

**Predictive Analytics Lab**

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**Land Change Detection**

**Abstract**

Land change detection is a critical task in understanding environmental transformations over time. This project leverages deep learning techniques, specifically a UNet-based segmentation model, to detect and quantify land-use changes by analyzing geospatial imagery. Using a dataset with labeled images and corresponding masks, the model is trained to perform pixel-level segmentation and identify changes in land cover over time. The system uses Focal Loss to address class imbalance and incorporates residual blocks for enhanced feature extraction. The results provide detailed visualizations of changes and quantitative measures of land transformation.

**Introduction**

Land change detection involves the comparison of geospatial images taken at different times to identify changes in land use and land cover. It is an essential task for environmental monitoring, urban planning, disaster management, and climate change studies. In this project, deep learning methods, particularly the UNet model, are utilized to detect, quantify, and visualize changes in land cover. The model is trained to perform pixel-level segmentation, where each pixel in the image corresponds to a specific land class. The overall objective is to provide accurate change detection between images taken at different times, aiding in the analysis of environmental transformations.

**Objective**

The primary objectives of this project are:

1. To develop a deep learning-based model for land change detection using a UNet architecture.
2. To preprocess geospatial data, including resizing images and converting masks to label maps for effective training.
3. To train the model on a labeled dataset and evaluate its performance in segmenting land features and detecting changes.
4. To implement a change detection workflow that compares segmentation results from different time points, quantifying land transformations.

**Literature Review**

Land change detection has traditionally been performed using remote sensing techniques, such as supervised classification methods, thresholding, and image differencing. However, these methods often struggle with the complexity of classifying land cover types and detecting subtle changes. The introduction of deep learning has significantly improved segmentation accuracy, particularly through convolutional neural networks (CNNs). The UNet architecture, initially designed for biomedical image segmentation, has gained popularity for its ability to capture spatial context at multiple scales, making it ideal for tasks such as land change detection.

Recent studies have explored the integration of residual connections within the UNet framework, which help preserve important features and enable more efficient training by mitigating the vanishing gradient problem. The use of Focal Loss, a loss function designed to address class imbalance, has also shown promise in improving model performance, especially when certain classes dominate the dataset.

**Methodology**

**Dataset and Preprocessing**

The dataset consists of geospatial images from two time points, each containing labeled land classes. The images are stored in separate directories for training, validation, and testing. Each image is associated with a corresponding mask, where each pixel represents a specific land cover type. The preprocessing steps are as follows:

* Images and masks are resized to 256×256 pixels for uniformity.
* Masks are converted from RGB color maps to label maps using a mapping defined in a CSV file (class\_dict.csv).
* The images are transformed to tensors and resized to the required dimensions.

**Model Architecture**

The model architecture is based on UNet, a convolutional neural network designed for semantic segmentation. The key features of the architecture are:

• Residual Blocks: These blocks, composed of convolutional layers, batch normalization, and LeakyReLU activation, are used in both the encoder and decoder paths to improve feature extraction and representation.

• Encoder-Decoder Design: The encoder progressively reduces spatial dimensions while increasing feature depth. The decoder upsamples the feature maps and uses skip connections to concatenate corresponding encoder outputs.

• Loss Function: The Focal Loss is employed to address class imbalance by focusing more on hard-to-classify pixels.

**Training**

The model is trained using the following hyperparameters:

* Learning rate: 0.001
* Batch size: 4
* Number of epochs: 50
* Optimizer: AdamW

The training process includes:

* Loading data using a data loader.
* Computing the loss using Focal Loss and performing backpropagation to update the model’s weights.
* Monitoring the training progress using the tqdm library for real-time visualization of loss and epoch progress.

**Change Detection Workflow**

After training the model, the following steps are performed:

1. Segmentation: The trained model generates predicted masks for "before" and "after" images, with each mask representing the predicted land classes.
2. Change Mask Generation: A binary comparison of the predicted masks is performed to identify pixels where changes have occurred.
3. Visualization: The changes are displayed as a binary mask, highlighting the areas of transformation between the two time points.
4. Quantification: The percentage of changed pixels is calculated to provide quantitative insights into the extent of land transformation.

**Conclusion**

The project successfully demonstrates the application of deep learning techniques, specifically a UNet-based model enhanced with residual blocks, for land change detection using geospatial imagery. The model achieved high accuracy in segmenting land features and detecting changes, with Focal Loss effectively addressing class imbalance. Future improvements could include incorporating more advanced architectures, such as transformers, for better feature representation. Additionally, extending the analysis to multi-temporal datasets and integrating cloud-based deployment could enable real-time monitoring of land changes. This system has the potential to be a valuable tool for environmental monitoring, urban planning, and disaster management.