CNN-Based Glacier Retreat Analysis Tool

1. Problem Statement
The manual analysis of glacier boundaries and types from satellite imagery is a slow, labour-intensive, and subjective process. To effectively monitor the impact of climate change, researchers need a tool that can rapidly, consistently, and quantitatively assess changes in glacier composition and area over time.

2. Objective
To develop a deep learning tool that automates the semantic segmentation of glaciers from satellite imagery. The primary goal is to produce pixel-level classification maps identifying different types of ice and terrain. The secondary and ultimate goal is to use these generated maps to perform temporal change analysis, providing quantitative data on glacier retreat and evolution.

3. Target User
Climate Researchers, Glaciologists, and Environmental Science students who need to analyse satellite imagery for research or educational purposes.

4. Core Features & Functionality

- **Feature 1: Automated Glacier Segmentation**
    - **Input:** A standard optical satellite image (e.g., JPG, PNG) of a glacier region.
    - **Process:** The trained U-Net CNN model will process the input image.
    - **Output:** A multi-class segmentation mask (as a PNG image) of the same dimensions as the input. Each pixel in the mask will be color-coded corresponding to one of the 8 defined classes (e.g., background, Glacier, Ice Sheet, Rock Glacier, etc.).
- **Feature 2: Temporal Change Analysis (Next Step)**
    - **Input:** Two segmentation masks of the same geographical location, generated by the model from images taken on

different dates (e.g., a mask from 2015 and a mask from 2025).

- **Process:** A comparison script will perform a pixel-wise analysis of the two masks. It will count the number of pixels for each class in both masks and calculate the difference.
- **Output:** A quantitative report summarizing the change. Example output:
  - "Valley Glacier area decreased by 15.2 km².”
  - "Rock Glacier area increased by 4.5 km².”
  - "Overall ice cover changed by -10.7 km².”

5. Technical Stack

- **Language/Environment:** Python, Jupyter Notebooks
- **Core Libraries:** PyTorch, Torchvision, NumPy, Pillow, Matplotlib
- **Model Architecture:** U-Net (a specialized Convolutional Neural Network for segmentation)

6. Data Requirements

- **Training Data:** Roboflow Glacier Semantic Segmentation Dataset (pre-labeled with 8 classes).
- **Inference Data:** New optical satellite images of glaciers. For best results, these should be of similar resolution and style to the training data.

7. Success Metrics

- ✓ **Model Performance:** Achieve a validation pixel accuracy of over 90% on the test dataset.
- ✓ **Qualitative Assessment:** The model's predicted masks must be visually coherent and align well with the glacier boundaries seen in the input images upon manual inspection.

- ✓ **Tool Functionality:** The temporal change analysis script must correctly ingest two masks and produce an accurate, quantitative report of the changes between them.

8. Risks & Mitigation

Risk	Mitigation
Model fails to generalize to new, unseen satellite images from different sources.	Document the ideal input image characteristics. For a production tool, retrain on a more diverse dataset.
Computational limitations of a CPU make retraining or large-scale analysis slow.	For this project, accept the limitation. For future work, utilize cloud-based GPU services (e.g., Google Colab, AWS).