This section should cite problems that have been previously addressed that relate to your work, and the key takeaways of the studies that explored that work. The idea here is to place the problem you’re working on in context and to let the reader know that you’re not working in a knowledge vacuum. For finding relevant literature, a good starting point is Google Scholar.

There are already some previous studies applied to machine learning methods to identify solar panels from satellite images. For example, “The DeepSolar Project” conducted by Stanford University, “constructed a comprehensive high-fidelity solar deployment database for the contiguous U.S.”[1] The purpose of the project is to create a database for people who interested in how the solar panels are installed in the different area in the U.S. to conduct further analysis or research. The team applied the classification method based on Google Inception V3 to identify whether there is any solar panel in the piece of the image.[1] If an image is classified as there exist any solar panel, segmentation that used the CAMs method[7], would be conducted to estimate the size of the solar panels. Though the purpose of the project is slightly different from our project, the basic step is the same as what our project is going to do- detect solar panels from satellite images.

To identify solar panels from satellite images, image processing and image classification are important steps in this project. Image processing is a subfield of signal processing, which uses computers to process digital images. This has been studied for decades since the 1950s according to Azriel Rosenfeld.[2] Since the digital images are represented using matrices, we can do scaling, color conversion, image enhancement, etc. to the image by adjusting the value in the matrices. Image processing now is often conducted before fitting any model since it can be used to filter out the information from the high dimension features of the images. In a study of detecting plant diseases, image processing was applied to the image such as transforming the color into greyscale [6] in order to filter out information then conduct image classification. Similar image processing methods are conducted in this project to prepare training data for our chose image classification models.

Image classification “refers to a process in computer vision that can classify an image according to its visual content”. [8] However, because of the high dimension of features of the images, it is computationally infeasible to use all these features to train models. Moreover, if we “look at high-resolution images it is very likely that a neighboring pixel belongs to the same land cover class as the pixel under consideration.”[5] Therefore, “implementing feature extraction, and selecting suitable variables for input into a classification procedure are all important” [3] since we can make full use of the features and also reduce the dimension of the data. Some image processing methods such as Histogram of Oriented Gradients (HOG) [9], Scale-Invariant Feature Transform (SIFT) [4] are famous as tools to extract informative features from the original image. With these filtered features, we can apply supervised machine learning methods to conduct image classification with high accuracy compared to using original images. One of the frequently used methods that can be applied to image classification is Support Vector Machines (SVM) [10]. In the study of image classification shows that SVM “can generalize well on difficult

image classification problems where the only features are high dimensional histograms.” [11] by comparing the performance with KNN-based models, tuning the SVM model itself, remapping the input data. [11] The analysis process of this project would be similar to the previous work since our goal is to find a good combination of transformed original data and a well-tuned model to identify solar panels in the image with high accuracy.

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