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Contents

Introduction

This technical report describes the evaluation process of various machine learning algorithms' performance used for supervised binary classification for occupant detection, using a dataset from a residential building in the North of Denmark. It supports the publication of *Development and Application of an XGBoost-Based Occupant Detection Model for Residential Buildings Using Supervised Learning* (sent to review in Building & Environment September 2023) [1].

The dataset used to test the algorithms

The dataset used in this study is Dataset 1 from the following repository [2], and is further described in the open-access technical report: [3]

The parameters used for the occupant detection models are indoor CO_2 concentration, indoor air temperature, indoor relative humidity, room type, and hour and day of the week. The models are further described in the sections below.

Code for running the various algorithms

For the full code and documentation for both modeling approaches, see the following GitHub repository [2].

Selection of algorithms for binary classification

Machine learning can be explored by several approaches depending on the type of problem to be solved, see Figure 1. This specific problem is delimited to a room-based occupant presence or absence (interpreted as 0 or 1 with interpreted ground truth) binary supervised classification.

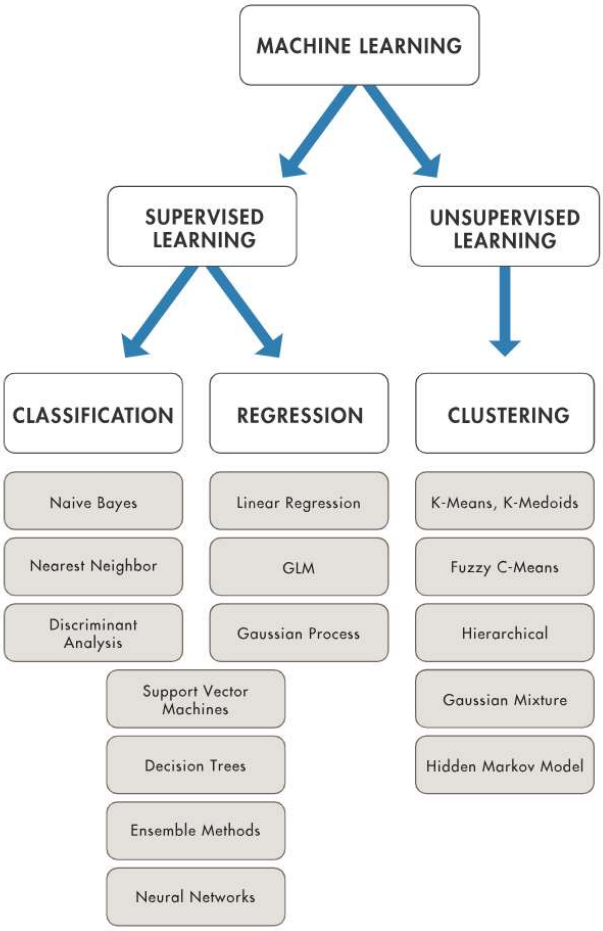

Figure 1: General overview of supervised- and unsupervised learning based on [4] [5].

Many unsupervised and supervised learning models have widely studied occupant detection problems in both residential- and non-residential buildings [6-10], [11, 12], [13]. The algorithms selected for this analysis were chosen based on 1) is tailored for supervised binary classification tasks, 2) what has existing literature explored earlier, 3) offer a diverse range of adjustable parameters and hyperparameters compatible with our dataset and 4) backed by comprehensive documentation and proven validation. Furthermore, it was important to consider the unique attributes of the dataset, the computational constraints, and the balance between model explainability and efficacy.

The choice of modeling approach often depends on the input data type (smart meter data, indoor environmental sensors, motion sensors, or others) and access to ground truth data. Supervised learning approaches use known inputs and output data. Here, classification or regression models are typically used. Existing algorithms in the literature are support vector machine (SVM), Naïve Bayes

(NB), Decision Trees (DTs), and Nearest Neighbour (NN). For supervised learning, labeled data (output) is necessary for testing the performance of the models. Traditional unsupervised learning approaches aim to find patterns, correlations, or structures in the input data. Hidden Markov Models, K-Means, and Hierarchical or physic-based algorithms are also used for occupant detection modeling. However, ground truth is always used to validate the developed method for this problem. [5] [14].

In the existing peer-reviewed (Scopus-indexed) literature with a focus on algorithms used for occupant detection in residential buildings, the following key algorithms were found (See Appendix) out of 19 articles:

- Support Vector variations or combinations were found in 9 articles
- Random Forest variations or combinations were found in 7 articles
- Variations of Neural Networks were used 6 times
- Gradient Boosting variations were used 5 times
- k-Nearest Neighbour was used 5 times
- Decision Tree variations were used 4 times
- Logistic Regression was used 2 times
- Naïve Bayes was used 2 times
- Other variations of algorithms found were Principal Component Analysis, expert systems (thresholds), and other unsupervised algorithms (Hidden Markov Models).

Supervised learning is predominantly used, as it was found in 12 out of 19 articles.

Therefore, the following algorithms were selected to be further tested with the selected dataset:

- Support Vector Machine
- Logistic Regression
- Random Forest
- k-Nearest Neighbor
- Naive Bayes
- XGBoost

The Decision Tree algorithm and Neural Network are neglected as it does not meet the criteria above.

A short outline of each algorithm is presented below [15, 16].

- **Logistic Regression (LR):** It models the relationship between the input features and the probability of the target class using a logistic function.
- **Support Vector Machine (SVM):** It finds an optimal hyperplane that separates the two classes by maximizing the margin between them.
- **Random Forest (RF):** Random Forest is an ensemble learning method that combines multiple decision trees. Each tree is trained on a random subset of features, and the final prediction is based on the majority vote of the trees.
- **k-Nearest Neighbor (kNN):** kNN is a type of instance-based learning method. The algorithm operates on the premise that similar instances will likely have similar outcomes. It finds the 'k' most similar instances in the training set for a given input and predicts based on their outcomes.
- **Naive Bayes (NB):** Naive Bayes is a probabilistic classifier based on Bayes' theorem. It assumes independence between features, given the class label.
- **Gradient Boosting Models (GBM):** Gradient boosting models, such as XGBoost, are powerful ensemble methods that combine multiple weak learners (decision trees) to make accurate predictions.

Table 1 describes a general overview of the selected algorithms for binary classification categorized by pros and cons [17, 18].

Table 1: General overview of the selected algorithms for binary classification categorized by pros and cons.

Algorithm	Pros	Cons	References
Logistic Regression (LR)	• Interpretable results (f.ex. odd ratios) • In general, fast training and prediction • Typically works well with small to medium-sized datasets • Less prone to overfitting with regularization with smaller number of features	• It may not capture complex relationships in the data • Can be sensitive to irrelevant or highly correlated features • Assumes a linear relationship between features and the target, which may not always be true • May underperform with non-linear data	[19, 20] [5]
Support Vector Machine (SVM)	• Effective in high-dimensional spaces • Works well with a clear margin of	• Computational complexity scales with the number of samples • Requires appropriate kernel	[17, 19, 20]

	separation • Can be robust to overfitting with regularization • Effective with small to medium-sized datasets • Can handle non-linear relationships with kernel tricks	selection • Training and tuning time can be high for large datasets • Generally memory-intensive for large datasets • It can be difficult to interpret the resulting models (non-linear kernels) • Can be sensitive to noise	
Random Forest (RF)	• Can handle high-dimensional data • Can capture complex feature interactions • Robust to outliers (due to averaging mechanism) • Can handle imbalanced datasets (f.ex. bootstrapping) • It might not require extensive feature engineering	• May overfit with noisy data • Longer training time compared to some algorithms (due to the necessity to train multiple trees) • Can lack interpretability compared to linear models due to the ensemble method of trees • It may require tuning for optimal performance	[21, 22]
k-Nearest Neighbor (kNN)	• Simple and easy to understand • There are no assumptions about the data distribution, making it useful for non-linear data • Can perform well with a sufficient number of data points • Model training is generally faster as it simply stores instances of the training data	• It can be computationally expensive and slow during the prediction phase, especially with large datasets • Sensitive to the scale of the data and irrelevant features • It needs appropriate choice of 'k' and the distance metric • Performance can degrade with high-dimension data (curse of dimensionality) • There is no model interpretability, as there is no explicit learning phase	[23]
Naïve Bayes (NB)	• Can have a fast training and prediction phase • Can perform well with high-dimensional data • Handles irrelevant features well (due to the probabilistic nature) • Can work well with small to medium-sized datasets • Low memory	• Assumes independence between features • It may not capture complex relationships (due to the naïve assumption) • It relies on the strong independence assumption • May underperform when independence assumption is violated	[24]

	footprint		
Gradient Boosting Models (GBM)	• Known for high performance and accuracy (if applied correctly) • Can handle imbalanced datasets (functions and hyperparameters) • It has a built-in feature importance analysis • Has parallel processing for scalability • It has a wide range of hyperparameters for the customization of model	• It can require more hyperparameter tuning compared to some other models • It can be computationally expensive with large datasets • Can require more data for training compared to simpler models • Less interpretable compared to simpler models (due to the ensemble and layers of decision trees)	[21, 25, 26]

Chosen performance metrics

The nine selected performance metrics are outlined below. An outline of the reasoning for these performance metrics can be seen in the [1].

1. **Accuracy [%]**

Calculated as the count of correct predictions over total number of predictions [27]:

$$\boldsymbol{Accuracy} = \frac{\mathbf{1}}{\boldsymbol{n_{samples}}} \sum_{\boldsymbol{i=0}}^{\boldsymbol{n_{samples}-1}} \mathbf{1}(\hat{\boldsymbol{y}}_{\boldsymbol{i}} = \boldsymbol{y}_{\boldsymbol{i}})$$

$$y_i = \text{Ground truth occupancy}$$
$$\hat{y}_i = \text{Predicted occupancy label}$$

2. **Confusion matrix**

The confusion matrix function evaluates classification accuracy by computing the confusion matrix with each row corresponding to the true class [28]. Figure 2 shows the confusion matrix and the classification of the predicted and actual classes.

		Predicted	
		Negative (N)	**Positive (P)**
Actual	**Negative**	True Negatives (TN)	False Positives (FP)
	Positive	False Negatives (FN)	True Positives (TP)

Figure 2: Confusion matrix example.

TP = The number of cases correctly predicted as positive

TN = The number of cases correctly predicted as negative

FP = The number of negative cases incorrectly predicted as positive

FN = The number of positive cases incorrectly predicted as negative

3. **Balanced accuracy [%]**

Calculated as the arithmetic mean of sensitivity (true positive rate) and specificity (true negative rate) [29, 30]:

$$\boldsymbol{Balanced\ accuracy} = \frac{\mathbf{1}}{\mathbf{2}} * \left(\frac{\boldsymbol{TP}}{\boldsymbol{TP + FN}} + \frac{\boldsymbol{TN}}{\boldsymbol{TN + FP}}\right)$$

4. **Precision [%]**

Calculated as the true positives divided by the true positives and the false positives [31]:

$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FP}}$$

5. **Recall [%]**

Calculated as the true positives divided by the true positives and the false negatives [32]:

$$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FN}}$$

6. **F1-score**

The F1 score can be interpreted as a harmonic mean of the precision and recall [33]. It ranges from 0 (bad prediction performance) to 1 (perfect prediction performance):

$$\boldsymbol{F1} = \mathbf{2} * \frac{(\boldsymbol{Precision} * \boldsymbol{Recall})}{(\boldsymbol{Percision} + \boldsymbol{Recall})}$$

7. **Matthew's correlation coefficient (MCC)**

The MCC is, in essence, a correlation coefficient value between -1 and +1. A coefficient of +1 represents a perfect prediction, 0 is a random prediction and -1 an inverse prediction [34, 35]:

$$\boldsymbol{MCC} = \frac{(\boldsymbol{TP} * \boldsymbol{TN}) - (\boldsymbol{FP} * \boldsymbol{FN})}{\sqrt{(\boldsymbol{TP + FP})(\boldsymbol{TP + FN})(\boldsymbol{TN + FP})(\boldsymbol{TN + FN})}}$$

8. Area Under the Receiver Operating Characteristic Curve (AUROC)

A receiver operating characteristic (ROC), or simply ROC curve, is a graphical plot that illustrates the performance of a binary classifier system as its discrimination threshold is varied. The ROC curve is plotted with the True Positive Rate (TPR), or Sensitivity, against the False Positive Rate (FPR) or 1 minus the Specificity, where TPR is on the y-axis and FPR is on the x-axis. AUC, or Area Under the Curve, is the area under the ROC curve. It represents the degree or measure of separability, indicating how well the model can distinguish between classes. [36, 37]. A 0 AUROC score corresponds to a poor prediction and a 1 AUROC score corresponds to a perfect prediction.

9. Briar-score loss [0-1]

The Brier score measures the mean squared difference between the predicted probability and the actual outcome [38]. The lower the Briar-score loss, the better the prediction:

$$\boldsymbol{Brier - score\ loss} = \frac{\mathbf{1}}{\boldsymbol{n\ samples}} * \sum_{\boldsymbol{i=0}}^{\boldsymbol{nsamples^{-1}}} * \boldsymbol{(y_i - p_i)^2}$$

$$y_i = \text{ actual outcome}$$
$$p_i = \text{ predicted probability estimate}$$

Modeling framework

This modeling framework consists of a basic application of each algorithm in Python 3.11 on SPYDER 5 without any parameter or hyperparameter optimization. The Scikit-learn library was used for these model implementations [39]. The computer specifications for running the models were the following: Intel Core i7-10510U CPU and 16GB of RAM.

Two different modeling approaches are applied. One **generalized model** consisting of the following 12 parameters:

1. CO_2 concentration [ppm]
2. Indoor air temperature [°C]
3. Relative humidity [%]
4. Room type, one-hot-encoded (5 rooms)
5. Day of the week (cycled encoded) (two encodings)
6. Hour of the day (cycled encoded) (two encodings)

Each **room-based model** consists of the following 7 parameters:

1. CO_2 concentration [ppm]
2. Indoor air temperature [°C]
3. Relative humidity [%]
4. Day of the week (cycled encoded) (two encodings)
5. Hour of the day (cycled encoded) (two encodings)

For the generalized model, a 10-fold grouped shuffle split cross-validation [40] was conducted for all models, grouping days consistently within different folds across all models. Whereas for each room-based model, a 5-fold stratified grouped shuffle split cross-validation [41] was conducted with the aim to have balanced folds across the splits and also due to the smaller amount of data points and variations of data characteristics of the room types.

The split of the model selection and model evaluation is 80 % and 20 %, respectively. This cross-validation type was performed as the aim is to perform hyperparameter optimization after the

evaluation of the algorithms. The reproducibility seed for all models is denoted as random_state = 42.

Figure 3 shows the overview of the cross-validation procedure.

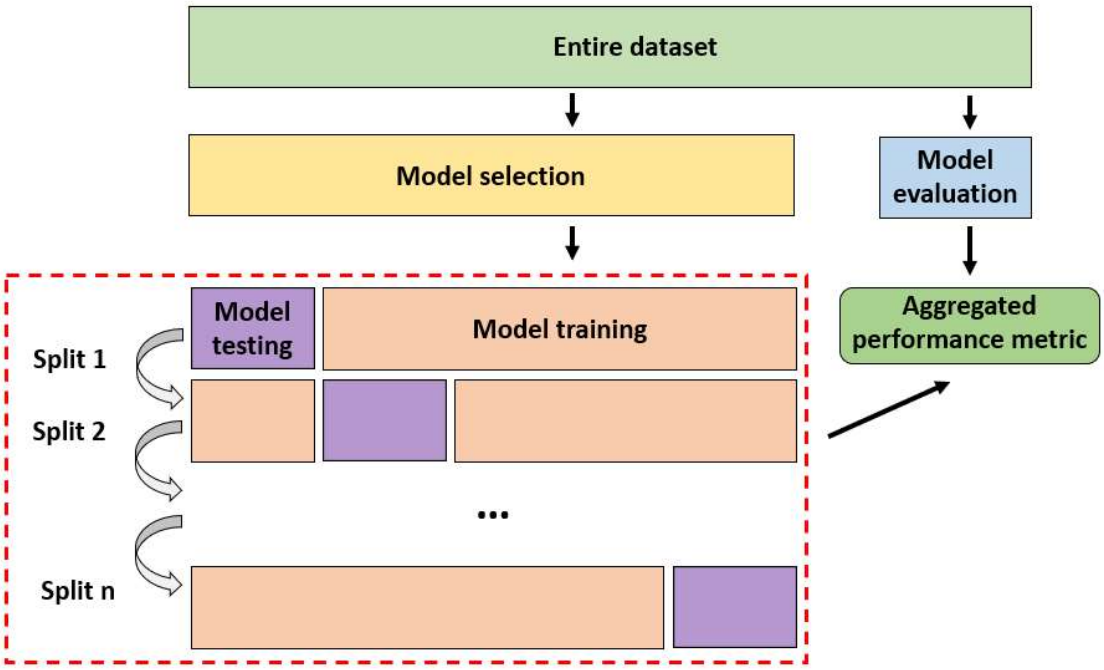

Figure 3: Cross-validation procedure for the modeling.

Generalized model performance

The generalized model's algorithm modeling results can be found in Table 2 to Table 4, where algorithms are arranged from left to right based on their performance. Due to the imbalance of the majority/minority class of the dataset, particular emphasis was placed on balanced accuracy, MCC, precision, recall, and the F1-score to ensure a more robust evaluation of model performance. The second line under each result is the standard deviation of the 10-fold.

1. CO_2 concentration, air temperature, and relative humidity

Table 2: Results of the occupant detection modeling performance metrics for the generalized model using CO2 concentration, air temperature, and relative humidity (average performance of 10-fold grouped shuffle split). The standard deviation is placed below the performance metric.

Model / perform. And evaluat. metric	Support Vector Machine	k-Nearest Neighbor	Naïve Bayes	Logistic Regression	XGBoost	Random Forest
Accuracy	75 % 2.7 %	78 % 0.020	80 % 2.1 %	81 % 2.1 %	88 % 0.9 %	90 % 0.9 %
Balanced accuracy	54 % 2.2 %	69 % 0.031	70 % 3.8 %	68 % 6.9 %	81 % 2.5 %	83 % 2.8 %
Confusion matrix	[1593 27] [533 59]	[1440 179] 299 293]	[1475 145] [306 286]	[1534 86] [341 250]	[1535 84] [191 401]	[1562 57] [174 417]
Precision	75 % 18 %	62 % 4.9 %	67 % 6.8 %	76 % 6.8 %	82 % 2.7 %	88 % 2.2 %
Recall	10 % 5 %	49 % 8.5 %	47 % 10 %	41 % 10 %	67 % 6.2 %	69 % 6.3 %
F1-score	0.16 0.077	0.54 0.058	0.55 0.066	0.52 0.066	0.74 0.036	0.77 0.039
MCC	0.19 0.070	0.41 0.051	0.44 0.051	0.45 0.051	0.66 0.032	0.72 0.035
AUC-ROC	0.72 0.050	0.76 0.022	0.77 0.033	0.78 0.033	0.92 0.016	0.93 0.017
Brier score loss	0.17 0.012	0.16 0.012	0.17 0.015	0.15 0.015	0.09 0.007	0.08 0.005
Comp. time	249 seconds	1.5 seconds	0.6 seconds	1.6 seconds	5.7 seconds	6.9 seconds

2. CO_2 concentration and air temperature

Table 3: Results of the occupant detection modeling performance metrics for the generalized model using CO_2 concentration and air temperature (average performance of 10-fold grouped shuffle split). The standard deviation is placed below the performance metric.

Model / perform. and evaluat. metric	Support Vector Machine	k-Nearest Neighbor	Naïve Bayes	Logistic Regression	XGBoost	Random Forest
Accuracy	75 % 2.6 %	82 % 0.016	80 % 1.9 %	81 % 2.3 %	88 % 1.2 %	89 % 0.8 %
Balanced accuracy	54 % 2.1 %	73 % 0.035	70 % 3.9 %	70 % 3.5 %	83 % 3 %	83 % 2.2 %
Confusion matrix	[1594 26] [534 58]	[1485 134] [267 325]	[1478 142] [309 283]	[1543 77] [333 259]	[1526 94] [169 423]	[1554 66] [174 418]
Precision	0.75 0.184	0.70 0.043	0.68 0.072	0.77 0.086	0.81 0.040	0.86 0.022
Recall	0.09 0.049	0.54 0.086	0.47 0.112	0.43 0.075	0.70 0.065	0.70 0.05
F1-score	0.16 0.075	0.61 0.062	0.54 0.068	0.55 0.073	0.76 0.046	0.77 0.030
MCC	0.19 0.069	0.50 0.056	0.44 0.050	0.47 0.072	0.68 0.048	0.71 0.026
AUC-ROC	0.72 0.056	0.81 0.025	0.77 0.034	0.78 0.042	0.93 0.013	0.93 0.019
Brier score loss	0.17 0.012	0.14 0.011	0.17 0.015	0.14 0.011	0.088 0.007	0.08 0.006
Comp. time	181.45 seconds	1.42 seconds	0.47 seconds	1.60 seconds	7.43 seconds	6.48 seconds

3. CO_2 concentration and relative humidity

Table 4: Results of the occupant detection modeling performance metrics for the generalized model using CO_2 concentration and relative humidity (average performance of 10-fold grouped shuffle split). The standard deviation is placed below the performance metric.

Model / perform. and evaluat. metric	Support Vector Machine	k-Nearest Neighbor	Naïve Bayes	Logistic Regression	XGBoost	Random Forest
Accuracy	75 % 2.6 %	78 % 0.019	80 % 2.1 %	80 % 1.7 %	88 % 1.4 %	89 % 1.1 %
Balanced accuracy	54 % 2.2 %	68 % 2.6 %	70 % 4 %	68 % 4.6 %	81 % 2.6 %	82 % 2.5 %
Confusion matrix	[1593 27] [533 60]	[1434 182] [306 285]	[1478 142] [298 294]	[1521 100] [334 258]	[1542 78] [192 400]	[1554 66] [184 408]
Precision	0.74 0.183	0.61 0.050	0.68 0.069	0.73 0.074	0.83 0.023	0.85 0.020
Recall	0.09 0.050	0.47 0.075	0.48 0.110	0.42 0.118	0.67 0.058	0.68 0.053
F1-score	0.17 0.077	0.53 0.051	0.56 0.070	0.53 0.091	0.74 0.035	0.76 0.036
MCC	0.19 0.070	0.39 0.044	0.45 0.054	0.44 0.066	0.67 0.034	0.70 0.035
AUC-ROC	0.72 0.056	0.76 0.021	0.77 0.033	0.80 0.033	0.93 0.011	0.92 0.019
Brier score loss	0.17 0.012	0.16 0.011	0.17 0.017	0.14 0.010	0.093 0.009	0.090 0.006
Comp. time	227.84 seconds	1.48 seconds	0.44 seconds	1.11 seconds	5.49 seconds	11.20 seconds

Room-based model performance

The results from the algorithm modeling for the room-based models can be found in Table 5 to Table 9, where algorithms are arranged from left to right based on their performance. Due to the imbalance of the majority/minority class of the dataset, particular emphasis was placed on balanced accuracy, MCC, precision, recall, and the F1-score to ensure a more robust evaluation of model performance. The second line under each result is the standard deviation of the 10-fold.

1. Bedroom model performance

Table 5: Results of the occupant detection modeling for the bedroom model performance metrics (average performance of 10-fold grouped shuffle split). The standard deviation is placed below the performance metric.

Model / perform. and evaluat. metric	Support Vector Machine	k-Nearest Neighbor	Naïve Bayes	Logistic Regression	XGBoost	Random Forest
Accuracy	78 % 3.5 %	78 % 3.8 %	89 % 3.3 %	92 % 1 %	93 % 1.5 %	94 % 1.5 %
Balanced accuracy	70 % 5.3 %	74 % 5.2 %	86 % 4.5 %	91 % 1.6 %	92 % 1.8 %	92 % 2 %
Confusion matrix	[428 12] [130 103]	[383 57] [91 142]	[427 13] [58 176]	[415 25] [28 206]	[420 14] [31 203]	[427 14] [29 204]
Precision	0.89 0.052	0.71 0.059	0.93 0.025	0.89 0.035	0.93 0.029	0.93 0.029
Recall	0.43 0.111	0.60 0.101	0.75 0.097	0.88 0.046	0.87 0.040	0.87 0.047
F1-score	0.58 0.109	0.65 0.080	0.83 0.065	0.88 0.013	0.90 0.018	0.90 0.030
MCC	0.52 0.091	0.49 0.096	0.77 0.067	0.83 0.020	0.85 0.029	0.86 0.031
AUC-ROC	0.79 0.064	0.80 0.058	0.97 0.006	0.97 0.004	0.98 0.006	0.98 0.006
Brier score loss	0.156 0.026	0.17 0.033	0.075 0.017	0.056 0.008	0.054 0.012	0.051 0.009
Comp. time	16.74 seconds	0.74 seconds	1.43 seconds	1.34 seconds	4.81 seconds	3.47 seconds

2. Kitchen / Living room model performance

Table 6: Results of the occupant detection modeling for the kitchen / living room performance metrics (average performance of 10-fold grouped shuffle split). The standard deviation is placed below the performance metric.

Model / perform. and evaluat. metric	Support Vector Machine	k-Nearest Neighbor	Naïve Bayes	Logistic Regression	XGBoost	Random Forest
Accuracy	67 % 7.3 %	62 % 4.7 %	78 % 3 %	76 % 4.4 %	84 % 2.4 %	85 % 3 %
Balanced accuracy	65 % 6 %	60 % 3.7 %	78 % 3.3 %	76 % 4.6 %	84 % 1.9 %	85 % 2.5 %
Confusion matrix	[63 58] [36 131]	[64 57] [53 114]	[94 28] [34 133]	[88 33] [34 133]	[110 21] [24 143]	[110 21] [21 146]
Precision	0.70 0.079	0.66 0.054	0.83 0.055	0.80 0.068	0.87 0.045	0.87 0.043
Recall	0.78 0.156	0.68 0.127	0.79 0.083	0.79 0.055	0.86 0.066	0.87 0.077
F1-score	0.72 0.093	0.66 0.081	0.81 0.032	0.79 0.051	0.86 0.027	0.87 0.036
MCC	0.33 0.135	0.21 0.075	0.56 0.069	0.52 0.090	0.70 0.045	0.71 0.055
AUC-ROC	0.71 0.061	0.66 0.040	0.87 0.040	0.86 0.040	0.92 0.025	0.93 0.022
Brier score loss	0.21 0.022	0.24 0.032	0.15 0.019	0.15 0.020	0.12 0.025	0.10 0.014
Comp. time	6 seconds	0.97 seconds	0.35 seconds	1.68 seconds	2.17 seconds	2.96 seconds

3. Living room model performance

Table 7: Results of the occupant detection modeling for the living room performance metrics (average performance of 10-fold grouped shuffle split). The standard deviation is placed below the performance metric.

Model / perform. and evaluat. metric	Support Vector Machine	k-Nearest Neighbor	Naïve Bayes	Logistic Regression	Random Forest	XGBoost
Accuracy	79 % 3.9 %	78 % 2.9 %	83 % 2.9 %	83 % 2.9 %	86 % 3.8 %	86 % 3.2 %
Balanced accuracy	50 % 0.3 %	61 % 2.9 %	66 % 7.5 %	67 % 6.2 %	73 % 5.1 %	77 % 5.1 %
Confusion matrix	[381 0] [99 0]	[345 36] [67 33]	[359 22] [58 41]	[354 27] [55 44]	[361 20] [48 51]	[352 29] [37 63]
Precision	0.2 0.400	0.47 0.103	0.69 0.122	0.64 0.096	0.72 0.088	0.69 0.071
Recall	0	0.32 0.075	0.38 0.183	0.42 0.159	0.51 0.104	0.62 0.117
F1-score	0	0.37 0.074	0.45 0.174	0.48 0.120	0.60 0.088	0.64 0.071
MCC	0	0.26 0.066	0.40 0.122	0.41 0.082	0.52 0.094	0.57 0.070
AUC-ROC	0.57 0.079	0.70 0.052	0.85 0.050	0.85 0.038	0.87 0.035	0.88 0.034
Brier score loss	0.15 0.001	0.16 0.016	0.11 0.018	0.11 0.015	0.10 0.021	0.11 0.028
Comp. time	7.09 seconds	0.99 seconds	0.74 seconds	1.13 seconds	3.66 seconds	2.37 seconds

4. Kitchen model performance

Table 8: Results of the occupant detection modeling of the kitchen performance metrics (average performance of 10-fold grouped shuffle split). The standard deviation is placed below the performance metric.

Model / perform. and evaluat. metric	Support Vector Machine	k-Nearest Neighbor	Naïve Bayes	Logistic Regression	Random Forest	XGBoost
Accuracy	81 % 4.6 %	77 % 4.9 %	78 % 4.1 %	80 % 4.4 %	79 % 4 %	78 % 3.5 %
Balanced accuracy	50 % 0	51 % 2.5 %	53 % 5 %	52 % 5.3 %	52 % 1.9 %	54 % 2.4 %
Confusion matrix	[391 0] [90 0]	[366 25] [82 8]	[365 27] [78 12]	[380 11] [86 1]	[376 16] [83 7]	[365 26] [77 13]
Precision	0	0.23 0.085	0.28 0.220	0.14 0.222	0.30 0.142	0.33 0.147
Recall	0	0.09 0.052	0.13 0.097	0.06 0.122	0.07 0.048	0.14 0.062
F1-score	0	0.13 0.058	0.17 0.127	0.07 0.147	0.10 0.064	0.20 0.072
MCC	0	0.03 0.071	0.09 0.138	0.05 0.128	0.06 0.065	0.11 0.070
AUC-ROC	0.57 0	0.57 0.040	0.74 0.062	0.71 0.067	0.71 0.050	0.68 0.042
Brier score loss	0.16 0.031	0.17 0.034	0.14 0.023	0.14 0.022	0.14 0.019	0.17 0.027
Comp. time	4.56 seconds	1.08 seconds	0.33 seconds	1.23 seconds	3.78 seconds	2.39 seconds

5. Office model performance

Table 9: Results of the occupant detection modeling of the office performance metrics (average performance of 10-fold grouped shuffle split). The standard deviation is placed below the performance metric.

Model / perform. and evaluat. metric	Support Vector Machine	k-Nearest Neighbor	Naïve Bayes	Logistic Regression	XGBoost	Random Forest
Accuracy	96 % 2.2 %	95 % 2.7 %	95 % 3.4 %	96 % 2.3 %	94 % 2.8 %	96 % 2.3 %
Balanced accuracy	50 % 0 %	50 % 1 %	56 % 8.3 %	50 % 0.1 %	49 % 1.8 %	53 % 4.3 %
Confusion matrix	[464 0] [2 0]	[456 0] [2 0]	[455 2] [2 1]	[464 0] [2 0]	[462 0] [2 0]	[460 1] [2 1]
Precision	0	0.11 0.190	0.16 0.175	0	0.01 0.046	0
Recall	0	0.013 0.020	0.15 0.182	0	0.01 0.035	0
F1-score	0	0.022 0.034	0.15 0.170	0	0.01 0.039	0
MCC	0	0.012 0.059	0.13 0.160	0	0	0.15 0.17
AUC-ROC	0.45 0.206	0.58 0.078	0.84 0.095	0.83 0.105	0.53 0.202	0.82 0.112
Brier score loss	0.040 0.020	0.047 0.022	0.040 0.024	0.038 0.021	0.051 0.026	0.040 0.022
Comp. time	2.22 seconds	0.71 seconds	0.37 seconds	0.67 seconds	1.07 seconds	2 seconds

Reflections

This technical report describes the evaluation of various algorithms' performance used for supervised binary classification for occupant detection using a dataset from a residential building in the North of Denmark. The following models were tested: Logistic Regression, Support Vector Machine, Random Forest, k-Nearest Neighbour, Naive Bayes, and XGBoost. Some reflections from the results of this technical report are presented below.

1. Algorithm performance and characteristics:

All models have varying performance, indicating that some algorithms do not have suitable characteristics or parameters for the chosen dataset. Furthermore, since there is no hyperparameter optimization, it makes the algorithm comparison less optimal but provides an indication of performance. However, some algorithms, such as Random Forest, are not directly sensitive to hyperparameters. Conversely, Support Vector Machine is very sensitive to hyperparameters, which can be reflected in the longer computational time (optimization of the kernel might be necessary).

2. Generalized model performance:
    - Three input variations were performed (solely CO_2 concentration, CO_2 concentration and relative humidity, and CO_2 concentration and air temperature). All three models have similar performance in all the various algorithms, varying from 54 % to 82 % balanced accuracy and from 0.19 to 0.72 MCC score.
    - The XGBoost and Random Forest models have the highest performance based on the performance metrics for all variations, and it is assumed that both algorithms are suitable for further modeling and exploration.

3. Room-based model performance:
    - There is a considerable variation in performance across the various algorithms. Generally, the models perform around 50 % to 93 % balanced accuracy and from 0 to 0.86 MCC score.
    - The bedroom room type-based model has the highest performance, while the office room type-based model has the poorest performance. Proper tuning might be required in some room-based models due to the data characteristics (imbalance ratio and internal correlations).
    - XGBoost and Random Forest have the highest performance based on the performance metrics, and it is assumed that both algorithms are suitable for further application.

However, XGBoost has a more extensive library for hyperparameter tuning than some of the other models and thus could be a suitable algorithm due to the varying room-based model performance.

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Appendix: Literature review

Table 10: Found literature (Scopus-indexed) on occupant detection in residential buildings.

Reference	Published	Sensor(s)	Scope / application	Learning approach	Type of ground truth data	Length of dataset	Data resolution	Model(s)	Dataset open access	Building level	Citations per August 2023
[42]	2022	CO2 concentration, air temperature and relative humidity	Develop a model	Supervised	Occupant survey	Two weeks	5 min.	CNN-XGBoost, CNN, XGBoost, Logistic Regression, Decision Tree, K-Nearest Neighbor, Random Forest, SV regression, K-means clustering, Gradient boosting	No	Room-based	2
[43]	2022	Air temperature, light, relative humidity, audio and images	Develop a model	Supervised	Uses dataset from [44], [45] and [46]	Uses dataset from [44], [45] and [46]	10 seconds to 8 kHz for audio	Occ.STPN, Random Forest, Few-shot model	[44] yes	Room-based	9
[47]	2017	Time User Survey data	Develop a model for occupancy forecast	Supervised	Motion sensor (PIR)	From 1 to four months	5 min.	Markov Model, Artificial Neural Network (ANN) and Support Vector Regression (SVR)	No	Room-based	73
[48]	2015	Power use of appliances and human-activated switching	Develop a model	Unsupervised but tested supervised algorithms	Google+ GPS module	Two months	10 seconds	Load curve data and readily-available appliance knowledge	No	Apartment-based	15

								Decision tree, SVM, KNN, Bayes			
[45]	2014	Power use	Development of a framework for non-intrusive monitoring	Semi-, unsupervised and supervised	Uses simulated, real and lab data (three diff. datasets) for the algorithms ECO: Tablet + PIR	- ECO: 8 months, 6 households	All datasets: 1 second	Parson, Baranski, Weiss and Kolter (HMM and clustering)	No ECO: Yes	Apartment-based	178
[49]	2017	Power use	Develop a model	Unsupervised	Uses dataset from [45]	Uses dataset from [45]	1 second	Base Learning (BL), Non-intrusive Learning (NL), and Transfer Learning (TL) SVM-PCA, Random Forest	-	Apartment-based	64
[50]	2013	Electricity use	Development of a NIOM framework	Unsupervised	Occupant actions and GPS (30 seconds ground truth)	Two household Not reported length?	Not reported?	Night as baseload, statistics	-	Apartment-based	88
[51]	2019	Electricity use	Test models with ECO, DRED and Smart* datasets	Supervised	See datasets	18 months 500 households Customer Behaviour Trials (CBT) in Ireland	30 minutes	Random Forests, Gradient Boosting, ANN, SVM, KNN	-	Apartment-based	91
[52]	2019	Thermostat data from Eco Bee (Donate you Data) Motion sensor (PIR)	Compare different algorithms	Semi- and supervised	Assumed GT with the thermostat data from Eco Bee (Donate you Data)	-	30. min	Logistic Regression, Random Forest, Markov model (MM), the hidden Markov	No	House-based	94

					Motion sensor (PIR)			model (HMM), and the recurrent neural network (RNN)			
[53]	2021	Indoor environment data: CO2, air temperature, illuminance, relative humidity and noise	Information of occupant presence could be extracted from indoor environment data by appropriate data mining approach	Supervised	GPS, app on phone	Approx. 1 month	5. minutes	Decision tree and curve description	No	Three bedrooms	3
[54]	2013	Electricity use	Develop a model	Unsupervised and supervised	PIR and Android application installed on phone	8. months	1 second	SVM, KNN, HMM, prior knowledge and threshold	No	House-based	282
[55]	2017	Air temperature, humidity, humidity ratio, CO2 and light time series data	Average occupancy schedules	Unsupervised	Not relevant	Uses dataset from [46]	Uses dataset from [46] Varies the resolution of 5 min, 10 min, 20 and 30. min	Hidden Markov Models	Yes	Room-based	107
[56]	2021	Temperature and motion + human-activities: door handle touch, water usage, and motion near the door area	Develop a two-layer model	Supervised	Switches that people have to activate	54 days in a living lab	Around seconds, cannot properly find	Random Forest, Decision Tree, K-Nearest Neighbor, and Support Vector Machine	No	Living lab	29
[57]	2015	CO2 concentration, fan power, room temperature, window opening	Develop a model	Unsupervised	Not applicable	Up to 6 days	1. minute	Mass balance	No	a kitchen and a big sleeping/living room of a residential building without mechanical ventilation	174

[58]	2021	CO2 and air temperature	Develop a model for real-time occupancy	Supervised	Occupants' logs	7 days	5. seconds	physics-informed pattern-recognition machine (PI-PRM)	No	Experimental setup (bedroom)	17
[59]	2018	Particulate matter + IE data	Develop a model	Unsupervised	Not applicable	4 months	1. minute	Point extraction algorithm is proposed to construct triangular shapes	No	Three studio type houses	64
[60]	2022	Occupant behavior (indoor handle temp., outdoor temp. handle)	Develop a model	Supervised/ unsupervised	PIR sensor	40 days	Not applicable, event-based	Trustworthy sequence matching module	No	Living lab: living room, a kitchen, a bedroom, a bathroom and a mechanical room	4
[61]	2019	CO2, air temperature, relative humidity, humidity ratio,	Toolkit	Domain-adaptive and supervised	Uses five datasets to develop the toolkit, see paper. Uses mainly camera and app with GPS	From 7 days to 1 year	From 10 seconds to 15 minutes	HMM, Particle Filtering (PF), SVM, Random Forest, Sparse Non-negative Matrix Factorization (SNMF), ANN and RNN/LSTM	Yes	35 various rooms	7
[62]	2018	Aggregated and appliance-specific power use data	Develop a model	Supervised	Uses the ECO data and e Clarkson smart housing dataset	Clarkson dataset: 12 days, GPS signal for GT	Clarkson dataset: 5 minutes, for el-use: unsure	Own app, prior-knowledge, SVM versions (PCA and SFS)	Yes	Apartment-based	11