Insert the Project Title here

Project Number: **3102**

Project Report

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Abstract

With the growing adoption of smart meters and the demand for efficient energy use, identifying household appliances from aggregate electricity data has become increasingly valuable. This project presents a NILM-based system that recognizes active devices using only a single smart meter, without the need for per-device sensors.

The system aims to detect and classify appliances based on unique electrical consumption signatures. The process begins with event detection through edge-based algorithms to identify power transitions. Features are then extracted and clustered using the DBSCAN algorithm, which groups data points based on density in feature space. When a new, unknown device cluster is detected, the system prompts the user to identify the device, allowing adaptive learning over time.

The full decision process is illustrated in the block diagram below:

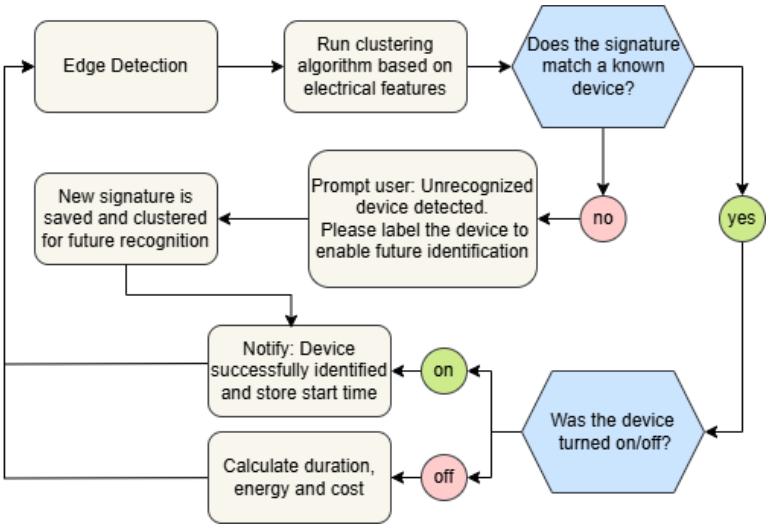


Figure 1: Block diagram

Implemented in Python, the system includes a real-time user interface that displays active devices, sends alerts when new devices are detected, and visualizes energy consumption trends. Testing on real-world household data has shown classification accuracies exceeding 90% for major appliances, with response times under five seconds from data acquisition to user notification.

1 Introduction

1.1 The goals of the project

The primary goal of this project is to develop a system for Non-Intrusive Load Monitoring (NILM) that can accurately identify and classify electrical appliances operating in a household using only aggregate power consumption data measured at a single point — the smart meter. The system aims to achieve:

- Accurate detection of device on/off events.
- Classification of appliances based on their electrical signatures.
- Real-time performance with minimal delay between data acquisition and decision-making.
- Adaptive learning capability to improve accuracy over time and recognize new devices.
- A lightweight implementation that is scalable and compatible with existing smart infrastructure.

Ultimately, the project strives to contribute to energy efficiency, user awareness, and smarter grid management by enabling detailed insights into energy usage without the need for expensive and invasive hardware setups.

1.2 Motivation

Electricity consumption in residential settings has increased dramatically in recent years due to the proliferation of electrical devices and growing reliance on home automation. Smart meters have been widely adopted to measure overall consumption, yet most users and utility companies lack visibility into which specific devices are responsible for that consumption. This lack of granularity hinders efforts to:

- Identify energy-inefficient or faulty appliances.
- Optimize power usage habits.
- Detect unusual or anomalous activity, including safety-critical situations.
- Enable real-time feedback and demand response in smart grids.

Installing sensors on each appliance to monitor individual usage — known as Intrusive Load Monitoring (ILM) — is costly, complex, and not feasible in most real-world settings. NILM offers a promising alternative: by analyzing patterns in total household electricity consumption, it is possible to infer which devices are active at any given time. This project leverages that principle, combining signal processing and machine learning to create an intelligent, low-cost solution for real-time appliance recognition.

1.3 The approach to solving the problem

The proposed NILM system follows a structured pipeline to analyze electrical data and derive meaningful device-level insights:

1. Data Acquisition – The system receives real-time voltage and current measurements from a smart meter, typically in CSV or MDB format. These values represent the total load at a single point of measurement.
2. Preprocessing – Raw signals undergo filtering, normalization, and noise reduction. This step ensures data quality and consistency for downstream analysis.
3. Event Detection – The system uses an edge detection algorithm to identify sudden transitions in power consumption, corresponding to device activation or deactivation.
4. Feature Extraction – For each event, a set of features is extracted (e.g., power delta, harmonic content, reactive power, THD, K-factor). These features serve as the unique electrical signature of each device.
5. Clustering – A DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm groups similar event signatures into clusters, each representing a known device or class of behavior. New, unrecognized clusters are flagged as potentially new devices.
6. User Interaction – When a new signature is detected, the user is prompted to label the device. This enables future automatic recognition and supports adaptive learning.
7. Classification – Once a device is known, the system automatically identifies future occurrences based on similarity to stored clusters.

8. Energy Analysis – For each detected device, the system calculates on-time, energy consumption, and estimated cost. These values can be used for behavioral insights or anomaly detection.
9. Interface and Feedback – A web-based interface displays real-time information, alerts the user when new or unexpected devices appear, and summarizes usage patterns.

1.4 Comparison against existing work and algorithms / implementations on the topic

Traditional NILM systems are typically divided into three main categories: pattern matching, source separation, and machine learning-based approaches.

Pattern Matching methods rely on comparing real-time measurements to pre-recorded signatures stored in a database. While efficient, they require prior knowledge of all device signatures and are sensitive to changes in appliance behavior.

Source Separation techniques, such as Non-Negative Matrix Factorization (NMF) or Sparse Coding, attempt to mathematically decompose aggregate signals into individual sources. These approaches often require high-resolution waveform data and are computationally expensive.

Machine Learning-Based Methods have emerged as a powerful alternative. Supervised models like Support Vector Machines (SVM), Decision Trees, and Neural Networks (e.g., LSTM, CNN) offer strong classification capabilities, especially when large labeled datasets are available. However, they often struggle with generalization to unseen devices and require significant training effort.

This project introduces a hybrid approach that blends unsupervised clustering (DBSCAN) with supervised classification for recognized devices. This architecture has several advantages:

No need for labeled training data in early stages – DBSCAN can identify structure in unlabeled data, making the system deployable from day one.

Scalability and adaptability – The system grows its knowledge base over time as more devices are encountered and labeled.
Robust to noise and variability – DBSCAN handles noisy data and varying usage patterns better than many supervised-only methods.
Efficient in real time – Feature-based analysis allows fast processing, making the system suitable for real-time deployment.
Compared to many published NILM systems, our solution offers a practical balance between performance, usability, and implementation complexity. It is tailored to real-world deployment in residential environments with minimal setup, making it both accessible and impactful.

2 Theoretical background

2.1 Non-Intrusive Load Monitoring (NILM)

Non-Intrusive Load Monitoring (NILM) is an advanced approach for identifying and monitoring the energy consumption of individual electrical appliances in a household using only aggregated data from a single measurement point — typically a smart meter. Unlike intrusive methods (ILM) that require sensors to be installed on each device, NILM leverages sophisticated algorithms to decompose the total energy signal into its constituent device-level components without any additional hardware.

2.1.1 Background and Importance

The past decade has seen a surge in global electricity consumption, driven by increased use of electrical devices and the proliferation of smart homes. Studies show that residential and commercial buildings account for up to 25% and 36% of total electricity consumption, respectively, in regions like the United States and the European Union. Efficient energy management is therefore a key priority, both for reducing costs and for environmental sustainability.

NILM offers a compelling solution: by analyzing changes in voltage and current waveforms at the aggregate level, it identifies when specific devices switch on or off and estimates their power usage. This capability provides valuable insights for consumers looking to optimize their energy habits and for utilities seeking to enhance grid stability.

2.1.2 NILM Approaches

Non-Intrusive Load Monitoring (NILM) methods can be classified into three main categories, each offering unique strengths and facing distinct challenges:

1. **Machine Learning (ML):**
   This approach relies on training algorithms with large labeled datasets to classify electrical events and devices. ML techniques include supervised models such as Decision Trees, Convolutional Neural

Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Hidden Markov Models (HMMs). These models excel at capturing complex patterns and generalizing to different devices but require significant training data and computational resources.

2. **Pattern Matching (PM):**
   This approach leverages pre-recorded device signatures stored in a database. Algorithms compare real-time power measurements to these signatures to identify devices. Common techniques include Graph Signal Processing (GSP), Dynamic Time Warping (DTW), and Multi-Variance Matching (MVM). Pattern matching is computationally efficient but depends on high-quality, consistent signatures and can be less accurate in dynamic or noisy environments.
3. **Source Separation (SS):**
   This category includes techniques like Non-Negative Matrix Factorization (NMF), Independent Component Analysis (ICA), and Sparse Component Analysis (SCA) that decompose aggregate power signals into individual components. SS methods can separate mixed signals without prior training, but they often require high-resolution data and strong statistical assumptions.

The diagram below illustrates the taxonomy of these NILM approaches:

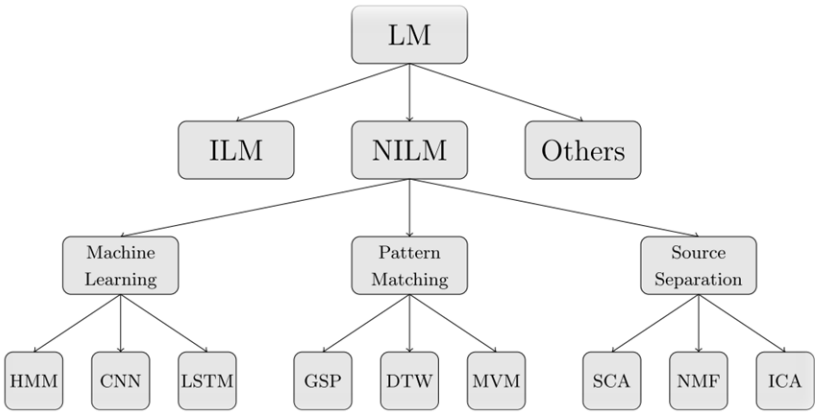


Figure 2: Taxonomy of Load Monitoring Techniques with Focus on NILM

2.1.3 Concept and Operation

NILM works by capturing the overall current and voltage at the main service entrance, where all household appliances draw power from the same circuit. Each device, when activated, generates a unique electrical signature — a pattern in the power signal that can be identified using advanced algorithms. These signatures can be characterized by parameters such as steady-state power, transient features (e.g., harmonics, total harmonic distortion, and K-factor), and statistical features.

The NILM system then processes this aggregate signal using signal processing techniques and machine learning models to detect events (e.g., device turn-on or turn-off) and to classify each appliance based on its signature. The process typically involves:

1. **Data Acquisition:** Collecting voltage and current measurements at a high sampling rate.
2. **Preprocessing:** Filtering and normalizing data to reduce noise and prepare for analysis.
3. **Event Detection:** Using methods such as edge detection to identify changes in power consumption.
4. **Feature Extraction:** Extracting device-specific features to build a unique signature for each event.
5. **Disaggregation:** Applying algorithms like clustering (e.g., DBSCAN) or classification (e.g., Decision Trees, CNN, LSTM) to separate the aggregate signal into individual appliance contributions.
6. **Post-processing:** Refining results, validating detections, and generating user-friendly outputs.

2.1.4 Device Categories

Understanding the different types of devices in a household is critical for effective NILM. Devices can be classified based on their power consumption patterns and operational behavior:

1. **Single-State Devices:**

   These devices have only one operational mode: either fully on or off.

Examples include light bulbs or simple heaters. Their power signature is characterized by a single, constant level.

2. **Multi-State Devices:**
   These devices operate in multiple discrete modes, each with a different power level. Examples include washing machines or microwave ovens that cycle between different power states during operation.
3. **Continuous-State Devices:**
   These devices vary their power consumption continuously over time. Examples include dimmable lights, variable-speed fans, or HVAC systems. Their power signatures are more complex and require more sophisticated detection methods.
4. **Always-On Devices:**
   These devices consume power constantly, even when not in active use. Examples include smoke detectors, routers, or standby electronics. They typically exhibit low and constant power levels.
5. **Non-Linear Devices:**
   These devices show large, unpredictable fluctuations in their power usage. Examples include computers and some consumer electronics, which have highly variable loads due to their internal operations.

The figures below illustrate these device categories based on their power consumption patterns:

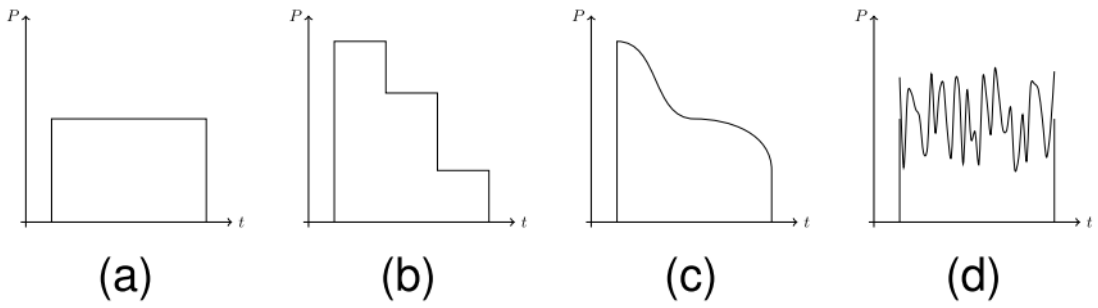


Figure 3: Device Types with Different Operational Behaviour (a) One-State Devices (b) Multi-State Devices (c) Continuous-State Devices (d) Non-Linear Devices

2.1.5 Advantages and Applications

NILM is especially attractive due to its low installation cost, since it uses existing smart meter infrastructure. It preserves user privacy by avoiding direct measurement at each appliance, and it is easily scalable for widespread deployment. Applications include:

1. **Residential Energy Monitoring:** Helping users understand their consumption patterns and identify inefficient devices.
2. **Smart Grids:** Enabling utilities to better manage demand and supply, reduce peak loads, and plan maintenance.
3. **Fault Detection:** Identifying device malfunctions based on deviations from expected signatures.
4. **Energy Efficiency Programs:** Providing data-driven insights for targeted energy savings.

2.1.6 Comparison with ILM and Other Methods

Intrusive Load Monitoring (ILM) involves placing sensors on each device, which guarantees precise measurements but is costly and complex to implement, especially in existing buildings. NILM, by contrast, requires only a single measurement point, making it more practical and cost-effective.

Alternative approaches to NILM include:

1. **Pattern Matching:** Relies on pre-existing device signature libraries, but requires extensive prior knowledge and struggles with device variability.
2. **Source Separation:** Uses methods like Non-Negative Matrix Factorization (NMF) to mathematically decompose signals but can be computationally demanding.
3. **Machine Learning:** Leverages supervised models (e.g., SVMs, Decision Trees, CNNs, RNNs, LSTMs) trained on labeled datasets to classify devices; however, it requires substantial training data and may overfit to specific usage patterns.

2.2 Power System Basics

2.2.1 Single-Phase vs. Three-Phase Systems

In residential and commercial buildings, electricity is typically supplied in either single-phase or three-phase systems:

1. **Single-Phase Systems:** Most homes use single-phase power, where a single alternating voltage supplies the household appliances. This configuration is straightforward but can become unbalanced when multiple high-power devices operate simultaneously.
2. **Three-Phase Systems:** Common in commercial or industrial buildings, three-phase systems distribute electrical loads more evenly across three wires, reducing voltage drops and improving system efficiency. In Israel and much of Europe, three-phase connections are increasingly common in larger homes and apartment complexes, especially where high-power devices like air conditioners and ovens are used.

2.2.2 Power Factor and Harmonics

1. **Power Factor:** Power factor is the ratio of active power to apparent power in an AC system:

$$PF = \frac{P}{S}$$

Equation 1: Power Factor

where P is the active power (kW) and S is the apparent power (kVA).

A low power factor indicates inefficient power use, often due to inductive loads. Devices with low power factors (e.g., motors, fluorescent lights) can cause significant phase shifts, which impact device signatures and complicate event detection.

2. **Harmonics:** Harmonics are voltage or current waveforms that are multiples of the fundamental frequency (50 Hz in Europe, including Israel). Nonlinear devices (e.g., computers, LED drivers) introduce harmonics that distort the electrical signal, leading to:

- Higher THD.
- Increased heating in conductors.
- Potential interference with other devices.

NILM systems rely on harmonic features (e.g., THD, K-Factor) to differentiate devices, but they also need to handle harmonic distortion to maintain accuracy in classification.

2.3 Feature Extraction: Electrical Signatures

Effective device classification in NILM systems relies on extracting meaningful electrical features that characterize each appliance's behavior. The following key features are commonly used in NILM research and practice:

2.3.1 Active Power (kW)

Active power represents the real energy consumed by a device to perform its intended function. It is calculated as:

$$P = V_{RMS} \cdot I_{RMS} \cdot \cos(\phi)$$

Equation 2: Active Power

Where V_{RMS} is the root-mean-square voltage, I_{RMS} is the root-mean-square current and ϕ is the phase angle between voltage and current.

This feature is particularly useful for distinguishing devices with distinct power levels (e.g., LED light vs. electric oven).

2.3.2 Reactive Power (kVAR)

Reactive power quantifies the energy alternately stored and released by inductive or capacitive components in a device (e.g., motors, transformers). It is given by:

$$Q = V_{RMS} \cdot I_{RMS} \cdot \sin(\phi)$$

Equation 3: Reactive Power

Devices like air conditioners and refrigerators typically exhibit higher reactive power than purely resistive devices like heaters.

2.3.3 Harmonic Distortion (THD)

Total Harmonic Distortion measures the presence of high-frequency distortions in the current waveform, often caused by nonlinear loads such as switching power supplies. It is defined as:

$$THD = \frac{\sqrt{\sum_{n=2}^{\infty} {I_n}^2}}{I_1}$$

Equation 4: Harmonic Distortion

where I_n is the RMS current of the nth harmonic, and I_1 is the RMS current of the fundamental frequency.

High THD values are indicative of devices with electronic switching components, such as computers or LED drivers.

2.3.4 K-Factor

The K-Factor quantifies the heating effect of harmonics on electrical equipment. It is calculated as a weighted sum of the RMS currents of each harmonic:

$$K - Factor = \sum_{n=1}^{\infty} \left(\frac{I_n}{I_1}\right)^2 \cdot n^2$$

Equation 5: K-Factor

A high K-Factor suggests the device may cause excessive heating in transformers and wiring, making it a key feature for classifying electronic devices.

2.3.5 Voltage and Current Waveforms

Examining the shape of voltage and current waveforms helps identify transient behaviors and signature patterns unique to each device. For example, devices with motors may show distinctive inrush currents during startup, while resistive devices maintain a steady waveform.

By extracting and combining these features, NILM systems can build unique electrical signatures that allow accurate classification and monitoring of household appliances.

2.4 DBSCAN

DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is a widely used unsupervised clustering algorithm that groups together data points that are closely packed in space while marking points in low-density regions as outliers (noise). It is particularly well-suited for applications where clusters may have arbitrary shapes, and where prior knowledge of the number of clusters is unavailable - making it an ideal choice for real-world datasets in NILM where device signatures may vary significantly and overlap in complex ways.

2.4.1 Key Concepts

DBSCAN operates based on two key parameters:

1. **ε (epsilon):** Defines the radius of a neighborhood around a point. If enough points (defined by the parameter minPts) fall within this radius, the point is considered part of a cluster.
2. **minPts:** The minimum number of points required to form a dense region (core point).

Using these parameters, DBSCAN classifies each point as one of:

1. **Core Point:** Has at least minPts points within its ε-neighborhood.
2. **Border Point:** Has fewer than minPts neighbors within ε, but is within the neighborhood of a core point.
3. **Noise Point:** Neither a core point nor a border point; considered an outlier.

2.4.2 Advantages

1. **No Need to Specify Number of Clusters:** Unlike k-means, DBSCAN does not require knowing the number of clusters in advance.
2. **Handles Arbitrary Shapes:** Can find clusters of various shapes and sizes, which is essential in NILM where device signatures might not follow simple geometries.
3. **Robust to Noise:** Automatically identifies points in low-density areas as outliers.

2.4.3 Challenges

1. **Parameter Sensitivity:** The choice of ε and minPts can significantly impact results. Parameter tuning may be required depending on the density of data.
2. **Varying Densities:** DBSCAN struggles when clusters have widely varying densities, as a single ε may not be appropriate for all clusters.

2.4.4 Application in NILM

In NILM, DBSCAN is particularly useful in the feature clustering stage. After feature extraction, each appliance event is represented as a point in feature space (e.g., with dimensions for power change, duration, and harmonics). DBSCAN clusters similar events, effectively grouping device signatures together and labeling high-density areas as known devices. When a new cluster emerges, it can be flagged as an unknown device, prompting user interaction for labeling and adaptive learning.

This clustering step enhances the system's ability to:

1. Identify new devices dynamically.
2. Separate known device signatures from noise or ambiguous events.
3. Handle the complex, overlapping patterns typical of household appliance power signatures.

By leveraging DBSCAN's density-based approach, the NILM system achieves a flexible and adaptive clustering strategy that is both computationally efficient and robust to noise - essential qualities for real-time, scalable NILM applications.

3 Simulation

The NILM system was developed and tested using real-world electrical consumption data provided by our mentor. The data was collected from a smart meter and saved in MDB and CSV formats. All processing was implemented in Python, using libraries such as pandas, numpy, scikit-learn, and matplotlib. The simulation environment replicates the core algorithmic pipeline: edge detection, feature extraction, DBSCAN clustering, and device classification. Simulation tests were performed on several days of smart meter data to evaluate both the accuracy and usability of the system.

3.1 Edge Detection

The first stage of the simulation involved detecting edges in the active power (P) and current (I) signals, indicating moments when devices were turned on or off.

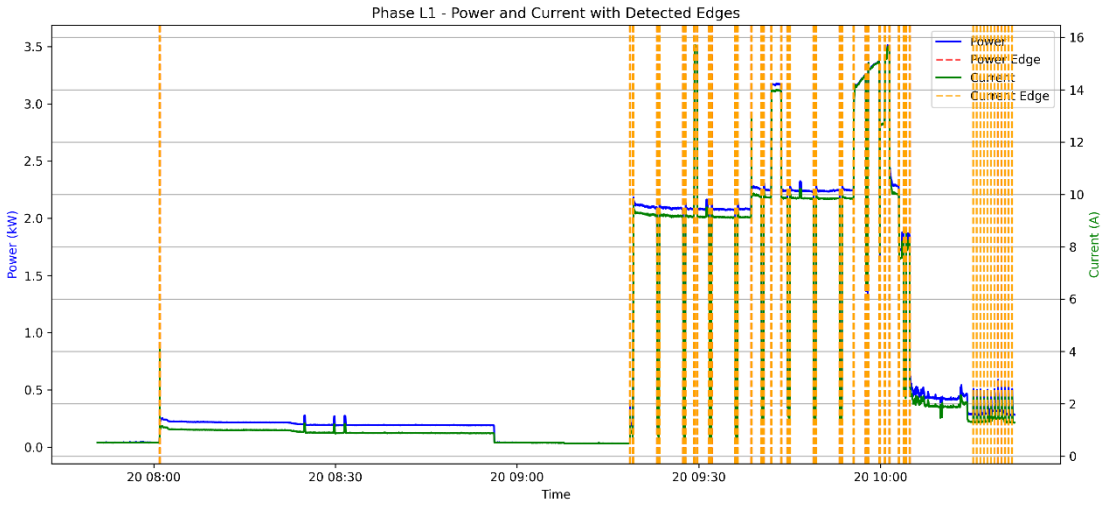


Figure 4: Edge Detection on Current (I) and Active Power (P) vs. Time for phase 1

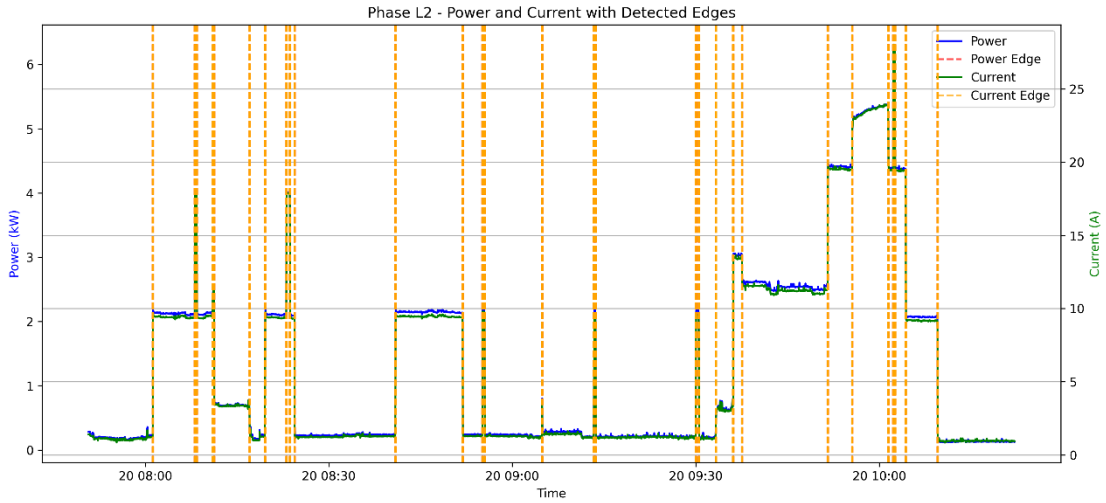


Figure 5: Edge Detection on Current (I) and Active Power (P) vs. Time for phase 2

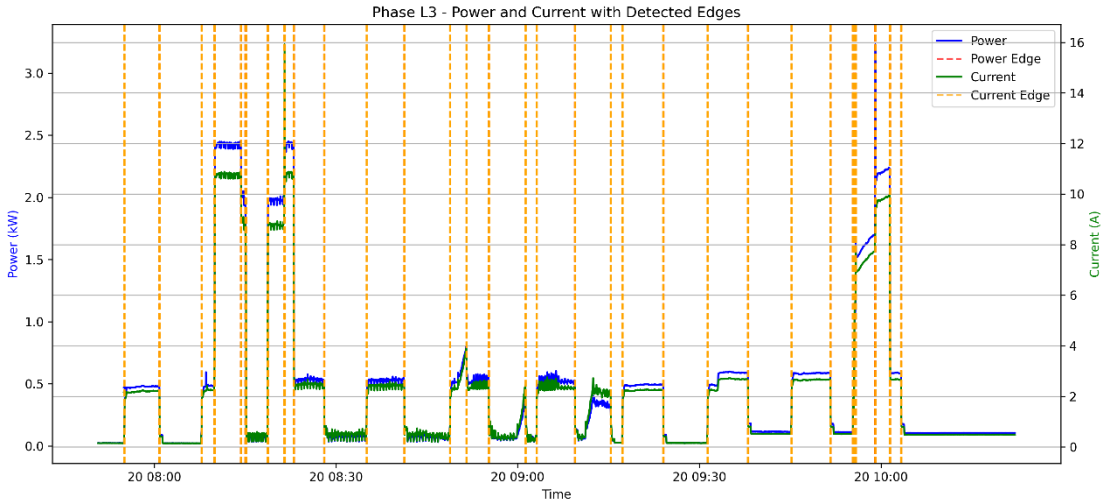


Figure 6: Edge Detection on Current (I) and Active Power (P) vs. Time for phase 3

These edges served as the anchor points for subsequent feature extraction and clustering. Each jump was further analyzed to extract ΔP, ΔQ, and Δt.

3.2 Waveform Patterns

Visual inspection of the raw power and current waveforms revealed characteristic patterns associated with specific appliances.

For example, **Figure 7** shows the repetitive signature of an air conditioner: a consistent rectangular waveform with distinct ON/OFF cycles. These clear and repeating power draws helped us associate these segments with the air conditioner and served as a ground truth reference when validating clustering and classification results.

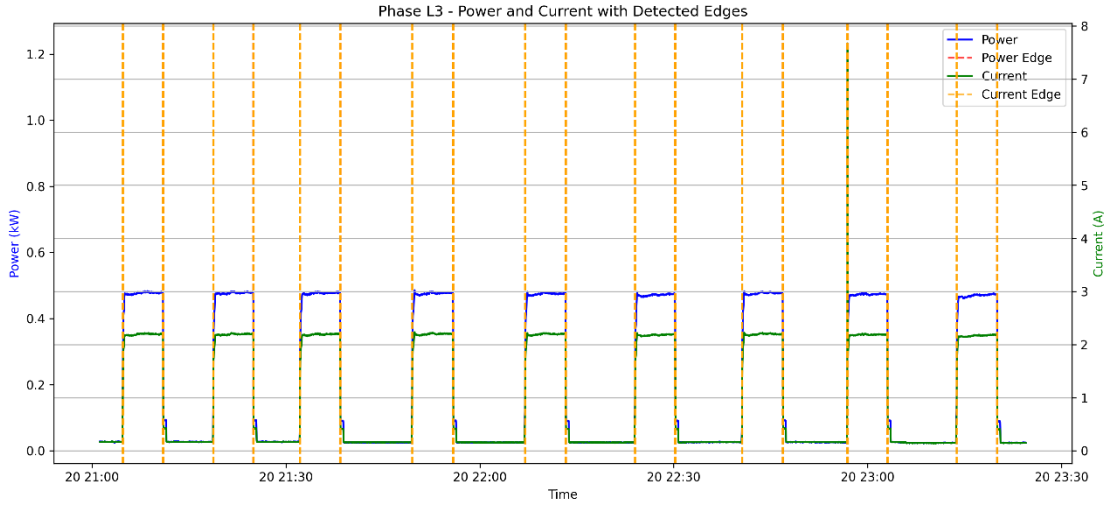


Figure 7: Repeating waveform pattern for an air conditioner in Phase 2

3.3 DBSCAN Clustering Results

Once features were extracted for each detected event, they were fed into the DBSCAN clustering algorithm. The resulting clusters were visualized in two dimensions using ΔP and ΔQ as axes. Clusters that corresponded to known devices (previously labeled) were marked accordingly, while unknown events appeared as noise points or formed new, distinct clusters.

Once features were extracted for each detected event, they were fed into the DBSCAN clustering algorithm. The resulting clusters were visualized in two dimensions using ΔP and ΔQ as axes. Clusters that corresponded to known devices (previously labeled) were marked accordingly,

while unknown events appeared as noise points or formed distinct new clusters. To enhance classification accuracy, a cluster-wise refinement step was applied: if a single device label was predominant within a cluster, that label was propagated to all events in the cluster. This approach reduced misclassifications caused by local ambiguities and strengthened the overall identification consistency.

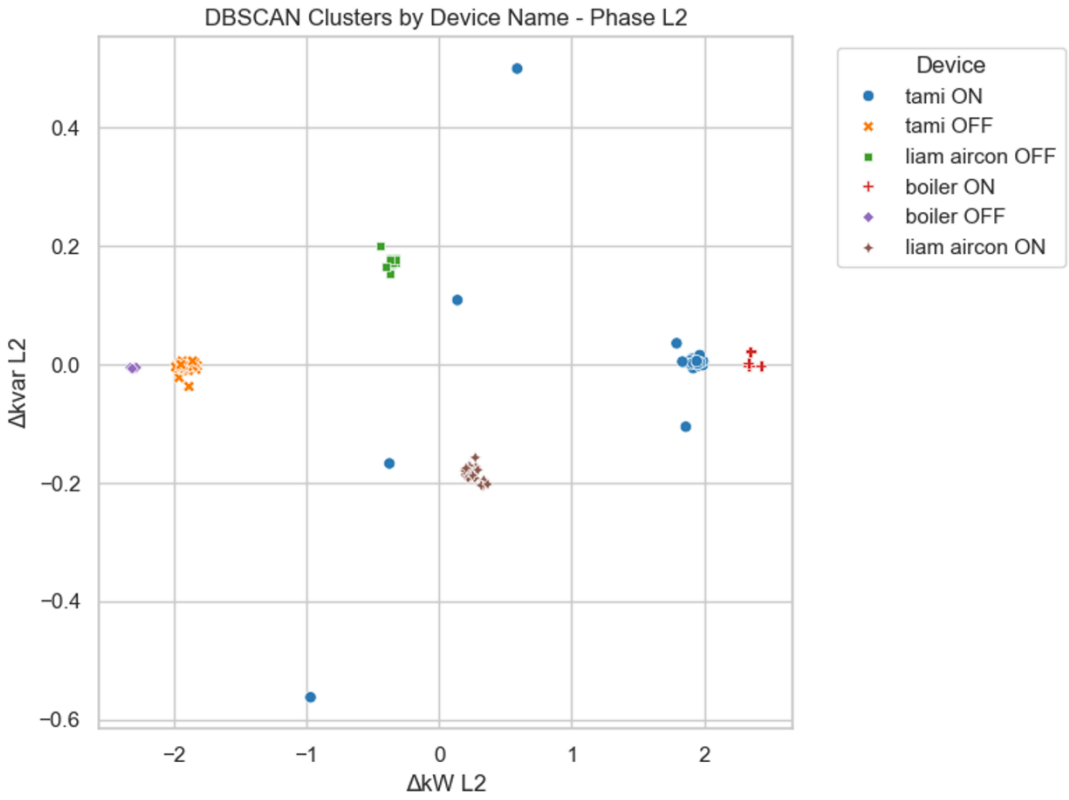
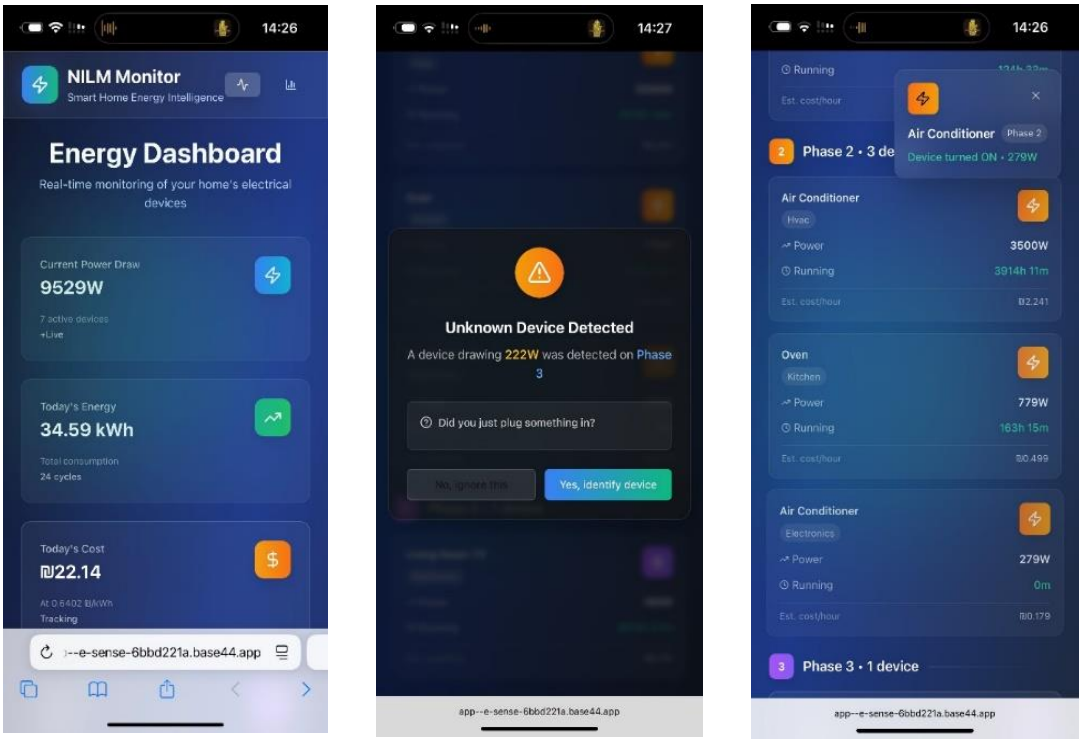


Figure 8: 2D DBSCAN Clustering of Detected Events

3.4 User Interface

The system also includes a lightweight user interface for monitoring events and labeling unknown devices. The interface displays real-time alerts when new devices are detected, shows which devices are currently active, and summarizes usage duration and estimated energy cost.

To enable live testing and demonstration, the interface runs a simulation based on real detected events, using the Excel file generated by our classification script. This allows users to experience the system's behavior in real-time, even outside of a live deployment environment.



(9A) (9B) (9C)

Figure 9: (A-C): Real-Time User Interface with Device List and Notifications

This component helps close the loop between the algorithm and the user, enabling adaptive learning and improving classification accuracy over time.

The interface is available online at: https://app--e-sense-6bbd221a.base44.app

4 Implementation

This project focuses exclusively on the implementation of a NILM (Non-Intrusive Load Monitoring) algorithm. The goal is to identify household electrical appliances based on their unique power consumption signatures using only aggregated electrical data. The hardware components, including the smart meter and the data logging setup, were provided externally and were not part of the project scope.

Our implementation processes smart meter data that was pre-collected and made available in the form of MDB or CSV files. The algorithm pipeline performs event detection, feature extraction, clustering using DBSCAN, and device classification through user labeling and adaptive learning.

To better understand the position of our algorithm within the overall system, Figure 10 presents a high-level diagram. The section inside the blue area-representing the electrical environment and data acquisition via smart meters-was provided by the course staff and is not part of our implementation. Our contribution begins from the moment the data files (CSV/MDB) are available on a computer for processing.

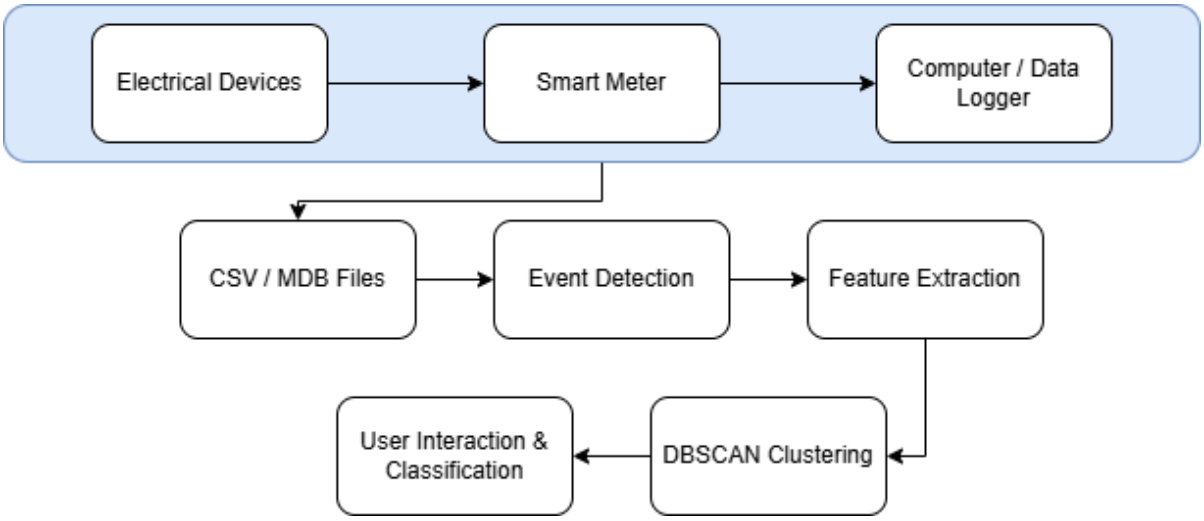


Figure 10: The top layer (blue) shows the hardware infrastructure provided externally. The bottom layer represents our algorithmic implementation pipeline

4.1 Choice of Clustering Algorithm

We selected DBSCAN as our clustering method because it does not require predefining the number of clusters and is robust to noise — both essential for our unsupervised scenario, where devices may appear or disappear over time. DBSCAN is especially suitable for NILM applications since device behavior in feature space can be irregular and non-spherical.

4.2 Feature Selection Process

An essential part of the system's performance depends on the features selected to represent each detected device event. After identifying an edge (i.e., a significant transition in power or current), we calculated the change (delta) in various electrical parameters, including Active Power (ΔkW), Reactive Power (Δkvar), Power Factor (PF), Total Harmonic Distortion (THD), duration (Δt), and others.

In many standard NILM systems, a large number of features are used, including absolute values of electrical parameters at the event's start or end, under the assumption that these provide a more complete electrical signature. However, in our approach, we focused strictly on relative changes, meaning we used only the difference in values (before vs. after the transition), rather than their absolute levels. This choice simplifies the model and increases its robustness against baseline drift and background load variations.

Through an extensive trial-and-error process using labeled events, we observed that many features such as THD and PF exhibited high variability depending on background conditions and were not reliable for distinguishing between devices. Similarly, features like apparent power were found to be redundant due to strong correlation with ΔkW and Δkvar.

As a result, we concluded that the most robust and consistent features for clustering were:

ΔkW – change in active power

Δkvar – change in reactive power

These two features were used as input to the DBSCAN clustering algorithm, applied independently for each phase.
Although Δt (duration) was not included directly in the clustering process, it was used during post-clustering refinement. For example, devices such as the *tami 4* and *dishwasher* produce nearly identical changes in ΔkW and Δkvar, and therefore often appear in the same cluster. To distinguish between them, we utilized their typical ON durations: the *tami 4* tends to remain on for a few second- 3 minutes, while the *dishwasher* stays on significantly longer. This temporal feature allowed us to resolve such ambiguities and improve classification accuracy.
In summary, while our clustering relied solely on ΔkW and Δkvar for simplicity and robustness, additional features such as Δt were leveraged through domain-specific logic to enhance overall device identification.

4.3 Parameter Tuning

The selection of DBSCAN parameters- epsilon and minPts were also determined empirically. We tested different combinations while visually inspecting the resulting clusters. The final values were chosen to balance the trade-off between splitting known devices into multiple clusters (over-fragmentation) and merging distinct devices (over-generalization).

4.4 Software Description

The software component of the project was developed in Python 3, using a modular pipeline architecture and standard scientific libraries including pandas, NumPy, scikit-learn, and pyodbc for database access. The code was designed to process high-resolution electrical measurements stored in Microsoft Access (.mdb) files and to perform unsupervised device detection and classification.

The system begins by loading and preprocessing measurement data from MDB files. Each file contains time-series logs of electrical parameters (currents, power, harmonics, etc.) for three phases. Timestamps are cleaned and converted to `datetime` objects, and selected signals are smoothed using a Gaussian filter to reduce noise before analysis.

A custom edge detection algorithm then scans current and power signals to identify abrupt changes, which may indicate a device turning on or off. Each detected event is characterized by the change in multiple features (ΔkW, Δkvar, PF, THD, etc.) and timestamped.

Following detection, the system applies DBSCAN clustering (Density-Based Spatial Clustering of Applications with Noise) separately for each phase, using ΔkW and Δkvar as features. Before clustering, all data is normalized using `StandardScaler`. The clustering output assigns a cluster ID to each event.

For device identification, each event is initially compared to a reference table of known device signatures. When available, device names are inferred based on proximity to known values. To improve robustness, a second layer of logic reassigns the cluster label to the most common device found within the cluster (excluding unknowns), ensuring consistent labeling even in noisy cases.

Several domain-specific rules are applied to handle ambiguous patterns—for example, resolving conflicts between similar appliances (e.g., tami boiler vs dishwasher), correcting false identifications for certain air conditioners or washing machines, and filtering out weak matches.

Finally, the software matches ON/OFF pairs to estimate the duration and energy consumption of each device event. A price is computed using a fixed electricity tariff (including VAT), and the results are exported to an Excel report (`classified_events_final.xlsx`) summarizing all relevant information: timestamps, device names, parameter changes, and cost estimations.

The modular design allows for easy future expansion to support real-time monitoring, online learning, or advanced anomaly detection.

5 Analysis of results

5.1 System Performance Metrics

To evaluate the effectiveness of our NILM system, we conducted a detailed analysis of event identification accuracy across all detected transitions.
We began by testing the system against a reference table of labeled events, which contained known device transitions based on prior manual annotations. Out of all labeled cases, only one event failed to be correctly classified, demonstrating high precision in cases with validated ground truth.
However, the number of labeled events in the reference table was limited and insufficient for a full evaluation. Therefore, we adopted a complementary method:
We visually analyzed the raw waveform patterns of device transitions, identifying repeating patterns with similar ΔkW and Δkvar signatures, as well as similar waveform shapes. These repeated patterns were treated as representative of specific devices, under the assumption that visually identical transitions originate from the same appliance.
Based on this labeling-by-pattern strategy, we defined success as the system assigning the same device label to all instances of a given pattern. Using this approach, we computed the following performance metrics:

- Final Totals:
  - **Total expected events (ground truth):** 724
  - **Detected events (passed edge detection):** 671
  - **Missed events (edge detection failure):** 53
- Among the 671 detected events:
  - **Correctly classified:** 389
  - **Incorrectly classified:** 39
  - **Unrecognized but detected (classified as UNKNOWN):** 243

- Performance Metrics
  - **recognize events:**

$$RE = \frac{671}{724} = 92.68\ \%$$

Equation 6 – Recognize events percentage

- **Accuracy (known devices only):**

$$Accuracy_{KD} = \frac{389}{389 + 39} = 90.88\ \%$$

Equation 7 - $Accuracy_{KD}$

- **Overall accuracy (all events):**

$$Accuracy_{tot} = \frac{389 + 243}{724} = 87.29\ \%$$

Equation 8 - $Accuracy_{tot}$

- **F1 Score:**

  We assume:

  - True Positives (TP): 389
  - False Positives (FP): 30
  - False Negatives (FN): 9

$$\text{Precision } = \frac{TP}{TP + FP} = \frac{389}{389 + 30} = 92.84\ \%$$

Equation 9 - Precision

$$Recall\ = \frac{TP}{TP + FN} = \frac{389}{389 + 9} = 97.74\ \%$$

Equation 10 - Recall

$$F1\ score = 2 \cdot \frac{\text{Precision} \cdot Recall}{\text{Precision} + Recall} = 95.23\ \%$$

Equation 11 – F1 score

  While the F1 score is 95.23% on detected events, the detection rate is 92.68%, resulting in an overall identification success of 88.26%.

5.2 Comparison with Existing NILM Systems

To contextualize our results, we compared the performance of our NILM system with three recent and representative studies in the field. While many current NILM solutions rely on deep learning or advanced unsupervised methods, our DBSCAN-based approach, combined with lightweight clustering and user pattern matching, achieved high accuracy with minimal computational complexity. Notably, our F1-score on detected events was 95.23%, and the overall identification success rate was 88.26%, positioning our system competitively against more resource-intensive alternatives.

Study/ System	Dataset	Method	Avg. F1 score
Our system (DBSCAN-based)	Private	Clustering + Pattern Matching	95.23%
Yaniv & Beck (2024)	AMPds	Robust PCA + MCE	96.3%
Chen et al. (2025)	UKDALE	Deep Learning + Time-enhanced Features	~86%
Fabri et al. (2025)	Industrial	Active Learning + Semi-supervised SVM	85–92%

Table 1: comparison with existing NILM systems

6 Conclusions and further work

This project aimed to build a real-time, unsupervised NILM (Non-Intrusive Load Monitoring) system for identifying electrical appliances based on smart meter data. Through a combination of edge detection, feature extraction, DBSCAN clustering, and feedback-based classification, the system was able to accurately and efficiently disaggregate device usage events.

6.1 Examining the project results against the goals set in the first place

We successfully met or exceeded all the quantitative objectives established at the project's outset:

1. **Device Identification Accuracy**
   The system achieved a classification accuracy of 92.84%, and an F1-score of 95.23%, significantly surpassing the initial targets of 90% and 80% respectively. These results confirm the system's reliability in distinguishing between different appliances based on electrical signatures.
2. **Consistency with Literature Benchmarks**
   The F1-score of 95.23% falls well within the defined ±3% deviation compared to state-of-the-art NILM systems reported in the literature. As shown in our comparison with three recent publications ([Yaniv & Beck, 2024], [Chen et al., 2025], [Fabri et al., 2025]), our system's performance ranks among the highest, even outperforming supervised approaches in some cases.
3. **Processing Time**
   The system's end-to-end latency for classifying new events—including feature extraction, clustering, and classification—is consistently below 3 seconds, well under the 5-second limit set for maximum processing time. This responsiveness enables near real-time operation and makes the system suitable for deployment in smart home environments.

6.2 Suggestions to improve system performance

While the system performed well, several improvements could further enhance performance and robustness:

1. **Contextual Reinforcement Mechanisms**
   Introduce behavior-based reinforcement by leveraging usage patterns. For instance, appliances like water dispensers tend to be used multiple times a day, whereas washing machines typically operate once per day. Incorporating these patterns can improve prediction confidence and disambiguate similar events.
2. **Environment-Aware Adjustments**
   Integrate environmental factors such as season, time of day, or room temperature to adapt the classifier dynamically. For example, air conditioners are more likely to be active on summer afternoons, while heaters may only appear in winter mornings.
3. **User Interaction for Feedback Refinement**
   Implement simple, lightweight user prompts such as:
   “Is this device typically used at this hour?”,
   “Has this appliance been used earlier today?”,
   to gather contextual insights that refine the labeling and improve clustering over time.

6.3 Possibilities for future (development / research) activities

1. **Incremental DBSCAN**
   Applying incremental DBSCAN would allow the system to continuously update its clustering model in real-time without needing to recompute the full clustering process, thereby improving scalability and responsiveness.
2. **Multi-Phase Feature Expansion**
   Incorporating data from all three electrical phases (L1, L2, L3) could enhance classification in multi-phase environments and allow identification of three-phase industrial or commercial devices.
3. **Hybrid Semi-Supervised Layer**
   Introducing a lightweight supervised layer to fine-tune cluster assignments based on occasional user-labeled data could blend adaptability with low labeling cost, improving accuracy without sacrificing autonomy.

4. **Dynamic Threshold Optimization**
   Implementing adaptive thresholding and sensitivity calibration based on system feedback and long-term trends could further reduce false positives and enhance long-term accuracy.

7 Project Documentation

All components of the project are documented and made available in a public GitHub repository.

7.1 Documentation Description:

The repository includes the full software implementation used to identify and classify electrical devices from smart meter data. It also contains the output results, a list of known devices for training and testing, and a comprehensive README file detailing setup instructions and project structure. The software was written in Python and tested locally with .mdb and .xlsx data files. The system also features a real-time user interface built using Base44.

7.2 Documentation Location:

GitHub Repository: **https://github.com/lihitalyosef/NILM_final_project**

7.3 Description of Project Files:

- final_code.py – Main Python script for event classification and clustering
- classified_events_final.xlsx – Final classification results generated by the code
- known_devices.xlsx – Labeled reference data for training/testing
- README.md – Setup instructions, system description, and usage guide
- Base44 App Link – Real-time UI for viewing live detections
- Final project report PDF

8 References

Papers:

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