User-Friendly Defective Solar Cell Detection using Artificial Intelligence

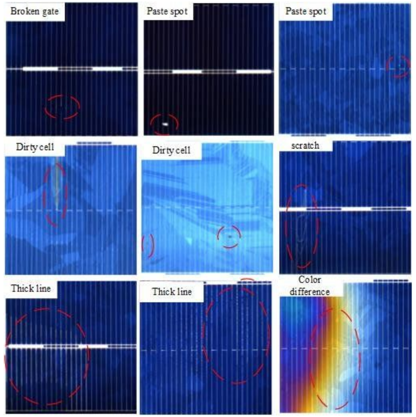
Project ID: 2677
Category: Earth and Environmental Sciences (EA)
Division: Senior

*All photos, graphs, and images are created by the researcher unless indicated otherwise.

Introduction

What are solar cells? Why are they important?:

- Solar cells use solar energy to produce energy and are the main component of solar panels
- Solar panels are a valuable source of clean, renewable energy
- Solar cells are subject to degradation due to weather (hail, snow, rain, etc.) and operational damage
- Defects can be detected through visual inspection of electroluminescence of the modules



Surface Defects of Solar Cells
Image Credit: ResearchGate

Challenges:

- Manual detection of defects in solar cells can be difficult and tedious
- Lack of detection can lead to solar system efficiency degradation, leading to an interruption in electric current and energy production

Research Question:

- Is there a way to make detecting defective solar cells more efficient (1) and accessible (2)?

Research Tasks:

1. Develop a high-accuracy (>80%) artificial intelligence model that can predict defect probability of a solar cell
2. Develop a web Django application in which users can upload solar cell images and receive rapid predictions

Existing Methods

My approach incorporates the ML method

<u>Thermodynamic Method</u>

- PRO: Thermodynamic "hotspot" defects can be detected through their thermal signature
- PRO & CON: Specific to one form of defect
- CON: High cost

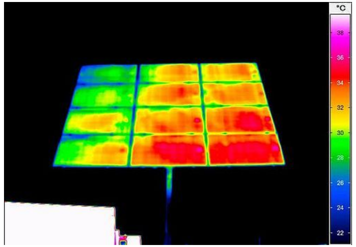
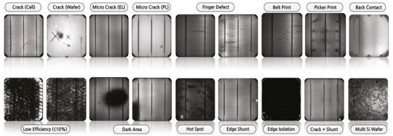


Image Credit: Infratec

<u>Imagery Method</u>

- PRO: Provides high quality solar cell imagery
- CON: Relies on manual detection of solar panel user which can be laborious and inefficient



Near-Infrared (NIR) Detection Camera Images
Image Credit: Alt Energy Mag

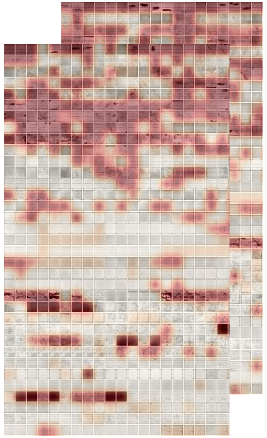
<u>Machine Learning (ML) Method</u>

- PRO: High efficiency for non-manual defect detection
- PRO: Provides functionality on a variety of defect types
- CON: Overfitting can lead to poor performance accuracy on test dataset
- CON: Model is rarely available in a format that can be used by the public

Image Classification & Django Background

- Image classification is an aspect of ML/AI that utilizes image processing, feature extraction and various classifiers to identify a label for an image. Either unsupervised learning and supervised learning can be used. A large problem of image classification is overfitting, which occurs when the model performs well on the training data but not on the test data
  - In the case of defective solar cells, the labels are known. Thus, a supervised approach is appropriate
  - Various classifiers can be used, including SVM, Random Forest (RF), a Convolutional Neural Network (CNN), Decision Trees (DT), etc. The best classifier depends on the situation. To avoid overfitting, these classifiers are tested for accuracy on validation data to establish the most accurate classifier for the situation
- Django is a python framework that makes it capable to create websites with built-in applications/models such as a solar cell detection model
  - Once the most accurate model is deduced, it can be integrated into a website that is easy-to-use and accessible

Solar Cell Image Classification Framework



images from elpv-dataset

Labeling data: Defective image labeled: Class ‘0’, ‘1’, and ‘2’ – based on probability of defect

Image preprocessing: Grayscale, gaussian blur, thresholding

Feature Extraction: Flattened thresholded images, image segmentation, etc.

Training & Testing: Various classifiers used: SVM, RF, CNN, etc.

Output: Prediction metrics (F1, accuracy, recall, precision)

Compare prediction metrics for classifiers.

Improve highest accuracy classifiers: Improvement techniques (image segmentation, processing changes, etc).

Part 1: Classifier comparison

- Models are trained under the same conditions (same amount of training/testing data, preprocessing, etc) and then compared

Part 2: Highest accuracy classifier improvement

- Highest accuracy classifiers from Part 1 are selected and improved, now with new parameters integrated to improve accuracy

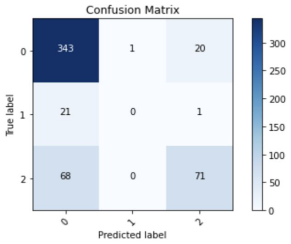
Part 1: Classifier Comparison

Various classifiers were compared to determine which best fits the elpv-dataset.

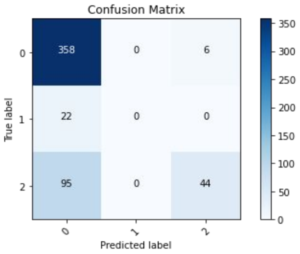
#Trained Images	# Tested Images	Image Processing Technique	Classifier	Prediction Accuracy
2099	525	grayscale, gaussian blur, thresholded	Random Forest	0.7886
2099	525	grayscale, gaussian blur, thresholded	CNN	0.77
2099	525	grayscale, gaussian blur, thresholded	SVM	0.781
2099	525	grayscale, gaussian blur, thresholded	Naive Bayes	0.2095
2099	525	grayscale, gaussian blur, thresholded	Decision Tree	0.7181
2099	525	grayscale, gaussian blur, thresholded	MLP	0.6952

- RF, CNN, and SVM performed most accurately
- Each model has its own strengths: RF can identify the higher level probability of defects much more accurately than the other models and CNN and SVM can detect the lower probability of defects with higher accuracy
- High prediction accuracies across top models demonstrate avoidance of overfitting

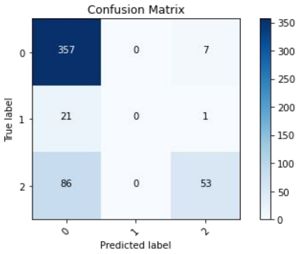
RF



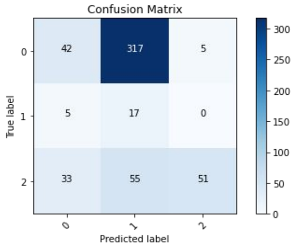
CNN



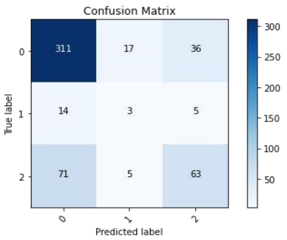
SVM



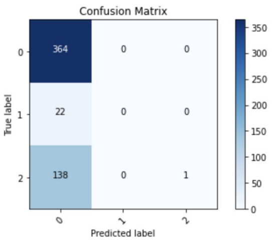
Naive Bayes



Decision Tree



MLP

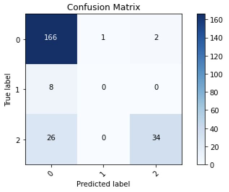


Part 2: RF, CNN, SVM Classifier Improvement

Since RF, CNN, and SVM performed with the highest accuracy, various techniques were integrated to improve each classifier accuracy, such as augmented feature extraction, image segmentation, image preprocessing changes and more. The most accurate result for each classifier is demonstrated below:

RF Highest Accuracy:

#Trained Images	# Tested Images	Trial Type	Image Processing Technique	Prediction Accuracy
2387	237	feature extraction (threshold flatten)	gaussian blur, threshold, no grayscale	0.8439



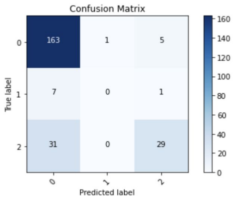

```
              precision    recall  f1-score   support

         0.0       0.83      0.98      0.90       169
         1.0       0.00      0.00      0.00         8
         2.0       0.94      0.57      0.71        60

    accuracy                           0.84       237
   macro avg       0.59      0.52      0.54       237
weighted avg       0.83      0.84      0.82       237
```

CNN Highest Accuracy:

#Trained Images	# Tested Images	Trial Type	Image Processing Technique	Prediction Accuracy
2387	237	only image processing	gaussian blur, threshold, grayscale	0.8101



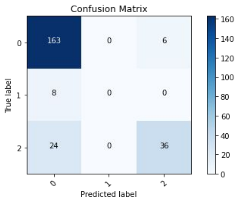

```
              precision    recall  f1-score   support

         0.0       0.81      0.96      0.88       169
         1.0       0.00      0.00      0.00         8
         2.0       0.83      0.48      0.61        60

    accuracy                           0.81       237
   macro avg       0.55      0.48      0.50       237
weighted avg       0.79      0.81      0.78       237
```

SVM Highest Accuracy:

#Trained Images	# Tested Images	Trial Type	Image Processing Technique	Prediction Accuracy
2387	237	image segmentation	no preprocessing	0.8400



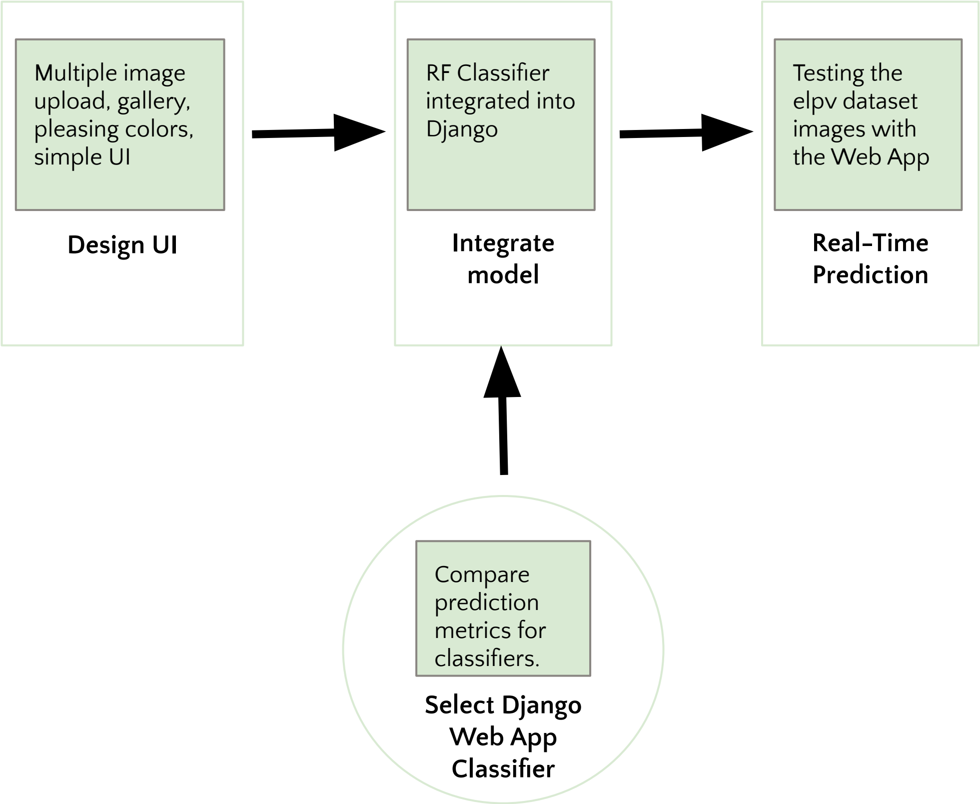

```
              precision    recall  f1-score   support

         0.0       0.84      0.96      0.90       169
         1.0       0.00      0.00      0.00         8
         2.0       0.86      0.60      0.71        60

    accuracy                           0.84       237
   macro avg       0.56      0.52      0.53       237
weighted avg       0.81      0.84      0.82       237
```

Conclusion: RF performed the best, with a 84.4% accuracy on testing data.

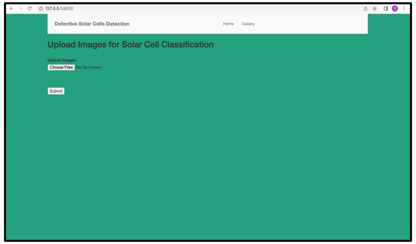
Django Approach/Framework



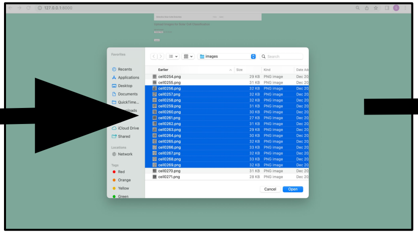
- Django Web App Goals:
  - Simple, easy-to-use UI
    - Labeled clearly, easy to understand and use
  - Multiple solar cells can be uploaded at once
    - Larger input indicates that users can more efficiently detect defects in their solar cell images
  - Rapid predictions, accurate
    - Users should receive predictions at a very fast rate (based on input size)
    - Over 80% accuracy

Django Web Application Results

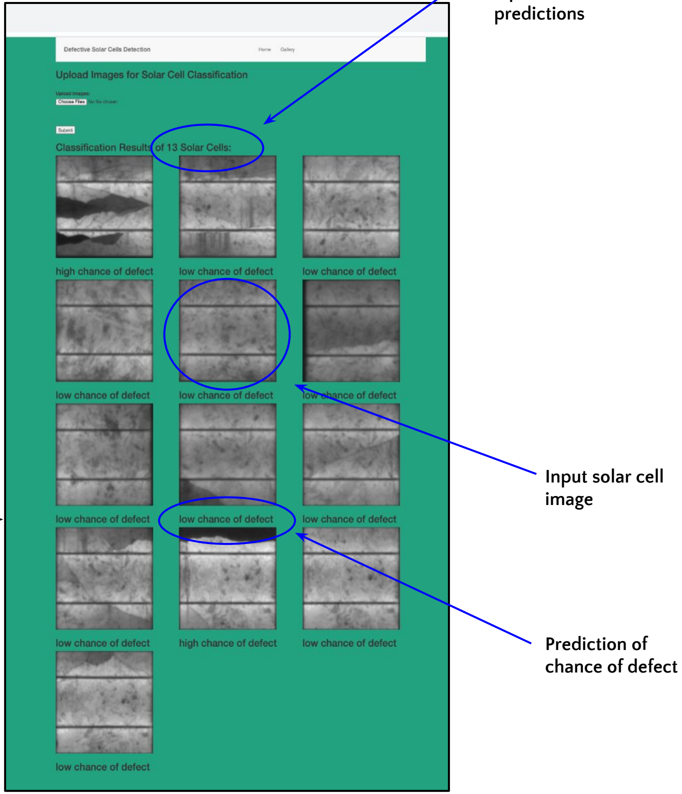
- *Concise*: returns the image along with a short description of likelihood of defect. UI is simple and clear
- *Efficient*: The web application supports predictions of thousands of images at once at rapid speed (loading time varies based on input size)
- *Accurate*: Predicts with 84.4% accuracy (based on test accuracy of RF model)



Home screen

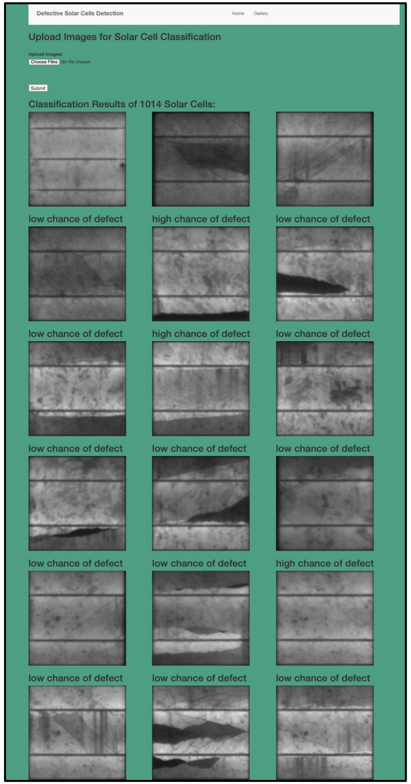


User selects images



User receives rapid predictions

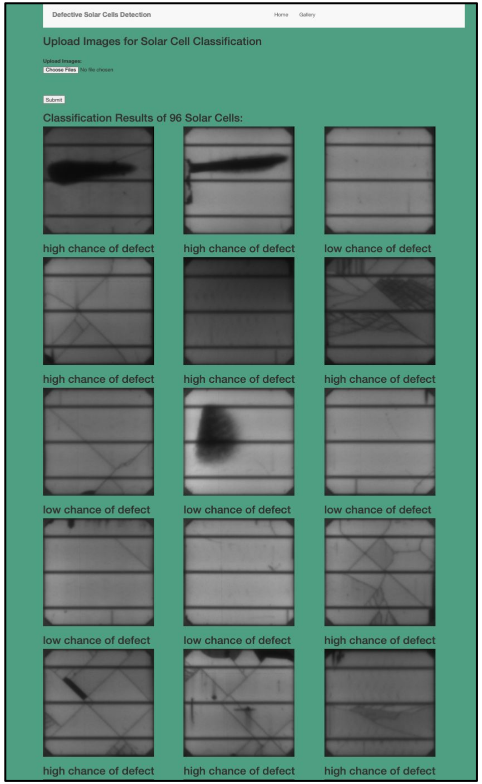
Web Application Examples



Over 1000 predictions loaded*

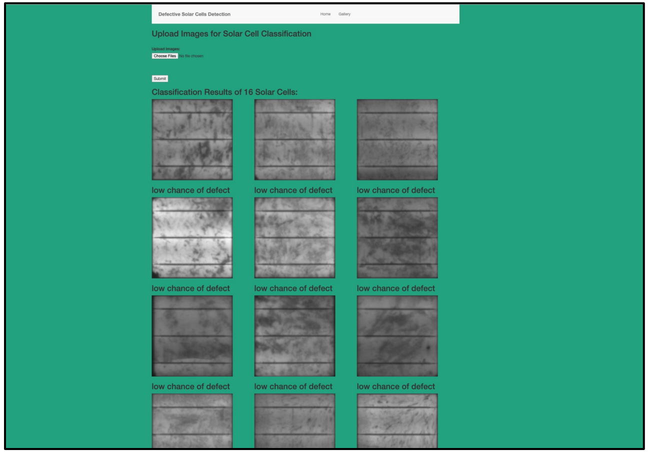
~10 seconds of loading time

*not all images/predictions are shown in the screenshot



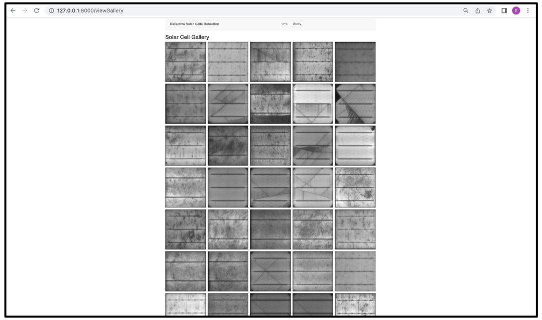
Predictions for a variety of image types

~1 second of loading time



Predictions for a small group of images

~0.1 seconds of loading time



Gallery with previously loaded solar cell images

Conclusions and Future Work

- The web application is a valuable tool to aid solar panel users in determining whether their solar cells are defective, leading to higher efficiency solar resources
- Criteria & Goals Reached
  - The model reports with 84.4% accuracy
    - The model is an efficient <u>tool</u> to establish the chance of defect in a solar cell
  - The model takes an easy-to-use, user-friendly approach
    - Simple UI with the ability to scan thousands of images at once
- Future Work
  - Use higher-level deep learning models to improve the accuracy of the model
  - Publish the website so that anyone can use its services
- Applications
  - The model could be used in outdoor electroluminescence inspection through unmanned aerial vehicles or drone-mounted systems
  - Solar panel maintenance systems

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