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AI-POWERED LANDSLIDE REGION MAPPING USING SEMANTIC SEGMENTATION

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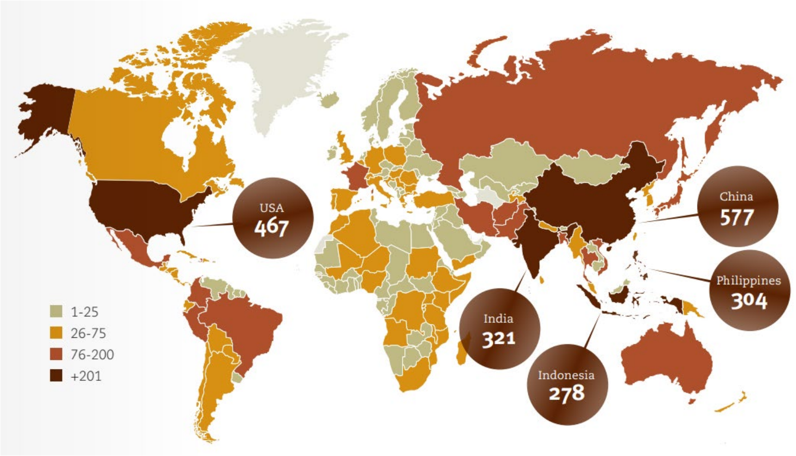
INTRODUCTION

- Landslides are one of the most common and dangerous natural disasters globally.
- It causes significant damage to infrastructure, agriculture, and human life.
- According to the UNDRR, over 4,000 people die each year globally due to landslides. [1]
- Rapid post-disaster mapping is vital for guiding rescue efforts and risk assessment.



1. UNDRR, *Human Cost of Disasters: An Overview of the Last 20 Years (2000–2019)*, United Nations Office for Disaster Risk Reduction, 2020. [Online]. Available: https://www.undrr.org/publication/human-cost-disasters-overview-last-20-years-2000-2019

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PROBLEM STATEMENT

- Manual mapping of landslide areas in post landslide assessment is slow, inconsistent, and risky.
- Precise, up-to-date landslide masks are needed for:
  - Damage assessment
  - Recovery planning
  - Updating geohazards maps
- A system is required to automatically generate post-landslide maps.

OBJECTIVE

- To develop a deep learning model for precise landslide mapping
- To obtain high performance in segmenting landslide regions from satellite and UAV imagery
- To enable real-time monitoring and support disaster management efforts

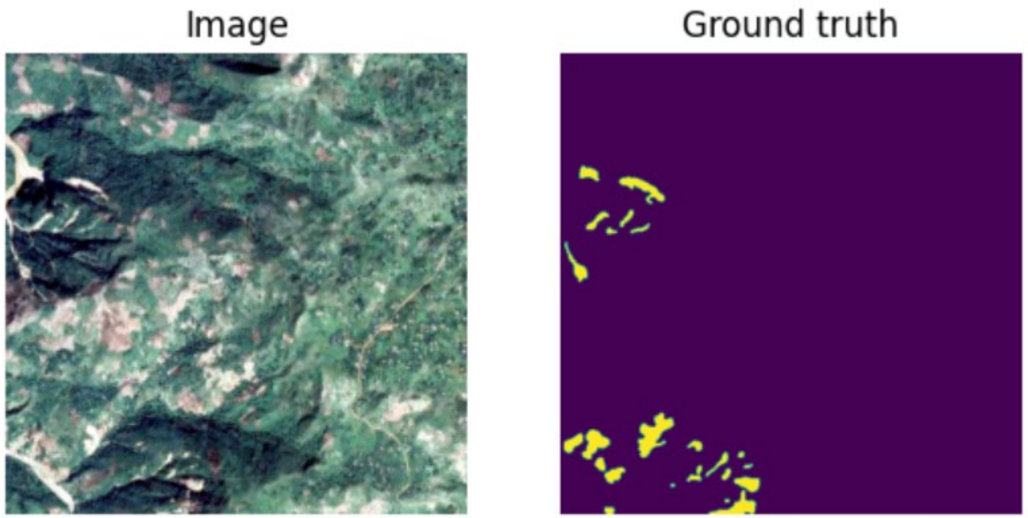

Figure Source: Zhao et al. (2023), *A global dataset of landslide inventories compiled from satellite imagery*. Scientific Data. https://doi.org/10.1038/s41597-023-02847-z

STATE OF THE ART

- Landslide Detection and Segmentation using Remote Sensing Images and Deep Neural Network[2]
  - Dataset: Landslide4Sense (128x128 pixels;14 channels)
  - Approaches:
    - Enhanced U-net structure with residual-convolutional layers
    - Custom multi-head attention layer (Pro-Att) to focus on landslide regions
    - Multi-resolution segmentation outputs: at 64×64, 128×128, and 256×256 (ensembled)
    - Generate 12 additional bands to improve input data
    - Combined focal loss and IoU loss as loss function (handle class imbalance)
  - It achieved an mIoU of 76.07 and F1-score of 84.07, surpassing the baseline.

2. C. Le, L. Pham, J. Lampert, M. Schlögl, and A. Schindler, "Landslide detection and segmentation using remote sensing images and deep neural network," *arXiv preprint arXiv:2312.16717*, 2023. [Online]. Available: https://arxiv.org/abs/2312.16717

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STATE OF THE ART

- LandslideSegNet: an effective deep learning network for landslide segmentation using remote sensing imagery [3]
  - Dataset: Landslide4Sense Modified (256x256;3 channels)
  - Approaches:
    - Proposed LandslideSegNet, a custom architecture for landslide segmentation.
    - It contains Encoder-decoder Residual Block, enhances feature extraction by combining local and contextual information.
    - And, Hybrid Attentional Atrous Convolution Module improves efficiency by focusing on critical features and suppressing irrelevant information.

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3. Şener, A., Ergen, B. LandslideSegNet: an effective deep learning network for landslide segmentation using remote sensing imagery. *Earth Sci Inform* **17**, 3963–3977 (2024). https://doi.org/10.1007/s12145-024-01434-z

STATE OF THE ART

- LandslideSegNet: an effective deep learning network for landslide segmentation using remote sensing imagery [3]
  - It achieved an mIoU of 73.65 and precision of 71.48.

3. Şener, A., Ergen, B. LandslideSegNet: an effective deep learning network for landslide segmentation using remote sensing imagery. *Earth Sci Inform* **17**, 3963–3977 (2024). https://doi.org/10.1007/s12145-024-01434-z

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STATE OF THE ART

- A landslide area segmentation method based on an improved UNet [4]
  - Dataset: Bijie Landslide Dataset (3 channels, 770 landslide images and 2003 non-landslide)
  - Approaches:
    - Enhanced U-net structure with dilated convolution and EMA attention.
    - Dilated convolution enlarges the receptive field and capture richer contextual information.
    - EMA attention helps with multi-scale feature extraction.
    - The proposed Pag module(skip conn.) enhances multi-scale feature fusion, improving transmission and reducing pixel information loss caused when resolution changes in U-Net.
  - It achieved an mIoU of 83.85 and precision of 80.26.

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4. Li, G., Li, K., Zhang, G. *et al.* A landslide area segmentation method based on an improved UNet. *Sci Rep* **15**, 11852 (2025). https://doi.org/10.1038/s41598-025-94039-5

STATE OF THE ART

- TransLandSeg: A Transfer Learning Approach for Landslide Semantic Segmentation Based on Vision Foundation Model [5]
  - Dataset: Bijie Landslide Dataset and Landslide4Sense
  - Approaches:
    - Proposed a custom architecture, based on Segment Anything Model (SAM).
    - Applies Adaptive Transfer Learning (ATL) to adapt SAM's segmentation capabilities for landslide semantic segmentation.
    - Image Encoder and Mask Decoder
    - ATL fine -tuning layer inserted between Transformer blocks that learns landslide-specific features.

5. C. Hou *et al.*, "A Transfer Learning Approach for Landslide Semantic Segmentation Based on Visual Foundation Model," in *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 18, pp. 11561-11572, 2025, doi: 10.1109/JSTARS.2025.3559884.

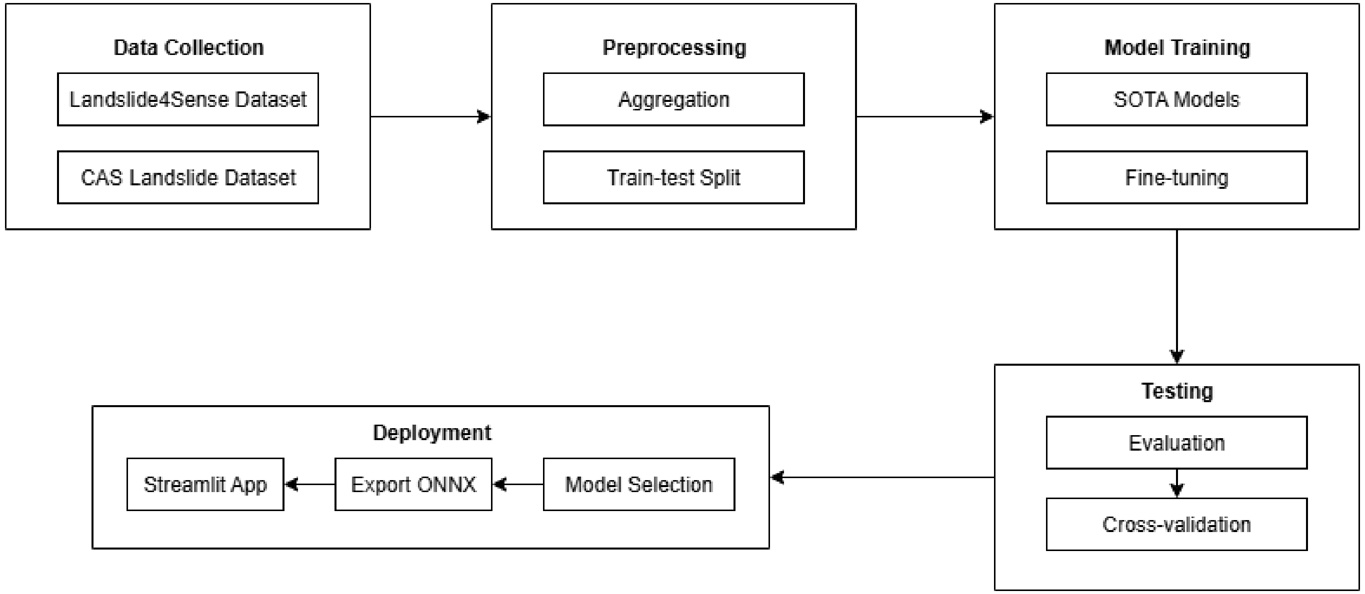
STATE OF THE ART

- TransLandSeg: A Transfer Learning Approach for Landslide Semantic Segmentation Based on Vision Foundation Model [5]
  - It achieved an mIoU of 88.10 and precision of 93.14 on bijie dataset.
  - It achieved an mIoU of 75.99 and precision of 84.99 on landslide4sense dataset.

5. C. Hou *et al.*, "A Transfer Learning Approach for Landslide Semantic Segmentation Based on Visual Foundation Model," in *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 18, pp. 11561-11572, 2025, doi: 10.1109/JSTARS.2025.3559884.

WORKFLOW

- General steps include: data collection, pre-processing, model training, testing, and deployment.
- The overall workflow of the project is illustrated in the figure below.



DATA ACQUISITION

- Landslide4Sense Dataset [6]
  - Source: Institute of Advanced Research in Artificial Intelligence (IARAI)
  - Regions: Collected from four regions (Iburi, Kodagu, Rasuwa, Taitung)
  - Include earthquake and rainfall triggers landslide
  - Satellite: Sentinel-2
  - Topographic: ALOS (Advanced Land Observing Satellite
  - Acquisition Process: Data aggregated from public satellite archives
  - Annotation Process: annotations via Object-Based Image Analysis (OBIA)

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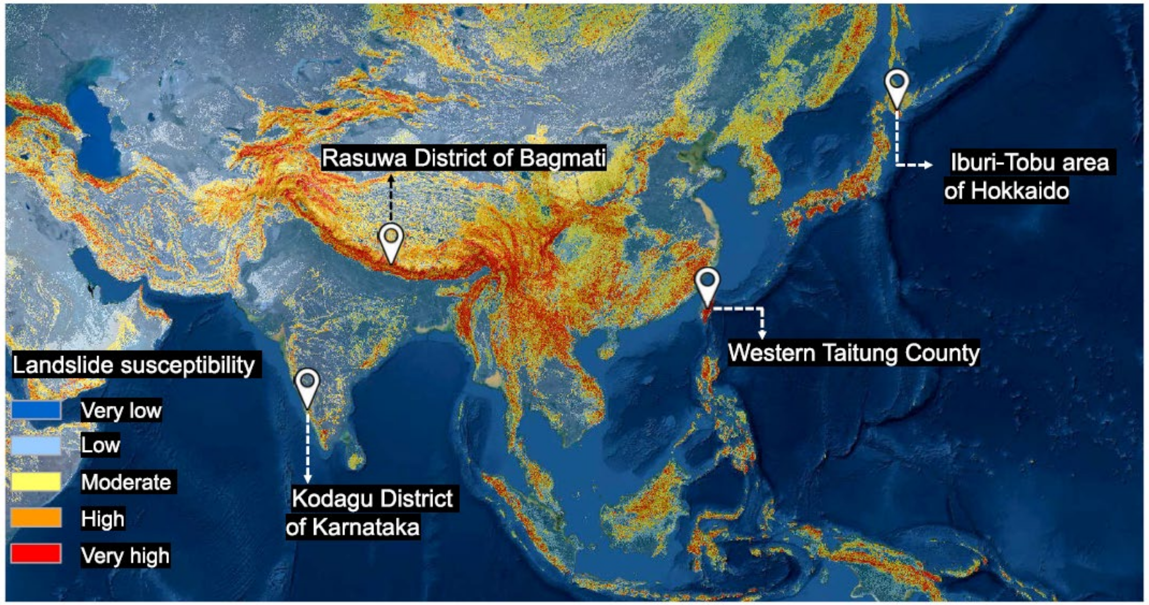
6. O. Ghorbanzadeh et al., "Landslide4Sense: Reference benchmark data and deep learning models for landslide detection," IEEE Trans. Geosci. Remote Sens., vol. 60, pp. 1–17, 2022, doi: 10.1109/TGRS.2022.3215209.

DATA ACQUISITION

- Landslide4Sense Dataset [6]
  - Geolocations of the selected case study areas shown on the global landslide susceptibility map.



6. O. Ghorbanzadeh et al., "Landslide4Sense: Reference benchmark data and deep learning models for landslide detection," IEEE Trans. Geosci. Remote Sens., vol. 60, pp. 1–17, 2022, doi: 10.1109/TGRS.2022.3215209.

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DATA ACQUISITION

- CAS Landslide Dataset [7]
  - Source: Institute of Mountain Hazards and Environment, Chinese Academy of Sciences.
  - Regions: Collected from nine diverse region
  - Include earthquake and rainfall triggers landslide
  - Satellite: Sentinel-2, Landsat, WorldView2/3, Planet, SuperView-1, GF-1
  - UAV: High-resolution imagery from Sichuan Geomatics Center and partners.
  - Acquisition Process: Satellite data sourced via Google Earth Engine, Digital Globe, and authorized providers; UAV data collected through drone.

7. Y. Xu, C. Ouyang, Q. Xu, D. Wang, B. Zhao, and Y. Luo, "CAS Landslide Dataset: A large-scale and multisensor dataset for deep learning-based landslide detection," Sci. Data, vol. 11, no. 12, Jan. 2024, Art. no. 12, doi: 10.1038/s41597-023-02847-z.

DATA ACQUISITION

- Annotation Process
  - Pixel-level annotations created using QGIS and LabelMe.
  - guided by landslide inventories, verified by geologists, cross-checked by team

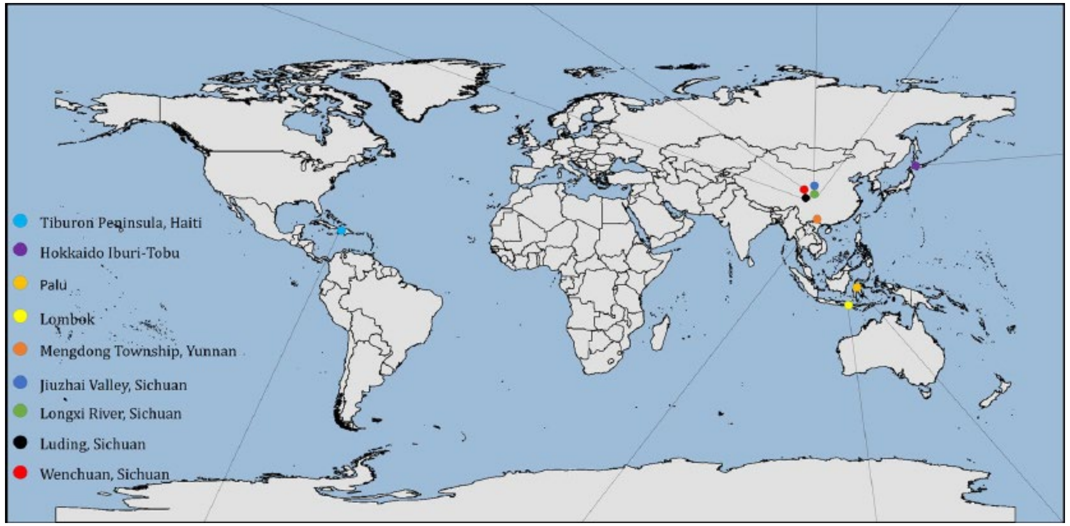

Figure Source: Y. Xu, C. Ouyang, Q. Xu, D. Wang, B. Zhao, and Y. Luo, "CAS Landslide Dataset: A large-scale and multisensor dataset for deep learning-based landslide detection," Sci. Data, vol. 11, no. 12, Jan. 2024, Art. no. 12, doi: 10.1038/s41597-023-02847-z.

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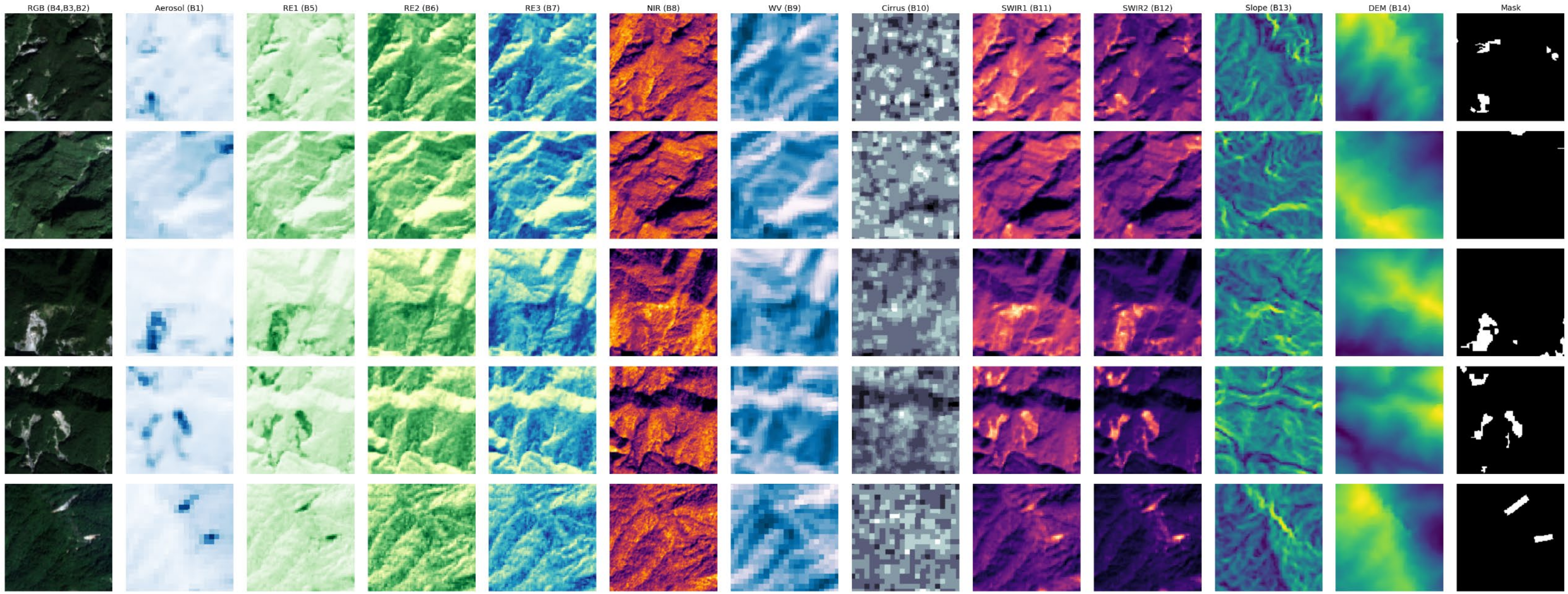
DATA STRUCTURE

- Landslide4Sense Dataset
  - Total Input: 3,799 images (128x128 pixels, 14 channels).
  - Channels: 12 Sentinel-2 bands (B1–B12), ALOS PALSAR slope (B13), DEM (B14).
  - Output: 128x128x1 binary mask
  - Split:
    - Training: 3,799, Validation: 245, Testing: 800
  - Distribution:
    - Train Set: 2,231 landslide, 1,568 non-landslide;
    - Valid Set: 146 landslide, 99 non-landslide;
    - Test Set: Test: 536 landslide, 264 non-landslide.

DATA STRUCTURE

Bands



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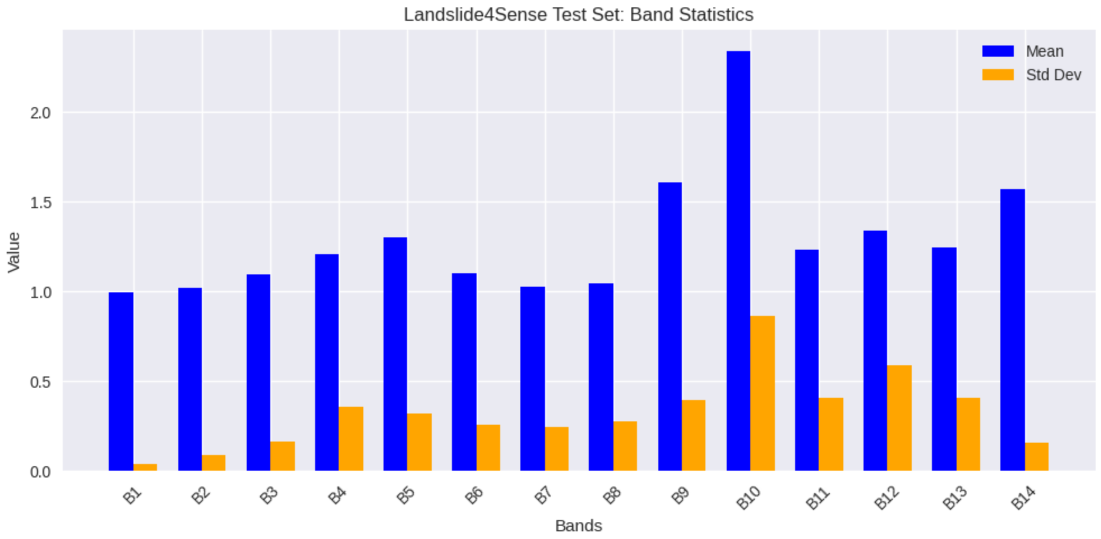
DATA STRUCTURE

- Landslide4Sense Dataset
  - Band Statistics:



DATA STRUCTURE

- CAS Landslide Dataset
  - Set 1: UAV
    - Total Inputs: 10,939 images (512x512 pixels, 3 channels)
    - Channels: RGB
    - Output: 512x512x1 binary mask
    - Split:
      - Training: 8,753, Validation: 1093, Testing: 1093
    - Distribution: All images have landslide region

DATA STRUCTURE

- CAS Landslide Dataset
  - Set 2: Satellite
    - Total Inputs: 7,422 images (512x512 pixels, 3 channels)
    - Channels: RGB
    - Output: 512x512x1 binary mask
    - Split:
      - Training: 5,938, Validation: 742, Testing: 742
    - Distribution: All images have landslide region

DATA STRUCTURE

Detailed Information on CAS Landslide Dataset (UAV set)

Subdataset	Amount	Acquisition Time	Source	Sensor	Ground Resolution (m)
Moxitaidi	984	2022.09–2022.10	Sichuan Geomatics Center	UAV	0.6
Moxitaidi	483	2022.09–2022.10	Sichuan Geomatics Center	UAV	1
Moxi Town	1635	2022.09–2022.10	Sichuan Geomatics Center	UAV	0.2
Moxi Town	160	2022.09–2022.10	Sichuan Geomatics Center	UAV	1
Longxi River	2504	2011.03–2011.05	Sichuan Geomatics Center	UAV	0.5
Jiuzhai Valley	5925	2017.08–2017.09	Sichuan Geomatics Center	UAV	0.2
Jiuzhai Valley	1752	2017.08–2017.09	Sichuan Geomatics Center	UAV	0.5

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DATA STRUCTURE

Detailed Information on CAS Landslide Dataset (Satellite set)

Subdataset	Amount	Acquisition Time	Source	Sensor	Ground Resolution (m)
Palu	817	2021.01–2021.11	Digital Globe Open Data Program	WorldView2/3	5
Lombok	436	2019.05–2019.12	Digital Globe Open Data Program	WorldView2/3	5
Hokkaido Iburi-Tobu	1484	2018.09–2018.10	Geospatial Information Authority of Japan	SAT	3
Tiburon Peninsula (Sentinel)	606	2020.03–2020.06	European Space Agency	Sentinel-2/L2A	5
Tiburon Peninsula (Planet)	325	2021.09–2021.12	Planet	Planet	4
Mengdong	1155	2018.11.04	Beijing Lanyu Fangyuan Technology Co., Ltd.	SuperView-1	0.5
Moxitaidi (SAT)	652	2022.09–2022.10	European Space Agency	Sentinel-2/L2A	0.6
Longxi River (SAT)	1769	2015.03–2015.12	China Centre for Resources Satellite Data and Application	GF-1	0.5
Wenchuan	178	2008.11–2008.12	U.S. Geological Survey	Landsat	5

DATA STRUCTURE

- Images and Labels of Samples from the Subdatasets of the CAS Landslide Dataset.

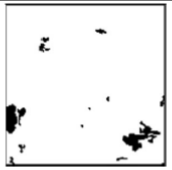
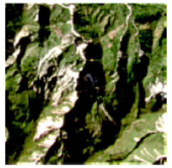
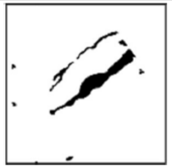
Subdataset	Image	Label	Subdataset	Image	Label
Palu			Hokkaido Iburi-Tobu		
Lombok			Tiburon Peninsula (Sentinel)		
Tiburon Peninsula (Planet)			Mengdong		
Moxitaidi (SAT)			Moxitaidi (UAV-0.6 m)		

Figure Source: Y. Xu, C. Ouyang, Q. Xu, D. Wang, B. Zhao, and Y. Luo, "CAS Landslide Dataset: A large-scale and multisensor dataset for deep learning-based landslide detection," Sci. Data, vol. 11, no. 12, Jan. 2024, Art. no. 12, doi: 10.1038/s41597-023-02847-z.

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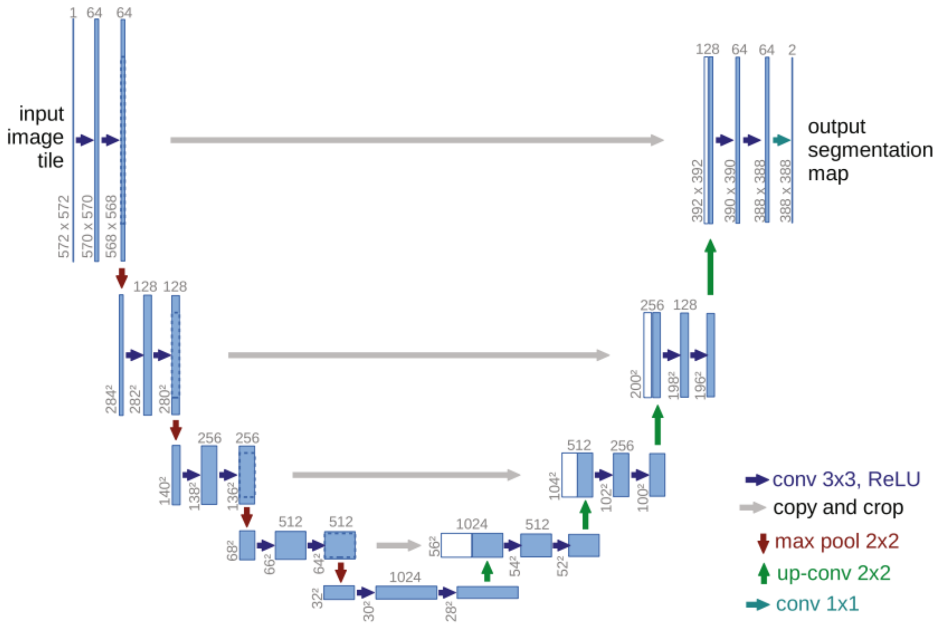
ML MODELS

- 1. Unet
  - A FCN originally designed for biomedical image segmentation.
  - Widely used in remote sensing for image classification and object detection, including landslide detection.
  - Encoder: Captures low-level features
  - Decoder: Captures high-level features and reconstructs image
  - Skip Connections: preserve fine-grained details and improve accuracy.



Source: O. Ronneberger, P. Fischer, and T. Brox, “U-Net: Convolutional networks for biomedical image segmentation,” in *Proc. Int. Conf. Med. Image Comput.-Assist. Intervent*. Cham, Switzerland: Springer, 2015, pp. 234–241.

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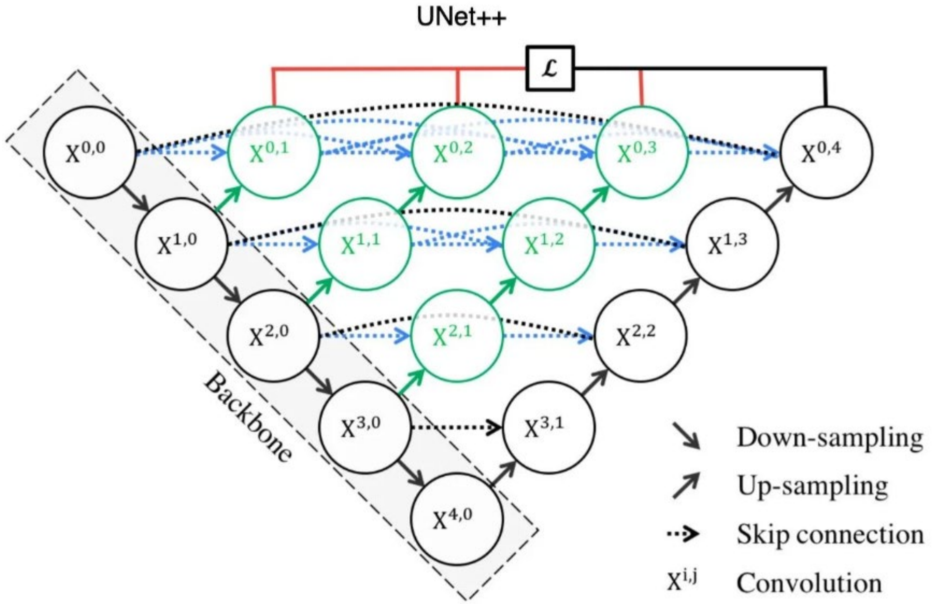
ML MODELS



- 2. Unet++
  - An improved version of U-Net.
  - redesigned skip pathways (shown in green): bridges the semantic gap between encoder and decoder
  - dense skip connections (shown in blue)
  - deep supervision (shown in red): allows pruning to trade off speed and accuracy by using multiple output branches.
  - Enhances feature fusion for improved accuracy and gradient flow.

Source: https://jinglescode.github.io/2019/12/02/biomedical-image-segmentation-u-net-nested/

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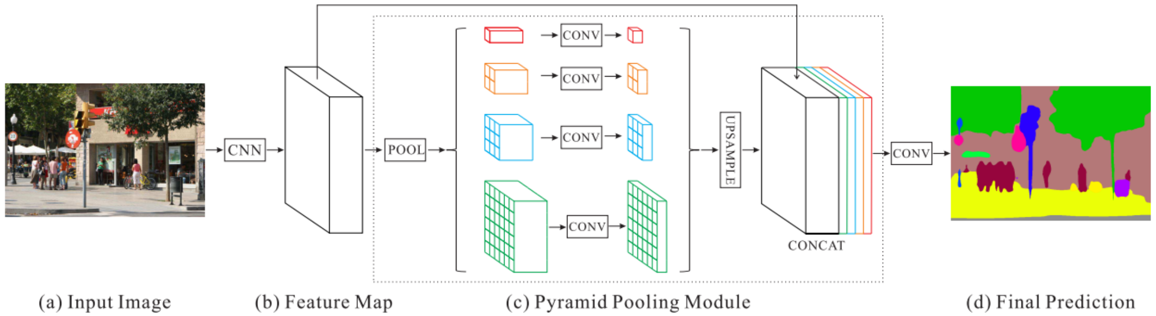
ML MODELS

- 3. PSPNet
  - Uses pyramid pooling to learn global context information.
  - Applies regional aggregation to capture multi-scale features.
  - Fuses features from four different pyramid scales
  - Achieves effective multi-scale feature learning
  - Can able to efficiently work with variable size objects of the image



Source: H. Zhao, J. Shi, X. Qi, X. Wang and J. Jia, "Pyramid Scene Parsing Network," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 2017, pp. 6230-6239, doi: 10.1109/CVPR.2017.660.

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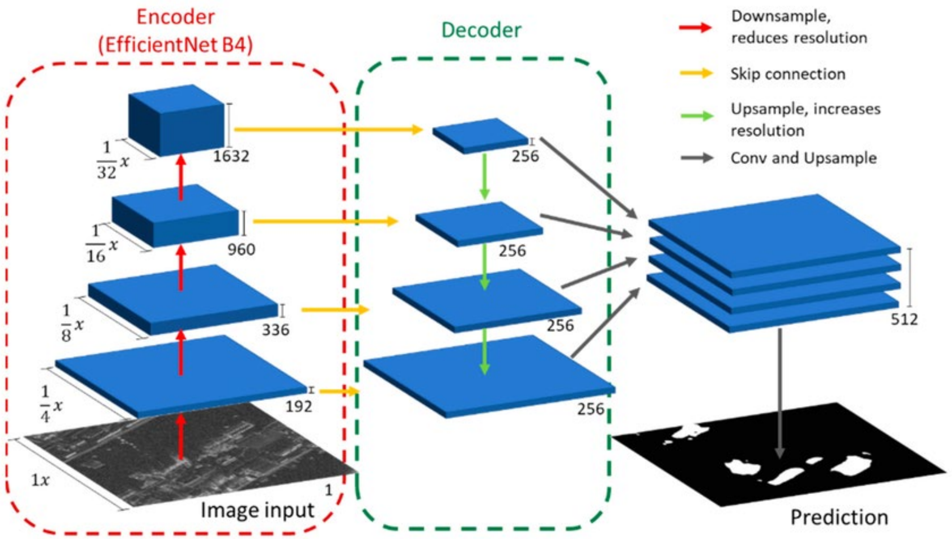
ML MODELS

- 4. FPN
  - Designed for multi-scale segmentation
  - Builds a top-down feature pyramid from deep to shallow layers
  - Combines low-resolution semantic-rich features with high-resolution spatial-rich features
  - Enhances segmentation of small, medium, and large objects



Source: Wangiyana, Sandhi & Samczynski, Piotr & Gromek, Artur. (2022). Data Augmentation for Building Footprint Segmentation in SAR Images: An Empirical Study. Remote Sensing. 14. 2012. 10.3390/rs14092012.

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ML MODELS

- 5. MANet
  - Focuses on fine-grained semantic segmentation
  - Utilizes multi-scale feature extraction for diverse object sizes
  - Incorporates attention mechanisms to highlight important regions
  - Enhances boundary details and small object recognition
  - Suitable for complex and cluttered scenes like satellite images

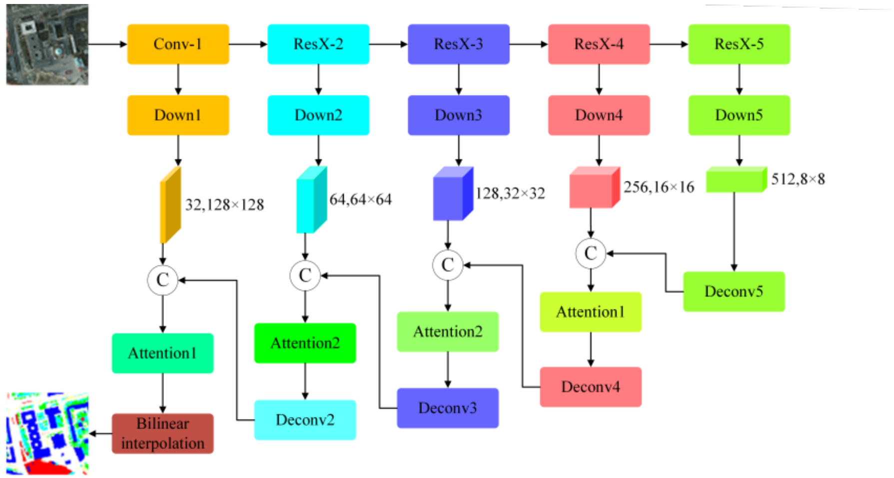


Fig. 5. The structure of the proposed MANet.

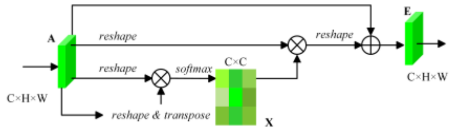


Fig. 3. Details of the channel attention mechanism.

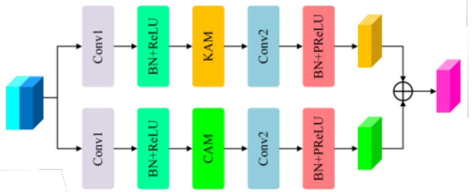
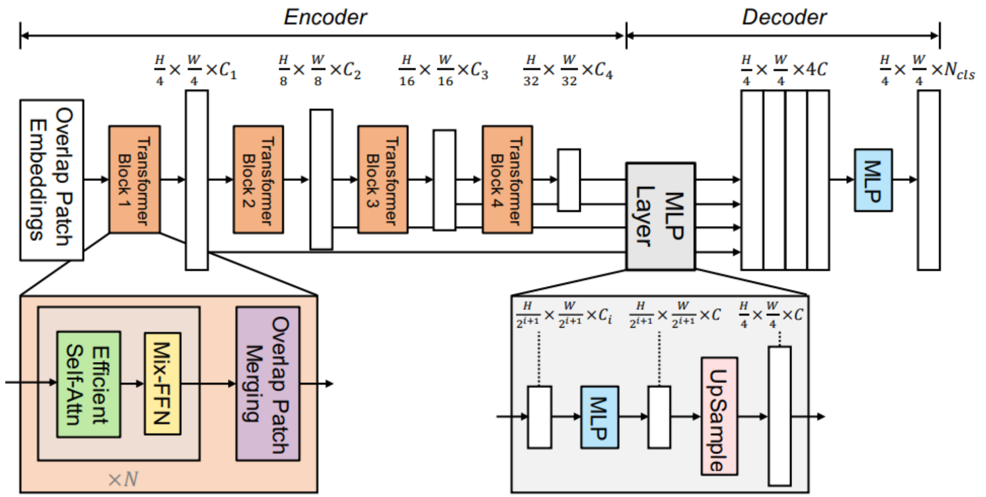


Fig. 4. Illustration of the attention block.

Source: R. Li, S. Zheng, C. Zhang, C. Duan, J. Su, L. Wang, and P. M. Atkinson, "Multiattention Network for Semantic Segmentation of Fine-Resolution Remote Sensing Images," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, pp. 1–13, 2022, doi: 10.1109/TGRS.2021.3093977.

ML MODELS

- 6. Segformer
  - Transformer-based architecture for semantic segmentation
  - Hierarchical Transformer encoder: extract coarse and fine features
  - Lightweight MLP decoder: directly fuse these multi-level features and predict the semantic segmentation mask
  - Achieves strong accuracy–efficiency trade-off for high-resolution images
  - FFN: Feed-forward Network



Source: E. Xie, W. Wang, Z. Yu, A. Anandkumar, J. M. Alvarez, and P. Luo, "SegFormer: Simple and Efficient Design for Semantic Segmentation with Transformers," *arXiv preprint arXiv:2105.15203*, 2021. [Online]. Available: https://arxiv.org/abs/2105.15203

FINE-TUNING

- Fine-tuning is decided based on the available hardware resources, datasets, and project timeframe
- Approach:
  - Used pre-trained encoders: by freezing the encoder weights (imagenet)
    - Resnet 18, Resnet34, Resnet50
    - Mobilenet V2
    - Densenet 161
    - Efficientnet-b2
    - Xception
  - Decoder part of the model is fine-tuned

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FINE-TUNING

- Experimental Setup
  - Hardware:
    - DA-Cluster: 8 CUDA-capable GPUs (NVIDIA Tesla P100, each with 12 GB)
  - Software:
    - Segmentation Models: Pytorch based library to build and train segmentatinon models
    - Streamlit: Python library to build interactive web apps

Segmentation Models Streamlit PyTorch

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FINE-TUNING

- Experimental Setup
  - Hyperparameters:
    - Batch Size: 8, 32
    - Learning Rate: 0.001 (Adam optimizer, LRscheduler: Cosine Annealing)
    - Number of Epochs: 300
    - Loss Function: Focal Loss
    - Early Stopping to avoid overfitting
  - Complete code for training, evaluation, and deployment is available in the following GitHub repository:
    - https://github.com/surajkarki66/AI-Powered_Landslide_Region_Mapping_using_Semantic_Segmentation

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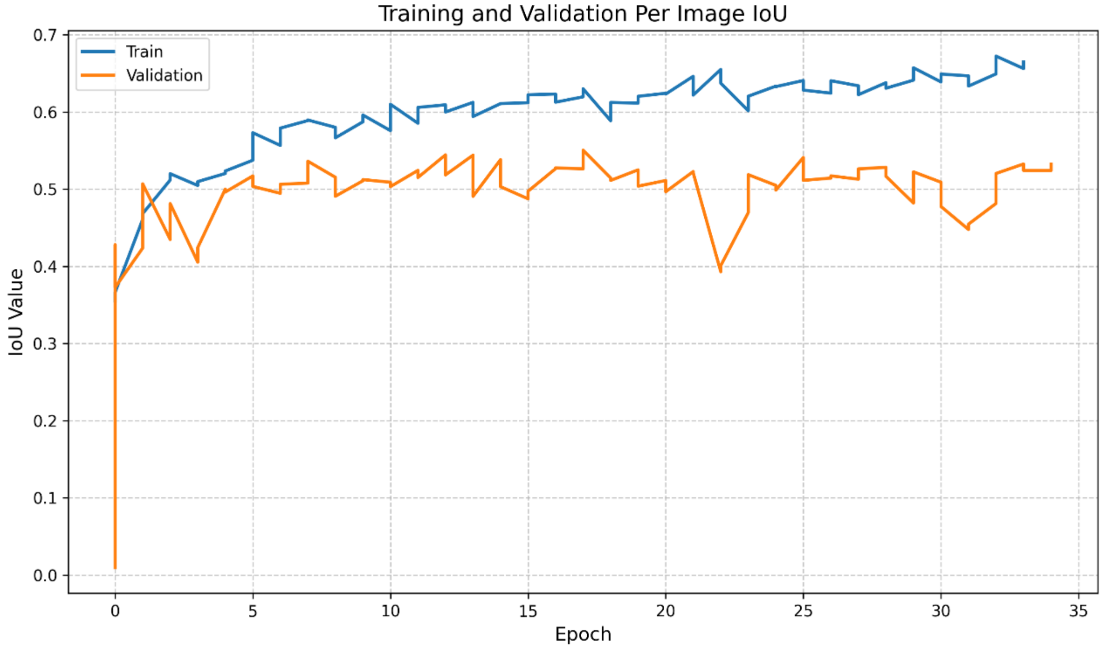
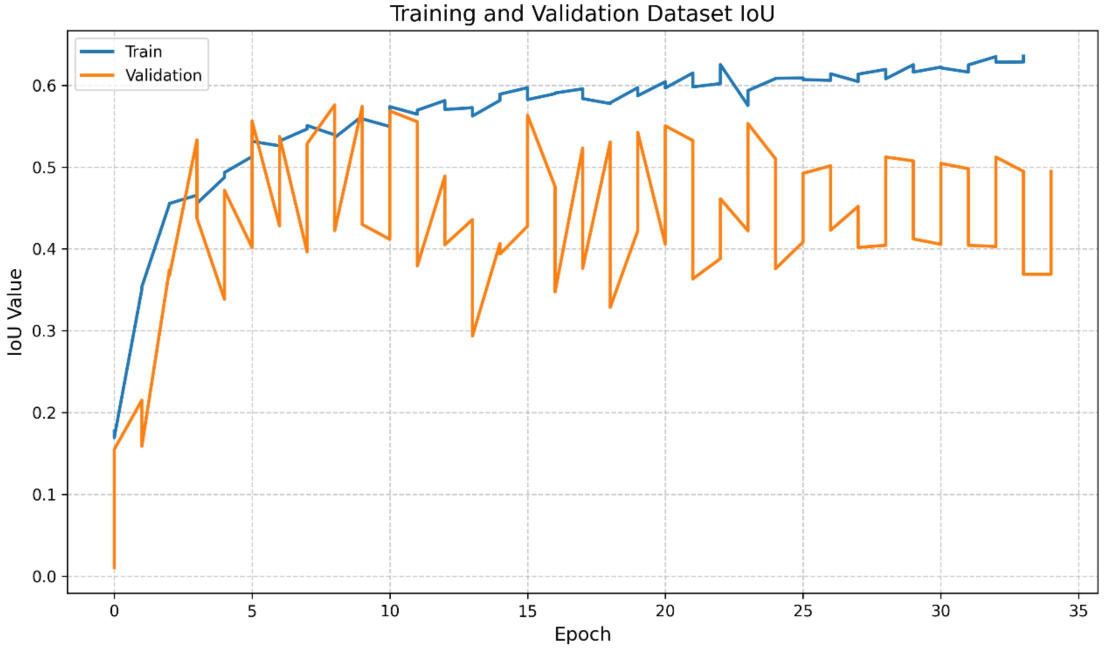
TRAINING RESULTS – LANDSLIDE4SENSE DATASET

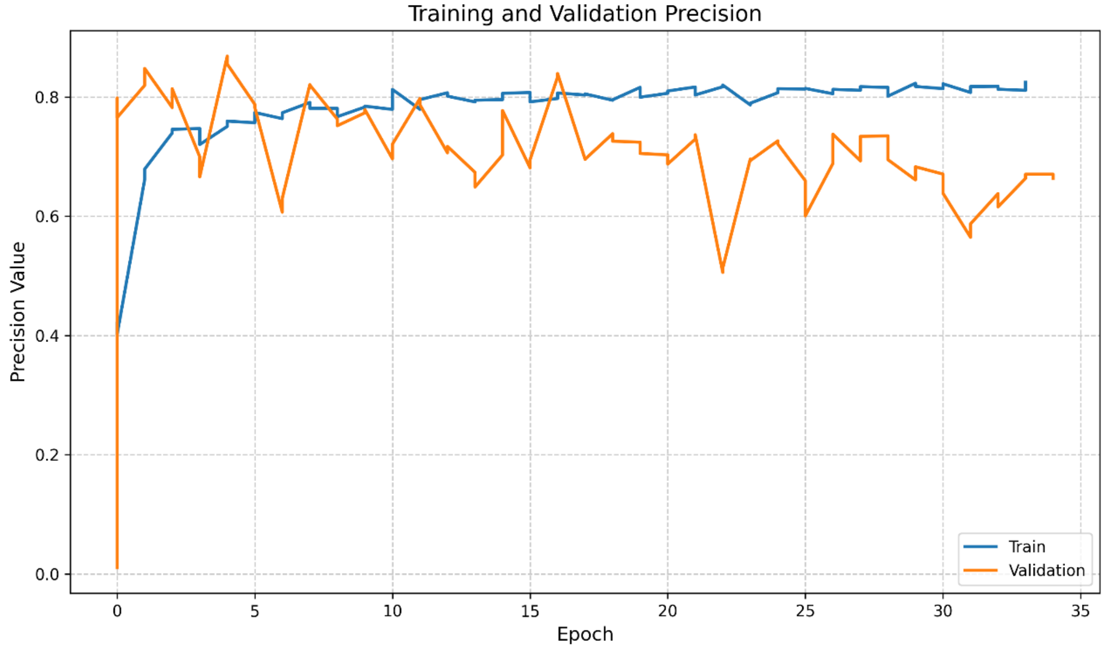
- Dataset and Per Image IoU of Unet with MobilenetV2 encoder, which is best performing model

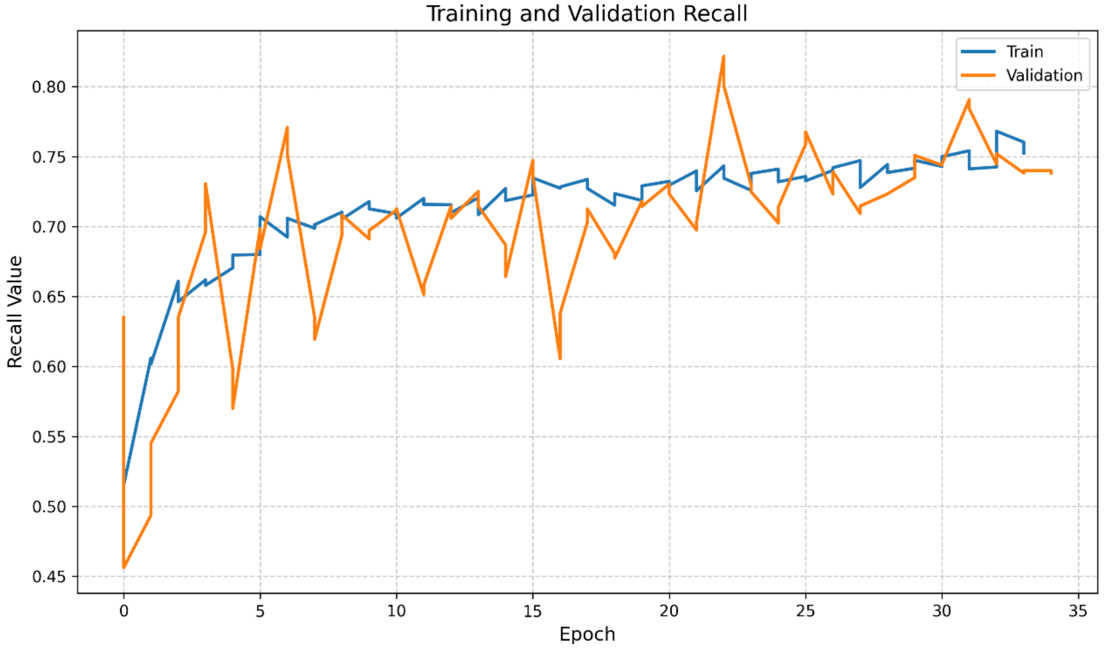




TRAINING RESULTS – LANDSLIDE4SENSE DATASET

- Precision and recall of Unet with MobilenetV2 encoder, which is best performing model





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EVALUATION RESULTS – LANDSLIDE4SENSE DATASET

Architecture	Backbone	Per-Image IoU	Dataset IoU	F1 Score	Accuracy	Recall	Precision
FPN	MobileNet	0.4419	0.4041	0.5756	0.9878	0.6212	0.6560
	ResNet18	0.4321	0.4141	0.5857	0.9873	0.6349	0.6214
	ResNet50	0.3906	0.3258	0.4915	0.9861	0.5522	0.6029
	Xception	0.3960	0.3122	0.4758	0.9857	0.6098	0.5842
MANet	Xception	0.3934	0.3784	0.5490	0.9866	0.6159	0.6037
	EfficientNet-B2	0.3451	0.3542	0.5231	0.9850	0.6267	0.5389
	MobileNetV2	0.4232	0.4283	0.5998	0.9834	0.6796	0.6256
	ResNet50	0.3319	0.3739	0.5443	0.9841	0.6928	0.5077
PSPNet	EfficientNet-B2	0.3855	0.3956	0.5669	0.9841	0.6219	0.5840
	MobileNetV2	0.3896	0.3717	0.5419	0.9861	0.5940	0.5794
	ResNet50	0.4074	0.3934	0.5646	0.9831	0.5971	0.6370
	Xception	0.3744	0.3541	0.5230	0.9862	0.5617	0.5930
	DenseNet161	0.3974	0.4205	0.5920	0.9841	0.6042	0.6663
Segformer	ResNet18	0.4272	0.4132	0.5847	0.9873	0.6399	0.6226
	ResNet34	0.4305	0.4120	0.5835	0.9845	0.6817	0.5924
UNet	DenseNet161	0.3192	0.4019	0.5734	0.9810	0.7495	0.4971
	MobileNetV2	**0.4444**	**0.4258**	**0.5973**	**0.9874**	**0.6996**	**0.6176**
	ResNet50	0.3619	0.4028	0.5743	0.9851	0.7218	0.5338
	Xception	0.4459	0.3536	0.5225	0.9814	0.6824	0.5856
UNet++	MobileNetV2	0.4373	0.4018	0.5733	0.9875	0.6295	0.6423
	Xception	0.3149	0.3505	0.5191	0.9813	0.7496	0.4440
	ResNet50	0.4215	0.3941	0.5654	0.9833	0.6272	0.6445
	EfficientNet-B2	0.3659	0.4173	0.5888	0.9840	0.7141	0.5721

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EVALUATION RESULTS – LANDSLIDE4SENSE DATASET

- Best Performing Models (Top-2) on Landslide4Sense Dataset

Architecture	Backbone	Per-Image IoU	Dataset IoU	F1 Score	Accuracy	Recall	Precision
UNet	MobileNetV2	0.4444	0.4258	0.5973	0.9874	0.6996	0.6176
UNet	Xception	0.4459	0.3536	0.5225	0.9814	0.6824	0.5856

- 10 Fold Cross Validation Result

Architecture	Backbone	Per-Image IoU	Dataset IoU	F1 Score	Accuracy	Recall	Precision
UNet	MobileNetV2	0.5898	0.5580	0.7208	0.9880	0.7248	0.7870

- Due to large number of experiments; detailed results available at the link below.
  - https://drive.google.com/drive/folders/1kx3PE8OjQAdeSY55L-80fjDuaGewYr5C?usp=sharing

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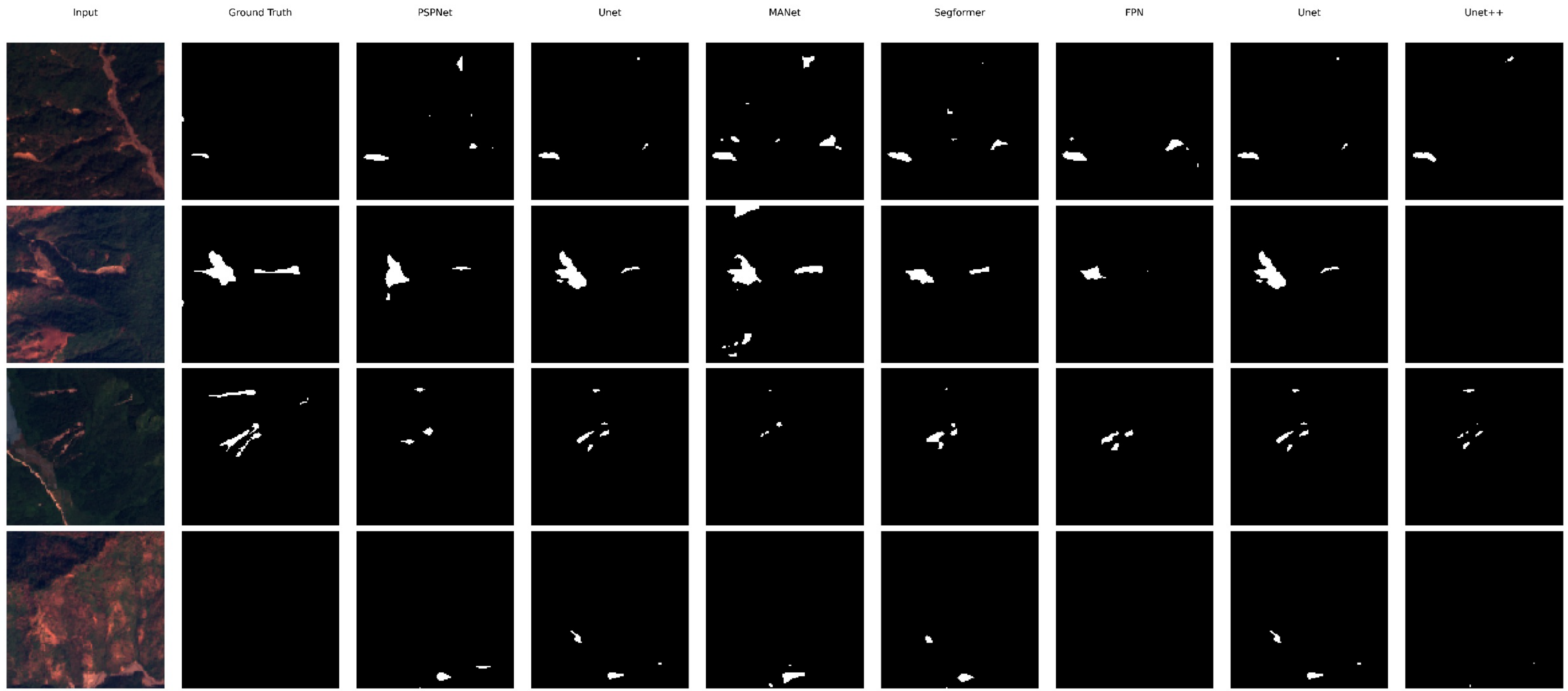
SAMPLE PREDICTIONS – LANDSLIDE4SENSE DATASET



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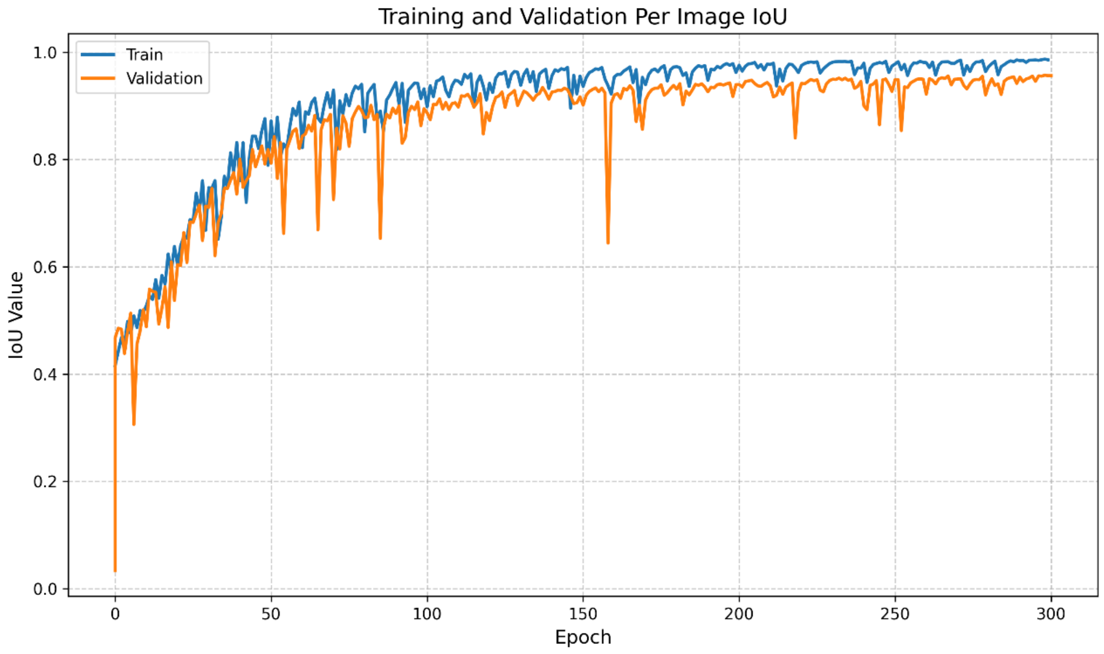
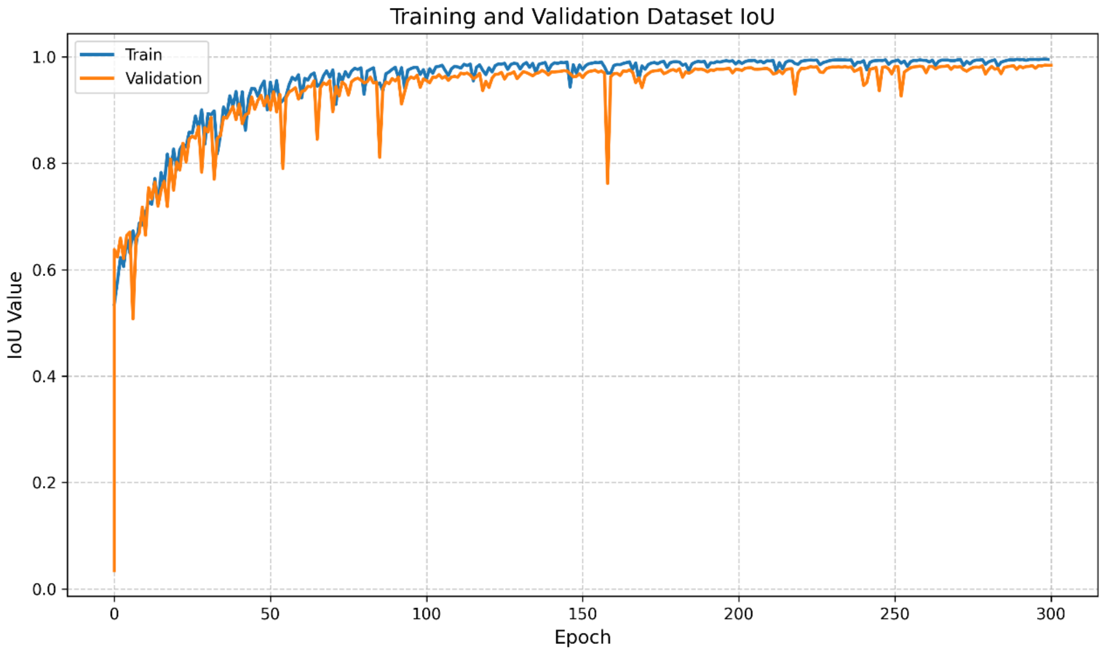
TRAINING RESULTS – CAS LANDSLIDE DATASET (UAV)

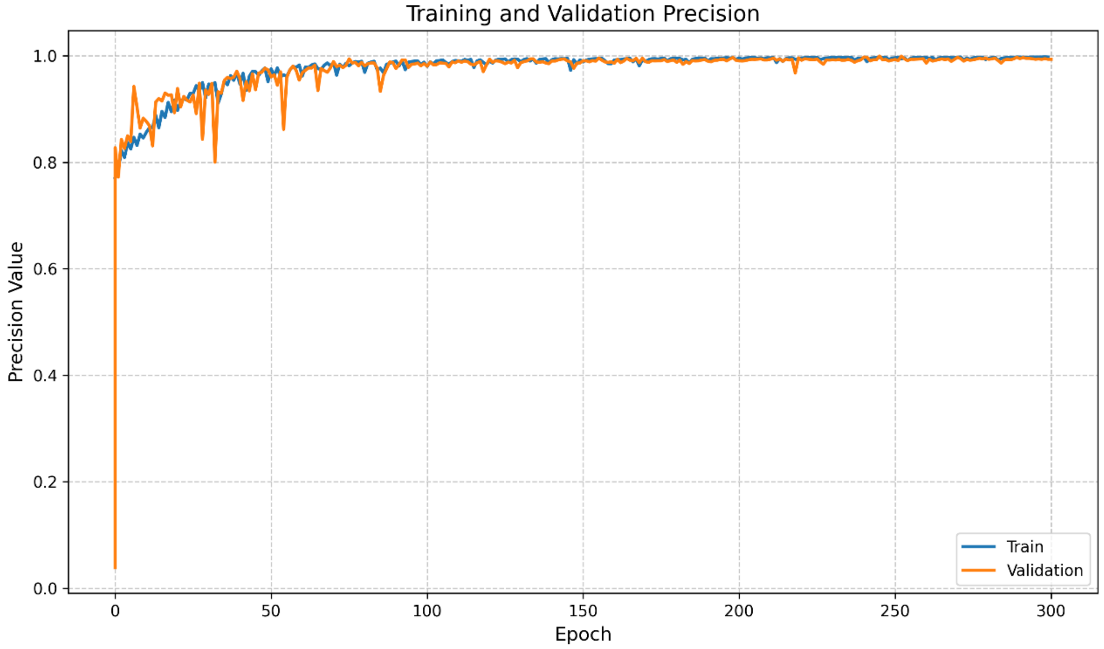
- Dataset and Per Image IoU of Unet++ with ResNet50 encoder, which is best performing model

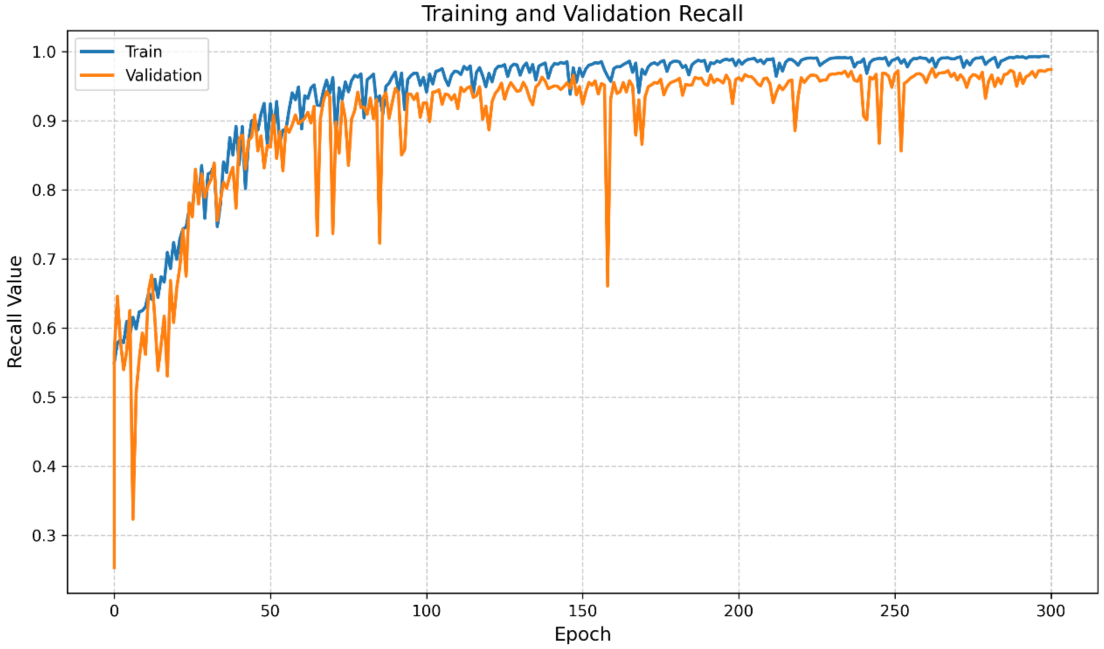




TRAINING RESULTS – CAS LANDSLIDE DATASET (UAV)

- Precision and recall of Unet++ with ResNet50 encoder, which is best performing model





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EVALUATION RESULTS – CAS LANDSLIDE DATASET (UAV)

Architecture	Backbone	Per-image IoU	Dataset IoU	F1 Score	Accuracy	Recall	Precision
FPN	MobileNet	0.7986	0.9181	0.9573	0.9844	0.8606	0.9643
	ResNet18	0.9002	0.9617	0.9805	0.9931	0.9386	0.9818
	ResNet50	0.8895	0.9589	0.9790	0.9923	0.9237	0.9835
	Xception	0.9153	0.9720	0.9858	0.9950	0.9382	0.9882
MANet	Xception	0.8171	0.9274	0.9623	0.9865	0.8359	0.9906
	EfficientNet-B2	0.8628	0.9491	0.9739	0.9905	0.8930	0.9848
	MobileNetV2	0.5350	0.6976	0.8218	0.9374	0.6456	0.8652
	ResNet50	0.8842	0.9597	0.9795	0.9924	0.9199	0.9820
PSPNet	EfficientNet-B2	0.7487	0.8811	0.9368	0.9769	0.8499	0.9271
	MobileNetV2	0.8230	0.9310	0.9643	0.9870	0.8583	0.9763
	ResNet50	0.8105	0.9223	0.9596	0.9855	0.8645	0.9660
	Xception	0.7600	0.8916	0.9427	0.9782	0.8890	0.9163
Segformer	MobileNetV2	0.7387	0.8981	0.9463	0.9806	0.7845	0.9671
	ResNet18	0.9042	0.9613	0.9803	0.9929	0.9453	0.9799
	ResNet34	0.9140	0.9653	0.9823	0.9937	0.9372	0.9893
	ResNet50	0.7020	0.8890	0.9412	0.9794	0.7085	0.9953
UNet	DenseNet161	0.8661	0.9485	0.9736	0.9903	0.9132	0.9794
	MobileNetV2	0.8178	0.9274	0.9624	0.9862	0.8725	0.9707
	ResNet50	0.9346	0.9732	0.9864	0.9951	0.9578	0.9888
	Xception	0.9290	0.9735	0.9866	0.9952	0.9468	0.9899
UNet++	EfficientNet-B2	0.8592	0.9454	0.9719	0.9897	0.9022	0.9816
	MobileNetV2	0.8181	0.9266	0.9619	0.9862	0.8642	0.9777
	ResNet18	0.8981	0.9582	0.9787	0.9925	0.9298	0.9842
	ResNet50	**0.9519**	**0.9816**	**0.9907**	**0.9966**	**0.9676**	**0.9919**

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EVALUATION RESULTS – CAS LANDSLIDE DATASET (UAV)

- Best Performing Models (Top-2) on CAS Landslide Dataset (UAV Version)

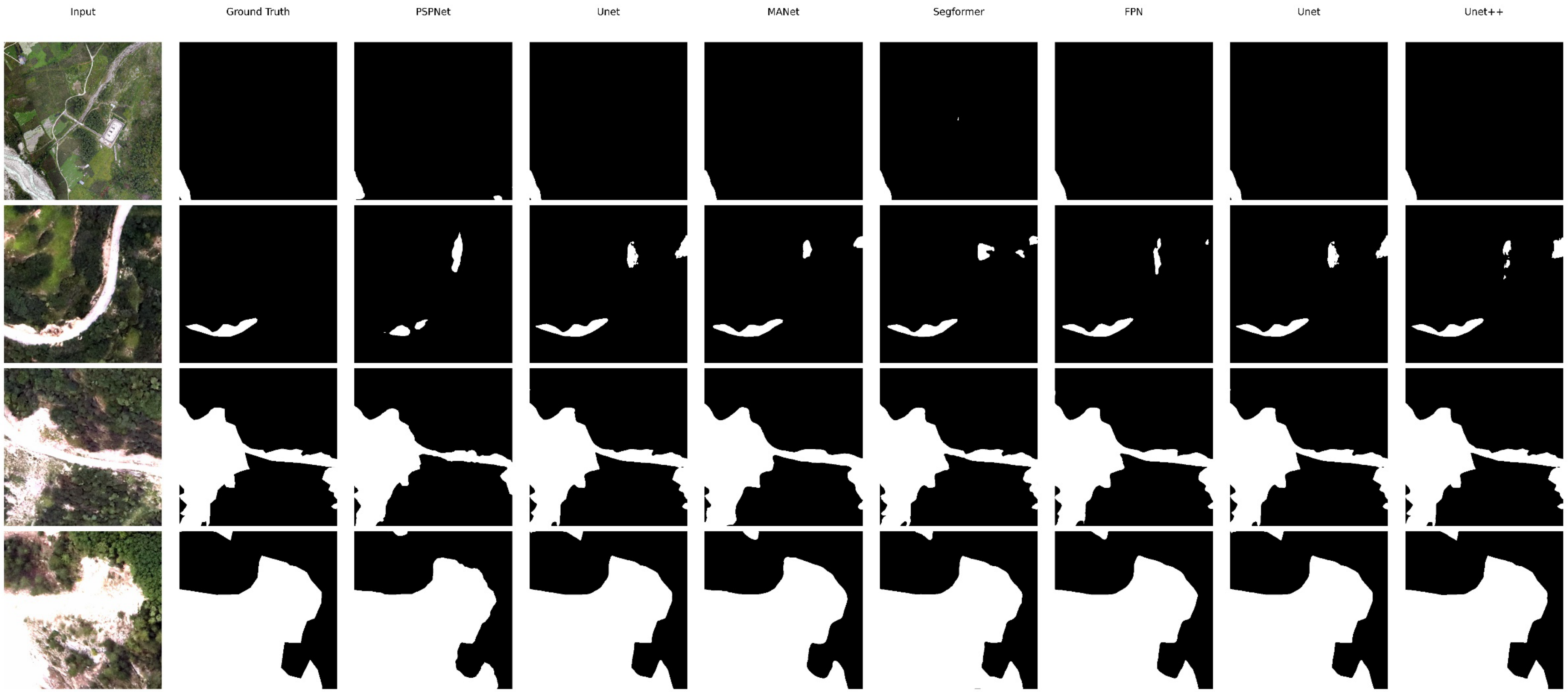
Architecture	Backbone	Per-image IoU	Dataset IoU	F1 Score	Accuracy	Recall	Precision
UNet++	ResNet50	0.9519	0.9816	0.9907	0.9966	0.9676	0.9919
UNet	ResNet50	0.9346	0.9732	0.9864	0.9951	0.9578	0.9888

- 5 Fold Cross Validation Result

Architecture	Backbone	Per-Image IoU	Dataset IoU	F1 Score	Accuracy	Recall	Precision
UNet++	ResNet50	0.9456	0.9786	0.9893	0.9962	0.9654	0.9908

- Due to large number of experiments; detailed results available at the link below.
  - https://drive.google.com/drive/folders/14RgcVSGZQITB6Kr225ZBBL_kVOwUb_L7?usp=sharing

SAMPLE PREDICTIONS– CAS LANDSLIDE DATASET (UAV)



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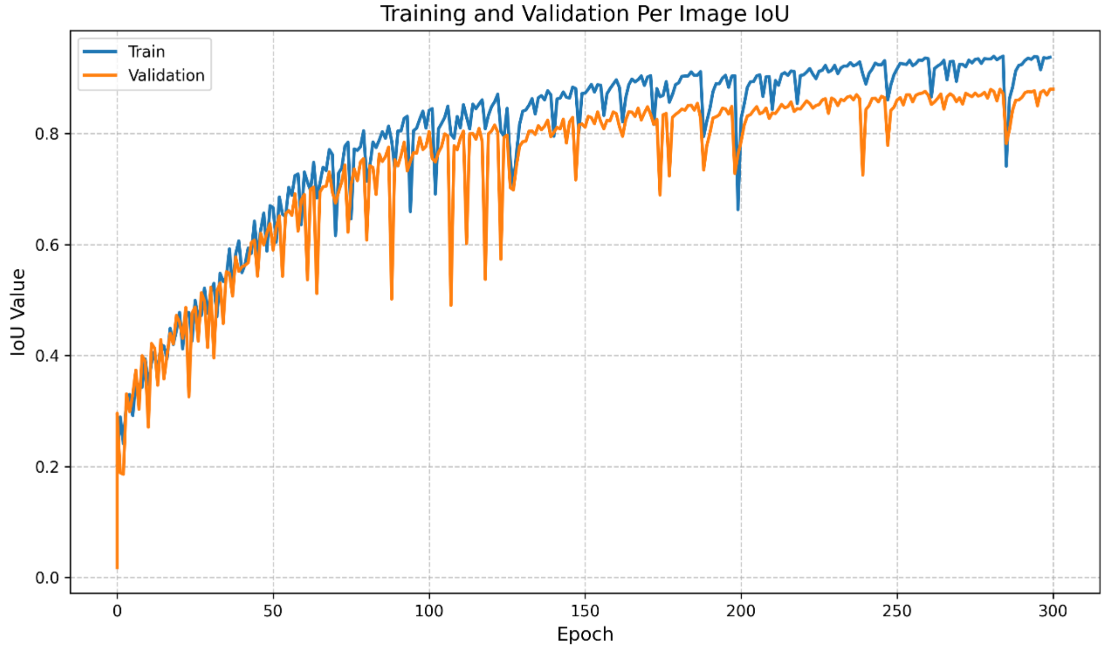
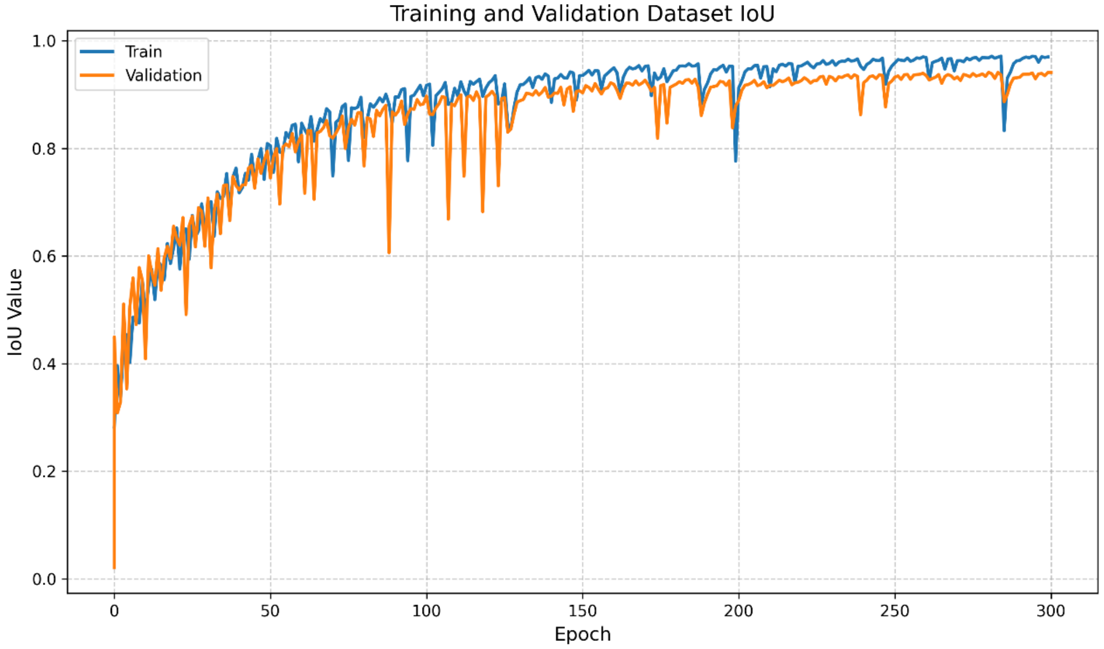
TRAINING RESULTS – CAS LANDSLIDE DATASET (SATELLITE)

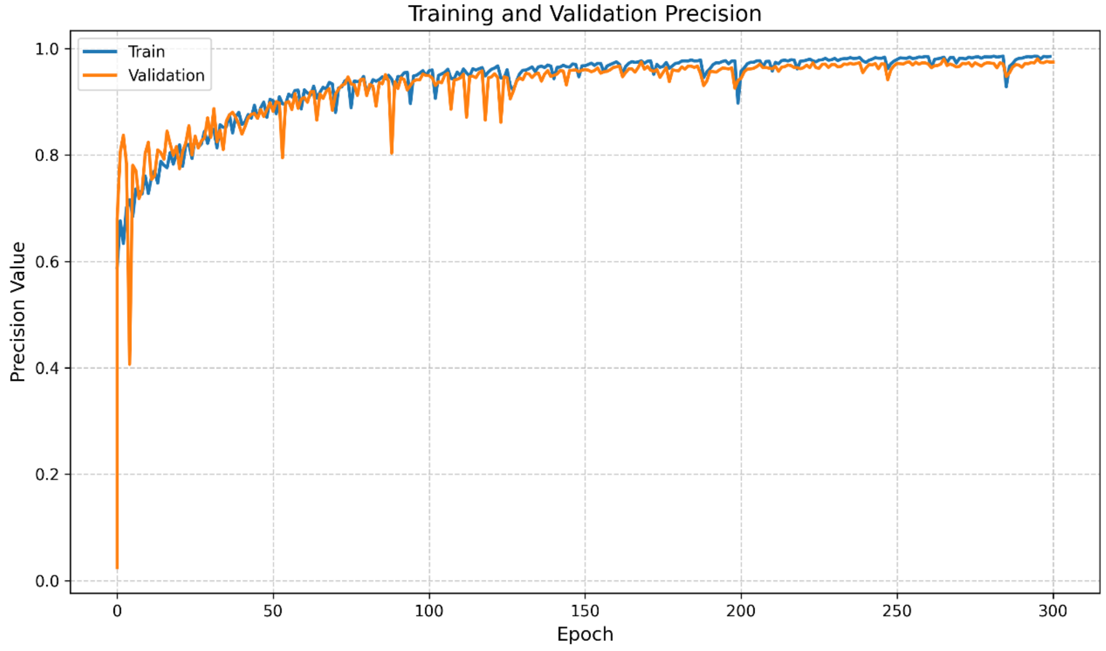
- Dataset and Per Image IoU of Unet with DenseNet161 encoder, which is best performing model





TRAINING RESULTS – CAS LANDSLIDE DATASET (SATELLITE)

- Precision and recall of Unet with DenseNet161 encoder, which is best performing model



EVALUATION RESULTS – CAS LANDSLIDE DATASET (SATELLITE)

Architecture	Backbone	Per-Image IoU	Dataset IoU	F1 Score	Accuracy	Recall	Precision
FPN	MobileNet	0.6485	0.7968	0.8869	0.9813	0.7609	0.8892
	ResNet18	0.7858	0.8609	0.9253	0.9889	0.8618	0.9293
	ResNet50	0.8004	0.9023	0.9486	0.9915	0.8699	0.9511
	Xception	0.8366	0.9065	0.9509	0.9928	0.8801	0.9658
MANet	Xception	0.8108	0.8830	0.9379	0.9909	0.8619	0.9566
	EfficientNet-B2	0.7721	0.8645	0.9273	0.9892	0.8554	0.9259
	MobileNetV2	0.7233	0.8412	0.9138	0.9866	0.8046	0.9258
	ResNet50	0.7958	0.8781	0.9351	0.9905	0.8542	0.9495
PSPNet	EfficientNet-B2	0.5845	0.7234	0.8395	0.9776	0.6455	0.9008
	MobileNetV2	0.5379	0.6757	0.8065	0.9712	0.6553	0.8060
	ResNet50	0.6999	0.8291	0.9066	0.9855	0.7697	0.9194
	Xception	0.5555	0.6711	0.8032	0.9657	0.8729	0.7011
	DenseNet161	0.6887	0.8285	0.9062	0.9845	0.7802	0.9077
Segformer	MobileNetV2	0.7326	0.8446	0.9157	0.9868	0.8119	0.9186
	ResNet18	0.4301	0.5907	0.7427	0.9695	0.4316	0.9959
	ResNet34	0.8074	0.9027	0.9489	0.9916	0.8607	0.9562
UNet	**DenseNet161**	0.8669	**0.9305**	**0.9640**	**0.9944**	**0.9121**	0.9704
	MobileNetV2	0.7541	0.8516	0.9199	0.9883	0.8159	0.9410
	ResNet50	0.8306	0.8979	0.9462	0.9921	0.8894	0.9549
	Xception	0.8172	0.8912	0.9425	0.9915	0.8793	0.9530
UNet++	MobileNetV2	0.7212	0.8229	0.9029	0.9854	0.8113	0.8957
	ResNet34	**0.8640**	0.9267	0.9620	0.9941	0.8953	**0.9780**
	ResNet50	0.8574	0.9131	0.9546	0.9933	0.9086	0.9579

EVALUATION RESULTS – CAS LANDSLIDE DATASET (SATELLITE)

- Best Performing Models (Top-2) on CAS Landslide Dataset (Satellite Version)

Architecture	Backbone	Per-Image IoU	Dataset IoU	F1 Score	Accuracy	Recall	Precision
UNet	DenseNet161	0.8669	0.9305	0.9640	0.9944	0.9121	0.9704
UNet++	ResNet34	0.8640	0.9267	0.9620	0.9941	0.8953	0.9780

- 5 Fold Cross Validation Result

Architecture	Backbone	Per-Image IoU	Dataset IoU	F1 Score	Accuracy	Recall	Precision
UNet++	ResNet50	0.848454	0.925360	0.960543	0.994151	0.898619	0.968419

- Due to large number of experiments; detailed results available at the link below.
  - https://drive.google.com/drive/folders/18iRsnAT7VtB0DBpdMv1XW5m5eAI67ml3?usp=sharing

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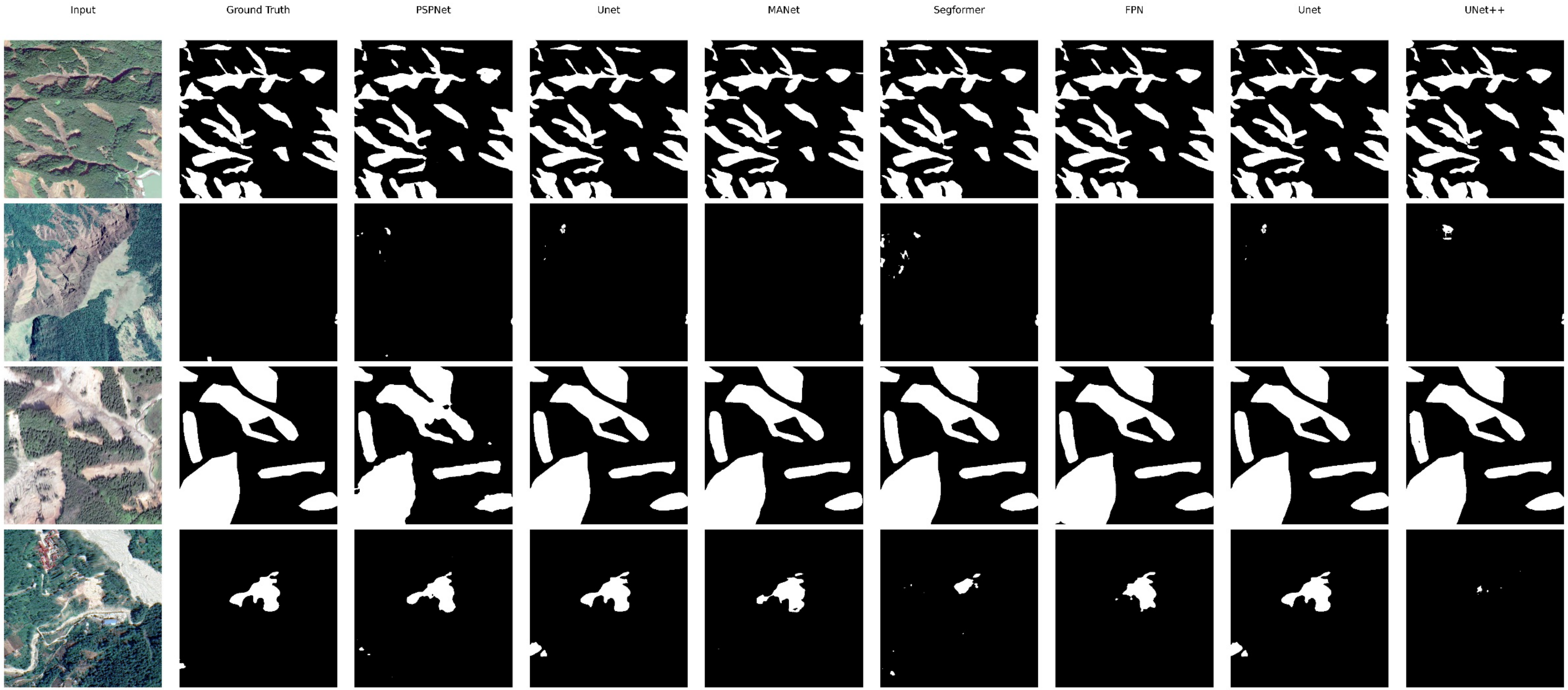
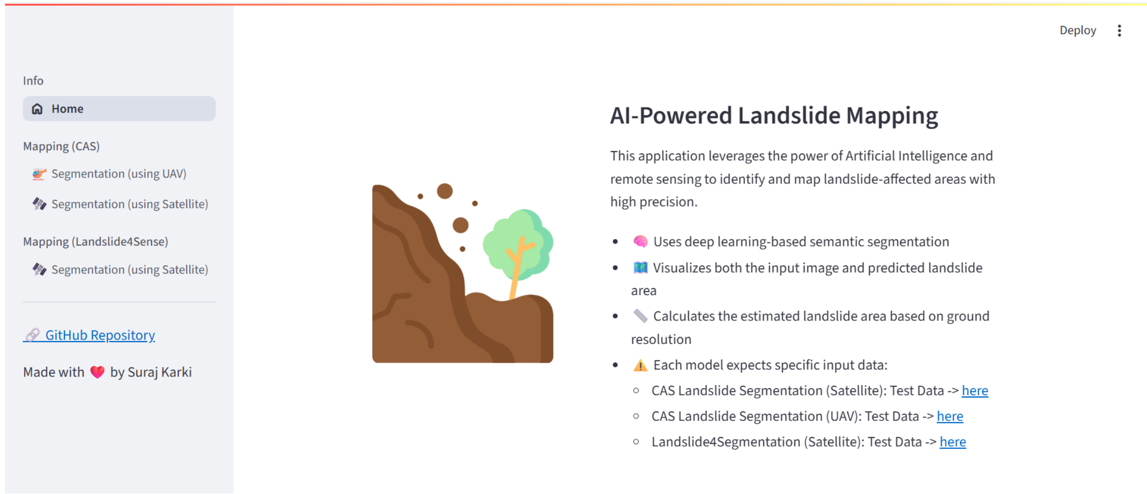
SAMPLE PREDICTIONS – CAS LANDSLIDE DATASET (SATELLITE)



DEPLOYMENT

- After evaluation, the best performing model is exported in ONNX format.
- Since, separate training is performed in three different datasets, three best performing model was exported.
- The exported ONNX models are integrated into a Streamlit application.



DISCUSSION

- Model Performance Analysis
  - High mIoU on CAS Landslide datasets (UAV: 95.19%, Satellite: 86.69%) due to high-resolution imagery and consistent annotations, surpassing benchmarks like Bijie (88.10%).
  - Lower performance on Landslide4Sense (44.44% vs. 76.07% SOTA) due to multi-spectral complexity, class imbalance, and small patch size.
- Streamlit application performing inference efficiently for landslide segmentation on Landslide4Sense and CAS Landslide datasets.

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DISCUSSION

- Limitations
  - Uneven data distribution and fixed pre-trained encoders reduce adaptability, causing lower performance.
  - High-resolution CAS Landslide dataset caused GPU resource constraints, limiting training from scratch and further experiments.
  - Because of large model size latency is little bit high on CPU.

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CONCLUSION

- Achieved up to 95.19% mIoU on UAV data;enabled precise post-disaster mapping.
- Also, done experiments with multi-sensor datasets.
- Deployed best performing model via Streamlit app.
- Demonstrated potential for real-monitoring.

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CONCLUSION

- Future Directions
  - Combining the CAS Landslide(UAV+Satellite) datasets to train and experiments with one ultimate landslide segmentation model.
  - For Landslide4Sense data, research on possible way to increase dataset, and training with different combination of loss function.
  - Perform model compression techniques(like quantization, distillation) to improve latency.


END
Thank you for your attention


ANY
QUESTIONS