Building Damage Assessment

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Problem Statement

Accurately predict the level of damage of buildings after natural disasters in order to assist with humanitarian assistance and disaster response.

The Data

- Maxar, Xview2
- Images - pre and post disaster
- Labels - metadata with coordinates of buildings and level of damage
- Types of disasters - fire, flooding, earthquake, volcano, hurricane and tsunami

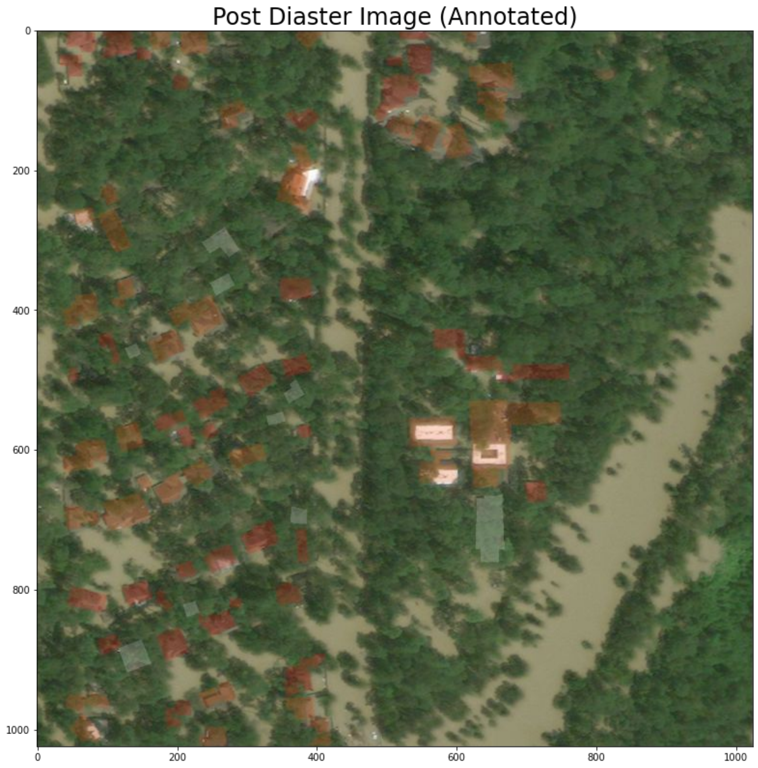
The Data


Pre Diaster Image (Not Annotated)
0
200
400
600
800
1000
0
200
400
600
800
1000


Post Diaster Image (Not Annotated)
0
200
400
600
800
1000
0
200
400
600
800
1000

The Data


Pre Diaster Image (Annotated)
0
200
400
600
800
1000
0
200
400
600
800
1000


Post Diaster Image (Annotated)
0
200
400
600
800
1000
0
200
400
600
800
1000

Joint Damage Scale

Score	Label	Visual Description of the Structure
0	No damage	Undisturbed. No sign of water, structural damage, shingle damage, or burn marks.
1	Minor damage	Building partially burnt, water surrounding the structure, volcanic flow nearby, roof elements missing, or visible cracks.
2	Major damage	Partial wall or roof collapse, encroaching volcanic flow, or the structure is surrounded by water or mud.
3	Destroyed	Structure is scorched, completely collapsed, partially or completely covered with water or mud, or no longer present.

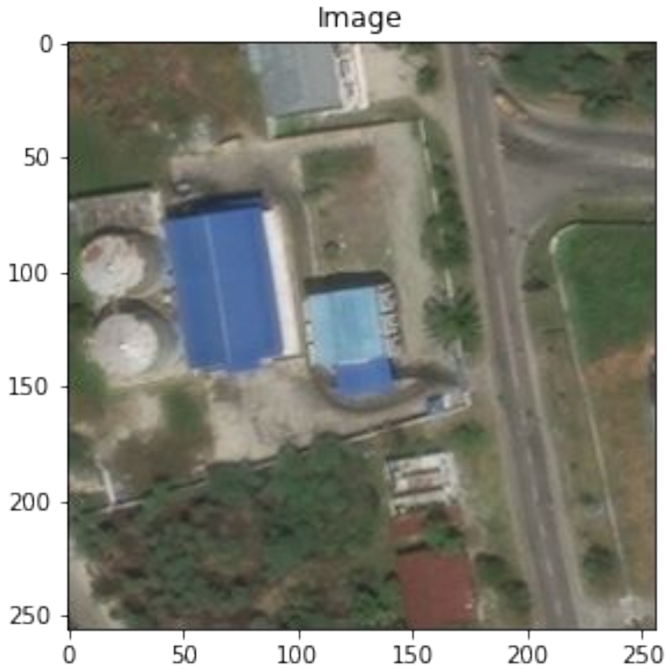
Source

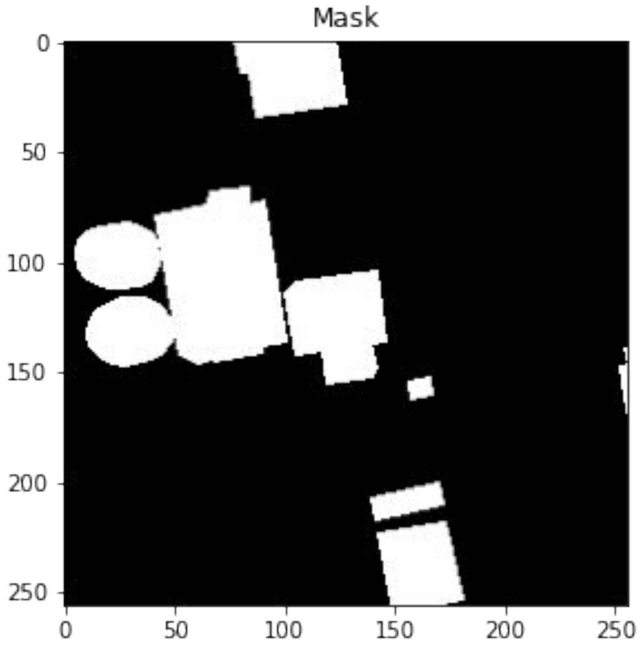
Data Preprocessing

Masks

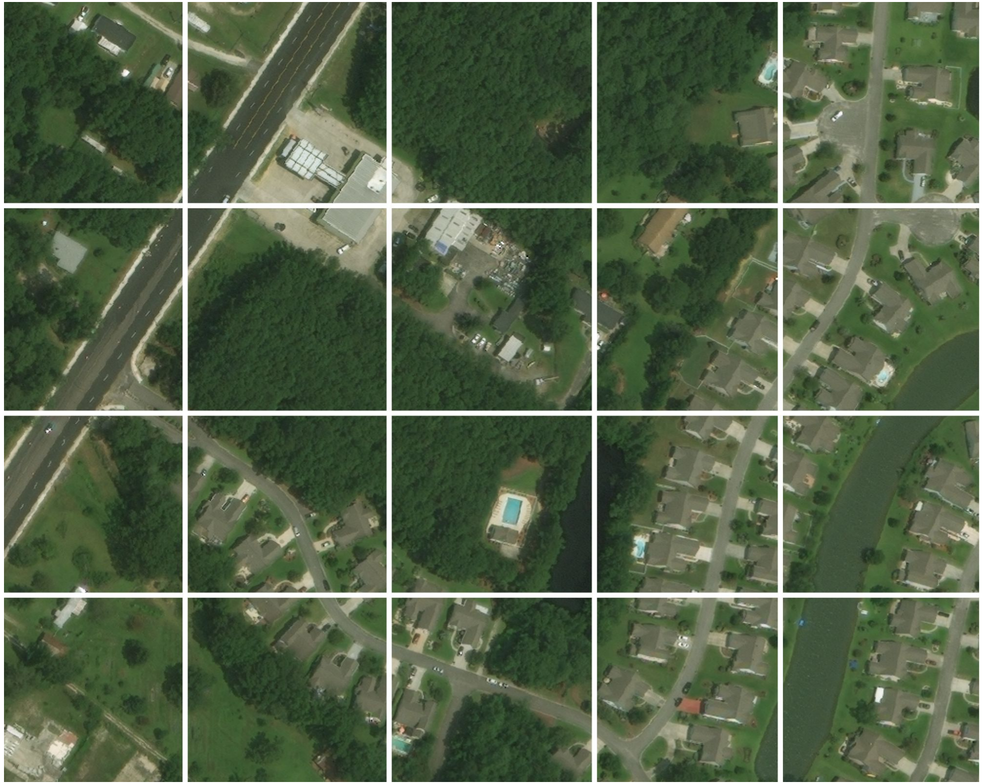
Patches

Data Preprocessing I - Masks





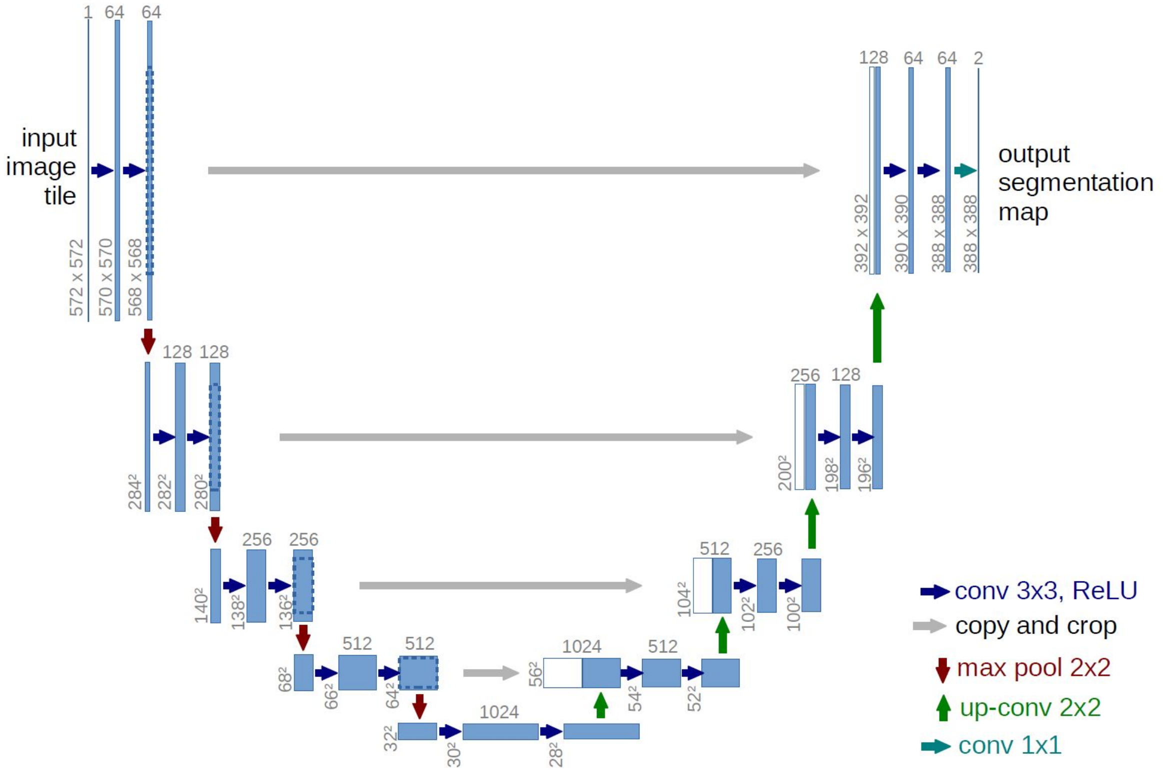
Data Preprocessing II - Patchify



Modeling

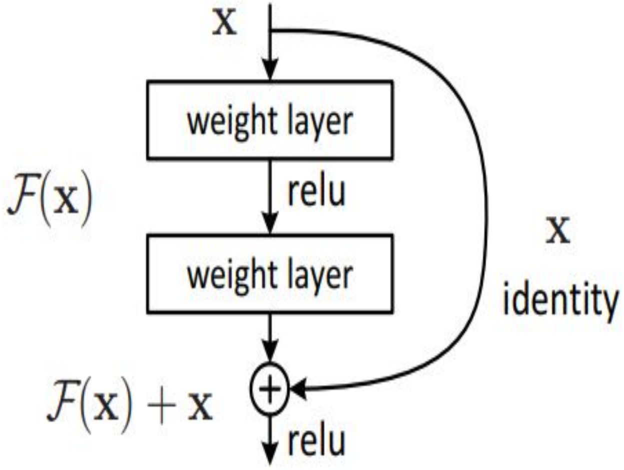
Model – uNet

- Initially introduced for biomedical segmentation
- Left - contractive path
- Right - expansive path

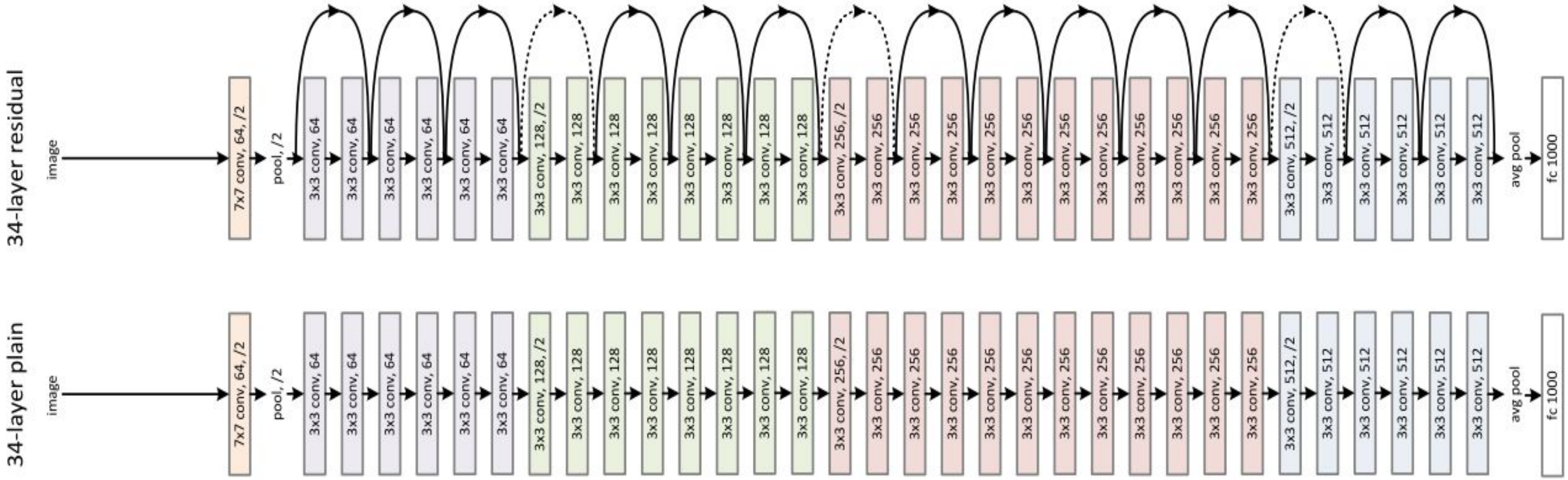


Model – ResNet

- Solve the vanishing gradient problem
- Uses skip connections
- The skip connection skips training from a few layers and connects directly to the output layer
- If any layer hurts the performance of the architecture, it will be skipped.



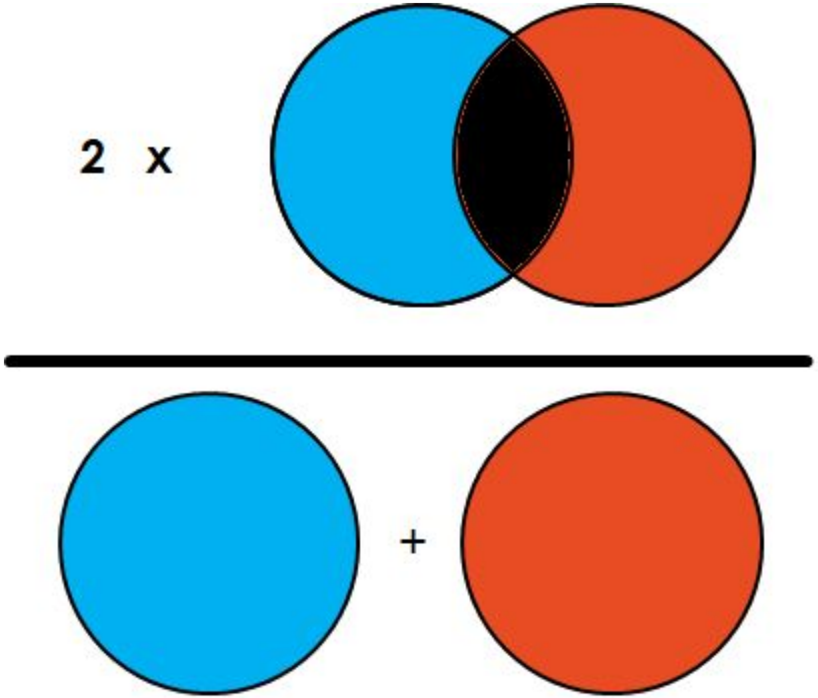
Model – ResNet



Metrics

- F1 score - Dice Coefficient
- Measures similarity between two sets of data
- Between 0 - 1, with 1 signifying the greatest similarity between predicted and truth
- 2 * the Area of Overlap divided by the total number of pixels in both images

Source



Results

Models	Loc Dice Coefficient	Cls Dice Coefficient
UNet	0.83	0.7
ResNet34	0.87	0.9
ResNet50	0.9	0.95

Conclusion & Recommendations

- The model was able to successfully detect buildings with an f1 score of 0.8 and an f1 score of 0.85 for classifying the damage level
- The model successfully identified undamaged buildings with an f1 score of 95% an predicts 3 damage classes (minor, major damage and destroyed) with 60%, 68.7% and 74.2% f1 scores respectively.
- Drawback - Weather (cloud cover) heavily impacts the predictions
- For efficiency and better computing time - remove patches that have no buildings
- Further testing can be done to determine the transferability of the model to other geographic areas and also the viability of introducing other kinds of images like social media images

ANY QUESTIONS?