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Neuro-Ensemble Intelligence for Autonomous Smart Building Ventilation Systems

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ABSTRACT

Smart building environments have become increasingly important due to the rising demand for energy efficiency and intelligent infrastructure management. Traditionally, ventilation and environmental control systems have relied on rule-based or threshold-driven mechanisms to regulate indoor conditions such as temperature and CO_2 levels. These conventional heating, ventilation, and air-conditioning (HVAC) systems often operate using fixed parameters, which limits their ability to adapt to dynamic environmental changes. As a result, they frequently lead to inefficient energy usage and inconsistent indoor comfort levels. The key challenge lies in the inability of traditional systems to model complex relationships between multiple factors such as temperature, humidity, occupancy, and device activity. Their static control strategies fail to respond effectively to real-time variations, resulting in energy wastage and reduced system performance. This highlights the need for intelligent, data-driven approaches that can improve prediction accuracy and optimize environmental control. To address this issue, the study proposes a smart building environmental analysis system that integrates machine learning models including Support Vector Regression (SVR), K-Nearest Neighbors (KNN), and Gradient Boosting (GB), along with a hybrid RecurrentForest (RCF) model combining Recurrent Neural Network (RNN) and Random Forest (RF). The system includes preprocessing, exploratory analysis, model training, evaluation, and prediction within a unified framework. The proposed RCF model achieved superior performance with R^2 (Coefficient of Determination) scores of 0.9233 for humidity and 0.9947 for light level. These results demonstrate improved accuracy and reduced error compared to traditional models. The system enhances energy efficiency and indoor comfort, making it suitable for modern smart building applications.

Keywords: Smart buildings, HVAC systems, Environmental control, Energy efficiency, Indoor air quality, Ventilation systems, Temperature regulation, Humidity monitoring, CO_2 monitoring, Intelligent infrastructure.

1. INTRODUCTION

Ventilation systems play a vital role in maintaining indoor air quality within buildings, particularly in situations where natural ventilation through windows is limited or unavailable. These systems typically operate by adjusting the airflow based on indoor CO_2 concentration levels to ensure a healthy environment for occupants. However, many existing control strategies are either time-based or rely on fixed threshold values, which limits their adaptability to dynamic indoor conditions. HVAC systems are among the largest energy consumers in buildings, accounting for nearly half of total energy usage and a significant share of global CO_2 emissions. This highlights the importance of designing efficient control mechanisms that balance energy consumption with occupant comfort.

To evaluate HVAC performance, key comfort factors such as visual comfort, acoustic comfort, thermal comfort, and indoor air quality must be considered. Among these, indoor air quality is particularly critical, as it directly impacts occupant health and overall environmental comfort while also contributing significantly to energy consumption, as shown in figure 1. CO_2 concentration is

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widely recognized as a key indicator for indoor air quality and plays an essential role in ventilation control strategies. Maintaining CO_2 levels within acceptable limits requires supplying an appropriate amount of fresh air, which must be carefully regulated to avoid unnecessary energy usage.

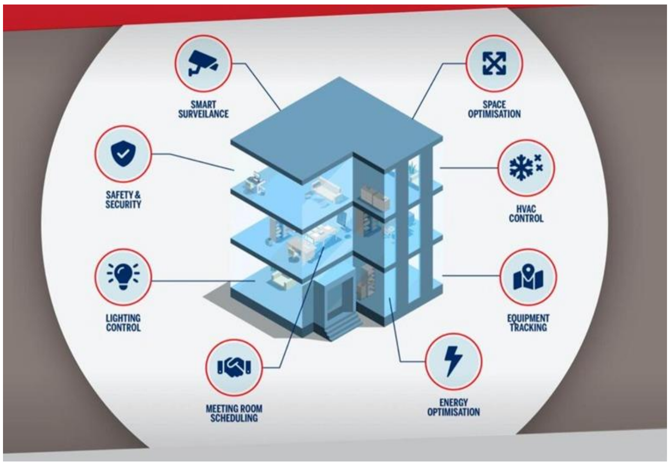

Figure 1: Smart building management

Conventional ventilation systems often rely on simple rule-based controllers such as ON/OFF mechanisms or basic PID controllers, which operate based on predefined parameters and fixed ventilation rates. These approaches lack the flexibility to adapt to changing environmental conditions, leading to inefficiencies in both energy consumption and comfort levels. Factors such as indoor temperature variations, occupancy patterns, and system response delays further complicate control performance. As a result, these systems may deliver inconsistent ventilation, causing energy wastage and reduced occupant productivity.

2.LITERATURE SURVEY

El Husseini, et al. [1] reviewed the application of machine learning (ML) in smart building management with a focus on enhancing energy efficiency and sustainability. The study analyzed ML applications in predictive analytics, energy forecasting, non-intrusive load monitoring (NILM), and predictive maintenance. Key challenges were identified, including data quality issues, privacy concerns, integration complexity, and scalability limitations. The review also highlighted opportunities such as renewable energy integration and IoT convergence, supported by case studies showing energy savings of 15%–40%. The authors emphasized a future trend toward autonomous, occupant-centric building management systems.

A transparent framework for automated energy management was presented in [2], which combined ML, expert knowledge, and semantic reasoning to enhance learning and foster trust. IEMSs can incorporate various renewable energy sources to optimize sustainable energy utilization while maintaining grid stability and ensuring energy availability. To function as a single high-power energy source, the authors in [3] suggested combining energy storage options with solar, wind, and hydroelectric energy sources. IEMSs are becoming increasingly interconnected with building automation systems as the idea of smart buildings develops. This enables buildings to operate more efficiently and effectively control energy usage while maintaining occupant comfort. To reduce environmental effects and achieve sustainability goals, building management must be approached holistically. Green Building, an intelligent system that monitors and automatically adjusts the energy usage of appliances in a building, was deployed by [4] and showed significant energy savings. By permitting two-way communication between energy providers and users, smart grids have further expanded the capabilities of EMS. This has enabled the implementation of demand response, dynamic pricing, and enhanced grid resilience. In [5], the authors described a sophisticated IoT-enabled intelligent energy management system for buildings that improves the interactivity of building energy management systems.

Zhang, et al. [6] classified the occupancy state of office rooms using sensor data and an SVM model. The model's high precision in determining room occupancy made it possible to operate the lighting, heating, and cooling systems more effectively. Belloni, et al. [7] proposed a neural network-based approach to characterize the thermal–energy relationship in commercial buildings, addressing the complexity of modeling non-residential structures. Energy consumption data were generated using EnergyPlus™ dynamic simulations across different Italian climatic zones and used to train artificial neural networks (ANNs). Uncertainty analyses were performed under varying weather conditions, and the models demonstrated good accuracy, with RMSE below 0.5 °C for southern regions and around 1.0 °C for northern regions. The study highlighted the method as computationally lightweight, with inference times under 5 ms, making it suitable for optimization and building automation applications.

Afzal et al. [8], three different artificial neural networks and regression models were used to predict cooling and heating loads, and the results were compared. A hybrid model was proposed (biogeography-based optimization (BBO) algorithm together with an extreme learning machine (ELM)), and the results demonstrated it was the best one in terms of correlation factor for the estimation of the consumptions. This approach has been adopted in previous studies, such as [9], where experimental measurements were collected from an educational building to train both direct and inverse ANN models. These models were then employed to simulate and optimize the operation of a renewable energy community (REC). In that study, environmental data from weather stations and energy consumption data from smart meters were used as ANN inputs, enabling the estimation of the mean indoor air temperature.

Adrian, et al. [10] conducted a building management system (BMSs) to examine current trends and classify data-driven solutions in the field. The study adopted a computer science perspective to analyze heterogeneous elements of BMSs and their adaptation to occupants' needs through ICT-driven advancements. The review identified major research topics, recent data-driven methods, underlying computing architectures, and features that contribute to building smartization. The findings synthesized existing work and outlined directions for future research in BMS. Piras, et al. [11] developed a system based on the Smart Building and Digital Twin paradigm to enhance workplace well-being, health, and productivity. The study focused on IoT integration, energy-efficient automation flows for lighting, HVAC, and indoor air quality, along with decision support through real-time data visualization and BIM-based dashboards. Machine learning algorithms were employed for monitoring, simulation, planning, and emergency management through visual analytics. The work further defined functional requirements, system architecture, and demonstrated preliminary results from the initial data collection campaign.

To understand how these factors affect workers, it is necessary to collect and integrate both the objective characteristics of buildings and the subjective conditions of workers. New approaches, such as the use of smartphone apps and wearable devices, are replacing traditional methods, such as post-occupancy surveys to collect real-time feedback from occupants [12]. Occupant-centered workplace management requires a system that integrates data generated by buildings and by workers themselves.

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Recent studies have demonstrated the potential of using BIM, sensor networks and semantic web technologies for this purpose [13]. However, specific solutions for the management of indoor work environments are still under development. Oh, K.C.; Park, et al. [14] developed an internal environment prediction model for smart greenhouses using machine learning techniques. The study analyzed the impact of training data size and model structure on performance, using weather data as inputs. Results showed that model performance improved with larger datasets, stabilizing after seven days of data, with the GRU algorithm achieving an average R2R^2R2 of 0.8811 and RMSE of 2.056. The work demonstrated the feasibility of predictive modelling for greenhouse environments while highlighting the need for broader validation across different climates and greenhouse types.

Ahn et al. [15] developed predictive models based on the transformer or RNN algorithm to evaluate the performance of predicting the inner environment in greenhouses. The transformer model demonstrated excellent capabilities in handling complex time dependencies and long sequence data, but it can be costly in terms of processing time and resources. In contrast, the LSTM model provided faster and more efficient training and prediction for shorter sequence data, with relatively lower computational costs. Therefore, researchers deemed RNN-based models like LSTM more suitable due to their practical applicability in real greenhouse environments.

3. PROPOSED SYSTEM

The proposed methodology follows a structured and systematic pipeline for analysing and classifying speech acts from textual data in an efficient and scalable manner. It begins with data ingestion, preprocessing, and contextual feature extraction, followed by multi-model learning and predictive analysis. Transformer-based feature extraction is used to capture semantic and contextual relationships within the text, which are then utilized by multiple machine learning models for classification. The integration of baseline models with an advanced ensemble approach improves classification accuracy, robustness, and adaptability. The overall framework ensures efficient handling of large-scale textual data while maintaining consistency in performance illustrated in figure 2.

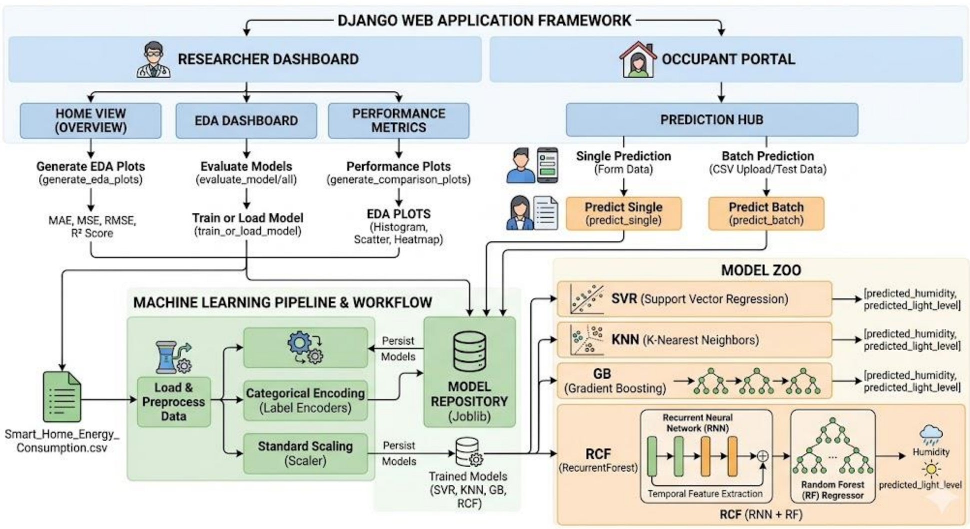

Figure 2: Proposed System Architecture.

User Interface (Web Browser)

- The user interacts with the system through a browser-based interface built using Django templates.

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- Users can perform actions such as login, viewing dataset insights, exploring EDA visualizations, selecting models, and performing single or batch predictions.
- The interface allows users to upload input data and view prediction results in real time.
- All interactions are converted into HTTP requests and sent to the Django backend.

Django Web Server (Backend)

- The Django server processes incoming requests and routes them to appropriate view functions.
- It manages authentication, dataset loading, prediction workflows, and model evaluation processes.
- The server coordinates communication between the frontend, machine learning models, and stored files.
- It also handles data processing triggers and ensures smooth integration of all system components.

Dataset (CSV Input)

- The system uses a smart building dataset stored in CSV format as the primary input source.
- It contains both numerical and categorical features such as device type, room, activity, temperature, power consumption, and time-based attributes.
- This dataset forms the foundation for training, evaluation, and prediction tasks.

Data Preprocessing & Feature Engineering

- Raw data undergoes cleaning, encoding, and transformation to prepare it for model input.
- Categorical features are converted using label encoding, while numerical features are standardized using scaling techniques.
- A consistent feature vector is generated to ensure compatibility across all models.
- The processed data is then used for both training and prediction phases.

Machine Learning Models (SVR, KNN, GB)

- The pre-processed data is fed into baseline models including SVR, KNN, and GB.
- SVR captures nonlinear relationships using kernel-based learning.
- KNN performs prediction based on similarity with nearest data points.
- GB improves prediction accuracy through sequential error correction.
- These models independently generate predictions for environmental parameters.

Proposed Hybrid Model: RCF (RNN + RF)

RNN Component

- The RNN processes sequential patterns in the feature set to extract deeper relationships.
- It captures temporal dependencies and hidden patterns in environmental data.
- The output from the RNN acts as enhanced feature representation.

RF Component

- The RF model takes both original and RNN-extracted features as input.
- It performs ensemble-based prediction to improve robustness and accuracy.
- This hybrid integration enables better handling of complex and nonlinear data patterns.

Model Evaluation and Comparison

- All models (SVR, KNN, GB, and RCF) are evaluated using performance metrics such as MAE, MSE, RMSE, and R^2 score.
- Comparative analysis helps identify the most effective model for prediction tasks.
- Visualization techniques are used to present performance differences clearly.

Prediction Output

- The system generates predictions for key environmental parameters:
  - Target 1: Humidity
  - Target 2: Light Level
- Results are displayed through the user interface for easy interpretation.
- Both single-instance and batch predictions are supported.

Model Storage and Management

- Trained models, encoders, and scalers are stored using serialization techniques.
- This allows quick loading of models without retraining, improving efficiency.
- The system ensures consistency between training and prediction pipelines.

Retraining Mechanism

- The system supports retraining when updated data becomes available.
- Data preprocessing and model training steps are repeated to improve performance.
- Updated models replace older versions, ensuring adaptability to new data patterns.

4. RESULTS ANALYSIS

The result analysis focuses on evaluating the performance of the implemented machine learning models in predicting environmental parameters such as humidity and light level. The study compares multiple models including SVR, KNN, GB, and the hybrid RCF to understand their effectiveness under different conditions. Each model is assessed using standard evaluation metrics to ensure accurate and reliable performance measurement. The results highlight how well the models capture complex relationships within the smart building data. Visualizations such as scatter plots and comparison graphs are used to interpret prediction accuracy and model behaviour. The hybrid RCF model demonstrates improved performance due to its ability to combine deep learning and ensemble techniques. The analysis provides a clear understanding of model strengths and limitations. The results validate the efficiency of the system in delivering accurate environmental predictions.

Figure 3 illustrates the performance evaluation of the RCF model for predicting environmental parameters within the system. The interface presents evaluation metrics such as MAE, MSE, RMSE,

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and R^2 score for both humidity and light level, indicating the effectiveness of the hybrid approach. The scatter plots display the relationship between actual and predicted values, showing a strong alignment with the ideal fit line. This reflects the ability of the RCF model to capture complex and nonlinear patterns in the data. The visualization highlights improved prediction accuracy compared to individual models. This representation supports comprehensive analysis of the hybrid model's performance within the system.

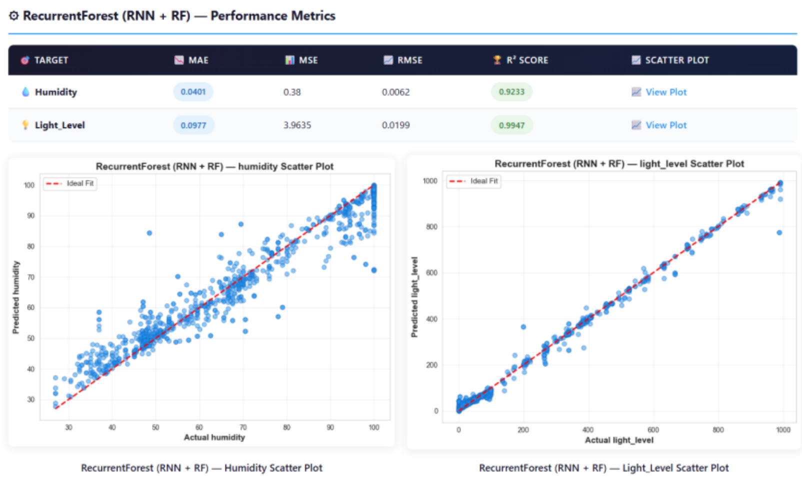

Figure 3: RCF model performance evaluation

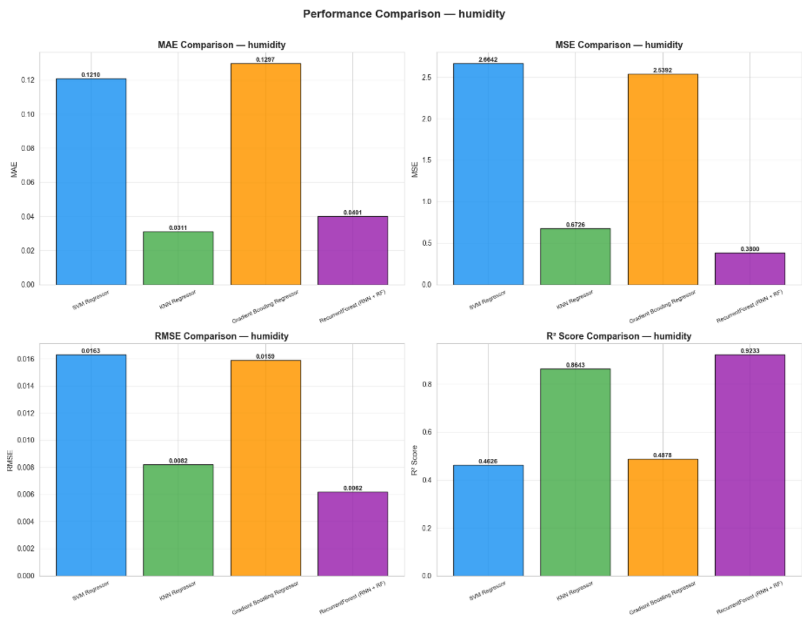

Figure 4: Model comparison for humidity prediction

Figure 4 illustrates the comparative performance analysis of all models for humidity prediction using evaluation metrics such as MAE, MSE, RMSE, and R^2 score. The visualization shows that the SVR model achieved MAE of 0.1210, MSE of 2.6642, RMSE of 0.0163, and R^2 score of 0.4626, indicating moderate performance. The KNN model performed better with MAE of 0.0311, MSE of 0.6726, RMSE of 0.0082, and R^2 score of 0.8643, showing strong prediction capability. The GB model recorded MAE of 0.1297, MSE of 2.5392, RMSE of 0.0159, and R^2 score of 0.4878, reflecting

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comparatively lower performance. The RCF model demonstrated the best results with MAE of 0.0401, MSE of 0.3800, RMSE of 0.0062, and R^2 score of 0.9233, indicating superior accuracy and reliability. This comparison clearly highlights the effectiveness of the hybrid RCF model over individual machine learning models.

Figure 5 illustrates the overall R^2 score comparison across all models for both humidity and light level prediction. The SVR model achieved R^2 scores of 0.4626 for humidity and 0.9047 for light level, indicating moderate performance for humidity and better fit for light level. The KNN model showed improved results with R^2 scores of 0.8643 for humidity and 0.9732 for light level, reflecting strong predictive capability. The GB model recorded R^2 scores of 0.4878 for humidity and 0.9650 for light level, showing moderate performance. The RCF model outperformed all others with R^2 scores of 0.9233 for humidity and 0.9947 for light level, demonstrating the highest accuracy and consistency. This comparison clearly highlights the superiority of the hybrid RCF model across both target variables.

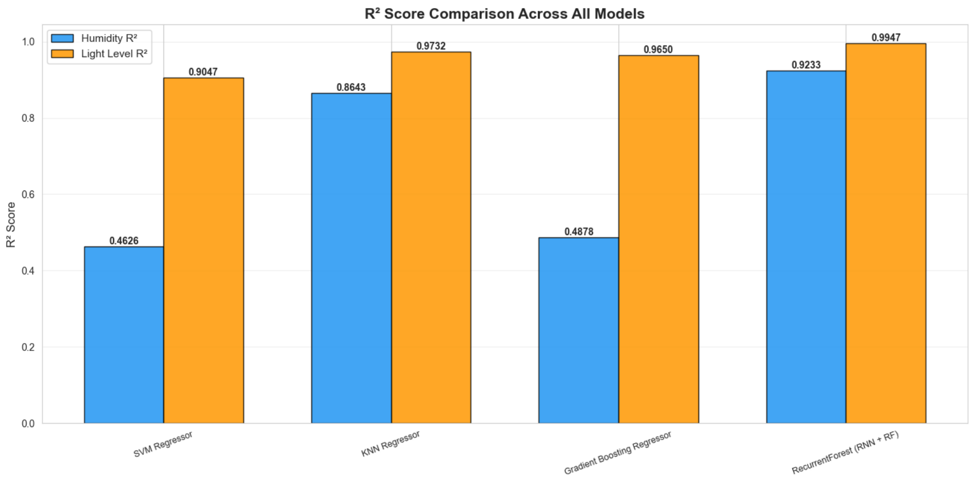
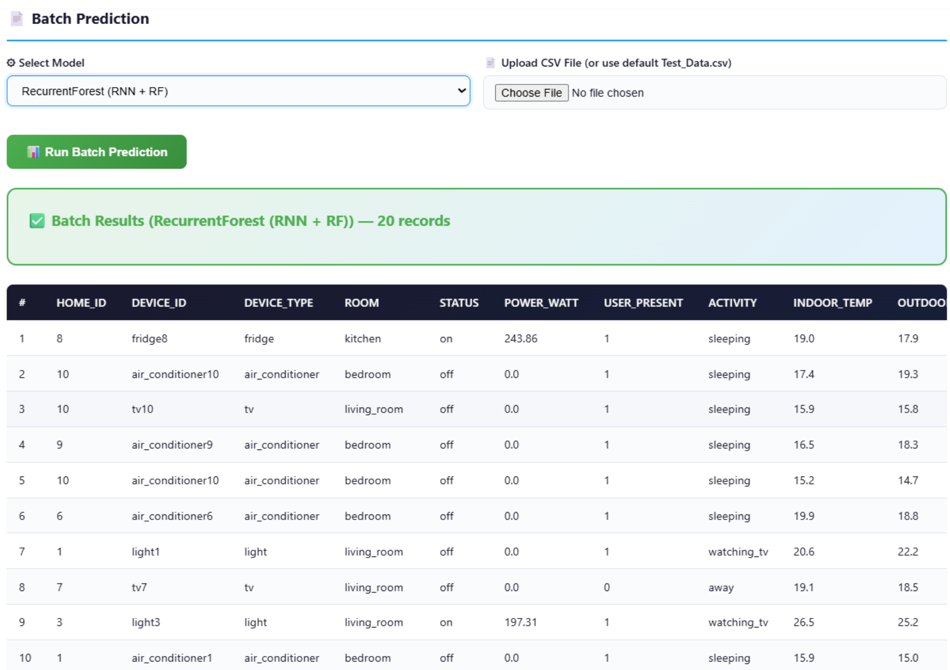


Figure 5: R^2 score comparison across models



#	HOME_ID	DEVICE_ID	DEVICE_TYPE	ROOM	STATUS	POWER_WATT	USER_PRESENT	ACTIVITY	INDOOR_TEMP	OUTDOO
1	8	fridge8	fridge	kitchen	on	243.86	1	sleeping	19.0	17.9
2	10	air_conditioner10	air_conditioner	bedroom	off	0.0	1	sleeping	17.4	19.3
3	10	tv10	tv	living_room	off	0.0	1	sleeping	15.9	15.8
4	9	air_conditioner9	air_conditioner	bedroom	off	0.0	1	sleeping	16.5	18.3
5	10	air_conditioner10	air_conditioner	bedroom	off	0.0	1	sleeping	15.2	14.7
6	6	air_conditioner6	air_conditioner	bedroom	off	0.0	1	sleeping	19.9	18.8
7	1	light1	light	living_room	off	0.0	1	watching_tv	20.6	22.2
8	7	tv7	tv	living_room	off	0.0	0	away	19.1	18.5
9	3	light3	light	living_room	on	197.31	1	watching_tv	26.5	25.2
10	1	air_conditioner1	air_conditioner	bedroom	off	0.0	1	sleeping	15.9	15.0

Figure 6: Batch prediction interface and results

Figure 6 illustrates the batch prediction interface of the system, demonstrating how multiple input records are processed simultaneously using the selected model. The interface allows users to choose the RCF model and upload a CSV file or use default test data for prediction. The results display shows processed outputs for 20 records, including input features such as device type, room, activity, and temperature conditions. Each record is evaluated through the trained model to generate predictions for environmental parameters. This functionality enables efficient large-scale prediction and supports practical real-world application of the system.

4.1 Comparative Analysis

The comparative analysis focuses on evaluating and comparing the performance of multiple machine learning models used in the system for predicting environmental parameters. It examines models such as SVR, KNN, GB, and the hybrid RCF to understand their effectiveness under the same dataset and conditions. Standard evaluation metrics including MAE, MSE, RMSE, and R^2 score are used to measure accuracy and reliability. The analysis highlights differences in prediction capability, error rates, and model consistency. Visual comparisons further assist in identifying strengths and weaknesses of each model. This process helps in determining the most suitable model for accurate environmental prediction. The comparative analysis provides clear insights into model performance and supports informed decision-making.

Table. 1: Comparative analysis table of humidity prediction

Model	MAE	MSE	RMSE	R^2 Score
SVR	0.1210	2.6642	0.0163	0.4626
KNN	0.0311	0.6726	0.0082	0.8643
GB	0.1297	2.5392	0.0159	0.4878
RCF	0.0401	0.3800	0.0062	0.9233

The table 1 presents the comparative performance analysis of different machine learning models for humidity prediction using evaluation metrics such as MAE, MSE, RMSE, and R^2 score. The SVR model achieved an R^2 score of 0.4626, indicating relatively lower predictive capability compared to other models. The KNN model showed significant improvement with an R^2 score of 0.8643, reflecting strong performance in capturing data patterns. The GB model recorded an R^2 score of 0.4878, which is slightly better than SVR but still limited in accuracy. The hybrid RCF model achieved the highest R^2 score of 0.9233, demonstrating superior prediction accuracy and consistency. Lower error values in RCF further confirm its effectiveness over traditional models. The analysis highlights the advantage of the hybrid approach in improving environmental prediction performance.

Table. 2: Comparative analysis table of light level prediction

Model	MAE	MSE	RMSE	R^2 Score
SVR	0.5678	70.7154	0.0841	0.9047
KNN	0.1389	19.8960	0.0446	0.9732

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GB	0.3751	25.9898	0.0510	0.9650
RCF	0.0977	3.9635	0.0199	0.9947

The table 2 presents the comparative performance analysis of different machine learning models for light level prediction using evaluation metrics such as MAE, MSE, RMSE, and R^2 score. The SVR model achieved an R^2 score of 0.9047, indicating good predictive capability but with higher error values. The KNN model improved performance with an R^2 score of 0.9732, showing strong accuracy and consistency. The GB model recorded an R^2 score of 0.9650, demonstrating reliable performance but slightly lower than KNN. The hybrid RCF model achieved the highest R^2 score of 0.9947, indicating excellent prediction accuracy and minimal error. The significantly lower error values in RCF further validates its effectiveness. The results highlight the superiority of the hybrid model in light level prediction.

5. CONCLUSION

The study successfully demonstrates the development of an intelligent smart building environmental analysis system capable of accurately predicting humidity and light levels using multiple machine learning models. The implementation of SVR, KNN, and GB provided a strong baseline for performance evaluation, while the hybrid RCF model significantly enhanced prediction accuracy. Comparative analysis shows that RCF achieved the highest R^2 scores of 0.9233 for humidity and 0.9947 for light level, indicating superior performance over traditional models. The reduction in MAE, MSE, and RMSE further confirms the effectiveness of the hybrid approach in minimizing prediction errors. The integration of RNN for feature extraction and RF for final prediction enabled the system to capture complex and nonlinear relationships efficiently. Visualization and evaluation modules provided clear insights into model behaviour and performance differences. The system also supports real-time and batch prediction, making it suitable for practical smart building applications. The study validates the effectiveness of combining machine learning and deep learning techniques for improved environmental prediction.

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