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SENSOR-BASED ROOM OCCUPANCY ESTIMATION FOR SMART BUILDINGS

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Abstract
Reliable room occupancy is crucial to energy efficiency, comfort of its inhabitants, and automated operation in smart buildings. In this study, a sensor-based machine learning system framework for binary room occupancy classification based on the measurements of the environment and human activities was developed. Data from temperature, light, sound, carbon dioxide, carbon dioxide slope, and passive infrared motion sensors were recorded on a time-stamped basis every ~30 seconds for a total of 10,129 observations. First, the original occupancy count was split into occupied classes and unoccupied classes, and then the data were split chronologically into 80% training and 20% testing. Five supervised classification algorithms (Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, K-Nearest Neighbors) were trained and evaluated using accuracy, precision, recall, F1-score and confusion matrix statistics. All sensor variables were significantly different for the occupied and unoccupied conditions, with light intensity, temperature, sound and carbon dioxide-related variables exhibiting the greatest discrimination. The logistic regression model has the highest accuracy of 99.85%, precision of 99.28%, recall of 99.64% and the F1 score of 99.46%. It correctly identified 274 occupied observations and 1,749 unoccupied observations with just two false positives and one false negative. The results show that by integrating several environmental sensors with an interpretable machine learning model, highly accurate, practical and computationally efficient occupancy estimation of smart building energy management and automation systems is achieved.

Keywords: *smart buildings; occupancy estimation; environmental sensors; machine learning; Logistic Regression*

Introduction

Smart buildings are now a key element of the modern urban infrastructure and combine sensing technologies, communication networks, and intelligent control systems for more efficient building operations, occupant comfort and resource use. The buildings continuously monitor the indoor environment and automatically control the lighting, heating, ventilation and air conditioning systems based on real-time requirements. In recent years, the capabilities of smart buildings to gather and analyze information from their environment for autonomous decision-making have been greatly improved by the development of wireless sensing, edge computing, and artificial intelligence (Elkhoukhi et al. 2025). In addition, extensive review has been conducted about the fast development of methodologies for occupancy estimation, especially the use of machine learning methodologies to increase the accuracy of the prediction in smart environments (Caballero-Peña et al. 2024).

Since room occupancy affects energy consumption, ventilation, thermal comfort and lighting control in buildings, accurate estimation of occupancy becomes a fundamental issue for efficient building operation. Traditional time-based control strategies can lead to wasting energy by running building services even when no one is in the room. With a reliable estimation of the occupancy, demand-driven control strategies can be implemented, which activate building systems only when needed, and therefore save on running costs without compromising the comfort of the occupants. The combination of machine learning (ML) with environmental sensing has been shown to significantly boost the accuracy of occupancy prediction and enhance the functionality of intelligent building management systems (Telaga, ’Aisy, and Arumi 2024). In addition, knowledge-fusion methods have demonstrated promising performance in real-time occupancy estimation under different indoor environmental conditions (Lu 2024).

One of the most popular methods to estimate the presence of human beings in indoor environments is sensor-based occupancy monitoring which is continuous, non-intrusive and automated. Occupancy patterns are frequently described using environmental variables like temperature, illumination, sound intensity, carbon dioxide concentration, and passive infrared (PIR) motion, either alone or in combination. Although PIR sensors are still broadly used due to their low cost and ease of installation, incorporating other environmental data sources into the occupancy estimation typically results in more accurate estimates than motion data alone (Shokrollahi et al. 2024). There has been recent work that further expanded occupancy monitoring with booking data, passive Bluetooth Low Energy scanning, Wi-Fi system logs, TinyML-based edge devices and video-based measurements to increase prediction accuracy while reducing the requirement for infrastructure (Shokrollahi et al. 2025).

In the context of smart buildings, occupancy estimation used for intelligent light control, occupancy-based heating/cooling, indoor air quality control, security monitoring, emergency response, and space utilization analysis, among others. By providing accurate occupancy information, building automation systems can then allocate energy resources dynamically based on actual demand, not on a schedule. The use of infrastructure-free sensing techniques and machine learning algorithms has also further extended the applicability of occupancy estimation, as they can reduce the cost of infrastructure while ensuring the prediction accuracy is reliable (Zeleny et al. 2024). In the same vein, integrated environmental sensing with survey information has shown potential for predicting residential occupancy and thereby helping to achieve more sustainable building management practices (Bouyakhsaine, Brakez, and Draou 2024).

Significant advances have been made in occupancy sensing technologies, but estimating the room's occupancy level is still difficult due to the interactions between different factors in the indoor environment. Temporal variability, heterogeneous building environments, differences in occupant behaviour and sensor noise may make the prediction less reliable and restrict the generalizability of machine learning models. Recent studies have revealed that there is a need for approaches to estimating occupancy that can consistently perform well in various residential and commercial environments and are computationally efficient for real-time implementation. Furthermore, interpretable machine learning methods have become a popular topic of study, as they boost the transparency of machine learning models and enable real-world decision-making in intelligent

systems (Zong et al. 2025).
In the current work, an accurate room occupancy estimation framework for smart buildings based on environmental sensor measurements and supervised machine learning techniques is developed. Specifically, the study aims to analyze the relationship between indoor environment variables and room occupancy, compare the performance of the Logistic regression, Decision tree, Random forest, Support vector machine and KNN models in predicting the occupancy and identify the most important sensor variables in estimating room occupancy. This study aims to find a reliable and understandable classification model to estimate occupancy from real-world sensor measurements that can be used for intelligent energy management and automated building controls.

2. Materials and Methods

2.1 Research Design

This study adopted a quantitative supervised machine learning design for the estimation of room occupancy based on the environmental and activity sensor data in a smart building. The problem was set up as a binary classification problem where each observation was labelled as occupied or not.

2.2 Description of the Dataset

Thus, the data comprised 10,129 observations of 19 variables recorded every 30 seconds or so. It was equipped with temperature, light, sound, carbon dioxide, carbon dioxide slope, and passive infrared motion sensors. The original target variable, Room_Occupancy_Count, had 4 different levels of occupancy ranging from 0-3 persons. No missing data or duplicated data was found. Humidity and humidity ratio were not considered since these variables were not provided in the dataset supplied (Adarsh Pal Singh 2018).

2.3 Sensor Variables

Predictor variables consisted of: four temperature sensors (S1_Temp, S2_Temp, S3_Temp, and S4_Temp), four light sensors (S1_Light, S2_Light, S3_Light, and S4_Light), four sound sensors (S1_Sound, S2_Sound, S3_Sound, and S4_Sound), one carbon dioxide sensor (S5_CO2), carbon dioxide slope (S5_CO2_Slope), and two passive infrared motion sensors (S6_PIR and S7_PIR). These variables were direct and indirect measures of human presence.

2.4 Target Variable

The original number of occupants was transformed to a binary target variable. A 0 indicated an unoccupied room, while 1, 2 or 3 indicated an occupied room. After transformation, the number of unoccupied observations was 8228 and the number of occupied observations was 1901, which showed a class imbalance.

2.5 Data Preprocessing

The dataset was cleaned to identify missing data, duplicate records, inconsistent data and outliers. There was no missing or duplicated observations. When the sensor value was extreme but physically feasible and potentially linked to an occurrence of occupation, the value was kept. The predictor set did not include date, time or the original number of occupants. Continuous variables were z-score normalized according to only the training data. Class weighting was used where available to minimize the effects of bias being introduced by the majority unoccupied class.

2.6 Exploratory Data Analysis

The sensor variables distribution and relationship were examined using descriptive statistics, histograms, box plots, and correlation analysis. Occupied and unoccupied observations were also compared to determine any temperature, light, sound, carbon dioxide and/or motion activity differences.

2.7 Machine Learning Models

Five classification algorithms were created: Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, and K-Nearest Neighbors. Logistic Regression was used as the baseline model; Decision Tree and Random Forest were used to identify nonlinear relationships. The sensor data were standardized and then used with Support Vector Machine and K-Nearest Neighbors.

2.8 Model Training and Testing

The dataset was split into 80% training and 20% testing data sets chronologically. A chronological splitting method was employed to ensure that no two adjacent sensor observations were created that were very similar to each other. Time-series-aware cross-validation on the training data was used for hyperparameter selection.

2.9 Performance Evaluation

The accuracy, precision, recall, F1-score and confusion matrix were used for the evaluation of the model performance. Due to the imbalance in the dataset, greater attention was brought to recall and F1-score of the occupied class. True and False positives and negatives were analyzed using confusion matrix. The model that had the highest correct room identification with a well-balanced overall performance was chosen.

3. Results

3.1 Descriptive Statistics of Sensor Variables

The environmental sensor variables descriptive statistics are displayed in Table 1. The data set comprised 10,129 observations made by environmental sensors of indoor temperature, light, sound level, CO2 concentration, and CO2 slope. During this monitoring period the temperatures were fairly constant but the light intensities had a large variance due to varying occupancy situations. Likewise, the levels of sound intensity and CO_2 concentration were also highly variable, depending on the level of activity within an indoor space. In sum, the variability observed demonstrates that there is enough information present for the sensor measurements to be used to create reliable room occupancy estimation models.

Table 1. Descriptive Statistics of Sensor Variables

Sensor Variable	Mean	SD	Median	Minimum	Maximum	Q1	Q3
S1_Temp	25.454	0.351	25.38	24.940	26.380	25.190	25.630
S2_Temp	25.546	0.586	25.38	24.750	29.000	25.190	25.630
S3_Temp	25.057	0.427	24.94	24.440	26.190	24.690	25.380
S4_Temp	25.754	0.356	25.75	24.940	26.560	25.440	26.000
S1_Light	25.445	51.011	0.00	0.000	165.000	0.000	12.000
S2_Light	26.016	67.304	0.00	0.000	258.000	0.000	14.000
S3_Light	34.248	58.401	0.00	0.000	280.000	0.000	50.000
S4_Light	13.220	19.602	0.00	0.000	74.000	0.000	22.000
S1_Sound	0.168	0.317	0.08	0.060	3.880	0.070	0.080
S2_Sound	0.120	0.267	0.05	0.040	3.440	0.050	0.060
S3_Sound	0.158	0.414	0.06	0.040	3.670	0.060	0.070
S4_Sound	0.104	0.121	0.08	0.050	3.400	0.060	0.100
S5_CO2	460.860	199.965	360.00	345.000	1270.000	355.000	465.000
S5_CO2_Slope	-0.005	1.165	0.00	-6.296	8.981	-0.046	0.000

The descriptive statistics show that light intensity, sound and CO2 levels had more variability than temperature sensors, which means that these are likely to make more significant contributions to the occupancy estimation.

3.2 Occupancy Distribution

The number of occupied observations and unoccupied observations are summarized in the frequency distribution (Table 2) and in the graphical representation (Figure 1). The total number of observations was 10,129, of which 8,228 observations (81.23%) were recorded as unoccupied and 1,901 observations (18.77%) were recorded as occupied. This means that the data is rather skewed, with about 4.3 blank observations to each observation.

Table 2. Distribution of Room Occupancy Status

Occupancy Status	Frequency	Percentage (%)
Unoccupied	8,228	81.23
Occupied	1,901	18.77

The data in Figure 1 show that the number of unoccupied observations is far greater than the number of occupied observations, indicating that there is a need to consider evaluation metrics other than overall accuracy when assessing a model.

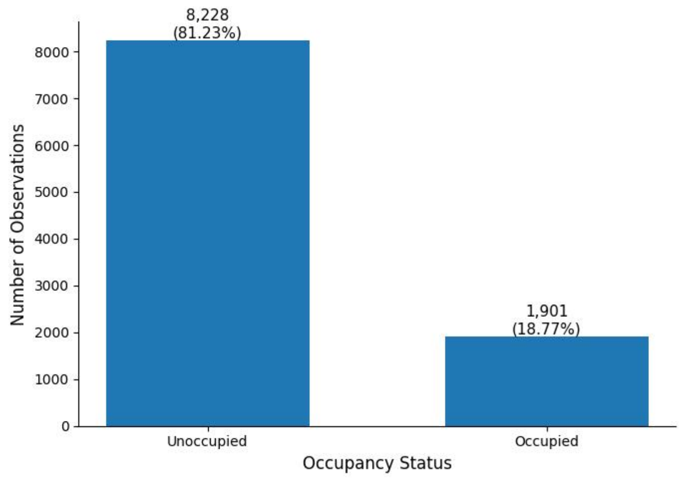

Figure 1. Distribution of Room Occupancy Status

3.3 Relationship Between Sensor Readings and Occupancy

Differences in environmental sensor measurements between occupied and unoccupied conditions are presented in Table 3, and the normalized comparison of sensor readings is depicted in Figure 2.

Table 3. Comparison of Sensor Readings by Occupancy Status

Sensor Variable	Unoccupied Mean ± SD	Occupied Mean ± SD	Mann–Whitney U	p-value
S1_Temp	25.336 ± 0.241	25.963 ± 0.296	1,114,918	<0.001
S2_Temp	25.371 ± 0.333	26.303 ± 0.804	1,683,186	<0.001
S3_Temp	24.929 ± 0.331	25.608 ± 0.354	1,505,903	<0.001
S4_Temp	25.660 ± 0.309	26.162 ± 0.241	1,725,566	<0.001
S1_Light	2.687 ± 5.152	123.950 ± 42.481	288,300	<0.001
S2_Light	3.053 ± 5.918	125.406 ± 108.756	355,048	<0.001
S3_Light	13.368 ± 24.262	124.622 ± 74.646	870,036	<0.001
S4_Light	9.235 ± 16.824	30.471 ± 21.355	2,457,904	<0.001
S1_Sound	0.077 ± 0.070	0.563 ± 0.567	788,920	<0.001
S2_Sound	0.053 ± 0.063	0.412 ± 0.506	856,810	<0.001
S3_Sound	0.064 ± 0.074	0.567 ± 0.826	1,041,934	<0.001
S4_Sound	0.080 ± 0.029	0.208 ± 0.246	3,884,298	<0.001
S5_CO2	404.446 ± 136.031	705.034 ± 244.105	1,250,042	<0.001
S5_CO2_Slope	-0.308 ± 0.836	1.308 ± 1.446	1,953,579	<0.001

There were significant differences in all environmental variables between occupied and unoccupied conditions ($p<0.001$). The highest variations were seen in the light intensity, carbon dioxide level and sound data, which all have a high degree of information for estimating occupancy.

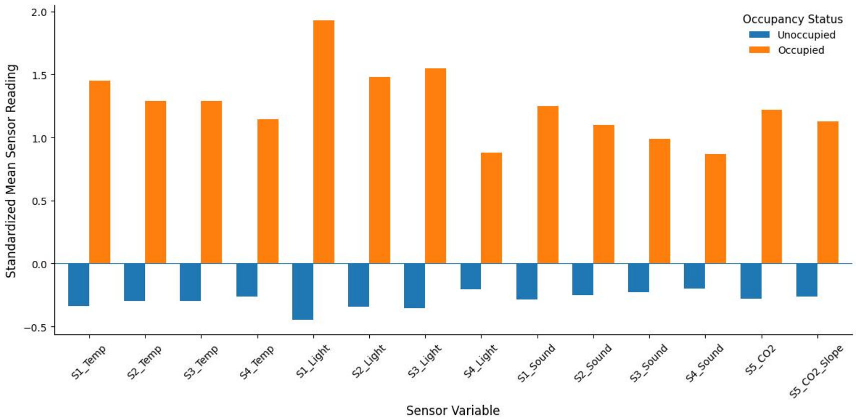

Figure 2. Standardized Sensor Readings According to Occupancy Status

This is illustrated in Figure 2, which shows that all the standardized values for temperature, illumination, sound intensity, carbon dioxide concentration, and carbon dioxide slope were higher during the occupied periods than during unoccupied periods.

3.4 Performance of Machine Learning Models

The predictive performance of the five machine learning algorithms is summarized in Table 4. High classification accuracy was obtained from all models but there was a difference in precision, recall and F1 scores.

Table 4. Performance Comparison of Machine Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Logistic Regression	99.85	99.28	99.64	99.46
Support Vector Machine	99.70	98.21	99.64	98.92
K-Nearest Neighbors	99.06	99.61	93.45	96.44
Decision Tree	98.96	97.39	94.91	96.13
Random Forest	96.84	100.00	76.73	86.83

Logistic Regression was most successful overall with Support Vector Machine being very close. Random Forest had a high precision yet low recall, thereby getting the lowest F1 score when tested against the models.

3.5 Comparison of Model Accuracy

The comparative performance of the five machine learning algorithms is illustrated in Figure 3.

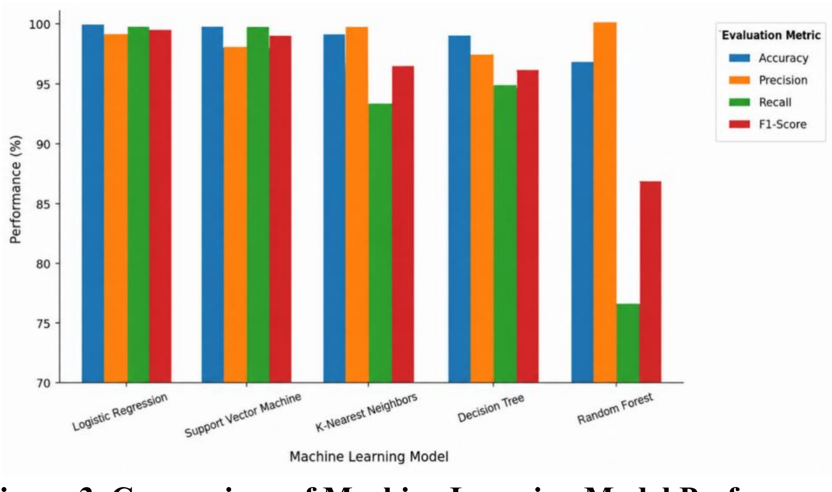

Figure 3. Comparison of Machine Learning Model Performance

As demonstrated in Figure 3, Logistic Regression consistently outperforms the other algorithms in all evaluation parameters. Support Vector Machine achieved similar accuracy and Recall while Random Forest had a significant drop in Recall even though it achieves 100% Precision.

3.6 Best-Performing Occupancy Estimation Model

By analyzing the independent test set, Logistic Regression was determined to be the best occupancy estimation model. Table 5 shows the significance of each predictor and Figure 4 shows the confusion matrix.

Table 5. Top 10 Logistic Regression Predictors Based on Absolute Standardized Coefficients

Rank	Sensor Variable	Standardized Coefficient	Odds Ratio	Direction
1	S1_Light	8.5812	5330.4455	Higher occupancy likelihood
2	S3_Temp	7.6243	2047.3922	Higher occupancy likelihood
3	S4_Temp	-5.0927	0.0061	Lower occupancy likelihood
4	S5_CO2_Slope	3.0122	20.3319	Higher occupancy likelihood
5	S5_CO2	-2.0490	0.1289	Lower occupancy likelihood
6	S2_Light	1.9710	7.1779	Higher occupancy likelihood
7	S4_Light	-1.6554	0.1910	Lower occupancy likelihood
8	S3_Light	1.4887	4.4314	Higher occupancy likelihood
9	S1_Temp	0.5925	1.8085	Higher occupancy likelihood
10	S2_Temp	-0.5090	0.6011	Lower occupancy likelihood

The model identified S1_Light, S3_Temp, S4_Temp, S5_CO2_Slope, and S5_CO2 as the most influential predictors of room occupancy. Overall, environmental variables contributed more strongly to occupancy prediction than the PIR motion sensors.

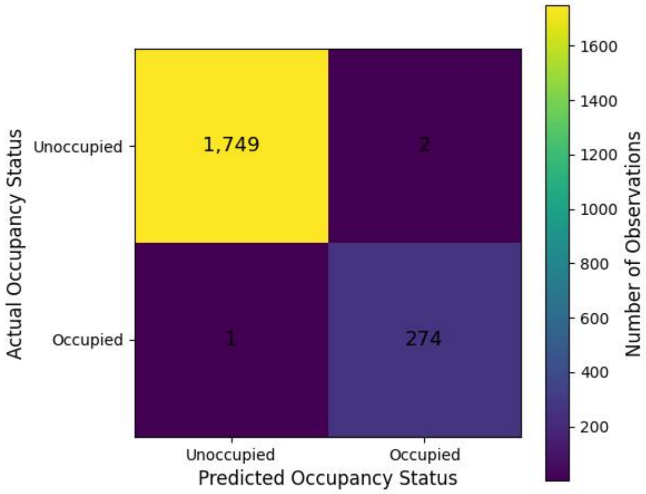

Figure 4. Confusion Matrix of the Best-Performing Logistic Regression Model

The confusion matrix is used to verify the excellent classification ability of the Logistic Regression model. A total of 2,026 testing observations were made; 1,749 of the unoccupied rooms were classified as unoccupied and 274 of the occupied rooms were classified as occupied, with only 2 false positive classifications and 1 false negative. The results show that by using multiple environmental sensors with Logistic Regression, room occupancy estimation with high accuracy can be achieved in the context of smart building.

4. Discussion

The results of the present study showed that the measurements of the environmental sensors can be used to accurately estimate the occupancy of a room in a smart building with supervised machine learning techniques. All the models evaluated showed high predictive performance, with Logistic Regression showing the best accuracy of 99.85% and F1-score of 99.46%. The results show that the combination of several environmental variables captures the occupancy pattern with good accuracy, confirming the results of previous studies that identified sensor fusion as a good method of estimating occupancy (Abade, Perez Abreu, and Curado 2018; Chen, Jiang, and Xie 2018). The findings also confirm previous studies showing that environmental sensor data can be effectively converted to an accurate occupancy prediction for use in intelligent buildings (Aliero et al. 2022; Toutiaee 2021).

Analysis indicated illumination, temperature, carbon dioxide concentration and rate of change of carbon dioxide concentration were the most significant predictors of occupancy, with S1_Light and S3_Temp most influential. CO_2-related features enhanced the detection whereas sound captured activity levels. Environmental variables showed higher predictive power compared to PIR sensors, which aligns with previous works on multi-sensor fusion (Abedi and Jazizadeh 2019; Zhao et al. 2018).

These findings are consistent with previous research that suggested ML is better than threshold-based occupancy detection methods. Previous studies have also validated the ability of non-intrusive environmental sensing and the benefit of having multiple sensor types for greater accuracy (Elkhoukhi et al. 2018; Pratama et al. 2018). Besides, the use of smart building applications with IoT and AI technologies for building occupancy estimation is one of the key applications for the efficient management of buildings (Daissaoui et al. 2020; Rejeb et al. 2022). Logistic Regression also demonstrates its high performance, indicating that even a relatively simple and interpretable model can be highly accurate when suitable environmental characteristics are utilized.

An accurate estimation of the occupancy is of direct importance for intelligent building management systems. Occupancy data can be used to control lighting, heating, ventilation and air-conditioning systems adaptively, based on the current room occupancy, not to a fixed schedule. This operation based on demand optimises occupant comfort and reduces superfluous energy consumption. Occupancy data can also be used to help monitor security, plan emergency evacuations, analyze space utilization, and facilitate intelligent facility management. These applications reflect the trend

towards adoption of IoT technologies and data-driven automation in smart buildings (Rejeb et al. 2022; Tanko et al. 2023).
If occupancy is accurately estimated, there are significant energy-saving opportunities in a building. In commercial and institutional buildings, lighting and HVAC are a significant portion of operational energy consumption, and occupancy-aware control strategies can boost their efficiency. Sensor-based occupancy estimation is one of the technologies that support sustainable building operation and building operational cost reduction by turning on building services only when the building is occupied. This is a similar conclusion to the findings of research on smart building technologies and their role in creating energy-efficient urban environments (Daissaoui et al. 2020; Li et al. 2024).
The results show that the environmental sensors coupled with machine learning algorithms can be an effective and economical approach towards real-time occupancy estimation. Due to the availability of the indoor environmental sensors, the proposed framework can be implemented with minimum additional infrastructure in the existing building management system. In addition, the Logistic Regression's good performance indicates that models that are simple, interpretable and computationally efficient, but not necessarily a complicated deep learning model, can be applied to real-time smart building applications. These features are especially beneficial for edge computing and smart building systems with IoT devices (Aliero et al. 2022; Kao et al. 2019).
Some caveats should be noted about the promising findings. A single publicly available data set was used in the analysis, under one indoor setting, so the models derived may not be widely applicable to different building floor plans and conditions. Furthermore, the study was only based on environmental sensor measurements and no additional sensing modalities were added. Also, only 5 conventional machine learning algorithms were tested and more advanced learning frameworks further enhance prediction performance (Toutiaee 2021; Zhang et al. 2024).
Future research should test the proposed methodology with multi-building data sets from a variety of climatic conditions and building use to better generalize the model. Further exploration of other sensing modalities such as wireless communication signals, vision based sensing, and wearable devices further improve occupancy estimation accuracy while keeping occupancy information private. Future research also explores explainable artificial intelligence, federated learning, reinforcement learning and adaptive online learning techniques to build more intelligent occupancy estimation systems that used to address the next generation of autonomous smart buildings and sustainable urban infrastructure.

5. Conclusion

A sensor-based room occupancy estimation framework for smart buildings, based on environmental sensor measurements and supervised machine learning techniques is developed and evaluated in this study. Environmental data such as temperature, light intensity, sound, carbon dioxide concentration, carbon dioxide slope, and passive infrared sensor data were analysed for classification of room occupancy status. Five Machine Learning model performances were compared and showed that all models had a high performance on prediction but among all models, Logistic Regression showed the best overall results with 99.85% accuracy, 99.28% precision, 99.64% recall, and 99.46% F1 score. Results also showed that light intensity, temperature, and carbon dioxide (CO_2) parameters were the most important factors contributing to occupancy, suggesting that use of multiple environmental sensors can help estimate occupancy more reliably than using a single sensor. The proposed framework is a practical and computation-efficient solution, which can be embedded in intelligent building management system (IBMS) for automated lighting control, HVAC optimization and energy-efficient operation of buildings. The methodology that was developed showed good potential for real-life applications and a very good predictive capability, even though only one dataset was publicly available. It is recommended that future research should validate the proposed approach with different building environments, larger multi-site datasets, and use of more advanced techniques in artificial intelligence to further improve occupancy estimation performance for next-generation smart building applications and generalizability of the models.

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