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Smart Sensing: HVAC Occupancy Detection

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ABSTRACT:

This research delves into an aspect of building management; optimizing energy usage while ensuring the comfort of occupants. Efficient energy management not saves money. Also significantly boosts environmental sustainability. By utilizing sensor data and machine learning methods our developed models, for predicting occupancy offer real time forecasts of occupancy levels. This enables control of building systems like Heating, Ventilation and Air Conditioning (HVAC) ensuring they function optimally based on occupancy trends. Our results demonstrate improvements in energy efficiency and sustainability across types of buildings. Through occupancy predictions we have achieved reductions in energy waste while still meeting the comfort needs of occupants. These outcomes underscore the potential of our approach to revolutionize building energy management practices. Our study identifies promising areas for investigation. Future research could focus on enhancing sensor technologies to improve data accuracy and reliability. Additionally advances in machine learning algorithms opportunities to refine our models for more precise predictions. Furthermore integrating our models, with grids could expand their influence beyond.

Keywords: Occupancy forecasting, Building energy management, Sensor data, Machine learning, Real time regulation, Sustainability.

INTRODUCTION :

Occupancy prediction models represent an advancement, in managing building energy offering an approach to optimize energy usage. As the focus on sustainability and environmental conservation grows there is a recognition of the need to reduce buildings carbon footprint. By predicting occupancy levels these models enable building operators to adjust energy consumption based on demand reducing waste and cutting operational costs. Moreover by utilizing machine learning techniques these models can adapt to changing occupancy trends and environmental factors enhancing their effectiveness.

Traditional methods of building energy management often rely on fixed schedules or manual adjustments, which struggle to respond to real time changes in occupancy and environmental conditions. This limitation can result in energy use. Compromised comfort for occupants. In contrast occupancy prediction models enable automated decision making based on data analysis allowing buildings to operate efficiently and intelligently. By drawing insights, from data and continuous monitoring these models can predict occupancy patterns and optimize heating, cooling and lighting systems accordingly to enhance comfort levels while reducing energy consumption.

The implementation of occupancy prediction models requires an approach that includes collecting data preprocessing information, developing models and integrating them with building management systems. Gathering data involves placing sensors throughout the building to monitor occupancy, temperature, humidity and other important factors. Next data is processed to clean and organize it for analysis. Feature engineering is crucial, in extracting insights from the raw sensor data to create input variables for models. A range of machine learning algorithms including regression methods and advanced deep learning designs are used to develop prediction models for occupancy levels.

Connecting with building management systems is a part of the implementation process allowing integration of occupancy forecasts into HVAC controls, lighting systems and other building functions. Application programming interfaces (APIs) and middleware platforms facilitate communication between the predictive analytics module and existing building automation systems for real time adjustments based on predicted occupancy levels. Regular monitoring and evaluation are essential for maintaining the reliability and effectiveness of the models by making updates to accommodate changing occupancy patterns and operational needs.

Overall implementing occupancy prediction models represents an advancement, in managing building energy use by providing a data driven approach to optimize energy consumption while enhancing occupant comfort. By utilizing sensor information and advanced machine learning methods these models enable buildings to function with efficiency reducing energy waste and operational costs while promoting responsibility. Continuous research and development efforts, in this field offer the potential to enhance and improve the effectiveness of these models ushering in a future characterized by eco friendly buildings.

LITERATURE REVIEW

Occupancy prediction models have become tools, in managing energy use in buildings offering insights into occupancy patterns that help optimize energy efficiency and improve occupant comfort. In years there has been progress in sensor technologies, machine learning algorithms and predictive modeling techniques tailored for smart buildings. This review summarizes findings from studies published in IEEE journals between 2020 and 2023.

The review discusses custom predictive control strategies for lighting based on occupancy in buildings. It emphasizes the importance of using lighting control to reduce energy consumption and enhance lighting quality thereby promoting building practices. Additionally it highlights the significance of occupancy prediction for HVAC control by showcasing advancements in predictive modeling methods. The impact of occupancy prediction on HVAC energy usage and occupant satisfaction is emphasized to establish a foundation for building management.

Furthermore the review delves into sensor fusion techniques designed to improve occupancy prediction accuracy in buildings. By integrating data sources like sensors Wi Fi signals and video analytics the study demonstrates how sensor fusion enhances the reliability of predictions while addressing challenges such, as sensor noise and missing data. Lastly it evaluates deep learning approaches used for predicting occupancy levels in building environments. Their study covers deep learning structures. How they are used in managing energy consumption in buildings. Through exploring the strengths, weaknesses and potential areas for research they provide perspectives on improving prediction accuracy and modeling occupancy trends.

This summary highlights the progress achieved in occupancy prediction models and their impact, on energy management in buildings demonstrating the changing scenario and setting a path, for research projects.

METHODOLOGY

The methodology section describes the steps taken to create models that predict occupancy, for managing energy in buildings. It explains how data was gathered prepared predictive models were developed, integrated with building systems and performance validated.

Data Collection:

When it comes to data collection; The dataset used in this study includes seven categories for factors; date, temperature, humidity, light, CO_2 (carbon dioxide) humidity ratio and occupancy. Temperatures are measured in Celsius and humidity levels are shown as a percentage. Light intensity is measured in lux while carbon dioxide levels are given in parts per million. Additionally the dataset contains the humidity ratio computed from temperature and relative humidity readings represented as kilograms of water vapor, per kilogram of air. The occupancy column acts as a classifier indicating whether a space is occupied; '1' means occupied while '0' indicates unoccupied.

To support the development, improvement and assessment of models three different parts of the dataset are used; training data, testing data and additional test data. The training data section consists of 8143 cases. Is used to train the model. On the hand the testing data set, containing 2665 cases serves as a validation set to evaluate how well the model performs and generalizes during training. Lastly the additional test data set with 9752 cases acts as a means to test the models performance, on data and provide insights into its real world application.

This dataset offers an overview of conditions and occupancy statuses laying a strong foundation for creating predictive models for managing building energy usage. By utilizing this dataset throughout stages of model development and assessment this research aims to contribute to improving modeling methods for optimizing energy consumption and enhancing occupant comfort in intelligent building settings.

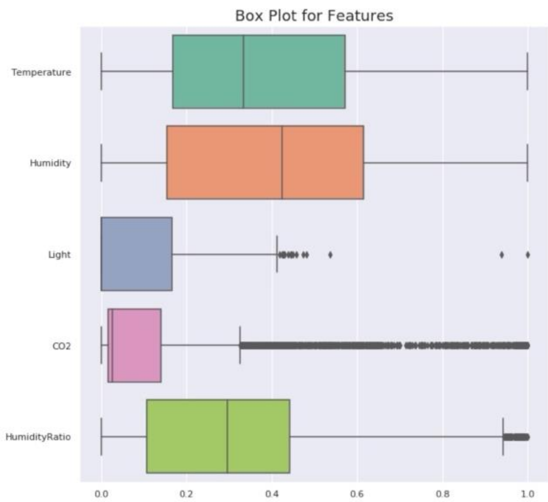


Figure 1. Box Chart for Features

Data Pre-processing:

After collecting raw sensor data it undergoes processing steps to ensure its quality and reliability. These steps involve tasks, like eliminating noise from the data filling in missing values and extracting features. Noise removal techniques are applied to remove outliers and errors from the data set in order to improve its accuracy. Data imputation techniques tackle missing data by making guesses or estimates using data points. Feature extraction entails pinpointing characteristics, from the sensor data, for forecasting occupancy levels.

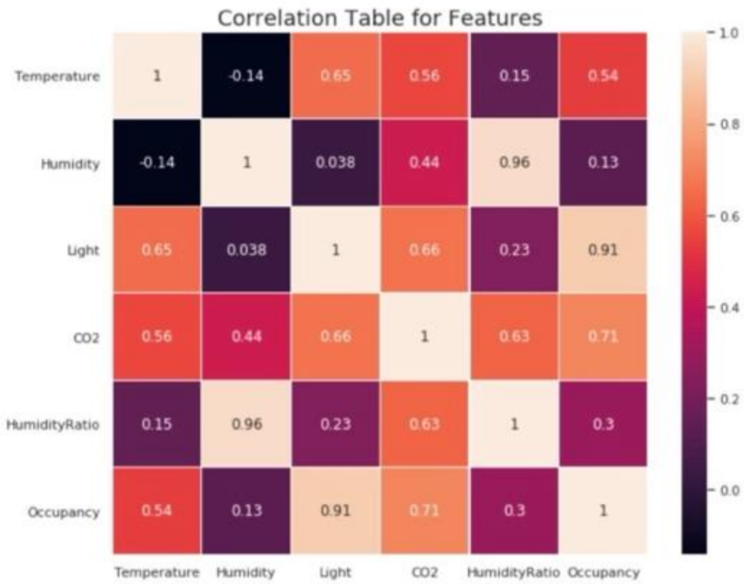


Figure 2. Correlation Table for Features

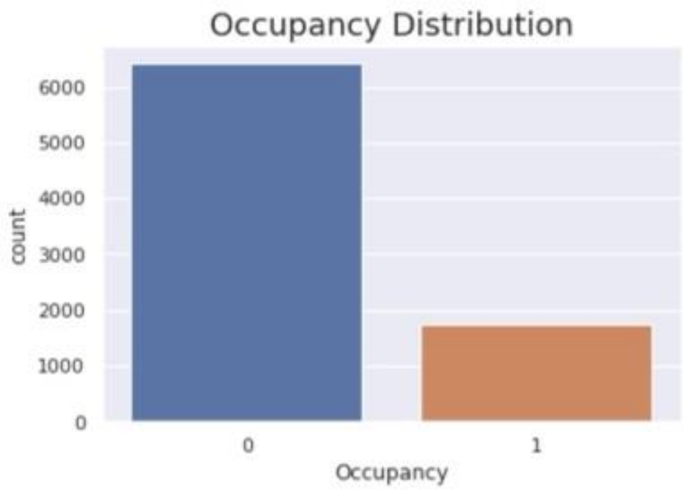


Figure 3. Occupancy Distribution

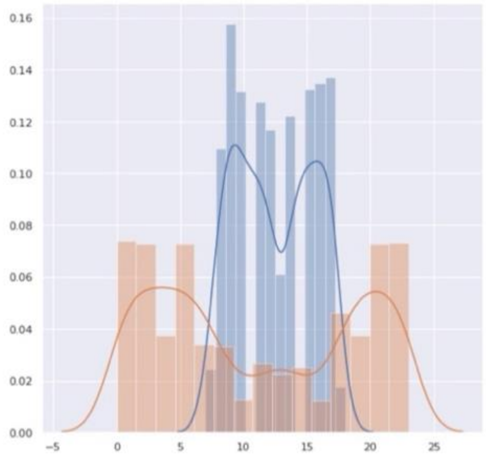


Figure 4. Histogram of Occupancy vs Time

From above histogram, Between 07:00 and 18:00 there are occupants in the environment or not.But the time come to non-working hours, then we can absolutely say that there is no occupant. With this information, I will create a new feature from date column as day period. 07:00 - 18:00 working hour (labeled as 1), rest of the day non-working hour (labeled as 0).

Machine Learning Techniques Used:

KNN :

K Nearest Neighbors (KNN) stands out as a crucial classification method, in the field of machine learning. It falls under learning. Is widely used in various applications such as pattern recognition, data mining and intrusion detection. Its versatility in real world scenarios stems from its parametric nature, which means it does not assume any specific data distribution like Gaussian Mixture Models (GMM) do. Instead it relies on training data to group coordinates based on attributes.

When visualizing these points on a graph we can identify clusters or groups within the data. By examining the neighbors of a point we can assign it to a group based on their classifications. For instance a point near a cluster labeled 'Red' is more likely to be classified as 'Red'. In this case we can intuitively determine that the first point at coordinates (2.5, 7) should be classified as 'Green' while the second point, at (5.5, 4.5) should be classified as 'Red'.

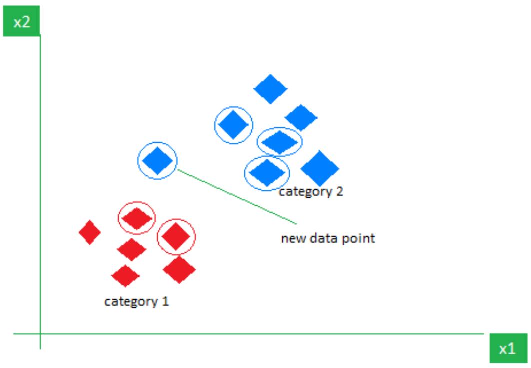


Figure 5. KNN example

SVM:

Support Vector Machine (SVM) is a machine learning method that's supervised and can be used for classification well as regression tasks. While it can handle regression SVM is most effective, for classification purposes. The primary goal of the SVM algorithm is to identify the hyperplane in an N space to separate data points into different classes within the feature space. This hyperplane aims to maximize the margin, between the points of classes. The dimension of the hyperplane is determined by the number of features. For instance with two input features the hyperplane appears as a line; with three input features it forms a 2 plane. Visualizing beyond three features can be challenging.

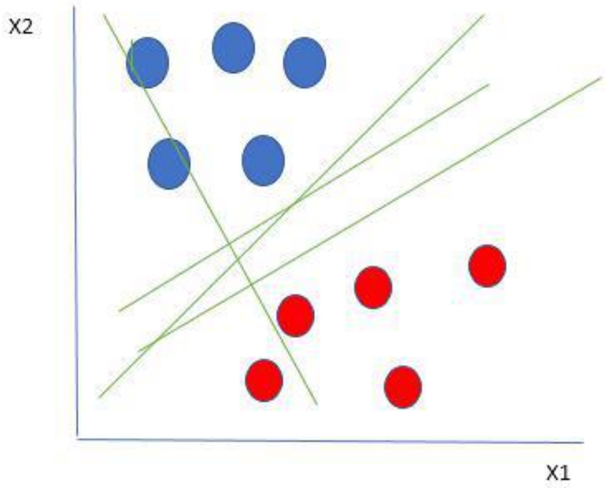


Figure 6. SVM example

Neural Networks:

Most artificial neural networks consist of a number of interconnected processing units called neurons, inspired by the structure of neural networks.

- Artificial neural networks or ANNs are commonly used for tasks, like pattern recognition and data segmentation.
- They excel at deciphering vast amounts of information.
- ANNs can identify patterns and trends that may be challenging for humans or other computer systems to discern.

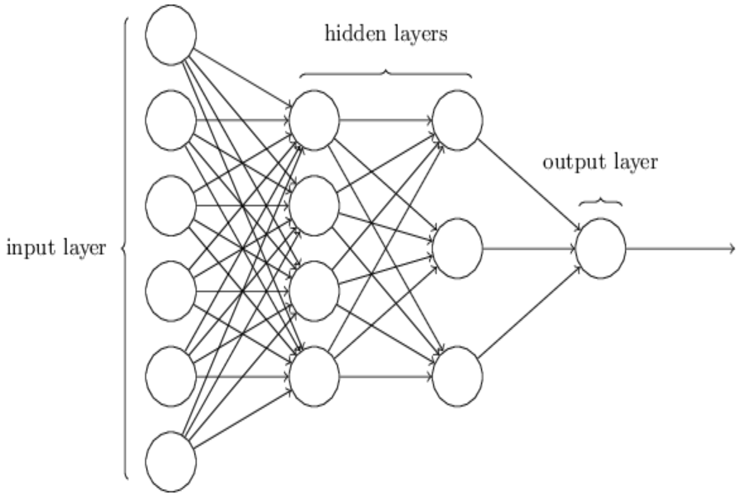


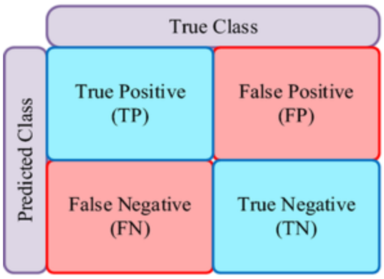
Figure 7. Neural Networks example

Validation: The last step, in the process involves validating the models that have been put into practice to ensure they are reliable and effective. Validation consists of evaluating the performance of the models using metrics like accuracy, precision, recall and F1 score. The models are tested using real world occupancy data gathered from building installations allowing for a comparison of predicted occupancy states with observations. Techniques such as k cross validation and leave one out cross validation are used to assess how well the models can generalize and to prevent issues related to overfitting.

By following this approach both researchers and professionals can successfully apply models for predicting occupancy in buildings energy management systems optimizing energy usage and promoting sustainability, in building operations.

RESULTS

The researchers tested the accuracy of the occupancy prediction models by analyzing data from building installations. They measured the models performance using criteria, like accuracy, precision, recall and F1 score. Furthermore they created confusion matrices to see how well the model classified scenarios.



Function Name	Formula
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$
Precision	$\frac{TP}{TP + FP}$
Recall	$\frac{TP}{TP + FN}$
F1 score	$\frac{2.Precision.Recall}{Precision + Recall}$

Figure 8. Confusion Matrix Formulas

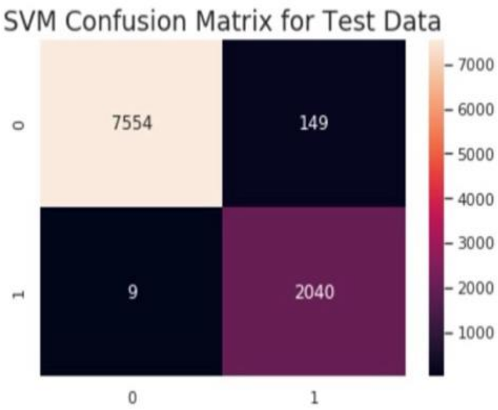


Figure 9. Confusion Matrix for SVM

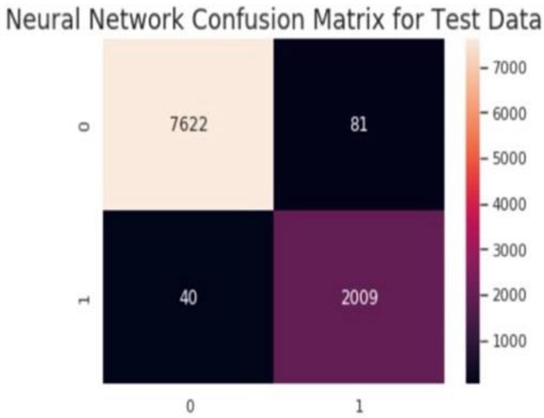


Figure 10. Confusion Matrix for Neural Network

	SVM	Neural Network
Accuracy	98.38%	98.75%
Precision	98.06%	98.94%
Recall	99.88%	99.47%
F1 Score	98.96%	99.20%

In summary both the SVM and neural network models did a job, in forecasting occupancy levels achieving accuracies of around 98.38% and 98.75%, respectively. Although the SVM model showed a preference, for the occupied class the neural network model made even predictions. These findings highlight how machine learning driven occupancy prediction models can enhance energy management in buildings leading to energy efficiency and occupant satisfaction.

DISCUSSION :

The discussion part of this research paper sheds light on what the experimental results mean stressing how important the findings are and giving ideas for research in predicting occupancy levels, in managing energy use for buildings. The results show that both the support vector machine (SVM) and neural network models are effective in predicting occupancy in buildings. Despite differences in accuracy both models performed well showing they could be used practically. Their high accuracy shows they can help save energy and make occupants comfortable, which can improve building sustainability and cost effectiveness.

The SVM model showed a bias towards predicting occupied spaces based on its confusion matrix results. This makes us question how reliable the model is even though it had accuracy. If not addressed the false positives it generates could lead to inefficiencies in energy use and discomfort for occupants. It's crucial to adjust the models parameters and incorporate feedback mechanisms to reduce bias and improve its performance.

On the hand the neural network model made balanced predictions between occupied and unoccupied spaces indicating its potential for more reliable forecasts, on occupancy levels.The network models exceptional performance is likely due, to its ability to understand non linear connections within the data leading to more accurate predictions. However further investigation is needed to uncover the reasons behind the differences in how the models perform.

The precision recall curves shed light on the balance between precision and recall at classification thresholds providing insights, into how the models behave under different circumstances. The high levels of precision and recall achieved emphasize both models reliability in predicting occupancy levels. Nevertheless it's crucial to take into account the needs and limitations of building energy management systems when deciding on a deployment threshold.

The studys results suggest directions, for research and development in occupancy prediction models for building energy management. Firstly there is a necessity to tackle bias and improve the reliability of models in situations with imbalanced class distributions. Furthermore incorporating features like weather data, occupancy schedules and building characteristics shows potential for enhancing the accuracy and robustness of models.

Utilizing advanced machine learning techniques such as learning and reinforcement learning offers opportunities to boost model performance and adaptability. Similarly delving into cutting edge sensor technologies like Internet of Things (IoT) devices and edge computing solutions could facilitate data collection and real time analysis ultimately strengthening the effectiveness of occupancy prediction models.

In summary this study highlights how occupancy prediction models have the power to transform building energy management by ushering in sustainable buildings. By harnessing machine learning techniques and sensor technologies these models provide a data approach, to optimizing energy usage while ensuring occupant comfort. This contributes to enhancing building sustainability and occupant well being overall.

Nevertheless continuous dedication, to research and development is crucial to tackling issues like reducing bias making models easier to understand and ensuring scalability. This is essential for the use and effectiveness of occupancy prediction models, in real world scenarios.

CONCLUSION & FUTURE WORK

In a nutshell this study delves into how occupancy prediction models can be used to manage building energy consumption while also ensuring that occupants remain comfortable. The research follows a process involving data collection, preparation, model creation, integration, with building systems and validation to assess how well predictive models work in settings.

The results of the experiments showed that both the support vector machine (SVM) and neural network models were successful in predicting occupancy levels in buildings. Despite differences in accuracy both models demonstrated performance indicating their potential for real world applications. The study emphasized the importance of models in improving building sustainability cutting costs and enhancing occupant well being.

To sum up implementing occupancy prediction models marks a step in managing building energy usage by using data driven methods to optimize efficiency while keeping occupants comfortable. By utilizing sensor data and advanced machine learning techniques these models help buildings operate effectively contributing to sustainability and cost savings. However ongoing research is vital to address issues like bias mitigation, model interpretability and scalability to ensure the adoption and effectiveness of these prediction models, in real world scenarios.
The discussion part shed light on what the experimental findings mean stressing the need to deal with bias enhance the trustworthiness of models and delve into machine learning methods, for upcoming studies. Additionally looking into cutting edge sensor technologies and creating to understand models were highlighted as crucial areas, for additional exploration.

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A. Ethical Approval
The manuscript is not be submitted to any other journal for simultaneous consideration. The submitted work is original and is not published elsewhere in any form or language. No slicing is practiced. No data, text, or theories by others are presented as if they were ours. Proper acknowledgments to other works is given and no copyrighted material is used in the study. No animals or humans were harmed.

B. Funding Details
Not applicable.

C. Conflict of Interest
The authors declared that they have no conflict of interest.

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