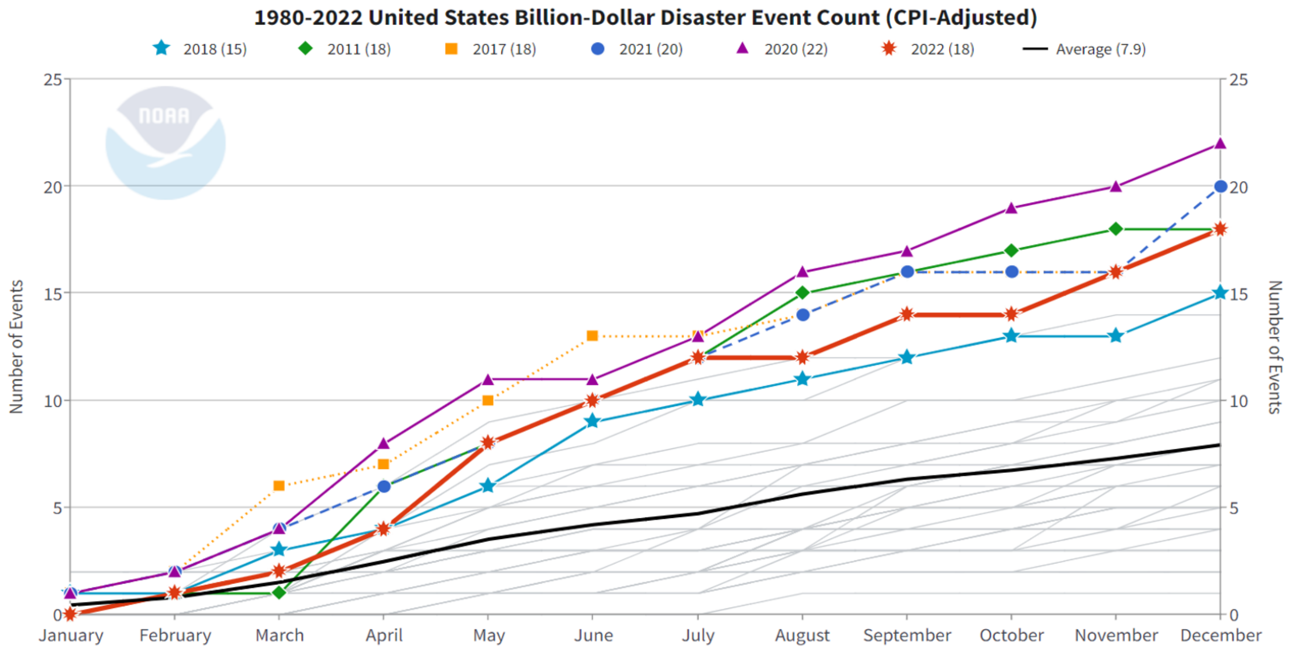
Enhancing Disaster Damage Assessment with Deep Learning

Tristan Goers, Todd Burns, and Caixia Wang
GeoComputing Lab
Department of Geomatics
University of Alaska Anchorage

Motivations

- As global warming continues to escalate, we're witnessing a significant rise in the frequency and severity of disasters and extremes.



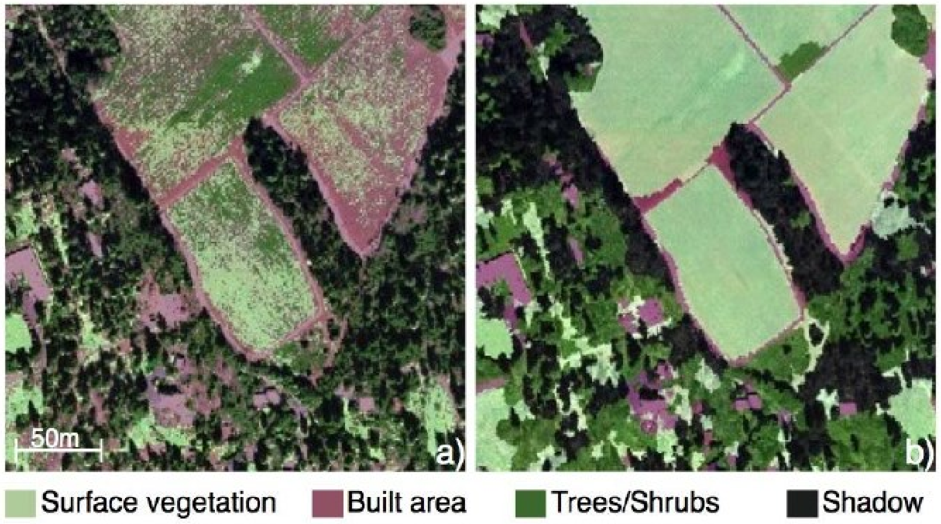
Source: NOAA National Centers for Environmental Information (NCEI)

Motivations

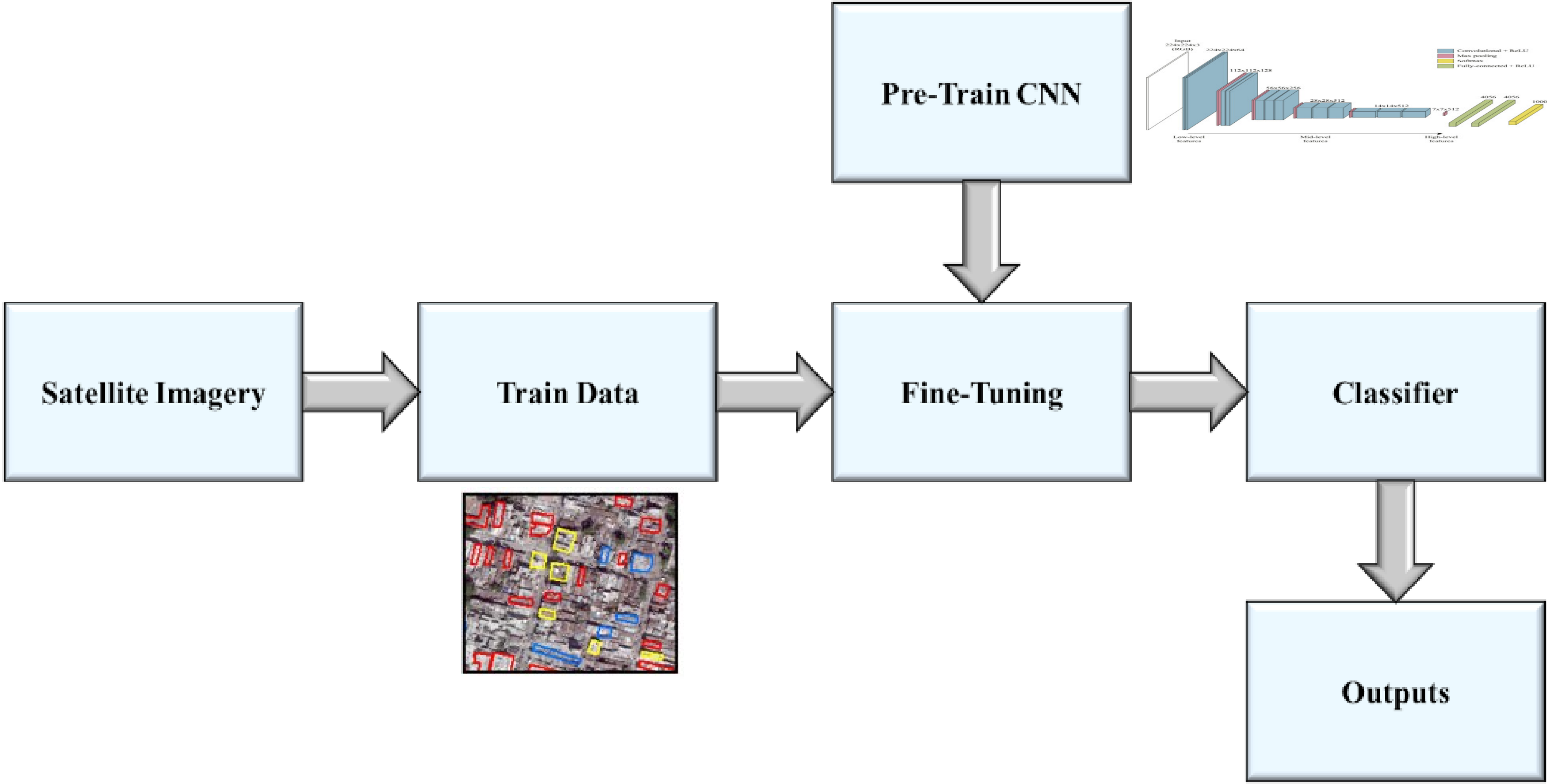
- It is vital that emergency responders receive timely information about location and extent of damage, particularly in the aftermath of earthquakes.

DIP Analysis Methods

- Pixel-based approaches rely on the spectral characteristics of surface features of images
  - Limited in classifying “mixed” pixels
- Object-based methods operate on homogeneous and spatially contiguous groups of pixels
  - Challenges remain

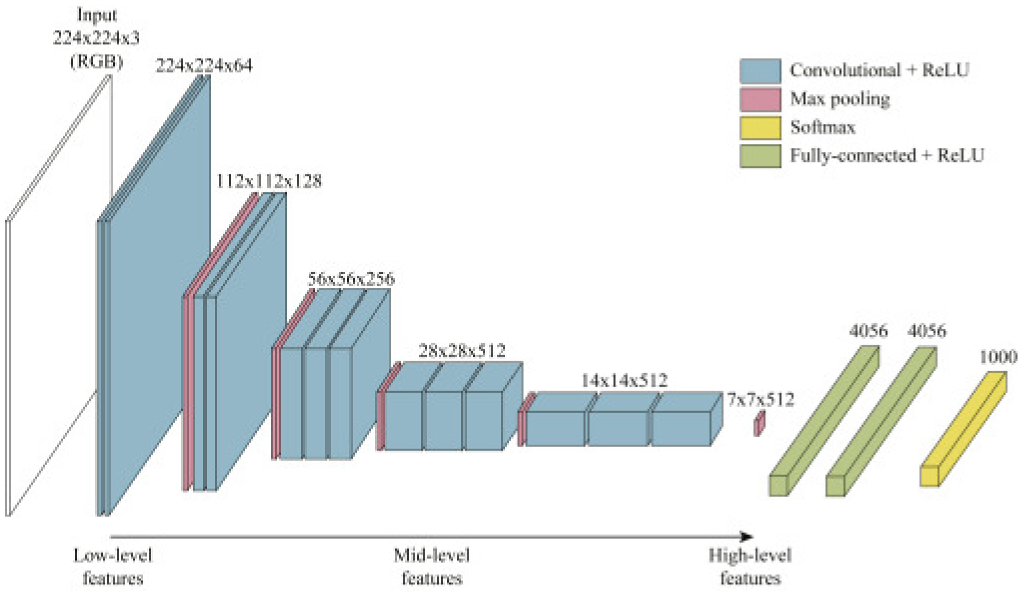


Proposed Deep-Learning Method



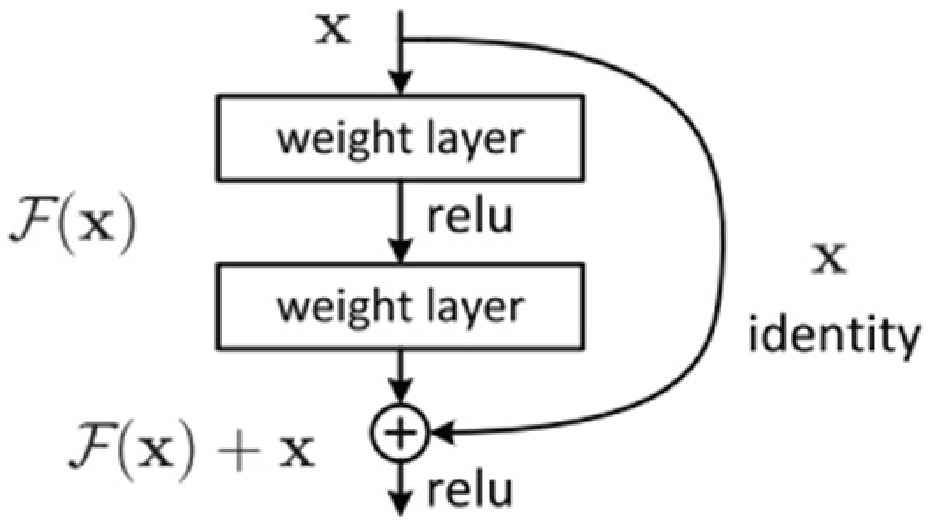
Convolutional Neural Network (CNN)

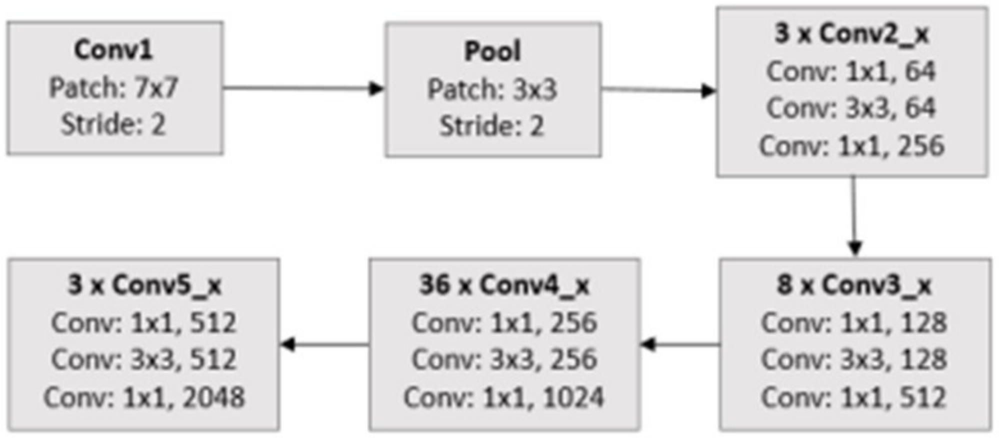
- It is a subclass of Artificial Neural Network (ANN)
- CNNs were specifically designed for computer vision and image classification tasks
- CNNs automatically detect important image features without human supervision
- Significant amounts of training data are necessary



ResNet-152 Architecture

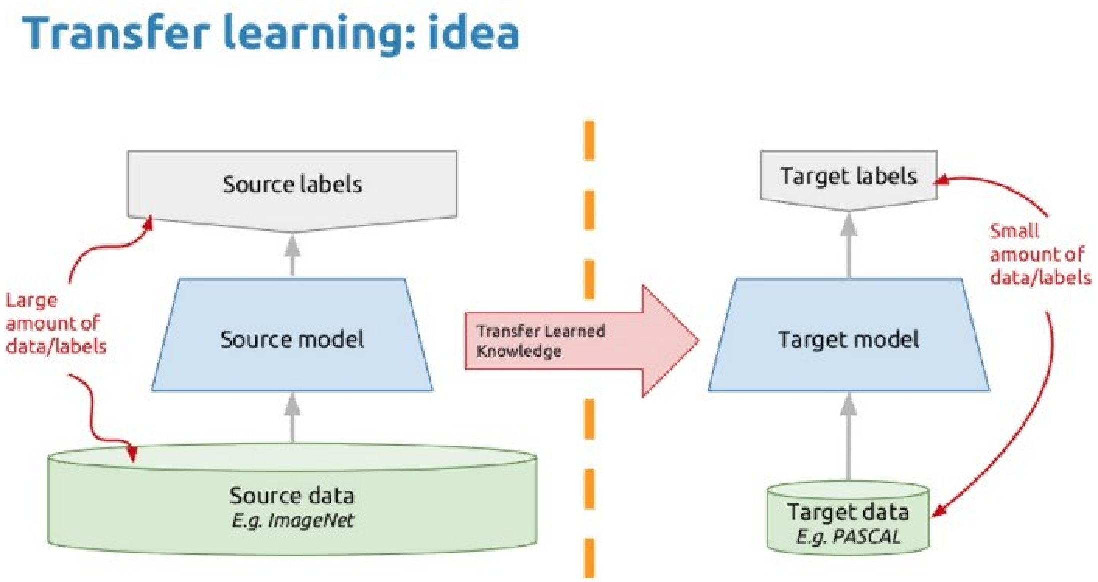
- Residual Network (ResNet) is one of the promising convolutional backbones.
- ResNet can have a very deep network of up to152 layers by learning the residual representation functions instead of learning the signal representation directly.





Transfer Learning

- Training deep models from scratch typically requires a dataset of sufficient size and training time (weeks or months).
- The ResNet152 model used in our work was pretrained on 1.2 million images from the ImageNet database.
- These learned features are then transferred to a second target network to be trained on the target dataset and task.



Study Area

- Port-au-Prince, Haiti after the magnitude 7.0 earthquake of January 12, 2010.
- WorldView-2 (WV2) satellite imagery with a spatial resolution of 1.84 meters on January 15, 2010.
- 4 mosaicked images with 3-bands each, RGB spectrum.
- Ground truth data was collected from the products in support of the Post Disaster Needs Assessment and Recovery Framework (PDNA), produced jointly by the United Nations and World Bank

Sample Datasets

- Building footprints were extracted and manually labeled as “Damage” or “No Damage.”
- Sample set:
  - 322 training samples
  - 46 validation samples
  - 93 testing samples
- These areas were chosen because:
  - Detailed building information is publicly available.
  - Buildings in these areas are representative in terms of density, size, and structure.

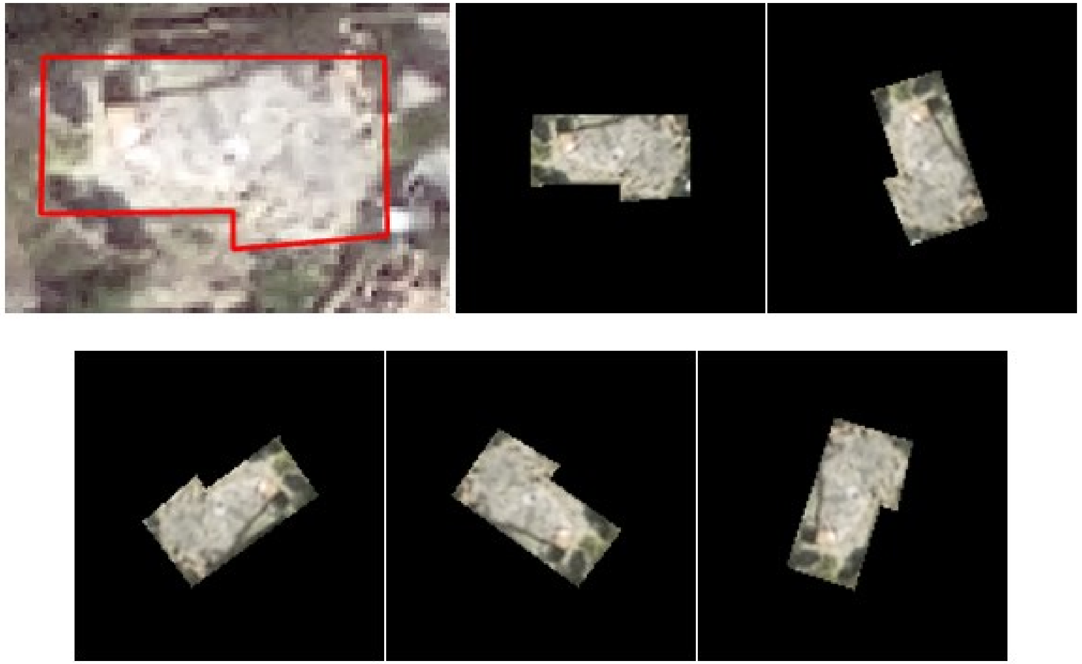
Orange – training, Yellow – validation,
Red – testing A, Blue – testing B

Sample Datasets

- The ResNet152 model was fine-tuned with the 322 training samples first (original).

- A second experiment used the augmented training samples (training^{+}), increasing the sample size to 1,610.

- Both experiments used zero padded training images.



Training Results

- The DA model is the optimal model for several reasons:
  - Training time for 1,610 samples
    - 20 epochs = 7.27 minutes
    - 34 epochs = 12.48 minutes
    - 50 epochs = 18.37 minutes
  - Training and Validation loss were closest at 20 epochs while taking into consideration low validation loss.
  - Early stopping will not only prevent overfitting but will also allow for better generalization.

epoch	train_loss	valid_loss	accuracy	time
1	1.042376	0.903653	0.515528	0:36
2	0.936403	0.731321	0.720497	0:22
3	0.874362	0.575533	0.770186	0:21
4	0.783001	0.508756	0.776398	0:21
5	0.767506	0.537253	0.782609	0:21
6	0.751107	0.613045	0.782609	0:21
7	0.729267	0.525315	0.751553	0:21
8	0.694654	0.46184	0.807453	0:21
9	0.660684	0.433513	0.807453	0:21
10	0.653519	0.441762	0.801242	0:21
11	0.605963	0.488908	0.813665	0:21
12	0.583887	0.500495	0.782609	0:21
13	0.562885	0.400379	0.819876	0:21
14	0.534634	0.310225	0.869565	0:21
15	0.523058	0.288835	0.850932	0:21
16	0.521369	0.366022	0.826087	0:21
17	0.498879	0.51325	0.807453	0:21
18	0.474929	0.376632	0.832298	0:21
19	0.440805	0.320855	0.869565	0:21
20	0.406367	0.316084	0.863354	0:21

Confusion Matrix & Results

- TP – True Positive
- TN – True Negative
- FP – False Positive
- FN – False Negative

- Positive refers to the "Damage" classification
- Negative refers to the "No Damage" classification

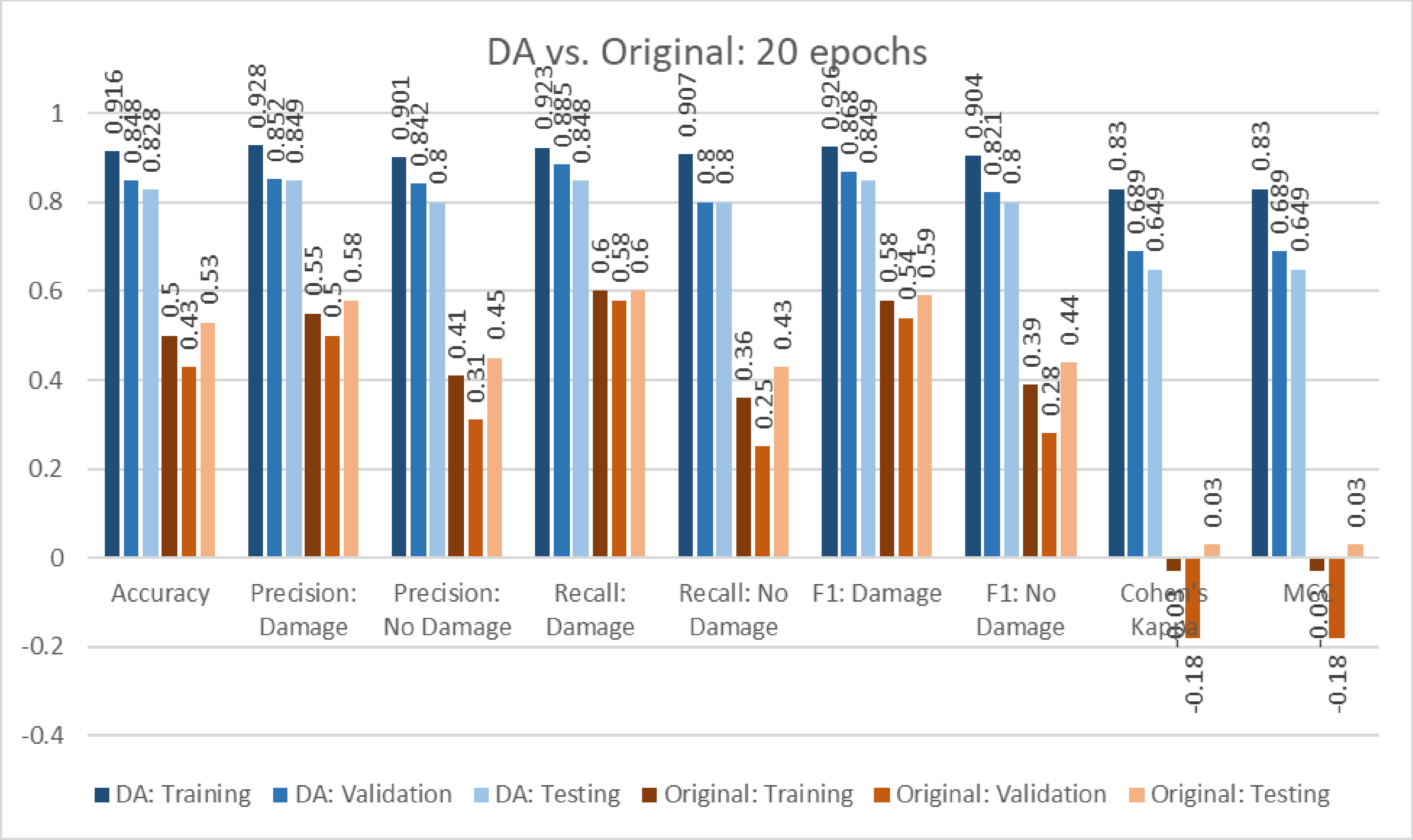
		Predicted	
		Damage (P)	No Damage (N)
True	Damage (P)	TP	FN
	No Damage (N)	FP	TN

Training	Predicted Label		
True Label		Damage	No Damage
	Damage	168	14
	No Damage	13	127

Validation	Predicted Label		
True Label		Damage	No Damage
	Damage	23	3
	No Damage	4	16

Testing	Predicted Label		
True Label		Damage	No Damage
	Damage	45	8
	No Damage	8	32

Results – Comparison of DA vs. Original



Conclusions and Future Work

- Transfer learning is an effective technique in CNN model development for custom applications
- Data Augmentation (DA) is effective in further boosting CNN performance and prevents over-fitting.
- Future work will integrate the building detection ML models to automatically extract building footprint