

AccessLens: Auto-detecting Inaccessibility of Everyday Objects

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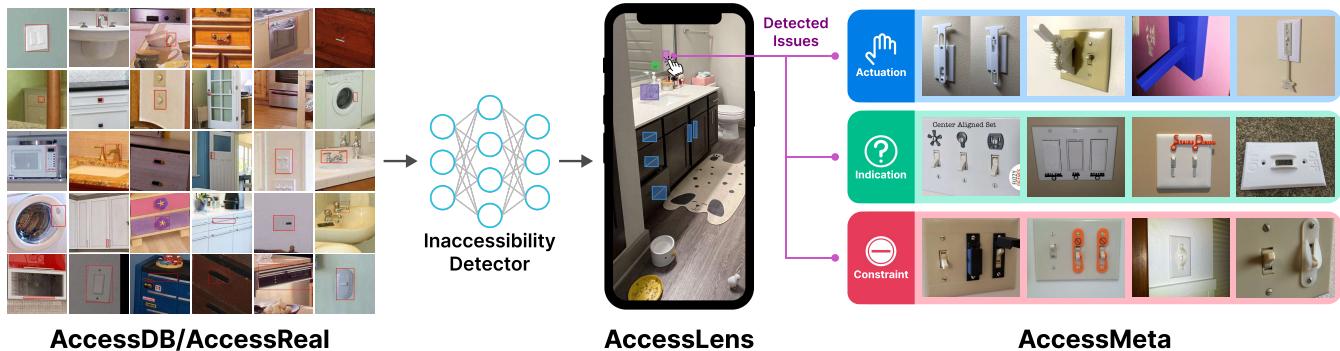


Figure 1: AccessLens system overview. AccessLens provides a mobile toolkit to scan indoor scenes and detect inaccessibility in everyday objects. Inaccessibility detection is developed on our dataset AccessDB and AccessReal, consisting of indoor scene images annotated w.r.t inaccessibility classes on daily objects. We contribute AccessMeta, a metadata that categorizes 3D assistive designs, enabling auto-suggestions to improve daily accessibility.

ABSTRACT

In our increasingly diverse society, everyday physical interfaces often present barriers, impacting individuals across various contexts. This oversight, from small cabinet knobs to identical wall switches that can pose different contextual challenges, highlights an imperative need for solutions. Leveraging low-cost 3D-printed augmentations such as knob magnifiers and tactile labels seems promising, yet the process of discovering *unrecognized* barriers remains challenging because disability is context-dependent. We introduce AccessLens, an end-to-end system designed to identify inaccessible interfaces in daily objects, and recommend 3D-printable augmentations for accessibility enhancement. Our approach involves training

a detector using the novel AccessDB dataset designed to automatically recognize 21 distinct Inaccessibility Classes (e.g., bar-small and round-rotate) within 6 common object categories (e.g., handle and knob). AccessMeta serves as a robust way to build a comprehensive dictionary linking these accessibility classes to open-source 3D augmentation designs. Experiments demonstrate our detector's performance in detecting inaccessible objects.

CCS CONCEPTS

- Human-centered computing → Collaborative and social computing systems and tools; Interactive systems and tools;
- Computing methodologies → Computer vision.

KEYWORDS

3D assistive design, object detection, end-user interface

ACM Reference Format:

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1 INTRODUCTION

While the traditional definition of disability has revolved around individuals' varied abilities, understanding disability as '*mismatched interactions*' [46] emphasizes diverse contexts that can create barriers within environments. Consider someone with a wrist injury struggling with everyday tasks like opening a water bottle or using a toothbrush single-handedly; new parents suddenly recognize potential hazards at home, such as electric outlets. However, recognizing such contextual disability and proactively rectifying them remains challenging for inexperienced users because they use prior experiences that could be biased. It is non-trivial to foresee unfamiliar interaction scenarios (e.g., managing everyday tasks by being one-handed), leading them to cope with difficulties without promptly addressing interaction challenges.

"If the design is accessible, everyone benefits" [1]; the accessibility community has highlighted the importance of engaging everyone in improving accessibility. Traditional approaches to raising awareness and fostering proactive efforts focused on cultivating empathy and mutual understanding among non-disabled individuals. The goal was to evoke recognition of unnoticed discomfort inherent in daily interfaces, particularly from the perspective of individuals with disabilities [18, 44, 55, 56, 58]. However, these approaches had inherent limitations in simulating disabilities, which could inadvertently lead to biases and cognitive gaps against individuals without disabilities [51]. Although well-structured textual guidelines and compliances [15, 27, 54] encompass exhaustive domain knowledge from experts, those remain static, exclaiming the need for interactive systems. However, while the disability is context-dependent, implying that anyone can experience challenges without permanent disability, the latest AI-powered interactive tools [53, 66] predominantly focus on specific target groups, such as wheelchair users or older adults, missing the contextual variances, i.e., temporary and situational cases [46]. Moreover, many solutions entail renovation or replacements, which is often costly thus mentally burdening, limiting the practicality/applicability of existing tools in promoting pro-social behaviors. There remain three major user challenges:

- Which objects are inaccessible?
- Why and when do these objects become inaccessible?
- How can a user without prior experiences identify them and find appropriate solutions?

We introduce **AccessLens**, an end-to-end system to automate detecting contextual barriers from everyday objects, and suggest 3D-printed assistive augmentations. Figure 1 shows system overview. AccessLens is built upon novel datasets, **AccessDB/AccessReal** to train inaccessibility detectors, and **AccessMeta**, metadata to understand interaction types and required human capabilities of physical objects presented as their interaction attributes. As existing datasets (e.g., [25, 37, 75]) with indoor scene images do not articulate inaccessibility to automate detection, AccessDB was built to imbue accessibility knowledge using 21 Inaccessibility Classes (IC). Designed to foster understanding of how 3D assistive augmentations can resolve contextual disabilities, AccessMeta provides the link between 3D augmentations and interaction types/contexts of existing objects, such as a lever extension for a door knob that removes sophisticated motor skills (Figure 2a-b) and an arm-pull extension for a lever for an alternative operation (Figure 2c-d).

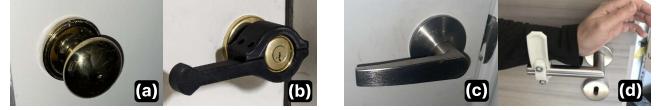


Figure 2: (a) A round knob's accessibility can be improved by (b) lever extension [69] while (c) a lever handle's accessibility is improved by an (d) arm extension [29]. Everyday objects portray different accessibility barriers to people under different contexts.

In sum, our contributions are three-fold:

- A holistic survey of large-scale 3D assistive augmentations in online repositories and understanding of their interaction properties, resulted in **AccessMeta**, a metadata to auto-classify them;
- **AccessDB & AccessReal**: A dataset for auto-detection of inaccessible objects and parts from indoor scenes with 10k annotated objects under 21 Inaccessibility Classes with realistic high-res dataset for testing;
- **AccessLens**: End-user system to detect inaccessibility and to obtain design recommendations through 3D printed augmentations to update legacy objects

We evaluate our contributions through user studies and technical experiments. First, a preliminary user evaluation of the AccessLens system prototype helps understand how AccessLens enhances awareness and willingness to take pro-social behaviors. Second, we assess an end-to-end pipeline—capturing the indoor environment to retrofitting 3D augmentations—with inexperienced users and two experts in assistive technology. The evaluation of AccessMeta engaged crowdworkers in annotating the dictionary with 280 3D augmentations. We also evaluate AccessDB/AccessReal with off-the-shelf detectors.

Our vision for AccessLens is to empower users with limited awareness to recognize hidden daily accessibility challenges thus to be more attentive to daily challenges under diverse contexts and extents. AccessLens does not require diagnosed disability, prior experience, and domain expertise to recognize inaccessibility. Figure 3 shows our scope on target demographics compared to existing approaches.

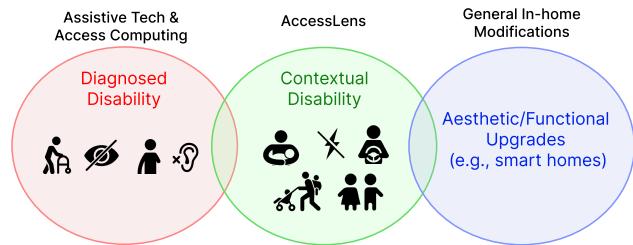


Figure 3: AccessLens's target user scope compared to existing assistive technique works and general in-home modifications. AccessLens supports users with limited awareness but who can easily become disabled under various contexts.

2 RELATED WORK

2.1 Recognizing and Accommodating Inaccessibility

There exist numerous standards and normative tools to help non-experts learn cumulative knowledge, particularly for a user who does not own prior experiences. The Americans with Disabilities Act (ADA) Standards for Accessible Designs [15] and the International Building Code (IBC) [27] represent comprehensive frameworks to alleviate mobility challenges. Increasing attempts are made toward interactive approaches. For instance, as aging becomes an imperative concern in our society, several works have focused on improving indoor access for older adults [10, 17, 40, 41, 53]. Homefit AR [53, 54] identifies key objects such as sinks and doors, guides users through questionnaires to precisely locate issues with object types, and recommends alternatives with better access. The closest prior work of ours is RASSAR [66], a mobile AR app to assess objects that do not meet the standards such as too-low tables, narrow doors, and dangerous items exposed, for wheelchair users and children, etc. While these works respond to the needs of special interest groups (e.g., older adults and wheelchair users), a broader population who have not experienced disabilities is often excluded from improving access, since they could overlook contextual or situational disabilities due to lacking knowledge/experience. We are to provoke solutions that foster inclusivity by recognizing exclusion and emphasizing the engagement of a more diverse community in creating accessible and accommodating indoor spaces.

2.2 Understanding Contextual Disability

Fostering empathy is discussed at the center of disability studies to elevate awareness about the lived experiences of disabled people [7, 55, 56]. While simulating disabilities such as blindfolding [58], having non-distinguishable components to understand how being colorblind effects [18] or putting non-disabled on wheelchairs [44] has gained popularity, disability advocates disparage the user of simulated disability [7, 26]; it is very difficult to accurately replicate the experiences of people with disabilities [4]. Empathy alone may not be sufficient to sustain attention [26], and simulations may inadvertently create biases or distress, ultimately failing to improve behavior toward individuals with disabilities [51]. These unintended consequences can perpetuate ableism and systems [24]. More recent efforts have centered their focus on co-designing *with* people with disabilities (e.g., [6, 31, 32, 72]); citizens, healthcare professionals, designers, and makers co-design personalized healthcare solutions [32], sighted and blind participants design building navigation together [31]. Collective efforts to enhance the user experience can extend the impact beyond individuals with disabilities alone, inheriting different abilities of all as universal design constraints [46, 59, 61]. Unfortunately, there have been only little to no systems to help everyone imagine daily innovations that cultivate inclusive spaces. Our approach is motivated by “*design for one, expand to all*” and “*learning from adaptations*”, a relatively new design principle suggested by [46] to promote understanding of barriers; by showing how people adapt to the given environments, we are to discover how considering one’s limitations as contextual disabilities can influence individuals.

2.3 Indoor Scene Understanding using Computer Vision

Visual perception of indoor places is critical in improving people’s quality of life and well-being [63]. Promoting visual understanding of indoor scenes, various research community has released datasets that can be useful for training dedicated detectors of real-world matters. Some early datasets such as MIT indoor scenes [57] and SUN RGB-D [64] have advanced techniques to train recognition models. Synthetic datasets such as HyperSim [60] can further assist better recognition models. While there exist relevant datasets such as Gibson [74], offering a virtual visual navigation platform, PartNet [49], focusing on part recognition of indoor objects, and BEHAVIOR-1K [33], data for embodied AI systems to foster human-robot interaction in virtual reality, none have centered focus on interaction types to understand objects’ inaccessibility characteristics and user contexts that make objects inaccessible. We find ADE20K [75] which is a large-scale indoor scene dataset with hierarchical annotations of objects in images at the pixel level promising. Refining the hierarchical taxonomy of objects and parts by ADE20K includes object categories and parts, we curate datasets by re-annotating potentially inaccessible objects to train and evaluate inaccessibility detectors.

2.4 3D-Printed Augmentations: Improving Access to Daily Objects

While it may not be feasible to replace all existing interfaces with inclusive designs overnight [3, 34], 3D-printed assistive designs [5, 9] promises low-cost, custom solutions for redressing everyday interaction challenges (e.g., [9, 13, 21]). These adaptations can range from magnifying cabinet knobs for improved grip (e.g., ‘ThisAbles’ project by IKEA [65]) to self-serving at-home medicine dispensers [3]. Similar to the modular approach employed in the modern software engineering paradigm, wherein updates are selectively applied only where changes are necessary [52], the augmentation allows for unit-by-unit enhancements tailored to specific needs. Because barriers to 3D printing have been significantly lowered [8], existing studies have revealed how and why online communities and opensource 3D repositories share assistive 3D designs caring for the community [9] and reveal computational customization solutions [13]. While documents based on similarity can classify online designs’ objectives [35], current search relies on designer-created descriptions, often failing users to explore viable or alternative designs to rectify hidden inaccessibility, particularly those who do not present diagnosed disabilities. Discovering suitable designs heavily relies on keyword-based searches, relying on the textual information provided by the authors: titles, descriptions, and tags only. Thus, this work introduces novel metadata to categorize existing 3D assistive augmentations for better identification of solutions.

In sum, Table 1 summarizes the position of Accesslens.

| | Compliances/ guidances e.g., [15, 54] | MS Inclusive Guidebook [46] | Project Sidewalk [62] | Homefit AR [53] | RASSAR [66] | AccessLens (ours) |
|----------------------------|---|-----------------------------------|-----------------------------|--------------------|----------------|----------------------|
| Interactive | ✗ | ✗ | ✓ | ✓ | ✓ | ✓ |
| Indoor accessibility | ✓ | ⚠ | ✗ | ✓ | ✓ | ✓ |
| Contextual disability | ✗ | ✓ | ✗ | ✗ | ✓ | ✓ |
| Auto detection | ✗ | ✗ | ✓ | ✓ | ✓ | ✓ |
| Interaction type detection | ✗ | ✗ | ✗ | ⚠ | ✗ | ✓ |
| Low-cost adaptations | ✗ | ✗ | ✗ | ✗ | ⚠ | ✓ |

Table 1: Position of AccessLens compared against prior works.

3 DESIGNING ACCESSLENS

AccessLens is built upon the understanding of different barriers under various contexts and design considerations to build state-of-the-art technology. We conducted design studies to develop AccessLens. The first study focused on understanding how people adapt to their environments using 3D printed augmentations, taking account into the design objectives and interactions that entail. In the design study, we created an interactive AccessLens prototype and invited 8 participants who were not experts in accessibility for preliminary evaluation, compared to existing methods that facilitate interest in inclusive design using normative tools.

3.1 Design Study #1. Understanding Interaction Contexts: In-the-Wild Survey

We conducted an exploratory survey on Thingiverse [28], to gain insights into why individuals are motivated to create 3D assistive augmentations and modify existing physical objects to address specific contextual or situational interaction challenges. First, we listed several indoor objects that are very common around us, including door knobs, light switches, etc. Then we retrieved 3D designs that are for those objects, indicating 3D designs tend to augment targeted real-world objects from Thingiverse. We employed an iterative process of affinity diagramming, which was collaboratively performed by four of our authors. In the affinity diagramming process, we classified augmentations considering three primary criteria: (1) their intended objective, which refers to the barriers the augmentations aim to address, (2) the type of objects the augmentations target, and (3) any related motions or actions associated with their use. Our empirical findings revealed that even for objects that are under the same class (e.g., door knob/handle, light switch), the augmentations are much more diverse due to differences in the object's type (e.g., single toggle light switch vs. rocker switch). This diversity emanates from shapes, motions, and objectives, which inspired us to develop AccessDB, our refined dataset with inaccessibility classes of AccessMeta. This iterative affinity study resulted in three high-level functions of adaptations as follows and example augmentations are shown in Figure 4.

- **Reducing motor requirements, change needed motion types [Actuation]:** Designs that shift types of motions needed to operate (e.g., rotation to linear push) or reduce workload (e.g., reduce required power to manipulate interfaces, or allow one hand instead of two hands); for people with motor limitations.

- **Furnishing with visual/tactile cues [Indication]:** Designs that create multi-modal functions for identification, providing labels (e.g., switch identifiers, toggling sound); for people with sensory limitations.
- **Adding constraints [Constraint]:** Designs that prevent a targeted population from operating a task by limiting their operation mainly due to safety reasons (e.g., cabinet lock, switch lock, stove knob stopper); for people with cognitive limitations or child-access/child-proof products.

3.2 Design Study #2. Prototype & Preliminary User Evaluation

We developed the first prototype of the AccessLens and conducted a comparative study to assess its validity and advanced features over the baseline, MS Inclusive Design Guidebook [46]. Compared to other normative tools that are targeted to diagnosed disabilities, e.g., ADA Standards for Accessible Design [15], the MS guidebook is the foremost design guideline that argues accessibility as a universal daily challenge *for all*, encouraging recognizing exclusion, extending the inaccessibility concept to contextual from a permanent problem. Herein, the disability is discussed not as a personal health condition, but as '*mismatched human interaction*' which we see the potential to rectify through augmentations. Thinking of solutions for those situational disabilities can allude to a design for one that can benefit all [59], empowering people to learn from diversity. AccessLens prototype (Figure 5) includes objects with detected potential accessibility challenges. Tapping on objects, the system displays relevant 3D augmentations depending on contextual needs. We provide the contexts through a catalog approach, helping users learn from viewing adaptations list, which also presents design implications to nurture people's understanding of solutions.

3.2.1 *Participants.* We recruited 8 participants from various backgrounds, including researchers who are not in the accessibility domain ($N=5$), educators (middle/high school teacher, college professor, $N=3$). Two self-identified as older adults ($N=2$). Aligning with our target users who do have limited experiences in the accessibility concepts, we recruited participants without diagnosed disabilities nor knowledge of accessibility study. We observed whether AccessLens promotes "*thinking about daily inaccessibility*".

3.2.2 *Procedure.* We chose a within-subject study. We counterbalanced the conditions to reduce learning effects; half of the participants started with the baseline condition, and the other half started with the experimental condition. The study sessions began with

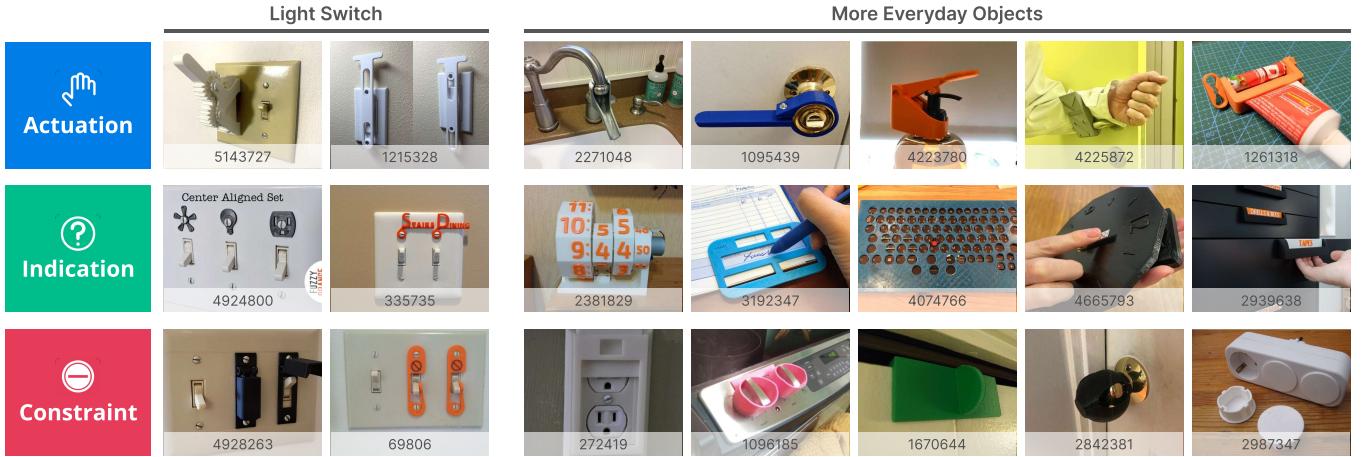


Figure 4: Examples of 3D assistive augmentations that belong to three categories, obtained from our in-the-wild survey with iterative affinity diagramming. Each design has a *thing_id* at the bottom, and the design page can be located at https://www.thingiverse.com/thing:thing_id. Examples show that various challenges, such as motor and sensory barriers, can present even for one object. 3D augmentations are actively used to address challenges without requiring total replacement.

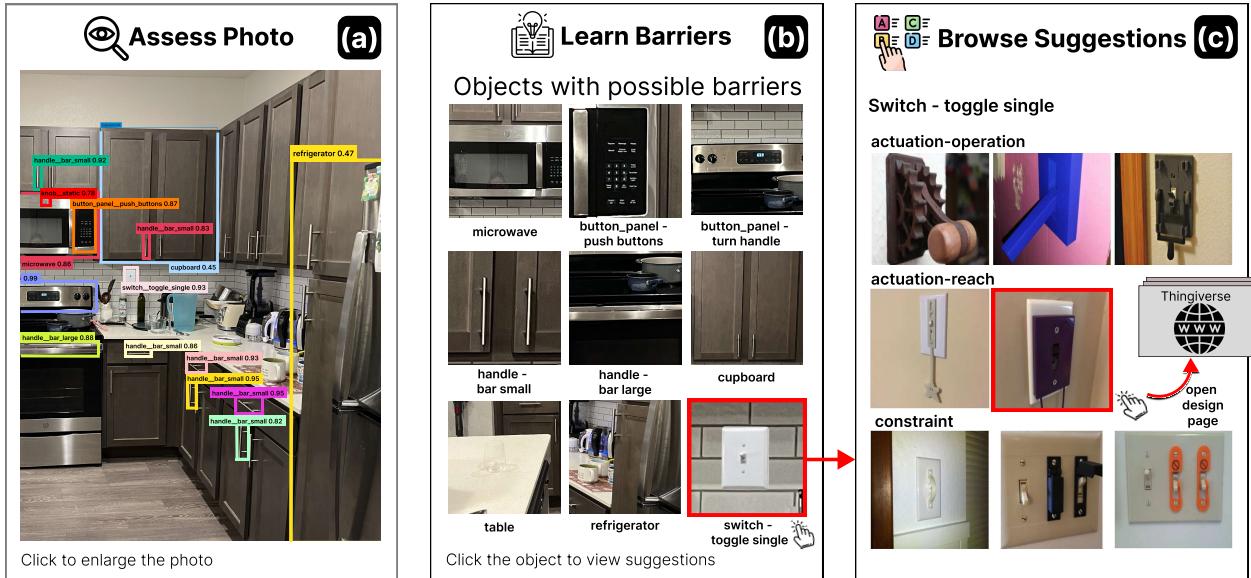


Figure 5: AccessLens prototype overview. AccessLens allows users to scan an uploaded photo (a), view the detected inaccessible objects (b), and upon a click of a detected object, browse through the available suggestions (c).

a pre-task interview. Participants then completed the same tasks under two conditions and finally, took a closing interview. In the pre-task interview, participants shared their prior experiences when they encountered difficulties in interacting with everyday objects or witnessed someone else having issues. They were also asked if they had implemented any solutions to address such barriers. One study condition is the Baseline condition, where participants access the link to the introduction video for MS Inclusive Design [47] and the MS Inclusive 101 guidebook [46] (MS guidebook, hereinafter). Participants were allowed to spend enough time reading the guidebook, without any time restrictions. During the task, participants were presented with indoor scene images and identified the objects

that could present potential accessibility barriers. They were then asked to propose solutions. Subsequently, participants were asked to rate each suggestion on a 5-point Likert scale. Participants were encouraged to use any necessary online resources (e.g., YouTube and Google Search) in the baseline. In the experimental condition, participants used AccessLens but were not permitted to access other online resources. As shown in Figure 5, the AccessLens displays indoor scene images of chosen, highlighted objects that could be inaccessible and offers applicable solutions. The task was repeated with a different indoor scene image. After both conditions, a brief interview followed for 15 minutes. We investigated their perceived usefulness by providing a survey questionnaire measuring three

sub-metrics on a 5-Likert scale: (1) recognizing inaccessible objects, (2) comprehending related contexts, and (3) identifying solutions. All responses and comments were documented for analysis. The entire session took 1.5 hours on average, not exceeding 2 hours. The study has been approved by the institution's review board (IRB No.: IRB2023-0648)

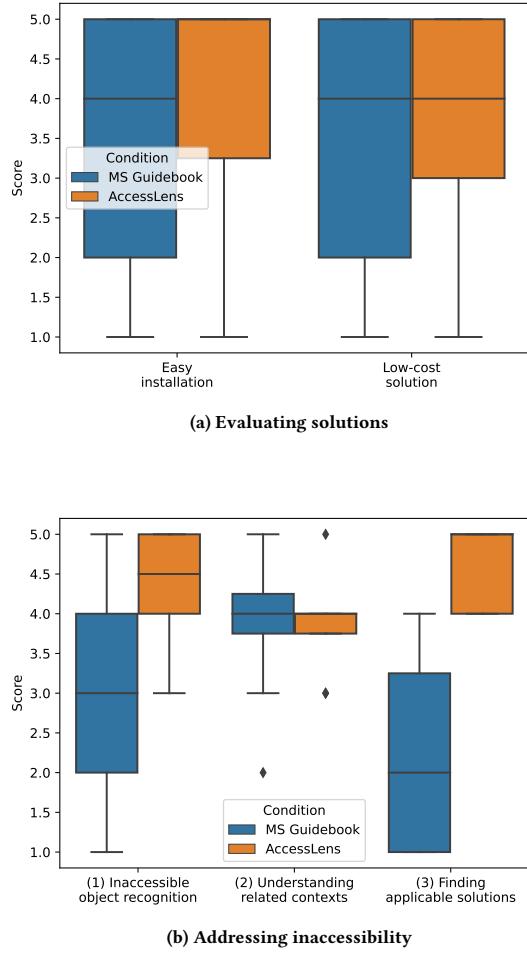


Figure 6: Perceived evaluation for two conditions: (a) solutions suggested by participants, (b) perceived helpfulness of both resources. (a) is assessed by two sub-metrics: (1) easy installation and (2) low-cost solution. (b) is assessed by three sub-metrics (1) inaccessible object recognition, (2) understanding contexts, and (3) retrieving solutions. (a) Scores for installation difficulty only vary little, with less perceived burden toward 3D augmentations. (b) AccessLens outperformed the written guidebook in assisting users.

3.2.3 Findings & Implications. #1. Ableism: Overlook Inaccessibility and Gaps toward an Action. During our pre-task interview, we observed oversight, and a gap between found inaccessibility and actions. Various cases were discussed about prior disability context

experiences including observed barriers of others. P0 worried about cross-contamination in the kitchen by touching and switching between various utensils and kitchen surfaces while cooking. Four (P2-3, P5, P7) recalled limb injuries that caused mobility restrictions with casts or crutches. P6 recalled the struggle to open a door while carrying large boxes. Four (P0, P1, P5-7) discussed issues related to the aging of self and their family, causing weaker physical abilities and impacting various daily tasks (e.g., using stairs). However, there was not much really happened to resolve them. P2 shared the story of their mother suffering from an ankle injury, leading her to stay seated at home until recovered. All often relied on family members for assistance, such as getting dressed with the help of a sibling (P2), and tried to circumvent challenges by struggling to use a non-dominant hand (P5) which was not perceived as a 'disability' at that moment. Internalized ableism might explain this, where individuals may think disability "has to cross some threshold of difficulty or suffering to count" [24] and do not think of their constraints as living disabilities to be addressed with solutions. Standing out to those who do not present diagnosed disabilities, ableism eventually misses the opportunities to renovate their environment for future contextual changes.

#2. Learning from Adaptations. Participants found that they could infer contexts from design recommendations even if explicit descriptions were provided. Several participants appreciated the persona spectrum from the MS guidebook, how permanent, temporary, and situational disability can relate to each other, broadening their understanding of disability. P5 mentioned that he now recalls he was temporarily disabled. AccessLens achieved the same effect by cataloging various augmentations, allowing participants to deduce the design contexts. In contrast, the AccessLens encouraged participants to follow a reversed cognitive process of "learning from adaptations" [46]. Several participants were surprised by the variety of 3D assistive designs, admitting they had not considered accessibility issues those designs could negate. "*I hadn't thought these [could be an] issue before I saw these designs*" (P2, P4). P3 remarked on the advantage of having detection & suggestion together. "*When I only saw the photo of the room, I had no idea [...], even when I see the detected objects, I didn't know which contexts it can pose barriers. When I saw the suggestions, I could imagine in which situations it can be helpful and what the objective is [of those or similar designs]*". We find presenting *better design examples* can inspire and let users comprehend the diversity. P5 preferred AccessLens highlighting its transformative impacts on perspectives; "*We usually think only of the disabled [when we were asked to think about disability]. AccessLens makes me think that even the non-disabled can get help and apply the solutions in their environments*".

#3. Mental Burdens in Disability Accommodation by Inexperienced Users. To qualitatively assess the mental load and practicality of the solutions, we questioned the estimated installation expenditure. Participants rated them under two sub-metrics toward installation: (1) *easy installation* and (2) *low-cost solution*. Figure 6a shows their estimation of easiness/affordability. The average score does not indicate notable differences, possibly due to the learning effect; participants who experienced the AccessLens first tended to use their knowledge obtained during the following baseline condition. Participants who began with the baseline guessed that the replacement of the object or extensive renovations as sole

solutions. While perceived difficulty and cost varied among participants based on their prior experiences, their perception of whole replacements leaned toward high cost and effort. In baseline, most participants were curious whether there exist such market products for their remedies. P5 imagined aggregated dials with small labels on a kitchen stove could be confusing for older adults, thinking individual knobs for each burner would be helpful, questioning whether he could get one off-the-shelf. In contrast, all found 3D augmentations straightforward and cost-effective. “*I thought that we always needed complete replacements or renovations [...] Reviewing the suggestions, I realized that these solutions can be easily installed so I really want to install them, [e.g., childproof augmentations] to ensure safety*” (P3). In baseline, while being allowed, none actively utilized external sources since they did not know what and how to search, implying low engagement and proactiveness. Only P1 tried general search keywords (e.g., assistive bathroom, accessible bathroom). “*I had to brainstorm to find the solutions. Even with online resources allowed, I believe it wouldn't be that helpful because I need to know what to search for*” (P1). This signifies the mental burden in searching, which may have hindered participants from engaging in solution-seeking/adaptations.

#4. Written Guidebook vs. Interactive System. In the closing interview, participants evaluated two conditions across three sub-metrics: (1) the ability to recognize inaccessible objects, (2) understanding related contexts with barriers, and (3) retrieving applicable solutions. Figure 6b summarizes participants’ assessment, showing AccessLens outperforms the guidebook in terms of detecting inaccessible objects and seeking solutions.

#5. Recommendations for Interaction Design. Several valuable suggestions emerged. (1) Implementing on a mobile reduces the user experience gap between capturing photos and inspection. (2) Context-based filtering would allow them to reconcile accessibility evaluations to certain scenarios, increasing the system’s versatility. (3) A summarized view of all detection with bounding boxes would simplify the inspection process for a quick overview at a glance. (4) Supplementary explanations for the categorization of designs, i.e., AccessMeta categories, will enhance in-depth appreciation of the suggestions and their design intention. (5) A tutorial or instructional guide on how to capture photos would help users in providing clear and relevant images. (6) A short summary or theme for each design suggestion in addition to the thumbnail image may help grasp the objectives of proposed accessibility enhancements swiftly. These collective enhancements were reflected in AccessLens improvements. We elaborate on an improved design in Figure 7.

3.3 Design & Implementation Considerations

3.3.1 Consideration #1: One-shot Image Input. From the HCI perspective, allowing users to upload a single photo of an indoor scene would offer a more pleasant experience, considering that our target users might not know where to focus. While detection performance can benefit from multiple photos of the indoor scene, it is more friendly for users to take a single photo of the entire room or scanner view to check whether there exist any accessibility concerns. We target one-shot imagery of indoor scenes of interest as input, i.e., a panoramic scan of a bathroom, living room, and office space.

3.3.2 Consideration #2: Semantic Understanding of Parts. To assist users with different needs as speculated in Design Study #2, detecting part (doorknob from a door) and discerning the *type* of the object (doorknob vs. lever) is critical to articulate contextual barriers beyond simple object detection. The system must detect target objects and the parts where actual user interaction occurs, since those parts present unique barriers that are associated with the interaction, for example, a knob for grab-pull vs. a knob for grab-rotate. The base image dataset that we will augment with interaction types must contain indoor scenes with part-level annotations. We examined datasets with indoor scenes, including object detection benchmarks (e.g., COCO [37], Pascal VOC [25]). We chose ADE20K [75], which provides a semantic segmentation on visual scenes with part-level annotations in 150 object categories (e.g., closet, cabinet, electric outlet, microwave) and their parts (e.g., knob, faucet, button panel), enabling augmentation of the hierarchical information.

3.3.3 Consideration #3: Recognizing Disability Attributes. Various contexts change the way that people with a wide spectrum of capabilities interact with everyday objects; a graphic designer wearing a splint due to chronic wrist pain, a door knob is not accessible as it requires hard grasping to rotate. People are often frustrated with a panel with identical toggle switches; without labels, they are forced to recall targets or try to get the right one turned on, sometimes causing safety breaches. No existing benchmarks contain attributes to detect inaccessible contexts (e.g., parents vs. one-handed) beyond the object-instance detection and parts semantics. The disability context attributes of the objects, as we name **Inaccessibility Classes**, can fortify the existing dataset for object detection.

In sum, we derive three design goals:

- (1) A user should be able to use a general view of scenes as input instead of a focused view of interested objects.
- (2) The system must be able to semantically understand the detected objects (e.g., cabinet knob vs. door knob).
- (3) A new dataset must account for understanding various inaccessibility contexts beyond object-instance detection.

4 ACCESSLENS: TOWARDS AUTO-RECOGNITION OF DAILY INACCESSIBILITY

AccessLens comprises AccessDB, AccessMeta, and the end-user toolkit, designed to seamlessly work together to assist end users in addressing accessibility challenges. The center of its functionality is AccessDB, a dataset used to train the inaccessibility detector, which analyzes images captured by users via a mobile user interface 1. The detector identifies inaccessible objects within various possible contexts. Leveraging AccessMeta, AccessLens suggests the design intentions and categories of 3D assistive augmentations.

4.1 AccessMeta: A Metadata to Understand 3D Assistive Augmentations

We define “*assistive augmentations*” herein as attachments to legacy physical objects assisting in manipulating them, addressing implicit barriers in varying contexts. Ever since numerous 3D printing practitioners have open-sourced their creations online, many design were posted with voluntary textual descriptions with “*assistive*”



Figure 7: AccessLens UI & System Overview: The (a) summary view displays bounding boxes highlighting detected inaccessible objects. (b) Users tap on each to access the suggestion, (c) swiping through all other detected instances. (d) Viewing suggestions for augmentations in three categories: actuation, indication, and constraint, users can (e-f) read the details available on Thingiverse [28].

to indicate the design intention. In addition, some not originally intended to be assistive missing relative tags could also be used for access [9] but makes shopping through millions of designs by searching exhausting. Navigating options is even more laborious due to ambiguity in language [35]. The structured rules or metadata to categorize assistive augmentations will broaden access to those designs, enabling users to explore easily.

4.1.1 Corpus for assistive augmentations through heuristics. To tackle this, we surveyed large-scale data about designs on Thingiverse [28], defining heuristic rules by observation such as retrieving relevant designs for target objects of interest. As our goal is to assist users in searching 3D augmentations based on target objects in mind as approached similarly in prior works [13] and practice (e.g., ThisAble project [65]), we initiated our search with target objects, e.g., “assistive door lever”. While the existing categorization and corpus [9] could be useful, designs classified under them do not necessarily represent augmentations. This also applies to CustomizAR taxonomy [35], which primarily focuses on adaptive designs but assistive designs are only a small set. Consequently, we opted not to directly adopt this taxonomy in our corpus formation process.

We selected the search keywords of common indoor objects: *door, drawer, cupboard, closet, outlet, light switch, switch, kitchen, utensil, cutlery, knife, spoon, fork, bottle, jar, bag, key, soap, shampoo, dispenser, nail clipper, can, pen, book, spray, phone, laptop, camera, toothbrush, toothpaste, clock, etc.* We started by observing the first 50 entries retrieved from Thingiverse and sought affinity and commonality to define the corpus. Then we expanded the search, resulting in ~1,600 entries retrieved by overlapping two sets of search keywords. After retrieving design entries, the first and second authors manually annotated assistive designs by their affinity, informed by the common interaction types (Section 3.1), and the last author validated results for agreement. With iterations and polishing, we define **AccessMeta**, with the three highest-level categories and their assistive functions, and common keywords and tags (Table 2).

4.1.2 Actuation: Reduce motor requirements. Designs that assist people with operational difficulties (e.g., fine motor impairments, occupied hands) by extending or magnifying parts; include designs that reduce the required strength or alter the needed motion types. Two functions are afforded if augmented: first, (help) *operation* and second, *reach*. *Actuation-operation* contains designs that enable alternative operations using other body parts (e.g., elbow to push instead of hands to grab-rotate) or motions, or reduce powers needed. As an example, a horizontal extension (as in Figure 2b) of the doorknob can replace the firm grasping-to-rotate with pushing-down. Figure 2d can allow people to use other body parts, arm or wrist in this example, instead of hands that might be unavailable at the moment. Another example is a plastic bottle opener [42] reduces the power needed to open a cap. Different types of pen grips (e.g., [43]) are popular for artists as they decrease wrist-power use. Designs under *Actuation-reach* magnify or extend the parts so that users can easily reach the target to operate. For example, light switch extension [20] is useful for children, people with short stature, or situations where large furniture placed underneath makes access difficult for people using walkers.

4.1.3 Constraint: Prevent operations. Designs often revert what *actuation* designs assist, preventing operating objects in special contexts (e.g., cabinet lock) for people with cognitive impairments or in child-access/child-proof products. Restraining access is another popular objective in augmentations to change the access (e.g., drawer lock [14]) often favored by parents, people with pets, and those who live with the cognitive retreat, especially for those who need to control access to certain objects for safety. Even for those who do not have such impairments, people label identical objects such as a series of wall switches to reduce confusion and misuse. Common target objects contain doors, drawers, wall switches (e.g., lights and garbage disposal), or outlets that are with known risks.

4.1.4 Indication: Furnishing with visual/tactile cues. Designs that furnish multi-modal feedback for easy identification of intention, function, or purpose by providing labels (e.g., switch labels,

| Category | Functions | Common keywords for 3D assistive augmentations |
|-------------------|--------------------|--|
| actuation | operation reach | lever/hand extension, string extension, opener, holder/gripper, grip, mount |
| constraint | limit access | cover, guard, protector, lock |
| indication | visual tactile | label, identifier, tag |

Table 2: AccessMeta corpus to categorize 3D assistive augmentation designs. We found that the majority of assistive designs fall into three categories depending on their desired functions by augmenting real-world objects, often described by common keywords.

toggling sound); greatly benefit people with sensory impairments. 3D printed tactile graphics have gained acceptance by many people with visual impairments [9]. Built upon those principles, tactile cues provide multi-modal information to help identify functionalities in identical-looking objects, for example, 3D-printed labels in the multi-switch panel [68]. Note that AccessMeta categories are not always mutually exclusive, as one can simultaneously furnish tactile cues and reduce motor requirements.

4.1.5 Assistive 3D Augmentation Dictionary. As a result of design exploration to define AccessMeta, we created an initial dictionary that contains 280 3D-printed augmentations for 52 everyday objects (e.g., handle, door, knob, book, nail clipper, knife, hair dryer, microwave, stove, table, etc.) with potential inaccessibility context, fully annotated with AccessMeta categories. Among 52 common object classes in AccessMeta, we found that 6 classes (i.e., handle, faucet, switch, knob, button panel, and outlet) are significant and difficult to be addressed by existing datasets with indoor scenes (e.g., ADE20K [75], COCO [37]) mainly due to (1) challenges caused by their small size in photos and (2) diverse types of the objects that might pose various kinds of barriers (e.g., door lever vs. knob). Focusing on these 6 classes (which are further divided into 21 inaccessible classes), we construct a new dataset, AccessDB/AccessReal.

4.2 AccessDB & AccessReal: Dataset for Inaccessibility Detection

Auto-detecting objects with their semantics and context from camera views (e.g., [48, 53, 66]) can assist visual perception for various interested groups and information processing, e.g., robotic affordance and different types of disability. Automation through a comprehensive dataset that provides a granularity of object classes is critical to infer necessary information from semantics. Yet, predicting contexts from images is more complex than detecting objects and instances; *object attributes* such as shapes (e.g., round, lever, cross-shaped) must relate their *functional properties* (e.g., grip, twist, pinch), to be able to derive their conceptual interaction types. Once interaction types are inferred regarding their visual and functional characteristics, those types can serve as clues to infer the original design intent as well as hidden barriers in various possible contexts. To train and evaluate our developed inaccessibility detector, we construct two datasets: AccessDB and AccessReal. Being built for semantic understanding of objects and their parts, ADE20K offers hierarchical annotations on object classes, such as *closet - door - handle* and *oven - door - handle*. AccessDB presents Inaccessibility Class (IC) to provide a nuanced understanding of diverse barriers that may manifest across various contexts, extracted from six distinct categories in ADE20K: button panels, electrical outlets,

faucets, handles, knobs, and switches. The granularity of IC permits the identification of specific accessibility challenges, thus enabling tailored design solutions. Table 3 in the Appendix B summarizes the statistics of the two datasets.

AccessDB is used to train inaccessibility detectors. We derive AccessDB from ADE20K [75], which contains >20k images including diverse indoor scene photos with pixel-level annotations on objects and their parts. ADE20K does not have labels of inaccessibility classes (ICs), therefore, we re-annotated objects for 21 pre-defined ICs (plus an “unidentifiable” class that we cannot discern due to extremely small sizes). We first select indoor scene images sampled from “home”, “hotel”, “shopping and dining rooms”, and “workplace”. We remove low-resolution images. While ADE20K annotates various objects, our work focuses on 6 object categories that are easily inaccessible to a broad population (Figure 8): handle, faucet, switch, knob, button panel, and electric outlet. Three annotators are HCI experts who are trained in assistive designs, and annotators also cross-verify each other’s annotations. This ensures the quality of our annotations. After annotation, we obtained 4,976 high-resolution images exhaustively annotated with ICs as illustrated in Figure 9. Inaccessible object parts occupy only small regions in the image, posing a visible challenge to object detectors.

AccessReal. Since AccessDB’s images are from the ADE20K dataset which was published five years ago, we are motivated to curate a new dataset for evaluation by collecting photos taken in ‘modern’ indoor scenes. To this end, we take 42 high-resolution photos (mostly 4032×3024) in diverse indoor scenes: bathroom, bedroom, kitchen, living room, and office (cf. Figure 10). We annotate them w.r.t the predefined 21 ICs (see data statistics in Appendix B Table 3), and end up with 428 annotated objects with ICs.

5 EVALUATION

5.1 An End-to-end User Pipeline: From Capturing Photos to Installing Augmentations

5.1.1 Participants & Procedure. To evaluate the potential of the AccessLens as an end-user system, we conducted a holistic end-to-end study in four stages: (1) capturing photos, (2) uploading photos for AI inspections, (3) viewing suggestions to address identified barriers, and (4) physically installing 3D printed results. We recruited six participants (U1-6) from our institution (female=4, male=2, ages 19-30) who have none to limited exposure to the field of accessibility, except for U6 who had moderate experience in technology for people with hearing impairments. Five (U1-5) had little or no prior experience in 3D printing, while U6 had 5+ years of experience. None of this group overlaps with the preliminary evaluation study

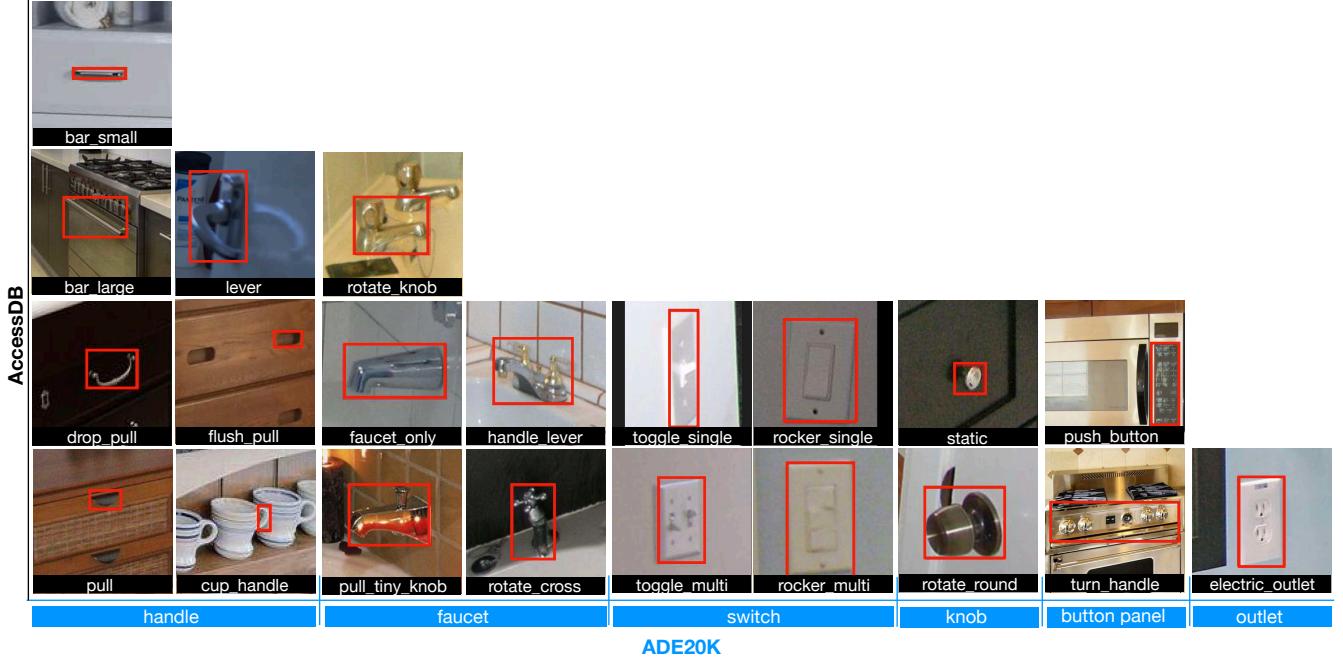


Figure 8: We derive our AccessDB dataset by annotating indoor images from the well-established ADE20K dataset [75] w.r.t 21 inaccessibility classes (noted under each exemplar image). We focus on 6 types of objects (blue-labeled names) which frequently appear to be inaccessible in daily life.



Figure 9: An example image (a) from AccessDB with two inaccessible object annotations: a flat button panel in a stove (b), and a handle into a drawer (c). These objects often are very small in the image, making their annotations and auto-detections difficult.

participants. All design studies were conducted individually. Participants first freely explored AccessLens, either on mobile or the web, uploading photos they took in personal indoor spaces. They then selected as many desired augmentations. Due to the time limitation, we 3D printed the chosen augmentations, except for U6 who self-printed. Participants applied these printed augmentations within their environments by themselves without any intervention by the researcher. Participants were asked to take photos and share the installation process and results. We concluded each study session with exit interviews. We took an approach similar to a contextual inquiry, with in-depth observation and interviews of users to gain a

robust understanding of user behaviors and their motivation about specific courses of action taken, by being minimally intervened. All conversations and responses were transcribed and documented for analysis through coding.

5.1.2 Results & Finding. Participants submitted an average of 3.7 photos/participant, totaling 22 of four indoor scenes: bathroom, bedroom, living room, and kitchen (e.g., Figure 11).

#1. Easy Process for Taking and Uploading Photos. AccessLens did not provide a step-by-step walkthrough on how to capture photos, as the facilitator minimized intervention to observe users' natural inputs. In line with our design consideration #1 (Section 3.3.1), all submitted photos were panoramic, capturing entire rooms to include as many objects as possible. U5-6 iteratively adapted their photo-shooting strategy as they got results. “*From the first try, I saw that the app detected door handles, so I ensured their visibility in subsequent photos*” (U5). None reported issues in taking and uploading photos, stating the system is very straightforward.

#2. Learning Accessibility from Adaptation. Before using AccessLens, all participants expressed their lack of confidence in recognizing inaccessibility. U5 guessed that it is possible only when obvious, e.g., seeing someone struggling in person. U1-3 stated they “*had not encountered accessibility challenges myself*”, and U4 found it hard “*to view things from the perspective of those with accessibility issues [because I am not disabled]*”.

After AccessLens use, we observed elevated confidence and awareness. “*By seeing all the examples and possible solutions in my room, I now have a better understanding of potential issues and how others interact with objects differently from I do*” (U1). U2 found the microwave button pusher [19] eye-opening, since they never



Figure 10: We use the AccessDB (left) and AccessReal (right) datasets to train and evaluate inaccessible-object detectors. Images of AccessDB are sampled from the well-established ADE20K dataset [75] with our re-annotation (cf. Table 3). AccessReal has high-resolution images captured by ourselves from diverse indoor scenes; we annotate these images using the same set of inaccessibility classes. Red boxes are zoom-in regions that contain inaccessible objects.



Figure 11: Examples of indoor scene photos submitted by case study participants through AccessLens. All participants took photos to show a full coverage of rooms, capturing the details as much as possible. Indoor scenes include: (a-b) bathroom, (c) bedroom, (d) living room, and (e-g) kitchen. (a-g) show bounding boxes overlaid, detected by AccessLens. Participants reported minor detection errors: undetected hair dryer (h) and air fryer misclassified as a toaster (i).

imagined that anyone could struggle with such simple pressing. Most participants (U1-4, U6) testified an expansion of their perspectives about accessibility; “*I never thought about outlets or stove buttons [that could be inaccessible], since I was expecting more about detecting objects for people who are visually impaired or with [more serious disabilities]. I gained a new perspective that disability is such a large spectrum*” (U3). U4 also stated, “*At first I thought that the challenges would only apply to people with [diagnosed disability, but it applies to] the general population with a variety of issues, including injuries, child locks, and having busy hands.*”, confirming that users learn “*potential contexts*” (U1-2, U6) through recommendations. U5 found being hands-free useful since the steel surfaces tend to become dirty. AccessLens also helped U3 & U6 redefine their experiences; “*I once had a cut on my thumb, which made squeezing the toothpaste tube very difficult. Toothpaste squeezer seems useful (in such situations) but also on a daily basis too*” (U6).

#3. Perceived Accuracy of Detection. All participants found the automated detection accurate, expressing confidence in interpreting the results. U3 was concerned about messy rooms but was impressed by the detector performance that captured objects successfully even from cluttered scenes. While focusing on the bathroom, U6 found that even a small reflection of the door knob in a mirror was correctly detected. AccessLens was thought accurate only except for U1’s hair dryer, possibly due to its uncommon design (Figure 11h), and U4’s air fryer is seen as a toaster (Figure 11i). All were thought minor and did not affect participants’ trust in overall detection results.

#4. AccessMeta and Dictionary Supporting Exploration. Participants particularly appreciated AccessLens’ presentations, organized by the objects with inaccessibility detected first along with related issues displayed following AccessMeta. Participants (U2-3, U5) found the explorer feature useful it shows all possible designs, depending on possible disability contexts. “*Before reading the dictionary, I was not aware of child safety and how they related*

to accessibility, but the dictionary helped me learn about potentially dangerous aspects of objects and how to help mitigate them” (U1). U3 perceived the variety of the dictionary as very useful for browsing especially “when moving to a new place, remodeling, or choosing new appliances”. U6 imagined augmenting standard spaces with various needs: “The standard apartment’s equipment is not designed for specific needs. People will find it very useful to augment their everyday environment with specific needs in mind”.

#5. Different Motivations to Adopt AccessMeta Recommendations. Participants selected 2-4 augmentations per each to apply to their real-world environments, such as a hands-free opener for large door handles, electric outlet covers, jar openers, stove knob protectors, Ziploc bag holders, microwave door openers, toothpaste squeezers, and hair dryer holders, etc (example retrofitting results seen in Figure 12). When asked about their selection criteria, their rationale varied: frequency of use (U1, U6), assistance when alone (U2), safety considerations (U3, U5), practicality, and sheer interest (U4). Some provided additional suggestions for objects that are not shown in the image, but are possibly inductive from the context. “*I know my parents or grandparents struggle using, such as a toenail clipper as they don’t have enough back flexibility. It’s nice to have the option to look at suggestions [without having the images] of their houses*” (U2). We imagine AccessLens’ advanced feature for such expanded recommendations. If the contextual disabilities are known through the user’s previous choices of recommended adaptations, AccessLens can also fetch common objects using AccessMeta that present similar accessibility barriers.

#5. Low-cost Upgrades through Retrofitting but Need to Handle Uncertainty. All were able to install the augmentations without the facilitator’s help and did not face major difficulties, with most only spending a maximum of a few minutes on the designs that required assembly. Many designs on Thingiverse are versatile and modular, often in standard dimensions or instructed to use screws for a tight fit. Participants found standalone designs (e.g., bag holders, knob covers) were easy to utilize. For example, U3 found that the stove knob lock fit perfectly, and found it useful for safety when children or cats are around. With assembly, participants were actively involved in the adaptation for real use. Participants found 3D-printed upgrades easy and cost-effective. U1 found that the microwave door opener [19] is slightly taller, so they tilted the microwave up to match the height. U4 and U5 did not have screws to put parts of the hands-free door opener [70], but still made it work by installing it using tape. For designs that need assembly, three participants (U1-3) thought having a step-by-step guide would be beneficial. While all successfully adopted and used selected designs, some dimensional challenges were highlighted; U3’s outlet covers did not fit so they had to put it over without fixation. U5’s hands-free fridge opener was loose and slid, failing to stay at arm height. For future work, we consider integrating well-established customization tools particularly focused on the fit, e.g., [23, 30] and auto-measurement [35].

#6. Additional Suggestions. Overall, participants were satisfied with AccessLens, and are willing to continue using it. Participants hope for a feature to improve users’ understanding of the augmentations, such as their functionalities or objectives in detail within the app for first-time use. Three participants (U3-5) suggested a detailed description for each augmentation clarifying the functionality so

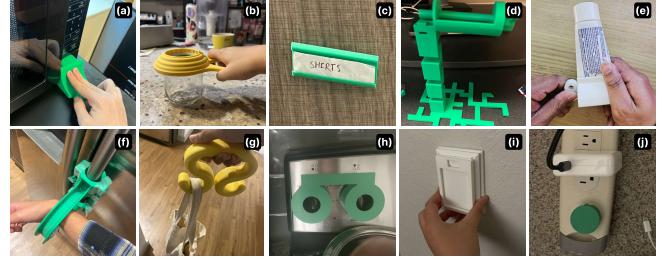


Figure 12: Retrofitting results with 3D-printed augmentations by case study participants. (a) microwave opener, (b) jar opener, (c) drawer label holder, (d-e) toothpaste squeezer, (f) hands-free door opener, (g) bag holder, (h) stove knob cover, (i-j) outlet cover.

that they could understand the purpose of the design without redirecting and reviewing the design page. U1-2 and U4 also mentioned that showing the required materials (e.g., screws, tape, clips) would be helpful so that they can make choices based on complexity and material availability. U6 also hoped to see an animated preview of how the augmentation could change the interaction.

5.2 User Experience Design for Assistive Technology: Expert Feedback

5.2.1 Participants. The expert feedback session was conducted to understand how AccessLens can support users to raise awareness about accessibility. We engaged two professionals (E1-2) with 10+ years of expertise in accessibility research and teaching access computing. E1’s expertise lies in robotics for people with movement disabilities and/or chronic conditions (e.g., people with Parkinson’s disease, and freezing of gait), and E2’s expertise is in assistive visual perception for the visually impaired through systems for human-AI interaction. After trying AccessLens, we sought their qualitative opinions about various topics of interest: user engagement, system functionality, empowerment in decision-making, alignment with standards, usability, potential impact, and future developments.

5.2.2 Findings. E1 and E2 both acknowledged the tool’s diverse and relevant suggestions, particularly for “*raising awareness of accessibility issues, aiding those without specialized accessibility knowledge*” (E1). E1 had concerns about non-experts due to the absence of clearly identifying related accessibility issues for people with diagnosed disabilities. While the system provides real examples and suggestions for environmental modification facilitating users’ perception of various possible contexts indirectly, it lacks “*explicit explanations*”, potentially hindering informed decision-making. Aligning with E2’s comment about possible design conflicts, “*if multiple people residing in the space with different accessibility needs, solutions could be in conflict with each other, or the design needs to be combined to satisfy multiple needs*”, it is also noted that AccessLens needs more targeted customization and alignment with *public accessibility standards* (E1). Similarly, while appreciating the system’s ability to identify numerous relevant objects, E2 suggested incorporating more diverse parameters, including configuration/layout of the environment (e.g., the width of a hallway) and interaction/spacing between objects (e.g., the distance between switch and floor), which we find incorporating physical assertion of adaptive designs [23]

critical. E1 sees long-term benefits, especially for growing 3D printing communities but limited accessibility knowledge. E2 also proposed allowing users to input specific disabilities to prioritize suggestions and emphasize the importance of customizing solutions for different needs within the spaces. E2 imagined crowd-sourcing more examples and offering an onboarding feature for new users to enhance the system's utility. In summary, both experts recognize AccessLens's potential to engage inexperienced users. Encompassing customization support responding to the physical dynamics, guidance, as well as user-defined disability prioritization at the input stage can further improve AccessLens.

5.3 AccessMeta Evaluation: Human Annotations by Crowdsourcing

5.3.1 Procedure. To further assess the acceptance of AccessMeta, we conducted an independent study on human annotators' perception and consensus on AccessMeta and a dictionary of 280 3D augmentations which were annotated by the research team. Using Amazon Mechanical Turk in which anyone can participate, we designed tasks to assess how well the general public understands AccessMeta's classification criteria. In each HIT, annotators engage with one 3D augmentation and categorize it under one of the three high-level categories from AccessMeta: 'actuation', 'constraint', and 'indication'. These categories are further organized into five sub-categories: 'actuation-reach', 'actuation-operation', 'constraint', 'indication-visual', and 'indication-tactile'. An additional 'others' option allowed annotators to recommend a custom label if they see none of the existing categories apply. Upon accessing the design page through a provided URL (e.g., Thingiverse), annotators chose the label(s) that best describe the augmentation. To avoid potential bias, we did not provide any image references. Instead, annotators are provided textual descriptions of these labels from AccessMeta. We consider a HIT submission acceptable in several scenarios: (1) If an annotator correctly identifies the specific label (e.g., 'actuation-reach'); (2) if an annotator chooses a subcategory under the correct high-level category (e.g., selecting 'actuation-operation' for an 'actuation' design); (3) if multiple labels are selected within the correct high-level category; and (4) if 'others' is chosen and a reasonable custom label is provided.

Submitted HITs were first reviewed by the second author and were subject to rejection only when they fell under these four cases: (1) if *all* annotations provided by a single annotator for different design entries were identical and incorrect (all HITs would be rejected); (2) if an annotator selected 'others' but provided irrelevant or inappropriate tags such as too generic comments ('good design'), unrelated phrases ('We and our 814 partners'), or simply copied the full title or description of the design page; (3) if all responses submitted by a single annotator were incorrect and completed in less than 40 seconds (threshold decided from the test run), which indicates insufficient time to thoroughly read the instructions, review the augmentation, and provide annotations; (4) if a single annotator submitted more than 100 HITs, any responses beyond the 100-HIT limit would be rejected. This is to ensure diversity in submissions and perspectives. Results were shared with the first author for approval. Following this criteria, $N=515$ HITs were rejected and republished for re-annotation. A worker was paid \$0.05 per HIT, and one worker submitted 16.8 annotations on average.

5.3.2 Results & Findings. Three different annotations were collected for each of the 280 designs, eventually obtaining 839 valid annotations from 83 workers. The median completion time was 6.8 minutes (8 sec. to 30 min., std = 6.8 min.)

Acceptability. If workers' annotations matched the ground truths of three main classes, they were marked as success, otherwise, failure. Accuracy was analyzed by the ratio of correct annotations over total annotations obtained ($N=839$) for 280 designs. Annotators showed 83% match ($N=697$) implying AccessMeta's acceptance. For about 20% of those correct annotations, workers' selection of subcategories could vary, e.g., 'actuation-reach' instead of 'actuation-operation', possibly due to the versatile nature of assistive designs. As discussed earlier, AccessMeta subcategories are not always mutually exclusive. For instance, tactile indications often provide effective visual cues, and object extensions to help reach items that could also facilitate alternative or smoother operation.

Category Expansion by Annotator-Adaptation. About 98% of annotations were made from AccessMeta categories. Despite not many (1.8%), 10 workers selected the 'Others' option for 13 designs, introducing new categories. Three new classes emerged, mostly for designs labeled as 'actuation-operation' (e.g., hands-free book holder [12], ziploc back holder [71], cup holder attachable to the sofa [67]): 'holder' ($N=6$), 'stabilizer' ($N=2$), and 'support' ($N=2$). Annotators also suggested 'protector' ($N=2$) and 'safety' ($N=1$) for child-proof designs—a child finger protector for drawers [11] and a sharp corner protector for tables [50], respectively, which are currently defined as 'constraint' in AccessMeta. Growing in complexity with diverse contexts and objects, we perceive AccessMeta to serve as a platform to expand through the collective input for more diverse & inclusive classifications. The immediate future work could involve mechanisms for reports/suggestions through a collaborative approach between stakeholders of end-users and designers for adaptive solutions.

5.4 AccessDB Qualitative Evaluation: Detector Performance

Our approach allows adapting any state-of-the-art detector architectures (e.g., GroundingDINO [39] and RetinaNet [36], cf. details in Appendix C) using our AccessDB/Real. Figure 13 displays example detection results on AccessReal images, showing good qualitative performance in detecting small inaccessible objects. Importantly, in the case study (Section 5.1), all participants showed trust in our detector's performance, stating that AccessLens detected their objects very well. Detection result visualizations for sample images in AccessReal (Figure 13) also show that the detector accurately captures small object occurrences. AccessDB and AccessReal datasets are open-sourced at <https://access-lens.web.app/> to foster future research for the community. While our work used a recent object detection method, any state-of-the-art modules can be trained on our dataset. For our detector's technical specifications, cf. Appendix C.

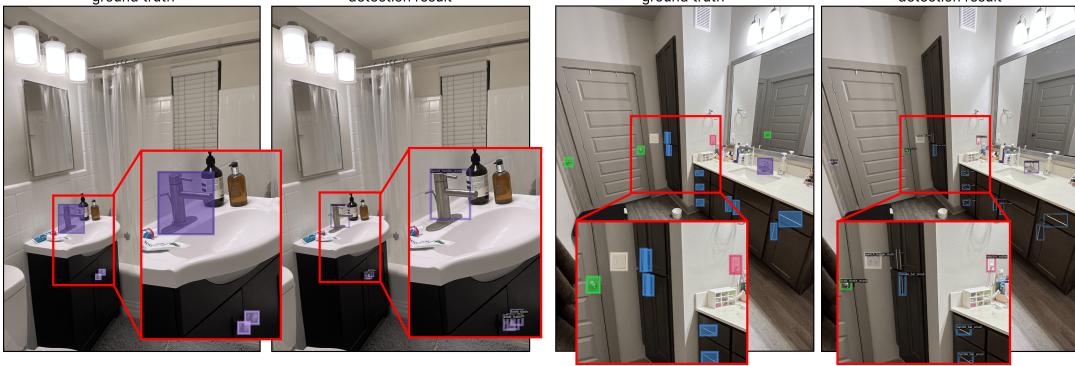


Figure 13: Ground-truth and detection results of our inaccessible-object detector on two example images in AccessReal. For brevity, we omit Inaccessibility Class labels (and detection confidence scores) in ground truth but present only labels for detection boxes. A visual examination of the results reveals that our detector exhibits a decent capability for identifying inaccessible objects.

6 DISCUSSION & FUTURE WORK

6.1 AccessLens for Collective Disability Accommodations

Engaging with a building ADA coordinator at our institution sheds light on the idea of a collective effort in identifying and reporting. The ADA coordinator admitted that many staff lack expertise in accessibility in reality, but consistently get requests from students, faculty, and visitors for disability accommodations within legacy university buildings. Typically, they resort to hiring external accessibility specialists to address these issues on demand. Encouraging citizen science within our initiative could mirror successful collective intelligence models like Project Sidewalk [62]. By adopting a reporting system where individuals contribute to accessibility assessment within commons, accommodating potentially inaccessible physical environments but have *not yet* discovered by people with diagnosed disabilities before they encounter barriers. Experts' recommendations about inputting disability types and validating possible conflicts must be applied to seek AccessLens at scale.

6.2 AccessMeta to Expand to 3rd-Party Solutions

AccessMeta benefits users evaluating accessibility concerns by linking the object types with their needed interaction, seeking solutions that might alter interaction types (e.g., grab-rotate-to-open vs. push-open). Once detected, we see the future of AccessMeta and the dictionary expanding the search for similarly-functioning 3rd-party alternatives, such as buying door lever replacements from hardware stores or online markets. While some simple replacements like doorknobs might be as cheap as 3D printing, more complex fixtures such as refrigerator handles (as in Figure 12) are not trivial, necessitating the disassembly or replacement of the whole appliances. Although our study participants agreed on the less mental burdens with AccessLens recommendations, some also were more inclined towards store-bought products as they have gone through market testing already (U3), given their perceived affordability and time cost for customization (U5). As AccessLens provides direct recommendations compared to “*for store-bought ones, I might have to look for products on my own that solve the highlighted challenge*”

for detected objects” (U2), offering users more options to support choices upon various rationale, control for materials (U5), easy-fix and remix (U6).

6.3 3D Model Customization

3D printing and personal fabrication have gained popularity to facilitate customization to adapt to unique needs. One notable example of this effort is seen in auto-filling numerics into parametric 3D designs [35] and in creating various branches of augmentations upon user’s changing needs to adapt common household items for people with motor impairments [13]. The current AccessLens prioritize the detection of inaccessible objects and assistive augmentation recommendation. As our work has been focusing on increasing awareness and low-cost solutions, dealing with fit [30] and other parametric customization was considered orthogonal. However, we recognize the potential synergy with existing works facilitating customization (e.g., [23]), complementing each other starting from the auto-detection and selection of a suitable design and culminating in the real-world applications. By seamlessly integrating two approaches sharing the goal towards adaptive designs, we can further empower individuals to take proactive steps toward creating more accessible and inclusive environments tailored to varying disability contexts. This synergy represents a promising avenue for future research and development in the field of accessible design and assistive technology.

6.4 Expanding AccessDB & AccessReal Dataset, Populating AccessMeta

This work provides two challenging datasets, AccessDB and AccessReal dataset for the automated inaccessibility detector. Communities’ interest in inclusive & assistive designs has grown significantly, and advances to automate everyday surroundings (e.g., smart switches, thermostats with touch screens) creating new challenges; touch screens often lack tactile feedback for people with visual impairments and presents more challenge in understanding the functionalities for the elderly). To be able to scale the dataset, this work elaborated on the re-annotation strategy of AccessDB in detail at our dataset website. We believe that the AccessMeta pipeline, guided by the evolving landscape of accessibility, should remain

open-ended and adaptable to accommodate emerging needs and novel designs. One approach to expanding the AccessMeta pipeline is to involve a community in reporting accessibility problems and suggesting additional metadata categories if needed. By actively engaging users and collecting their input, we can ensure that the system remains responsive to real-world needs, identifying new challenges and make the recommendation process more accurate and inclusive. Accordingly, we can leverage the existing metadata to build a more comprehensive dictionary of designs related to accessibility, beyond the objects that this work scopes.

6.5 Intervention Study: How Can AccessLense Promote Pro-social Behaviors?

We expect the use of AccessLens will help people become more aware of implicit inaccessibility and more engaged in improving accessibility in every aspect of their physical interactions, including space accessibility of lecture rooms and shared dormitory community rooms. The time constraints of our study limited us to observe positive behavioral changes of participants, whether they were more actively engaged in improving accessibility for the whole community. We plan to conduct deployment study to evaluate whether AccessLens raises people's awareness and such increased awareness brings about collective actions, similar to how altruism motivates voluntary sharing of designers online for free. An expert interview from more diverse domains including HCI, accessibility, visualization, and citizen science will be conducted to receive critique on the user interface and systematic user study design to assess the effect without any biases towards using AccessLens over other existing tools.

7 CONCLUSION

Motivated to a tool to improve everyday objects' accessibility by a broader community, in this work, we introduced AccessLens. AccessLens provides an end-user tool that helps users without diagnosed disabilities or prior experiences in accessibility assess the accessibility challenges. We adopted computer vision techniques (i.e., object detection) to train inaccessible-object detectors on our derived dataset AccessDB. On our collected dataset AccessReal which consists of images of modern indoor scenes, we show that our detector can detect inaccessible-objects quite well. We also designed AccessMeta to link inaccessibility classes to keywords of 3D assistive augmentations.

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A EXAMPLE ASSISTIVE AUGMENTATIONS

We introduce example augmentations that are applicable for common scenarios in Figure 14.

B DATASET DETAILS

AccessDB/Real comprises around 10k re-annotated objects across 21 ICs. Further details regarding the breakdown of our dataset can be found in Table 3.

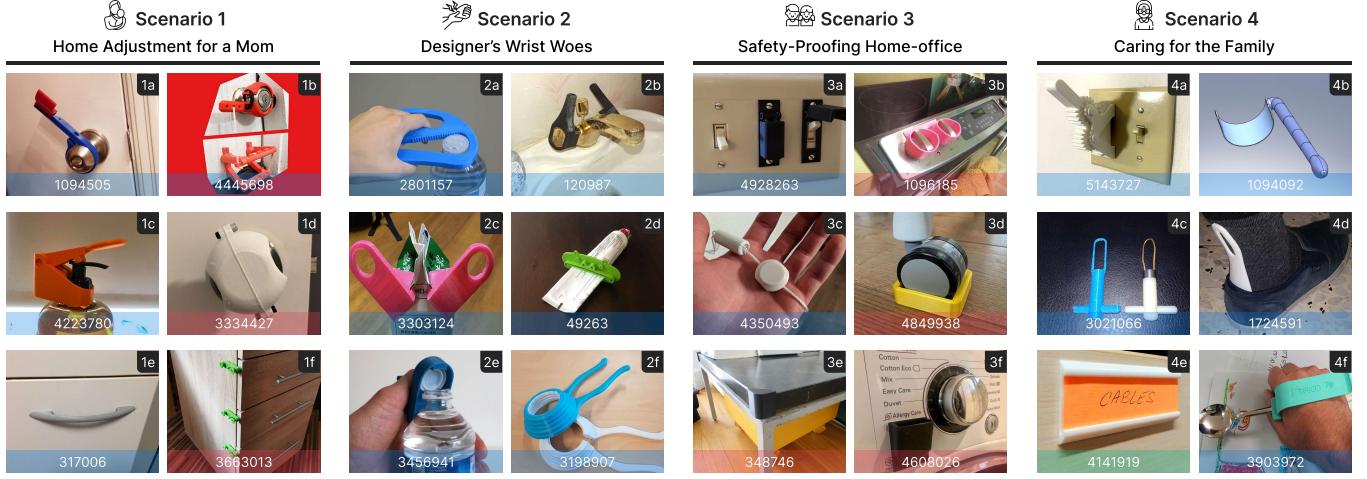


Figure 14: Augmentations recommended by AccessLens for four example scenarios: (1) home adjustment for a new mom, (2) designers who has chronic wrist pain, (3) safe-proofing home office, and (4) caring for the family member who is an older adult. Each design has a *thing_id* at the bottom label, and the design page locates by https://www.thingiverse.com/thing:thing_id. Labels indicate blue: actuation, red: constraint, green: indication.

| id | inaccessibility class | AccessDB | AccessReal |
|--------------|------------------------------|-----------------|-------------------|
| 1 | button_panel_push_buttons | 83 | 14 |
| 2 | button_panel_turn_handle | 165 | 8 |
| 3 | electric_outlet | 1,382 | 33 |
| 4 | faucet_faucet_only | 169 | 3 |
| 5 | faucet_handle_lever | 351 | 13 |
| 6 | faucet_pull_tiny_knob | 29 | 0 |
| 7 | faucet_rotate_cross | 86 | 0 |
| 8 | faucet_rotate_knob | 96 | 0 |
| 9 | handle_bar_large | 375 | 19 |
| 10 | handle_bar_small | 1,712 | 191 |
| 11 | handle_cup_handle | 243 | 31 |
| 12 | handle_drop_pull | 491 | 0 |
| 13 | handle_flush_pull | 43 | 0 |
| 14 | handle_lever | 211 | 10 |
| 15 | handle_pull | 289 | 14 |
| 16 | knob_rotate_round | 205 | 26 |
| 17 | knob_static | 3,026 | 38 |
| 18 | switch_rocker_multi | 84 | 3 |
| 19 | switch_rocker_single | 57 | 4 |
| 20 | switch_toggle_multi | 103 | 8 |
| 21 | switch_toggle_single | 115 | 13 |
| 22 | unidentifiable | 724 | 0 |
| total | | 10,039 | 428 |

Table 3: Counts of annotated objects per inaccessibility classes in AccessDB and AccessReal datasets. There are 21 inaccessibility classes plus an “unidentifiable”. AccessDB and AccessReal contain 2,388 and 42 indoor scene images, respectively. We use AccessDB for training and validation, and AccessReal as the testing set for evaluation.

C DETECTOR PERFORMANCE

C.1 Evaluation Metrics.

The literature of object detection commonly uses the standard metric of mean Average Precision (mAP) at interaction-over-union (IoU) thresholds ranging from 0.5 to 0.95, with a step size 0.05 [38].

We use mAP as the primary metric. Following other prior works [2, 16, 45], we also report performance with respect to the metrics of AP₅₀ and AP₇₅ [22], meaning the Average Precision (AP) at IoU threshold 0.5 and 0.75, respectively.

C.2 Training a detector with AccessDB

AccessLens supports detection for all object classes in the 3D assistive augmentation dictionary and ICs. Although any detector structure can be chosen, we utilized two different state-of-the-art methods, RetinaNet [36] for ICs with training on AccessDB, and GroundingDINO [39] for zero-shot detection without training for more common classes (e.g., sofa, table, cup, etc.) Specifically, we trained RetinaNet [36] with ResNet-50-FPN backbone with 3x LR schedule, implemented by detectron2 [73]. In training, we employed COCO pretrained weights retrieved from Model Zoo of detectron2. As Figure 8 illustrates, AccessDB contains a total of 21 inaccessibility classes, and one more extra class, unidentifiable instances due to their extremely small size to get the type identified with human eyes. For training and validation of the detector, we randomly split the dataset having 85% as training and the rest 15% as validation (2,029 and 359 images for training and validation set, respectively). We used the AccessReal dataset for testing (42 images) to understand and compare how the detector works on AccessDB and more high-resolution images in AccessReal. For the ‘unidentifiable’ class, we still included it as an individual class in training but did not use it for evaluation. This is because, ‘unidentifiable’ objects are still in the 6 categories of our interests, so those might have overlapping visual features with other inaccessibility classes that the human eye could not capture due to the blurry images. By treating it as one class in training a detector, we can avoid unwanted penalizing of the other classes’ correct predictions.

C.3 Detector Analysis

Evaluation of the detector on validation and test sets was performed per each epoch. The detector achieved its best performance for the

| id | inaccessibility class | AccessDB | AccessReal |
|-----------|------------------------------|-----------------|-------------------|
| 1 | button_panel_push_buttons | 13.91 | 11.43 |
| 2 | button_panel_turn_handle | 26.48 | 7.72 |
| 3 | electric_outlet | 29.94 | 16.65 |
| 4 | faucet_faucet_only | 21.36 | 4.90 |
| 5 | faucet_handle_lever | 29.92 | 12.85 |
| 6 | faucet_pull_tiny_knob | 38.52 | n/a |
| 7 | faucet_rotate_cross | 34.84 | n/a |
| 8 | faucet_rotate_knob | 32.92 | n/a |
| 9 | handle_bar_large | 13.04 | 5.7 |
| 10 | handle_bar_small | 16.78 | 10.37 |
| 11 | handle_cup_handle | 3.21 | 0.04 |
| 12 | handle_drop_pull | 27.99 | n/a |
| 13 | handle_flush_pull | 0.80 | n/a |
| 14 | handle_lever | 12.38 | 15.71 |
| 15 | handle_pull | 9.40 | 1.03 |
| 16 | knob_rotate_round | 29.08 | 23.01 |
| 17 | knob_static | 16.34 | 2.26 |
| 18 | switch_rocker_multi | 14.31 | 23.50 |
| 19 | switch_rocker_single | 1.53 | 2.02 |
| 20 | switch_toggle_multi | 31.36 | 64.21 |
| 21 | switch_toggle_single | 10.52 | 36.20 |
| average | | 18.85 | 14.86 |

Table 4: Breakdown results of our inaccessible-object detector on AccessDB validation set and AccessReal. Performance is measured by AP for each inaccessibility class. AP metrics on AccessDB are generally higher than AccessReal, showing a reasonable domain gap. Yet, on some inaccessibility classes such as switch_toggle_single and switch_toggle_multi, AP metrics on AccessReal are higher, presumably because images of AccessReal are higher in resolution that these small inaccessible objects are clearer and easier to detect than AccessDB images.

detector started overfitting to AccessDB, resulting in the lower mAP (13.36) for AccessReal. Even though AccessDB and AccessReal both contain real-world indoor images, we could still see the domain gap between the two as the detector shows about 4 less mAP. We attribute this performance difference, in part, to the significantly higher resolution of images in AccessReal, which poses a challenge for a detector primarily trained on smaller images. Furthermore, AccessDB inherently exhibits a long-tailed distribution in terms of class counts (Detailed breakdown of the number of classes is described in Table 3). This distribution presents an additional challenge to the detector, particularly when recognizing classes with a relatively small number of objects, which may not provide sufficient data for the model to learn distinctive visual features. Despite the challenges, visual results created by our detector (Figure 13) showcase its ability to perform well on high-resolution indoor images. In the zoomed regions of Figure 13 (second and fourth images), results show that the detector successfully recognized our interested objects, including knob_rotate_round, faucet_handle_lever, electric_outlet, and handle_bar_small. Table 4 provides a breakdown of mAP for each inaccessibility class. The average mAP indicates that, as a whole, the detector performs better on AccessDB compared to AccessReal. However, it's worth noting that the detector exhibits superior performance on AccessReal for certain classes, such as switch_toggle_multi, switch_toggle_single, and handle_lever. We hypothesize that for these classes, AccessReal may offer clearer object representations or exhibit fewer visual variations, possibly due to its smaller sample size, thereby contributing to improved detection accuracy.

| | mAP | AP₅₀ | AP₇₅ |
|------------|------------|------------------------|------------------------|
| AccessDB | 18.85 | 33.41 | 19.03 |
| AccessReal | 14.86 | 28.24 | 11.55 |

Table 5: We evaluate our inaccessible-object detector (based on the RetinaNet architecture [36]) on the validation set of AccessDB, and the AccessReal (as the testing set). Quantitative results show a clear domain gap between the two datasets; visual results in Figure 13 demonstrate that our detector (trained on AccessDB’s training set) can detect inaccessible objects quite well in AccessReal, representing modern indoor scenes.

AccessReal dataset after around 51 epochs, yielding an mAP of 18.85 for the validation set and 14.86 for the test set. Additional performance metrics are provided in Table 5. AccessDB validation set showed the best mAP (19.86) at epoch 61, but after 51 epochs the