REVIEW 0 - FINAL YEAR PROJECT

OPTIMIZED PLACEMENT OF PV PANELS BY USING ENSEMBLING APPROACH FOR ROOFTOP SEGMENTATION

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INTRODUCTION

Climate change has become a global concern over the last few decades and it has affected various life forms, and the ecosystem as a whole.. One of the primary causes for this could be attributed to burning of fossil fuels for generating electricity which emits huge amounts of CO_2 in the atmosphere. Continual usage of generating electricity this way could cause huge havoc to the environment.

This has led to turning towards renewable resources for sustainable development. Renewable resources include biomass energy (such as ethanol), hydropower, geothermal power, wind energy, and solar energy. In recent years, potential tapping of solar power for generating electricity has gained immense popularity and interest. A lot of buildings now have PV panels fitted in their rooftops.

However, managing stochastic power generation from distributed rooftop solar photovoltaic (PV) arrays, such as predicting and reacting to the variations in electric grids have become more challenging in recent times. Traditional approaches such as online assessment and utilities interconnection filings are time consuming and costly, and involve a lot of human effort where concerned people have to go to the site to look into the rooftop area to determine the installation of PV panels.

Previous works have used one CNN model like U-Net for rooftop segmentation of aerial imageries. The AIRS dataset contains nearly 220k buildings with masked images. But previous works haven't classified the rooftops as flat or slope.

In our project, we wish to further annotate the images as flat or roof and use an ensemble approach combining 3 models namely, the U-Net model, DeepU-Net and U-Net with watershed transformation.

We finally also provide optimized placement of solar PV cells using a maximum fitting algorithm to maximize the potential of energy consumption.

OVERALL OBJECTIVES

To estimate the placement of photovoltaic panels on the rooftop for an aerial satellite image, the following steps are to be performed:

- ❑ Annotate the AIRS dataset for the type of roofs using the VIA tool.
- ❑ Perform rooftop segmentation from aerial satellite image to identify buildings.
- ❑ Try different approaches for rooftop segmentation:
    - ★ U-Net Baseline model.
    - ★ DeepUNet model.
    - ★ U-Net with watershed transformation.
- ❑ Ensemble all the above approaches to classify the type of roof as flat or tilted.
- ❑ Use a maximum fitting algorithm to find the optimized no of solar panels based on type of roof.

LITERATURE SURVEY

S.NO	CITATION	METHODOLOGY	ADVANTAGES	LIMITATION
1.	**SolarFinder: Automatic Detection of Solar Photovoltaic Array, 2020** Qi Li, Yuzhou Feng, Yuyang Leng and Dong Chen in 2020 19th ACM/IEEE International Conference on Information Processing in Sensor Networks (IPSN)	1. Leverages publicly available map APIs - Google Maps API, OpenStreetMap to create a dataset. 2. Use K-Means to automatically segment rooftop images to contours. 3. SolarFinder employs a hybrid linear regression approach that integrates SVM modeling with a deep CNN approach to accurately identify solar PV arrays and characterize each solar deployment.	1. SolarFinder is the best unsupervised model that yields the same accuracy as supervised pure CNN-based approach. Hence, SolarFinder reduces the preprocessing overhead and training overhead. 2. Works well with non-VHR(Very high resolution) images also. 3. SolarFinder does not need to be re-trained when more solar PV arrays become online.	1. This does not detect the type of roof (flat or tilted). PV installation varies based on the type of roof. 2. No profiling done on the no of PV panels to be installed. 3. Mask images are not annotated using any SOTA tools but trained using an unsupervised model which might not be very accurate.

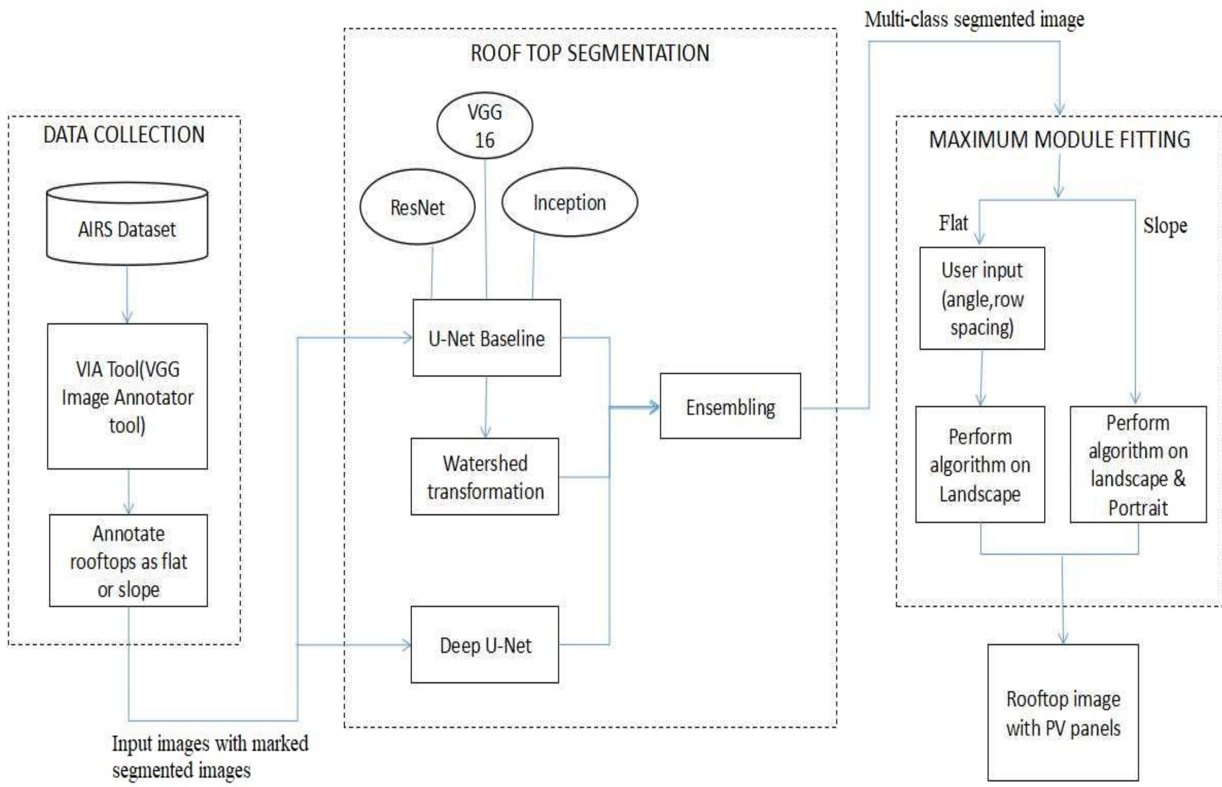
2.	**Unsupervised azimuth estimation of solar arrays in low-resolution satellite imagery through semantic segmentation and Hough transform, 2021** Ayobami S. Edun, Kirsten Perry, Joel B. Harley and Chris Deline in Applied Energy Journal, Elsevier	1. Segmentation model is performed using an encoder-decoder architecture. 2. If the output of the segmentation showed multiple solar arrays in a single satellite image with dissimilar orientations, the connected components algorithm was implemented. 3. Azimuth detection is done using Canny Edge detection and Hough transform method.	1. This method does not rely on simulated data, meter readings, and it is completely unsupervised. 2. The work also uses only a single convolutional neural network (CNN) and does not require several pre-processing and post-processing steps. 3. This work offers a great reduction in error, as compared to self reporting and voluntary surveys, when metadata such as azimuth may not be provided.	1. Orientation of rooftops are not given and hence the azimuth predicted were not correct and had a difference of 180° and 90° in few cases. 2. The model cannot classify the mounting type (fixed tilt, tracking) for solar installations in satellite imagery. 3. Not enough test images to evaluate the accuracy.

3.	**On Building Classification from Remote Sensor Imagery Using Deep Neural Networks and the Relation Between Classification and Reconstruction Accuracy Using Border Localization as Proxy, 2019** Bodhiswatta Chatterjee, Charalambos Poullis in 2019 16th Conference on Computer and Robot Vision (CRV)	1. ICTNet: a novel network with the underlying architecture of a fully convolutional network, infused with feature re-calibrated Dense blocks at each layer. 2. It is combined with dense blocks, and Squeeze-and-Excitation (SE) blocks. 3. Reconstruction is done by extruding the extracted boundaries of the buildings and comparative analysis is made between the two.	1. Has addressed the task of using few parameters to process large chunks of data. 2. With no 3D information on the buildings, the authors have used the building boundaries as a proxy for the reconstruction process. 3. Has got better overall IoU compared to other methods.	1. There is no loss function for the reconstruction accuracy. 2. Need extensive hardware specifications to train the model.

4.	**Convolutional Neural Network Based Solar Photovoltaic Panel Detection in Satellite Photos, 2017** Vladimir Golovko, Sergei Bezobrazov, Alexander Kroshchanka and Anatoliy Sachenko in 9th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications	1. Collect data from Google Maps. 2. Perform pre-processing techniques like image resizing, image sharpening. 3. Train a 6 layer CNN model.	1. Here, the authors have used the low-quality satellite imagery (Google Maps photos), instead of the high resolution color satellite orthoimagery that enables decreasing the requirements for the approach. 2. Simple 6 layer CNN model.	1. Better segmentation could have been performed by training with other CNN models. 2. Bad quality satellite images have led to inaccurate classification. 3. No validation on the dataset as in some cases solar panels look similar to roof tops.

5.	**Solar Potential Analysis Of Rooftops Using Satellite Imagery, 2019** Akash Kumar, Delhi Technology University, in *ArXiv* abs/1812.11606	1. Dataset is manually collected for India. 2.Adaptive Edge Detection and Contours are focused to segment out rooftop boundaries and obstacles present inside them along with polygon shape approximation.	1.Provides a comparative analysis of the solar potential of the building. 2. Several types of the rooftop are considered to learn the intra-class variations.	1.The image quality of satellite imagery is very deficient hence the edges are not detected properly. 2.There are some outliers that are plotting solar panels outside the building rooftop area.
6.	**Deep Convolutional Neural Network Application on Rooftop Detection for Aerial Imagery, 2019** Mengge Chen, Jonathan Li, in Journal of Computational Vision and Imaging Systems	1. It is primarily based on Mask R-CNN with 3 stages. 2. Feature extraction is based on existing deep learning model. 3. RPN (Regional Proposal Network) is used to find RoI. 4. Object classification is then performed.	1. Efficient and feasible approach to extract detached house from aerial images. 2. RoIAlign method is used instead of RoIPool for better feature extraction.	1. Edges of the building are not detected properly. 2. Training data was less and hence less accuray. 3. Comparatively less precision with other new state of art models.

ARCHITECTURAL DIAGRAM



The above block diagram gives a high level overview on the 3 modules.

The 1st module contains annotating the AIRS dataset using the VIA software. This is fed to the next module to segment the rooftop images.

We combine 3 models (U-Net, Deep U-Net and U-Net with watershed transformation) using ensembling approach and give the multi-class segmented image.

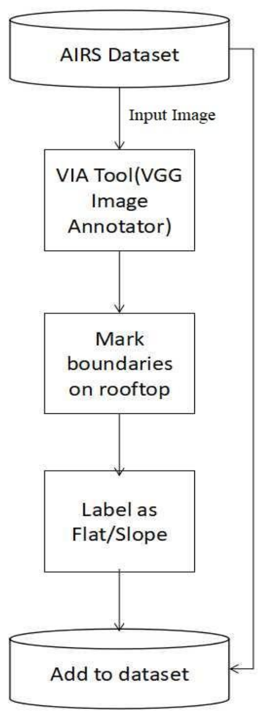
Based on the segmented roofs, we set a size for solar panels that gets overlaid on the rooftop image. The no of panels to be fitted needs to be maximized in order to get maximum efficiency and this is done with the help of maximum fitting algorithm

LIST OF MODULES

- Module I - Data collection and annotation.
- Module II - Rooftop segmentation using ensembling methods.
- Module III - Maximum Fitting Module.

MODULE DESIGN

MODULE I - DATA COLLECTION AND ANNOTATION



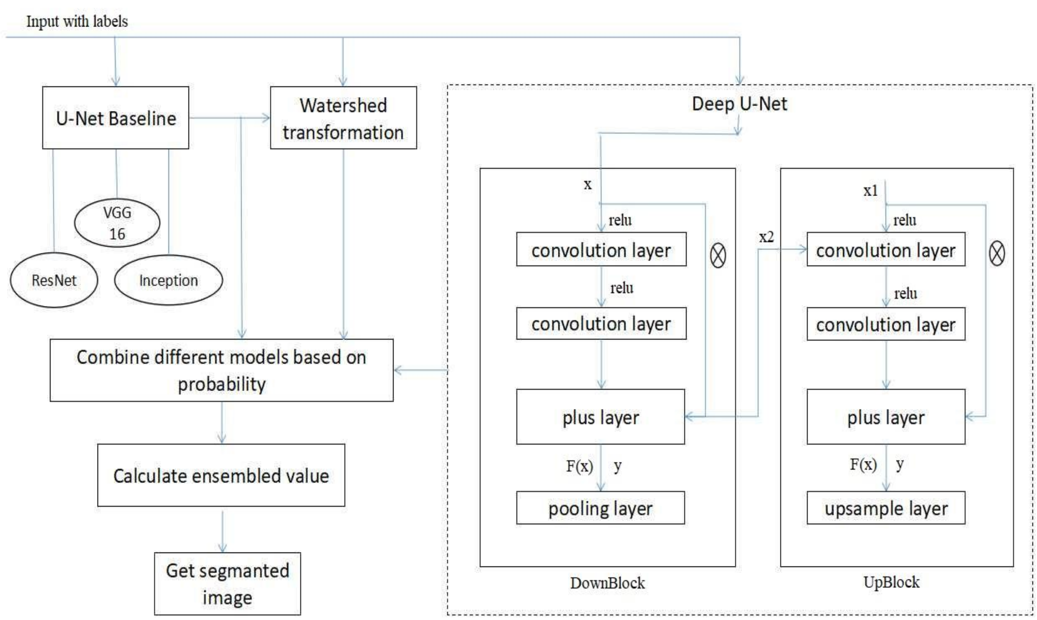
INPUT: AIRS Dataset
OUTPUT: Masked segmented images

- ➔ We use AIRS dataset and select around 1k images from the dataset.
- ➔ Using VIA tool, we annotate each of the input rooftop images as flat or tilted.

➔ This is done by using the software and marking boundaries on the rooftop and assigning labels.

➔ The masked image along with input is stored in a new database.

MODULE II - ROOFTOP SEGMENTATION USING ENSEMBLING METHODS



INPUT: Newly annotated AIRS dataset
OUTPUT: Multi-class segmented image

➔ The input images are fed to 3 models.

➔ The first model uses U-Net for multi-class image segmentation. It is trained using 3 different backbones namely, ResNet, VGG16 and Inception.

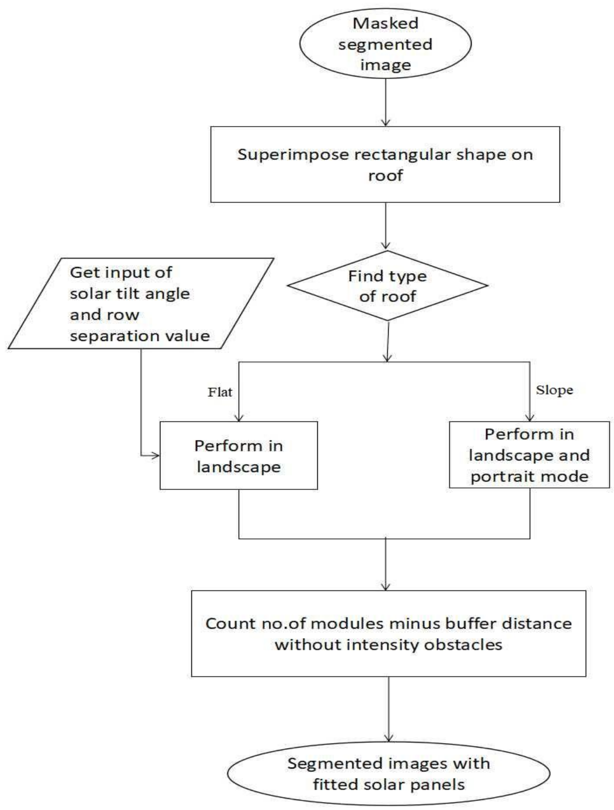
➔ As a next step, the binary segmented U-Net image can be integrated with watershed transformation. This brings us to the second model.

➔ In the 3rd model, we use Deep U-Net. Here, we have 2 blocks namely the Downblock and Upsampling block.

- ➔ The DownBlock has two convolutional layers that are concatenated through the ReLU layer. It is then passed to the max pooling layer. The output of DownBlock is passed to the next DownBlock and also to the UpBlock.

- ➔ The UpBlock is similar to the DownBlock except that here we have the upsampling layer instead of the max pooling layer.

MODULE III - MAXIMUM FITTING MODULE



INPUT: Masked segmented image.
OUTPUT: Segmented image with solar panels of specific size fitted.

- ➔ The masked segmented image stored in the new database is taken and the roofs are superimposed with rectangular shape.

- ➔ Then the type of the roof is determined as flat or slope.

- If the type of the roof is flat, we get user input(solar tilt angle and row separation value) and perform a maximum fitting algorithm on landscape mode.
- If the type of the roof is slope, we perform a maximum fitting algorithm on landscape and portrait mode.

➔ The buffer distance without intensity obstacles is subtracted from the count of the number of modules.

➔ The segmented images are fitted with the solar panels.

PERFORMANCE MEASURES

❑ **IoU - Intersection over Union /Jaccard Coefficient**

To quantify the accuracy of our model to predict size for solar PV arrays, we use Jaccard coefficient which is widely used in prior work to measure the similarity between detected regions and ground truth regions. Jaccard Similarity Index(JSI) measures the similarity for the two sets of pixel data, with a range from 0% to 100%. The higher the percentage, the more precise prediction. It is defined as follows:

$$JSI = \frac{r_d \bigcap r_g}{r_d \bigcup r_g}$$

where r_d denotes the detected region for a solar PV array, and r_g indicates the groundtruth region for a solar PV array

❑ **DICE Coefficient**

We use DICE coefficient to compare the pixel-wise agreement between a predicted segmentation and its corresponding ground truth. DICE coefficient is 2 times the area of overlap divided by the total number of pixels in both the images.The formula is given by:

$$\frac{2*|X \cap Y|}{|X|+|Y|}$$

where X is the predicted set of pixels and Y is the ground truth.

- **MCC - Matthews Correlation Coefficient**

  We use the MCC , a standard measure of a binary classifier’s performance, where values are in the range −1.0 to 1.0, with 1.0 being perfect roof segmentation, 0.0 being random roof segmentation, and −1.0 indicating roof segmentation is always wrong. The expression for computing MCC is below, where TP is the fraction of true positives, FP is the fraction of false positives, TN is the fraction of true negatives, and FN is the fraction of false negatives, such that TP+FP+TN+FN= 1.

$$\frac{TP * TN - FP * FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

- **Accuracy**

  Accuracy is the percentage of correct predictions for the test data. It can be calculated easily by dividing the number of correct predictions by the number of total predictions.

$$\text{accuracy} = \frac{\text{correct predictions}}{\text{all predictions}}$$

DATASET

AIRS Dataset - The AIRS (Aerial Imagery for Roof Segmentation) dataset provides a wide coverage of aerial imagery with 7.5 cm resolution and over 220k buildings.

AIRS dataset covers almost the full area of Christchurch, the largest city in the South Island of New Zealand during the flying seasons of 2015 and 2016, and the supplied images are ortho-rectified DOMs with RGB channels.

It contains around 800 images in the training set, 90 each in testing and validation set. We select around 1000 images from residential areas and use the VIA tool to annotate the type of roofs and combine both the images to form an annotated dataset.

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