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A Review of the Recent Developments in Integrating Machine Learning Models with Sensor Devices in the Smart Buildings Sector with a View to Attaining Enhanced Sensing, Energy Efficiency, and Optimal Building Management

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The Supplementary Materials file presents the comprehensive summarization tables, containing the identified papers tackling the machine learning models that are most suitable to be used with sensor devices in the smart buildings sector, synthetized in the following tables:

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Table S1. Scientific articles tackling the Support Vector Machines integrated with sensor devices in smart buildings

Reference	Publication Year	Type of smart building	Type of sensors	Reason for using the SVM method with sensor devices	SVM-only or hybrid	Performance metrics
[1]	2019	smart building	indoor environment sensors: thermocouple TX-FF-0.32-1P (FUKUDEN) for the temperature; photosensor HD2021T AA-SP (Deltaohm) for the illuminance; OPUS20 TCO (Lufft) sensor for the relative humidity and CO_2 concentration; occupancy information sensor: PN1500 (Botem); electricity meters: PR300 (Yokogawa) for the lighting power; Enertalk Plug (Encored Technologies) for the PC electricity consumption and EHP electricity meter	assessing the occupancy status information in order to improve the energy prediction performance of a building energy model	Support Vector Machine compared with Decision Tree and Artificial Neural Networks	Overall Accuracy and Standard Deviation
[6]	2018	smart home	motion sensors, item sensors (kitchen items), door sensor, temperature sensor, electricity usage, burner, cold water, hot water sensors	human activity recognition in order to help disabled persons	Support Vector Machines with a polynomial kernel of degree 3 (P-SVM); a comparison with other four classifiers: Radial Basis Function kernel – Support Vector Machine (RBF-SVM), Naïve-Bayes, Logistic Recognition, Recurrent Neural Network (RNN)	True Positives, False Positives, Precision, Recall, the F-Measure, the Receiver-Operating-Characteristic (ROC) Curve
[7]	2018	smart home	smart phones' built-in three-axis acceleration sensors and Kinect motion sensors	human fall detection	Support Vector Machine (SVM)	True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN), Sensitivity or True Positive Rate (TPR), Specificity (SPC) or True Negative Rate (TNR), Accuracy (ACC)
[8]	2018	smart home	passive radar-based sensor to achieve multiple level activities detection by adjusting Doppler resolution	human activity recognition and classification	Support Vector Machine (SVM) in order to classify the feature vectors into corresponding activity groups	Confusion Matrices, Classification Accuracy
[2]	2018	smart building	thermal sensor	human behavior recognition	Support Vector Regression (SVR) and Recurrent Neural Network (RNN)	Average Error, Error Rate
[9]	2018	smart home	unobtrusive sensor (ARGUS)	human activity recognition	the SVM classifier along with two different feature extraction methods: a manually defined method, and a Convolutional Neural Network (CNN)	Accuracy, Root Mean Square Error (RMSE)

[3]	2018	smart building	Light-Emitting Diode (LED) luminaires used as light sensors	human activity recognition	Support Vector Machine (SVM), Convolutional Neural Network-Hidden Markov Model (CNN-HMM), Long Short-Term Memory networks (LSTM) learning algorithms	Accuracy and Mean Square Error (MSE)
[10]	2017	smart home	embedded sensors	human activity recognition	hybrid, combining Beta Process Hidden Markov Model (BP-HMM) and support vector machine (SVM)	Overall Accuracy, Mean Recognition Rate
[4]	2017	smart building	modern smartphones embedded with a variety of sensors from which it is used only the acceleration sensor data	robust human activity recognition	a Coordinate Transformation and Principal Component Analysis (CT-PCA) scheme; comparison among the results obtained using the K-Nearest Neighbor (KNN), Decision Tree (DT), Neural Network (NN), Support Vector Machine (SVM); developing an Online Support Vector Machine (OSVM) based online updating algorithm to eliminate the effects of orientation, placement and subject variations	Time: Absolute mean, Variance, Median absolute deviation, Maximum, Minimum, Signal magnitude range, Power, Interquantile range; Frequency: Maximum, Mean, Skewness, Kurtosis, Power
[14]	2017	smart home	unobtrusive sensing module including a gateway and a set of passive sensors	human activity recognition in order to monitor the activities of elderly, who are living alone	Neural Network, C4.5 Decision Tree, Bayesian Network, and Support Vector Machine	Sensitivity (SN), Specificity (SP), Area Under The Receiver Operating Characteristic Curve (AUC)
[15]	2016	smart home	Pyroelectric Infrared (PIR)	human activity recognition and classification in home-based assisted living.	SVM - linear kernel, multinomial kernel, Radial Basis Function (RBF) kernel, compared with K-Nearest Neighbor, Gaussian Mixture Hidden Markov Model (GM-HMM), Naïve Bayes	Correct Classification Rate (CCR) and Confusion Matrix
[61]	2016	smart home	wireless sensor network comprising binary sensors like reed switches to determine the open-close state of the doors and cabinets; pressure mats to determine if one is staying laid down in the bed or on the couch; float sensors to determine if the toilet has been flushed	assessing the occupancy status information and detecting the human behavior in view of assisted living	hybrid, combining resampling methods like Over-Sampling and Under-Sampling with Support Vector Machines and Linear Discriminant Analysis (LDA)	Accuracy, Precision, Recall and F-measure
[5]	2016	smart building	high sensitivity underfloor mounted accelerometers	classifying the gender of occupants in a building	Bagged Decision Trees, Boosted Decision Trees, Support Vector Machines (SVMs), and Neural Networks in order to classify the gender	Classification Accuracy (Classification Error Results)

[59]	2015	smart home	binary sensors: motion, contact switch, absent/present status of item, door open/close, status of cabinet sensors; analog sensors for temperature, status of water and burner	human activity recognition and classification	Activity Recognition in Smart Homes with the capability of Self Verification (ARSH-SV) method, based on Support Vector Machines	Precision, Recall, Specificity, False Positive Rate, Matthews Correlation Coefficient, F1-Score and Accuracy, obtained From True Positives, False Negatives, True Negatives and False Positives
[30]	2015	smart home	Passive Infrared (PIR) sensors in order to detect motion	human activity recognition and classification in home-based assisted living	learning classification algorithms: Naive Bayesian (NB), Support Vector Machine (SVM) and Random Forest (RF).	Average Specificity, Sensitivity, Precision and F-Measure
[63]	2015	smart home	Accelerometer, temperature sensor, altimeter embedded on the CC430F6137 Microcontroller with theMSP430 CPU from Texas Instruments; Gyroscope, barometer, and light sensor implemented on Gadgeteer FEZ Cerberus board with the 168-MHz 32-bit Cortex M4 processor; heart rate monitor chest strap from BlueRobin	activity recognition of elderly people	Multilayer Perceptron Neural Network (MLP), Radial Basis Function (RBF) neural network, Support vector machine (SVM)	Mean, Standard Deviation (STD), Maximum, Minimum, Median, Mode, Kurtosis, Skewness, Intensity, Difference, Root-Mean-Square (RMS), Energy, Entropy, and Key Coefficient
[31]	2015	smart home	binary sensors	human activity recognition and classification in home-based assisted living	Support Vector Machine (SVM), Evidence-Theoretic K-nearest Neighbors (ET-KNN), Probabilistic Neural Network (PNN), K-Nearest Neighbor (KNN), Naive Bayes (NB)	Classification Accuracy (Classification Error Results)
[62]	2015	smart home	sensor networks in a pervasive environment; sensors installed in everyday objects such as doors, cupboards, refrigerator, and toilet flush to record activation/deactivation events (opening/closing events)	human activity recognition and classification	methods for feature extraction: Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Linear Discriminant Analysis (LDA); The new features selected by each method are then used as the inputs for a Weighted Support Vector Machines (WSVM) classifier; experiments were implemented on multiple real-world datasets with: Conditional Random Fields (CRF), standard Support Vector Machines (SVM), Weighted SVM, and	Accuracy, Precision, Recall and F-Measure

					combined methods PCA+WSVM, ICA+WSVM, and LDA+WSVM	
[29]	2014	smart home	binary and ubiquitous sensors	human activity recognition and classification	hybrid, combining Synthetic Minority Over-sampling Technique (SMOTE) with Cost Sensitive Support Vector Machines (CS- SVM)	Accuracy, Precision, Recall and F-Measure
[32]	2014	smart home	embedded electronically controllable sensors and actuators	human activity recognition in view of assisted living	Support Vector Machine in order to identify the occurrence of anomalies within human activities	Similarity Degree
[44]	2014	smart building	energy smart meters, building management systems, and weather stations	energy consumption forecasting	a model based on Support Vector Regression (SVR) using the Scikit-learn module, which provides a Python front-end to LIBSVM, a widely cited Support Vector Machine library	Coefficient of Variation (CV) and Standard Error In%
[52]	2013	smart building	Video acquisition system covering all the rooms	human behavior detection and classification in view of maximizing the comfort with an optimized energy consumption	a SVM-based classification method to determine the behavior of the people residing in the smart building	Classification Rate
[60]	2013	smart building	motion sensors embedded in a smart phone in building environments	human activity recognition and energy expenditure estimation	hierarchical Support Vector Machine classifier	Average Recognition Rate
[64]	2013	smart home	multi-appliance recognition system, which designs a single smart meter using a current sensor and a voltage sensor in combination with a microprocessor to meter multi-appliances	recognizing the household appliance in order to assess its usage and develop habits of power preservation.	hybrid, combining Support Vector Machine with Gaussian Mixture Model (SVM/GMM) classification model in view of classifying electric appliances	Accuracy, Success Rate, Recognition Rate
[65]	2007	smart home	sensors for HVAC Chillers	optimal sensor selection in complex system monitoring problems	comparison of: Support Vector Machines (SVMs), Principal Component Analysis (PCA), and Partial Least Squares (PLS)	Recognition Rate

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Table S2. Scientific articles tackling the Discriminant Analysis integrated with sensor devices in smart buildings

Reference	Publication Year	Type of smart building	Type of sensors	Reason for using the Discriminant Analysis method with sensor devices	Discriminant Analysis-only or hybrid	Performance metrics
[16]	2019	smart home	wearable sensor, accelerometer providing inertial information of human activity	human activity recognition	Kernel Fisher Discriminant Analysis (KFDA) technique, Extreme Learning Machine (ELM); comparison among Best Base ELM, SVM, Bagging, AdaBoost and the proposed method	Accuracy, Recall
[17]	2018	smart buildings	a scalable wireless sensor network with CO_2-based estimation	human activity recognition	comparison of Gradient Boosting, K-Nearest Neighbors (KNN), Linear Discriminant Analysis, and Random Forests	Accuracy, Root-Mean-Square Error (RMSE), Normalized Root-Mean-Square Error (NRMSE), Coefficient of Variance (CV)
[61]	2016	smart home	wireless sensor network comprising binary sensors like reed switches to determine the open-close state of the doors and cabinets; pressure mats to determine if one is staying laid down in the bed or on the couch; float sensors to determine if the toilet has been flushed	assessing the occupancy status information and detecting the human behavior in view of assisted living	hybrid, combining resampling methods like Over-Sampling and Under-Sampling with Support Vector Machines and Linear Discriminant Analysis (LDA)	Accuracy, Precision, Recall and F-measure
[66]	2016	smart home	sensors for motion detection	human fall detection	Discriminant Analysis	Accuracy
[33]	2016	smart home	four kinds of biosensors: Electro-Dermal Activity sensor (EDA), Electrocardiogram sensor (ECG), Blood Volume Pulse sensor (BVP) and surface Electromyography sensor (EMG)	ambient assisted living framework for emergency psychiatric state prediction	Hidden Markov Model (HMM), Viterbi path counting, scalable Stochastic Variational Inference (SVI)-based training algorithm Generalized Discriminant Analysis	Prediction Accuracy (Acc), Sensitivity (Sen), Specificity (Spe), F-Measure (FM) and Area Under the ROC Curve (AUC)
[62]	2015	smart home	sensor networks in a pervasive environment; sensors installed in everyday objects such as doors, cupboards, refrigerator, and toilet flush to record activation/deactivation events (opening/closing events)	human activity recognition and classification	methods for feature extraction: Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Linear Discriminant Analysis (LDA); the new features selected by each method are then used as the inputs for a Weighted Support Vector Machines (WSVM) classifier; experiments were implemented on multiple real-world datasets with: Conditional	Accuracy, Precision, Recall and F-Measure

					Random Fields (CRF), standard Support Vector Machines (SVM), Weighted SVM, and combined methods PCA+WSVM, ICA+WSVM, and LDA+WSVM	

Table S3. Scientific articles tackling the Naïve Bayes integrated with sensor devices in smart buildings

Reference	Publication Year	Type of smart building	Type of sensors	Reason for using the Naïve Bayes method with sensor devices	Bayes-only or hybrid	Performance metrics
[11]	2019	smart hospital	biomedical sensors, providing medical data (based on physiological signals), behavioral patterns (e.g. smoking, drinking alcoholics, taking medications, etc.), ambient data (e.g. humidity, temperature, noise, etc.), contextual information (e.g. location, activity, etc.).	achieving remote monitoring of patients outside the hospital in real time	a hybrid algorithm of Naïve Bayes (NB) and Whale Optimization Algorithm (WOA); a comparison between six classifiers: Decision Tree (J48), Random Forest (RF), Ripper (JRip), Naïve Bayes (NB), Nearest Neighbor (IBK), Support Vector Machine (SVM)	Accuracy, Recall, Precision, F − Measure
[67]	2018	smart home	acoustic sensor network	accurate knowledge of the positions of surrounding objects useful for autonomous systems and smart devices	Bayesian filter	Mean Value and Standard Deviation
[68]	2018	smart home	carbon dioxide, total volatile organic compounds, air temperature, and air relative humidity sensors.	occupancy detection in smart homes	comparison of the supervised learning models: Naïve Bayes (NB), C4.5 Decision Tree, Logistic Regression, K-Nearest Neighbors, Random Forest	for occupancy: Accuracy, True Positive Rate, True Negative Rate; for the number of occupants: Mean Absolute Error, Root Mean Square Error
[36]	2018	smart home	WI-FI enabled sensors for food nutrition quantification, and a smart phone application that collects nutritional facts of the food ingredients	Internet of Things (IoT)-based fully automated nutrition monitoring system	Bayesian algorithms and 5-layer Perceptron Neural Network method for diet monitoring	Accuracy of Classification of food items and meal prediction
[34]	2016	smart home	Passive Infrared Sensor (PIR) and environmental sensors to measure pressure, temperature, humidity, and the light intensity in a particular area of the home	human presence identification and location with sub room accuracy in view of home-based assisted living	Bayes filter algorithm	Error Rate

[30]	2015	smart home	passive infrared (PIR) sensors in order to detect motion	human activity recognition and classification in home-based assisted living	learning classification algorithms: Naive Bayesian (NB), Support Vector Machine (SVM) and Random Forest (RF).	Average Specificity, Sensitivity, Precision and F-measure
[31]	2015	smart home	binary sensors	human activity recognition and classification in home-based assisted living	Support Vector Machine (SVM), Evidence-Theoretic K-nearest Neighbors (ET-KNN), Probabilistic Neural Network (PNN), K-Nearest Neighbor (KNN), Naive Bayes (NB)	Classification Accuracy (Classification Error Results)
[69]	2013	smart home	14 binary sensors installed in doors, cupboards, toilet flush	human activity recognition in smart home environments	Dempster–Shafer theory compared with the Naïve Bayes classifier and J48 Decision Tree	Average Precision, Recall, and F-Measure
[70]	2012	smart home	motion sensors, sensor network	human activity recognition in smart home environments	Naïve Bayes classifier, Hidden Markov Model and Viterbi algorithm	Recognition Accuracy Rate

Table S4. Scientific articles tackling the Nearest Neighbor integrated with sensor devices in smart buildings

Reference	Publication Year	Type of smart building	Type of sensors	Reason for using the Nearest Neighbor method with sensor devices	Nearest Neighbor -only or hybrid	Performance metrics
[17]	2018	smart buildings	a scalable wireless sensor network with CO_2-based estimation	human activity recognition	comparison of Gradient Boosting, K-Nearest Neighbors (KNN), Linear Discriminant Analysis, and Random Forests	Accuracy, Root-Mean-Square Error (RMSE), Normalized Root-Mean-Square Error (NRMSE), Coefficient of Variance (CV)
[68]	2018	smart home	carbon dioxide, total volatile organic compounds, air temperature, and air relative humidity sensors.	occupancy detection in smart homes	comparison of the supervised learning models: Naïve Bayes (NB), C4.5 Decision Tree, Logistic Regression, K-Nearest Neighbors, Random Forest	for occupancy: Accuracy, True Positive Rate, True Negative Rate; for the number of occupants: Mean Absolute Error, Root Mean Square Error
[71]	2018	smart home	a single point Electromagnetic Interference (EMI) smart sensor	detect and track the operation of the Information Technology (IT) appliances (such as desktops and printers), operating in non-working hours in office buildings	Nearest Neighbor -only	Precision and Recall

[72]	2015	smart home	an accelerometer in order to indicate a potential fall and the Kinect sensor in order to authenticate the eventual fall alert	human activity recognition and fall detection	K-Nearest Neighbor (k-NN) classifier and comparison with the results obtained using linear SVM	Sensitivity, Specificity, Precision, Classification Accuracy
[31]	2015	smart home	binary sensors	human activity recognition and classification in home-based assisted living	Support Vector Machine (SVM), Evidence-Theoretic K-nearest Neighbors (ET-KNN), Probabilistic Neural Network (PNN), K-Nearest Neighbor (KNN), Naive Bayes (NB)	Classification Accuracy (Classification Error Results)

Table S5. Scientific articles tackling the Neural Networks for Classification Purposes integrated with sensor devices in smart buildings

Reference	Publication Year	Type of smart building	Type of sensors	Reason for using the Neural Networks for Classification method with sensor devices	Neural Networks for Classification -only or hybrid	Performance metrics
[18]	2019	smart home	wearable hybrid sensor system comprising motion sensors and cameras	human activity recognition in medical care, smart homes, and security monitoring	hybrid approach, combining Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) methods	Confusion Matrices, F1 Accuracy
[27]	2019	smart home	a two-dimensional acoustic array	human activity recognition	Convolutional Neural Networks compared with traditional recognition approaches such as K-Nearest Neighbor and Support Vector Machines	Overall Accuracy
[23]	2019	smart building	Wireless Sensor Network (WSN)	energy consumption forecasting	Multilayer Perceptron (MLP) compared with: Linear Regression (LR), Support Vector Machine (SVM), Gradient Boosting Machine (GBM) and Random Forest (RF)	Coefficient of Determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE)
[1]	2019	smart building	indoor environment sensors: thermocouple TX-FF-0.32-1P (FUKUDEN) for the temperature; photosensor HD2021T AA-SP (Deltaohm) for the illuminance;	assessing the occupancy status information in order to improve the	Support Vector Machine compared with Decision Tree and Artificial Neural Networks	Overall Accuracy and Standard Deviation

			OPUS20 TCO (Lufft) sensor for the relative humidity and CO_2 concentration; occupancy information sensor: PN1500 (Botem); electricity meters: PR300 (Yokogawa) for the lighting power; Enertalk Plug (Encored Technologies) for the PC electricity consumption and EHP electricity meter	energy prediction performance of a building energy model		
[73]	2018	smart home	environmental sensors: Passive Infrared (PIR) and temperature sensors	human activity recognition	Deep Convolutional Neural Network (DCNN) compared with Naïve Bayes (NB), Back-Propagation (BP) algorithms	Precision, Specificity, Recall, F1-Score, Accuracy, Total Accuracy, Confusion Matrix
[38]	2017	smart home	sensors of devices in IoT (smart TV, smartphone, light, air-conditioner, humidifier)	obtaining an advanced connectivity between devices, systems, and services that continuously obtain enormous amounts of data from sensors in iot	Bayesian network approach compared with decision tree and monolithic Bayesian network	Classification Confusion Matrix, Precision, Recall, Accuracy
[77]	2017	smart home	temperature, CO_2, humidity sensors, and microphones	human activity recognition in smart home care	Artificial Neural Network based on the Levenberg–Marquardt Algorithm (LMA)	Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE)
[14]	2017	smart home	unobtrusive sensing module including a gateway and a set of passive sensors	human activity recognition in order to monitor the activities of elderly, who are living alone	neural network, C4.5 Decision Tree, Bayesian Network, and Support Vector Machine	Sensitivity (SN), Specificity (SP), Area Under The Receiver Operating Characteristic Curve (AUC)
[5]	2016	smart building	high sensitivity underfloor mounted accelerometers	classifying the gender of occupants in a building	Bagged Decision Trees, Boosted Decision Trees, Support Vector Machines (SVMs), and Neural Networks in order to classify the gender	Classification Accuracy (Classification Error Results)

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[74]	2016	smart home	wearable and environmental sensors	human activity recognition	Recurrent Neural Networks (RNNs) used for the activity recognition process	Accuracy, Recall, Precision and F1 Score
[63]	2015	smart home	accelerometer, temperature sensor, altimeter embedded on the CC430F6137 Microcontroller with theMSP430 CPU from Texas Instruments; gyroscope, barometer, and light sensor implemented on Gadgeteer FEZ Cerberus board with the 168-MHz 32-bit Cortex M4 processor; heart rate monitor chest strap from BlueRobin.	activity recognition of elderly people	Multilayer Perceptron Neural Network (MLP), Radial Basis Function (RBF) neural network, Support Vector Machine (SVM)	Mean, Standard Deviation (STD), Maximum, Minimum, Median, Mode, Kurtosis, Skewness, Intensity, Difference, Root-Mean-Square (RMS), Energy, Entropy, And Key Coefficient
[29]	2014	smart home	binary and ubiquitous sensors	human activity recognition and classification	hybrid, combining Synthetic Minority Over-sampling Technique (SMOTE) with Cost Sensitive Support Vector Machines (CS- SVM)	Accuracy, Precision, Recall and F-Measure
[76]	2012	smart home	sensor networks	human activity recognition in smart homes	Bayesian Belief Network (BBN) improved using an Edge-Encode Genetic Algorithm (EEGA) approach; the developed approach is compared with the Naive Bayesian Network (NBN) and Multiclass Naive Bayes Classifier (MNBC).	Accuracy, Precision, Recall and F-Measure
[75]	2011	smart home	Passive Infra-Red (PIR) sensors or motion detectors; door/window entry point sensors; electricity power usage sensors; bed/sofa pressure sensors; flood sensors	human activity recognition for detecting and predicting abnormal behavior	Echo State Network (ESN), Back Propagation Through Time (BPTT) and Real Time Recurrent Learning (RTRL).	Root Mean Square Error (RMSE)

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Table S6. Scientific articles tackling the Decision Trees integrated with sensor devices in smart buildings

Reference	Publication Year	Type of smart building	Type of sensors	Reason for using the DT method with sensor devices	DT-only or hybrid	Performance metrics
[19]	2019	smart building	smartphone sensors and Bluetooth beacons data	group activity detection and recognition	a framework for indoor Group Activity Detection And Recognition (GADAR) and Hierarchical Clustering, along with Decision Tree classifier, K-Neighbors classifier, Deep Neural Network, Gaussian Process classifier, Logistic regression, Support Vector Machine, Linear Discriminant Analysis, Gaussian Naïve Bayes (comparison)	Confusion Matrix, Accuracy (Mean), Accuracy (Variation), Precision, Recall, F1-score
[1]	2019	smart building	indoor environment sensors: thermocouple TX-FF-0.32-1P (FUKUDEN) for the temperature; photosensor HD2021T AA-SP (Deltaohm) for the illuminance; OPUS20 TCO (Lufft) sensor for the relative humidity and CO_2 concentration; occupancy information sensor: PN1500 (Botem); electricity meters: PR300 (Yokogawa) for the lighting power; Enertalk Plug (Encored Technologies) for the PC electricity consumption and EHP electricity meter	assessing the occupancy status information in order to improve the energy prediction performance of a building energy model	Support Vector Machine compared with Decision Tree and Artificial Neural Networks	Overall Accuracy and Standard Deviation
[50]	2019	smart office buildings	air temperature, relative humidity, air speed, CO2	personal thermal comfort	comparison between Decision Tree, Random Forests, Boosted Trees	the Overall Prediction Accuracy, the On-State Accuracy, the Present State Accuracy, Confusion Matrix, the Mean Squared Error (MSE), the Root-Mean-Squared Error (RMSE) and the Average Test Accuracy
[21]	2019	smart building	wireless sensor networks	forecasting Packet Delivery Ratio (PDR) and Energy Consumption (EC) in Internet of Things (IoT)	comparison between Linear Regression, Gradient Boosting, Random Forest, Baseline and Deep Learning Neural Networks	Root Mean Square Error (RMSE), Mean Percentage Error (MPE), and Mean Absolute Percentage Error (MAPE)

[78]	2019	smart office building	common sensors: motion detection, power consumption, CO_2 concentration	estimating the number of occupants	Decision Tree C4.5, parameterized rule-based classifier	Average Error of Occupancy Estimation
[17]	2018	smart buildings	a scalable wireless sensor network with CO_2 -based estimation	human activity recognition	comparison of Gradient Boosting, K-Nearest Neighbors (KNN), Linear Discriminant Analysis, and Random Forests	Accuracy, Root-Mean-Square Error (RMSE), Normalized Root-Mean-Square Error (NRMSE), Coefficient of Variance (CV)
[68]	2018	smart home	carbon dioxide, total volatile organic compounds, air temperature, and air relative humidity sensors.	occupancy detection in smart homes	comparison of the supervised learning models: Naïve Bayes (NB), C4.5 Decision Tree, Logistic Regression, K-Nearest Neighbors, Random Forest	For occupancy: Accuracy, True Positive Rate, True Negative Rate; For the number of occupants: Mean Absolute Error, Root Mean Square Error
[80]	2018	smart home	temperature, humidity inside the building, in different rooms; temperature, humidity, pressure, wind speed, visibility outside the building,	predicting unusual energy consumption events	an improved version of Very Fast Decision Tree (VFDT) classification algorithms compared: CART Decision Tree version 4.8; Active learning classifier; Fast incremental model trees with drift detection (FIMT-DD); Hoeffding Tree or VFDT; K-Nearest Neighbors algorithm; Naive Bayes; Online Regression Tree with Options; Stochastic Gradient Descent	Accuracy, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), True Positive (TP), False Positive (FP), Precision, Recall, F-Measure, Receiver Operating Characteristic (ROC) curve
[79]	2017	smart home	Wireless sensor networks	identifying behavioral patterns	ordered decision tree compared with ClaSP and CMCla	Runtime
[81]	2017	smart home	sensors embedded in the environment: motion sensor, sensors for selected items in the kitchen, door sensor, burner sensor, hot water sensor, cold water sensor, temperature sensors, electricity usage sensor	complex activity recognition	complex Activity Recognition using Emerging Patterns and Random Forest (CARER) compared with Hidden Markov Model, Bayesian Network, Naive Bayes, SVM, Decision Tree, Random Forest	F-Measure
[53]	2017	smart building	wrist-worn health monitoring devices to measure skin temperature, heart rate, activity level; wireless sensors and probes to measure building indoor environment data as temperature, humidity, CO_2 level, window state; weather station to get real-time outdoor conditions (temperature and humidity)	predict and improve occupants' thermal comfort	Comparison between Logistic Regression, K-Nearest Neighbor, Support Vector Machine, Random Forest	Accuracy

[83]	2017	smart space	binary infrared sensors	human activity recognition	Fuzzy Decision Tree	Identification Rate
[14]	2017	smart home	unobtrusive sensing module including a gateway and a set of passive sensors	human activity recognition in order to monitor the activities of elderly, who are living alone	Neural Network, C4.5 Decision Tree, Bayesian Network, and Support Vector Machine	Sensitivity (SN), Specificity (SP), Area Under The Receiver Operating Characteristic Curve (AUC)
[82]	2016	smart home	simple non-intrusive sensors, PIR sensors, door sensors and occupancy sensors placed in chairs and beds.	detecting deviating human behavior	Random forests and third order Markov Chain	Local Outlier Factor (LOF), the Z-Score values, cluster transition probability
[5]	2016	smart building	high sensitivity underfloor mounted accelerometers	classifying the gender of occupants in a building	Bagged Decision Trees, Boosted Decision Trees, Support Vector Machines (SVMs), and Neural Networks in order to classify the gender	Classification Accuracy (Classification Error Results)
[74]	2016	smart home	wearable and environmental sensors	human activity recognition	recurrent neural networks (RNNs) used for the activity recognition process	Accuracy, Recall, Precision and F1 Score
[30]	2015	smart home	passive infrared (PIR) sensors in order to detect motion	human activity recognition and classification in home-based assisted living	learning classification algorithms: naive Bayesian (NB), support vector machine (SVM) and random forest (RF).	Average Specificity, Sensitivity, Precision and F-Measure
[84]	2013	smart home	3-D camera (including people tracking algorithm), Ethernet camera (with people counting, tracking, and face detection), microphone array (with angle of arriving voice detection), accelerometer (with orientation recognition and basic gestures), multisensor board (for simple digital/analog I/O-based sensors, such as contact switches) and PC monitoring (with the detection of active applications, mouse and keyboard activity), external sensors integrated to the user's home automation system	human activity recognition	decision-tree only	Mean Absolute Error (MAE), Recognition Success Rate
[69]	2013	smart home	14 binary sensors installed in doors, cupboards, toilet flush	human activity recognition in smart home environments	the Dempster–Shafer theory compared with the Naïve Bayes classifier and J48 Decision Tree	Average Precision, Recall, and F-Measure

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Table S7. Scientific articles tackling the Ensemble Methods integrated with sensor devices in smart buildings

Reference	Publication Year	Type of smart building	Type of sensors	Reason for using the Ensemble Methods with sensor devices	Ensemble Methods-only or hybrid	Performance metrics
[20]	2019	smart building	smartphone sensors (acceleration, gyroscope)	human activity recognition	Extreme Learning Machine (ELM) for ensemble learning, compared with Artificial Neural Networks (ANN), Extreme Learning Machine (ELM), Support Vector Machine (SVM), Random Forest (RF), and Deep Long Short-Term Memory (LSTM) approaches	Accuracy
[16]	2019	smart home	wearable sensor, accelerometer providing inertial information of human activity	human activity recognition	Kernel Fisher Discriminant Analysis (KFDA) technique, Extreme Learning Machine (ELM); comparison among Best Base ELM, SVM, Bagging, AdaBoost and the proposed method	Accuracy, Recall
[3]	2018	smart building	Light-Emitting Diode (LED) luminaires used as light sensors	human activity recognition	Support Vector Machine (SVM), Convolutional Neural Network-Hidden Markov Model (CNN-HMM), Long Short-Term Memory networks (LSTM) learning algorithms	Accuracy and Mean Square Error (MSE)
[85]	2014	smart home	wireless sensors associated with different objects, monitoring the activities	human activity recognition	Cluster-Based Classifier Ensemble (ensemble method)	Confusion Matrix presenting number of True Positives, True Negatives, False Positives and False Negatives, Precision, Recall and F-Measure
[86]	2013	smart home	embedded sensors: stove-sensor, refrigerator-sensor, door-sensor.	activity recognition	ensemble method, combining one of the methods: Artificial Neural Networks (ANN), Hidden Markov Model (HMM), Conditional Random Fields (CRF) with the Genetic Algorithm (GA) approach	Precision, Recall, F-measure and Accuracy

Table S8. Scientific articles tackling the Gaussian Process Regression (GPR) integrated with sensor devices in smart buildings

Reference	Publication Year	Type of smart building	Type of sensors	Reason for using the Gaussian Process Regression with sensor devices	Gaussian Process Regression-only or hybrid	Performance metrics
[20]	2019	smart building	smartphone sensors (acceleration, gyroscope)	human activity recognition	Extreme Learning Machine (ELM) for ensemble learning, compared with Artificial Neural Networks (ANN), Extreme Learning Machine (ELM), Support Vector Machine (SVM),	Accuracy

					Random Forest (RF), and deep Long Short-Term Memory (LSTM) approaches	
[87]	2017	smart home	smart meter	human activity monitoring	Non-Intrusive Load Monitoring (NILM) algorithm, Dempster-Shafer theory compared with the Gaussian Mixture model	Score for test events
[88]	2017	smart home	smart phones as sensors to capturing voice signals, Electroglottography (EGG) electrodes as sensors to capture EGG signals	voice pathology assessment	Gaussian Mixture model-based classifier, using different numbers of Gaussian mixtures	Accuracy
[89]	2017	smart home	wearable sensors providing inertial data, environment sensors and data processed video streams that anonymize the individual	machine monitoring of human health	linear-Gaussian transition model with hard boundaries, Nonlinear-Gaussian observation model, Post-Regularized Particle Filter (C-ERPF), compared to other methods: Extended Kalman Filter (EKF), constrained-EKF, and Extended Regularized Particle Filtering (ERPF) without transition constraints	Average Error
[35]	2017	smart home	the smart meter or another third-party device	ambient assisted living	The developed PQD-PCA Classifier along with the Gaussian Mixture Mode (GMM) and the Dempster-Shaffer Theory (DST) compared with other classifiers (k-nearest-neighbors kNN, Gaussian Naïve Bayes GNB, Logistic Regression Classifier LGC, Decision Tree DTree and Random Forest Rforest).	True Positive Percentage (TPP), False Positive Percentage (FPP), Precision, Recall, F1-Score, F2-Score
[90]	2016	smart home and smart building	electricity, water and natural gas consumption	developing a framework for automatic leakage detection in smart water and gas grids	comparison between Gaussian Mixture Model (GMM), Hidden Markov Model (HMM) and One-Class Support Vector Machine (OC-SVM)	the probability to correctly detect an anomaly, the probability to erroneously detect an anomaly, the Receiver Operating Characteristic (ROC) curve, Area Under the ROC Curve (AUC)
[64]	2013	smart home	multi-appliance recognition system, which designs a single smart meter using a current sensor and a voltage sensor in combination with a microprocessor to meter multi-appliances	recognizing the household appliance in order to assess its usage and develop habits of power preservation	hybrid, combining Support Vector Machine with Gaussian Mixture Model (SVM/GMM) classification model in view of classifying electric appliances	Accuracy, Success Rate, Recognition Rate

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Table S9. Scientific articles tackling the Linear Regression integrated with sensor devices in smart buildings

Reference	Publication Year	Type of smart building	Type of sensors	Reason for using the Linear Regression method with sensor devices	Linear Regression-only or hybrid	Performance metrics
[21]	2019	smart building	wireless sensor networks	forecasting Packet Delivery Ratio (PDR) and Energy Consumption (EC) in Internet of Things (IoT)	comparison between Linear Regression, Gradient Boosting, Random Forest, Baseline and Deep Learning Neural Networks	Root Mean Square Error (RMSE), Mean Percentage Error (MPE), and Mean Absolute Percentage Error (MAPE)
[91]	2018	smart building	three virtual sensors: temperature, airflow, and fan speed	improving electricity consumption by correctly identifying faults within a smart building's ventilation system	Linear Regression compared with Autoregressive Moving Average With Exogenous Variables (ARMAX) models, Support Vector Machine (SVM), Artificial Neural Network (ANN).	Coefficient of Determination (for linear models) and Acceptable Ranges (for non-linear ones)
[92]	2018	smart home	wireless sensor networks	adaptive interference suppression	Linear Regression	range of power savings, ratio of received packet
[41]	2017	smart home	temperature and humidity sensors from a wireless sensor network	forecasting the energy use of appliances	comparing: Multiple Linear Regression, Support Vector Machine with Radial Kernel, Random Forest, Gradient Boosting Machines (GBM)	Root Mean Square Error (RMSE), Coefficient of Determination, Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE)
[93]	2014	smart home	passive radio-frequency identification antennas various sensors: ultrasonic, infrared, load cells	gesture recognition	Linear Regression	Accuracy
[94]	2014	smart building	wireless sensor network	controlling smart lighting	Linear Regression model and Support Vector Regression (SVR)	Root Mean Square Error (RMSE) Normalized Mean Square Error (NMSE)

Table S10. Scientific articles tackling the Neural Networks for Regression Purposes integrated with sensor devices in smart buildings

Reference	Publication Year	Type of smart building	Type of sensors	Reason for using the ANN Regression method with sensor devices	ANN Regression-only or hybrid	Performance metrics
[22]	2019	smart buildings	sensors for registering the electricity consumption	forecasting the electricity consumption	ANN compared with Linear Regression (LR), Auto-Regressive Integrated Moving Average (ARIMA), Evolutionary Algorithms	Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE)

					(EAs) for Regression Trees (EVTree), Generalized Boosted Regression Models (GBM), Random Forests (RF), Ensemble, Recursive Partitioning and Regression Trees (Rpart), Extreme Gradient Boosting (XGBoost)	
[23]	2019	smart building	Wireless Sensor Network (WSN)	energy consumption forecasting	Multilayer Perceptron (MLP) compared with: Linear Regression (LR), Support Vector Machine (SVM), Gradient Boosting Machine (GBM) and Random Forest (RF)	Coefficient of Determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE)
[95]	2018	smart home	smart metering system and sensors installed at a residential consumer, corresponding to 15 individual appliances (water heater, refrigerator, microwave, furnace, master bedroom, front bedroom, kitchen stove wall, dishwasher disposal, kitchen sink wall, family room, kitchen half-bath foyer, washing machine, guest bedroom, dryer, basement)	forecasting the electricity consumption	mixed Artificial Neural Network (ANN) approach using both Non-Linear Autoregressive with Exogenous Input (NARX) ANNs and Function Fitting Neural Networks (FITNETs)	Mean Squared Error (MSE), Correlation Coefficient (R), the differences between the real consumption and the forecasted ones
[12]	2018	smart commercial and residential buildings	weather sensors	forecasting the electricity consumption	Deep Recurrent Neural Network (RNN) models	Root Mean Square Error relative to Root Mean Squared (RMS) average of electricity consumption in test data, Root Mean Square Error relative to Root Mean Squared (RMS) average of electricity consumption in training data, Pearson Coefficient
[43]	2018	smart home	flowmeter sensor	identifying the occurrence of a specific pattern in a Water Management System (WMS)	three types of ANN for Multi-Step-Ahead (MSA) forecasting: "Multi-Input Multi-Output (MIMO), Multi-Input Single-Output (MISO), and Recurrent Neural Network (RNN)"	Accuracy, Precision, Recall, and F-Measure
[98]	2018	smart building	two temperature sensors (outdoor and indoor), an external humidity sensor, and a solar radiation sensor	indoor temperature forecasting	Artificial Neural Network (ANN) with Multilayer Perceptron (MLP) structure	Mean Squared Error (MSE), Coefficient Of Correlation (R)

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[2]	2018	smart building	thermal sensor	human behavior recognition	Support Vector Regression (SVR) and Recurrent Neural Network (RNN)	Average Error, Error Rate
[97]	2017	smart building	passive infrared motion detecting sensors	short-term prediction of occupancy	ANN compared with traditional inhomogeneous Markov Chain model, New Markov Chain model, Probability Sampling model, Support Vector Regression (SVR)	Accuracy (Correctness)
[45]	2017	smart home	Wireless Sensor Network (WSN)	forecasting the electricity consumption	A hybrid approach, combining the Bluetooth Low Energy Home Energy Management System (BluHEMS) and an Artificial Neural Network (ANN) approach	Mean Squared Error (MSE), Root Square Mean Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE)
[96]	2015	smart home	Wireless Sensor Network (WSN)	monitor and forecast the indoor temperature	Two ANNs: a linear model and a Multilayer Perceptron (MLP) model with one hidden layer, comparison with Bayesian standard model	Mean Absolute Error
[75]	2011	smart home	Passive Infra-Red Sensors (PIR) or motion detectors; door/window entry point sensors; electricity power usage sensors; bed/sofa pressure sensors; flood sensors	human activity recognition	Echo State Network (ESN), Back Propagation Through Time (BPTT) and Real Time Recurrent Learning (RTRL) - recurrent neural networks.	Root Mean Square Error (RMSE)

Table S11. Scientific articles tackling the Support Vector Regression (SVR) integrated with sensor devices in smart buildings

Reference	**Publication Year**	**Type of smart building**	**Type of sensors**	**Reason for using the Support Vector Regression method with sensor devices**	**Support Vector Regression-only or hybrid**	**Performance metrics**
[23]	2019	smart building	wireless sensor network	energy consumption forecasting	Multilayer Perceptron (MLP) compared with: Linear Regression (LR), Support Vector Machine (SVM), Gradient Boosting Machine (GBM) and Random Forest (RF)	Coefficient of Determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE)
[2]	2018	smart building	thermal sensor	human behavior recognition	Support Vector Regression (SVR) and Recurrent Neural Network (RNN)	Average Error, Error Rate
[51]	2017	smart building	wireless sensor networks	thermal comfort optimization	Support Vector Regression	Prediction Error
[97]	2017	smart building	passive infrared motion detecting sensors	short-term prediction of occupancy	ANN compared with traditional inhomogeneous Markov Chain model, New Markov Chain model, Probability Sampling model, Support Vector Regression (SVR)	Accuracy (Correctness)

[41]	2017	smart home	temperature and humidity sensors from a wireless sensor network	forecasting the energy use of appliances	comparing: Multiple Linear Regression, Support Vector Machine with Radial Kernel, Random Forest, Gradient Boosting Machines (GBM)	Root Mean Square Error (RMSE), Coefficient of Determination, Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE)
[13]	2016	commercial buildings	occupancy and light sensors	estimation of the energy savings	Support Vector Regression	Comparison between the actual energy consumption per day and predicted energy consumption per day
[44]	2014	smart building	energy smart meters, building management systems, and weather stations	energy consumption forecasting	a model based on Support Vector Regression (SVR) using the Scikit-learn module, which provides a Python front-end to LIBSVM, a widely cited Support Vector Machine library	the Coefficient of Variation (CV) and Standard Error in%
[94]	2014	smart building	wireless sensor network	controlling smart lighting	linear regression model and Support Vector Regression (SVR)	Root Mean Square Error (RMSE), Normalized Mean Square Error (NMSE)

Table S12. Scientific articles tackling the Fuzzy C-Means integrated with sensor devices in smart buildings

Reference	Publication Year	Type of smart building	Type of sensors	Reason for using the Fuzzy C-Means method with sensor devices	Fuzzy C-Means-only or hybrid	Performance metrics
[24]	2019	smart building	more than 450 sensors and actuators related to the primary heating circuits and power generation system, managed by a Supervisory Control and Data Acquisition (SCADA) system	appropriate energy management	a state-of-the-art scalable distributed genetic fuzzy system (GFS) based on scalable fuzzy rule learning through evolution for regression (S-FRULER)	Root Mean Square Error (RMSE), Rules, Time
[99]	2019	smart home	Telecare Medicine Information System (TMIS) comprising specialized sensors that provide key health data parameters	identifying the patients based on their biometric data using a fuzzy extractor within a proposed security protocol	Fuzzy Extractor	the performance is assessed at the level of the whole developed protocol, taking into account the computational costs, user anonymity, mutual authentication, off-line password guessing attacks, impersonation attacks, replay attacks, and the assurance of formal security
[100]	2018	smart home	distributed sensors	object localization	Fuzzy logic techniques compared with similar approaches from other papers: Wireless Network, Radio-Frequency Identification (RFID), Visional Approach	Inaccuracy Rate, Experiment Environment Dimension and Root-Mean-Square Error (RMSE), the dependency of the localization approach to the number of wireless nodes

						(topology), which are employed to localize the objects
[101]	2018	smart buildings	temperature, humidity and flame sensors	fire monitoring and warning	Fuzzy Logic	Accuracy
[49]	2018	smart building	string-type strain gauge	integrity of the building, assuring public safety	Fuzzy Theory	Coefficient of Determination (R^2)
[54]	2018	smart buildings	temperature and occupancy sensors	achieving energy savings without sacrificing user comfort	Fuzzy Inference System	Energy consumption, Electricity Cost, Peak-to-Average Ratio (PAR)
[103]	2017	smart home	environment sensors for measuring indoor illuminance, temperature-humidity, carbon dioxide concentration and outdoor rain and wind direction	improving indoor environments	Fuzzy microcontroller performed by Arduino UNO	testing on laboratory prototype
[39]	2017	smart buildings	sensors for measuring the indoor and outdoor temperature and an IoT platform providing data regarding the humidity	assuring a comfortable living environment for the inhabitants while saving energy and therefore monetary resources	Fuzzy Logic	the percentages of energy saving in different working scenarios
[55]	2017	smart buildings / smart office	High Dynamic Range (HDR) vision sensor	reducing the electricity consumption by automatically controlling sun shadings and artificial lighting while assuring the visual comfort of the people inside the office rooms	Fuzzy Logic	Standard Error of Mean (SEM), Horizontal Illuminance, Daylight Glare Probability, paper based Landolt test, Freiburg Visual Acuity Test (FrACT), Electric Lighting Energy Consumption, Total Number of Shading as Well as Lighting Commands
[56]	2017	smart buildings	a customized Sensor Network comprising a Draught probe, a Capacitive Hygrometer, a Radiometer, an Ellipsoidal Thermometer, Platinum Resistors, Thermo Hygrometers, Tacogonioanemometers. The Sensor Network is used for collecting climate data regarding both the indoor and outdoor environment along with thermal data concerning the inside part of the glazed facade and the ducts of the fan coil	and assessing the potential improvement in the indoor thermal comfort of an overheated office environment	Fuzzy Logic	Turbulence intensity, draught rates, operative temperature, Predicted Mean Vote (PMV) and Percentage of People Dissatisfied (PPD)

[83]	2017	smart space	binary infrared sensors	human activity recognition	Fuzzy Decision Tree	Identification Rate
[105]	2017	smart building	motion detectors and light sensors; meteorological sensors for the Wind (m/s) and solar radiation (W/m^2) data	Smart indoor Light-Emitting Diode (LED) lighting design	Fuzzy-expert system for testing the light	Measuring the energy consumption in order to highlight the energy savings; highlighting the illumination level
[106]	2016	smart building	light and motion sensors	energy savings	Fuzzy logic controller	Energy Savings (percentage)
[107]	2016	smart homes	environmental sensors for measuring/sensing: temperature, humidity, light, water; human activity sensors for measuring/sensing: motion, tactile carpet infrastructure sensors for measuring/sensing: contact, pressure, smoke/fire, tap, vibration	identifying user location within the smart home using fuzzy set theory in decision making	fuzzy set theory	experiments and simulations
[108]	2016	smart home	in-house sensors: temperature, luminosity and humidity sensors city sensors: mobility sensors, traffic and parking sensors, environmental sensors, park and garden irrigation sensors	enhancing the smart home environment	a set of concepts and their Fuzzy semantic relations are defined, extracted and used	experiments
[104]	2015	smart home	smart home sensor network	assessing the behavior of a smart home sensor network's nodes	Fuzzy Logic	detection Accuracy, energy consumption, memory consumption, processing time estimation
[47]	2015	residential building	wireless sensors	residential load reduction	Fuzzy logic decision-making algorithm	experiments and scenarios highlighting energy saving, load reduction, providing thermal comfort
[46]	2015	smart building	meteorological stations, mounted to walls or windows, inserted into a specific device	monitoring and control the energy management processes of a smart building	the Fuzzy controller generates the output settings for the building actuators according to a general fuzzy-set processing scheme	experiments
[102]	2013	smart home	wearable wireless sensors, smart home sensors, remote monitoring system, data and video review system.	providing personalized healthcare services for elderly	The pervasive healthcare system, Context-Aware Real-time Assistant (CARA), combining case-based reasoning engine and Fuzzy logic	True positive, False positive, True negative, False Negative, Accuracy

[109]	2013	smart home	temperature sensor, infrared sensor, actuators to control the lights, air conditions, as well as the fans appropriately	detects the number of people in a room, adjusts a proper temperature for the air condition, turns on the fan if needed, turns on and off the light appropriately, leading to energy savings	Fuzzy temperature controller	experiments, comparing the electric appliances' usage with the developed control and the baseline usage
[110]	2013	smart house	temperature sensors	achieving the temperature control by minimizing the consumption of resources	Fuzzy cognitive map (FCM) used for developing a genetic algorithm in view of identifying the connection matrix of FCM	Accuracy
[111]	2013	smart home	outside home sensors: video sensorinside home sensors: radio frequency, ultrasonic, temperature, light, sound and video	smart home security	Adaptive Network Fuzzy Inference System (ANFIS)	Experiments, scenarios, comparison with the simple Fuzzy logic approach
[112]	2012	smart home	more than a hundred of different sensors and effectors	Passive Radio-Frequency Identification (RFID) localization in smart homes	Hybrid: elliptical trilateration and Fuzzy logic	accuracy, comparison with results presented in related works (based on ultrasonic, ultrasonic/RFID, ZigBee, Active RFID, Passive RFID)
[113]	2010	smart structures	smart systems for controlling vibration of building structures by means of smart dampers	identifying and isolating sensors faults	A semi-active nonlinear Fuzzy control system operating a magnetorheological damper on a seismically excited building is used to assess the performance of a proposed principal component analysis (PCA) based methodology for identifying and isolating sensors faults	fault detection index values for certain fault magnitudes, residual values for individual sensors corresponding to different fault magnitudes
[48]	2008	smart home	virtual sensor based on a fisheye video camera	evaluate visual comfort of daylight into buildings	Fuzzy logic algorithm	Comfort level (comparison of the comfort sensor evaluation and people comfort evaluation in different light configurations)
[114]	2007	smart house	indoor and outdoor light sensors	developing a smart system in a distributed intelligent environment	Fuzzy logic and neuro-Fuzzy system	experiments

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Table S13. Scientific articles tackling the Hidden Markov Model integrated with sensor devices in smart buildings

Reference	Publication Year	Type of smart building	Type of sensors	Reason for using the Hidden Markov Model with sensor devices	Hidden Markov Model-only or hybrid	Performance metrics
[25]	2019	smart home	34 sensors (3 door and 31 motion sensors)	sensor based activity recognition and abnormal behavior detection	Convolutional Neural Networks (CNNs) for detecting abnormal behavior related to dementia, the results being compared with methods such as Naïve Bayes (NB), Hidden Markov Models (HMMs), Hidden Semi-Markov Models (HSMM), Conditional Random Fields (CRFs)	Precision, Recall, F-Measure and Accuracy, Sensitivity, Specificity
[115]	2019	smart building	wireless sensor network	presence detection in a building	Hidden Markov Model (DS-HMM)	Accuracy
[116]	2019	smart home	unobtrusive sensing infrastructures, environmental sensors monitoring the interaction of the inhabitant with home artifacts, context conditions (e.g., temperature) and presence in certain locations	human activity recognition	the developed newNECTAR framework, based on Markov Logic Network compared with state-of-the-art techniques such as Multilayer Perceptron, Random Forest, Support Vector Machine, Naive Bayes	Average F1 Score, Confusion Matrix,
[117]	2019	smart home	passive infrared motion sensors and door sensors	human activity recognition	Hidden Markov Models and Regression Models	Average Accuracy using real data, synthetic data and randomly generated data; Accuracy first using only the real data and then Accuracy using the real data enlarged with a month of synthetically generated data
[118]	2018	smart home	motion sensors, beacons, switches, thermometers	determining the risk of an anomaly related to the healthcare of a resident happening and provide adequate actions to be taken so that a real anomaly does not occur	Markov Logic Network	Precision, Recall, and Correctness

[134]	2018	smart building	real and virtual sensors replacing the real ones that have been predicted as not functioning properly in future time intervals	fault-tolerant maintenance of a networked environment in the domain of the internet of things	continuous-time Markov chains, together with a cooperative control algorithm	a numerical case study highlighting the efficiency of the developed model
[119]	2018	smart home and building	wireless sensor network	proximity services in smart home and building automation	Markov chain model	thread latency
[135]	2018	smart building	radar sensors used to collect Doppler signatures of two human targets	human presence and activity recognition	hybrid, two layers of classifiers: a first-level Bayesian classifier whose inferential results are passed as input for the second level Hidden Markov Model (HMM)	Precision, Recall, evaluating energy savings
[136]	2018	smart home	MEMS sensors for 3-axis accelerometer data	human activity recognition	Hidden Markov models in order to train the device to recognize various gestures	Accuracy with which the various gestures are selected, the memory and response time requirements
[3]	2018	smart building	Light-Emitting Diode (LED) luminaires used as light sensors	human activity recognition	Support Vector Machine (SVM), Convolutional Neural Network-Hidden Markov Model (CNN-HMM), Long Short-Term Memory networks (LSTM) learning algorithms	Accuracy and Mean Square Error (MSE)
[97]	2017	smart building	passive infrared motion detecting sensors	short-term prediction of occupancy	ANN compared with traditional inhomogeneous Markov Chain model, New Markov Chain model, Probability Sampling model, Support Vector Regression (SVR)	Accuracy (Correctness)
[10]	2017	smart home	embedded sensors	human activity recognition	Hybrid, combining Beta Process Hidden Markov Model (BP-HMM) And Support Vector Machine (SVM)	Overall Accuracy, Mean Recognition Rate
[120]	2017	smart home	wireless sensor networks comprising motion, temperature and detection sensors	human activity recognition	Hidden Markov Model and Conditional Random Field model that integrate temporal and spatial relationships between actions to improve the detection accuracy	Accuracy
[81]	2017	smart home	sensors embedded in the environment: motion sensor, sensors for selected items in the kitchen, door sensor, burner sensor, hot	complex activity recognition	Complex Activity Recognition using Emerging patterns and Random forest (CARER) compared with	F-Measure

			water sensor, cold water sensor, temperature sensors, electricity usage sensor		Hidden Markov Model, Bayesian Network, Naive Bayes, SVM, Decision Tree, Random Forest	
[129]	2017	smart home	heterogeneous sensors: infrared presence sensors, door contacts, microphones	modelling the decision process in the context of a voice controlled smart home	Markov Logic Network	Confusion matrix, Leave-One-Subject-Out-Cross-Validation (LOSOCV)
[130]	2017	smart home	ambient sensors; single occupancy sensors (pressure mats, contact sensors, photocells) that can only be assigned to a single resident at a given time-step; multiple occupancy sensors (infrared sensors that can sense the use of the remote controller for the TV and motion and presence sensors that can detect multiple people) that can be assigned to more than one resident.	human activity tracking and recognition	First approach: a factorial Hidden Markov Model for modeling two separate chains corresponding to two residents; second approach: nonlinear Bayesian tracking for decomposing the observation space into the number of residents	F-Measure
[121]	2017	smart home	wireless sensor networks	human activity recognition	Markov Logic Network (MLN) compared with Artificial Neural Network (ANN), Support Vector Machine, Bayesian Network (BN) and Hidden Markov Model	F-measure
[137]	2017	smart home	distributed sensor networks	event recognition in cyber-physical systems	Semantical Markov Logic Network	Precision of recognition
[127]	2016	smart home	wearable sensors (a smartphone's tri-axial accelerometer and gyroscope) and Ambient sensors (infrared motion sensors for occupancy detection installed in the ceiling)	human activity recognition	Coupled Hidden Markov Model	activity classification accuracy, confusion matrix, execution speed
[82]	2016	smart home	simple non-intrusive sensors, PIR sensors, door sensors and occupancy sensors placed in chairs and beds.	detecting deviating human behavior	Random Forests and third order Markov chain	Local Outlier Factor (LOF), the Z-Score values, cluster transition probability
[122]	2016	smart workplace environment	wireless sensor network comprising 29 static wireless sensor nodes installed in the ceiling, each node being equipped with a passive infrared motion sensor	The sensors of the nodes use a Hidden Markov Model algorithm to forecast the locations of other sensor nodes where residents will arrive based on their activity patterns and extracted knowledge from their trajectories	Hidden Markov Model	APL: Average Path Length; LTA: Location and Time Accuracy; PRDOS: pressure of receiving data on sink node; APRDOS: average PRDOS of sink node

[124]	2016	smart home	wireless sensor networks, infrared sensors.	state estimation for a special class of flag Hidden Markov Models	a special class of flag Hidden Markov Models (HMMs)	Probability of error
[125]	2016	smart home	multiple sensors, such as binary presence detectors (Presence Infra-Red sensors or PIR), continuous microphone signals or temperature measurement, along with actuators and home automation equipment	human activity recognition	Hidden Markov Model (HMM), Conditional Random Fields (CRF) and a sequential Markov Logic Network (MLN); results compared to those of three non-sequential models: a Support Vector Machine (SVM), a Random Forest (RF) and a non-sequential MLN	Accuracy measure over the full dataset, Average Accuracy per class
[128]	2016	smart home	off-the-shelf binary sensors that measure motion, pressure on the bed, toilet flush, the opening and closing of cabinets and doors	the detection of visits in the home of older adults living alone	Markov modulated multidimensional non-homogeneous Poisson process (M3P2) compared with the classical Markov modulated Poisson process (MMPP)	Experiments, Precision, Recall and F -value
[132]	2016	smart home	for the electrical plugs; light, humidity and temperature; to measure the position of the shutter, the opening/closing of the doors and of the windows; Infra-red sensors, positioned at strategic locations in the rooms, to know where the person is; Actuators to command the heaters, the light, to turn on/off the different electrical outlets/plugs, to change the positions of the windows shutters	human activity recognition in smart home environments	semi-supervised learning algorithms and Markov-based models	simulation tests in order to compare the Generalized Version Space (GVS) algorithm with a simple method using an epsilon greedy mechanism
[33]	2016	smart home	four kinds of biosensors: Electro-Dermal Activity sensor (EDA), Electrocardiogram sensor (ECG), Blood Volume Pulse sensor (BVP) and surface Electromyography sensor (EMG)	ambient assisted living framework for emergency psychiatric state prediction	Hidden Markov Model (HMM), Viterbi path counting, scalable Stochastic Variational Inference (SVI)-based training algorithm Generalized Discriminant Analysis	Prediction Accuracy (Acc), Sensitivity (Sen), Specificity (Spe), F-Measure (FM) and Area Under the ROC Curve (AUC)
[138]	2015	smart home	smart meter	load disaggregation	Nonintrusive Load Monitoring (Nilm), Hidden Markov Models	Accuracy
[133]	2014	smart building	wireless Netatmo room climate sensors to measure temperature, relative humidity, barometric pressure, acoustics and CO_2	occupancy detection in view of energy saving	Hidden Markov Model used in a supervised and unsupervised way	Accuracy, Precision, Sensitivity, Specificity and F1 Score
[131]	2012	smart home	non-wearable ambient sensors consisting in: RFID sensors, Temperature sensors, Humidity sensors, Infrared sensors, Electromagnetic sensors, Pressure detectors,	human activity recognition	the proposed model is compared with the results obtained when using the Hidden Markov Model and the Conditional Random Field Model	Recognition Accuracy (%)

			Switch contacts, Door and closet contacts, Flow sensors, Item sensors, Burner Hot water sensors, Cold water sensors, Electricity sensors, Phone sensors, Medicine container sensors, Contact switches			
[126]	2012	health smart home	passive presence infrared sensors	human activity recognition in view of detecting the loss of a patient's autonomy through means of simulating normal behavior and comparing it with the actual behavior resulting from the sensors' data	Hidden Markov Model	correlation factors depicting the similarities between simulated and real displacement activities
[70]	2012	smart home	motion sensors, sensor network	human activity recognition in smart home environments	Naïve Bayes classifier, Hidden Markov Model and Viterbi algorithm	Recognition Accuracy Rate
[123]	2011	smart home	wireless sensor network highlighting the user movement (i.e., both hands), user location, human–object interaction (i.e., objects touched and sound), human-to-human interaction (i.e., voice), environmental information (i.e., temperature, humidity and light)	human activity recognition	Coupled Hidden Markov Model (CHMM) and Factorial Conditional Random Field (FCRF)	Accuracy, the heuristic merit of a sensor feature subset S containing k features

Table S14. Scientific articles tackling the Hierarchical Clustering integrated with sensor devices in smart buildings

Reference	Publication Year	Type of smart building	Type of sensors	Reason for using the Hierarchical Clustering approach with sensor devices	Hierarchical Clustering-only or hybrid	Performance metrics
[19]	2019	smart building	smartphone sensors and Bluetooth beacons data	group activity detection and recognition	a framework for indoor Group Activity Detection And Recognition (GADAR) and Hierarchical Clustering, along with Decision Tree classifier, K-Neighbors classifier, Deep Neural Network, Gaussian Process classifier, Logistic regression, Support Vector Machine, Linear Discriminant Analysis, Gaussian Naïve Bayes (comparison)	Confusion Matrix, Accuracy (Mean), Accuracy (Variation), Precision, Recall, F1-score
[37]	2019	smart building	WiFi-enabled IoT device-user	personalized location-based service	hybrid: Hierarchical Clustering and Location Similarity Matching	Accuracy

[139]	2014	smart building	smart meters organized into clusters	data collection in hierarchical smart building networks	hybrid Hierarchical Clustering containing a two-layer transmission process	simulations scenarios, comparison of the proposed scheme's performance with the performance of the Uniform Algorithm

Table S15. Scientific articles tackling the K-Means integrated with sensor devices in smart buildings

Reference	**Publication Year**	**Type of smart building**	**Type of sensors**	**Reason for using the K-Means method with sensor devices**	**K-Means-only or hybrid**	**Performance metrics**
[26]	2018	smart home	binary sensors	extraction of behavioral patterns	hybrid: K-Means Algorithm combined with Nominal Matrix Factorization method	"comparison with existing methods based on both synthetic and publicly available real smart home datasets"
[140]	2018	smart buildings	sensor network	discovering electricity consumption patterns	Cluster Validation Indices (CVIs) for establishing the optimal number of clusters k for the dataset, combined with the Parallelized Version of K-Means Clustering Algorithm for discovering patterns from the dataset	Cluster Analysis, Centroids of the electricity consumption clusters, Centroids of the clusters with lower consumptions, Computing times
[42]	2018	smart building	smart meters, Personal Weather Stations (PWS), sensors providing data useful in computing the mean values of: hourly indoor temperature, hourly outdoor temperature, hourly value of precipitation, hourly value of wind direction, hourly value of solar radiation, hourly value of ultraviolet index, hourly value of humidity, hourly value of pressure	managing energy consumption	Data Mining Engine, METATECH (METeorological data Analysis for Thermal Energy CHaracterization)	Support, Confidence and Lift

energies

Table S16. Scientific articles tackling the Deep Learning techniques integrated with sensor devices in smart buildings

Reference	Publication Year	Type of smart building	Type of sensors	Reason for using the Deep Learning method with sensor devices	Deep Learning-only or hybrid	Performance metrics
[18]	2019	smart home	wearable hybrid sensor system comprising motion sensors and cameras	human activity recognition in medical care, smart homes, and security monitoring	hybrid approach, combining Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) methods	Confusion Matrices, F1 Accuracy
[27]	2019	smart home	a two-dimensional acoustic array	human activity recognition	Convolutional Neural Networks compared with traditional recognition approaches such as K-Nearest Neighbor and Support Vector Machines	Overall Accuracy
[28]	2019	smart home	daily activities recognition sensors, infrared motion and temperature sensors	human activity recognition	hybrid, using Term Frequency-Inverse Document Frequency (TF-IDF), along with each of the Support Vector Machine (SVM), Sequential Minimal Optimization (SMO), and Random Forest (RF), Long Short-Term Memory (LSTM) methods and comparison between them	Accuracy, Precision, and F-Measure
[25]	2019	smart home	34 sensors (3 door and 31 motion sensors)	sensor based activity recognition and abnormal behavior detection	Convolutional Neural Networks (CNNs) for detecting abnormal behavior related to dementia, the results being compared with methods such as Naïve Bayes (NB), Hidden Markov Models (HMMs), Hidden Semi-Markov Models (HSMM), Conditional Random Fields (CRFs)	Precision, Recall, F-Measure and Accuracy, Sensitivity, Specificity
[21]	2019	smart building	wireless sensor networks	forecasting Packet Delivery Ratio (PDR) and Energy Consumption (EC) in Internet of Things (IoT)	comparison between Linear Regression, Gradient Boosting, Random Forest, Baseline and Deep Learning Neural Networks	Root Mean Square Error (RMSE), Mean Percentage Error (MPE), and Mean Absolute Percentage Error (MAPE)
[141]	2019	smart building	wireless sensors nodes for controlling the lighting fittings, a combination of chair sensors and wireless PIR motion sensors for occupancy detection	Small and Big Data management	Deep Neural Networks for system monitoring and optimization	Root Mean Square Error (RMSE), Mean Percentage Error (MPE), and Mean Absolute Percentage Error (MAPE)

[146]	2018	smart home	smartphone inertial sensors: triaxial gyroscope and accelerometer, at a sampling rate of the raw signals of 50 Hz for both the sensors.	human activity recognition	Deep Belief Network (DBN) compared with Support Vector Machine (SVM) and Artificial Neural Network (ANN)	Overall Accuracy, Mean Recognition Rate
[142]	2018	smart home	motion and environment sensors	human activity recognition for senior daily care	hybrid Deep Learning-based gesture/locomotion recognition model, integrating CNN and RNN	Accuracy, Precision, Recall, and F1 Score
[143]	2018	smart home	motion sensors, temperature sensors, door sensors and actuators	human activity recognition	different Deep Learning (DL) models based on the Long Short-Term Memory (LSTM) compared with Hidden Markov Model (HMM), Conditional Random Field (CRF) and Naive Bayes (NB) approaches	Accuracy, Precision, Recall, and F1 Score
[144]	2018	smart home	infrared motion sensors, tactile sensors, temperature sensors, power meter, seven microphones in the ceiling	adaptive decision-making in smart homes	hybrid method, Adaptive Reinforced Context-Aware Deep Decision System (ARCADES) combining Deep Neural Networks and Reinforcement Learning (RL)	Reward per episode, Precision, Recall, F1 score
[145]	2018	smart home	Wireless Sensor Network (WSN) including Passive InfraRed (PIR) sensors for motion detection, magnetic contact sensors for monitoring open/close states of different objects, bed occupancy sensor, chair occupancy sensor, toilet presence sensor, fridge sensor, power meter to monitor home appliances use, such as TV, microwave oven, air conditioning, etc.	human behavioral analysis	a comparison between: Recurrent Neural Networks (Long-Short Term Memory, Gated Recurrent Units), Convolutional Neural Network, Behavior Explanatory Models, Sensor Profiles	methods discussed and evaluated on real-life data; the confusion matrix
[147]	2018	smart home	Microsoft Kinect as a non-wearable sensor	human gesture recognition	Deep Learning technique, namely the recurrent neural network (RNN) using the long short-term memory (LSTM) architecture	Root Mean Square Error (RMSE), Mean Percentage Error (MPE)
[9]	2018	smart home	unobtrusive sensor (ARGUS)	human activity recognition	the SVM classifier along with two different feature extraction methods: a manually defined method, and a Convolutional Neural Network (CNN)	Accuracy, Root Mean Square Error (RMSE)
[40]	2018	smart building	Wireless Sensor Network (WSN) for the environmental data (air temperature, relative humidity)	thermal comfort modeling	an Intelligent Thermal Comfort Management (iTCM) system black-box neural network (ITCNN); the performance of ITCNN is compared with the Fanger's predicted mean vote (PMV) model, and six classical machine learning	Energy cost savings

energies

					approaches: three traditional white-box machine learning approaches and three classical black-box machine learning methods.	
[73]	2018	smart home	environmental sensors: Passive Infrared (PIR) and temperature sensors	human activity recognition	Deep Convolutional Neural Network (DCNN) compared with Naïve Bayes (NB), Back-Propagation (BP) algorithms	Precision, Specificity, Recall, F1-Score, Accuracy, Total Accuracy, Confusion Matrix
[12]	2018	smart commercial and residential buildings	weather sensors	forecasting the electricity consumption	deep Recurrent Neural Network (RNN) models	Root Mean Square Error relative to Root Mean Squared (RMS) average of electricity consumption in test data, Root Mean Square Error relative to Root Mean Squared (RMS) average of electricity consumption in training data, Pearson Coefficient
[36]	2018	smart home	WI-FI enabled sensors for food nutrition quantification, and a smart phone application that collects nutritional facts of the food ingredients	Internet of Things (IoT)-based fully automated nutrition monitoring system	Bayesian algorithms and 5-layer Perceptron Neural Network method for diet monitoring	Accuracy of classification of food items and meal prediction
[148]	2017	smart home	binary sensors	human activity recognition	Activity Recognition (AR) model based on Deep Learning, developed in two cases: one-layer Denoising Autoencoder (DAE) and two-layer Stacked Denoising Autoencoder (SDAE), compared with five commonly used baselines: Naïve Bayes (NB), Hidden Markov Model (HMM), Hidden Semi-Markov Model (HSMM), K-Nearest-Neighbor (KNN), and Support Vector Machine With Linear Kernel (SVM)	time-slice Accuracy and Class Accuracy