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Machine Learning-Based Non-Intrusive Load Monitoring for Three-Phase Smart Energy Consumption Disaggregation

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ABSTRACT

Non-Intrusive Load Monitoring (NILM) has emerged as a pivotal technology for promoting energy efficiency and sustainability by disaggregating aggregate household or industrial energy consumption into appliance-level usage profiles. This capability enables consumers and utilities to gain deeper insights into consumption behavior, reduce wastage, and improve energy management practices. In this study, a machine learning-based NILM framework is presented, focusing on enhancing accuracy, adaptability, and scalability across three-phase energy systems, which are common in residential and industrial applications. The proposed approach employs the Cubic K-Nearest Neighbor (Cubic KNN) algorithm for effective classification and disaggregation of energy data. Unlike traditional NILM methods, the Cubic KNN model demonstrates robustness in handling challenges such as low sampling rates, overlapping appliance signatures, multi-state appliances, and dynamic operational profiles. The methodology integrates feature extraction, supervised machine learning, and rigorous validation against real-world energy data obtained from a Tenaga Nasional Berhad (TNB) household smart meter. Both online and offline energy monitoring and data logging systems were developed to ensure data reliability and continuity. Experimental evaluations show that the Cubic KNN classifier achieves high accuracy, exceeding 95% for most appliances, with negligible misclassification errors. Furthermore, comparative analysis against utility billing data confirms the reliability of the proposed system, with overall error rates below 6%. The findings underscore the potential of advanced machine learning algorithms in NILM applications, contributing toward the development of scalable, efficient, and accurate solutions. This research highlights the role of NILM in supporting smarter energy monitoring, conservation initiatives, and sustainable energy management strategies for future smart grid systems.

Keywords: NILM; energy efficiency; energy consumption; machine learning

INTRODUCTION

The increasing demand for electricity and concerns over energy efficiency have driven research into energy monitoring and consumption optimization (Himeur, Alsalemi, et al. 2021; Himeur, Ghanem, et al. 2021; Mariano-Hernández et al. 2021). According to a web survey, approximately 29% of domestic users are unaware that their electrical appliances continue to consume power even in standby mode, and around 80% of respondents leave their appliances connected to the power source when not in use (Ajay-D-Vimal Raj et al. 2009; Putra et al. 2015). Standby power consumption contributes to nearly 10% of overall household energy usage (Anastasi et al. 2011), emphasizing the need for efficient electricity utilization. While the introduction of energy-efficient appliances has helped reduce unnecessary consumption, user behavior remains a critical factor in energy wastage. As a result, energy monitoring systems have become increasingly important.

Early energy monitoring systems focused on hardware-based solutions such as Arduino-based wireless power meters and ZigBee-based low-power communication systems (Putra et al. 2015). While these technologies enabled real-time energy usage tracking, they suffered from limitations such as data loss, high latency, and limited scalability. Further advancements integrated cloud computing and IoT technologies for remote monitoring, as seen in (Alhasnawi et al. 2021; Hashmi et al. 2021; Kuzlu et al. 2011; Nasab et al. 2021; Yang et al. 2023). However, these systems were primarily designed for energy data collection rather than appliance-level disaggregation. The field of Non-Intrusive Load Monitoring (NILM), first introduced by Hart (1992), addressed this challenge by leveraging machine learning-based classification techniques to disaggregate household energy consumption into appliance-specific data. By detecting ON/OFF states and operational patterns, NILM systems provide insights into appliance-level energy usage, allowing users to make informed decisions about their consumption.

Despite the progress in NILM research, several challenges remain unresolved, limiting its practical implementation across different environments. One major limitation is the lack of effective NILM integration into real-time smart energy monitoring systems. Govindarajan et al. (2020) explored IoT-based energy monitoring but did not incorporate advanced NILM disaggregation techniques, preventing granular insights into individual appliance consumption. Similarly, scalability remains a concern, particularly for three-phase systems. Gowrienanthan et al. (2023) introduced a deep learning ensemble model for NILM in industrial settings, but their work was primarily focused on large-scale applications and did not address mixed-use residential environments. The lack of real-time smart grid integration and anomaly detection further limits NILM's applicability in dynamic energy consumption scenarios.

Another persistent challenge in NILM research is appliance-level classification accuracy, particularly for multi-state appliances. Yu et al. (2023) proposed a dilated residual aggregation network (DRA-net) to improve feature extraction and enhance the classification of low-energy appliances. However, their approach focused on sequence-to-sequence data, limiting adaptability to varying household conditions and multi-phase electrical systems. Similarly, Zhang et al. (2023) introduced a Self-Supervised Learning (SSL) framework that reduces reliance on labeled training data. While SSL significantly improves NILM model generalization, it struggles to maintain accuracy for rarely used or complex appliances. Additionally, hybrid deep learning models, such as CNN-LSTM frameworks (Zhou, 2021), have improved classification accuracy but remain dependent on high-resolution datasets like REFIT.

Scalability and adaptability of NILM models remain key challenges, particularly when applied to different household environments. Karuna et al. (2024) introduced a Smart Home Energy Management System (SHEMS) using Gradient Boosting (GB) for real-time energy prediction. However, the system exhibited difficulties in generalizing across diverse household energy patterns due to its dependence on supervised learning, which requires extensive labeled datasets. Similarly, Moreno et al. (2024) explored ensemble learning using weighted average confidence voting (WeCV), achieving high accuracy on UK-DALE. Despite its success, the reliance on image-based CNN architecture limited its applicability to real-time NILM tasks involving noisy or irregular time-series data. The need for lightweight, adaptable NILM models that can generalize across different household environments while maintaining high accuracy remains an important research direction.

Furthermore, Pan et al. (2024) introduced PerFedNILM, a personalized Federated Learning (FL) framework designed to preserve user privacy while improving model generalization. However, FL-based NILM approaches suffer from slow convergence and performance degradation due to local-global update conflicts, particularly in non-identically distributed (non-IID) data settings. Additionally, client dropout during FL training negatively impacts model accuracy, highlighting the need for improved aggregation techniques and real-time adaptation strategies. To address these challenges, this study proposes a machine learning-based NILM disaggregation approach that integrates feature engineering, hybrid deep learning, and optimized classification techniques to enhance energy consumption analysis. Unlike previous studies that rely on a single NILM methodology, this research combines Cubic KNN, sparse optimization, and ensemble learning to improve classification accuracy and disaggregation efficiency. Additionally, the proposed model is designed for scalability and real-time deployment, ensuring it remains computationally efficient while maintaining high accuracy across diverse datasets.

This paper is structured into four main sections. Section 1 provides the Introduction, covering the background, literature review, and justification for the study, highlighting the role of NILM and machine learning in energy disaggregation. Section 2 details the Methodology, describing the development of the Energy Monitoring and Data Logger (EMDL) system, data collection, and machine learning-based classification techniques. Section 3 presents the Results, evaluating NILM disaggregation accuracy through confusion matrices and performance comparisons of different classifiers. Finally, Section 4 concludes the study by summarizing key findings, contributions, and limitations while suggesting future improvements in real-time NILM scalability and classification accuracy.

METHODOLOGY

ENERGY MONITORING AND DATA LOGGER (EMDL) SYSTEM

The Energy Monitoring and Data Logger (EMDL) system was designed to provide a robust and versatile solution for monitoring and analyzing household energy consumption. It employs a combination of hardware and software technologies to collect, log, and analyze energy data. The system operates in two configurations online and offline to ensure both real-time monitoring and reliable data backup. These configurations complement each other, enabling seamless functionality in environments with and without internet access.

The EMDL system was built around an Arduino Uno microcontroller, which served as the core processing unit. Current transformers (CT sensors) were used to measure the current drawn by household appliances. These sensors provided voltage outputs proportional to the current, which were then scaled down and stabilized using voltage divider circuits for compatibility with the Arduino's input pins. The system was configured to measure and log three-phase current data, which was processed to calculate energy consumption values. The use of non-intrusive CT sensors ensured that the system could be installed without modifying existing electrical infrastructure, making it suitable for residential applications.

First, the online EMDL system extended the basic EMDL setup by integrating an Arduino Ethernet shield, Google Spreadsheets, and the PushingBox API. The Ethernet shield added internet connectivity to the system, enabling real-time data transfer to the cloud. Figure 1 shows the circuit connection for the online system, modeled using Fritzing software. The Ethernet shield was interfaced with the Arduino Uno through digital pins 10 to 13, which facilitated communication between the Arduino and the internet. The system was designed to transmit energy data every 90 seconds, corresponding to a sampling rate of 0.011 Hz (DeBell et al. 2019). This sampling interval was chosen to stay within the 1000 API requests per day limitation of the free version of PushingBox. Energy data, including three-phase current measurements and calculated power consumption values, were sent to a Google Spreadsheet, where it was stored and organized for real-time access.

The data transmission process involved several steps to establish a reliable connection between the Arduino, Ethernet shield, and the internet. Two methods were used to interface the Ethernet shield: connecting it to a Wi-Fi router via an Ethernet cable or connecting it directly to a laptop's internet connection. In the first method, as shown in Figure 2, the Ethernet shield was connected to a router using an Ethernet cable. The Arduino IDE's DHCP sketch was employed to automatically assign an IP address to the system, or alternatively, the IP address could be manually configured using the command prompt. In the second method, illustrated in Figure 3, the Ethernet shield was connected to a laptop's Ethernet port. Network sharing settings in the laptop's operating system were configured to allow the Arduino to access the internet through the laptop's connection. These setups ensured reliable internet connectivity, enabling seamless data transmission.

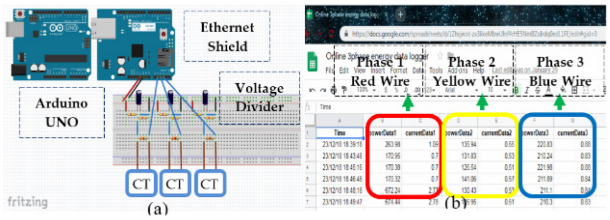


FIGURE 1. (a) Online EMDL (b) Example real-time power and current data

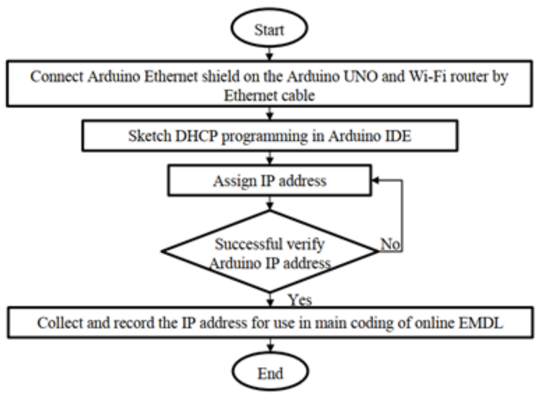


FIGURE 2. Flowchart of connecting Arduino UNO, Arduino Ethernet shield and WiFi router

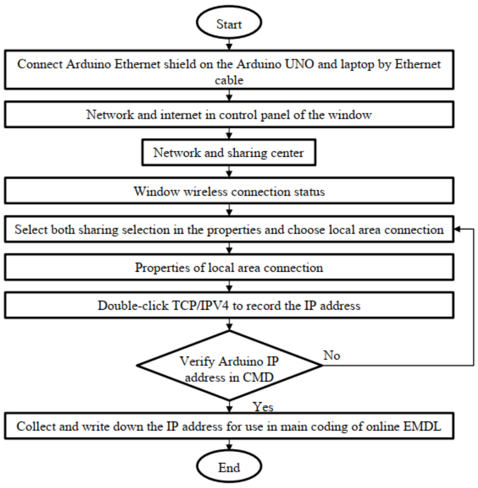


FIGURE 3. Flowchart of connecting Arduino UNO, Arduino Ethernet shield and laptop

Google Spreadsheets served as the cloud database for storing the energy data collected by the online EMDL system. A spreadsheet file was created, and its unique URL key was extracted for use in the PushingBox API. Custom scripts were written in the Google Apps Script editor to process and populate the spreadsheet with incoming data. The scripts were deployed as web applications, generating a unique URL that linked PushingBox to the spreadsheet. PushingBox acted as an intermediary, ensuring efficient data transfer between the Arduino and the spreadsheet. A device ID generated by PushingBox was incorporated into the Arduino program to establish a secure connection.

Second, the offline Energy Monitoring and Data Logger (EMDL) system was developed as an enhancement of the basic EMDL framework to address data continuity challenges during internet interruptions or system downtime in the online configuration. It operates as a backup mechanism by integrating a Real-Time Clock (RTC) module and a Micro SD card module into the Arduino Uno setup. While the online EMDL system allows data to be temporarily stored in the Ethernet shield's flash memory slot, it is vulnerable to data loss in the event of internet or system failures. The offline configuration eliminates this risk by providing an independent, locally stored record of energy consumption data. The circuit connection of the offline EMDL system is depicted in Figure 4.

To ensure consistency with the online system, the offline EMDL system maintains the same sampling rate of 0.011 Hz, capturing one data point every 90 seconds. This ensures that the system collects and records detailed energy data continuously. The data logging process runs until the user manually stops the system, at which point the collected data can be downloaded, transferred, and analyzed to calculate energy consumption for a specified time period, such as daily or monthly intervals. The addition of the RTC module and Micro SD card module significantly enhances the reliability and robustness of the EMDL system, making it suitable for scenarios where uninterrupted internet connectivity cannot be guaranteed.

The RTC module (DS1302) plays a critical role in providing precise timestamps for the recorded data, ensuring that the logged information is chronologically accurate. This module is connected to the Arduino Uno through dedicated pins for power, ground, and data communication, as shown in Figure 5(a). A 3V CR2032 lithium battery powers the RTC module, enabling it to retain the current time even when the system is powered off. During the initial setup, a custom program written in the Arduino IDE is used to set the correct date and time on the RTC board. Once the time has been configured, the setup code is removed to prevent accidental resets, ensuring that the module continuously tracks the correct time.

Data storage in the offline system is managed by the Arduino Micro SD card module, which acts as the primary component for recording and securing collected energy data. This module is connected to the Arduino Uno via designated pins for power, ground, and SPI communication, as illustrated in Figure 5(b). Before using the module, the SD library is installed in the Arduino IDE to enable efficient data writing and file handling operations. The module stores the recorded data, including timestamps from the RTC module, current measurements, and calculated power values, in a structured format that is easy to retrieve and analyze. The use of local storage ensures that all collected data is preserved even during extended periods of system downtime or internet disruptions.

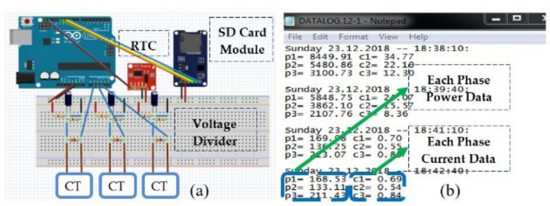


FIGURE 4. (a) The offline EMDL system (b) Example of real-time power and current data for every phase saved in Micro SD card

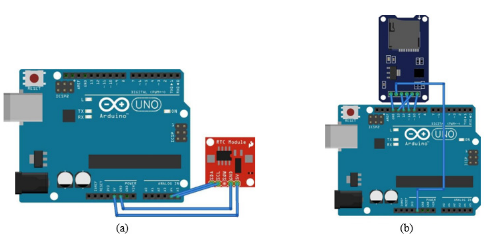


FIGURE 5. (a) Wire connection between Arduino UNO and RTC module in stage setup current real-time (b) Wire connection between Arduino UNO and Micro SD card module in stage setup writing data into the SD card

The complete offline EMDL system combines the functionalities of the RTC and SD card modules with the core energy monitoring framework provided by the Arduino Uno. The program for the offline system integrates all required operations, including hardware initialization, data acquisition, and file storage. Each recorded data point includes a timestamp, current measurement, and corresponding power value, allowing for detailed energy analysis. Once the system has completed its data logging process, users can access the stored data for further evaluation. The offline EMDL system ensures that no data is lost, providing a reliable backup mechanism for energy monitoring.

EXPERIMENT SETUP

The selected site was a double-story bungalow with a net built-up area of 1800 square feet, occupied by a middle-income family of five (two adults and three children), representing typical household energy consumption in Malaysia. The house was powered by a three-phase electrical supply, and the experiment was conducted over two months, from December 26, 2023, to February 25, 2024. Both the online and offline EMDL systems were installed at the main electrical distribution board, as shown in Figure 6, to monitor and record the energy consumption of household appliances distributed across the three phases. The setup was designed to be non-intrusive, eliminating the need for modifications to the existing wiring. Current transformers (CT sensors) were clamped directly onto the phase wires to measure the current flow. Each phase wire was connected to two CT sensors one for the online EMDL system and the other for the offline EMDL system ensuring simultaneous data collection by both configurations.

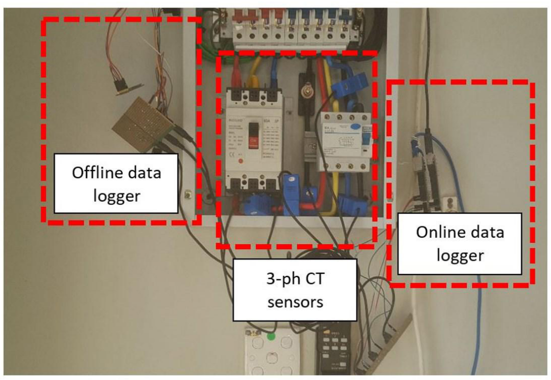


FIGURE 6. Installation of offline and online EMDL system

The house's three-phase electrical supply distributed power to various appliances, categorized as follows: Phase 1 powered lighting, fans, a refrigerator, a water heater, and a pressure cooker. Phase 2 supplied energy to lighting, fans, a washing machine, a rice cooker, a modem router, a home security system, and an air conditioner. Phase 3 supported lighting, fans, computers, air conditioners, a water dispenser, and a television. The detailed distribution of electrical appliances across the three phases is shown in Figure 7. The systems were configured to record current and power consumption data every 90 seconds, corresponding to a sampling rate of 0.011 Hz. The online system transmitted data in real-time to a cloud-based database, while the offline system stored data locally as a backup. Both systems operated simultaneously to ensure redundancy and provide a basis for validation. The recorded data was analyzed to calculate total energy consumption and evaluate the systems' performance under realistic residential conditions.

Appliance-level ground truth labels were obtained directly from the smart meter installed at the household. The smart meter was capable of recording energy consumption at the individual appliance circuit level, which allowed precise identification of ON/OFF events and operational states. These labels were automatically synchronized with the Energy Monitoring and Data Logger (EMDL) data stream through their shared timestamps. By using the smart meter as the ground truth source, the training dataset contained accurately labeled appliance states without requiring manual observation, ensuring reliable supervision for machine learning model development and validation.

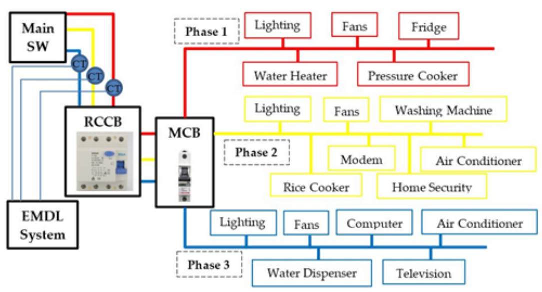


FIGURE 7. Electrical appliances in each phase of the load circuit

ENERGY CONSUMPTION AND LOAD ANALYSIS

Data collection was carried out using the EMDL online and offline systems, which recorded energy data every 90 seconds. With 40 data points collected every hour, the system captured 960 data points daily and approximately 29,760 data points in a month. The monthly total energy consumption in kilowatt-hours (kWh) was calculated for each phase using Eq. (1) and (2). These equations take into account the total power consumption in each phase and the summation of three-phase power usage, ensuring accurate calculations. The results were cross-verified against Tenaga Nasional Berhad (TNB) utility bills to validate the system's accuracy.

$$P_{i\ total} = \left\{ \left[\frac{\sum_{t=1}^{N} P_t}{1000} \right] \times \frac{90s}{3600s} \times 0.95 \right\} \tag{1}$$

$$P_{S\ total} = \sum_{i=1}^{3} P_{i\ total} \tag{2}$$

Where, P_t = power consumption for each phase in kWh, $P_{i\ total}$ = total power consumption, $P_{S\ total}$ = sum of 3 phase power consumption, 90s/3600s = conversion of 90 seconds into hours, P_i = the power measured every 90 seconds, N = the total power data recorded for a particular phase, and 0.95 is assumed as a typical value of power factor.

The aggregated load data was analyzed using NILM techniques. Current sensors clamped onto the three-phase wires at the distribution board measured the total load at a single point. Disaggregation algorithms were applied to identify specific appliances, their operational states, and usage times. Since the household utilized a variety of appliances, including ON/OFF devices, finite state machines (FSMs), continuously variable devices (CVDs), and periodically cycling devices (PCDs), the disaggregation process required advanced techniques to maintain accuracy. Power consumption ranges for each appliance were determined and are summarized in Table 1. For example, water heaters consumed between 1900 W and 3800 W, while refrigerators operated within a range of 40 W to 210 W.

TABLE 1. Power consumption range for each main electrical appliance in each phase circuit estimated from measurement data

Phase Wire	Types of Appliances	Min. Power (W)	Max. Power (W)
Phase 1 (Red)	Fridge	40	210
	Water Heater	1900	3800
	Pressure Cooker	830	1400
Phase 2 (Yellow)	Air Conditioner	700	1030
	Washing Machine	420	700
	Rice Cooker	230	340
Phase 3 (Blue)	Air Conditioner	900	1200
	Water Dispenser	120	820
	Television	140	180

Graph plotting and feature extraction methods were employed to visualize power consumption patterns over monthly, weekly, and daily intervals. Monthly power graphs highlighted overall energy usage trends, while weekly graphs allowed for the identification of high-power appliances such as air conditioners and water heaters. By analyzing the ON/OFF transitions and power fluctuations in the weekly graphs, the operation states of specific appliances were accurately determined. To enhance disaggregation accuracy, supervised machine learning techniques were implemented using the Classification Learner toolbox in MATLAB R2015a. The toolbox processed labeled datasets consisting of power and current measurements, enabling the classification of appliance operation states. Ten machine learning algorithms were evaluated, and ensemble classifiers. The best-performing model was exported and used to predict appliance usage in the remaining data. This approach was effective in identifying appliance types and improving disaggregation precision.

Moreover, a custom NILM disaggregation algorithm was developed in MATLAB to address the limitations of the Classification Learner toolbox. This algorithm calculated power differences between successive time points to determine appliance ON/OFF states. The mathematical relationship for this analysis is expressed in Eq. (3). By comparing the calculated power differences to predefined ranges, the algorithm identified appliance operations with high accuracy. The results were organized into matrix tables, capturing details such as the number of ON/OFF cycles, total operational time, and specific timestamps for each appliance.

$$DP_{t+1,t} = P_{t+1} - P_t \tag{3}$$

Where, DPt+1, t = Difference power value between previous power value and latest power value. P_{t+1} = Power value at time, t+1. P_t = Power value at time, t. When DPt+1, $t > 0$ and in between power consumption range of the load = Load start to operate. DPt+1, $t < 0$ and in between power consumption range of the load = Load stop to operate.

RESULTS AND DISCUSSION

POWER CONSUMPTION ANALYSIS

The graphical analysis of power consumption trends provided valuable insights into the energy usage patterns for each phase during the experimental period. Figure 8 depicts the power consumption trends for the January cycle (December 26, 2023, to January 25, 2024), while Figure

9 illustrates the corresponding data for the February cycle (January 26, 2023, to February 25, 2024). In Phase 1, peak power consumption reached approximately 3.7 kW, attributed to the simultaneous operation of high-power appliances, such as water heaters. Phase 2 displayed fluctuations in power usage, likely caused by the presence of reactive loads, while Phase 3 showed a relatively stable consumption pattern, with an average power consumption of around 700 W, dominated by the continuous operation of the water dispenser.

During the first experimental month, from December 26, 2023, to January 25, 2024 (January cycle), the total recorded energy consumption was 127.629 kWh for Phase 1, 123.294 kWh for Phase 2, and 125.841 kWh for Phase 3, yielding a total consumption of 358 kWh. The corresponding TNB bill for the same period recorded a total consumption of 338 kWh, resulting in a percentage error of 5.92%. In the second experimental month, from January 26, 2023, to February 25, 2024 (February cycle), the total recorded energy consumption was 94.268 kWh for Phase 1, 143.635 kWh for Phase 2, and 95.704 kWh for Phase 3, summing up to a total of 334 kWh. The TNB bill for this period reported 354 kWh, with a percentage error of 5.65%. These results are summarized in Figure 10, demonstrating the EMDL system's accuracy and reliability.

The discrepancies between the total power consumption recorded by the EMDL system and TNB bills can be attributed to several factors. One significant factor is related to the differences in data collection cycles. The EMDL system records energy consumption continuously and summarizes it on a daily basis, while TNB billing cycles depend on manual meter readings, which do not follow exact schedules. Consequently, some energy usage data for the next billing cycle may be included in the measurements of the previous cycle. For instance, during the January cycle, the recorded energy usage exceeded the TNB bill by approximately 20 kWh. Conversely, in the February cycle, the recorded data was around 20 kWh less than the TNB bill. This misalignment occurs because the TNB billing system does not account for the specific time when the meter reading is taken, whereas the EMDL system uniformly summarizes daily consumption. This overlap causes energy usage data to be carried over between billing cycles, affecting the comparison.

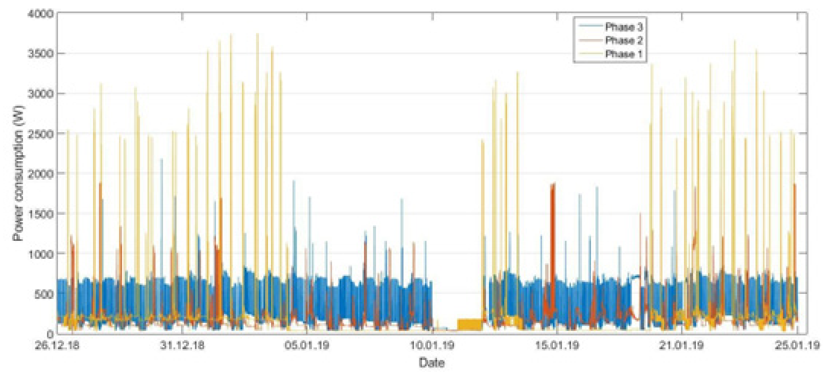


FIGURE 8. Power consumption of three-phase system from 26.12.2023 to 25.01.2024 (January)

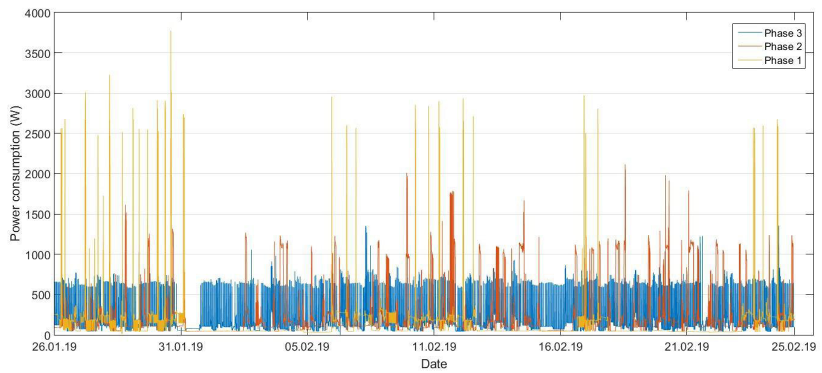


FIGURE 9. Three-phase power consumption from 26.01.2023 to 25.02.2024 (February)

Another factor contributing to the percentage difference is the assumption of Root-Mean-Square (RMS) voltage values used in the calculation of power data. Voltage supply in real-world systems is not constant, especially when partially reactive loads are present. Voltage fluctuations occur due to the dynamic nature of inductive and capacitive loads, such as electric motors and air conditioners. Although TNB ensures that voltage remains within the regulatory range of +10% to -6% for both single-phase and three-phase systems (Tenaga Nasional Berhad, 2011), variations within this range can still impact the recorded energy consumption. During the experiment, the measured RMS voltage values were different for each phase: 243 V for Phase 1, 248 V for Phase 2, and 252 V for Phase 3. These variations introduce a degree of uncertainty in the calculated power data, as real-time voltage fluctuations were not continuously monitored.

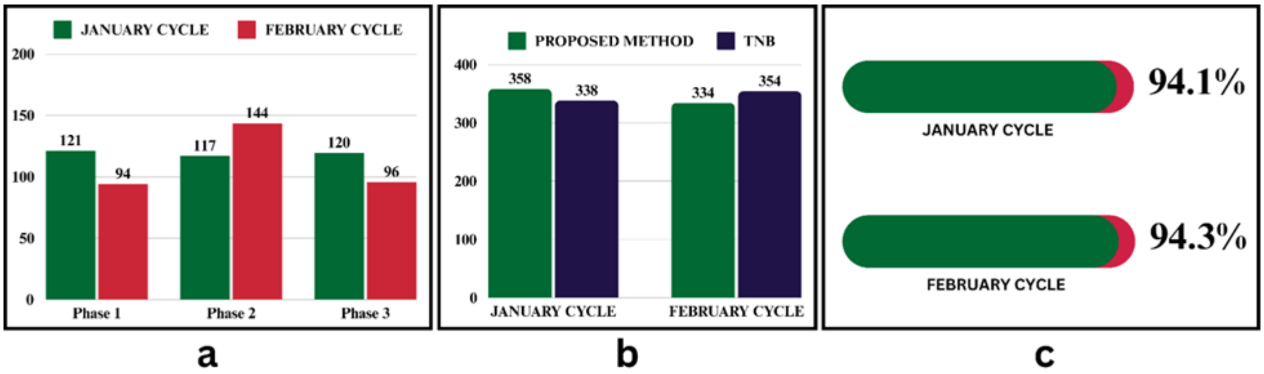


FIGURE 10. (a) Power consumption during the January and February cycles (in kWh), (b) Comparison of power consumption differences between the proposed method and TNB (Tenaga Nasional Berhad) data (in kWh), and (c) Accuracy of the proposed method for the January and February cycles (in kWh)

The composition of household electrical loads also plays a role in the observed discrepancies. Household appliances typically consist of resistive and partially reactive loads. Resistive loads, governed by Ohm's Law, produce instantaneous power, which is the product of voltage and current at a given time. The mean value of this instantaneous power represents the real or active power consumed by the appliance. In contrast, partially reactive loads have inductive, capacitive, and resistive components, which result in a phenomenon known as reactive or imaginary power. Reactive power represents energy that oscillates between the appliance and the power source, without contributing to net energy consumption. Apparent power, which combines real and reactive power, is determined as the product of RMS voltage and RMS current without considering the phase angle. Lastly, the assumption of a constant power factor contributes to the minor inaccuracies. While purely resistive loads have a power factor of 1 (real power equals apparent power), household appliances with partially reactive loads exhibit varying power factors. For instance, during the operation of a washing machine, the power factor fluctuates due to changes in the ratio of real power to apparent power (Chui et al. 2018). Although the assumed power factor of 0.95 was deemed acceptable, as it falls within the typical residential range of 0.9 to 1.0 (Tenaga Nasional Berhad, 2011), it does not account for dynamic changes in reactive power during appliance operation.

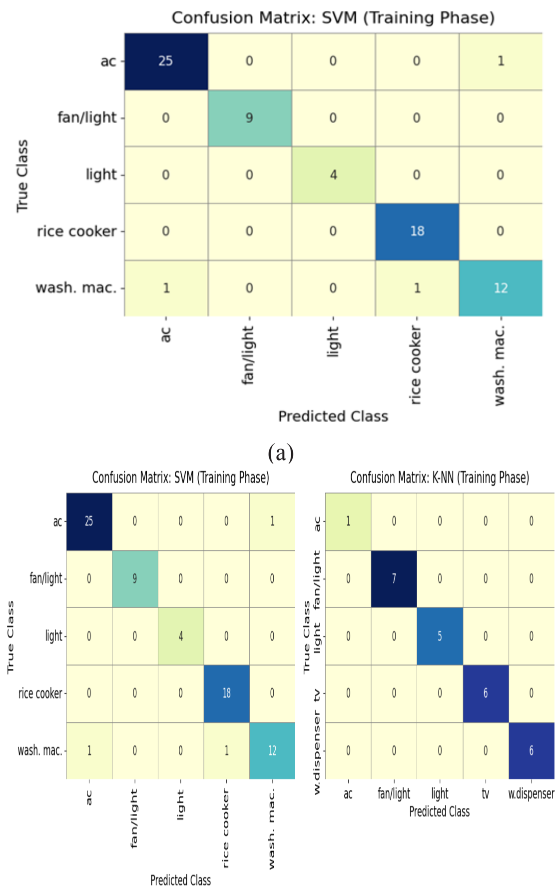
TRAINING ALGORITHM ANALYSIS

To improve the accuracy of identifying appliance types and detecting small power consumption loads, the Classification Learner application was implemented in this study. This approach utilized the first month's dataset to train multiple classification algorithms, allowing for a comparative evaluation of their performance. Among the models tested, Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) were prominently analyzed during the training phase. The performance of these algorithms was visualized through confusion matrices, as shown in Figure 11 (a) and (b), while the overall accuracy of various classification algorithms across the three phases is summarized in Table 2.

The confusion matrices serve as an essential tool for assessing the classification performance of these models by providing detailed insights into true positives, false positives, and false negatives for each appliance class. In the case of the SVM algorithm, as illustrated in Figure 11(a), high accuracy was achieved for several classes, with true positive rates (TPR) exceeding 85% for most appliances. For instance, the air conditioner (ac) class demonstrated a TPR of 96.2%, with only one instance misclassified as a washing machine (wash. mac.). Similarly, the rice cooker and light classes achieved perfect classification, with no false positives or negatives, reflecting 100% accuracy. However, the washing machine class exhibited the lowest TPR at 85.7%, with one instance misclassified as "ac" and another as "rice cooker." These errors highlight potential issues with overlapping features between appliance classes, noisy data, or insufficient differentiation in the SVM's decision boundaries. Such limitations suggest that further refinement of hyperparameters or additional training data may be required to enhance the algorithm's performance.

In contrast, the KNN algorithm, as shown in Figure 11 (b), displayed exceptional performance, with no misclassifications observed across all appliance classes. This resulted in perfect classification accuracy for the air conditioner, fan/light, light, television (tv), and water dispenser (w.dispenser) classes, achieving 100% TPR for each. The results indicate that KNN effectively captured the subtle differences between data points during training and was capable of handling complex variations in appliance features. This superiority over SVM underscores the robustness of KNN in scenarios where data distributions require flexible and adaptive decision boundaries.

The broader performance of classification algorithms is detailed in Table 2, which compares their accuracy across three phases. Among the algorithms tested, Cubic KNN consistently achieved high accuracy, recording a perfect score of 100% for Phase 1 and Phase 3, and 98.4% for Phase 2. Weighted KNN and several SVM variants, including Linear, Quadratic, and Gaussian SVMs, also demonstrated excellent results, achieving 100% accuracy in multiple phases. In contrast, Coarse KNN and Cosine KNN exhibited significantly lower accuracy, with scores as low as 38.9% in Phase 1 and 28% in Phase 3, highlighting their limitations in handling intricate data structures or differentiating between similar features.



(a)

(b)

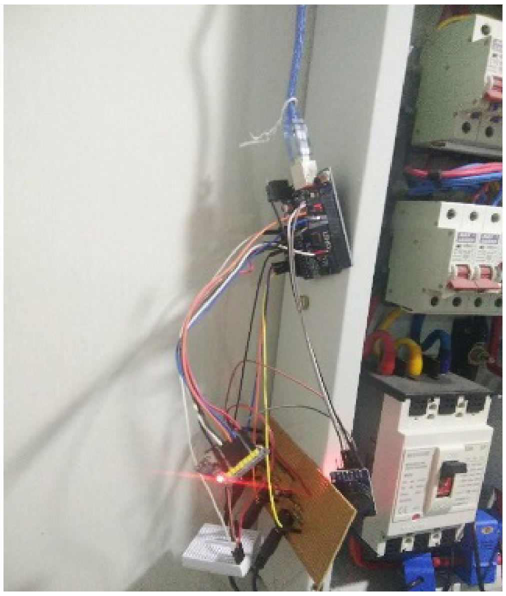
FIGURE 11. (a) Confusion matrix of SVM during training phase (b) Confusion matrix of K-NN during training phase

TABLE 2. Accuracy of each classification algorithms methods

Classification algorithms	Overall accuracy of each classification algorithms (%)		
	Phase 1	Phase 2	Phase 3
Coarse KNN	38.9	69.0	28.0
Cosine KNN	66.7	62.0	52.0
Cubic KNN	100.0	98.4	100.0
Weighted KNN	100.0	93.0	100.0
Linear SVM	100.0	95.8	100.0
Quadratic SVM	100.0	95.8	100.0
Cubic SVM	100.0	94.4	100.0
Fine Gaussian SVM	100.0	94.4	100.
Medium Gaussian SVM	100.0	94.4	100.0
Coarse Gaussian SVM	100.0	94.4	96.0

Based on these results, the Cubic KNN algorithm emerged as the most suitable classification method for NILM disaggregation. Its ability to capture large differences between data points using a cubic distance metric ensures clear class separation and enhances its performance when working with high-dimensional data. Unlike simpler models, Cubic KNN effectively addresses the complexity of appliance-level energy data, making it particularly useful in scenarios where linear decision boundaries fail to provide adequate differentiation. Additionally, its flexibility in modeling complex relationships within the dataset further validates its selection as the optimal algorithm for this study.

(a)



(b)

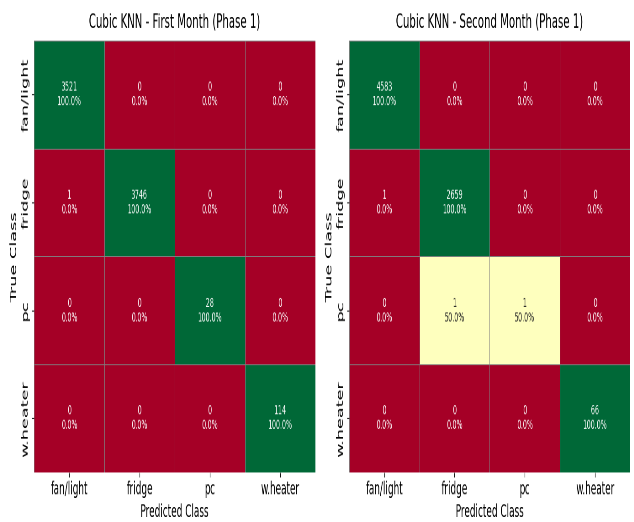
FIGURE 12. (a) Online EMDL system installed at the distribution board (b) Offline EMDL system installed at the distribution board

Once selected, the Cubic KNN model was exported and applied to the full recorded dataset for both the first and second months of data collection. The model successfully disaggregated the aggregated power consumption data, identifying the ON/OFF states and usage patterns of individual appliances with high accuracy. This capability not only underscores the efficacy of Cubic KNN in NILM applications but also demonstrates its potential for advancing energy monitoring technologies. By enabling detailed disaggregation of household energy data, the Cubic KNN model lays the groundwork for more effective energy management and optimization strategies.

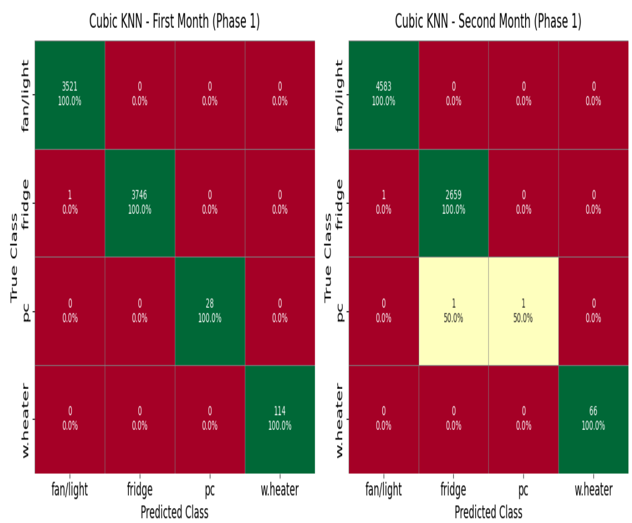
CLASSIFICATION ACCURACY ANALYSIS

The classification accuracy of the Cubic K-Nearest Neighbor (Cubic KNN) algorithm was evaluated across Phase 1, Phase 2, and Phase 3 for two months of data collection. The results provide a comprehensive analysis of the algorithm's effectiveness in identifying appliance operation states based on their power consumption patterns. The confusion matrices generated for each phase illustrate the robustness of the algorithm, highlighting its high accuracy and reliability while also identifying minor areas for improvement.

For Phase 1, the algorithm demonstrated strong performance in both months. During the first month, as shown in Figure 13 (a), the Cubic KNN algorithm achieved perfect classification for most appliance classes. The fan/light class achieved a True Positive Rate (TPR) of 100%, with 3,521 instances correctly classified. Similarly, the fridge class exhibited a TPR of 99.97%, with only one misclassification as "fan/light." Other classes, such as PC (Personal Computer) and Water Heater (w.heater), achieved perfect classification accuracy, reflecting the algorithm's ability to handle distinct power consumption profiles with minimal error. In the second month, shown in Figure 13 (b), the algorithm maintained its robust classification performance, with a perfect TPR of 100% for fan/light and water heater, while fridge maintained 99.96%. However, the performance for PC declined to 50%, highlighting challenges in distinguishing between appliances with overlapping power profiles.



(a)

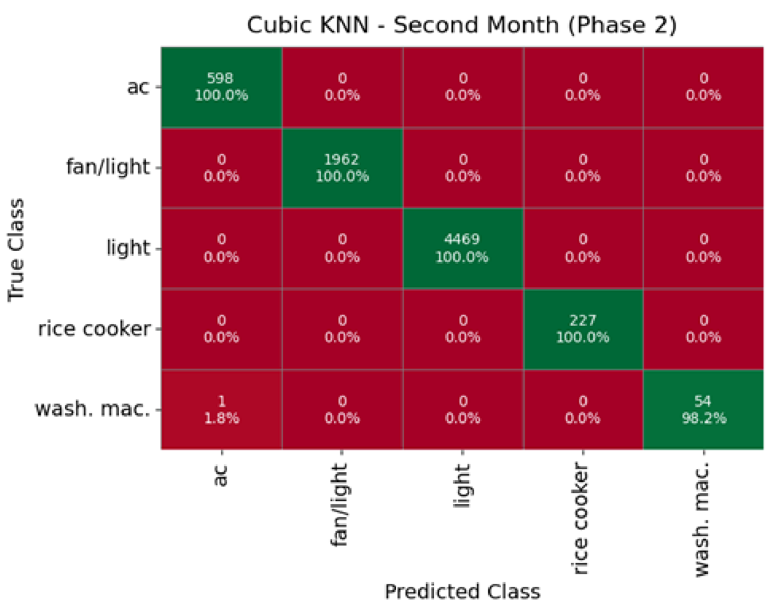


(b)

FIGURE 13. (a) Classification algorithms result for phase 1 in the first month by Cubic KNN (b) Classification algorithms result for phase 1 in the second month by Cubic KNN

Similarly, Phase 2 demonstrated high accuracy across both months. In the first month, as seen in Figure 14 (a), the air conditioner (ac), fan/light, light, and rice cooker classes all achieved perfect classification, with TPRs of 100%. Only the washing machine (wash. mac.) class exhibited a minor decline, with a TPR of 97.7% and one misclassification, reflecting slight overlap in power profiles. In the second month, as illustrated in Figure 14 (b), the results were consistent, with 100% classification accuracy for most classes, including air conditioner, fan/light, and light. The washing machine class improved slightly, achieving a TPR of 98.2%. These results underscore the effectiveness of Cubic KNN in Phase 2, with only minimal misclassifications. Addressing these issues through adjustments to hyperparameters or additional training data could further enhance accuracy.

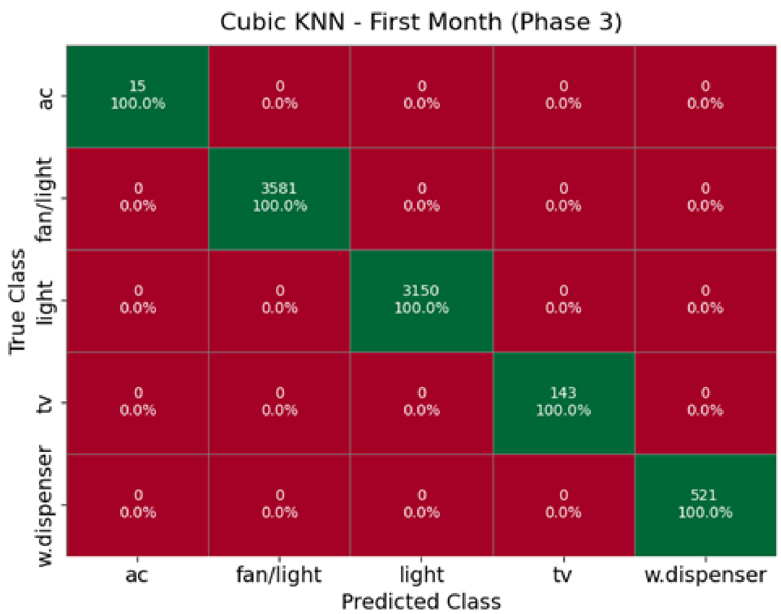
(a)



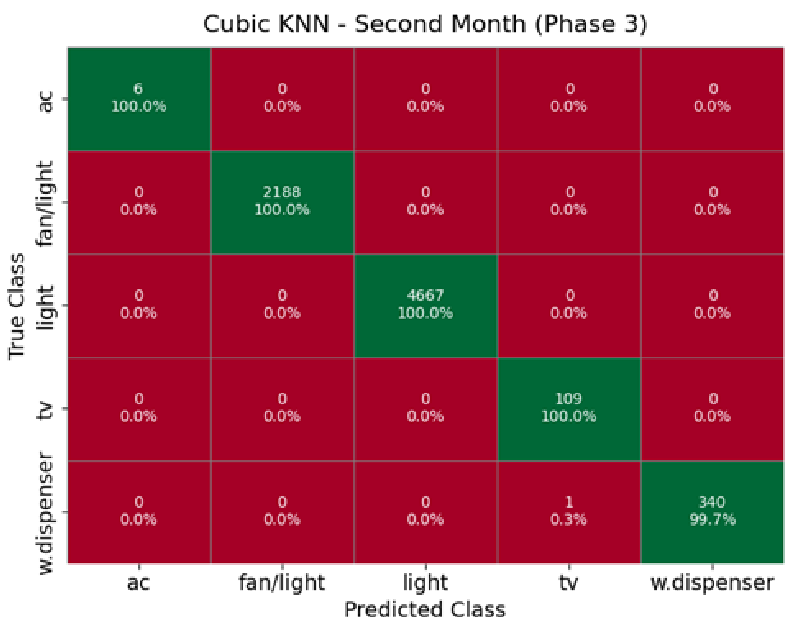
(b)

FIGURE 14. (a) Classification algorithms result for phase 2 in the first month by Cubic KNN (b) Classification algorithms result for phase 2 in the second month by Cubic KNN

In Phase 3, the Cubic KNN algorithm maintained its robust performance. During the first month, shown in Figure 15 (a), all appliance classes, including air conditioner, fan/light, light, television (tv), and water dispenser, achieved 100% TPRs with no misclassifications. This highlights the algorithm's ability to handle diverse power consumption profiles effectively. In the second month, as depicted in Figure 15 (b), the results remained strong, with perfect classification for fan/light, light, and water dispenser classes. The air conditioner class also maintained a TPR of 100%. However, the television class experienced a minor misclassification, resulting in a TPR of 99.7% and a False Negative Rate (FNR) of 0.3%. This minimal misclassification underscores the algorithm's robustness while identifying potential areas for improvement, particularly for appliances with similar power characteristics.



(a)



(b)

FIGURE 15. (a) Classification algorithms result for phase 3 in the first month by Cubic KNN (b) Classification algorithms result for phase 3 in the second month by Cubic KNN

Across all phases, the classification accuracy results validate the effectiveness of the Cubic KNN algorithm in accurately identifying appliance operation states and distinguishing between power consumption patterns. The high TPRs achieved for key appliances, such as fan/light, fridge, light, and water dispenser, highlight its suitability for NILM applications. The minor misclassifications observed, particularly for appliances like PC, washing machine, and television, indicate the need for targeted enhancements to the algorithm. These adjustments could involve increasing the diversity and size of the training dataset, refining feature extraction methods, or optimizing the algorithm's hyperparameters.

CONCLUSION

This study presented a machine learning-based approach to enhance Non-Intrusive Load Monitoring (NILM) systems, focusing on accurate appliance-level energy disaggregation. By employing the Cubic K-Nearest Neighbor (Cubic KNN) algorithm, the proposed method addressed key challenges such as handling low sampling rates, overlapping appliance signatures, and dynamic operational profiles. The evaluation, conducted across three-phase systems and validated against TNB data, demonstrated the robustness and reliability of the approach, achieving high classification accuracy and minimal errors for various appliances. The research underscores the importance of integrating advanced machine learning techniques to improve NILM performance, offering a scalable and efficient solution for real-world applications. These findings contribute significantly to the development of smarter energy management systems, promoting energy efficiency and conservation in both residential and industrial environments. However, the use of a 90-second sampling interval (0.011 Hz) may limit the ability to detect short-duration appliance events, as very brief activations or rapid transitions could be missed. This constraint should be considered when interpreting the results, and future work may explore higher sampling rates or event-triggered logging to improve detection of such short appliance activities. Moreover, future work could explore hybrid frameworks and real-time processing capabilities to further enhance NILM systems' adaptability and scalability across diverse operational scenarios.

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DECLARATION OF COMPETING INTEREST

None.

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