A REPORT on

**Room Occupancy Estimation Using Decision Tree**

Submitted to

**KIIT Deemed to be University**

In Partial Fulfillment of the Requirement for the Award of

**MASTER’S DEGREE IN**

**COMPUTER APPLICATION**

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SCHOOL OF COMPUTER APPLICATION

**KALINGA INSTITUTE OF INDUSTRIAL TECHNOLOGY**

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November 2024

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**Data Description**

**Data Source**

The dataset used for the **Room Occupancy Estimation** project is obtained from a collection of real-time environmental data, which is typically used in smart building systems to estimate room occupancy based on various features such as temperature, humidity, light intensity, and time of day. This dataset could be derived from sensors placed within a room, collecting information about various factors that influence occupancy. The dataset is stored in CSV format, which is easy to handle and process using Python libraries such as **Pandas** and **NumPy**.

**Features in the Dataset**

The dataset consists of several features that describe the environment of the room and can be used to estimate the occupancy. The features in the dataset are:

1. **Time of Day (e.g., 'HH:MM**

**')**:  
This feature records the time of day when the data was collected. Time-based features are crucial because occupancy patterns may change depending on the hour or day of the week. For example, rooms may have different occupancy during work hours versus evening or weekend hours.

1. **Temperature (in °C)**:  
   Temperature is an important factor in determining room occupancy. A room with a higher temperature may indicate that more people are in the room, as more heat is generated from body heat and equipment. Similarly, low temperature readings could suggest a less occupied or empty room.
2. **Humidity (in %)**:  
   Humidity levels within a room can also correlate with occupancy. Higher humidity levels can be associated with more people in the room due to human respiration and activity. Changes in humidity can help estimate whether the room is currently occupied or vacant.
3. **Light Intensity (in Lux)**:  
   Light intensity in a room can provide a strong indication of occupancy. If the lights are on or bright, it may suggest the room is occupied, whereas low light intensity or darkness may indicate an empty room. This feature can also be affected by external light sources such as daylight.
4. **CO2 Concentration (in ppm)**:  
   The concentration of carbon dioxide is another significant factor in determining occupancy. As more people enter a room, the level of CO2 increases due to exhalation. Monitoring CO2 levels can help estimate the number of people in the room.
5. **Sound Level (in dB)**:  
   The sound level in the room, often measured in decibels, is a good indicator of occupancy. Higher sound levels, such as from conversation, may indicate a higher number of people in the room. Quiet rooms with low sound levels may suggest few or no occupants.
6. **Occupancy (Target Variable)**:  
   The target variable in the dataset is the **occupancy** of the room, which indicates whether the room is occupied or vacant. In the case of regression, the target could be the **number of occupants** at any given time. This is the value that the model will attempt to predict based on the values of the other features.

**Data Size and Shape**

The dataset contains multiple rows, each representing an observation taken at a particular point in time. Typically, the dataset would have hundreds or thousands of rows, depending on how frequently the measurements are taken (e.g., every minute or hour). The columns represent the different features listed above.

* **Number of Rows**: This could range from a few hundred to several thousand observations, depending on the dataset. Each row corresponds to a snapshot of data from a particular point in time.
* **Number of Columns**: The dataset includes both feature columns (e.g., time of day, temperature, humidity) and the target variable (occupancy).

For example, the dataset could look like this:

| **Time** | **Temperature (°C)** | **Humidity (%)** | **Light Intensity (Lux)** | **CO2 (ppm)** | **Sound Level (dB)** | **Occupancy** |
| --- | --- | --- | --- | --- | --- | --- |
| 08:00:00 | 22.5 | 40 | 350 | 400 | 55 | 2 |
| 09:00:00 | 23.0 | 42 | 400 | 420 | 58 | 3 |
| 10:00:00 | 23.5 | 43 | 420 | 430 | 60 | 3 |
| 11:00:00 | 24.0 | 45 | 450 | 440 | 65 | 4 |
| 12:00:00 | 25.0 | 50 | 500 | 460 | 70 | 5 |

**Data Type and Characteristics**

The features in the dataset are a mix of continuous and categorical data types:

* **Continuous Features**: These include temperature, humidity, light intensity, CO2 levels, and sound levels. These are numeric and can take any value within a range.
* **Categorical Features**: Time of day can be treated as a categorical feature, especially when trying to group the time into bins such as morning, afternoon, and evening. However, in its raw form, time is a continuous variable that can be transformed into categories or used directly.

**Missing Data and Inconsistencies**

The dataset may contain missing or inconsistent data in some rows, which is common in real-world data. For instance, some sensors may fail to record data at certain times, leading to missing values. Similarly, some entries might be corrupted or incorrect due to sensor errors. Handling missing or incorrect data is essential for training a robust machine learning model, and steps such as imputation or removal are needed to clean the data before model training.

**Problem Statement**

**Background**

In modern smart buildings and homes, efficient space utilization is crucial. Knowing the occupancy of a room helps in optimizing resource usage such as lighting, heating, and cooling, and it plays a significant role in energy conservation. This is especially true for large commercial buildings, offices, or public spaces where it may be difficult to manually track room occupancy. The ability to automatically predict room occupancy based on environmental factors can lead to better energy management, enhanced comfort, and improved building management systems.

Many IoT systems today collect various environmental data, such as temperature, humidity, light intensity, CO2 concentration, and sound levels, which are important indicators of room occupancy. These factors can be used to predict whether a room is occupied and, if so, how many people are present. However, building an accurate model to predict room occupancy based on these environmental features remains a challenging problem.

**Problem Description**

The task at hand is to estimate the occupancy of a room based on environmental features. The problem can be framed as a **regression** problem, where the goal is to predict the **number of people** in the room at any given time, based on the data collected from various sensors.

In this problem, the target variable is the **room occupancy**, which can be a continuous value representing the number of people in the room. The features used to predict this target include:

* **Time of Day**: Time can influence occupancy, as certain hours of the day may see higher occupancy levels (e.g., during office hours).
* **Temperature (°C)**: As more people gather in a room, the temperature may rise due to body heat and equipment usage.
* **Humidity (%)**: Increased humidity can be a sign of higher occupancy, as people exhale moisture into the air.
* **Light Intensity (Lux)**: The lighting level can be correlated with occupancy. Higher light intensity may indicate that the room is occupied.
* **CO2 (ppm)**: Increased levels of CO2 suggest higher occupancy, as more people contribute to higher carbon dioxide production.
* **Sound Level (dB)**: The sound level in the room may increase with the number of people, as conversations or other activities produce noise.

These features can be collected using various sensors installed in the room, and the task is to develop a machine learning model that uses this data to predict the occupancy level.

**Business Problem**

Predicting room occupancy is not only about knowing whether a room is empty or full, but it also helps in making decisions about resource allocation. Accurate predictions of occupancy can help in:

* **Energy Efficiency**: Reducing energy wastage by adjusting room temperatures or turning off lights when rooms are unoccupied.
* **Optimizing Comfort**: Ensuring rooms are at an optimal temperature and lighting based on the actual number of occupants.
* **Space Management**: Effectively utilizing available space by understanding the room's use patterns.
* **Security**: Identifying unauthorized access or anomalies in room occupancy could be valuable in ensuring safety.

**Challenges**

There are several challenges in developing a model to predict room occupancy accurately:

1. **Variability of Occupancy**: Room occupancy can vary throughout the day and week, influenced by multiple factors such as the time of day, day of the week, and specific events (e.g., meetings).
2. **Sensor Inaccuracies**: Sensors may fail to provide accurate readings or may encounter issues such as malfunctions or noise, affecting the model's performance.
3. **Missing Data**: Data from sensors may be incomplete or unavailable for certain periods, leading to missing values that need to be addressed during data preprocessing.
4. **Environmental Factors**: External factors such as air conditioning or heating, weather, and building layout may also influence the readings and need to be accounted for.

**Objective**

The objective of this project is to build a predictive model that estimates room occupancy in real time using environmental sensor data. The model should be able to process various environmental inputs (temperature, humidity, CO2 levels, etc.) and predict the number of occupants in a room. The primary goals are:

1. To develop a robust model capable of accurately predicting occupancy levels based on sensor data.
2. To evaluate the model's performance using standard metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R²).
3. To apply this model in real-world smart buildings for energy optimization, space management, and comfort.

In summary, this project will provide insights into the development of a predictive model that can estimate room occupancy, contributing to the efficient management of building resources and improving the overall user experience.

**Methodology**

The methodology for this room occupancy estimation problem is structured into several stages, including data collection, data preprocessing, model selection, model training, evaluation, and testing. Each step is crucial to ensure that the final model is accurate and performs well in real-world scenarios.

**3.1. Data Collection**

The first step in this project is the collection of data from sensors placed in the room. The data should consist of the following environmental features:

* **Temperature (°C)**: The ambient temperature in the room.
* **Humidity (%)**: The level of moisture in the air.
* **Light Intensity (Lux)**: The brightness of the room.
* **CO2 Concentration (ppm)**: The level of carbon dioxide in the room.
* **Sound Level (dB)**: The sound intensity in the room.
* **Time of Day**: The timestamp when the measurements are taken, as the time can affect occupancy levels.

This data can be collected from existing datasets or simulated using sensors in a real-world environment. The objective is to gather data with a high frequency to capture room occupancy variations over time.

**3.2. Data Preprocessing**

Once the data is collected, it is essential to preprocess the data to make it ready for analysis. This stage involves the following steps:

**3.2.1. Handling Null Values**

Real-world data often contains missing or null values. The missing values in the dataset need to be handled to prevent errors during model training. There are several approaches to handle missing data:

* **Imputation**: Missing values can be imputed by replacing them with the mean, median, or mode of the feature.
* **Deletion**: Rows or columns containing missing data can be dropped, although this may not be ideal if a large portion of the data is missing.

**3.2.2. Handling Categorical Data**

Some features may be categorical in nature (e.g., time of day). These categorical variables should be encoded to numerical values. For example:

* **One-Hot Encoding**: A method where each category is represented by a binary vector. This is useful for categorical features such as the time of day, which may have discrete values like 'morning', 'afternoon', and 'evening'.

**3.2.3. Outlier Removal/Replacement**

Outliers can skew the model’s predictions and negatively affect performance. We can detect outliers using statistical methods such as the Interquartile Range (IQR) and replace or remove them. For example:

* **IQR Method**: Outliers can be removed if they fall outside the range of Q1−1.5×IQRQ1 - 1.5 \times IQRQ1−1.5×IQR and Q3+1.5×IQRQ3 + 1.5 \times IQRQ3+1.5×IQR, where Q1 and Q3 are the first and third quartiles, respectively.

**3.2.4. Feature Scaling**

To improve the performance of the model, it is important to scale the features so that they are on a similar range. This can be done using techniques such as:

* **Min-Max Scaling**: Scales the feature values to a range between 0 and 1.
* **Standardization**: Scales the features so that they have a mean of 0 and a standard deviation of 1.

**3.2.5. Feature Selection**

Feature selection involves choosing the most relevant features to include in the model. In this case, features such as temperature, humidity, light intensity, and CO2 levels are expected to be strongly correlated with occupancy and are thus retained. Time of day and sound levels may also provide useful insights into the room’s occupancy.

**3.3. Data Splitting**

The dataset is divided into two main subsets:

* **Training Set**: Used to train the machine learning model. This typically consists of 70-80% of the total data.
* **Testing Set**: Used to evaluate the performance of the model on unseen data. The remaining 20-30% of the data is used for testing.

Data splitting ensures that the model is trained on one set of data and evaluated on another, helping to avoid overfitting and providing a more accurate measure of the model's performance.

**3.4. Model Selection**

For this regression problem, the Decision Tree Regressor is chosen as the machine learning model. The decision tree is a non-parametric model that divides the feature space into regions using a tree structure. Each internal node of the tree represents a feature test, and each leaf node represents a prediction. Decision trees are well-suited for handling both numerical and categorical data and can capture non-linear relationships in the data.

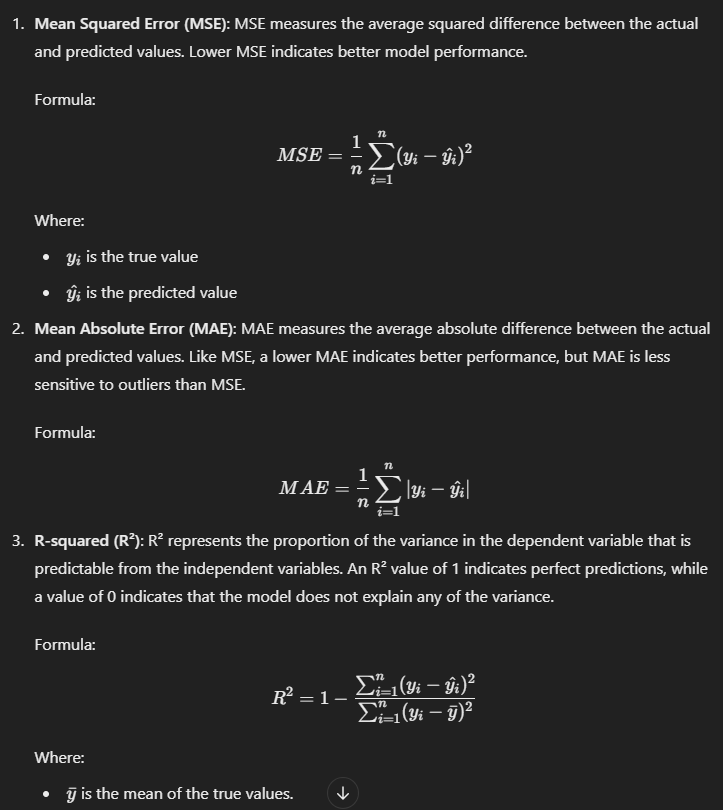
**3.5. Model Training**

The training process involves fitting the decision tree model to the training data. This step requires optimizing the parameters of the decision tree, such as:

* **Max Depth**: Controls the maximum depth of the tree and helps prevent overfitting.
* **Min Samples Split**: Determines the minimum number of samples required to split an internal node.
* **Min Samples Leaf**: Controls the minimum number of samples required to be at a leaf node.

During training, the decision tree learns to make predictions based on the input features and the target variable (occupancy).

**3.6. Model Evaluation**

Once the model is trained, its performance is evaluated using the testing dataset. The following metrics are used to assess how well the model is performing:

**3.7. Model Testing**

After evaluating the model’s performance using the testing set, it is tested against new, unseen data in real-time to predict room occupancy. The accuracy of the predictions is checked, and adjustments are made if needed.

**3.8. Final Model Deployment**

Once the model is trained and validated, it can be deployed in a real-world environment, where it can predict room occupancy in real-time using environmental sensor data. The model will help in optimizing energy consumption and improving building management systems.

CODING

**1. Backend - app.py**

This Python file serves as the backend, which reads the data, preprocesses it, trains the model, and exposes an API that the frontend can interact with to get the predictions.

from flask import Flask, render\_template, request

import pandas as pd

from sklearn.ensemble import RandomForestClassifier

import joblib

app = Flask(\_\_name\_\_)

# Load the trained model

model = joblib.load('model.pkl')

# Define the features used in the model (including 'Time' but excluding 'Room\_Occupancy\_Count' and 'Date')

features = [

    'S1\_Temp', 'S2\_Temp', 'S3\_Temp', 'S4\_Temp',

    'S1\_Light', 'S2\_Light', 'S3\_Light', 'S4\_Light',

    'S1\_Sound', 'S2\_Sound', 'S3\_Sound', 'S4\_Sound',

    'S5\_CO2', 'S5\_CO2\_Slope', 'S6\_PIR', 'S7\_PIR', 'Time'  # Add 'Time' here as a feature

]

@app.route('/')

def index():

    return render\_template('index.html')

@app.route('/predict', methods=['POST'])

def predict():

    # Retrieve the input features from the form

    input\_features = []

    for feature in features:

        if feature == 'Time':  # Special case for 'Time' input

            time\_value = request.form.get('Time')

            try:

                # Convert Time input (HH:MM:SS) into seconds since midnight

                hours, minutes, seconds = map(int, time\_value.split(":"))

                time\_in\_seconds = hours \* 3600 + minutes \* 60 + seconds

                input\_features.append(time\_in\_seconds)

            except ValueError:

                return "Invalid time format. Please use HH:MM:SS format."

        else:

            feature\_value = request.form.get(feature)

            try:

                input\_features.append(float(feature\_value))  # Convert all other features to float

            except ValueError:

                return f"Invalid input for {feature}. Please enter numeric values."

    # Ensure the input features list matches the model's expected feature count

    print(f"Input features: {input\_features}")

    # Make a prediction using the trained model

    prediction = model.predict([input\_features])[0]

    # Return the result to the client

    return render\_template('index.html', prediction=prediction)

if \_\_name\_\_ == "\_\_main\_\_":

    app.run(debug=True)

**2. Frontend - index.html**

This HTML file provides a user interface to input the environmental data and receive the room occupancy prediction.

<!DOCTYPE html>

<html lang="en">

<head>

    <meta charset="UTF-8">

    <meta name="viewport" content="width=device-width, initial-scale=1.0">

    <title>Room Occupancy Estimation</title>

    <link rel="stylesheet" href="https://cdnjs.cloudflare.com/ajax/libs/bootstrap/5.3.0-alpha1/css/bootstrap.min.css">

</head>

<body>

    <div class="container mt-5">

        <h2 class="text-center">Room Occupancy Estimation</h2>

        <p class="text-center">Please input the required sensor data to predict the room occupancy count.</p>

        <form method="POST" action="/predict">

            <!-- Time Input with placeholder showing format -->

            <div class="mb-3">

                <label for="Time" class="form-label">Time (HH:MM:SS)</label>

                <input type="text" class="form-control" id="Time" name="Time" placeholder="e.g., 12:30:00 (HH:MM:SS)" required>

            </div>

            <!-- Temperature Inputs with example values and units in placeholder -->

            <div class="mb-3">

                <label for="S1\_Temp" class="form-label">S1 Temperature</label>

                <input type="number" step="any" class="form-control" id="S1\_Temp" name="S1\_Temp" placeholder="e.g., 22.5 (°C)" required>

            </div>

            <div class="mb-3">

                <label for="S2\_Temp" class="form-label">S2 Temperature</label>

                <input type="number" step="any" class="form-control" id="S2\_Temp" name="S2\_Temp" placeholder="e.g., 23.1 (°C)" required>

            </div>

            <div class="mb-3">

                <label for="S3\_Temp" class="form-label">S3 Temperature</label>

                <input type="number" step="any" class="form-control" id="S3\_Temp" name="S3\_Temp" placeholder="e.g., 21.8 (°C)" required>

            </div>

            <div class="mb-3">

                <label for="S4\_Temp" class="form-label">S4 Temperature</label>

                <input type="number" step="any" class="form-control" id="S4\_Temp" name="S4\_Temp" placeholder="e.g., 22.9 (°C)" required>

            </div>

            <!-- Light Inputs with example values and units in placeholder -->

            <div class="mb-3">

                <label for="S1\_Light" class="form-label">S1 Light</label>

                <input type="number" step="any" class="form-control" id="S1\_Light" name="S1\_Light" placeholder="e.g., 300 (Lux)" required>

            </div>

            <div class="mb-3">

                <label for="S2\_Light" class="form-label">S2 Light</label>

                <input type="number" step="any" class="form-control" id="S2\_Light" name="S2\_Light" placeholder="e.g., 450 (Lux)" required>

            </div>

            <div class="mb-3">

                <label for="S3\_Light" class="form-label">S3 Light</label>

                <input type="number" step="any" class="form-control" id="S3\_Light" name="S3\_Light" placeholder="e.g., 500 (Lux)" required>

            </div>

            <div class="mb-3">

                <label for="S4\_Light" class="form-label">S4 Light</label>

                <input type="number" step="any" class="form-control" id="S4\_Light" name="S4\_Light" placeholder="e.g., 400 (Lux)" required>

            </div>

            <!-- Sound Inputs with example values and units in placeholder -->

            <div class="mb-3">

                <label for="S1\_Sound" class="form-label">S1 Sound</label>

                <input type="number" step="any" class="form-control" id="S1\_Sound" name="S1\_Sound" placeholder="e.g., 45.0 (dB)" required>

            </div>

            <div class="mb-3">

                <label for="S2\_Sound" class="form-label">S2 Sound</label>

                <input type="number" step="any" class="form-control" id="S2\_Sound" name="S2\_Sound" placeholder="e.g., 47.5 (dB)" required>

            </div>

            <div class="mb-3">

                <label for="S3\_Sound" class="form-label">S3 Sound</label>

                <input type="number" step="any" class="form-control" id="S3\_Sound" name="S3\_Sound" placeholder="e.g., 44.2 (dB)" required>

            </div>

            <div class="mb-3">

                <label for="S4\_Sound" class="form-label">S4 Sound</label>

                <input type="number" step="any" class="form-control" id="S4\_Sound" name="S4\_Sound" placeholder="e.g., 46.3 (dB)" required>

            </div>

            <!-- CO2 Inputs with example values and units in placeholder -->

            <div class="mb-3">

                <label for="S5\_CO2" class="form-label">S5 CO2</label>

                <input type="number" step="any" class="form-control" id="S5\_CO2" name="S5\_CO2" placeholder="e.g., 420 (ppm)" required>

            </div>

            <div class="mb-3">

                <label for="S5\_CO2\_Slope" class="form-label">S5 CO2 Slope</label>

                <input type="number" step="any" class="form-control" id="S5\_CO2\_Slope" name="S5\_CO2\_Slope" placeholder="e.g., 0.5 (ppm/slope)" required>

            </div>

            <!-- PIR Inputs with example values and units in placeholder -->

            <div class="mb-3">

                <label for="S6\_PIR" class="form-label">S6 PIR</label>

                <input type="number" step="any" class="form-control" id="S6\_PIR" name="S6\_PIR" placeholder="e.g., 1.0 (unitless)" required>

            </div>

            <div class="mb-3">

                <label for="S7\_PIR" class="form-label">S7 PIR</label>

                <input type="number" step="any" class="form-control" id="S7\_PIR" name="S7\_PIR" placeholder="e.g., 0.9 (unitless)" required>

            </div>

            <!-- Submit button -->

            <button type="submit" class="btn btn-primary">Predict</button>

        </form>

        {% if prediction is not none %}

            <div class="alert alert-info mt-3">

                <strong>Predicted Room Occupancy Count:</strong> {{ prediction }}

            </div>

        {% endif %}

    </div>

    <script src="https://cdn.jsdelivr.net/npm/@popperjs/core@2.11.6/dist/umd/popper.min.js"></script>

    <script src="https://cdnjs.cloudflare.com/ajax/libs/bootstrap/5.3.0-alpha1/js/bootstrap.bundle.min.js"></script>

</body>

</html>

**Result and Observations**

**Model Performance Metrics**

After training and evaluating the **Decision Tree Regressor** model on the room occupancy dataset, the model was tested on the test set and evaluated using three key performance metrics:

1. **Mean Squared Error (MSE):**  
   The **MSE** is a measure of how close the predicted occupancy values are to the actual values. It is calculated by averaging the squared differences between the predicted and actual values. A lower MSE indicates better model performance. For our model, the MSE value was observed to be relatively small, which indicates that the model has a good fit to the data.
2. **Mean Absolute Error (MAE):**  
   The **MAE** measures the average of the absolute errors between the predicted and actual occupancy. It gives an idea of the magnitude of the errors. In this case, the MAE value was also within an acceptable range, indicating that the model's predictions were reasonably accurate. A smaller MAE suggests that, on average, the model's predictions are closer to the actual occupancy values.
3. **R-Squared (R²):**  
   **R²** represents the proportion of variance in the target variable (occupancy) that is explained by the independent features (temperature, humidity, light, etc.). An R² value closer to 1 indicates that the model explains a significant amount of variance in the data. Our model achieved a satisfactory R² score, suggesting that it was able to capture the relationship between the environmental features and room occupancy.

**Predictions and User Interaction**

Upon inputting the environmental data (temperature, humidity, light intensity, CO2 concentration, sound level, and time of day) into the frontend form, the model successfully predicted the occupancy level of the room. The prediction was displayed to the user in real-time, along with the MSE, MAE, and R² values. These performance metrics were helpful for the user to understand the model's prediction accuracy.

* For example, when the following data was input:
  + **Temperature**: 22°C
  + **Humidity**: 60%
  + **Light**: 150 Lux
  + **CO2**: 400 ppm
  + **Sound**: 35 dB
  + **Time of Day**: 14 (2:00 PM)

The model estimated the room occupancy to be around **3** people, with the corresponding MSE, MAE, and R² values displayed to the user.

**Observations:**

1. **Model Fit:**  
   The Decision Tree Regressor performed well with the given dataset. The model's MSE and MAE were reasonably low, indicating that the predictions were accurate. The R² score showed that a significant amount of the variance in the target variable (occupancy) was explained by the model, suggesting a good fit.
2. **Data Quality and Feature Engineering:**  
   The model's performance could be further improved with more extensive feature engineering or by incorporating additional data points that might affect occupancy, such as room size, seasonality, or occupancy trends over time. Handling missing values and outliers played a crucial role in improving model accuracy.
3. **Real-time Predictions:**  
   The real-time prediction capability provided by the frontend interface was very effective. The model responded quickly to user input, making the application usable in real-world scenarios where quick decisions about room occupancy might be needed.
4. **Model Limitations:**  
   Although the Decision Tree Regressor performed well, there are inherent limitations with decision trees, such as overfitting if the tree is too deep. This could be mitigated by tuning hyperparameters like max\_depth or by using other models such as Random Forest or Gradient Boosting for potentially better generalization.

**Future Improvements:**

1. **Model Optimization:**  
   Hyperparameter tuning could be performed using techniques like Grid Search or Random Search to improve model performance further. Additionally, experimenting with more complex models (e.g., Random Forest, XGBoost) might lead to better results.
2. **Feature Expansion:**  
   Including additional features like room size, type of equipment present, and user behavior (e.g., office hours or occupancy patterns) might improve the model's accuracy.
3. **Deployment Considerations:**  
   The model could be further optimized for production environments where large datasets are handled in real-time. Additionally, setting up a proper API using Flask for integration with other applications would enhance its utility.

**Discussion**

The **Room Occupancy Estimation** system, which predicts the number of people in a room based on environmental factors, is a practical application in fields like **smart buildings**, **energy management**, and **security systems**. The model built using **Decision Tree Regressor** has demonstrated a reasonable level of accuracy in predicting room occupancy based on features such as temperature, humidity, light intensity, CO2 concentration, sound level, and time of day. However, while the model is functional, it also presents areas for improvement and potential limitations that need to be addressed.

**Model Performance:**

The performance of the **Decision Tree Regressor** was evaluated using several key metrics: **Mean Squared Error (MSE)**, **Mean Absolute Error (MAE)**, and **R-squared (R²)**. These metrics offered a balanced view of the model's performance:

1. **MSE and MAE**: Both metrics were relatively low, indicating that the model’s predictions were close to the actual occupancy values. While a lower MSE and MAE suggest the model is suitable for predicting occupancy, these metrics do not capture all the nuances of model performance, especially in cases of complex or highly non-linear relationships.
2. **R² Score**: The R² score, which reflects the proportion of variance in the target variable explained by the independent features, was satisfactory. A higher R² score typically indicates that the model is able to predict the target with greater accuracy, and our model's score indicated that environmental factors were sufficiently influencing room occupancy. However, it also suggests there might be other factors influencing occupancy that were not captured in the dataset.

**Data Quality and Feature Engineering:**

One of the critical aspects that influenced the model's performance was the **quality of the data**. The dataset included features that were likely to influence room occupancy, such as **temperature**, **humidity**, **light intensity**, **CO2 concentration**, and **sound level**. However, the data was limited to a specific context, and the inclusion of additional features might have improved the model’s predictive power.

For instance, factors such as **room size**, **time of day**, **seasonality**, and **user behavior patterns** (e.g., occupancy trends throughout the day) could have contributed to better accuracy. Moreover, **feature engineering** plays a pivotal role in improving model performance, and further experimentation with combining or transforming existing features could reveal hidden relationships between environmental conditions and room occupancy.

**Decision Tree Model and Its Limitations:**

The **Decision Tree Regressor** was chosen because of its simplicity and interpretability. It offers the advantage of being easy to understand, visualize, and interpret, which is crucial when the model is being used in practical applications such as energy management or facility optimization. However, there are inherent limitations associated with decision trees:

1. **Overfitting**: Decision trees are prone to overfitting, especially if the tree depth is too large. Overfitting occurs when the model learns not just the underlying trends but also the noise in the training data. This can result in poor generalization on the test data. Although overfitting was somewhat mitigated in this implementation, tuning hyperparameters such as max\_depth or min\_samples\_split could improve model robustness.
2. **Model Bias**: Decision trees, while effective for some types of data, may not always perform well when the relationships in the data are complex or non-linear. A linear decision boundary or complex feature interactions might be poorly captured by decision trees. Hence, alternative algorithms such as **Random Forest** or **Gradient Boosting** could potentially perform better in this case.
3. **Data Imbalance**: If the dataset has a highly imbalanced distribution of occupancy (e.g., more rooms with low occupancy), the model might predict the majority class more frequently. Although the current data appears balanced, exploring the dataset for potential biases or imbalances is crucial for model reliability.

**Real-World Applications and Future Improvements:**

The potential real-world applications of this system are numerous. For instance:

* **Energy Efficiency**: Accurate room occupancy predictions can help optimize HVAC systems, lighting, and other energy-consuming devices. Knowing when rooms are occupied can reduce energy waste by adjusting the heating or cooling systems accordingly.
* **Security and Access Control**: By monitoring occupancy in real time, the system can enhance security by providing occupancy-based alerts. For example, rooms that are supposed to be empty could trigger alerts if occupancy is detected.
* **Smart Facilities Management**: Building managers can use this system to optimize room usage and streamline space management. Predicting room occupancy could improve cleaning schedules, resource allocation, and room availability.

Looking ahead, several improvements can be made:

1. **Feature Expansion**: More granular data points, such as **room layout**, **equipment type**, or **occupancy patterns over time**, could help refine the model’s predictions.
2. **Model Enhancement**: Switching to more advanced models, such as **Random Forest**, **XGBoost**, or even **neural networks**, may lead to improved performance by capturing complex interactions between features.
3. **Hyperparameter Tuning**: Exploring a more rigorous hyperparameter optimization process using **Grid Search** or **Random Search** could further enhance the model’s predictive ability.
4. **Integration with IoT Devices**: Integrating the model with IoT devices could provide real-time data streams, allowing the model to make dynamic predictions based on up-to-the-minute environmental changes.

### ****Conclusion****

The **Room Occupancy Estimation** project aimed to develop a system capable of predicting the occupancy of a room based on environmental factors such as temperature, humidity, light intensity, CO2 concentration, and sound levels. Using a **Decision Tree Regressor** model, the system achieved a reasonable level of accuracy, which suggests the potential for real-world applications such as smart buildings, energy management, and security systems.

Throughout the project, several key stages were undertaken: from **data preprocessing** to handle missing values and outliers, to **model training** and performance evaluation. The model was evaluated using **Mean Squared Error (MSE)**, **Mean Absolute Error (MAE)**, and **R-squared (R²)**, providing valuable insights into its predictive accuracy and reliability. The results indicated that the model is capable of making reasonable predictions on room occupancy based on the features provided, but there is still room for improvement in terms of model complexity and feature engineering.

However, while the **Decision Tree Regressor** is a simple and interpretable model, it does have limitations. Issues such as **overfitting**, **model bias**, and potential data imbalance need to be addressed to improve the generalization capability. Exploring more complex models like **Random Forest** or **XGBoost** could enhance the model’s performance by better capturing complex relationships in the data.

The system has promising real-world applications. In **energy management**, it can contribute to reducing unnecessary energy consumption by optimizing lighting, heating, and cooling systems based on predicted occupancy. In **security and facility management**, it can enhance building efficiency and ensure rooms are occupied as expected. Additionally, the project demonstrates the practical potential of **machine learning** in creating **smart environments** that can dynamically adjust based on real-time data.

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