Detection of Room Occupancy in Smart Buildings

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Abstract. *Recent advancements in occupancy and indoor environmental monitoring have encouraged the development of innovative solutions. This paper presents a novel approach to room occupancy detection using Wi-Fi probe requests and machine learning techniques. We propose a methodology that splits occupancy detection into two distinct subtasks: personnel presence detection, where the model predicts whether someone is present in the room, and occupancy level detection, which estimates the number of occupants on a six-level scale (ranging from 1 person to up to 25 people) based on probe requests. To achieve this, we evaluated three types of neural networks: CNN (Convolutional Neural Network), LSTM (Long Short-Term Memory), and GRU (Gated Recurrent Unit). Our experimental results show that the GRU model exhibits superior performance in both tasks. For personnel presence detection, the GRU model achieves an accuracy of 91.8%, outperforming the CNN and LSTM models with accuracies of 88.7% and 63.8%, respectively. This demonstrates the effectiveness of GRU in discerning room occupancy. Furthermore, for occupancy level detection, the GRU model achieves an accuracy of 75.1%, surpassing the CNN and LSTM models with accuracies of 47.1% and 52.8%, respectively. This research contributes to the field of occupancy detection by providing a cost-effective solution that utilizes existing Wi-Fi infrastructure and demonstrates the potential of machine learning techniques in accurately classifying room occupancy.*

Keywords

Occupancy detection, probe requests, Wi-Fi, energy savings, machine learning

1. Introduction

Knowing the occupancy of rooms and buildings can be useful in a wide range of circumstances. In smart buildings, there is a significant interest among facility managers in using occupancy monitoring systems to improve property management [1], which can lead to reduced energy consumption of lighting and HVAC (Heating, Ventilation and Air Conditioning) systems [2], efficient use of reserved rooms, and also to the detection of user behavior patterns. In other areas, such as libraries, corridors, or restrooms, effective maintenance planning can be implemented. Additionally, having knowledge of the number of people in a building can prove highly beneficial in crisis situations. For instance, in the event of a fire or a breach in the building, this information can be utilized by rescue services to locate trapped persons in time [3].

Occupancy patterns vary according to the building type. Differences can be expected for residential areas compared to commercial [4] and other buildings, such as universities and hospitals. Residential buildings are mainly occupied in the morning, evening, and during the night. Commercial objects and university campuses are heavily used during working hours, but sporadically during weekends, holidays, or summer vacations. Hospital facilities and some factories operate continuously 24 hours a day [5]. Occupancy can be detected in several ways, from a surveillance camera system, through a network of motion and environmental sensors, to the use of wireless communication in users' mobile devices by the 802.11 wireless interface, whose packets are easy to capture and the management frames do not use any type of encryption.

The paper is structured as follows. The next section provides a summary of relevant works on room/building occupancy. Section 3 reviews the methodology and background of used approaches. Section 4 explains the data collection process and its transformation for use in deep learning. In Section 5, the data analysis, including the space use management study and occupancy predictive modeling is presented. Subsequently, Section 6 presents the discussion of experimental results and Section 7 concludes the topic and presents possible goals for the future.

2. Literature Review

Advancements in sensor and communication technologies have provided plenty of opportunities for occupancy and indoor environmental monitoring applications. For exam-

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ple, space use management in public buildings is enabled by long-term monitoring using sensor-based occupancy detection instead of manual surveys [6]. Various sensors and tools allow occupancy detection in commercial and university buildings, such as PIR (Passive InfraRed) sensors, infrared arrays, ultrasonic sensors, and power consumption metering systems [7], [8]. In order to make the estimation more accurate, these sensors are usually supplemented by others, such as video cameras [9], [10], environmental sensors [11], [12], or radio signal monitoring [13], [14].

Jia et al., in [15], used existing video cameras from the surveillance system, detected people from video frames using machine learning classifiers, and tried to follow them through the zones of a building. They proposed the estimation algorithm, which detected arrival and departure events at the boundaries of zones.

In [16], information from the existing ventilation system and indoor CO2 (Carbon Dioxide) concentration levels was used in a university environment together with supervised machine learning techniques, namely Random Forests and Extreme Learning Machine Neural Networks, for indirect occupancy profile estimation. Depending on the type and size of the rooms, they achieved RMSE determination errors between 2.75 and 8.39. A test-bed for an open-plan office building was provided in [17]. They combined pollutant, heat, and noise environmental sensors, namely CO2, CO (Carbon Monoxide), TVOC (Total Volatile Organic Compounds), PM2.5 (Particulate Matter), acoustics, illumination, motion, temperature, and relative humidity. Three machine learning techniques were used to study occupancy detection. Despite the significant temperature dependence of CO2 measurements, the absolute testing accuracy from SVMs (Support Vector Machines) and the ANN (Artificial Neural Network) were both around 75%. Because of the dynamic Markov properties, the estimated occupancy achieved by Hidden Markov Models (HMMs) was, on average, 73% during the test periods.

In [7], authors used thermal imaging provided by 8×8 infrared sensor arrays placed on top of doorways in offices and laboratory rooms. By using human heat maps, they were able to count the number of people crossing the doorway in each room and track their direction. The recognition system depended on the walking speed of passing people, the differing distance of the sensor, and the temperature noise. However, the authors report an average accuracy of detecting passing persons at 95%. Nevertheless, this method may suffer from cumulative error.

Existing systems for detecting occupancy and efficient use of rooms can also be supplemented by other approaches. One such approach utilizes radio waves from common wireless protocols for detecting people, both by wearable device presence tracking and by device-free presence detection [18–20]. Individualized occupancy detection systems can be developed using radio frequency identification. Li et al., in [21], used tracking tags to detect the occupants' locations based on the known location of reference tags in an educational building. The occupancy estimator was based on the k-Nearest Neighbor algorithm and was able to detect both stationary and mobile occupants. In a more dynamic environment test, the zone level detection rate was 76%.

Research using existing infrastructure in the form of Wi-Fi networks to estimate occupancy is published by Mohottige et al. in [22] and Çiftler et al. in [23]. The number of Wi-Fi connections from a large university campus was collected during four weeks. Using Wi-Fi and Beam counters in each room, the authors were able to measure the number of connected devices. Their study shows that data from existing Wi-Fi infrastructure is a viable way to monitor the behavior of students in various places on the campus during the day, e.g. in teaching spaces, on-campus accommodation areas, the gymnasium, library, or food court.

This research work is related to the RUGGEDISED project, which is dedicated to testing, implementing, and accelerating the smart city model across Europe [24]. By using practical experience from implementation in the Lighthouse city of Umeå, this work proposes a new solution to estimate occupancy levels in an enclosed space in Brno based on users' wearable wireless devices. To this end, our contributions are as follows:

- We analyzed space use management at a Swedish university using PIR sensors and evaluated its impact on energy consumption.
- We conducted a field experiment at a Czech university recording probe requests from students and employees within a laboratory environment.
- We processed all data with special regard to the participants' privacy and we published the anonymized dataset for scientific purposes.
- We proposed a methodology for classifying the number of people in a room using Wi-Fi (Wireless Fidelity) communication.
- We discussed the possibilities of merging with other detection systems to strengthen room occupancy monitoring and the possibility of implementing this system for building management.

3. Methodology

In this paper, we present two studies applicable to the detection of people inside buildings and rooms. The studies were carried out at Umeå University and Brno University of Technology. It is essential to point out that the occupancy estimation system in Umeå is based on motion, while in Brno, it is dependent on the number of users' wearable wireless devices and machine learning. Both studies have the potential to be combined into one system in the future.

3.1 PIR-Based Space Occupancy

Various occupancy sensing technologies may be suitable for different applications, with each presenting its own set of advantages, disadvantages, and limitations [25]. Among these technologies, PIR sensors have garnered wider acceptance in buildings, primarily due to their affordability and energy efficiency. However, the reliability of occupancy data significantly impacts the effectiveness of intended applications. The accuracy and reliability of PIR data are influenced by the placement of sensors within a space [26]. Many factors contribute to this influence, such as the proximity of sensors to occupants, the ambient temperature, and the angle of view for detecting subtle movements.

The trials conducted at Umeå University concerning PIR sensors had two primary objectives: (a) to investigate how sensor placement affects the reliability and accuracy of occupancy detection, and (b) to explore the utilization of PIR sensors in space management and efficiency. Both studies utilized identical infrastructure for sensor deployment, data transmission, storage, and accessibility. The sensors operated on battery power and transmitted data wirelessly, eliminating the need for extensive wiring and simplifying installation. Data transmission relied on the LoRa (Long-Range) wireless network, known for its low-power, wide-area coverage, commonly utilized in IoT (Internet of Things) applications.

In general, when installing sensors, it is important to avoid blind spots while simultaneously minimizing the overlap between the sensors. However, evenly distributing sensors without any overlap is often challenging in practice. The distance between the sensors depends on the sensors' detection range. The vendor recommendation for the installation range of the sensors used in this study was within the 5 m range. Nevertheless, the sensors were installed to cover the 2–3 m range to reduce the probability of blind spots.

The resulting data were in the form of a time series, which developed regularly, instead of being event-based, such as data transmitted when a motion is detected on an irregular basis. This strategy facilitated combining data from several sensors by making them time-aligned. The data were transmitted every 10 minutes, which is a typical time-delay set for PIR sensors. The data from all sensors could be accessed via the internet as they were collected and stored in a middleware database platform.

3.2 Wi-Fi Probe Requests

Wi-Fi enabled devices use several types of management frames of the 802.11 protocol. One such frame is the probe request, which is broadcast from mobile devices for active scanning of nearby Wi-Fi APs (Access Points) to find previously associated ones and to replace cellular connectivity with WLAN (Wireless Local Area Network) [27]. Even while connected to a Wi-Fi network, the device transmits probe requests for localization purposes [28]. When a device transmits probe requests, it receives response packets from the APs in the vicinity. The list of nearby APs can be used for assisted global positioning systems to approximate the user's location. To estimate the approximate location, the SSIDs (Service Set Identifiers) of nearby APs are compared to the online database of wireless APs. Note that developers of mobile operating systems use their own private databases, but a public one is also available.

The probe request consists of Header and Information Element fields [28]. The Header contains information about the MAC (Media Access Control) addresses (globally unique or locally assigned) of the source and destination devices, as well as the size of the probe request. The Information Element usually contains supported transmission speeds, but the rest of the fields vary depending on the device manufacturer. The additional fields can contain vendor specific information, usually related, but not limited, to the manufacturer of the wireless interface. While not as common as vendor specific information, the WPS (Wi-Fi Protected Setup) field can contain information ranging from device model to the name of the device. In the worst case scenario in terms of privacy, this contains the owner's name.

In the last decade, many mobile devices implemented MAC address randomization to prevent tracking [29]. From our previous research, the MAC address does not change during a single scan instance [30] and devices often reuse the same locally assigned address in the presence of known APs. This knowledge allows us to rely on MAC addresses as device identifiers despite the MAC address randomization. In this work, we determined that, while using a short detection window, the influence of MAC address randomization on the assessment of room occupancy is negligible. As one MAC address disappears and another one takes its place, the resulting room occupancy prediction ends up being the same, even if there is a small delay in updating.

There are several benefits in using Wi-Fi management frames for room occupancy estimation. The main advantages of this solution are:

- It is not dependent on users carrying specialized hardware like Bluetooth or RFID tags. Conscious user cooperation is also unnecessary, making the system robust as users do not need to perform any tasks.
- It is cost effective, as the probe requests data can be either captured by existing Wi-Fi infrastructure, by a cheap microcontroller (such as ESP32 by Espressif) equipped with a Wi-Fi interface supporting monitoring mode.
- It is a simple solution as the capture of probe requests and extraction of the needed information is not difficult.
- It is easily deployed.

There are a few main disadvantages of using this approach with the RSSI (Received Signal Strength Intensity) measurements:

- The user must have a Wi-Fi enabled device on them for the system to detect their presence. This could be resolved by using CSI (Channel State Information) instead of RSSI. On the other hand, the CSI based approach would require considerably more time during the offline phase to gather the information on how the radio channel changes with people in different parts of the room.

- The RSSI threshold is different based on the size of the monitored room. If the RSSI threshold is not set correctly for all individual rooms, the system might incorrectly identify the room as occupied by detecting movement outside of the room.

3.3 Machine Learning

Machine Learning describes an area of artificial intelligence that focuses on the development of models and algorithms capable of learning from data on their own. In machine learning, there are two primary methodologies: Supervised Learning and Unsupervised Learning. Supervised learning involves models that learn to perform tasks from labeled data, which includes both the input data and the corresponding expected outputs. Unsupervised learning, on the other hand, does not rely on labeled data and is employed to perform tasks that derive insights directly from the data without predefined labels. Machine learning models learn to perform tasks through training, which is a process of adjusting the model's parameters to minimize the difference between its predictions and the desired output. Model parameters are usually optimized using techniques like gradient descent, which updates the parameters in a direction that minimizes error. After achieving sufficient accuracy on the training data, the model is then evaluated on validation data to assess its performance on data it has not previously encountered [31].

Deep learning, a subset of machine learning, primarily relies on neural networks, which are mathematical models inspired by the neuronal structures of the human brain. These deep learning models are constructed with many successive layers, where each layer itself functions as an independent neural network. There are two main types of neural networks: RNNs (Recurrent Neural Networks) and CNNs (Convolutional Neural Networks). The CNNs, or ConvNets, are neural networks designed for grid-shaped data and are based on a set of predefined learnable filters that are applied to each section of the input data. The output of ConvNet is called a feature map and is often further processed using pooling layers to decrease its spatial dimensions [32].

RNNs are built to handle sequences and time series data using something called a hidden state as a form of memory. They have a feedback loop that carries this hidden state from one time step to the next. This loop helps the RNN remember important information from earlier in the sequence, which allows it to make accurate predictions. Although RNNs can be highly effective for certain tasks, they are generally difficult to train. This challenge prompted the creation of more advanced recurrent units: LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit) units [31].

LSTM units are designed to retain information over an arbitrary time, commonly referred to as memory. LSTM units consist of input, output, and forget gates, which control the flow of information. They also include a hidden state and memory state, which help to retain information over long-term periods. The forget gate uses the input data and the previous hidden state to control how much information the memory state will use to calculate the output values, the new memory state, and the new hidden state [32].

GRU units are similar to the LSTM units, however, they do not use a memory state and forget gate to control the flow of information. Instead, they use the reset gate and update gate to generate a new hidden state and output values. The update gate determines how much of the previous hidden state will be passed along, while the reset gate decides how much of it will be forgotten. GRU units are usually faster to train and require less data to generalize; however, in some cases, especially with large datasets, LSTM may significantly outperform GRU-based networks. The architecture of both LSTM and GRU units can be seen in Figs. 1 and 2, respectively. Both were used to obtain an effective occupancy estimator [31].

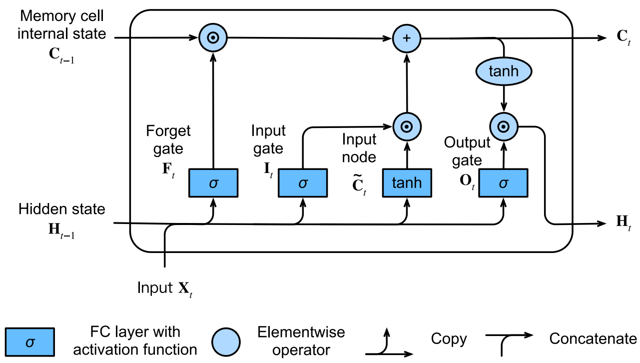

Fig. 1. Long-short term memory [31].

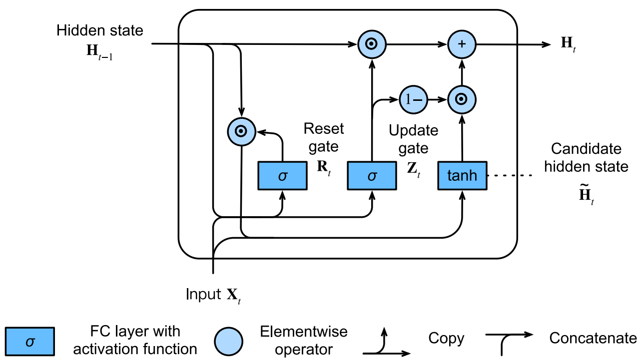

Fig. 2. Gated recurrent units [31].

3.4 Ethics and Sensitive Information Collection

With the capture of Wi-Fi probe requests, the question of user privacy is raised. Since some devices share private user information that can be used for user identification, it is necessary to state that our firmware stores the probe requests as they are received in industry standard binary PCAP (Packet Capture) files, all user data included. The only information necessary for presence detection is the probe request headers with the MAC address to identify non-wearable devices like computers that might be left in the office while the owner of the device leaves. To protect users' privacy rights, we have adhered to the following procedures and recommendations:

- We informed the university department that tests related to the collection of attendance data will be taking place.
- The participants of the experiment were informed about the recording of probe requests as well as video recording for the determination of the ground truth occupancy.
- Modules with an on-board antenna providing a limited radius were used for the measurements. In addition, a signal strength indicator threshold was set to select the probe request to be stored.
- During the Wi-Fi experiment, we did not extract personal information, such as user information stored in WPS or any other sensitive data.
- MAC addresses and SSIDs from preferred network lists were hashed before storing.
- All video recordings from the rooms were deleted after their analysis.
- During the testing period, the scanned data was stored only during the selected interval, i.e., a maximum of 15 minutes.

The aspect of user security and privacy is very important. Therefore, the measurement and evaluation of the information itself served to educate users about the presence of Wi-Fi probe requests and the data structure of these requests.

4. Dataset

To support the functionality for estimating room occupancy, we created a dataset of probe requests, collected within two Fall and two Spring semesters from October 2022 to March 2024 at the Brno University of Technology, Department of Radio Electronics. The department is located on the 6th, i.e., the second highest floor of the university campus building. The dataset was created in a regular laboratory with a floor area of 73 m^2, see Fig. 3.

The testing was conducted during regular university operations and involved participation from over 350 individuals. Throughout the entire measurement period, a total of 3,453,658 probe requests were recorded, with 1,442,437 (41.8%) using randomized MAC addresses. For the replicability of our results and also for the needs of the scientific community, the entire dataset is available in a public repository on GitHub [33].

It is important to note that these probe requests were collected not only during selected working hours but also throughout various nights and weekends to capture information regarding static wireless background activity. In total, data was recorded over 158 days. Figure 4 displays the total number of probe requests recorded during the month of September 2023, aggregated into 15-minute intervals. Increased wireless communication activity is evident after Monday, September 18, coinciding with the start of the Fall semester, while minimal activity is observed during weekends. It is worth noting that on the afternoon of Wednesday, September 20, classes were canceled due to the University music festival, leading a decrease in probe request numbers.

These requests came not only from mobile devices of students and department employees, but also from fixed wireless devices, devices of maintenance employees, and devices situated on higher or lower floors. Today, Wi-Fi devices are very popular and it is likely that a single occupant owns more than one device. Likewise, it is likely that another occupant has wireless connectivity completely turned off or does not have any Wi-Fi device at all, see Fig. 5. Still, our efforts are to demonstrate that we were able to interpret the number of people based on received data and real observations. All measurements were performed on an ESP32 based platform with an embedded camera module and custom C/C++ firmware. The collected data were processes using Python.

Fig. 3. Wi-Fi sniffer position in the laboratory.

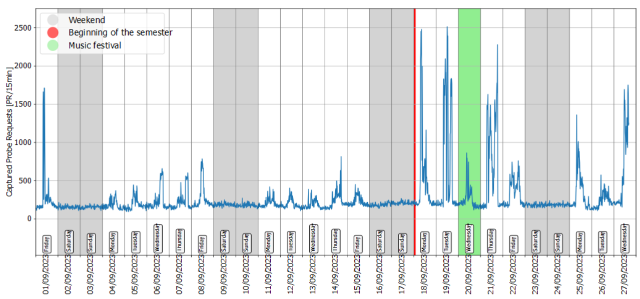

Fig. 4. Probe request density (requests per 15 minutes) recorded in September 2023.

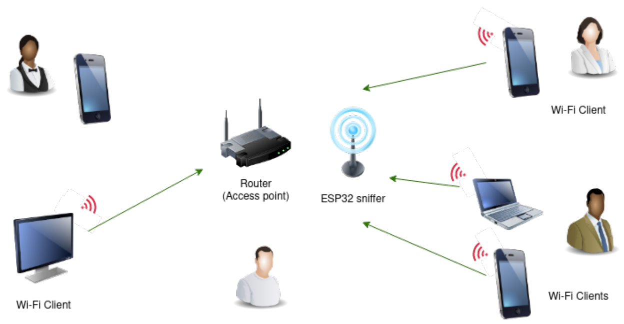

Fig. 5. Sensing system concept.

Probe requests collected for occupancy classification typically offer a limited set of features for analysis. The anonymized data consists of features that can be categorized as either temporally or spatio-temporally dependent, or as static across both time and space. From each probe request packet, a total of 13 features were extracted and organized into a table. Each row within this table, sorted chronologically, represents an individual probe request alongside its respective features in columns. However, certain utilized features, namely the OUI (Organization Unique Identifier) and Dot11Elt (802.11 Information Element), contained lists of numerical labels representing device capabilities, which may vary in both length and value. To ensure optimal utilization of these features in the neural network input, each of these features was padded to attain uniform length. Subsequently, each value was transformed into a distinct column labeled oui_n or $dot11elt_m$, where n and m denote values from zero up to the maximal lengths of lists of respective features within the whole dataset.

To reduce the influence of external sources (devices outside of the monitored room) and static devices (such as embedded devices or Wi-Fi enabled computers), we filtered the probe requests based on the RSSI level. To accurately estimate the RSSI threshold, a series of tests was conducted across the entire footprint of the laboratory. Based on these measurements, the appropriate threshold was estimated to be -66 dBm. To identify static devices, an overnight probe request collection was conducted and static devices present during this period were subsequently filtered out. Additionally, MAC addresses were used to identify some of the vendors of embedded devices whose MAC stays static, which were also filtered out during this process.

To facilitate predictions at regular intervals of N minutes, the dataset was partitioned into time windows based on the timestamps of each probe request. The end of each window represented the start of the following window. Since probe requests were broadcast randomly and the number of devices varied in each time window, the sample (representing a time window of N minutes) contained varying numbers of probe requests (rows). Consequently, padding became necessary to ensure uniformity in the shape of the input data, thereby leading to faster training, simplified implementation, improved memory usage, etc. Algorithm 1 shows how the data were transformed from a simple 2D table of shape [Time, Features] to the input and output arrays (or tensors) of shape [Windows, Time, Feature] and [Windows, Classes(one-hot encoded)], respectively.

Algorithm 1. Data preprocessing.

Load probe requests from PCAP or CSV file(s)
Convert `oui` column to float
Convert `dot11elt` column to float
Filter out probe requests below RSSI threshold

Group probe requests into N-minute windows
for all *window* in windows **do**
  Merge probe requests with identical MAC addresses
  Create `occurrence` feature to count merged requests
  Average RSSI and aggregate remaining features
  Convert SSID to binary values
  Pad rows with zeros for uniform length
end for
$K \leftarrow$ Stack windows into 3D array of shape [Windows $\times$ Probe requests $\times$ Features]
$X \leftarrow$ Slice K to extract input features
$Y \leftarrow$ Slice K to extract truth values

Aggregate Y per window using max() function
Map Y to classes
Limit examples per class and generate list of selected sample indexes
$Y \leftarrow$ Slice Y vector using selected indexes

$X \leftarrow$ Slice X using selected indexes
$Y \leftarrow$ One-hot encode Y
return X, Y

5. Experimental Results

The in situ data collection approach meant that the occupants continued their daily routines, much like in other unmonitored spaces. This approach has several advantages compared to laboratory studies and is suitable for long-term data collection due to its cost-effectiveness. Moreover, monitoring the occupants in their natural environment reduces the probability of alteration of their behavior by disturbances from data collection - this is known as the Hawthorne effect. This section presents the results obtained from both the PIR- and Wi-Fi-based occupancy methods.

5.1 Space Use Management Study in Umeå

The space utilization study was carried out in eight lecture rooms (named S1, S2, S3, M1, M2, M3, L1, L2) at Umeå University, utilizing data collected from 71 sensor devices over a four-month period. As a supplement, another study was conducted for two weeks in three single-occupant offices. Six sensors were installed in each of the three offices at various positions to detect the occupants' motions, see Fig. 6. A primary focus of this investigation was to devise informative indicators for visualizing sensor data and generating insights into space utilization patterns.

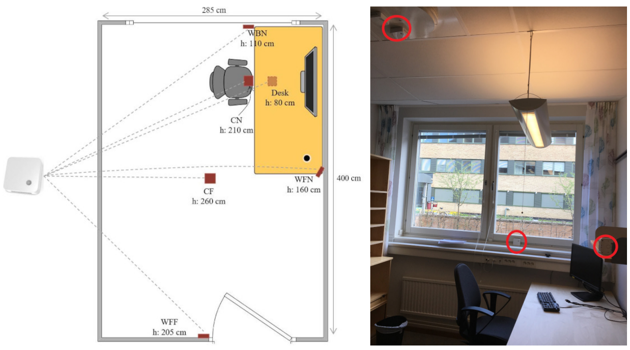

Fig. 6. Position of sensors in the office.

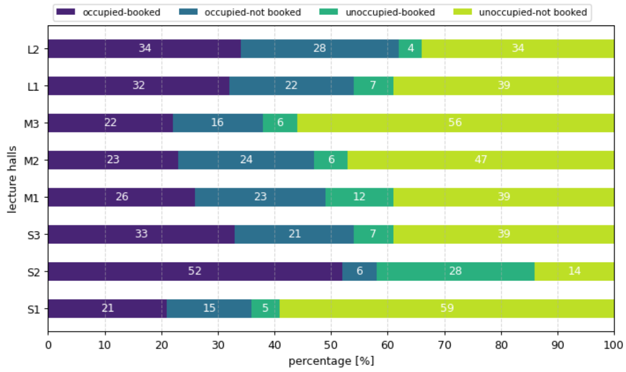

Fig. 7. Proportion of usage statuses of eight lecture rooms, adopted from [6].

Four indicators were introduced to evaluate space use and to track the changes resulting from the implemented interventions. The space use indicators are used to transform data into useful information that represents usage time and occupancy density of the space. Figure 7 shows the results of one of the space use indicators named the PUS (Proportion of Usage Statuses). This indicator enabled the monitoring of space utilization in relation to four defined statuses that were assigned to the lecture rooms based on booking and occupancy information. The status *occupied-booked* was used when the lecture hall was booked and the PIR sensors showed occupancy. *Unoccupied-booked* occurred when the lecture hall was booked but the sensors did not detect the presence of occupants. The status *occupied-not booked* was when the lecture hall was not booked but the PIR sensors showed the presence of occupants. Lastly, *unoccupied-not booked* was when the lecture hall was neither booked nor occupied.

From Figure 7, it can be seen that the lecture hall marked S2 was the most booked room and furthermore that the average room occupancy (booked or not booked) was 49.8%. The practical results from eight lecture rooms thus showed the possibility of closing one or two rooms without impairing everyday activities - this could save up to 19% of the energy consumed in the lecture rooms. Similarly, the other space use indicators provide views on how the lecture rooms are used and enable improvements in the efficiency of their use.

5.2 Personnel Presence Detection

In order to obtain accurate classification and estimation of room occupancy, a variety of architectures were tested to ensure thorough evaluation. A number of neural networks architectures was tested, including basic RNN, LSTM, and GRU models. Furthermore, combinations of RNNs and CNNs were tested to address the problem of feature extraction within RNNs. Based on a thorough evaluation, two models were developed to solve two tasks in room occupancy estimation. The following subsections briefly explain the goals of each task and presents the experimental results of the developed models. Initial testing showed the occupancy level estimation to be very problematic when using seven levels of occupancy, where the first level (class) represents zero personnel presence and the remaining uniformly cover the range of personnel from 1 to 25. In this case, the models had problems learning the correct prediction as the first class was for no personnel present, and the data in this class essentially represented the probe requests from devices outside of the room, which were not filtered out by the RSSI threshold. The remaining classes represented bins of different personnel occupancies and, in many cases, also contained probe requests from outside of the room that were collected as if they came from the inside. It was very problematic for the models to learn to distinguish between these distributions and due to these issues, we decided to split the occupancy surveillance into two simpler sub-tasks: personnel presence detection and occupancy level detection.

Personnel presence detection is a task in which the deep learning model has to distinguish between two states of the room: *occupied* and *unoccupied*. This essentially means the model learns to distinguish if, during the given time window, the probe requests came from outside (unoccupied) or inside the room (occupied). Using the dataset processing algorithm, the actual personnel occupancy was converted into two classes - unoccupied (0 personnel) and occupied (1–25 personnel). This makes the task essentially a binary classification task. To ensure smooth training and avoid bias, the occurrence of each class within the training and validation sets was limited, resulting in 960 samples per class for training and 240 samples per class for validation. The temporal CNN, LSTM, and GRU models were implemented and optimized using techniques such as grid search, random search, and genetic algorithms. The best configurations (see Tab. 3) of individual networks were evaluated based on multiple training runs with randomly generated training and validation sets. The results of the evaluation, shown in Tab. 1, present very good performance of both the CNN and GRU models. The LSTM model, on the other hand, showed very poor performance and often reached a point during the training where the model stopped learning. This led to large differences in final loss, which is reflected in the mean accuracy (and precision) and also in the standard deviation.

5.3 Occupancy Level Detection

Unlike a binary presence detector, occupancy level detection determines the specific number of people in a room and is often limited to three levels: low, moderate, and high. To refine this categorization and enhance its specificity, the dataset for this task was split into six bins, accommodating occupancy ranging from 1 to 25 personnel. This approach allows control of six distinct levels of occupancy. To ensure an unbiased representation across all classes, the dataset was constrained to 210 samples per class, promoting a balanced distribution in both the training and validation sets (70% and 30% respectively). Leveraging the same optimization techniques utilized in personnel presence detection, the GRU architecture once again demonstrated superior performance, reaching an accuracy of up to 75.1%. The CNN and LSTM models, on the other hand, were not able to capture the relations between the input data and output labels and showed an accuracy of about 47.1% and 52.8%, respectively. The summary of performance of all models can be seen in Tab. 2 and configuration of all models can be found in Tab. 3. The example of confusion matrix of the best GRU model can be seen in Figure 8.

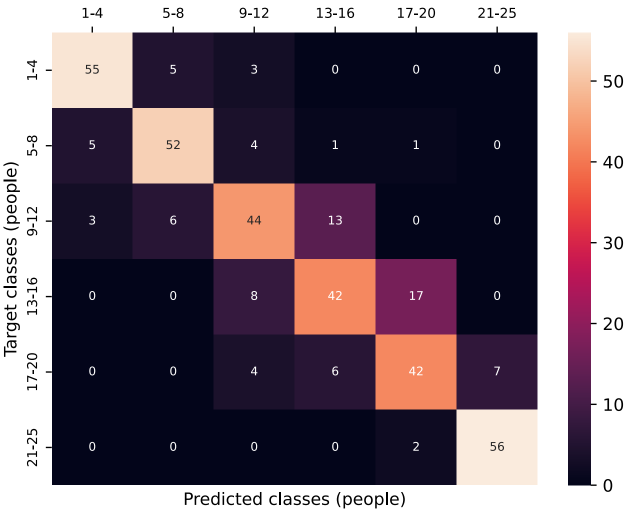

Fig. 8. Confusion matrix of GRU occupancy level detector.

	CNN model	LSTM model	GRU model
Accuracy [%]	88.7 ± 1.0%	63.8 ± 17.2%	91.8 ± 0.8%
Precision [%]	89.8 ± 0.9%	59.1 ± 25.9%	92.0 ± 0.8%

Tab. 1. Performance of evaluated models for personnel presence detection.

	CNN model	LSTM model	GRU model
Accuracy [%]	47.1 ± 1.6%	52.8 ± 5.1%	75.1 ± 1.3%
Precision [%]	45.4 ± 1.6%	53.3 ± 7.4%	74.7 ± 1.5%

Tab. 2. Performance of evaluated models for occupancy level detection.

6. Discussion of Results

The research findings from both Umeå and Brno demonstrate the viability of the proposed systems for estimating room occupancy on university campuses. These outcomes are also transferable to office buildings with smart management systems. The Swedish approach relies on detecting human movement within the monitored area. Utilizing PIR-based technology, this method employs battery-powered units with wireless data transmission, offering the advantage of straightforward and cost-effective implementation. Based on the use of multiple sensors, the occupancy of larger rooms can be evaluated, and thus, the behavior of students, employees, or customers can be estimated.

The Brno method is based on the assumption that every (or nearly every) person carries at least one device with an activated Wi-Fi interface. Especially in commercial and university spaces, this assumption is more than justified. The proposed system uses passive sensing of the data these devices constantly transmit. Occupancy information can be used for building management, lighting, and HVAC systems.

The experimental results show that the single sniffer setup is very capable, and in combination with the GRU model, which outperforms all the other models, can estimate personnel presence with an accuracy of up to 91.8% and the levels of occupancy with an accuracy of about 75.1%. The models ended up using only 5 relevant input features, whereas the RSSI is the only feature that is space and time-dependent. Features oui and $dot11elt$ are static for each device type, and thus, multiple probe requests may contain the same values. Occurrence and SSID are synthetic features since they may be used only to identify how often certain devices broadcast probe requests and/or if they publicly share previously known SSIDs. While this helps the model to make decisions on multiple levels, the information thus featured within probe requests might be a limiting factor and the generation of synthetic features might be required to further improve the model's performance.

Some aspects were not taken into account when analyzing the room occupancy, which may be viewed in some cases as a disadvantage of this approach. Firstly, neither the model nor the algorithm takes into consideration an absolute zero presence of devices, which would consist of all input data being zero for a given time window. In real-world applications, this would automatically represent an unoccupied room and

Task	Personnel presence detection			Occupancy level detection		
Network type	CNN(Temporal)	LSTM	GRU	CNN(Temporal)	LSTM	GRU
Layers	3	1	3	2	3	2
Kernels	2, 16, 2	-	-	32, 4	-	GRU
Hidden size	36	159	70	139	158	130
Activation function	Logaritmic Softmax					
Learning rate	0.002					
Optimizer	RMSprop					
Epochs	Maximum of 1000 epochs with early stop					

Tab. 3. Summary of best network architectures of personnel presence and occupancy level detections.

would not need to be processed by the model. Secondly, the model is not capable of detecting "ghosts," e.g., personnel with no Wi-Fi enabled devices. While it is a rare situation, this can lead to errors in ground truth labels in the dataset as well as make the model ineffective in areas where personnel are not allowed to bring Wi-Fi-capable devices. Lastly, the dataset ground truth labels are based on personnel count, not on the number of devices present, which can vary between personnel or even certain demographics and can impact the model's performance.

7. Conclusion

Our research in Umeå and Brno highlights promising methods for estimating room occupancy in educational and office buildings, leveraging PIR-based motion detection and Wi-Fi signal sensing. These approaches offer scalable, cost-effective means for smart building management, optimizing the use of space, energy, and resources. The Umeå method's simplicity and low-cost installation makes it appealing for existing structures, enabling detailed occupancy analysis with minimal adjustments. Furthermore, detailed evaluation showed this method could save up to 19% of the energy consumed in the monitored lecture rooms. Therefore, this method could be used in real-world applications to minimize energy costs and consumption. The Brno method's use of Wi-Fi signal detection showcases high accuracy and adaptability, exploiting the prevalence of Wi-Fi-enabled devices for passive occupancy sensing. The GRU model has shown the best performance with an accuracy of about 91.8% on previously unseen data for the personnel presence task and about 75.1% for the occupancy level task.

The future goals will be focused on enhancement of the presented methodology, live testing of proposed systems in Brno, and energy savings estimation. Furthermore, a thorough evaluation of the single-sniffer system and multiple-sniffer system is set to be tested. Lastly, to mitigate some of the disadvantages of individual approaches, the fusion of PIR and Wi-Fi-based sensing will be implemented and evaluated to maximize the efficiency and reliability of occupancy detection.

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