Non-Intrusive Load Monitoring Using Machine Learning for Household Appliances with IOT

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ABSTRACT

The project proposes a real-time non-intrusive Load Monitoring (NILM) gadget designed for home appliances, utilization of machine learning (ML) algorithms and Internet of Things (IoT) technologies. The middle goal is to identify and classify electrical devices based on their special power intake pattern, without the need for extra sensors or invasive hardware changes. By using real-time data from modern, voltage and temperature sensors, a random classifier (RFC) is used to check and predict the use of machine equipment correctly. This ML-based perfect method makes it possible to detect smart power management and deviations, which contributes to adapted power use and machine reluctance. The proposed NILM gadget is initially integrated into an IoT network to allow real-time monitoring and decision-making. The figures earned from the sensor module are treated and an IoT communication interface is transferred to a centralized thing that meets the type and load identity. The unit supports power optimization from the way the algorithm uses the algorithm that detects the use of use and falls into peculiar patterns, which may affect the machine's disabilities or errors. User-aligned interface-Savan provides insight into the intake, giving customers the opportunity to reduce power waste and fee. Experimental verification of real-world dataset validated an excessive type of accuracy, with RFC receiving 92% accuracy rate. The modular design of the unit ensures scalability, safety through encrypted communication and adaptability for different family environments. This work offers a significant contribution to smart home energy management by providing a non-invasive, cost-effective, and efficient load monitoring solution that promotes sustainable energy usage.

1.1 INTRODUCTION

Like global energy demand continues to increase, intelligent, skilled and lasting energy management requirements have focused a significant focus in both academic and industrial sectors. Such an emerging technology is monitoring of non-intrusive load (NILM), which provides an innovative method of monitoring the energy consumption at equipment level without the need for individual sensors on each unit. NILM systems analyze total electrical signals—usually at a single entrance point in a house—and separate the data to identify the operating patterns of different devices. This method reduces hardware costs and installation complexity, which makes it particularly favorable for smart energy systems for homes [1], [2]. Traditional load monitoring methods, although accurate, often depend on the methods of infiltration that include extra sensors or smart plugs for each unit, leading to high distribution and maintenance costs. NILM eliminates these requirements by taking advantage of the progress of computer science and artificial intelligence (AI) to gain meaningful insight from the existing electrical infrastructure. Development of machine learning (ML) techniques, especially Random One Classifier (RFC), have improved the ability to classify the power load exactly based on functions such as model clothing, voltage, power and power factor [3], [4].
The integration of NILM with the Internet of Things (IoT) technology enables data collection in real time, cloud-based analysis and user-friendly interfaces to monitor energy consumption and control. IoT network sensors facilitate spontaneous communication between processing units and user interfaces, making energy management more interactive, data-powered and available. This synergy between NILM and IoT provides home an actioned energy insight, which allows for behavioral adjustment, energy saving and environmental stability [1], [5]. Recent literature NILM highlights different promotion in the function. For example, deep learning models such as deep flexible transmitter networks [6] and attention-based architecture [10] have performed better in disagreement about overlapping load signatures. Adaptation-based approaches, such as artificial BI colonials, have also been used to increase classification accuracy and system adaptation [7]. In addition, comparative studies [8] have assessed different machine learning models to determine the optimal configuration for different load properties, and emphasized the importance of convenience choice and model setting.

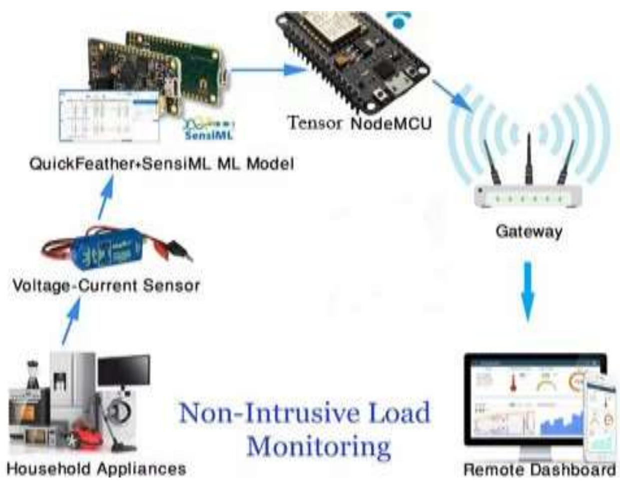
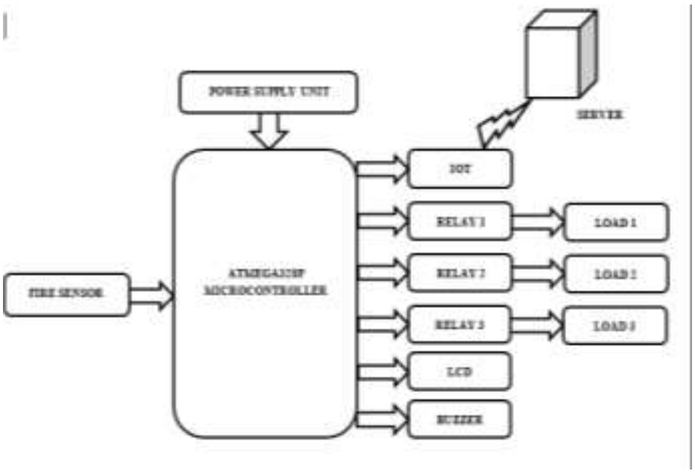


Fig 1: Non-Intrusive Load Monitoring

Dash and Sahoo performed complete evaluations on NILM technologies, figuring out trends in electric power disaggregation and providing interest-based multitask studying frameworks capable of concurrently detecting multiple home appliances in real-world situations [9], [10]. These advances address key challenges in NILM, along with classification accuracy, generalization to unseen appliances, and robustness towards noise and data imbalance. Motivated by using these traits, this task provides a real-time NILM gadget using a Random Forest Classifier included with an IoT framework for household programs. The gadget uses non-intrusive voltage, current, and temperature sensors to collect energy signatures from appliances. These features are analyzed using supervised machine learning to classify appliance types, detect anomalies, and optimize energy consumption. The proposed device not only improves user awareness and control over power usage but also helps broader goals of cost savings and grid efficiency.

PROPOSEDSYSTEM

This section outlines the architecture and workflow of the proposed real-time Non-Intrusive Load Monitoring (NILM) system for residential energy management. The system leverages Internet of Things (IoT) technologies, non-intrusive sensors, and a Machine Learning-based Random Forest Classifier (RFC) to accurately identify appliance usage, optimize energy consumption, and detect operational anomalies without requiring device-level instrumentation.



The proposed system consists of the following integrated components:

Non-Intrusive Sensors:
The voltage, power and temperature sensors are distributed at the most important electrical distribution point for capturing the total electrical signals. These sensors do not interfere with individual devices and preserve system integrity. The current sensor load detects variations, while the voltage sensor captures the supply. Temperature readings are included to correlate equipment operations with thermal conditions at the environment or unit level, which combines reference to energy consumption patterns.

Data collection module:
Analog signals from the sensor are fed into a microcontroller (e.g., ESP32), where they are digitized using an ADC (analog-to-digital converter). A smooth window approach is used to fragment the time series data for better temporary pattern analysis. Pre-treatment involves normalization, signal leveling, and removal of outliers, which ensures high model accuracy and stability during training and estimation.

IoT -Communication Network:
An IoT module built into a microcontroller transmits pre-processed data to a centralized server or via Wi-Fi to a cloud platform. MQTT protocol or HTTP REST API is used for secure data transfer. This connection enables external monitoring in real time and long-term storage of energy consumption data.

Machine Learning Classification:
The random one classifies is trained on a dataset with different tools representing separate tools. RFC is selected due to non-life-long conditions and ability to handle high-dimensional data. This decision works by making a

dress of trees, and the final predictions are taken through the majority mood. The model is trained offline and distributed on the ship or server to guess in real time. Matrix as accuracy, accurate and recall is used to validate model performance, with more than 90%target classification accuracy.

Divergence by deviation:
The system contains rules -based and statistical non -cooked algorithms that analyze load patterns. For example, unpredictable spikes trigger in power consumption or usually extended activity alerts from short -circuit equipment. These mechanisms can identify malfunctions, detect unauthorized use or help predict potential defects before failure.

User Interface:
A web-based or mobile dashboard is implemented to provide users with real-time visibility into their energy consumption. The interface displays appliance-wise energy usage, system alerts, energy-saving recommendations, and historical trends. Custom alerts via SMS or email can be configured for critical events such as overheating or abnormal load detection.

Security Layer:
Given the sensitivity of household energy data, security is a key component. The system supports data encryption (e.g., TLS/SSL), user authentication, access control lists (ACLs), and secure firmware updates. These measures ensure data integrity, confidentiality, and resilience against cyber threats.

EXISTINGSYSTEM

Non-Intrusive Load Monitoring (NILM) has emerged as a key technique in smart energy systems, enabling detailed appliance-level energy usage analysis without deploying intrusive sensors. Recent developments have leveraged machine learning and IoT to enhance classification accuracy, scalability, and real-time performance.
Ahammed Mehedi and Hasan [1] suggested a real-time NILM framework on IoT using low-frequency data to handle the challenges generated by the inaccessibility of smart meters. Their approach used a customized data collection system (DAS) to capture voltage variability for load classification and used machine learning algorithms.
Athanasiadis and Doukas [2] introduced a scalable NILM solution, including an event detection module, a Convolutional Neural Network (CNN)-based classifier, and a power assessment algorithm. Their modular system architecture provided real-time load classification in different appliances. Yaemprayoon and Srinonchat [3] emphasize transient behavior using the internal power signature of the CNN-based NILM model. This method improved the load identity, especially during the coupling stages of the equipment.
Li et al. [4] leveraged transfer learning for multi-objective NILM in smart buildings, enhancing generalization capabilities and minimizing training overhead. Their solution emphasized the environmental impact of energy monitoring by contributing to reduced carbon emissions.
Additionally, several recent works have introduced novel deep learning and optimization-based approaches. Ma and Yin [5] proposed Deep Flexible Transmitter Networks for NILM in distribution systems, enabling adaptive and precise load disaggregation using deep learning architectures. Ghosh and Chatterjee [6] implemented an Artificial Bee Colony (ABC) optimization technique to improve load disaggregation efficiency in smart homes.

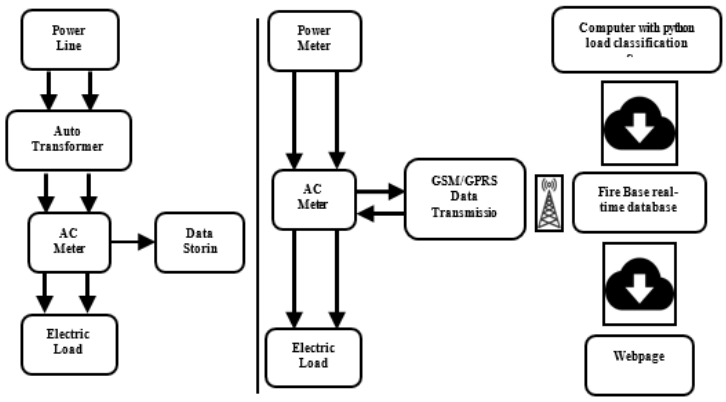


Fig 2: Existing Block Diagram

METHODOLOGY

The proposed methodology follows a pipeline model, comprising six key stages:

Data collection:

Real time sensor data is collected in fixed time intervals (e.g., 1 second). The parameters include RMS voltage, RMS current, active strength, reactive power and temperature. These readings are time stamped and stored for further analysis.

Functional recovery:

Characteristics such as unit, standard deviation, power factor, harmonic deformation and energy consumption are deducted from raw data. These properties occupy behavioral signature of the devices and are important for accurate classification.

Model training:

The RFC model is trained using monitored teaching techniques. A labeled dataset with patterns used from different devices (e.g., fans, refrigerators, lights, washing machines) is used. Cross-validation is used to prevent overfitting, and hyper parameters such as the number of trees and maximum depth are tuned.

Model suggestions:

The trained model is series and is distributed on each edge unit or shooter. In the edge setup, the delay decreases, enables careful classification. For cloud -based systems, scalability and learning across devices can be used.

Detection and response of deviations:

Different detection module continuously compares the current behavior of historical criteria. Threshold and prediction intervals are used to flag deviations. The system provides feedback to users through visual indicators, e -post messages or app alerts, enabling active intervention.

Energy adaptation:

Depending on classification and deviations, users have personal recommendations such as optimal time to use heavy devices, identification of high energy units and suggestions to reduce the top load. This tool helps to reduce the bill and promote environmentally conscious behavior.

RESULT&DISCUSSION

Hardware Implementation Results

Hardware Implementation of the proposed non - intrusive Load Monitoring (NILM) system was performed using an ESP32 microcontroller with voltage, current and temperature sensors. The system was designed to measure real -time electrical parameters from regular home equipment such as fans, pears and engines. Based on the ACS712 module, the current sensor effectively captured the currents loaded with different devices attached to the main distribution line. During testing, resistance loads demonstrated that glowing pears a consistent and stable power wave, while fans and engines that inductive loads showed the characteristic of the insertion flows during the start -up. In today's behavior, these distinctions provided useful patterns for strain identity.

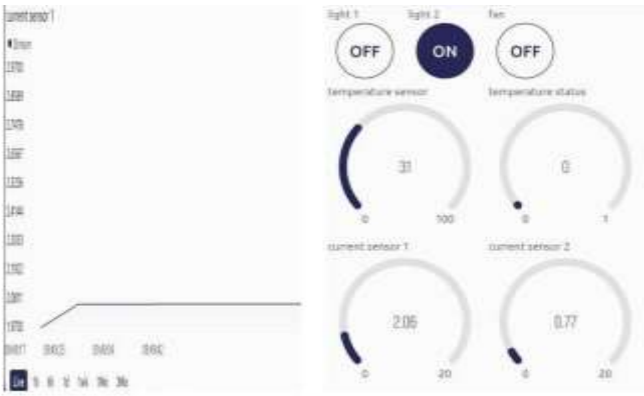


Fig 5: Current sensor-1 (load2) Current sensor-1 (waveform)

The voltage sensor was used, ZMPT101b, provided a stable reading, which usually reflects the main voltage levels mainly between 215V and 230V in the test environment. These voltage readings, combined with current data, enabled the power consumption and the real -time calculation of the power factor. The accuracy and responsibility of tension and current measurements formed the basis for energy and classification processes implemented in the machine learning algorithm.

Fig 6: Current sensor-2 (load1) Current sensor-2 (waveform)

In addition, an LM35 temperature sensor was used to monitor both the environment and the load-specific temperature. During operation, the fan and motor appliances showed measurable thermal increments, with temperature rising by approximately 5–12°C depending on load intensity and duration. These readings were critical not only for energy analysis but also for anomaly detection, as sudden or excessive heat generation could indicate abnormal device behavior or impending faults.

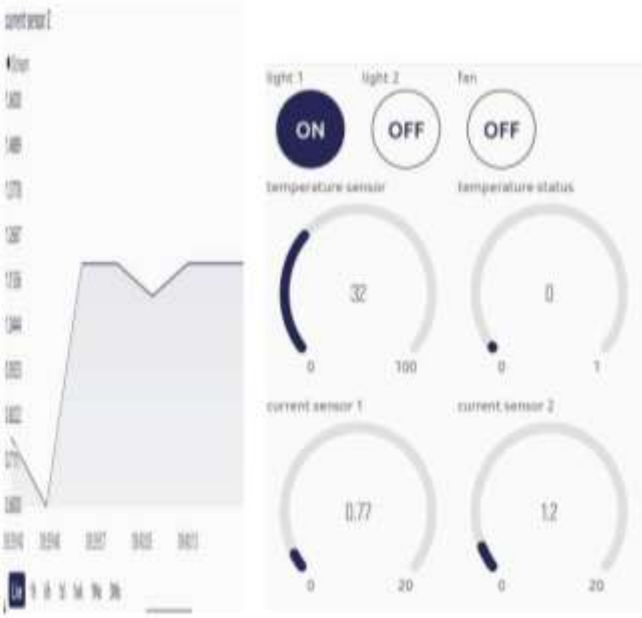


Fig 7: Temperature sensor Temperature sensor (waveform)

ESP32 Microcontroller provided comfortable broadcast of sensor data on clouds via Wi-Fi, which enables remote monitoring via IoT dashboard. The data was thought of platforms such as Blynk IoT and a customized network interface, which showed the real -time position for voltage, power, power and equipment. The user can inspect the dynamic graph, receive notice and even perform the equipment using the MQTT-based command, and perform the reaction capacity of the system in real time.
In order to validate the system security and control functions, a relay module was included in the design. The relay reacted to the user command and system -generated conditions, such as overload detection or the thermal threshold is crossed. For example, when the system detected overfire conditions for a long time beyond a defined area, the relay automatically cut the corresponding equipment. This action demonstrated the system's responsiveness and strengthened its suitability for security -modified applications in domestic energy management.
Overall, the hardware implementation confirmed the system's ability to perform real-time sensing, classification, and control. The sensors delivered accurate and consistent measurements, the IoT platform ensured timely data delivery and user interaction, and the control mechanism responded effectively to both user inputs and system-generated alerts. These results validated the practicality, reliability, and effectiveness of the proposed NILM system for intelligent home energy monitoring.

SIMULATION RESULTS

The proposed NILM system was simulations using Python, and used libraries such as Scikit-Learn for implementation of machine learning, data management pandas and food Matplotlib for visualization. A well -structured dataset was developed, consisting of regular home appliances such as fans, pipe lights and electrical parameters registered with engines. The main functions used for training were voltage, current, real power, power factor and unit level. These functions were normalized to ensure continuity and used to train a randomly classify (RFC).

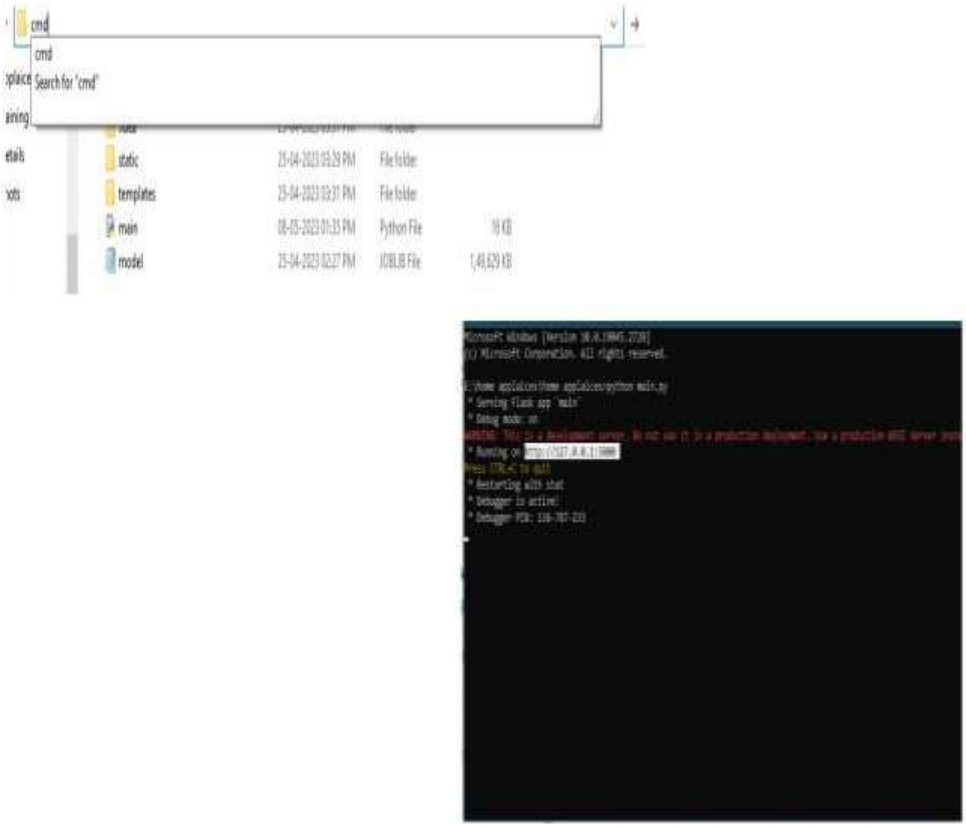


Fig 8: Command Window Output

The dataset was divided into a department of 80:20 respectively for training and test purposes respectively. The RFC was configured with 100 estimates (decision trees), which allowed the model to make a strong dress that was able to handle non-led and high-dimensional data. In the event of an evaluation, the classifier gained an accuracy of 92.5%, with an accuracy of 91.3%, a 92.8%memory and an F1 point of 92.0%. These results reflect the model's strong ability to distinguish between different units based on their energy consumption signature.

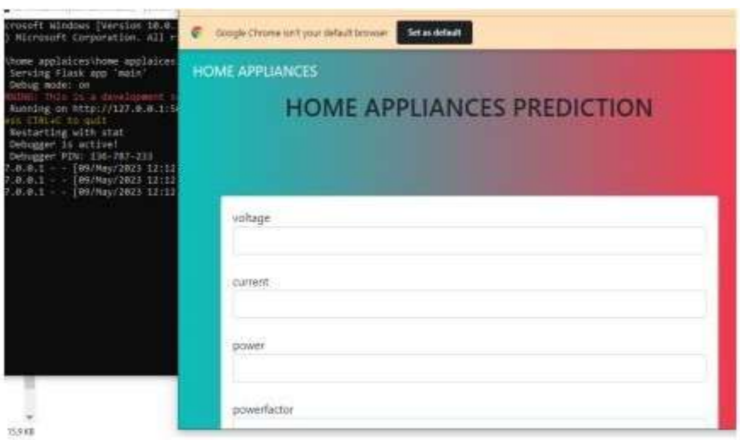


Fig 9: Confusion Matrix of Appliance Classification

To evaluate the performance, an illusion was generated to analyze the matrix how well each class of the tool was predicted. The model showed high prediction accuracy for various loads such as glowing bulbs and fans, where the load signatures were unique and stable. However, units with overlapping power profiles such as motor

-based equipment presented a little less abortion. It was responsible for equality in the current draw and operating cycles. Confusion matrix highlighted these challenges and emphasized the importance of convenience diversity and data set size to improve the strength of the classification.

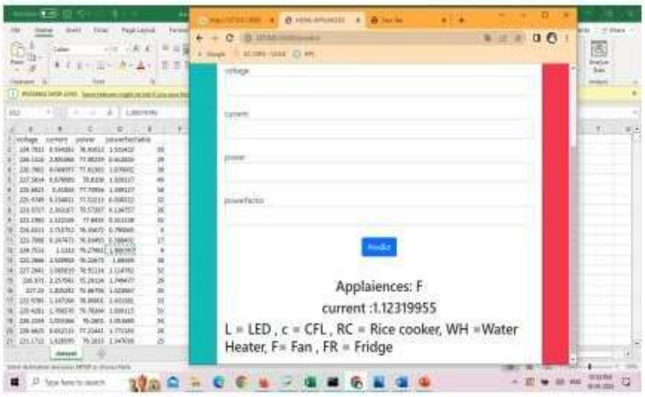


Fig 10: Anomaly Detection Plot

The deviation for deviations to assess the system's ability to identify unusual operating conditions was also integrated into the simulation pipeline. The algorithm flag successfully deviated as current, unexpected voltage drops and sudden spikes in unusually low power factors. Temperature -based deviations were also mimicked, where the rapid temperature increase beyond predefined threshold triggers the notice. In alerts, the security interventions in the real world mimic, such as stopping the burden to prevent losses or sending notification to the user interface.

The final simulation output included real-time predictions of appliance usage, graphical representation of power usage trends, and anomaly detection logs. Visual outputs such as plotted waveforms, predicted vs. actual classification results, and heatmaps of the confusion matrix provided an intuitive understanding of system performance. The simulation environment validated the overall functionality of the system, demonstrating its ability to perform accurate load classification and proactive fault detection, and confirmed its suitability for real-time deployment in smart home applications.

CONCLUSION

Machine learning-based real-time non-intrusive electrical load monitoring over the Internet of Things is a promising technology that has a number of advantages, including improved security, scalability, and energy economy. Although this technology may have some drawbacks, such as limited accuracy and privacy concerns, these can be resolved with proper design and execution. In order to enable real-time load classification, energy optimization, and anomaly detection while also preserving user security and privacy, the proposed system for real-time non- intrusive electrical load classification over using machine learning would make use of non-intrusive sensors machine learning algorithms, and IoT technology. This technology has the potential to completely transform the way that energy is managed by allowing users to optimize their energy use, reduce waste, lower their energy costs, and increase the effectiveness and dependability of their system.

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