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Application of AI for Detection of Urban Heat Island Effect via Semantic Segmentation of Satellite Images

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Abstract

Urban areas globally face escalating challenges from Urban Heat Islands (UHI), characterized by elevated temperatures in urban regions compared to surrounding areas. This paper addresses the urgent need for comprehensive UHI analysis and mitigation strategies by harnessing advanced Artificial Intelligence (AI) and Computer Vision techniques. The primary objectives encompass leveraging high-resolution satellite imagery and semantic segmentation algorithms for accurate UHI detection through detailed land cover classification. Additionally, the study integrates weather information application programming interfaces (APIs) to correlate real-time and historical weather data with UHI intensity, providing a holistic understanding of UHI effects. Our proposed methodology involves a twofold architectural design, comprising the preprocessing of satellite images using patchify-ing and semantic segmentation for land cover classification. Experimental results demonstrate the model's ability to differentiate between urban and rural areas, showcasing its potential for automated UHI detection. The research emphasizes the importance of acquiring ample satellite data to enhance accuracy and resolution, acknowledging current limitations in the available dataset. In conclusion, this paper underscores the necessity of a holistic approach to UHI, combining AI and Computer Vision for precise detection and comprehensive analysis. While presenting a case study for a single city, the outlined pipeline provides essential steps for detecting UHI effects in any area equipped with necessary satellite imagery and temperature data, contributing to the broader understanding and mitigation of UHI in urban environments.
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Keywords
Image Processing, Satellite Images, Image Segmentation, Urban Heat Island effect, Deep Learning, AI detection

1. Introduction
The ongoing growth and development of urban areas have presented societies with unprecedented opportunities for economic growth but have also given rise to a range of environmental challenges. Among these challenges, the phenomenon of Urban Heat Islands has emerged as an urgent concern, demanding extensive attention for detecting the phenomenon and innovative approaches to mitigate it. The Urban Heat Island (UHI) effect can be defined as the increase of temperature in urban areas, compared to surrounding rural or suburban areas.

Globally, extensive research efforts have been dedicated to understanding and quantifying microclimates at the local level, often with the objective of offering design recommendations to enhance the overall quality of urban environments (Hathway and Sharples 2012). The anthropogenic heat generation in cities, due to air conditioning and combustion engines also impacts their microclimate. This anthropogenic heat flux is mainly caused by the energy consumption with space heating. Another factor is urban building materials such as concrete, asphalt, and steel that absorb solar radiation and release heat back into the urban environment (Sachindra et al. 2023). Besides urban structure and hard surfaces, the shortage of vegetation cover in cities are cited as the major contributors to the artificial temperature increase in cities (Soltani and Sharfi 2017). All these factors contribute to worsening the effect of UHI in urban cities.

It is possible to mitigate the effects of UHI enhancing surface porosity, and increasing the availability of water for evaporative cooling, through the evapotranspiration process (Hathway and Sharples 2012). Bande (2017) proposes solutions to mitigate the UHI effect that include utilizing cool roofs, cool facades, innovative pavement and asphalt materials with high albedo, shading trees and shading designs for urban cities.

1.1 Objectives

This study addresses the challenges of urban heat islands (UHI) by employing state-of-the-art Artificial Intelligence (AI) and Computer Vision techniques for the accelerated and automated analysis of weather and climatic data. Our key research objectives are:

1. Leveraging high-resolution satellite imagery and semantic segmentation algorithms, for precise UHI detection through detailed land cover classification.
2. Integrating weather information application programming interfaces (APIs) to draw conclusions about the effects of UHI by correlating real-time and historical weather data with UHI intensity.

2. Literature Review

Previous research and scholarly work have been conducted to examine, detect, and understand the UHI effect. Case studies are the most common type of research in heat islands research, including an analysis of the climate, temperature, and changes in these factors over time in some urban cities around the globe.

Works such as Sachindra et al. (2023) and Mohammed et al. (2020) focus on data analysis for a developing city over time. This is done using historical data to simulate future results, while reporting the results in figures, charts, and regression lines to visualize the UHI effect. This approach requires access to weather data from weather stations, over long period of time, which is not always available. Metrics involved in these studies include the normalized difference vegetation index (NDVI), The diurnal temperature range (DTR), Sen's slope (SS) and more.

On the other hand, Makido et. al (2016), Voelkel and Shandas (2017) and Soltani and Sharfi (2017) collect their own temperature data with a temperature sensor placed on top of a vehicle, more commonly known as traverse data. This data can be more accurate and provide more insight about the city's micro-climate compared to publicly/privately owned weather stations. The traverse data can be used to create heatmaps and visualize the temperature in the city, for better understanding of UHI. These studies also compare surface and air temperatures which are collected while traversing the city, which further report the effect of UHI.

Furthermore, it is possible to draw conclusions about the UHI effect for a location based on the Land Surface Temperature (LST). There is prominent correlation between urbanization and LST rise, and further significant evidence for LST and the quantification of UHI effect (Maharjan et al. 2021). Urbanized and populated cities tend to have changes in surface albedo, emissivity, and evapotranspiration, in addition to replacing green land cover with impervious land surfaces, such as concrete buildings. By evaluating these factors, there is a trend in detecting UHI effect with the increase of the LST for the urban cities. This is more evident in works such as Maharjan et al. (2021), where UHI zones are more concentrated near the urban business centers with high population density and rising LST.

Finally, more recent works include more advanced and automated techniques, more specifically satellite imagery. Satellite images consist of rows and columns of image pixels, in addition to *bands* or channels describing the wavelength or color of these pixels. Red band, Green band, Blue band, Infrared band are examples of bands in satellite images. In Liu and Zhang (2011), the authors use Landsat band data (NASA 2021), Terra Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) (USGC 2024) and the mono-window algorithm (Qin et al. 2001) to retrieve LST data. NDVI and Normalize Difference Build-up Index (NDBI) were also computed to quantify the UHI effect. Similarly, Badugu el al. (2023) utilizes aerial images, in addition to European Space Agency (ESA) World Cover and the MODIS Land Cover Type to classify the study area into multiple land types including build-up, trees, cropland and more. By developing an algorithm for the MODIS, the authors estimated the LST over 20 years, and were able to identify the UHI effect.

3. Methods

Our work aims to build on previous work, while offering solutions for up-to-date, accurate results. This section is split into 2 parts, regarding the technologies we are employing in our architectural design. Part 1 focuses on preprocessing the satellite images by means of patchify-ing and reconstructing the satellite images. Part 2 explains the semantic segmentation of land cover for classification and differentiation between vegetation versus build-up, or rural areas versus urban cities.

3.1 Data Pre-processing for Satellite Images

Satellite images can vary in size, due to multiple factors including but not limited to the type of satellite, sensor specifications, resolution, and the spectral bands used. With images of very high resolution, it would require a lot of time and computational resources to process them and generate segmentation masks for the areas of interest (rural vs urban). It is possible to resize the images, but this comes with a loss of data that may impact the segmentation results. Therefore, creating patches of the image, passing them to the segmentation model and then reconstructing the original image, is a successful approach to avoid losing any information from the image, while correctly creating segmentation masks for regions in the image. This method of creating patches is known as *patchify-ing* the image, and a sample of this process is shown in Figure 1.

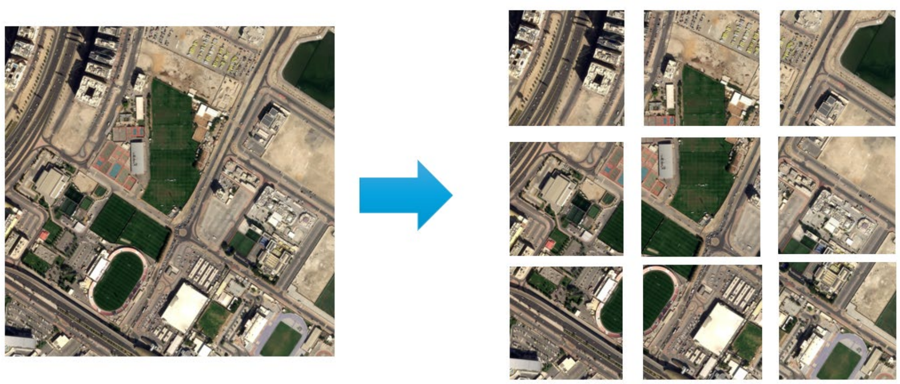


Figure 1: Example of image patchify-ing. The original image is split into 9 patches that when recombined, would create the original image again.

3.2 Semantic Segmentation for Satellite Images

Our research suggests an automatic labeling of land-cover to identify urban cities and rural areas, to allow for the comparison between the two categories. This approach, utilizing computer vision techniques, is referred to as Semantic Segmentation. Semantic segmentation is applied to many fields, but recently, more datasets concerning satellite images have been published, and deep learning models trained on these datasets can be found online.

The segmentation model in this paper combines Grounded DINO (Liu 2023) and Segment Anything (SAM) (Kirillov et al. 2023) models, to create the Grounded Segment Anything model (Grounded-SAM Contributors 2023), that detects and segments anything with text prompts. The model performs well on high resolution satellite images, as it first detects objects in the image, then segments them, and creates the appropriate mask. This process can be seen in Figure 2.

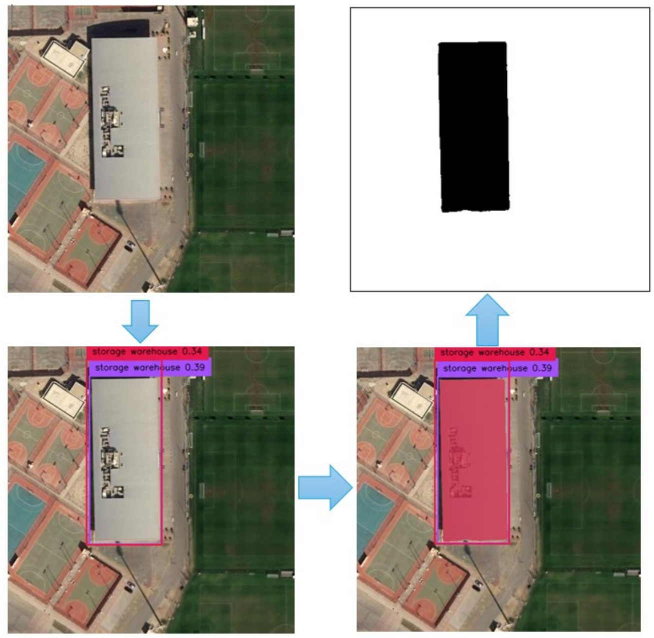


Figure 2: First the original image is passed to the model to create bounding boxes around the object of interest (storage warehouse in this case). then a mask is created around the object filling the bounding box, finally, the mask is extracted.

For our work, two labels were selected to differentiate between the rural and urban sections needed for the UHI comparison. These labels are *rural barren fields* and *urban city*. Although the two patches are to be selected to represent these two labels, it is possible to extend this to bigger images with more sections, to differentiate the density of rural areas and urban cities.

3.3 Integration of Weather Data API

By using a weather data Application Programming Interface (API), it is possible to retrieve data about the temperature of a location by inputting its latitude and longitude data. This creates the following full pipeline in Figure 3.

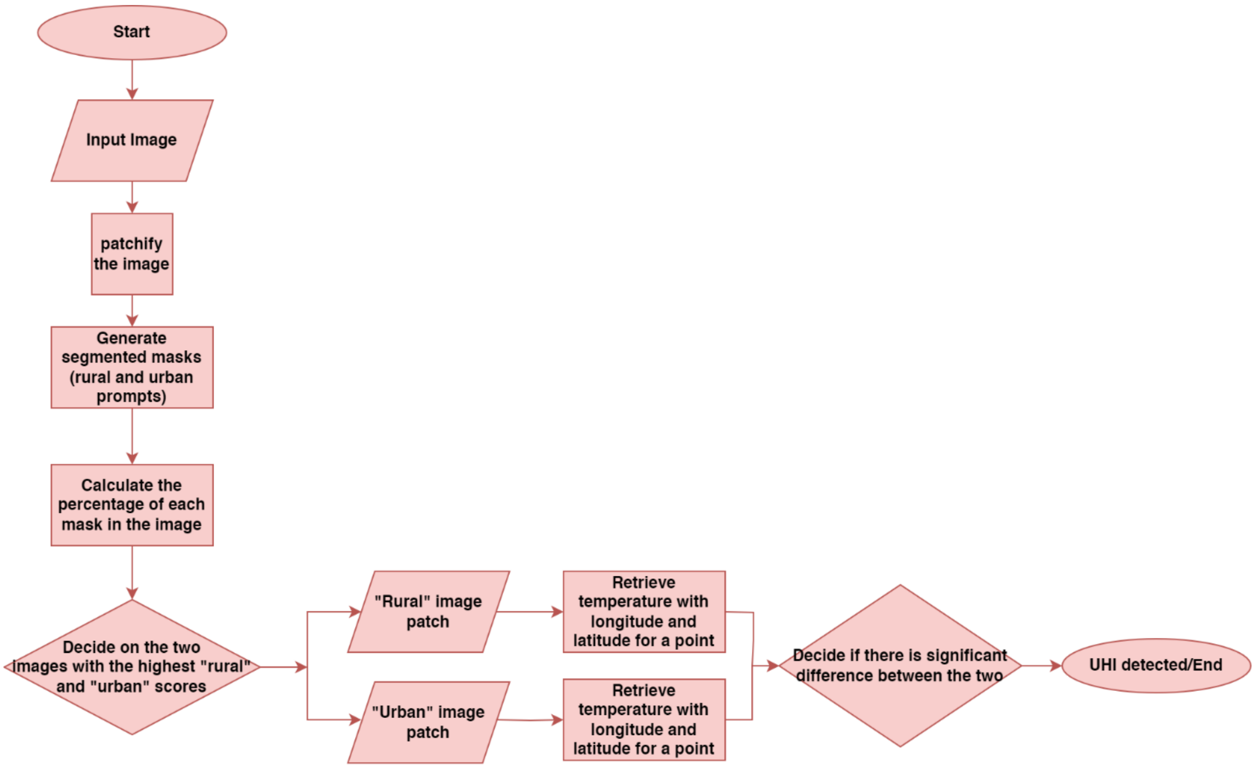


Figure 3: Pipeline of UHI detection using segmentation and temperature data. The input image is first patchified, segmentation masks are then created, two patches are chosen as *rural* vs *urban* depending on their masks. The API is used to retrieve temperature data of each patch, and UHI is detected when the difference is considerably high.

4. Data Collection

4.1 High-Definition Satellite Imagery

The abundance of information embedded in high-definition satellite images contributes to environmental studies, facilitating the identification and evaluation of various phenomena, including UHI. For instance, the study by Voelkel and Shandas (2017) highlights the systematic prediction of urban heat islands through the integration of high-resolution satellite data but stresses over the limited availability of such data for general research. On the other hand, the resolution of satellite images dictates how accurate land regions can be. Sentinel-2 images, with relatively low resolution of 10m, are difficult to work with for segmentation purposes, as land regions become blurry the more you zoom in. This requires additional effort to extract segmentation areas from the satellite images and involves developing a specific algorithm as done by the ESA World Cover, which is static data limited to 2021.

Consequently, low-resolution images are more attainable but difficult for segmentation, whereas high-resolution images are uncommon but rich in information. Luckily, high resolution image sources, similar to Maxar Imagery (used in Google Maps) and Airbus OneAtlas (OneAtlas 2024), provide resolutions down to 30 cm, while providing enough samples to test the research direction of this paper. A comparison between the low-resolution and high-resolution images (from OneAtlas) can be seen in Figure 4, showcasing the difference in colors and the identification of objects.

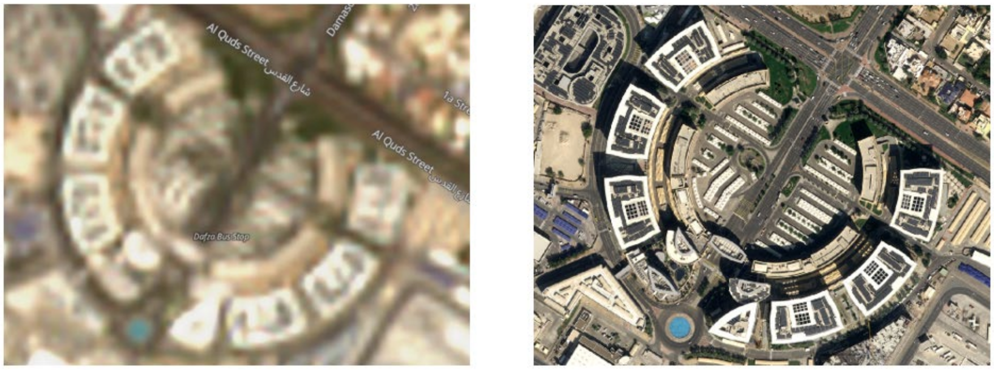


Figure 4: Comparison between low resolution image (left) and high-resolution image (right). Higher resolution images have clear objects, and easily identifiable structures.

4.2 Weather Data Retrieval

The satellite images acquired are not 2D images, but rather a raster of pixel data, channels/bands, and meta data regarding the coordinate system of the image. With the meta data, it is possible to map the image to latitude and longitude data, and after identifying the two regions of interest for the UHI analysis, it is possible to use these latitude and longitude data to extract temperatures and other weather data using a weather API. Open-Weather (OpenWeather 2024) is an example of an API that can provide temperature, humidity, pressure, minimum and maximum temperatures for a point of interest. An example of this is shown in Figure 5 where the satellite image raster is visualized with QGIS.

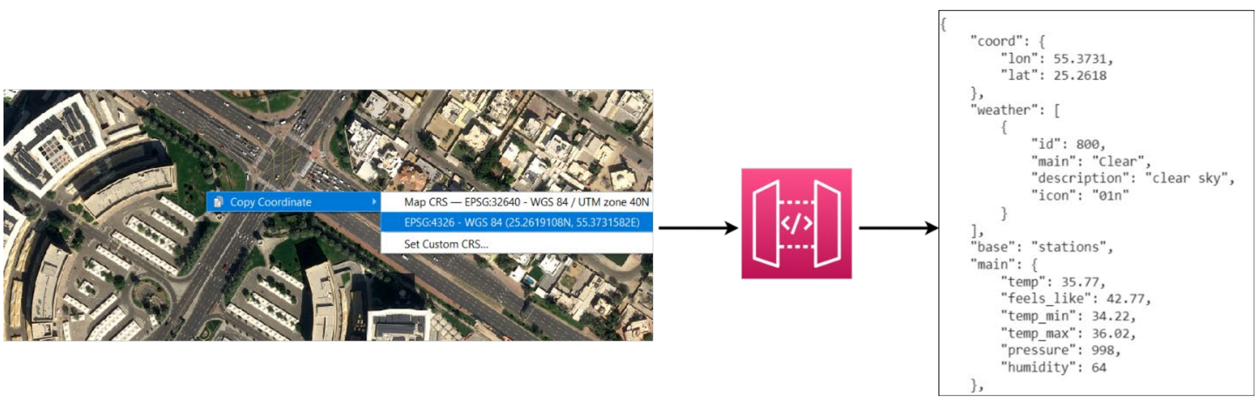


Figure 5: Example of OpenWeather API given location data for an area of interest. The API provides weather data such as temperature and humidity.

Figure 6: Satellite view of Renmark, Australia

5. Results and Discussion

Although this work can be extended to any city with high resolution satellite images available, this work uses a sample image from Airbus for the city of Renmark, Australia, and some of the rural areas surrounded it. The sample space can be seen in Figure 6.

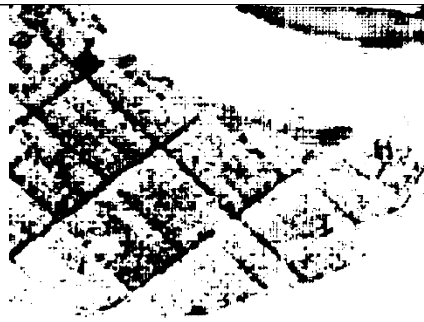
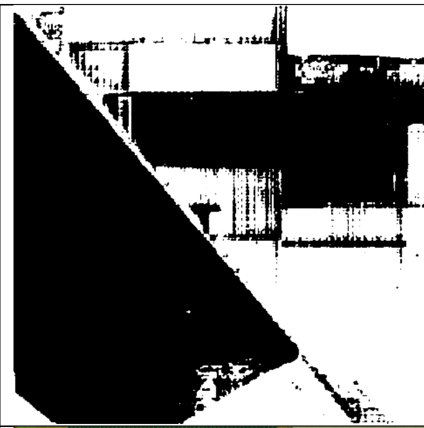
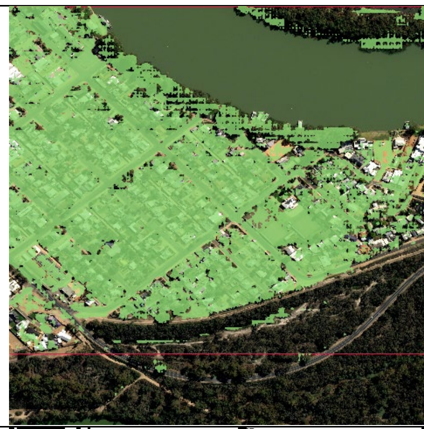
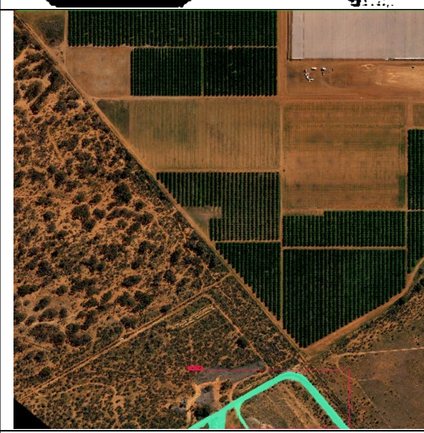
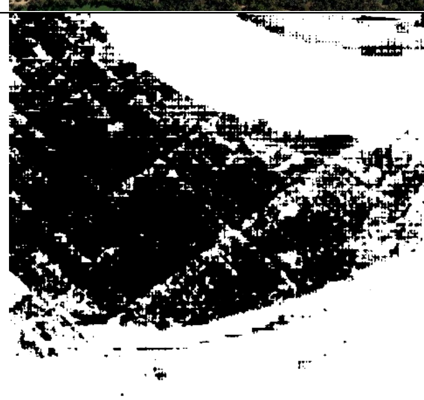
By first processing the image through RasterIO, the RGB image was extracted and saved. Following this, the image was then ’patchified’ and two image patches were chosen, one representing an urban city with human buildup, including houses, roads, cars and boats. In addition to some green areas including house yards, and trees surrounding the roads. The second image represents a rural area, including agricultural fields and barren lands.

5.1 Graphical Results

In Table 1, the input images (left image representing the urban city patch, and the right image representing the rural agricultural patch) are passed to the model with two labels. It can be seen that the *rural barren fields* label covers a larger area in the image patch representing the rural area, while the *urban city* label is covering more area in the heavy buildup patch. This is experimental proof that the model can differentiate between the two patches, and the labels can be used to categorize one as urban and the other as rural. This step can be automated to calculate the percentage of each mask compared to the total size of the image, where a larger percentage of *rural barren fields* indicates the rural area, whereas larger percentage for the *urban city* label points to the urban area.

Table 1: Comparison between two input images for two labels through Grounded DINO + SAM. Label 1 is the rural barren fields and Label 2 is the urban city. The masks for each label for each image are also visualized. Label 1 occupies more space in the second image (rural), while label 2 occupies more space in the first image (urban).

Input image		
Label 1		

Label 1 mask		
Label 2		
Label 2 mask		

5.2 Numerical Results

After identifying the urban and rural sides, the coordinates can be extracted from the patch by reversing the process of converting the RGB to the raster. By doing this, the center of the rural area and the center of the city are obtained and are used for the comparison in terms of temperature data. The center values are listed in Table 2.

Table 2: Coordinates of the center of each section for the UHI analysis. The coordinate system is also mentioned for reference.

	Longitude	Latitude	Coordinate System
Urban City	140.754	-34.179	EPSG 4326
Rural Area	140.681	-34.183	EPSG 4326

Table 3: Temperature acquired through the API at the center of each section as of July 2023. The rural area has a considerably lower temperature compared to the urban area.

	Longitude	Latitude	Temperature (°C)
Urban City	140.754	-34.179	14.23
Rural Area	140.681	-34.183	13.97

Afterwards, the temperature can be processed from the API for both locations for a specific date (in this case, July 2023). It is also possible to summarize the historical data over a period of 40 years (1983 - 2023) with the paid version of the API, in steps of 5 years. The data is tabulated in Table 3.

The temperature data acquired clearly indicates a rise of temperature in the urban city compared to the rural area, heavily implying signs of the UHI in this city.

5.3 Proposed Improvements

It is possible to further improve the results of this research by acquiring a large number of satellite data for cities, to accurately choose the rural and urban patches for comparison. Currently, this research is limited by the amount of satellite images available, and their resolution which heavily impacts the performance of the segmentation model. Additionally, the segmentation model is very sensitive to the label provided to differentiate between urban or rural patches. This requires tweaking the label provided until a suitable mask is generated, however, the labels provided in this paper worked on multiple patches in this case study. Finally, comparing results between the current year and historical data can further indicate the seriousness of the UHI effect for a city, although this requires a paid subscription to the weather API. This paper focused on open-source resources, and this part was not possible to implement.

6. Conclusion

Addressing Urban Heat Islands (UHI) demands a holistic approach integrating AI and Computer Vision. First requiring the utilization of high-resolution satellite imagery and semantic segmentation for precise UHI detection through land cover classification. Then, integrating weather data from APIs to correlate real-time and historical weather data with UHI intensity.

There are many solutions to mitigate the effects of UHI, however, it is still a tiring task to fully prove the existence of the phenomenon within many cities in the world. This paper provides a case study for a single city, put outlines the necessity steps in a pipeline to detect the UHI effect in any area provided with the necessary satellite imagery and temperature data.

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Biography

Hosam Elgendy is currently a master's student at the Mohamed bin Zayed University of Artificial Intelligence in the department of Computer Vision. He received his bachelor's degree in electrical engineering from the American University of Sharjah in 2021. His research areas include object detection and segmentation for remote sensing data, in addition to classification of hematology blood cells and medical report generation for medical data with chest Xray images.

Patrick Mukala is an Assistant Professor of Artificial Intelligence and Data Science. With a background and training in Computer Science, He teaches computer science courses and conduct research pertaining to AI and Data Engineering. He holds a double PhD in Computer Science. His research interests are in AI for Data and Process analytics (Applied Analytics) and Software Engineering. In Applied Analytics, his interests are in Learning Analytics, Process-Centric Analytics, Healthcare Analytics and Governance analytics. The objectives of these research endeavors are centered around understanding and determining the appropriateness of analytics techniques regarding current data analysis demands as demonstrated by issues in the real world; developing and providing novel process-centric paradigms for data analysis and their application; as well as working in close collaboration with industry to understand the demands and provide timely and relevant solutions thereto. He also does extensive work in semantic web, abstract state machines, model checking and automata theory. Dr Mukala has numerous years in research and teaching from the Tshwane University of Technology in South Africa, the Technical University of Eindhoven, and the Fontys University of Applied sciences in the Netherlands. For over 5 years, He worked for several companies in the Netherlands in various capacities in data architecting, data engineering, data science and AI.