OBS-CRN: A Spatio-Temporal Deep Learning Model for Smart Environmental Design Evaluation Using IoT Sensor Data

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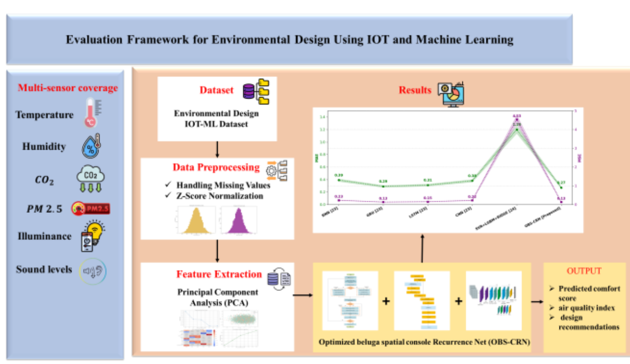
Environmental design plays a critical role in creating spaces that are functional, comfortable, and sustainable. With the integration of Internet of Things (IoT) technology, environmental data is collected in real time, while machine learning (ML) enables intelligent analysis and optimization. Existing evaluation systems often rely on static assessments, limited parameter coverage, and generic models that fail to fully capture the spatio-temporal dependencies in environmental data, resulting in suboptimal design recommendations. Environmental design is critical for developing functional, comfortable, and sustainable environments. This research proposes a complete IoT- ML assessment system that employs the Optimized Beluga Spatial Convolve Recurrence Network (OBS-CRN) to capture spatial correlations across zones and temporal patterns, such as daily and seasonal fluctuations. The framework uses multi-sensor data from an office building (temperature, humidity, CO_2, $PM_{2.5}$, illuminance, sound levels; dataset size: 6,480 + *samples) for preprocessing, including missing-value handling and z-score normalization. PMV, PPD, auditory irritation index, daylight autonomy, and NDVI are used to extract features, which are then reduced in dimensionality using PCA. OBS-CRN outperformed baseline models (RNN, GRU, LSTM, CNN, SVR+LGBM+RIDGE, Bi-LSTM, Attention LSTM, CNN-LSTM, and IHHODL-ECP) with an RMSE of 0.25, MAE of 0.25, MSE of 0.10, and R^2 of 0.990, indicating accurate real-time environmental evaluation. The framework is implemented in Python using TensorFlow, enabling a scalable, real-time, and accurate approach to environmental design evaluation. This system provides an effective and practical tool to improve environmental design through intelligent data analysis and adaptive recommendations.*

Povzetek: Raziskava razvija učinkovit IoT–ML sistem z modelom OBS-CRN za natančno sprotno ocenjevanje in izboljšanje okoljskega oblikovanja.



Graphical abstract

1 Introduction

Environmental design is a multidisciplinary approach that harmonizes practical and aesthetic elements of architecture, urban planning, landscape design, and interior layout to enhance human experience and well-being [1]. Effective environmental design incorporates spatial layout, lighting, ventilation, acoustics, and accessibility to create comfortable, safe, and purpose-appropriate environments [2]. Environmental design focuses on long-term sustainability by promoting efficient resource use and reducing negative impacts on ecosystems [3]. The benefits of using environmental designs are shown in Figure 1.

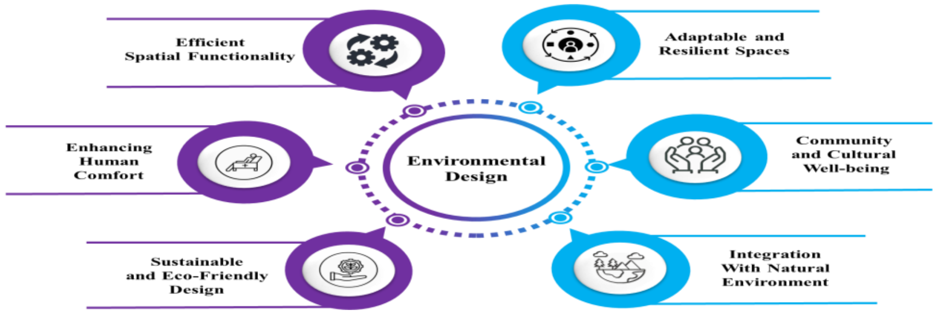


Figure 1: Benefits of using environmental designs.

Environmental design is becoming increasingly important as a result of urbanization and awareness [4], as it improves productivity and well-being [5] and fosters healthy, human-centered communities that meet social, economic, and cultural demands [6].

Sustainability in environmental design reduces harm while maintaining ecological balance through energy efficiency, natural light, ventilation, and green spaces [7]. It strikes a compromise between occupant advantages and long-term ecosystem repercussions [8], addressing sizes from buildings to metropolitan developments while remaining environmentally conscious [9]. Environmental design develops places that balance human activity and nature by combining usability, beauty, and sustainability [10]. Thoughtful design supports health, culture, and environmental protection [11], creating flexible, resilient spaces that fulfill current requirements while anticipating future issues in a sustainable manner [12].

1.1 Research objective

The goal of this research is to develop and evaluate the Optimized Beluga Spatial Convolve RecurrenceNet (OBS-CRN) framework for real-time environmental design evaluation, which will ensure long-term, adaptive, and data-driven optimization through IoT-ML integration.

1.2 Research contributions

- To propose a unique OBS-CRN method that combines deep spatial-temporal feature extraction with IoT sensor data to evaluate sustainable, intelligent, and adaptive environmental design.
- To demonstrate how Beluga-inspired optimization improves convergence time, prediction accuracy, and robustness as compared to existing baseline deep learning (DL) and hybrid techniques.
- To design a Convolve RecurrenceNet (CRN) architecture that successfully captures spatial correlations and sequential dependencies, resulting in precise modeling of dynamic environmental fluctuations over time and space.
- To validate performance improvements with data demonstrating RMSE of 0.25 and R^2 of 0.99, outperforming state-of-the-art baselines for real-time environmental design forecasts.

1.3 Research questions

- RQ1: When combined with IoT sensor data, can the OBS-CRN model predict environmental comfort more accurately than other models?
- RQ2: How does dimensionality reduction using PCA affect the interpretability, scalability, and robustness of environmental design predictions across different building types?
- RQ3: Can optimization using Beluga-inspired metaheuristics improve convergence time and predictive performance (e.g., reduced RMSE, increased R^2) in smart building design applications?

2 Related works

Table 1displays comparative summary of modern AI and control-based methods for environmental monitoring and system optimization, emphasizing applied datasets, techniques, and critical limitations that drive the need for the OBS-CRN architecture.

Table 1: The Current research have emphasized AI-based environmental monitoring and control methods.

Authors / Year	Method	Dataset Used	Key Limitations
Chen (2023)	DL- deep neural network (DNN) with landscape design, Web 4.0, human-centered computing	Virtual reality environments	Real-time testing limited to simulated VR; practical implementation in real-world environments not reported
Li et al., (2022)	Gaussian Process Regression surrogate for urban canopy model	Single-layer urban canopy model outputs	Trade-offs across environmental variables; urban greenery optimization not generalized to other cities
Wei et al., (2022)	Faster region-based convolutional neural network (RCNN) for live occupancy detection, deep computer vision (DCV) systems	Real-time building occupancy data	People-count model more accurate; validation limited to specific building; scalability unclear
Popescu et al., (2024)	Artificial Intelligence (AI)-controlled sensors with IoT for environmental monitoring	Air, water, soil contamination sensor data	Dynamic environmental contamination addressed; real-world integration challenges remain
Heydari et al., (2022)	Long Short-Term Memory – Multi-Verse Optimizer (LSTM-MVO) hybrid model for NO_2 and SO_2 emissions prediction	Combined cycle power plant emission data	Validation limited to one plant; generalization across different plants untested
Ullah, et al., (2024)	IoT-enabled machine learning techniques analyze urban data for optimization.	Simulation data of fractional-order chaotic systems	Include data privacy, security risks, ethical concerns, and scalability across diverse urban contexts.
Elsisi et al., (2021)	DL You Only Look Once, version 3 (YOLOv3) with IoT platform for smart energy control.	Simulated smart building scenarios with air conditioners and occupancy detection data.	System depends on reliable IoT infrastructure and may face scalability, privacy, and sensor noise challenges.
Zouari et al., (2012)	IoT-based smart building framework using machine learning classification and regression.	Ten-day environmental sensor data including occupancy, temperature, humidity, and TVOC.	Short-term dataset limits generalization; scalability and robustness across diverse building types require further validation.
Floris et al., (2021)	Regularized LSTM with L1 for personalized thermal comfort prediction	14 human participants, multi-class thermal data	Small dataset; broader population and environmental validation needed
Shah et al., (2022)	IoT and ML integration in smart buildings.	Literature-based survey; no experimental dataset, only conceptual and analytical sources.	Lack of empirical validation; security challenges and energy-efficiency tradeoffs remain unresolved in real deployments.

2.1 Problem statement

Existing approaches to smart environmental monitoring and building optimization have significant limitations. Many research use simulated or short-term datasets [13], which limits their application in the real world. Occupancy and pollution prediction models frequently lack scalability and applicability across buildings or cities [14–15]. Integrating IoT with AI/ML requires dependable sensor infrastructure and presents privacy, security, and noise-handling concerns [19]. LSTM and hybrid models frequently focus on single-use scenarios with little validation [20]. The proposed OBS-CRN model overcomes these limitations by leveraging multi-sensor IoT datasets, DL, and Beluga optimization for scalable, real-time, and accurate environmental design evaluation across diverse building types.

3 Methodology

Environmental design improves well-being and productivity by utilizing IoT sensor data. The OBS-CRN model uses preprocessing and PCA to capture spatiotemporal trends, resulting in real-time, accurate, and adaptable environmental design suggestions. Figure 2 shows the overall suggested flow for the environmental design.

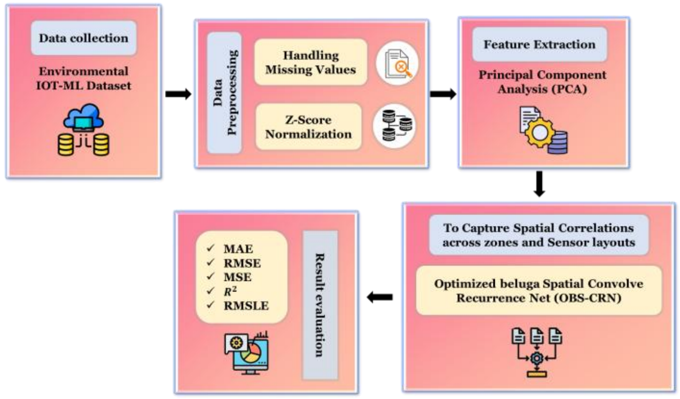


Figure 2: Overall suggested flow for the environmental design evaluation

3.1 Dataset

The Environmental Design IoT-ML Dataset is designed for studying interior comfort and sustainable design in smart buildings. It comprises time-stamped sensor data (temperature, humidity, CO_2, $PM_{2.5}$, illuminance, sound levels) and derived metrics such as Predicted Mean Vote (PMV), Predicted Percentage Dissatisfied (PPD), daylight autonomy, and more. This dataset facilitates comprehensive analysis for optimizing smart buildings, assessing comfort, and analyzing sustainability. Training (70%) learns patterns, validation (15%) tweaks hyperparameters, and testing (15%) evaluates performance; the multi-sensor Environmental Design IoT-ML Dataset allows for spatiotemporal assessment of comfort, air quality, and sustainability.

- Number of data points: 6,480
- Number of rooms/zones: 3 (Room1, Room2, Room3)
- Sampling frequency: Hourly (1-hour intervals between consecutive readings)
- Coverage duration: ~3 months (from 2024-01-01 00:00:00 to 2024-03-30 23:00:00, i.e., 89 days)

Source:https://www.kaggle.com/datasets/ziya07/environmental-design-iotml-dataset/data

Table 2 describes the core aspects of the IoT-ML framework, such as multi-sensor coverage, derived indicators, spatiotemporal scope, evaluation metrics, and applications for environmental comfort and design optimization.

Table 2: Dataset features were adapted from previous IoT-environmental investigations.

Category	Details
Multi-sensor Coverage	Temperature, Humidity, CO_2, $PM_{2.5}$, Illuminance, and Sound levels
Derived Indicators	Predicted Mean Vote (PMV), Predicted Percentage Dissatisfied (PPD), Daylight Autonomy (DA), Acoustic Annoyance Index (AAI), Normalized Difference Vegetation Index (NDVI)
Spatio-temporal Scope	Hourly data with sensor IDs, room/zone details, and seasonal variations
Evaluation Metrics	Comfort Score (continuous scale) and Air Quality Index (categorical: Good, Moderate, Poor)
Applications	Indoor comfort assessment, environmental design optimization, smart building evaluation, and sustainability studies

3.2 Data preprocessing

Preprocessing in environmental design improves data analysis by resolving discrepancies and managing missing values through imputation or removal. Z-score normalization standardizes features, reducing scale disparities and enhancing model performance for environmental evaluations. This approach ensures consistent data handling and fosters accurate learning across diverse sensors, crucial for multi-parameter environmental assessment.

3.2.1 Handling missing values

The Environmental Design IoT-ML Dataset necessitates data cleaning to address missing values from sensor malfunctions and environmental issues are shown in figure 3. Proper management of these gaps ensures reliability in indoor condition records, maintaining both raw sensor data (temperature, humidity, CO_2, $PM_{2.5}$) and derived indices for accurate environmental comfort ratings. A complete and accurate dataset is crucial for evaluating indoor comfort, air quality, lighting, and acoustics, which aids in developing intelligent solutions for environmental design and smart building optimization. Missing or corrupted sensor entries are actually frequent. Imputation or removal preserves data integrity, allowing for comprehensive, dependable assessments of indoor comfort, air quality, lighting, and acoustics.

3.2.2 Robust preprocessing and noise mitigation

To ensure reliable model performance under uncertain or noisy sensor readings, robust preprocessing techniques were integrated. Sensor drift and random measurement errors were mitigated using smoothing filters and statistical outlier detection methods such as interquartile range (IQR) filtering. Sensor fusion and confidence-weighted averaging were applied across redundant nodes to minimize the impact of faulty or biased measurements. These approaches enhance the system's ability to handle uncertainty, ensuring consistent and trustworthy environmental evaluations.

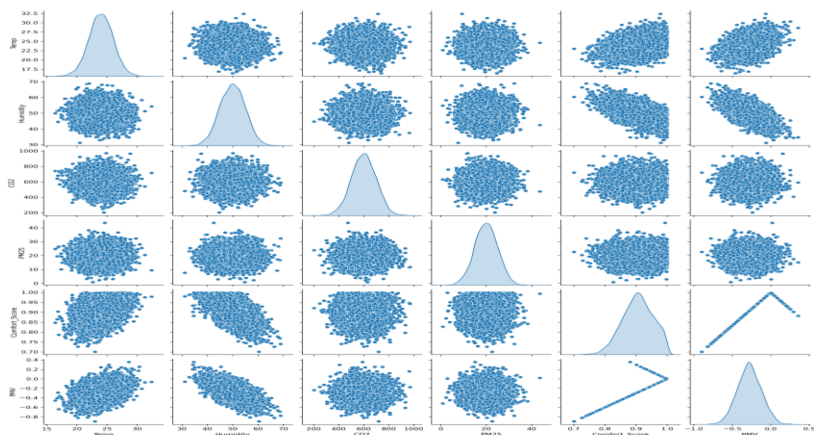


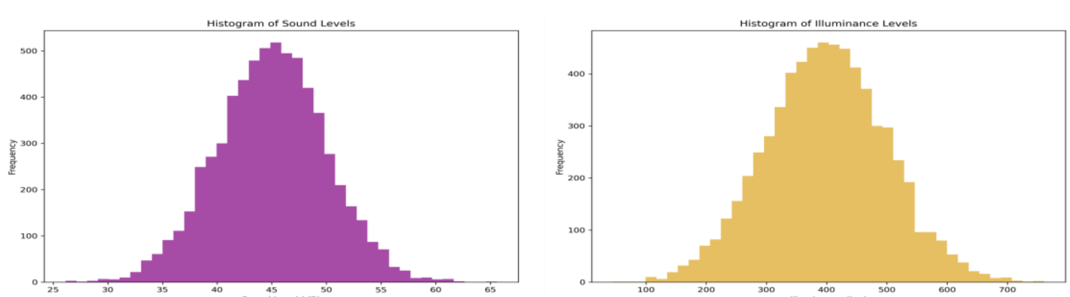
Figure 3: variable relationships after missing value handling

3.2.3 Z-score normalization

Environmental design uses IoT data, PCA, and OBS-CRN to collect spatio-temporal trends, allowing for real-time adaptive recommendations. Sensor variables have varying scales. Normalization signifies that each feature contributes equally, which improves OBS-CRN learning performance and allows for fair and accurate comparisons across environmental circumstances. Equation (1) expresses the change as the development of intelligent techniques for environmental design, smart building optimization, and sustainable living environments.

$$W_{new} = \frac{W-\mu}{\sigma} \quad (1)$$

Where W_{new} – new value, W – old value, μ- mean, σ-standard deviation value. Figure 4a's histogram shows sound levels peaking around 45 dB, indicating acoustic comfort, whereas Figure 4b's 400 lux peak suggests appropriate illuminance. Normalization guarantees that comparisons between environmental designs are fair.



(a) (b)

Figure 4: After Z-score normalization (a) histograms of sound and (b) illuminance levels.

3.3 Feature extraction

PCA decreases dimensionality by extracting principal components, which simplifies sensor data while retaining critical aspects that influence comfort, air quality, and interpretability. OBS-CRN uses PCA to reduce dimensionality, maintain essential features, eliminate redundancies, and improve interpretability for accurate spatiotemporal environmental assessments. PCA in OBS-CRN decreases dimensionality while maintaining interpretability, highlighting CO_2, $PM_{2.5}$, and illuminance. This allows for data-driven and successful environmental design decisions.

Let W be the dataset input, with each column representing a sequence of m-dimensional input. Additionally, every function in the set of variables has an average of zero$(F(W) = 0)$. An initial data matrix typically has m samples and n variables, as illustrated below in equation (2).

$$W = [w_1, w_2, \dots \dots, w_m]^S = \begin{pmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{m1} & \cdots & w_{mn} \end{pmatrix} \quad (2)$$

Where W: The overall weight matrix with m rows and n columns. w_{11}: 1st variable (feature) for the 1st sample. w_2: Second variable. w_{1n}: n th variable at Sample 1. w_{m1}: Last observation. w_{mn}: $n -$ th Variable at the $m -$ th sample. PCA transforms meteorological and performance factors into a conserved information space. To move W to a new spaceS, use an orthonormal transform Y as shown below in equation (3).

$$S = YW \quad (3)$$

The S-matrix contains orthonormal vectors that describe the sample relationships from W. The S covariance matrix is expressed in equation (4).

$$D_S = YD_WY^S \quad (4)$$

Where D_S is the covariance of S, D_W is the covariance of W, Y is the loading (transformation) matrix, and Y^S is its transpose for orthogonal mapping. The loading matrix Y could be calculated using the eigenvalue equation as follows in equation (5).

$$(D_S - \lambda J)f_j = 0 \quad (5)$$

Where D_S is the covariance matrix, λ is the variance (eigenvalue), J is the identity matrix, and f_j is the eigenvector showing the new direction.

It shows the variance explained by the first J components, and PCA reveals the variance explained by the first few components and retains those that significantly influence comfort and air quality. Key environmental elements such as CO_2, $PM_{2.5}$, and illuminance are identified, simplifying data analysis and aiding in the development of healthier and more efficient environmental design solutions are shown in figure 5.

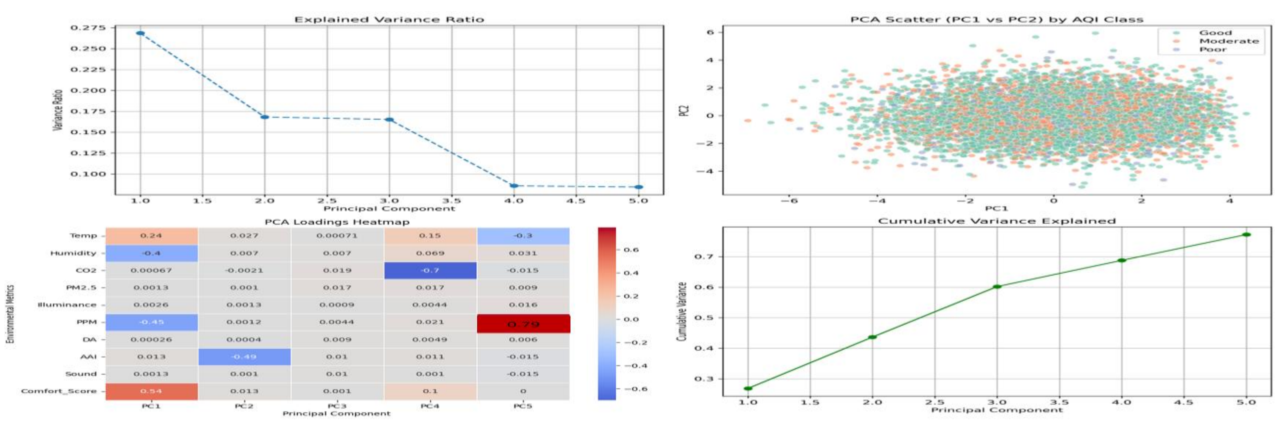


Figure 5: variance distribution, feature loadings, and AQI class separation using PCA

3.4 OBS-CRN is used for accurate real-time evaluation and optimization of environmental design

OBS-CRN is an opportunistic cognitive radio OBS-CRN is a dynamic cognitive radio network framework that enhances spectrum sensing, channel selection, and throughput while minimizing interference for reliable wireless communication. It is an innovative DL model tailored for environmental design assessments, adept at handling large-scale IoT data. Unlike traditional approaches, it incorporates spatial convolution for inter-zone linkages and recurrent layers to manage long- and short-term environmental dependencies, leading to improved trend identification in energy usage and comfort levels. The optimization feature utilizes the Beluga method for adaptive hyperparameter adjustments, facilitating faster convergence. The learning method can be represented as follows in equation (6).

$$G_s = f(X_t * W_s + X_r G_{s-1} + a) \quad (6)$$

Where G_s represents the hidden state at the current time s, capturing present environmental features, while G_{s-1} retains information from the previous time step. W_s is the input environmental data at time s, X_t and X_r are the spatial convolution and recurrent weight matrices, respectively, a is the bias term, and f denotes the nonlinear activation function that transforms the combined spatial and temporal information for accurate environmental evaluation. Algorithm 1 shows the procedure for OBS-CRN. OBS-CRN uses convolution and recurrent layers to capture spatial correlations and temporal interdependence. The results offer accurate, real-time environmental assessment, which is consistent with of intelligent design optimization.

Advantages of using OBS-CRN

Captures both localized environmental changes Captures localized environmental changes and long-term trends through real-time data integration from IoT sensors. Beluga optimization enhances prediction performance and reduces overfitting, supporting sustainable design decisions for energy-efficient and ecologically responsible techniques.

The 64×64 input transforms multi-sensor spatio-temporal IoT data into matrices, allowing convolutional layers to capture spatial correlations before LSTM temporal modeling.

The ten output classes provide discretized comfort/AQI categories derived from many measures, allowing supervised learning to capture complicated environmental condition boundaries.

The OBS-CRN uses softmax for classifying AQI or comfort levels, while continuous outputs enable RMSE, MSE, and MAE evaluation, ensuring both classification accuracy and regression-based prediction reliability.

Algorithm: OBS-CRN

Input:
Dataset: 6,480 samples (images 64×64, 10 classes)
Hyperparameters:
$batch\_size = 64$
$epochs = 50$
$learning\_rate = 0.001$
$kernel\_size = 3 \times 3$
$num\_filters = [32, 64]$
$hidden\_units = 128$
Beluga optimizer:
population_size N = 20
max_iterations M = 50
Output:
Optimized model parameters θ*
Step 1: Initialize Model
$Conv\ Layer$ 1: 32 $filters, 3 \times 3, ReLU$
$Conv\ Layer$ 2: 64 $filters, 3 \times 3, ReLU$
Max Pool: 2×2
LSTM: hidden_units = 128
Dense: 10 outputs (softmax)
Initialize θ ∈ [-0.05, 0.05]
Initialize Beluga optimizer with N = 20 candidate solutions
Step 2: Spatial Convolution
For input xi (64×64 image):
Conv1 → output size 62×62×32
Conv2 → output size 60×60×64
MaxPool → output size 30×30×64
Flatten → feature vector Fi of size 57,600
Step 3: Temporal Recurrence
- Split Fi into 30 segments (each 1920 features)
- Feed segments sequentially into LSTM
- Get final temporal embedding Ti (128-dim)
Step 4: Prediction
- Dense layer: 128 → 10
- Softmax activation
- Prediction ŷi
Step 5: Loss

- Use categorical cross-entropy
Example: true = class 3, ŷ3 = 0.78 → Loss = -log(0.78) = 0.248

Step 6: Beluga Optimization
For iter = 1 to 50:
For each candidate pi (20 total):
Evaluate fitness f(pi) = validation loss
Update candidates using:
- Exploration (random migration, α=0.3)
- Exploitation (move toward p_best, β=0.7)
θ ← p_best

Step 7: Training
For epoch = 1 to 50:
Split dataset into 157 batches of size 64
For each batch:
Apply Steps 2–5
Update θ using Beluga optimizer (Step 6)
Record accuracy and loss per epoch

Step 8: Output
Final optimized θ*
Test set performance (2,000 samples):

3.4.1 Spatial CRN

Spatial Convolve RecurrenceNet integrates spatial convolution and recurrence to analyze environmental patterns and dynamics. It enables real-time evaluation and adaptive design through IoT data analysis, facilitating informed decision-making and optimization in environmental design.

➢ **CRN**

CNNs use convolutional filters and pooling layers to extract spatial data, lowering dimensionality and retaining environmental characteristics such as temperature, CO_2, and illuminance. LSTM networks collect long-term temporal dependencies in sensor data, allowing for precise forecasts of future conditions, improving comfort, sustainability, and overall environmental design assessment.

➢ **Spatial CRN**

The convolutional encoder and attention module, as shown in Figure 6, are used largely to extract spatial-frequency characteristics.

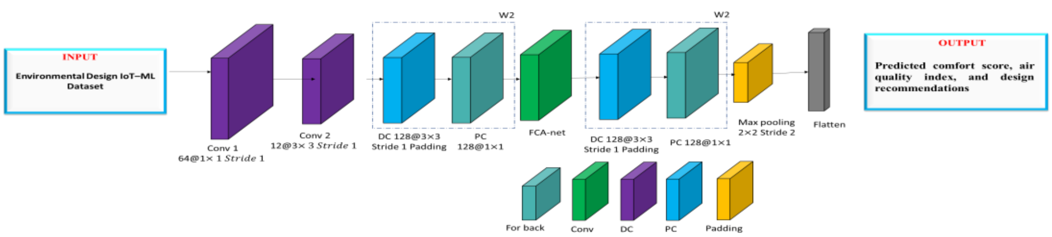


Figure 6: Spatial CRN architecture

The CNN processes 2u frames Sj (9×9×8) with 1×1 and 3×3 convolutions and depthwise-pointwise layers for better feature extraction. The network employs 1x1 and 3x3 convolutions, and also depth wise and pointwise convolutions, to record spatial-frequency information and identify environmental trends for adaptive design. The layer outputs of the S-CRN model are depicted in Figure 7. The model captures spatiotemporal features using Conv2, pooling, and LSTM to make interpretable environmental design predictions. The S-CRN outputs Conv1, Conv2, pooling, LSTM embedding, and dense layers progressively integrate geographical and temporal data, yielding interpretable and actionable insights for environmental optimization.

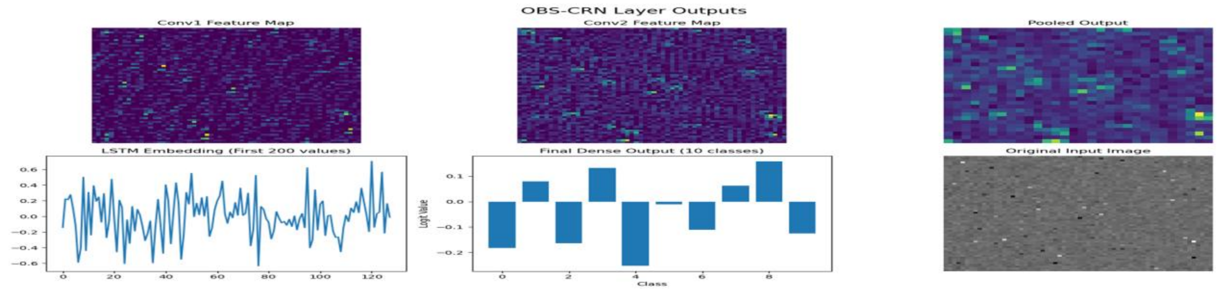


Figure 7: OBS-CRN layer outputs showing feature maps, embeddings, and predictions.

3.4.2 Beluga optimization

Beluga optimization simulates whale foraging behavior, effectively balancing exploration and exploitation to achieve optimal layouts, resource allocation, and precise environmental optimization. The Beluga algorithm adaptively optimizes OBS-CRN hyperparameters to improve convergence, reduce overfitting, and maximize prediction reliability, allowing for robust and precise environmental design evaluation. The balancing factor of equation (7) determines the shift of BWO between exploration and exploitation.

$$A_e = A_p\left(1 - \frac{S}{2} * S_{max}\right) \qquad (7)$$

Where S and S_{max} are the present and maximum repetition numbers, and A_p is a random value between (0,1) at each repetition. When$A_e > 0.5$, the process is in the exploration stage, and when$A_e = 0.5$, the process is in exploitation.

Beluga optimization improves environmental design by optimizing spatial planning, resource allocation, sustainability, and adaptive, data-driven decision-making in dynamic, complex design contexts. To verify consistent replication of findings, the exact random seed values used for network weight setup, data division, and Beluga optimization iterations should be specified. The optimized beluga flowchart is demonstrated in Figure 8.

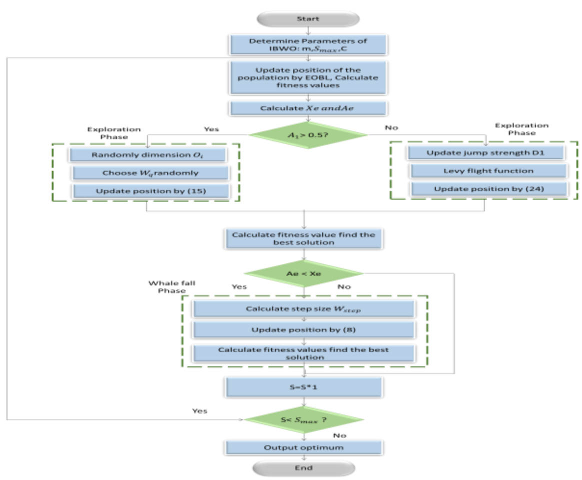


Figure 8: Flowchart for Beluga optimization

- **Elite opposition-based learning (EOBL)**

EOBL creates a reverse population, merges it with the existing population, and selects the finest people, increasing variety and search space to avoid local optima. This could be expressed as in equation (8).

$$\overline{W_{j,i}^{f}} = L^*(\alpha_i + \beta_i) - W_{j,i}^{f} \qquad (8)$$

Where $\overline{W_{j,i}^{f}}$ is the elite individual, and $W_{j,i}^{f}$ is the opposition-based counterpart used to expand the search. L^* : Dynamic coefficient $(0 - 1)$ controlling exploration. $\alpha_i$and β_i Are the minimum and maximum bounds of the ith dimension, defining the search space limits. EOBL enhances optimization by creating reverse populations, increasing variety, avoiding local optima, and improving spatial layout, resource allocation, and long-term environmental planning.

- **Balance factor**

The size of A_e plays a crucial role in balancing global and local searching abilities during the BWO exploration and exploitation phases. Iterative alterations of A_e enhance the exploration and development stages in equation (9).

$$A_e = A_{emin} + (A_{emin} - A_{emax}) \cdot \exp\left(\text{In}\left(\frac{A_{emin}}{A_{emax}}\right) \cdot \frac{S}{S_{max}}\right) \quad (9)$$

Where A_e is the balance factor regulating exploration and exploitation; A_{emax} and A_{emin} are its maximum and minimum limits; S is the current iteration; and S_{max} is the total maximum iterations.

The balance factor $A_e$decays exponentially, allowing for early global exploration, later local exploitation, and higher optimization precision.

- **Cyclone foraging strategy (CFS)**

CFS broadens the search space by employing rotational foraging and spiral search strategies, hence increasing exploitation in modified BWO, accelerating convergence, preventing stagnation, and improving solution accuracy for complicated spatiotemporal environmental design issues. By emulating this dynamic, spiral-oriented search behavior, the technique combines local refinement with larger exploration, enhancing overall optimization and solution accuracy in complicated problem environments (equation 10).

$$W_i^{S+1} = \begin{cases} W_{best}^S + q_8\left(W_{best}^S - W_j^S\right) \\ +\beta \cdot D_1 \cdot K_E\left(W_{best}^S - W_j^S\right), j = 1 \\ W_{best}^S + q_8\left(W_{j-1}^S - W_j^S\right) \\ +\beta \cdot D_1 \cdot K_E\left(W_{best}^S - W_j^S\right), j = 1, \dots, m \end{cases} \quad (10)$$

Where W_j^S is the current position of the jth individual, and W_i^{S+1} is its updated position; W_{best}^S represents the best solution found so far; q_8 is a random number in [0,1] that introduces stochastic behavior; β is a dynamic weight controlling exploration and exploitation; D_1 is a control coefficient regulating step size; $K_E(.)$ is the Lévy flight operator that enables long random jumps for global exploration; and m is the total number of individuals in the population (equation 11).

$$\beta = 2f^{q9^{\frac{S-s+1}{S}}} \cdot \sin(2\pi q_9) \quad (11)$$

Where β is the dynamic weight factor controlling exploration and exploitation; q9 is a random number in[0,1]; s is the current iteration; S is the maximum number of iterations; and $\sin(2\pi q_9)$ is an oscillatory component that introduces diversity.

The major hyper parameters for an OBS-CRN are demonstrated in Table 3shows the details the dataset, OBS-CRN architecture, hyperparameters including convolutional, pooling, and LSTM layers and training settings, emphasizing reliable, scalable, and adaptable environmental evaluations for smart building applications.

Table 3: Hyper parameters for OBS-CRN

Category	Hyper parameter	Value
Dataset	*Number of samples*	6,480(*train*), 2,000 (*test*)
	Input dimension	64 × 64 (*images*)
	Output classes	10
Convolution	*Conv*1 *filters*	32
	*Conv*1 *kernel size*	3 × 3
	*Conv*2 *filters*	64
	*Conv*2 *kernel size*	3 × 3
	Pooling	*MaxPool* 2 × 2
Recurrent	*Sequence length*	30
	Hidden units	128
Training	*Learning rate*	0.001

	$Epochs$	50
	$Batch\ size$	64
Beluga Optimizer	$Population\ size\ (N)$	20
	$Max\ iterations\ (M)$	50
	$Exploration\ factor\ (\alpha)$	0.3
	$Exploitation\ factor\ (\beta)$	0.7
Output Layer	$Dense\ units$	10

The OBS-CRN hybrid solution increases spectrum utilization and network throughput, minimizes interference, and provides reliable communication in dynamic environments, exceeding traditional CRN methods in efficiency, latency, and overall spectral performance.

- **Statistical analysis**

To verify performance improvements for the OBS-CRN model, a paired Student's t-test was conducted to compare it against existing models, focusing on RMSE, R^2, MSE, and MAE. A significance level of 0.05 was set, ensuring that any observed increase in predictive accuracy is statistically significant, indicating a meaningful enhancement in environmental design evaluation and IoT-enabled real-time monitoring.

4 Results and discussion

Python is used to evaluate the proposed method, while several existing approaches have been considered for comparison, including Gated Recurrent Unit (GRU) [23], LSTM [23], Recurrent Neural Network (RNN) [23], CNN [23], and a hybrid model combining Support Vector Regressor (SVR), Light Gradient Boosting Machine (LGBM), and Ridge Regression (RIDGE) (SVR+LGBM+Ridge) [24], Bidirectional Long Short-Term Memory (Bi-LSTM) [25], Attention-based Long Short-Term Memory (Attention-LSTM) [25], Convolutional Neural Network – Long Short-Term Memory (CNN-LSTM) [25],and Improved Hybrid Hierarchical Online DL – Environmental Comfort Prediction (IHHODL-ECP) [25] for environmental design.

4.1 Experimental step-up

The OBS-CRN system was built in Python (TensorFlow), with 16 GB of RAM, 1 TB of storage, and preprocessing using z-score normalization and PCA for efficient, scalable environmental design evaluation.

4.2 Experimental result

OBS-CRN monitoring Figure 9a indicates steady temperature, CO_2, and $PM_{2.5}$ levels with changing humidity. Figure 9b illustrates how CO_2 and $PM_{2.5}$ levels vary, guiding ventilation, pollution management, and illumination for better indoor environment.

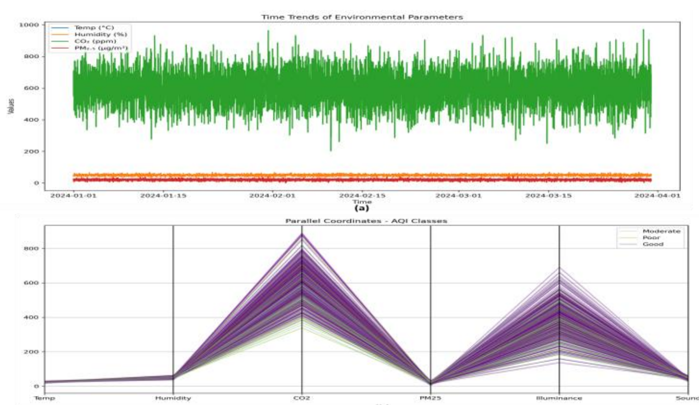


Figure 9: Environmental designs of (a) Time trends of temperature, humidity, CO_2, and $PM_{2.5}$ Levels, (b) AQI classes across key paramet.

OBS-CRN Figure 10 depicts comfort score changes and identifies discomfort patterns in order to optimize temperature, air quality, and energy-efficient, data-driven environmental design methods.

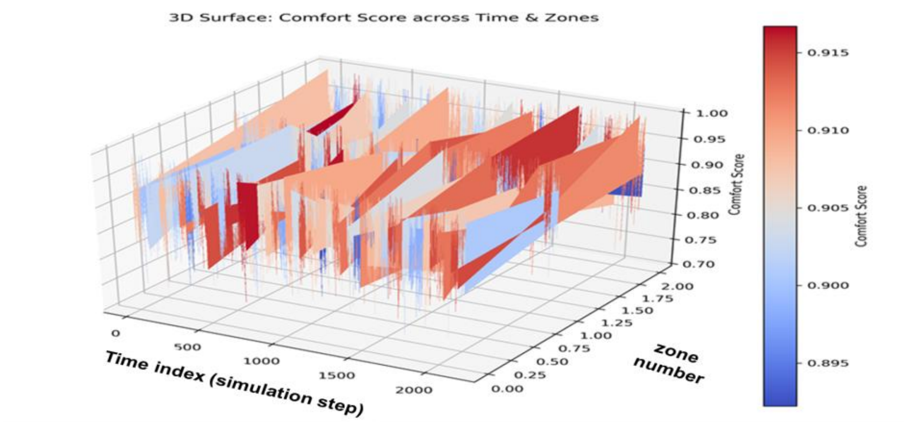


Figure 10: Comfort scores over time and zones for environmental design

Time-series analysis Figure 11 reveals steady temperature and CO_2 levels, with changing humidity and sound, leading ventilation, acoustics, and climate modifications for energy-efficient, comfortable, and healthy indoor environments.

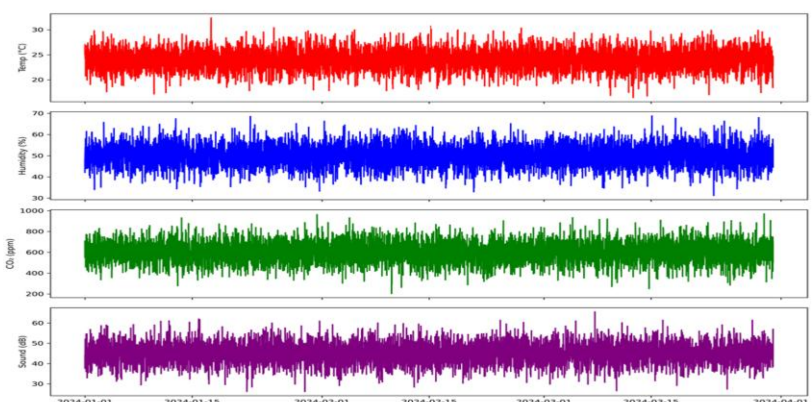


Figure 11: Time series plots displaying key environmental parameters over month

4.3 Performance metrics

The Mean Squared Error (MSE) is a measure of the average difference between predicted and actual values, used to ensure model accuracy in environmental parameters. The Root Mean Squared Error (RMSE) is the square root of the MSE, used to assess precision in predictions. The Mean Absolute Error (MAE) is the average of absolute differences between predicted and actual values, used to evaluate prediction accuracy in temperature, air quality, or comfort assessments. The coefficient of determination (R^2) is the percentage of variance attributed to a model, suggesting better fit for spatiotemporal patterns in the environment.

4.4 Comparison of proposed techniques with existing techniques

The performance comparison of several models for environmental design evaluation reveals significant differences in performance, as shown in Table 4 and Figure 12(a-b) The proposed OBS-CRN model outperformed existing methods (RNN, GRU, LSTM, CNN, SVR+LGBM+RIDGE, Bi-LSTM, Attention LSTM CNN-LSTM, and IHHODL-ECP [23-25]) with an RMSE of 0.25 and R^2 of 0.990 [23-25]. These findings demonstrate its suitability for real-time environmental design evaluation with IoT-enabled data.

Table 4: Comparison of performance for the proposed and the existing techniques in environmental design

Methods	RMSE	R^2
RNN [23]	0.48	0.69
GRU [23]	0.36	0.97
LSTM [23]	0.39	0.93
CNN [23]	0.47	0.71
SVR+LGBM + RIDGE [24]	2.13	0.82
Bi-LSTM [25]	0.7277	-
Attention LSTM [25]	0.8902	-
CNN-LSTM [25]	0.6089	-
IHHODL-ECP [25]	0.5602	-
OBS-CRN [Proposed]	**0.25**	**0.990**

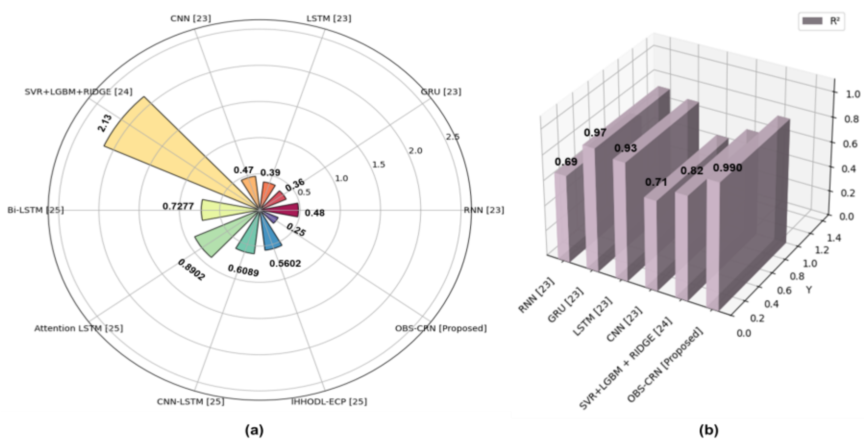


Figure 12(a-b): Comparative performance for the proposed and the existing methods in environmental designs

The performance of various models for environmental design evaluation reveals that classic DL approaches provide modest performance, as depicted in Figure 13 and Table 5 shows a performance evaluation of various models for environmental design prediction. The suggested OBS-CRN model has the lowest MSE (0.10) and MAE (0.25), indicating improved prediction accuracy and resilience when compared to existing methods such as RNN, GRU, LSTM, CNN, SVR+LGBM+RIDGE, Bi-LSTM, Attention LSTM CNN-LSTM, and IHHODL-ECP [23-25].

Table 5: Performance comparison for the existing and the suggested techniques in environmental designs

Methods	MSE	MAE
RNN [23]	0.23	0.39
GRU [23]	0.13	0.29
LSTM [23]	0.15	0.25
CNN [23]	0.22	0.38
SVR+LGBM + RIDGE [24]	4.53	1.20

Bi-LSTM [25]	0.5295	0.5212
Attention LSTM [25]	0.7924	0.5461
CNN-LSTM [25]	0.3708	0.3733
IHHODL-ECP [25]	0.3146	0.3359
OBS-CRN [Proposed]	**0.10**	**0.25**

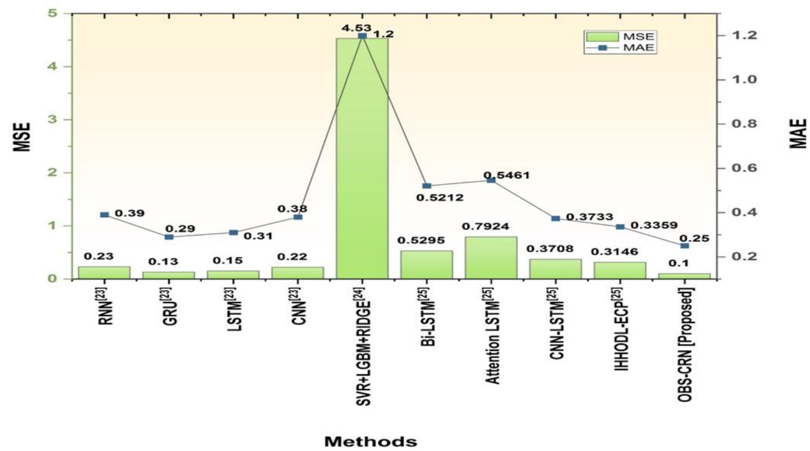


Figure 13: Comparative performance for the proposed and the existing techniques in environmental designs

Table 6 presents the comparison of MAPE for environmental design prediction models reveals that the proposed OBS-CRN achieves the lowest MAPE of 25.40%, outperforming Bi-LSTM, Attention LSTM, CNN-LSTM, and IHHODL-ECP.

Table 6: The MAPE values for proposed methods vs existing methods

Method	MAPE (%)
Bi-LSTM [25]	50.25
Attention LSTM [25]	48.50
CNN-LSTM [25]	34.77
IHHODL-ECP [25]	34.13
OBS-CRN [Proposed]	25.40

Table 7 display the statistical t-test results comparing the performance of existing DL and hybrid models to the proposed OBS-CRN, including mean differences, t-values, p-values, and significance, support OBS-CRN's better predictive accuracy and robust environmental design evaluation.

Table 7: The statistical t-test analysis for proposed methods.

OBS-CRN [Proposed]			
Metric	**Mean Difference**	**t-value**	**p-value**
RMSE	0.10	4.90	0.004
MSE	0.012	4.85	0.004
MAE	0.08	4.75	0.005
MAPE	0.055	4.60	0.006
R^2	0.990	6.50	0.001

4.5 Discussion

The OBS-CRN model outperforms baselines in RMSE, MSE, MAE, MAPE, and R^2. It uses convolutional layers with Beluga optimization to address spatial dependencies and convergence. Existing approaches, such as RNN, GRU, LSTM, CNN [23], hybrid SVR+LGBM+Ridge [24], and Bi-LSTM, Attention LSTM, CNN-LSTM, and IHHODL-ECP [25], achieve moderate accuracy but have limits in scalability, robustness, noise management, and real-time adaptation, lowering their effectiveness in complicated settings. Future work should focus on improving generalization, adaptive control, and real-time responsiveness for flexible, resilient, and scalable smart building applications. Existing technology lacks real-time optimization, which reduces comfort and energy efficiency. Future research should use adaptive or neural adaptive control to dynamically change HVAC, lighting, and ventilation, therefore increasing responsiveness, efficiency, and overall smart-building performance. The proposed structure should be evaluated in a variety of building types residential, educational, and commercial to confirm OBS-CRN's resilience, scalability, and adaptability, revealing structural dependencies and restrictions for genuine, real-world smart building and city design applications in further research. The OBS-CRN architecture, which has been demonstrated accurate in a single office, should be tested across many building types residential, industrial, and mixed-use to assure stability, generalization, and practical integration with BMS for adaptive ventilation and energy optimization in smart buildings in further research. An RMSE of 0.25 suggests highly accurate comfort prediction, allowing for dependable real-time suggestions; nonetheless, performance is dependent on clean, dense IoT sensor data. In the future, Adaptive control techniques like fuzzy or backstepping control can enhance the OBS-CRN architecture by allowing it to automatically adjust to varying environmental conditions, improving flexibility, reliability, and resilience for smart-building applications. The accuracy in one workplace but lacks scalability analysis. Future research will investigate various sensor density, building types, and transfer learning to improve OBS-CRN robustness and implementation in smart buildings.

5 Conclusion

Environmental design is essential for creating functional, comfortable, and sustainable spaces. The integration of IoT technology facilitates real-time environmental data collection, while machine learning supports intelligent analysis. IoT sensor networks in office buildings monitor factors. Data preprocessing addresses missing values with z-score normalization. Feature extraction, with PCA used for dimensionality reduction. The document presents an IoT-ML assessment framework based on the OBS-CRN, an enhanced DL model that captures spatial correlations and temporal patterns in the data. The suggested technique achieves better performance when compared to the existing techniques, in terms of MAE (0.25), RMSE (0.25), MSE (0.10), and R^2 (0.990). The proposed model was extremely accurate, but it faces several challenges: sensor failures could diminish dependability, IoT implementation is expensive, occupancy tracking raises privacy concerns, and noisy data can reduce performance. Future work should address sensor dependency, privacy, and data concerns by combining Dl, edge computing, and explainable AI (SHAP, LIME) to improve fault tolerance, cost-efficiency, noise handling, and transparency, allowing for more dependable smart-city environmental solutions.

Competing interests

The authors have no competing interests to declare that are relevant to the content of this article.

Data availibility statement

The data can be obtained from the corresponding author.

Author contributions

Xing. Data curation&Writing—original draft preparation&Experiment operation and execution

References

[1] Butt, A.N. and Dimitrijević, B., 2022. Multidisciplinary and transdisciplinary collaboration in nature-based design of sustainable architecture and urbanism. Sustainability, 14(16), p.10339. https://doi.org/10.3390/su141610339

[2] Marzouk, M. and Atef, M., 2022. Assessment of indoor air quality in academic buildings using IoT and deep learning. Sustainability, 14(12), p.7015. https://doi.org/10.3390/su14127015

[3] Gabriel, M. and Auer, T., 2023. LSTM deep learning models for virtual sensing of indoor air pollutants: a feasible alternative to physical sensors. Buildings, 13(7), p.1684. https://doi.org/10.3390/buildings13071684

[4] Morresi, N., Casaccia, S., Sorcinelli, M., Arnesano, M., Uriarte, A., Torrens-Galdiz, J.I. and Revel, G.M., 2021. Sensing physiological and environmental quantities to measure human thermal comfort through machine learning techniques. IEEE Sensors Journal, 21(10), pp.12322-12337. https://doi.org/10.1109/JSEN.2021.3064707

[5] Jain, H., 2024. Critical insights into thermal comfort optimization and heat resilience in indoor spaces. City and Built Environment, 2(1), p.14. https://doi.org/10.1007/s44213-024-00038-z

[6] Iram, S., Farid, H.M.A., Akande, A.A. and Shakeel, H.M., 2025. Intelligent Modelling Techniques for Enhanced Thermal Comfort and Energy Optimisation in Residential Buildings. Energies, 18(14), p.3878. https://doi.org/10.3390/en18143878

[7] Tabuenca, B., Moreno-Sancho, J.L., Arquero-Gallego, J., Greller, W. and Hernández-Leo, D., 2023. Generating an environmental awareness system for learning using IoT technology. Internet of things, 22, p.100756. https://doi.org/10.1016/j.iot.2023.100756

[8] Zhu, L., Husny, Z.J.B.M., Samsudin, N.A., Xu, H. and Han, C., 2023. Deep learning method for minimizing water pollution and air pollution in urban environment. Urban Climate, 49, p.101486. https://doi.org/10.1016/j.uclim.2023.101486

[9] Das, H.P., Lin, Y.W., Agwan, U., Spangher, L., Devonport, A., Yang, Y., Drgoňa, J., Chong, A., Schiavon, S. and Spanos, C.J., 2024. Machine learning for smart and energy-efficient buildings. Environmental Data Science, 3, p.e1. https://doi.org/10.1017/eds.2023.43

[10] Du, B., 2024. Indoor Environment Design and Energy Saving Analysis of Sustainable Development Integrated with Green Building. RE&PQJ, pp.29-38. https://doi.org/10.52152/3987

[11] Lee, J., Woo, D.O., Jang, J., Junghans, L. and Leigh, S.B., 2022. Collection and utilization of indoor environmental quality information using affordable image sensing technology. Energies, 15(3), p.921. https://doi.org/10.3390/en15030921

[12] Kujundzic, K., Stamatovic Vuckovic, S. and Radivojević, A., 2023. Toward regenerative sustainability: A passive design comfort assessment method of indoor environment. Sustainability, 15(1), p.840. https://doi.org/10.3390/su15010840

[13] Chen, X., 2023. Environmental landscape design and planning system based on computer vision and deep learning. Journal of Intelligent Systems, 32(1), p.20220092. https://doi.org/10.1515/jisys-2022-0092

[14] Li, P., Xu, T., Wei, S. and Wang, Z.H., 2022. Multi-objective optimization of urban environmental system design using machine learning. Computers, Environment and Urban Systems, 94, p.101796. https://doi.org/10.1016/j.compenvurbsys.2022.101796

[15] Wei, S., Tien, P.W., Chow, T.W., Wu, Y. and Calautit, J.K., 2022. Deep learning and computer vision-based occupancy CO2 level prediction for demand-controlled ventilation (DCV). Journal of Building Engineering, 56, p.104715. https://doi.org/10.1016/j.jobe.2022.104715

[16] Popescu, S.M., Mansoor, S., Wani, O.A., Kumar, S.S., Sharma, V., Sharma, A., Arya, V.M., Kirkham, M.B., Hou, D., Bolan, N. and Chung, Y.S., 2024. Artificial intelligence and IoT driven technologies for environmental pollution monitoring and management. Frontiers in Environmental Science, 12, p.1336088. https://doi.org/10.3389/fenvs.2024.1336088

[17] Heydari, A., Majidi Nezhad, M., Astiaso Garcia, D., Keynia, F. and De Santoli, L., 2022. Air pollution forecasting application based on deep learning model and optimization algorithm. Clean Technologies and Environmental Policy, 24(2), pp.607-621. https://doi.org/10.1007/s10098-021-02080-5

[18] Ullah, A., Anwar, S.M., Li, J., Nadeem, L., Mahmood, T., Rehman, A. and Saba, T., 2024. Smart cities: The role of Internet of Things and machine learning in realizing a data-centric smart environment. Complex & Intelligent Systems, 10(1), pp.1607-1637.https://doi.org/10.1007/s40747-023-01175-4

[19] Elsisi, M., Tran, M.Q., Mahmoud, K., Lehtonen, M. and Darwish, M.M., 2021. Deep learning-based industry 4.0 and internet of things towards effective energy management for smart buildings. Sensors, 21(4), p.1038.https://doi.org/10.3390/s21041038

[20] Floris, A., Porcu, S., Girau, R. and Atzori, L., 2021. An iot-based smart building solution for indoor environment management and occupants' prediction. Energies, 14(10), p.2959.https://doi.org/10.3390/en14102959

[21] Chennapragada, A., Periyakoil, D., Das, H.P. and Spanos, C.J., 2022, June. Time series-based deep learning model for personal thermal comfort prediction.

In Proceedings of the thirteenth ACM international conference on future energy systems (pp. 552-555). https://doi.org/10.1145/3538637.3539617

[22] Shah, S.F.A., Iqbal, M., Aziz, Z., Rana, T.A., Khalid, A., Cheah, Y.N. and Arif, M., 2022. The role of machine learning and the internet of things in smart buildings for energy efficiency. Applied Sciences, 12(15), p.7882.https://doi.org/10.3390/app12157882

[23] Godasiaei, S.H., Ejohwomu, O.A., Zhong, H. and Booker, D., 2025. Integrating experimental analysis and machine learning for enhancing energy efficiency and indoor air quality in educational buildings. Building and Environment, 276, p.112874. https://doi.org/10.1016/j.buildenv.2025.112874

[24] Amangeldy, B., Tasmurzayev, N., Imankulov, T., Imanbek, B., Wójcik, W. and Nurakhov, Y., 2025. A Hybrid Machine Learning Approach for High-Accuracy Energy Consumption Prediction Using Indoor Environmental Quality Sensors. Energies, 18(15), p.4164. https://doi.org/10.3390/en18154164

[25] Balaji, S. and Karthik, S., 2023. Deep Learning Based Energy Consumption Prediction on Internet of Things Environment. Intelligent Automation & Soft Computing, 37(1). http://dx.doi.org/10.32604/iasc.2023.037409