AI/ML-DRIVEN AUTOMATED FEATURE DETECTION AND CHANGE ANALYSIS

We propose creating a future-proof geospatial intelligence system that uses Artificial Intelligence (AI) and Machine Learning (ML) algorithms to detect, categorize, and monitor three primary environmental and infrastructural characteristics: glacial lakes, road networks, and urban drainage networks. The system integrates multi-source satellite imagery — optical, multispectral, and Synthetic Aperture Radar (SAR) — and applies state-of-the-art deep learning techniques to model spatial and temporal patterns. The principal goal is to computerize a process that is presently reliant on manual surveys, expert analysis, and time-consuming GIS processes, and speed it up, make it scalable, and geographically accessible.

This solution tackles climate change adaptation concerns, infrastructure mapping, and disaster preparedness. In the context of glacial lakes, increased global temperatures are speeding up glacier melting, particularly at higher altitudes and polar regions, resulting in the rapid development and growth of glacial lakes. The lakes are frequently dammed by unstable moraines and possess a high risk of Glacial Lake Outburst Floods (GLOFs), which can destroy downstream ecosystems and human settlements. Existing glacial lake monitoring methods are manual or semi-automated and weather, visibility, and area coverage restricted. Our solution employs SAR and multispectral imagery in combination with segmentation models such as U-Net and DeepLabV3+ to outline lake boundaries, calculate area, and evaluate volume change over time. Real-time monitoring supports early warning and planning for mitigation.

For road networks, especially in disaster or developing regions, digital maps are typically not present or unreliable. New roads emerge, others become blocked or destroyed by natural disasters, and manual updates of maps take time and are not regular. Our system automatically extracts road infrastructure from high-resolution optical imagery using convolutional neural networks trained on OpenStreetMap-labeled data. Change detection methods such as image differencing and Siamese networks support automatic map updating and highlighting new development. These results can be fed into government GIS systems to support logistics, transportation planning, and emergency evacuation planning.

Urban drainage systems are generally overlooked in conventional satellite analysis but are critical for flood prevention as well as sanitation. Unmapped or obsolete drainage systems are typical in most cities, especially informal settlements and rapidly expanding cities. Clogged or poor drainage systems are a major reason for urban flooding, especially during the monsoon season. Our framework employs high-resolution satellite imagery and pre-trained models to annotate discernible drainage networks, identify urban land cover changes, and mark obstructions or shifts in water flow paths.

The detections are overlaid on urban planning maps to assist municipalities to upgrade and maintain their drainage systems more effectively. Another major discriminator of our solution is its multi-source integration and temporal analysis ability. By integrating SAR data (e.g., Sentinel-1) with optical and multispectral sources (e.g., Sentinel-2, Landsat-8/9, MODIS), we mitigate common problems such as low visibility, cloudiness, and seasonal variability. Google Earth Engine (GEE) is a primary data access and satellite dataset preprocessing platform, and Rasterio and GDAL provide raster conversion locally when necessary. Preprocessed images are input into deep learning models constructed with TensorFlow and Py-Torch, and we train and fine-tune segmentation and classification algorithms.

For semantic segmentation, we employ established architectures such as U-Net and DeepLabV3+, and more recent transformer-based architectures such as Swin Transformer and Seg-Former for better accuracy and generalization for regions. Change detection is done using methods such as Change Vector Analysis (CVA) and bi-temporal Siamese networks to detect sudden as well as gradual changes in the landscape. For time-series forecasting and anomaly detection (e.g., forecasting sudden increases in lakes), we try using LSTM-based models.

We train our models using labeled data from trusted sources: ICIMOD and NASA's GLIMS for glacial lake, OpenStreetMap (OSM) for road networks, and hand-labeled urban drainage data using CVAT, Label-box, and QGIS. The labeled samples are fine-tuned for model weights and cross-validation of predictions in varied terrain and urban settings. To present these insights to the users, we are creating an interactive front-end using Stream-lit, Flask, or Django. Users can view maps, set their own bounding boxes, filter by time range or feature type, and export data layers for visualization in GIS software. We also employ Leaflet.js and Kepler.gl to present dynamic map interfaces, and Post-GIS and QGIS for advanced spatial queries and visualization. The entire platform is hosted using Docker containers and orchestrated by Kubernetes for scalability. Model inference is offered by Fast-API, and continuous integration and deployment (CI/CD) is managed using GitHub Actions and Docker-Hub.