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AI-driven appliance recognition using smart plugs: a review of non-intrusive load identification and consumption classification

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ABSTRACT

The growing adoption of smart electrical plugs has created opportunities for identifying appliances and understanding their electricity consumption through accessible device-level measurements. However, accurate appliance recognition remains challenging because different devices may exhibit similar power ratings, variable operating states, and changing consumption patterns. Artificial intelligence offers methods for extracting meaningful electrical features and classifying appliances from measured voltage, current, power, and energy data. This review examines AI-driven appliance recognition using smart plugs, emphasizing non-intrusive load monitoring, consumption-pattern analysis, load classification, and machine learning. Research published up to 2022 is reviewed to explain the relationship between smart-plug measurements and conventional non-intrusive load monitoring architectures. The discussion covers feature extraction, event-based and event-independent recognition, supervised and unsupervised learning, and deep-learning approaches. It also considers public datasets, evaluation metrics, and practical challenges involving measurement resolution, appliance variability, overlapping signatures, and model generalization. The review finds that smart plugs can provide useful electrical signatures for appliance identification, while AI algorithms improve the interpretation of complex consumption patterns. Reliable deployment nevertheless requires representative training data, robust validation, and careful consideration of measurement and installation conditions.

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1. INTRODUCTION

Understanding how individual electrical appliances consume energy is an important requirement for intelligent energy management. Conventional electricity meters generally report total consumption, which makes it difficult to determine which appliances are responsible for particular consumption patterns. Smart plugs provide an accessible means of collecting electrical measurements at individual outlets, including power, current, voltage, and accumulated energy. These measurements can support appliance identification, operating-state recognition, and the analysis of energy consumption behavior [1], [2].

Artificial intelligence has expanded the possibilities for interpreting electrical measurements because appliance signatures are not always distinguishable through simple power thresholds. Two appliances may have similar rated power while exhibiting different transient responses, harmonic characteristics, or operating patterns. Conversely, the same appliance may produce different measurements under different operating modes or supply conditions. Machine learning can identify relationships between these electrical features and appliance categories, providing a foundation for automated recognition and consumption classification [3], [4].

This review examines AI-driven appliance recognition using smart plugs, with emphasis on non-intrusive load identification and consumption classification. An important distinction is that a smart plug measures a connected appliance directly at the outlet, whereas conventional non-intrusive load monitoring

(NILM) estimates individual appliance consumption from an aggregate measurement point. Smart-plug recognition is therefore a device-level or outlet-level monitoring approach, while conventional NILM is an aggregate-load inference approach. Both approaches share feature extraction and classification techniques, and their complementary characteristics are considered throughout this review [5], [6].

2. SMART-PLUG MEASUREMENTS AND APPLIANCE RECOGNITION ARCHITECTURE

An AI-enabled smart-plug recognition system typically contains a measurement unit, a data acquisition interface, a processing platform, and an appliance classification model. The measurement unit records electrical quantities from the connected load, while the acquisition interface transfers the resulting data to an embedded processor, computer, or cloud platform. The processing stage prepares the measurements for feature extraction and classification. Finally, the recognition model estimates the appliance category or operating state and provides information for energy management [7], [8].

Smart plugs can collect both steady-state and transient electrical information. Steady-state measurements describe the relatively stable operating characteristics of an appliance, while transient measurements capture changes associated with switching events and operating-state transitions. Depending on hardware capability, additional features may be derived from voltage-current waveforms, harmonic components, and power-factor measurements. Combining these characteristics can provide more discriminative information than relying on a single power value [3], [9].

The architecture can be implemented locally or through an edge-cloud arrangement. Local processing allows appliance classification to occur close to the measurement device, potentially reducing communication delays and limiting the transfer of detailed electrical data. Cloud processing provides access to larger computational resources and centralized model management, but it introduces network and privacy considerations. A hybrid arrangement can perform preliminary feature extraction locally and transfer selected information to a central platform for further analysis [8], [10].

3. ELECTRICAL SIGNATURES AND CONSUMPTION-PATTERN RECOGNITION

Appliance recognition depends on identifying electrical characteristics that distinguish one device from another. Common features include active power, reactive power, apparent power, current magnitude, power factor, and energy consumption over selected time intervals. Transient characteristics can provide additional information because appliances often exhibit distinctive electrical responses when switched on or off. Research on NILM has shown that feature selection is important because redundant or weakly discriminative variables may reduce classification performance [3], [11].

Voltage-current trajectories and harmonic characteristics offer more detailed representations of appliance behavior. A voltage-current trajectory describes the relationship between instantaneous voltage and current over an electrical cycle, while harmonic features describe deviations from an ideal sinusoidal waveform. These characteristics can help distinguish loads with similar average power consumption but different electrical operating principles. Their usefulness depends on measurement bandwidth, sampling frequency, sensor accuracy, and the quality of signal preprocessing [9], [12].

Consumption patterns also contain temporal information that can improve recognition. A refrigerator, for example, may exhibit recurring compressor operation, whereas an electronic device may maintain a relatively stable power profile with intermittent changes. Heating appliances may show extended periods of high power followed by reduced or intermittent consumption, depending on their control systems. AI models can learn these temporal relationships and use them to distinguish appliance categories or operating states [4], [13].

4. ARTIFICIAL INTELLIGENCE METHODS FOR APPLIANCE CLASSIFICATION

Machine learning provides several approaches for classifying appliances from smart-plug measurements. Supervised methods such as support vector machines, decision trees, random forests, K-nearest neighbors, and artificial neural networks learn relationships between measured features and predefined appliance labels. These methods require labeled training data representing the appliances and operating conditions that the system is expected to recognize. Their performance depends on feature quality, dataset diversity, class balance, and the separation between appliance signatures [4], [7].

Unsupervised learning is useful when labeled measurements are limited or unavailable. Clustering methods can group measurements according to similarities in power levels, waveform characteristics, or temporal behavior. These groups may represent different appliances or operating states, although additional

interpretation is often required to assign meaningful labels. Unsupervised approaches can therefore support exploratory appliance discovery and help identify unusual consumption patterns [6], [14].

Deep learning provides an alternative when electrical measurements contain complex relationships that are difficult to represent through manually selected features. Convolutional neural networks can learn spatial or local patterns from waveform segments and transformed electrical signatures, while recurrent neural networks can model temporal dependencies in consumption sequences. Hybrid architectures can combine feature extraction and temporal modeling to recognize appliances whose behavior changes over time. Nevertheless, deep-learning models generally require sufficient training data and computational resources, and their performance may decline when applied to appliances or environments that differ from the training dataset [10], [15].

5. EVENT-BASED AND EVENT-INDEPENDENT RECOGNITION

Event-based recognition identifies appliance activity by detecting significant changes in electrical measurements. A switching event may be represented by a sudden increase or decrease in active power, current, or another electrical feature. The detected event is then analyzed using a classification model to determine the likely appliance category. This approach is useful when switching events are sufficiently distinct and can be captured with adequate measurement resolution [5], [8].

Event-independent approaches analyze measurements over time without requiring every appliance transition to be explicitly detected. Statistical models and neural networks can estimate operating states from sequences of electrical measurements, allowing recognition to continue even when switching events overlap or are not clearly defined. Hidden Markov models and factorial hidden Markov models have been widely investigated for this purpose because they represent appliance states and their temporal transitions. These approaches are particularly relevant to conventional NILM, where the measured signal may contain contributions from several simultaneously operating appliances [16], [17].

The relationship between these approaches and smart plugs is summarized in Table 1. Smart plugs can directly measure an individual connected load, simplifying the recognition task compared with aggregate NILM. However, when several appliances are connected through a shared measurement point or when smart-plug measurements are combined with a main meter, the classification problem becomes more complex. The table therefore distinguishes direct outlet-level recognition from aggregate-load identification and highlights their respective analytical requirements [18].

Table 1. Comparison of appliance recognition approaches

Approach	Measurement input	Typical AI methods	Main advantage	Main limitation
Direct smart-plug recognition	Individual appliance voltage, current, and power	SVM, random forest, ANN, CNN	Appliance measurements are separated at the outlet	Requires a smart plug for each monitored outlet
Event-based NILM	Aggregate measurements and switching events	SVM, decision trees, CNN	Uses identifiable changes in electrical signals	Overlapping or weak events may be missed
Event-independent NILM	Continuous aggregate power sequences	HMM, FHMM, RNN, LSTM	Can model appliance states over time	Greater inference complexity
Hybrid recognition	Transient, steady-state, and temporal features	CNN-RNN, feature fusion, ensemble learning	Combines complementary electrical characteristics	Requires more complex training and validation
Unsupervised recognition	Unlabeled electrical measurements	K-means, hierarchical clustering, density-based clustering	Reduces dependence on labeled datasets	Appliance labels and cluster interpretation remain challenging

6. DATASETS AND PERFORMANCE EVALUATION

The development of reliable appliance recognition models depends on representative datasets. Public datasets allow researchers to compare algorithms, investigate different measurement conditions, and evaluate model performance using common experimental data. The Reference Energy Disaggregation Dataset (REDD), UK-DALE, and other household energy datasets are frequently used in conventional NILM research. The Plug-Level Appliance Identification Dataset (PLAID) is particularly relevant to appliance recognition because it contains voltage and current measurements collected from individual appliances [5], [11].

Dataset selection should reflect the intended recognition task and measurement architecture. High-frequency waveform datasets can support transient and voltage-current feature analysis, whereas low-frequency power datasets are more suitable for long-term consumption patterns and operating-state

estimation. A model trained on one dataset may not perform equally well on another because appliance models, usage behavior, electrical conditions, and measurement systems differ. Consequently, cross-dataset validation is important when assessing whether an AI model can generalize beyond its original training environment [11], [14].

Classification accuracy alone is insufficient to evaluate a recognition system. Precision, recall, F1-score, confusion matrices, and class-specific performance provide a more complete picture of classification quality. For energy disaggregation, additional measures such as mean absolute error and normalized disaggregation error can assess the accuracy of estimated appliance consumption. Dataset documentation, reproducible preprocessing, and consistent evaluation procedures are also essential for meaningful comparisons [11], [16].

7. PRACTICAL CHALLENGES AND RESEARCH OPPORTUNITIES

A major challenge is the similarity between electrical signatures produced by different appliances. Devices with comparable power ratings may be difficult to distinguish when only low-resolution measurements are available. Multi-state appliances create an additional problem because one device may exhibit several distinct consumption profiles. Combining steady-state, transient, harmonic, and temporal features can improve discrimination, but it also increases measurement and processing requirements [3], [9].

Another challenge is model generalization across different appliances and operating environments. Variations in manufacturer, model, age, supply voltage, and user behavior can change an appliance's electrical signature. Training data may also be imbalanced, with some appliance categories represented by many measurements and others by very few. Transfer learning, data augmentation, semi-supervised learning, and adaptive classification are potential approaches for reducing dependence on large, fully labeled datasets [10], [13], [15].

Smart-plug-based recognition also raises practical questions concerning cost, scalability, privacy, and system integration. Installing an individual smart plug on every appliance provides detailed measurements but may increase hardware and maintenance costs. Centralized NILM can reduce the number of measurement devices, although it requires more complex signal separation and inference. Future systems should therefore investigate hybrid architectures that combine selected smart plugs with aggregate metering, local AI processing, and privacy-aware data management [6], [8], [14].

8. CONCLUSION

AI-driven appliance recognition using smart plugs provides a practical approach to identifying electrical devices and understanding their consumption patterns. Smart plugs supply outlet-level measurements that can be analyzed using electrical feature extraction, machine learning, and deep-learning methods. These methods can classify appliance types, identify operating states, and distinguish consumption patterns that are difficult to interpret through simple power thresholds. Conventional NILM provides a complementary approach by estimating appliance-level consumption from aggregate electrical measurements.

The effectiveness of appliance recognition depends on measurement quality, representative datasets, suitable feature selection, and robust model validation. Supervised learning is useful when labeled appliance data are available, while unsupervised and deep-learning approaches offer alternatives for discovering complex consumption patterns. However, similar appliance signatures, changing operating conditions, and limited training data remain significant barriers to reliable deployment. Future research should prioritize generalizable recognition models, standardized benchmarking, efficient edge implementation, and hybrid smart-plug/NILM architectures to support practical intelligent energy management.

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