

DER Imagery Classification

nationalgrid

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Scope

Solar PV impact is a critical input to electric load forecasting. Currently, two types of solar PV are modeled in the load forecasting process: ground-mounted and rooftop. It is necessary to differentiate the historically connected projects to use them for modeling each type. However, information to distinctly classify an existing solar project as roof-top versus ground-mounted is not available in the Company's DG interconnection database. This project is designed to analyze site images (e.g. satellite images, Google street images, etc.) to help categorize these unclassified projects into rooftop or ground-mounted projects.

Project Setup

Data

- Sales Force data of customers with PV panels provided by DMA team in excel (converted to csv)
- From DG Fuel Source category, removed all values other than “Solar”, sliced for only Service Address Information, and dropped missing values
    - Service Address information
        - Premise Address
        - Service Address City
        - State
- Longitude and Latitude determined from Google Geocode API with service address information
- Static Map determined from Google Maps API with Longitude and Latitude information
- Images downloaded and stored into “images” folder (looping through takes 9 hours with current hardware specs and will utilize 60% of API Key credits)

Project Setup (cont.)

Modeling

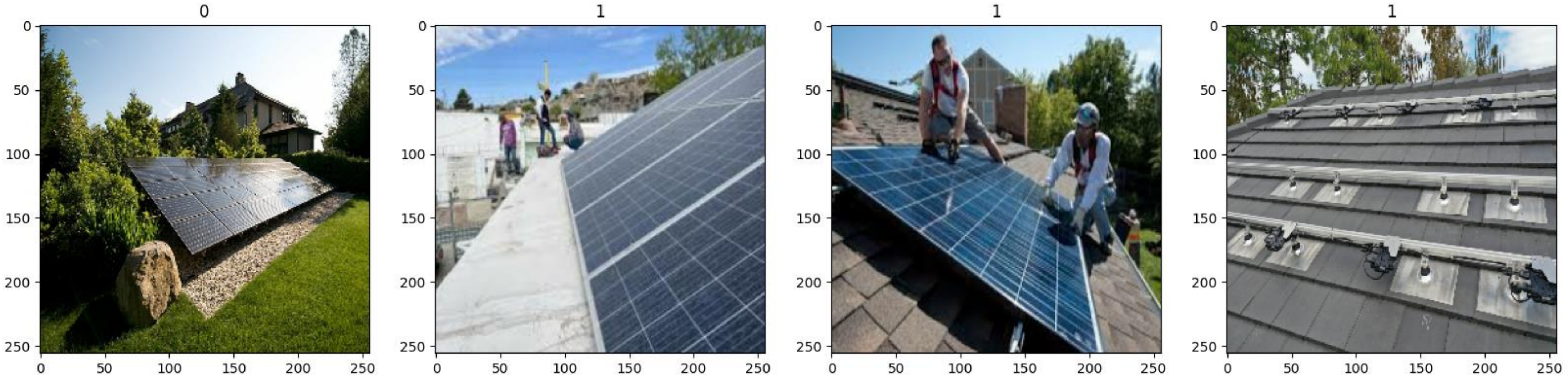
Our approach to start was to obtain aerial images and train Convolutional Neural Network model with images of roof and ground mounted panels

- Import from Google Images, scale images (scaled by 255), and train model
- tune and optimize model (100 epoch yields best results but takes 2 hours)
- Save model for future predictions

Performance Measures

- Accuracy
- Recall
- Precision
- Loss

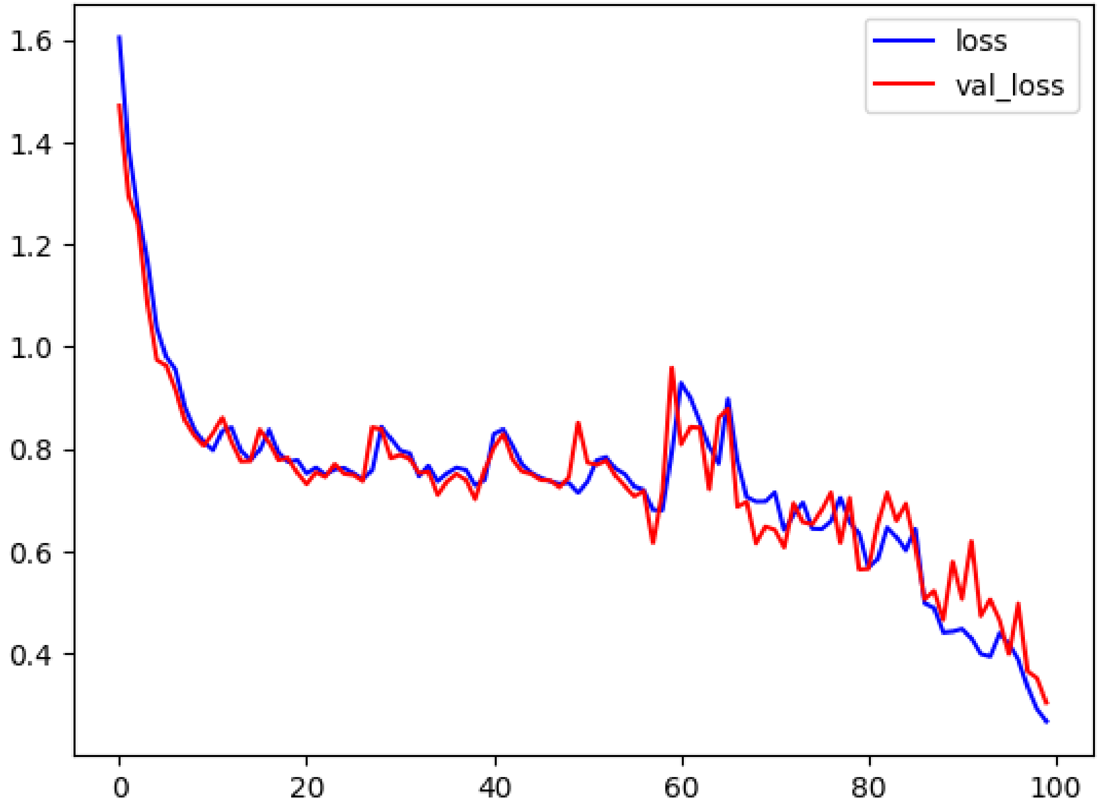
Classification



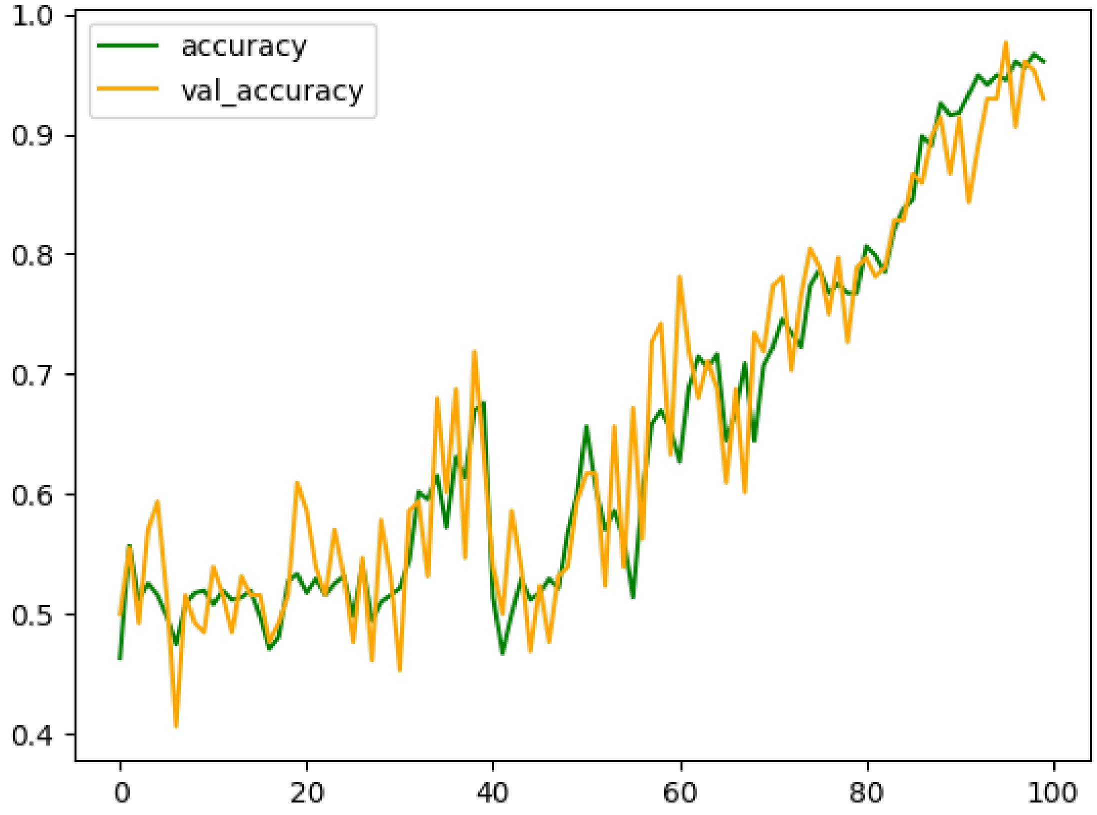
A batch (4) of images that are classified based on ground level (0) or rooftop (1) above each image. Images are downloaded from Google Images (339 ground and 266 rooftop images).

Model Performance

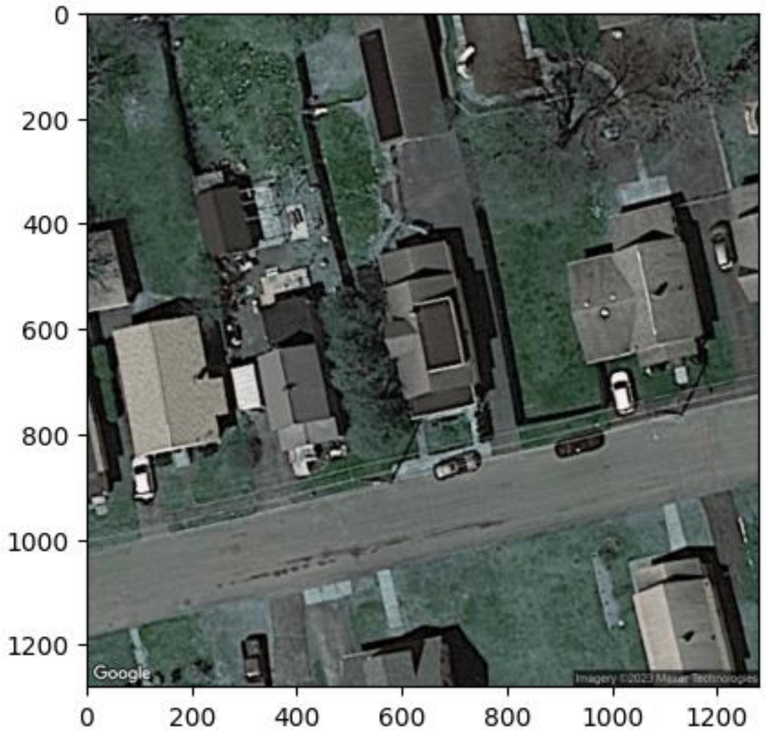
Loss



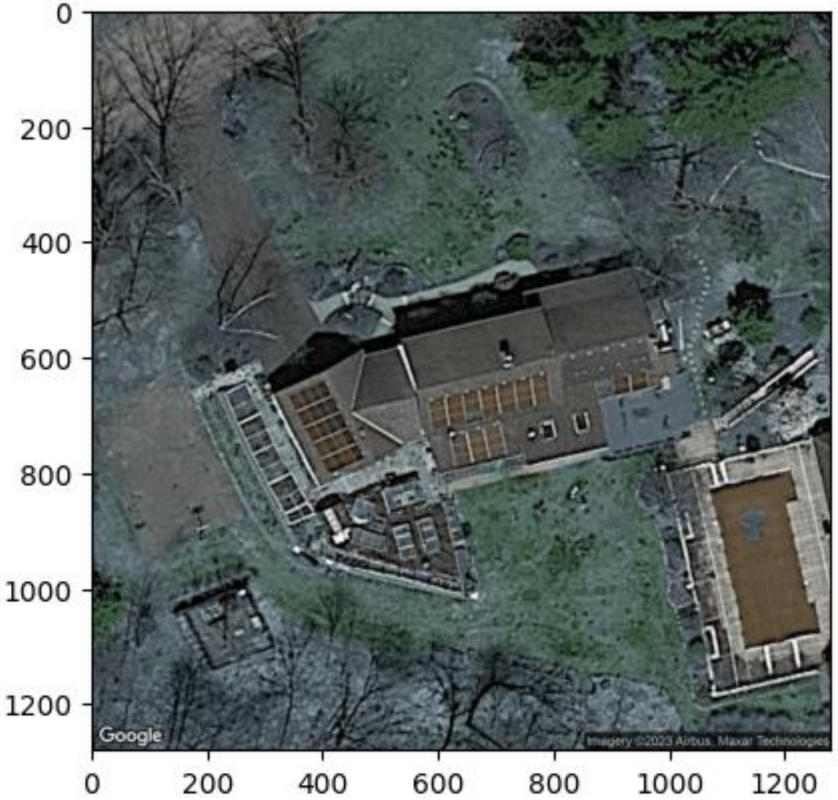
Accuracy



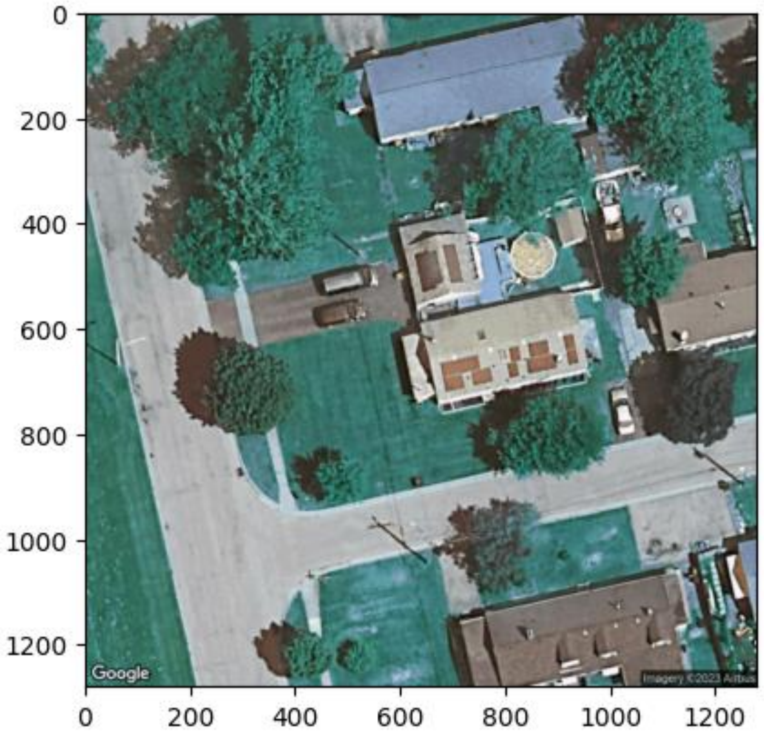
True Predictions



Prediction: Rooftop 0.93932515
[Index 20 Google Maps]

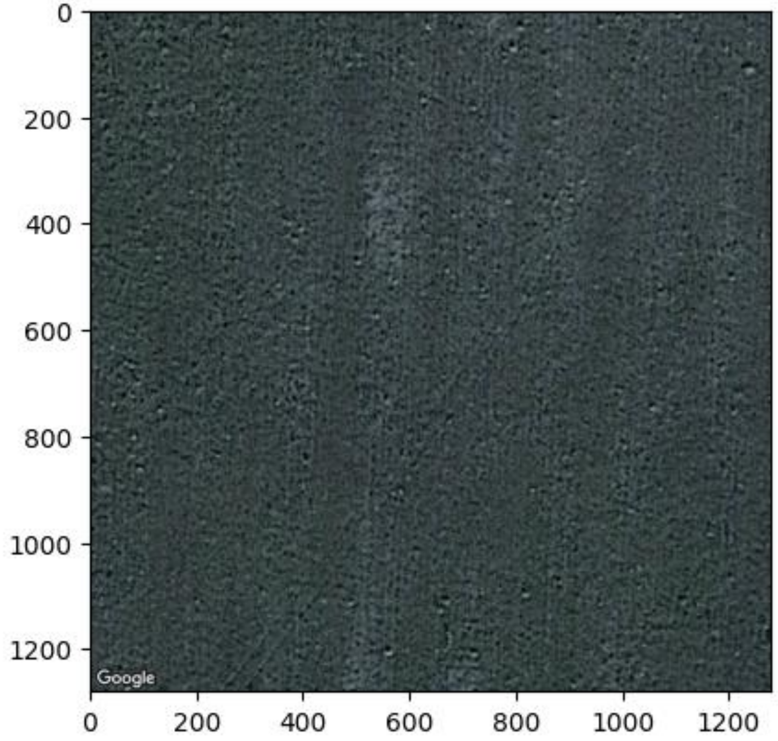


Prediction: Rooftop 0.9946679
[Index 19 Google Maps]

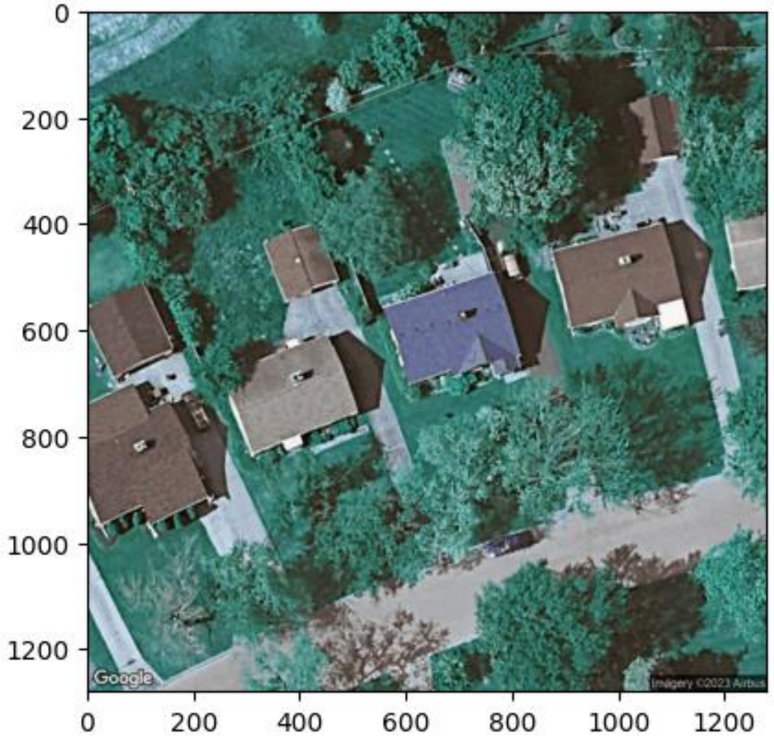


Prediction: Rooftop 0.91113377
[Index 23 Google Maps]

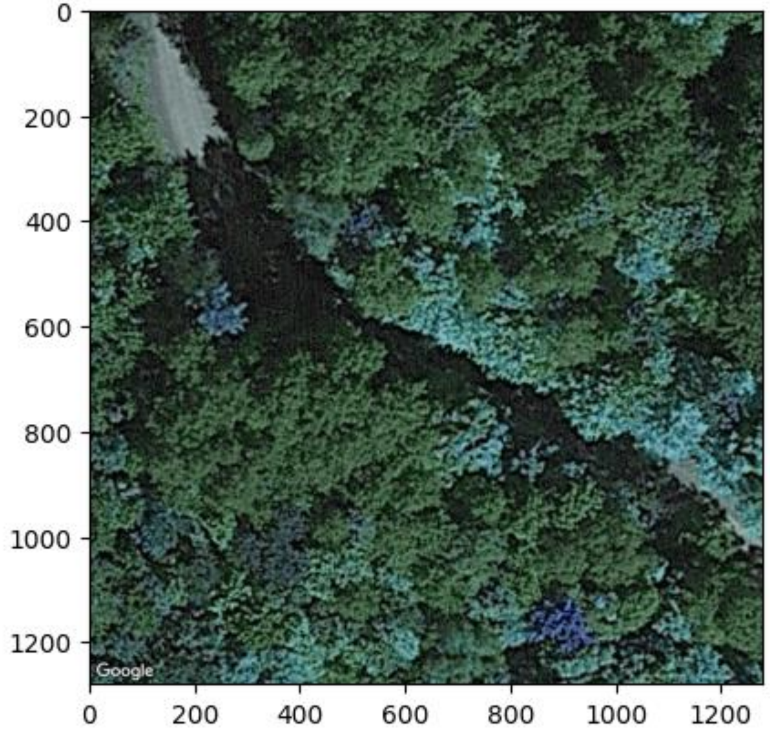
Prediction W/O Info



Prediction: Rooftop 0.58909047
Index 0 Google Maps



Prediction: Rooftop 0.96378679
Index 1 Google Maps



Prediction: Rooftop 0.99273795
Index 11 Google Maps

Recommendations

- Determine property limits for image capturing
- Consider alternative imagery platform with higher resolution and frequent updates
- Add Labeller package to focus on solar panels in images prior to downloading
- Consider 4 classes: No Rooftop Solar, Rooftop Solar, No Ground Mount, Ground Mount
- Train model with larger quantity and quality, relevant images
- Improve model with additional hyper-tuning parameters and features

	Rooftop Solar	Ground Mount	Total
Total Predictions	14	10	24
True Predictions	11	2	13
True Percent	78.57%	20.00%	54.16%

References

- Medium.com (François Andrieux)
- TensorFlow.org
- Google Geocoding
- Google Static API
- TowardsDataScience.com
- CNN Model Explained

Gridtern Experience

- Learned how models are interpreted and implemented into real-world scenarios
- Enhanced coding, modeling, and communication skills
- Better understanding of the utility industry and department necessities
- Learned the information used to make business decisions
- Future directions toward a successful career