Transferability of photovoltaic (pv) arrays from high resolution satellite imagery data for semantic segmentation

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Motivation

- **Rapid Growth in Renewable Energy**:

- Renewable energy has increased rapidly worldwide in recent years.
- International Energy Agency predicts a 50% growth in total renewable-based power capacity from 2019 to 2024.

- **Solar PV as the Fastest-Growing Energy Source**:

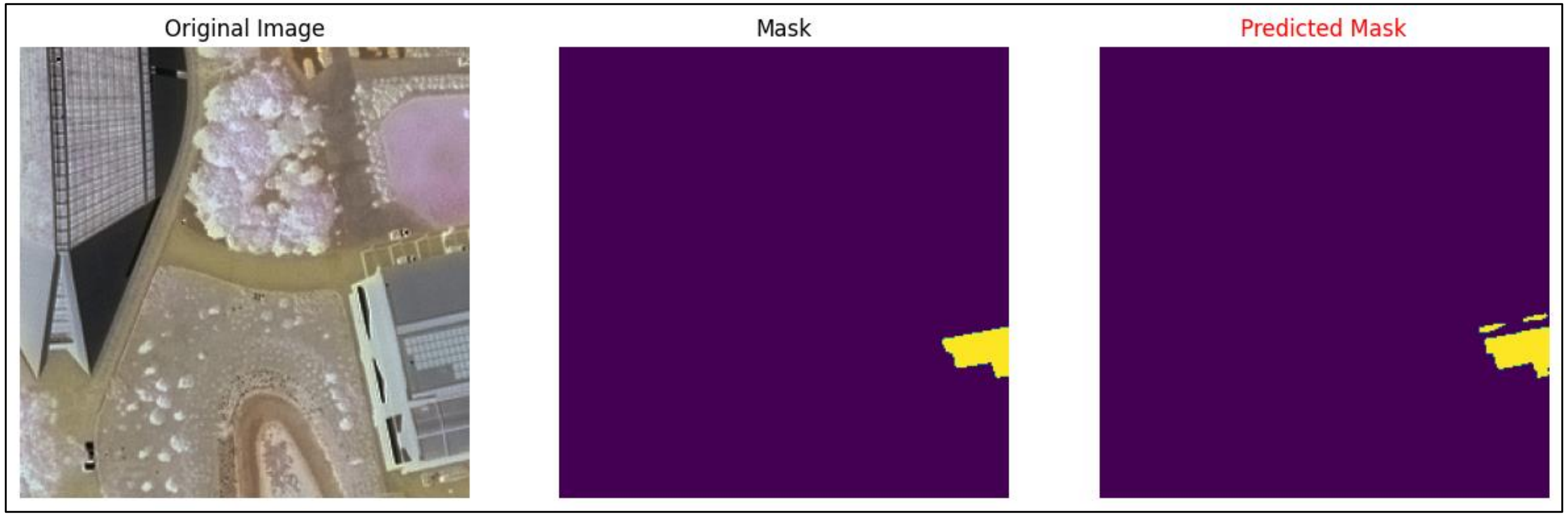
- Solar photovoltaic (PV) generation expected to account for 60% of this growth.
- Solar PV is the fastest-growing form of energy generation today.

- **Challenges of Integrating PV Arrays into Power Grids**:

- Integrating distributed PV arrays into existing power grids is challenging.
- Information on location, power capacity, and energy production of distributed PVs is difficult to obtain (Malof, 2016).

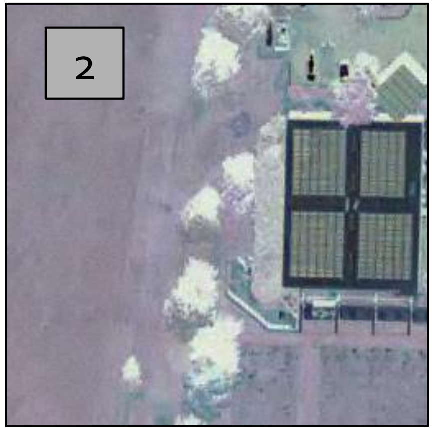
Semantic Segmentation

- Semantic segmentation is a technique in computer vision where every pixel in an image is assigned a specific label. Think of it as coloring different parts of a picture based on what they are.
- In our case semantic segmentation identifies and highlights solar panels on the roof, distinguishing them from other features like the house and pool.

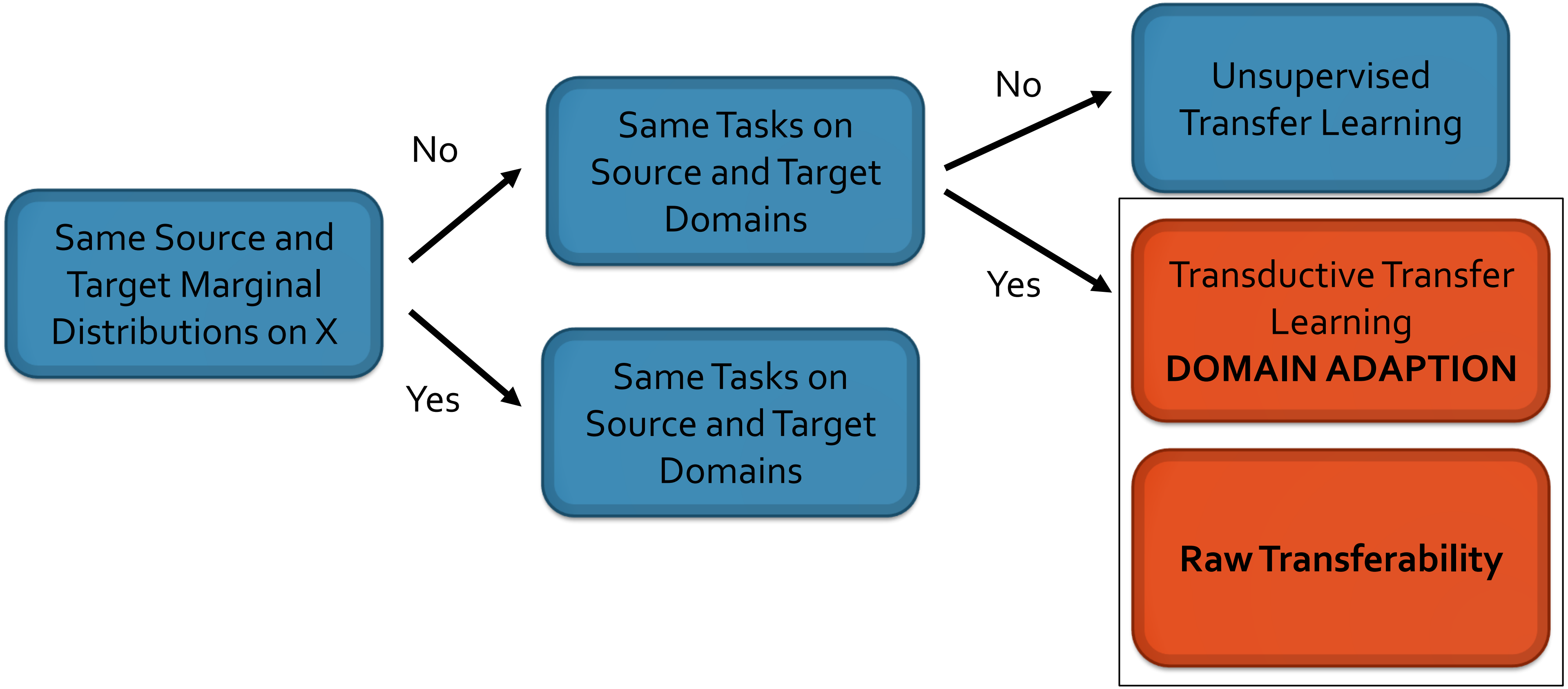


Transfer Learning

- Transfer learning is a deep learning technique where knowledge acquired from one task is repurposed to enhance performance on a related task.
- For instance, in image classification\segmentation:
  - cars can be leveraged to recognize trucks.
  - knowledge gained from identifying solar panels in aerial images from one region of the world, such as the Australia (1), can be applied to segment solar panels in a different region, like the United States (2).

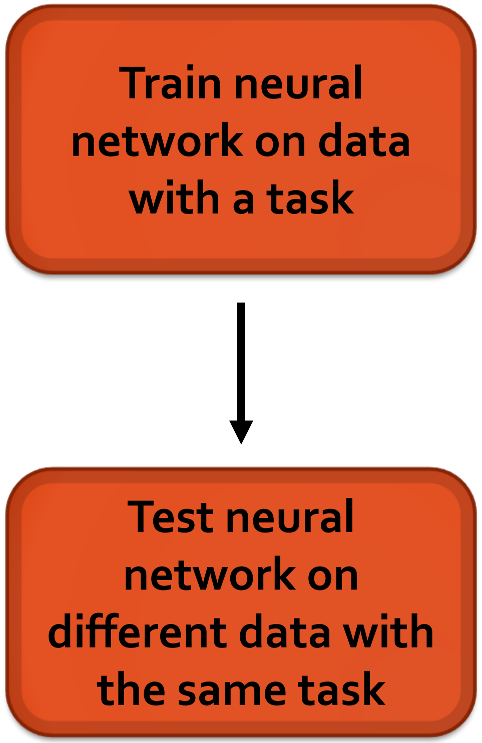


Transfer Learning – Decision Tree

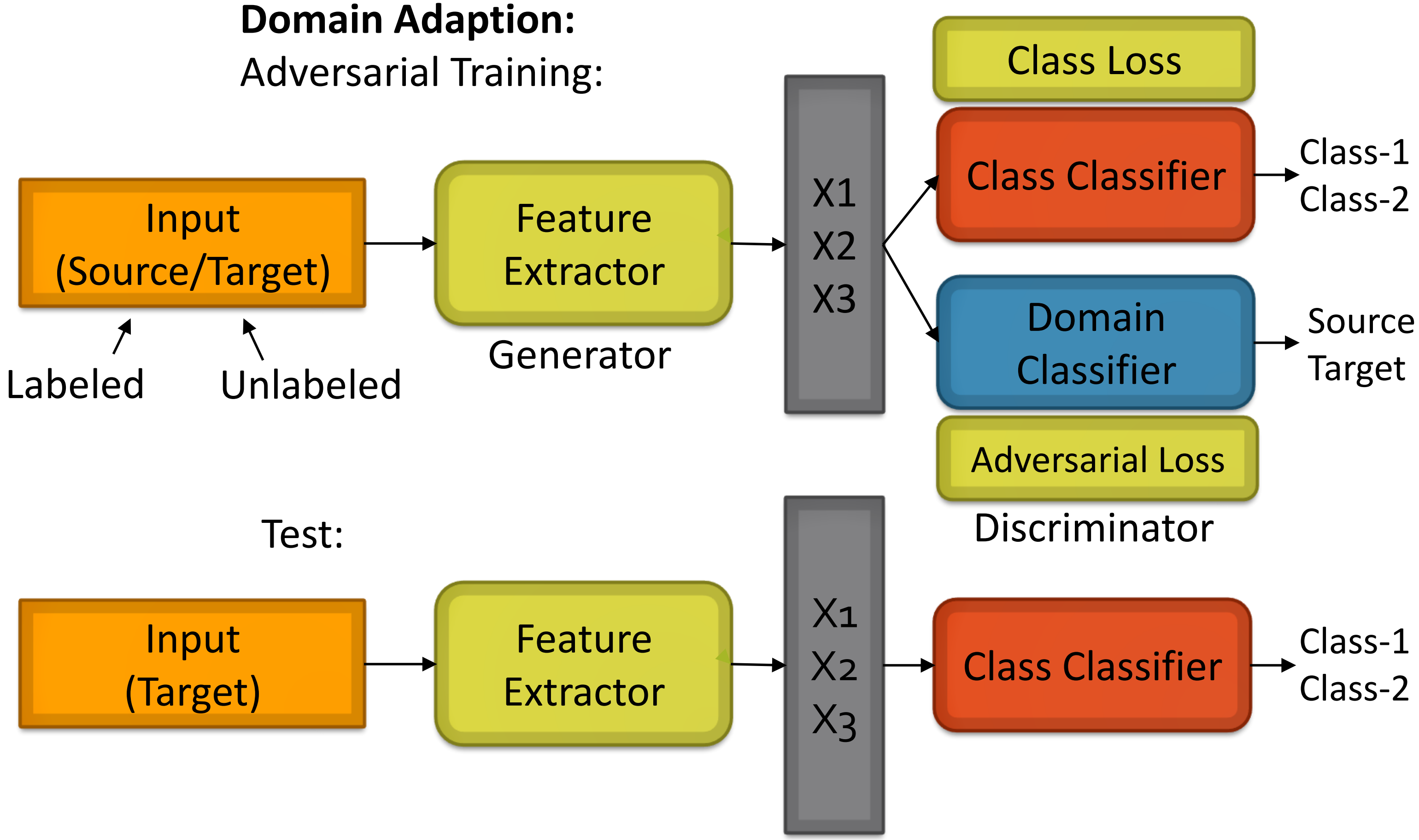


Transfer Learning - Methods

Raw Transferability:
Train on data and test on different data



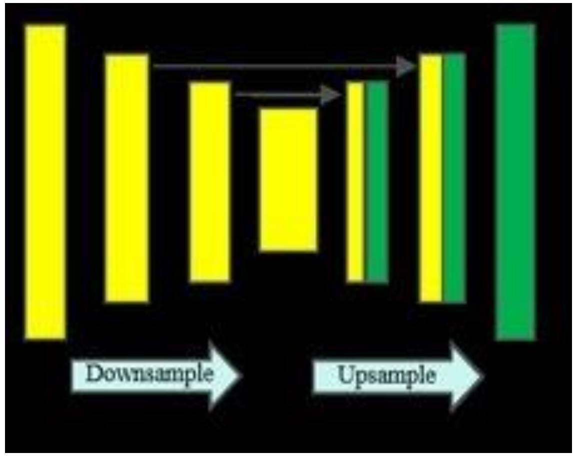
Domain Adaption:
Adversarial Training:



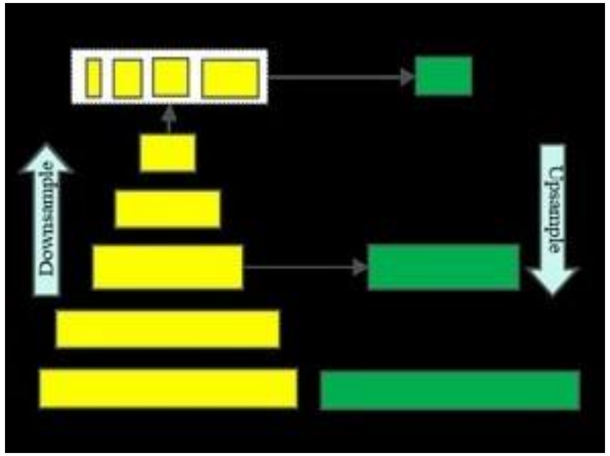
Modeling - Architectures

- Used 4 different models with back bone of ResNet18 (Encoder) for segmentation mission and comparison:
    - **Encoder:** Compresses input data into essential features.
    - **Decoder:** Reconstructs data from the compressed features.

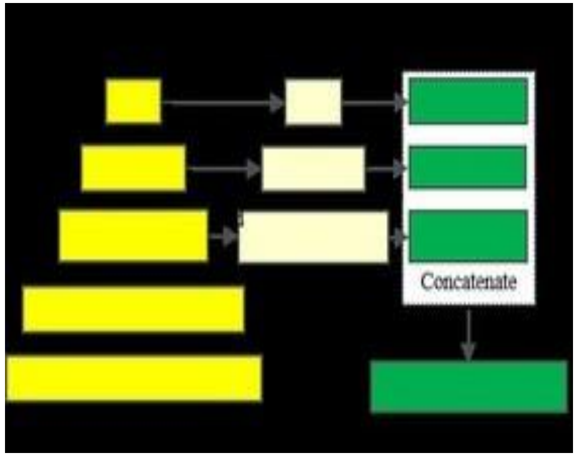
U-Net: A symmetric encoder-decoder architecture for precise image segmentation.



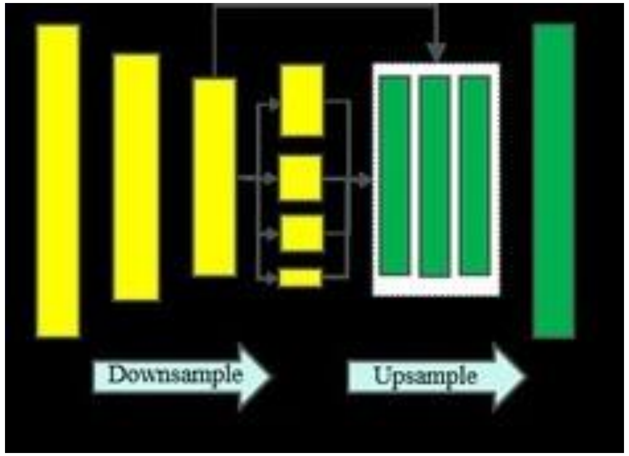
DeepLabV3Plus: enhances DeepLabv3 by adding a decoder module to refine segmentation details and improve accuracy.



FPN (Feature Pyramid Network): Combines multi-scale feature maps for robust object detection and segmentation.

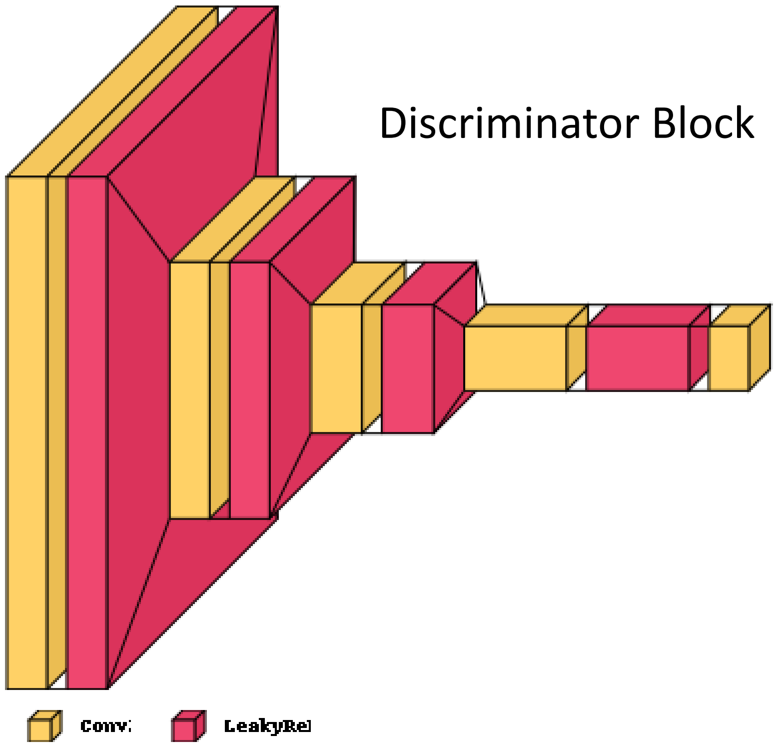


PSPNet (Pyramid Scene Parsing Network): Aggregates contextual information from multiple scales for improved scene parsing.



Discriminator - Architecture

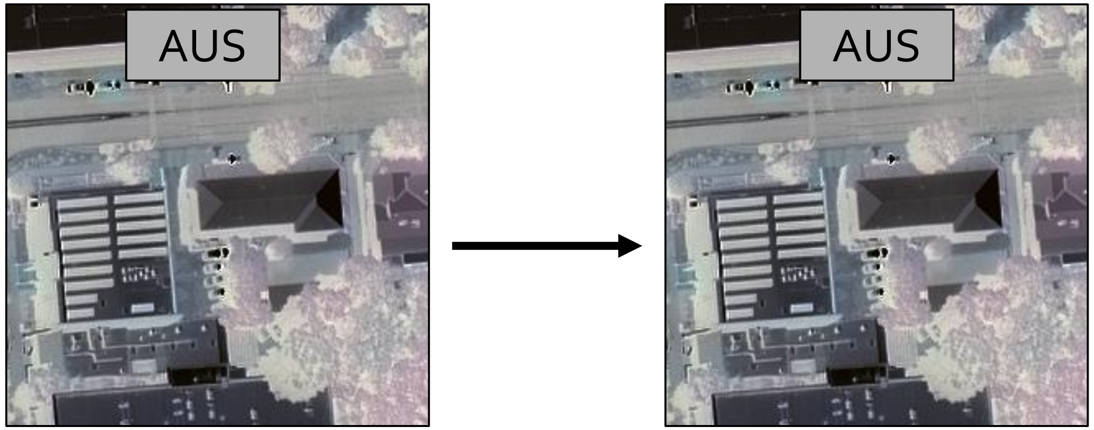
- We will add the same discriminator (Discriminator Block) to each model for adversarial training.
- The Discriminator Block helps in domain adaptation by using convolutional layers to capture and differentiate patterns between domains. Convolutions with larger steps and LeakyReLU activations focus on high-level features and maintain sensitivity to variations. The final layer produces an output for adversarial training, promoting domain-invariant feature learning.



Model Evaluation – Stages and results

- Stage 1 – Check 4 models with no transferability on Australia data set:

Model/metrics	mIoU	Precision	Recall	F1-Score
Uet	0.7358	0.7076	0.5871	0.6417
DeepLabV3Plus	0.6883	0.6289	0.4859	0.5482
PSPNet	0.6319	0.6079	0.3199	0.4192
FPN	0.6187	0.6702	0.2704	0.3853



Model Evaluation – Prediction examples

Unet

Test Image

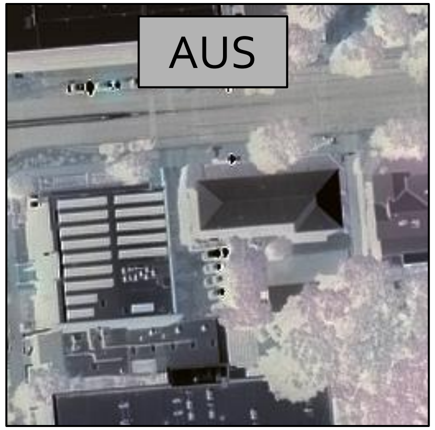
Ground Truth Overlay

Predicted Overlay

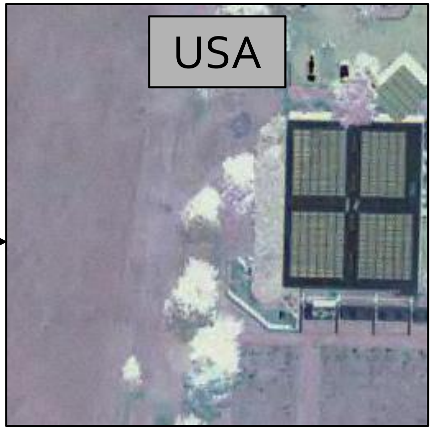
Model Evaluation – Stages and results

- Stage 2 – Raw transferability: **AUS data → USA data**

Model/metrics	mIoU	Precision	Recall	F1-Score
Unet	0.5202	0.4762	0.0466	0.0848
DeepLabV3Plus	0.5247	0.1688	0.0746	0.1035
PSPNet	0.5260	0.6110	0.0573	0.1048
FPN	0.5201	0.6934	0.0450	0.0845

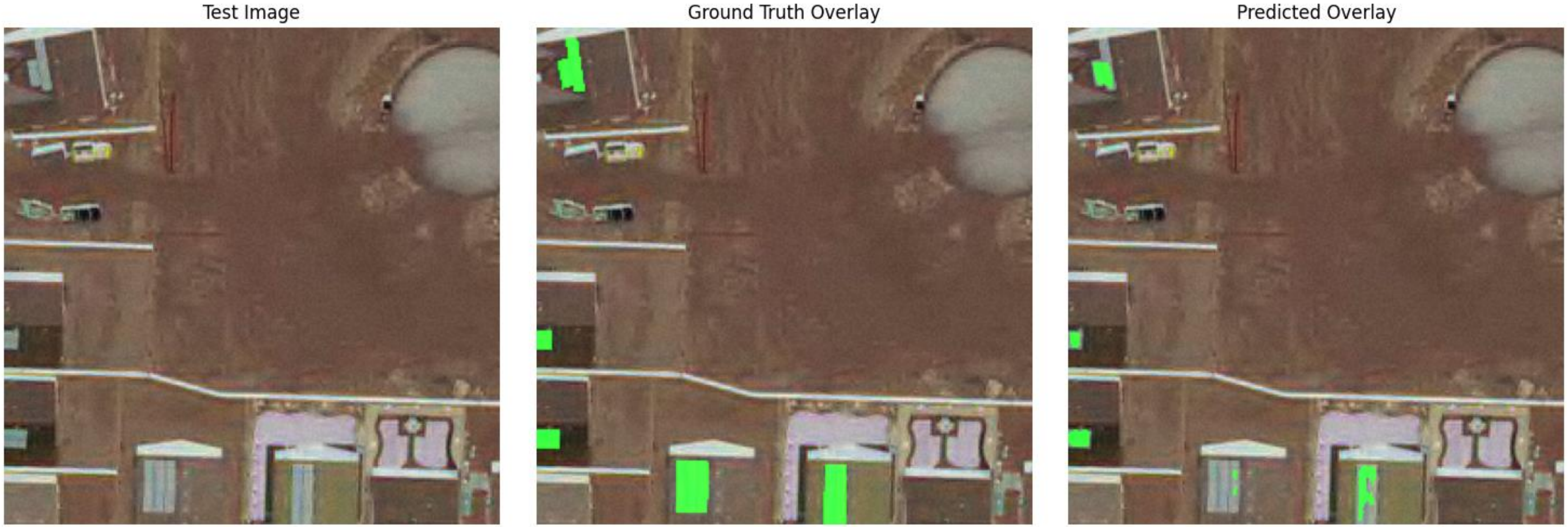


Test neural network on different data with the same task



Model Evaluation – Prediction examples

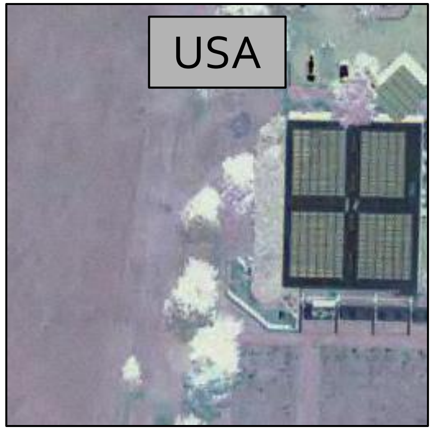
Unet

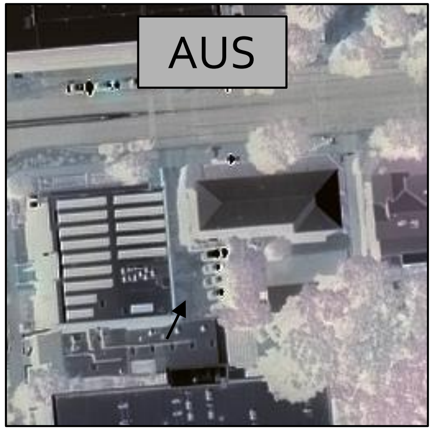


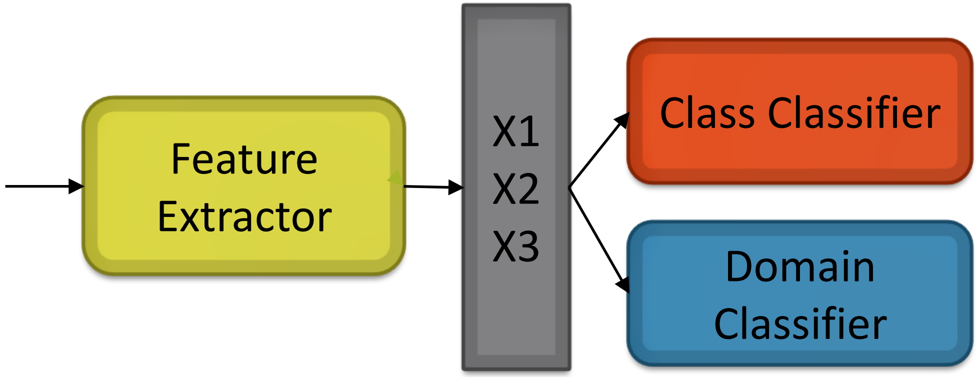
Model Evaluation – Stages and results

- Stage 3 – Domain Adaption: **AUS data → DA → USA data**

Model/metrics	mIoU	Precision	Recall	F1-Score
Unet	0.5166	0.6383	0.0385	0.0727
DeepLabV3Plus	0.4991	0.7722	0.0016	0.0032
PSPNet	0.5181	0.7557	0.0400	0.0759
FPN	0.5099	0.4474	0.0238	0.0452

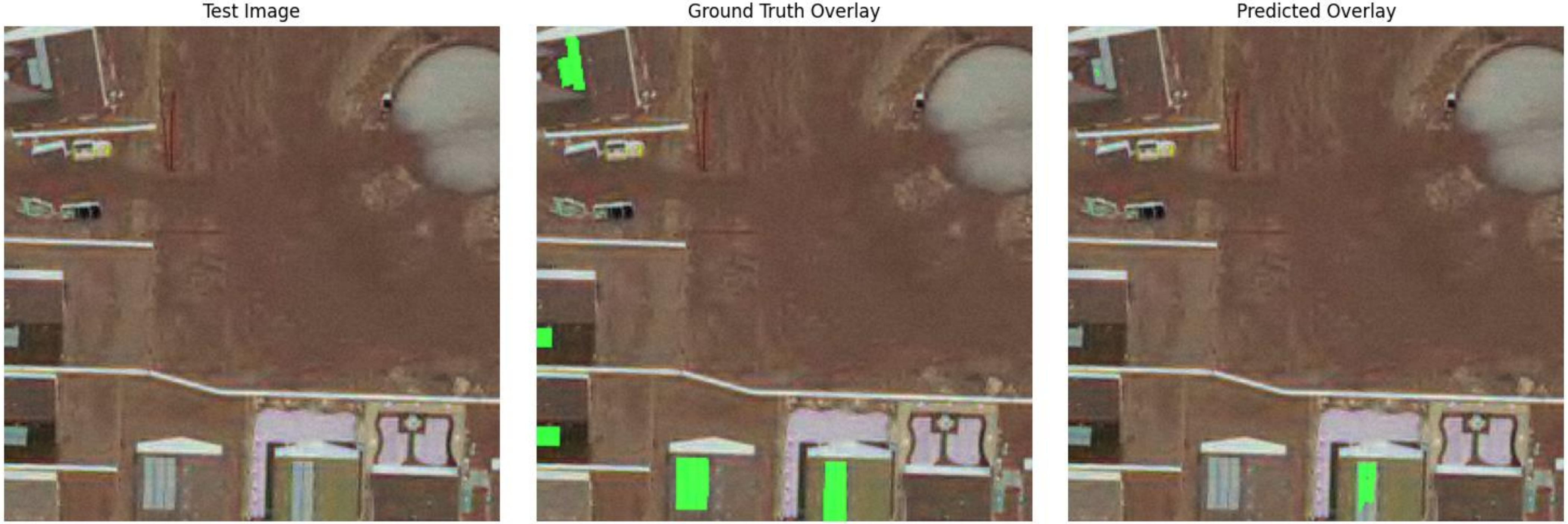






Model Evaluation – Prediction examples

Unet



Discussion and Conclusions

Summary of findings:

- Four models tested - U-Net was best when trained on same data, PSPNet was better for both kinds of transferability.
- Raw transfer and DA techniques faced significant performance drops of almost 20% in mIoU for each model.

Future Work:

- Further research in transfer learning especially in Transductive Transfer area.
- Domain adaptation and adversarial training needs more improvement and understanding for reliable global application.

Thank you for listening

Bibliography

[1] Jordan M Malof, Kyle Bradbury, Leslie M Collins, and Richard G Newell. Automatic detection of solar photovoltaic arrays in high resolution aerial imagery. Applied energy, 183:229–240, 2016.

[2] Jordan M Malof, Leslie M Collins, Kyle Bradbury, and Richard G Newell. A deep convolutional neural network and a random forest classifier for solar photovoltaic array detection in aerial imagery. In 2016 IEEE International conference on renewable energy research and applications (ICRERA), pages 650–654. IEEE, 2016.

[3] Rongjun Qin, Guixiang Zhang, and Yang Tang. On the transferability of learning models for semantic segmentation for remote sensing data. arXiv preprint arXiv:2310.10490, 2023.