Intelligent Power Usage Analytics for Optimized Home

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***Abstract*—The Intelligent Power Usage Analytics for Optimized Home designs a smart electricity monitoring system, using a CNN-LSTM combined NILM model for real-time monitoring of energy usage at an appliance level. It uses a smart meter PZEM-004T, ESP32 Microcontroller, a cloud server, and a Flutter mobile application for proper data visualization.CNN-LSTM model used for appliance-level energy disaggregation which can effectively used to find individual appliance consumption.Anomaly detection are included in the system use machine learning to send alerts about anomalous energy. The objective is that of make the energy usage efficiently , hence reducing electricity costs, and provides reports about the key information on appliance Consumption.**

***Index Terms*—Intelligent power usage, energy monitoring, Non-Intrusive Load Monitoring (NILM) ,CNN-LSTM model, smart metering, electricity cost reduction**

I. Introduction

Household energy management is important with rising energy bills and environmental issues. Traditional monitoring systems only record aggregate data, which makes it complicated to track the energy consumption of individual devices by homeowners. Installing smart plugs on every appliance is expensive and not feasible as most homes house hundreds of appliances. This is achieved through Non-Intrusive Load Monitoring whereby appliance-specific data is disaggregated from the total power consumption through a single smart meter. The "Intelligent Power Usage Analytics for Optimized Home" system integrates NILM with applications for mobile use, where real-time energy usage information is provided. It overcomes the drawbacks of conventional methods because it provides detailed consumption records that help home owners make decisions in aspects of energy efficiency. Advanced technologies applied in this project are focused on improving energy management, reducing costs, and promoting more sustainable living environments.

A. Background and Motivation

With the increasing demand for efficient energy management in households, the need to monitor appliance level came up, though traditional methods such as individual smart plugs are very costly and even unrealistic for larger setups. With the aim to come up with a cost-effective solution, the "Intelligent Power Usage Analytics for Optimized Home" uses the Non-Intrusive Load Monitoring (NILM) method. It monitors energy usage per appliance without the need for additional devices through a smart meter, ESP32 microcontroller, and cloud-based data processing. It enables users to know how to best manipulate energy use as it gives real-time data through a mobile app.

Another excellent feature is machine learning, which catches anomalies in power usage, thus warning users about potential energy waste and cost implications. The mobile app will further allow house owners to track historical data and print reports, thereby providing a space for more efficient and sustainable energy management. It provides a scalable and practical solution for what is required to overcome energy challenges encountered with modern life.

B. Problem Statement

- **Lack Of Visibility:** Unable to find which device consumes more energy
- **Absence Of Timely Awareness:** Only through monthly bills we can identifyhigh consumption.
- **Unnoticed Anomalies:** The abnormal energy consumption often go unnoticed so it lead energy wastage and applience problems.
- **Lack Of Data Presentation:**Lack of data presentation tool to view the data about the energy used.

II. Objectives

The major goals of system are:

- **Appliance Level Real-Time Monitoring:** NILM can divides the total energy consumption into applience level data.
- **Anomaly Detection:** Alerts to Users for detected any abnormal Consumption pattern by Applying Machine Learning Models.
- **Cost Estimation:** Estimate the energy cost data in terms of appliance level and based on their consumption.
- **App For Monitoring And Reporting:** Display real-time and history data in a mobile app with the features of notifications reporting.

III. Literature Survey

1. Design, Implementation, and Deployment of an IoT-Based Smart Energy Management System (2021) [1]: An IoT-based smart energy management system that integrates smart meters to provide real-time monitoring, analysis, and control of energy consumption across multiple appliances, enabling efficient demand-side management and remote appliance control.

2.Energy Consumption Monitoring in Smart Home System (2021) [2]: A sophisticated IoT-based energy monitoring system for smart homes that uses an ACS712 current sensor and NodeMCU microcontroller to capture real-time power usage, coupled with an Android application that displays energy consumption and predicts monthly electricity expenses through a regression model.

3. Energy Management Strategy of Microgrids in Joint Energy, Reserve, and Regulation Markets Based on Non-Intrusive Load Monitoring (2021) [3]: An innovative energy management strategy for microgrids utilizing non-intrusive load monitoring (NILM) technologies to disaggregate HVAC power consumption, preserving consumer privacy while providing valuable insights into appliance usage and optimizing bidding strategies in energy markets.

4. IoT-Based Approach for Load Monitoring and Activity Recog- nition in Smart Homes (2021) [4]: An advanced IoT-based approach combining intrusive and non-intrusive load monitoring techniques with machine learning models (feed-forward neural networks, LSTM, and SVM) to classify appliance usage and recognize activities of daily living, extending beyond traditional energy monitoring.

5. A Smart Home Architecture for Smart Energy Consumption in a Residence with Multiple Users (2020) [5]: A multi-user Home Energy Management System (SmartCom) that uses Smart Outlets with Near Field Communication technology and Wi-Fi handover tracking to attribute energy usage to individual residents, offering personalized energy management profiles and user-controlled consumption adjustments.

6. Energy Management Using Non-Intrusive Load Monitoring Tech- niques – State-of-the-Art and Future Research Directions (2020) [6]: A comprehensive review of non-intrusive load monitoring techniques, emphasizing their potential in smart sustainable cities and exploring their applications in smart grids, home automation, and demand-side management.

7.A Review on Non-Intrusive Load Monitoring Approaches Based on Machine Learning (2020) [7]: An in-depth analysis of machine learning-based non-intrusive load monitoring techniques, examining supervised, unsupervised, and reinforcement learning approaches in the context of residential energy smart management and smart grid systems.

8. IoT-Based Application for Monitoring Electricity Power Con- sumption in Home Appliances (2019) [8]: A low-cost, Wi-Fi-enabled IoT application using an ESP8266 microcontroller and ACS712 current sensor to monitor home appliance electricity consumption in real-time, storing data in a cloud-based MySQL database for remote access and tracking.

9. Non-Intrusive Load Monitoring: A Review and Outlook (2016) [9]: A comprehensive review of non-intrusive load monitoring techniques, categorizing household appliances, exploring learning approaches, and identifying challenges in developing more accurate and scalable energy monitoring algorithms.

10. Unsupervised Algorithms for Non-Intrusive Load Monitoring: An Up-to-Date Overview (2015) [10]: A detailed examination of unsupervised approaches in non-intrusive load monitoring, focusing on methods that require minimal user intervention and can effectively analyze aggregated energy data through load classification and source separation techniques.

IV. Methodology

It develops an NILM-based smart energy monitoring system to achieve an efficient appliance-level understanding of energy consumption in homes. In this manner, the users could monitor the individual appliances without additional meters, and the system improves on energy efficiency through advanced algorithms and machine learning to disaggregate total power data. The hardware and software units integrate well to allow for real-time collection and analysis,user friendly mobile application in tracking consumption, anomalies, and generate reports.

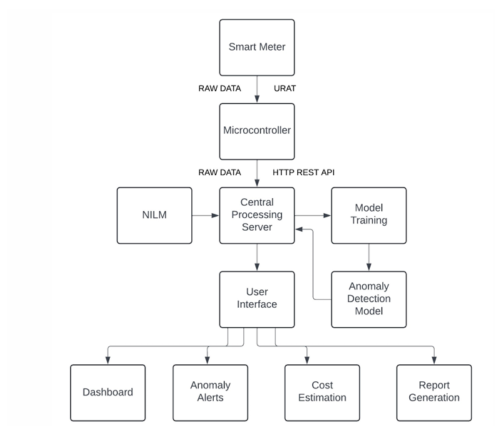


Fig. 1. Architectural Diagram

A. *System Architecture*

1) Hardware Components:

- **PZEM-004T Smart Meter:** The smart meter that takes measures of the cumulative power consumption of several appliances which are attached. It is the main device for data collection.
- **ESP32 Microcontroller:** The data on the power consumption will be transmitted to ESP32 Microcontroller wherein it receives the same and transmits the data to the cloud server using UART communication.
- **Power Strip:** All fans, chargers, lights, etc. are plugged into a common power strip so the smart meter will read them in bulk for their combined power usage.

2) Software Components:

- **NILM Algorithms:** The NILM technique is used to disaggregate the total power consumption data into appliance-level data. In addition, it avoid the requirement of a single meter per appliance.
- **Machine Learning for Anomaly Detection:** The machine learning model shall be implemented in the monitoring process to catch any anomalies in inefficient working of specific devices or malfunctioning of specific devices.
- **Flutter Mobile Application:** Reads and displays real time data, alerts the user of anomalies, generates reports, and can send notifications to the user.
- **Cloud Server:** processes the data received from ESP32, runs the NILM algorithms, performs anomaly detection, and communicates with the mobile app to display live results.

B. Data collection and transmission

The data collecting and transmitting methodology is focused on real-time monitoring of energy consumption.

- **Data Collection:** Smart Meter Readings: The PZEM-004T smart meter continuously monitors the power consumption from all the appliances connected. Data is captured in real-time to ensure that the monitoring system may promptly detect changes in consumption patterns.
- **Data Transmission:** For reliability, data will be transmitted to the cloud server through UART communication.
- **Data Processing:** NILM Algorithm:With the data received in the cloud server, it then runs NILM algorithms which decompose the overall power consumption into individual appliances; thereby determining which apparatus consumes the most power.
- **Machine Learning Based Anomaly Detection:**Disaggregated data check for anomalies with the help of machine learning, and with the proper algorithms, it tries to identify anomalies. When it finds such irregularities, then the user is notified with a mobile application.

C. User Interface and Mobile App

Some of the key features of the mobile application developed in Flutter are:

- **Real-Time Monitoring:** It shows the real-time energy consumption for each device so that the user could monitor what he is consuming and optimize the usage accordingly.
- **Anomaly Alerts:** An alert is raised from the system for users whenever an anomaly is encountered in the system at a given point in time, when a particular appliance is consuming energy unusually high.

This is an app of report and notify. That encompasses the generation of reports and can allow them to be exported, showing energy consumption in various time frames. Additionally, access to historical data is provided so users can analyze trends in order to make informed decisions about energy saving measures.

Development of the CNN-LSTM model

CNN:

- **Conv1D layers:** Capture spatial information, power data; this has made the model identify singular signatures of appliances.
- **Batch normalization**: Normalizes layer by layer, stabilizes the training.

LSTM: Long Short-Term Memory:

Bidirectional LSTM captures temporal dependencies from backward and forward directions of previous consumption patterns, making real-time prediction robust.

- **dropout:** Avoiding overfitting by making random neurons drop during the time of training.

Dense Output Layer

- Activation Function: Applied sigmoid function to decide the on or off status of appliances.

Training and Evaluation

- **Loss Function:** Used is the cross-entropy loss.
- **Optimizer:** The optimizer, Adam will change the learning rate along with performance during the model phase.
- **Early Stopping:** It will be stopped with training if it is a case where there is a failure to show an improving validation loss which helps from overfitting.

Cloud Processing

- **Data Reception:**JSON-formatted data arrives through an HTTP REST API at the cloud server.
- **Data Storage:** The server will store the incoming data in a database sorted by timestamps and appliance identifiers.
- **NILM Processing:** The cloud server disaggregates the aggregated power data using the trained CNN-LSTM model.

D. Anomaly Detection Mechanism

During machine learning models, the process includes anomaly detection in energy consumption patterns in the project by adopting the following:

- **Training data:** For this purpose, all historical data on energy usage from those appliances are collected and used in training the machine learning models. In the further optimization process, the models will be trained to identify what constitutes normal deviations from these consumption patterns. The model is then fine-tuned for accuracy concerning anomaly detection.

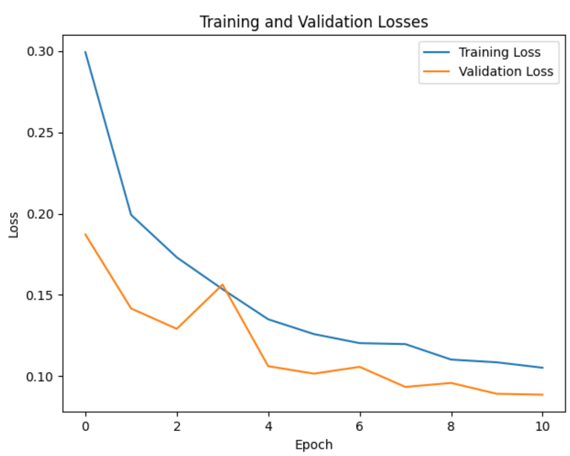
- **Real Time Analysis:** Once this model is trained, it will start sending alerts after alerts to the user concerning the real-time data analysis over unusual usage patterns in power.

V. Results and Discussion

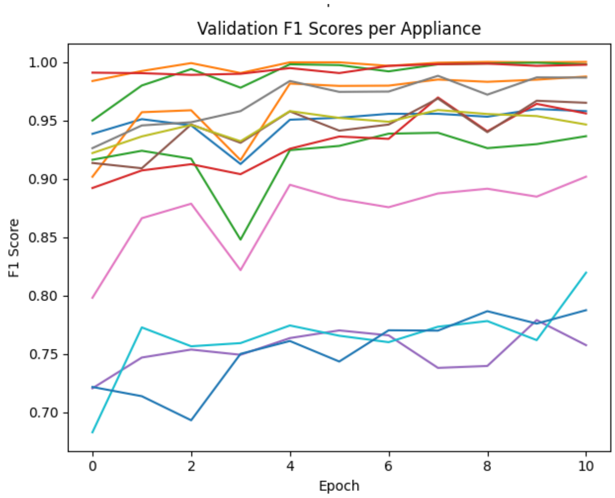
In the "Intelligent Power Usage Analytics for Optimized Home" project, NILM was successfully implemented using a CNN-LSTM model to be used for appliance disaggregation and an Isolation Forest model for anomaly detection.

A. Model Training Infrastructure

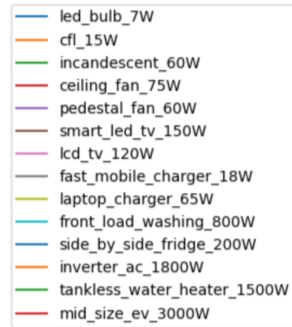
A robust training pipeline was designed to ease the model development process. This infrastructures will automate data pre-processing, control training hyperparameters, and monitor metrics for maximum model accuracy.

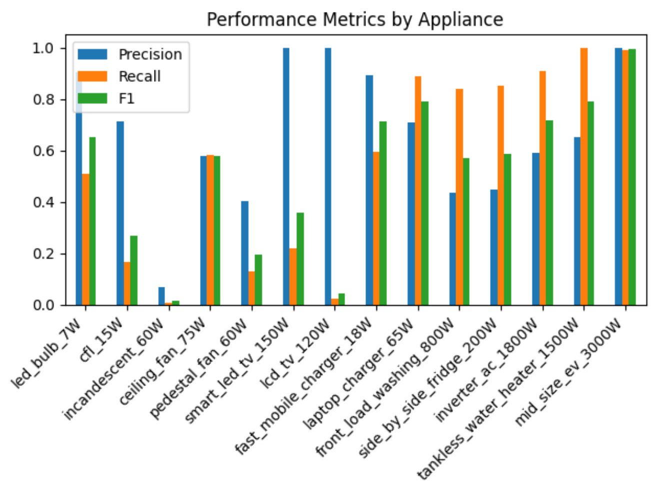


Training and Validation Loss

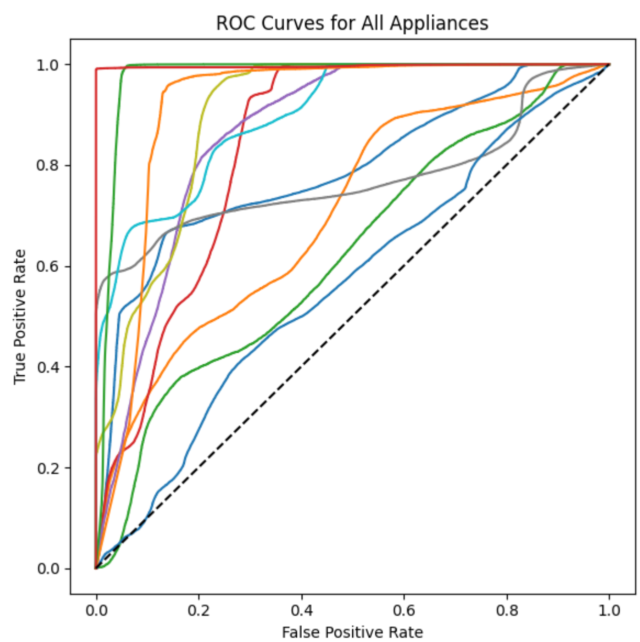


F1 Score





Performance Metrics



ROC Curves

- Data is standardized training is done in batch mode to handle large datasets efficiently.
- Its learning rate is dynamic to adapt the training process with early stop-ping overfitting.

- Model checkpoints combined with extensive metrics tracking will then enable consistent evaluation of improvement.

B. Anomaly Detection:

The Isolation Forest algorithm effectively detected anomalies in energy consumption with an estimated accuracy of 86 percentage for probable malfunctioning and inefficiency.

C. Mobile App Functionality:

The mobile application had the ability to provide live monitoring, send alerts to anomalies, and display the history of consumption data that would give the end-user actionable insights toward reducing consumption.

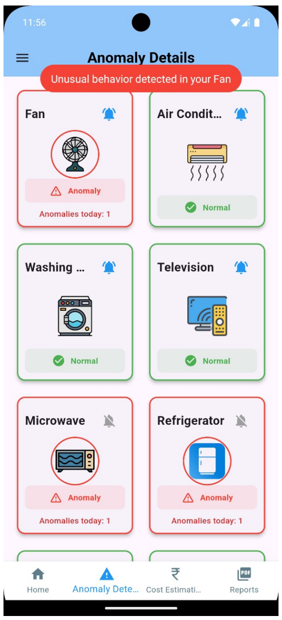


Fig. 2. Anomaly Details

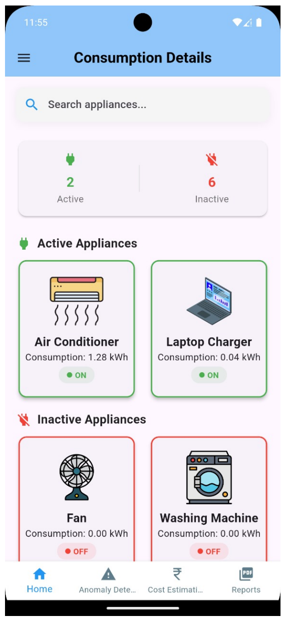


Fig. 3. Consumption Details

Fig. 2. represents the "Anomaly Details" interface of a smart energy monitoring system.

Key Features

- Anomaly Detection: Identifies appliances with abnormal energy usage and flags them with a red "Anomaly" label.
- Normal Status Indicators: Highlights appliances operating correctly with a green "Normal" label.
- Daily Anomaly Count: Displays the number of anomalies detected for each appliance.
- Notification Controls: Allows users to enable or mute alerts for specific appliances.

Fig. 3. represents the "Consumption Details" interface of a smart energy monitoring system.

Key Features

- Appliance Categorization: Divides appliances into "Active" and "Inactive" categories based on their operational state.
- Energy Consumption Metrics: Displays real-time energy usage for each active appliance in kilowatt-hours (kWh).
- Operational Status: Uses visual indicators like "ON" (green) and "OFF" (red) to show the current status of appliances.
- Search Functionality: Includes a search bar for users to easily find specific appliances.

VI. FUTURE DIRECTION

- **Advanced predictive analytics:** By using advanced machine learning models, the system can evolve to predict appliance failures and recommend maintenance schedules, ensuring appliance longevity and reducing downtime.
- **Enhanced User Personalization:** The implementation of AI-driven personalization can provide tailored recommendations to users, such as optimal usage times and energy savings tips based on individual consumption patterns.
- **Integration with IoT Ecosystems:** The system can be enhanced to integrate seamlessly with popular IoT platforms like Amazon Alexa, Google Home, or Apple HomeKit, offering greater convenience and automation through voice commands and centralized controls
- **Real-Time Cost Optimization:** Incorporating real-time pricing algorithms and predictive energy cost analytics can help users plan energy consumption to minimize costs, particularly in regions with dynamic electricity pricing.
- **EV charging monitoring:** Extend the system to monitor EV charging, providing real-time information on charging duration, battery status, and energy usage.

VII. CONCLUSION

The "Intelligent Power Usage Analytics for Optimized Home" project demonstrates the potential of using NILM techniques and machine learning to enhance energy efficiency at the appliance level. By successfully implementing a CNN-LSTM model for energy disaggregation and the Isolation Forest algorithm for anomaly detection, the system provides real-time monitoring, actionable insights, and cost-saving opportunities for users. The Flutter-based mobile application further ensures accessibility and user engagement by offering real-time alerts, historical consumption data, and anomaly notifications.

This work highlights the practicality and cost-effectiveness of using non-intrusive energy monitoring methods to tackle modern energy challenges, paving the way for more sustainable and efficient energy management solutions.

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