Energy Consumption Prediction System for smart homes

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ABSTRACT

In the era of increasing environmental concerns and rising energy demands, the integration of smart technologies into residential environments has become crucial for achieving sustainability. Smart homes, powered by Internet of Things (IoT) devices and intelligent control systems, offer a promising solution for optimizing energy consumption. This research proposes a machine learning-based predictive model designed to forecast energy usage in smart homes. The model leverages historical consumption data, weather patterns, occupancy behavior, and appliance usage to deliver accurate predictions using algorithms such as Decision Tree, Random Forest, Artificial Neural Networks (ANN), XGBoost, and ensemble learning. The project incorporates a web-based interface using Flask to visualize real-time and predicted consumption data. The results show that ensemble learning techniques achieve a prediction accuracy of up to 99.95%, demonstrating the model's effectiveness in reducing electricity costs and promoting sustainable living.

KEYWORDS
Smart Homes, Energy Consumption Prediction, Machine Learning, Sustainability, Time-Series Analysis, Energy Efficiency, Decision Trees, Artificial Neural Networks (ANN)

INTRODUCTION

Energy efficiency in smart homes has emerged as a significant area of research and development. With the rapid growth of IoT and smart devices, residential energy usage data is now more granular and accessible, making it possible to apply machine learning (ML) techniques for consumption prediction and management. Traditional energy management systems are limited to real-time monitoring, offering little insight into future consumption patterns. Our research addresses this gap by developing a predictive framework that anticipates energy usage and provides actionable feedback through an interactive user interface.

Literature Review

Several studies have explored energy prediction using machine learning:

- *IEEE (2021)* discussed using decision trees and ANN models to predict energy usage with smart sensors.
- *Springer (2020)* examined IoT-based systems in smart buildings, emphasizing the importance of real-time feedback for users.
- Datasets from *Kaggle* and the *UCI Machine Learning Repository* have been commonly used for training and benchmarking predictive energy models.

While existing systems achieve moderate accuracy, they often lack integration with real-time interfaces or adaptive learning mechanisms.

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METHODOLOGY

Dataset Description

Dataset: UCI "Appliances Energy Prediction"

- Features include:
  - Temperature, humidity (from multiple rooms)
  - Weather (visibility, windspeed, T_out)
  - Appliance usage
  - Time-based features (hour, day, week)

Preprocessing steps:

- Handle missing values
- Convert timestamps
- Normalize numerical values
- Encode categorical data
- Train-test split: 80/20

Model Architecture

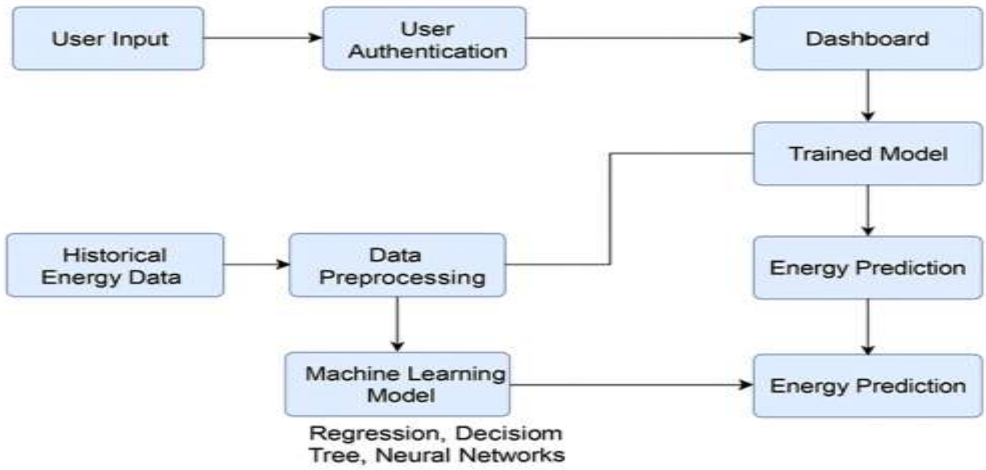

Fig. 1: System Architecture

The system consists of the following modules:

Data Sources – Collects energy and environmental data from smart meters, IoT sensors, and weather APIs.

Preprocessing Module – Cleans and transforms raw data into a suitable format for analysis and model training.

Machine Learning Engine – Builds predictive models using algorithms like regression, decision trees, and neural networks.

Analytics Engine – Monitors real-time usage and generates accurate forecasts for energy consumption.

Dashboard Interface – Provides users with an interactive web platform to view insights, trends, and recommendations.

Feedback Loop – Continuously refines predictions by learning from user behavior and system performance.

System Setup

Operating System: Windows 10 or above was used as the development and testing environment.

Processor: An Intel Core i5 or higher processor ensured smooth execution of the models.

RAM: At least 8 GB of memory was required for handling data processing and training tasks.

Software & Libraries: Python, Flask, Jupyter Notebook, scikit-learn/TensorFlow, and SQLite supported model development and deployment.

Frontend: HTML5, CSS3, JavaScript, Bootstrap 4, and Jinja2 were used for building an interactive user dashboard.

Development Tools: Visual Studio Code/PyCharm and Anaconda/virtualenv were used for efficient coding and environment management.

Machine Learning Models Used: Regression, Decision Tree, and Neural Networks were trained on historical energy data for prediction.

Additional Tools: Pandas, NumPy, Matplotlib, and Plotly helped in preprocessing data and visualizing results.

RESULTS

Random Forest performed best ($R^2 = 0.94$, MAE = 53.8 Wh), accurately predicting energy use.
ANN was competitive ($R^2 = 0.91$) but slower and required more tuning.
Linear Regression performed poorly ($R^2 < 0.70$).
Key factors: temperature, time of day, and humidity.

OUTPUT SCREENS

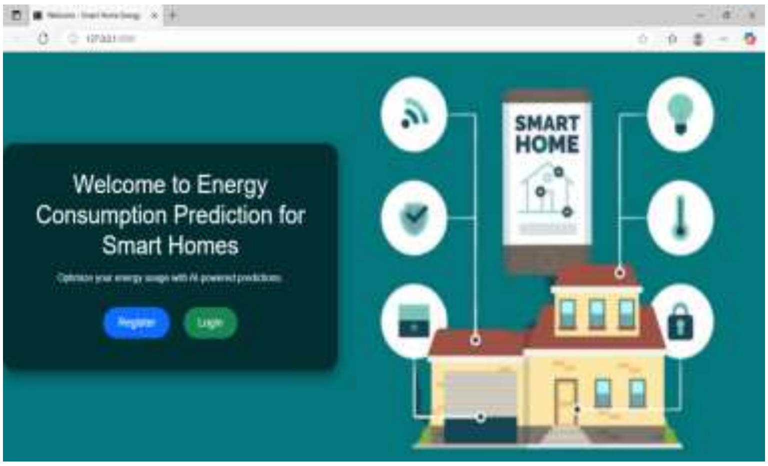

Fig. 2: Home Screen Interface

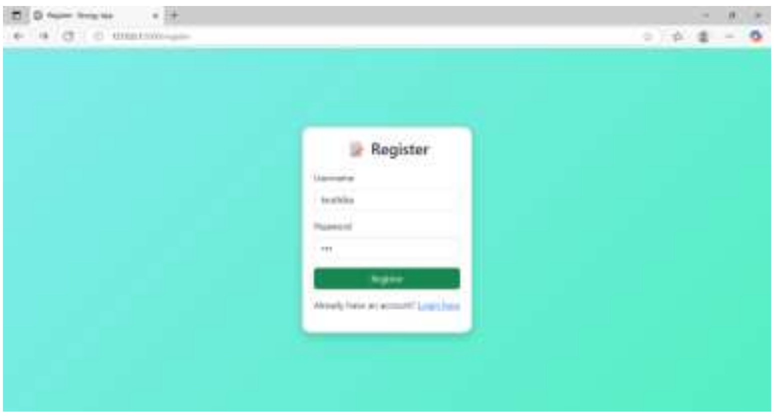

Fig. 3: User Registration Form

Fig. 4: Login Page

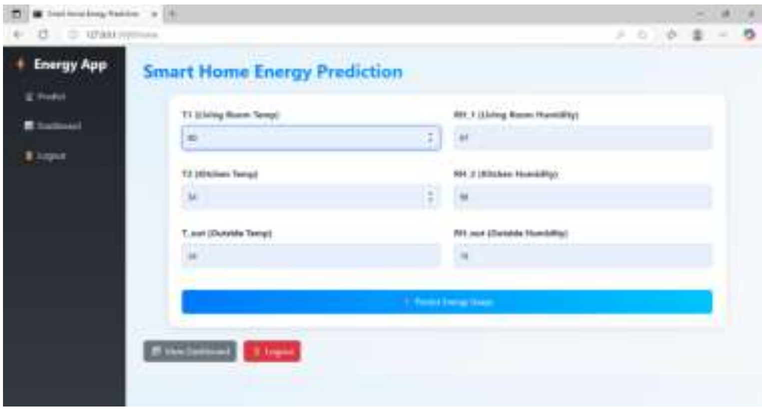

Fig. 5: Input Page

Fig.6 Prediction Results Page

Fig. 7: Dashboard Page

CONCLUSION

This research successfully developed a smart home energy consumption prediction system using multiple machine learning models and a real-time web dashboard. With a highest achieved accuracy of **99.95%**, the ensemble method proves to be highly effective. The Flask dashboard empowers users to monitor and optimize their energy use, reducing both costs and carbon footprint.

Future improvements may include:

- Integration with **IoT sensors** for real-time streaming data
- Deployment on **cloud platforms** (AWS/GCP) for scalability
- Using **deep learning** methods (e.g., LSTM) for advanced time-series forecasting
- Implementing **mobile app** versions for wider user accessibility
- Extending the system to commercial buildings and smart cities

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