Detecting, Mapping, and Grading Sidewalks using Street View Images and Secondary Sources for the city of Dallas

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**Abstract.** In this paper, we use machine learning methods to find and map sidewalks and to then assess their quality and accessibility. Using a dataset shared by researchers at the University of Maryland, we create a training set of images that is used to train a convolutional neural network to correctly identify and grade Street View images. This project focuses on the city of Dallas; however, this approach provides meaningful results to all municipalities.

1 Introduction

Documentation and mapping of a neighborhood feature, such as sidewalks, has previously been carried out through in-person (subjective) “Neighborhood Audits” or through information cataloged in Geographic Information Systems. The completeness, timeliness, and quality of the information gathered in these methods may be lower than what is needed for a comprehensive view of the availability of a feature like sidewalks across a city. There is a myriad of reasons for the city of Dallas to focus a portion of spending on sidewalk creation and repair. For the mobility impaired, availability of sidewalks is an essential requirement for moving about the metropolitan area. Additionally, sidewalks allow citizens to move in a safe manner around the city without the risks associated with walking in the streets amongst cars driven by ever-increasingly distracted drivers. Sidewalks also provide health benefits since they provide a means of pedestrian travel to near-home destinations for those who may otherwise choose to not travel. Lastly, sidewalks in disrepair tend to contribute to the “broken-windows” theory surrounding many under-privileged areas of the metroplex. Overall, sidewalks represent a worthwhile investment for the city and provide a means of safe and healthy travel for those who choose pedestrian transportation.

In the fiscal year 2015, Dallas had a proposed budget for infrastructure projects, such as sidewalks, of $7,135,208. That number has grown each of the past several years as the city has increased in size. The city of Dallas has grown in both its inhabited sprawl and in the density of the population at double-digit rates over the past 5 years. This growth can be explained by the city’s pro-business mentality and the relative value proposition that such a large city provides. Dallas boasts a centrally located position in the country, and the city’s status as a transportation hub allows businesses to send employees to any destination in the world with relative ease and efficiency. The City and State have pro-business tax and incentive policies, which have encouraged this growth. With this growth, the city must acquire a better way of allocating the budget for sidewalks and other infrastructure. Today, the city of Dallas essentially responds to complaints about sidewalks through its street services program. As inquiries come in, the city will generally put that particular inquiry on a list for assessment. There is no priority granted for severity of the situation. Additionally, maintenance in suburban areas is the responsibility of the home or property owner and this is not necessarily considered in the ranking process. The current process takes 2-3 months in order to get an assessment and cost estimate for each incident or property owner. Once the assessment has been done, either the city or the property owner will plan and fund the project. One program in Dallas allows the city to reimburse homeowners up to $500 or 50% of the repair cost, whichever is less.

Under these circumstances, the city spends significant time and resources just doing the assessments. Using the algorithmic approach that this paper describes, the city would be able to feed images of these incidents into the model and immediately receive a grading of the sidewalk in question. The city officials could then compare this grading to the grading of previous works to know whether this sidewalk was an immediate issue, who owns the sidewalk, and how much the repair may cost. This would allow the city to prioritize project desires into bins such as: critical, severe, moderate, and low-risk. Therefore, Dallas could dispatch crews to the areas where their services will be the most impactful to the safety and health of the public.

This paper presents a means of grading and prioritization of sidewalk projects to the city of Dallas via an unbiased, algorithmic approach to sidewalk repair recommendation and scoring.

YOUR INTRODUCTION SECTION SHOULD BE AN EXECUTIVE SUMMARY OF THE PAPER. YOU SHOULD HAVE A CLEAR MOTIVATION FOR THE PROBLEM BEING ADDRESSED (YOU BASICALLY HAVE THIS), A CLEAR STATEMENT OF THE PROBLEM ADDRESSED (YOU ABSOLUTELY DO NOT HAVE THIS), A BASIC DESCRIPTION OF WHAT YOU HAVE DONE TO SOLVE THE PROBLEM (COMPLETELY MISSING EXCEPT FOR SOME SUGGESTION OF AN “ALGORITHMIC APPROACH”), A SUMMARY OF THE MAIN RESULTS, A SUMMARY OF THE MIAN CONLCUSIONS, AND USUALLY AN OVERVIEW OF THE REST OF THE PAPER ORGANIZATION.

2 Problem Statement

Many municipalities struggle with how to correctly allocate funding for necessities such as pedestrian sidewalks. Oftentimes, it is hard to prioritize those items that are in the most need for repair. The city of Dallas faces limited resources and budget, and requires assistance in cataloging and prioritization of potential sidewalk construction and repair. In a large metropolitan area like Dallas, projects often are prioritized by towards projects garnering the highest number of complaints or those areas with the most political influence.

In this paper, we present a method for grading sidewalks, consistent with methods previously employed in city planning and neighborhood survey research. This grading system considers features such as “obstacles”, condition of the sidewalk, and presence of sidewalk transitions to provide a grade for a set of sidewalk training data. Using an appropriate training set obtained from prior research from the Project Sidewalk team, this project trains a convolutional neural network to correctly classify ungraded sidewalks to recommend and prioritize sidewalk repairs. After the initial training phase is complete, the model is modified to take into account other open-source data structures such as satellite imagery and personal geo-location data in order to help the model better generalize to the test data.

3 Previous Research

Image recognition is not a new field. The use of machines to recognize images has been around for decades. As early as 1963, the electrical engineering department at MIT began using computers to recognize 3D images. While these initial applications were somewhat simple compared to those that we currently use today, they paved the way for what has now become a commonplace practice across industries.

Bahlman, Zhu, and Pelkofer’s work [3] provided meaningful advancements in image element detection and classification. In this paper, the authors built upon their previous research involving shape and color recognition to help classify street signs and traffic signals. Their work is interesting in that it has a 2-step approach where if the model fails on the first classification step, the image is thrown out. This model is important to our work, because it shows how an algorithm such as Adaboost can be used to detect both anomalous and important features for an image-based problem proposal.

Another important piece of research is Perona’s “A Bayesian Hierarchical Model for Learning Natural Scene Categories” [4]. In this paper, the authors provided an approach that allowed for very hands-off model building. This model will potentially provide a structure for our model should we encounter any issues with sparse image objects that are hard to classify correctly. In the model, the computer attempts to use human-based rules to classify image objects. Essentially, each image is broken down into a series of codebook images and reoccurring elements are scanned and classified. Each of these codebook images is additionally clustered using k-means clustering. This portion of the model is used to eliminate features that occur with low frequencies in the training data. The remarkable aspect of this paper is that the model was able to achieve a 78% accuracy rate with such a low amount of supervision.

Goodfellow and a team from Google [5] showed an application of neural networks for image recognition. In this work, Goodfellow applied the DistBelief method for neural networks combined with Google Streetview images to recognize multi-digit numbers, namely street addresses. In the model, the researchers first addressed training the model to identify house numbers. This was a very important step as many variables come into play with these image captures. For instance, lighting, obstructions, and changing conditions can provide potential issues when identifying numbers from images. Additionally, varying font sizes, colors, and styles can impact the ability of the algorithms to correctly identify an image. An important aspect of this type of recognition is that if a single digit is misidentified, the entire interpretation is irrelevant and meaningless. Once the model was trained on house numbers, a more complete Streetview dataset was used. The final approach involved subtracting the mean from each image. In the end, the researcher’s models were able to achieve a 97.84% accuracy with this approach, which was just short of the human benchmark of 98% that was the target of the project. This piece of research and the approach acted as an important catalyst for our approach to identifying sidewalk obstructions and sidewalk grading.

Convolutional neural networks have also been used to improve the solutions submitted in the ImageNet Large-Scale Visual Recognition Challenge. In the work of Simonyan, Karen, and Zisserman [6], the team used convolutional neural networks combined with several other approaches to achieve one of the highest accuracy levels seen in the competition. Their application of multiple models to solve the problem provides a solid reference point for the problem that we solve in this model.

Clarke et al’s [13] audit of Streetview images as compared with an individual’s in-person audit. The study involved researchers in neighborhoods in Chicago walking each block from the inside to the outside, essentially walking the block twice, and assessing the quality of the sidewalks. This study found that subjective measures like sidewalk quality have much lower consistency between observation via Streetview and in-person observation and grading. Essentially, the conclusion is that features requiring high levels of precision can be hard to attain via Streetview images. This poses an interesting aspect to our research. For instance, our model will need to stay informed of areas that have been treated in the previous time periods. Therefore, if a database of previously updated sidewalks does not exist, we will need to provide a means of storing projects within a database that allows for those items or coordinates to be referenced. This will prevent outdated Streetview images from being used in the classification and scoring process.

In Haina et al [11], the researchers looked at signal data such as walkability of neighborhoods in relation to the overall health of the individuals in the area. The evidence used to provide insight into the improved environment of an area was sanitation practices and tobacco sales restriction. This coupled with increased walkability of an area leads to higher levels of physical activity and better health over time.

Deehr and Shumann [7] provided work for five different neighborhoods in the Seattle area. Their research considered the incidence of pedestrian strikes by motorists, the health factors of walking, and the current modes of transportation that pedestrians were using. Their research led to the city adding additional walking paths, and trails. Additionally, much of the research sparked additional community involvement in the design of multi-model transportation infrastructure. Additionally, in Richardson,Troxel et al [10], the authors sought to understand whether factors such as green space and walkability resulted in “moderate to vigorous physical activity” for the residents of randomly selected neighborhoods in Pittsburg, PA. When controlling for factors such as crime, green space, and walkability in the selected targets, it was discovered that variables such as gender, age, education, and overall walkability of the neighborhood did play significant roles in the levels of physical activity for an area..

4 Algorithm Design and Solution

For this model WHAT MODEL? YOU HAVEN’T DEFINED ONE YET, we will be applying a convolutional neural network to train and ultimately score a series of Google Streetview images of the Dallas metropolitan area. This project will help the City of Dallas better prioritize infrastructure projects with potential extensions beyond applications to sidewalks. For this model, we have considered several inputs: the training data, the testing data, and the scoring algorithm used to correctly classify images.

The training data used in this model came from the University of Maryland’s Project Sidewalk [CITE NEEDED HERE]. Project Sidewalk is part of a crowd-sourced approach to classifying images for potential issues in the image. This tool can be thought of as an application of the same methodology used by the Wayz application for smartphones, with the only difference being that users are not physically in the environment that they are assessing, rather they assess the sidewalk from their home computers. Users are dropped into a Google Streetview environment and then told to identify and grade a potential feature in the given image. The grading scale falls from a best value of “passable” (numerical value of 1) to a worst value of “not passable” (numerical value of 5). Thsi grading schema is based off of subjective, visual inspection and not actual user experience feedback. Understandably, this does introduce the potential for some bias in the training data. However, it is believed that the data cleaning methods in place from the University of Maryland are sufficient for our model. NEED TO DEFINE THESE METHODS Additionally, our model YOU HAVEN’T DEFINED YOUR MODEL YET is more concerned with the obstacle identification in the actual image rather than the grade given. Our hope is that we can incorporate grading into the actual algorithm based on some sort of dispersion measure amongst the pixels in the image itself. The data has been shared via a Box repository on the cloud where a series of panoramic images have been dropped for our consumption into the algorithm. (**UPDATE** – we are currently working on a piece of code that is able to ingest these images and understand which pixel values constitute obstacles or sidewalk features that we are interested in for this study.)

The test data that we are using is an area of focus on the South side of the City of Dallas. This is an area where a great deal of funding and gentrification has been focused. To ensure that the neighborhoods are getting the correct amount of funding, we focus in on this area of the city to start. We use the Google Streeview API in Python in order to download the proper number of images to test for the area. (We have currently not decided on image spacing as we are still working on the process for loading the images into the environment appropriately. Once we have the data downloaded into the appropriate repository we will be able to test the data collected.)

The algorithm that we are using is a convolutional neural network. Convolutional neural networks have been applied to this sort of problem on many occasions and are basically the go-to approach to solving this sort of problem. These algorithms are especially strong when the training data is of the level of quality that we have from the University of Maryland. While the convolutional neural network approach is the approach that we start with, we may take an approach using different deep learning approaches such as Deep Believe Networks or stacked denoising autoencoders. However, we are still some time off with this approach for our project. We are still working on the best approach for ingesting images into memory in an efficient manner.

5 Project Plan

Domain Knowledge Research

Understand Social and Public Health considerations of sidewalks

Pedestrian Safety concerns

Persons with Physical Difficulties

Other Approaches to the Problem – Neighborhood Audits

Python Image Processing Knowledge

Google/Bing Street View API Knowledge

Machine Learning/Neural Networks with Images

Best Practices for improving performance in image classification problems

GIS (Geographic Information System) file formats and interchanges

Development of Machine Learning/Neural Network, Cross Validation, Testing

Documentation

Final Poster Presentation

6 Github

The address for this project’s Github page is: [github.com/dpmurraygt/CapstoneProject](file:///C:\SMU%20Data%20science\capstone\AppData\Local\Temp\Temp1_CapstoneProject-master.zip\CapstoneProject-master\github.com\dpmurraygt\CapstoneProject)

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