
Team Name : KETER

Team Leader Name : ARYAN GUPTA

Problem Statement :

Novel Approaches for Optimizing Deep Learning in Earth Observation with Imbalanced Data

# Team Members

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Brief about the Idea:

**Title:**
Crowd-Driven Loss Function for Rare Class Segmentation
**Brief:**
In challenging image segmentation tasks—such as detecting rare or visually ambiguous features (e.g., puddles of muddy water, quicksand in deserts) that closely resemble their surroundings—standard loss functions often fail because visual cues are insufficient.
We propose a novel loss function that dynamically integrates human-sourced data (such as crowd reports, social media posts, or expert annotations) to guide the model's learning. By weighting the loss higher in regions where human reports indicate the presence of rare classes, and enforcing consistency with these reports, our approach helps the model focus on difficult, otherwise indistinguishable areas.
This "Crowd-Attentive Loss" allows the model to leverage collective human knowledge, improving segmentation accuracy for rare or subtle features that are often missed by conventional methods.
**Example:**
Suppose a satellite image of a desert contains a patch of quicksand that looks identical to the surrounding sand. Local hikers report the quicksand's location, but it's nearly invisible to the model based on pixels alone.
With the crowd-driven loss function, these human reports guide the model's learning to focus on and correctly segment the rare quicksand area, improving accuracy even when visual cues are weak.

# How is this different from existing ideas?

Most segmentation models rely only on visual cues and standard loss functions, which struggle when rare features visually blend with their surroundings.
Existing approaches for rare classes focus mainly on data augmentation or class re-weighting, but do not actively incorporate real-time, location-specific human knowledge into the loss calculation.
Our method is unique in directly integrating crowd-sourced human reports as spatial guidance within the loss function, dynamically focusing model learning where visual cues are insufficient.

## How will it solve the problem?

By leveraging human-sourced data (e.g., field reports, social media), our loss function guides the model to pay special attention to ambiguous or visually hidden rare classes.
The model is explicitly penalized for missing features identified by people, even if they are not visually obvious, improving accuracy for hard-to-detect cases.

## USP (Unique Selling Proposition) of the Solution

- **Human-guided attention:** Directly fuses collective human intelligence into model training, not just data labeling.
- **Dynamic focus:** Actively adapts to real-world, location-specific feedback, making the model robust to subtle or camouflaged features.
- **Generalizable:** Can be applied to any segmentation scenario where rare or ambiguous classes are better identified by human knowledge than by pixels alone.

**1. Human-Guided Segmentation**
Leverages crowd-sourced or expert reports to guide model attention to rare, hard-to-detect regions.

**2. Dynamic Loss Weighting**
Automatically increases learning focus in locations where human data signals rare or ambiguous classes.

**3. Consistency Enforcement**
Adds a penalty if the model disagrees with trusted human reports, ensuring alignment with real-world knowledge.

**4. Adaptive Curriculum Learning**
Prioritizes “easy” (high confidence) regions first and gradually adapts to harder, more ambiguous areas as training progresses.

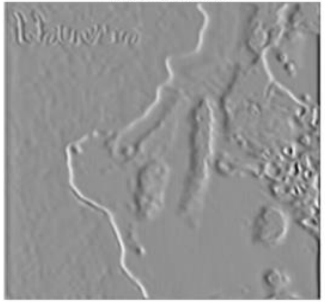
**5. Edge-Aware Sensitivity**
Boosts model attention and precision along the boundaries of rare features, improving boundary accuracy.

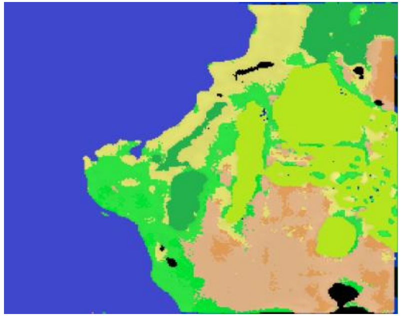
**6. Generalizable Framework**
Works for any segmentation task where human insight can supplement or correct visual ambiguity—satellite, medical, or industrial images.

**7. Robustness in Ambiguous Scenarios**
Significantly improves detection of camouflaged or visually subtle features, outperforming standard vision models.

Original Satellite Image


Prediction Edges





Using our function to fill edges with public data

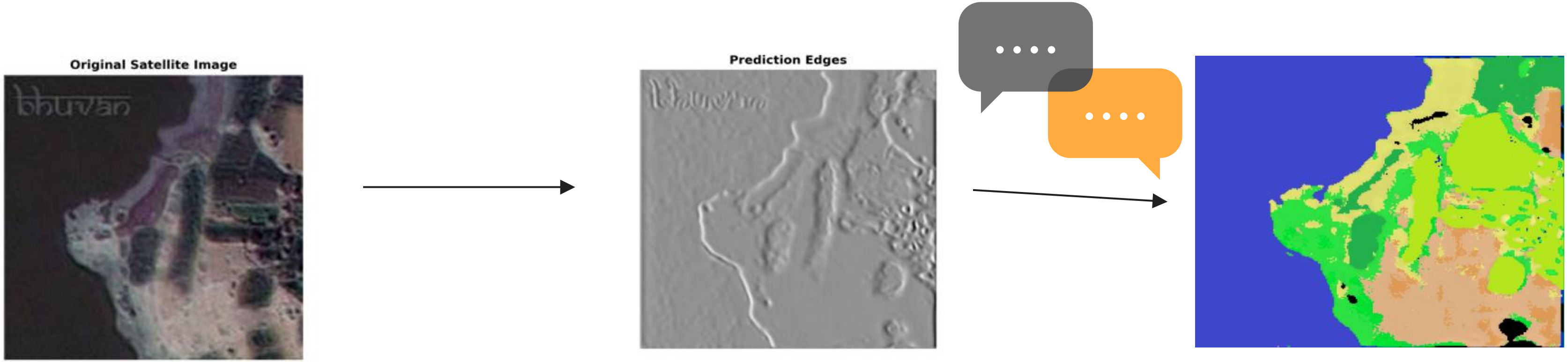
Using normal functions rare classes are ignored

# Process flow diagram or Use-case diagram

Input Image
|
v
Human Reports Layer
(Crowd/expert data, location tags)
|
v
Model Prediction
(Initial segmentation mask)
|
v
Crowd-Driven Loss Function
(Weighted by human data & consistency penalties)
|
v
Model Training/Update
|
v
Improved Segmentation Output
(Rare features accurately detected)

**Data Sources**
Social Media Scraping
Field Reports
Crowdsourcing Apps
↓
**Human Reports Acquisition Layer**
Gather location-tagged reports about rare features
↓
**Location Matching & Validation**
Match reported locations to map coordinates
↓
**Compare with Govt Datasets**
Cross-check reports with official hazard/location datasets
↓
**Validated Human Reports Layer**
Filtered, trustworthy human insights
↓
**Integration with Model Pipeline**
Use as weighted input for crowd-driven loss in segmentation model

# Wireframes/Mock diagrams of the proposed solution (optional)



# Architecture diagram of the proposed solution

```
Input Image
     |
     v
Human Reports Layer
  (Crowd/expert data, location tags)
     |
     v
Model Prediction
  (Initial segmentation mask)
     |
     v
Crowd-Driven Loss Function
  (Weighted by human data & consistency penalties)
     |
     v
Model Training/Update
     |
     v
Improved Segmentation Output
  (Rare features accurately detected)
```

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# Technologies to be used in the solution:

| | |
|---|---|
| Data Collection | Scrapy, BeautifulSoup, APIs |
| Geospatial Data | GeoPandas, PostGIS, Shapely |
| Model Training | PyTorch, TensorFlow, Keras |
| Image Processing | OpenCV, PIL |
| Loss Function | Custom Python (PyTorch/TensorFlow) |
| Visualization | Matplotlib, Folium, Kepler.gl, Streamlit |

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# BHARATIYA ANTARIKSH HACKATHON 2025

# THANK YOU