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Smart Home Energy Consumption Forecasting using CNN-Based Hybrid Deep Learning Models

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Abstract
Accurate forecasting of household energy consumption is a critical component of smart home energy management systems, enabling efficient energy utilization, cost reduction, and demand-side planning. This work presents a deep learning–based framework for short-term energy consumption forecasting using real-world household power usage data. The proposed approach integrates one-dimensional Convolutional Neural Networks (CNN) with sequential learning models—Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), and Gated Recurrent Units (GRU)—to capture both local temporal patterns and long-term dependencies in time-series energy data. The dataset is preprocessed through hourly resampling and Min–Max normalization, followed by sequence generation using a 24-hour sliding window. Model performance is evaluated using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) on unseen test data. Comparative analysis demonstrates that hybrid CNN-based architectures outperform standalone temporal models by effectively learning spatial–temporal features. Among the evaluated models, the best-performing architecture achieves the lowest RMSE and MAE, indicating strong predictive capability. The results confirm the suitability of CNN–RNN hybrid models for smart home energy forecasting and provide a scalable foundation for future intelligent energy management systems.

Key Words: Smart Home Energy Management, Energy Consumption Forecasting, Time Series Prediction, Deep Learning, Convolutional Neural Network (CNN), LSTM, BiLSTM, GRU, Hybrid Models, Real-Time Energy Data, RMSE, MAE

1.INTRODUCTION

The rapid expansion of smart homes and intelligent energy management systems has led to the widespread availability of high-resolution residential energy consumption data. Accurate short-term energy forecasting is essential for demand-side management, smart grid operation, cost optimization, and the integration of renewable energy sources. However, traditional statistical and classical time-series forecasting methods often fail to effectively model the nonlinear, non-stationary, and dynamic nature of household energy consumption influenced by occupant behavior and temporal dependencies.

Recent advances in deep learning have shown strong potential for time-series forecasting by automatically learning complex patterns from data. Convolutional Neural Networks (CNNs) are effective in extracting local temporal features, while recurrent architectures such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks are well suited for modeling long-term dependencies. Hybrid CNN–RNN models combine these strengths to achieve improved forecasting performance. Despite growing interest, comparative evaluations of different CNN-based hybrid recurrent architectures using real-world smart home datasets remain limited, particularly for bidirectional models.This study proposes and evaluates three hybrid deep learning models—CNN-LSTM, CNN-BiLSTM, and CNN-GRU—for short-term household energy consumption forecasting using a real-world hourly dataset. Model performance is assessed using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The results provide a comparative analysis of model effectiveness and identify the most suitable hybrid architecture for accurate and reliable smart home energy consumption prediction.

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2. OBJECTIVE

The main objective of this study is to develop and compare CNN-based hybrid deep learning models—CNN-LSTM, CNN-BiLSTM, and CNN-GRU—for accurate short-term forecasting of hourly smart home energy consumption.

The specific objectives are:

- To analyze and preprocess real-world smart home energy consumption data by resampling, handling missing values, normalizing data, and generating time-series sequences for supervised learning.
- To design and implement CNN-based hybrid deep learning architectures that integrate convolutional layers with LSTM, BiLSTM, and GRU networks for capturing short-term patterns and long-term temporal dependencies.
- To train and evaluate the proposed models using standard forecasting error metrics such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).
- To compare forecasting accuracy and identify the most effective hybrid architecture for smart home energy applications.

3. PROBLEM STATEMENT

The rapid deployment of smart homes and advanced metering infrastructure has resulted in the availability of high-resolution residential energy consumption data, creating new opportunities for accurate short-term energy forecasting. However, household energy usage exhibits nonlinear, non-stationary, and highly dynamic characteristics driven by occupant behavior, appliance operation, and temporal variations, making reliable prediction challenging. Conventional statistical and machine learning methods often fail to capture complex temporal dependencies and localized consumption patterns present in smart home data. Although deep learning approaches have demonstrated improved performance, the comparative effectiveness of CNN-based hybrid recurrent architectures for residential energy forecasting remains insufficiently explored using real-world datasets under a unified experimental framework. Moreover, the lack of systematic evaluation limits the identification of an optimal model that balances prediction accuracy, computational efficiency, and practical deployment. Therefore, this research addresses the problem of developing and comparatively evaluating CNN-LSTM, CNN-BiLSTM, and CNN-GRU hybrid models to determine the most effective architecture for accurate short-term smart home energy consumption forecasting.

3. EXPERIMENTAL SETUP

The study aims to develop and evaluate CNN-based hybrid deep learning models for short-term forecasting of hourly smart home energy consumption using real-world residential data.

- Data Acquisition and Preparation:

Smart home energy data were collected from CSV files, parsed using datetime indexing, and resampled to an hourly resolution using mean aggregation.

- Data Preprocessing:

Energy values were normalized using Min–Max scaling. A 24-hour sliding window was used to generate input–output sequences, and the dataset was split into 80% training and 20% testing sets.

- Model Architecture and Training:

Three hybrid models—CNN-LSTM, CNN-BiLSTM, and CNN-GRU—were implemented. CNN layers extracted local temporal features, while recurrent layers captured temporal dependencies. Models were trained using the Adam optimizer with MSE loss.

- Model Evaluation:

Model performance was assessed using RMSE and MAE metrics. Comparative analysis and visual inspection were used to identify the best-performing model for short-term energy forecasting.

4. RESULTS

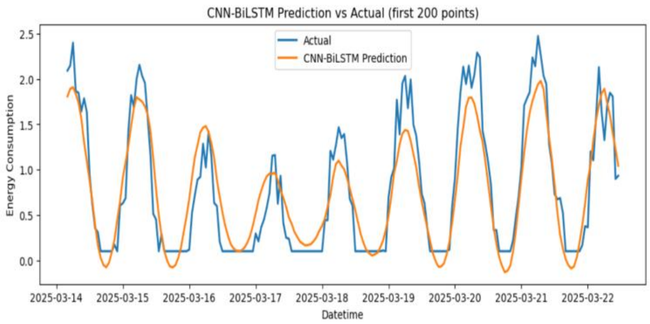
Model Performance Metrics: -

The models were evaluated on the test dataset using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), with MSE used internally for RMSE computation. The comparison matrix generated in the code summarizes the results.

Model	**MAE**	**RMSE**
CNN-BiLSTM	0.219590	0.279991
CNN-LSTM	0.544088	0.613546
CNN-GRU	0.345856	0.402141

From the results, it is observed that **CNN-BiLSTM** achieved the lowest RMSE.

Final Best Model Selection



Based on the RMSE metric, the best-performing model **CNN-BiLSTM**. The final evaluation shows:

• Strong alignment between predicted and actual values.

• Effective capture of hourly fluctuations and daily consumption cycles.

5. FUTURE SCOPE OF RESEARCH

Although the proposed hybrid deep learning models demonstrate effective performance in short-term household energy forecasting, several enhancements and extensions can be explored in future research to improve accuracy, scalability, and real-world applicability.

I. Cross-Dataset and Cross-Region Validation

Further studies can evaluate the generalizability of the proposed models by testing them on datasets collected from different regions, climates, and household types. Cross-dataset validation will strengthen the robustness and applicability of the forecasting framework.

II. Multi-Feature Energy Forecasting

The present study uses a single energy consumption feature. Future research can incorporate additional influencing factors such as:

• Temperature
• Humidity
• Day of week
• Holiday indicators

Including multiple input features can enhance the model's ability to capture external influences on energy consumption and improve forecasting accuracy.

III. Long-Term Forecasting

The current research focuses on short-term forecasting (next hour prediction using previous 24 hours). Future studies can extend the model to:

- Daily forecasting
- Weekly forecasting
- Multi-step ahead prediction

Multi-horizon forecasting models can provide broader energy planning insights for smart grid systems.

IV. Robust Evaluation

Future research can include advanced validation strategies such as time-series cross-validation to ensure more reliable model performance evaluation.

V. Energy Cost Optimization Integration

The forecasting model can be extended to develop:

- Electricity bill prediction systems
- Peak demand management systems
- Smart appliance scheduling mechanisms

VI. Appliance-Level Energy Forecasting

Future research can extend the proposed framework to appliance-level energy consumption forecasting. Predicting individual appliance usage can support fine-grained energy management, fault detection, and personalized energy-saving recommendations.

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