Leveraging Neural Networks For Real-Time Energy Usage Fore casting In Smart Home Environments

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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 machine learning models, including the Decision Tree Regressor (DTR) and Convolutional Neural Network (CNN) Regressor, imbues SHEMS with intelligence, enabling it to analyse 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. The results demonstrate the performance of both models in predicting energy consumption for smart homes. The Decision Tree Regressor (DTR) achieved an R^2 score of 0.60, MAE of 2087.99, MSE of 8,428,375.78, and RMSE of 2903.17, reflecting its ability to explain 60% of the variance in the target variable. However, the CNN Regressor significantly outperformed DTR, achieving an R^2 score of 0.978, MAE of 466.99, MSE of 406,838.05, and RMSE of 637.84, demonstrating its superior accuracy in energy forecasting. The CNN model's substantial improvement highlights the potential of deep learning techniques in achieving precise energy predictions. With the rising demand for efficient energy management in smart homes, real-time energy usage forecasting plays a critical role in reducing energy consumption, optimizing utility costs, and enhancing overall system performance. This study further explores the application of deep learning models to enhance energy prediction capabilities, demonstrating the transformative impact of IoT and ML in smart home energy management.

Keywords:Smart Home Energy Management System (SHEMS),Internet of Things (IoT), Machine Learning (ML),Energy Optimization,IoT Sensors ,Energy Management System (EMS),Feature Extraction, Data Transformation, Decision Tree Regressor (DTR),Convolutional Neural Network (CNN) Regressor,Energy Consumption Prediction ,Pattern Detection, Data-Driven Decisions,Real-Time Forecasting ,Energy Efficiency, Deep Learning, Performance Metrics (R^2, MAE, MSE, RMSE),Energy Forecasting

1. INTRODUCTION

The Smart Home Energy Management System (SHEMS) integrates cutting-edge technologies, such as IoT and Machine Learning (ML), to optimize energy consumption in residential buildings. The rapid adoption of connected devices, smart meters, and renewable energy sources in homes has intensified the need for efficient energy management. In India, where energy consumption is rising steadily due to population growth and urbanization, smart homes present an opportunity for significant energy savings and reduced environmental impact. According to the India Smart Grid Forum, India's power demand is expected to grow at a rate of 6-7% annually. To address these challenges, SHEMS provides real-time monitoring, control, and predictive insights into energy consumption patterns. By using deep learning models, it anticipates consumption spikes and dynamically adjusts energy usage. The system's architecture involves IoT sensors to gather data, a gateway for preprocessing, and an EMS that uses ML for predictive analytics. This synergy ensures that energy consumption is optimized without compromising comfort or convenience. Applications include reducing electricity costs, enabling energy-efficient behaviour, and contributing to sustainability goals.

Before the integration of machine learning techniques, energy management in smart homes was largely reactive, relying on manual tracking and simple heuristics that failed to adapt to dynamic household usage patterns, leading to inefficiencies and higher costs. Traditional methods lacked the ability to analyse vast real-time data from IoT sensors, preventing proactive energy optimization. With urbanization accelerating in India and energy consumption rising, there is an urgent need for intelligent, data-driven solutions to manage energy efficiently. This research leverages deep learning models, particularly neural networks and Gradient Boosting, to predict real-time energy consumption, uncover hidden usage patterns, and enable personalized, adaptive energy management. By integrating ML algorithms with IoT data, this approach enhances efficiency, reduces costs, and minimizes energy wastage, supporting global sustainability efforts and optimizing the use of renewable energy resources in smart homes.

2. LITERATURE SURVEY

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.,[1] 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., [2] and behaviours of homeowners. At the paper's core is a sophisticated smart grid integrating AI and communication technologies Alimi &Ouahada [3] 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 focuses on designing an effective demand response (DR) program for smart homes to optimize energy usage based on user preferences Chen et al., [4] 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. Automatic optimal multi-energy management of smart homes Fiorini and Aiello, [5] 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.

Home energy management system in a Smart Grid scheme to improve reliability of power systems Hartono et al. [6] This paper envisions the development of intelligent homes fostering automated, adaptable interactions between users and appliances, with a focus on optimizing electricity consumption. This study proposes a smart home energy management system (SHEMS) that leverages neurocomputing-based time-series load modelling and forecasting, facilitated by energy decomposition, for smart home automation Lin et al., [7] 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. Smart Home Energy Management System Based on Artificial Intelligence Ma et al., [8] 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 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 et al., [9].

These developments have spurred a paradigm shift in how individuals interact with their home energy systems, necessitating a holistic and intelligent approach to energy management Priyadarshini et al., [10] 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. This research work reports the use of deep neural networks (DNN) to design and implement smart home management systems Shakeri et al., [11] 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.

The evolving landscape of residential energy management is characterized by a confluence of factors, including rapid technological advancements Shareef et al., [12] 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 holistic and intelligent approach to energy management. Evolution of Smart Home Energy Management System Using Internet of Things and Machine Learning Algorithms Singh et al. [13] 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. Highlighting the importance of accurately forecasting energy usage for sustainable urban development, the study focuses on exploring deep learning Syamala et al., [14] 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. This study proposes a smart home energy management system (SHEMS) that leverages neurocomputing-based time-series load modelling and forecasting, facilitated by energy decomposition, for smart home automation Lin et al. [15] 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.

3. PROPOSED METHODOLOGY

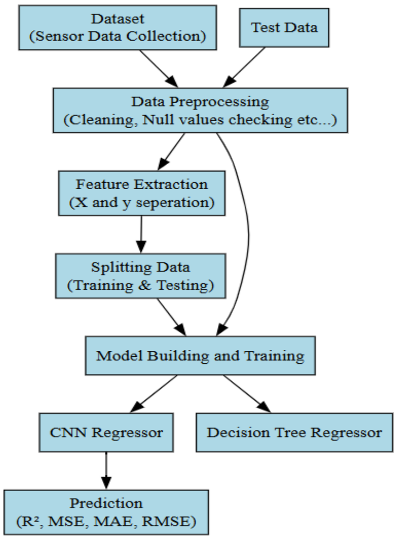

Figure 1:Proposed system Block Diagram

Data preprocessing is a crucial step in preparing the dataset for machine learning models by transforming raw data into a suitable format. Initially, missing data is addressed by identifying null values and either removing incomplete entries using the dropna() function or imputing values through statistical methods. Feature scaling is then applied using the StandardScaler, which standardizes features by subtracting the mean and dividing by the standard deviation, ensuring uniform feature distributions for optimal model performance. The dataset is subsequently divided into features and the target variable, where energy consumption serves as the output to be predicted based on factors such as environmental conditions, time of day, and appliance usage. Exploratory Data Analysis (EDA) is performed to visualize data distributions and feature correlations using histograms and heatmaps, enabling anomaly detection and feature selection. Following preprocessing, the dataset is split into training and testing sets, typically with an 80-20% ratio, using the train_test_split function from the sklearn.model_selection module to ensure unbiased performance evaluation. Data shuffling is employed to prevent biases in ordering, and while stratified sampling can help maintain distribution balance in imbalanced datasets, it is not explicitly used in this project. For model development, a Decision Tree Regressor is implemented as a supervised learning algorithm for regression tasks. It constructs a hierarchical tree structure, where nodes represent features, branches define decision rules, and leaves store predicted values. The algorithm initiates splitting at the root node based on the feature that minimizes variance or error, using metrics such as mean squared error (MSE) or mean absolute error (MAE). Recursive partitioning follows, selecting the optimal feature at each step until a stopping criterion is met, such as reaching a maximum tree depth or a minimum sample size per node. During prediction, the tree is traversed based on feature values until reaching a leaf node, where the predicted value is computed as the average of the target values in that node. This approach enables efficient and accurate energy consumption forecasting by capturing complex relationships within the data, thereby facilitating intelligent energy management in smart homes.

CNN Regressor

A Convolutional Neural Network (CNN) Regressor is a deep learning model typically used for regression tasks that involve predicting continuous values, such as forecasting energy consumption. While CNNs are most commonly used for image processing, they can also be applied to time-series data or sequential data, which is the case in the project for predicting energy consumption. CNNs are particularly useful for capturing local dependencies and patterns in data through the use of convolutional layers.

In the context of regression, CNNs work by learning features from the data, applying convolutions to extract high-level patterns, and then using these features for making predictions. The final output layer is a regression layer that outputs continuous values, typically using a linear activation function.

Advantages:

Feature Learning: CNNs can automatically learn relevant features from the raw input data, which reduces the need for manual feature engineering.

Local Pattern Recognition: CNNs are great at capturing local patterns in the data, whether they are spatial (in images) or temporal (in time-series data).

Robustness: CNNs are robust to variations in the data, such as small shifts or distortions, making them more reliable for real-world applications.

Scalability: CNNs can scale well with large datasets and can be trained on large amounts of data to improve accuracy.

Dimensionality Reduction: The use of convolution and pooling layers helps reduce the dimensionality of the data, which can lead to more efficient models and faster training times.

4. EXPERIMENTAL ANALYSIS

The first step involves gathering the relevant dataset that includes energy usage information in smart homes. The dataset contains sensor readings and usage patterns over time. Features in the dataset include timestamps, electricity usage, weather conditions, occupancy, and other environmental factors.

Model Building (CNN Regressor):

Input Layer: The input layer is designed to take time-series data, where each sample consists of a window of past time steps (e.g., the last 24 hours of energy usage and environmental factors).

Convolutional Layers: The convolutional layers apply multiple filters to the time-series data to learn relevant patterns in the sequential data. These layers extract temporal features, such as trends and periodic behaviours in energy usage.

Activation Function: RELU (Rectified Linear Unit) is used after each convolutional layer to introduce non-linearity and allow the model to learn complex patterns.

Pooling Layers: Max pooling layers are employed after the convolutional layers to down sample the feature maps and reduce the dimensionality of the data, enhancing computational efficiency while retaining important patterns.

Flatten Layer: The feature maps produced by the convolutional and pooling layers are flattened into a 1D vector to feed into the fully connected layers.

Fully Connected Layers: These layers combine the learned features and generate a prediction based on the temporal patterns identified by the convolutional layers.

Output Layer: The output layer consists of a single neuron with a linear activation function, predicting the future energy usage as a continuous value.

Model Training:

The CNN Regressor is trained using the training set, where the model learns to minimize the loss function (Mean Squared Error) by adjusting its weights through backpropagation and gradient descent. The training process continues until the model reaches an optimal state based on the validation set performance.

Model Evaluation:

After training, the model is evaluated on the test set using performance metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared (R^2). These metrics provide insights into the model's prediction accuracy and generalization ability.

Hyperparameter Tuning:

To optimize the model’s performance, hyperparameters such as the number of convolutional filters, kernel size, number of layers, and learning rate are fine-tuned. This is done through a process like grid search or random search.

Model Deployment:

Once the model achieves satisfactory performance on the test set, it is deployed into a real-time environment where it can make predictions on new data. In a smart home environment, the model is integrated with the home automation system to forecast energy usage and optimize power consumption.

Continuous Monitoring and Updating:

After deployment, the model is continuously monitored to ensure its performance remains consistent. If there is a significant drift in energy usage patterns, the model is retrained on new data to adapt to the changes.

Dataset Description:

The dataset used for energy usage forecasting in smart home environments contains various columns representing different environmental factors, weather conditions, and energy generation metrics. Each column contributes valuable information that helps in predicting the total energy load.

temp, temp_min, temp_max: These columns represent the temperature readings. temp refers to the current temperature, while temp_min and temp_max denote the minimum and maximum temperatures recorded over a specified period, respectively. Temperature is a crucial factor influencing energy usage patterns in homes.

pressure: This column records atmospheric pressure data, which can provide insight into weather patterns and their impact on energy consumption.

humidity: Humidity levels are included to capture the effect of moisture in the air, which affects heating and cooling needs in smart homes.

wind_speed, wind_deg: These columns represent wind speed and wind direction. Wind data plays a role in understanding how wind generation (such as wind turbines) may influence the overall energy generation and usage.

rain_1h, rain_3h, snow_3h: These columns capture precipitation data. rain_1h and rain_3h record rainfall over 1-hour and 3-hour periods, while snow_3h records snowfall. These weather conditions can impact energy consumption, particularly in heating or cooling scenarios.

clouds_all: This column represents cloud coverage as a percentage, which affects solar generation. More cloud cover typically reduces the effectiveness of solar panels.

weather_id: This column categorizes different weather conditions, which can have direct impacts on energy consumption patterns and the efficiency of renewable energy sources.

generation columns (hydro, solar, wind, nuclear, etc.): These columns represent the energy generated by various sources. They include:

forecast columns (solar, wind onshore): These columns contain the forecasted values for solar and wind energy generation one day ahead. They are crucial for predicting future energy loads based on weather patterns and renewable energy production.

total load forecast: This column provides the predicted total energy consumption for a specified period, typically representing the smart home or grid's anticipated energy demand.

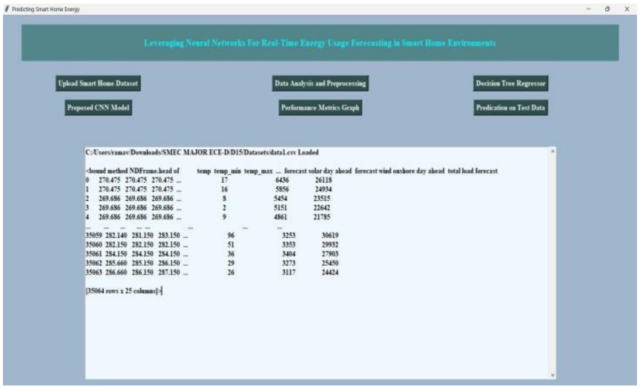

Figure 2:Upload of Energy Dataset

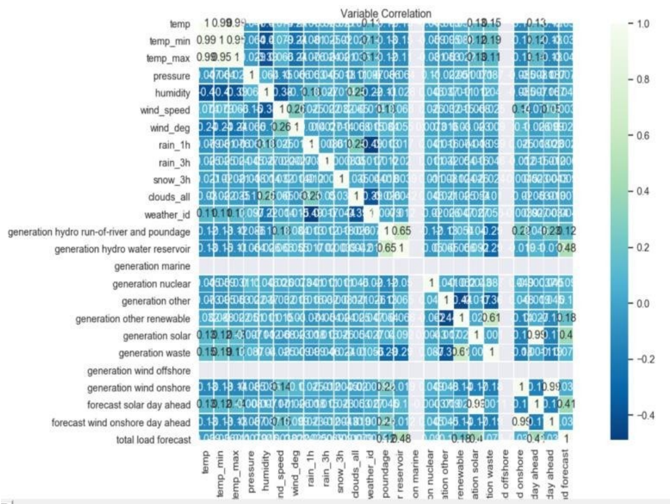

Figure 3: EDA Plots of the Project

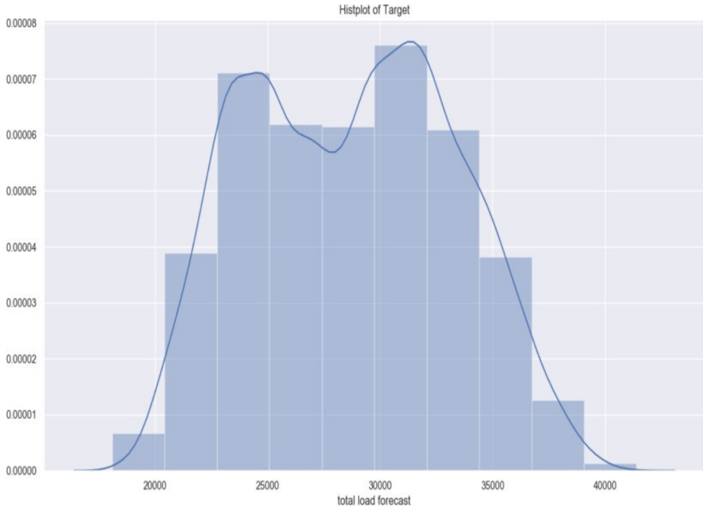

Figure 4: Data Preprocessing in the GUI

Figure 5: Performance Metrics of Decision Tree Regressor

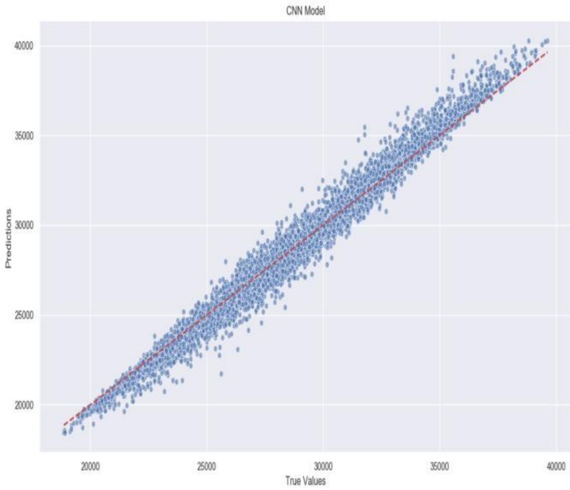

Figure 6: Performance Metrics of CNN Model

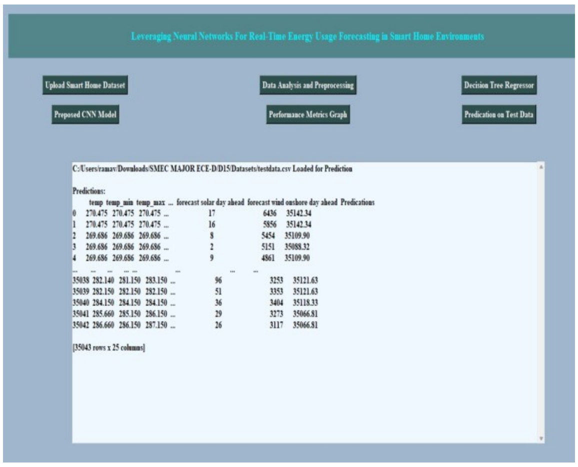

Figure 7: Model Prediction on Test Data

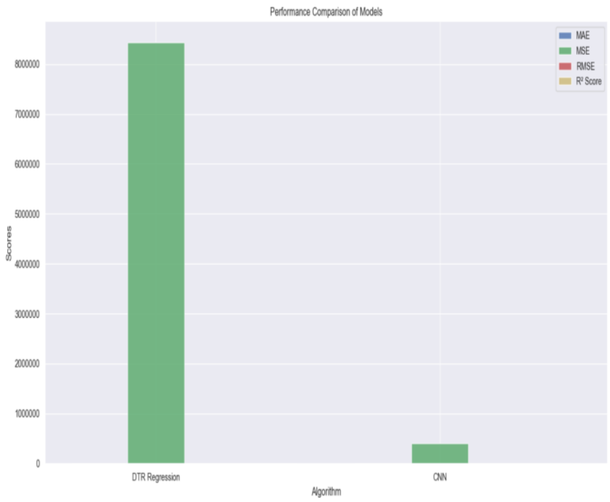

Figure 8: Performance Comparison Graph for All Models

Model name	RMSE	R^2-score
Decision Tree Regressor	2903.16	0.59
CNN	637.83	0.977

Table 1: Comparison of all models

5. CONCLUSION

This project focused on leveraging machine learning techniques for real-time energy usage forecasting in smart home environments. By utilizing environmental and weather-related data alongside renewable energy generation forecasts, the model is able to predict energy consumption accurately. The combination of traditional machine learning algorithms like Decision Tree Regressor (DTR) and advanced deep learning models such as Convolutional Neural Networks (CNN) demonstrated a significant improvement in predictive accuracy. The proposed CNN-based model, by effectively capturing complex patterns and interactions between various input features, outperformed the traditional models, offering better adaptability for dynamic smart home environments. The integration of diverse data sources, including weather forecasts and energy generation statistics, ensures that the model can deliver timely and relevant predictions, aiding in more efficient energy management in smart homes.

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