Unlocking the Potential: How AI-Driven Solar PV Detection can Revolutionise Municipalities

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1. Introduction

South Africa's energy market evolution is disrupting current utility revenue streams. One such evolution involves the integration of Small-Scale Embedded Generator (SSEG) Solar PV energy sources to the grid, resulting in loss of revenues and overall system vulnerabilities due to inaccurate Solar PV installation data measurements and visibility.

Advances in digitalisation allow municipalities to leverage digital technologies to further adapt within the current energy transition, enabling transformation to current business models, creating new revenue streams, and value-producing opportunities. One such technological advancement is the capability to leverage artificial intelligence (AI) and machine learning.

This case study will explore the use and benefit of artificial intelligence (AI) and machine learning, for a municipality to automate the task of obtaining information about solar panel installations at scale. This assisted verification of SSEG applications, whether registered with the municipality or not, would significantly reduce the time and effort to collect and manage this information; compared to the traditional way of man-powered surveys and on-site visits. AI-assisted solar panel detection could enable wide-area data generation, aggregation, and synthesising.

Ultimately, the goal of this study is to provide municipalities with a solution to obtain and act on information regarding the current spread of rooftop Solar PV systems within their areas of supply, to help bring in compliance and mitigate the impact of solar generation on utility revenue.

2. Study Area

The study area for this investigation is a selection of nine adjacent suburbs located in the north of Durban – a major city in KwaZulu Natal, South Africa. The suburbs – namely Prestondale, La Lucia, Somerset Park, Umhlanga, Cornubia, Umhlanga Rocks, Umhlanga Ridge, Mount Edgecombe Estate, Mount Edgecombe North – all fall within the eThekwini Metropolitan Municipality. The entire study area covers about 37km^2.

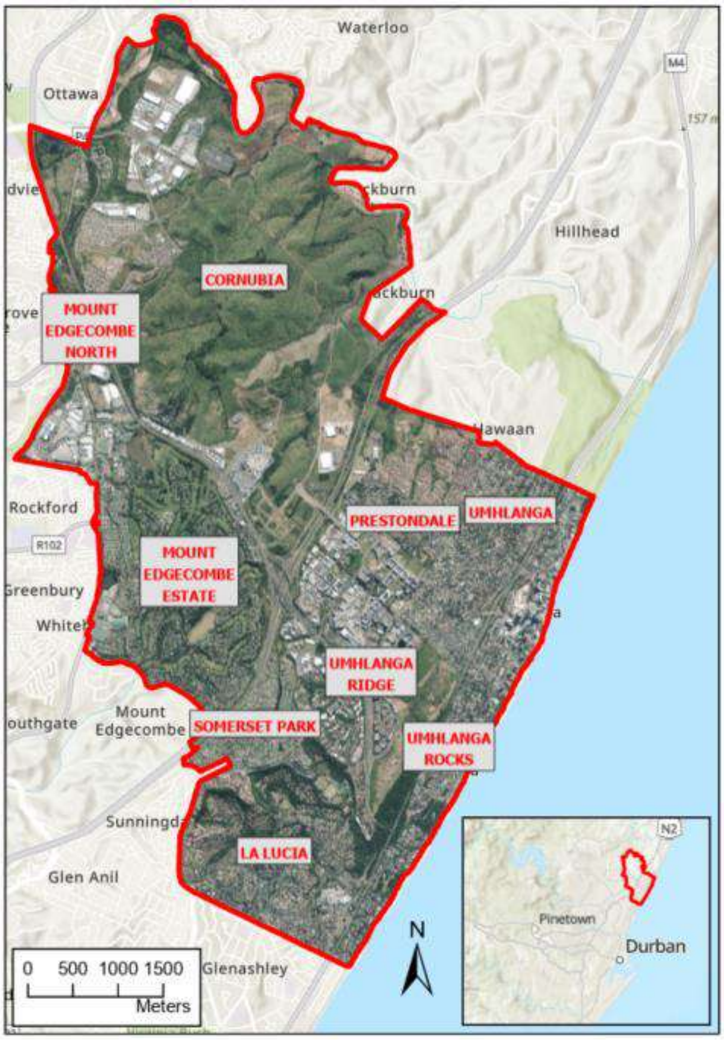

Figure 1: Study area

3. Methodology

This study makes use of RGB-combination aerial photographs. Municipalities typically procure local, up-to-date, aerial imagery every two years. Due to the 2024 aerial photographs not being readily available for this study, photographs captured in 2022, with a spatial resolution of 10cm, were used. To optimise processing, the source images were mosaiced together and then masked (cropped) to the area of interest. This reduced the need to process photographs that were not part of the study area.

To identify solar panels, the "Detect Objects Using Deep Learning" tool from Esri's ArcGIS toolbox was used. There are three main input parameters for this tool: 1) the input imagery, 2) the output feature class (in this case, the solar panel areas), and 3) the model definition file. The model definition (.dlpk file extension) is a file that contains the necessary parameters for the pre-trained deep learning model.

While one could go about creating/training their own model using other tools available within ArcGIS Pro, this does require a large amount of training and testing data. Fortunately, there are a variety of pretrained deep learning models available on [ArcGIS Living Atlas of the World](). There are two authoritative models that ESRI recommends for solar panel detection, namely the USA model and the New Zealand model. Apart from these models being trained on data from the country after which they are named, they are almost identical in that they both use the same deep-learning model. The USA model calls for 5-15cm RGB imagery and has a precision score of 0.764, while the New Zealand model calls for RGB imagery with 7.5cm spatial resolution and has a precision score of 0.83.

	USA	**New Zealand**
Input Imagery	5-15cm RGB	7.5cm RGB
Model Architecture	Mask R-CNN	Mask R-CNN
Average Precision Score	0.764	0.83

This investigation made use of both models and briefly compared them; however, the purpose of this investigation is not to recommend which model to use, but to use the outputs of these models to highlight the benefit that the use of this workflow could provide to various stakeholders.

Once extracted, the results from each model were aggregated to registered land parcels within the study area. The output of this allows one to identify the registered land parcels that contain solar panels.

4. Discussion of Results

The USA model took 125 minutes to run and identified 1 386 features with a total area of 76 499.724 m^2 and an average area of 55.195 m^2 per feature. The New Zealand model ran for 110 minutes and identified 7 530 features with a total area of 20 034.853 m^2 and an average area of 2.661 m^2. Quite notably, it did not take a substantial amount of time to scan the large area at hand – being all of the suburbs part of this study – making it advantageous to municipalities to utilise minimal resources to obtain meaningful information about what is happening on the ground. The statistics below are based on the dissolved outputs to remove any potential overlapping areas.

	USA	**New Zealand**
Areas	1 386	7 530
Average Area (m^2)	55.195	2.661
Total Area (m^2)	76 499.724	20 034.853

The values in the table seem to have vastly different results, and upon visual inspection of the output areas, it was immediately evident why these values differed. The USA model identifies an entire solar panel array as a single output area, while the New Zealand model identifies each panel as a separate area. These different approaches were likely brought about by the difference in training data used for each model. The implication of this is that area and/or number of features may not be used as a basis of comparison of the model's results to each other.

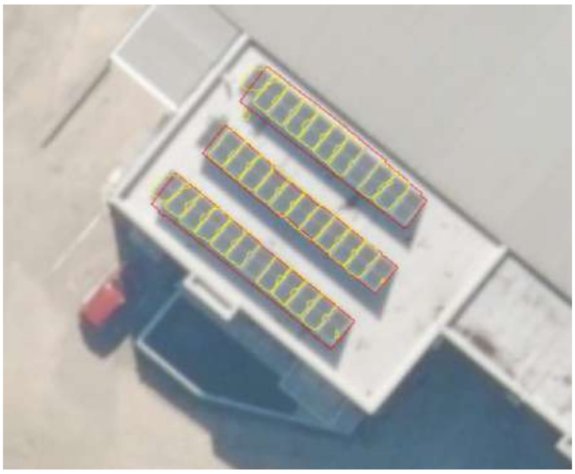

Figure 2: The USA model (red areas) identifies the entire solar panel array as a single feature, while the New Zealand model (yellow areas) differentiates according to individual panels.

Visually inspecting the results highlights the fact that the USA model contained significantly more errors of commission than the New Zealand model. Painted sidewalks, vehicles, transparent roof surfaces, and shadows are all examples where the USA model has erroneously "detected" a solar panel.

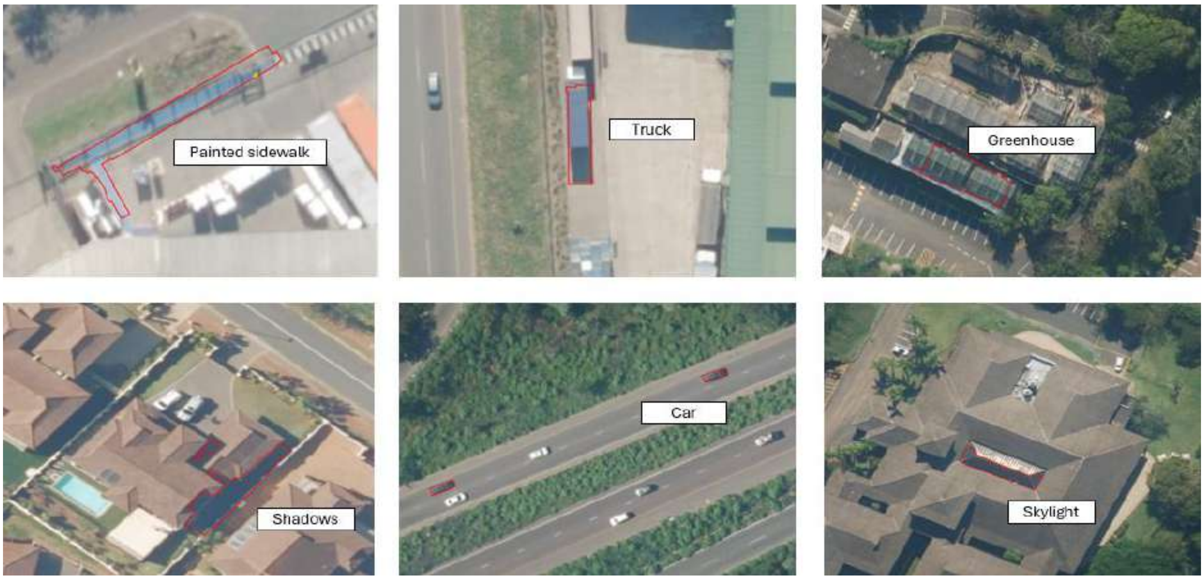

Figure 3: Errors of commission (red areas) in the USA model results

The New Zealand model was particularly weaker in detecting large solar arrays. There are multiple instances where the USA model had detected an entire (or a major part of a) solar array, however, the New Zealand model failed to identify all the panels. This is referred to as an error of omission.

Figure 4: Errors of omission in the New Zealand model are particularly prevalent in large solar arrays

The purpose of this investigation is only to determine which registered land parcels (i.e., end customers to the municipality) contain solar panels, and not to quantify the number or area coverage of the solar panels. As a result, the shortfalls highlighted above are of little concern. If the results from each model are combined, one would be able to "score" each land parcel based on how confident one is that it contains a solar panel. Land parcels with solar panels identified by both models would have a greater score than parcels that only contain solar panels identified by one model.

Of the 6397 registered parcels in the study area, 521 land parcels contained solar panels. More specifically, 374 of the 521 identified land parcels contained solar panels that had been identified by both the USA and the New Zealand model, and 147 parcels contained solar panels that had only been identified by the New Zealand model. Interestingly, there were no parcels that contained solar panels that had been detected by only the USA model. This means that despite the numerous commission errors highlighted earlier, there are no additional parcels that have been highlighted due to misclassification from the USA model.

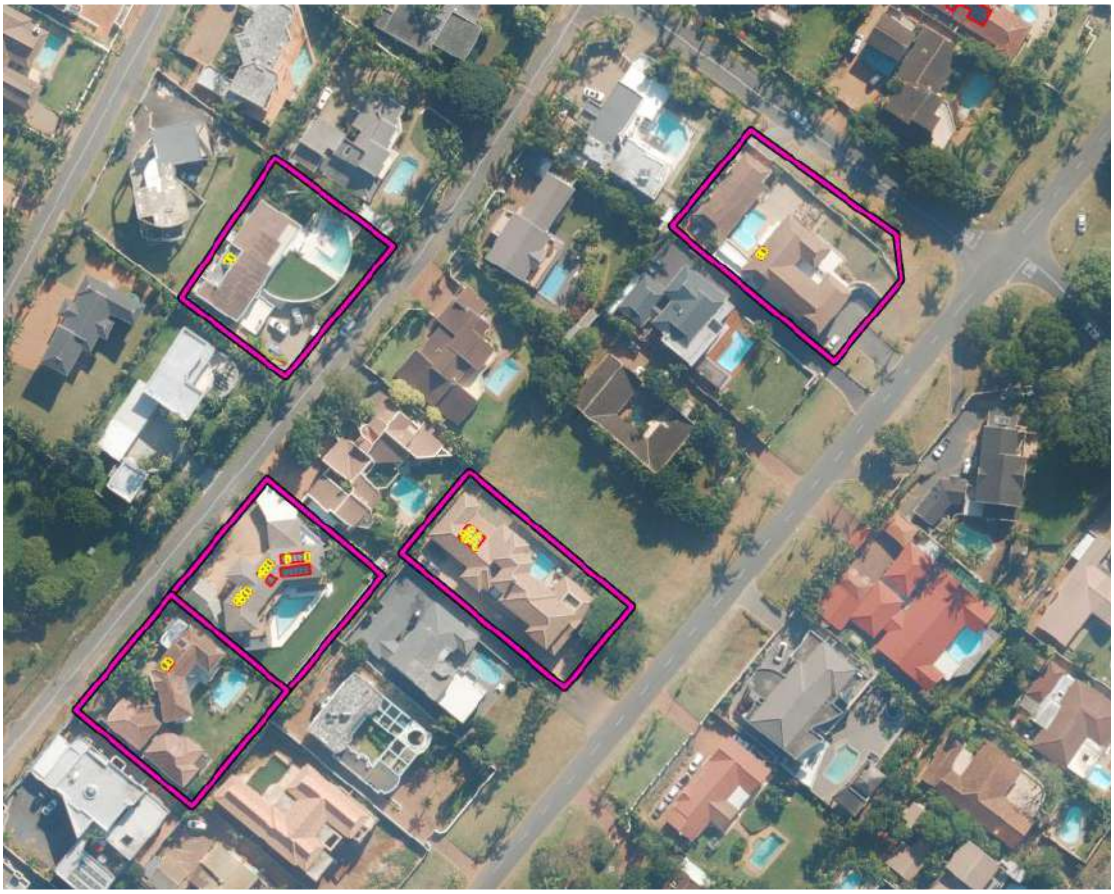

Figure 5: Registered land parcels (pink areas) where solar panels have been detected by at least one of the models

5. Conclusion

In parallel with a SSEG application management system, municipalities can use AI-driven solar panel detection to improve on real-time visibility over the network and to monitor the status of Solar PV on their localised electricity grids. Additionally, by municipalities having access to more insights into where Solar PV installations likely are across their areas of supply, these insights could contribute towards orchestrating renewable integration to the grid, optimising infrastructure operations, and applying a data-driven approach to complement the implementation of adaptive business models, such as offering feed-in-tariffs to residents, net metering, grid access fees, installation and connection fees, selling green certificates, or introducing Power Purchase Agreements.

References and Acknowledgements

- Key acknowledgement to eThekwini Municipality, and specifically eThekwini Electricity, for the supply and use of data (Imagery, suburbs, land parcels) for this case study.
- A notable contribution by Andre Cloete, Sean Cullen, and Nicholas De Kock from Esri South Africa.