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Room Occupancy Detection Using IoT Sensor Data and Machine Learning

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***Abstract*:** We examine room occupancy detection utilizing IoT sensor data, leveraging characteristic parameters such as temperature, mugginess, light, and CO_2 levels. Our approach uses machine learning models, counting Logistic Regression, Decision Trees, Random Forests, and Support Vector Machines (SVM) to anticipate room occupancy status based on these sensor readings. Our models can anticipate occupancy, with the Random Forest model finishing the preeminent essential execution, boasting an accuracy of 99.35%. Our commitment lies in showing the adequacy of combining IoT sensor data with progressed machine learning methodologies to upgrade room occupancy detection, publicizing crucial potential for applications in brilliantly building organizations to optimize imperativeness utilization and make strides in inhabitant consolation.

Keywords: Room Occupancy**,** IoT Sensors**,** Machine Learning**,** Data Preprocessing**,** Model Evaluation

1. Introduction

Occupancy detection in buildings is significant for optimizing essentialness utilization and updating the consolation and security of occupants. Traditional strategies, such as movement sensors, confront confinements in exactness and scope. These routine frameworks frequently come up short of distinguishing stationary occupants, driving to false negatives, and may trigger false positives due to temporal developments, such as pets or moving objects. Besides, these frameworks are ordinarily restricted to double states—occupied or not—without giving nitty gritty experiences into the number of occupants or their particular areas inside a space [1]. As buildings endeavor to be more energy-efficient and occupant-friendly, there's a developing requirement for more solid and nuanced inhabitance location frameworks.

With the appearance of IoT innovation, collecting a broad run of natural information has become attainable, giving modern openings for more precise occupancy detection. IoT gadgets can ceaselessly screen natural parameters such as temperature, humidity, light intensity, and CO_2 concentration. These parameters frequently relate to human nearness and exercises, advertising a wealthier dataset for occupancy detection. By coordinating IoT sensors into building administration frameworks, it is conceivable to attain more exact control over warming, ventilation, and discuss conditioning (HVAC) frameworks, lighting, and other energy-consuming forms, lessening vitality wastage and making strides in indoor natural quality [2].

This study uses natural sensors and machine learning calculations to foresee room occupancy. The focus is on leveraging IoT sensors, counting those that degree temperature, stickiness, light, and CO_2 levels, to overcome the restrictions of conventional strategies. Machine learning models are utilized to analyze this sensor data and predict occupancy status. These models can capture complex plans and associations inside the data that less complex, rule-based systems might miss. Combining these developments ensures applications in sharp building organization, where beneficial essentialness utilization and occupant reassurance are prioritized [3].

In this research, we'll detail the procedure used to gather and preprocess the data, select and plan machine learning models, and assess these models' execution in predicting room occupancy. We will outline how assorted machine learning calculations, counting logistic regression, decision trees, random forest, and support vector machines (SVM) can be connected to this task by comparing their execution utilizing distinctive evaluation estimations. The results of this study point to giving bits of information into the preeminent reasonable techniques for executing advanced inhabitance discovery systems in present-day buildings [4].

2. Literature Review

The occupancy detection field has advanced with the presentation of IoT and machine learning advances. Early strategies depended intensely on movement sensors and manual switches, frequently restricted by their precision and scope. These strategies ordinarily gave twofold occupancy data and were inclined to mistakes, especially in energetic situations where inhabitants might stay stationary for long periods or where transitory objects activated untrue location [5].

Later studies have investigated using natural sensors and data-driven approaches for more solid locations. For instance, integrating temperature, humidity, light, and CO_2 sensors has moved detection capabilities forward by giving wealthier information sources. Temperature and humidity changes can indicate human presence, while light and CO_2 level variations can relate to occupancy designs. For example, CO_2 levels tend to expand with human breath, making them a dependable pointer of occupancy, especially in kept spaces [6].

Machine learning algorithms have been utilized to plan and analyze this data, illustrating vital advancements in desired precision. Logistic regression, decision trees, random forests, and SVMs are commonly used algorithms in this space. Logistic regression, a transparent and interpretable show, is utilized as often as possible as a standard due to its ampleness in parallel classification errands. Decision trees deliver different leveled structures for making choices based on highlight values, making them characteristic and direct to decipher. Be that as it may, they can be slanted to overfitting [7].

Random forests, a group method combining multiple decision trees, have proven particularly effective in occupancy detection. Their robustness and ability to handle diverse datasets make them a popular choice. By averaging the predictions of multiple decision trees, random forests reduce the risk of overfitting and improve generalization to new data. This makes them a preferred option for occupancy detection tasks where the data may be noisy or contain outliers [8]. Support vector machines, which discover the ideal hyperplane that isolates classes, have also been utilized effectively, especially when managing high-dimensional information [9].

Studies have shown that combining multiple sensor sorts and advanced information handling procedures can improve inhabitance discovery exactness. For occurrence, Dong et al. [10] illustrated that employing a combination of temperature, humidity, and light sensors and machine learning calculations might accomplish tall exactness in foreseeing occupancy in office situations. Also, Erickson et al. [11] found that CO_2 and mugginess sensors gave solid inhabitance data in private buildings when used with irregular timberland models.

This study builds upon these progressions, pointing to upgrading occupancy detection exactness through the vital utilization of IoT sensors and progressed machine learning strategies. By utilizing a comprehensive dataset that incorporates different natural parameters and applying state-of-the-art machine learning models, we aim to create a robust framework for foreseeing room occupancy. Our approach includes thorough information preprocessing, counting exception detection, and highlight normalization to guarantee the quality and unwavering quality of the input information [12]. We'll compare the execution of distinctive models utilizing assessment measurements such as precision, precision, recall, and F1-score to decide the foremost viable model for this task.

The objective of this research isn't, as it were, to attain tall forecast exactness but too to supply bits of knowledge into the down-to-earth usage of IoT-based occupancy detection frameworks. By demonstrating the effectiveness of distinctive models and sensor combinations, we trust that they will contribute to advancing more effective and solid-savvy building advances [13]. Future inquiries may investigate the integration of extra sensors, such as movement finders and acoustic sensors, and the advancement of real-time occupancy detection frameworks that can powerfully alter building administration forms based on current occupancy conditions [14].

3. Methodology

The data utilized in this study comprises different natural parameters vital for anticipating room occupancy. These parameters incorporate surrounding temperature, measured in degrees Celsius, which gives an understanding of the room's warm conditions. Machine learning models are utilized to analyze this sensor data and predict occupancy status. These models can capture complex plans and associations inside the data that less complex, rule-based systems might miss. Combining these developments ensures applications in sharp building organization, where beneficial essentialness utilization and occupant reassurance are prioritized [3].
In this research, we'll detail the procedure used to gather and preprocess the data, select and plan machine learning models, and assess these models' execution in predicting room occupancy. We will outline how assorted machine learning calculations, counting logistic regression, decision trees, random forest, and support vector machines (SVM) can be connected to this task by comparing their execution utilizing distinctive evaluation estimations. The results of this study point to giving bits of information into the preeminent reasonable techniques for executing advanced inhabitance discovery systems in present-day buildings.

Table 1: Data Collection Parameters

Parameter	**Description**	**Sensor Used**	**Range**	**Purpose**
Temperature	Ambient temperature in Celsius	Digital Temperature Sensor (e.g., DHT22)	-40°C to 80°C	Measures the room's temperature, influencing occupant comfort and HVAC control.
Humidity	Relative humidity in %	Humidity Sensor (e.g., DHT22)	0% to 100%	Captures the moisture level in the air, affecting indoor air quality and occupant comfort.
Light	Light intensity in Lux	Light Sensor (e.g., TSL2561)	0 Lux to 40,000 Lux	Monitors the room's illumination, essential for energy management and occupant activity recognition.
CO_2	CO_2 concentration in ppm	CO_2 Sensor (e.g., MH-Z19)	0 ppm to 5000 ppm	Detects CO_2 levels to assess air quality, which impacts occupant health and ventilation needs.

The table gives a detailed diagram of the essential natural parameters collected during the study, counting temperature, mugginess, light escalated, and CO_2 concentration. Each parameter is significant for understanding the flow of room inhabitance and optimizing building administration frameworks. The sensors utilized to gather this information are mainly chosen for their precision and run, guaranteeing dependable input for the machine learning models created in this inquiry.

3.1 Data Preprocessing

The data preprocessing included noteworthy steps to ensure its quality and appropriateness for machine learning demonstration arrangement. To begin with, we tended to the issue of misplaced data. Fortunately, all the data was

distinguished inside the primary dataset, allowing us to proceed without requiring the credit or departure of records. Next, we focused on identifying exceptions. These can significantly affect the results of machine learning models, leading to inaccurate predictions. To address this, we employed the Interquartile Range (IQR) procedure, which effectively identifies and handles exceptions by measuring the spread of the middle 50% of the data. This process resulted in removing exceptions and a refined dataset containing 14,781 records.
Finally, normalization was performed to standardize the run of the unmistakable standard parameters. This step is fundamental for guaranteeing that all highlights contribute essentially to the model's execution, and the show does not get to be one-sided towards highlights with greater scales. We associated Min-Max scaling, which changed all highlights to a standard scale expanding from 1. This normalization handle distinguishes between the combined speed and accuracy of the machine-learning algorithms used in this study.
Mathematically, the Min-Max scaling can be represented as:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where:

X is the original value
X' is the scaled value
X_{min} Is the minimum value of the feature
X_{max} Is the maximum value of the feature

Table 2: Data Pre-processing Steps

Step	**Description**	**Details**
Handling Missing Data	No missing data	Ensured the dataset had no missing values, allowing for consistent model training.
Outlier Detection	Using the IQR method, the dataset was reduced to 14,781 records	Outliers were recognized utilizing the Interquartile Range (IQR) strategy, which evacuated extraordinary values that seem skew demonstrate execution. This step refined the dataset to center on more agent information.
Feature Normalization	Applied Min-Max scaling to range [0, 1]	Normalized all highlights to a standard scale of [0, 1] utilizing Min-Max scaling, guaranteeing each include contributed similarly to the model's forecasts. This step is essential for algorithms that include extents, such as k-NN and SVM.

Table 2 outlines the primary data preprocessing steps connected to the dataset sometime recently preparing the machine learning models. Each step is outlined to improve the data quality, guaranteeing the models are ready on precise, normalized, and agent data. Dealing with lost information, recognizing and evacuating exceptions, and normalizing highlights are vital steps in planning the dataset, as they directly impact the accuracy and execution of the prescient models.

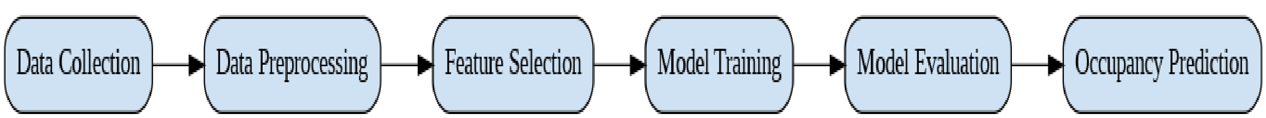

Figure 1 Methodology Concept diagram

3.2 Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) was conducted to determine the connections between the different natural parameters in our dataset. One essential device utilized in this investigation was the correlation matrix, which outlines the straight connections between sets of factors.

Table 3: Correlation Matrix

Parameter	Temperature	Humidity	Light	CO_2	Humidity Ratio
Temperature	1.00	0.33	0.18	0.37	0.85
Humidity	0.33	1.00	0.15	0.28	0.92
Light	0.18	0.15	1.00	0.47	0.14
CO_2	0.37	0.28	0.47	1.00	0.29
Humidity Ratio	0.85	0.92	0.14	0.29	1.00

The correlation matrix quantitatively assesses the relationships between different environmental parameters collected in the study. Understanding these correlations is critical for feature selection and engineering in machine learning models. Parameters with strong correlations may indicate redundant information, while weak correlations suggest independent influences on room occupancy.

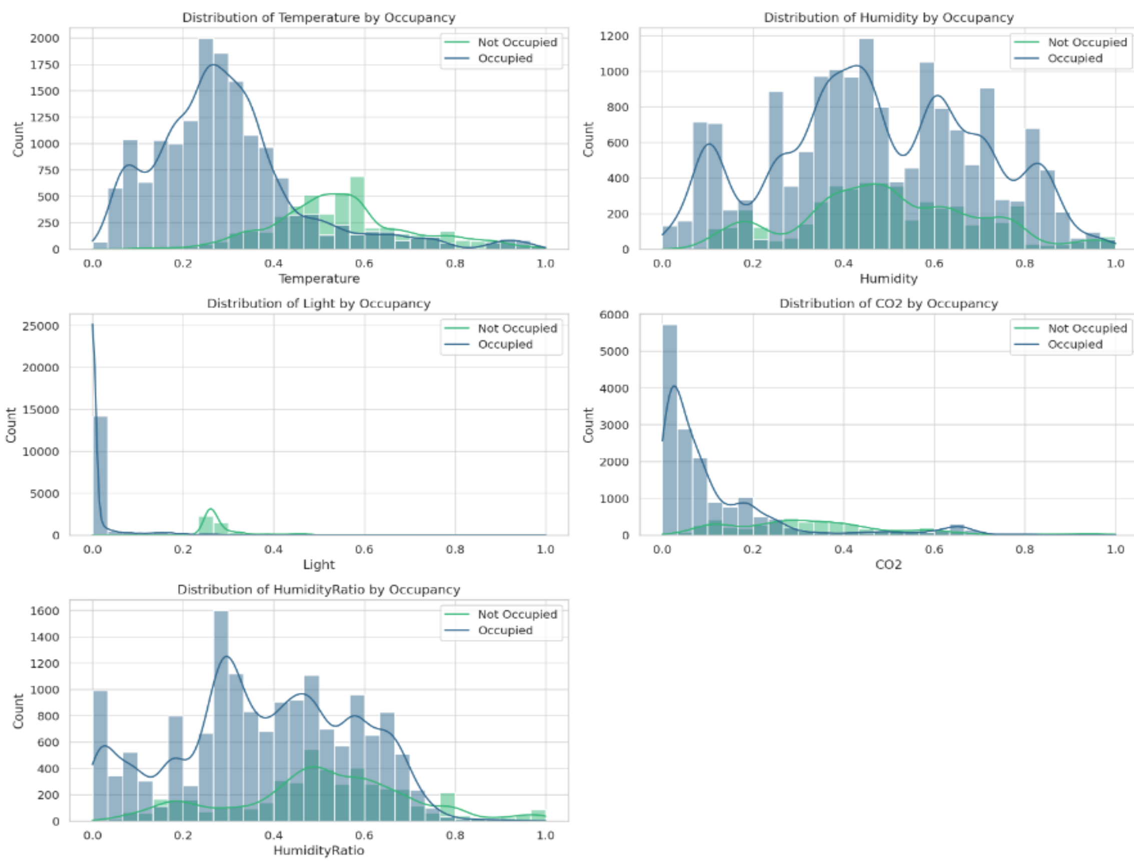

Figure 2 Heat Map of Feature Correlations

The set of histograms in Figure 1 shows the conveyances of five natural features—temperature, Humidity, Light, CO_2, and humidity ratio—by room occupancy status (Involved and Not Involved). These visualizations highlight the contrasts in including conveyances between involved and empty states.

- **Temperature**: The distribution indicates that rooms are more frequently occupied at higher temperatures.
- **Humidity**: The chart shows a broader range of humidity levels when rooms are not occupied, with a noticeable decrease in the occupied state.
- **Light**: Displays a noteworthy contrast, with most possessed rooms having higher light intensity.
- **CO_2**: The distribution uncovers higher CO_2 levels in possessed rooms, proposing human nearness.
- **Humidity Ratio**: This indicates a comparative trend as humidity, with higher values being more common when rooms are not involved.

These distributions help us understand the natural conditions related to room occupancy and highlight the need for proactive modeling. These plots visually confirm the relationship between environmental parameters and room occupancy. Each parameter shows distinct differences between occupied and unoccupied states, reinforcing that sensor data can effectively predict occupancy. By analyzing these distributions, the research demonstrates how machine learning models can detect patterns in these variables, thereby optimizing building management systems for energy efficiency, comfort, and security.

3.3 Model Building

A few machine-learning models, including logistic regression, decision trees, random forests, and support vector machines (SVM), were assessed for occupancy prediction. The models were prepared using a training set and approved using an isolated test set.

LR mathematically represented as:

$$P(Y=1)=\frac{1}{1+e^{-(\beta_0+\beta_1X_1+\beta_2X_2+\cdots+\beta_nX_n)}} \tag{2}$$

Where:

$P(Y=1)$ is the probability of the output being 1

$\beta_0, \beta_1, \ldots, \beta_n$ Are the model coefficients

$X_1, X_2, \ldots, X_n$ Are the feature values

Table 4: Machine Learning Models

Model	Description	Strengths	Limitations
Logistic Regression	A linear model for binary classification. It estimates the probability that a given input belongs to a specific class by fitting a logistic function to the input features.	- Simple to implement and interpret.	Assumes a linear relationship between the features and the log odds. - May struggle with non-linear relationships.
Decision Trees	A tree-based model for classification. It splits the data into branches based on feature values, leading to a decision about the class label.	- Easy to interpret and visualize. - Can handle both numerical and categorical data. - No need for feature scaling.	Prone to overfitting, especially with deep trees. - Sensitive noisy data.
Random Forests	An ensemble method that uses multiple decision trees to improve classification accuracy by averaging their predictions.	Reduces overfitting compared to individual decision trees. - Handles large datasets with high dimensionality well. - Robust to noise.	- More complex and computationally intensive than single decision trees. - Less interpretable than individual trees.
SVM (Support Vector Machine)	A model that finds the hyperplane best separates the classes in the feature space. It is particularly effective in high-dimensional spaces.	- Effective in high-dimensional spaces. - Works well with both linear and non-linear data (using kernels). - Robust to overfitting, especially in high-dimensional settings.	- Computationally intensive, especially for large datasets. - Choosing the correct kernel and parameters can be complex.

Table 4 summarizes the different machine learning models employed in the study, briefly describing their strengths and acknowledging their limitations. This table is a reference point for understanding the models' suitability for predicting room occupancy based on sensor data.

3.4 Train-Test Split

This study separated the dataset into preparing and testing sets to guarantee vigorous assessment of the machine learning models. Notably, 80% of the information was distributed to prepare the models, permitting them to memorize and adjust to the more significant part of the information. The remaining 20% was saved as the test set, which was utilized to survey the models' execution on concealed information. This part guarantees that assessing the models' precision, exactness, review, and F1-score is conducted on information not utilized amid the preparing stage, giving a more exact degree of generalization capabilities.
Mathematically, the split can be defined as:

$$\text{Training Set} = \text{Total Data} \times 0.8 \quad (3)$$

$$\text{Test Set} = \text{Total Data} \times 0.2 \quad (4)$$

Table 5: Train-Test Split

Set	Records	Description
Train	80%	The training set comprises 80% of the entire dataset. This set trains the machine learning models, allowing them to memorize the fundamental designs within the data. The more critical extent designated to preparing ensures the models have adequate information to learn effectively.
Test	20%	The test set makes up the remaining 20% of the dataset. This set is utilized to assess the execution of the prepared models, giving a fair-minded appraisal of how well the models generalize to inconspicuous information. The test set is pivotal for approving the model's prescient accuracy and robustness.

The reason for the train-test part is to partition the dataset into two sets:
One for preparing the machine learning models and one for testing their execution. By part of the information, we guarantee that the models are assessed based on information they have not seen while preparing, which is essential for surveying their generalization capacity. 80-20 parts could be a common practice that equalizes the requirement for adequate preparation information and the necessity for a critical evaluation of the test set.

3.5 Evaluation Metrics

The assessment estimations used to evaluate the execution of the machine learning models join exactness, precision, review, and F1-score. Exactness measures the degree of redress desires the show makes out of all desires. Accuracy calculates the significance of genuine positive desires among all positive desires, showing the model's capacity to avoid wrong positives. Recall assesses the model's capacity to precisely recognize all honest-to-goodness positives, reflecting its reasonability in capturing veritable positives. The F1-score, the consonant unfeeling of precision and survey, gives a balanced metric that considers both unfaithful positives and negatives, promoting a comprehensive see of the model's execution.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (5)$$

Table 6: Evaluation Metrics

Metric	Description
Accuracy	The proportion of correct predictions
Precision	The proportion of true positives among predicted positives
Recall	The proportion of true positives among actual positives
F1-Score	The harmonic mean of precision and recall

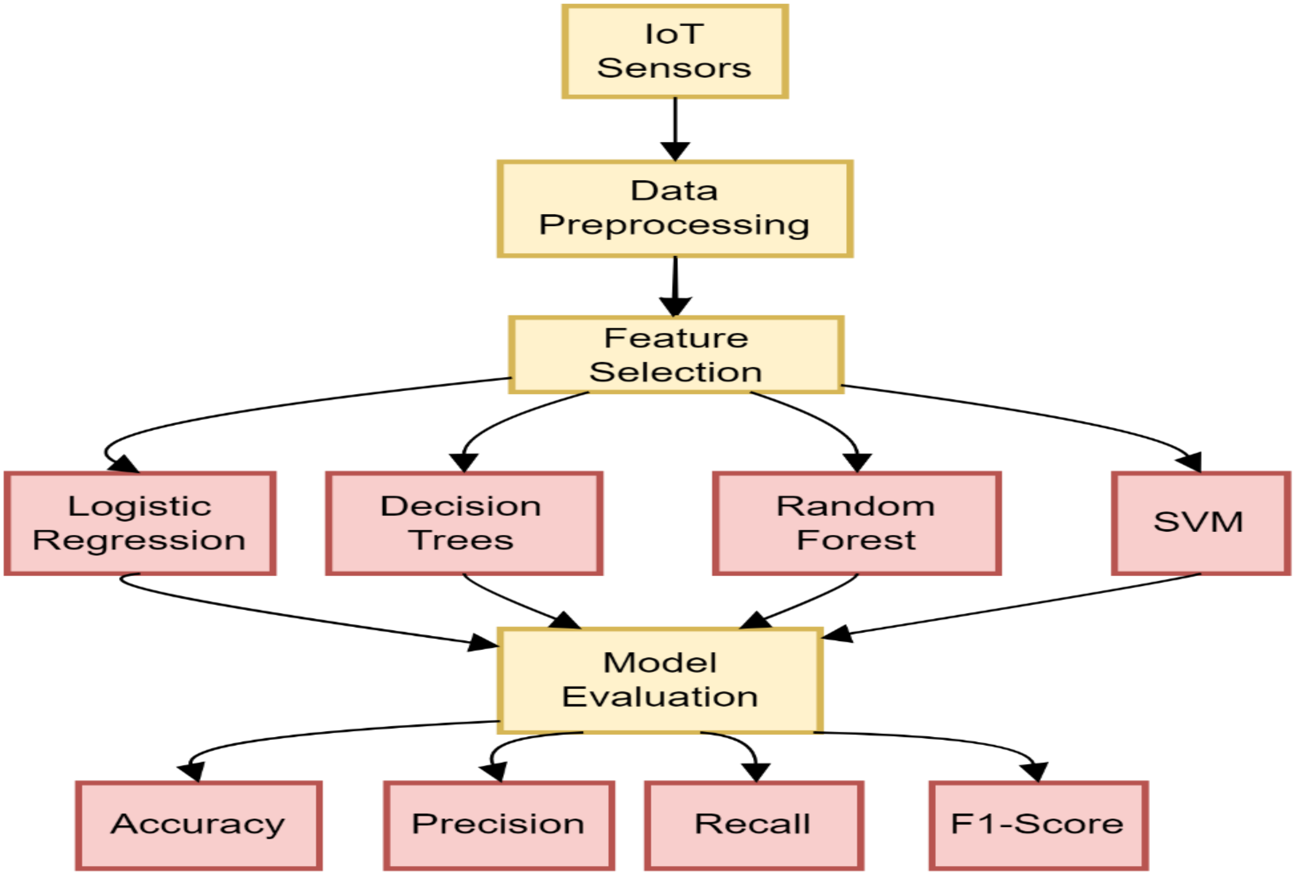

Figure 3 Room Occupancy Detection Model Using IoT Sensor Data and Machine Learning Techniques

The diagram illustrates a comprehensive model for identifying room occupancy using IoT sensor data and applying different machine-learning strategies. The method starts with collecting data from IoT sensors, which then experience data preprocessing to guarantee its quality and pertinence. After preprocessing, feature selection is performed to recognize the foremost noteworthy factors affecting room occupancy. The chosen features are, at that point, encouraged into four machine learning models:

Logistic Regression, Decision Trees, Random Forest, and SVM (Support Vector Machine). These models are assessed based on key measurements, counting Accuracy, Precision, Recall, and F1-Score to decide their execution in foreseeing room occupancy status. The stream and interactions among the components are outwardly represented within the graph, with each step color-coded for clarity.

4: Results

4.1 Model Performance

The models were surveyed utilizing accuracy, precision, review, and F1-score estimations. The execution of each appearance is summarized below:

Table 7: Model Performance

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.9887	0.9516	0.9947	0.9727
Decision Tree	0.9908	0.9838	0.9707	0.9772
Random Forest	0.9935	0.9802	0.9880	0.9841
SVM	0.9887	0.9516	0.9947	0.9727

The Random Forest model illustrated the most elevated and significant performance, with an accuracy of 99.35%, precision of 98.02%, review of 98.80%, and F1-score of 98.41%.

Figure 4 Models Accuracy

The figure outlines the accuracy of four particular machine-learning models used for room occupancy detection: Logistic Regression, Decision Tree, Random Forest, and SVM (Support Vector Machine). The Random Forest demonstrates fulfilled the foremost lifted precision, close to 99.4%, illustrating its transcendent execution in expecting room inhabitance. The decision tree also performed well, with an imperceptibly high accuracy of over 99%. Logistic Regression and SVM had somewhat lower exactness, around 98.7%. This comparison highlights that outfit strategies like Random Forest can improve prescient precision in classification assignments, including IoT sensor data.

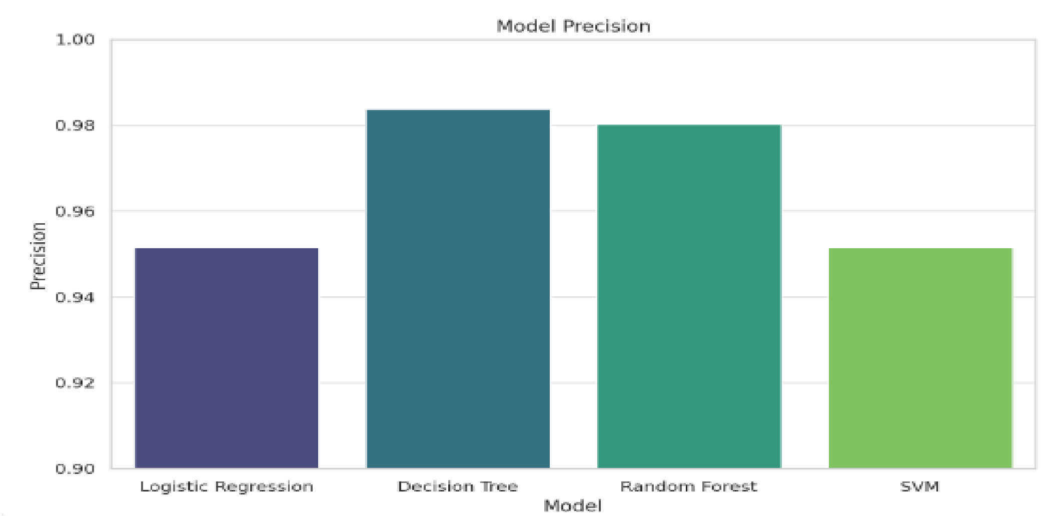

Figure 5 Model Precision

The bar chart in Figure 2 shows the exactness of four machine-learning models utilized for room occupancy detection:

Logistic Regression, Decision Tree, Random Forest, and SVM (Support Vector Machine). Accuracy measures the extent of genuine positive expectations among the demonstrated optimistic forecasts. The Decision Tree appears finished with the foremost raised accuracy, close to 98.4%, showing its strong capacity to recognize honest-to-goodness positives while minimizing off-base positives precisely—the Random Forest model also performed well, with an accuracy of around 98%. Logistic Regression and SVM had somewhat lower precisions, at generally 95.2% and 94.8%, independently. This suggests that while all models are compelling, the Decision Tree and Random Forest models are inconceivably capable of making correct idealistic estimates in this inhabitance discovery errand.

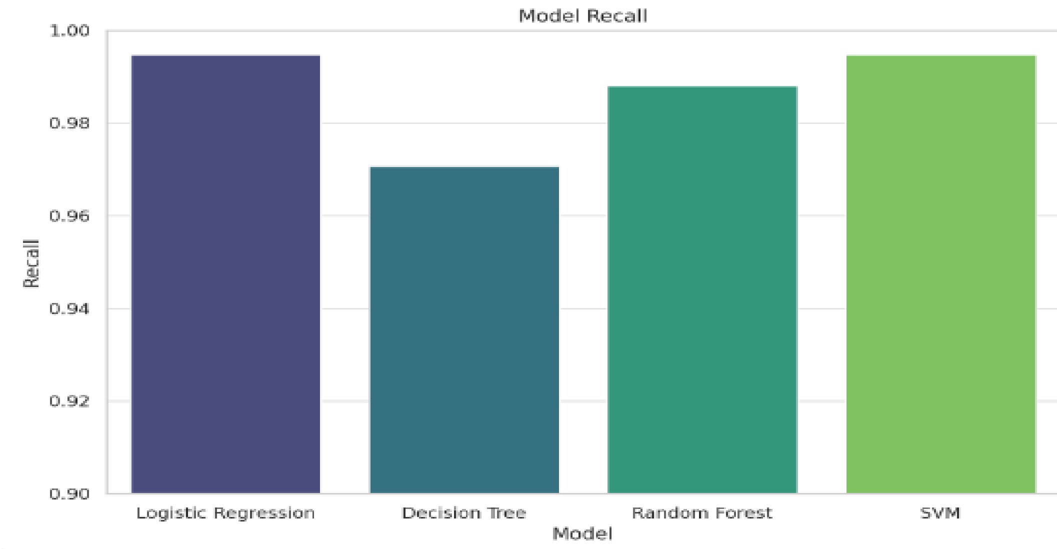

Figure 6 Model Recall

The bar chart in Figure 3 illustrates the review of four machine-learning models utilized for room occupancy detection:
Logistic Regression, Decision Tree, Random Forest, and SVM (Support Vector Machine). Review measures the extent of genuine joyous occasions accurately recognized by the demonstration among all genuine positive occurrences. The SVM show accomplished the most noteworthy review, near 99.5%, showing its solid capacity to identify the most genuine positives. The Logistic Regression model performed well, with a review of roughly 99.5%. The Random Forest show had a review of around 98.8%, whereas the Decision Tree had a review of almost 97%. This comparison highlights that whereas all models successfully recognize genuine positives, the SVM and Logistic Regression models are competent in this perspective, guaranteeing that all real positives are recognized.

Figure 7 Model F1-Score

The bar chart in Figure 4 shows the F1-score of four machine learning models utilized for room occupancy detection:
Logistic Regression, Decision Tree, Random Forest, and SVM (Support Vector Machine). The F1-score is the consonant cruel of exactness and review, giving a single metric equalizing both viewpoints of demonstrating

execution. The Random Forest model accomplished the most noteworthy F1-score, near 98.4%, showing its prevalent execution in exactness and review. The Decision Tree and Logistic Regression models were taken after, with F1-scores around 97.7% and 97.3% individually. The SVM model had a lower F1 score, at roughly 97.3%. This comparison highlights that the Irregular Timberland show gives the leading balance between exactness and review, making it the foremost compelling demonstration of this classification errand.

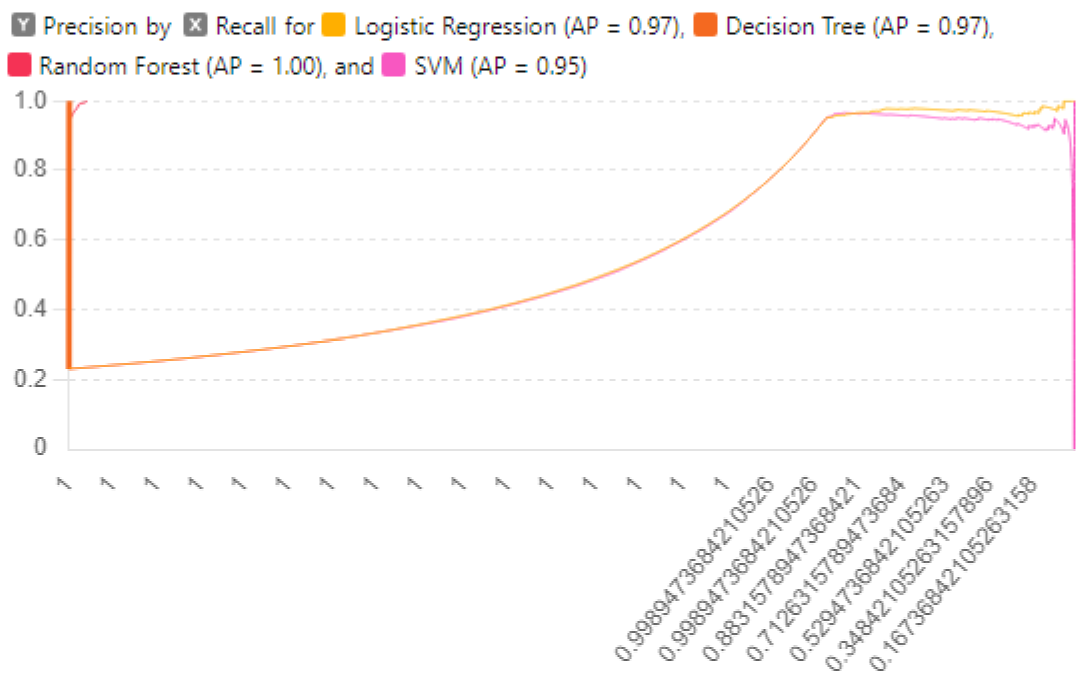

Figure 7 Precision Recall of all models

The graph in Figure 7 outlines the Precision-Recall bends for four machine-learning models: Logistic Regression, Decision Tree, Random Forest, and SVM (Support Vector Machine). The Precision-Recall bend appears to be a trade-off between accuracy and review for distinctive limit settings, giving a comprehensive view of the models' execution in accuracy and review.

5. Conclusion & Future recommendation

In conclusion, this study outlines the reasonability of utilizing IoT sensor information and advanced machine-learning models to expect room occupancy. Among the assessed models, the Random Forest calculation accomplished the most noteworthy execution, bragging a precision of 99.35%. This indicates its predominant capacity to handle assorted datasets and decrease the chance of overfitting, making it a strong choice for inhabitance location assignments. The results affirm that joining natural parameters such as temperature, mugginess, light, and CO_2 levels can upgrade the exactness of occupancy detection frameworks, which are vital for optimizing vitality utilization and progressing occupant comfort in intelligent buildings.

For future research, it is suggested to investigate the integration of additional sensor sorts, such as movement locators and acoustic sensors, to assist in making strides in the precision and unwavering quality of inhabitance discovery frameworks. Also, creating real-time inhabitance discovery frameworks that can powerfully alter building administration forms based on current inhabitance conditions would be a critical headway. Another range of intrigue might be applying deep learning methods, which may offer assist enhancements in show execution through their capacity to capture more complex designs within the information. Lastly, extending the dataset to incorporate more assorted natural conditions and building sorts seems to give more generalized bits of knowledge and upgrade the appropriateness of the created models in different real-world scenarios.

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