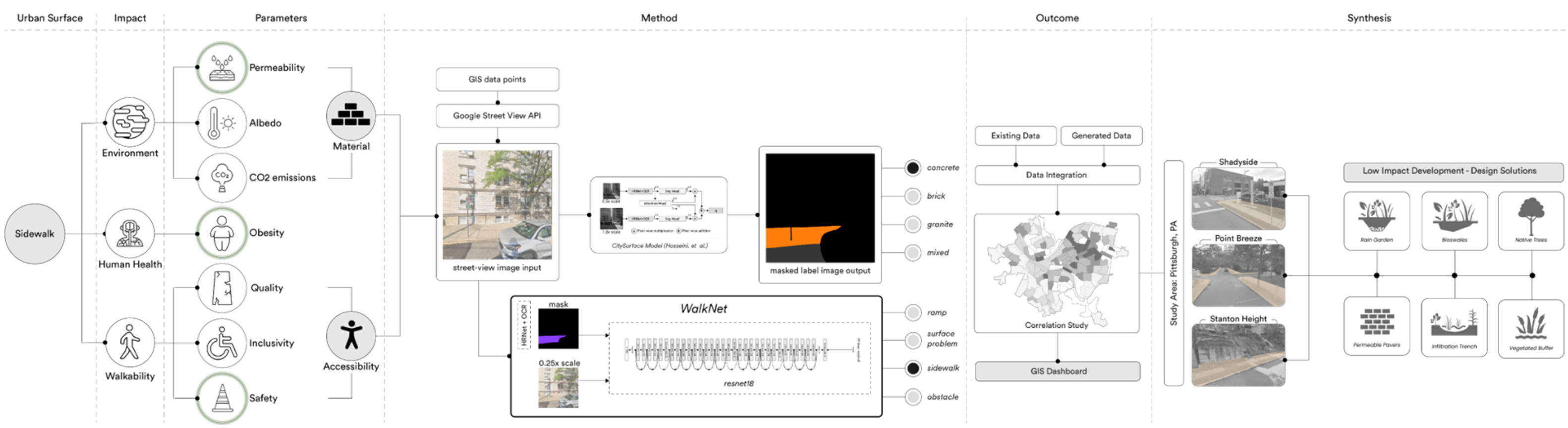
Pixels To Pavement

Analyzing City Sidewalks Using Deep Learning and Vision-based Frameworks for Data-driven Solutions in Urban Planning



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2. Abstract

City sidewalks have a significant impact on the social and environmental aspects of urban life. Unfortunately, due to the high cost and time-consuming nature of data collection and evaluation, cities lack records of their sidewalks at street level and census-tract granularity. In fact, only 34% of cities offer data on sidewalks and even fewer on other forms of pedestrian and accessibility infrastructure such as crosswalks, curb ramps, and sidewalk gaps. This lack of data hinders research on city sidewalks, limiting our understanding of their current conditions and spatial distribution.

To address this issue, recent research aims to demonstrate the viability of an automated methodology that integrates deep learning, computer vision, and geospatial processes. This methodology utilizes openly available street-level images to classify sidewalk surface data, such as material, accessibility, and quality. The objective is to employ deep learning models to classify pavement materials and detect the presence of open green covers around sidewalks. The study also developed a multi-label classification model to classify accessibility parameters. This model was trained on a set of manually labeled data from Pittsburgh, Seattle, Oradell, and Newberg. Various metrics, including mean IoU, F1 score, accuracy, precision, and recall, were used to evaluate the model's predictive accuracy.

The research offers several results, including generating a scalable and generalizable workflow to automate data extraction from street-level imagery, conducting a preliminary correlation study between sidewalk surface data, environmental factors, and human health and safety factors, and developing an interactive mapping tool with an open dataset. This mapping tool can aid researchers, governments, and the public in finding better policies and strategies contributing to the sustainable development of cities.
By providing explicit and extendable methods to gather city surface data, this research provides urban analysts and city planners with the necessary information to address urban sustainable development concerns and promote data-informed planning and design development.

Keywords: urban surfaces, sidewalk, sustainable development, pedestrian safety, health, semantic segmentation, deep learning, computer vision, urban analytics, geographic information systems

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6. Abbreviations

API: Application Programming Interface
CV: Computer Vision
CNN: Convolutional Neural Network
DL: Deep Learning
GIS: Geographic Information System
GSV: Google Street View
IOU - Intersection over Union
LID: Low-impact Development
ML: Machine Learning
OSM: Open street map
SUDS: Sustainable Urban Drainage System
UHI: Urban Heat Index

7. Definitions

Computer vision: Computer vision lies within the field of artificial intelligence with the aim of interpreting and understanding the world using digital images and videos from cameras.

F1-score: A metric to measure the accuracy of test data on DL models. The F1 score is computed using precision and recall of the test. Appendix 14.1. It contains the formula to compute the metric. The metric is generally considered to be most useful when the dataset is unbalanced, i.e., when one or two more classes represent the majority of the dataset, and there aren't enough examples of other classes to model to learn better.

Precision-Recall: Precision and recall are performance metrics applied to data results from training DL models. Precision is computed to measure quality, and recall is computed to measure quantity. A high precision value indicates that the model performed well and returned more relevant results than irrelevant ones. Recall is computed to measure quantity. A high recall value refers to most of the relevant results (whether or not irrelevant ones are also returned). Refer to Appendix 14.1. for a pictorial representation of precision-recall and the formula to compute them.

Sustainable development: According to the 1987 Bruntland Commission Report, sustainable development is described as the "development that meets the needs of the present without compromising the ability of future generations to meet their own needs."

Semantic image segmentation: It is a computer vision task used to divide an image into distinct regions based on the meaning of each pixel. i.e., Each pixel in the image is assigned a label based on what they represent. As a result, dividing the image into semantically meaningful parts.

Sidewalk Network: A network of routes a pedestrian can take while staying on a sidewalk or using the crosswalk.

Street-level imagery: A virtual representation of our surroundings. For example, google street views show built environments.
Discontinuity in Sidewalk Network: Gaps in sidewalk networks where sidewalks could have existed that force pedestrians to take significantly longer routes. Significant discontinuities can lead to the alienation of neighborhoods from the rest of the city.

Urban heat island effect: When an urban area is significantly hotter than its surrounding areas due to surface material, quality, and/or human activities.

Urban surfaces: Urban surfaces refer to all the surfaces that physically and morphologically characterize the built space. They provide critical benefits to the environment n the form of rainwater retention, controlling surface temperature, and also human health and quality of life. They can be broadly divided into 4 categories: streets and sidewalks, roads and parking lots, roofs, and building facades.

8. Introduction

8.1. Background

By 2050, it is estimated that more than 6 billion inhabitants will be living in urban environments. (United Nations, Department of Economic and Social Affairs 2015). This massive urbanization will accentuate various energy and environmental issues. Multiple research works have established a direct link between urban development and climate change, such as deluges and extreme air temperatures. Similarly, the impact of sidewalks on climate, particularly in urban areas, can be significant. According to the United States Environmental Protection Agency (EPA), pavement and other hard surfaces cover approx. 40% of urban areas contribute to the urban heat island effect, which can lead to increased energy consumption for cooling surrounding buildings, increased air pollution, and heat-related illnesses. Additionally, urban surfaces like streets and sidewalks can contribute to urban flooding by preventing the absorption of rainwater into the ground, leading to runoff that can overwhelm stormwater systems. Here, the urban surfaces, their material characteristics, and their use case play a vital role in sustainable development.

The terminology 'urban surface' represents all surfaces (vertical or horizontal) that have physically and geomorphologically characterized the built environment from thermal and hydrological perspectives while hosting several other functions. The urban surfaces directly influence the social and health quality of human life in urban areas. The two key characteristics of surface materials, reflectivity, and permeability, are responsible for environmental issues such as the urban heat island effect and rainwater runoff. The reflectance to solar radiation, known as the albedo of material, when low, will absorb the solar radiation, which increases the surface temperature and surrounding air temperature. The increase in the air temperature affects outdoor thermal comfort, which in turn impacts human health and also increases building energy demands for cooling. Additionally, low material permeability leads to high chances of flood risks and rainwater runoff.

Rapid urbanization has led to the increased use of impermeable and non-reflective urban surfaces and the consequential reduction in the number of open green spaces. Multiple strategies have been explored to mitigate the challenges related to urbanization and the correlated effects of serious environmental degradation and loss of urban biodiversity. A study by the University of Maryland found that replacing 30% of paved surfaces in a city with green infrastructure could reduce peak runoff by up to 54%. Manufacturing the cement that goes into sidewalks, driveways, and other structures accounts for about 8 percent of global carbon emissions, according to one estimate (Leah et al. 2019). This research work proposed believes that the material design of urban surfaces plays an important role.

Figure. 1. Statistics on Sidewalk Infrastructure

In addition to the challenges around evaluating the impact of sidewalk surfaces on the environment, there are also unresolved issues regarding accessibility data. These include the identification and mapping of sidewalks, ramps, crosswalks, and surface problems. Despite the growing demand for accessible infrastructure, many areas still lack comprehensive data on the availability and condition of these critical features. As a result, it can be difficult to accurately assess the accessibility of different locations, which can present significant barriers to individuals with disabilities. The presence or absence of sidewalks can have social and mental health effects on the communities in the surrounding areas. Regions disconnected from a city's sidewalk network end up being isolated from other areas and are only reachable by cars. This compels residents to depend on vehicular transportation and discourages them from venturing out of their homes to socialize in their community. As a result, community social interaction decreases, which is associated with an increased incidence of mental health issues. The same holds for areas where the sidewalk network is not maintained. Addressing these issues is crucial to ensuring that everyone has equal access to public spaces and infrastructure. Among all the

urban surfaces, sidewalks represent a unique case because they are used by nearly all members of society, yet data collection and communication are vastly missing.
Large-scale analysis of pedestrian infrastructures, particularly sidewalks, is critical to human-centric urban planning and design. Municipalities across the United States continue to struggle to properly allocate infrastructure spending. While 90% of cities offer data for streets in general, only 34% offer it for sidewalks and even fewer for other forms of pedestrian and accessibility infrastructure such as crosswalks and curb ramps.
Moreover, the lack of available information on sidewalks and pedestrian infrastructure isn't just frustrating for people trying to reach destinations on foot- it also means that there's no way for cities to address the gaps in their sidewalks, as there's no way for them to comprehensively assess the problem.

8.2. Related works

In recent years, urban surfaces have been recognized as key opportunities to reduce environmental impact and optimize resource efficiency rather than simply serving as cost-effective and low-maintenance infrastructure solutions. For instance, roofs offer several possibilities, such as generating electricity, collecting rainwater, and even harvesting food. Meanwhile, permeable pavers allow rainwater to seep into the soil and recharge groundwater instead of causing run-off. Recent scientific literature highlights the importance of utilizing urban surfaces comprehensively for their accessibility and in overcoming environmental challenges, moving away from designing surfaces with a single long-term goal in mind. However, the data required to perform the identified actions are lacking.

Some recent literature has attempted to address the issue of data scarcity for urban surfaces. For example, a study by MIT's Senseable City Lab, called Treepedia, measures and maps greenery in the city from a pedestrian viewpoint, while NUS's Urban Analytics Group's research on Roofpedia provides a scalable workflow to extract data on solar and green roofs. For sidewalks in particular, NYU's VIDA-Urban Team, with their research on CitySurfaces, extract information about sidewalk materials by semantically segmenting street view images, although it does not evaluate them. Tile2Net provides a scalable approach to generating sidewalk networks using aerial imagery, but qualitative and inclusive parameters of the surface remain unknown. Furthermore, many recent studies focus on qualitative analysis in assessing street space quality, walkability, semantic perception of riverscape, and pedestrian safety. The common goal among these research projects is the modular nature of the workflow that enables replication and extensibility. Despite multiple studies aimed at extracting and evaluating city surfaces, there is a gap in understanding sidewalks in a similar manner as has been done for roofs in Roofpedia or the Green View Index by Treepedia. Sidewalks are a critical component of a sustainable transportation system, yet there have been few studies conducted to understand their social and environmental impact.

8.3. Significance of the research

Recent studies has revealed the importance of converting the knowledge on urban surfaces, their impact on the environment and human health, and solutions to mitigate them through actionable practices. An urban environment is governed by a myriad of factors; thus, areas at an urban scale and user scale have quite a lot of variability, and finding a direct cause for a specific issue becomes non-trivial. Therefore , research findings are currently limited in their scope to convert that critical decision into actionable practices of designing sustainable built environments through changes in urban surface quality, materiality, and functionality. To account for all these variabilities and to find patterns within them, a framework to access the missing data is required. This research thesis focuses on developing such a framework..

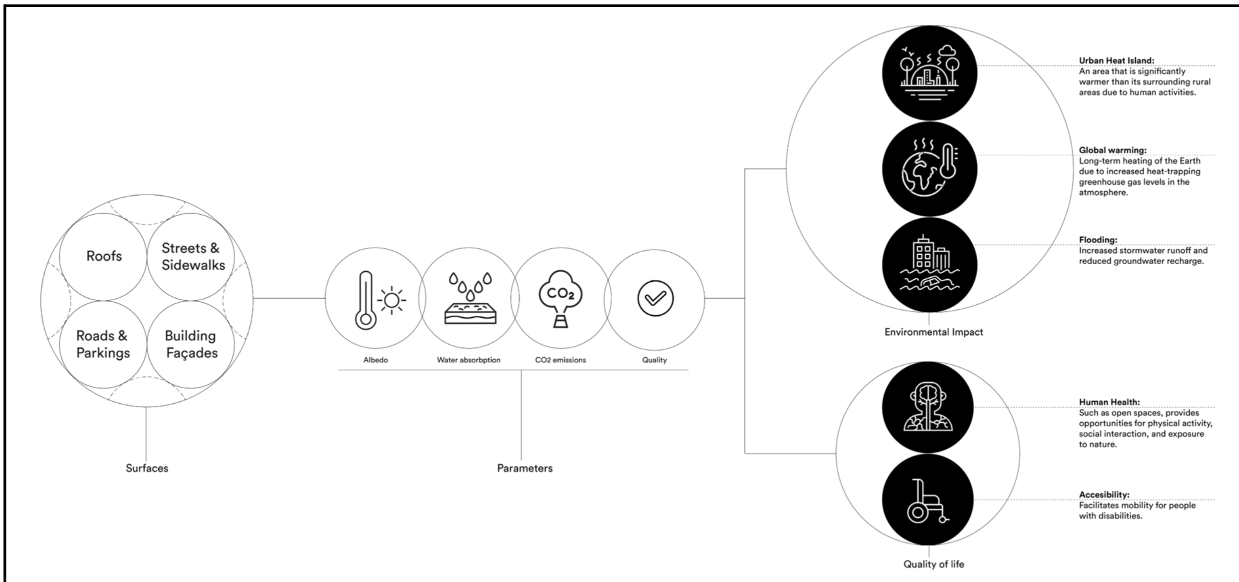


Figure. 2. Urban Surface Parameters and Impact Areas

Advancements in technology have made it possible to overcome the knowledge gap caused by data scarcity and provide a platform for ease of communication and opportunities for design translation. The spatial distribution characteristics of sidewalk materials can be beneficial in many domains of study apart from filling the data gap. For example, allow correlation study between material permeable state and flood risk rates or evaluate walkability aspects of the urban area based on width, material quality, and physical condition of the sidewalk, urban landscape quality, or even analyze elderly pedestrian safety.

8.4. Impact and contributions of the research

The thesis research will primarily focus on contributing to the following four levels of knowledge and evaluation:

1. **Decision-making Barrier:** Currently, the focus is limited to the benefits of the surfaces, which does not always translate to actionable practices because of the lack of data.
2. **Knowledge Gap:** The aim was to formulate a generalizable workflow that can be utilized to scale data development for multiple cities.
3. **Communicate Gap:** To enhance communication between stakeholders by creating an interactive dashboard that facilitates sharing data and results with city agents and for public awareness. The dashboard allows information extraction to propose sustainable design solutions.
4. **Solution Gap:** The research strived to synthesize the results and assist in design development using LID strategies for sidewalks.

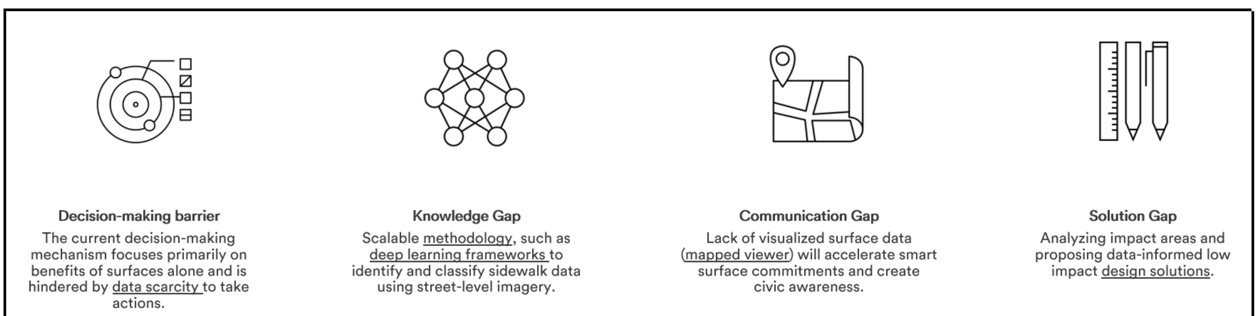


Figure. 2. Research Scope

The thesis report is structured as follows. In Section 9, the discussion on current research and state-of-the-art is elaborated to identify the gaps and develop the research question and thesis scope. Section 10 describes the methodology and its challenges in extracting, evaluating, and mapping sidewalk data in environmental, health, and safety domains. Section 11 outlines the correlational study outcomes and their usage for a wide range of audiences, such as city planners, designers, urban analysts, and the general public and highlights the design synthesis nature of the research. Section 12, discusses the limitation around the research and its future direction. Finally, Section 13 concludes the paper and briefly mentions the main contributions.

9. Literature Review

After collecting sufficient literature on urban surfaces and their impact on the environment and society, it had to be analyzed and synthesized. Hence, approximately 30 papers were organized for review.

Urban surfaces play a key role in addressing the issues arising from massive urbanization and change in the global climate as they significantly influence the quality of life and impact the environment. (Croce S, Vettorato D, 2021). Therefore, choosing the right surface material is vital to overcome various energy and environmental issues caused by increased anthropogenic activities. Sidewalks and streets cover the major part of the urban ground surfaces. Currently, impervious surface materials such as concrete and asphalt have become the pavement of choice due to their durability and low installation cost. However, these benefits came with high environmental costs. (Li, Z. et al., 2022)

The choice of surface materials significantly affects air temperature, surface-water management, and thermal comfort conditions. An increase in urban surface temperature, also known as Urban Heat Island (UHI) directly associated with the surface material's thermal performance, and its reflectivity characteristics give rise to challenges that adversely transform public well-being and urban liveability. (Du H. et al., 2017) These characteristics can also induce micro-climates within the city by absorbing heat during the day and then expelling that heat into the atmosphere later in the evening. On the other hand, green-cover and natural surfaces can reduce the prevailing temperature and create a cool island effect. Streets and sidewalk materials directly impact the surface-water/stormwater runoff capacity with the aim of reducing the risk of flooding. But with, the advent of low-cost and high longevity of impermeable materials restricts the penetration of water into the underlying soil, thereby reducing groundcover recharge and affecting the water quality. Moreover, sidewalks' quality significantly impacts multiple community health dangers, such as falling or tripping, particularly for the vulnerable population, senior citizens, and specially-abled users, or poses an obstacle to walkability and accessibility of public areas.

Despite all the environmental, public health, and safety implications of sidewalk surfaces, what truly lacks is information on the material details, location, and the existing condition of the sidewalks in most cities. The data scarcity creates a barrier to quantitatively analyzing the ecological as well as social influences of various materials and constrains our capacity to evaluate the surface's sustainability index. For instance, measuring UHI, calculating the permeable and impermeable coverage percentage for the city for correlation study with surface water management, etc. The lack of data makes it difficult to measure and analyze neighborhood variability and consequently impedes sustainable development. Studies so far have mainly relied on remote-sensing images due to the unavailability of fine-scale data, requiring analysts and researchers to combine multiple sources of data collection and extraction techniques to overcome the data gap, which can create collector bias and affect the reliability of the results. [2]

Generating fine-scale high-resolution data using conventional methods is laborious, costly, and time-consuming. Current technological advancements in data collection and generation are able to track elements at higher temporal and spatial scales. (Wu, A. et all, 2021) Moreover, street-level images for urban analytics have been a popularly rising domain focus since the beginning of GSV. [12] Together, developments in DL and CV algorithms have allowed researchers to not only automate the process but to start measuring the unmeasurable.

The proposed research will overcome one of the fundamental research gaps of data scarcity with respect to sidewalk surface materials and engage the community to respond to the conditions of their neighborhood sidewalks with the help of a framework that can generate city-wide sidewalk material information by utilizing existing and generating new urban datasets. (Hosseini, M., 2022) The research will combine deep learning techniques and computer-vision-based semantic segmentation models to categorize material data from the popularly available street-level images. (Cordts, M. et al, 2016).

Figure 5. Illustrates the literature review for this thesis and maps out individual papers to their themes to identify the gap. The diagram shows that a lot of research has been done to understand the role of urban surfaces and their impact on the environment and society, as well as correlating studies with respect to features of surfaces and qualitative aspects such as walkability, safety, and thermal comfort. With recent advances in technology, there have been studies around remote sensing data and mapping technologies. This mapping process highlighted the gap in combining these spheres of knowledge to utilize remote sensing data to map the extracted information on sidewalk surfaces. The extracted information will go beyond reporting the result and evaluating the environmental impact of that data.

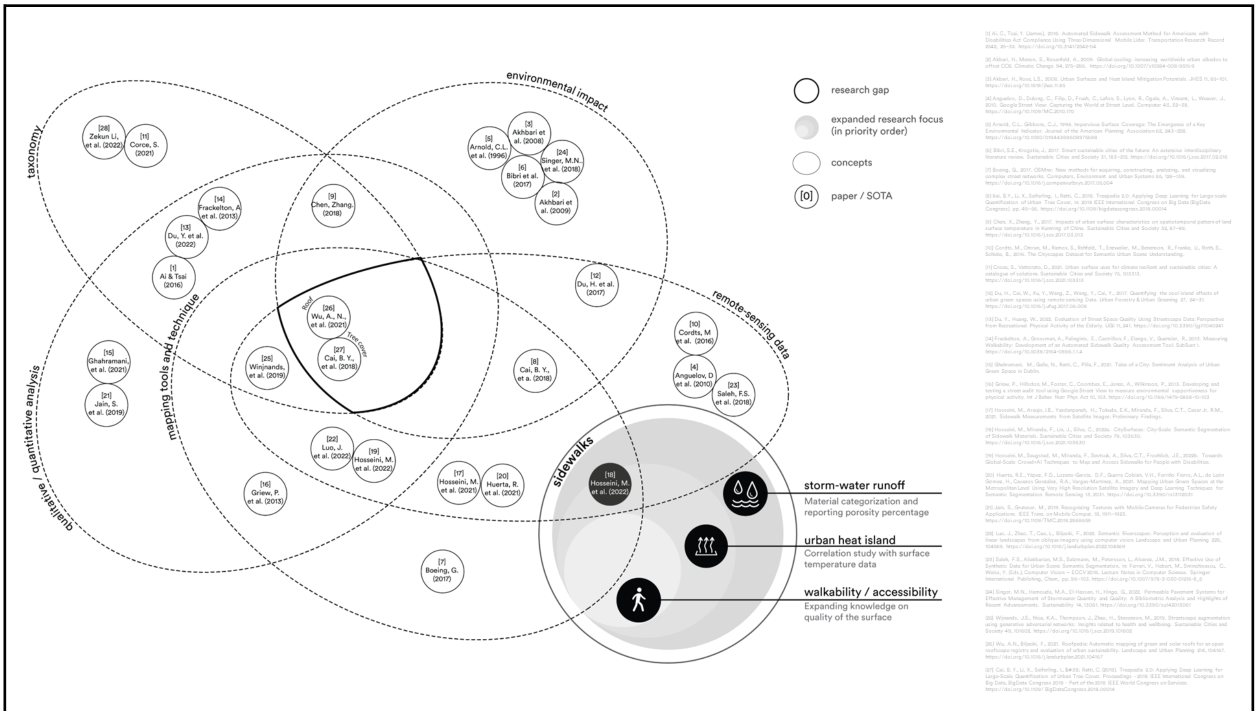


Figure. 4. Literature Review Diagram identifying the gap and scope of the research

9.1. Identified gaps in the research

Despite the increasing attention on sustainable urban development, there is a significant research gap when it comes to identifying and understanding sidewalk infrastructure. While some studies, such as the CitySurface material classification and Tile2Net network mapping from Hosseini et al., have attempted to address this issue, most of the research fails to account for the data scarcity when it comes to mapping the sidewalk infrastructure and evaluating their environmental and accessibility impact. This limitation poses a challenge for city planners, urban analysts, and designers who need comprehensive and accurate information to make critical design decisions. As such, there is a need for research that utilizes innovative methods and technologies to generate reliable and high-quality data on sidewalks, which can inform sustainable urban development strategies and enhance the quality of life for urban residents.

9.2. Research Questions

- How can recent advancements in deep learning and computer vision, and the availability in both quantity and quality of street-level imagery, provide new opportunities for cities to extract, evaluate, and map sidewalk data with a generalizable workflow?

- How can we overcome the lack of city-wide and community-wide impact analysis and visualization for sidewalk data for better communication and engagement with city decision-makers?

- Can we achieve a framework that allows scalability and generalization to include locations beyond research training/test cases with the scope of customization to address regional specificity.

10. Methodology

The purpose of the research is to develop a pipeline that utilizes openly available street-level imagery to extract, develop, and map relevant data points for analysis and correlation studies on an urban level. The focus is on creating a framework to identify and investigate the environmental and social impact of sidewalk surfaces in urban areas and using quantifiable parameters to demonstrate the pipeline's robustness in spatial data development and analysis. The research aimed to develop sidewalk surface data that incorporates information about the material porosity state, and sidewalk continuity. The ultimate goal is to then provide a reliable and efficient approach to analyze and synthesize this data. The developed data is then mapped using GIS and evaluated and correlated with climate data for evaluation.

The first task was to develop the sidewalk surface data. This involved gathering data on sidewalk material type (concrete, brick, stone, and others), its porosity state, and missing sidewalks or gaps in the sidewalk network. To obtain this data, street-level imagery was downloaded from Google Street View API at 20-meter intervals. These images were used for inference with the CitySurface's material classification model and SegFormer segmentation models to obtain sidewalk surface material and terrain data, respectively. The porosity percentage data were obtained from material specification data published in the Journal of Materials Science 2006, while sidewalk gap information was developed using a binary classification model trained on a manually-labeled dataset.

The next task was to map the developed data using GIS to create a comprehensive sidewalk surface map of the study area. The GIS mapping allowed for the spatial representation of the sidewalk surface data, where the sidewalk material permeability state, along with their crack presence status, were plotted and visualized on a map.

Finally, the sidewalk surface data was evaluated using environmental and walkability data, including flood risks, landslide-prone, obesity rate, pedestrian accidents (crash data), and walk score. The material permeability state data were correlated with flood risk data to evaluate the potential flooding risks associated with different sidewalk materials. The walk score was complimented by the overall quality of the sidewalk surface and its impact on pedestrian safety and mobility.

The framework quantifies the results for comparative and derivative assessment of the neighborhood and the impact of its sidewalk on climate. To address the data gap and be able to explore the surfaces of our city sidewalks, the framework has developed a city-scale street-level sidewalk material information by utilizing a collection of urban datasets and advancements in DL and CV.

Overall, the research aimed to provide insights into the impact of sidewalk surface materials on the environment and help inform decisions related to the design and maintenance of sidewalk materials. The methodology involved the collection and analysis of sidewalk surface data, mapping the data using GIS, and evaluating the data using climate data. The results of the study provided valuable information that can be used to improve the sustainability of urban areas and promote environmentally-friendly infrastructure.

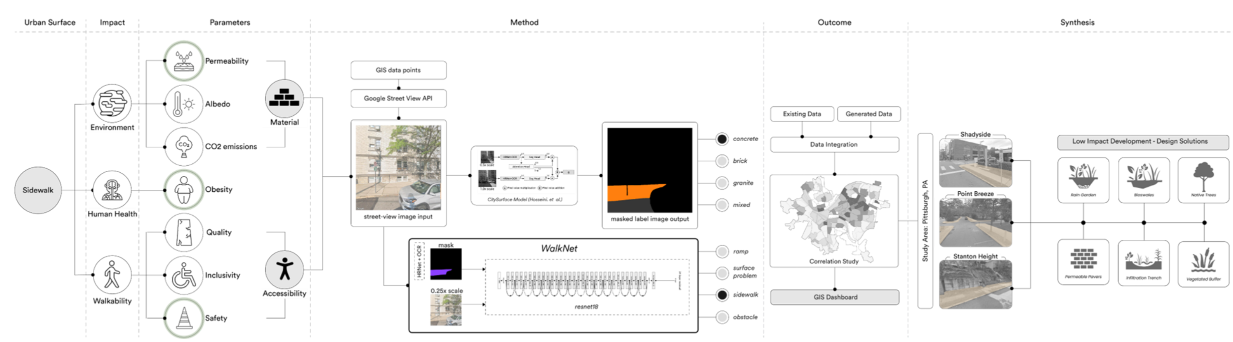


Figure. 5. Methodology overview

10.1. Tools and techniques

Both aerial and street-level imagery have shown value in extracting vital information for geospatial data analysis. However, for this research aiming to extract sidewalk surface material information, it will be necessary to work with imagery that gives the closest look to the surface texture, patterns, and color. Street-level imagery is the ideal choice as it provides a user-level perspective of the captured environment. Moreover, street-level imagery ensures high availability with a low storage cost. [7]

Using algorithms instead of manually extracting sidewalk data from street-level imagery is cost-effective and scalable. Neural networks-based Classification models, CV algorithms, and geospatial techniques together provide a robust tool to be able to learn complex representations of images and other unstructured data to quantify urban metrics.

The tools and techniques to implement the research problem will involve (i) GSV API for extracting data, (ii) an existing attention-based, active learning classification neural network called CitySurfaces for extracting material information from the street-view image, (iii) an existing transformers based segmentation model called Segformer trained on CityScapes dataset (iv) a binary classification model developed from scratch on manually labeled dataset to detect presences of cracks on sidewalks or missing sidewalks using street-view images, and (v) finally mapping the post-processed information to maps using ArcGIS Pro and its online dashboard platform for public access.

10.1.1. Google Street View (GSV)

GSV API is a powerful tool that allows users to extract street-level imagery and metadata from Google's massive database of street-level photos. The API provides easy access to the Google Street View image library, allowing users to extract images and meta-data such as camera parameters, GPS coordinates, and image data. One of the main advantages of using GSV over other street-level imagery databases, such as Mapillary, is the quality of the imagery and the ability to specify camera view angle and pitch. Google Street View images are taken using high-resolution 360 cameras mounted on specialized vehicles that capture images at regular intervals, providing a comprehensive view of the surroundings. On the other hand, Mapillary relies on crowdsourced imagery, which can be of varying quality and taken from different angles, making it less consistent and reliable for some applications.

However, there are some costs associated with accessing Google Street View API. While some basic use of the API is free, more extensive use may require the purchase of additional credits. Additionally, access to certain features, such as the use of the Street View Image Metadata API, may also require a paid subscription. Despite these costs, Google Street View API remains a valuable tool for extracting street-view images and meta-data for a wide range of applications, from urban planning and transportation to environmental analysis and research.

Even though GSV API has a lot of features, it is still not perfect. There are occasions when the API is unable to find any image for the specified GPS coordinates. But this only happens about once in 1000 image queries, so this issue can be ignored. The bigger issue happens when GSV returns an invalid or unclean image. There are more frequent issues with GSV returning images that are from inside a property, sometimes inside a store or an office. There are also occasions when the returned image is mostly blocked by some object, like a tree or a bus/truck. These cases are not as trivial to deal with, and if allowed to stay in the evaluation dataset, they might end up mapping incorrect properties to the specified GPS coordinates. Generally, these invalid or unclean images have a large portion of them covered by a single object like a tree, truck, bus, or cupboard, so we use the SegFormer segmentation model trained on the CityScapes dataset. This allows us to identify what percent of the image is covered by what kind of object, and if a certain object covers more than 30% of the image, the image, and its corresponding GPS coordinate are removed from the dataset.

The GSV API was used to download street view images for all the neighborhoods in Pittsburgh. A script was developed to take GPS coordinates sampled at 20-meter intervals from GIS and download images from each of them. In total, around 153,000 images were downloaded for the Pittsburgh region using the GSV API.

10.1.2. CitySurfaces Model

CitySurfaces is a framework that uses active learning and semantic segmentation to identify and classify sidewalk paving materials from street-level images. It incorporates a high-performing semantic segmentation model called OCRNet that captures long-range dependencies and fine-grained details using hierarchical multi-scale attention and object-contextual representation. The framework selects informative images for annotation and model training through an active learning strategy, providing an accurate and cost-effective method for collecting sidewalk material data. This data is crucial for addressing sustainability issues like climate change and surface water management.

The framework was trained on 1,000 images from New York City and Boston, with 800 images for training and 200 for testing. The framework can classify five types of sidewalk materials, namely: brick, concrete, granite, mixed concrete and brick, and hexagonal asphalt pavers. These materials were chosen based on their prevalence and relevance for sustainability issues in the two cities of New York and Boston. However, the framework can be easily extended to include more materials or categories as needed. The evaluation metrics were mean Intersection over Union (mIoU) and pixel accuracy, with an accuracy percentage of 90.5% mIoU and 96.1% pixel accuracy. However, the framework may face challenges in handling low-contrast or highly occluded images, which may require additional training data or techniques.

Concrete	Brick	Granite	Mixed concrete bricks	Hexagonal Pavers

Figure. 6. Sidewalk Materials classified by CitySurface Model

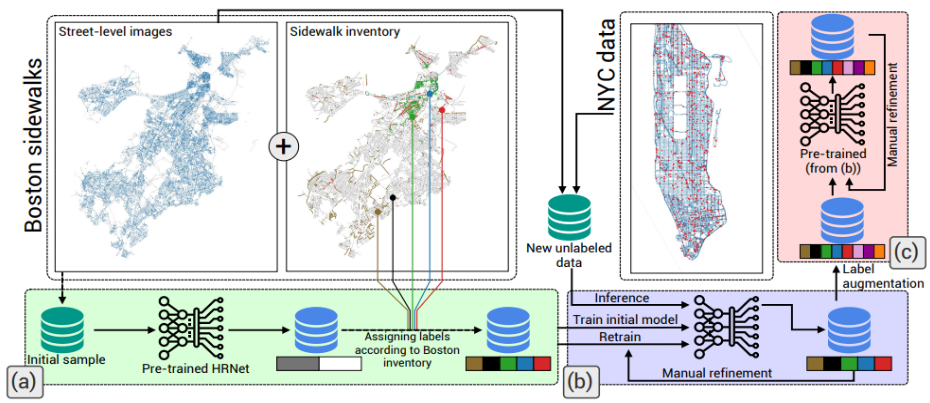


Fig. 4. CitySurfaces workflow. Block (a): Creating the initial ground truth labels using the Boston sidewalk inventory and GSV images. A sample of unlabeled images is fed to a pre-trained HRNet, which outputs annotation labels containing two classes of interest: roads and sidewalks. The labels are manually refined to represent the five sidewalk paving classes, forming our ground truth set; Block (b): Training the base model to classify five classes of surface materials, plus roads. The data from block (a) is used for the first stage of training. The model is then iteratively retrained for multiple stages on new samples. In each stage, the most representative and informative samples are chosen, and the annotations are manually refined and added to the training set to retrain the network; Block (c): Introducing three new classes of materials. The pre-trained model from block (b) is retrained on the newly annotated image with three new classes. The final model can classify eight classes of different materials.

Figure. 7. CitySurface Workflow by Hosseini et al. [23]

10.1.3. SegFormer Model

The SegFormer model by Xie et al. [27] is a segmentation model based on the Transformer architecture, which was released by Nvidia in 2021. It has been trained on the CityScapes dataset, which focuses on the semantic understanding of urban street scenes. The dataset comprises more than 25,000 daytime street view images from 50 German cities that have been semantically segmented and labeled with 30 classes. The chosen classes reflect the objects commonly encountered in urban settings, such as roads, sidewalks, cars, sky, vegetation, terrain, and people. The SegFormer model has achieved an 84.0 mean Intersection over Union on the CityWalk validation dataset.

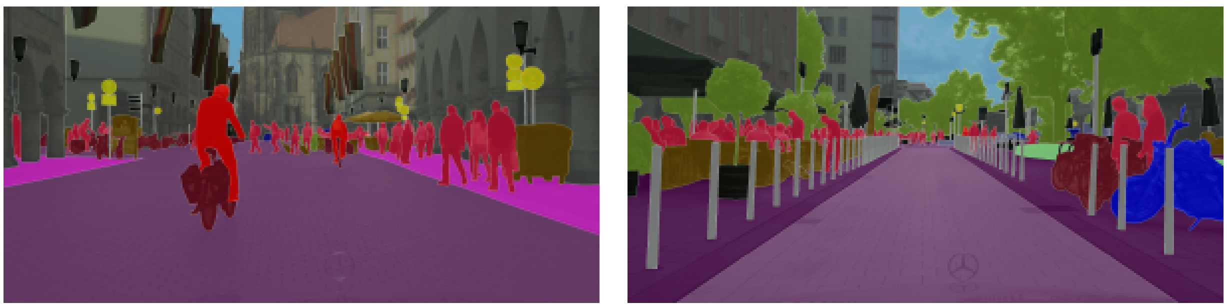


Figure. 8. NVIDIA SegFormer by Xie et al. provides output on 19 CityScape classes

10.1.4. WalkNet

As previously mentioned, there is a significant disparity in the available data on sidewalk infrastructure in urban areas. Collecting this data manually is not feasible due to physical and financial constraints. To address this issue of data scarcity, the WalkNet model was developed from scratch as part of this research. WalkNet is a multi-label classification model capable of detecting various characteristics of a sidewalk, including the presence of sidewalks, the existence of curb ramps, invalid locations, and surface problems on sidewalks to assess their quality.

The WalkNet model was trained on data labeled based on the specifications of the Americans with Disabilities Act (ADA) and aimed at identifying different accessibility problems. Initially, the plan was to use data labeled as part of the Project Sidewalk initiative by the University of Washington, which contained over 200,000 labels. However, this was a crowdsourced dataset, and some of the guidelines provided were vague and inconsistent, leading to poor model performance. Appendix 15.3 provides further details on the Project Sidewalk dataset.

To address this issue, the data had to be manually relabeled. The manually relabeled dataset consisted of only 3356 labels and included labels for Sidewalk or NoSidewalk, i.e., whether a sidewalk exists in an image or not. However, training the model with this dataset resulted in significantly more consistent results.

10.1.5. GIS

GIS mapping allows for the visualization and spatial analysis of sidewalk data, making it easier to understand and interpret the data in a geographic context. By mapping sidewalk data on a GIS dashboard, urban designers and researchers can identify patterns and trends in sidewalk infrastructure, such as areas with high levels of deterioration or flooding risks. The dashboard can also incorporate other relevant data, such as climate data and walkability score, to provide a comprehensive understanding of the environmental impact of sidewalks. The dashboard development process involves integrating sidewalk surface data with ArcGIS Pro software, designing the user interface, and selecting appropriate visualization techniques to communicate the data effectively.

10.2. Part A: Sidewalk Material for Permeability Index

10.2.1. Framework

In this stage, the focus was on gathering relevant data on sidewalk materials, including concrete, brick, stone, and others. To do so, data points were collected at 20-meter intervals along the sidewalk network to obtain Google Street View images. These images were utilized with two deep learning models, namely the CitySurface Classification Model and SegFormer Segmentation.

The CitySurface model provided five material classes, which were used to infer sidewalk material data. On the other hand, the SegFormer model generated segmentation masks for 19 CityScape classes, enabling the extraction of terrain data. The objective was to identify vegetated buffers alongside the sidewalks as they serve as the permeable component of the sidewalk.

Once the material and terrain data were extracted, GIS was utilized to map the data for analysis of its spatial distribution and correlation with other factors, such as flood risk.

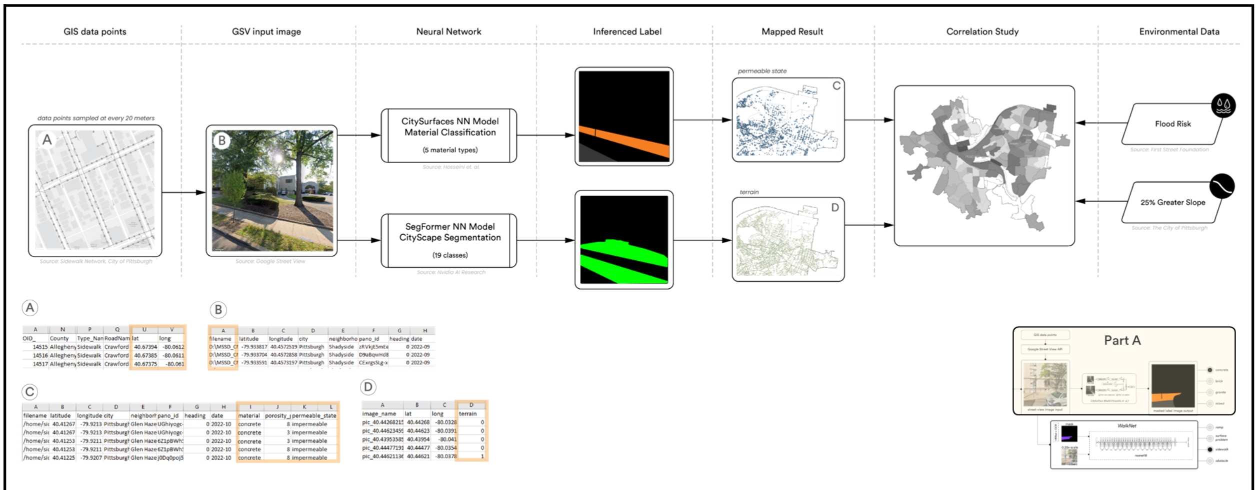


Figure. 9. Overview of Sidewalk Material Data Development Process

10.2.2. CitySurface Material Inference Result

CitySurfaces combines active learning and semantic segmentation to locate, delineate, and classify sidewalk paving materials from street-level images.

The first step in developing material data involved using a sidewalk network shapefile to plot xy points at every 10m distance. The xy points were then used to extract latitude and longitude information, which served as input data for the Google Street View (GSV) API to retrieve street view images and associated metadata, including the heading and date of capture, for that location. Once the street view image was procured, it was passed through the CitySurface Model, and the output was a side-by-side image of the input street view and the labeled output segmentation. The material type was extracted from the color index of the segmented image. To further categorize the materials, multiple construction journals were consulted to identify the porosity percentage of each material, which was then used to classify them into permeable and impermeable categories.

However, there are some limitations to how much we can infer from the data and model classification. For example, there are some challenges with the input data, as the referenced location sometimes leads to images of the interior spaces or poor sidewalk angles that don't provide a direct view for material classification. To address this, images with less than 3% of sidewalk masks were discarded. Additionally, there is a limit to the number of API calls that can be made in a month, which can slow down the overall data collection process. Another challenge was related to the accuracy of the CitySurface model used to identify sidewalk materials. The accuracy of the model can be impacted by factors such as the presence of cracks on the sidewalk, poor view angles, and the presence of shadows. Moreover, it seems like the CitySurface model didn't generalize well on certain types of sidewalk materials, such as stones or sidewalks with overlapping grass. This resulted in multiple material predictions, which required manual inspection.

These challenges required careful consideration and adjustments in the data development process to ensure the accuracy and reliability of the sidewalk material data. Despite these limitations, the CitySurface model provided valuable insights into sidewalk materials.

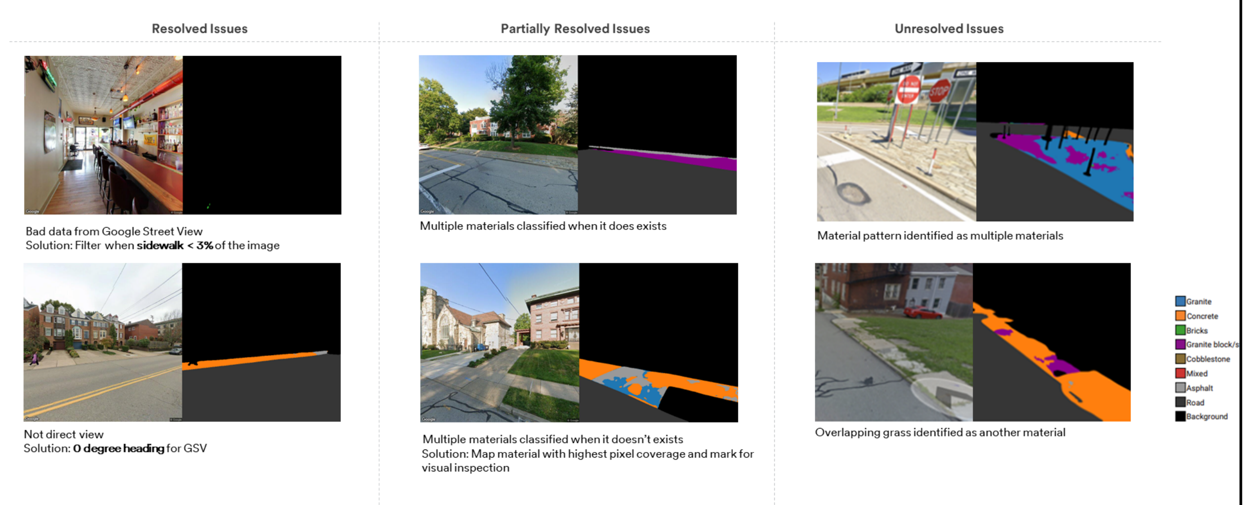


Figure. 10. Issues and Solutions when inferencing data from CitySurface Model

10.2.2.1. Permeable, Conditioned, and Impermeable Classification

To determine the porosity percentage of sidewalk materials, multiple construction and material journals were referred to. It was observed that the porosity percentage depends on various factors besides the materials used, such as layout patterns, spacing between them, etc., which are not known. Therefore, a percentage range index was taken for each material based on the literature review. These ranges were then classified into permeable, impermeable, and conditioned categories for mixed materials. This helped to categorize the sidewalk materials based on their porosity and identify areas where permeable materials could be used to improve surface water management and reduce the risk of flooding.

The permeability status classification went through three versions of development. (Appendix 15.3. Provides an illustrative overview)

Material	Factors	Porosity %	Permeability class
Concrete	mix design, curing conditions, and finishing techniques	15% to 20% [A]	Permeable
Brick	type of brick and its manufacturing process	18% to 45% [B]	Permeable
Hexagonal Paver	material used to make the pavers	Concrete: 11.8% to 19.8%; granite and sandstone: 1.4% to 8.4% [D]	Conditioned
Granite	texture and composition	0.2% to 1.5%. [C]	Impermeable

Table. 1. Sidewalk pavement materials and permeability state classification

[A] "Permeability and Porosity of Concrete as Influenced by Curing Methods" by N.P. Rajamane, P. N. Shende, and P.G. Ranade, published in the Journal of Materials in Civil Engineering in 2004, [B] Journal of Building Engineering in 2018, [C] Journal of Applied Sciences in 2011, [D] Journal of Building Engineering in 2019 and Journal of Testing and Evaluation in 2015.

10.2.3. SegFormer Inference for Terrain including Sidewalk Green Strip

The permeability and other properties of the area surrounding the sidewalk depend not only on the material of the sidewalk, but also on other factors such as the presence of greenery or a green strip. Identifying vegetated buffers along the sidewalks was of interest, as these green tree line patches act as the permeable component of the sidewalk. To identify such situations, the segmentation masks from the SegFormer model were used.

The SegFormer model predicts segmentation masks for each image, classifying each pixel into one of the 19 classes specified in the CityScapes dataset. One of the classes in the dataset is terrain. To identify the presence of greenery around the sidewalk, each image was passed through the SegFormer model to generate the terrain mask for it. If more than 3% of the segmentation mask of the image contained the terrain class, this would imply a significant amount of greenery surrounding the sidewalk.

After extracting the material and terrain data, the data was mapped to GIS to analyze the spatial distribution and correlate it with other factors.

Figure. 11. Example outputs from SegFormer Model for label 'Terrain'
Terrain = All horizontal vegetation areas that are considered undriverable such as grass, soild,or sand.

10.2.4. GIS output

This section shows the network output and permeability classification were successfully mapped at three distinct scales, beginning with street-level point data, density map, and census tract levels. To calculate the Permeability Index for each neighborhood or census tract, we used a weighted sum of permeable and conditioned pavers. The histogram chart at the bottom of the Figure. 15. illustrates the distribution of the Permeability Index throughout the city of Pittsburgh.

Calculation of permeability index (at census tract level):
•permeable-state = no. of permeable pavers / total no. of pavers
•conditioned-permeable-state = no. of conditioned permeable pavers / total no. of pavers
•Impermeable-state = no. of impermeable pavers / total no. of pavers

Permeability Index = 0.6 * permeable-state + 0.25*sidewalk-green-strip + 0.15*conditioned-permeable-state (at census tract level)

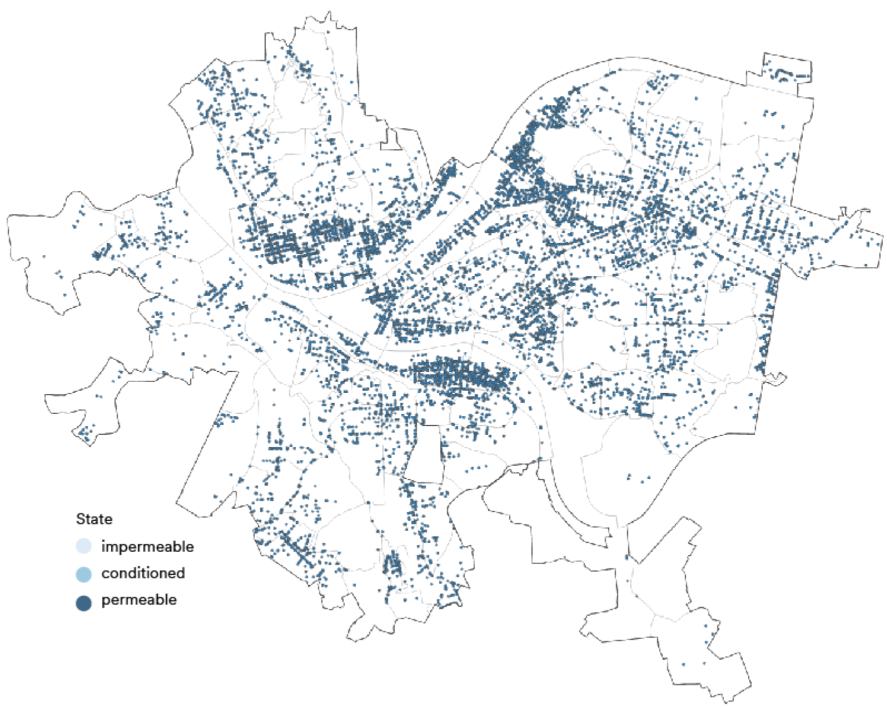


Figure. 12. Street-level distribution of sidewalk surface material permeability index for Pittsburgh, PA

Each data point was sampled at a distance of 20 meters along the sidewalk network provided by the WRPDC organization for the City of Pittsburgh. However, it should be noted that not all cities have readily available sidewalk network GeoJSONs, and additional steps may be required to extract such data. Technologies such as OSMnx by Boeing et al. and Tile2Net by Hosseini et al. can be utilized to perform this task.

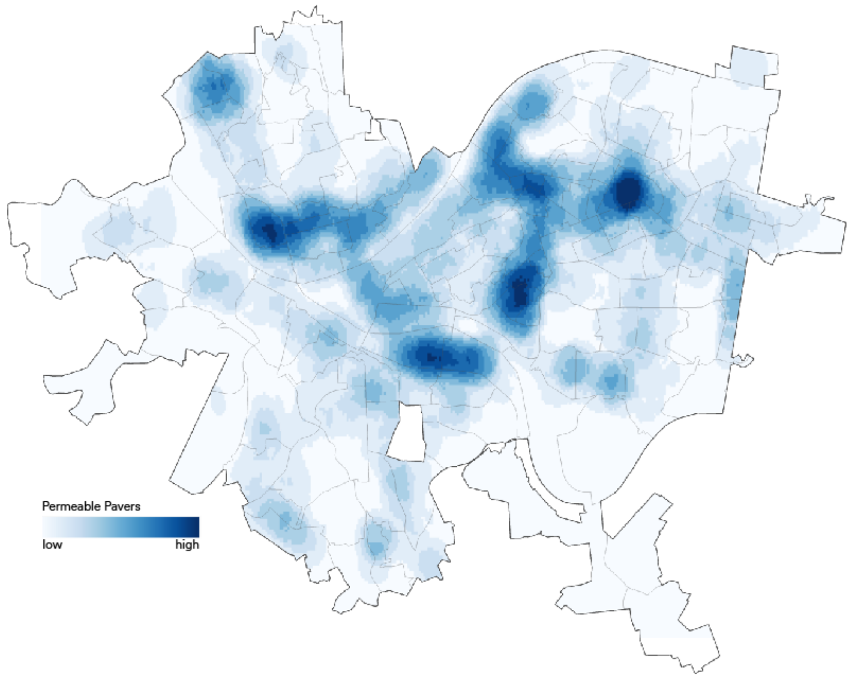


Figure. 13. Density Map of sidewalk surface material permeability index for Pittsburgh, PA

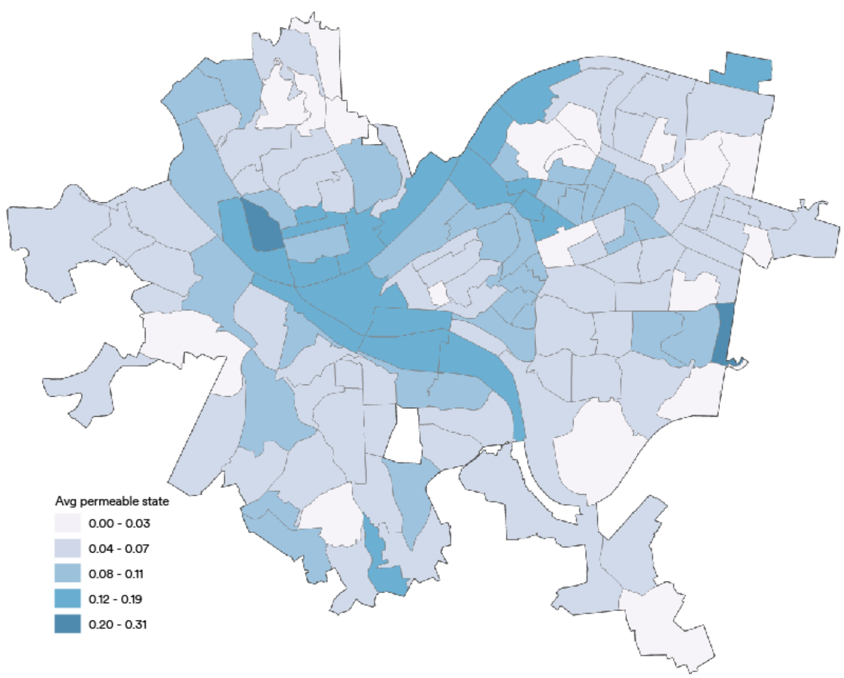


Figure. 14. Census-tract level distribution of sidewalk surface material permeability index for Pittsburgh, PA

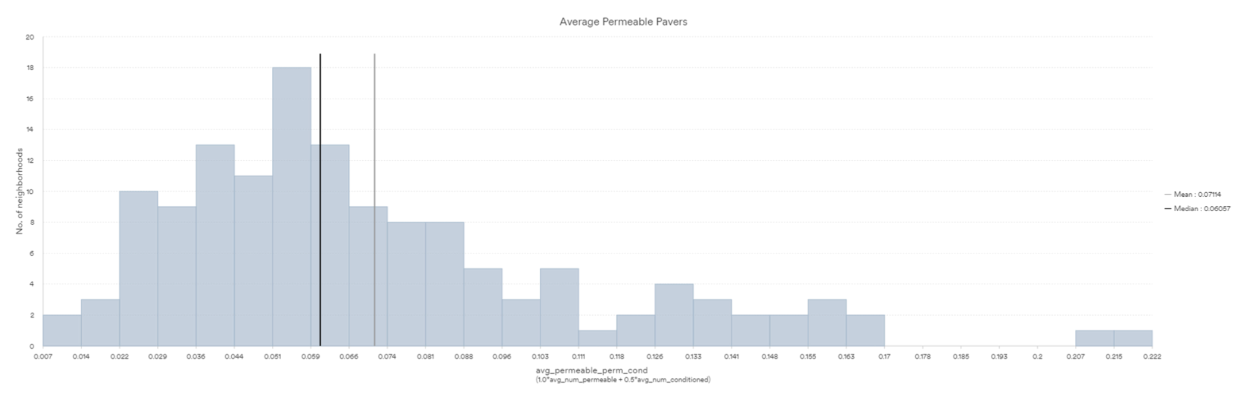


Figure. 15. Histogram chart displaying the distribution of the Permeability Index for Pittsbrugh, PA.
X-axis: Permeability Index, Y-axis: No. of census-tracts

Calculation of terrain average index (at census tract level):

Average Terrain = No. of terrain data points / Total no. of sampled data points (at census tract level)

Data points for terrain masks that includes sidewalk (above 1% coverage in the image) in its vicinity are the ones used for average terrain index calculation and mapping the results.

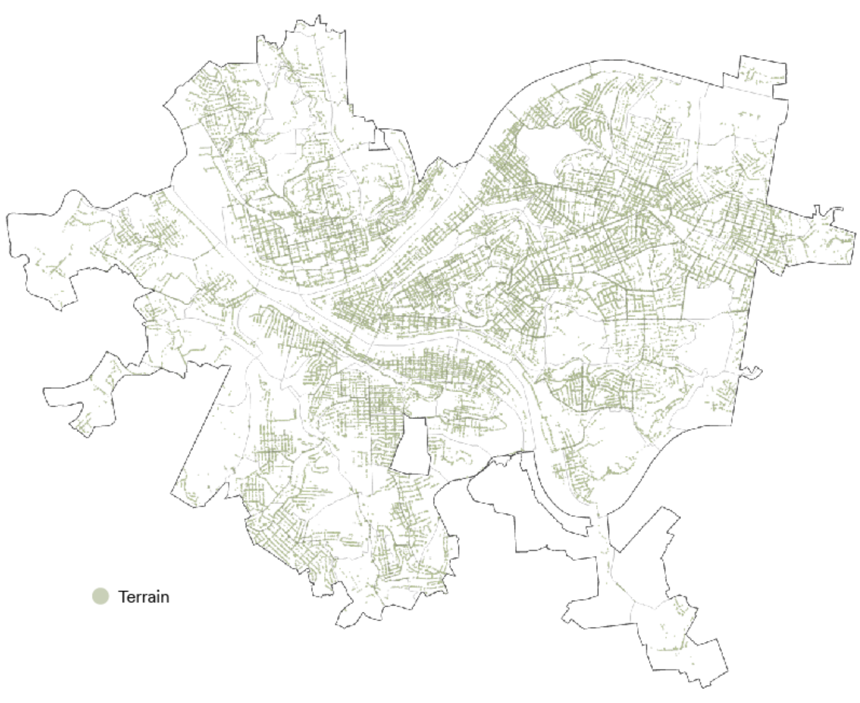


Figure. 16. Street-level distribution of terrain including sidewalk green strip for Pittsburgh, PA

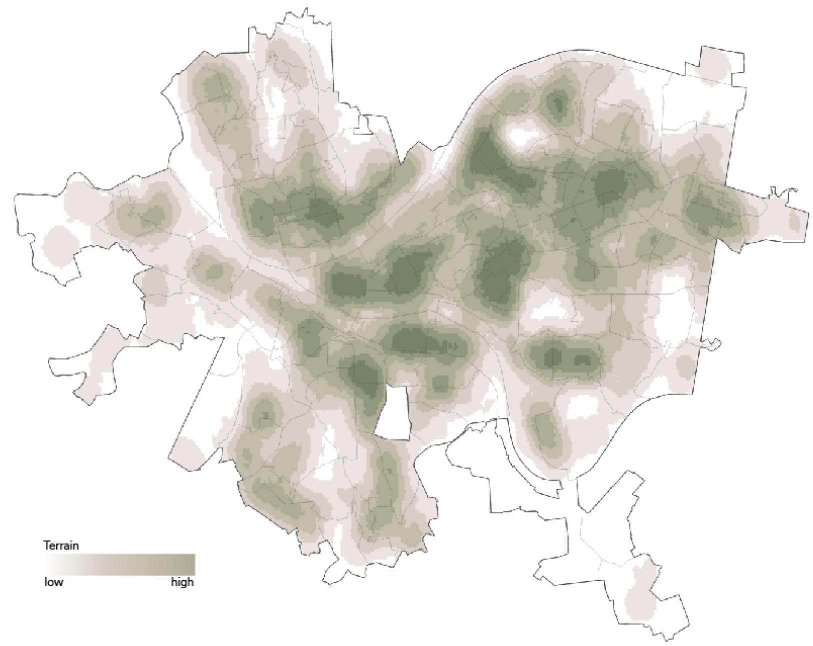


Figure. 17. Density Map of terrain including sidewalk green strip for Pittsburgh, PA

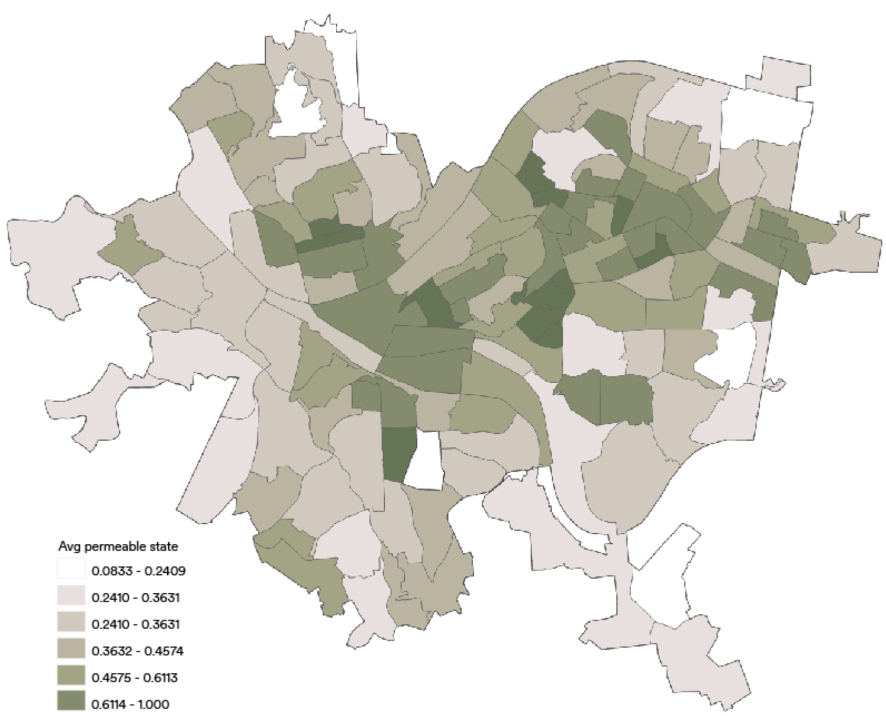


Figure. 18. Census-tract level distribution of terrain including sidewalk green strip for Pittsburgh, PA

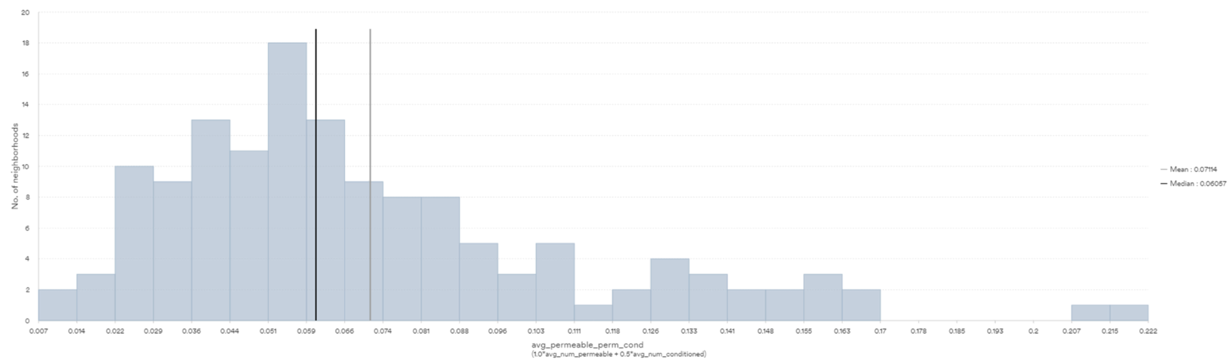


Figure. 19. Histogram chart displaying the distribution of terrain including sidewalk green strip for Pittsburgh, PA
X-axis: Terrain Average, Y-axis: No. of census-tracts

10.2.5. Data for correlation study

Data on flood zones slopes greater than 25%, landslide-prone areas from the Federal Emergency Management Agency (FEMA) and the United States Geological Survey (USGS), and floor risk rate from First Street Foundation for Pittsburgh were obtained for correlation study (Section 11.2.1.). These datasets are geo-referenced at the census tract level. These datasets are essential for understanding the risk of flooding and landslides in different areas of Pittsburgh, which can have a significant impact on the stability and quality of sidewalk surfaces. Sidewalks located in flood-prone or landslide-prone areas may be more susceptible to damage and may require more frequent maintenance and repair. Additionally, sidewalks located on steep slopes may require special materials or construction techniques to ensure stability and prevent erosion.

To address the challenge of the limitation on the number of API calls, the collection of data was done in batches to optimize the usage of the API calls. Additionally, the issue with indirect views and indoor images was managed by changing the heading of the image view when the percentage of the sidewalk in the image was less than 5%, as observed after reviewing the initial results. These solutions helped to improve the accuracy and efficiency of the material data development process.

10.3. Part B: Accessibility data with WalkNet

WalkNet is a multi-label classification model designed to identify different characteristics of a sidewalk, such as the presence of sidewalks, the existence of curb ramps, invalid locations, and surface problems for assessing sidewalk quality. However, the model was originally developed to operate on a single image at a time. Therefore, a framework was developed around the model to scale the data generation process.

10.3.1. Framework

The steps used in the data generation process are presented in Figure. 13.

1. ArcGIS was used to sample GPS coordinates for all the neighborhoods in the Pittsburgh region, i.e., 96 neighborhoods. The points had to be sampled at 20m distances to keep a balance between how precisely representative the generated output would be v/s the financial and computational costs involved in processing the data.
2. A Python script was developed to query the Google Street View API for each GPS coordinate extracted from ArcGIS. The images were downloaded with a yaw value of 0, as this case mostly corresponds to the camera pointing directly at the sidewalk.
3. Each image downloaded using Google Street View was passed into the trained WalkNet model. WalkNet predicts True or False for each of the class labels, these predictions were converted to one-hot encoded format and stored along with the GPS coordinates.
4. The one hot encoded classes were mapped to GIS as point data. These point data were then used to generate density maps and compute metrics for accessibility on a census tract level on GIS.
5. The density maps and accessibility metrics were then correlated with pedestrian accidents/safety metrics, were correlated to obesity rate/health metrics, and walk score.

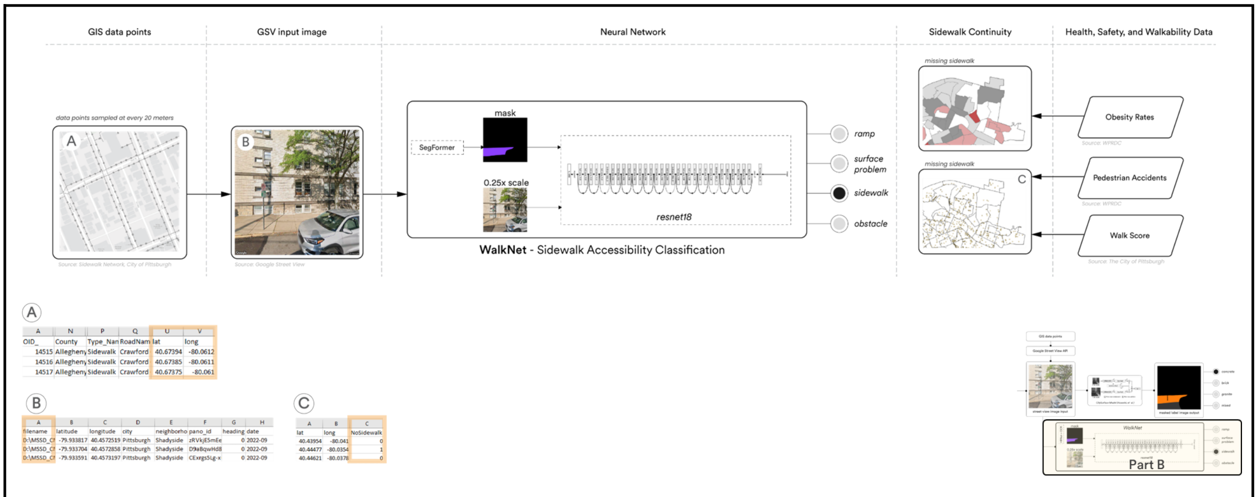


Figure. 20. Overview of the accessibility data development using WalkNet

10.3.2. Dataset for training

The WalkNet model was trained using data labeled according to the specifications of the Americans with Disabilities Act (ADA), with the aim of identifying accessibility problems in different locations.

As a publicly accessible dataset for sidewalk data was not available, the data had to be manually labeled. To assist with the labeling process, a tool was developed to present images in a chosen directory one at a time and allow users to select applicable labels for each image. Labels included options to mark images as invalid or unclean, such as when an image was taken from inside a building or when a single object occluded a large portion of the sidewalk. A "None" label was also available if no labels were applied to the image. Once all labels were selected, they were saved to a CSV in one-hot encoded format, and the next image was presented to the user.

Data was labeled for street view images from Pittsburgh, Newburgh, Oradell, and Seattle. Due to the time-consuming nature of labeling, data was only labeled for the Sidewalk/NoSidewalk label. The final dataset contained 3,356 images, with 1,016 belonging to the NoSidewalk label and 2,340 belonging to the Sidewalk label. The dataset was then split into a training dataset with 2,688 images and a validation dataset with 672 images.

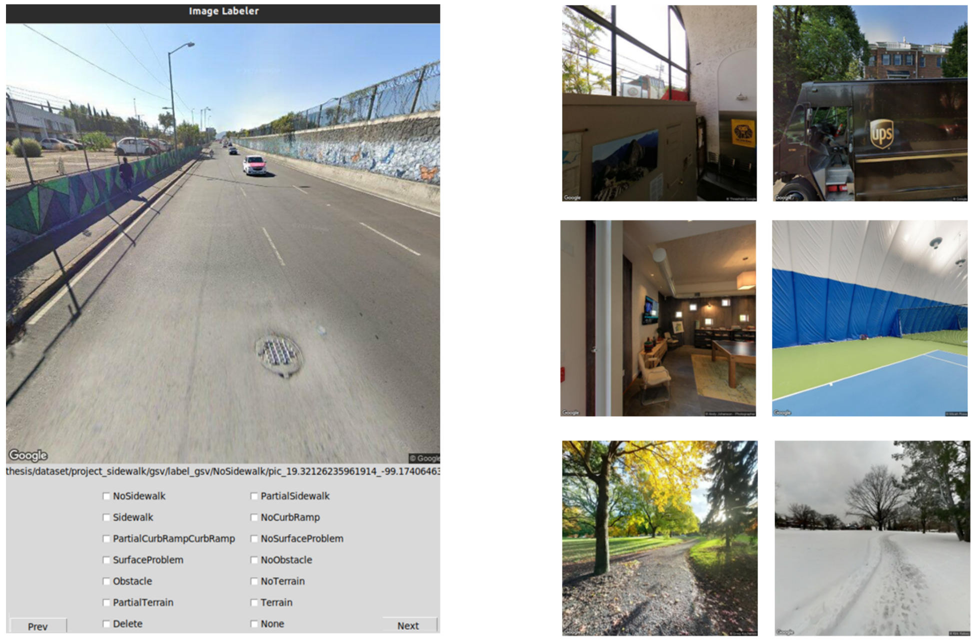


Figure. 21. Dataset development for training WalkNet: (left to right) Data labeling interactive tool, bad examples, and thresholds to remove bad examples.

Class	Pixel %	Solution
Road	If a class covers more than **50%** of an image, it becomes unreliable for assessing the presence of sidewalks in that image. For instance, an image with road pixels covering 50% of the image is likely taken from an angle that does not directly show the sidewalk.	Discard from the dataset
Sky		
Vegetation		
Building		
Vehicles	If more than **20%** of the image is occupied by vehicles, it is likely that the sidewalk is not visible. Hence, it will be wrongly classified as missing sidewalk, although there might be one that exists but is blocked by vehicles.	

Table. 2. WalkNet Dataset Cleaning Thresholds

During inference, some images were invalid or unclean and could impact the accuracy of results for Geographic Information System (GIS) analysis. To address this, each image from the full dataset was passed through the SegFormer model to perform semantic analysis. If the segmentation mask for an image covered a significant amount of a particular class as mentioned in Table. 2., the image was discarded from inference.

10.3.3. Network Architecture

WalkNet model employed a network architecture as described below:

1. The input to the model was a 3-channel (R, G, B) color image.
2. The model then passed this input image through a pre-trained SegFormer model, which was trained on the CityScapes dataset.
3. The output of the SegFormer model was concatenated with the original image to provide contextual information about the image, resulting in 21 channels (3 color channels and 19 segmentation channels from SegFormer).
4. The concatenated image was next passed through a pre-trained ResNet18 backbone, which was trained on the ImageNet dataset.
5. The output of the last convolution layer from the ResNet18 backbone was used as input to a separate head for each label type. In this case, only one head was used for Sidewalk/Nosidewalk classification.
6. Each head for the label type consisted of two additional convolution layers, followed by three linear layers. The output of the final linear layer was of size 1.
7. This final output from the model was passed through a sigmoid layer to ensure that the output value fell within the range of [0, 1]. If the output value was above 0.5, the model predicted that the corresponding label was True, indicating that the label applied to the current image.

Accuracy, Precision, Recall, and F1 score were the metrics used for evaluating the model's performance.

10.3.3.1. Experiments Overview

Multiple experiments were performed to get optimal results on the validation set.
The current model architectures started off just a stack of convolution layers, and each addition to the architecture was A/B tested and kept if it improved model performance. Overfitting is when the model tries to remember the whole training dataset instead of actually finding patterns in the dataset, as a result, the training and validation metrics are significantly different. Hyperparameters were tuned to avoid issues caused due to overfitting.

10.3.3.2. Best Performing experiment results

The best-performing model, which had a training accuracy of 0.92 and a training F1 score of 0.90, was selected for inference. The validation accuracy of this model was 0.86, and the validation F1 score was 0.82.

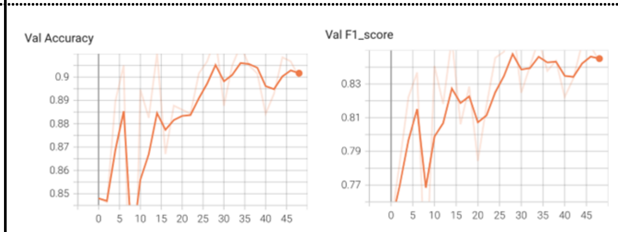
Despite the model's relatively strong performance, it is important to note that there are limitations to its ability to generalize to missing sidewalks. These limitations are likely due, in part, to the small size of the dataset, as well as class imbalance; for example, the dataset contains 2.3 times more Sidewalk labels than NoSidewalk labels.

Although the model performed well overall, there were instances in which it failed to predict the presence of a sidewalk, instead classifying the area as having no sidewalk. The images in the bottom-most row of our results indicate some of these instances. For example, in one image, the model failed to recognize a sidewalk made of brick, which is a relatively infrequent sidewalk material in the training dataset. In another image, the model misclassified a walking path made of concrete as a road without a sidewalk, likely because this sidewalk material is also relatively infrequent in the training data. In yet another image, only a portion of the sidewalk was visible, or the sidewalk was too far away for the model to identify it.

However, we did not observe instances in which the model predicted the presence of a sidewalk when there was none. Thus, we can conclude that whenever the model predicts the presence of a sidewalk, it is likely that a sidewalk is indeed present in the image.

Train Accuracy: 0.92; F1 Score: 0.90

Validation Accuracy: 0.86; F1 Score: 0.82



Metrics

Figure. 22. Training and Validation Results of WalkNet model

10.3.4. GIS Output

This section shows the WalkNet model output, i.e., the missing sidewalk data points were successfully mapped at three distinct scales, beginning with street-level point data, density map, and census tract levels. The sidewalk Gap metric was computed for each neighborhood at the census tract by averaging the number of missing sidewalk points over the total number of sampled data points. The histogram chart at the bottom of the Figure. 16. illustrates the distribution of the Permeability Index throughout the city of Pittsburgh.

To compute **sidewalk continuity rate** = 2 * road network (if no highways exist for that area)

Figure. 23. Street-level distribution of missing sidewalk points for Pittsburgh, PA

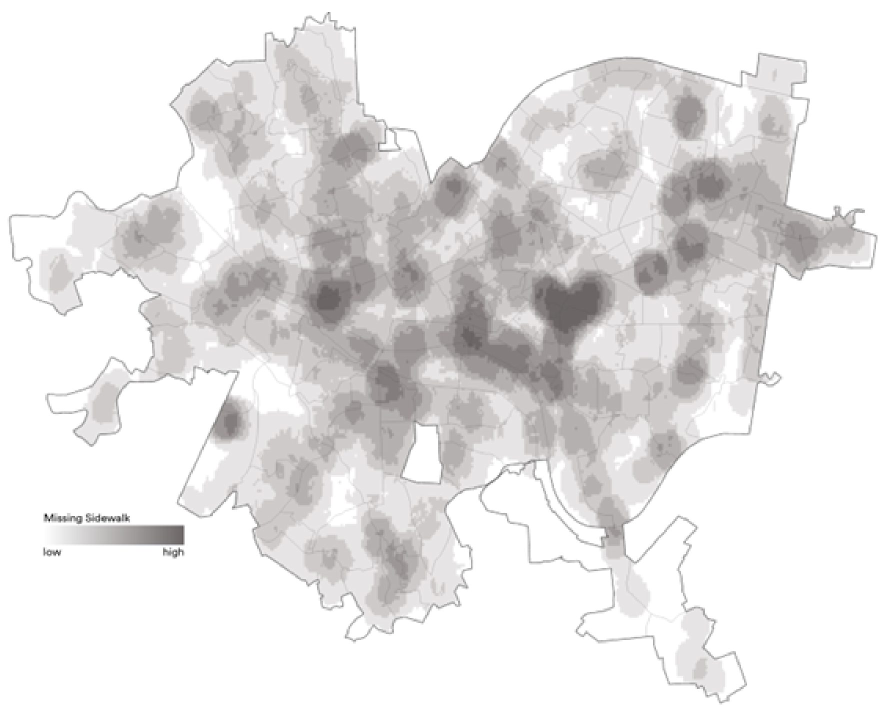


Figure. 24. Density Map of missing sidewalk points for Pittsburgh, PA

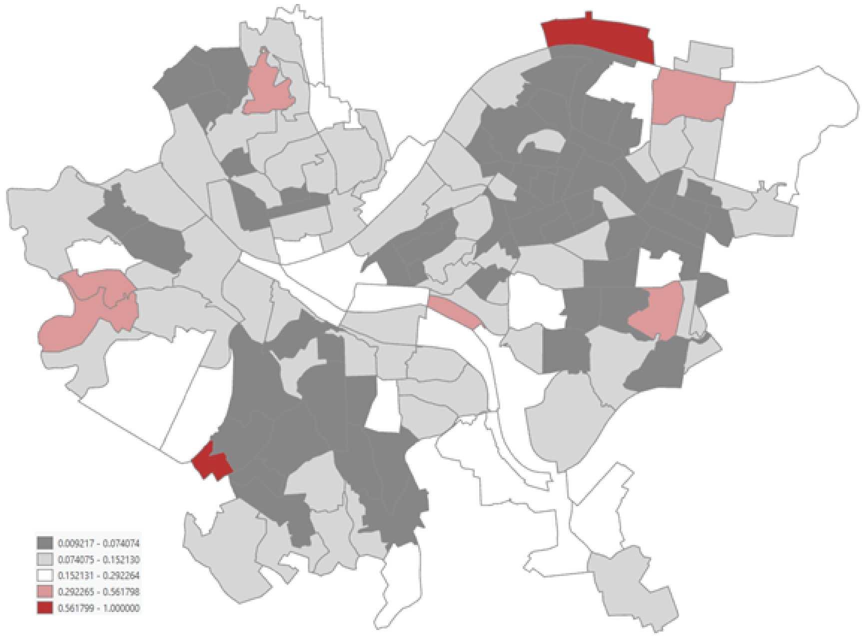


Figure. 25. Census-tract level distribution of missing sidewalk points for Pittsburgh, PA

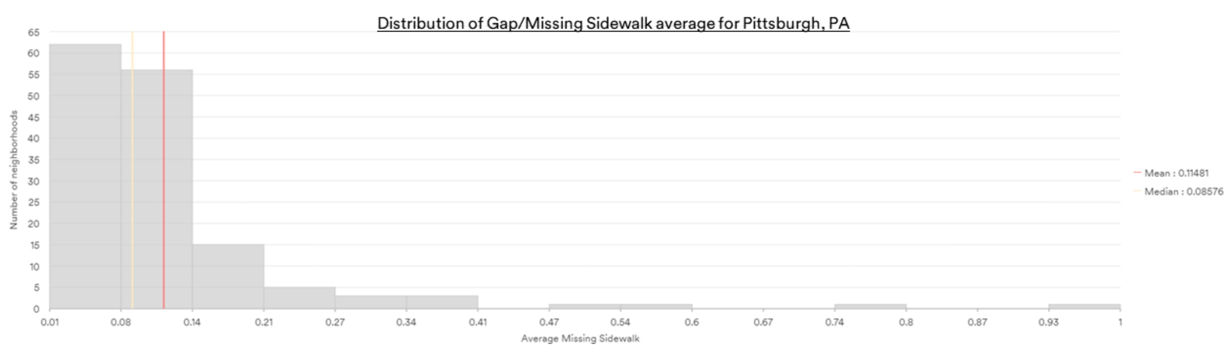


Figure. 26. Histogram chart displaying the distribution of missing sidewalk points for Pittsburgh, PA
X-axis: Average Missing Sidewalks, Y-axis: No. of census-tracts

10.3.5. Data for correlation study

Pedestrian safety can be closely linked to the existence of better sidewalks. When sidewalks are well-maintained, clearly marked, and wide enough to accommodate foot traffic, pedestrians are less likely to have accidents or be involved in collisions with cars. In contrast, poorly designed or maintained sidewalks can pose significant safety risks to pedestrians, such as uneven surfaces, obstructions, or narrow passages that force pedestrians into the street. Crash Data Dashboard by City of Pittsburgh provides data that can be mapped onto GIS to perform correlation analysis for this data. This data was obtained from Smart Surface Research Group.

The quality of sidewalks and the prevalence of obesity in a community can be closely linked. Good quality sidewalks can encourage people to walk more often, which is an effective form of physical activity and can help combat obesity. A study published in the Journal of Transport and Health found that individuals who lived in neighborhoods with sidewalks that were well-maintained, had good lighting, and were separated from the road had lower rates of obesity. This is because these features make it easier and safer for people to walk or cycle, which can increase their physical activity levels and reduce the likelihood of obesity. Conversely, neighborhoods with poor quality sidewalks may discourage physical activity, and therefore, contribute to higher rates of obesity. First street foundation provides obesity data for each census tract which can be mapped onto GIS. This data was obtained from Smart Surface Research Group.

The **Walk Score** data is important for evaluating the walkability and accessibility of an area and can be used to identify areas where sidewalk improvements are needed to enhance pedestrian safety and mobility. The Walk Score data, which was obtained from the Western Pennsylvania Regional data center, can be mapped at a census tract level in Pittsburgh, providing an overview of the walkability of different neighborhoods.

With an efficient and accurate assessment strategy, city agents can utilize and expand the model to understand urban sidewalks' spatial and material distribution and make actionable plans for their impact on climate and human health. The methodology will be useful for researchers researching topics that rely on estimations of city surface data, including their environmental impact assessment and urban heat island models.

11. Results

In this section, I evaluate the data developed using WalkNet to identify gaps in sidewalk continuity (Section 10.4 Part A of Methodology) and existing neural networks - CitySurface and SegFormer to extract material classes and terrain including sidewalk green strips segment masks, respectively (Section 10.3 Part A of Methodology). The results are presented in three parts: (i) a correlation study of sidewalk material permeability state and flood risks, as well as sidewalk continuity or gap data with health and pedestrian safety data; (ii) an interactive dashboard for mapping and communicating the spatial data to stakeholders; and (iii) two design synthesis case studies to solidify the idea of being able to overcome decision-making barriers and identify actionable areas for sustainable design development.

11.1. Area of study

Pittsburgh, Pennsylvania, was selected as the area of study for researching sidewalk materials and their accessibility due to its unique climate and geographical conditions. With a humid continental climate, the city experiences four distinct seasons and high levels of precipitation, making it susceptible to flooding. Therefore, mapping and evaluating sidewalk data in Pittsburgh, and correlating it with flood risk percentage, is crucial for understanding and mitigating the negative impacts of urban surfaces, such as streets and sidewalks, on the city's climate. Additionally, Pittsburgh's hilly terrain and 16.8% of the population aged 65 or above [23] raises questions about walkability and sidewalk accessibility. Hence, identifying gaps in sidewalk continuity aids in assessing quality and walkability, which is essential for pedestrian safety and accessibility.

This study can be replicated in other US cities with different climatic conditions but with restricted 5 classified sidewalk surface materials (Section 10.3.1). Conducting similar research in other cities can provide a better understanding of the impact of urban surfaces on the environment, facilitate comparisons between cities, and help develop sustainable and resilient urban areas throughout the country.

11.2. Correlation Study

Scatter plots are commonly used for correlation studies because they provide a visual representation of the relationship between two or more variables. They help to identify patterns or trends in the data and to determine the strength and direction of the correlation. Scatter plots are also useful for identifying outliers or anomalies in the data that may affect the correlation analysis. Therefore, I used Scatter Plot Chart on ArcGIS to conduct correlation analysis between multiple sidewalk parameters.

11.2.1. Material Permeability State, Terrain with Green Strip, and Flood Risk Factor

The aim of the study was to identify the prevalence of different sidewalk surface materials in flood risk areas and assess the correlation between material permeability, green strips, and flood risk in order to inform future sidewalk designs in flood-prone areas.
Sidewalk surface material data was categorized into permeable, conditioned permeable, and impermeable classes (Section 10.3.2.) and mapped at the census tract scale (Section 10.3.4.). A scatter plot chart was used to analyze the data in ArcGIS Pro.

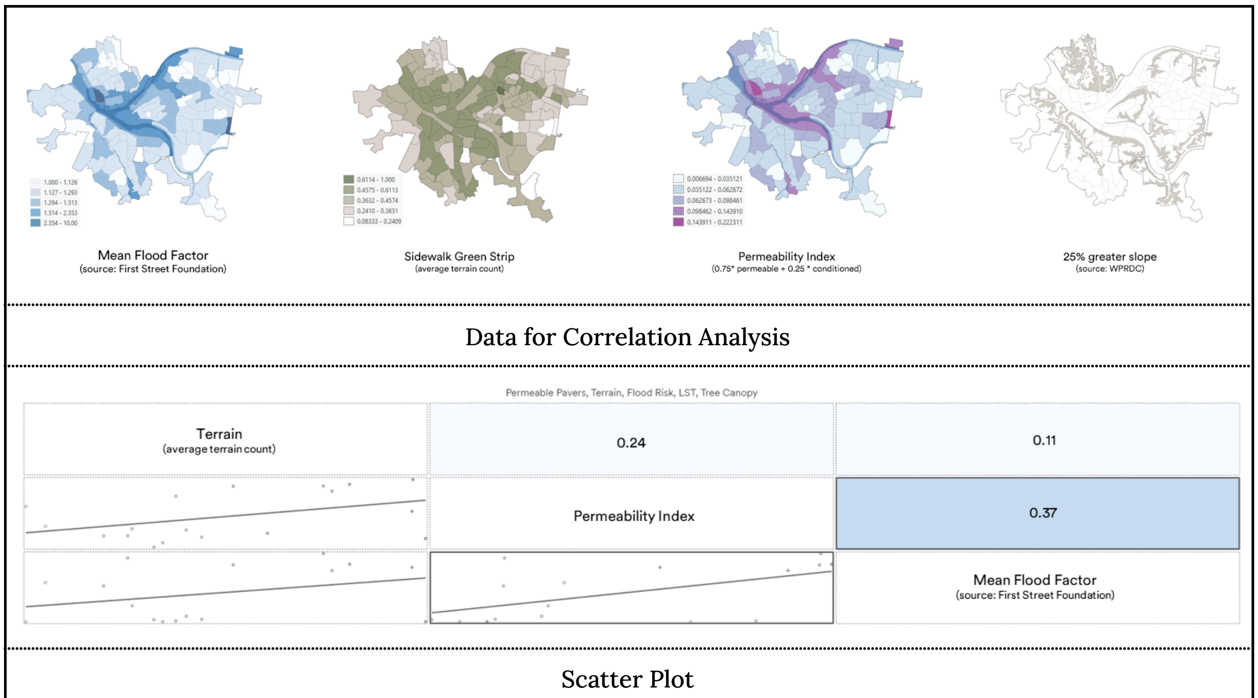


Figure. 27. Sidewalk Permeability State and Flood Risk Rate Correlation Analysis at census-tract level

The correlation study revealed the following:

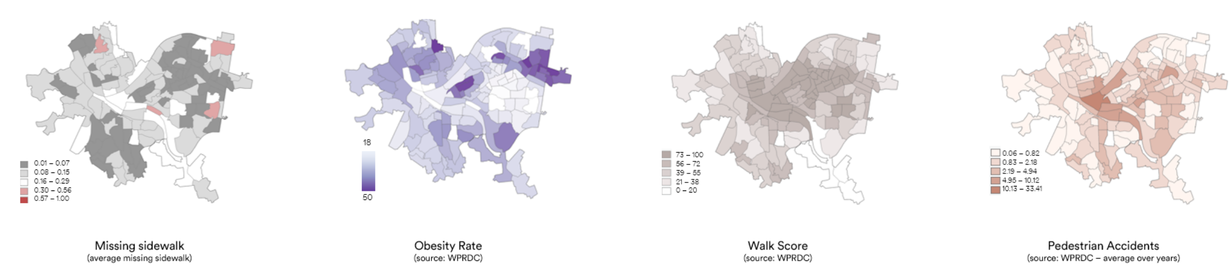
1. There is a slight positive correlation between permeability index and flood factor, indicating that certain neighborhoods in Pittsburgh have more resilient sidewalk infrastructure to floods.
2. The correlation between terrain and permeability index was also positive, suggesting that there are many pavers built with natural vegetation strategies in Pittsburgh.

3. However, sidewalk green strip and flood factor were found to be weakly correlated. Improving this would be good for dealing with flood risk

The study was significant as it provides valuable insights into the selection of materials for future sidewalk construction and rehabilitation projects in flood-prone areas. The findings also inform decision-making processes in urban planning to improve community resilience to flooding. While other urban infrastructure, such as roads, streets, and stormwater systems, may have a more direct relationship with flood risk rates than sidewalks, there are limitations to sustainable design in these areas. Sidewalks, on the other hand, present an opportunity for quicker and easier implementation of sustainable design practices, making them an important aspect to consider in mitigating flood risks in urban areas.

11.2.2. Gaps in Sidewalk Network (missing sidewalk), Pedestrian Accidents, Obesity Rate, and Walk Score

The study aimed to explore how the absence of sidewalks affects pedestrian safety and health. By identifying areas with missing sidewalks and combining this information with walk scores, the study could provide valuable insights into walkable areas and guide city officials in identifying areas that require improvement.



Data for Correlation Analysis

Scatter Plot

Figure. 28. Missing Sidewalks, Obesity Rate, Walk Score, and Pedestrian Accidents Correlation Analysis at census-tract level

The scatter plot in Figure 17. shows the following:

1. There is a weak correlation between missing sidewalks and Walk score, suggesting that the Walk score metric does not adequately consider the absence of sidewalks, indicating the need for further refinement of the metric.
2. No significant correlation was found between missing sidewalks and pedestrian accidents. However, poorly developed neighborhoods for walking may contribute to some pedestrian accidents.

The study's preliminary findings highlight the potential of using accessibility data, such as missing sidewalks, to identify factors impacting walk score and pedestrian safety. While no strong correlations were found, the study suggests that further refining the missing sidewalk data and exploring additional analysis techniques could yield valuable insights.

The findings from the two studies can assist in decision-making processes in urban planning to improve community resilience and walkability.

11.3. CityWalk Dashboard

The results from neural network models and existing data on the city's environmental and pedestrian data were used to create an interactive map that visualizes the spatial distribution of sidewalk data. The idea is to create city-scale summarised indicators for sidewalks' surface data by grouping them into two categories, i.e., (i) environmental factors and (ii) health and safety factors. With this understanding, we should note that a city can still be considered environmentally responsible without a sustainable sidewalk surface. The sidewalk permeability index and sidewalk green-strip average will complement existing sustainability indices by adding a new dimension of consideration in evaluating the overall sustainability of an area. With respect to pedestrian health and safety, the computed sidewalk gap average should be used with complement to the neighborhood Walk Score to get a holistic view of pedestrian accessibility status.

The proposed framework will hope to raise general public awareness on the significance of the role of sidewalks, their current conditions, and the scope of improvement in supporting sustainable development, by mapping the distribution of sidewalk surface data across cities in the US and expanding eventually expanding it worldwide. It will also assist in urban analytics and follow-up studies. Figure. 17. The CityWalk dashboard provides information at macro and micro levels with the help of the color gradation visualization and the index value range scale. It allows side-by-side comparison with the different parameters or spatial layers. This feature is helpful in making comparative assessments as required.

The dashboard can be used by planners, policymakers, and other stakeholders to make informed decisions about sidewalk design, construction, and maintenance to improve community resilience to the impact of urban surfaces.

The dashboard is currently restricted to Carnegie Mellon University community as it contains data developed by the Architecture Department's Smart Surface Research group. The link to the dashboard can be found here.

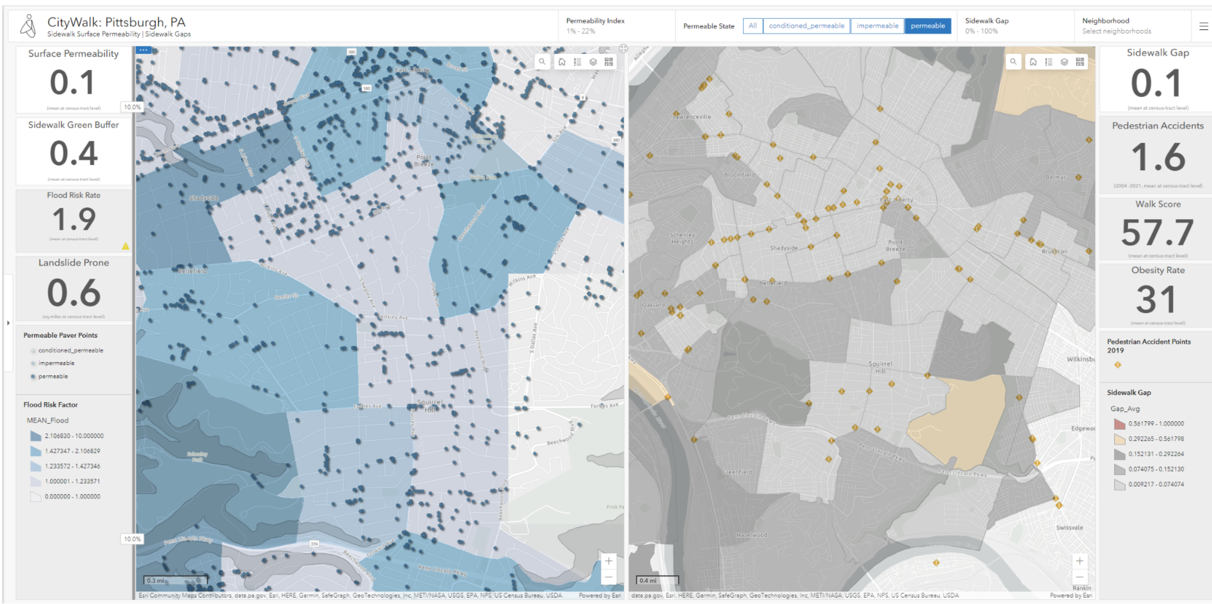


Figure. 29. CityWalk Dashboard

11.3.1. Dashboard Development Steps

The data developed and correlation study results were visualized using GIS maps and numeric indicators to help users understand the spatial patterns and relationships between the variables. This tool will assist in identifying areas where certain variables are strongly correlated or identifying patterns or trends in the data.

The following steps were performed to develop the dashboard using ArcGIS Dashboard builder after creating the web layers on ArcGIS Pro:

1. Choose a dashboard design that is user-friendly, easily understandable, and informative. This was achieved by providing two map windows to allow users to select the various sidewalk spatial layers, such as the permeability index layer, flood risk factor layer or sidewalk gap average layer, and pedestrian accident layers, to gain insights through visual comparisons.
2. Ensure that the dashboard is interactive and allows users to explore the data by zooming in and out, filtering based on neighborhood selection, and querying certain permeability index ranges and sidewalk gap averages.
3. Validate the dashboard's accuracy and completeness by identifying areas of intervention for the design synthesis study in Section 11.4.

4. Deploy the GIS dashboard and ensure that it is accessible to all users

11.4. Design Synthesis

The Design Synthesis section of the thesis research provides a practical application of the methodology developed in the study. With a clear understanding of the status of sidewalks in terms of material, permeability, and missing gaps, the section identifies actionable areas where design-oriented developments can be implemented to improve the sustainability and functionality of sidewalks.

11.4.1. LID Solutions

Low-impact development (LID) strategies for sidewalks and streets help to improve sustainability, reduce environmental impact, and promote pedestrian health. Following are a few examples of LID solutions for sidewalks:

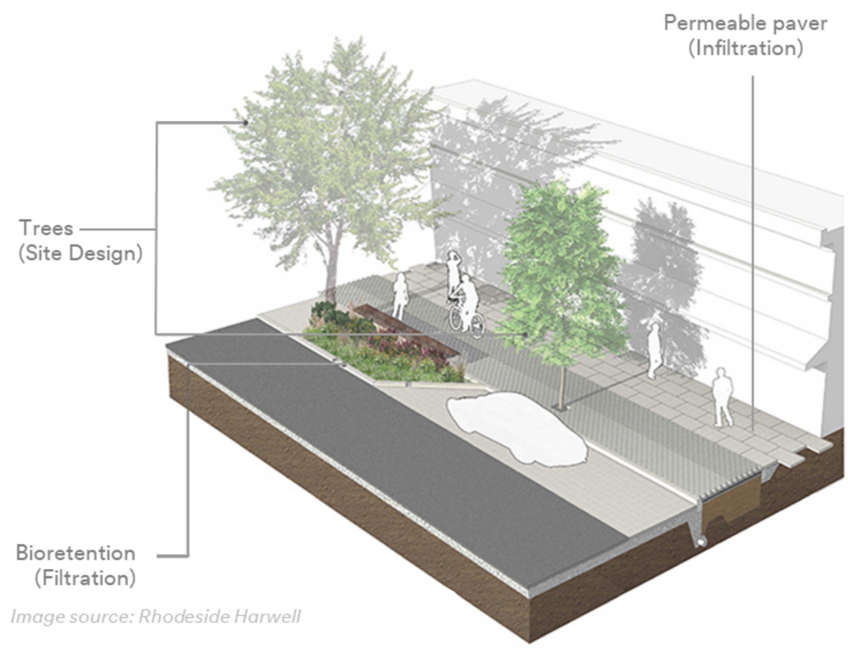


Figure. 30. LIDs for sidewalks (IImage Source Rhodeside Hornwell)

Permeable pavers are one of the most commonly used LID solutions for sidewalks. These pavers are designed to allow water to infiltrate through the surface, which helps to reduce the amount of stormwater runoff that is generated. Permeable pavers are typically made from concrete or other porous materials, and they can be designed in a variety of patterns to enhance their aesthetic appeal. When used in combination with a properly designed drainage system, permeable pavers can help to reduce the impact of stormwater runoff on the surrounding environment.

Bioswales are another effective LID solution for sidewalks. These are vegetated drainage channels that are designed to filter stormwater runoff as it flows through them. Bioswales are typically planted with a variety of vegetation species, which helps to promote infiltration and filtration of stormwater runoff. In addition to providing an effective stormwater management solution, bioswales can also enhance the aesthetic appeal of a sidewalk and provide a habitat for wildlife.

Vegetated buffers typically consist of a strip of vegetation located between the sidewalk and the road, and they are designed to capture and filter stormwater runoff before it reaches nearby waterways. **Trees** can help to intercept rainfall, which reduces the amount of stormwater runoff that is generated. Trees also provide shade, which helps to reduce the surface temperature of sidewalks and surrounding areas.

The reason why LID solutions work for sidewalks is that they mimic natural hydrological processes and allow water to infiltrate into the ground, reducing the amount of stormwater runoff that flows into storm drains and local waterways. LID solutions also provide other benefits, such as reducing the urban heat island effect, improving air quality, providing habitat for wildlife, and enhancing the aesthetic value of urban areas. LID solutions can also be cost-effective, requiring less maintenance and reducing the need for costly stormwater infrastructure projects. They are an effective way to address the environmental challenges associated with traditional sidewalk materials.

Table 3. Lists the LID strategies that are applicable when designing a sidewalk to improve its functionality and resilience to climatic conditions.

Strategy	*Type*	*Significance*	*Implementation*	*Maintenance*
Native Landscape	Site Design	Protect natural resources, prevent flooding and erosion, enhance water resources, and	Consideration of topography, soil, drainage patterns, and sun exposure is important for the use of native vegetation.	Requires less routine maintenance than conventional landscaping.

		promote their preservation and restoration.		
Bioretention	Filtration	Uses that incorporate natural pollutant removal mechanisms, filtering runoff through prepared soil mix and mulch.	Best suited to shallow slopes, using deep-rooted perennial plantings and incorporating design features for pretreatment, treatment, conveyance, maintenance reduction, and landscaping.	Need periodic maintenance including watering, mulching, mowing, inspecting soil, and replacing dead vegetation.
Filter Strip	Filtration	Slows runoff velocities and filtering out pollutants, but maintaining sheet flow can be challenging.	Treat runoff from small parking lots, roads, and pervious surfaces, but only for very small drainage areas and on slopes between 2 and 6 %.	Remove sediment, inspect diaphragm for clogging, replace vegetation if needed.
Permeable Paver	Infiltration	Best suited for low to medium traffic areas such as residential roads and parking lots.	Key considerations including soil permeability, flatness of the stone reservoir, siting, and design features.	Maintain porous pavement regularly with skilled contractors. Inspect monthly, sweep/vacuum/mow 3-4 times/year.
Infiltration Trench	Infiltration	Primarily removes pollutants by filtering through the soil.	Use is limited due to groundwater contamination, clogging, and soil; their suitability depends on drainage area, slope, soil infiltration rates, distance from groundwater sources,	Sediment and oil/grease removal, access path clearing, and overflow structure cleaning.
Grassed Swale	Infiltration	Treats through sedimentation, filtering, and/or infiltration; they come in various designs such as grassed, dry, wet, and biofilters/bioswales.	Treat road runoff on flat slopes <4%, with check dams for larger slopes.	Litter control and maintaining the grass or wetland plant cover. Swale bottom should be at least 2 ft above the groundwater table.

Table. .2. Six LID Solutions applicable to sidewalks

11.4.2. Case Study

To promote sustainable development and enhance the functionality of sidewalks, six Low Impact Development (LID) strategies were utilized. These strategies included permeable pavers, bioswales, and other eco-friendly methods that help improve the permeability and drainage of sidewalks. By incorporating these LIDs, the aim was to reduce the negative environmental impact of traditional sidewalk materials and enhance their functionality, making them more efficient and safer for pedestrians. This approach supports the development of sustainable infrastructure and is part of a larger effort to promote eco-friendly practices in urban design and development.

11.4.2.1. Case Study 01: Shadyside Neighborhood

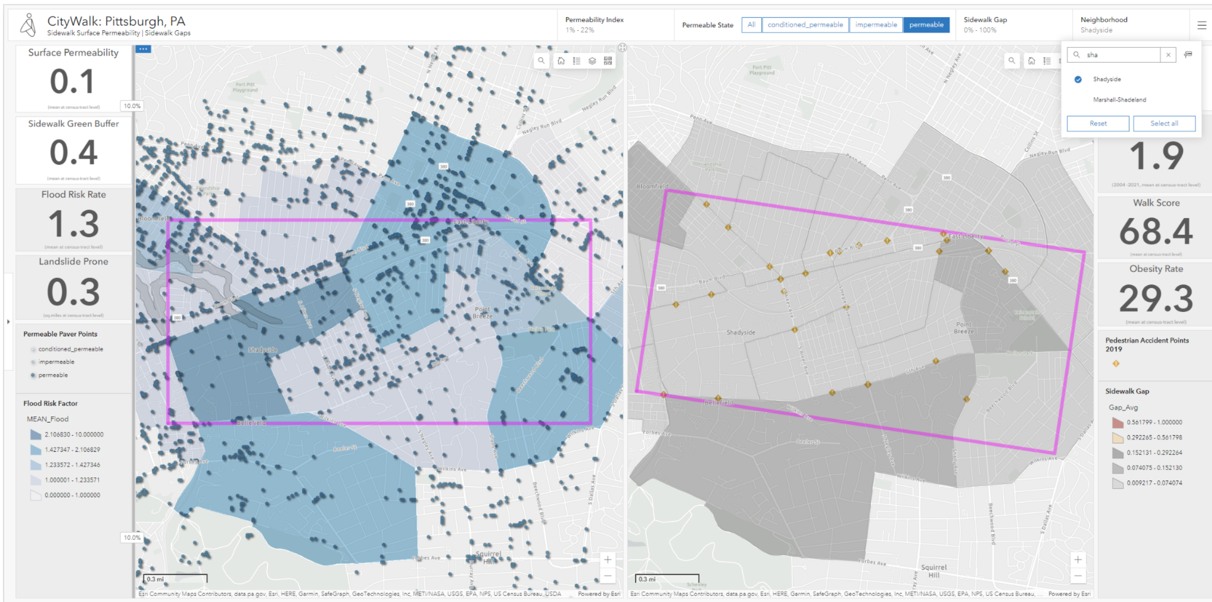


Figure. 31. Analyzing sidewalk data for Shadyside neighborhood using CityWalk Dashboard

Figure. 32. Design implementation for Walnut Street at Shadyside

For design development in Shadyside, a neighborhood with high walkability, medium flood risk, and low missing sidewalks. However, a street-level data point at Walnut Street exhibited a missing green strip and impermeable sidewalk material, leading to the visualization of a design solution as shown in Figure 22.

11.4.3. Case Study 2: Stanton Heights Neighborhood

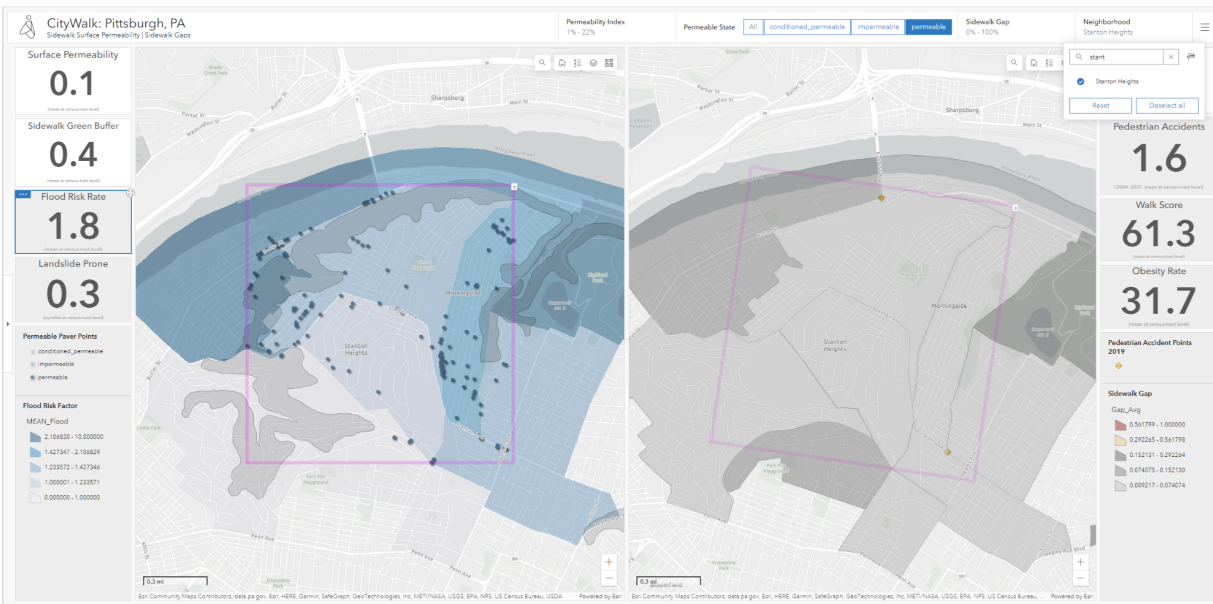


Figure. 33. Analyzing sidewalk data for Stanton Heights neighborhood using CityWalk Dashboard

Figure. 34. Design implementation for Stanton Avenue

In the second case study, Stanton Heights was selected, as it had many scattered missing sidewalk points and low walkability. A missing sidewalk point was identified, and its design solution was visualized as shown in Figure 34.

12. Discussion

12.1. Research Limitations

The study has several limitations that need to be considered. Firstly, the street-level images used in the research were from 2019, which means that the results do not reflect the current situation. To update the data, it would require more recent street view images from organizations such as Google Street View or crowd-sourcing with external validation. Moreover, Google Street View API has limitations on monthly downloads, which resulted in the street-level image points having to be kept at a resolution of 20m. Secondly, for training the WalkNet, the dataset had to be manually labeled using a labeling tool developed to speed up the process. This was necessary because the open-source dataset that the network was going to utilize was not validated and labeled correctly. As a result, the scope of the multi-label classification of the WalkNet was narrowed down to a binary classification between ‘sidewalk’ and ‘nosidewalk’ labels, as there was not enough time left to label the other dataset classes. Lastly, the lack of consistency between the mapping standards used by different municipalities may lead to differing correlation studies between cities, which could restrict a fair comparison inter-city.

12.2. Future Works

The research has several potential future directions that could enhance its methodology and significance. Firstly, integrating other forms of data, such as land surface temperature, could provide better insights into selecting appropriate sidewalk surface materials. Secondly, conducting a correlation study with vulnerable groups and demographics could reveal information about fairness in sidewalk infrastructure development and highlight areas that require improvement. Thirdly, expanding WalkNet's scope to address other accessibility parameters, such as surface problems, crosswalks, and curb ramps, could provide a more comprehensive understanding of sidewalk conditions. Additionally, testing WalkNet on data from cities not included in the training could demonstrate the generalizable capabilities of the framework. Cities such as Singapore and Mumbai could be considered for testing for sidewalk continuity detection and other accessibility and walkability parameters.

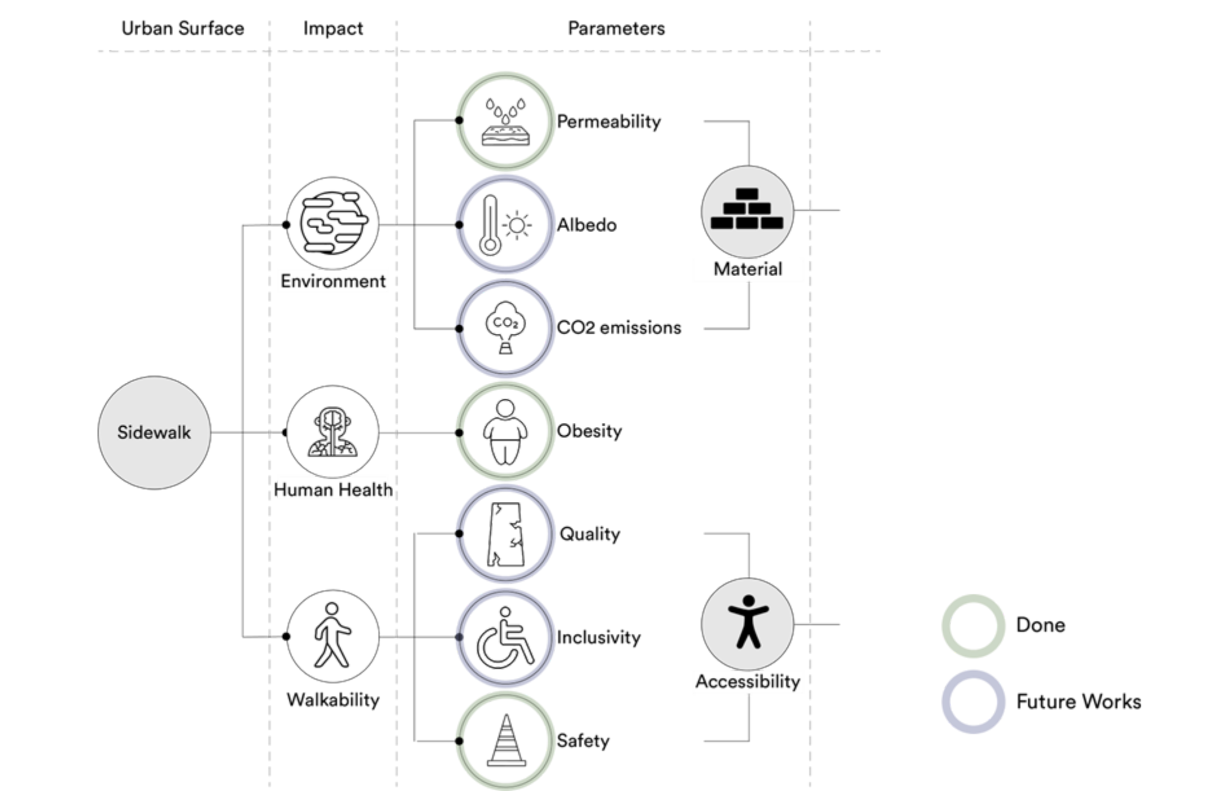


Figure. 35. Sidewalk Parameters to address in future works

Lastly, creating a Sidewalk Score, similar to Treepedia and Roofpedia, could communicate the results beyond technical jargon and enable easy comparison between neighborhoods and cities.

13. Conclusion

The research introduces a data-driven workflow for analyzing the material and accessibility distribution of sidewalk data at the street and census-tract level. The approach leverages remote sensing data, computer vision, and deep learning techniques to overcome the data scarcity challenge in sidewalk infrastructure analysis, highlighting the importance of sidewalks in sustainable urban design.

The DL model developed as part of the workflow, WalkNet, accurately detects sidewalk presence and identifies gaps in sidewalk continuity. The CityWalk dashboard provides an intuitive interface for visualizing and analyzing sidewalk data. This thesis contributes to the field of urban analytics, sustainable design, and deep learning frameworks to inform design development strategies. The proposed LID strategies offer a sustainable approach to sidewalk design and maintenance, promoting urban resilience and enhancing pedestrian accessibility.

By achieving the research objectives, city planners, urban analysts, and designers can make informed decisions to improve sidewalk infrastructure with respect to material permeability, geographical flood risk factors, and pedestrian accessibility. The research framework addresses the data scarcity challenge of sidewalk conditions and proposes actionable solutions. However, data availability and mapping standards consistency should be addressed in future research. Overall, the research has significant implications for urban planning and infrastructure development, emphasizing the critical role of sidewalks in creating walkable, sustainable, and inclusive cities.

14. References

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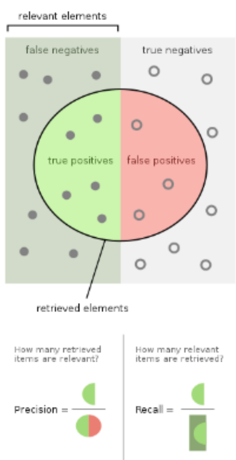
15. Appendix

15.1. Precision and Recall



$$\text{precision} = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{retrieved documents}\}|}$$

$$\text{recall} = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{relevant documents}\}|}$$

$$F_1 = \frac{2}{\text{recall}^{-1} + \text{precision}^{-1}} = 2\frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} = \frac{2\text{tp}}{2\text{tp} + \text{fp} + \text{fn}}$$

Figure. 36. Versions of permeability status classification

15.2. Permeability Status Classification

v.1.

Porosity %
(absolute % and city-level threshold)

City-level threshold to perform binary classification on the porosity status of the identified material.

9% — **Impermeable**

24% — **Permeable**

v.2.

Range
(min-max porosity %)

Material	Porosity %
Concrete	5 – 8
Brick	18 – 35
Granite	0.2 - 1.5
Granite block stone	< 1
Hexagonal Pavers	3 – 8
Mixed	Unidentified

Porosity percentage sources:
- "Permeability and Porosity of Concrete as Influenced by Curing Methods" by N.P. Rajamane, P. N. Shende, and P.G. Ranade, published in the Journal of Materials in Civil Engineering in 2004.
- Journal of Building Engineering in 2018
- Journal of Building Engineering in 2020
- International Journal of Pavement Engineering in 2014
- Journal of Construction and Building Materials in 2020

v.3.

State
(permeable, conditioned permeable, impermeable)

Material	Permeability Status
Brick	Permeable
Hexagonal Pavers	Conditioned Permeable
Concrete	Impermeable
Granite	Impermeable
Granite block stone	Impermeable
Mixed	Unidentified

Figure. 37. Versions of permeability status classification

15.3. Challenges with Project Sidewalk's Accessibility Data

Parameter	Available
No sidewalk	35,816
Surface Problem	34,703
Curb	65,286
No curb	22,806
Crosswalk	1,869
Obstacle	27539

Figure. 38. Project Sidewalk dataset

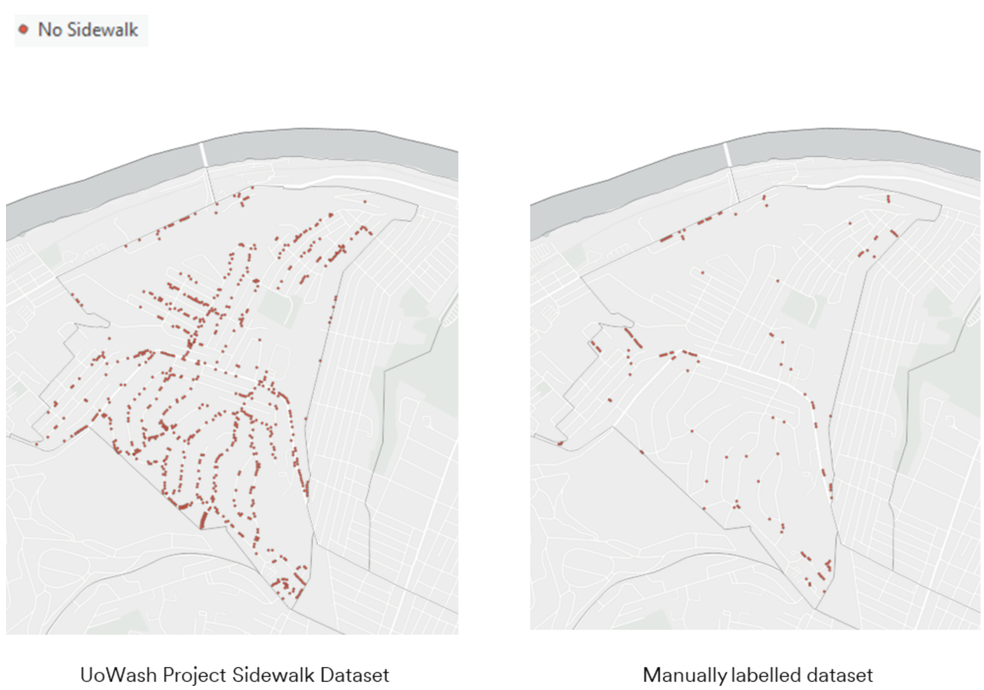


Figure. 39. Training results of WalkNet with UoWash Dataset and Manually labeled dataset

15.4. WalkNet Experiment Log

experiment_name	pretrained_model	hrent	mask_input	network_architecture	batch_size train/val	lr	lr_scheduler	optim	epochs	train_acc	train_f1	val_acc	val_f1	train_dataset	val_dataset	label_classes	t_dataset_size	v_dataset_size	NOTE
	resnet_imagenet	yes	yes	pre_resnet_conv_layers, resnet18_linear, class_head_linear	32, 32	1.00E-04	CosineAnnealingLR	Adam	30	0.9398	0.8766	0.7307	0.4298	columbus, mex_uni, mexico, newberg, oradell, seattle,	piittsburgh	4	40064	3712	NoSidewalk, CurbRamp NoCurbRamp, Surface Problem
7HrnetClass_SmallMaskedX_AllCities_top4Labels_pretrainedResnetImagenet_perClassRenet18ConvBackbone	resnet_imagenet	yes	yes	pre_resnet_conv_layers, resnet18_conv, class_head_conv_linear	32, 32	1.00E-04	CosineAnnealingLR	Adam	10	0.8407	0.6303	0.7457	0.4037	columbus, mex_uni, mexico, newberg, oradell, seattle,	piittsburgh	4	40064	3712	NoSidewalk, CurbRamp NoCurbRamp, Surface Problem
7HrnetClass_SmallMaskedX_AllCities_top4Labels_pretrainedResnetImagenet_perClassRenet18ConvBackbone	resnet_imagenet	yes	yes	pre_resnet_conv_layers, resnet18_conv, class_head_conv_linear	32, 33	1.00E-03	CosineAnnealingLR	Adam	22	0.866	0.705	0.7589	0.4417	columbus, mex_uni, mexico, newberg, oradell, seattle,	piittsburgh	4	40064	3712	NoSidewalk, CurbRamp NoCurbRamp, Surface Problem
7HrnetClass_SmallMaskedX_AllCities_top4Labels_pretrainedResnetImagenet_perClassRenet18ConvBackbone	resnet_imagenet	yes	yes	pre_resnet_conv_layers, resnet18_conv, class_head_conv_linear	32, 34	1.00E-03	CosineAnnealingLR	Adam						columbus, mex_uni, mexico, newberg, oradell, seattle,	piittsburgh	1	40064	3712	NoSidewalk
7HrnetClass_SmallXWMaskedChannels_AllCities_UniqueImagesAllLabels_pretrainedResnetImagenet_perClassRenet18ConvBackbone_NoSidewalk	resnet_imagenet	yes	No, concatenated channels	pre_resnet_conv_layers, resnet18_conv, class_head_conv_linear	32, 32	1.00E-03	CosineAnnealingLR	Adam	30	0.82	0.79	0.72	0.59	columbus, mex_uni, mexico, newberg, oradell, seattle,	piittsburgh	1	20047	3712	Cleaned Dataset
7HrnetClass_SmallXWMaskedChannels_AllCities_UniqueImagesAllLabels_pretrainedResnetImagenet_perClassRenet18ConvBackbone_NoSidewalk	resnet_imagenet	yes	No, concatenated channels	pre_resnet_conv_layers, resnet18_conv, class_head_conv_linear	32, 32	1.00E-03	CosineAnnealingLR	Adam	30	0.93	0.86	0.9	0.82	project sidewalk, pittsburgh	project sidewalk, piittsburgh	1	1580	600	Manual Dataset

Model performed well:

Sidewalk: Yes

Sidewalk: No

Model performed poorly:

Sidewalk: Yes

Sidewalk: No

Figure. 40. Experiment Log for WalkNet