

# Identifying Rural Communities Using Satellite Imagery and Deep Learning

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## Overview

> U-Net model is trained using the OpenEarthMap satellite imagery dataset to identify land features.

> Features are buildings, roads, trees, water, cropland, bare land, agriculture land, rangeland, and developed areas.

## Goal

> This project aims to develop a semantic image segmentation model with high accuracy in classifying various land features and objects in satellite images.

> The main distinctive aspect of this study is in its primary focus on diverse rural regions across the globe.

## Motivation

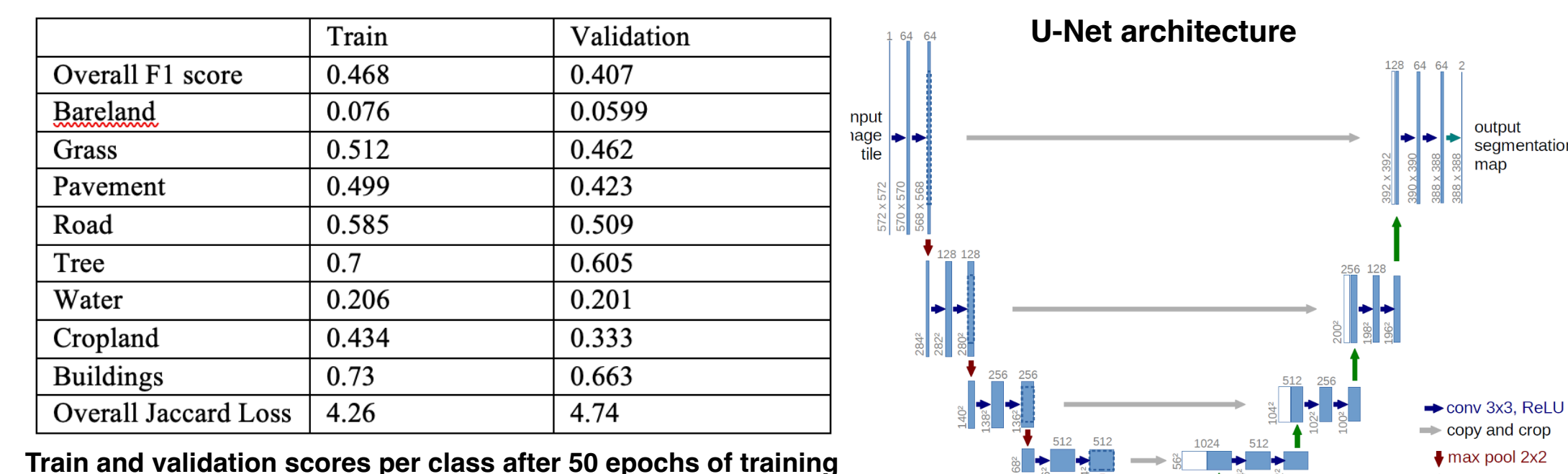
> Enabling humanitarian organizations and community health systems to gain knowledge about the communities in the area to meet the needs of people in rural areas in cases of crisis or natural disasters.

> Implications in various domains, including urban planning, environmental monitoring, disaster management, and resource allocation.

## Methods: U-Net model

> To identify remote communities on satellite images, a UNET-based model was trained using the OpenEarthMap dataset.

> The model was trained for 50 epochs, batch size of 4, learning rate of 0.0001, F1 score as a metric, and Jaccard loss. The overall F1 score reached to about 40% with training the model from scratch.



## Methods: U-Net with ResNet34 and LinkNet with ResNet34

	Training F1 Score	Training Loss	Validation F1 Score	Validation Loss
U-Net	65.96%	46.58%	58.31%	54.41%
LinkNet	60.38%	52.35%	53.79%	58.81%

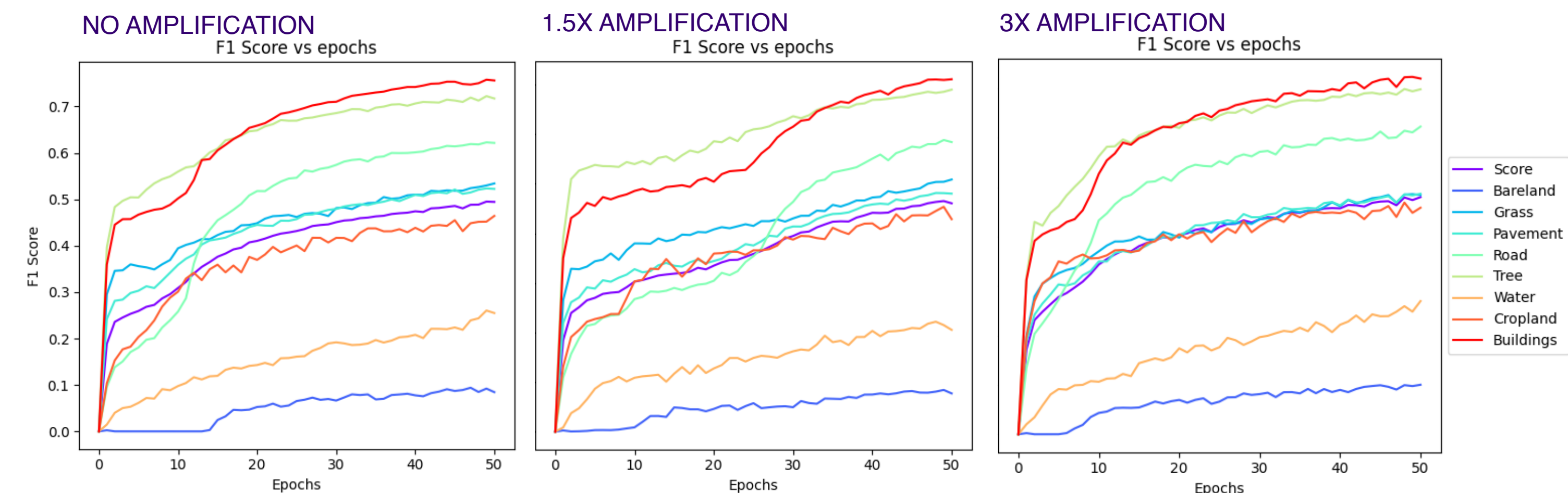
Training and Validation F1 scores and Losses for U-Net and LinkNet models with ResNet34 backbone.

> To improve the performance of the model, U-Net and LinkNet models are combined with ResNet34 as a backbone pre-trained model.

> Both models are trained for 10 epochs with batch size of 4, F1 and IoU scores as metric, dice and focal losses, adam optimizer, and learning rate of 0.0001.

## Experiment: Amplifying loss for rural data classes

> To improve the model's performance, the loss was amplified by for rural classes or classes that the model is performing bad with. The results with loss amplified for bareland, cropland, water, and road classes. Both models were trained for 50 epochs.



	No Amplification	1.5x amplification	3x amplification
Overall score	0.4804	0.4605	0.4798
Bareland	0.0891	0.0772	0.1001
Grass	0.5185	0.5085	0.4838
Pavement	0.5117	0.4799	0.4866
Road	0.6158	0.5839	0.6225
Tree	0.7096	0.6896	0.6979
Water	0.2187	0.2053	0.2695
Cropland	0.4312	0.4284	0.4583
Buildings	0.7483	0.7106	0.7195

> Amplifying the loss for certain classes improves the model's predictions for those classes, but at a cost of decreased predictions for classes that it was doing well, such as buildings or trees.

> However, the change in F1 score is very low for all classes.

## Conclusion

> Despite significant efforts, the developed model did not achieve the initially desired level of accuracy.

> The primary limitation of this project was the scarcity of labeled rural satellite imagery accessible for training the model.

> This research project serves as a valuable learning experience and highlights the challenges of satellite image semantic segmentation.

> Other CNNs and data augmentation can be used in future work.

## Dataset: OpenEarthMap

> 5000 high-resolution satellite images

> 97 different regions across

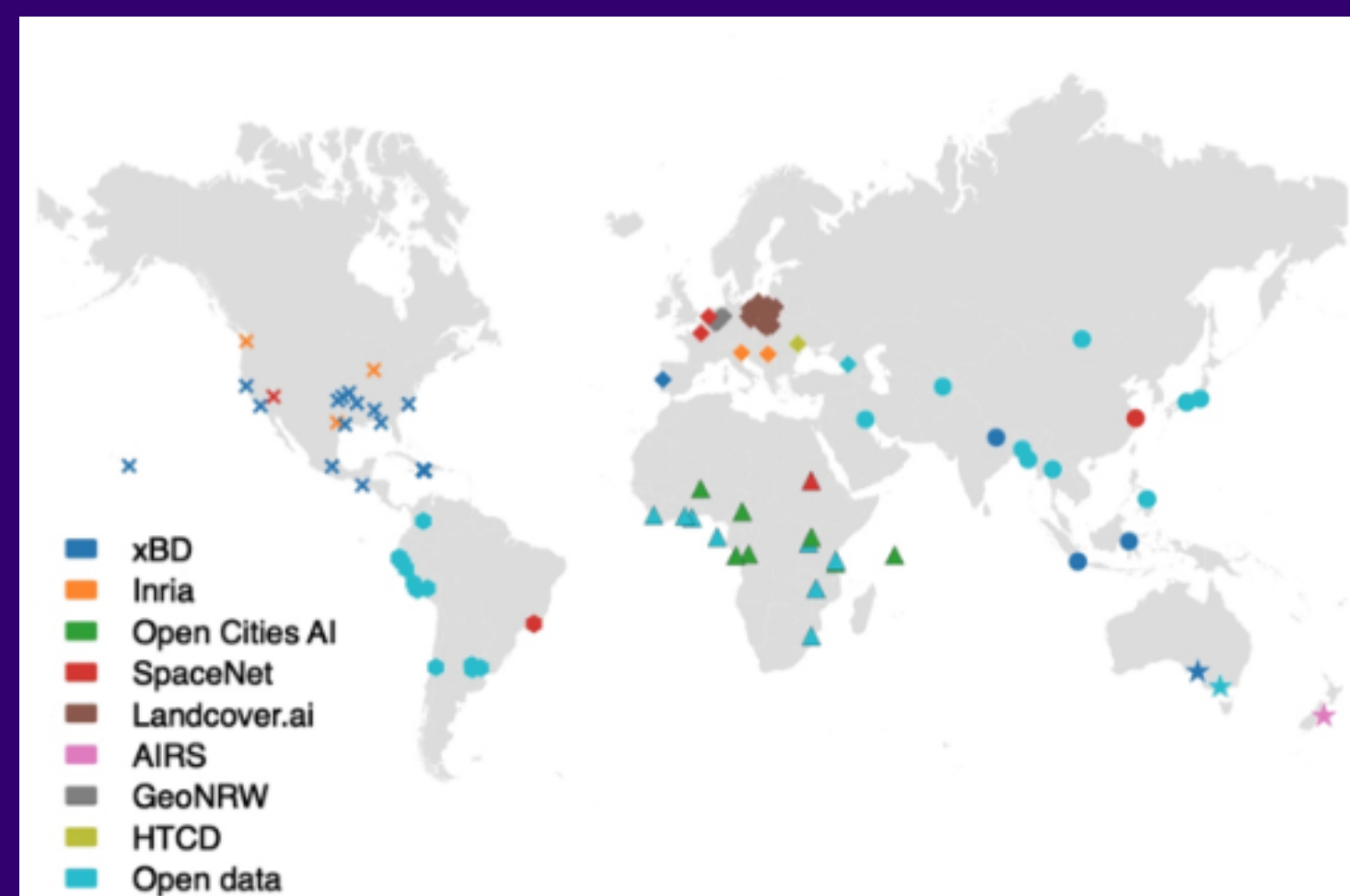
> 44 countries

> 6 continents

> 8-class annotated land cover labels

> 2.2 million segments

> 0.25-0.5m ground sampling distance



## Dataset classes and percentages per class

Color (HEX)	Class	%
800000	Bareland	1.5
00FF24	Rangeland	22.9
949494	Developed space	16.1
FFFFFF	Road	6.7
226126	Tree	20.2
0045FF	Water	3.3
4BB549	Agriculture land	13.7
DE1F07	Building	15.6

## Results: Zanzibar satellite image tested on U-Net model

