Advancing Behavior Modeling in Smart Buildings through Open Set, Universal, and Generalized Domain Adaptation

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Abstract

Advancing Behavior Modeling in Smart Buildings through Open Set, Universal, and Generalized Domain Adaptation

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Smart buildings use intelligent automation systems which optimize energy consumption while improving occupant comfort and promoting sustainable development. The core of this vision depends on strong Occupancy Estimation and Activity Recognition models which support dynamic control of HVAC systems and lighting and other essential building operations. These models face significant deployment challenges because real-world settings differ from training environments and suffer from insufficient availability of labeled data and evolving activity patterns. This thesis examines how Open Set Domain Adaptation, Universal Domain Adaptation, and Generalized Domain Adaptation enhance the adaptability and generalization potential of Occupancy Estimation and Activity Recognition models in smart buildings. Our research begins with the exploration of Open Set Domain Adaptation techniques designed to distinguish known activity classes from unknown ones during domain shifts by implementing adversarial learning frameworks along with rejection-aware classifiers specifically for smart building sensor data. Our work presents a combined Universal Domain Adaptation approach which uses optimal transport and angular margin constraints to achieve flexible alignment between domains while operating without knowledge of overlapping labels. Our study examines generalized domain adaptation methods that allow adaptation across domain and label shifts in previously unencountered environments through self-training and hybrid learning approaches combined with distribution-agnostic strategies. Extensive experiments show that the proposed methods excel in classification accuracy, unknown class detection capabilities and stability against label imbalance. The research provides scalable, privacy-conscious solutions for adaptive behavior modeling in intelligent environments, which help improve the energy efficiency of intelligent building systems.

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Chapter 1

Introduction

1.1 Problem statement

The evolution of cities toward smarter infrastructure necessitates smart buildings to play a fundamental role in managing energy use while improving indoor conditions and occupant comfort. At the core of smart building intelligence are two key tasks: Occupancy Estimation (OE) Dalhoumi, Amayri, and Bouguila (2022); Guo, Amayri, Bouguila, and Fan (2021); Nikroo, Amayri, and Bouguila (2022); Zamzami, Amayri, Bouguila, and Ploix (2019) and Activity Recognition (AR) Amayri, Ali, Bouguila, and Ploix (2021); Ploix, Amayri, and Bouguila (2021). Automated systems use these tasks to adjust lighting, and HVAC (heating, ventilation, and air conditioning) systems in response to current data about occupant presence and behavior. Building robust and transferable models for the tasks of OE and AR remains an ongoing challenge despite their potential impact on energy efficiency and automation. The majority of current OE and AR approaches utilize supervised learning methods that demand extensive collections of labeled data designed for the specific deployment setting. The models show excellent performance in their initial environment but experience reduced accuracy when they face new buildings with different layouts or sensor arrangements and occupant profiles. Domain shift represents a prevalent challenge in practical applications that occurs when training data distributions (source) show significant differences from deployment data distributions (target). New data collection for each building demands high expenses and extensive labor while becoming impractical because of privacy issues along with limited sensor reach and variable activity patterns. Domain Adaptation (DA) techniques help reduce domain shift effects by transferring knowledge between a labeled source domain and a target domain with little or no labels. Traditional DA methods face limitations because they rely on restrictive assumptions. The closed-set assumption represents a widespread limitation since it assumes that both the source and target domains have identical activity or occupancy label sets. Dynamic smart building environments often invalidate this assumption because they produce previously unknown activities in the target domain. Models that use closed-set assumptions during training tend to label unknown target samples as known source classes resulting in decreased reliability and robustness. Traditional domain adaptation approaches which depend on full original training data availability are less suitable because real-world situations often restrict access to source data through privacy rules or computational limitations. The need arises for domain adaptation strategies that can scale and respect privacy constraints while managing label set mismatches and unknown target classes without the necessity of source data availability.

1.2 Theoretical background and related works

1.2.1 Theoretical background of Domain Adaptation (DA)

Domain adaptation is a subfield of transfer learning where a model trained on one domain (referred to as the **source domain**) is adapted to work effectively on a different domain (referred to as the **target domain**) Dridi, Amayri, and Bouguila (2024a). This is useful in cases where collecting labeled data for the target domain is expensive or impractical Gheisari and Baghshah (2015). Domain adaptation aims to minimize the discrepancy between the source and target domains, ensuring that the model performs well on the target domain despite differences in data distributions Lee and Lee (2023b). Formally, a domain $\mathcal{D}$ is defined as a pair:

$$\mathcal{D} = (\mathcal{X}, P(X))$$

where $\mathcal{X}$ is the feature space (e.g., temperature, motion, CO_2 levels), and $P(X)$ is the marginal probability distribution over the features.

A **learning task** $\mathcal{T}$ associated with a domain is defined as:

$$\mathcal{T} = (\mathcal{Y}, f)$$

where $\mathcal{Y}$ is the label space (e.g., activity classes or occupancy states), and $f : \mathcal{X} \to \mathcal{Y}$ is the predictive function that maps input features to corresponding labels.

In domain adaptation, we are given a **source domain** $\mathcal{D}_S = (\mathcal{X}_S, P_S(X))$ with task $\mathcal{T}_S = (\mathcal{Y}_S, f_S)$ and a **target domain** $\mathcal{D}_T = (\mathcal{X}_T, P_T(X))$ with task $\mathcal{T}_T = (\mathcal{Y}_T, f_T)$. Typically, $\mathcal{X}_S = \mathcal{X}_T$, but $P_S(X) \neq P_T(X)$, indicating a distribution shift between domains.

The goal of DA is to learn a function f_T that performs well on the target domain $\mathcal{D}_T$, even in the absence of labeled target data. In the *unsupervised* domain adaptation setting, the source domain provides labeled samples:

$$\mathcal{D}_S = \{(x_i^S, y_i^S)\}_{i=1}^{N_S} \quad \text{with} \quad x_i^S \in \mathcal{X}_S,\ y_i^S \in \mathcal{Y}_S$$

while the target domain provides only unlabeled samples:

$$\mathcal{D}_T = \{x_j^T\}_{j=1}^{N_T} \quad \text{with} \quad x_j^T \in \mathcal{X}_T$$

Depending on the relationship between the label spaces $\mathcal{Y}_S$ and $\mathcal{Y}_T$, several domain adaptation scenarios arise. In Closed-Set Domain Adaptation (CSDA), it is assumed that the source and target domains share an identical label space, i.e., $\mathcal{Y}_S = \mathcal{Y}_T$. In contrast, Open Set Domain Adaptation (OSDA) considers scenarios where the target domain contains unknown classes that are not present in the source domain, such that $\mathcal{Y}_S \cap \mathcal{Y}_T \neq \emptyset$ and $\mathcal{Y}_T \setminus \mathcal{Y}_S \neq \emptyset$. Universal Domain Adaptation (UniDA) further generalizes this setting by making no assumptions about the overlap between label spaces, allowing the model to adapt flexibly under partial or uncertain class correspondence. Finally, Generalized Domain Adaptation (GDA) extends DA by jointly addressing both distributional shift and label space mismatch, often in the absence of prior knowledge about the relationship between source and target domains.

The learning objective in domain adaptation is to minimize the expected risk on the target domain:

$$\mathcal{R}_T(f) = E_{(x,y)\sim P_T(X,Y)}[\ell(f(x), y)]$$

where ℓ is a suitable loss function (e.g., cross-entropy). Because target labels cannot be accessed during training, most DA methods focus on creating domain-invariant features to help source-trained models perform well across target environments. Domain adaptation enables smart buildings to recognize occupancy and activities across different environments without extensive retraining or manual labeling. The subsequent sections present a comprehensive examination of key domain adaptation methods like CSDA, OSDA, UniDA, and GDA and discuss their application to behavioral modeling through sensor data analysis.

1.2.2 Related works

Closed-Set Domain Adaptation (CSDA)

Closed-Set Domain Adaptation (CSDA) assumes that the source and target domains share the same set of classes Dridi et al. (2024a). In this scenario, the goal of domain adaptation is to transfer knowledge from the labeled source domain to the unlabeled target domain, assuming that both domains contain only instances of the same classes Gretton, Borgwardt, Rasch, Scholkopf, and Smola (2012). This assumption simplifies the adaptation process, as the model does not need to handle new or unseen classes in the target domain Dridi et al. (2024a). CSDA has been applied to various tasks, such as image classification and activity recognition, with successful results Long, Zhu, Wang, and Jordan (2017). Popular methods in CSDA include discrepancy-based techniques like Maximum Mean Discrepancy (MMD) and Correlation Alignment (CORAL), as well as adversarial-based methods like Domain-Adversarial Neural Networks (DANN) Fu, Wu, Zhang, and Yan (2019); Long et al. (2017). These methods have shown effectiveness in domains where the source and target label spaces are identical Fu et al. (2019). However, CSDA has a critical limitation: it assumes that all classes in the target domain are known and present in the source domain Gretton et al. (2012). In dynamic real-world scenarios, such as smart buildings, new or unforeseen activities or occupancy patterns may emerge in the target domain, which CSDA methods cannot handle effectively Long et al. (2017).

Open Set Domain Adaptation (OSDA)

Open Set Domain Adaptation (OSDA) is adapting models to a target domain that includes unknown classes which are not represented in the source domain Engelbrecht and du Preez (2020). The main challenge with OSDA is how to handle these unknown classes without compromising performance on the known classes that it shares with the source domain Jang et al. (2022). There are two very important tasks that must be accomplished in order to do OSDA properly. The first task that the model must perform is to differentiate between the known classes and the unknown ones Engelbrecht and du Preez (2020). It should precisely discriminate the known classes in the source domain from the unknown classes in the target domain. The model should also not exhibit negative transfer, which is when knowledge from known classes is applied to unknown classes in a harmful way, thereby degrading performance Jang et al. (2022). The second requirement is that the model has to focus on aligning the attributes across domains, ensuring that the known classes in both the source domain and the target domain are properly matched, even when unseen classes are present Jang et al. (2022). It is crucial to align the features correctly to make precise predictions on the known classes, as any misalignment would degrade performance on the known class prediction task Engelbrecht and du Preez (2020). Many OSDA methods have been developed to address these issues. One of the original methods, OpenMax, builds on the softmax layer to allow for rejection of unknown classes by predicting the probability of an input being from an unknown class Engelbrecht and du Preez (2020). Another significant method, UADAL, uses adversarial learning to explicitly distinguish known classes from unknown ones Jang et al. (2022). Finally, Soft Rejection techniques have been incorporated, where the model automatically rejects samples deemed to have a high probability of belonging to one of the unknown classes based on confidence scores Singhal, Walambe, Ramanna, and Kotecha (2023).

Universal Domain Adaptation (UniDA)

UniDA extends DA by doing away with the need of the label set overlap knowledge between the source and target domain Z. Cai, Zhang, Ma, and Jing (2022). In contrast to OSDA, which explicitly distinguishes between what is known and what is not known, UniDA can automatically identify shared patterns during clustering of private target classes Chang, Shi, Tuan, and Wang (2022). As an example of this endeavor, the Unified Optimal Transport (UniOT) framework provides novel optimal transport-based alignment methods that enable the discovery of shared categories even without thresholding Chang et al. (2022). Furthermore, UniOT builds on adaptive filling techniques to overcome data imbalances and guarantee that knowledge can be transferred even when label is unequal. With these evolutions UniDA is in a unique position to become an essential method for applications in the real-world, especially in smart buildings where activity distribution is inherently dynamic and changing.

Generalized Domain Adaptation (GDA)

GDA goes beyond domain adaptation by concurrently resolving domain and label mismatch Q. Wang, Okabe, Lee, and Koshinaka (2023) making certain that the models detect any novel, unidentified actions that show up in their data source and help them check if these actions are also showing up in their target or destination data. GDA uses methods including uncertainty estimation, entropy minimization, and hybrid adversarial learning to enhance generalization, in contrast to conventional methods that presume total overlap between source and target labels Long, Zhu, Wang, and Jordan (2016). In order to provide strong adaptation even in cases when the target domain shows high variance, recent studies have suggested GDA frameworks that combine self-training with pseudo-label refinement. GDA demonstrates a significant advancement in smart buildings, allowing users to engage with gadgets in various ways and carry out a variety of tasks. In contrast to current work that is carefully planned beforehand, GDA enables behavior models to operate well even in scenarios we have never constructed before. In recent work, concepts such as contrastive learning and reducing entropy have been used, coupled with some more sophisticated training involving adversarial material Boudiaf et al. (2020). We use all that advanced techniques in our new approach. In our work, we present GDA approaches specifically for smart buildings and identify different activities that people do there. By focusing on one-dimensional data from IoT sensors - which poses special difficulties such as shifting environmental conditions, different sensor locations, and a range of occupant behaviors - our method sets itself apart from earlier studies F. Wang, Liu, Shu, and Tao (2017). When evaluating how well these three methods function together to manage various tasks, we combine them into a single, large unified framework.

1.3 Contributions

The research examines advanced domain adaptation techniques including Open Set Domain Adaptation (OSDA), Universal Domain Adaptation (UniDA), and Generalized Domain Adaptation (GDA) to find solutions for behavior modeling challenges in smart buildings. The contributions of this thesis are listed as follows:

- **Open Set Domain Adaptation for Behavior Modeling in Smart Buildings** In this work, we have adapted OSDA methods to solve the traditional domain adaptation methods' limitations within dynamic smart building environments. Specifically, we adapt four OSDA approaches: The work presents four Open Set Domain Adaptation methods including OSDA by Back-propagation and Soft Rejection OSDA together with Unknown-Aware Domain Adversarial Learning (UADAL) and Adjustment and Alignment (ANNA). The proposed methods enable accurate identification of known and unknown activity classes in the target domain to minimize negative transfer while boosting generalization performance. We apply adversarial learning and calibrated decision boundaries to increase the accuracy of occupancy estimation and activity recognition tasks with different sensor configurations and data distributions.

- **Open Set and Universal Domain Adaptation for Enhancing Activity Recognition in Smart Buildings** In this work, we have adapted domain adaptation methods through the integration of OSDA with UniDA inside a single framework dedicated to activity recognition tasks. We proposed an angular margin-based OSDA technique for better class separation and developed a new UniDA model using optimal transport theory, which handles unknown class distributions without requiring label set overlap information. The unified framework provides scalable activity recognition capabilities in diverse settings while improving system adaptability to new behaviors and smart building conditions.

- **Generalized Domain Adaptation for Scalable Activity Recognition Using IoT Sensor Data** In this work, we have adapted three advanced Generalized Domain Adaptation (GDA) techniques - Stochastic Weight Averaging Densely (SWAD), Distribution-Free Domain Generalization (DFDG), and Empirical Risk Minimization (ERM) - for use in activity recognition through 1D IoT sensor data. Generalized Domain Adaptation enables models to handle domain and label variations without requiring labeled target dataset unlike conventional Domain Adaptation methods. Our evaluation shows these models sustain recognition accuracy through domain changes in real-world scenarios and prove their adaptability to new environments. Our work fosters scalable and energy-efficient intelligent systems that are ready for deployment in smart building applications.

1.4 Thesis Overview

This thesis is organized into five chapters organized as follows:

- Chapter 1 provides background information and purpose of the research along with defining the problem statement and reviewing domain adaptation theories and literature while highlighting the thesis main contributions.
- Chapter 2 examines OSDA approaches for modeling behaviors within smart buildings. The chapter introduces different OSDA methods that handle unknown target domain classes. Occupancy estimation and activity recognition tasks provide the evaluation ground for these methods when subjected to realistic domain shift conditions.
- Chapter 3 examines how OSDA and UniDA techniques can be combined to improve adaptability in dynamic deployment scenarios. This chapter describes adaptable methods which handle unknown target classes and varying degrees of label space overlap to boost model generalization in diverse smart environments.

- In Chapter 4 we examine three different GDA methods designed for sensor-based activity recognition tasks to demonstrate their generalization abilities. The methods demonstrate their ability to generalize across new domains and activity patterns without requiring labels from those target domains.
- Chapter 5 concludes the thesis by summarizing its primary findings and contributions.

Chapter 2

Open Set Domain Adaptation for Behavior Modeling in Smart Buildings

2.1 Introduction

As global energy demands continue to rise and concerns about sustainability become more pressing, optimizing energy usage in buildings has become a critical area of focus Hafez et al. (2023). Smart buildings, which integrate advanced technologies to control and monitor building systems, have emerged as a key solution to this challenge Dridi et al. (2024a). These buildings aim to minimize energy consumption, and enhance indoor environmental quality (IEQ) by dynamically adjusting heating, ventilation, air conditioning (HVAC), and lighting systems based on real-time occupancy data and activity patterns Guo, Amayri, Najar, Fan, and Bouguila (2022). Accurate Occupancy Estimation (OE) and Activity Recognition (AR) are therefore essential for achieving these goals Dridi (2023). However, developing machine learning models capable of performing OE and AR in smart buildings presents significant challenges Dridi, Amayri, and Bouguila (2024b). The sensor data collected in smart buildings is influenced by factors such as differences in sensor types, building layouts, and occupant behavior Liu, Zhang, Sun, and Zhou (2023). This variability results in a phenomenon known as domain shift, where the properties of data differ between environments Guan and Liu (2023). For instance, the same sensor setup might behave differently in two buildings due to varying environmental factors such as temperature, humidity, and room occupancy rates

Z. Chen et al. (2017). These differences complicate the task of training models that generalize well across buildings, making it difficult to deploy robust OE and AR systems Alanne and Sierla (2021). Traditional Closed-Set Domain Adaptation (CSDA) methods attempt to mitigate this problem by enabling models trained on a labeled source domain (such as one building) to work effectively on an unlabeled target domain (another building) Han, Xu, Chen, Liu, and Zhu (2022). However, CSDA assumes that the target domain contains only known classes-i.e., the same classes present in the source domain. This assumption does not hold in real-world scenarios where new, unseen classes can emerge in the target domain Singhal et al. (2023). For example, an activity such as ”meeting” might be common in one building but absent in another, or new activities might arise in the target domain that were not part of the training data. As a result, CSDA models often struggle to estimate accurately occupancy or recognize activities in smart buildings when faced with novel patterns, leading to decreasing of the model performance W. Li, Liu, Han, and Yuan (2023). Unlike CSDA, OSDA is designed to handle the presence of unknown classes in the target domain. In an open set scenario, the model is trained to transfer knowledge from the source domain to the target domain while also learning to recognize when it encounters previously unseen or ”unknown” classes Jang et al. (2022). This flexibility makes OSDA particularly suitable for dynamic environments like smart buildings, where occupancy patterns and activities can change unpredictably. The ability to distinguish between known and unknown classes allows for more robust and accurate OE and AR, which in turn leads to more effective energy management, improved IEQ, and better occupant comfort. Despite the potential of OSDA, there has been limited research on applying it to smart building data for OE and AR tasks. Most existing OSDA approaches have been applied to computer vision or natural language processing domains Ghaffari et al. (2023), where the nature of unknown classes and domain shifts differ significantly from the challenges faced in smart buildings Fu et al. (2019). To address this gap, we propose four novel OSDA techniques tailored specifically for smart building environments. OSDA (Open Set Domain Adaptation) by Backpropagation Fu et al. (2019) is an adversarial learning method that attempts to match the feature distributions of the source and target domains. It works by training the feature extractor to fool the domain discriminator so that the model learns domain-invariant features and therefore generalizes better. OSDA with Soft Rejection Singhal et al. (2023) adds a rejection mechanism to the classifier so it can refuse to classify instances about which it is unsure instead of mislabeling them, this makes it better able to cope with unknown classes. Unknown-Aware Domain Adversarial Learning (UADAL) Jang et al. (2022) is an extension of the adversarial learning framework that adds an unknown class label into the domain discriminator so it can directly recognize unknown classes. While on the other hand ANNA (Adjustment and Alignment for Unbiased OSDA) W. Li et al. (2023) attempts to align the feature space between the source and target domains and then compensate the classifier for these ”unknown” classes so that it is more accurate when the environment changes. By leveraging these approaches, we aim to improve the generalization capabilities of OE and AR models in smart buildings, enabling them to perform well across a range of environments and handle novel scenarios effectively. Through extensive experimentation on smart building datasets, we demonstrate that our proposed OSDA methods significantly outperform CSDA techniques in both accuracy and robustness. Our results suggest that integrating OSDA into smart building management systems can lead to substantial energy savings, reduced carbon emissions, and enhanced sustainability without compromising occupant comfort. This chapter is structured as follows: Section 2 presents different OSDA techniques and explains their implementation. Section 3 discusses the experimental setup and results.

2.2 The proposed approaches

In this section, we propose OSDA by backpropagation, OSDA with soft rejection, Unknown Aware Domain Adversarial Learning (UADAL) for OSDA, and Adjustment and alignment (ANNA) for unbiased OSDA methods, specifically designed to address the challenges of domain shift and unknown classes in Occupancy Estimation (OE) and Activity Recognition (AR) within smart buildings. These methods leverage advanced techniques such as adversarial learning, and soft rejection to enhance the performance of OE and AR models in dynamic environments.

2.2.1 OSDA by Backpropagation

We adapted the OSDA by Backpropagation method, originally developed for visual domains, to the context of smart buildings, specifically for Activity Recognition (AR) and Occupancy Estimation (OE) Fu et al. (2019). The original approach uses adversarial learning and was developed to deal with unknown classes, which are present in the target domain but not in the source domain. The main objective of this method is to recognize the known classes in the target domain as accurately as possible and reject the unknown classes. The feature extractor G, takes the input samples and maps them down to a lower dimensional feature space, and the classifier C, takes the features and outputs the probabilities of the various classes. This method uses adversarial training to map the source and target domain features to the same distribution, but also incorporates a scheme to distinguish and reject samples of unknown classes in the target domain Ganin et al. (2016). It predicts a probability for each known class and has an extra dimension for unknown class detection. In adapting this method to smart building data, we primarily focused on sensor data (such as motion sensors and CO2 levels) for AR and OE tasks. This is unlike the original application in two-dimensional domains because smart building data does not have distinct borders or patterns, but rather continuous variations due to environmental changes, occupant behavior Lassen and Goia (2021). Therefore, additional preprocessing steps and feature engineering were required to address these domain-specific challenges. Thus, the key adaptations were in feature extraction and unknown class rejection. We tailored the feature extractor G to cope with smart building sensor data by adding domain-specific feature transformations. This modification ensures that the extracted features represent the underlying activity or occupancy level in smart environments. The rejection mechanism for unknown classes, essential for detecting previously unseen activities or new occupancy patterns, was adapted to the smart building context. We used a confidence threshold τ for OE to better detect unknown patterns that may arise from new occupants or changes in building utilization Tzeng, Hoffman, Saenko, and Darrell (2017). The adversarial loss aligns the feature distributions between the source and target domains, while the classification loss ensures that the known classes are classified correctly and that unknown classes are rejected M. Chen, Zhao, Liu, and Cai (2020). These loss functions were adapted for smart buildings as follows: the adversarial loss forces feature alignment between the source and target domains. This encourages the feature extractor G to learn domain-invariant features, meaning that the source domain and target domain will have similar feature distributions. The domain discriminator D is trained to distinguish between source and target features, while the feature extractor is trained to confuse D. This minimax game encourages the learning of features that generalize well across domains.

The adversarial loss is defined as:

$$L_{adv} = -E_{x \sim P_S(X)} [\log D(G(x))] - E_{x \sim P_T(X)} [\log(1 - D(G(x)))] \tag{1}$$

where $P_S(X)$ and $P_T(X)$ represent the marginal distributions of the source and target domains, respectively, and $G(x)$ represents the features extracted from the input sample x. The classification loss comprises two parts: the classification of known classes and the rejection of unknown classes. For known classes, the loss is calculated using cross-entropy Martin-Donas, Gomez, Gonzalez, and Peinado (2018). The classifier outputs a probability distribution over the known classes, and the loss penalizes incorrect predictions. The classification loss for known classes is:

$$L_{classification} = -E_{(x,y) \sim D_S} \sum_{k=1}^{|\mathcal{Y}_S|} y_k \log P(y_k|x)$$

where $P(y_k|x)$ is the predicted probability for class k, and y_k is the true label. For unknown classes, the model minimizes a rejection loss. This mechanism recognizes and rejects samples that belong to classes not observed in the source domain. The rejection loss penalizes misclassification of unknown samples:

$$L_{unk} = E_{x \sim P_T(X)} [\log(1 - \max P(y|x))]$$

where $\max P(y|x)$ is the maximum predicted probability for a known class, and the loss penalizes samples that are not confidently classified, effectively rejecting them as unknown. The training process follows an adversarial framework, with the feature extractor G and the domain discriminator D playing a minimax game Zhang and Davison (2021). The feature extractor is trained to minimize the adversarial loss L_{adv}, ensuring that the source and target domain features are aligned. Simultaneously, the classifier is trained to minimize the classification loss $L_{classification}$, ensuring that known classes are correctly classified and unknown classes are rejected. The combined loss function for the entire model is:

$$L_{total} = L_{adv} + L_{classification}$$

The model is trained using this total loss, allowing it to handle both known and unknown classes effectively, resulting in a robust model that generalizes well to other domains in smart buildings.

2.2.2 OSDA with Soft Rejection

The OSDA with Soft Rejection algorithm was originally created for visual domains and was designed to solve the open set domain adaptation problem of discerning known from novel classes Singhal et al. (2023). This method introduces a mechanism of "soft rejection" that does not rely on hard classification rules or strict thresholds. Rather than simply rejecting those samples whose predicted class probability is below some threshold, it assigns weights to samples in the target domain based on the entropy of the classifier's predictions K. Li, Lu, Zuo, and Zhang (2024). This allows for a much more dynamic and subtle approach to rejecting unknown classes. In our adaptation, this method has been tailored to handle data from smart building environments, such as sensor data from motion detectors or CO2 levels Dong, Prakash, Feng, and O'Neill (2019). The tasks are Activity Recognition (AR) and Occupancy Estimation (OE). AR is concerned with recognizing what human activity is taking place in a building, and OE focuses on counting how many people are in a room Hao, Cha, and Kim (2019). In our version, the feature extractor G processes sensor data from the smart building and outputs features that can be classified into one of the known activities or occupancy levels. The unique aspect of this method is the "soft rejection" idea, meaning it doesn't quickly decide whether or not a sample belongs to an unknown class. Rather, it computes a confidence score using the entropy of the classifier's predictions and uses this to "softly" reject samples with high uncertainty. The feature extractor G takes in both the source domain (labeled data) and the target domain (unlabeled data) and maps them to a common feature space J. Wang, Chen, Lin, Sigal, and de Silva (2021). Classifiers C_1 and C_2 are trained to predict the known classes in the source domain. For unknown class detection in the target domain, entropy-based confidence scores are used for soft rejection. The classifiers are forced to provide low-entropy responses for known classes, meaning the probability distribution must be a sharp function for these classes. The entropy will be higher for unknown classes, which is used to assign soft rejection weights to target domain samples that may belong to unknown classes. The loss function consists of the cross-entropy loss on the known classes, the weighted classifier discrepancy (WCD) for domain adaptation, and the soft rejection loss for the unknown classes Xu and Klabjan (2022). These loss functions are tuned for optimal performance across both tasks. The weighted classifier discrepancy (WCD) is calculated as follows:

$$WCD(f_1(x), f_2(x)) = w(x) \cdot |f_1(x) - f_2(x)| \tag{2}$$

where $f_1(x)$ and $f_2(x)$ are the predictions of the two classifiers and $w(x)$ is the entropy-based weight of each sample:

$$w(x) = \frac{1}{Z} \exp\left(- \sum_{c=1}^{|C|} p_c(x) \log p_c(x) \right) \tag{3}$$

Here, Z is a normalization factor, $p_c(x)$ is the predicted probability for class c, and $|C|$ is the number of known classes. This weighting function guarantees that samples with greater entropy (likely unknown classes) will be weighted less and essentially excluded from the adaptation process Xu and Klabjan (2022). The total loss function is composed of three parts: Cross-Entropy Loss for Known Classes: This loss ensures that the model classifies known classes correctly using labeled source data.

$$L_{\text{known}} = -E_{(x_s, y_s) \sim D_S} \sum_{c=1}^{|C|} y_s \log P(y_s \mid x_s) \tag{4}$$

where D_S is the source domain and y_s is the true label for some sample x_s. Weighted Classifier Discrepancy (WCD) Loss: This loss minimizes the difference between the predictions of the two classifiers on target domain samples, allowing the feature extractor G to learn domain-invariant features.

$$L_{\text{WCD}} = E_{x_t \sim D_T} w(x_t) \cdot |f_1(x_t) - f_2(x_t)| \tag{5}$$

where D_T is the target domain and $w(x_t)$ is the entropy weight of sample x_t from the target data. Soft Rejection Loss for Unknown Classes: This loss penalizes high-confidence predictions for unknown samples, encouraging the model to reject them:

$$L_{\text{unk}} = E_{x_t \sim D_T} \left[\log(1 - \max P(y \mid x_t)) \right] \tag{6}$$

The final objective is to minimize the total loss:

$$L_{\text{total}} = L_{\text{known}} + \lambda_{\text{WCD}} L_{\text{WCD}} + \lambda_{\text{unk}} L_{\text{unk}} \quad (7)$$

where λ_{WCD} and λ_{unk} are hyperparameters that weight the WCD loss and the soft rejection loss. The training procedure alternates between training the classifiers C_1 and C_2 to maximize the WCD and training the feature extractor G to minimize the WCD. This adversarial process forces the feature extractor to learn domain-invariant features, and the classifiers improve their ability to identify samples that don't fit into the known classes L. Li, Yang, Kong, Zhang, and Ma (2022). By leveraging the soft rejection mechanism, the model is able to handle the presence of unknown classes more effectively, particularly in the context of smart building data, where new activities or occupancy patterns may emerge Barcina-Blanco, López Lobo, Bringas, and Del Ser (2024). This ensures more precise predictions and makes the system more adaptable to real-life situations, leading to better energy management and a safer environment for the occupants of the smart building. The main contributions of our adaptation of the OSDA with Soft Rejection method for smart buildings include the modification of the feature extraction process to handle sensor data, the implementation of an entropy-based soft rejection mechanism tailored to activity recognition and occupancy estimation, and the optimization of the loss functions to ensure robust performance in dynamic and evolving smart building environments.

2.2.3 Unknown Aware Domain Adversarial Learning (UADAL)

The UADAL (Unknown-Aware Domain Adversarial Learning) approach was originally developed to address the challenges associated with open set domain adaptation (OSDA), specifically dealing with unknown classes in the target domain that are absent from the source domain Jang et al. (2022). This approach is unique in that it can match the known classes between the source and target domain while separating the unknown classes. Other methods often fail because they attempt to match unknown classes to known ones, which causes negative transfer. In our version of UADAL for smart building data, we concentrated on AR and OE. In smart buildings, sensor data is influenced not only by environmental parameters like temperature and CO2 concentration but also by dynamic human behaviors and occupancy patterns. These factors introduce significant domain shifts, making traditional domain adaptation methods less effective A.K., Sanodiya, Jose, and Mathew (2023). UADAL's method of aligning the known classes while separating the unknowns lends itself well to this type of dynamic, constantly changing data. The feature extractor G is used to extract domain-invariant features from both the source and target domains. The domain discriminator D is a multi-class discriminator that is trained to recognize features as originating from the source domain, the target-known classes, or the target-unknown classes J. Li, Lü, and Li (2022). By introducing this multi-class discriminator, UADAL explicitly segregates the target-unknown features from both the source and target-known features, which is a significant improvement over traditional adversarial learning methods that do not handle unknown classes effectively. The classifier C must not only correctly classify the instances in the known class set but also recognize instances that do not belong to the known classes as belonging to the unknown class. This is accomplished using posterior inference, which calculates the entropy of the classifier's predictions and assigns a probability that a sample belongs to the known or unknown class Nicora, Rios, Abu-Hanna, and Bellazzi (2022). In this way, UADAL can align the known class features while isolating the unknown classes in the target domain, making it robust in the face of changing activities and occupancy trends in smart buildings. The domain discrimination loss is key to ensuring that the model does not align target-unknown samples with the source domain, thereby preventing negative transfer J. Li, li, and Lü (2020). The domain discrimination loss is defined as:

$$L_d = E_{x \sim P_{S(X)}}[-\log D_s(G(x))] + E_{x \sim P_{T(X)}}[-w_x \log D_{tk}(G(x)) - (1-w_x) \log D_{tu}(G(x))] \quad (8)$$

where $D_s(G(x))$, $D_{tk}(G(x))$, and $D_{tu}(G(x))$ represent the output of the domain discriminator for the source, target-known, and target-unknown classes, respectively. The weight w_x is the probability that a sample belongs to the target-known class, calculated using open-set recognition and posterior inference. We also define the adversarial loss for the feature extractor G to ensure that the features align properly Mayer, Paul, and Timofte (2021). The adversarial loss aims to align the source and target-known features while ensuring that the target-unknown features are not aligned:

$$L_G = E_{x \sim P_S(X)}[-\log D_s(G(x))] + E_{x \sim P_T(X)}[-w_x \log D_{tk}(G(x)) + (1 - w_x) \log D_{tu}(G(x))] \tag{9}$$

This alternating minimax game between the feature extractor and the domain discriminator allows the model to align the known classes and learn to separate the unknown classes effectively. In addition to the domain adversarial losses, we also define a classification loss L_{cls} that ensures correct classification of known classes. This loss is defined as:

$$L_{cls} = E_{(x_s, y_s) \sim D_S}[L_{ce}(C(G(x_s)), y_s)] + E_{x_t \sim D_T}[(1 - w_x) L_{ce}(C(G(x_t)), y_{unk})] \tag{10}$$

where L_{ce} is the cross-entropy loss for classifying both known and unknown classes. For target-known samples, the classifier minimizes the standard cross-entropy loss, while for target-unknown samples, the model learns to reject them by minimizing the cross-entropy loss for the unknown class. The total loss function is a combination of the domain adversarial loss and the classification loss:

$$L_{total} = L_G + \lambda_d L_d + \lambda_{cls} L_{cls} \tag{11}$$

where λ_d and λ_{cls} are hyperparameters that balance the importance of domain alignment and classification accuracy. In doing so, UADAL not only performs domain adaptation effectively but also handles unknown classes in the target domain robustly. Our contribution to this method includes adapting the feature extraction process for sensor data in smart buildings, modifying the posterior inference for open-set recognition, and tailoring the loss functions to ensure optimal performance on AR and OE tasks. These modifications enable UADAL to accommodate the dynamic and evolving nature of smart building data, thereby enhancing energy management, occupant safety, and HVAC system optimization.

2.2.4 Adjustment and Alignment for Unbiased OSDA (ANNA)

The fourth and final approach, Adjustment and Alignment for Unbiased OSDA (ANNA) W. Li et al. (2023), focuses on minimizing bias introduced by unknown classes during the feature alignment process. This method introduces adjustment techniques that ensure the model adapts to both known and unknown classes without bias Lee and Lee (2023a). Front-Door Adjustment (FDA) and Decoupled Causal Alignment (DCA) are two crucial modules in the ANNA method. These modules aim to correct biased learning in the source domain and facilitate an unbiased transfer to the target domain, which is essential for handling both known and unknown classes in Open Set Domain Adaptation (OSDA). In our adaptation of ANNA to smart building data, specifically AR and OE, we encountered sensor data with significant domain shifts caused by variations in human behavior, environmental conditions, and sensor placement Ahn, Kim, and Jeong (2023). These fluctuations cause new activity or usage patterns to develop over time, and thus a robust OSDA system is necessary. The main problem is matching the known classes in the source and target domains while separating the unknown classes to avoid negative transfer. This is why ANNA's mechanism, based on causality-driven debiasing, is well-suited to handle these fluctuations in smart buildings. A feature extractor G is applied to the sensor data to obtain fine-grained features, which are then fed into the FDA module to discover the novel class regions embedded in the data Zhu, Xu, and Luo (2023). The DCA module separates the base and novel class regions so that the model can adjust to the target domain without bias. The result of these two modules working together is that ANNA performs domain adaptation without being hindered by the semantic bias and misalignment problems that traditional methods face. The training process in ANNA focuses on two main components: correcting the biased learning in the source domain using Front-Door Adjustment (FDA) and transferring the model to the target domain using Decoupled Causal Alignment (DCA) W. Li et al. (2023). These processes ensure that the distributions of both the base and novel classes are aligned, preventing bias in the transfer of knowledge from one domain to another. The first part of ANNA, FDA, identifies novel-class regions in the original data and applies a front-door adjustment to them. The learning objective for FDA is defined as:

$$L_{\text{FDA}} = \eta_b L_b + \eta_n L_n \tag{12}$$

where η_b represents the probability of the base region and η_n the probability of the novel-class region. L_b is the normal closed-set classification loss used to optimize $P(Y \mid X_b)$, while L_n is the loss that maximizes the probability of the novel class over the X_n novel-class regions discovered.

$$L_n = -\frac{1}{|X_n|} \sum_{x_n \in X_n} \log P(y = K + 1 \mid x_n) \tag{13}$$

where $P(y = K + 1 \mid x_n)$ is the probability that a sample belongs to the unknown class. The second part, DCA, separates the base and novel class regions in the target domain through the creation of orthogonal masks. DCA loss matches the base and novel-class regions in the source and target domains by using a double-head discriminator, one for the base-class head and one for the novel-class head M. Cai et al. (2024). The alignment loss for DCA is defined as:

$$L_{\text{DCA}} = -\sum_{i=1}^{|X_s|} \sum_{o \in \{b,n\}} M_{o,s}^i \log f_o(x_s^i) - \sum_{i=1}^{|X_t|} \sum_{o \in \{b,n\}} M_{o,t}^i \log(1 - f_o(x_t^i)) \tag{14}$$

where $M_{o,s}^i$ and $M_{o,t}^i$ are the orthogonal masks for the base and novel-class regions, and $f_o(x)$ is the output of the respective head for a given input sample x. The total loss function for ANNA combines the FDA and DCA losses with a baseline loss for the base-class alignment in the source domain:

$$L_{\text{total}} = \lambda_1 L_{\text{FDA}} + \lambda_2 L_{\text{DCA}} + L_{\text{base}} \tag{15}$$

where λ_1 and λ_2 are hyperparameters that balance the contribution of FDA and DCA, and L_{base} is a baseline loss used for the base-class alignment in the source domain. The training process alternates between optimizing the feature extractor G, the FDA module, and the DCA module, ensuring that the model learns domain-invariant features while correctly identifying and isolating the novel-class regions in the target domain Yang, Zhang, Li, Kim, and Wang (2022). This results in a model that is robust to domain shifts and can handle unseen classes in dynamic smart building environments. Our adaptation of ANNA to smart buildings involved modifying the feature extraction method to handle sensor data, altering the front-door adjustment mechanism to accommodate the dynamic nature of AR and OE tasks, and tweaking the loss functions to perform well in environments where new activities or occupancy patterns frequently emerge. These modifications have improved energy management, occupant safety, and HVAC system optimization in smart buildings.

2.3 Experimental setup and results

2.3.1 Experimental Setup

To evaluate the effectiveness of the proposed OSDA methods, we conducted a series of experiments on two specialized datasets designed for OE and AR in smart buildings. These datasets reflect the dynamic and diverse nature of activities and occupancy patterns commonly found in smart building environments.

Datasets

The private dataset used for OE was collected from two university offices (H355 and H358) located at the Grenoble Institute of Technology Dridi et al. (2024b). This data is gathered from CO2 concentration sensors in the smart building, which monitor CO2 levels across different areas. CO2 levels correlate with the number of individuals present in a space; as occupancy increases, CO2 concentration rises, making it a dependable metric for estimating occupancy. The data ranges from no one present, to one, two, three individuals, and finally, more than three individuals in the area. In this research, the data was analyzed to determine occupancy levels and their impact on energy usage and building system optimization. For AR, the data was sourced from the publicly available Washington State University (WSU) dataset Tapia, Intille, and Larson (2004) available in this website Intille et al. (2005). This data was collected through the use of Internet of Things (IoT) sensors, mostly motion sensors collected from two single-person apartments during two weeks, using proximity binary sensors attached to different appliances and objects. The sensors record the presence of people in certain locations throughout the building. These sensors offer vital information on the number of people in an area, how often they move around, and what they are doing. The dataset contains a variety of daily human activities such as cooking, toileting, and watching TV. Specifically in this research, it was limited to energy management, HVAC systems optimization, data privacy, and occupant safety. The specific activities examined include toileting, cooking breakfast, watching TV, cooking lunch, and cooking dinner. These are the activities that the models were tested on for this study, using the dataset, that captures the many different ways that occupants interact with their surroundings, and how those activities relate to energy consumption. The AR and OE data sets were very important because they were used to test the effectiveness of the new innovative methods as far as energy efficiency and occupant comfort and data security in smart buildings.

Choice of Unknown Classes in OE and AR

The term ”Unknown classes” refers to new, unseen classes of data that are not present in the source domain. In fact the goal of OSDA is to handle unknown classes and train the model on known classes. To further validate the effectiveness of the OSDA methods, we take as example some real-world-inspired scenarios that could be classified as unknown, like health monitoring contexts in households with elderly occupants, activities like ”taking medication,” or activities involving children, such as ”playing with toys,” introduced movement patterns that were distinct from adult activities. Handling unknown classes is done either by rejecting it or classifying it as unknown. Hence the importance of categorizing the classes in the OE and AR datasets as known and unknown. For the OE dataset, the known classes in the source domain include ”no occupant,” ”one occupant,” and ”two occupants.” The unknown classes include more complex occupancy levels like three or more than three occupants. In AR, the known classes in the source domain included common activities such as ”sleeping,” ”eating,” and ”watching TV.” The unknown classes in the target domain were less frequent or more complex activities, such as ”taking medication,” ”doing laundry,” and ”listening to music.”

Evaluation Metrics

The following evaluation metrics were used to assess the performance of the OSDA methods:

Accuracy is defined as the proportion of correct predictions made by the model out of the total number of predictions. Mathematically, it is expressed as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{16}$$

where TP (True Positives): The number of correctly predicted positive samples. TN (True Negatives): The number of correctly predicted negative samples. FP (False Positives): The number of incorrectly predicted positive samples. FN (False Negatives): The number of incorrectly predicted negative samples.

These metrics evaluate the model's ability to correctly identify known classes, particularly focusing on minimizing misclassification of unknown classes.

Precision measures the accuracy of the model's positive predictions. It is calculated as:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{17}$$

This represents the proportion of true positives out of all predicted positives.

Recall (also known as Sensitivity or True Positive Rate) measures how well the model identifies actual positives. It is calculated as:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{18}$$

This represents the proportion of true positives out of all actual positives.

F1-Score is the harmonic mean of Precision and Recall, providing a single metric that balances both concerns. It is calculated as:

$$\text{F1-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{19}$$

The F1-Score provides a balance between precision and recall, especially useful when the data are imbalanced.

Unknown Class Detection Rate (UCDR) is used to evaluate how well the model identifies and correctly rejects samples from unknown classes. It is defined as the proportion of correctly identified unknown class samples out of the total number of unknown samples:

$$\text{UCDR} = \frac{\text{True Unknowns Detected}}{\text{Total Unknowns in Target Domain}} \tag{20}$$

This metric is crucial in open set domain adaptation, where the model must distinguish between known and unknown classes. The following tables show the performance of the proposed OSDA methods on the OE and AR tasks. We compare the techniques based on accuracy, F1-score, and the Unknown Class Detection Rate (UCDR) which measures their performance on known and unknown classes in the target domain.

Occupancy Estimation (OE)

The results for OE are summarized in Table 2.1 and Table 2.2. The proposed OSDA methods showed good performance, with Adjustment and Alignment for Unbiased OSDA (ANNA) outperforming the other methods in all metrics. ANNA achieved the highest accuracy at 90.1%, precision at 89.0%, recall at 88.6%, and F1-score at 88.8%. Its UCDR was also the highest at 85.7%, reflecting its strong ability to detect unknown occupancy patterns.This is mainly because of ANNA's use of FDA(Front-Door Adjustment) and DCA(Decoupled Causal Alignment) modules, which allow it to effectively realign features while minimizing bias from the unknown classes. Unknown Aware Domain Adversarial Learning (UADAL) also performed well, achieving an accuracy of 88.4%, precision of 87.2%, and a recall of 87.0%. UADAL's UCDR of 80.6% indicates that it was effective at handling unknown classes, though slightly less so than ANNA. OSDA with Soft Rejection achieved 87.1% accuracy and a UCDR of 78.3%. Its soft rejection mechanism worked well but was less precise at distinguishing unknown classes compared to ANNA and UADAL, leading to slightly lower performance in recall and F1-score. OSDA by Backpropagation achieved 85.6% accuracy and a UCDR of 72.8%, the lowest among the OSDA methods. Its threshold-rejection scheme was good at aligning features, but it was not as effective at recognizing unknown classes, leading to lower precision and recall. Furthermore, for each model, we compared the precision on known classes to that on unknown classes in the target. By comparing the two, one can easily see how well each model does at classifying what it knows versus what it doesn't know. The results in Table 3 show the precision of each OSDA method for known and unknown classes.

Table 2.1: Occupancy Estimation Results for OSDA Methods

Method	Accuracy	Precision	Recall	F1-Score
OSDA BP	85.6%	83.8%	84.2%	84.0%
OSDA SR	87.1%	85.5%	86.2%	85.8%
UADAL	88.4%	87.2%	87.0%	87.1%
ANNA	**90.1%**	**89.0%**	**88.6%**	**88.8%**

Table 2.2: Unknown Class Detection Rate for OSDA Methods

Method	Unknown Class Detection Rate
OSDA BP	72.8%
OSDA SR	78.3%
UADAL	80.6%
ANNA	**85.7%**

Table 2.3: precision in terms of known unknown

Method	**Precision (Known)**	**Precision (Unknown)**
OSDA BP	83.8%	72.1%
OSDA SR	85.5%	75.8%
UADAL	87.2%	80.3%
ANNA	89.0%	84.5%

Activity Recognition (AR)

The results for AR, summarized in Table 2.4 and table 2.5, show that ANNA again outperformed the other methods, achieving the highest accuracy of 88.1%, precision of 86.8%, recall of 86.5%, and F1-score of 86.6%. ANNA's UCDR of 84.9% demonstrates its strong ability to detect unknown activities, which is a crucial metric in open set scenarios with unknown activities. UADAL achieved 85.6% accuracy and a UCDR of 79.0%, demonstrating its ability to handle unknown classes, though its precision and recall were slightly lower than ANNA, particularly in AR tasks where activities are more dynamic and varied. OSDA with Soft Rejection performed slightly worse, with an accuracy of 83.3% and a UCDR of 75.0%. Its soft rejection mechanism struggled more with activity variability, leading to a higher rate of false positives compared to ANNA and UADAL. OSDA by Backpropagation performed the lowest, with an accuracy of 81.2% and a UCDR of 70.1%, highlighting its limitations in handling the complexity of activity recognition, especially with novel or unknown activities.

The AR results show that ANNA's alignment and bias correction mechanisms are effective at

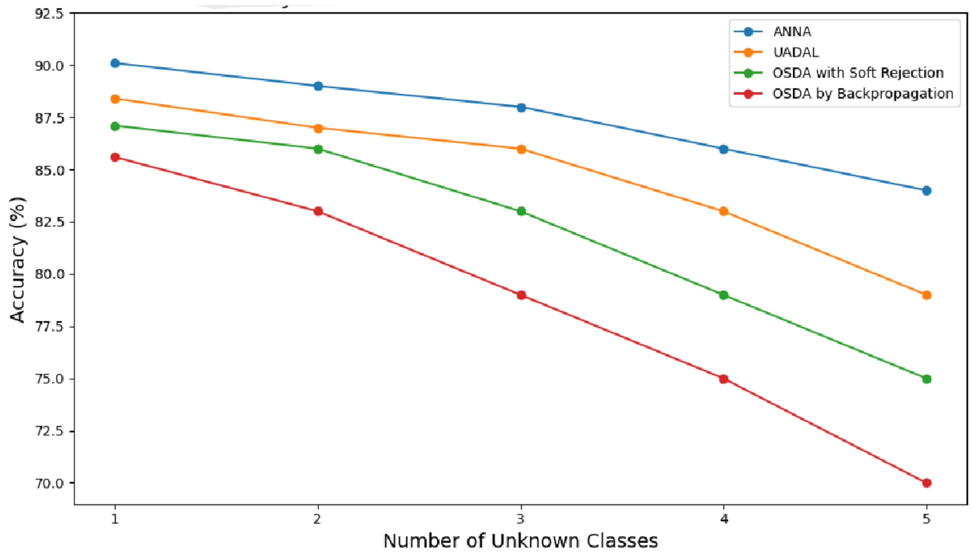

Figure 2.1: Accuracy vs number of unknown classes.

Table 2.4: Activity Recognition Results for OSDA Methods

Method	Accuracy	Precision	Recall	F1-Score
OSDA BP	81.2%	79.5%	78.8%	79.1%
OSDA SR	83.3%	81.5%	80.8%	81.1%
UADAL	85.6%	84.3%	84.1%	84.2%
ANNA	**88.1%**	**86.8%**	**86.5%**	**86.6%**

Table 2.5: Unknown Class Detection Rate for OSDA Methods in AR Dataset

Method	Unknown Class Detection Rate
OSDA by BP	70.1%
OSDA with SR	75.5%
UADAL	79.0%
ANNA	**84.9%**

distinguishing between known and unknown tasks. UADAL's performs well but lacks the precision of ANNA, especially in environment as dynamic as AR. OSDA with Soft Rejection and Backpropagation performed adequately but showed limitations in handling the complexities of open set domain adaptation, especially when faced with unknown activities. The results demonstrate that the combination of feature alignment and bias correction mechanisms of ANNA give the best method for adapting to new occupancy patterns in smart building. UADAL also used adversarial learning to differentiate between known and unknown classes and this worked effectively, and OSDA with Soft Rejection and Backpropagation performed well overall but struggled more with recognizing

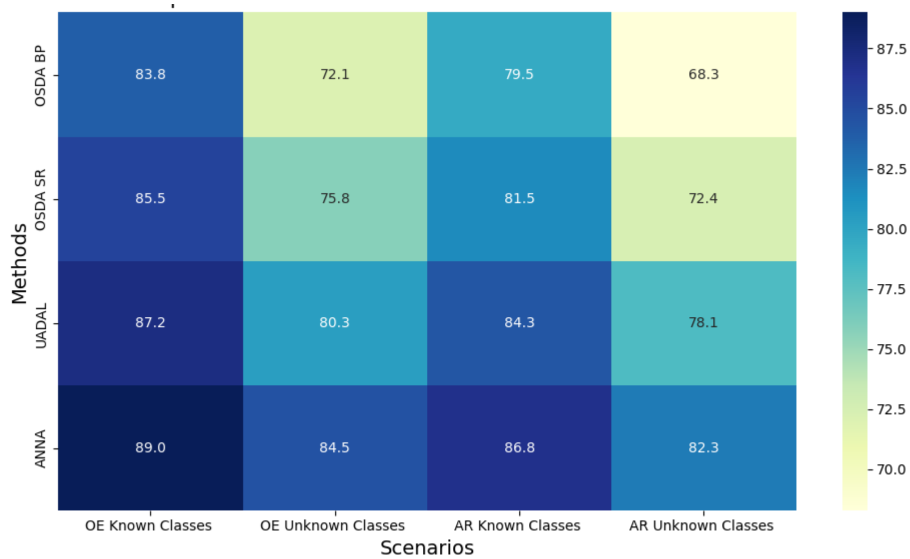

Figure 2.2: Comparison of Precision Across Methods and Scenarios.

unknown classes. The results in Table 6 illustrate the performance of each OSDA method in terms of precision for known and unknown classes in the AR dataset. The results of these experiments

Table 2.6: precision in terms of known unknown

Method	Precision (Known)	Precision (Unknown)
OSDA BP	79.5%	68.3%
OSDA SR	81.5%	72.4%
UADAL	84.3%	78.1%
ANNA	86.8%	82.3%

shed light on how each approach deals with the problems of domain adaptation, or more specifically, unknown class detection, and adaptation to unseen data in the context of the Occupancy Estimation (OE) and Activity Recognition (AR) tasks. To better understand the models' scalability and limitations, we also evaluated the performance of each class, particularly in terms of the maximum number of unknown classes each model could handle. We found that ANNA could handle well 5 unknown classes, proving to be a stable classifier of unknown patterns. UADAL was able to manage 4 unknown classes, but after that its performance started to fall off. The OSDA with Soft Rejection did a great job with 3 unknown classes, but after that it started to fall apart. The most restrained was OSDA by Backpropagation, it could only handle 2-3 unknown classes before its performance dropped off dramatically. This experiment gives a better sense of just how well each method copes

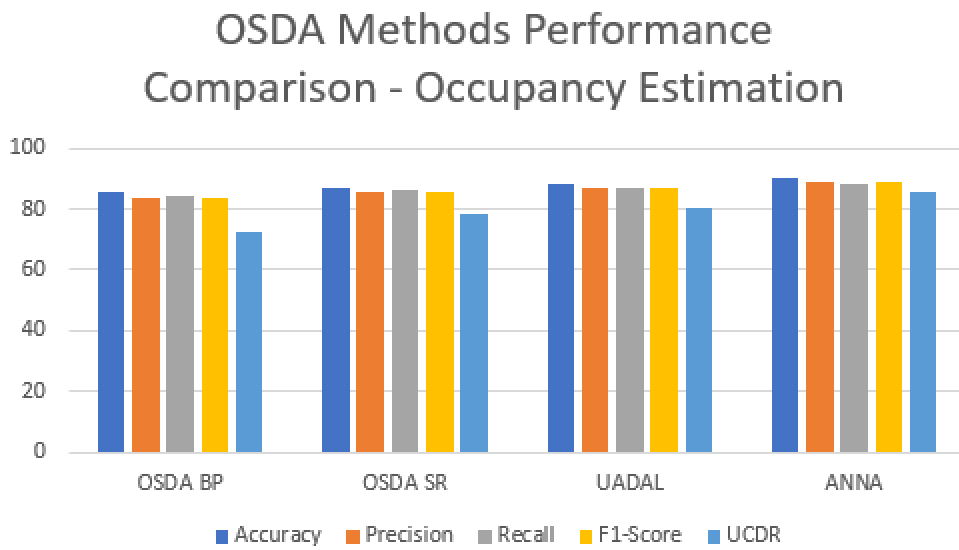

Figure 2.3: OSDA Methods Performance Comparison - Occupancy Estimation.

with the rising number of ”unknown classes” and where each method truly excels and fails.

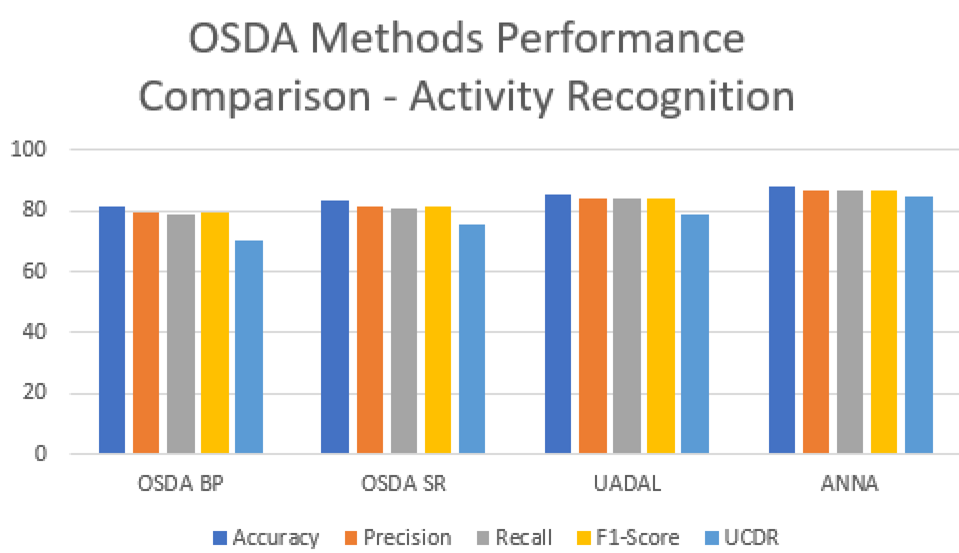

Figure 2.4: OSDA Methods Performance Comparison - Activity Recognition.

Chapter 3

Open Set and Universal Domain Adaptation for Enhancing Activity Recognition in Smart Buildings

3.1 Introduction

Smart buildings are an important part of current infrastructure through the use of intelligent automation to improve both energy efficiency and sustainability and, consequently, user comfort Moreno, Santa, Zamora, and Skarmeta (2014). AR is the basis for accomplishing these goals since it enables the construction of systems that can intuitively adjust to future occupant activities L. Chen, Hoey, Nugent, Cook, and Yu (2012). Classical supervised learning models are hard to generalize across buildings as data distribution, the use of sensor and the appearance of a new activity pattern can evolve Qiu et al. (2022). There has been a great deal of use of DA techniques to overcome these challenges so that models trained in one domain can be generalized across different domains Dridi (2023). On the other hand, closed-set DA methods assume the same label sets in the source and target domain, which makes the DA methods ineffective in the real-world scenarios Jing, Liu, and Ding (2021). To overcome these limitations, Open Set DA and Universal DA provide effective solutions by allowing models to identify and adapt for oversampling novel activities in novel environments Q. Li, Wen, Zheng, Zhang, and Fu (2024). This paper presents OSDA and UniDA frameworks that are specifically designed for smart buildings, with the goal of improving activity recognition for better energy efficiency and environmental quality of indoor space. We adapt two methods, which integrates adversarial learning and optimal transport theory, to enhance domain alignment and the classification accuracies. Experimental evaluation on an AR dataset show significant improvements in adaptive AR, achieving accuracy up to 88.3% and F1-scores to 87.9% that highlight the real-world applicability for energy-conserving smart buildings.

3.2 The proposed approaches

In this research, we introduce two domain adaptation-based schemes for AR in smart building systems. The traditional OSDA-based approach is applied to adapt OSDA via Angular Margin Separation to sensor data from smart buildings X. Li, Li, Du, Zhu, and Li (2022). This version guarantees a better structured partition of known and unknown activities and uses sophisticated kernel techniques to further improve classification accuracy. The second one is based on UniDA, by which we adapt the Unified Optimal Transport framework for UniDA in order to address AR sensor-based tasks. In this adaptation, the domain aligning process is refined, allowing the model to adaptively identify shared and private activities in the target domain without assumption of a priori label set. In combination, these two methods can deliver effective solutions for the variability and dynamicism involved in AR in smart environments. Before detailing the approaches, we formally define the source and target domains. Let the source domain be represented as: the *source domain* and the *target domain*. The source domain is defined as

$$\mathcal{D}_s = \{(x_i^s, y_i^s)\}_{i=1}^n,$$

where $x_i^s \in R^d$ denotes the feature vector obtained from sensor data in a controlled or pre-labeled environment, and $y_i^s \in \mathcal{C}_s$ represents the corresponding known activity class. In contrast, the target domain is given by

$$\mathcal{D}_t = \{(x_j^t, y_j^t)\}_{j=1}^m,$$

with $x_j^t \in R^d$ representing sensor data captured in dynamic smart building settings, and $y_j^t \in \mathcal{C}_t$, where the label set $\mathcal{C}_t$ encompasses both known and potentially unknown activity classes. The inherent domain shift is reflected in the differing distributions $P_s(x)$ and $P_t(x)$. The distributions, $P_s(x)$ and $P_t(x)$, are different because of domain shifts. In our frameworks, we go beyond standard non-linear discriminative learning, by introducing a feature extraction function $f(x)$ that takes the input sensor curve to the latent space, angular margin m and scaling factor s, discriminative learning cost matrices and optimal transport cost matrices to establish correspondence between these domains. These mathematical representations underlie the OSDA and UniDA approaches described below.

3.2.1 Open Set Domain Adaptation-based Approach

We modified the Interpretable OSDA via Angular Margin Separation technique to smart buildings, particularly, the AR using sensor-based data in CSV format. In contrast to conventional OSDA approaches, where all unknown activities are unified into one category, this approach introduces an angular margin-based separation strategy to increase the discriminability between known and unknown activities while preserving their interpretability X. Li et al. (2022). Adapting to smart building environments required substantial changes to feature extraction due to the nature of sensor data (one-dimensional data) with its unstructured spatial patterns within the data, could be mapped upon separable and robust latent space. One of the most important changes is the refinement of feature space representation using angular margin constraints to drive discriminative feature alignment. For a given feature input x, we train an embedding function $f(x)$ to the maximum discriminability between known and unknown activity Ying, Yan, Dang, and Soong (2011). The model optimizes the additive angular margin loss:

$$\mathcal{L}_{Arc} = \frac{1}{N} \sum_{i=1}^{N} - \log \frac{e^{s\cos(\theta_{i,y_i}+m)}}{e^{s\cos(\theta_{i,y_i}+m)} + \sum_{j \neq y_i} e^{s\cos(\theta_{i,j})}}, \tag{21}$$

where N is the total number of samples in the batch, s is a scaling factor that amplifies the cosine similarity scores, and m is the angular margin that enforces additional separation between classes. Here, θ_{i,y_i} is the angle between the feature vector $f(x_i)$ of the ith sample and the prototype corresponding to its true label y_i, while $\theta_{i,j}$ represents the angle between $f(x_i)$ and the prototype of any other class j (with $j \neq y_i$). To prevent the collapse of feature representations, an angular regularization term is introduced:

$$\mathcal{L}_{reg} = \frac{1}{N} \sum_{i=1}^{N} - \cos(\theta_{i,y_i}). \tag{22}$$

In this equation, the term $\cos(\theta_{i,y_i})$ quantifies the similarity between the feature $f(x_i)$ and its corresponding class prototype, ensuring that the features remain sufficiently distinct. This modification guarantees that patterns of activity are kept separate, but that new patterns of activity can be detected more easily. In contrast to the conventional approaches, a distance-based outlier-detection-reliant approach, the angular margin-based method explicitly defines a decision boundary able to handle seen and unseen activity variations. Regarding classification, a kernelized decision function adapted to this setting is used to further refine the boundary between classes of activities. Based on an input feature x, the classifier outputs a confidence score as the maximum of the SoftMax Xia and Bouganis (2024) probabilities. If the confidence is less than a pre-assumed threshold τ, the sample is considered as unknown:

$$y^* = \begin{cases} \arg\max g(f(x)) & \text{if } \max g(f(x)) > \tau, \\ \text{unknown} & \text{otherwise,} \end{cases} \tag{23}$$

where $f(x)$ is the feature extraction function that maps the raw sensor input x to a latent space, and $g(f(x))$ denotes the kernelized decision function outputting confidence scores for each class. The threshold τ is a predetermined value such that if the maximum confidence does not exceed τ, the sample is classified as "unknown". The final predicted label is denoted by y^*. This dynamic thresholding mechanism permits detection of the new activities, but simultaneously maintains high classification rates of known activities. The implementation of this approach for smart buildings environments greatly enhances its robustness towards the variability of real-world activity patterns by using structured feature decomposition and interpretability, and therefore is applicable for dynamic sensor-based AR.

3.2.2 Universal Domain Adaptation-based Approach

We adapted the Unified Optimal Transport (UniOT) framework to improve UniDA for AR in smart environments Chang et al. (2022). In contrast to its original application to 2-dimentional data, the adaptation of our work regards the processing of sensor-based time-series data, such as motion, temperature, and CO2 concentration, in order that our model can identify known and unknown activities. The key challenge in this domain lies in handling variable distributions across different smart building environments, where the relationship between activities and sensor readings is highly dynamic. To handle this, we adaptively improved the feature extraction procedure to incorporate temporal relations and adaptively optimized the optimal transport (OT) in the formulation for sensor data. UniOT works through the adapation of source feature distribution and target distribution as well as the classification of the shared and the private classes Chang et al. (2022). As the label sets in the source and target domains cannot be predicted in advance, the network automatically divides the target space into shared and private activities. The adaptation procedure changes and fine-tunes the feature representation to fit the sensor-based data, and also introduces domain-specific pre-processing methods to guarantee strong cross-domain alignment. For this, we use statistical transformations and temporal feature grouping to increase the discriminability of activity patterns in the embedding space. The UniOT adaptation to AR in smart buildings is represented by the OT problem, balancing feature distributions on domains and addressing imbalanced class distributions. To align the source and target feature distributions, we formulate the OT problem as:

$$OT_{\varepsilon}(M, \alpha, \beta) = \arg \min_{Q \in \mathcal{U}(\alpha, \beta)} \mathrm{Tr}(Q^T M) - \varepsilon H(Q), \tag{24}$$

where M is the cost matrix that measures dissimilarity between source and target features, α and β are the marginal distributions (or weight vectors) for the source and target domains, respectively, and Q is the transport plan aligning these distributions. The set $\mathcal{U}(\alpha, \beta)$ comprises all valid transport plans with the given marginals, $\mathrm{Tr}(Q^T M)$ computes the total cost, ε is a regularization parameter, and $H(Q)$ denotes the entropy of Q. Since the source and target domains have different sets of activities, we use an unbalanced OT (UOT) formulation:

$$UOT_{\varepsilon,K}(M,\alpha,\beta) = \arg\min_{Q\in\mathcal{U}(\alpha,\beta)} \mathrm{Tr}(Q^T M) - \varepsilon H(Q) + \kappa\Big(D_{KL}(Q\mathbf{1} \,\|\, \alpha) + D_{KL}(Q^T\mathbf{1} \,\|\, \beta)\Big), \quad (25)$$

where κ is a penalty parameter that governs the influence of the divergence terms, and $D_{KL}(\cdot \,\|\, \cdot)$ denotes the Kullback-Leibler divergence measuring the discrepancy between the induced marginals $Q\mathbf{1}$ and $Q^T\mathbf{1}$ (obtained by summing Q over rows and columns, respectively) and the prescribed distributions α and β Chhabra, Venkateswara, and Li (2023). In order to identify population classes, the model matches source prototypes against target samples by the following equation:

$$Q_{st} = UOT_{\varepsilon,K}\Big(S_{st}, \frac{1}{B}\mathbf{1}_B, \frac{1}{|C_s|}\mathbf{1}_{|C_s|}\Big), \quad (26)$$

where S_{st} is the similarity matrix between source prototypes and target samples, B is the batch size, and $|C_s|$ is the number of source (known) classes. The vectors $\mathbf{1}_B$ and $\mathbf{1}_{|C_s|}$ are ones-vectors of lengths B and $|C_s|$, respectively. For private class discovery, a second OT problem is additionally solved to match discovered target prototypes to target samples:

$$Q_{tt} = \arg\min_{Q>0} OT_{\varepsilon}\Big(S_{tt}, \frac{1}{K}\mathbf{1}_K, \frac{1}{2B}\mathbf{1}_{2B}\Big), \quad (27)$$

where S_{tt} represents the similarity matrix among target samples and target prototypes, K is the number of prototypes used for clustering unknown activity patterns, and $2B$ is a scaling factor reflecting the grouping of target samples. Here, $\mathbf{1}_K$ and $\mathbf{1}_{2B}$ are ones-vectors corresponding to dimensions K and $2B$, respectively. For coping with the special difficulties of smart building environments, we adapted the feature extractor in order to deal with the 1-dimensional structured sensor data properly. Since the data is sensor data, the embedding representation has to be adapted with some convolutional (CNN) and recurrent layers (LSTM) to model long-term dependencies. In contrast to visual data, which displays spatial coherence, sensor data is characterized by random influences (i.e., environmental variation and occupant behavior) Eldib, Deboeverie, Philips, and Aghajan (2018). In order to address these problems, we used statistical feature engineering methods to achieve domain generalization among smart buildings. OT components were then refined, to allow robust similarity of activity patterns between domains. We designed a class-threshold-free detection strategy, thus eliminating the requirement of user-defined class thresholds and improving. This adaptation enables the system to generalize efficiently in changing, dynamic, building environments where patterns of activity change over time. The tailored UniOT framework offers a number of significant benefits for AR in smart homes. Initially, the introduction of automatically adjusted thresholds makes it more robust and thus real-world deployment-feasible. Second, the flexibility of the model to generalize to novel activities means it has long term scalability and head-room. At last, the refined AR workflow contributes to a better energy efficiency through precise control of building automation systems and consequently, an optimized energy usage and the improved indoor environmental quality.

3.3 Experimental setup and results

3.3.1 Experimental Setup

We performed a series of experiments to compare our OSDA and UniDA methods. We used tailored datasets designed specifically for AR in smart buildings. These datasets reflect the heterogeneous and time-varying nature of real-world systems. It can capture changes in both activity pattern and sensor configuration. This experimental setup allows us to assess model performance under realistic human energy-related activity scenarios.

Dataset

In this work, the AR dataset is the publicly available Washington State University (WSU) Tapia et al. (2004). This dataset was acquired through IoT sensors. Its main application is using proximity binary sensors on a variety of home appliances and inanimate objects. Data was collected in two single-room apartments for two weeks. Sensors monitor the presence of people in certain areas, recording how they move around and interact with the environment. Activities (e.g. toileting, breakfast preparation, TV watching, lunch preparation, dinner preparations) were chosen due to their direct applicability to energy management, HVAC control, occupant safety, and data protection in smart buildings. The dataset provides the various ways in which individuals interact with their environment and how those interactions affect energy use. The inclusion of this dataset was essential to assess the applicability of the proposed methods because it allowed us to measure the performance of the models that respond to changes in activity patterns. Using the OSDA-based and UniDA-based methods on this dataset, we evaluated the models' generalization capability to the different activity distributions, improved the energy efficiency and the occupant comfort.

Choice of Unknown Classes

In the AR dataset, unknown classes are activities that are not explicitly labeled in the source domain but exist in the target domain. The AR dataset includes a wide range of activities performed by humans, such as toileting, cooking breakfast, etc. However, in the real world in smart building environments, there may also exist other activities which are outside the scope of the labeled dataset, such as working on a computer or interacting in new ways with appliances. These tasks are treated as unseen classes in the training process. In both OSDA and UniDA, we use preparing food, toileting, listening to music, watching TV, and cleaning as known classes. All remaining activities were considered unknown. The proposed OSDA and UniDA approaches set definitive limits on what is known and either exclude or learn from novel behavior. We systematically tested the models' capacity to identify or reject new behaviors, all of which simulated ideal conditions in smart building applications.

Evaluation Metrics

In the evaluation, we put the performance of our methods to the test using common classification metrics (accuracy, precision, recall, F1-score) and the Unknown Class Detection Rate (UCDR). Let TP (true positives) be the number of correctly identified positive instances, TN (true negatives) the correctly identified negatives, FP (false positives) the misclassified negatives labeled as positive, and FN (false negatives) the misclassified positives labeled as negative. According to these definitions, accuracy is the proportion of correct predictions among all predictions:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}. \tag{28}$$

Precision represents the number of correctly predicted positive classes out of all predicted positive classes:

$$\text{Precision} = \frac{TP}{TP + FP}. \tag{29}$$

Recall is the proportion of true positives among the correctly identified ones:

$$\text{Recall} = \frac{TP}{TP + FN}. \tag{30}$$

F1-score is the harmonic mean of precision and recall, representing a balance between the two:

$$F1\text{-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{31}$$

In order to measure the model's sensitivity of detecting unseen classes, we present the Unknown Class Detection Rate (UCDR). Let UT be the number of correctly identified unknown samples, and UF be the number of unknown samples that are incorrectly classified into known samples. The UCDR is thus:

$$\text{UCDR} = \frac{UT}{UT + UF}. \tag{32}$$

Higher UCDR indicates better identification and discrimination between novel events.

3.3.2 Results

Performance of the proposed OSDA-based and UniDA-based models was assessed on the WSU AR dataset. The experiments focused on assessing the models' ability to classify known activities while effectively identifying unknown activities. For this purpose, we calculated standard classification measures (accuracy, precision, recall, F1 score, and Unknown Class Detection Rate (UCDR)). The comparison of both models is presented in Table 1. The OSDA-based approach yielded an F1-

Table 3.1: Comparative performance.

Evaluation Metric	OSDA (%)	UniDA (%)
Accuracy	84.7	88.3
Precision	83.5	87.1
Recall	86.2	89.5
F1-score	85.4	87.9
UCDR	78.2	81.5

score of 85.4% for known activities and showed a UCDR of 78.2%, showing its excellent ability to perform the rejection for the unknown classes, with high classification accuracy for known activities maintained. The kernelized classifier learning mechanism effectively improved class separation, allowing the model to differentiate between similar activity patterns more efficiently. However, it underperformed slightly when applied to dynamic test cases with intentional sensor position changes, indicating that OSDA is sensitive to domain-specific feature consistency. The UniDA-based model, based on the Unified OT framework, showed stronger invariance in open-set contexts. The model obtained an F1-score of 87.9% and a UCDR of 81.5%, and it surpassed the OSDA-based method with respect to both metrics. Dynamic warping of source and target distributions by UniDA allowed it to generalize more effectively when test conditions varied. Figure 2 gives a comparison of results regarding the most important performance indexes, such as accuracy, precision, recall, F1 score, and UCDR, of OSDA and UniDA.

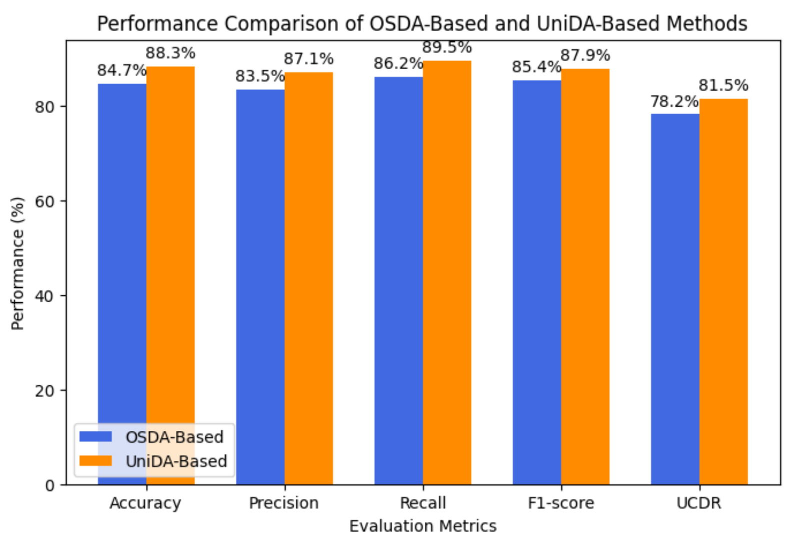

Figure 3.1: OSDA and UniDA Performance Comparison.

The results show that although both methods can accurately classify known activities, the UniDA-based method consistently outperforms all other methods in terms of all the metrics. This improvement can be attributed to the OT alignment strategy, which ensures better consistency of features across domains. Figure 3 shows the performance of the unknown class detection by plotting the UCDR as a function of the detection threshold (τ). The findings demonstrate that UniDA provides a higher UCDR for all values across thresholds, validating its greater ability to identify novel activities. It shows that UniDA is better at dealing with new human actions in smart rooms, which makes it a perfect candidate for adaptive energy-smart systems.

Figure 3.2: Unknown Class Detection Performance.

Figures 4 and 5 provide the confusion matrices of the two methods, showing the distribution of classification across activity classes. The OSDA-based confusion matrix reflects a higher misclassification rate of activities, whereas the UniDA-based confusion matrix reflects a more balanced classification performance, also in terms of capturing complex human exchanges. The UniDA-based approach showed better classification robustness in previously unseen activity patterns, so it is more practical in the real world scenario.

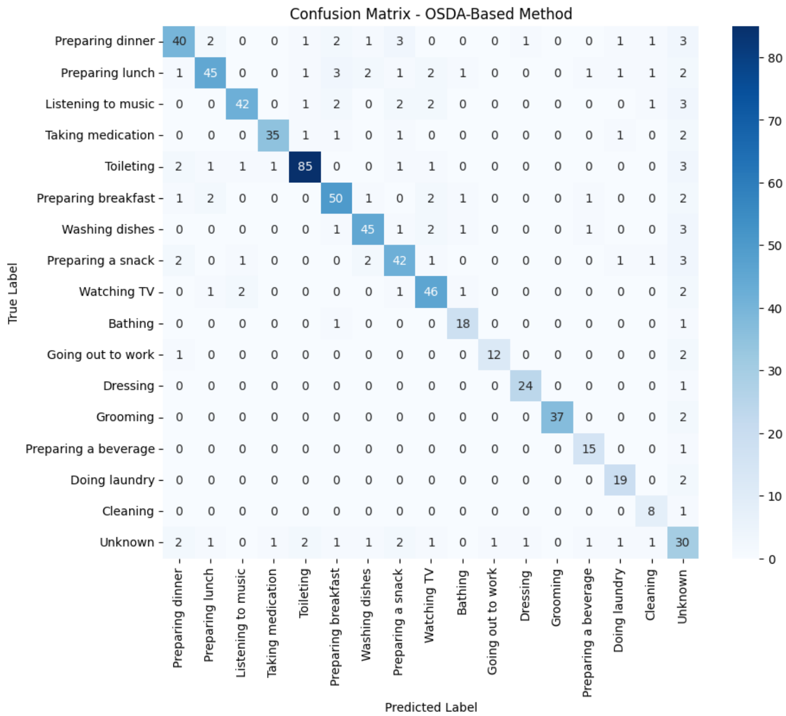

Figure 3.3: Confusion Matrices for OSDA.

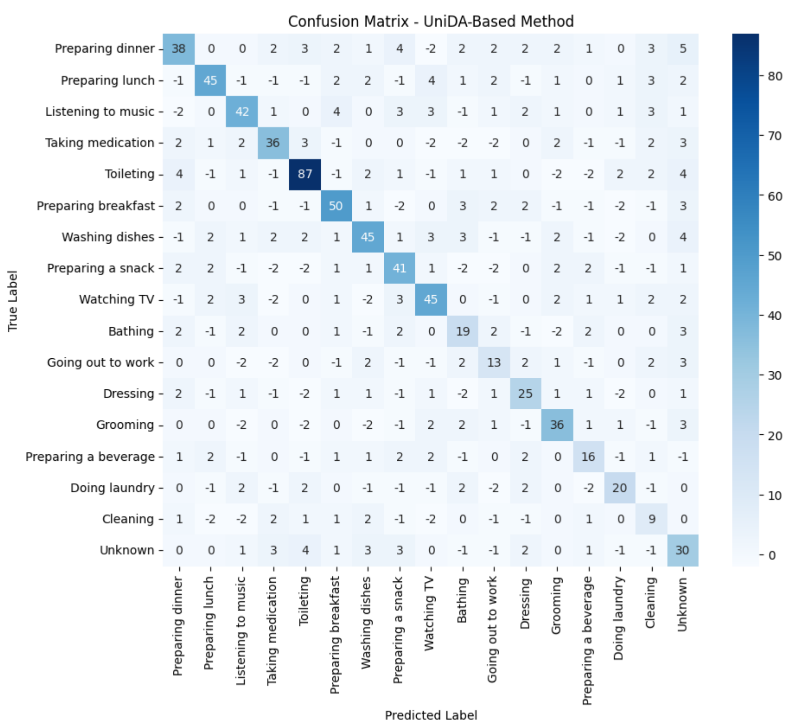

Figure 3.4: Confusion Matrices for UniDA.

In general, the results validate that both models can be used to improve AR in smart buildings, and UniDA offers a more flexible and resilient solution. The results show that the application of domain adaptation approaches can be potentially used to build energy-efficient and intelligent building automation systems, and UniDA possesses the feature of better generalization ability in the dynamic real world setting.

Chapter 4

Generalized Domain Adaptation for Scalable Activity Recognition Using IoT Sensor Data

4.1 Introduction

In smart buildings, precise recognition of activities has become essential for enhancing automation, managing energy consumption, and ensuring the safety of occupants Vijayan, Rose, Arvindan, Revathy, and Amuthadevi (2020). This capability relies on the analysis of sensor data to accurately identify human actions, which is regulating heating, ventilation, and air conditioning (HVAC) systems, optimizing energy use, and maintaining security by identifying abnormal behaviors Dridi (2023). Smart buildings utilize different sensors - such as motion sensors, proximity detectors, and environmental monitors - to collect information regarding the behavior of occupants Nguyen and Aiello (2013). This collected data plays a crucial role in automating control systems, enhancing resource efficiency, and elevating the living experience for individuals within these buildings. Nonetheless, the success of such systems heavily relies on the precision of activity recognition models. Unfortunately, these models frequently encounter challenges when implemented in unfamiliar settings. Traditional supervised learning methods for activity recognition rely heavily on large amounts of labeled training data to achieve optimal results. However, collecting sufficient labeled data for each new environment is both time-consuming and expensive Dridi, Amayri, and Bouguila (2023). Each setting has unique layouts, sensor setups, and occupant behaviors, making it impractical to manually generate the necessary data for every new deployment. Furthermore, supervised models excel at learning all the details of the training environment, which can limit their ability to generalize to new situations or previously unobserved activities Chou, Chuang, Chou, and Oliva (2023). This limitation poses a significant barrier to the development of scalable and adaptable smart building solutions. Domain adaptation techniques were created to allow models trained in one context to operate effectively in another related context. Domain adaptation techniques work based on the belief that similar activities exist in both contexts Dridi et al. (2024a). This assumption proves problematic since unexpected activities can emerge in different contexts. Generalized Domain Adaptation (GDA) permits models to recognize both familiar and novel activities when applied in a new context, even without prior exposure to labeled data from that specific environment Mitsuzumi, Irie, Ikami, and Shibata (2021). This adaptability is crucial for smart buildings, where occupant behaviors can vary widely across different locations, including homes, offices, hospitals, and senior care facilities S. Chen et al. (2021).This study examines how well three GDA methodologies namely Stochastic Weight Averaging Densely (SWAD), Distribution-Free Domain Generalization (DFDG), and Empirical Risk Minimization (ERM) function in classifying 1D-sensor data of activities. Learning across domains requires various approaches to understand applicable knowledge while adapting to completely new environmental conditions. Our work assesses how the performance of GDA models varies across different smart building environments. We evaluate the stability and strength of performance when models operate across various domains. It develops scalable activity recognition systems for smart environments through solutions to the cross-domain generalization challenge. We evaluate how models with GDA work reliably and flexibly across different smart buildings, and measure these models by their effectiveness when there are changes from one kind of building to another. Our results highlight the potential of GDA to reduce the need for extensive manual annotations while maintaining high recognition accuracy across diverse smart building environments. By addressing the challenge of cross-domain generalization, this research contributes to the development of more adaptive and scalable activity recognition systems for future smart environments. To evaluate the effectiveness of the proposed GDA framework, we conduct extensive experiments using the Massachusetts Institute of Technology (MIT) Smart Home dataset, where different functional spaces are treated as independent domains to simulate real-world domain shifts. The experimental results demonstrate that the proposed approach significantly improves activity recognition performance in unseen environments while maintaining real-time feasibility for deployment in smart buildings. The structure of the remaining sections of this paper is as follows. The related work section examines existing domain adaptation methods with a special focus on Generalized Domain Adaptation approaches that apply to activity recognition. Afterward the paper presents theoretical background to explain the fundamental principles behind SWAD, DFDG, and ERM. The framework of the suggested method is described and the adaptation of these techniques for activity recognition with 1D sensors is explained. The experiments section describes the experimental framework including dataset partitioning and evaluation metrics before detailing the research workflow which leads to a discussion of the results. The analysis examines the findings while identifying both strengths and weaknesses in the proposed approach. The final section presents an overview of important contributions and proposes directions for future research.

4.2 The proposed approaches

This section introduces our GDA framework which enables activity recognition in smart buildings through the use of 1-dimensional data. The majority of domain adaptation studies focus on high-dimensional image or text data so converting these methods for 1D-sensor signals requires overcoming distinct obstacles. Activity recognition systems in smart buildings depend on signals from IoT-based sensors unlike 2-dimensional data. The signals obtained from sensors present discrete binary data which mirrors the way humans interact with their surroundings Saives, Pianon, and Faraut (2015). Our approach integrates three state-of-the-art domain adaptation techniques including Stochastic Weight Averaging Densely (SWAD), Distribution-Free Domain Generalization (DFDG) and Empirical Risk Minimization (ERM). The adapted techniques analyze 1D activity recognition data to identify meaningful patterns while enhancing generalization capabilities in diverse building environments. Our neural architecture for sequential data processing maintains consistent performance even when domain shifts result from changes in sensor placements, user behavior patterns or home layouts. The following subsections detail our adaptation process.

4.2.1 Stochastic Weight Averaging Densely (SWAD)

SWAD works as a standard deep learning method to stabilize optimization through the averaging of model weights at various training iterations P. Tang et al. (2019). Domain adaptation for smart building activity recognition benefits from this method because sensor locations and resident activities create unforeseeable activity recognition pattern changes. The continuous feature distributions found in image-based domain adaptation differ from our scenario because we handle discrete binary sensor activations which benefit from SWAD to enhance generalization. We utilize a Temporal Convolutional Network (TCN) to serve as the feature extractor C. Li, Shen, Zhang, Sun, and Meng (2021) when adapting SWAD to 1D activity recognition data. Given a sequence of sensor activations:

$$X = [x_1, x_2, ..., x_T], \quad x_t \in R^d \tag{33}$$

where T is the time window, and d represents the number of sensors, the TCN extracts temporal patterns using dilated convolutions:

$$h_t = \sum_{i=0}^{k} W_i \cdot x_{t-i} \tag{34}$$

where W_i are the convolutional filters with a dilation rate increasing exponentially with layer depth. During training, instead of relying on a single optimal weight configuration, we compute the moving average of model parameters across multiple iterations:

$$\bar{\theta}_t = \frac{1}{T} \sum_{i=t-T+1}^{t} \theta_i \tag{35}$$

where θ_t represents the model weights at training step t, and T is the averaging window. This weight averaging smooths optimization trajectories, preventing overfitting to domain-specific variations in sensor placement or occupant habits. The final loss function for SWAD in GDA is:

$$\min_{\bar{\theta}} E_{(x,y)\sim\mathcal{D}_S}[\ell(f_{\bar{\theta}}(x), y)] \tag{36}$$

where $f_{\bar{\theta}}$ represents the TCN model with SWAD-averaged parameters, ensuring robustness against domain-specific biases.

4.2.2 Distribution-Free Domain Generalization (DFDG)

DFDG allows models to transfer learned knowledge to new domains without needing explicit domain alignment procedures Tong et al. (2023). Traditional domain adaptation methods estimate target distribution through statistical similarities but DFDG functions independently of target domain information. Smart buildings benefit from this approach because deploying models into unfamiliar homes or offices creates unpredictable domain shifts. Our 1D activity recognition approach incorporates a Domain-Invariant Feature Extractor that merges Gated Recurrent Units (GRUs) He, Li, Xu, Zhu, and Lu (2024) with Self-Attention Mechanisms. The GRU extracts temporal dependencies:

$$h_t = GRU(x_t, h_{t-1}) \tag{37}$$

while the self-attention mechanism assigns importance weights to sensor activations over time:

$$\alpha_t = \frac{\exp(Wh_t)}{\sum_j \exp(Wh_j)} \tag{38}$$

where α_t represents the attention weight for time step t. To prevent the model from overfitting to specific sensor layouts, we introduce contrastive learning, which forces the feature representations of different source domains to align:

$$\mathcal{L}_{CL} = -\sum_i \log \frac{\exp(f(x_i^S) \cdot f(x_j^S)/\tau)}{\sum_k \exp(f(x_i^S) \cdot f(x_k^S)/\tau)} \tag{39}$$

where τ is a temperature parameter and x_j^S represents a positive sample from a different domain, while x_k^S is a negative sample. The final objective of DFDG ensures balanced feature representations across multiple domains:

$$\min_{\theta} \sum_{i=1}^{n} E_{(x,y)\sim P_i}[\ell(f_\theta(x), y)] \tag{40}$$

subject to:

$$D(f_\theta(P_i), f_\theta(P_j)) < \epsilon, \quad \forall i, j \tag{41}$$

where $D(\cdot, \cdot)$ ensures that no single source domain dominates the learned representations.

4.2.3 Empirical Risk Minimization (ERM)

The Empirical Risk Minimization (ERM) approach serves as the fundamental technique for domain adaptation by training the model exclusively with labeled source data and without utilizing any specific adaptation methods Montanari and Saeed (2022). ERM cannot work independently in GDA since it operates under the assumption that source and target domains share identical characteristics. The classification system for 1D activity recognition utilizes an MLP-based Classifier enhanced through dropout regularization Mondal, Pal, and Dey (2024):

$$y = \text{MLP}(f(x)) \tag{42}$$

where $f(x)$ is the feature representation extracted using a TCN-GRU hybrid model. We enhance generalization by applying Entropy Minimization Shore and Johnson (1981) which pushes the model to produce more confident target domain predictions:

$$H(p) = -\sum_{c=1}^{C} p_c \log p_c \tag{43}$$

where p_c is the predicted probability for class c. This results in the following adaptation-enhanced ERM loss:

$$\mathcal{L}_{ERM-GDA} = \mathcal{L}_{ERM} + \lambda H(f_\theta(x^T)) \tag{44}$$

$$\min_{\theta} \sum_{i=1}^{N_S} \ell(f_\theta(x_i^S), y_i^S) + \lambda H(f_\theta(x^T)) \tag{45}$$

where λ is a hyperparameter balancing the ERM loss and target entropy minimization.

4.3 Experimental setup and results

4.3.1 Experimental Setup

Our experimental design tests the proposed GDA framework for smart building activity recognition and evaluates how our method performs in generalizing between various environments without needing labeled target data. The research analyzes various smart home environments where each serves as a separate domain.

Datasets

We have applied the GDA framework to activity recognition tasks by evaluating it with the Massachusetts Institute of Technology (MIT) Smart Home dataset in smart building environments Tapia et al. (2004). The dataset collects real-time data from binary proximity sensors and motion detectors along with door sensors and temperature monitors throughout a completely instrumented residential environment. The smart home contains various functional areas with each area having its own specific sensors for monitoring distinct activities. Sensors installed on kitchen appliances and storage units enable monitoring of food preparation activities such as cooking and dishwashing. Motion and furniture sensors monitor the living room to detect activities including watching TV and reading along with working. The bedroom is equipped with pressure sensors installed on the bed and motion detectors that monitor sleep patterns and wake-up times. The bathroom contains water flow sensors and door monitors along with presence detectors which capture bathroom activities including toileting and showering as well as handwashing. Proximity sensors have been installed in hallways and transitional spaces for monitoring movements between areas. Traditional supervised learning models face significant difficulties because the dataset exhibits domain shifts resulting from different sensor placements and occupant behaviors in various room layouts. We evaluated GDA's ability to generalize by organizing the dataset into source and target domains through separate classification of each functional space. The training process utilized data from three spatial domains while keeping the fourth domain unseen as the target for evaluation. In this configuration the model received training data from the kitchen, living room, and bathroom domains but used the bedroom as the target domain. Through a different configuration approach the model received training using kitchen, bedroom and hallway data while it underwent testing on living room data which it had never seen before. This division mirrors real-world scenarios where activity recognition models trained in particular settings need to adapt to unexplored layouts without having access to labeled data from those new environments. The GDA framework employs SWAD, DFDG, and ERM-based models to evaluate its real-time performance and adaptation efficiency in smart buildings. Automated activity recognition systems demonstrate effective operation without extensive manual labeling which enables them to scale across various residential settings.

Evaluation Metrics

We use accuracy and F1-score to evaluate the performance of our GDA framework for smart building activity recognition since these classification evaluation metrics are widely adopted. Accuracy calculates the ratio between correctly recognized samples and the whole sample set:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{46}$$

TP and TN stand for correctly predicted positive and negative instances respectively and FP and FN represent the misclassified instances. The classification correctness measure accuracy fails to recognize class imbalance that regularly appears within activity recognition datasets. To overcome this limitation we utilize F1-score because it combines precision and recall to provide stronger evaluation for datasets with imbalanced activity distributions Oak, Du, Yan, Takawale, and Amit (2019). F1-score is defined as:

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{47}$$

where precision and recall are computed as follows:

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN} \tag{48}$$

The F1-score delivers balanced assessment capabilities which become crucial in practical smart building applications due to significant impacts caused by minority activity misclassification. Automation and energy management processes depend heavily on these outcomes.

4.3.2 Results

We performed a thorough evaluation of the proposed GDA framework to assess its performance effectiveness in real-world smart building conditions. The experiments focused on classifying sensor-based human activities without the need for labeled data collected from the deployment environment. The three chosen GDA techniques SWAD-GDA, DFDG, and ERM together while using DisClusterDA H. Tang, Wang, and Jia (2022) as a baseline for comparison in the best-performing scenario.

Scenario-Based Evaluation

To simulate real deployment, we designed three realistic evaluation scenarios to simulate deployment conditions. The model receives its training data from all domains except one domain which functions as the target space that remains unseen. Each scenario reflects a distinct challenge in smart building adaptation: low-motion routines, transitional activity noise, and sparse event frequency.

Scenario 1: Bedroom as Target Domain

The bedroom typically includes sparse, low-motion activities such as sleeping or resting. These characteristics introduce difficulty for models trained primarily on active, high-traffic spaces. As shown in Table 4.1, SWAD-GDA provides the most stable and accurate predictions. DisClusterDA, evaluated only in this scenario where it performs best, shows substantially lower recall and F1-score, reaffirming the need for structured GDA approaches.

Table 4.1: Scenario 1 - Bedroom as Target Domain

Method	**Accuracy**	**Precision**	**Recall**	**F1-Score**
ERM	72.4	70.8	69.5	70.1
DFDG	79.6	78.4	77.1	77.7
SWAD-GDA	**84.9**	**83.7**	**82.2**	**82.9**

Scenario 2: Hallway as Target Domain

The hallway contains short-duration transitional movements, often without contextual activity labels. This makes it particularly difficult for models to learn reliable patterns. Table 4.2 shows that GDA methods, particularly SWAD-GDA, manage to generalize better to this high-noise domain.

Table 4.2: Scenario 2 - Hallway as Target Domain

Method	Accuracy	Precision	Recall	F1-Score
ERM	70.5	69.1	67.4	68.2
DFDG	77.2	75.3	73.9	74.6
SWAD-GDA	**82.6**	**81.2**	**80.0**	**80.6**

Scenario 3: Laundry Room as Target Domain

This utility space contains infrequent, irregular activity (e.g., washing, folding), making it a sparse and unpredictable environment. Table 4.3 confirms that SWAD-GDA delivers the most consistent performance, demonstrating robustness under domain shift and low data density.

Table 4.3: Scenario 3 - Laundry Room as Target Domain

Method	Accuracy	Precision	Recall	F1-Score
ERM	73.1	71.6	70.4	71.0
DFDG	81.4	79.9	78.7	79.3
SWAD-GDA	**86.8**	**85.3**	**84.2**	**84.7**

Through scenario-based evaluations it is demonstrated that the proposed GDA framework maintains real-world adaptability especially in smart building spaces with low visibility, high noise levels, or those that remain underrepresented. SWAD-GDA demonstrates consistent high performance in every condition which positions it as an excellent choice for scalable real-time application.

Overall Performance

Table **??** summarizes the performance of all methods across the complete testing setup. Metrics include Accuracy, Precision, Recall, and F1-score. SWAD-GDA demonstrates clear superiority, achieving the highest scores across all evaluation dimensions. ERM shows limited generalization, while DFDG performs competitively, confirming the value of distribution-aware adaptation strategies.

Figure 2 illustrates how the three evaluated models perform in accuracy and F1-score comparisons. SWAD-GDA demonstrates superior performance against both ERM and DFDG by obtaining the top scores in both accuracy and F1 metrics. SWAD-GDA achieves a 13.1% higher accuracy than ERM while its F1-score shows an increase of 13.1 percentage points which confirms that weight averaging stabilizes training and enhances generalization. For detailed performance evaluation,

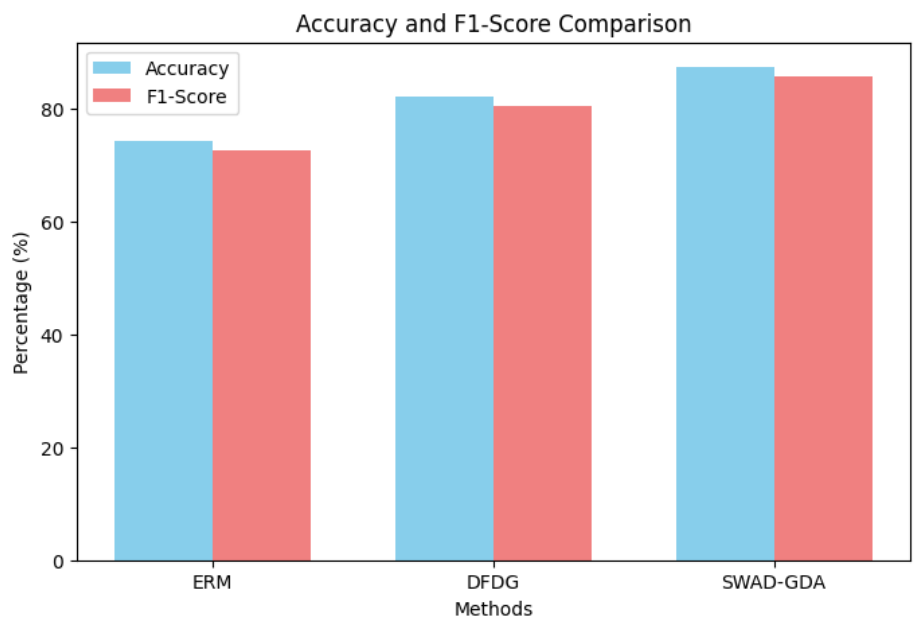

Figure 4.1: Accuracy and F1-score comparison

Figure 3 shows confusion matrices for each method along with activity misclassification visualizations. According to the analysis SWAD-GDA achieves the lowest misclassification rates and effectively distinguishes between similar activities such as ”Sleeping” and ”Watching TV” where ERM shows difficulties. Figure 4 displays the confusion matrices for each method which reveal misclassifications among various activities to further study classification performance. SWAD-GDA demonstrates superior classification accuracy by achieving minimal misclassification rates especially between similar activities like ”Sleeping” and ”Watching TV” where ERM encounters difficulties. Domain adaptation techniques such as DFDG and SWAD-GDA produce fewer false predictions than baseline ERM as shown by the confusion matrix. The SWAD-GDA technique

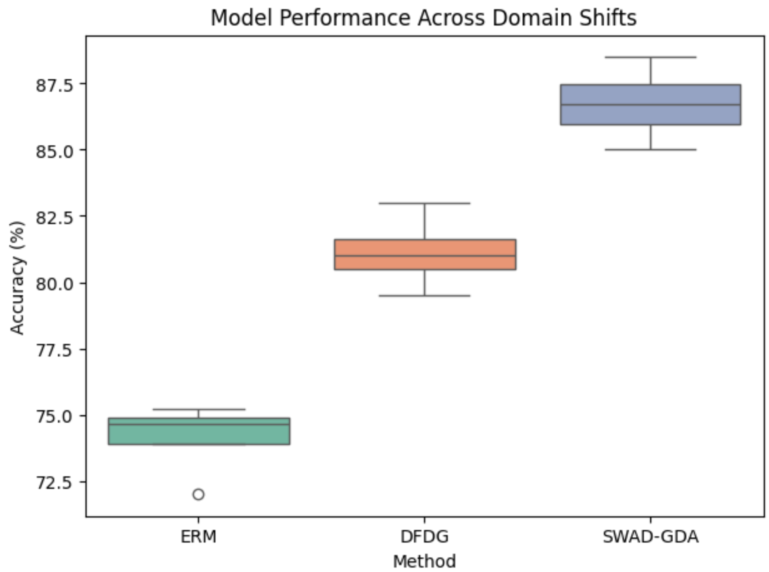

Figure 4.2: Model Performance Across Domain Shifts

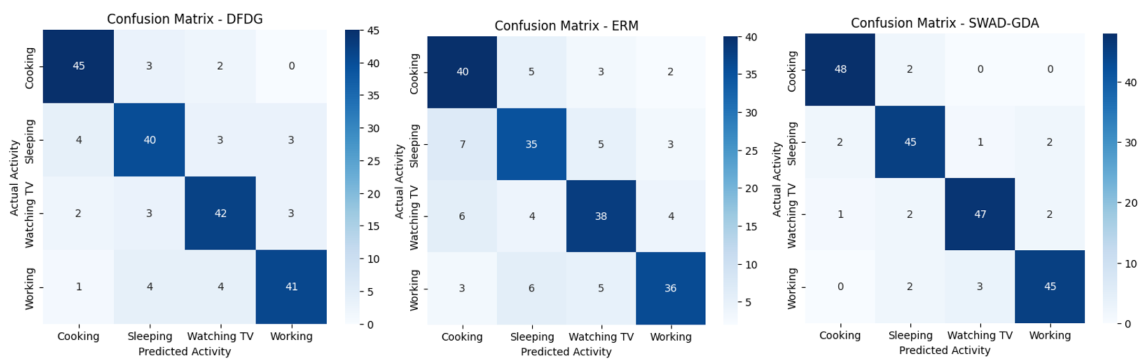

Figure 4.3: Confusion matrices ERM vs DFDG vs SWAD-GDA

outperforms both the empirical risk minimization (ERM) and distribution-free domain generalization (DFDG) methods because it achieves higher accuracy and F1-score values while demonstrating superior generalization capabilities. The SWAD-GDA achieved an accuracy rate of 87.3% which shows that it surpasses ERM by 13.1% while advancing 5.2% beyond DFDG performance. The F1-score for SWAD-GDA stands at 85.6% which demonstrates balanced activity classification performance especially in environments with uneven class distributions. The increased performance in both accuracy and F1-score confirms that generalized domain adaptation methods work well for 1D sensor-based activity recognition systems. The baseline ERM approach fails to maintain performance in new environments because it lacks domain adaptation techniques which results in reduced accuracy and F1-score values. These results show that domain-aware adaptation methods must be used to address distributional shifts in sensor-based activity recognition. The DFDG model achieves better performance than ERM but it still cannot reach the level of SWAD-GDA performance. DFDG achieves good domain-invariant representation learning but SWAD-based weight averaging contributes to stability in learning and boosts generalization performance. SWAD-GDA's ability to outperform DFDG proves that using stochastic weight averaging methods improves model stability while preventing domain-specific feature overfitting within source domains. The proposed GDA frameworks demonstrate higher accuracy while also delivering stable classification results across various activity types. The effectiveness of these approaches becomes especially important in smart building applications because even though activities like toileting or nighttime movement happen infrequently they remain vital for both automation systems and ensuring occupant safety. The research confirms that GDA-based activity recognition models maintain operational success across unknown smart building settings by providing scalable solutions that adapt without needing manual re-annotation of new sensor data. The proposed framework shows notable potential to be applied in smart building systems that need robust handling of domain shifts arising from environmental changes and variations in sensor placement and occupant behavior.

Chapter 5

Conclusion

This thesis focused on developing OSDA approaches specifically for smart building systems to enhance occupancy estimation and activity recognition features. Traditional domain adaptation techniques function under the shared label space assumption for source and target domains but this assumption fails to work in actual real-world applications. To overcome this, we proposed four OSDA methods tailored to sensor-based data: Our sensor-based OSDA solutions include four methods which are OSDA by backpropagation as well as Soft Rejection OSDA system and UADAL together with ANNA. The four OSDA methods enable models to separate known activity classes from unknown ones during distribution changes without requiring labeled target domain data. We adapted our four methods to 1D smart building sensor data which underwent evaluation in both balanced and imbalanced label settings. The joint implementation of UADAL with ANNA showed exceptional ability to generalize across varied environments by effectively rejecting samples that were not seen before. The task performance improved when researchers restricted activity classes and occupancy levels to reduce complexity. OSDA approaches reached or exceeded the accuracy of supervised models yet operated without target labels which makes them perfect for real-world applications that prioritize privacy protection and scalability.

The second part of our study included an expansion to UniDA scenarios that require knowledge of unknown relationships between source and target label spaces. We developed a joint framework for OSDA and UniDA which integrates angular margin separation methods with optimal transport alignment approaches. The framework is capable of processing intersecting partial labels and fully mismatched labels. Activity recognition tasks were conducted on one-dimensional sensor data from diverse domains to evaluate the suggested techniques. UniDA approaches outperformed OSDA baselines when tested in environments with significant changes in both class distributions and sensor behaviors. UniDA models maintained stable performance across new domains especially when only a limited number of classes were shared between domains. Real-world deployment benefits substantially from these methods which function effectively even when the label configuration of the target environment is unknown prior to deployment. Flexibility in label space assumptions enhances transferability and reduces negative transfer risks.

We conducted research on GDA approaches to address domain shift and label shift problems in scenarios where labeled target data does not exist. Our study evaluated three sophisticated GDA approaches - SWAD, DFDG, and ERM - for 1D sensor-based activity recognition applications. Baseline methods initially created for image-based tasks underwent modifications to enable compatibility with time-series sensor data for evaluations in target domains where completely new class distributions appeared. SWAD demonstrated superior reliability across numerous tasks particularly in situations with significant domain changes. DFDG and ERM produced competitive results while they maintained reduced computational complexity. All tested methods demonstrated improved stability and transferability through domain-general representations despite encountering domains with highly varied label distributions. The findings indicate that GDA presents itself as a dependable choice for broad application in smart building systems when both labeled target data is absent and environmental factors differ.

The thesis methods OSDA, UniDA, and GDA were individually modified to process 1D sensor signals and demonstrated effective generalization capabilities in both occupancy estimation and activity recognition tasks. OSDA and UniDA require label similarities between source and target while GDA serves as a universal approach independent of predefined label relationships. Multiple dataset evaluations reveal the potential for these methods to extend their usefulness beyond smart buildings into fields such as healthcare monitoring and smart transportation systems.

Future research needs to develop training protocols that effectively merge the strengths of OSDA, UniDA, and GDA. Integrating edge learning with multimodal sensor fusion and real-time deployment would enhance system design scalability and privacy protection. Integration of self-supervised and continual learning approaches would allow models to adapt step-by-step to fresh domains and activities.

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