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LONG SHORT-TERM MEMORY DEVELOPMENT IN EVALUATION AND FORECAST OF ROOM OCCUPANCY BASED ON SENSORS DATA

Minh Long Hoang[1]

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A B S T R A C T

This paper presents a Deep Learning-based approach for estimating and forecasting room occupancy to enhance building energy efficiency. The study utilizes sensor data from temperature, light, sound, CO_2 levels, and passive infrared (PIR) sensors as input features to train a Long Short-Term Memory (LSTM) model. The proposed model demonstrates high accuracy with minimal prediction errors: mean absolute error of 0.03 and mean squared error 0.04 during testing, highlighting its effectiveness in capturing temporal dependencies in occupancy patterns. Various Machine Learning models are also tested to compare with LSTM model, and the results show that LSTM significantly overcomes the ML performance in this application Furthermore, a rolling forecasting strategy is implemented, enabling real-time predictions for the next 60 minutes. This capability is essential for proactive energy management, allowing intelligent control systems to optimize heating, ventilation, and air conditioning (HVAC) operations based on predicted occupancy trends. The results underscore the potential of deep learning models in smart building applications, contributing to improved energy savings and sustainable building management.

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1. INTRODUCTION

Energy consumption in buildings accounts for a significant portion of global energy use, with heating, ventilation, and air conditioning (HVAC) systems being major contributors (Pérez-Lombard, Ortiz, & Pout, 2008). To improve energy efficiency and reduce operational costs, smart building technologies have increasingly relied on occupancy estimation and forecasting to optimize HVAC control strategies (Esrafilian-Najafabadi & Haghighat, 2021). Traditional methods for occupancy detection, such as motion sensors and manual scheduling, often lack accuracy and adaptability, leading to energy wastage or discomfort for occupants (Duarte, Van Den Wymelenberg, & Rieger, 2013). In contrast, machine learning and deep learning approaches have demonstrated significant potential in enhancing occupancy prediction by leveraging multi-sensor data and temporal dependencies (Zhang, Wu, & Calautit, 2022).

[1] Corresponding author: Minh Long Hoang
Email: minhlong.hoang@unipr.it

Recent advances in deep learning, particularly Long Short-Term Memory (LSTM) networks, have shown promising results in time-series forecasting applications, including human activity recognition, environmental monitoring, and occupancy estimation (Tekler & Chong, 2022). LSTM networks are well-suited for capturing long-term dependencies in sequential data, making them ideal for occupancy prediction based on sensor inputs such as temperature, light, sound, CO_2 concentration, and passive infrared (PIR) motion detection (Hamza Elkhoukhi, Bakhouya, Majdoulayne Hanifi, & Driss El Ouadghiri, 2019). Studies have demonstrated that deep learning models outperform conventional statistical and rule-based approaches regarding accuracy and adaptability to dynamic occupancy patterns (Rafi et al., 2024).

This paper works on the dataset which was collected in (Singh et al., 2018). With this dataset, the previous publication presented the accuracy estimation with various Machine Learning models that receive the input sensor data and output the current people inside the room. In this study, we develop and deploy an LSTM-based deep learning model to estimate and forecast room occupancy in real time. The proposed model leverages a rolling forecasting strategy to predict occupancy for the next 60 minutes, providing valuable insights for energy-efficient HVAC control and smart building automation. Unlike conventional forecasting methods, the rolling approach continuously updates predictions based on the latest sensor readings, enhancing reliability and responsiveness to changing occupancy trends.

Traditional models like linear regression or deep feedforward neural networks struggle with time dependencies. Regular RNNs (Recurrent Neural Networks) were introduced to handle sequential data, but they suffer from Vanishing Gradient Problem (Hochreiter, 1998) and Short-Term Memory (Sherstinsky, 2020). During training, gradients become too small, making it hard for RNNs to learn long-term dependencies. Regular RNNs forget past information quickly. Thus, we applied LSTM, which is capable of solving these problems by introducing a memory cell and gates that control the flow of information. Furthermore, we evaluate the model's performance using multiple error metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2) to assess its accuracy and robustness. Then, a verification of the long-term forecast for 1 hour is carried out.

The results of this research highlight the effectiveness of artificial intelligence (Peng, Rysanek, Nagy, & Schlüter, 2018; Hoang & Pietrosanto, 2021; Hoang, Nkembi, & Pham, 2023; Hoang & Delmonte, 2024; Hoang, Matrella, & Ciampolini, 2024; Hoang, 2026), based on the sensors (Hoang & Pietrosanto, 2020; Hoang, 2019; Hoang & Pietrosanto, 2021; Hoang & Pietrosanto, 2022; Hoang, Carratù, Paciello, & Pietrosanto, 2023; Hoang & Delmonte, 2024; Hoang, 2024; Hoang, Matrella, & Ciampolini, 2024; Hoang, 2025; Hoang, Guido Matrella, & Paolo Ciampolini, 2025; Hoang, 2025), in real-time occupancy prediction and its potential application in optimizing energy consumption within intelligent building management systems.

The remainder of this paper is as follows: Section 2 discusses the classical ML models and the significant role of LSTM in the sequential occupancy prediction. Section 3 is about datasets. Section 4 is about ML model performance and analysis. Section 5 demonstrates LSTM architecture. Then, section 6 analyzes the training, validation and testing evaluation of LSTM models. Additionally, the long-term forecast is also presented. Finally, Section 7 concludes the reserach with key achievements and future research directions.

2. BACKGROUND OF LSTM 'S IMPORTANCE FOR SEQUENTIAL OCCUPANCY PREDICTION

Although classical machine learning models such as Support Vector Regression (SVR) (Hua, Chen, Ye, & Tan, 2016) and K-Nearest Neighbors (KNN) (Emad-Ud-Din & Wang, 2023) can be utilized in predictive performance for occupancy estimation. Generally, these ML models still have limitations associated with flattened sequential learning approaches. These limitations strongly motivate the adoption of LSTM networks for future occupancy prediction systems.

In the present study, temporal information was incorporated by flattening the previous 10 timesteps into a single high-dimensional feature vector. While this approach partially preserves historical information, it fundamentally removes the explicit temporal structure of the sequence. Classical machine learning algorithms treat the flattened inputs as independent variables rather than ordered temporal observations. Consequently, the intrinsic sequential relationships among consecutive timesteps are not optimally modeled.

Occupancy dynamics are inherently temporal and sequential in nature. Human presence inside indoor environments evolves continuously over time and is strongly influenced by previous occupancy states, movement transitions, environmental changes, and behavioral patterns. Environmental sensor readings such as CO2 concentration, temperature, humidity, and light intensity often exhibit delayed responses to occupancy variations. Therefore, accurate occupancy prediction requires models capable of learning long-term temporal dependencies and dynamic sequence evolution.

LSTM networks are specifically designed to address these challenges. Unlike conventional regression models, LSTM architectures contain recurrent memory cells that preserve temporal information across multiple timesteps. Through gating mechanisms including input gates, forget

gates, and output gates, LSTM models can selectively retain important historical information while discarding irrelevant temporal noise.

This capability provides several major advantages for occupancy estimation tasks. Firstly, LSTM networks explicitly preserve temporal ordering within sensor sequences. Rather than flattening the previous timesteps into static vectors, LSTM models process sequential data step-by-step, enabling the network to learn occupancy evolution patterns directly from temporal observations. This process is particularly important for indoor occupancy behavior, where transitions often follow smooth temporal trajectories rather than independent random events.

Secondly, LSTM models are highly effective at capturing long-term temporal dependencies. Occupancy changes may depend not only on recent sensor readings but also on patterns occurring several minutes earlier. For example, gradual CO2 accumulation, delayed ventilation effects, and human movement persistence introduce temporal dependencies that classical machine learning models cannot fully capture. LSTM memory mechanisms allow the network to model these delayed interactions more effectively.

Thirdly, LSTM networks naturally model nonlinear temporal dynamics. Occupancy estimation involves highly complex relationships between environmental variables and human behavior. These relationships are often nonlinear, time-varying, and context-dependent. While SVR partially addresses nonlinear mapping through kernel transformations, LSTM networks simultaneously learn both nonlinear feature representations and temporal sequence dependencies within a unified framework.

The experimental results obtained in this study further reinforce the potential advantages of LSTM architecture. The superior performance of SVR and KNN compared to Linear Regression and Decision Tree models indicates that occupancy estimation contains strong nonlinear temporal patterns. Since even flattened sequential representations substantially improved prediction performance, it is highly likely that preserving the complete temporal structure through recurrent neural networks would lead to additional performance gains.

Furthermore, classical machine learning models exhibit several scalability limitations when applied to larger or more complex sequential datasets. KNN prediction complexity increases with dataset size, while SVR training complexity grows significantly for large-scale datasets. In contrast, LSTM networks can learn generalized temporal representations that scale more effectively with increasing sequence complexity and sensor dimensionality.

Another important limitation of flattened classical machine learning approaches is the loss of contextual temporal relationships. In flattened representations, adjacent timesteps become separated individual features without explicit temporal continuity. Consequently, the model cannot directly learn transition dynamics such as occupancy increase rates, temporal periodicity, or behavioral movement sequences. LSTM networks overcome this limitation by maintaining recurrent hidden states that continuously evolve across time.

From a smart building perspective, accurate occupancy estimation is essential for energy optimization, HVAC control, indoor comfort management, and intelligent automation systems. In these applications, prediction robustness and temporal adaptability are critical. Since LSTM networks are capable of continuously learning occupancy evolution patterns over time, they are particularly suitable for real-world deployment in dynamic indoor environments.

Overall, the findings of this study strongly suggest that LSTM-based architecture represents a promising direction for future occupancy estimation research. While classical machine learning models provide useful baseline performance, recurrent deep learning approaches are expected to achieve superior accuracy by fully exploiting temporal dependencies, nonlinear sequence dynamics, and long-term occupancy behavior patterns inherent in environmental sensor data.

3. DATASET

The experimental testbed for occupancy estimate was established in a room measuring 6m by 4.6m. The arrangement had seven sensor nodes and one edge node arranged in a star topology, with the sensor nodes transferring data to the edge node every 30 seconds using wireless transceivers. Sensor nodes S1-S4 were equipped with temperature, light, and sound sensors; S5 included a CO2 sensor, while S6 and S7 each featured a PIR sensor, all positioned on ceiling ledges at an angle to optimize the field of vision for motion detection. The data was systematically gathered over a span of four days, with room occupancy fluctuating between zero and three individuals. The accurate occupancy count in the room was recorded manually (Singh et al., 2018).

The model output is the occupancy number of the next timestamp based on the 10 previous instances. 80 % of data is used for training and validation, 20% is used for test process.

4. ML REGRESSION MODELS FOR SEQUENTIAL OCCUPANCY ESTIMATION

4.1. Regression Performance Comparison

Five popular ML regression models are taken into account for occupancy estimation using flattened sequential environmental sensor data. The models include Linear Regression (LR) (Lu et al., 2024) , Decision Tree (DT) (Tsang, Kao, Yip, Ho, & Lee, 2011),

Random Forest (RF) (Li et al., 2025), Support Vector Regression (SVR), and KNN. The input data were constructed using a sliding-window sequence approach in which the previous 10 timesteps were utilized to predict the next occupancy value.

Table 1 summarizes the quantitative performance comparison using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and coefficient of determination (R^2 score).

Table 1. ML models Comparison Metrics

Model	MAE	MSE	RMSE	R^2 Score
Linear Regression	0.20	0.43	0.66	0.48
Decision Tree	0.17	0.48	0.69	0.43
Random Forest	0.21	0.40	0.63	0.53
SVR	0.10	0.11	0.34	0.86
KNN	0.11	0.15	0.39	0.81

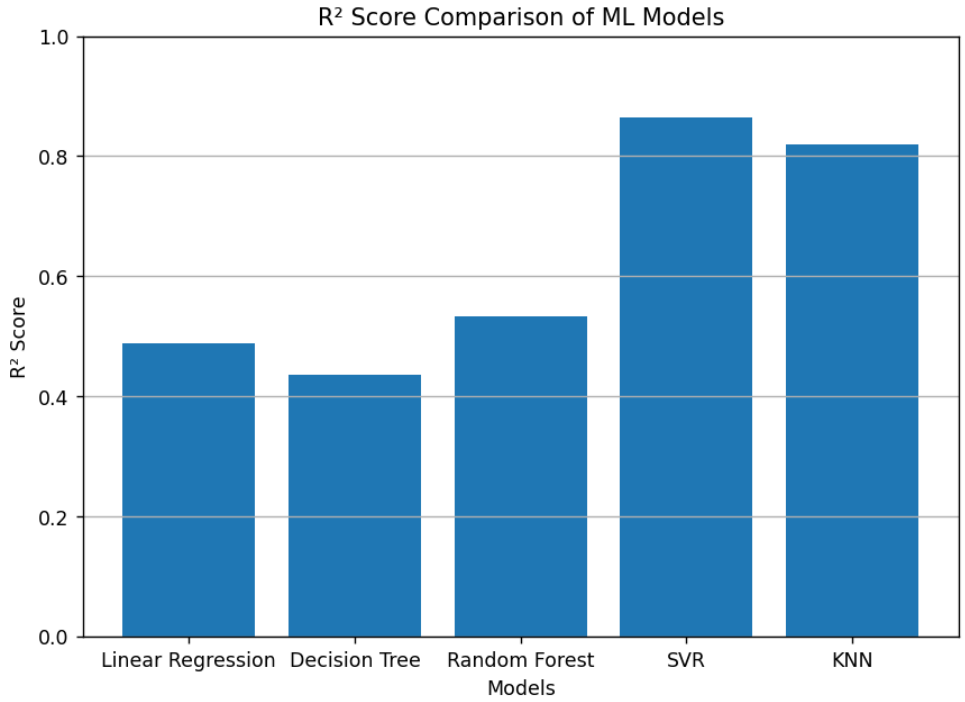


Figure 1. R^2 score chart of ML models

Among the evaluated regression models, SVR achieved the best predictive performance for occupancy estimation using flattened sequential sensor data. SVR obtained the highest coefficient of determination (R^2 = 0.86) and the lowest prediction errors (MAE = 0.101, RMSE = 0.341), demonstrating strong capability in modeling nonlinear temporal dependencies present in occupancy dynamics.
The R^2 score indicates the proportion of variance in occupancy behavior successfully explained by the regression model. The SVR model achieved an R^2 value of 0.86, meaning that approximately 86 % of occupancy variability was captured by the learned nonlinear mapping between sequential sensor patterns and occupancy levels.

The superior performance of SVR indicates that occupancy estimation exhibits complex nonlinear relationships and temporal correlations that cannot be effectively captured by linear regression models or individual decision trees. K-Nearest Neighbors (KNN) also achieved strong performance (R^2 = 0.820), suggesting the presence of repetitive occupancy patterns and locally similar temporal behaviors within the dataset. In contrast, Linear Regression and Decision Tree models showed significantly lower predictive accuracy, confirming that occupancy prediction from environmental sensor sequences is inherently nonlinear and sequence-dependent. These findings demonstrate the importance of temporal feature engineering and nonlinear machine learning techniques for intelligent occupancy estimation systems.

4.2. Analysis of Support Vector Regression Performance

The superior performance of SVR can be attributed to its capability to model nonlinear relationships through the radial basis function (RBF) kernel. Occupancy estimation is inherently nonlinear due to complex interactions among environmental variables such as temperature, humidity, illumination, and CO2 concentration. These variables do not exhibit simple linear relationships with occupancy count.

Moreover, occupancy dynamics are strongly time-dependent. Human movement and occupancy transitions typically follow smooth temporal trajectories rather than abrupt random changes. By utilizing the previous 10 timesteps as input features, the sequential representation preserves short-term temporal dependencies and occupancy evolution patterns. SVR effectively captures these nonlinear temporal correlations through kernel-based feature transformation.

The low MAE value of 0.10 indicates that the average prediction error is approximately 0.1 occupants, demonstrating very high prediction precision after integer rounding. Furthermore, the low RMSE value of 0.34 suggests that the SVR model produces stable predictions with very limited large-error deviations.

The small difference between MAE and RMSE also confirms prediction consistency. Since RMSE penalizes large errors more heavily than MAE, the relatively close values indicate that SVR rarely produces extreme prediction failures.

4.3. Analysis of K-Nearest Neighbors Performance

KNN achieved the second-best performance with an R^2 score of 0.82, demonstrating strong predictive capability for occupancy estimation. The success of KNN suggests that occupancy behavior within the dataset exhibits repetitive temporal patterns and locally similar trajectories.

KNN operates by identifying neighboring sequential patterns within the feature space. In occupancy estimation scenarios, similar environmental conditions and recent occupancy histories often lead to similar future occupancy states. Therefore, KNN benefits from repeated occupancy cycles commonly observed in indoor environments such as classrooms, laboratories, offices, and meeting rooms.

The low MAE and RMSE values obtained by KNN confirm that local similarity-based prediction is highly effective for this dataset. However, KNN may face scalability limitations when applied to larger datasets because prediction complexity increases proportionally with the number of training samples.

4.4. Analysis of Random Forest Performance

Random Forest achieved moderate predictive performance with an R^2 score of 0.53. Although Random Forest is capable of modeling nonlinear relationships, its performance remains significantly lower than SVR and KNN for sequential occupancy prediction.

This behavior can be explained by the nature of flattened sequential features. While flattening preserves historical sensor values, tree-based models do not explicitly capture temporal continuity or sequential evolution. Instead, Random Forest treats each flattened feature independently during decision splitting. Consequently, temporal relationships among consecutive timesteps are partially lost during model learning.

Nevertheless, Random Forest still outperformed Linear Regression and Decision Tree models, indicating the presence of nonlinear interactions among environmental sensor variables.

4.5. Analysis of Linear Regression Performance

Linear Regression produced relatively weak performance with an R^2 score of 0.488. This result demonstrates that linear assumptions are insufficient for accurately modeling occupancy dynamics.

Occupancy estimation involves highly nonlinear phenomena influenced by environmental interactions, temporal dependencies, and human behavioral patterns. Linear Regression assumes a direct linear mapping between input variables and occupancy values, which limits its capability to represent complex temporal sensor relationships.

The relatively high RMSE value further indicates that the model frequently fails to accurately predict occupancy transitions and nonlinear occupancy fluctuations.

4.6. Analysis of Decision Tree Performance

Decision Tree achieved the lowest R^2 score among all evaluated models. Although the MAE value remains moderate, the RMSE value is considerably larger, indicating occasional large prediction deviations.

Single decision trees are prone to overfitting and often generate discontinuous decision boundaries. For sequential occupancy prediction, such discontinuities reduce the model's ability to generalize smooth temporal occupancy evolution.

The large difference between MAE and RMSE suggests that while most predictions remain reasonably close to ground truth values, the Decision Tree model occasionally produces significantly incorrect occupancy estimations.

4.7. Overview of ML Model Performance

Overall, comparative analysis demonstrates that Support Vector Regression is the most suitable classical machine learning model for occupancy estimation using flattened sequential sensor data. SVR consistently achieved the best performance across all evaluation metrics due to its ability to model nonlinear temporal dependencies and smooth occupancy transitions. Although classical machine learning models such as SVR and KNN achieved strong performance, they still rely on flattened sequential inputs, which partially lose the inherent

temporal structure of occupancy data. Occupancy estimation is fundamentally a time-series problem where current occupancy depends on previous environmental conditions and historical occupancy patterns.

LSTM networks are specifically designed for sequential learning and can preserve temporal dependencies through recurrent memory mechanisms. Unlike classical regression models, LSTM processes sensor data in chronological order, enabling the model to learn occupancy evolution, delayed environmental responses, and long-term behavioral patterns more effectively.
The strong performance improvement observed when using previous timesteps in this study indicates that temporal information plays a critical role in occupancy prediction. Therefore, LSTM-based architectures are expected to further improve prediction accuracy by fully exploiting nonlinear temporal dynamics and sequential correlations inherent in environmental sensor data.

5. LSTM MODEL

LSTM handles sequential data and long-term dependencies. LSTM can remember information for long periods, making them ideal for time series forecasting.
The developed model uses LSTM layers to predict room occupancy based on past sensor readings and the Each LSTM unit consists of following components:

- Cell State: The memory that preserves long-term information.
- Hidden State: The short-term memory output passed to the next step.
- Three Gates:
    - Forget gates decide what past information should be forgotten.
    - Input gate decides what new information should be added.
    - Output gate decides what the next hidden state should be.

Each gate uses a sigmoid activation function (σ), which outputs values between 0 and 1 to determine how much information should pass through.

5.1. Model structure and training

As demonstrated in Figure 2, the first LSTM layer, which has 50 units and a Rectified Linear Unit (ReLU), captures sequential dependencies and passes them to the next LSTM layer.

The second LSTM Layer with 50 units and ReLU activation extracts deeper time-based features.

Dense Layer with 25 neurons and ReLU activation learns additional patterns. The final Dense Layer (1 neuron, no activation) outputs a single numerical value (predicted occupancy).

The model training includes the optimizer, which is an adaptive learning rate. Loss function means squared error, which is suitable for regression.

- Epoch number is 100, which is fine-tuning required to avoid overfitting).
- Batch Size is 16 for balancing training speed and performance.
- Predictions are rounded to ensure integer values for occupancy.

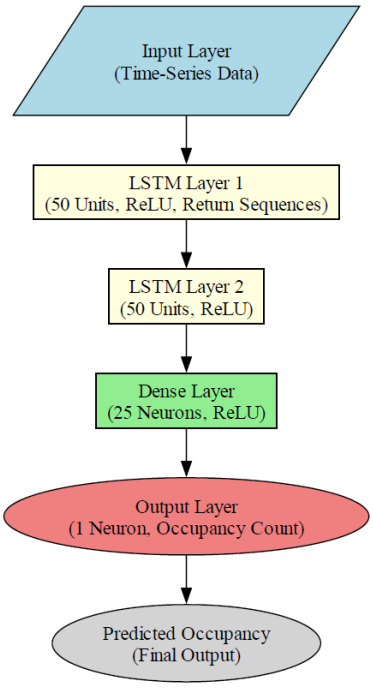


Figure 2. LSTM designed structure

5.2. Rolling forecast function

A rolling forecast approach is employed to generate multi-step-ahead predictions by iteratively using the model's output as input for subsequent time steps. The forecasting function operates as follows:

Step 1: The model extracts the last observed sequence from the test dataset as the last sequence.

Step 2: The iterative prediction is processed. It uses the trained LSTM model to predict the next occupancy value. Then, the predicted value is appended to the predictions list. The input sequence is updated by shifting all values left and inserting a smoothed value based on past data.

Smooth strategy can be applied as a stabilization technique to reduce noise and prevent extreme fluctuations in the predicted sequence. If the raw prediction were used directly, the model might accumulate errors as it rolls forward, leading to drift or instability. In this case, the rolling LSTM model was trained using sequences of 10 previous time steps to predict the next occupancy value.

However, in the rolling forecast, the input sequence is shifted left after making a prediction, and the newest row (the last row) is updated with a smoothed value instead of the direct prediction. The smoothed value here is the average of the last 3 rows of the sequence

Step 3: System returns the final predictions. Depending on the set-up prediction steps, 120 iterations are required for 60 minutes since new data is acquired every 30s. After completing 120 iterations, the predicted occupancy values are returned as an array.

6. RESULTS AND ANALYSIS OF LSTM MODEL

6.1. Training and validation

The model output is the occupancy number of the next timestamp based on the 10 previous instances. Figure 3 shows the training loss and validation loss of 100 training epochs. After the significant transition in the 1st period, the training loss is reduced drastically. After 20 episodes, both training and validation loss are minimized with small MSE, which demonstrates that the LSTM model was trained properly. At the epoch 100, the Mean Squared Error (MSE) of training and validation are around 0.

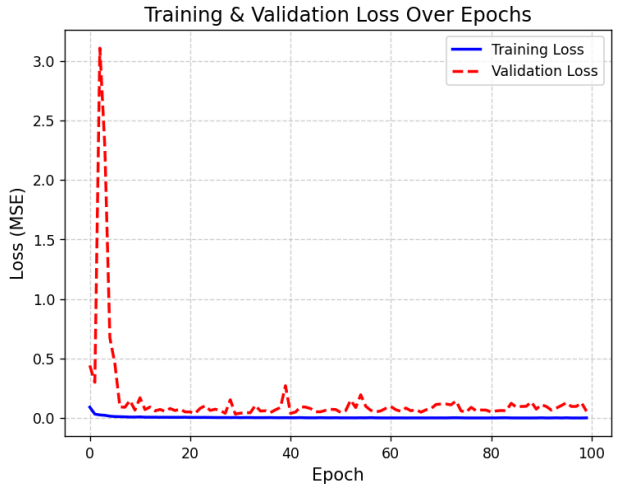


Figure 3. Training and Validation Loss over Epochs

6.2. Test process

Table 2 reports the errors of the model and R^2 which is a statistical measure that represents the goodness of fit of a regression model. Small value of MAE and MSE indicate the model successfully predicts the future value properly. MAE reflects the average error in predicting the number of people in a room at any given time. A low MAE indicates that the model's predictions are generally close to the actual occupancy values. An MAE of 0.03 implies that, on average, the predicted number of people is off by 0.03 individuals.

MSE provides an understanding of the error quantity in the model but places a higher penalty on more significant discrepancies between the predicted and actual values. The MSE of 0.04 indicates that the error is relatively small on average but emphasizes larger mistakes more than MAE.

R^2 indicates how well the independent variables (sensor data) explain the variance in the target variable (occupancy). An R^2 value of 0.94 means that the sensor data can explain 94% of the variance in occupancy predictions, which is a strong indicator of the model's predictive power.

Table 2. Metric Evaluation of LSTM model

Metric Evaluation	Value
MAE	0.03
MSE	0.04
R^2	0.94

Figure 4 shows the prediction of the model and the actual data in test dataset. The model correspondingly predicts to the actual data, with only a few mismatches.

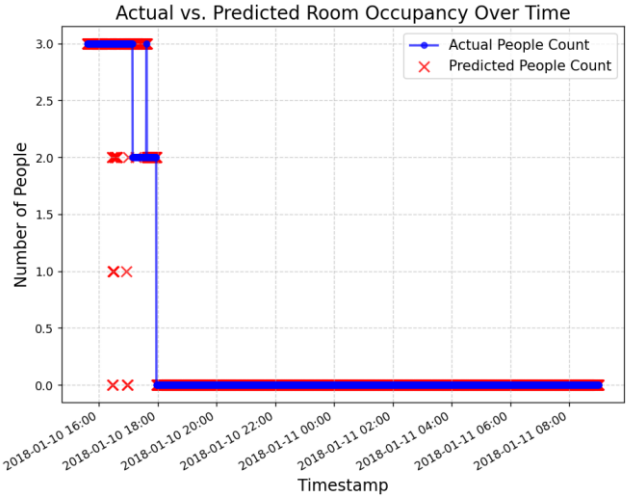


Figure 4. Actual and forecast room occupancy over time

Comparing with the best ML model (SVR), the experimental results clearly demonstrate that the LSTM model significantly outperformed the best classical machine learning approach across all evaluation metrics

Table 3. Comparison between MLmodel and LSTM model

Model	MAE	MSE	R^2 Score	
SVR (Best Classical ML)	0.10	0.11	0.86	
LSTM	0.03	0.04	0.94	

The LSTM model achieved a Mean Absolute Error (MAE) of 0.03, which represents a substantial reduction compared to the SVR model (MAE = 0.10). This indicates that the average prediction deviation produced by LSTM is extremely small, corresponding to highly accurate occupancy estimation. Similarly, the Mean Squared Error (MSE) was reduced from 0.116 in SVR to 0.04 in the LSTM model. Since MSE penalizes large prediction errors more heavily, this result confirms that

LSTM produces more stable predictions with fewer extreme deviations. The most significant improvement is observed in the coefficient of determination (R^2 score). The LSTM model achieved an R^2 value of 0.94, indicating that approximately 94% of occupancy variability was successfully explained by the learned temporal model. In comparison, SVR explained approximately 86.4% of the variance. This improvement demonstrates the superior capability of LSTM in learning complex temporal occupancy dynamics.

The performance gain can be attributed to the fundamental architectural differences between classical machine learning models and recurrent neural networks. In the SVR approach, sequential sensor observations were flattened into static feature vectors before regression. Although this strategy partially preserves historical information, it does not explicitly maintain temporal continuity among consecutive timesteps. The superior performance of the LSTM model strongly suggests that occupancy estimation is fundamentally a sequential learning problem rather than a static regression task. The obtained results demonstrate that preserving temporal structure and long-term sequence dynamics is essential for achieving highly accurate and robust occupancy estimation in intelligent indoor monitoring systems.

6.3. Rolling forecast

To validate long term forecast of the LSTM model. About the last 60 minutes of the data is removed from the training and testing time. These data are utilized to verify the long-term forecast function of the designed model, which will provide the predictions for the next hour, based on the last 10 instances of the sensor data. As shown in **Figure 5**, the LSTM model is able to forecast the same output with the actual data, demonstrating high potential ability in long-term performance.

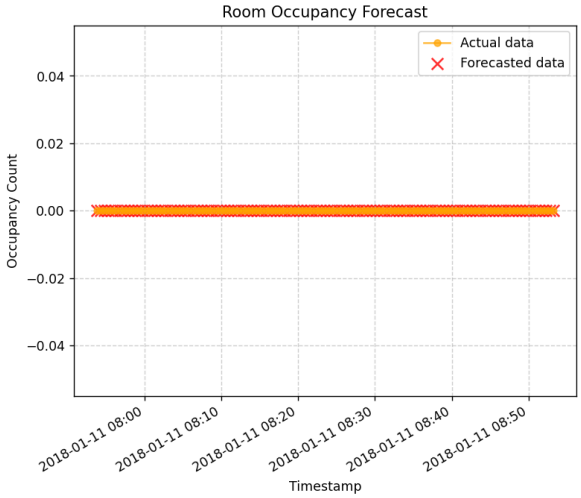


Figure 5. One hour forecast occupancy

7. CONCLUSION

This work successfully forecasted room occupancy using LSTM networks, leveraging sensor data for accurate predictions. The proposed model was trained on time-series data, where sensor readings were used to predict the number of people in a room over the next hour, employing a rolling forecasting strategy. The small errors demonstrate that the LSTM model is highly effective in predicting room occupancy, with high accuracy and a strong fit to the data. The model's performance not only meets the requirements for real-time forecasting but also demonstrates its potential for deployment in smart building systems and energy management, where accurate occupancy predictions are crucial.

In the future, the model will be involved with other applications with larger datasets to verify further the full capability of the developed LTSM model.

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Minh Long Hoang
Department of Engineering and
Architecture, University of Parma,
43124,
Parma,
Italy
minhlong.hoang@unipr.it
ORCID 0000-0002-3622-4327