# Rooftop Detection for Planning of Solar PV Deployment: a Case Study in Abu Dhabi

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**Abstract.** Photovoltaic (PV) technology is one of two modes of energy generation which utilize solar energy as its source. The rooftops of buildings can be utilized for solar power generation using this technology, and are considered to be highly promising sites for urban PV installations due to land space limitations. However, to properly plan such installations decision makers would need to have detailed information about the amount of rooftop area that is available, as well as the distribution of individual rooftop sizes. In this paper a machine learning based approach for detecting rooftops is proposed and its utility for planning rooftop PV installations is demonstrated via a simple pilot study on two different residential areas in Abu Dhabi, UAE. The proposed method uses a two-stage classification model to estimate the rooftop area that is available for solar panel installation. Next, a comparative study of three different types of PV technologies is conducted in terms of energy generation and economic viability. The results obtained from these experiments suggest that thin-film panels may have a distinct advantage over other PV technologies. Even though the cost of PV panels is still quite high, this could be balanced by the potential benefits to the environment. If reasonable subsidies and feed-in tariffs are implemented, PV technology can become a cost effective option for the UAE.

**Keywords:** Rooftop Detection, PV systems, Energy Generation, Economic Analysis

## 1 Introduction

### 1.1 Background and Motivation

The World Energy Council has estimated that the earth's surface receives around 3,850,000 EJ (exajoules; 1 EJ $\approx 10^8$J) of solar energy annually; this translates to the annual global energy consumption in 2002 being received in an hour. However, in 2007 only 0.1 % of the world's total energy consumption is fulfilled by solar energy, indicating that solar energy is still greatly under-utilized. However, more recent reports show that the cumulative installed capacity of solar PV has exceeded 35000 MW in IEA member countries, up from 500 MW at the end of 1994. This points to the increasing popularity of PV systems as a source of energy. Also, recent studies have shown that since 1994 the installation of solar PV systems has increased at an annual average of greater than 25% [1].

The United Arab Emirates (UAE) is rich in conventional energy resources i.e. petroleum and natural gas. 9.3% of the worlds oil reserves and 4.1% of worlds gas reserves are in the UAE. Abu Dhabi, the capital of the UAE and dubbed the "richest city in the world" by CNN, contains the majority of the UAE's fossil fuel reserves, with 95% of oil and 92% of gas deopsits. However, Abu Dhabi is already planning ahead and has begun to invest heavily in renewable energy technologies (RETs). In this way it hopes to maintain its position as a global leader in energy well into the post-fossil fuel era [2].

With a rapidly growing population and urbanization, there is a continuous need for energy. The opportunity for renewable energy sources to become popular has been driven by this increasing demand for energy. In last three decades, there was an exponential increase in the electricity consumption in the UAE. Also, this demand for electricity in Abu Dhabi is expected to increase four fold from 5616 MW in 2008 to 25,530 MW in 2028. Furthermore, as a wealthy city in UAE, Abu Dhabi can afford to have solar energy projects, which requires high investment [2].

By announcing the goal of generating 7% of its power from renewable energy sources by the year 2020,the UAE has plotted an ambitious route towards the national uptake of renewable energies. The number of rooftop PV stations in the UAE is expected to increase significantly in the near future and could include installations on both residential or commercial buildings. The proper use of rooftop space for PV deployment can help to avoid potential land use. More benefits offered by rooftops for deployment of renewable solar energy include access to sunlight, low-cost solar real estate, and attractive investment. However, to properly plan such installations decision makers would need to have detailed information about the amount of rooftop area that is available, as well as the distribution of individual rooftop sizes. One way to address this requirement is via the use of computational methods of rooftop detection, which will be discussed next.

### 1.2 Rooftop Detection

Computational solutions for rooftop detection are based on image processing operations such as edge detection, corner detection and image segmentation. The basic approach is to first generate rooftop candidates using image segmentation techniques and then to identify true rooftops using features like shape, area and the presence of shadow [3][4]. Machine learning methods have proved particularly popular in recent studies, where Artificial Neural Networks (ANN) and Support Vector Machines (SVM) have been widely used.

In [5] an ANN is used to facilitate effective rooftop identification in the presence of noise and artifacts. In [6] a review is presented of ANN based approaches in various related areas including shape segmentation in medical images, biometric patterns and gestures extraction, letters and characters detection, edge and contour detection. For each of these applications ANNs performed reasonably well, thus demonstrating its potential for solving image processing tasks. Neural network based methods have also been used to segment images into parts that meet certain criteria [7]. Most of these approaches are based on pixel-level segmentation, which assign each pixel to a given segment based on features generated for the pixel in question. However this approach does not perform well for rooftop detection; in particular these methods fail to detect rooftops when applied to test images containing objects (e.g. cars, roads) which are of the same color as rooftops.

To address these apparent shortcomings, we use an innovative method which is based on two consecutive classification stages [**?**,**?**]. A Multi-Layer Perceptron (MLP) neural-network is first used to provisionally classify candidate segments as either rooftop or non-rooftop. New features are then extracted from the outputs of the MLP which are based on rooftop properties inferred using results gathered over the entire image. The second classification stage is then performed on these features using an SVM. While this is not unique, we also note that there appear to be relatively few studies in which SVMs are used for object detection (notable examples are [8] and [9]). Dividing the classification process into two separate stages appears to reduce the number of false positives, resulting in a significant improvement in the performance of the model in comparison with traditional approaches.

### 1.3 Objectives

The overall goal of our work is to assess the potential of solar PV energy production from residential rooftops in Abu Dhabi, UAE. This is achieved via two key stages.

Firstly, we describe an innovative dual-stage rooftop detection system which accurately estimates the location and size of rooftops within satellite images. This information is then used to evaluate the viability of solar PV installations based on the following two aspects:

- **Technical analysis of solar PV system**: We first estimate the total annual energy generated and peak power of the solar PV panels when installed on the rooftops of residential buildings.
- **Economic analysis of the system** in terms of economic indicators such as NPV, IRR, payback period etc. for different types of solar PV panels.

We intend to evaluate each of these aspects for the three different types of solar PV panels (Monocrystalline, Polycrystalline and Thin-film panels) and present comparative analysis of different PV panels.

## 2 Methodology

The proposed methodology consists of three main steps: image segmentation, first- then second-stage classification. Each of these steps will now be discussed in greater detail:

### 2.1 Image Segmentation

Bilateral filtering is first used to enhance the image, which is then divided into a set of segments using $k$-means clustering. Each of these segments is considered as a candidate for being a rooftop or part of rooftop. The clustering of the color images is performed in the RGB intensity space.

By trying different values of $k$, it was determined that $k$=4 gave the best segmentation result for our images. After all the pixels had been divided into 4 clusters, candidate regions were generated by finding connected-regions - i.e. regions where pixels of the same cluster were adjacent to each other. The 4-connected flood fill algorithm was used for this purpose.

### 2.2 First Classification Stage

A set of 15 training images were prepared by manually labelling rooftops present in these images. Each of these training images were then segmented into regions from which a set of 14 features were extracted. Features are numerical attributes which allow rooftop and non-rooftop regions to be distinguished from each other. In this study, 14 features which were relevant to the classification task at hand were selected. These are: (1) Area (2) Minor to major axis ratio (3) Mean intensity (4) Solidity (5) Variance (6) Entropy (7) Roundness (8) Rectangularity (9) Contrast (10) Correlation (11) Homogeneity (12) Number of Corners (13) Energy. Each row in the dataset hence corresponds to one image segment and is manually labeled as "1" (if it corresponds to a rooftop) or "0" (if not).

The training dataset then is then used to train an MLP, which is then presented with each test image. The output will then be the predicted labels and class probabilities for each candidate region.

### 2.3 Second Classification Stage

In practice, the MLP will not be able to detect all of the rooftop regions in the image. In particular we noticed the presence of many false positives in this first pass of labeled regions. To address this problem, a second classification stage is performed which uses information from the results of the first classification stage. This also helps to identify some of the rooftops which were missed in the first-stage classification. The two main components of this stage are:

- **Feature "Re-extraction"**
  The following features are used for the second stage classification:
  1. *Class Probability*: This is the output of the MLP for each segment of the test image.
  2. *Confidence*: Rooftops in one region are similar to each other. So, the result of first-stage classification shows the most prevalent intensity value of rooftop. A histogram is used to characterize the intensity values of the rooftops identified by first-stage classification. The intensity range is divided into 8 bin, and the number of pixels falling into each bin provides an associated confidence value. During the second classification stage this confidence value is then used as a feature.

3. *Shadow*: We also use building shadows as a feature for the second-stage classification. It is obvious that a building rooftop region should be accompanied by its shadow.

In particular, note that the second item in the list above serves to incorporate information from the entire image into the classification of individual regions. It was felt that this was of particular importance in improving the performance of our method.

– **Classification using Support Vector Machine(SVM)**
SVM is a supervised learning technique which finds an optimal decision boundary to separate the feature space into the corresponding classes. One important consideration during the use of SVM is the choice of kernel function. Preliminary investigations found that the polynomial kernel function gave the best results and this was used for all subsequent experiments.
First, we trained a SVM using the training images. Then we test each of our test images using the trained SVM model. Thus, we get our final rooftop and non-rooftop labels.

### 2.4 Estimation of Energy Generation

The solar energy incident on a surface for a particular period of time depends on the solar insolation, and is calculated by the product of insolation level, the surface area under study and duration of exposure. The amount of energy that can subsequently be extracted as electricity is further dependent on the efficiency of the PV panel used as well as its surface inclination, irregularities and dust particles. These accumulated losses are accounted for by a factor known as the *performance ratio*, for which a reasonable estimate for many situations is 0.75[1]. The solar radiation can be direct radiation, diffused radiation or reflected radiation. We have used the Global Solar Radiation (GSR) which accounts for all these forms of radiation and is measured in terms of kWh/m$^2$/day. The GSR data is estimated by NASA by averaging the 22 years of study is used from [2]. The highest intensity of radiation is received in May and June, at 7.6 kWh/m$^2$/day while the minimum intensity is in December at 4 kWh/m$^2$/day. The energy converted by the solar panel can be estimated as:

$$\begin{aligned} E_{gen} &= \eta \times GSR \times A_{eff} \times N_{days} \times PR \\ Where&, \\ E_{gen} &= \text{Energy generated in kWh} \\ \eta &= \text{ Efficiency of solar cell} \\ GSR &= \text{Global Solar Radiation} \\ N &= \text{ Number of days} \\ A_{eff} &= \text{ Effective rooftop area} \\ PR &= \text{ Performance Ratio} \end{aligned} \tag{1}$$

[1] http://photovoltaic-software.com/PV-solar-energy-calculation.php

These statistics can be used to calculate the annual energy generation by summing the energy generation for all the months. As per [10], 65% of the aggregate rooftop area is actually available for solar PV installation, which is referred to as effective rooftop area. Hence, the utilization factor for area is taken as 0.65. This effective rooftop area is used in all the subsequent calculations. Performance Ratio (PR) is used to evaluate the quality of PV installation as it gives the performance of the installation independent of the orientation, inclination of the panel. It includes all the losses in the PV system.

The PV panel capacity that can be installed in the effective roof area is calculated using Equation 2.

$$\text{Potential Power} = \frac{\text{Annual Energy Generation}}{\text{Annual Peak Sunshine Hour}} \tag{2}$$

Here, the peak sunshine hours refers to the average sunshine hours that has 1 $kW/m^2$ radiation. The peak sunshine for Abu Dhabi is 2179.5 hours/year [2].

## 2.5 Economic Analysis of PV system

The main objective of economic analysis of PV power plant for three different PV technologies is to draw out the most feasible technology for rooftop. It also takes into account of the elements that effect the profitability of the project. The project life is assumed to be 25 years [2]. We have taken into account the following transactions for the economic analysis:

1. Upfront Cost: The total upfront cost of solar PV system installation is estimated by summing up the cost of installation of individual components of solar system, which in turn is primarily determined by the cost of the Inverter and the Solar Panels themselves[2]. These are estimated as follows:
   (a) Cost of inverter: We know that, power is the rate at which energy is generated. Power is specified in terms of kW (kilowatts) for electrical appliances. So, the overall cost of the inverters can be calculated as:

   $$Cost_{inverter} = P_{peak,inverter} \times Cost_{inverter,kW} \times \text{Number of inverters} \tag{3}$$

   Where, $Cost_{inverter,kW}$ is cost of inverter per kilowatt and $P_{peak,inverter}$ is the peak power of the inverter.
   (b) Cost of solar panels: The total cost of solar panels can be calculated using the below formula:

[2] http://www.nmsea.org/Curriculum/7_12/Cost/calculate_solar_cost.htm

$$
\begin{aligned}
Cost_{panels} &= P_{peak,panels} \times Cost_{panels,kW} \qquad (4)\\
Where, &\\
P_{peak,panels} &= \text{Total peak power of panels}\\
Cost_{panels} &= \text{Total cost of panels}\\
Cost_{panels,kW} &= \text{Cost of panels per kW}
\end{aligned}
$$

The panel cost per W for different PV panels are shown in Table 5.

2. Operation and Maintenance (O&M) Cost: This is the annual cost of operating and maintaining the system. It is assumed to be fixed throughout the lifetime of the project, and is fixed at an estimated level of 33.5 \$/kW.
3. Inverter Replacement (IR) Cost: Inverters have finite operating lifetimes, which depend on the specific type and manufacturer. Here, an average lifetime of 5 years is assumed [2]. This sets up a replacement cost which recurs every 5 years until the end of the project.
4. Revenue from Electricity Generation: This is the main income from the project. We assume that electricity generated from the PV installations will be sold directly to the electric grid at the prevailing feed-in tariff; for the UAE a figure of 0.0816 is used[2].
5. Salvage Value: At the end of the project, the components of the project will still have monetary value, which is known as salvage value. The salvage value is usually assumed to be 10% of the initial investment [2].

### 2.6 Economic Indices

The following indices are used to evaluate the economic feasibility of the different PV technologies:

1. Net Present Value (NPV): NPV is the difference between the present value of all cash inflows and the present value of all cash outflows, where the "present value" of a cash flow is the amount of this flow discounted to its present value as shown in equation (5). The net present value of an economically feasible project should be positive [11].

$$F = P(1 + i)^N, \qquad (5)$$

where $F$ =Future Value, $P$ =Present Value, $i$ =Discount Rate,$N$ =time.

2. Internal Rate of Return (IRR): The Internal Rate of Return measures the compound rate at which benefit is made from a project. It is the rate at which NPV becomes zero. IRR of any project can be estimated by using the NPV expression shown in Equation 5 and equating it to zero. This equation is non linear and has many solutions. Out of multiple solutions, the required IRR should be positive. [12].

3. Simple Payback Period (SPP): The period of time in years at which a project earns all of its investment and after which it starts making profit. Lower payback period signifies a higher project feasibility. Simple Payback Period is calculated using Equation 6.

$$SimplePaybackPeriod = \frac{InitialInvestmentCost}{AnnualOperatingSavings} \tag{6}$$

4. Benefit Cost Ratio (BCR): Benefit Cost Ratio compares the profit from the project with the costs involved. The revenues and profits are taken as benefits whereas the investment and expenses as taken as positive cost. The salvage value is taken as negative cost. Finally, benefit by cost ratio can be expressed as shown in Equation 7.

$$BenefitCostRatio(BCR) = \frac{PVofrevenue}{PVofcost - PVofsalvage} \tag{7}$$

## 3 Result and Discussion

### 3.1 Rooftop Area Calculation

Images depicting residential areas of Abu Dhabi were used. In order to check the generality of proposed model, images from two separate areas with different characteristics were used. The two image datasets were named the Khalifa and Raha datasets corresponding to the names of the two residential areas.

To facilitate better image segmentation, the images were divided into 512 x 512 pixel sized tiles, which corresponds to approximately 70 x 70 square metres of land area. Both Khalifa and Raha dataset consist of 25 images each of which 15 images were used for training and 10 were used for testing.

Classification Precision and Recall are used to evaluate the performance of the system, defined as:
Precision $= \dfrac{TP}{TP + FP}$ Recall $= \dfrac{TP}{TP + FN}$

Where TP,FP,TN and FN are True Positive, False Positive, True Negative and False Negative rates respectively.

Sample result of our algorithm is shown in Fig. 1 It can be seen that the result of first-stage classification contains many false positive regions. This is what our second-stage classification helps to improve. Second-stage classification reduces false positives largely, which in turn significantly improves the precision. Even though there is slight decrease in recall values as some of the rooftops identified in the first-stage may be lost, the improvement in precision and false positives is significant.
The overall performance of our method in the "Khalifa" and "Raha" datasets is shown Tab. 1. This shows the overall precision, recall and FP values for the test datasets.

As explained in the methodology section, aggregate rooftop area is estimated using the two-stage classification procedure. 65% of the aggregate rooftop area is

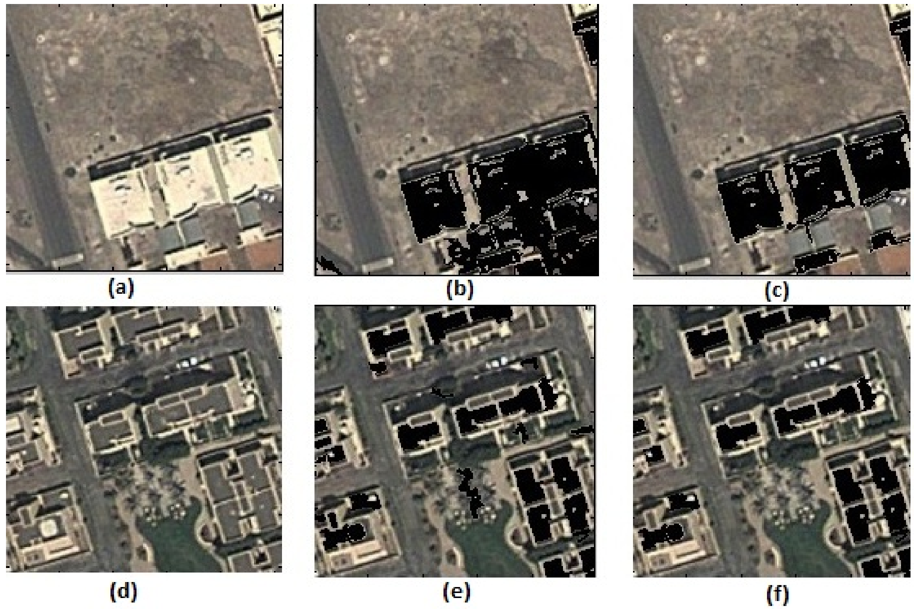

**Fig. 1.** The original image from Khalifa City A (a) The result after first-stage classification (b) The result after the second-stage classification (c) The original image from Raha Gardens (d) The result after first-stage classification (e) The result after the second-stage classification (f)

| | **First-Stage** | | | **Second-Stage** | | |
|---|---|---|---|---|---|---|
| | Precision | Recall | FP | Precision | Recall | FP |
| Khalifa | 89.95 | 82.39 | 9.21 | 92.24 | 81.16 | 6.82 |
| Raha | 87.78 | 86.69 | 12.16 | 92.29 | 83.08 | 7.07 |

**Table 1.** Results using Khalifa and Raha test dataset

available for solar PV installation, which is referred to as effective rooftop area. The calculated values of aggregate rooftop area and effective rooftop area for both the datasets are listed in Table 2.

| | Khalifa | Raha |
|---|---|---|
| Actual Aggregate Area ($m^2$) | 13929.61 | 6119.83 |
| Detected Aggregate Area ($m^2$) | 13958.06 | 6304.23 |
| Effective Area ($m^2$) | 9072.74 | 4097.75 |

**Table 2.** Area Calculation for Khalifa and Raha Datasets

### 3.2 Annual Solar Energy Generation

Equation 1 and 2 are then used to estimate the solar energy generation and solar peak power for three types of solar panels. The parameters used for this calculation are listed in Table 3. The calculated values of annual energy generation and peak power are shown in Table 4. the chart, the energy generation from thin-film cells is significantly less than that for the other two types of solar panels. Whereas the energy generation from monocrystalline solar panels is slightly higher than that for polycrystalline panels.

| | |
|---|---|
| Efficiency of monocrystalline panels (%) | 20 |
| Efficiency of polycrystalline panels (%) | 18 |
| Efficiency of thin-film panels (%) | 10 |
| Global Solar Radiation (kWh/$m^2$/year) | 2179 |
| Performance ratio assuming losses | 0.75 |

**Table 3.** Parameters for Energy Calculation

| Panel | Energy Generation (kWh) | | Plant Capacity (kW) | |
|---|---|---|---|---|
| | Khalifa | Raha | Khalifa | Raha |
| Mono | 2965424.74 | 1339349.42 | 1360.91 | 614.66 |
| Poly | 2668882.27 | 1205414.48 | 1224.82 | 553.19 |
| Thin-film | 1482712.37 | 669674.71 | 680.46 | 307.33 |

**Table 4.** Energy Generation and Peak Power

### 3.3 Upfront Cost Calculation

Following the approach presented in methodology section, we calculated the upfront cost of the PV system. Various data such as market price, specification et.al. obtained from [13][3,4] are used for this calculation. These parameters used for this calculation are listed in Table 5. Table 6 presents the calculated values of upfront costs for three types of solar panels. As expected, the upfront cost of monocrystalline solar panels is maximum, whereas it is slightly less for polycrystalline panels and it is lowest for thin-film panels.

### 3.4 Economic Analysis

Data obtained from [11, 13, 2, 14, 15] and the results presented in the previous sections are then used to analyze the economic viability of the PV system when

[3] http://grensolar.com/solar_products/solar_panel/
[4] http://www.nmsea.org/Curriculum/7_12/Cost/calculate_solar_cost.htm

| Parameter | Mono | Poly | Thin-film |
|---|---|---|---|
| $P_{peak,inverter}(kW)$ | 3 | 3 | 3 |
| $Cost_{inverter,kW}(\$)$ | 200 | 200 | 200 |
| $Cost_{panel,\$/kW}$ | 3000 | 2000 | 1000 |
| $RoofArea_{Khalifa}(m^2)$ | 150 | 150 | 150 |
| $RoofArea_{Raha}(m^2)$ | 70 | 70 | 70 |

**Table 5.** Input parameters for upfront cost calculation

| Solar panel type | Upfront cost ($) | |
|---|---|---|
| | Khalifa | Raha |
| Monocrystalline | 4119023.51 | 1879110.84 |
| Polycrystalline | 2485930.49 | 1141515.93 |
| Thin-film | 716746.38 | 342454.78 |

**Table 6.** Total upfront cost for Khalifa and Raha datasets

implemented using different PV panel technologies. The various parameters used in the calculation are listed in Table 7.

| Parameter | Mono | Poly | Thin-film |
|---|---|---|---|
| O&M cost ($/kW) | 33.5 | 33.5 | 33.5 |
| IR Cost Khalifa($) | 36216.99 | 36216.99 | 36216.99 |
| IR Cost Raha($) | 34096.19 | 34096.19 | 34096.19 |
| Discount Rate(%) | 7.55 | 7.55 | 7.55 |
| Lifetime (years) | 25 | 25 | 25 |
| Salvage Value Khalifa($) | 411062.79 | 248086.35 | 71528.55 |
| Salvage Value Raha($) | 182414.65 | 110812.64 | 33243.79 |
| Feed-in-tariff ($/kWh) | 0.0816 | 0.0816 | 0.0816 |
| Panel Cost ($/Watt) | 3 | 2 | 1 |

**Table 7.** Parameters for economic analysis

Using these parameters, we calculated the NPV, IRR, SPP and BCR for three types of panels for both Khalifa and Raha dataset. The results are shown in Tables 8 and 9.

| Index | Mono | Poly | Thin-film |
|---|---|---|---|
| NPV | -1936091 | -547424 | 321260 |
| IRR (%) | 1.71 | 4.99 | 12.30 |
| SPP (Years) | 20.94 | 14.23 | 7.66 |
| BCR | 0.58 | 0.82 | 1.31 |

**Table 8.** Economic Indices for Khalifa Dataset

| Index | Mono | Poly | Thin-film |
|---|---|---|---|
| NPV | -925595 | -298396 | 93949 |
| IRR (%) | 1.38 | 4.47 | 10.54 |
| SPP (Years) | 21.87 | 15.03 | 8.71 |
| BCR | 0.57 | 0.79 | 1.18 |

**Table 9.** Economic Indices for Raha Dataset

The NPV and BCR for mono and poly crystalline panels are negative and less than unity respectively. These values of NPV and BCR indicate that the project is economically infeasible with mono and polycrystalline panels. In contrast, the NPV and BCR for thin-film panels are much more positive. Even though more electricity can be generated using mono and poly crystalline panels, the associated costs are also a lot higher. The IRR value for thin-film panels is 10-12% and its payback period is 7-8 years. Again, these figures are better than those obtained for mono and poly crystalline panels. In addition, similar conclusions were reached when studying the results for both datasets i.e. Khalifa and Raha.

## 4 Conclusion and Future work

In this paper, a two-stage classification technique is used to determine the roof area for quantifying rooftop solar PV potential. Images obtained from Google Maps were used in the experiments.

Based on these estimates, three different PV technologies were then evaluated based on the respective energy generation potentials and economic feasibility. The case study was done for building rooftops in two residential regions of Abu Dhabi, UAE.

Abu Dhabi has huge potential for electricity generation using rooftop PV systems. As per the results of this project, the NPV for the monocrystalline and polycrystalline PVs are negative whereas it is positive for thin film panels. This shows that monocrystalline and polycrystalline PVs are unlikely to be profitable even though they generate more energy. One main reason for this is the low feed-in-tariff in the UAE. However, if the feed-in-tariff is increased by some extent, the NPV of monocrystalline and polycrystalline panels can be improved. In contrast, the thin film panels were found to be cheaper and economically feasible for rooftop power generation. The payback period and IRR of thin film was found to be around 7-9 years and 11-13% respectively. Thin film panel was found to have higher IRR, NPV and BCR in comparison to mono and polycrystalline cells.

PV technology provides significant environmental benefits, even though the associated costs are still quite high. The adoption of rooftop solar PV technology will have social and environmental benefits beyond the cost considerations. However, it will be difficult to attract investors for PV installations without a strong economic case and, if required, attractive incentives. The latter could be in the form of subsidy or improved feed-in-tariff. The work presented in this paper can be further extended in the following directions:

1. In this paper we calculated the aggregated rooftop area for two residential regions of Abu Dhabi city using machine learning based technique. Similar study can be performed for a different geographical region and the approach can be tested in a large geographical area.
2. In Abu Dhabi, most of the residential buildings are of same height. However, if the buildings are of uneven heights, the shadow of one building falls on another. In such cases, the portion of shadowed roof should be discarded while calculating energy generation. So, we plan to study the effect of such shadow on energy generation from PV.
3. The carbon saving from PV installation can also be considered in terms of monetary value and taken as a benefit in the economic analysis. This would certainly improve the NPV, IRR, SPP and benefit cost ratio.

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