the UK-DALE dataset. Salerno, V.M. et.al, employed LSTM, regression networks and denoising autoencoders in their study, surpassing previous methods like combinatorial optimization and factorial hidden Markov models on real aggregate power data from five appliances. Their models demonstrated notable performance on unseen homes. In their work they address the challenges in power disaggregation, highlighting issues with Artificial Neural Networks (ANNs) and Factorial Hidden Markov Models (FHMMs). ANNs demand extensive training and large datasets for optimal performance, while FHMMs face computational burdens and scalability issues [21]. To overcome these, the study suggests employing extreme learning machine technique, utilizing randomly selected hidden units and analytically computed output weights. Results demonstrate its superiority over FHMMs and ANNs on the UK-DALE dataset [17], showing better generalization to new homes and reducing the need for extensive training data. In Section III the methodology to this is explained which includes the dataset preprocessing steps and NILM dataset generation based on the provided combinational formulations. The architecture of the classifier selected is also explained including its feature extraction methods. In Section IV, results and discussion section the results generated from the classifier used and the other available classifiers of the AEON toolkit are listed.

Methodology:

The choice of a high-quality dataset is crucial for successful AI project which influences the subsequent model selection and preprocessing methods. Typically, iterative trial-and-error processes determine the most suitable models and techniques. For this study, the ACS-F2 dataset, which has signatures for the most common daily use appliances and has a low sampling frequency which is similar to that of the commercial energy meters, was selected based on these factors.

Dataset:

For this study, the icosys Institute-owned ACS-F2 opensource dataset [8] was selected. The measurements in this dataset are 2 hours long and are kept in separate files with the labels A1 and A2. There are 15 different appliance kinds and each appliance kind has been sampled from 15 different manufacturers, thus the dataset contains 225 samples for training and an additional 225 samples for testing. Among the electrical variables for classification in the dataset are really power (W), reactive power (var), RMS current (A), frequency (Hz), RMS voltage (V), and phase of voltage relative to current (φ). Among them, real power, reactive power, perceived power, power factor, and RMS current are considered for classification purposes.

The ACS-F1 dataset comprised the following items: microwaves, coffee machines, mobile phones (with battery chargers), LCD TVs, Hi-Fi systems with CD players, laptops, computer stations with monitors, refrigerators and freezers, and printers. More appliances, including fans, kettles, incandescent lights, shavers, and monitors, were added in the second version. There are originally around 360-time steps in each sample for every device in the collection. The total number of samples per appliance is changed after preprocessing, which handles NaN values and performs zero padding to match the sample lengths. Figure 3 shows the algorithm flow, research workflow, and the procedure from dataset preprocessing to the result generation of the trained model.

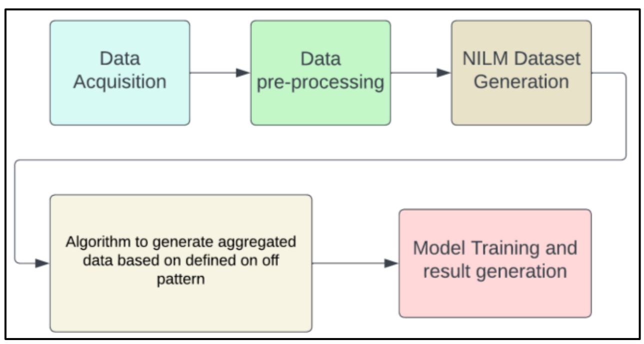


Figure 3: NILM algorithm workflow

Preprocessing:

The dataset is preprocessed to address any discrepancies or missing values before model training and assessment. Among the preprocessing actions are:

- **Extracting Data from Dataset Files:** The dataset is made up of files in different formats. Data extraction from these files is needed to make additional processing and model training easier.
- **Handling Outliers:** Removal of Nan values and other outliers is essential to ensure the authenticity of training results.
- **Padding Values and Interpolation:** The sample size might decrease for certain subclasses due to outlier removal. If deleted values lie between two adjacent ones, they can be substituted with an interpolated value. Also, if the sample counts across subclasses aren't balanced, padding should be applied to minimize impact on the original dataset.
- **Normalization:** To promote model convergence and ensure consistency across features, the dataset is standardized to a uniform scale.

- **Storing Preprocessed Dataset:** The preprocessed dataset is stored separately from the original files. This facilitates efficient model training by reducing the computational overhead.

NILM Dataset Generation:

To train a model for NILM, we combine data from individual appliances using various combinations of appliances for the training and testing data. In this study, four appliances of daily use are selected and controlled by their on/off states using software filters for all relevant electrical parameters during the training session to generate the desired NILM dataset. Amongst the selected four appliances, all of their 15-appliance model categories are included. For this, we apply binary logic to turn on and off all four appliances sequentially and one appliance model from each appliance at a time so in total 16 aggregated classes are generated since, each appliance has 15 different models, turning on and off all 15 models of the same appliance at a time makes the total count of unique aggregated appliance data to be 3375 for classification. Making use of both A1 and A2 instances of data provided the total data instances will be 6750. By applying this logic and generating all aggregated patterns, all possible combinations for anyone using any model of these four appliances are covered. As the dataset lacks apparent power, we calculate it using equation (3,4). This aids in better training of the model by incorporating more relevant features, given the large number of overall classes in this approach.

Real Power is combined using equation (1), where the summation of all powers from different appliances is used in the aggregation of data. Reactive Power using equation (2) reactive power is aggregated directly using the summation of several appliances. Since power factor couldn't be added direclty, its obtained using the relational formula of power which is obtained from equations (1,2,3,4). When all the powers are obtained, the aggregated powerfactor is caluclated using the genral formula from equation (5)

$$P_{total} = \sum_{k=0}^{n} P_k \tag{1}$$

$$Q_{total} = \sum_{k=0}^{n} Q_k \tag{2}$$

$$S_{total} = \sqrt{P_{total} + Q_{total}} \tag{3}$$

$$S_{total} = \sqrt{\left(\sum_{k=0}^{n} P_k\right)^2 + \left(\sum_{k=0}^{n} Q_k\right)^2} \tag{4}$$

$$\Phi_{total} = \frac{\sum_{k=0}^{n} P_k}{\sum_{k=0}^{n} S_k} \tag{5}$$

In Table 1 below, the samples of raw data collected from listed appliances are shown. Each row represents a single timestamp, with measurements recorded for different appliances. One notable aspect observed in the table is the variation in the load characteristics, ranging from predominantly inductive loads to those exhibiting slight capacitive behavior. Accurate load disaggregation and appliance identification in NILM systems depend on an understanding of these distinctions.

Table 1: Samples of Mentioned Appliances

Appliance	Single Sample from Dataset		
	Real Power	**Reactive Power**	**Apparent Power**
Coffee Machine	0.104	-3.226	3.227675944
Fridge	48.551	18.53	51.96691737
Kettles	955.803	-1.035	955.8035604
Laptops	36.115	-13.426	38.52986765

The NILM measurement data for the identical group of appliances shown in Table 1 are reported in Table 2. It is crucial to remember that Table 2 showcases just one of the numerous combinations possible in NILM analysis. In this particular combination, highlighted in green, the characteristics of the two appliances are aggregated, while the other two appliances are turned off, as indicated in gray. Such combinations allow for the examination of various scenarios to better understand the behavior of individual appliances and their collective impact on the overall power consumption profile.

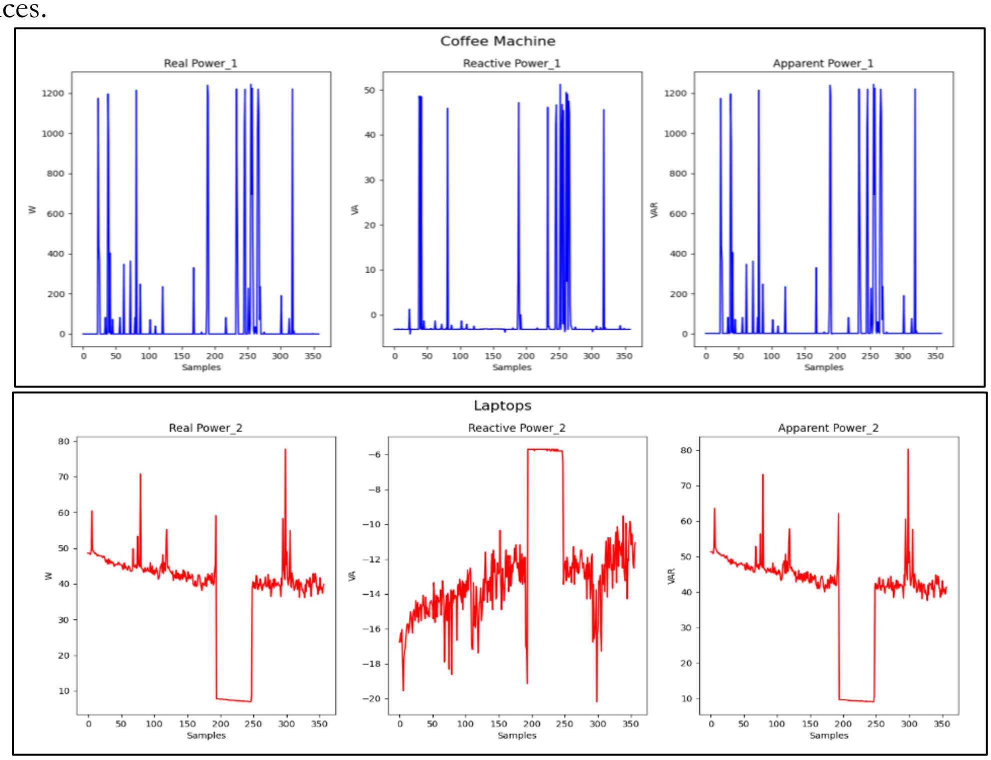
Note: The raw data samples in the table represent measurements recorded at single timestamps for various appliance types. The data for each appliance type is from a certain model of that appliance and doesn't represent the total number of appliance models in that appliance type category. Different load characteristics, such as inductive or capacitive, might affect the overall profile of power consumption. Data collected from [8].

Table 2: New Data Generated Based on NILM Algorithm

Appliance	Data Generated For NILM		
	Real Power	Reactive Power	Apparent Power
Coffee Machine	0.104	-3.226	3.227675944
Fridge	0	0	0
Kettles	0	0	0
Laptops	36.115	-13.426	38.52986765
Total	36.219	-16.652	41.75754359

Note: Table 2 displays measurement values for NILM analysis, representing one of several possible combinations of appliance states. Green highlights denote active appliances, while gray indicates inactive ones. The data presented offers insight into the aggregated characteristics of appliances under different operational scenarios.

The continuous graphical representation of Table 1 and 2 for the Coffee Machine and Laptop including their loads separately is represented in Figure 4. This data represents just one instance among many. Among the listed appliances only one of their models is taken into account, as demonstrated in Table 2. To streamline the process, for this research, an algorithm is developed that's capable of directly aggregating data according to the proposed algorithm and feeding it to the model without additional processing or storage requirements as shown in Figure 5. Through this approach, we anticipate generating 6750 unique combinations of aggregated appliances.



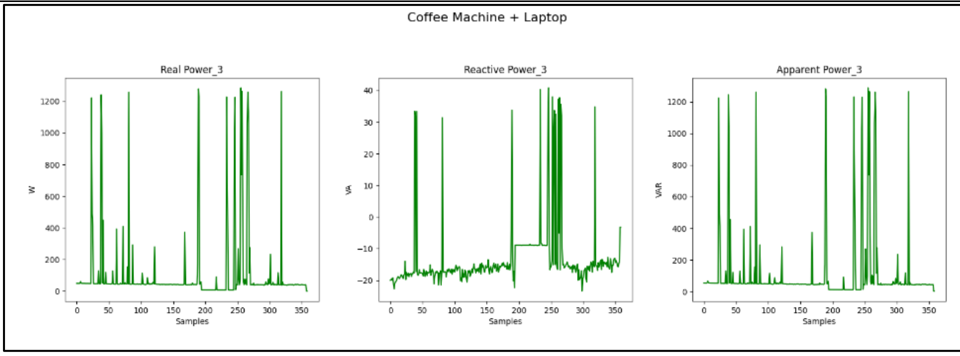


Figure 4: Appliance Load Combinational Graphs

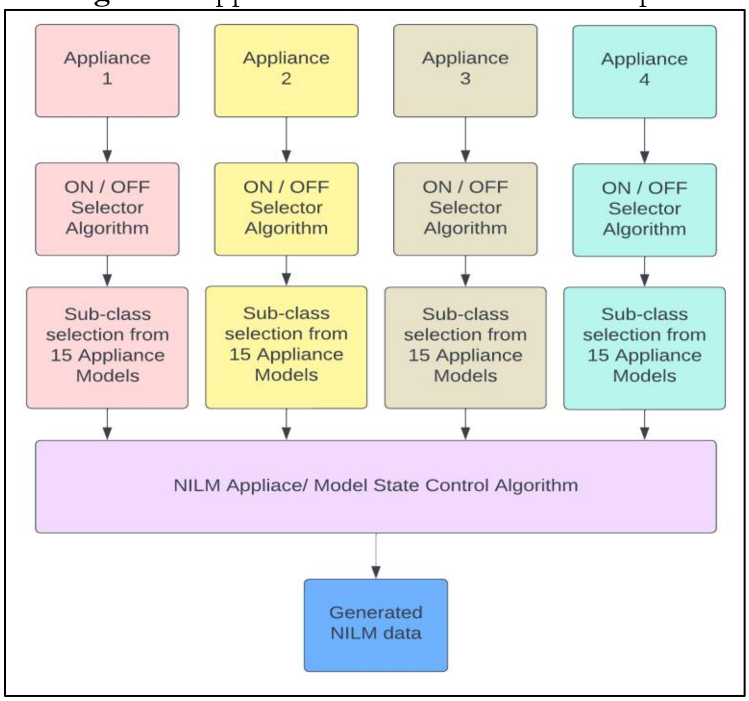


Figure 5: Auto appliance on/off algorithm for training of NILM system

Models from AEON Toolkit:

Designed to make machine learning research and testing easier, the AEON toolkit [11] is a flexible python package. Time series analysis, picture classification, and other techniques are supported by AEON, which provides a large selection of models and algorithms. Both practitioners and researchers may easily investigate and use cutting-edge machine learning techniques. Research in a variety of areas, including data analysis, pattern recognition, and beyond, benefits greatly from the use of AEON because of its versatile and strong capabilities.

The models utilized in this research comprise those found in the AEON toolkit [11], which offers a variety of models for different approaches. However, for this research, only the time series classification models are considered. The types of classification techniques used by models in the AEON toolkit are listed below:

- Feature Based
- Convolution Based
- Distance Based
- Interval Based
- Shapelet Based

Carl H. Lubba et al. [22] utilized 7700 features from the HCTSA feature extractor. After filtering the raw HCTSA features and applying a threshold to their calculated p-values through classification problems, the feature count was reduced to 4791. These filtered features underwent additional classification tasks, and by arranging them according to their accuracies and applying a threshold value, the top-performing 22 features were identified, resulting in the creation of the CATCH22 Classifier. The feature extraction process for CATCH22 is summarized in Figure 6.

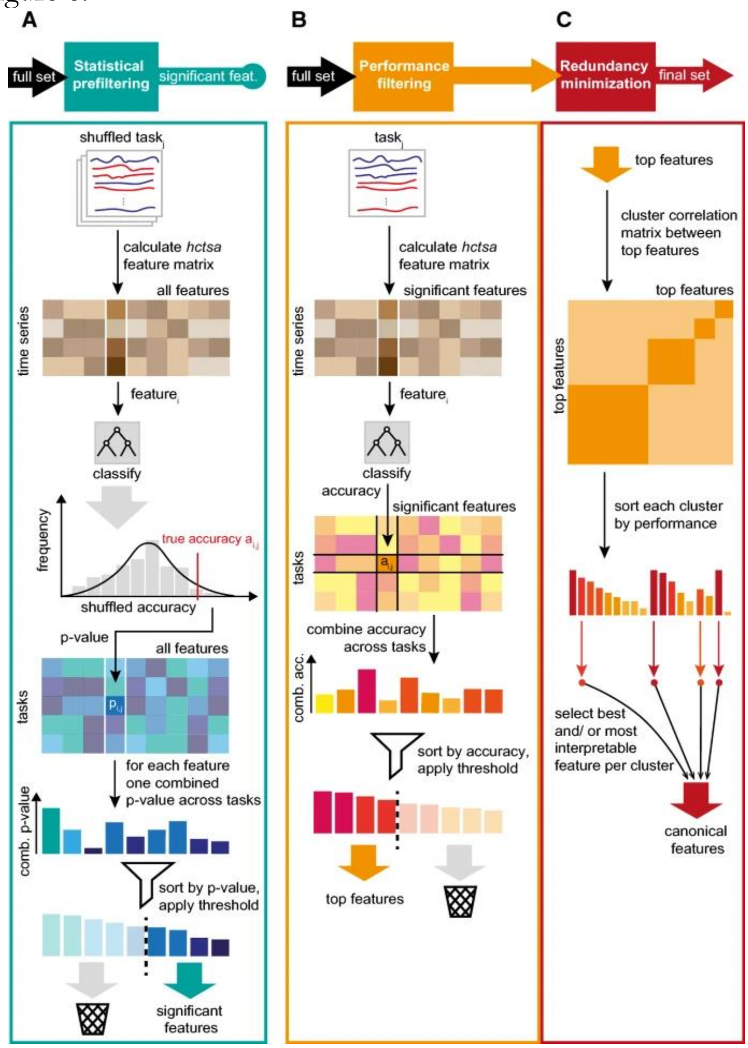


Figure 6: Process of CATCH22 feature selection [22]

Utilizing these techniques researchers have developed and modified numerous models some of them tested for this research are; the CATCH22 Classifier (Canonical Time-series Characteristics) [22], ROCKET Classifier (Random Convolutional Kernel Transform) [23], Signature Classifier, Arsenal Classifier [12], Supervised Time Series Forest Classifier, Time Series Forest Classifier, Canonical Interval Forest Classifier [24], K Neighbor Time Series Classifier [25], RDST Classifier (Random Dilated Shapelet Transform) [26], CATCH22 [22], an acronym for CAnonical Time-series CHaracteristics is a very efficient classifier for efficiently classifying time series data. The working principle of CATCH22 mostly revolves around the selection of best-performing features from the Highly comparative time-series analysis (HCTSA) [27]. MATLAB toolbox. This toolbox has the capability of extracting a massive number of features. Its total capacity consists of over 7700 features in which each feature has a unique scientific formulation.

These finalized 22 features are computationally less expensive than the total 7700 features of HCTSA. The CATCH22 features computationally take around 0.5sec for a total of 10,000 samples which is comparably 1000 times faster than the total computation of HCTSA from MATLAB. These extracted features are then fed into a chosen classifier. CATCH22 itself is not a model but rather it's a feature extraction method. Its 22 features are extracted from the input time series data and after the transformation is applied to the data the CATCH22 Classifier, which is a wrapper provided with the Canonical feature extraction method, uses the random forest classifier from scikit-learn.

Results and Discussion:

The ACS-F2 dataset was utilized to create a NILM dataset specifically for this study, focusing on four selected appliances of our daily use, mimicking real-world scenarios where multiple appliances may be in use concurrently. Each appliance in the ACS-F2 dataset encompasses data from 15 different models from various manufacturers, providing a diverse range of appliance characteristics. The selection of the ACS-F2 dataset was driven by its low-frequency sampling, which aligns with the sampling frequency of many commercial energy meters. This compatibility ensures that the generated NILM dataset closely resembles real-world energy consumption patterns. The confusion matrix for CATCH22 on the test aggregated dataset can be seen in Figure 7.

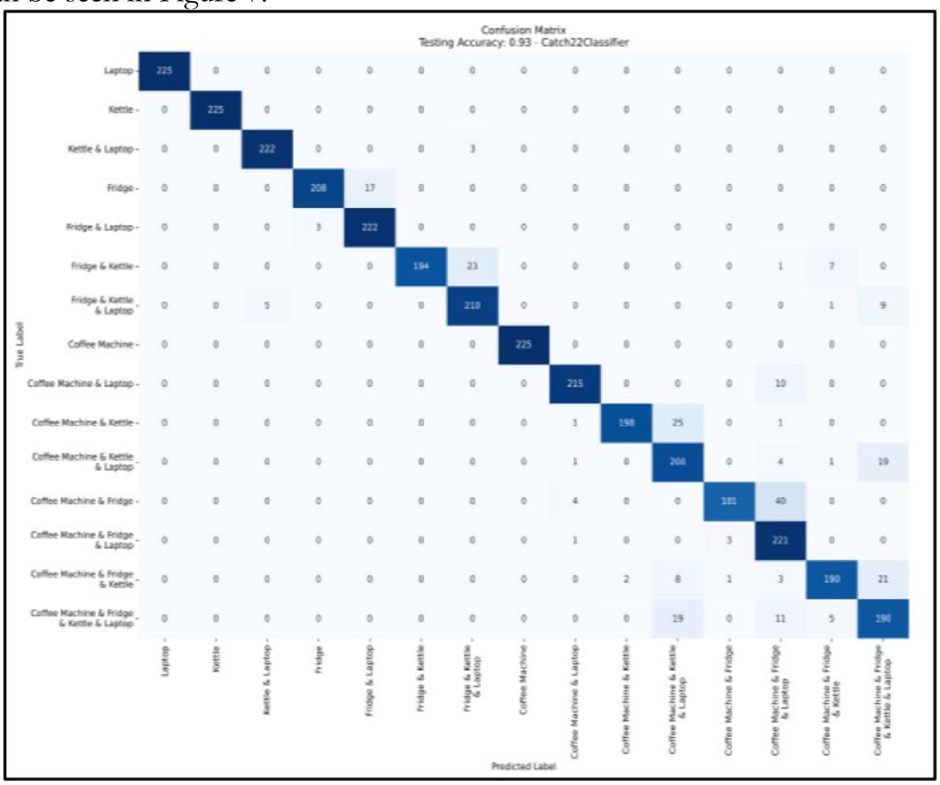


Figure 7: Confusion Matrix for CATCH22 Classifier

Table 3: Performance Comparison Table

CLASSIFIER	COMPUTED RESULTS			
	ACCURACY	F1 SCORE	PRECISION	RECALL
ROCKET	0.85	0.86	0.87	0.86
Arsenal	0.86	0.85	0.86	0.85
CATCH22	**0.92**	**0.92**	**0.93**	**0.92**
Signature	0.73	0.73	0.76	0.73
KNeighbours Time Series	0.58	0.57	0.62	0.58
Canonical Interval Forest	0.84	0.85	0.86	0.84
Supervised Time Series	0.57	0.5	0.53	0.57
Time Forest Classifier	0.73	0.73	0.77	0.73

Note: These values were obtained from the test set

A set of machine learning classifiers were utilized in this study making use of best best-performing time series classifier. Amongst all listed Classifiers the CATCH22 classifier outperformed all of the other ones. That's because of its operational methodology of extracting the best performing 22 features which results in its exceptional performance. The accuracy for the total of 3375 test samples of aggregated data comes out to be 92.1%. The precision, recall, and F1 score being 93%, 92%, and 92% respectively. The performance comparisons for the different models benchmarked on the proposed NILM dataset are included in Table 3.

Conclusion:

To summarize, this study on Energy Disaggregation has significantly addressed the technology gap between energy generation and consumption. It not only gauged state-of-the-art algorithms essential for implementing NILM but also pioneered a unique framework for generating aggregated appliance electrical patterns using disaggregated appliance data from the ACS-F2 dataset. The CATCH22 Classifier has been effectively implemented for Energy Disaggregation using the proposed dataset, achieving a staggering accuracy of 92% on the test set. This approach is the first of its kind on the ACS-F2 dataset as per our knowledge. The significance of this research lies in the compatibility of the dataset's sampling frequency with that of commercially used energy meters, ranging from 1 Hz to 10 Hz. Moreover, by utilizing disaggregated signals from appliances, it could become feasible to analyze their electrical or mechanical health in the future to enable predictive maintenance. This study concludes by demonstrating how successfully the proposed data generation methodology and the CATCH22 classifier can be used together for NILM. The study emphasizes the usefulness of NILM in situations found in the real world, highlighting their effectiveness and possible influence on energy management strategies.

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