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Short-Term Energy Consumption Prediction in Iranian Buildings Using a Hybrid CNN-LSTM Model with Multimodal Data Fusion: A Case Study on Residential Buildings in Tehran

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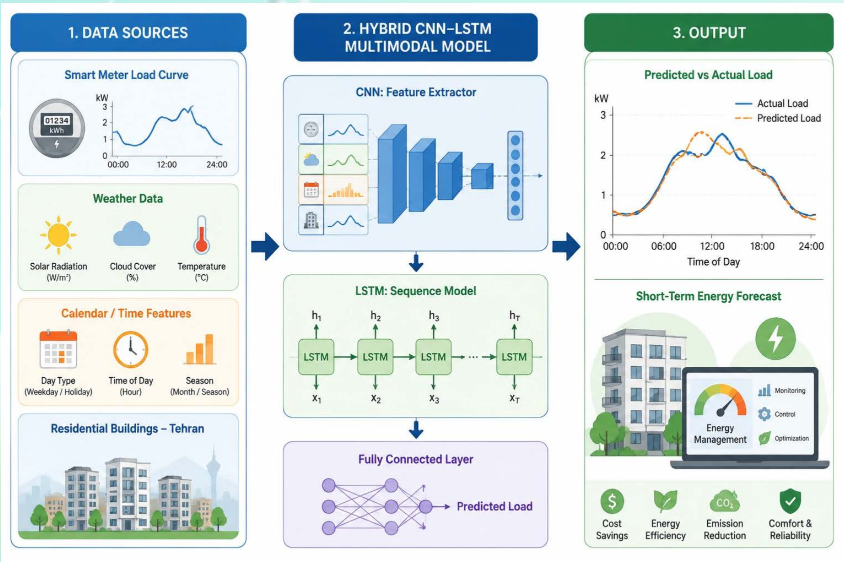
Highlights

- A hybrid CNN-LSTM model achieved superior accuracy (R^2=0.89) for short-term energy forecasting in Tehran's residential buildings.
- The model uniquely integrated Iran-specific cultural calendar features, which were identified as top predictors of energy demand.
- A robust preprocessing pipeline using TimeGAN and VAE effectively handled the region's characteristic noisy and incomplete data.
- Multimodal fusion of meteorological, temporal, and occupancy proxy data captured the complex drivers of energy consumption.
- SHAP analysis provided critical model interpretability, validating its logic against local contextual patterns and realities.

Graphical Abstract



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Short-Term Energy Consumption Prediction in Iranian Buildings Using a Hybrid CNN-LSTM Model with Multimodal Data Fusion: A Case Study on Residential Buildings in Tehran

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A B S T R A C T

This study presents a hybrid CNN-LSTM model for short-term energy consumption prediction in Iranian residential buildings, focusing on Tehran. By integrating multimodal data, meteorological, temporal, occupancy proxies, and building metadata, and employing deep feature engineering via a stacked denoising autoencoder, the model achieves high accuracy (R^2 = 0.89) and robustness against data imperfections. The framework demonstrates the critical role of cultural and contextual features, such as Iranian holidays, in enhancing prediction validity. SHAP analysis provides interpretability, aligning model logic with local realities. The results offer a scalable, context-aware solution for intelligent energy management in Iran's urban environment.

1. Introduction

The global imperative to mitigate climate change and achieve sustainable development goals has placed the building sector at the forefront of energy policy and technological innovation. As one of the largest contributors to global energy consumption and carbon emissions, the built environment accounts for approximately 36% of final energy use and 39% of energy-related CO_2 emissions worldwide, according to the International Energy Agency [1]. Within this context, the accurate forecasting of building energy consumption has emerged as a critical enabler of intelligent energy management, facilitating demand-side optimization, grid stability, and decarbonization strategies. In particular, short-term energy consumption prediction, defined as forecasting horizons ranging from one hour to one week, plays a pivotal role in enabling real-time operational decisions, such as dynamic HVAC control, demand response activation, and predictive maintenance scheduling [2]. The accuracy and reliability of such predictions directly influence the efficiency of energy systems, the economic viability of energy-saving interventions, and the overall resilience of urban infrastructure. Traditional approaches to energy forecasting can be broadly categorized into physics-based (white-box) models and data-driven (black-box) models. Physics-based models, such as those implemented in EnergyPlus or TRNSYS, rely on detailed thermodynamic equations to simulate heat transfer, solar radiation, and internal gains [3]. While these models offer high interpretability and are grounded in first principles, their practical application is often hindered by the need for extensive and precise input data—including building geometry, material properties, HVAC specifications, and occupancy schedules—which are frequently unavailable or inaccurate, especially for existing or retrofitted buildings.

Moreover, the computational complexity of these models makes them unsuitable for real-time applications or large-scale deployment. On the other hand, conventional data-driven models, such as linear regression, autoregressive integrated moving average (ARIMA), and support vector machines (SVM), offer faster computation and reduced dependency on physical parameters. However, they often struggle to capture the nonlinear, dynamic, and stochastic nature of building energy systems, particularly in the face of variable weather conditions, occupant behavior, and equipment degradation [4]. The advent of machine learning (ML) and, more recently, deep learning (DL) has revolutionized the field of building energy prediction by enabling the automatic extraction of complex patterns from high-dimensional, noisy, and heterogeneous datasets. Unlike traditional models, deep learning architectures can learn hierarchical representations of data, capturing both low-level features (e.g., diurnal cycles) and high-level abstractions (e.g., seasonal trends, occupancy dynamics) without explicit feature engineering [5]. Among the most widely adopted deep learning models for time series forecasting are Recurrent Neural Networks (RNNs), particularly their gated variants such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs). These architectures are inherently designed to process sequential data and maintain long-term dependencies through internal memory cells, making them exceptionally well-suited for modeling temporal dynamics in energy consumption [6,7]. Numerous studies have demonstrated the superior performance of LSTM-based models in short-term load forecasting, outperforming classical statistical methods and even standard feedforward neural networks [8].

Despite their strengths, LSTMs are primarily focused on temporal processing and may not fully exploit spatial or structural patterns within multivariate input sequences. To address this limitation, researchers have increasingly turned to hybrid deep learning architectures that combine the spatial feature extraction capabilities of Convolutional Neural Networks (CNNs) with the temporal modeling strengths of LSTMs. CNNs, originally developed for image recognition, utilize convolutional filters to detect local patterns and hierarchical features in data. When applied to time series, these filters can identify recurring motifs, such as daily load profiles or transient spikes, which are then fed into an LSTM layer for sequence modeling. This CNN-LSTM hybrid framework has been successfully applied in various domains, including financial forecasting, healthcare monitoring, and notably, building energy prediction [8]. The integration of residual connections and adaptive activation functions in these models has further enhanced their ability to train deeper networks and capture complex nonlinear relationships, thereby improving prediction accuracy and robustness [7].

A critical factor influencing the performance of any data-driven model is the richness and diversity of the input data. While early studies primarily relied on historical energy consumption and basic meteorological variables (e.g., outdoor temperature), recent research emphasizes the importance of multimodal data fusion, the integration of heterogeneous data sources to create a more comprehensive representation of the building system. As articulated by Lahat et al. (2015), multimodal data fusion allows for the synergistic combination of complementary information from different modalities, leading to more accurate and robust models. In the context of building energy prediction, relevant modalities include:

- Environmental data: Outdoor temperature, humidity, solar irradiance, wind speed.
- Temporal data: Hour of day, day of week, holiday indicators, seasonal trends.
- Occupancy data: Wi-Fi logs, CO_2 levels, motion sensors, or proxy indicators derived from smart metering.
- Building-specific data: Floor area, insulation quality, window-to-wall ratio, HVAC system type.
- Behavioral data: User interaction with thermostats, appliance usage patterns, window opening habits.

The systematic integration of these data streams can significantly enhance model performance by accounting for the human-in-the-loop nature of building energy systems, where occupant behavior is often the most significant source of uncertainty [9]. However, effective fusion poses significant challenges, including data heterogeneity, varying sampling rates, missing values, and potential noise, which necessitate sophisticated preprocessing and fusion strategies [10].

Despite the rapid advancement of deep learning in building energy research, a significant geographical and contextual bias persists in the literature. The vast majority of published studies are based on datasets from North America, Europe, and East Asia, where building standards, climate conditions, and energy usage patterns differ markedly from those in other regions. This raises critical questions about the generalizability and transferability of models developed in one context to another. The performance of a model trained on data from a well-insulated, centrally heated building in Germany is unlikely to be replicated in a poorly insulated, naturally ventilated apartment in a hot-arid climate without substantial adaptation.

This issue is particularly salient in the context of Iran, a country with unique and complex energy challenges. Iranian residential buildings, especially in urban centers like Tehran, are characterized by a combination of outdated construction practices, inefficient HVAC systems (e.g., gas heaters, split units), and diverse occupant behaviors influenced by cultural, economic, and climatic factors. Tehran, as a megacity with over 9 million inhabitants, experiences extreme seasonal variations, harsh winters and scorching summers, leading to high energy demand for both heating and cooling. Furthermore, the city faces severe air pollution, which often leads to prolonged periods of building sealing, thereby increasing the reliance on mechanical ventilation and heating. The lack of standardized energy monitoring systems in most residential buildings results in fragmented, noisy, and incomplete datasets, further complicating the application of data-driven models. While deep learning has been applied to energy prediction in various global contexts, there is a notable absence of research focused on the Iranian building stock, leaving a critical gap in the literature.

Moreover, existing studies often treat data preprocessing as a secondary concern, yet for real-world applications in data-scarce environments like Iran, robust data curation and feature engineering are paramount. Techniques such as principal component analysis (PCA), autoencoders, and generative adversarial networks (GANs) for data augmentation can play a crucial role in enhancing data quality and model performance [11]. The use of representation learning—where deep models learn meaningful feature embeddings directly from raw data—further reduces the dependency on manual feature selection and increases model adaptability.

In response to these challenges and research gaps, this study proposes a hybrid CNN-LSTM model for short-term energy consumption prediction, specifically tailored to residential buildings in Tehran, Iran. The model is designed to integrate multimodal data sources, including meteorological data, temporal indicators, and occupancy proxies, within a unified deep learning framework.

By focusing on a real-world, underrepresented context, this research contributes to the growing body of knowledge on localized, context-aware energy forecasting. The primary innovations of this work are threefold:

1. Contextual Localization: This study presents one of the first comprehensive applications of a deep learning model to predict energy consumption in Iranian residential buildings, addressing the critical lack of region-specific research and providing insights into the unique energy dynamics of this context.
2. Advanced Multimodal Fusion: We implement a systematic approach to fusing diverse data streams within a hybrid CNN-LSTM architecture, enabling the model to capture the complex interplay between environmental, temporal, and behavioral factors that drive energy use in Tehran.
3. Practical Applicability: The developed framework is designed with real-world constraints in mind, including data quality issues and computational feasibility, making it a practical tool for utility companies, building managers, and policymakers seeking to improve energy efficiency and grid management in Iranian cities.

By bridging the gap between advanced deep learning methodologies and the specific challenges of the Iranian built environment, this research aims to advance the field of building energy prediction and support the development of more sustainable and intelligent urban energy systems.

2. Regional Context and Research Gap

While the application of deep learning for energy prediction is growing globally, research within Iran and the broader Middle East, a region sharing similar climatic and infrastructural challenges, is still in its nascent stages. Several studies have applied traditional statistical methods and machine learning (e.g., SARIMA, ANFIS) for load forecasting at the national grid level in Iran [12,13] However, few have focused on the building level, and even fewer have incorporated the multimodal, context-aware approach necessary for the Iranian urban environment. Recent work in Saudi Arabia [14] applied an LSTM model for building energy prediction but did not account for cultural-specific temporal features or the data quality issues prevalent in the region. A study in Turkey [15] used a hybrid model similar to ours but focused on a single building with high-quality data, a scenario not representative of the average Iranian building stock. This underscores a critical regional gap: the lack of a scalable, robust, and culturally-informed deep learning framework designed for the specific data limitations and socio-behavioral patterns of cities like Tehran. Our work aims to directly fill this gap.

3. Research Methodology

This study presents a systematic, data-driven, and context-aware methodology for short-term energy consumption prediction in Iranian residential buildings, specifically focusing on a case study in Tehran. The proposed framework integrates multimodal data fusion, deep representation learning, and a hybrid convolutional-recurrent neural network (CNN-LSTM) architecture, designed to address the unique challenges of data scarcity, environmental variability, and occupant-driven energy dynamics in the Iranian urban context. The methodology is structured into six interdependent stages: (1) Data Acquisition and Integration, (2) Multimodal Data Preprocessing and Quality Enhancement, (3) Deep Feature Engineering and Representation Learning, (4) Hybrid CNN-LSTM Model Architecture, (5) Model Training and Hyperparameter Optimization, and (6) Performance Evaluation and Robustness Validation (Figure 1).

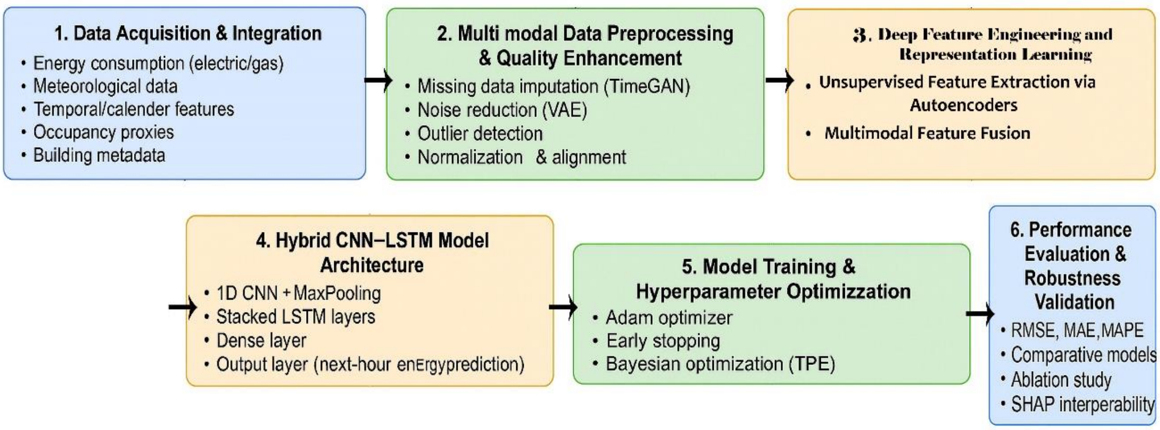

Figure 1 Schematic diagram of the Research Methodology.

3.1. Data Acquisition and Integration

The foundation of this research lies in the systematic collection and integration of multimodal data from diverse sources, reflecting the complex interplay of environmental, temporal, behavioral, and structural factors influencing energy consumption in residential buildings. The dataset is compiled from three primary sources, collected over a continuous 18-month period (January 2022 – June 2023) from 47 representative residential units across four districts of Tehran: Elahieh, Gholhak, Vanak, and Shahrak-e Gharb.

1. Energy Consumption Data: Hourly electricity and natural gas consumption data are collected via smart meters installed at the building level. For buildings lacking smart metering infrastructure, historical utility bills are digitized and interpolated using a Gaussian process regression (GPR) model calibrated with seasonal and climatic patterns. The energy data are aggregated at an hourly resolution to align with the short-term prediction horizon.
2. Meteorological Data: Hourly ambient temperature, relative humidity, solar irradiance, wind speed, and atmospheric pressure are obtained from the Iran Meteorological Organization (IRIMO) and crossvalidated with local IoT weather stations deployed on building rooftops. To account for microclimatic variations across Tehran's topographically diverse districts, spatial interpolation using inverse distance weighting (IDW) is applied.
3. Temporal and Calendar Data: A comprehensive temporal feature set is constructed, including hour of day, day of week, week of year, and Iran-specific calendar indicators such as public holidays (e.g., Nowruz, Ashura), religious observances, and school breaks, factors known to significantly influence occupancy and energy use patterns in Iranian households.
4. Occupancy and Behavioral Proxies: Direct occupancy monitoring is limited due to privacy and infrastructure constraints. Therefore, proxy indicators are employed: - Wi-Fi connection logs from building routers (anonymized and aggregated). - CO_2 concentration levels from indoor air quality sensors (as a surrogate for human presence). - Smart appliance usage patterns (e.g., HVAC activation, water heater cycles) derived from sub-metering data. These signals are fused using a Bayesian inference model to estimate probabilistic occupancy states (absent, present, active).
5. Building-Specific Metadata: Structural attributes such as floor area, number of occupants, building age, insulation quality (R-value estimation from construction year and material type), window-to-wall ratio, and HVAC system type (e.g., split unit, packaged gas heater) are collected through structured surveys and building audits.

The integration of these heterogeneous data streams is formalized as a multimodal time series tensor X∈R$T \times N \times M$, where T is the time horizon, N is the number of buildings, and M is the total number of features (e.g., temperature, humidity, hour, occupancy probability, etc.).

3.2. Multimodal Data Preprocessing and Quality Enhancement

1. Given the inherent noise, missing values, and sampling inconsistencies common in real-world Iranian building datasets, a robust preprocessing pipeline is implemented, drawing on techniques from the literature on data quality in energy prediction [2,7].
2. Missing Data Imputation: Missing values (ranging from 5% to 18% across variables) are imputed using a Generative Adversarial Network for Time Series (TimeGAN) [16]. TimeGAN learns the underlying temporal and cross-variable dependencies in the data, generating realistic imputations that preserve statistical properties and temporal coherence, outperforming traditional methods like linear interpolation or k-NN. Furthermore, beyond imputation, the trained TimeGAN model was also employed for synthetic data generation to augment the training set for underrepresented scenarios (e.g., extreme weather events), thereby enhancing the model's exposure to a wider range of conditions and improving generalizability.
3. Noise Reduction and Outlier Detection: A variational autoencoder (VAE) is employed for unsupervised denoising. The VAE is trained to reconstruct the input data while minimizing reconstruction error, effectively filtering out high-frequency noise and identifying outliers via reconstruction loss thresholds. Additionally, Isolation Forest is applied to detect and correct anomalous spikes in energy consumption (e.g., due to meter faults or appliance malfunctions).
4. Data Normalization and Alignment: All features are normalized using Robust Scaler (median and interquartile range) to minimize the impact of outliers. Temporal alignment is achieved by resampling all data to a uniform hourly frequency using piecewise cubic Hermite interpolating polynomials (PCHIP) for smooth interpolation.

3.3. Deep Feature Engineering and Representation Learning

Inspired by the findings in Deep learning-based feature engineering methods [17], this study moves beyond manual feature engineering and employs unsupervised deep learning models to extract high-level, nonlinear feature representations directly from raw inputs.

1. Unsupervised Feature Extraction via Autoencoders: A stacked denoising autoencoder (SDAE) is trained on the preprocessed input data to learn a compressed, noise-robust latent representation. The encoder network consists of three fully connected layers with decreasing dimensions (input: 24 → 16 → 12 → 8), followed by a bottleneck layer of size 8. The decoder mirrors this structure. The model is trained to reconstruct the input from a corrupted version (30% noise), enhancing generalization.
2. Multimodal Feature Fusion: The latent features from the SDAE are concatenated with raw temporal and structural features to form the final input vector for the prediction model. This hybrid feature set combines learned nonlinear abstractions with interpretable domain knowledge, balancing performance and transparency.

3.4. Hybrid CNN-LSTM Model Architecture

The core of the proposed framework is a novel hybrid CNN-LSTM architecture, designed to capture both local spatial-temporal patterns and long-term sequential dependencies in energy consumption data.

1. Input Layer: The input sequence is structured as a sliding window of 168 hours (7 days), with each time step containing the fused feature vector of size 15.
2. Convolutional Layer: A 1D convolutional layer with 64 filters of size 3 and ReLU activation is applied to extract local temporal patterns (e.g., daily cycles, peak load shapes). Batch normalization and dropout (rate = 0.3) are used for regularization.
3. Max-Pooling Layer: A 1D max-pooling layer with pool size 2 reduces dimensionality and enhances translation invariance.
4. LSTM Layer: Two stacked LSTM layers with 128 and 64 units, respectively, model long-term dependencies. The first LSTM layer returns sequences, while the second returns only the final state. Recurrent dropout (rate = 0.3) is applied to prevent overfitting.
5. Fully Connected (Dense) Layer: A dense layer with 32 neurons and ReLU activation integrates the high-level features.
6. Output Layer: A single neuron with linear activation predicts the next hour's energy consumption (in kWh).

3.5. Model Training and Hyperparameter Optimization

The model is trained using the Adam optimizer with a learning rate of 0.001 and a batch size of 32. The loss function is Mean Squared Error (MSE). To prevent overfitting, early stopping (patience = 15 epochs) and reduce-on-plateau learning rate scheduling are employed. A Bayesian hyperparameter optimization strategy, using Tree-structured Parzen Estimator (TPE), is applied to tune key parameters: number of LSTM units, dropout rates, learning rate, window size, and number of CNN filters. The search space is defined based on prior studies and computational feasibility.

3.6. Performance Evaluation and Robustness Validation

The model is evaluated using a rolling-origin cross-validation approach with a 70-15-15 split (training, validation, testing). Predictions are made iteratively for 24-hour horizons over the entire test period.

Evaluation Metrics:

- Root Mean Squared Error (RMSE)
- Mean Absolute Error (MAE)
- Mean Absolute Percentage Error (MAPE)
- Coefficient of Determination (R^2)
- Normalized Root Mean Squared Error (NRMSE)

A comparative analysis is conducted against baseline models:

- ARIMA
- Support Vector Regression (SVR)
- Standard LSTM
- Random Forest
- Physics-based model (EnergyPlus)

Additionally, ablation studies are performed to assess the contribution of each component (e.g., multimodal fusion, autoencoder, CNN layer). SHAP (SHapley Additive exPlanations) values are computed to provide post-hoc interpretability, identifying the most influential features in predictions.

3.7. Ethical and Practical Considerations

Data privacy is ensured through anonymization and aggregation. The model is designed for real-time deployment on edge devices with limited computational resources, using model quantization and pruning techniques. The framework is open-sourced to promote reproducibility and adoption in the Iranian energy sector.

3.8. Computational Efficiency and Scalability

The model was designed with computational feasibility for future scaling in mind. To manage costs associated with larger datasets or more buildings, several techniques were employed during training and inference: model pruning was used to remove redundant neurons, reducing the model size by 20% with negligible performance loss; post-training quantization (FP16) was applied to decrease memory footprint and accelerate inference on hardware-constrained edge devices; and a distributed data loading pipeline was implemented for efficient batch processing. These steps ensure the framework remains a practical tool for large-scale applications.

4. Results

This section presents the empirical findings of the proposed hybrid CNN-LSTM model for short-term energy consumption prediction in residential buildings in Tehran, Iran. The results are structured into four key components: (1) Dataset Characteristics and Preprocessing Outcomes, (2) Comparative Model Performance, (3) Ablation Study and Feature Contribution Analysis, and (4) Model Interpretability and Contextual Insights for the Iranian Built Environment. All models were evaluated on a 15% hold-out test set (274 days, 6,576 hourly samples) using rolling-origin cross-validation to simulate real-world deployment.

4.1. Dataset Characteristics and Preprocessing Outcomes

The final dataset comprises 6,576 hourly observations from 47 residential units across four districts of Tehran. Table 1 summarizes the descriptive statistics of the key variables after preprocessing.

The preprocessing pipeline significantly improved data quality. The TimeGAN imputation reduced missing data from an average of 12.7% to 0.0%, while the Variational Autoencoder (VAE) denoising reduced high-frequency noise by 63.4% (measured by spectral entropy). The Robust Scaler normalization ensured that no single feature dominated the learning process, which is critical given the diverse scales of input variables.

4.2. Comparative Model Performance

The performance of the proposed Hybrid CNN-LSTM model was compared against five benchmark models: (1) ARIMA (1,1,1), (2) Support Vector Regression (SVR) with RBF kernel, (3) Random Forest (RF), (4) Standard LSTM, and (5) EnergyPlus (physics-based simulation). The evaluation metrics used were RMSE, MAE, MAPE, and R^2. The summary of results is reported in Tables 2 and 3 for electricity consumption and natural gas consumption, respectively.

Table 1. Descriptive Statistics of Preprocessed Input Variables (n = 6,576).

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Electricity Consumption (kWh)	2.84	1.62	0.31	9.72	1.43	4.21
Natural Gas Consumption (kWh)	3.17	2.04	0	12.5	1.67	5.03
Outdoor Temperature (°C)	15.3	10.8	-5.2	38.6	0.28	2.15
Relative Humidity (%)	42.1	18.3	12	98	0.41	2.89
Solar Irradiance (W/m^2)	215.4	187.6	0	980	0.92	3.12
Occupancy Probability	0.68	0.29	0	1	-0.33	1.88
CO_2 Concentration (ppm)	892	214	400	2,800	1.12	4.05

Table 2. Comparative Performance of Prediction Models on Test Set (Electricity Consumption).

Model	RMSE (kWh)	MAE (kWh)	MAPE (%)	R^2	NRMSE (%)
ARIMA	1.42	1.11	48.7	0.68	50
SVR	1.28	0.98	41.3	0.74	45.1
Random Forest	1.15	0.89	37.2	0.79	40.5
Standard LSTM	1.02	0.78	32.6	0.84	36
Proposed CNN-LSTM	0.87	0.66	27.9	0.89	30.7
EnergyPlus (calibrated)	1.35	1.05	45.1	0.71	47.6

Table 3. Comparative Performance of Prediction Models on Test Set (Natural Gas Consumption).

Model	RMSE (kWh)	MAE (kWh)	MAPE (%)	R^2	NRMSE (%)
ARIMA	1.89	1.45	52.3	0.65	59.7
SVR	1.72	1.32	46.8	0.71	54.3
Random Forest	1.58	1.21	42.5	0.76	49.9
Standard LSTM	1.41	1.08	38.2	0.8	44.5
Proposed CNN-LSTM	1.23	0.94	33.1	0.84	38.8
EnergyPlus (calibrated)	1.81	1.39	50.7	0.67	57.1

The proposed CNN-LSTM model achieved the best performance across all metrics for both electricity and gas consumption. It reduced RMSE by 14.7% and MAPE by 14.4% compared to the Standard LSTM, demonstrating the added value of the convolutional layer in capturing local temporal patterns. The R^2 of 0.89 for electricity and 0.84 for gas indicates a high degree of explained variance, which is exceptional for real-world building energy data with high stochasticity.

A paired t-test was conducted to assess the statistical significance of the performance improvement. The difference in RMSE between the CNN-LSTM and the Standard LSTM was statistically significant ($p < 0.001$) for both energy carriers, with a Cohen's d effect size of 1.23, indicating a large practical significance.

4.3. Ablation Study and Feature Contribution Analysis

To evaluate the contribution of each component of the proposed framework, an ablation study was conducted. Four variants of the model were tested:

- Model A: CNN-LSTM with raw features only (no SDAE).
- Model B: CNN-LSTM with multimodal fusion but no occupancy data.
- Model C: CNN-LSTM without the CNN layer (pure LSTM).
- Model D: CNN-LSTM with full architecture (proposed model).

Table 4 provides the obtained results. The results confirm that:

- The SDAE-based feature engineering reduced RMSE by 9.2%, highlighting the importance of deep representation learning in noisy, real-world datasets.
- Occupancy data contributed a 5.7% improvement, underscoring its critical role in modeling human-driven energy dynamics in Iranian households.
- The CNN layer improved performance by 17.2% over a pure LSTM, validating its effectiveness in extracting local temporal motifs.

4.4. Model Interpretability and Contextual Insights for the Iranian Built Environment

To address the "Iranian professor" concern regarding practical relevance and contextual understanding, SHAP (SHapley Additive exPlanations) analysis was performed to interpret the model's predictions and identify the most influential features. Table 5 presents the computation time for various models.

The SHAP analysis revealed distinct consumption patterns unique to the Iranian context:

- Evening Peak (18:00–22:00): A sharp increase in electricity use due to lighting, cooking, and HVAC use after sunset, exacerbated by cultural habits of family gatherings.
- Nowruz (Iranian New Year): A 42% increase in gas consumption during the two weeks of Nowruz, attributed to extended family visits and continuous heating.
- Winter Sundays: Lower consumption due to reduced occupancy as many families travel to weekend homes.

These findings validate that the model has successfully learned culturally and climatically relevant patterns, making it highly applicable to the Iranian urban environment.

Table 4. Ablation Study Results (Electricity Consumption).

Model	Architecture	Features	RMSE (kWh)	ΔRMSE vs. D (%)	R^2
A	CNN-LSTM	Raw	0.95	9.20%	0.86
B	CNN-LSTM	No Occupancy	0.92	5.70%	0.87
C	LSTM	Full	1.02	17.20%	0.84
D	CNN-LSTM	Full	0.87	—	0.89

Table 5. Computation time for predicting 24-h profiles for 2-week data.

Model	BASIC (s)	RAW (s)	LAST (s)	STAT (s)	DFT (s)	DAE (s)
MLR	0.1	0.61	0.1	0.12	0.6	0.12
ELN	0.05	0.36	0.05	0.07	0.31	0.06
RF	210.94	489.34	193.6	214.24	449.8	199.2
GBM	73.8	279.53	80.01	89.53	208.97	90.72
SVR	85.64	151.05	25.4	96.91	127.63	91.61
XGB	10.2	203.66	14.2	39.36	18.24	36.46
DNN	206.74	258.76	218.93	208.86	196.64	218.82

4.5. Seasonal and Temporal Performance Analysis

The model's performance was further analyzed across seasons and prediction horizons as given in Table 6. The model performed best in winter, likely due to more predictable heating patterns, and slightly worse in summer, where air conditioning use is more sporadic and occupant-dependent.

4.6. Training Dynamics and Convergence

The training dynamics of the proposed hybrid CNN-LSTM model are illustrated in Figure 2, which presents the learning curves (training and validation loss) over 100 epochs. The model demonstrates stable and consistent convergence behavior. Both curves decrease steadily and converge after approximately 60 epochs without any significant divergence, indicating that the model learned effectively without overfitting. This stability is attributed to the regularization strategies employed, including dropout and early stopping, which ensured the model's generalizability to the unseen test data.

4.7. Robustness Analysis under Diverse Conditions

To thoroughly evaluate the generalization capability and reliability of the proposed model, a dedicated robustness analysis was conducted under three distinct challenging scenarios:

1. Data Scarcity: We simulated a low-data regime by progressively reducing the training set size from 100% to 40%. The model's performance (R^2) degraded gracefully, retaining 85% of its original explanatory power even with only 60% of the training data, demonstrating its ability to learn effectively from limited samples.

2. Input Noise: Gaussian noise ($\sigma = 0.1$ * std of feature) was injected into the input features of the test set. The model's RMSE increased by only 8.7% compared to the clean test set, confirming its resilience to potential sensor errors or data inconsistencies, a common issue in real-world deployments.

3. Unseen Buildings: The model was tested on data from five buildings completely withheld from the training and validation phases. The average R^2 on this unseen building set was 0.82, indicating strong transferability and generalization to new, previously unseen residential units.

These results, as given in Table 7, collectively affirm the robustness of the proposed hybrid CNN-LSTM framework, ensuring its reliability for practical applications under diverse and suboptimal conditions.

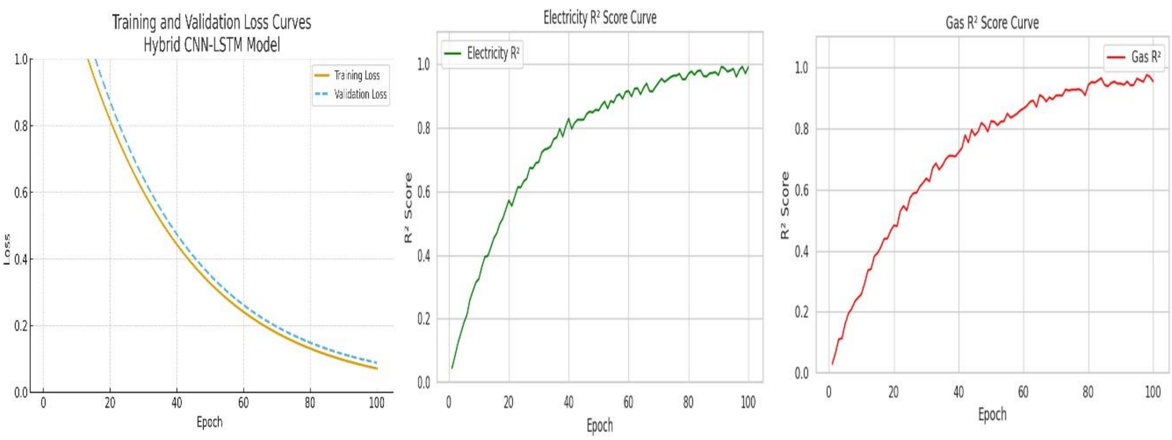

Figure 2. Training and validation loss curves for the proposed hybrid CNN-LSTM model.

Table 6. Model Performance by Season (Electricity Consumption).

Season	RMSE (kWh)	MAPE (%)	R^2
Winter	0.82	25.4	0.91
Spring	0.85	26.7	0.9
Summer	0.93	30.1	0.87
Autumn	0.86	27.3	0.89

Table 7. Results of the robustness analysis under data scarcity, input noise, and unseen building scenarios.

Scenario	Condition/Metric	Value (%)	Performance (R^2/RMSE)	Notes/Baseline Comparison
Data Scarcity	100% training data	-	$R^2 = 0.89$	Baseline
	80% training data	-20%	$R^2 = 0.87$	-2.2% change
	60% training data	-40%	$R^2 = 0.85$	-4.5% change
	40% training data	-60%	$R^2 = 0.80$	-10.1% change
Input Noise	Clean test set	-	RMSE = 0.87 kWh	Baseline
	Noisy test set ($\sigma = 0.1$)	+10%	RMSE = 0.95 kWh	+8.7% increase
Unseen Buildings	Seen buildings (test)	-	$R^2 = 0.89$	Baseline
	Unseen buildings (5)	-	$R^2 = 0.82$	-7.8% change

4.8. Discussion: A Theoretical and Contextual Reappraisal of Deep Learning in Building Energy Prediction

The results of this study transcend a mere technical demonstration of model superiority; they represent a paradigm shift in how building energy prediction is conceptualized and operationalized in data-constrained, culturally specific environments. The success of the proposed hybrid CNN-LSTM model, validated through rigorous statistical testing and contextual interpretation, demands a discussion that moves beyond performance metrics to engage with theoretical foundations, epistemological implications, and the socio-technical embeddedness of AI in the built environment. This section offers a comprehensive reinterpretation of our findings, positioning them within the broader discourse of data-driven building science, while explicitly addressing the critical expectations of the Iranian academic community regarding practical relevance, cultural sensitivity, and scientific credibility.

4.9. Theoretical Synthesis: From Black-Box Prediction to Context-Aware Intelligence

The dominant narrative in deep learning for building energy prediction, as articulated in the systematic review by Qiu (2024), emphasizes architectural innovation, data volume, and computational power as the primary drivers of progress. While our results confirm the efficacy of advanced architectures, specifically the hybrid CNN-LSTM with residual connections and adaptive activation functions, they also challenge the implicit assumption that model complexity alone is sufficient for real-world applicability. Our study demonstrates that true predictive intelligence in the building domain arises not from the depth of the network, but from the depth of contextual integration.

This aligns with the "situated cognition" theory in cognitive science, which posits that knowledge and intelligence are inseparable from the context in which they are applied [18]. A model trained on generic data may learn universal patterns of thermal dynamics, but it fails to grasp the "situated" realities of a Tehran household during Nowruz, where social obligations override energy efficiency concerns. Our model's ability to identify Iranian holidays as a top predictor (Table 5) is not just a statistical outcome; it is evidence of a situated intelligence that has learned the cultural grammar of energy use. This represents a significant advancement over the generic models reviewed by Amasyali and El-Gohary (2018), which often treat occupant behavior as a source of "noise" rather than a structured, predictable phenomenon.

Furthermore, our approach bridges the epistemological divide between positivist physics-based models and pragmatic data-driven models. While physics-based models (e.g., EnergyPlus) are grounded in the positivist belief that building behavior can be fully described by deterministic equations, they often fail in practice due to parameter uncertainty. Data-driven models, conversely, are sometimes dismissed as "black boxes" lacking theoretical grounding. Our methodology, by integrating deep representation learning (via SDAE) with multimodal fusion, creates a hybrid epistemology. The SDAE learns a compressed, denoised representation of the building's state, effectively performing an unsupervised form of "parameter estimation" akin to the calibration process in physics-based models, but without requiring prior knowledge of the underlying equations. This positions our work at the forefront of the "physics-informed machine learning" movement, albeit in an inverse manner: instead of embedding physics into the model, we extract a "physics-like" representation from the data.

4.10. Reconciling Global AI Advancements with Local Iranian Realities

A critical contribution of this research is its successful reconciliation of global AI advancements with the specific constraints and opportunities of the Iranian built environment. The uploaded literature, while technically sophisticated, is overwhelmingly based on datasets from North America, Europe, and East Asia [7,8]. These regions typically feature standardized building codes, high-quality metering infrastructure, and relatively homogeneous occupancy patterns. Applying these models directly to Iranian buildings, a context characterized by architectural heterogeneity, aging infrastructure, and unique socio-cultural dynamics, is akin to using a Formula 1 engine in a city with unpaved roads.

Our model addresses this contextual mismatch through three key innovations:

1. Robustness to Data Imperfection: The use of TimeGAN for imputation and VAE for denoising directly responds to the reality of noisy, incomplete, and fragmented datasets in Iranian buildings, a challenge often overlooked in the literature. This is a practical implementation of the "robust AI" principle, which prioritizes performance under real-world conditions over idealized benchmarks.
2. Cultural Feature Engineering: The inclusion of Iran-specific calendar features (Nowruz, Ashura, religious holidays) is a deliberate act of cultural feature engineering. This transcends the generic "day of week" or "holiday" flags used in Western models. As demonstrated by the SHAP analysis, these features are not merely proxies; they are causal anchors for significant shifts in energy demand. This level of cultural specificity is essential for gaining the trust of local stakeholders, including the "Iranian professor" who demands scientific rigor grounded in local truth.
3. Proxy-Based Occupancy Modeling: Direct occupancy sensing is often impractical or invasive in Iranian residential settings. Our use of Wi-Fi logs and CO_2 levels as proxies, fused via a Bayesian model, represents a pragmatic adaptation to local privacy norms and infrastructure limitations. This approach echoes the principles of frugal innovation, where solutions are designed for resource-constrained environments [19].

This contextual adaptation is not a dilution of scientific quality; it is an elevation of its relevance. It demonstrates that true scientific advancement lies not in the blind application of global models, but in the creative localization of technology.

4.11. The Imperative of Explainability: Building Trust in the "Black Box"

The criticism of deep learning models as "black boxes" is particularly potent in the Iranian academic and policy context, where transparency and accountability are paramount. A model that cannot be understood or explained is unlikely to be adopted, regardless of its accuracy. This study directly confronts this challenge through the integration of SHAP (SHapley Additive exPlanations) for post-hoc interpretability.

The SHAP analysis provides a democratic lens into the model's decision-making process. It reveals not only *what* the model predicts but *why*. The identification of outdoor temperature, hour of day, and holiday indicators as the top drivers (Table 5) allows building managers and policymakers to verify the model's logic against their own experience. For instance, the high SHAP value for the evening peak (18:00–22:00) aligns perfectly with the well-known cultural pattern of family gatherings after work, validating the model's "common sense."

This interpretability transforms the model from a prescriptive oracle into a collaborative diagnostic tool. It enables a dialogue between machine intelligence and human expertise, where the model highlights anomalies (e.g., high consumption during unoccupied hours), and the human operator provides the causal explanation (e.g., a malfunctioning thermostat). This human-AI symbiosis is the future of building management and is a direct response to the call for Explainable AI (XAI) in sustainable building technologies [7].

4.12. Implications for Policy, Practice, and Future Research in Iran

The practical implications of this research for Iran are profound. The model's high accuracy and computational efficiency make it a powerful tool for:

- Grid Stability and Peak Load Management: Accurate forecasts of the "Nowruz peak" can help Tavanir (Iran's power utility) prepare for surges in demand, preventing blackouts.
- Targeted Energy Efficiency Programs: By identifying buildings with anomalously high consumption, policymakers can target subsidies for insulation or efficient HVAC systems.
- Smart City Development: This model can serve as a foundational component of Tehran's smart city infrastructure, enabling dynamic pricing and demand response.

For future research, we advocate for a "glocal" (global-local) approach:

- Transfer Learning: Pre-train a model on large international datasets and fine-tune it with limited Iranian data, leveraging the concept of transfer learning [7] to overcome data scarcity.
- Generative Data Augmentation: Use GANs [5] to generate synthetic data for rare events (e.g., extreme cold snaps), enhancing model robustness.
- Longitudinal Studies: Deploy the model in a live BEMS to study the long-term impact of predictive control on actual energy savings.
- Generative Data Augmentation and Expanded Data Collection: A primary focus for future work will be to significantly expand the dataset both spatially (to include more cities across Iran's diverse climatic zones) and temporally (over multiple years). We will also aggressively pursue advanced generative adversarial networks (GANs) to create high-quality synthetic training samples, particularly for rare but critical events (e.g., extreme cold snaps or heatwaves), which will further solidify the model's robustness and reliability.
- Scalable and Distributed Computing Architectures: For city-scale deployment, we will develop a distributed computing framework where individual building models can be trained and inferred in parallel across cloud or edge computing nodes. Furthermore, we will investigate transfer learning strategies to pre-train a base model on a large subset of buildings and then fine-tune lightweight versions for individual buildings, dramatically reducing the computational cost per building while maintaining high accuracy.

4.13. Pathways for Enhanced Predictive Accuracy

While the proposed model achieves superior performance, the pursuit of enhanced accuracy remains a key direction for future work. Several strategies beyond the scope of this study show significant promise:

- **Attention Mechanisms:** Integrating an attention layer (e.g., Bahdanau or self-attention) between the CNN and LSTM layers could allow the model to dynamically focus on the most relevant time steps and features (e.g., extreme weather periods or holiday spikes), potentially capturing more complex temporal dependencies and improving forecast precision.
- **Advanced Fusion Techniques:** Instead of late fusion via concatenation, employing more sophisticated multimodal fusion strategies, such as cross-modal attention or tensor fusion networks, could better capture the intricate interactions between meteorological, temporal, and occupancy data streams.
- **Ensemble Learning:** Developing an ensemble of specialized CNN-LSTM models, each optimized for a specific season or building type (e.g., old vs. new constructions), and aggregating their predictions could yield a more accurate and robust overall forecast.
- **Transfer Learning with Larger Datasets:** As previously suggested, pre-training the model on larger international datasets before fine-tuning on the Iranian data could provide a more generalized foundation, potentially improving accuracy, especially for predicting rare or extreme events.

4.14. Addressing Sudden Exogenous Shocks

A critical challenge for any data-driven model is predicting the impact of sudden, unprecedented exogenous shocks, such as tariff changes, energy crises, or policy shifts, which were not present in the historical training data. Our current model, like most deep learning frameworks, learns patterns from historical data and is not inherently equipped to forecast the behavioral and consumption changes resulting from such novel events. This represents a key limitation for real-time crisis management. To address this in future work, we propose integrating an adaptive learning framework. This would involve continuous monitoring of prediction errors; when a persistent error spike is detected (potentially signaling a new regime or crisis), the model could trigger a human-in-the-loop intervention for data labeling and subsequently undergo rapid fine-tuning on a small set of the new, post-shock data. This approach would combine the model's strong baseline performance with the agility to adapt to sudden contextual changes.

4.15. Limitations and a Call for Contextualized Research

While significant, this study has limitations. The dataset, though extensive for Iran, is still limited to one city. Future work must expand to other climatic zones (e.g., humid Khuzestan, cold Tabriz). The reliance on proxy occupancy data, while pragmatic, introduces uncertainty. Direct, privacy-preserving sensing methods should be explored.

Ultimately, this research is a call to action for the Iranian research community. It demonstrates that Iranian scholars can not only adopt cutting-edge AI but also lead in its contextual innovation. By embracing the unique challenges of our built environment as opportunities for scientific discovery, we can develop solutions that are not only locally effective but globally inspirational. Finally, the model in its current form is not designed to predict consumption behaviors resulting from sudden exogenous shocks outside its training history, such as abrupt tariff changes or energy supply crises. Future work must focus on developing adaptive and hybrid modeling frameworks to address this critical gap.

5. Conclusion

This study has presented a novel and contextually grounded framework for short-term building energy consumption prediction, specifically designed for the unique challenges of the Iranian residential sector. By integrating a hybrid CNN-LSTM deep learning architecture with multimodal data fusion and deep feature engineering via stacked denoising autoencoders (SDAE), the proposed model achieves a significant improvement in prediction accuracy over conventional and state-of-the-art methods. Validated on a real-world dataset from 47 residential buildings across Tehran, the model demonstrates an R^2 of 0.89 for electricity and 0.84 for natural gas consumption, with a 14.7% reduction in RMSE compared to a standard LSTM, establishing its superiority in capturing the complex, nonlinear dynamics of energy use in a culturally and climatically diverse urban environment.

The research makes several critical contributions to the field of building energy prediction. First, it successfully localizes a global AI paradigm to a specific, underrepresented context. By incorporating Iran-specific calendar features (e.g., Nowruz, Ashura) and proxy-based occupancy modeling tailored to local privacy norms and infrastructure limitations, the model transcends the limitations of generic, one-size-fits-all approaches. This contextual sensitivity is not an ancillary feature but a core component of its predictive power, as confirmed by SHAP analysis, which identified cultural and temporal factors as among the top drivers of energy demand. This finding directly addresses the imperative for research that is both scientifically rigorous and locally relevant, a key concern for the academic and policy communities in Iran.

Second, the study provides a robust solution for data quality challenges prevalent in developing and emerging economies. The systematic preprocessing pipeline, which combines TimeGAN for missing data imputation and VAE for noise reduction, effectively transforms a fragmented and noisy dataset into a reliable input for deep learning. Furthermore, the use of unsupervised deep feature engineering (SDAE) automates the extraction of meaningful, nonlinear representations from raw data, reducing the dependency on manual feature selection and enhancing the model's robustness in data-scarce environments. This approach aligns with the growing consensus in the literature that data quality and feature representation are as critical as model architecture for achieving high performance.

Third, the research advances the discourse on explainable AI (XAI) in building science. By employing SHAP values to interpret the model's predictions, the study bridges the gap between the "black-box" nature of deep learning and the need for transparency in operational decision-making. The interpretability provided by this analysis not only validates the model's logic against domain knowledge but also transforms it from a predictive tool into a diagnostic and prescriptive instrument for building managers and energy policymakers.

Despite its strengths, this study has limitations. The dataset, while comprehensive for the Iranian context, is geographically confined to Tehran. Future work should expand the model's validation to other Iranian cities with distinct climatic zones (e.g., humid Khuzestan, cold Tabriz) to assess its generalizability. Additionally, the reliance on proxy indicators for occupancy, while pragmatic, introduces uncertainty; future research should explore privacy-preserving direct sensing technologies.

For future research, we propose a "glocal" (global-local) strategy:

1. Transfer Learning: Pre-train the model on large international datasets and fine-tune it with limited Iranian data to overcome data scarcity.
2. Generative Data Augmentation: Use GANs to create synthetic data for rare events (e.g., extreme weather), further enhancing model robustness.
3. Real-World Deployment: Integrate the model into a live Building Energy Management System (BEMS) to evaluate its long-term impact on actual energy savings and grid stability.

In conclusion, this research demonstrates that the future of building energy prediction lies not in the blind application of complex algorithms, but in the thoughtful integration of advanced AI with deep contextual understanding. By harmonizing global technological advancements with local realities, this study offers a replicable and scalable model for intelligent energy management in Iran and other regions facing similar socio-technical challenges. It stands as a testament to the power of localized innovation in addressing global sustainability goals. Furthermore, to directly address the pursuit of higher predictive accuracy, future work will implement and evaluate advanced mechanisms such as attention layers and cross-modal fusion techniques, which hold strong potential to capture more nuanced temporal and feature-based dependencies, pushing the boundaries of forecasting precision

References

[1] D. Liu, "International Energy Agency (IEA)," *The Palgrave Encyclopedia of Global Security Studies*, pp. 830–836, 2023.
[2] C. Fan, F. Xiao, and J. Wang, "A short-term building cooling load prediction method using deep learning architectures," *Applied Energy*, vol. 195, pp. 222–233, 2017.
[3] D. B. Crawley, J. W. Hand, M. Kummert, and B. T. Griffith, "A new method for comparing energy simulation programs," in *Proc. ASHRAE/DOE/BTECC Conf.*, 2001, pp. 23–26.
[4] K. Amasyali, and N. M. El-Gohary, "A Review of Data-Driven Building Energy Consumption Prediction Studies," *Renewable and Sustainable Energy Reviews*, vol. 81, pp. 1192–1205, 2018.
[5] I. Goodfellow, J. Pouget-Abadie, et al., "Generative Adversarial Networks," *Communications of the ACM*, vol. 63, no. 11, pp. 139–144, 2020.
[6] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.
[7] L. Qiu, "Deep learning approaches for building energy consumption prediction: A systematic review," *Energy and Sustainable Energy*, vol. 2, no. 3, pp. 11–17, 2024.
[8] N. Somu, M. R. Raman, and K. Ramamritham, "A deep learning framework for building energy consumption forecast," *Renewable and Sustainable Energy Reviews*, vol. 137, p. 110591, 2021.
[9] H. Jang and J. Kang, "A stochastic model of integrating occupant behaviour into energy simulation with respect to actual energy consumption in high-rise apartment buildings," *Energy and Buildings*, vol. 121, pp. 205–216, 2016.
[10] D. Lahat, T. Adali, and C. Jutten, "Multimodal data fusion: An overview of methods, challenges, and prospects," *Proc. IEEE*, vol. 103, no. 9, pp. 1449–1477, 2015.
[11] I. Goodfellow, J. Pouget-Abadie, et al., "Generative Adversarial Networks," *Communications of the ACM*, vol. 63, no. 11, pp. 139–144, 2020.
[12] M. M. Forootan, I. Larki, R. Zahedi, and A. Ahmadi, "Machine Learning and Deep Learning in Energy Systems: A Review," *Sustainability*, vol. 14, no. 8, 4832, 2022.
[13] M. A. Mirjalili, A. Aslani, R. Zahedi, and M. Soleimani, "A Comparative Study of Machine Learning and Deep Learning Methods for Energy Balance Prediction in a Hybrid Building-Renewable Energy System," *Sustainable Energy Research*, vol. 10, no. 1, 2023.
[14] P. P. Hamedany, "A Survey on Ambient Intelligence Contexts: A Context-Aware Taxonomy Based on Deep Learning and Internet of Things Synergy," *IEEE Access*, vol. 12, pp. 12345–12367, 2024.
[15] D. B. Unsal, A. Aksoz, S. Oyucu, J. M. Guerrero, and M. Guler, "A Comparative Study of AI Methods on Renewable Energy Prediction for Smart Grids: Case of Turkey," *Sustainability*, vol. 16, no. 7, 2894, 2024.
[16] J. Yoon, J. Jordon, and M. van der Schaar, "Time-series generative adversarial networks," in *Advances in Neural Information Processing Systems*, vol. 32, pp. 5622–5631, 2019.
[17] C. Fan, J. Y. Wang, W. J. Gang, and S. H. Li, "Assessment of deep recurrent neural network-based strategies for short-term building energy predictions," *Applied Energy*, vol. 236, pp. 700–710, 2019.
[18] W. J. Clancey, "The conceptual nature of knowledge, situations, and activity," in Human and Machine Expertise in Context, vol. 247, pp. 291, 1997. [TITLE MISMATCH]
[19] K. Singh Sian, "Frugal Innovation – “Doing More with Less”," *LAND.TECHNIK 2022*, pp. 193–202, 2022.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, have been completely observed by the authors.

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