Mapping the Potential for Solar and Wind Power in Montreal, Canada

SolarWind.ai

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Abstract

SolarWind.ai is a geospatial analytics platform designed to identify optimal locations for solar panel installation within urban settings. The software uses satellite imagery and machine learning to identify underutilized rooftop space that can be used to harvest solar energy, with Montreal serving as the pilot region. The vision of the SolarWind.ai team is to be able to provide clients with a tool capable of performing remote consultations by accurately assessing their site's solar potential. This platform addresses the growing demand for renewable energy by combining advanced geospatial analysis, terrain classification, and environmental data to provide recommendations for energy installations. Our key goals include maximizing renewable energy potential while considering site-specific factors such as shading, roof angles, climatic conditions, and proximity to existing infrastructure. An important objective of the project is to design this software to be accessible for any property owner, regardless of technical ability. This platform will help clients recognize that energy self-sufficiency is now within reach by providing accurate analysis and insights such as available area and energy estimations at different solar panel efficiencies and price points.

This semester, our team implemented roof and obstacle recognition with Facebook's Detectron2 framework and its implementation of the Mask R-CNN machine learning model. The model was then tested using the Inria Aerial Image Labeling dataset. The group worked on rooftop segmentation, obstacle removal using masking and pixel-to-metre conversions for surface area estimation. The user interface is designed to be intuitive and simple, keeping accessibility in mind. In the future, the team will focus on model scalability, also working with more data to produce more reliable energy output estimates depending on climate and other factors, and an expansion into the urban wind energy industry by providing recommendations for wind turbines along highways and other settings. SolarWind.ai seeks to contribute to the broader adoption of renewable energy in urban environments by aligning with Montreal's sustainability goals.

Acknowledgements

We would like to acknowledge the graduate students who work closely with Dr. Hemmerling, and with ITAG Lab. We were fortunate to receive guidance from Sean Jeffries, who, as a graduate student, was able to use his past experiences to steer us in the right direction. He also helped logistically by meeting with us on behalf of our advisor and ensuring that we stayed on the right course throughout the semester. Sean also provided us with some academic papers that would help with our research and building our knowledge base.

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1. Introduction

The growing demand for renewable energy sources has created the need for innovative tools to optimize the deployment of solar panels and wind turbines. Urban areas have very dense populations and have substantial energy consumption, this presents unique opportunities to offer homeowners renewable energy alternatives and installations. However, identifying optimal locations for such installations requires precise analysis and assessment, which introduces several challenges, including assessing rooftop suitability, evaluating environmental conditions, and identifying proximity to existing energy infrastructure. SolarWind.ai seeks to address these challenges by leveraging advanced technologies like satellite imagery, machine learning, and geospatial analysis to deliver data-driven solutions for renewable energy site selection.

The goal of the project is to design an accessible platform that can remotely identify and evaluate rooftops that are suitable for housing solar panels. The project focuses on Montreal as a pilot region due partly to its urban complexity, diverse building structures, and varied climate conditions. By integrating environmental factors such as sunlight exposure, roof slope, shading, and seasonal weather patterns, the platform aims to provide accurate and actionable recommendations for energy installations

A key motivation for this project is the global push for sustainable development and the increasing reliance on clean energy sources. Montreal's sustainability goals emphasize reducing greenhouse gas emissions and increasing renewable energy adoption, aligning perfectly with the objectives of SolarWind.ai. By enabling precise and efficient site selection, this project supports the city's efforts to meet these goals while promoting the adoption of renewable energy technologies in other urban environments worldwide.

The project involves several core components: high resolution aerial satellite image processing, geospatial analysis, machine learning model development, instance segmentation and solar panel efficiency research. First, satellite images are processed to identify rooftops, assess their suitability for solar panel installations, and detect obstacles such as shaded regions or air conditioning units. Mask R-CNN implemented through Detectron2 is employed to enhance the accuracy of rooftop recognition and obstacle detection. Datasets such as the Inria Aerial Image Labeling dataset and OpenStreetMap play a critical role in training and testing these models.

The project also emphasizes interdisciplinary collaboration and a systematic approach to problem-solving. Each stage of the project has challenged the team to communicate effectively, to thrive while working with deadlines and function within a group and work to achieve our goals. This project has required each group member to incorporate parts of their McGill studies into the problem solving methodology, and use experiences and functional skills from outside of the classroom to overcome technical challenges to complete a milestone or goal. Eric Dayan and Maximillian Railton focus on machine learning model development, dataset integration, and implementing the instance segmentation process to produce rooftop masks using pixel detection and bounding boxes around each roof. They took a lead on training and fine tuning the Mask R-CNN model, adjusting some hyperparameters to improve performance, and ensure that the model would work accurately with the constraint of computational power available to the group. Aidan Bienstock worked on roof surface area estimation and energy output calculations, in order to understand other projects that have tried to enter the urban solar energy market and to create a proper methodology for assessing solar potential on a citywide scale. Model adjustments were made by comparing outputs from early development stages to real-world data. Regulatory constraints and environmental factors were also researched and will be incorporated within the model in future stages. Platon Leftakis on researching solar panel technologies suitable for Montreal's climate. He also worked on designing and testing the graphical user interface. With the core principles of accessibility and simplicity in mind, he tested different setups to find one that will work efficiently and smoothly for the target clientbase. This division of tasks ensures comprehensive coverage of the project's technical and analytical aspects.

In addition to the technical challenges, the project addresses practical considerations such as cost-effectiveness and alignment with local regulations. Research into Montreal's municipal guidelines for renewable energy installations and the economic viability of proposed solutions ensures that the project's outcomes are both feasible and impactful. SolarWind.ai's significance extends beyond its technical achievements. The project contributes to the broader understanding of renewable energy deployment in urban areas, offering insights into how advanced technologies can be applied to real-world problems. SolarWind.ai has the potential to accelerate the adoption of clean energy solutions, reduce environmental impacts, and enhance urban sustainability by providing a scalable, accurate, and practical tool for site selection.

2. Background

In order to determine where renewable energy installations like solar panels and wind turbines are most effective in an urban setting, we need to combine knowledge from several technical fields. First, understanding how solar and wind energy systems work is crucial. Solar panels capture sunlight and convert it into electricity, while wind turbines harness the kinetic energy of moving air. The amount of energy each device produces depends on factors such as the intensity of sunlight, wind speed, the angle of a rooftop, and any nearby structures that may cause shading or turbulence.

We rely on satellite imagery and geospatial data to analyze and identify the best locations for these installations. Satellite imagery provides an overhead, bird's-eye view of the city, showing rooftops, streets, and other surfaces. By applying computer vision techniques—automated methods for interpreting images—researchers can detect and classify specific features such as building outlines, roof types, and obstacles like chimneys or air conditioners. Geospatial data, often obtained from sources like OpenStreetMap, adds information like building footprints, land use patterns, and regional boundaries.

A machine learning model, like Mask R-CNN implemented with Detectron2, is an essential tool for analyzing the complex information in these images [1]. These algorithms are trained to "learn" what rooftops and other features look like and automatically identify them in new images. Before training, however, we need suitable datasets—large collections of labelled images—to teach the model how to recognize relevant features. This is why gathering and preparing the right datasets is a critical step. By refining these models, we can help city planners, building owners, and energy providers quickly and accurately determine which rooftops are best suited for solar panels or where small wind turbines might perform most efficiently.

To make informed recommendations for solar panel installations, it is necessary to understand the three primary types of solar panels: monocrystalline, polycrystalline, and thin-film. Each type has specific characteristics that influence its efficiency, cost, and suitability for urban environments. Monocrystalline panels, with their high efficiency (15% to 20% [2]) and long lifespan (up to 40 years [3]), are particularly advantageous in space-constrained areas. However, their higher upfront costs must be weighed against their long-term energy production. Polycrystalline panels offer a more cost-effective alternative with slightly lower efficiency (13% to 16% [2]), making them suitable for installations with more available rooftop space. Thin-film panels, known for their flexibility and lightweight design, are best suited for unconventional or industrial settings, though their lower efficiency (10% to 18% [2]) limits their viability in densely populated areas.

Environmental conditions, such as temperature, also play a critical role in the performance of solar panels. The temperature coefficient, which is a measure of how much power output decreases as temperatures rise above 25°C, varies between panel types. Monocrystalline and polycrystalline panels typically have similar coefficients, while thin-film panels exhibit better temperature performance. In Montreal's colder climate, all solar panel types benefit from increased efficiency, as cooler temperatures prevent overheating. This provides an advantage when compared to installations in warmer climates where high temperatures reduce energy output.

3. Requirements

3.1 Problem Description

The core issue SolarWind.ai seeks to address is the informed integration of solar panels and wind turbines within urban landscapes like Montreal. While renewable energy systems are increasingly cost-effective and publicly supported, pinpointing the most suitable installation sites within dense, architecturally diverse environments remains challenging. Factors such as variable roof geometries, shading from surrounding buildings, structural integrity, and local microclimates introduce significant complexity. Beyond the technical challenges, there is also a need to consider broader societal factors, including aesthetic preferences, noise concerns, ecological impacts, and community acceptance. Achieving a balance between environmental gains, economic feasibility, and public support is central to the problem at hand.

3.2 System Objectives

SolarWind.ai aims to establish a robust, data-driven platform that integrates satellite imagery, geospatial data, and environmental parameters to identify optimal locations for renewable installations in urban settings. The objectives include accurately detecting and classifying rooftops and open spaces suitable for solar or wind energy generation, estimating seasonal and site-specific energy yields, and providing actionable recommendations. The ultimate goal is to assist city planners, utility providers, and property owners in making informed, sustainable decisions that consider both technical criteria and societal values.

3.3 Project Requirements

3.3.1 Data Acquisition and Preprocessing

Accessing and processing high-resolution satellite imagery, and data from sources like Google Earth Pro and Aeria is fundamental. The raw data must undergo cleaning, normalization, and conversion into uniform formats compatible with machine learning models. Ensuring a reliable and continuously updated data pipeline allows SolarWind.ai to reflect current urban environments accurately.

3.3.2 Machine Learning and Algorithmic Constraints

The chosen model—Mask R-CNN implemented through Detectron2—must handle various variations in building shapes, roof colours, and seasonal lighting conditions. The model must detect viable installation surfaces accurately, even with occlusions or lower-quality imagery. Continuous retraining with annotated datasets, performance benchmarking, and refinement cycles are necessary to guarantee reliable and trustworthy recommendations.

3.3.3 Environmental and Physical Constraints

Urban environments present numerous physical and climatic variables that influence energy production. Different roof structures, load-bearing capacities, and construction materials affect how and where systems can be installed. Additionally, variations in solar irradiance, local wind patterns, and microclimatic conditions must be factored into energy yield estimates. The platform must also consider the entire lifecycle of installations, including maintenance requirements and eventual disposal or recycling.

4. Results

4.1 Types of Solar Panels

In urban environments like Montreal, optimizing rooftop space for solar energy generation necessitates carefully evaluating solar panel types, considering both efficiency and cost. The primary solar panel technologies include monocrystalline, polycrystalline, and thin-film panels, each with distinct characteristics that influence their suitability for specific applications. In the figure below we can see how these three solar panels look like.

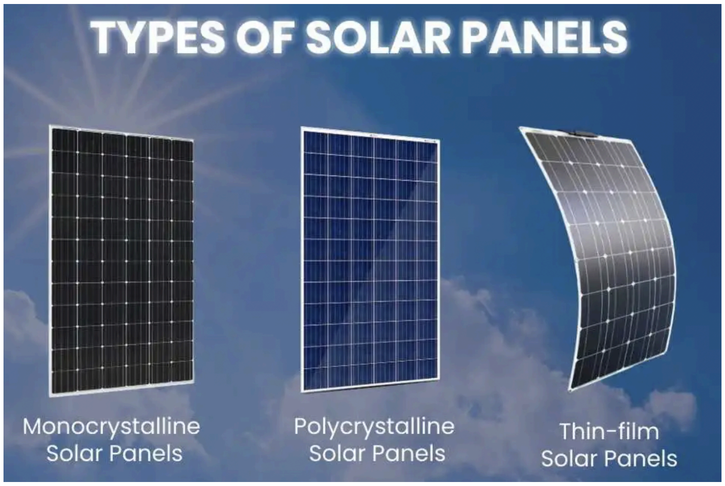

Figure 1: The three main types of solar panels [3]

4.1.1 Monocrystalline Solar Panels

Monocrystalline panels are crafted from single-crystal silicon, resulting in high-efficiency rates typically ranging from 15% to 20% [2]. This high efficiency makes them particularly advantageous in urban settings where rooftop space is limited, as they can generate more power per unit area compared to other panel types. Additionally, monocrystalline panels exhibit a moderate performance in low-light conditions and have a longer lifespan than their counterparts, reaching up to 40 years [3].

However, these benefits come with higher manufacturing costs, making monocrystalline panels more expensive than polycrystalline and thin-film panels, with prices ranging from $1 to $1.50 per watt [3]. Outfitting a 6kW system ranges from $6,000 to $9,000 [3]. However, efficiency and longevity can offset initial costs over time, as savings in energy costs justify the higher upfront price.

In terms of temperature robustness, cold temperatures (below freezing) do not affect power efficiency, that's because solar panels absorb energy from our sun's abundant light, not the sun's heat. In fact, cold climates are actually optimal for solar panel efficiency. So long as sunlight is hitting a solar panel, it will generate electricity [4]. This is true for all types of solar panels. Where temperature is affected is in the higher temperatures (25℃ and above). This is measured with the use of a temperature coefficient, which is a measurement of how much its power output decreases for every 1°C rise over 25°C. For monocrystalline panels, the temperature coefficient ranges between -0.3% / °C to -0.5% / °C [5]. Which is moderate compared to the other options.

4.1.2 Polycrystalline Solar Panels

Polycrystalline panels are composed of multiple silicon crystals, leading to efficiency rates between 13% and 16% [2]. While their lower efficiency means they require more space to produce the same amount of energy as monocrystalline panels, their simpler manufacturing process results in reduced costs. Typical costs are $0.75 to $1 per watt, totaling $4,500 to $6,000 for a 6kW system, with a lifespan of 25 to 30 years [3]. Polycrystalline solar panels have around the same temperature coefficient as their singular crystal counterpart, at approximately -0.3% / °C to -0.5% / °C [5]. In urban areas with ample rooftop space, polycrystalline panels can be a cost-effective option.

4.1.3 Thin-Film Solar Panels

Thin-film panels are created by depositing photovoltaic materials onto a substrate, resulting in lightweight and flexible modules with efficiency rates ranging from 10% to 18% [2]. Their flexibility allows for installation on unconventional surfaces, and they perform better in high-temperature and low-light conditions compared to crystalline panels [2]. The temperature coefficient for thin-film solar panels is typically around -0.2% / °C [5], making it a good option for higher temperature climates if power output is a top priority. However, their lower efficiency necessitates more space to achieve comparable energy output. Thin-film panels cost between $0.75 and $1.10 per watt, are more economical but have a shorter lifespan of 10 to 20 years, suitable for specific applications like industrial settings or smaller projects [3]. In urban settings where rooftop space is at a premium, thin-film panels may be less suitable unless specific structural considerations dictate their use.

4.1.4 Recommendation

Considering the unique characteristics of urban environments like Montreal, selecting the optimal type of solar panel involves a careful balance of efficiency, cost, available rooftop space, and climatic conditions. Based on these factors, monocrystalline panels emerge as the most suitable choice for installations where rooftop space is limited. Their high efficiency, typically ranging from 15% to 20% [2], allows for greater energy generation per unit area compared to other panel types. This makes them particularly advantageous in densely populated urban areas where maximizing energy output is essential. Despite their higher upfront costs, which range from $1 to $1.50 per watt [3], their long lifespan of up to 40 years [3] and superior performance offset these initial expenses over time, making them an excellent long-term investment.

Polycrystalline panels offer a cost-effective alternative for installations with larger rooftop areas or less stringent space constraints. While their efficiency, between 13% and 16% [2], is slightly lower than monocrystalline panels, their affordability, with prices ranging from $0.75 to $1 per watt [3], makes them an attractive option for budget-conscious projects. These panels are particularly well-suited for mid-sized commercial buildings or residential complexes where sufficient rooftop space compensates for lower efficiency. With a lifespan of 25 to 30 years [3], polycrystalline panels strike a balance between cost and performance, making them a viable option for projects that prioritize affordability.

Thin-film panels, on the other hand, are best suited for niche applications. Their lightweight and flexible design makes them ideal for unconventional rooftops or curved surfaces. These panels also perform well in high-temperature conditions due to their lower temperature coefficient of -0.2% / °C [5], ensuring stable energy output even in warmer environments. However, their lower efficiency, ranging from 10% to 18% [2], and shorter lifespan of 10 to 20 years [3] limit their applicability in urban areas with limited rooftop space. Thin-film panels are better suited for temporary or industrial installations where adaptability and cost outweigh efficiency and longevity.

	Monocrystalline	**Polycrystalline**	**Thin-Film**
Cost	$1 to $1.50 per watt	$0.75 to $1 per watt	$0.75 and $1.10 per watt
Efficiency	15% to 20%	13% and 16%	10% to 18%
Temperature Coefficient	-0.3% / °C to -0.5% / °C	-0.3% / °C to -0.5% / °C	-0.2% / °C
Lifespan	Up to 40 years	25-30 years	10-20 years

Figure 2: Summary of findings for Monocrystalline, Polycrystalline and Thin-Film Solar Panels

Montreal's colder climate provides an advantage for all panel types, as solar panels generally perform better in cooler temperatures. While panels with lower temperature coefficients, such as thin-film panels, offer slight advantages in high-temperature conditions, this is not a significant factor for Montreal, where temperatures rarely exceed 25°C for extended periods. Monocrystalline and polycrystalline panels remain highly viable for consistent year-round performance in such climates.

When optimizing for both energy production and cost savings, life cycle cost analysis is essential. Monocrystalline panels, with their high efficiency and extended lifespan, offer the best long-term savings despite their higher initial costs. Polycrystalline panels present a middle ground, balancing affordability with reasonable efficiency and durability. Thin-film panels should only be considered for installations that demand unique design features, such as non-standard surfaces or structures where flexibility is critical.

Ultimately, selecting the appropriate solar panel type requires a comprehensive evaluation of site-specific factors. Variables such as shading, roof orientation, structural integrity, and available space significantly influence the effectiveness of a solar installation. By aligning solar panel selection with the specific needs of each rooftop, SolarWind.ai can deliver efficient, cost-effective, and sustainable energy solutions for Montreal and similar urban settings.

4.2 Model

Rather than designing a model from scratch, we leveraged Facebook's Detectron2 framework and its robust implementation of Mask R-CNN. This model was pre-trained on the large-scale COCO dataset, providing a powerful foundation for object detection and instance segmentation tasks. Mask R-CNN is especially well suited for our application because it produces both bounding boxes and pixel-level segmentation masks, which are critical for accurately delineating rooftops in aerial imagery.

Our initial experiments began with the Mask R-CNN model configuration using a ResNet-50 backbone (mask_rcnn_R_50_FPN_3x.yaml). However, after evaluating performance, we transitioned to the more powerful ResNet-101 backbone (mask_rcnn_R_101_FPN_3x.yaml). The ResNet-101 architecture contains significantly more parameters than ResNet-50, leading to richer feature representations and improved detection accuracy—especially for complex scenes and smaller objects. This upgrade was crucial in enhancing the model's capability to accurately detect and segment rooftops.

During training, we observed that the model converged between 10,000 and 12,000 iterations, indicating a suitable balance between overfitting and underfitting on our augmented dataset. In early trials, we experimented with processing images at 5000×5000 resolution, but these high-resolution inputs required up to 40 GB of GPU VRAM—well beyond our hardware capabilities. To address this limitation, we applied random cropping (to 2500×2500 pixels) to effectively manage GPU memory while preserving essential features of the rooftops. We anticipate that with access to greater processing power, using full-resolution images (up to 8K) could provide even more precise segmentation masks and further enhance obstacle detection.

Training was conducted using Detectron2's DefaultTrainer, which handled checkpointing and logging seamlessly. We set the solver parameters with a base learning rate of 0.00025, a batch size of 6 images, and trained for 13000 iterations. Additionally, we adjusted the confidence threshold (cfg.MODEL.ROI_HEADS.SCORE_THRESH_TEST) to 0.4 during inference to ensure that even smaller rooftops were detected reliably. Post-training evaluation was performed using Detectron2's DefaultPredictor for inference and the Visualizer for qualitative output, which can be seen in Figure 4. For quantitative performance, we employed the COCOEvaluator on our validation subset to measure metrics such as Mean Average Precision (mAP), which confirmed the robustness of the model in diverse scenarios.

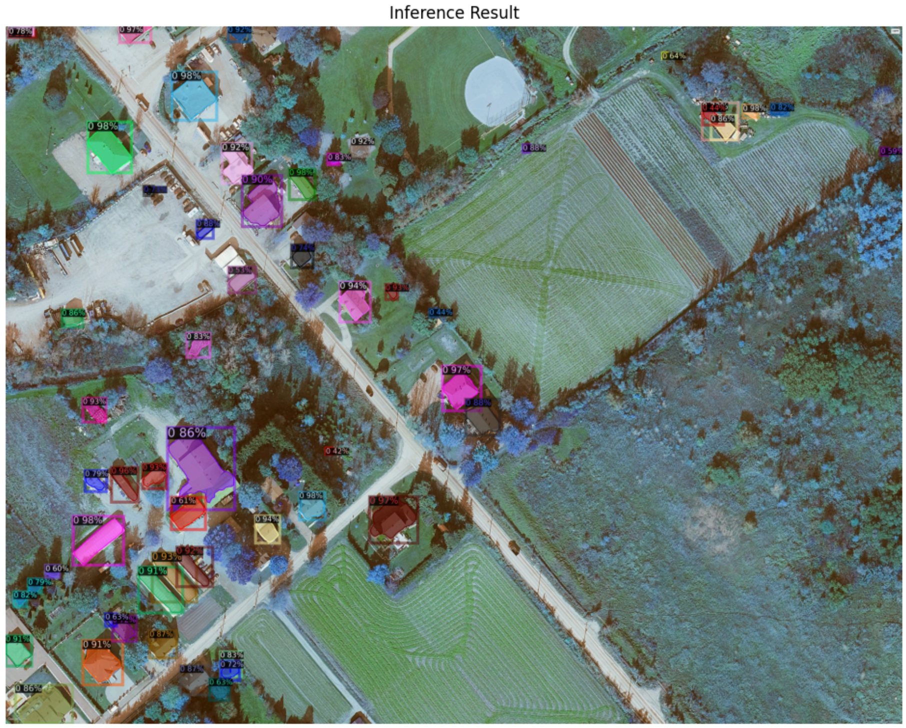

Figure 4: Inference result on Montreal satellite image

4.3 Dataset

The success of our rooftop detection system is equally reliant on the quality and diversity of the dataset used for training and evaluation. For the primary training data, we utilized the Inria Aerial Image Labeling dataset, which offers high-resolution aerial imagery over a total area of 810 km². This dataset is divided equally into 405 km² for training and 405 km² for testing. The imagery is orthorectified and provided in color, with a spatial resolution of 0.3 m, enabling detailed segmentation of building structures. The ground truth annotations classify regions as either building or not building.

Our data preparation process involved converting the provided polygon annotations into binary masks using OpenCV for thresholding and contour detection. We implemented a custom function, get_inria_dicts_split, to read image-mask pairs from designated directories, extract contours, and construct dataset dictionaries containing image dimensions, bounding boxes, segmentation polygons, and category labels in a format compatible with Detectron2. An example of the processed test data can be seen in Figure 5.To enhance the diversity of the dataset and improve model generalization, we augmented the data by rotating and mirroring the original image-mask pairs. This data augmentation increased the dataset to 1440 pairs, exposing the model to a wide variety of rooftop orientations and configurations.

For model evaluation, we assembled and used a custom test set of Montreal imagery alongside the Inria test set. These images were sourced from Google Earth Pro and were carefully selected to cover different times of day and seasons, thereby ensuring the model's robustness under varying lighting and environmental conditions. Importantly, all the Montreal images were captured from a constant elevation, which enabled us to accurately calculate the area of the masks (i.e., the usable rooftop space for solar panel installations) by correlating pixel dimensions with real-world measurements.

Moreover, the dataset was deliberately split by geographical regions rather than adjacent areas. For instance, images from Chicago were exclusively allocated to the training set, while images from San Francisco formed the test set. This approach was designed to rigorously assess the model's generalization capabilities across dissimilar urban landscapes, ensuring that the detection performance is not limited to a single type of urban environment.

Overall, the integration of high-resolution, diverse aerial imagery with robust data processing and augmentation techniques has been fundamental in developing a model capable of accurately detecting rooftops and assessing their suitability for solar panel installations.

Sample Data Visualization

Figure 5: Visualization of Sample Test Data

4.4 Obstacle Detection and Area Calculation

4.4.1 Obstacle Detection

In our system, the obstacle detection module was developed through an iterative process. Initially, I focused on perfecting the model on individual roofs. For each isolated roof, the code extracts the relevant roof area based on the bounding box computed from the segmentation mask and applies the mask from the original image to isolate that region. The isolated roof is then preprocessed by converting it to grayscale and applying a Gaussian blur, which smooths out noise and minor variations. Following this, Otsu's thresholding is used with an initial threshold value of 50 to convert the image into a binary format, effectively highlighting the potential obstacles.

Once this binary image is obtained, contours are identified, representing possible obstacles such as vents, chimneys, or shadows. These obstacles are then drawn and filled on a separate image to generate an obstacle mask. By inverting this mask, the obstacles are effectively removed from the original roof mask. The cleaned roof mask, where only the usable roof area remains white, is then merged back into the overall mask.

After establishing this procedure on individual roofs, the code was enhanced to loop through all the roofs in a given image. This involved iterating over every roof region detected in the segmentation mask, applying the same obstacle detection and removal steps to each roof, and then reintegrating the updated regions back into the original mask. The final output is a comprehensive, updated mask in which obstacles are consistently removed from all rooftop regions, thus presenting an accurate depiction of the usable area for solar panel placement.

4.4.2 Area Calculation

Once the final processed mask was produced—with obstacles removed from each detected roof—the next step was to quantify the usable roof area available for solar panel installation. This was done by first counting the number of white pixels in the final mask using a function like OpenCV's cv2.countNonZero, which effectively gives an estimation of the total usable area in pixel units. Since the physical dimensions of the captured image are known (986.58 meters in width and 708.28 meters in height), the area that one pixel represents can be calculated. Specifically, by dividing the physical width by the image's pixel width and the physical height by the image's pixel height, we obtain the dimensions of one pixel in meters. Multiplying these two values provides the area per pixel in square meters. Finally, by multiplying the area per pixel with the total count of white pixels, we obtain the total usable roof area in square meters. Converting the resulting value into square kilometers gives a more comprehensible measure for large-scale planning and evaluation. This method ensures that the mask's pixel-level information accurately translates into a physical area, enabling precise assessments of potential solar panel installation sites.

4.5 User Interface

The user interface (UI) for the Solarwind.AI application was built using Python's Tkinter library to provide users with a simple, clean, and effective way to analyze rooftop images. The interface is designed with clarity in mind, minimizing the complexity while presenting the results in an informative and engaging manner. Its design accommodates non-technical users such as homeowners, inspectors, or municipal staff who may need to evaluate the suitability of rooftops for solar panel installation.

4.5.1 Visual Design and User Flow

Upon launching the application, users are presented with a centered window featuring the logos of McGill University, the Solarwind.AI logo, and a solar panel icon, as seen in Figure 6. Below the logos is a prompt inviting users to upload an aerial image of a rooftop.

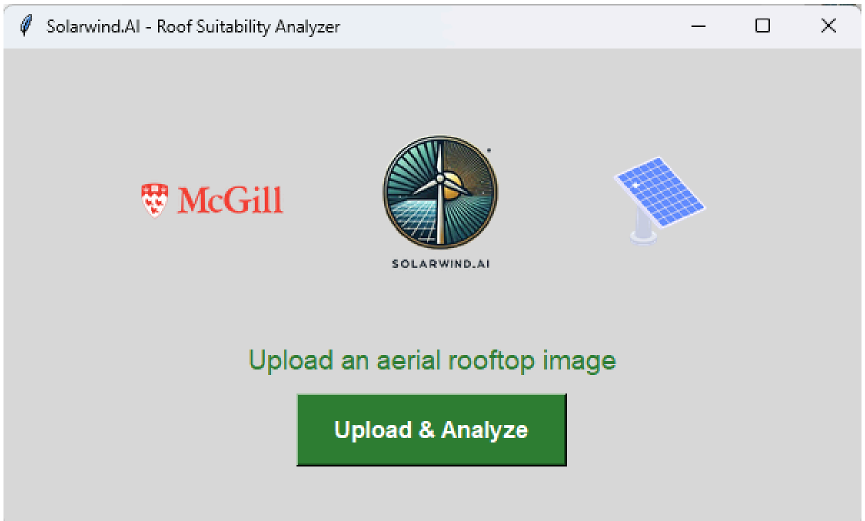

Figure 6: GUI main screen

The main action available to the user is an "Upload & Analyze" button. When clicked, the system opens a file dialog where the user can select a rooftop image from their computer. Once an image is selected, the system takes over and performs the full analysis pipeline automatically, there are no additional steps required from the user. This flow ensures the interface remains streamlined and easy to use.

4.5.2 Processing and Visualization

After an image is uploaded, the application runs inference using a pre-trained deep learning model (Mask R-CNN via Detectron2) that segments rooftop areas from the image. The model outputs a binary mask highlighting the detected rooftops, which is saved to disk for further analysis.

The next step involves detecting obstacles on the rooftop. The application uses image processing techniques, as mentioned previously, to identify features that may interfere with solar panel installation, including vents, chimneys, and air conditioning units. These obstacles are removed from the rooftop mask using a carefully filtered contour detection method, which ensures that only rooftop pixels free of obstructions are considered usable.

Once the cleaned rooftop mask is generated, the application calculates the total usable rooftop area in square meters by relating the image's pixel dimensions to real-world measurements. Based on this area, the software estimates how many standard solar panels (approximately 1.6 m^2 each) could fit on the roof. The system provides two estimates: the maximum number of panels (90% of the theoretical max), and a recommended estimate (60% of the maximum) to account for spacing, wiring, and real-world limitations.

To communicate the results to the user, the application opens a visualization window displaying three images side by side. The first shows the original uploaded image. The second shows the model's inference result with rooftop areas highlighted. The third shows the final cleaned rooftop mask after obstacle removal, with text overlay summarizing the usable area and estimated panel counts. This layout helps the user clearly see how the rooftop was interpreted and what parts of it are suitable for panel placement. The output can be seen in Figure 7.

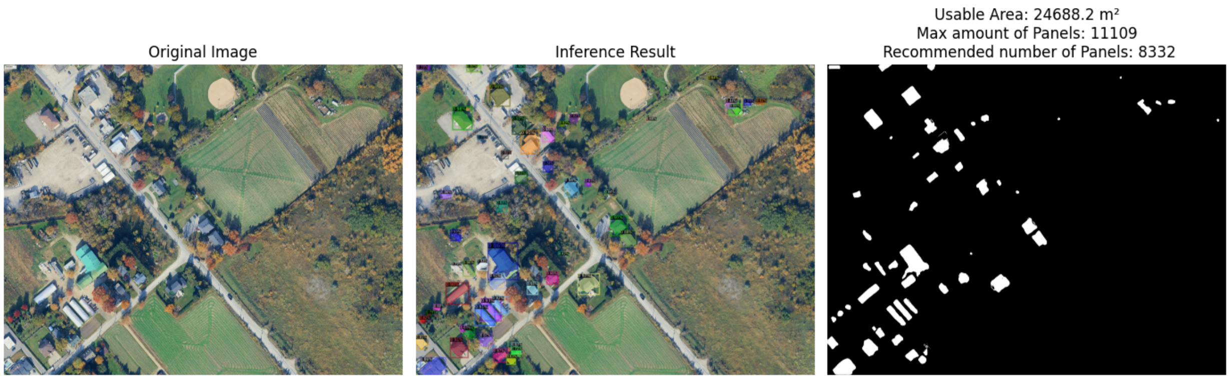

Figure 7: Output of the User Interface

4.5.3 User Experience and Extensibility

The UI was designed to be lightweight and responsive. All major tasks are performed automatically after a single image is selected, minimizing the learning curve and ensuring the system can be used without technical knowledge. Because the results are presented visually and numerically, users receive immediate and interpretable feedback on the solar potential of the rooftop in question.

While the current interface meets its core objective, several improvements are possible in future versions. One idea is to allow users to export the analysis results to a PDF or CSV file for record-keeping or sharing. Another enhancement could be a batch mode where users can analyze multiple images in a single session. More advanced features might include allowing users to manually adjust the rooftop mask, correct false obstacle detections, or factor in sun exposure and roof orientation using geolocation data. Additionally, performance could be improved by adding support for GPU acceleration if available on the user's system.

In its current form, the interface strikes a balance between functionality and simplicity, delivering meaningful insight into rooftop usability while keeping the user experience smooth and accessible.

5. Future Plans

As SolarWind.ai arrives at the final stage of the initial development and successfully launches its first fully functional prototype, the team's primary focus shifts to refining the software to improve its accuracy, scalability, and usability. Given the diversity in urban metropolises, their climates and their layouts, a future goal is to have the platform be capable of giving adaptable feedback across various city settings in North America. SolarWind.ai is proud of the foundation of the project that has been built over the past two semesters, the team recognizes that the model must be improved and more real-world factors and data must be integrated in order to set this product apart in the market and deliver the best analysis and recommendations for clients.

The core objectives of future stages will revolve around refining the model to produce more accurate, reliable and repeatable results. With access to more powerful GPUs and more computational power, the model will be retrained using higher-resolution imagery to improve performance. Using full-resolution imagery will enable better edge detection and roof segmentation. The improved model accuracy will help with roofs of irregular shape and those covered by overhanging trees or other obstacles. The models will also be fine-tuned to handle larger and more diverse datasets, extending beyond the initial training set to include different topological and geographical regions. This scalability is critical for transitioning the product from the Montreal pilot project to a broader North American market, enabling the platform to provide reliable site recommendations across varied urban environments. Simultaneously, research will be conducted on the biggest North American metropolises to verify the model's performance in new cities and compare to surface area estimations that are calculated using the rudimentary method. This method is shown below in Figure 8, where the variables are defined as follows: the energy from a photovoltaic system is given by the product of the area of the panels (A), the solar panel efficiency (r), the annual average solar radiation on the panels (H) and the performance ratio (Pr) [6]. Poly or mono crystalline silicon modules will have a solar panel efficiency of around 15% and a performance ratio of about 86% for these systems [6]. The values A and H will be unique to the pilot project, Montreal, Canada, and will need to be determined in the coming months through further research.

$$E_{\text{yr}} = A * r * H * P_r$$

Figure 8: Formula to Calculate Electrical Energy from Photovoltaic Systems [1]

Another critical improvement will be to make the model provide and predict more nuanced estimations, that take into consideration a wide range of important real world factors. These factors will include sun-path depending on geographical location, seasonal climate variation, city-specific building and zoning codes, roof tilt and panel tilt which are also dependent on geographical location. For example, for the pilot region of Montreal, this will include incorporating the Solar Ready Guidelines, a preliminary step to narrow the roofs that are usable will be to identify the ones that have at least 3.7 m by 3.0 m of unobstructed area that will be available for use, not shaded or obstructed by trees or other obstacles and is ranging from east to west [9]. The area for use must also be located above the wall line or extend beyond the roof edge, and the roof should ideally have a pitch between angles of 23º and 56º above the horizontal [9].

The improved model will aim to detect and distinguish between static obstacles like chimneys and HVAC units, and dynamic factors that could obscure rooftop suitability data. This will ensure the software generates more precise and actionable recommendations for solar panel placement. By integrating research on solar panel types and their performance under different conditions, this feature will personalize recommendations, balancing efficiency and cost considerations. A user will be able to input their location and budget, and receive one or more suitable recommendations that specify total cost and predicted energy generation. This customization will enhance the software's value proposition, making it more appealing to potential clients and ensuring that recommendations are both technically feasible and economically viable. Improvement to UI key functionalities will also be important in future releases, such as interactive maps for exploring recommendations and customizable filters. The team will prioritize accessibility, ensuring that the software remains easy to use while maintaining its technical sophistication.

SolarWind.ai also plans to expand the software to be compatible for clients looking to enter the wind energy market. With access to higher computational power and the ability to process high-resolution imagery, the team is aiming to provide wind turbine placement recommendations within cities. This phase of expansion will focus on recognizing corridor areas alongside highways, industrial parks and similar environments that offer unobstructed airflow, converting them into stable and suitable areas for wind energy harvesting. A model will need to be developed to consider average wind speeds, elevation data and geographical constraints to provide personalized and proper recommendations. Depending on the location and surroundings, the recommendations will include different turbine tower heights, blades configurations and turbine systems to offer the maximum amount of energy possible. By integrating each of these components into the software, SolarWind.ai is confident the expansion into the wind energy sector will be a success, similar to the original solar panel analysis platform. The results will now be able to provide two types of renewable energy solutions to clients, and will use the software as a complete tool to understand the possibilities that clean, green energy offers and how they can become energy self-sustainable for their home or business.

By addressing these goals in future developmental stages, the SolarWind.ai team is confident in its ability to deliver future versions of the product that will meet higher standards of accuracy, scalability, and usability. The final software will be capable of producing accurate results across a wide variety of datasets, balancing energy and cost efficiency, and standing out among competing solutions. SolarWind.ai's ability to provide personalized recommendations will be a key differentiator, positioning the platform as an indispensable tool for renewable energy site selection in urban environments.

6. Impact on Society and Environment

The SolarWind.ai project aims to guide urban renewable energy installations by leveraging satellite imagery and machine learning to identify optimal locations for solar panels and wind turbines in Montreal. While the primary objective is to support the transition toward cleaner energy sources, this endeavour has complex social and environmental implications that must be critically evaluated.

6.1 Environmental Impact

From an environmental perspective, the widespread adoption of solar and wind technologies—if informed by accurate site selection—can significantly reduce greenhouse gas emissions and air pollution. By favouring renewable installations on existing rooftops or underutilized urban spaces, the project can help limit the expansion of traditional power plants and reduce reliance on non-renewable resources such as coal and natural gas. These benefits are intensified compared to conventional energy systems, lowering the overall carbon footprint and mitigating the environmental degradation associated with fossil fuel extraction, transportation, and combustion. However, manufacturing solar panels and wind turbines requires raw materials, including rare earth metals and silica, which may require intensive mining. These extraction processes can harm ecosystems, generate hazardous waste, and pose long-term sustainability challenges. While improved recycling methods for solar panels and better end-of-life management strategies for turbine components mitigate some of these concerns, the project must acknowledge that these technologies are not entirely free from environmental costs.

6.2 Societal Impact

From a societal standpoint, the project offers substantial potential benefits. By enabling more informed energy planning, SolarWind.ai can guide policies that make renewable energy cheaper and more accessible. This accessibility can, in turn, stimulate local economies and improve quality of life through stable energy prices and reduced health risks associated with pollution. The platform's capacity to highlight optimal sites for installations can also spur local industries related to renewable energy, create jobs, and foster a culture of innovation and sustainability in urban environments. Additionally, improved air quality and reduced noise pollution contribute positively to public well-being, increasing support for renewable initiatives and reinforcing the social fabric.

6.3 Trade-Offs

Nonetheless, societal risks and challenges exist. Deploying wind turbines in urban areas may raise concerns about aesthetics, noise, and the potential impact on birds or other wildlife. While these issues are partially mitigated by thoughtful placement and modern turbine designs, they remain valid considerations. On the safety front, the project team must ensure secure data handling and accurate machine learning models to avoid recommending installations in unsuitable or structurally compromised areas. Equally, the interface must convey information transparently, empowering decision-makers and communities rather than creating confusion or mistrust. Ensuring that local populations are included in decision-making is critical to maintaining public support and avoiding social tensions.

In summary, SolarWind.ai has the potential to guide a transition toward cleaner, more sustainable urban energy systems, delivering tangible environmental and societal benefits. Yet, it also highlights the inherent complexities of any technological intervention. Balancing the reduced environmental footprint and societal gains against the costs of manufacturing, potential ecological disruptions, and the need for responsible data use remains crucial. By proactively addressing these issues, the project will advance renewable energy deployment and foster a more equitable and sustainable future.

7. Teamwork Report

7.1 Individual Contributions

Throughout the second half of the project, the team was able to build on the progress that was made during the first semester. By the time the final development phase of the project had begun, the roles and responsibilities within the teams had already been properly divided to ensure each team member was focusing on tasks that highlight their strengths. Eric and Maxx worked together on the tasks related to building and testing the machine learning model. They built the instance segmentation model that is used to identify usable rooftops from the user-inputted satellite image. Their work also involved integrating the different datasets such as the Inria Aerial Image dataset and OpenStreetMap dataset. Their work is described in depth in Section 4 of the report. Platon and Aidan first worked to build a foundational knowledge base that would later be used for developing the logic for potential solar energy recommendations. Aidan focused on using real-world data to estimate a baseline comparison for surface area estimations. These baseline values were essential in the different model development stages to ensure that the pixel-to-metre conversions were accurate and performed well with each image from the dataset. Platon researched the various types of solar panels, their similarities and differences, and situations in which each of them are deployed. This research is summarized in above sections of the report, and will be used for better accuracy in future versions of the software. Once this knowledge base wss compiled, Platon took the lead in developing the graphical user interface. The style and aesthetic of the platform is designed to align with SolarWind.ai's core values of simplicity and accessibility. The interface for the first prototype launched is fully functional and easy to interact with. As future project stages progress, the knowledge base will be integrated into the model, and provide more in-depth analysis when generating the GUI output.

7.2 Team Collaboration and Challenges

Overall, the team collaborated effectively throughout the project, with each member contributing their unique expertise to achieve the collective goal—Eric and Maxx focused machine learning model development and testing, Aidan worked in quantitative mapping techniques, surface area validation and researched different limiting factors that affect overall output. Platon worked in technical research on energy systems and the development of the user interface. Meetings were conducted regularly to synchronize progress, clarify objectives, and share data requirements. In these meetings, the goal of each group member was to inform the rest of the group of their recent progress, explain any concepts or terms that may be unfamiliar to other group members, and to seek advice or opinions on how the remaining design phases should be conducted. This open communication ensured that each individual's work was informed and complemented by the others'. One of the primary challenges encountered was coordinating data integration with ongoing model refinement. As new datasets were introduced, updating the machine learning pipelines and reprocessing imagery demanded careful scheduling to avoid confusion and repetitive work. Additionally, ensuring that everyone maintained a shared understanding of the evolving technical requirements proved time-consuming.

8. Conclusion

Over the project lifespan, the SolarWind.ai team successfully developed and deployed the first prototype of the rooftop recognition software. Key milestones include conducting research into the solar energy industry and studying urban building codes in Montreal and Quebec to understand the different limiting factors that need to be factored into the development methodology. Another achievement is to complete the research surrounding the most efficient solar panels available, and eventually be able to recommend these to clients upon deployment of the user interactive software. The next phase of the project focused on implementing a machine learning model using Mask R-CNN and Detectron2, while simultaneously gathering high resolution aerial satellite imagery datasets to properly train and validate the model. Once this development phase was complete, the team worked on rooftop segmentation, obstacle detection and pixel-to-metre conversion for surface area estimations. Lastly, the team integrated the rooftop segmentation and surface area estimations in a sleek and intuitive graphical user interface. Using the model output, the interface helps a client visualize all of the optimal solar panel compatible rooftops, and estimates the amount of panels needed for efficient energy harvesting.

Moving forward, the next phases of the SolarWind.ai project will include improvement to model accuracy, improving the scalability of the platform to be able to analyze wider-scale images and bigger sites and incorporating more personalized limiting factors for solar panel placement. Adding a price point range feature to the user interface, and incorporating these factors will set the SolarWind.ai product apart from the rest of the market. Another important upgrade that the team is looking to make will be the expansion into the solar energy market. The goal of the expansion will be to identify safe spaces along highways, near isolated warehouses and similar environments to install wind turbines. Wind power is another type of renewable energy that is efficient and reliable, but has not seen much development within urban settings.

This project has provided the group members with important experience in completing an engineering project as a team, understanding how to overcome obstacles and meet deadlines and integrate machine learning into real-world applications that can help Montreal meet its energy sustainability goals. The team hopes to be able to eventually release a commercially viable product that will help raise awareness about the role that artificial intelligence can play in helping build cleaner energy infrastructure within cities.

9. References

[1] H. Chopra, “Machine Learning For Roof Detection and Solar Panel Assessment,” *Medium*, Oct. 12, 2020. https://medium.com/omdena/machine-learning-for-roof-detection-and-solar-panel-installment-9ddeb0b70109 (accessed Dec. 19, 2024).

[2] superadmin, “Best Solar Panels: Monocrystalline, Poly & Thin-Film,” *SolarCo Energy*, Aug. 19, 2024. https://solarcoenergy.com/comparing-types-of-solar-panels-monocrystalline-polycrystalline-and-thin-film/ (accessed Dec. 19, 2024).

[3] “Solar Panels Guide: Exploring Types, Efficiency, and Costs - solarpowersystems.org,” *solarpowersystems.org*, Feb. 03, 2023. https://solarpowersystems.org/blog/types-of-solar-panels/ (accessed Dec. 19, 2024).

[4] Sunrun, “Do Solar Panels Work in Cold Weather?,” *Sunrun*, Mar. 06, 2019. https://www.sunrun.com/go-solar-center/solar-articles/do-solar-panels-work-in-cold-weather

[5] Aurora Solar, “Comprehensive Guide to Solar Panel Types,” *Aurora Solar*, Jan. 16, 2021. https://aurorasolar.com/blog/solar-panel-types-guide/

[6] A. Tian, D. Zünd, and L. M. A. Bettencourt, “Estimating Rooftop Solar Potential in Urban Environments: A Generalized Approach and Assessment of the Galápagos Islands,” *Frontiers in Sustainable Cities*, vol. 3, Jun. 2021, doi: https://doi.org/10.3389/frsc.2021.632109.

[7] How, “How to measure a roof with google maps,” *YouTube*, Jun. 02, 2020. https://youtu.be/JBwp-auKfkg?si=QNwqzvwM21HB_4Aa (accessed Dec. 19, 2024).

[8] D. Todd, “Metro Vancouver is the fourth-most dense region in North America,” *vancouversun*, Sep. 05, 2024. https://vancouversun.com/opinion/columnists/metro-vancouver-is-the-fourth-most-dense-region-in-north-america

[9] “for solar domestic hot water and photovoltaic systems.” Available: https://natural-resources.canada.ca/sites/nrcan/files/canmetenergy/files/pubs/SolarReadyGuidelines_en.pdf