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Comparative Analysis of Machine Learning Models for Occupancy Detection in AI-IoT Based Indoor Air Quality Smart Surveillance Systems

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Abstract
Indoor Air Quality (IAQ) plays a significant role in maintaining healthy, comfortable, and energy-efficient indoor environments. With the rapid growth of Artificial Intelligence (AI) and the Internet of Things (IoT), occupancy-aware smart surveillance systems have become an important component of intelligent buildings and automated environmental management. Accurate occupancy detection enables efficient Heating, Ventilation, and Air Conditioning (HVAC) control, reduces unnecessary energy consumption, and improves indoor comfort by adapting environmental conditions according to the presence of occupants.

This study presents a comparative analysis of three machine learning models, namely Decision Tree, Random Forest, and Long Short-Term Memory (LSTM), for occupancy detection using environmental sensor data. The analysis is based on the UCI Occupancy Detection Dataset containing Temperature, Humidity, Light, CO_2, and Humidity Ratio measurements. All models are evaluated using identical testing conditions and assessed through Accuracy, Precision, Recall, F1-score, and ROC-AUC metrics.

The comparative results demonstrate that the Random Forest model consistently outperforms the Decision Tree and LSTM models across all evaluation metrics. It achieves an accuracy of 97.30%, precision of 90.12%, recall of 97.90%, F1-score of 93.85%, and ROC-AUC of 0.994, making it the most reliable model for occupancy detection. The analysis also reveals that Light and CO_2 are the most influential features in predicting occupancy, whereas humidity-related parameters contribute comparatively less. Furthermore, Random Forest requires lower computational resources, no sequence buffering, and minimal preprocessing, making it highly suitable for deployment on edge-computing platforms for real-time AI-IoT applications.

The findings of this study support the adoption of Random Forest as the preferred occupancy detection model for AI-IoT-based indoor air quality smart surveillance systems while providing insights for future research in intelligent occupancy prediction and edge AI deployment.

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Keywords: Indoor Air Quality, Occupancy Detection, Artificial Intelligence, Internet of Things, Random Forest, Decision Tree, Long Short-Term Memory, Smart Buildings, Machine Learning, Environmental Monitoring

1. Introduction

Indoor environments have become increasingly important because people spend a significant portion of their daily lives inside offices, educational institutions, hospitals, commercial buildings, and residential spaces. The quality of indoor air directly affects human health, productivity, thermal comfort, and overall well-being. Poor ventilation and ineffective environmental control can lead to increased carbon dioxide concentration, discomfort, reduced cognitive performance, and higher energy consumption. Consequently, intelligent monitoring and management of Indoor Air Quality (IAQ) have become essential components of

modern smart buildings.

Recent advancements in Artificial Intelligence (AI), the Internet of Things (IoT), and edge computing have enabled the development of intelligent surveillance systems capable of continuously monitoring environmental conditions using low-cost sensors. These systems collect real-time information such as temperature, humidity, carbon dioxide concentration, light intensity, and humidity ratio, allowing machine learning algorithms to infer occupancy status without relying on cameras or wearable devices. Occupancy-aware systems support automated decision-making for Heating, Ventilation, and Air Conditioning (HVAC) systems, thereby improving energy efficiency while maintaining occupant comfort.

Several machine learning and deep learning techniques have been investigated for occupancy detection. Conventional machine learning algorithms such as Decision Trees and Random Forests are widely recognized for their simplicity, robustness, and computational efficiency, whereas deep learning models such as Long Short-Term Memory (LSTM) networks are capable of learning temporal dependencies in sequential sensor data. However, the selection of an appropriate model depends not only on predictive accuracy but also on deployment complexity, computational requirements, inference latency, and suitability for resource-constrained edge devices.

The occupancy model comparison conducted for the AI-IoT Air Quality Smart Surveillance System evaluates three candidate models—Decision Tree, Random Forest, and LSTM—using the same occupancy detection dataset and evaluation methodology. The comparison examines predictive performance, feature significance, deployment feasibility, and operational characteristics to identify the most appropriate model for real-time occupancy detection.

1.1. Key Objectives

The primary objectives of this study are:

1.1.1 To compare the performance of Decision Tree, Random Forest, and LSTM models for occupancy detection.

1.1.2 To evaluate each model using standard classification performance metrics, including Accuracy, Precision, Recall, F1-score, and ROC-AUC.

1.1.3 To analyze the influence of environmental sensor features on occupancy prediction.

1.1.4 To investigate the deployment suitability of each model for AI-IoT-based edge computing applications.

1.1.5 To recommend the most appropriate occupancy detection model for indoor air quality smart surveillance systems.

1.2. Problem Statement

Occupancy detection is a fundamental component of intelligent indoor air quality management systems because it enables demand-based ventilation, energy-efficient HVAC operation, and automated environmental control. Although numerous machine learning and deep learning algorithms have been proposed for occupancy prediction, selecting a model that simultaneously achieves high prediction accuracy, computational efficiency, robustness, and real-time deployment capability remains a significant challenge.

The occupancy comparison report indicates that different learning algorithms exhibit distinct strengths and limitations. Decision Trees provide interpretability but are susceptible to overfitting, while LSTM models possess temporal learning capability but require additional computational resources, sequence buffering, and threshold calibration. These factors may limit their effectiveness for deployment on resource-constrained edge devices. Consequently, there is a need for a comprehensive comparative evaluation to determine the most suitable occupancy detection model for AI-IoT smart surveillance systems operating under real-time conditions.

1.3. Research Hypothesis

Based on the objectives of this study, the following hypotheses are considered:

H1: Environmental sensor measurements consisting of Temperature, Humidity, Light, CO_2, and Humidity Ratio are sufficient to accurately predict indoor occupancy using machine learning techniques.

H2: Among the evaluated models, Random Forest provides superior classification performance compared with Decision Tree and LSTM in terms of Accuracy, Precision, Recall, F1-score, and ROC-AUC while remaining suitable for real-time edge deployment.

H3: Light intensity and CO_2 concentration contribute more significantly to occupancy prediction than humidity-related environmental parameters.

2. Literature Review

Indoor Air Quality (IAQ) monitoring has become a major research area due to its direct impact on human health, environmental sustainability, and energy-efficient building management. The literature summarized in the reviewed studies demonstrates that recent advances in Artificial Intelligence (AI) and the Internet of Things (IoT) have significantly improved the ability to monitor, analyze, and predict indoor environmental conditions. Researchers have focused on integrating intelligent sensing platforms with machine learning algorithms to support real-time occupancy detection, pollution monitoring, thermal comfort assessment, and automated ventilation control.

Sokhi *et al.* (2022) [1] provided a comprehensive overview of current and emerging challenges in air quality research, emphasizing the need for integrated monitoring systems that combine low-cost sensors, satellite observations, unmanned aerial vehicles (UAVs), and ground-based monitoring stations. Their study highlighted that AI-driven analytics and multi-source environmental data are essential for addressing the increasing complexity of urban and indoor air pollution.

Focusing on the health implications of air pollution, Bala *et al.* (2021) [5] reported that prolonged exposure to pollutants such as $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, O_3, and volatile organic compounds (VOCs) significantly increases the risk of respiratory diseases. Their work emphasized the importance of continuous air quality monitoring in both indoor and outdoor environments, thereby reinforcing the need for intelligent sensing systems capable of providing real-time environmental assessment.

The challenges associated with indoor air quality in developing countries were investigated by Karmakar *et al.* (2024) [3], who analyzed IAQ dynamics across households, laboratories, classrooms, and public spaces in India. Using measurements of particulate matter, CO_2, VOCs, ethanol, temperature, and humidity, the study highlighted the influence of occupant activities, ventilation patterns, and environmental conditions on indoor air quality. The authors recommended AI-enabled monitoring frameworks for continuous environmental assessment and timely

intervention.

The application of machine learning for intelligent indoor monitoring was demonstrated by Balta *et al*. (2022) [4] through a distributed sensor-based fuzzy decision tree model for simultaneously evaluating indoor air quality and thermal comfort. Their system integrated CO_2, temperature, humidity, airflow, illumination, and occupancy sensors to support real-time decision-making in university classrooms. The study demonstrated that combining multiple environmental parameters with intelligent decision models can significantly improve monitoring accuracy while maintaining computational efficiency.

A more recent contribution by Chatterjee *et al*. (2025) [5] proposed an AI-based predictive framework for indoor air wellness using multiple environmental sensors, including temperature, humidity, CO, NO_2, NH_3, ozone, and particulate matter. The study highlighted the capability of advanced AI techniques to predict pollution levels and recommend preventive measures for residential, commercial, industrial, and green building environments. The authors emphasized that predictive analytics can enhance indoor environmental management beyond traditional threshold-based monitoring systems.

Across the reviewed literature, several AI techniques have been employed, including Decision Trees, Fuzzy Decision Trees, Random Forest, Artificial Neural Networks (ANN), Deep Learning, and hybrid intelligent models. Conventional machine learning techniques are generally preferred because of their lower computational complexity, ease of implementation, and suitability for real-time inference. Deep learning approaches provide improved capability for modelling complex relationships but typically require larger datasets, higher computational resources, and more extensive parameter optimization.

The reviewed studies consistently identify temperature, humidity, CO_2 concentration, particulate matter, volatile organic compounds, and light intensity as the most frequently monitored environmental parameters. While comprehensive environmental monitoring remains important, several studies indicate that occupancy prediction can often be achieved effectively using a smaller subset of highly informative features, particularly CO_2 concentration and illumination, thereby reducing computational overhead.

Another important trend observed across the literature is the increasing integration of AI with IoT-enabled sensing platforms. Cloud computing, wireless sensor networks, and edge computing architectures are increasingly adopted to enable real-time monitoring, automated decision-making, and intelligent building management. These technologies support applications such as smart classrooms, hospitals, commercial buildings, industrial facilities, and residential environments by improving energy efficiency and maintaining acceptable indoor air quality.

2.1. Research Gap

A critical analysis of the reviewed studies reveals several research gaps that motivate the present work:

2.1.1 Most studies concentrate on air quality prediction rather than occupancy detection using environmental sensing data.

2.1.2 Comparative evaluations of Decision Tree, Random Forest, and LSTM under identical experimental conditions are limited.

2.1.3 Existing research primarily emphasizes prediction accuracy, while deployment factors such as computational complexity, inference latency, memory consumption, and edge-device suitability receive comparatively less attention.

2.1.4 Few studies investigate the influence of decision threshold calibration on the performance of deep learning models such as LSTM.

2.1.5 Although IoT-based monitoring systems are widely reported, limited work integrates occupancy detection with AI-IoT smart surveillance systems for real-time indoor air quality management.

2.1.6 Feature importance analysis is often insufficiently explored, despite its potential to reduce sensing costs and improve model efficiency.

These identified research gaps form the basis of the present study, which performs a systematic comparison of Decision Tree, Random Forest, and LSTM models using a common occupancy detection dataset while evaluating both predictive performance and practical deployment suitability for AI-IoT-based indoor air quality smart surveillance systems.

Experiment Design and Data Collection

3. Research Framework

The objective of this study is to identify the most suitable machine learning model for occupancy detection in AI-IoT-based Indoor Air Quality (IAQ) smart surveillance systems. A comparative experimental framework was adopted to evaluate the predictive performance and deployment feasibility of three widely used machine learning models: Decision Tree (DT), Random Forest (RF), and Long Short-Term Memory (LSTM). The framework was designed to ensure a fair comparison by training and evaluating all models using the same dataset, input features, and evaluation metrics.

3.1. The experimental workflow consisted of the following phases:

3.1.1 Collection of environmental sensor data.

3.1.2 Data preprocessing and feature preparation.

3.1.3 Model development and training.

3.1.4 Performance evaluation.

3.1.5 Comparative analysis.

3.1.6 Model selection for AI-IoT deployment.

3.2. Dataset Description

The experiments were conducted using the UCI Occupancy Detection Dataset, which is one of the most widely used benchmark datasets for occupancy prediction research. The dataset contains time-series environmental measurements collected from an office environment under different occupancy conditions.

The dataset includes five environmental parameters:

3.2.1 Temperature (°C)

3.2.2 Relative Humidity (%)

3.2.3 Light Intensity (Lux)

3.2.4 Carbon Dioxide (CO_2) Concentration (ppm)

3.2.5 Humidity Ratio

The output variable is a binary occupancy label representing:

Occupied (1)

Unoccupied (0)

According to the occupancy comparison report, the dataset contains:

Table I: Sample Dataset

Dataset	Number of Samples
Training Dataset	8,143
Testing Dataset	9,752

The testing dataset corresponds to the door-open experimental condition, allowing all models to be evaluated under identical environmental settings.

3.3. Data Collection

Environmental measurements were continuously collected through indoor environmental sensors installed in an office environment. Each observation records the values of temperature, humidity, light intensity, CO_2 concentration, and humidity ratio at a specific time, together with the corresponding occupancy status.

The training dataset contains approximately 79% unoccupied observations and 21% occupied observations, indicating a moderate class imbalance. Therefore, evaluation metrics beyond overall accuracy, such as Precision, Recall, and F1-score, are essential for assessing model performance.

3.4. Data Preprocessing

Before model development, the collected data were prepared for machine learning analysis. The preprocessing stage included:

3.4.1 Feature selection using the five environmental variables.

3.4.2 Separation of predictor variables and occupancy labels.

3.4.3 Preparation of independent training and testing datasets.

3.4.4 Standardization of input features for the LSTM model, as neural networks are sensitive to differences in feature scales.

The occupancy comparison report notes that Decision Tree and Random Forest models are inherently scale-independent and therefore do not require feature standardization, making them operationally simpler for deployment.

3.5. Machine Learning Models

Three supervised learning algorithms were evaluated in this study.

3.5.1. Decision Tree

The Decision Tree model constructs a hierarchical structure of decision rules based on environmental sensor measurements. It offers high interpretability and fast prediction but is susceptible to overfitting, particularly when trained using limited datasets.

3.5.2. Random Forest

Random Forest is an ensemble learning algorithm that combines predictions from multiple decision trees. According to the occupancy comparison report, the implemented model consists of 200 decision trees, enabling improved prediction accuracy and reduced model variance compared with a single Decision Tree.

3.5.3. Long Short-Term Memory (LSTM)

LSTM is a recurrent neural network architecture designed to learn temporal dependencies in sequential data. Unlike tree-based algorithms, LSTM requires sequence generation, feature standardization, and additional computational resources. The model was evaluated using its default decision threshold to maintain consistency with the other classifiers.

3.6. Performance Evaluation

The comparative analysis was performed using five standard classification metrics.

3.6.1 Accuracy

Measures the proportion of correctly classified occupancy observations.

3.6.2 Precision

Measures the proportion of predicted occupied instances that are actually occupied.

3.6.3 Recall

Measures the capability of the model to correctly identify occupied rooms.

3.6.4 F1-Score

Represents the harmonic mean of Precision and Recall, providing a balanced evaluation of classification performance.

3.6.5 ROC-AUC

Measures the overall discrimination capability of a classifier across different decision thresholds.

All three models were evaluated using their default operating thresholds to ensure an unbiased comparison.

3.7. Experimental Environment

To ensure consistency, the following experimental conditions were maintained throughout the evaluation:

3.7.1 Common occupancy dataset for all models.

3.7.2 Identical environmental input features.

3.7.3 Same testing dataset (door-open condition).

3.7.4 Uniform evaluation metrics.

3.7.5 Default decision thresholds.

3.7.7 Comparative performance analysis based on predictive accuracy and deployment suitability.

This standardized evaluation framework enables a fair comparison of Decision Tree, Random Forest, and LSTM models while minimizing experimental bias.

4. Results and Findings

4.1. Comparative Performance Analysis

The experimental results obtained from the occupancy comparison report are summarized in Table 2

Table 2: Comparative Performance of Occupancy Detection Models

Performance Metric	Decision Tree	Random Forest	LSTM
Accuracy	0.925	0.973	0.8836
Precision	0.8411	0.9012	0.6774
Recall	0.7931	0.979	0.8475
F1-Score	0.8164	0.9385	0.7529
ROC-AUC	Not Computed	0.994	0.9557

The results clearly demonstrate that the Random Forest model consistently outperformed the Decision Tree and LSTM models across all evaluation metrics. It achieved the highest classification accuracy (97.30%), precision (90.12%), recall (97.90%), F1-score (93.85%), and ROC-AUC (0.9940), indicating excellent predictive capability and robustness.

In comparison, the Decision Tree model provided

satisfactory performance but exhibited lower recall and F1-score due to its susceptibility to overfitting and higher prediction variance. Although the LSTM model achieved a relatively high ROC-AUC value, its overall accuracy and precision were lower than those of Random Forest when evaluated using the default decision threshold.

The occupancy comparison report also indicates that improving LSTM recall required reducing the decision threshold from 0.50 to 0.149, which increased recall but substantially decreased precision. This demonstrates that LSTM performance is highly dependent on threshold calibration, whereas Random Forest achieved balanced performance without requiring additional tuning.

4.2. Feature Importance

Analysis of the environmental variables indicates that Light Intensity and CO_2 concentration are the most influential predictors of occupancy. Light exhibited the strongest correlation with occupancy, followed by CO_2 concentration, whereas Humidity and Humidity Ratio contributed comparatively less to prediction accuracy. These findings suggest that a limited set of highly informative environmental parameters can effectively support occupancy detection while reducing sensing complexity.

4.3. Deployment Considerations

Beyond predictive performance, the comparative analysis assessed the practical suitability of each model for AI-IoT deployment. The Random Forest model offers several operational advantages, including lower computational complexity, no requirement for sequence buffering, minimal preprocessing, and naturally balanced decision thresholds. These characteristics make it particularly suitable for real-time inference on resource-constrained edge devices. In contrast, the LSTM model requires sequential input windows, feature standardization, and greater computational resources, increasing deployment complexity in edge-based smart surveillance applications.

4.4. Real-World Applications of the Research Outcome

The findings of this study have significant practical implications for AI-IoT-based indoor environmental monitoring and smart surveillance systems. Accurate occupancy detection enables intelligent decision-making by integrating environmental sensor data with machine learning algorithms, thereby improving operational efficiency, occupant comfort, and energy conservation.

One of the primary applications of the proposed Random Forest-based occupancy detection model is in smart building management. By accurately identifying occupancy status in real time, building automation systems can dynamically regulate Heating, Ventilation, and Air Conditioning (HVAC) operations. This demand-driven approach minimizes unnecessary energy consumption while maintaining acceptable indoor air quality and thermal comfort.

In educational institutions, occupancy-aware monitoring can optimize classroom ventilation based on actual occupancy levels rather than fixed schedules. Such adaptive control improves the learning environment, reduces carbon dioxide accumulation, and contributes to lower energy costs. Similar benefits can be achieved in office buildings, where intelligent occupancy detection supports efficient workspace utilization and environmental control.

The proposed model also has important applications in healthcare facilities. Hospitals and clinics require continuous monitoring of indoor environmental conditions to protect patients, healthcare professionals, and visitors. Occupancy-aware ventilation can help maintain healthier indoor environments by automatically adjusting airflow according to occupancy levels, thereby improving infection control and patient comfort.

Another promising application is AI-IoT-based smart surveillance, where occupancy detection serves as an additional layer of intelligent monitoring. Unlike camera-based surveillance systems, environmental sensor-based occupancy detection preserves user privacy while providing reliable information regarding space utilization. This capability is particularly valuable in offices, libraries, laboratories, conference rooms, and public buildings where privacy concerns limit the use of video surveillance.

The proposed framework also supports energy-efficient smart cities by enabling intelligent environmental management across interconnected buildings. Integration with IoT platforms allows occupancy information to be shared with building management systems, facilitating centralized monitoring, predictive maintenance, and optimized resource allocation.

Furthermore, the deployment analysis demonstrates that Random Forest is particularly suitable for edge computing environments because it requires no sequential data buffering, minimal preprocessing, and relatively low computational resources. These characteristics enable real-time occupancy prediction on embedded AI-IoT devices while reducing communication latency and cloud dependency.

Overall, the research outcomes contribute to sustainable building management by combining intelligent occupancy detection with real-time environmental monitoring, thereby supporting healthier indoor environments, reduced energy consumption, and improved operational efficiency.

5. Conclusion

This study presented a comparative evaluation of three machine learning models—Decision Tree, Random Forest, and Long Short-Term Memory (LSTM)—for occupancy detection in AI-IoT-based Indoor Air Quality (IAQ) smart surveillance systems. The comparison was conducted using the UCI Occupancy Detection Dataset under identical experimental conditions to ensure a fair assessment of predictive performance and deployment suitability.

The experimental results demonstrate that the Random Forest model consistently achieved the best performance among the evaluated algorithms. It obtained an accuracy of 97.30%, precision of 90.12%, recall of 97.90%, F1-score of 93.85%, and ROC-AUC of 0.994, outperforming both the Decision Tree and LSTM models across all evaluation metrics. These findings support the research hypothesis that ensemble learning provides superior occupancy prediction while maintaining computational efficiency suitable for real-time applications.

The study also revealed that Light Intensity and Carbon Dioxide (CO_2) are the most influential environmental parameters for occupancy detection, whereas humidity-related variables contribute comparatively less to predictive performance. Moreover, the analysis highlighted that Random Forest requires neither feature standardization nor sequential input buffering, making it simpler to deploy on resource-constrained edge devices than LSTM-based

approaches.

The literature reviews further indicated that existing research has primarily focused on improving prediction accuracy, with comparatively limited attention given to deployment complexity, computational efficiency, threshold calibration, and edge AI implementation. By integrating predictive performance with deployment considerations, this study addresses these research gaps and provides practical guidance for selecting occupancy detection models in AI-IoT-based smart surveillance systems.

Based on the overall experimental evaluation, Random Forest is recommended as the most appropriate occupancy detection model for AI-IoT indoor air quality monitoring applications because it offers an optimal balance between predictive accuracy, robustness, computational efficiency, and deployment feasibility.

Future research may extend this work by evaluating larger and more diverse occupancy datasets, investigating transformer-based deep learning architectures, incorporating Explainable Artificial Intelligence (XAI) techniques for model interpretability, and validating occupancy detection performance in real-world multi-building smart city environments.

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