Predicting Thermal Conditions of Urban Environments using Google Street View Images

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***Abstract*—Across the globe, heatwaves have become more common than ever before, resulting in everything from discomfort to several deaths in extreme cases. Heatwaves can hit hard in cities, partly because of urban infrastructure that both exacerbates and fails to handle extreme heat. With over half the world's population residing in densely populated urban areas, there is now a necessity to mitigate these effects via city planning. Predicting the spatial and temporal distribution of heat in cities will allow city planners to implement effective mitigation strategies and allocate resources more efficiently. This paper uses publicly available Google Street View (GSV) images to predict the temperature in urban environments by extracting features like water bodies, greenery, etc. A python script automatically downloads thousands of recent GSV images of areas based on their latitude and longitude and using a CNN[1], temperatures are predicted based on extracted geographical features.**

I. Introduction

Global warming and climate change are both, unfortunately, very real. As time passes, their effects worldwide have only worsened. Across the globe, hot days are growing hotter and fewer cold days are being experienced. Several countries in the Middle East, including Iran, Kuwait, Oman, and the United Arab Emirates, surpassed 50 degrees Celsius this summer. Moscow and Helsinki, Finland, also saw their hottest June temperatures on record, indicating that relatively colder countries are not immune to these rising temperatures. This has led to heatwaves becoming more frequent and hazardous.

In the month of June 2021, a severe heatwave in the usually temperate Pacific Northwest of the United States and western Canada brought record-breaking temperatures of 42 degrees Celsius or higher. Oregon and Washington states reported nearly 200 heat-related deaths, and British Columbia's Coroners Service recorded over three times the number of sudden deaths than usual. Laborers in kitchens, warehouses, factories, and fields suffered from heat exhaustion. Thousands of people lost power, and some public transportation services shut down due to melting operating infrastructure. The severity of this heatwave was partially due to the urban infrastructure of the affected areas.

Cities are typically warmer than non-urban environments due to an effect called urban heat island. This is due to

[1] Github Repository
https://github.com/aprosekov/CS_5824

common urban infrastructure practices - for example, asphalt provides dark surfaces that reflect less light while absorbing more heat, and closely packed buildings allow for fewer trees, and by extension, lesser shade. The natural cooling effect that comes with plants absorbing moisture from the ground to dissipate surrounding heat is also lost. The urban population today has thus had to resort to man-made means of cooling, such as air conditioners and fans. However, with temperatures rising in general, so has the demand for electricity. In extreme weather events like heatwaves, this demand often exceeds the capacity of energy grids in the city, leading to system overflows and loss of power, leaving city dwellers at extreme risk.

As heatwaves are extremely difficult to accurately predict and react to, there is a necessity to prepare in advance to prevent calamitous effects like loss of life. This can only be done in cities via implementing heat mitigation strategies such as reflective surfaces, adaptive buildings, etc. However, these resources are both expensive and limited, thus a means of prioritization is required. Predicting which areas are likely to be affected worse to expend resources appropriately is hence crucial. Our research tries to predict the spatial and temporal distribution of heat in cities since there is a direct link between the former and the potential severity of the effects of heatwaves to aid in this prioritization.

II. Existing Work

A. Examining Spatial Distribution and Temporal Change of Green View Index

Proposed by Xiaojiang Li (2020), this study uses deep learning to derive the quantitative information of street tree canopies from street-level images and map the spatial distribution of the green view index[1]. This data is then used to provide insight into the potential disparities in terms of the green view index across different racial/ethnic groups in New York City. It proves the usability of historical GSV images for monitoring temporal changes in urban areas.

B. Urban Environment Assessment Based on Street View Images

Authors He and Li (2021) systematically review the research trends of existing publications on the use of street view images for the quantitative analysis of urban neighborhood environments[2]. They found that combining deep learning with advanced image processing and data analysis methods on street view images has been reliably used several times to extract features of interest to evaluate urban neighborhoods for factors like radiation, human perception, environmental evaluation, etc.

C. Quantifying Urban Surroundings using Deep Learning Techniques

Verma et al. (2018) developed a mobile-based application to collect street-level imagery to make visual datasets, which they then analyzed using deep learning and image processing techniques to find out how environmental variables could correspond to human satisfaction and well-being[3]. They found that access to greenery and open spaces play an important role in determining satisfaction and happiness. Their research also helps identify and create aesthetically pleasing experiences.

D. Using GSV for Street-Level Urban Form Analysis

Authors Li and Ratti (2019) propose a method to quantify urban built environments to understand the potential impact on urban dwellers. Their study is restricted to Cambridge, Massachusetts, and uses GSV images to map and analyze the influence of street enclosure on solar radiation reaching the street canyons by estimating the sunlight duration in street canyons[4]. Their method is automatic and can rapidly estimate sky view factor (SVF) and sunlight duration. However, their data is restricted to street canyons without any focus on human interaction, which could provide finer details.

E. Exploring Effects of Roadside Vegetation on Urban Thermal Environment using Street View Images

While previous studies have shown that the thermal environment is related to the type and configuration of vegetation, an efficient solution to extracting vegetation on a roadside scale had not yet been offered. Li et al. (2022) solve this problem by using street view images[5]. Plants and trees are extracted and identified from these images using semantic segmentation and are compared to the corresponding land surface temperatures (LSTs) to determine a relationship. Their results indicate that the same vegetation can have varying cooling effects in different spaces. For example, they find that grass cools areas densely populated by people and vehicles most effectively, while trees are more effective in areas with roads and buildings. Their research provides useful insights for site-specific vegetation layout planning.

F. *Using GSV and DL to estimate neighborhood demography*

Gebru et al. (2017) propose a method to replace the American Community Survey (ACS) to estimate socioeconomic characteristics. While the ACS is a comprehensive source of data, the authors argue that it is labor-intensive, often uncovers demographic shifts years later, and since the survey costs about $250 million a year to conduct, extremely expensive. Thus, they present a cheaper, automated solution that uses deep learning techniques to determine the make and model of cars in the neighborhood from millions of GSV images to estimate income, race, education, and even voting patterns[6]. For example, they find that if sedans outnumber trucks in a city, its citizens are more likely to vote Democrat, and Republican if it is the other way around. They have remarkably high accuracy for most of their estimates, very comparable to that of the ACS, and while their accuracy for predicting voting patterns differs from precinct to precinct, it's still consistently above 85%. However, this method only works at a higher level and has no way to measure demographics at a finer spatial resolution.

G. *Automated Building Age Prediction using Street View Images*

Sun et al. (2021) presents an automated workflow to estimate building age from GSV images[7]. They use Amsterdam as a case study alongside publicly available street view images and a deep convolutional neural network to do this. They achieve an accuracy of 81% and state that their research could play an important role in saving both time and money in the valuation of real estate, building energy efficiency, disaster vulnerability prediction, and urban planning. Their research is novel in that building age can provide very relevant information as to a building's condition, however, there was no real way to predict this before their model was published. However, while the model is rapid and requires little pre-processing thanks to the DCNN, it has trouble ignoring irrelevant features in images, which is likely why the accuracy isn't incredibly high.

H. *Predicting Traffic-Related Air Pollution using GSV Images*

Ganji et al. (2020) developed a set of algorithms to extract built environment features from GSV images in order to recognize the different functions of buildings[8]. Using these features alongside measurements of ultrafine particles and black carbon, a Bayesian Regularized Artificial Neural Network (BRANN) is trained to predict road air quality. They compared their BRANN model with existing ANN models and found that their solution had comparatively higher predictive power and by extension, accuracy, since previous models used GSV images alone.

III. Problem Description

Urban heat assessment is one of the prime objectives of Urban Planning. Center for disease control and prevention (CDC) reported 702 heat-related deaths from 2004 to 2018 in the US, which shows the gravity of the heat issues in metropolises. Illnesses due to prolonged heat exposure in urban areas are becoming increasingly common, yet they are highly preventable. By studying street view data, we can determine zones of a city that are prone to extreme heat, and interventions can be done efficiently during a heatwave and prevent a crisis. Identifying "heat islands" in a city can also be useful in urban greening, thereby reducing the number and/or efficacy of heat islands in the city.

IV. Datasets

A. *Urban Heat Data from Heat Watch Campaign*

We collected the temperature data from the CAPA Heat Watch website for various parts within the city of Roanoke, Virginia between the range 25°C to 35°C, and extracted the geo-coordinates (latitude and longitude) associated with those parts[10].

We chose Roanoke as a case study because the problem of Urban heat islands is a serious problem in Roanoke[11]. It is expected that this situation will only worsen in the coming years if no steps are taken. Roanoke itself is a medium-sized city with a population little over 100,000 persons and growing. It is simple enough to model and subsequently, we can apply our findings to much larger cities using the same model. Hence, it seems a fitting case for our study and we can expect high-quality data with good coverage available for the city as well. Studying the major problem up close also provides us with information on how to plan mitigation methods for the urban heat problem, so that we can prevent it in time.

We chose the temperature range, from 25°C to 35°C because this is the range of average temperatures, the lower limit being the hottest daily average temperature in July while the upper limit is the hottest maximum average temperature in July [12][13]. This, of course, does not include outlier values like 20°C or 40°C since temperatures below 25°C are not hot enough to be an issue, while the temperatures higher than 35°C are very rare so it would be better if we train our model on more commonly occurring temperatures.

B. Google Street View Image Data

Using Python scripts, we extracted the existing PanoIDs of the aforementioned locations using the Street View Static API. We then constrained the result to the range between pictures from the years 2015 to 2020 and compiled all the images into a collection of around 23,000 elements. Subsequently, we randomly sample a total of 4,800 images out of those 23,000 images. This is a fairly large sample space since it is about 20% of the total dataset. Ultimately, we did a run with our model over that sample size.

V. Methodology

A. Approach

The GSV API provides us with a decent source of data for modeling various characteristics of the urban environment, such as foliage, its density, surface materials of various elements such as metal (from vehicles), gravel or asphalt (from roads), concrete (from buildings), and so on, building density in a particular region, traffic data, etc. Analyzing these as well as other constituent elements of an urban area yields insights into key aspects of that area such as air pollution, urban heat islands, lack of sunlight in a region, as well as other environment-related variables. The Google Street View image is an ever-growing and freely available dataset that provides extensive and invaluable outputs when used for modeling purposes.

B. Model Design

We have designed our model by using Machine Learning algorithms and trained datasets of temperature data and physical characteristics. We used a CNN with a continuous value for temperature as output. The loss function applied to the CNN was Mean Squared Error.

Our model has a convolution layer followed by a max-pooling layer. After that, we added a dropout layer to reduce overfitting. Then, we have two more convolution layers and max-pooling layers. Finally, we have a layer to flatten the data and then a dense layer with a linear activation function to output our temperature.

VI. Results

A. The Experiment and our findings

We ran our model over the sample dataset for three epochs. We found a loss of 1.04 on the testing dataset. As we can see from the diagram, the loss function becomes minimum as the number of epochs increases.

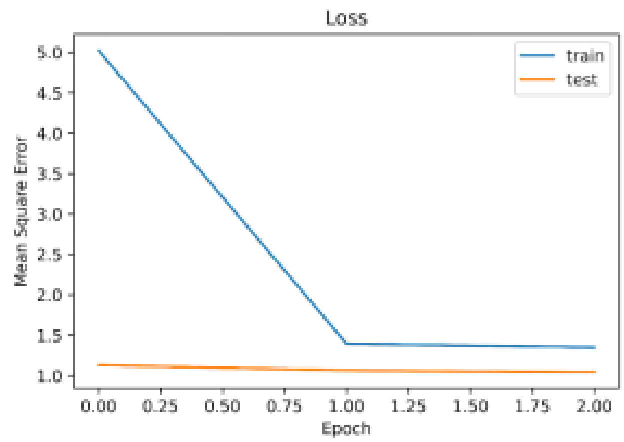

Fig. 1: Mean Square Error vs Epoch. The above chart shows that as the number of epochs increases the mean square error decreases to a certain minimum value.

	Difference between prediction and true temperature
Mean	0.793
Standard Deviation	0.64
Min	0
25%	0.26
Median	0.65
75%	1.16
Max	2.94

Fig. 2: Differences between our prediction and the true values recorded for the temperature. The above chart shows the accuracy of our model by comparing the predicted value of temperature from our model with respect to the actual observed values of temperature.

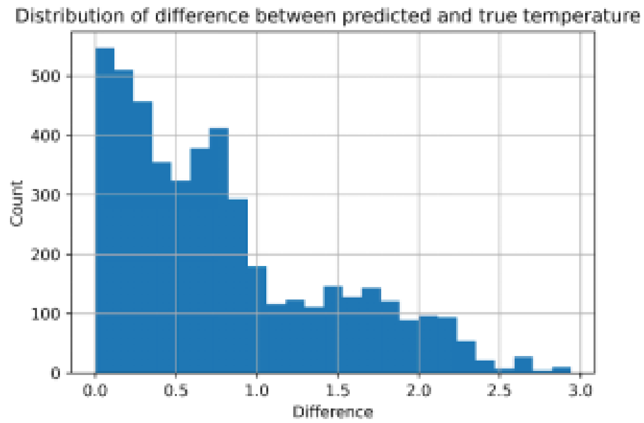

Fig. 3: Distribution of differences between predicted and observed temperature values. The above chart shows how many readings differ by how much. As we can see, most (~39%) of our predicted values are either the same as observed values or very close to it (<0.5). Only a small number (~27%) of readings do vary by a greater value (>1.0). Most values remain below the difference of 2.5 and values above that are scarcely observed.

VII. Conclusion

Our model was able to predict the temperature of a given location with high accuracy. Most of the average absolute difference between the prediction and true temperature was 0.793, however, this data was skewed to the right and the majority of data points (about ~39%) were within 0.5 degrees of the actual temperature. Another ~34% were within 0.5 to 1 degree of the actual temperature. This is a very low percentage difference as actual temperature ranges are much higher. A difference of even 2.94 degrees at our max is still valuable information in predicting the temperature based on the urban landscape. The main contribution of the project is a model that can predict urban thermal conditions from street view images. One of the literature reviews was similar in that it specifies which vegetation is better at cooling given the surroundings on Google Street View. However, it does not make a prediction of the environment temperature itself. We learnt that there is always room for making the model larger and more complex, but understanding the needs and what we are trying to solve will make it much easier. These two studies had a lot of similarities, but the use cases of the predictions vary because of the slightly different problem definition.

VIII Discussion and Future work

A. Importance of Research

With climate change being such a pressing issue, researchers are scrambling to save energy and cut emissions as much as possible. However, the damage has been done and it will take time to repair it. Data analysis and similar tools as ours can help mitigate the impact of climate change on society by helping us understand the environment better. A greater understanding of the environment can aid in safer development of land, more eco-friendly industries (fishing, lumber, power generation), and healthier lives. Being able to predict urban heat waves can lead to healthier lives, especially for those who are more prone to extreme weather and temperature. Heatstroke, sunburn, and even skin cancer are all affected by heat and sunlight on a day-to-day basis. In a busy city, there are always pressing concerns at hand and "small" environmental factors with large consequences as these will be ignored.

B. Barriers in Advancement

There is a lot of disbelief in science and people take it with a grain of salt at best. If a heatwave is reported but someone has to show up to work, he or she may just wear lighter clothing and then change out of it later on. If there was a way to show the direct effects of heatwaves or other natural phenomena on the human body, it would be a lot easier to get the public to believe in such tools and data science. This wouldn't be a future improvement for this project in particular, but public trust is a large barrier for many researchers and scientists in improving daily lives.

C. Future Work with wider input types

Future work for this project could include looking at other cities or using more real-time data, such as from the Landsat 8 satellite. It orbits the earth once every 99 minutes, and most areas on earth are imaged once every 16 days[9]. The data is downlinked and streamed to many websites that access the data for users to see. Another benefit of using satellite data is that it provides more information than regular imaging sensors. The satellite covers a much larger range of electromagnetic radiation and could help in improving the prediction data by drawing conclusions on ultraviolet light, infrared heat from buildings and fires, and even atmosphere quality. However, more data also means many more relationships and we might not be able to draw causations, just correlations between data. For example, more reflected light may mean that the city has less absorbent materials, but it could also mean the atmosphere quality is good and scatter less light, or there is cloud cover. But looking at UV and infrared radiation levels may be able to show if it is truly atmospheric conditions or city planning and eco-friendly materials.

D. Computing Resources for Higher Performance

Lastly, in order to improve the model performance, larger datasets may be needed. The training of our models took a very long time as is, and upgrading to high-powered computing (such as the VT ARC servers) may improve the prediction capabilities of our machine learning model. Another option would be to run the training software on a cloud computing instance. This would also help in splitting workloads for certain model types that can be run in parallel.

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