# Chapter 2

# Review of Related Literature

This chapter discusses about existing sidewalk accessibility standards, appropriate sidewalk designs, remote sensing, object detection and semantic segmentation algorithms, and crowdsourcing practices that are related to the study.

## 2.1 Urban Studies

The modern urban landscape comprised of advanced infrastructure is a sign of the times of the capabilities of today's technology. Our cities have boosted the global economy and created business capitals all over the world by bringing commerce and residency together into what our ancestors would only imagine as a utopia. The landscape of each city is unique, but one common thing among all great cities is the use of sidewalks and streets which allow its inhabitants to traverse the city itself. Aside from that sidewalks have three essential uses: safety, establishing contact among street users, and assimilating children into society (Jacobs, 1961). Keeping a city safe is the fundamental task of streets and sidewalks, and their design is what determines the whole feel of a city. Sidewalks cannot be unseen as they implicitly keep people safe by keeping them in view of other people. Often we think of law enforcement as public peacekeepers, but it is the people who occupy the streets themselves that casually enforce safety among each other. The common pedestrian doesn't usually think about the path to his destination and how each turn he makes is a question of safety. Instead, he trusts that these sidewalks will keep him safe either because of past experience using these streets, or the feel of the sidewalk itself which had been designed by urban planners who built the city. As we realize the great role sidewalks play in keeping people safe, we try to match technological advancements with furthering urban studies to take us into a new urban landscape.

Many factors go into the urban experience of an individual, so it is understandable why research in the field of urban studies is very specific. One such example is the work of Quercia et al. (2015) on the SmellyMaps project, a research into the influence smell has on our perception of places (as seen in Figure 2.1). The researchers in this project aimed to record and analyze smell data at scale by going on "smellwalks" throughout cities and also by collecting geo-tagged data through social media posts. With the data gathered, they created visualizations of the urban smellscapes in major cities such as Barcelona and London, and they validated this data with government air quality indicators. They then supported the significance of the study by citing scientific explanations of the impact of smell to human behavior, attitude, and health. Despite this importance, smell as a factor in urban planning has been severely overlooked, just like many other factors that can go into the optimal development of a city.


Figure 2.1: Smelly Maps - Mid-level notes of urban smell for London. This was lifted from Quercia et al. (2015).

.

Smell is definitely important in providing a pleasant city experience, but a recurring problem in cities all over the world is how accessible a city may be for one trying to get around it, especially if that person is physically limited by their disabilities. Manaswi Saha is one pioneer leading the way in accessible technology by providing new tools to gather data on urban accessibility. She is developing a suite of tools to address these issues while documenting her research of crowdsourcing, street view imagery, geo-visualization, and narrative visualization techniques that will hopefully provide the field with a deeper understanding of urban accessibility.

If we do aim to address urban accessibility issues, we should start with addressing them for PWDs who are the most affected by this situation (Harkin, 1990).

A significant part of urban accessibility has to do with sidewalk design and purpose. A good design for a sidewalk is one where a person with disability (PWD) can safely cross a street or make use of public transportation (AYRES, 2017). Governments in many different countries author bills which mandate sidewalks to be designed in an accessible manner. Urban planners should take this into account when designing new urban locations to prevent additional costs needed for reconstruction and adjustments. Architectural firm, Ayres Associates, mentions certain factors which go into the design of new sidewalks including placement, compliance with local laws, width, drainage, and driveway design. Because of the role sidewalks play in our society, specific measures must be put in place to ensure accessibility for all individuals. In our research, we aim to determine the level of accessibility of certain sidewalks in the Philippines, so it would be beneficial to our project to know what makes a good sidewalk. With the data we acquire from our research, we hope to create a platform where data on accessibility can easily be obtained by urban planners capable of making a significant impact on accessibility in the Philippines.

Table 2.1: Urban Studies Table of Comparison

| **Paper** | **Focus** | **Urban Data Collection** | **Purpose** |
|---|---|---|---|
| Saha (2020) | Sidewalk Accessibility and making sidewalk data easily accessible and visible to citizens and government | Branching off from Data from Project Sidewalk as well as interviews and studies with stakeholder groups | To develop tools to facilitate deeper understanding of accessibility |
| Quercia et al. (2015) | Urban Smellscapes | Used geo-referenced social media data to map locations and their smells | Introducing the positive role that smell has to play in city life |
| Jacobs (1961) | The Uses of Sidewalks in Cities | A collection of insights on urban studies gathered from years of experience of activist and urbanist Jane Jacobs | To highlight the positive and negative aspects of cities |
| AYRES (2017) | Good sidewalk design and accessibility standards | Ayres Associates is an architectural and engineering firm with their own means of data collection through market research | To educate the public on sidewalk design standards |

## 2.2 Measuring Accessibility

Accurately measuring accessibility has long been an issue in the field of urban planning and infrastructure as a universal guideline for measuring accessibility has not been established. Guidelines vary from different locations to cater to different urban landscapes and to achieve varying results, depending on the implementer of these guidelines in those specific locations. Instead of sidewalks and roadside accessibility, the roads themselves are more often the focal point of infrastructure research, even though the majority of most populations rely on public transportation and pedestrian pathways to commute to their destinations (BusinessMirrorEditorial, 2019). Despite not having a universal measure of accessibility, there are still many credible metrics from different organizations, one of them is the American Disabilities Act (ADA).

The ADA is a civil rights law which was sparked from discrimination against disabled persons, and evolved into a means of providing equal opportunity to all individuals. This was implemented by creating provisions to allow disabled persons to enjoy the same environments as able ones. The ADA 2010 Standards for Accessible Design, also known as the 2010 Standards, encompasses all the benefits and compromises required of public utilities to cater to disabled persons. The United States Department of Justice (2010) released the 2010 Standards as a metric for measuring accessibility in urban settings. It include provisions on how to properly construct facilities and public spaces to cater to disabled persons. Streets and roads which have curbs should have curb ramps at any intersection to allow PWD's to smoothly traverse through a connected network of roads to get from one place to another. Assembly areas such as stadiums and auditoriums should have wheelchair spaces, and all public facilities should have accessible amenities such as handicap-friendly restrooms, drinking fountains, telephones, and alternate routes for disabled persons. The 2010 Standards are still the basis for sidewalks constructed post-2019, and must adhere to the ADA provisions regarding sidewalk width, slope, curb ramps, and surface texture, summarized by ADA Solutions (2020). The ADA is a credible source for sidewalk accessibility in the United States, and in the Philippines the National Council on Disability Affairs (NCDA) is in charge of implementing the rules and regulations which adhere to the *Batas Pambansa 344* (BP344), or the accessibility law of the Philippines.

The National Council on Disability Affairs (n.d.) have created the implementing rules and regulations (IRR) of the accessibility law which, much like the ADA 2010 standards, enumerates the minimum requirements needed for public buildings, facilities, and utilities to be accessible for disabled persons. The minimum requirements for accessibility are stated in Rule II of the IRR under the design criteria section which covers anthropometrics, the measurement of human individuals, with the consideration of wheelchairs in those measurements as a guide for designing public facilities. Using anthropometry is unique to the IRR of BP 344 compared to other accessibility metrics, and is most likely included here to address the high population density of major cities in the Philippines. This section of the IRR also mentions that no group of people shall be deprived of full participation in a physical environment, and facilities must provide complete accessibility, reachability, and usability to all persons. Although these three measures are not explained in depth in the IRR, they imply a similar goal to the ADA which is to provide equal opportunity and access to all persons. Curb ramps and audio-visual aids are a requirement at every pedestrian crossing, adding further to the metrics which fall under the design criteria section of the IRR. Aside from the NDCA, the Metropolitan Manila Development Authority (MMDA) (2002) have also created their own set of guidelines on the clearing of sidewalks and streets of obstructions to pedestrian travel in Resolution 02-28, series of 2002. The directives in this resolution indicate the strict removal of all street and sidewalk structures including makeshift stalls, basketball courts, and other illegal structures. These obstructions are a threat to the accessibility of disabled persons because they unexpectedly impede the movement of PWD's throughout cities, even if the public facilities around them comply with the IRR of BP 344. These rules are implemented in order to effect the smooth flow of traffic, persons, and goods throughout Metro Manila.

The fundamental role of sidewalks in cities is to keep its individuals safe and the design of the sidewalk determines the overall feel of the city. In the eight principles of the Sidewalk, Santos (2018) highlights design principles which help create more active cities. The eight principles are *proper sizing*, *quality surfaces*, *efficient drainage*, *universal accessibility*, *secure connections*, *attractive spaces*, *permanent security*, and *clear signage*. Majority of these eight principles are seen being implemented in both the ADA and in Philippine regulations such as the relation between proper sizing and anthropometry, the relation between clear signage and audio-visual aids in pedestrian crossing, and the principle of universal accessibility being the focal point of all accessibility guidelines covered. Of those principles which have not been extensively covered by other readings, secure connections and quality surfaces are the most relevant to measuring accessibility. Secure connections refer to the integration of sidewalks with larger transport networks, and PWD's see this in curb ramps and curb extensions which allow them to use streets without coming into contact with the traffic. The ADA 2010 Standards glosses over creating a network of travel by placing sidewalks in appropriate locations. The quality of surfaces is also vital in creating accessible sidewalks as surfaces should be slip-resistant in any weather, and the surface shouldn't snag on any mobility equipment such as wheels, walkers, or canes. The surface should be even and absent of irregularities to ensure the safety of the pedestrians walking on it.

Table 2.2: Measuring Accessibility Table of Comparison

| **Paper** | **Focus** | **Accessibility Measures** |
|---|---|---|
| BusinessMirrorEditorial (2019) | Private and Public Transportation | Statistics on the economy of the ownership of private cars compared to those who take public transportation |
| United States Department of Justice (2010) | The 2010 ADA Standards for Accessible Design | Highlights the accessible design section of the ADA including technical requirements for public spaces and facilities |
| ADA Solutions (2020) | Designing Accessible Sidewalks | Provides specific metrics and properties for sidewalk accessibility such as width, slope, surface texture, etc. |
| National Council on Disability Affairs (n.d.) | Implementing Rules and Regulations of the Accessibility Law of the Philippines | Contains a design criteria section covering accessibility, reachability, usability |
| Metropolitan Manila Development Authority (MMDA) (2002) | Resolution 02-28, series of 2002 - the removal of street obstructions which restrict movement | Discusses the presence of obstructions in sidewalks which are a hindrance to accessibility |
| Santos (2018) | Proper sidewalk design to build active cities | Physical structure of the sidewalk and its surface, sidewalk connections to other sidewalks, other design principles |

## 2.3 Remote Sensing

Remote sensing is defined as the process of detecting and monitoring physical characteristics of an area by measuring its reflected and emitted radiation at a distance. It is the use of sensors to capture images on the Earth's surface to gather information of large geographical areas without the need to be physically present at the location (USGS, 2020).

Remote sensing technologies such as drones, aircrafts, and Earth orbit satellites are able to capture overhead images or top view level of the cities. However, the lack of ground-level details make it a difficult task to gather more information on the geographical area. Fortunately, the growing accessibility to different sources of geo-tagged data makes it possible to fuse remote sensing imagery with data of different modalities and observations. Google Street View (GSV) serves users with street-level panoramic imagery captured in thousands of cities worldwide, which makes it possible to observe street scenes in big cities and thus provides proximate sensing ability and ground-level details that overhead images lack (Cao et al., 2018). The images obtained from remote-sensing instruments are still considered to be raw. For this reason, the images must undergo an analysis in order for users to extract comprehensive information from the data.

Analysis of remote-sensing data involves the identification of various targets inside an image in order to extract useful information about them. Targets inside an image include features such as points, lines, or an area in the image. A target must also be distinguishable and contrast with the other features in the image. These features can be used to shape out objects inside an image. Objects provide valuable information that can help contextualize the image. For example, autonomous vehicles classify several objects to understand whether it must continue to drive or to stop. These objects may be cars, road lanes, road blocks, traffic signs, or obstructions on the road.

Remote-sensing data can be analyzed manually by a human interpreter. Interpreters can easily identify objects and contexts inside an image due to the inherent intelligence of human beings. Project Sidewalk is an example study that made use of human volunteers to collect data on city streets (Saha et al., 2019). By virtually walking through the city in Google Street View, the volunteers were tasked to remotely label pedestrian-related accessibility problems such as curb ramps, missing curb ramps, obstacles, and surface problems (as seen in Figure 2.2). Through this crowdsourcing approach, their study has contributed to the collection of sidewalk data as 205,385 labels and 2,941 miles of Washington DC streets had been labelled in an 18-month deployment study.

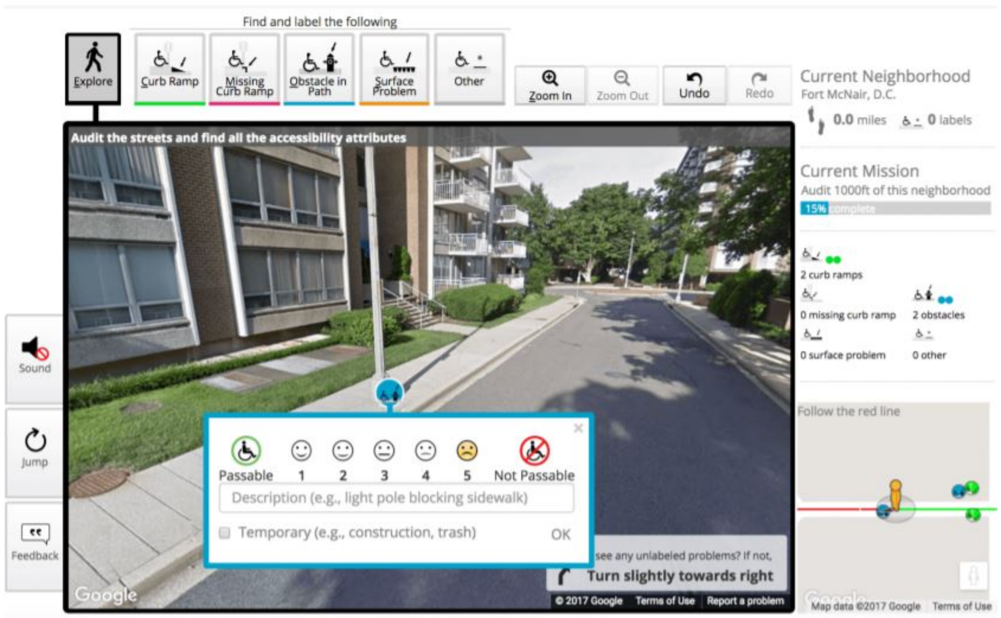


Figure 2.2: Project Sidewalk's crowdsourcing tool to label pedestrian-related accessibility problems such as curb ramps, missing curb ramps, obstacles, and surface problems. This is lifted from Saha et al. (2019).

However, using human interpreters to analyze remote-sensing data is time-consuming with the amount of data to be analyzed and the speed limitations of a human being. Because of this, machine learning has been explored as an efficient alternative for image analysis. The strengths of machine learning include the capacity to handle data of high dimensionality and to map classes with very complex characteristics (Maxwell, Warner, & Fang, 2018). Through the introduction of artificial intelligence (AI) in remote sensing, we can remove the manual efforts of human crowdworkers. An AI-assisted approach in remote sensing uses a workflow where a model has the ability to learn without the help of human interpreters. This allows for objects in images to be classified and detected through computer vision related tasks. Some of these tasks include image classification, object localization, object detection, and semantic segmentation.

Image classification is a process that involves predicting the class of one object in an image. It categorizes the entire image into a class such as *"people"*, *"animals"*, or *"outdoors"*. Object localization refers to identifying the location of one or more objects in an image an drawing a bounding box around them. Object detection combines the tasks of both image classification and object localization to detect and classify one of more objects in an image (Brownlee, 2019). Object detection algorithms are used to label objects in an image, similar to how a human interpreter would do the task. These techniques in computer vision are performed through various deep learning technologies.

Neural networks are often used for object localization and object detection. Sun and Jacobs (2017) trained a model to locate citystreet regions where curb ramps are missing. The researchers' model is based on a convolutional neural network that focuses on standalone context representation of a target object, similar to an object detector. Their approach includes generating a probability heat map to detect objects labelled with bounding boxes, then assigning it to a binary map where detected box regions are labelled as 0, and null box regions as 1 (as seen in Figure 2.3). Among the street view intersections in the test set, their model was able to achieve a recall of 27% when locating missing curb ramp regions using the proposed method.

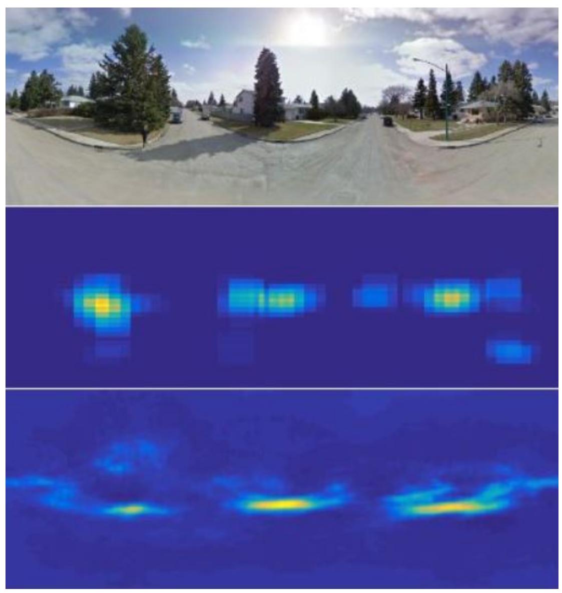

Figure 2.3: Generating a probability heat map to detect curb ramps on a raw image. This is lifted from Sun and Jacobs (2017).

In contrast, Weld et al. (2019) developed a model using Residual Neural Network (ResNet-18) capable of automatically validating and labeling curb ramps, missing curb ramps, obstructions, and surface problems on Google Street View images. The purpose of their auto-validation task is to validate the annotations of crowdsourced workers provided with a pre-cropped image around a human-supplied label, while the auto-labeling task searches through an entire panorama attempting to find and classify accessibility problems. The researchers claim that their model performed better than the convolutional neural network model built by Sun and Jacobs (2017) for detecting missing curb ramps, with their ResNet-based neural network achieving 58.6% recall compared to the 27.0% recall of the convolutional neural network model. The researchers also stated that by adjusting their hyperparameter, the automated system is able to perform as good as human labelers when it comes to labeling objects located on the street image.

On the other hand, the YOLO or “You Only Look Once” model family is a state-of-the-art computer vision model used to detect objects in real-time. The model uses a single neural network trained end to end that takes a photograph as input and predicts bounding boxes and class labels for each bounding box directly. In the context of collecting street data, Majidifard et al. (2020) were able to develop a deep machine learning approach to predict pavement condition of asphalt-surfaced roadways. Using a YOLOv2 model, their model detected and classified nine types of pavement distresses (as seen in Figure 2.4). Their findings are useful in the development of pavement condition models and crack detection methods. Sidewalk pavements that contain cracks can affect how accessible an area is towards pedestrians, especially for wheelchair users.

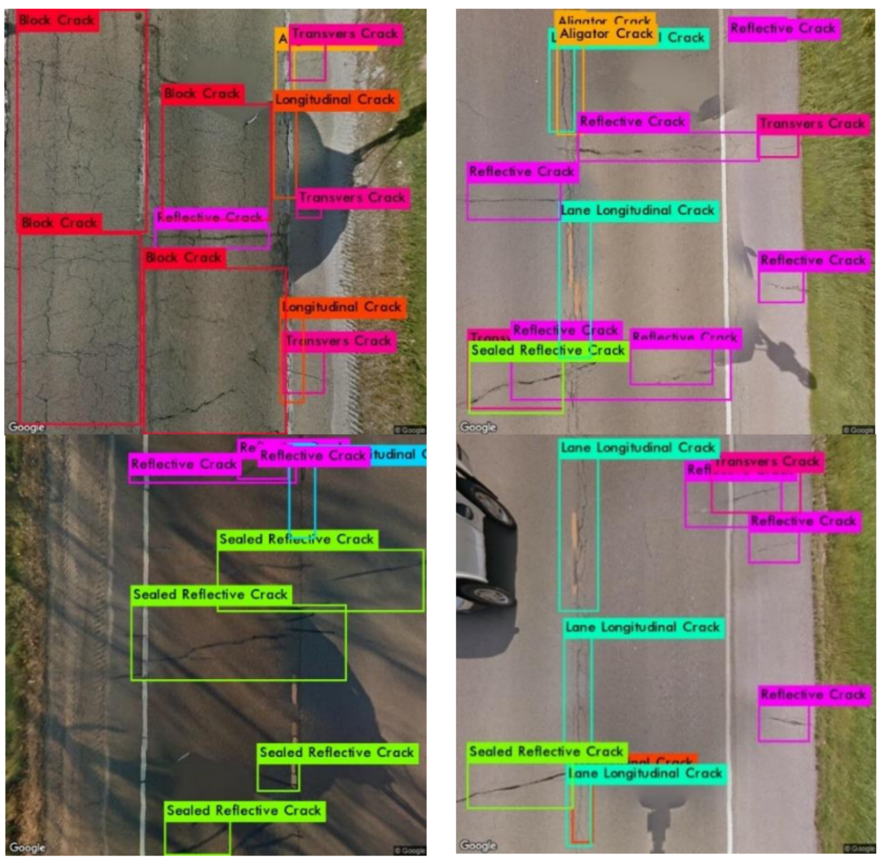


Figure 2.4: YOLOv2 used in detecting pavement distresses. This is lifted from Majidifard et al. (2020).

Another process involved in computer vision is semantic segmentation, which classifies all the pixels of an image into meaningful classes of objects. For instance, all the pixels of an object in an image could be isolated and assigned with a specific color. In the context of urban studies, a study conducted by Naik et al. (2016) used semantic segmentation techniques in establishing a connection between the physical appearance of cities and the socioeconomic status and safety of its inhabitants by quantifying street view images. The researchers developed a model named Streetscore, which segments objects located on images using a Geometric Layout algorithm that allows the classification of regions of an image into four different categories: Ground, Building, Trees, or Sky. From the results of their study, cities with more population and lesser overall area are perceived to be safer than cities with low population and large areas (as seen in Figure 2.5). Their findings suggest that streets which are densely populated with buildings are perceived to have higher income residents and higher safety.

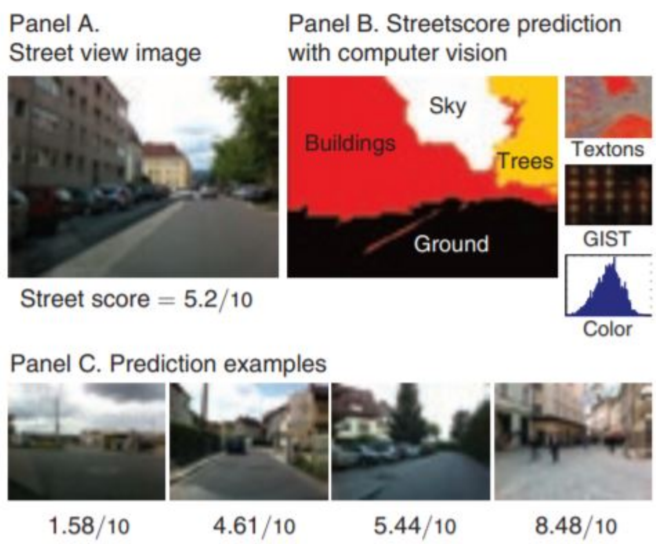


Figure 2.5: Streetscore using semantic segmentation in quantifying street view images on its overall safety. This is lifted from Naik et al. (2016).

With the approach of using AI-assisted for remote sensing, it has removed the efforts of humans having to manually label objects on the image. However, a challenge of the AI-assisted approach is that there is no feedback loop between the human and the model. It does not offer an option to validate results of the model where it can learn and perform better when given more data. With this, a hybrid (human-guided) methodology framework can be used in remote sensing. It is similar to an AI-assisted approach, but it includes a bi-directional feedback loop from humans to validate the results of the model. This allows them to guide and fine-tune the results, correcting its predictions and labels to improve how it should respond to data (Robinson et al., 2020). The presence of a feedback loop between the human interpreter and the computer vision model allows it to work much more efficiently than workflows that require crowdsourcing.

A research that made use of a hybrid approach is Tohme, which is a project conducted by Hara et al. (2014) focused on finding curb ramps remotely through Google street view image by using two modes of data interpretation. The project introduced a system that used a human labeling approach, and a computer vision labeling approach with human verification to compare the performance of both methods. Tohme used a machine learning workflow scheduling algorithm to predict poor performances from the computer vision classifier and route these images to human labelers. The algorithm was able to identify about 86.3% of the failures of the computer vision classifier and assign them to human labelers for verification. With the use of the computer vision classifier and the machine learning workflow schedule algorithm, Tohme performed similarly to the human labeling approach, with curb ramp detection results of 84% accuracy compared to the 86% accuracy of the latter. Tohme also reduced time consumption by 13% which is a large improvement from the human labeling approach.

With all three approaches mentioned for remote sensing, following the hybrid approach would be the most ideal for our research. It has been proven to perform better than workflows that only make use of crowdsourcing to gather data, as the crowdsourcing approach heavily relies on resources and manpower. It also yields to more desirable results compared to AI-assisted remote sensing with the presence of the feedback loop between the human and the machine. The feedback of the human for verification allows the correction of the models' predictions and labels, improving the way it responds to data.

Table 2.3: Remote Sensing Table of Comparison

| Paper | Source of Data | Types of Data Collected | Machine Learning Model/s Used | Purpose | Results |
|---|---|---|---|---|---|
| Sun and Jacobs (2017) | Google Street View | Missing Curb Ramps | Convolutional Neural Network / Siamese Neural Network | Predict missing curb ramp regions in street view images | Missing curb ramps in GSV panoramas and achieved a 27% recall (precision is not reported). |
| Hara et al. (2014) | Google Street View images, Crowdsourcing | Curb Ramps | Support Vector Machine | Using CV and ML to automate and reduce data collection cost. | Their model performed similarly to a human labeling approach, with curb ramp detection results of 84% accuracy compared to the 86% accuracy of the latter. Tohme also reduced time consumption by 13% which is a large improvement from the human labeling approach. . |
| Saha et al. (2019) | Google Street View | Curb ramps, missing curb ramps, obstacles, and surface problems. | N/A | To label sidewalk accessibility issues | 205,385 labels and 2,941 miles of Washington DC streets had been labelled in an 18-month deployment study. |
| Naik et al. (2016) | Google Street View images | Streetscapes | Support Vector Machine | Using CV to establish a connection of physical change and socioeconomic characteristics of neighborhoods | Their findings suggest that streets which are densely populated with buildings are perceived to have higher income residents and higher safety. |
| Weld et al. (2019) | Project Sidewalk's open dataset | Image-based sidewalk accessibility labels | Residual Neural Network | Automatically validating crowdsourced labels and automatically labeling sidewalk accessibility issues | In detecting missing curb ramps, their model performed better than (Sun & Jacobs, 2017), with their ResNet-based neural network achieving 58.6% recall compared to the 27 % recall of latter. |
| Majidifard et al. (2020) | Google Street View images | Pavement condition / Road cracks | YOLOv2 | To classify and locate pavement distresses on roadways | Across the nine types of pavement distresses, the model performed an average precision of 93%, average recall of 77%, and an average F1 score of 84%. |

## 2.4 Crowdsourcing

This section presents works that focus on the usage of crowdsourcing to gather data on urban roads.

Kietzmann (2016) defines crowdsourcing as "*the use of IT to outsource any organizational function to a strategically defined population of human and non-human actors in the form of an open call.*" Crowdsourcing can be used in rapidly acquiring data with the use of volunteers and paid workers. In the next paragraphs, we state how crowdsourcing has influenced contemporary studies on location based data gathering and its relevance to our research.

Project Sidewalk used crowdsourcing to annotate sidewalk accessibility data in a street exploration environment as seen in Figure 2.6 (Saha et al., 2019). The project enlisted the help of volunteers and paid crowdworkers in contributing to their data. It also applied gamification techniques such as on-boarding, guided missions, and making the process intuitive for users to train crowdworkers and improve the quality of their data. In its 18-month deployment study, Project Sidewalk successfully labeled 205,385 geo-referenced tags on sidewalk accessibility with the help of 797 users. In relation to our project, we would like to integrate the idea of Project Sidewalk in training crowdworkers.

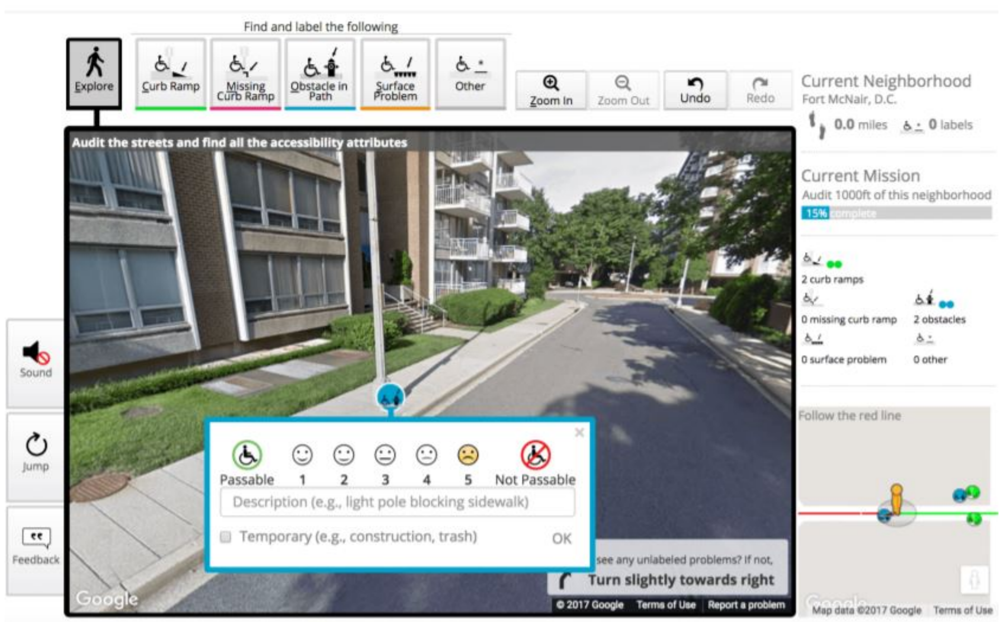


Figure 2.6: Project Sidewalk's crowdsourcing tool to label pedestrian-related accessibility problems such as curb ramps, missing curb ramps, obstacles, and surface problems. This image is taken from (Saha et al., 2019).

Bolten and Caspi (2019) created a customized online map routing service for pedestrians with mobility problems called *AccessMap* (as seen in Figure 2.7). The application was an open source, city-scale, and interactive website, based on open data. AccessMap reported to have 500 to 1,000 unique monthly users. It gathers and transforms data from open data sources such as open municipal data sources, OpenStreetMap and the USGS. The crowdsourcing aspect of the research stems from user behavior tracking the researchers applied to measure the usefulness of the platform. The research also concluded with the recommendation of fine-tuning accessible routes by looking into user behavior tracking to further quantify accessibility. To relate with our project, the aspect of using user behavior is a great insight in improving the quality of data we will be generating.

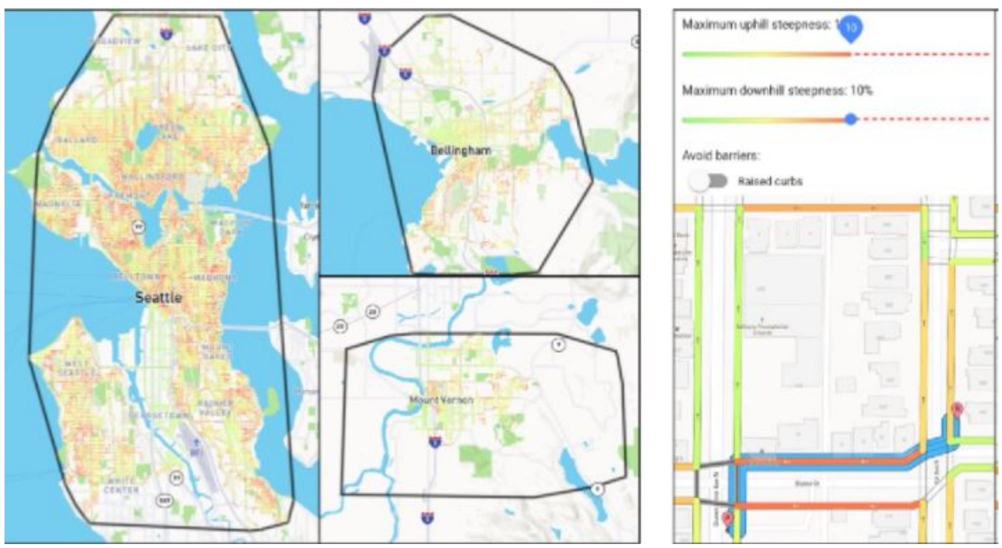


Figure 2.7: AccessMap, a customized online map routing service for pedestrians with mobility problems. This is lifted from Bolten and Caspi (2019).

Lastly, Mobasheri et al. (2017) created *Wheelmap* that maps points of interest for wheelchair accessibility (see Figure 2.8). Wheelmap relied on accessibilities community to crowdsource their data. The researchers created a standard web interface, an Android app, and an iOS app to allow users to tag locations as accessible, partially accessible, and not accessible. With this, Wheelmap has created the most extensive database on wheelchair accessible places, with more than 800,000 entries as of 2017.

In retrospect, three key factors are crucial in building a successful crowdsourcing platform: *scalability*, *availability*, and *data quality*. First, crowdsourcing platforms should be able to scale. When working with geospatial data, it is important to ensure that we use the standard or open data such as OpenStreetMaps. In addition, the platform should be able to handle expansive growth. Second, the

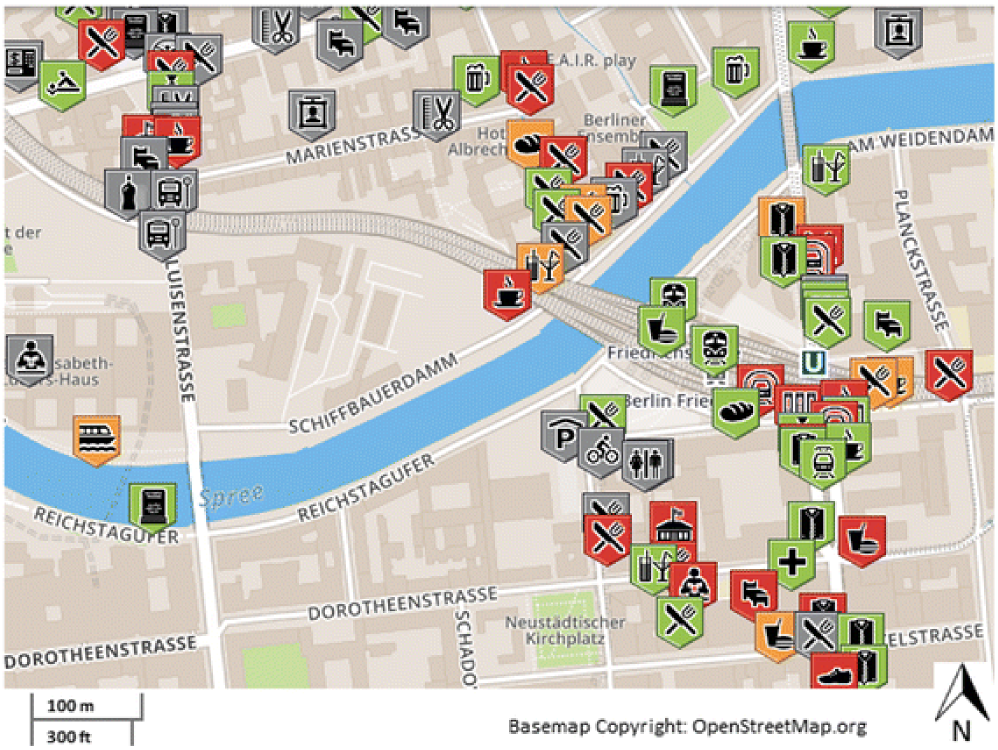


Figure 2.8: WheelMap, an online map that maps points of interest for wheelchair accessibility. This is lifted from Mobasheri et al. (2017).

platform should be available in different platforms, such as web, iOS and Android. The availability of the platform depends on how well we integrate and connect to crowdworkers. Lastly, quality assurance of the collected data can be done through proper training of crowdworkers and ensuring ease of use. Applying the techniques mentioned above, such as on-boarding, gamification, and behavior tracking, may be useful in getting quality data.

In summary, crowdsourcing is not relatively new in gathering data for urban infrastructure and location mapping. As seen in Project Sidewalk, AccessMap, and Wheelmap, crowdsourcing has been used to tag data with regards to accessibility problems and often ignored features of urban development data. Moving forward, these studies will serve as our benchmarks in building a crowdsourcing platform. The crowdsourcing concepts mentioned previously are things that we plan to take into account during our system design.

Table 2.4: Crowdsourcing Studies Table of Comparison

| **Paper** | **Focus** | **Participants and data collected** | **Medium for collecting data** |
|---|---|---|---|
| Saha et al. (2019) | An open-world exploring tool that allows users to annotate sidewalk accessibility data | 205,385 geo-referenced tags on sidewalk accessibility with the help of 797 users | Standard web interface |
| Bolten and Caspi (2019) | Online map routing service for pedestrians with mobility issues | 500 to 1000 unique monthly users. They used open data for maps and tracked user behavior | Mobile web interface |
| Mobasheri et al. (2017) | Map for wheelchair-accessible places | 800,000 entries | Standard web interface, Wheelmap-android, Wheelmap-iphone |