Appliance Energy Prediction Using Deep Learning

Introduction

This project focuses on building a predictive model for household appliance energy consumption using both baseline models and deep learning techniques. The purpose is to leverage time series and environmental data to predict energy usage patterns and inform potential energy-saving strategies.

Dataset Overview - data set

A real dataset was used, capturing household energy consumption patterns between January 11, 2016, and May 27, 2016, with data sampled every 10 minutes. The dataset includes:

- **Target Variable**: Appliance energy consumption
- **Features**: Indoor/outdoor temperatures and humidity, windspeed, visibility, pressure, light usage, and time-based features (hour, day, week).

Data Shape: 19,735 rows × 29 columns
Date Range: 2016-01-11 to 2016-05-27

Exploratory Data Analysis (EDA)

- **Appliance Energy Over Time**
  - Shows daily and seasonal variation
  - Clear cyclical patterns observed in consumption
- **Distribution of Energy Consumption**
  - Right-skewed distribution
  - Most values are between **50–100 Wh**
- **Correlation Matrix**
  - Top correlations with: lights (0.197), T2 (0.120), T6 (0.118)
  - Negative correlation observed with RH_out and RH_8

◆ **Average Consumption by Hour**

- Peaks in early morning (18:00–20:00)
- Lowest usage around 00:00–06:00

Data Preprocessing

- **Outlier handling**: Applied IQR-based capping
- **Missing values**: None observed
- **Feature encoding:** Binary encoding for categorical variables
- **Scaling**: Standardization using *StandardScaler*

Feature Engineering

- **Cyclical encoding:** *hour, month, and optionally weekday*
- **Rolling averages:** Applied to appliances, temperature, and humidity readings
- **Lag features:** Past values for appliance usage and lights
- **Statistical features:** Mean and standard deviation of temperature/humidity readings
- **Interaction features:** T1 * RH_1, T_out * RH_out

Final dataset shape: *19,591 rows × 64 features*

Feature Selection

- Applied Random Forest feature importance
- **Top feature:** *Appliances_lag_1* (previous energy usage)
- Selected top 30 features for modeling

Training & Testing

- **80%** for training, **20%** for testing
- Temporal split to avoid data leakage
- **Train size**: 15,672 rows
- **Test size**: 3,919 rows

Baseline Models

The following table summarizes the performance of the baseline models:

Model	MAE	RMSE	R^2
Linear Regression	28.13	57.30	0.566
Random Forest	43.26	81.74	0.117

These models provide strong initial benchmarks.

Evaluation Results

While the **LSTM model** captures long-term dependencies and temporal patterns, it slightly underperforms the linear model due to regular cyclic behavior in the dataset.

Model	MAE	RMSE	R^2
Deep Learning (LSTM)	28.44	60.34	0.519
Linear Regression	28.13	57.30	0.566
Random Forest	43.26	81.74	0.117

Final Visualizations

1. **Predicted vs Actual**
   - Close alignment along the identity line
   - Slight underprediction in high-energy cases
2. **Residual Plot**
   - Randomly scattered residuals around 0
   - Suggests model generalization without major bias
3. **Time Series Comparison**
   - Predicted line follows actual energy trend
   - Minor smoothing effect due to LSTM averaging
4. **Training History**
   - Rapid drop in loss initially, then plateaued
   - Early stopping helped prevent overfitting

EDA visualizations

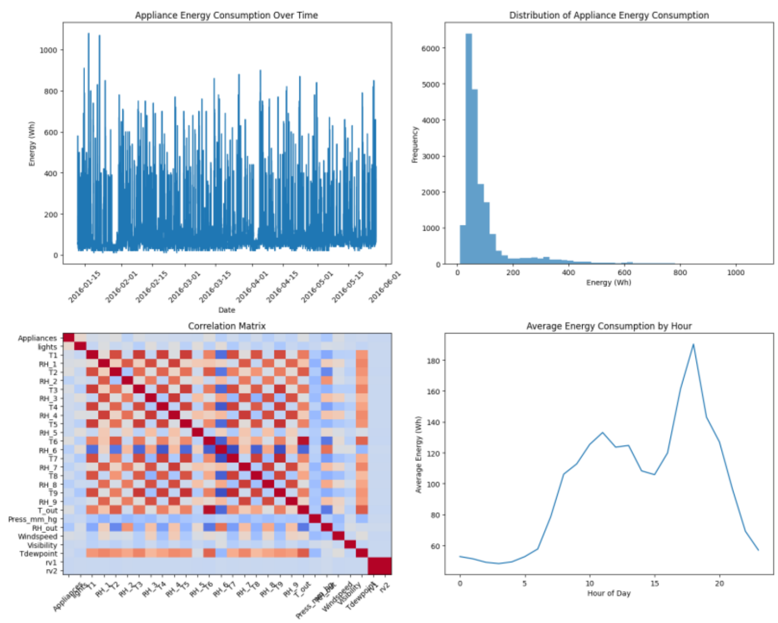

Figure 1

Provides insights into time-based variation, energy distribution, and key correlations. Strong correlation with lighting and temperature features supports their use in prediction.

Model evaluation and training history

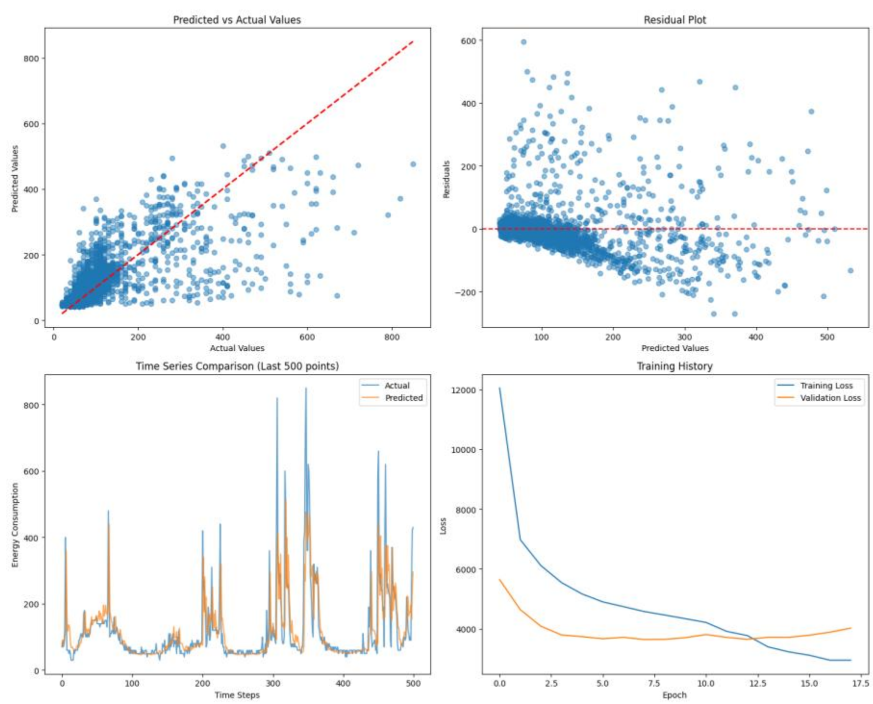

Figure 2

Evaluates LSTM prediction quality. Shows good trend following, unbiased residuals, and a healthy training process.

Recommendations & Future Work

1. Use real-world data to validate findings.
2. Apply model interpretability techniques (e.g., SHAP, LIME).
3. Test hybrid DL models like CNN + LSTM,GRU.
4. Use AutoML for hyperparameter tuning.
5. Deploy the model in a dashboard or home app.
6. Extend for anomaly detection in consumption.

Executive Summary

This project develops a robust appliance energy prediction pipeline using both traditional ML and deep learning. After preprocessing and engineering temporal features, we trained and compared three models:

1. Linear Regression (best R^2: 0.566)

2. LSTM-based Deep Learning (R^2: 0.519)

3. Random Forest (R^2: 0.117)

Despite LSTM's ability to learn time-dependent patterns, linear regression performed best, likely due to the regular structure in the data. The system is extensible and ready for real-time applications.

Conclusion

- Deep learning models can model complex temporal relationships.
- Simpler models can outperform in clean, regular datasets.
- Future work on real data, hybrid models, and deployment will add more value.