Tracking Climate Change Using Satellites and Artificial Intelligence

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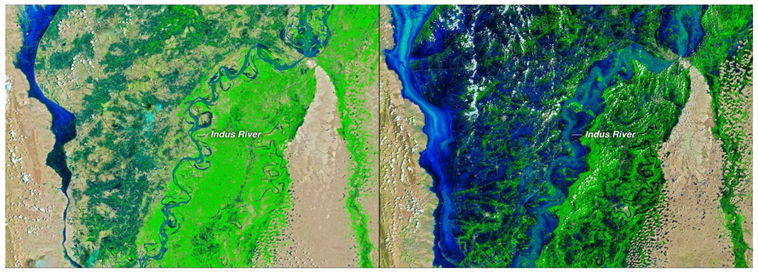
1 Introduction

Our project seeks to provide automated data tracking of the causes and consequences of anthropogenic climate change for evidence-based policy and decision-making. Satellite imagery and AI tools can be used to accomplish this.

Example Cause of Climate Change: Deforestation in Bolivia

1986 2022

Example Effect of Climate Change: Flooding in Pakistan



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However, accumulating labeled data is **costly** and increasing the **frequency** of such analysis is also challenging. We face two significant hurdles:

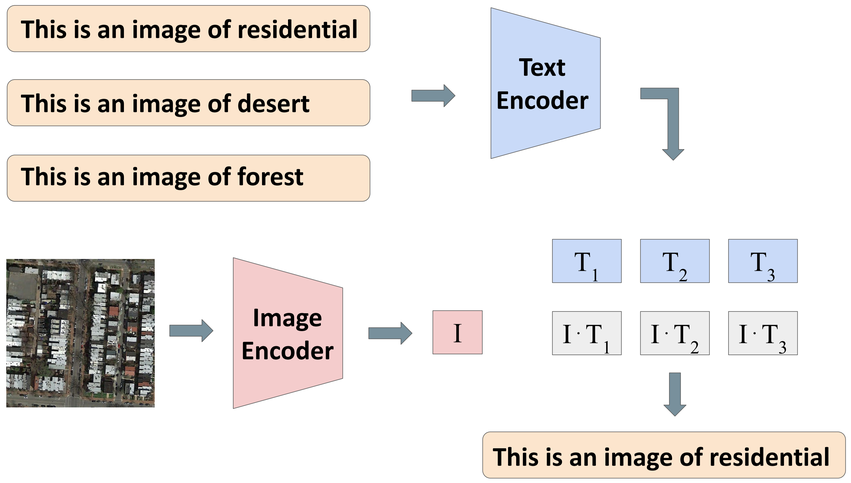
- **High resolution training data** are **limited.**
- Monitoring climate change **requires** a **global scope** to effectively track environmental trends worldwide, but most algorithms are only locally-applicable.

Acquiring labels for satellite imagery is costly and it varies significantly across different regions

2 Proposed Solution: Zero-shot Learning

- To address the challenges posed by limited labeled data, we propose a novel approach leveraging **embedding space** techniques (alternative representations of the data).
- **Zero-shot learning** is a cutting-edge technique that involves aligning embedding space representations of both textual and visual data.
- This alignment enables the model to comprehend the intrinsic relationship between text and images, even in scenarios where direct labeled examples may be sparse or absent.

Illustration of the zero-shot learning concept



Note: I represents an image embedding, and T represents a text embedding.

3 Experimental Design

- We explore a wide variety of state-of-the-art zero-shot learning models in our experiments.
- These language-image models are **not trained on the satellite imagery used for model evaluation.**
- We test their performance on the classification of **unseen classes of data** across diverse datasets of satellite imagery.

Example Classes of Evaluated Dataset

Forest Desert Residential

4 Results

- The model has demonstrated a remarkable ability to accurately classify images never seen before, with an average classification accuracy of 78.2% across datasets.

Comparison of Image Classification Accuracy (%)

		Random Guess	**Zero-shot (LHRS-BOT)**	Supervised Learning
Dataset	EuroSAT	10.0	**52.8**	98.7
	AID	3.3	**87.8**	97.4
	RESISC45	2.2	**94.1**	96.8
Average		5.2	**78.2**	97.6

5 Conclusions

- Our findings highlight the potential of zero-shot learning in handling limited training data in remote sensing imagery.
- By extending this approach to diverse image resolutions and regions, we can further bolster the **efficiency of global climate change monitoring** efforts.
- This may pave the way for more informed decision-making **on a global scale** and a broad **adaptation in other geographic domains** as well.

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