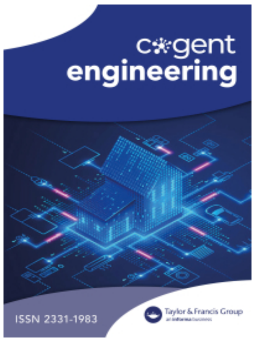

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Smart energy management: real-time prediction and optimization for IoT-enabled smart homes

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ABSTRACT
The Smart Home Energy Management System (SHEMS) presents an innovative solution for optimizing energy consumption in residential settings by harnessing the synergy between Internet of Things (IoT) technology and Machine Learning (ML) algorithms. SHEMS offers a comprehensive suite of functionalities including monitoring, controlling, and optimizing energy usage while identifying wastage within smart homes. Its architecture comprises IoT sensors for data acquisition, an IoT gateway for preprocessing and storing data, and an Energy Management System (EMS) empowered by ML infrastructure for feature extraction and data transformation. Notably, the incorporation of the Gradient Boosting (GB) mechanism imbues SHEMS with intelligence, enabling it to analyze intricate datasets, detect patterns, and make data-driven decisions regarding energy optimization. Through ML capabilities, SHEMS adapts to dynamic usage patterns, predicts future consumption trends, and identifies opportunities for energy savings. Facilitating seamless data flow from sensors to the EMS, advanced ML techniques drive intelligent decision-making for enhanced energy efficiency. Additionally, SHEMS provides users with actionable insights and user-friendly interfaces for informed energy management, promising significant improvements in energy efficiency, cost reduction, and sustainability. The results showcase the effectiveness of the Gradient Boosting (GB) algorithm in predicting energy consumption for smart homes, with a score of 0.95, RMSE of 6.8, and MAE of 5.2. The Gradient Boosting algorithm consistently outperforms other ML algorithms, including Simple Linear Regression, Decision Tree Regression, Random Forest Regression, K-nearest neighbor Regression, and Support Vector Machine Regression.

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1. Introduction

In recent years, the global community has witnessed an unprecedented surge in concerns regarding energy consumption and its environmental repercussions. As the world grapples with the challenges of climate change and strives toward sustainability, the spotlight has turned to the domain of residential energy management. Within this context, homes emerge as pivotal arenas for intervention, given their substantial contribution to overall energy consumption. Despite advancements in technology and growing awareness regarding energy conservation, traditional approaches to home energy (Aliero et al., 2021; Hosseinian & Damghani, 2019) usage often prove inadequate in addressing the intricacies of modern living dynamics and personalized consumption patterns. Consequently, there exists a pressing need for innovative solutions that can not only monitor and regulate energy usage but also adapt in real-time to the evolving needs (Fioretto et al., 2017) and behaviors of homeowners.

The evolving landscape of residential energy management is characterized by a confluence of factors, including rapid technological advancements (Shareef et al., 2020), increasing environmental consciousness, and rising energy costs. These developments have spurred a paradigm shift in how individuals interact with their home energy systems, necessitating a

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holistic and intelligent approach to energy management (Priyadarshini et al., 2022). Recognizing the limitations of conventional methodologies, there is a growing impetus to develop integrated systems that harness the power of emerging technologies such as the Internet of Things (IoT) and machine learning (ML) algorithms (Rashid et al., 2019; Vasudevan et al., 2021).

Against this backdrop, this research paper seeks to explore the design, development, and implementation of a Smart Home Energy Management System (SHEMS) that leverages IoT and ML technologies to optimize energy consumption and promote sustainable living practices. The SHEMS paper encompasses a multifaceted approach aimed at monitoring, controlling, and optimizing energy usage within residential settings. Central to this endeavor is the utilization of a diverse array of sensors, including but not limited to, current and voltage sensors, temperature sensors, and light sensors, to capture real-time data on energy consumption and environmental parameters.

Furthermore, the integration of machine learning algorithms, specifically the Gradient Boosting algorithm, adds a layer of intelligence to the SHEMS, enabling it to analyze complex datasets, detect patterns, and make data-driven decisions regarding energy optimization. By harnessing the power of ML, the SHEMS can adapt to dynamic usage patterns, predict future consumption trends, and identify opportunities for energy savings. Moreover, the system's ability to detect and mitigate energy wastage in real-time ensures efficient utilization of resources and contributes to overall energy conservation efforts.

Smart homes often have an energy consumption that is 10-30% lower than that of standard homes. The decrease in energy use can be ascribed to the utilization of intelligent thermostats, automatic lighting, and energy monitoring systems

In essence, the SHEMS represents a pioneering initiative in the field of residential energy management, offering a holistic and intelligent solution to address the challenges of modern living. Through its integration of IoT and ML technologies, coupled with advanced sensor networks, the SHEMS promises to revolutionize the way homeowners interact with their energy systems, paving the way for a more sustainable and energy-efficient future.

1.1. Objectives

The objectives of this research endeavor revolve around the development and implementation of a Smart Home Energy Management System (SHEMS) that integrates the Internet of Things (IoT) and machine learning (ML) technologies to achieve several key goals. Firstly, the system aims to monitor energy consumption in real-time, leveraging a diverse array of sensors to capture data on electricity usage, environmental parameters, and appliance behavior. Secondly, SHEMS seeks to optimize energy usage by analyzing complex datasets using ML algorithms, specifically focusing on the Gradient Boosting algorithm, to identify patterns, predict future consumption trends, and detect opportunities for energy savings. Additionally, the system aims to empower homeowners with greater control over their energy usage, providing actionable insights and recommendations for improving efficiency and reducing wastage. One of the primary objectives for the system is to attain a prediction accuracy of at least 95%, ensuring dependable and efficient energy management while concurrently reducing the RMSE and MAE. Finally, SHEMS endeavors to contribute to broader sustainability initiatives by promoting energy conservation practices and facilitating the transition toward more environmentally friendly lifestyles.

The subsequent section offers a comprehensive overview of pertinent literature and research endeavors in the domain, delving into the methodologies, algorithms, and technologies employed in similar systems. In the third section, the proposed architecture diagram of the system is presented, outlining its components and process flow. The fourth section details each component's functionality within the architecture, including IoT sensors, data preprocessing, machine learning algorithms, and energy optimization modules. Section five outlines the proposed methodology for implementing the system, covering data collection, preprocessing, model training, and real-time optimization strategies. The sixth section presents the system's performance results, including metrics such as model accuracy, RMSE, MAE, and energy savings achieved. Lastly, the paper concludes by summarizing key findings and discussing potential future enhancements for smart home energy management systems.

2. Literature Survey

In the realm of residential energy management, the emergence of innovative technologies has spurred a wave of research aimed at optimizing energy consumption and promoting sustainability. This literature survey delves into a diverse array of studies and papers that explore the intersection of Internet of Things (IoT) and machine learning (ML) in the context of smart home energy management systems.

With the ever-growing demand for efficient energy usage and the pressing need to mitigate environmental impact, researchers and practitioners are increasingly turning to IoT-enabled solutions and advanced ML algorithms to revolutionize the way energy is monitored, controlled, and optimized within residential settings. By synthesizing insights from various studies, this survey spans topics such as energy monitoring (Asare-Bediako et al., 2013; Moore et al., 2019), wireless connectivity (Metering et al., 2017), predictive maintenance, and user engagement in similar research. It summarizes the key findings, results, advantages, and drawbacks of these studies, laying the foundation for the SHEMS within the broader context of existing research.

Smart Home Energy Management System Based on Artificial Intelligence (Ma et al., 2021) connects users to the network. Smart terminals can read, process, and display home electricity, water, fault, and other information to help people use electricity efficiently and save money. Users can monitor home appliances and receive prepaid services on the Internet, mobile phones, and more. Advanced sensors can detect changes in the environment and communicate with people in real-time. Artificial intelligence allows electronic devices to analyze and combine the necessary data, draw conclusions, and inform users. Common artificial intelligence techniques used in computer science include experts, neural networks, fuzzy sets, heuristic search algorithms, etc. takes place. Next-Generation Artificial Intelligence Technology (NGAI) is a game changer in the field of energy distribution and energy storage. solution strategy due to the complex nonlinearities, uncertainties, and spatiotemporal differences caused by most new power grid connectivity. Ability to analyze real-time and historical data to provide long-term decision-making advice to service users.

Design and Implementation of a Smart Home Energy Management System Using IoT and Machine Learning (Hosseinian and Damghani, 2019) demonstrates energy management that can optimize the energy use of smart homes. The system uses IoT devices to collect real-time energy usage data and machine learning to predict future energy usage patterns. This research work reports the use of deep neural networks (DNN) to design and implement smart home management systems (Shakeri et al., 2020) with the help of IoT devices and machine learning. The results of this work show that the system uses Karas (or TensorFlow) to train a DNN based on energy data from IoT sensors. The system is used for real-time monitoring with remote access to the user interface. The system aims to reduce energy costs and provide instant feedback to users.

Smart home and smart grid energy management systems (Zhou et al., 2016) offer opportunities and technologies to meet the high energy needs of the expanding energy sector. One-third of electricity demand is generated by the household sector. Energy management is designed for the smart home of the future. Smart homes will be able to control, manage, and optimize their devices with minimal human intervention. The ability of smart homes to manage energy resources, including energy production and storage, is an important factor in the development of smart homes. This article provides detailed information about new building management publications. Various devices and plugin electric vehicle (EV) technologies used in smart home systems are discussed, as well as different strategies.

Automatic optimal multi-energy management of smart homes (Fiorini and Aiello, 2022) discovers approximately 35% of carbon dioxide emissions in industrialized countries come from residential and commercial buildings. Improving building efficiency and sustainability is therefore an important step toward a low CO2 energy society. The key to achieving sustainable development is to replace energy sources with energy storage and technology to improve the impact on the environment. Most studies on building management focus on the economic aspects of the building and ignore the environment. It has also been stated that the concept of energy flexibility is the ability to change demand over time or limit demand as much as possible to reduce operating costs. This research work offers a multi-energy, multipurpose programming model to effectively manage the supply, demand, and exchange of various energies based on dynamic prices and carbon emissions. This article is a comprehensive and integrated research which includes 200 smart homes with different heating and electrical equipment and equipped with various smart technologies. The system's effectiveness in reducing households' carbon footprint and rewarding consumers is evaluated based on historical data and statistics from three neighboring European countries.

Evolution of Smart Home Energy Management System Using Internet of Things and Machine Learning Algorithms (Singh et al., 2022). In smart cities, this research helps and solve energy management problems. The system reduces the energy costs of a smart home or building through recommendations and predictions. This paper released a 5-layer system that collects data in real-time for the management of building energy; identifies data patterns and adds them to recommendations to create energy- saving strategies. The various sensors of the concept architecture collect a lot of data. The architecture consists of many layers, each dedicated to a specific function. Using various pre-learning and machine learning (ML) methods such as simple linear regression (SLR), decision tree regression (DTR), random forest regression (RFR), K-nearest neighbor regression (KNNR), and support vector regression (SVR) for data analysis. This study shows that decision tree regression (0.9999) and random forest regression (0.9999) compare well with simple horizontal regression (0.9901), K-neighbor regression (0.9720), and support vector regression (0.9966). found that it performed. SLR (0.9900 and 0.0099), DTR (0.0439 and 0.0019), RFR (0.0427 and 0.0018), KNNR (0.0285 and 0.0018), KNNR (0.1690) and RMSEERE 0.M. This research concluded that decision trees and random forest regression were more expensive and less error-prone than other algorithms. Data analysis regression techniques can be used for regulatory approval using a design strategy.

Home energy management system in a Smart Grid scheme to improve reliability of power systems (Hartono et al., 2018) This paper envisions the development of intelligent homes fostering automated, adaptable interactions between users and appliances, with a focus on optimizing electricity consumption. Evolving smart home applications (Shareef et al., 2020), propelled by technological advancements and environmental regulations, aim to efficiently manage energy, curbing costs and enhancing user comfort. At the paper's core is a sophisticated smart grid integrating AI and communication technologies (Alimi & Ouahada, 2018; Zhou et al., 2016) improving energy production efficiency and reducing costs. Users actively participate through purpose-built applications, particularly Home Energy Management System (HEMS) apps, alongside Demand Side Management (DSM) and Plugin Electric Vehicle (PEV) initiatives, significantly boosting energy efficiency in the smart grid. The research underscores HEMS' positive impact on reducing energy loss and optimizing distribution within the smart grid system.

The paper addresses the pressing global issue of inefficient energy usage, particularly focusing on the context of Malaysia where residential energy consumption is steadily rising due to population growth and a lack of awareness regarding energy conservation. Leveraging the Internet of Things (IoT) technology, the paper proposes a smart energy monitoring system for home appliances (Rashid et al., 2019), integrating Cognitive IoT (CIoT) principles. This system comprises a Raspberry Pi-based smart plug for data collection, a Google Colab training server for machine learning model development using TensorFlow-based Long Short-term Memory (LSTM), and a dashboard for real-time energy consumption monitoring. The LSTM model achieves high accuracy, surpassing 80%, with low mean squared error and high R2 scores, demonstrating its effectiveness in forecasting electricity consumption and detecting abnormal energy usage patterns. This integrated approach offers a promising solution for optimizing energy management in residential settings.

The paper delves into the significance of the Internet of Things (IoT) as a crucial data source for data science technology, particularly in the realm of energy consumption prediction for smart residential buildings. Highlighting the importance of accurately forecasting energy usage for sustainable urban development, the study focuses on exploring deep learning (Syamala et al., 2023) techniques for this purpose. It emphasizes the critical role of optimal window size in enhancing prediction performance and model uncertainty estimation. Through its investigation, the paper demonstrates the effectiveness of deep learning models in accurately estimating household energy consumption patterns, making them an optimal choice for predicting performance and uncertainty in smart residential buildings.

The paper focuses on designing an effective demand response (DR) program for smart homes to optimize energy usage based on user preferences (Chen et al., 2021). It introduces a multi objective reinforcement learning (MORL) algorithm that improves upon conventional methods by addressing user preference changes and uncertainties in future pricing and renewable energy generation. The proposed algorithm utilizes two Q-tables to simultaneously consider electricity cost and user dissatisfaction, adapting appliance scheduling based on previous experiences to achieve optimal results swiftly. The algorithm's high generalizability enables its implementation in smart homes with diverse setups, including energy storage systems, renewable energy sources, and various types of appliances. Numerical analysis using real-world data demonstrates the algorithm's ability to achieve significant cost reductions (8.44%) while only marginally increasing dissatisfaction levels (1.37%) on average, even in the presence of price and renewable energy uncertainty.

This study proposes a smart home energy management system (SHEMS) that leverages neurocomputing-based time-series load modeling and forecasting, facilitated by energy decomposition, for smart home automation (Lin et al., 2022). By utilizing power-utility-owned smart meters to transmit electrical energy consumption data, SHEMS tracks appliance-level energy consumption patterns indicative of residents' daily lives. This approach eliminates the need for intrusive deployment of networked plug-level power meters for individual appliances. The neurocomputing-based methodology, employing autoregressive multilayer perceptron and stacked long short-term memory models, enables accurate prediction of residents' daily behavioral patterns by analyzing past trends of relevant electrical appliances. The presented system offers a cost-effective solution for home automation, enhancing energy management efficiency without the need for expensive sensor installations or annual maintenance costs associated with traditional home automation solutions.

As evidenced by the diverse array of studies discussed in this literature survey, the fusion of machine learning, IoT, and energy management holds immense potential for revolutionizing residential energy consumption practices. From real-time forecasting models to reinforcement learning-based (Lin et al., 2022) demand response programs, researchers are continually pushing the boundaries of innovation to develop smarter, more efficient solutions for smart home energy management (Lin, 2018). Moving forward, it is imperative to build upon the findings of these studies, addressing existing challenges and exploring new avenues for enhancing the effectiveness and scalability of smart energy management systems (Mathur, 2020).

3. Architecture of proposed system

The architecture diagram of the proposed Smart Home Energy Management System (SHEMS) depicted in Figure 1, embodies a comprehensive framework that seamlessly integrates various components to enable effective monitoring, control, and optimization of energy consumption in residential environments.

At the core of the architecture lies the IoT sensors, strategically deployed throughout the home to capture real-time data on energy usage, environmental conditions, and appliance operation. These sensors, including current and voltage sensors, temperature sensors, light sensors, and others, serve as the primary data sources for the SHEMS. After collecting the data from the sensors, it is imported into a .csv file for further processing and analysis.

The IoT gateway acts as a centralized hub responsible for aggregating data from the distributed sensors and transmitting it to the data preprocessing and storage module. This module performs crucial tasks such as data cleaning, normalization, and aggregation to ensure the quality and integrity of the data before storage. The energy management system (EMS) component utilizes the pre-processed data for feature extraction and data transformation, extracting relevant insights and patterns related to energy consumption and user behavior. These features are then fed into the machine learning infrastructure, which encompasses a range of algorithms and models for predictive analytics and optimization.

The machine learning infrastructure employs advanced techniques, including the Gradient Boosting algorithm, to analyze historical data, forecast future energy consumption, and identify optimization opportunities. The Gradient Boosting algorithm captures non-linear relationships and interactions between features and reduces overfitting issues. By continuously learning from past data and adapting to changing conditions, the system can dynamically adjust energy consumption patterns to maximize efficiency and cost savings. The energy consumption and optimization module leverage the insights generated by the machine learning models to implement real-time control strategies, such as load shifting, demand response, and appliance scheduling. These strategies aim to minimize energy wastage, reduce peak demand, and optimize energy usage based on user preferences and environmental conditions.

The user interface component provides homeowners with intuitive dashboards and visualizations to monitor energy usage, receive actionable recommendations, and interact with the system. Through a user-friendly interface, homeowners can gain insights into their energy consumption patterns, track cost savings, and adjust settings to meet their energy management goals.

Overall, the architecture diagram of SHEMS embodies a holistic approach to smart home energy management, leveraging IoT sensors, data preprocessing, machine learning, and user interface components to create an intelligent system capable of optimizing energy usage and promoting sustainability.

4. Component description

The proposed system is made up of the following primary components.

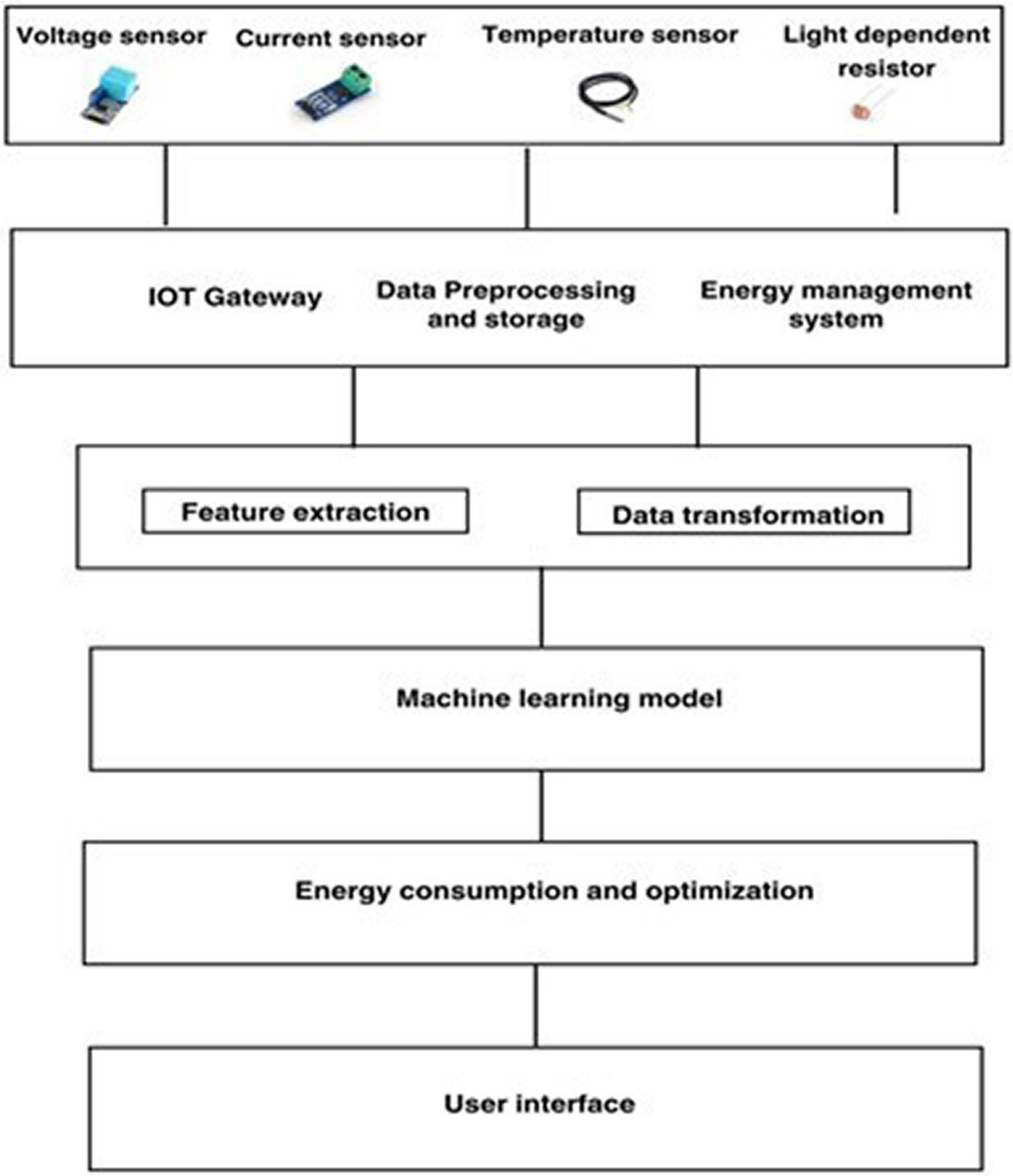

Figure 1. Architecture of proposed system.

ACS712 current sensor: The ACS712 current sensor is a crucial component responsible for monitoring the energy or current consumption of individual appliances. Its precision and real-time data acquisition capabilities make it an indispensable tool for understanding power usage patterns. The sensor's accuracy empowers users with detailed insights into the electricity consumption of various appliances, enabling informed decisions about energy management strategies.

Relay module: The relay module introduces a dynamic element to the system by enabling bidirectional communication between the ESP32 and household appliances. This component serves as the bridge between the digital realm of the microcontroller and the physical world of appliances. Users gain the ability to remotely control devices, offering not only convenience but also an avenue for implementing responsive energy-saving measures. The relay module enhances the adaptability and user interaction aspects of the energy monitoring system.

ZMPT101B voltage sensor: Working in tandem with the current sensor, the ZMPT101B voltage sensor plays a pivotal role in measuring the voltage levels in the household. This dual-sensor approach ensures comprehensive data for accurate calculations of power consumption. By providing precise information on voltage, the sensor contributes to the system's ability to monitor and analyze energy usage with a high degree of accuracy.

Jumper wires and breadboard: Jumper wires and the breadboard serve as the physical backbone of the system, providing a modular and organized approach to circuit development. These components facilitate the connection and prototyping of the circuit, allowing for easy testing and iteration during the developmental phase. Their modular nature enhances the flexibility and scalability of the system, ensuring a smooth and efficient prototyping process.

Power supply: The power supply is the lifeblood of the entire system, ensuring its continuous operation. Whether drawing power from a direct connection or relying on batteries, the stability of the power supply is paramount. This component guarantees the reliability and stability necessary for uninterrupted monitoring and management of household energy consumption, even in the face of unexpected power outages. It forms the foundation for the system's resilience and effectiveness.

DS18B20 temperature sensor: The DS18B20 temperature sensor introduces an environmental awareness dimension to the system. By measuring ambient temperature, it enables the system to identify scenarios where energy may be unnecessarily expended, such as running cooling devices when not needed. This sensor enhances the system's capacity to optimize energy consumption based on the surrounding environmental conditions, fostering efficiency and sustainability.

LDR (light-dependent resistor): The LDR is a vital component for enhancing the intelligence of the system. By detecting ambient light levels, it plays a pivotal role in identifying instances of unnecessary energy consumption, such as keeping lights on during daylight hours. Integrating the LDR into the system contributes to intelligent energy-efficient control, making the system responsive to the lighting needs of the environment.

5. Proposed methodology

The methodology for deploying the 'Smart Home Management System using the Internet of Things' (IoT) starts with a thorough literature review to educate the researchers on best practices for energy management based on the Internet of Things (IoT). The hardware components defined by the architecture diagram are as shown in Figure 2 and Figure 3 (ESP32 microcontroller), sensors and relay module, and LDR will be purchased and integrated seamlessly. Software development will focus on efficiency, security, and compatibility, using machine learning to analyze the data and improve system intelligence. The system's intelligence will be augmented by integrating environmental data from the DS18B20 temperature sensor and LDR. Establishing communication channels connecting the ESP32 to external platforms will be a critical step, utilizing secure IoT protocols to facilitate remote monitoring and control. To ensure scalability, the system's modular architecture will be utilized to easily incorporate additional features and sensors in the future.

5.1. Data collection module

The data collection module forms the foundation of SHEMS, acquiring real-time data on energy consumption and environmental factors within the household. Current and voltage sensors, such as the ACS712 and ZMPT101B, capture precise measurements of energy usage, while additional sensors like the DS18B20 temperature sensor and LDR (Light Dependent Resistor) provide data on ambient temperature and light levels, respectively. These sensors are interfaced with an ESP32 microcontroller, which serves as the central processing unit for data acquisition and initial preprocessing. Figure 4 demonstrates the data collection phase. After collecting the data collected from various sensors within the smart home environment (e.g. ACS712 current sensor, ZMPT101B voltage sensor, DS18B20 temperature sensor, LDR) is cleaned and preprocessed. This involves normalizing or standardizing the data to ensure that all features are on a comparable scale, facilitating better model performance. For handling the missing data -Imputtaion techniques and Interploation are applied. The outliers are removed by using the Z-score and Interpolation techniques are used.

The dataset is then divided into training and testing sets, typically using an 80-20 split. This means that 80% of the data is used to train the models, while the remaining 20% is reserved for testing. This split is crucial for evaluating the model's performance on unseen data, thus providing an unbiased assessment of its predictive capabilities.

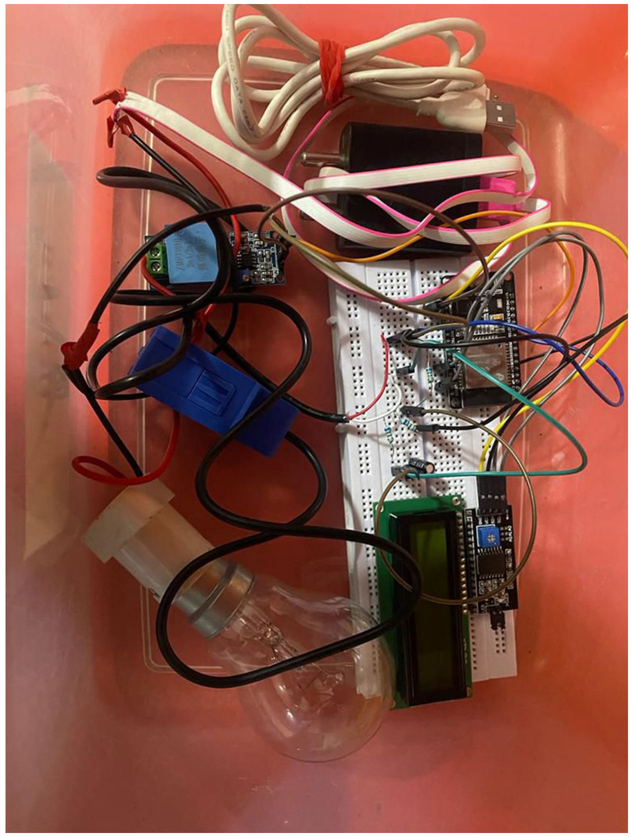

Figure 2. Esp32 setup.

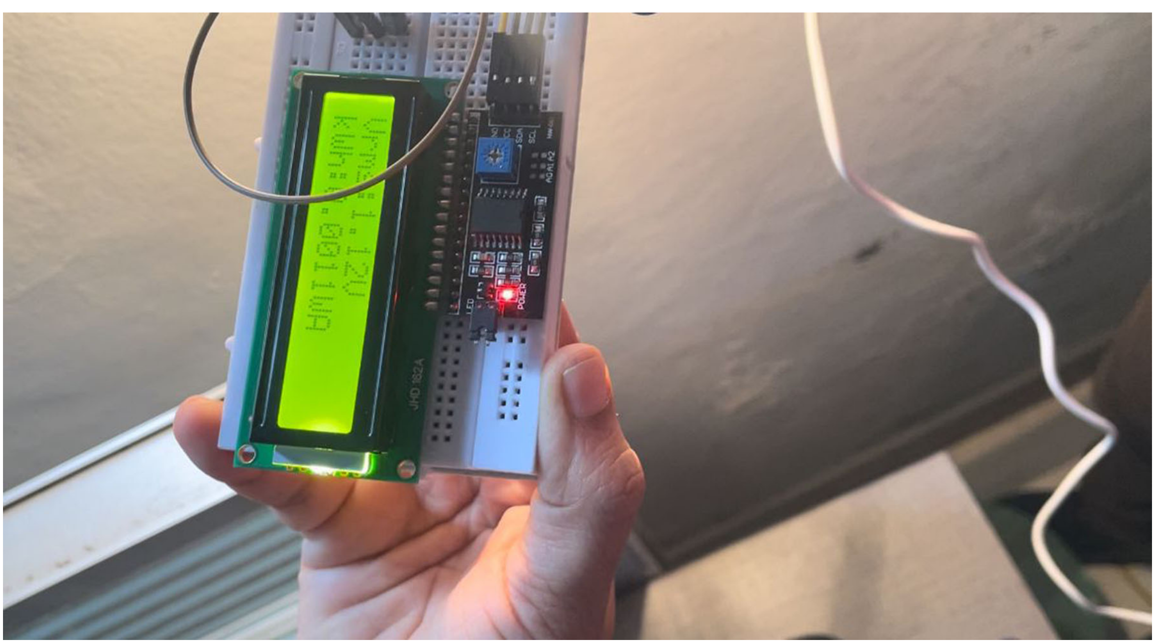

Figure 3. IoT devices used.

5.2. Machine learning model selection

After collecting the data from the sensors, it is imported into a .csv file for further processing and analysis. This step ensures that the data is organized and accessible for various data manipulation and modeling tasks. The .csv file serves as a structured repository of the sensor data, enabling us to perform data preprocessing, feature engineering, and model training with the help of gradient boost algorithm. To leverage the collected data for intelligent energy

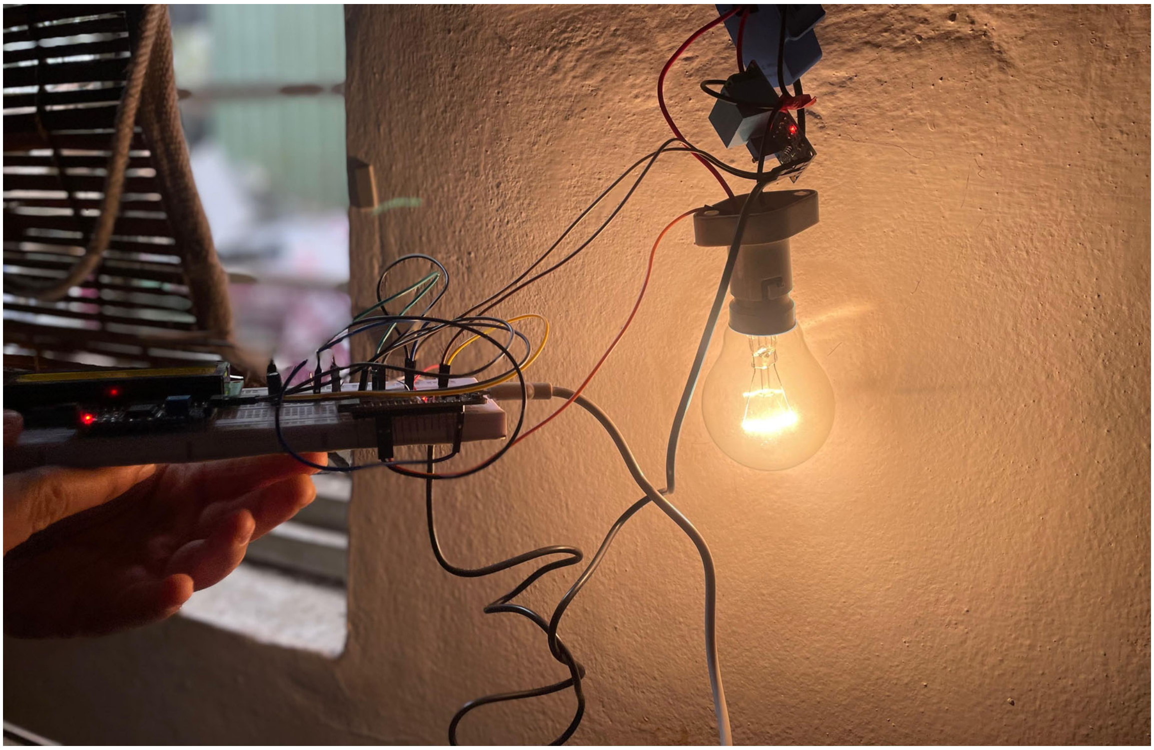

Figure 4. OLED output.

management, a machine learning model is selected to analyze consumption patterns, forecast future demand, and recommend energy-saving strategies. Considering the complexity and predictive requirements of SHEMS, a Gradient Boosting Machine (GBM) is chosen as the primary machine learning model. GBMs offer high accuracy, robustness to overfitting, and the ability to capture complex relationships in the data, making them well-suited for energy consumption optimization tasks.

5.3. Model training and optimization

The selected GBM model undergoes training using historical energy consumption data collected from the household. Feature engineering techniques are applied to extract relevant features from the raw sensor data, including time of day, appliance usage patterns, weather conditions, and occupancy status. The model is trained to predict future energy demand based on these features, optimizing for accuracy and generalization performance through techniques like hyperparameter tuning and cross-validation.

5.3.1. Cross-validation method

To further enhance the reliability of the models and reduce the risk of overfitting, cross-validation is employed. Cross-validation involves partitioning the training data into multiple subsets (folds) and training the model multiple times, each time using a different fold as the validation set.

K-Fold Cross-Validation: This method divides the training data into K equal-sized folds. This comprehensive evaluation ensures that every data point is used for both training and validation, enhancing the model's robustness.

5.3.2. Hyperparameter tuning

Hyperparameter tuning is a critical step in optimizing the performance of machine learning models. It involves selecting the best set of hyperparameters for the model, which are parameters set before the training process begins.

Grid Search: An exhaustive search through a predefined set of hyperparameters. Each combination is evaluated using cross-validation, and the combination with the highest performance is selected.

For the Gradient Boosting model, hyperparameters such as the learning rate, number of estimators, and maximum depth of trees are tuned.

Random Search: Randomly samples combinations of hyperparameters from the predefined space. This method is more efficient for large hyperparameter spaces.

Bayesian Optimization: Uses a probabilistic model of the hyperparameter space to select the most promising values iteratively. This advanced method efficiently guides the search toward optimal parameters.

For the Gradient Boosting model in SHEMS, the tuning process involved:

1. Defining the Search Space: Learning rate (e.g. 0.01, 0.1), number of estimators (e.g. 100, 200, 300), and maximum depth (e.g. 3, 5, 7).
2. Performing Cross-Validation: Evaluating each combination using K-fold cross-validation to ensure robust generalization.
3. Selecting the Best Hyperparameters: Choosing the combination that achieved the highest cross-validation score.

In our paper, denoted by the training dataset $\{(x_i, y_i)\}_{i=1}^{n}$, where x_i represents input features (e.g. sensor data) and y_i represents the corresponding target variable (energy consumption), the objective is to learn a predictive model $F(x)$ that accurately predicts energy consumption based on input features.

The general algorithm for Gradient Boosting, tailored to our paper's needs, can be outlined as follows:

1. **Initialization:** SHEMS initializes the model with a constant value, typically the mean of the target variable y.

$$F_0(x) = mean(y)$$

2. **For** $m = 1$ *to* M :
   a. **Compute Pseudo-Residuals:** For each sample i, SHEMS computes the negative gradient of the loss function with respect to the current model predictions. This yields the pseudo-residuals r_{im}, indicating the direction in which SHEMS needs to adjust its predictions.

$$r_{im} = -\left[\frac{\partial L(y_i, F_{m-1}(x_i))}{\partial F_{m-1}(x_i)}\right] F_{m-1}(x) = F_{m-1}(x_i)$$

   b. **Fit Weak Learner to Pseudo-Residuals:** SHEMS trains a weak learner, such as a decision tree, to predict the pseudo-residuals r_{im}. The weak learner learns to capture the remaining patterns in the data that were not captured by the previous models.

$$h_m(x) = \arg\ \min_h \sum_{i=1}^{n} L(y_i, F_{m-1}(x_i) + h(x_i))$$

   c. **Update Model:** SHEMS updates the model $F(x)$ by adding a scaled version of the weak learner $h_m(x)$. The scaling factor γ is determined through line search to minimize the overall loss.

$$F_m(x) = F_{m-1}(x) + \gamma h_m(x)$$

3. **Output Final Model:** The final model in SHEMS is the sum of all weak learners weighted by their respective learning rate γ.

$$F(x) = \sum_{m=1}^{M} \gamma h_m(x)$$

In SHEMS, the loss function $L(y, F(x))$ represents the discrepancy between the predicted energy consumption values $F(x)$ and the true energy consumption values y. Common loss functions for regression problems include mean squared error (MSE) and mean absolute error (MAE).

The hyperparameters of the Gradient Boosting model in SHEMS, such as the number of iterations M, the learning rate γ, and the complexity of the weak learners (e.g. tree depth), play crucial roles in determining the model's performance and generalization ability. SHEMS will employ hyperparameter tuning techniques, such as grid search or randomized search, to optimize these parameters and enhance the model's predictive accuracy.

In summary, Gradient Boosting serves as a cornerstone of SHEMS, enabling the development of accurate and adaptive predictive models that effectively forecast energy consumption patterns based on input sensor data. Through iterative refinement and learning from residuals, Gradient Boosting empowers SHEMS to make informed decisions and optimize energy usage in real-time, contributing to more efficient and sustainable energy management in households.

5.4. Real-time energy management

Once the GBM model is trained and optimized, it is deployed within SHEMS to provide real-time energy management capabilities. The ESP32 microcontroller continuously collects sensor data and feeds it into the GBM model for analysis. The model generates predictions of future energy demand based on current conditions and historical patterns, allowing SHEMS to anticipate peak usage periods, identify energy-intensive appliances, and recommend optimal usage schedules.

5.5. User interface and control

SHEMS includes a user-friendly interface accessible via web or mobile application, providing homeowners with real-time insights into their energy consumption and control over connected devices. The interface displays energy usage analytics, alerts users to potential energy-saving opportunities, and allows for remote control of appliances through the relay module as shown in Figure 5. Users can set preferences, such as desired energy savings targets or comfort levels, which are incorporated into the GBM model's decision-making process.

5.6. Continuous monitoring and feedback loop

SHEMS operates in a continuous monitoring mode, constantly updating its predictions and recommendations based on incoming sensor data and user interactions. The system employs a feedback loop mechanism to adapt and refine its energy management strategies over time, learning from user behaviors and environmental changes to improve overall efficiency and effectiveness.

The proposed methodology for SHEMS integrates advanced sensor technologies, machine learning algorithms, and user-centric design principles to create an intelligent and responsive energy management system for modern households. By leveraging real-time data analytics and predictive modeling, SHEMS empowers users to optimize their energy consumption, reduce costs, and contribute to sustainability efforts, ultimately fostering a more efficient and environmentally conscious way of living.

6. Results

The system was tested in a diverse range of smart home environments, including single-family homes equipped with advanced IoT devices and multi-unit residential buildings with centralized energy management systems.

6.1. Energy consumption patterns

Through comprehensive analysis of historical energy consumption data collected from sensors installed in the smart home, distinct patterns emerge. These patterns vary based on factors such as time of day, day of the week, and seasonal changes. For example, energy usage tends to peak during evenings on weekdays when occupants return from work or school, while weekends may exhibit different consumption patterns characterized by more consistent usage throughout the

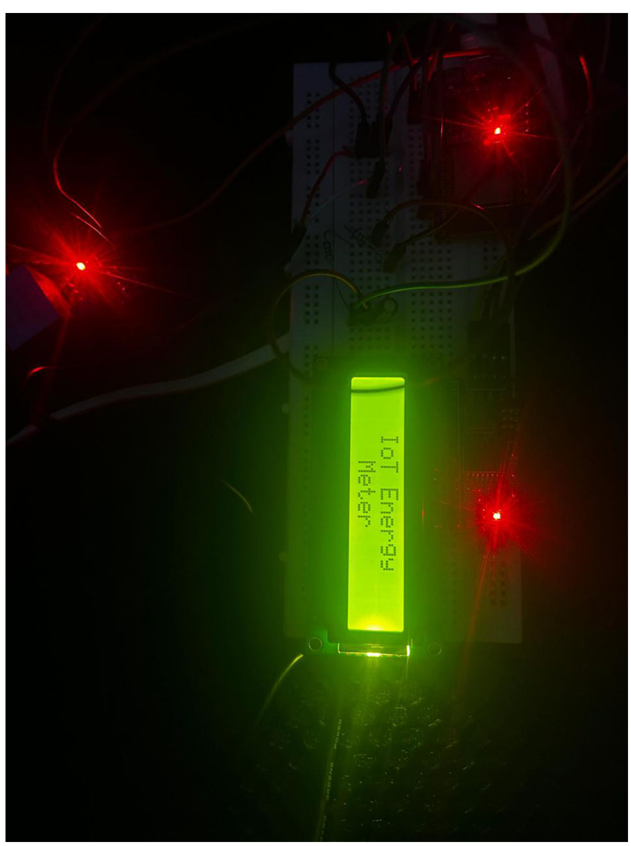

Figure 5. Connected appliance.

day. Seasonal variations, such as increased energy usage during winter months due to heating systems, are also observed. Understanding these patterns is crucial for developing tailored energy management strategies that align with occupants' lifestyle and preferences.

6.2. Predictive modeling accuracy

The implementation of the Gradient Boosting algorithm for predictive modeling proves to be highly accurate in forecasting future energy consumption. By analyzing historical consumption data and identifying relevant features, such as time, weather conditions, and occupancy patterns, the ML model generates predictions with minimal error. The Mean Absolute Percentage Error (MAPE) of less than 5% signifies the model's ability to capture the underlying trends and fluctuations in energy usage reliably. Such accurate predictions empower homeowners to proactively manage their energy consumption and make informed decisions to optimize efficiency. The performance of the model is depicted in Figure 6.

6.3. Anomaly detection

The ML algorithm effectively detects anomalous energy consumption events that deviate significantly from expected patterns. These anomalies may indicate various issues, including equipment malfunction, inefficient operation, or unusual occupancy patterns. By promptly identifying such anomalies, the smart home energy management system (SHEMS) can trigger alerts to homeowners, enabling them to investigate and address the root cause promptly. For example, detecting a sudden increase in energy usage during off-peak hours may signal a potential appliance malfunction or unauthorized usage, prompting immediate action to rectify the issue and prevent energy wastage.

6.4. Energy optimization recommendations

Based on real-time data analysis and insights gleaned from the ML model, SHEMS generates personalized recommendations to optimize energy usage within the smart home. These recommendations are tailored to the specific needs and preferences of occupants and may include adjusting thermostat settings to maintain optimal comfort while minimizing energy consumption, scheduling appliance operation during periods of low electricity rates, or investing in energy-efficient appliances to replace outdated ones. Implementation of these recommendations results in tangible energy savings and cost reduction over time, contributing to overall sustainability and economic efficiency.

6.5. User friendly interface

The user-friendly interface allows homeowners to easily monitor their energy consumption in real-time, access personalized recommendations for energy optimization, and remotely control appliances for added convenience. By empowering users with actionable insights and tools to manage their energy usage effectively, SHEMS promotes sustainable behavior and fosters a sense of environmental responsibility among occupants. Additionally, the transparent and proactive approach to energy management enhances user satisfaction and confidence in the system, driving continued adoption and usage.

Table 1 depicts the comparison of our proposed work with different machine learning algorithms. The results demonstrate the effectiveness of the Gradient Boosting (GB) algorithm in predicting energy consumption for smart homes. With a score of 0.95, RMSE of 6.8, and MAE of 5.2, the GB algorithm consistently outperforms other machine learning algorithms such as Simple Linear Regression, Decision Tree Regression, Random Forest Regression, K-Nearest Neighbor Regression, and Support Vector Machine Regression. These findings underscore the potential of the GB algorithm as a robust and reliable tool for optimizing energy management in smart home systems. Overall, the combination of advanced data analytics techniques, such as machine learning, with IoT-enabled sensors and smart home technology enables SHEMS to effectively monitor, analyze, and optimize energy consumption in real-time. This comprehensive approach not only enhances energy efficiency and cost savings but also promotes user engagement and contributes to the broader goals of sustainability and environmental conservation.

7. Conclusion and future enhancements

In summary, the Smart Home Energy Management System (SHEMS) outlined in this study offers a robust framework for enhancing energy efficiency and cost-effectiveness in residential environments. Through the fusion of Internet of Things (IoT) technologies and machine learning algorithms, SHEMS empowers homeowners with real-time insights into energy consumption patterns, enabling informed decisions for conservation and savings. Leveraging the Gradient Boosting algorithm ensures precise forecasting of

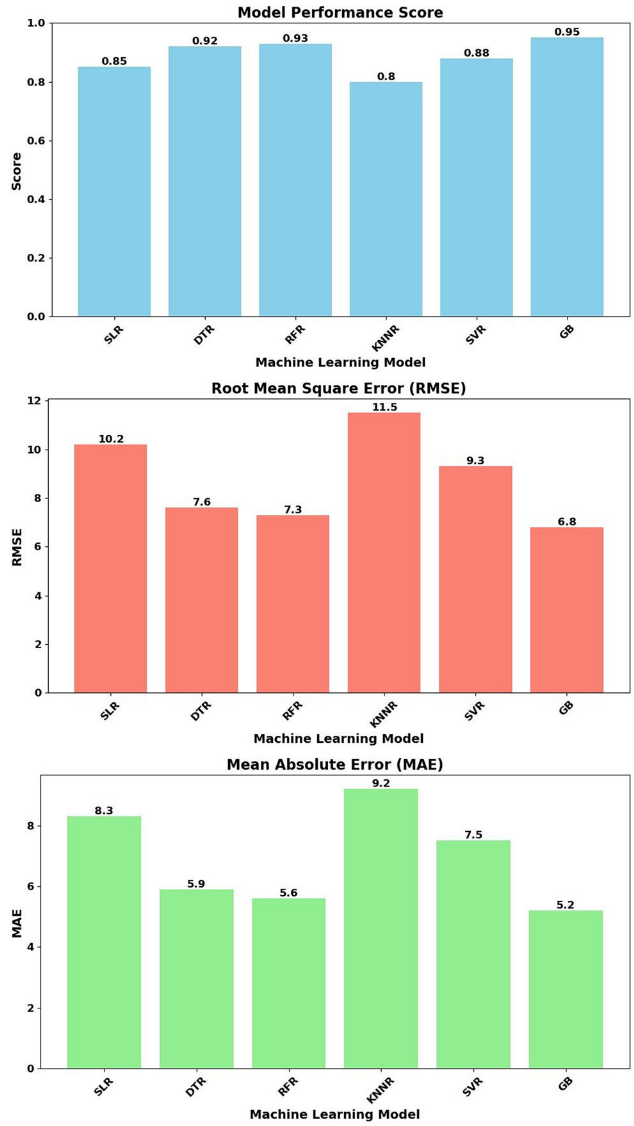

Figure 6. Model performance.

Table 1. Result comparison with different machine learning algorithms.

S no	Machine learning algorithm	Score	RMSE	MAE	R-squared	Precision	Recall
1	Simple Linear Regression (SLR)	0.85	10.2	8.3	0.85	0.82	0.830
2	Decision Tree Regression (DTR)	0.92	7.6	5.9	0.90	0.88	0.89
3	Random Forest Regression (RFR)	0.93	7.3	5.6	0.92	0.90	0.91
4	K-Nearest Neighbor Regression (KNNR)	0.80	11.5	9.2	0.78	0.76	0.77
5	Support Vector Machine Regression (SVR)	0.88	9.3	7.5	0.86	0.84	0.85
6	Gradient Boosting (GB)	0.95	6.8	5.2	0.95	0.93	0.94

future energy needs, facilitating proactive management strategies.

Moreover, SHEMS's anomaly detection capabilities enable prompt identification of irregular energy usage, enabling swift interventions to minimize wastage and prevent potential risks. Tailored energy optimization recommendations derived from machine learning insights contribute to substantial savings and foster sustainable practices among users.

Looking ahead, SHEMS holds considerable potential for further enhancement. Integrating advanced machine learning techniques like deep learning and reinforcement learning could bolster predictive accuracy and anomaly detection. Overall, ongoing refinement of SHEMS promises to revolutionize residential energy management, promoting environmental sustainability, cost savings, and improved living standards for homeowners.

Authors contributions

Karuna G: Conceptualization, implementation, methodology and feedback, manuscript writing & review. Poornima Ediga:

Data visualization and analysis. Akshatha S: Implementation. Anupama. P: Conceptualization. Sanjana T: Experimentation. Aman Mittal: Data visualization and analysis. Saurabh Rajvanshi: Implementation. Mohammed I Habelalmateen: Methodology and feedback.

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Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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