Integrating ML, AI and IoT for Smart Home Energy Management

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***Abstract* – This research introduces a smart IoT (Internet of Things) system for enhancing household energy efficiency by integrating real-time electricity monitoring, predictive analytics, and AI (Artificial Intelligence)-driven personalized guidance. Traditional home energy management often lacks a level of detail, leading to uninformed usage patterns and increased energy waste. The developed system consists of a developed IoT-enabled monitoring unit, time-series forecasting, and generative AI to deliver proactive and intelligent electricity management experience. The IoT-enabled unit monitors individual appliance consumption and implements threshold-based control mechanisms to prevent overuse. The machine learning algorithm analyzes historical usage data to forecast future electricity demand, supporting preemptive consumption planning. The Large Language Model (LLM) generates personalized energy-saving recommendations based on the overall electricity usage data collected from the system. Power monitoring portal enhances user interaction through real-time energy movements and feedback mechanisms. This study contributes to sustainable living by promoting energy-conscious behavior, reducing household energy expenditure, and aligning domestic energy usage through a data-driven solution.**

Keywords: Smart Energy Management, IoT Monitoring, Time-Series Forecasting, Generative AI, Household Sustainability, Human-Computer Interaction

I. INTRODUCTION

The increasing demand for electricity, coupled with rising electricity costs and environmental concerns, necessitates efficient electricity management systems for households. With appliances like air conditioners, refrigerators and water heaters consuming significant electricity, it becomes essential to monitor, manage, and predict their energy usage. Current solutions often provide limited insights, focusing solely on aggregated energy consumption without offering actionable feedback for individual devices. These limitations hinder users from understanding and optimizing their electricity usage at a granular level, leaving them unable to take precise measures to reduce electricity bills.

Furthermore, as climate change emphasizes sustainable practices, there is a growing interest in personalized energy-saving recommendations. Existing systems fail to leverage advancements in ML (Machine Learning) and AI (Artificial Intelligence) to predict future electricity consumption trends or offer tailored suggestions based on specific user behavior. The lack of integrated solutions that combine device-level electricity monitoring, predictive analytics, and personalized recommendations through an accessible platform represents a significant gap in home energy management. Addressing this gap requires an innovative approach that not only measures energy usage but also provides users with forward-looking insights and actionable advice.

This research introduces a comprehensive system that utilizes advanced technologies in IoT (Internet of Things) sensing, time-series forecasting, and generative AI to improve home energy management via intelligent automation and user engagement. The system integrates real-time electricity usage data and contextual environmental factors to predict energy consumption patterns through an XGBoost (Extreme Gradient Boosting) model and provides personalized recommendations using a fine-tuned GPT-Neo-1.3B (Generative Pre-training Transformer) model. A significant gap in existing energy management solutions is addressed by providing a developed IoT enabled monitoring unit with device-level monitoring, proactive energy-efficiency recommendations included in an interactive user interface, all integrated into a single platform. The study aims to empower households with smarter energy decisions, reduce electricity waste, and contribute sustainable living practices. In order to highlight present limitations, the following sections address relevant work and current systems. The methodology describes the fundamental elements of the system, such as real-time recommendation procedures, model training, and data collection. The accuracy and responsiveness of the system is verified by experimental findings. Extended personalization through ongoing IoT data collecting and additional model improvement are potential future directions. Environmental AI-powered energy management to influence residential settings' behavior and environmental impact is highlighted in the conclusion of the paper.

II. RELATED WORK

Smart home energy management systems aim to reduce electricity usage via monitoring and automation. While effective in addressing energy waste, most lack a unified approach that combines IoT-based monitoring, predictive analytics, dashboards, and LLM-powered support. Without this, insights and device-level predictions remain limited. Smart plugs are central to HEMS, enabling appliance-level monitoring and control. However, many studies overlook physical actuation and edge intelligence. For example, Prathyusha et al. [1] proposes an IoT-based system without appliance-level sensing, while Bharadwaj et al. [2]includese device monitoring but no relay control. Banu Priya et al. [3] add scheduling but not dynamic shutdown. In contrast, the developed plug integrates ACS712 and ZMPT101B sensors with logic for threshold-based cut-off. Jayaprakash et al. [4] present billing alerts without automation. Optimization works such as Loganayagi et al. [5] and Ebrahimi et al. [6] miss device firmware and AWS IoT integration. Our system unifies actuation, WiFi setup, cloud publishing, and dynamic thresholds into a low-cost, adaptable plug.

Energy prediction and user engagement are also vital. Deepa et al. [7] focus on grid analytics, overlooking device forecasting. Prathyusha et al. [1] lack forecasting, while Bharadwaj et al. [2] present raw trends without predictive ML. Our system trains XGBoost on device-level data for short-term forecasts, explained to users through chatbot. Deb et al. [8] validated XGBoost's superiority at the building level, while Machorro-Cano et al. [9] proposed a robust IoT-big data framework, and Bai & Wang [10] emphasized AI personalization. However, these ignore appliance "energy fingerprints." Our device-trained XGBoost fills this gap with granular predictions.

IoT–AI integration in HEMS has been studied extensively. Singh et al. [9] lacked predictive models, while Kumar et al. [11] applied generative AI but without IoT streams. Condon et al. [12] built cloud monitoring without AI insights. Sardianos et al. [13] enabled real-time feedback but required user input, while Kabalci et al. [14] focused on monitoring only. Deb et al. [8] addressed prediction, Bai et al. [10] highlighted behavior, and Brown et al. [15] explored LLM personalization, but integration remains fragmented.

Research has also examined renewable energy and interoperability. Khan et al. [16] proposed a Zigbee-enabled system with grid selling; Prathyusha et al. [1] simulated IoT-based models; Argyros et al. [17] built a mobile app for monitoring; Chen Li et al. [18] presented iSHome, a Bluetooth app without saving algorithms; and Stolojescu-Crisan et al. [19] integrated solar energy but faced cost and security challenges. Polprasert et al. [20] explored microgrids but lacked appliance-level control.

These works highlight IoT, mobile/web platforms, and smart grid integration, but persistent issues remain real-time responsiveness, interoperability, personalization, and scalability. Building on this, our system develops a web dashboard integrated with IoT plugs, predictive analytics, and configurable controls, advancing user-centric home energy optimization.

III. METHODOLOGY

The developed system integrates IoT-based smart plugs with AWS IoT Core for real-time monitoring and control. React and Laravel are used in the development of the web application, and Chart.js and Recharts are used for data visualization. The LLM model, integrated with LangChain, offers tailored energy-saving suggestions, while an XGBoost model forecasts energy consumption at the device level. An OCR (Optical Character Recognition) module enables the system to extract device specifications and usage details directly from images of electricity bills, appliance labels, or manuals, enhancing automation and reducing manual input. Interactive user support is provided by a chatbot acting as a smart assistant. Key features include automatic cut-off, bill estimation, OCR-driven data extraction, and user-friendly dashboards designed around actual household energy usage requirements.

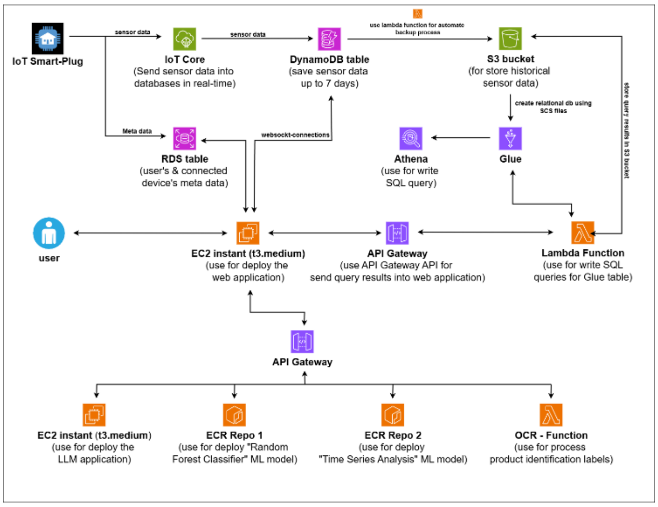

Figure 1: System Diagram

A. Smart Plug Hardware Design

This smart plug hardware is built around the ESP32 WROOM 32D Devkit V1 microcontroller, chosen for its integrated Wi-Fi capabilities and suitability for edge-level processing.

This eliminates the need for external networking modules, simplifying the design while ensuring reliable connectivity to the cloud. Energy monitoring is achieved by interfacing the ESP32 with current and voltage sensing modules that generate real-time consumption data.

For centralized monitoring, a separate IoT-based main switch device uses the same ESP32 foundation but integrates a multifunctional PZEM-004T energy meter for whole-house analysis. All devices are powered through a compact AC-DC converter, allowing direct plug-and-play functionality. Once operational, the ESP32 publishes collected sensor data to AWS IoT Core over the MQTT protocol, enabling secure and scalable cloud integration. AWS IoT Core serves as the primary communication bridge, where real-time energy data is securely ingested and routed to downstream services for storage, analytics, and event-driven processing.

Minimal pseudocode for RMS voltage and current measurement with adaptive zero-point calibration on ESP32.

```
CONST: ADC_MAX=4095, VREF=3.3
PINS: V_PIN, I_PIN
PARAMS: CAL, SENS, N, M, W
STATE: zero=2.38, hist[W]=2.38, idx=0

fn getZeroPoint(): return measure_midpoint()

fn rmsVoltage():
  sum=0
  repeat N:
    raw=read(V_PIN)
    v=(raw/ADC_MAX)*VREF*CAL
    sum+=v*v
    wait 2ms
  return sqrt(sum/N)

fn rmsCurrent():
  z=getZeroPoint()
  if z<2.1: return 0
  hist[idx]=z; idx=(idx+1)%W
  zero=avg(hist)

  sum=0
  repeat M:
    raw=read(I_PIN)
    v=(raw/ADC_MAX)*VREF
    i=abs((v-zero)/SENS)
    sum+=i*i
    wait 1000us
  return sqrt(sum/M)
```

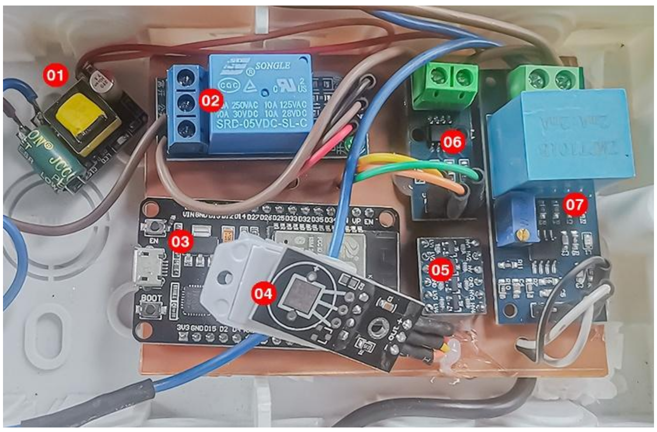

Figure 2: IoT Smart Plug

01: AC-DC converter, 02: 5V Single Channel Relay Module, 03: ESP32 Microcontroller, 04: DHT22 Temperature Sensor, 05: 4 Channel Logic-Level Shifter, 06: ACS712 Sensor Module, 07: ZMPT101B Sensor

B. Energy Consumption Forecasting Feature

To forecast future energy consumption, an XGBoost Regressor model is trained on high-frequency, device-level IoT data. A robust data preprocessing pipeline which began with collecting high-frequency energy consumption data from a specific IoT device identified by its MAC address, was loaded and cleaned. This involved converting UNIX timestamps into a formal datetime index and isolating the relevant features for a single appliance. Feature engineering step was then performed with new features that were created to provide the model time-based features to capture daily and weekly cycles, lag features for short-term memory, and rolling-window statistics to represent recent trends.

Following data preparation, a specialist forecasting model was trained using an XGBoost Regressor. The prepared data was divided using a chronological 80/20 train-test split, ensuring the model was trained on past data and validated on the unseen future. The model was trained efficiently using an early stopping technique to prevent overfitting and find the optimal configuration. The performance of the trained model was then rigorously evaluated on the test set using both numerical metrics, primarily the Mean Absolute Error (MAE), and visual analysis of prediction and residual plots, which confirmed a high degree of accuracy and lack of bias. To generate the final user output, the validated model was used in a recursive forecasting loop to project a multi-hour forecast of future energy consumption.

C. Integrated Chatbot Assistant Feature

The integrated chatbot allows for natural language interaction with the forecast results. User questions are sent to the Gemini large language model along with the current forecast and key model features as context. The AI then synthesizes this information to provide an expert, data-driven answer directly to the user.

D. Personalized Suggestions and Appliance Recognition Feature

A structured process of data collection, model adaptation, appliance identification, and recommendation generation was undertaken for model development and domain-specific fine-tuning. IoT-enabled devices continuously captured household electricity usage parameters such as voltage, current, runtime, energy consumption, and temperature, with records preprocessed to ensure consistency and accuracy. The generative AI component was built on EleutherAI/GPT-Neo-1.3B, sourced from the Hugging Face Hub and fine-tuned on the RunPod cloud platform using GPU resources. A Parameter-Efficient Fine-Tuning (PEFT) strategy combined with Low-Rank Adaptation (LoRA) was employed to reduce computational cost while maintaining model performance, with training performed for three epochs and validated against held-out IoT data to ensure contextual relevance. To enrich outputs, an appliance identification module enabled user input of electrical labels, which were cross-referenced with external knowledge via the OpenAI API to retrieve specifications and efficiency practices. After optimization, the fine-tuned model was pushed back to the Hugging Face Hub, ensuring reproducibility, deployment, and potential reuse in future applications. The system then generated personalized, context-aware recommendations—such as optimal operating times, runtime adjustments, and energy-saving modes—delivered through a web-based interface with intuitive visualizations, thereby enhancing accessibility, encouraging proactive user engagement, and supporting sustainable energy practices.

E. Machine Learning Model for Energy Consumption Scenario Detection

To enhance safety and intelligence, the smart plug system integrates with AWS machine learning and data services for scenario detection. Collected IoT data streams are stored and processed in Amazon DynamoDB, while DynamoDB Streams and AWS Lambda enable real-time updates to the web application via WebSockets. A Random Forest classification model, trained on 60,000 samples, is deployed through an API endpoint hosted on AWS SageMaker. This model detects and categorizes different electrical safety conditions ranging from normal operation to high-risk states. Feature importance analysis supports continuous model refinement and validation. By combining edge-level sensing with AWS-based machine learning and event-driven architecture, the system achieves both real-time monitoring and proactive electrical safety detection, offering users graduated alerts and actionable insights directly through the cloud-enabled platform.

F. Power Monitoring Portal

The Power Monitoring Portal forms a core component of the VoltFlow system, designed to deliver real-time and historical insights into household energy consumption at both device-level and aggregate levels. IoT-enabled smart plugs continuously transmit electrical parameters—current, power, energy, and total usage—via WebSocket communication. These metrics are visualized through dynamic real time metric cards and charts, a design choice supported by prior research demonstrating its effectiveness in fostering user awareness and engagement. The front end of the portal is implemented using React with Vite and Tailwind CSS, ensuring responsiveness and accessibility. The backend is powered by Laravel 12, which exposes multiple RESTful APIs for secure data exchange. Real-time device data is streamed from DynamoDB through Websockets, while high-volume, historical data is queried efficiently from Amazon S3 using AWS Athena and Glue, with orchestration via Lambda functions. This multi-layered architecture supports both rapid updates and scalable long-term storage, aligning with established system design principles in IoT-based energy management. To enhance analytical capabilities, the portal computes and presents multiple derived metrics. These include average current and power values, updated continuously and also aggregated into daily averages over the past three months. Users can additionally view total energy usage and corresponding device-wise cost estimations, with tariff-based calculations enabling clearer visibility into individual appliance contributions—an approach consistent with findings on the value of cost transparency. At the household level, overall energy usage and associated costs are also calculated and presented for comparative analysis. The system incorporates threshold management functionality, allowing users to set and reset consumption limits for individual devices. Notifications and warnings are triggered when thresholds are exceeded, thereby promoting proactive energy conservation. Reports can also be generated and downloaded, enabling offline review and record-keeping. Accessibility and usability form central design principles of the portal. A user-friendly dashboard provides intuitive navigation, while color-blind-friendly themes (supporting protanopia and deuteranopia) ensure inclusive access for all users. The use of Recharts for visualization enables smooth integration of interactive and responsive charts, further reinforcing engagement. Finally, the Power Monitoring Portal provides structured data feeds to other components of VoltFlow, including LLM and ML models, which depend on consistent, device-level time-series data for predictive analytics. Strong security mechanisms—including encrypted communication and authenticated access—safeguard user data, addressing concerns highlighted in related smart home research.

IV. RESULTS

The IoT-based smart plug system, with one main switch and six plugs, showed reliable performance over three months. The ESP32 with ACS712 and ZMPT101B sensors delivered accurate energy data, while health monitoring ensured stable devices, Wi-Fi, and AWS operations. AWS DynamoDB enabled seamless real-time data handling. A Random Forest model trained on 60,000 samples effectively classified four safety scenarios—normal, low, medium, and high danger—triggering timely risk alerts. Overall, the system proved robust, reliable, and ready for residential use.

The XGBoost Regressor model showed outstanding accuracy in predicting device-level electricity usage. Using high-frequency IoT data with engineered temporal, lag, and rolling-window features, it effectively captured complex consumption patterns. For example, on unseen laptop test data, it achieved a MAE of just 2.37e-05 kWh, with predictions closely matching real energy spikes and idle periods. These results confirm the model's reliability in providing precise, actionable insights for proactive smart home energy management.

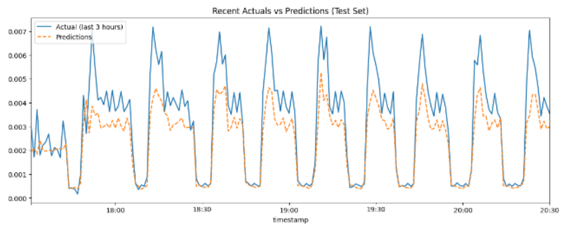

Figure 3: Actual vs Predictions Test Set (AC)

The generative AI chatbot serves as an interactive energy assistant, translating forecast data into natural language. It explains predicted usage spikes, anomalies, and offers personalized energy-saving tips, improving user engagement and energy literacy for everyday use.

During evaluation, model development and fine-tuning showed strong results in performance, accuracy, and appliance-level personalization. The EleutherAI/GPT-Neo-1.3B model was fine-tuned for three epochs on the custom IoT dataset using PEFT and LoRA on RunPod.

The training loss curve dropped from ~1.6 to <0.1 within a few thousand steps and stabilized near 0.05, showing effective learning, convergence, and good generalization. This confirms the model's reliability for accurate real-time personalized recommendations Test cases showed the fine-tuned model achieved over 85% accuracy in generating actionable, context-aware energy-saving suggestions, which users rated as more relevant than generic advice.

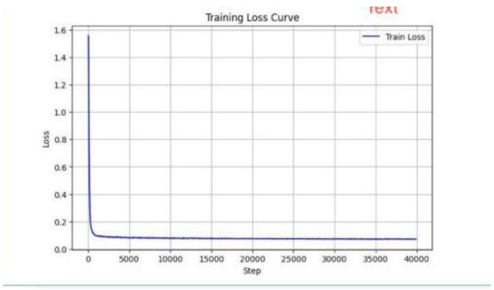

Figure 4: Training Loss Curve

An Appliance Recognition System via the OpenAI API matched user-input labels with IoT data to give targeted tips—like adjusting fridge settings or limiting washing loads—enhancing personalization, trust, and overall system interaction.

The Power Monitoring Portal was successfully deployed as part of the VoltFlow system, providing a robust, user-focused platform for real-time monitoring, historical analysis, and cost estimation. It streams voltage, current, power, and energy data from IoT smart plugs via WebSockets, with AWS DynamoDB, Athena, Glue, and Lambda ensuring reliable, low-latency performance. Features include real-time metric cards, interactive consumption charts, multi-month trend analysis, and device- or household-level cost calculations based on user tariffs, improving transparency and supporting informed energy use.

The portal adds threshold management, letting users set/reset device limits and receive alerts for proactive energy control. Downloadable reports are used for personal, household, or institutional tracking. Built with React, Vite, and Tailwind CSS, the dashboard is responsive, user-friendly, and inclusive, featuring color-blind-friendly modes (Protanopia/Deuteranopia) to address accessibility needs. Overall, the Power Monitoring Portal meets its objectives by uniting real-time monitoring, visualization, and user-focused features. With cost-awareness, accessibility, and cloud scalability, it delivers a comprehensive smart home energy monitoring solution.

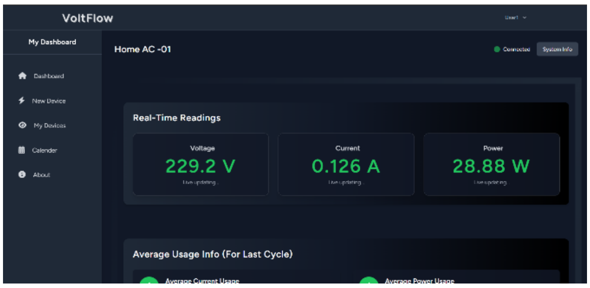

Figure 5: Real Time Data Visualization on Web App

V. FUTURE WORK

Future enhancements will advance the smart plug system beyond real-time monitoring and thresholds. A custom PCB will integrate the relay, sensors, and microcontroller into a compact, efficient, and safe design suitable for large-scale residential and commercial use. Intelligence will be improved with a refined Random Forest model trained on larger datasets to classify appliance behavior, detect anomalies, and enable low-latency edge detection. OTA updates will maintain security and features, while a centralized touchscreen hub will allow multi-plug management, usage tracking, and fault alerts. The architecture will scale to industrial settings such as factories, hotels, and venues, supporting scheduling, predictive optimization, and BMS integration. The forecasting engine will be enhanced with Optuna-based hyperparameter tuning, advanced features, and global models for benchmarking. GPT-Neo will be further fine-tuned with IoT datasets, RLHF, and multimodal inputs (tariff, weather, occupancy) to deliver contextual, personalized recommendations. The chatbot will evolve into a proactive guide, explaining forecasts and offering real-time advice during high usage. The Power Monitoring Portal will expand inclusiveness and scalability through accessible themes, mobile-first PWA design, advanced analytics (comparisons, drilldowns), and AWS-backed large-scale data handling. Collectively, these improvements will create a comprehensive, intelligent, and scalable energy management ecosystem for homes, businesses, and industries.

VI. CONCLUSION

This research successfully developed an integrated Smart Home Energy Management System, demonstrating the effective combination of IoT-based monitoring, predictive modeling, and an AI-powered conversational interface. The final outcome is a dynamic Power Monitoring Portal where users can track device-level energy consumption and receive highly accurate short-term forecasts from a specialist Machine Learning model. A key strength of the system is the high user engagement achieved through the integrated, domain-specific Large Language Model, which provides transparent, data-driven support for better household energy decisions and sustainability. While the forecasting is highly accurate, the system in its current state does not yet include a fault detection methodology for appliance anomalies, and the personalization of the AI-generated energy insights could be further improved. Ultimately, this work serves as a successful bridge between conventional home energy monitoring and intelligent automation, laying a strong foundation for smarter and more sustainable domestic energy ecosystems.

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