# DeepSolar Bangladesh: A Novel Convolutional Neural Network (CNN) Architecture for the Detection of Solar Panels from Low Resolution Satellite Imagery in Developing Countries

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***Abstract*— Due to its environmental benefits and decreasing costs, the supply of solar energy is growing at an accelerating pace globally. However, the decentralised nature of solar makes it difficult to keep track of the different photovoltaic (PV) systems deployed across a country. There is a critical need for highly accurate, comprehensive national databases of solar systems, which would allow policymakers, researchers, and the government to study socioeconomic trends in solar deployment. Manual surveys have shown to be inaccurate. The 2018 DeepSolar study by Yang et. al developed a deep-learning framework and national solar deployment database for the US using high-quality satellite imagery, which proved to be a much more efficient and accurate approach. However, satellite imagery in developing countries such as Bangladesh is of much lower resolution and quality, and performed poorly with the original DeepSolar model by Yang et. al. Our study highlights the implementation of a novel convolutional neural network (CNN) in detecting solar panels through low resolution Google Static Maps API satellite imagery data. The model was trained over 500 epochs and had 49,859,906 parameters, and classified image samples as positive (indicating presence of solar panels) or negative (absence of solar panels). Our accuracy was 86.49%, F1 score was 86.49%, precision was 91.95%, and recall score was 81.63%, which are comparable scores to the original DeepSolar CNN that was trained on much higher quality data. This was the first CNN to detect solar panels using low-resolution satellite imagery (which is usually the only option for developing countries), and showed to be highly accurate and computationally efficient. Future plans include gathering funding to be able to purchase Google API satellite imagery to be able to cover all of Bangladesh to create a comprehensive public national database, as well as expanding to other developing countries.**

## I. INTRODUCTION

Solar energy is becoming the cheapest form of energy in most parts of the world, with the renewable energy seeing a 22% global growth in 2021 [1]. However, there are still some key challenges to the integration of solar into the electrical grid; as the energy is intermittent and decentralized, national databases tracking solar deployment are "critically needed", however, "currently unavailable" for most of the world. Self-reports and voluntary surveys such as the OpenPV project have shown to be inaccurate and ineffective [2].

Using a convolutional neural network (CNN) and a manually labelled image dataset, a 2018 study by Yang et. al overcame many of these limitations, creating the first public, comprehensive, highly accurate model and dataset for solar panel detection. However, this was created using high-quality satellite imagery from Google Static Maps API for the United States. The main limitation of the study was that for other parts of the world, particularly developing countries such as Bangladesh, the same data from Google Static Maps API is of much lower resolution and quality.

We tried applying the original DeepSolar CNN model to satellite data from Bangladesh, however, the accuracy was quite low as the data quality was quite low and the original model was trained on high quality data. Fig. 1 shows a side-by-side comparison of a satellite image of a rooftop PV system from Bangladesh versus one from the US, to show the disparity in the resolution. Therefore, the purpose of this research was to construct a novel convolutional neural network architecture (DeepSolar Bangladesh), the first CNN to detect solar panel deployment using low-resolution satellite imagery (which is all that is usually available to developing countries). Such a model is crucial to track trends of solar deployment, for government policy-making objectives, researchers, and solar developers, especially when compared with correlations of socioeconomic data of the geographical areas.

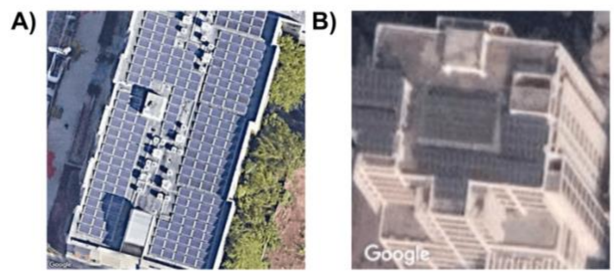

Figure 1. Comparison of Image Quality and Resolution. A) United States positive sample, used to train original Yang et. al's DeepSolar model. B) Bangladesh positive sample, used to train our DeepSolar Bangladesh model.

## II. METHODS

The image data was sourced from Google Static Maps API. To prevent training bias, an equal amount of positive samples (includes solar panels) and negative samples (does not include solar panels) were included in the dataset. The data was collected by finding the coordinates of solar farms and rooftop solar systems in Bangladesh by manually searching on Google Maps. Images were gathered at zoom 19, size 160 px by 160 px, at the 'satellite' maptype. The alpha channel was deleted as it was not pertinent to the model and added unnecessary dimensionality to the model, giving each pixel three channels of data (RGB). The data was split between training and testing with a 80:20 ratio respectively. 0.5 is used as the probability threshold for panel identification. Negative samples were found by generating random coordinates, then visually verifying them. Table 1 shows the data distribution used to train our CNN.

TABLE I. DISTRIBUTION OF THE DATA USED IN DEEPSOLAR BANGLADESH

| **Data Type** | ***Positive*** | ***Negative*** | ***Total*** |
|---|---|---|---|
| Train | 364 | 375 | 739 |
| Test | 98 | 87 | 185 |
| | 462 | 462 | |

The architecture of the CNN consisted of 8 layers, as shown in Fig. 2.

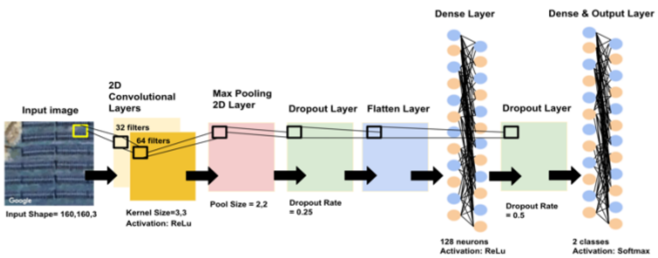


Figure 2. CNN Architecture: two 2D convolutional layers, 1 max pooling 2D layer, 1 dropout layer, 1 flatten layer, 1 dense layer, 1 dropout layer, 1 dense output layer.

The ReLu activation function (1) was used between all layers, with a Softmax activation function (2) at the end to predict the probability of the output being between 0 and 1 (0 being negative, 1 being positive). The model was trained over 500 epochs and had 49,859,906 parameters. Binary cross-entropy (BCE) was used as the loss function (3).

$$\text{ReLu function: } f(z) = \max(0, z) \qquad \textbf{(1)}$$

*where z = input vector.*

$$\text{Softmax function: } \sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \qquad \textbf{(2)}$$

*where σ = softmax function,* $z_i$ *= input vector,* $z_j$ *= output vector, K = number of samples in the dataset.*

$$\text{BCE: BCE} = -(y\log(p) + (1-y)\log(1-p)) \ \textbf{(3)}$$

*where y = true class (0 or 1) p = predicted probability of being 0 or 1.*

## III. RESULTS AND DISCUSSION

Our model was evaluated on accuracy, precision, recall, and F1 score. Table 2 shows a summary of these metrics. We compared our scores with the original DeepSolar CNN's performance on the high-res US data (*note: the averages of the residential and non-residential metrics are taken as reported in the original DeepSolar paper), and the original DeepSolar CNN's performance on the low-res Bangladesh data [2].

TABLE II. ACCURACY METRICS FOR DEEPSOLAR BANGLADESH

| ***Model*** | ***Data*** | ***Accuracy*** | ***Precision*** | ***Recall*** | ***F1 Score*** |
|---|---|---|---|---|---|
| ***DeepSolar Bangladesh (our CNN)*** | Low-res, Bangladesh | 86.49% | 91.95% | 81.63% | 86.49% |
| ***Original DeepSolar**** | High-res, US | 93.3% | 93.4% | 89.5% | 91.4% |
| ***Original DeepSolar*** | Low-res, Bangladesh | 51.47% | 100% | 2.94% | 5.71% |

Fig. 3 shows a confusion matrix of true positives, true negatives, false positives, and false negatives. Overall, our model's accuracy was 86.49% (Table 2), with a precision of 91.95%, recall of 81.63%, and F1 score of 86.49%. These scores are slightly lower than but still comparable with the original DeepSolar model by Yang et. al which was trained on high res US data. The results of our CNN, however, are much higher than the original DeepSolar CNN applied to the low-res Bangladesh data (row 3 of Table 2). The 100% precision score in that row indicates all true positives and zero false positives, but the recall score takes into account false negatives as well. The comparative low recall score of 2.94% indicates that due to the low resolution of the data, the model classified positives correctly, but had trouble distinguishing between negatives. Despite the disadvantage of low quality data, our model's comparable accuracy to the state-of-the-art original DeepSolar CNN show our model's robustness in multiple metrics.

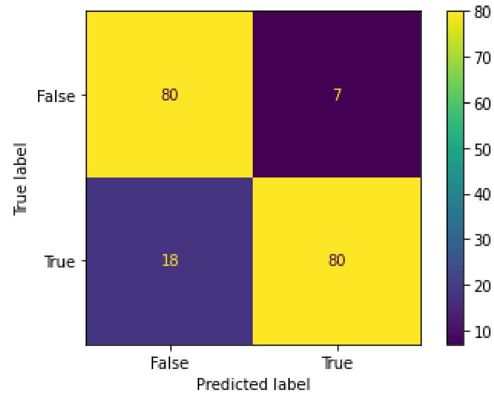


Figure 3. Confusion Matrix for our CNN: DeepSolar Bangladesh on low-res Bangladesh data.

## IV. CONCLUSIONS

This study showcases the first CNN for detecting solar panel deployment on low-res and low-quality satellite data, which is what is most common for developing countries via sources such as Google Static Maps API. Future plans for this study include gathering funding and collaborating with the government to purchase enough Google Static Maps API satellite images to cover all of Bangladesh in order to create a comprehensive national public solar deployment database. This CNN can be applied to low-res data of other developing nations as well. Further investigations should look to add segmentation capabilities to the model so it can identify panel size dimensions, as well as find ways to 'spot-check' the database by comparing it to manual surveys. Researchers, government policymakers, and solar developers can use such a database in addition to socioeconomic factors to study solar deployment trends.

## V. ACKNOWLEDGMENT

Thanks to InspiritAI for the platform for this research!

## VI. REFERENCES

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