Geospatial Analysis and Classification of Land Features Using Deep Learning

Batch A ,Group 8

Final Review

Faculty Guide: Mr. SajithVariyar VV
School Of AI

Team Members

Name	Roll Number
Suda Haripriya	CB.EN.U4AIE21067
Sykam Sumanjali	CB.EN.U4AIE21068
Hema Radhika Reddy	CB.EN.U4AIE21050
Likhitha Shree S	CB.EN.U4AIE21052

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Problem Statement

- Limited access to high-resolution satellite imagery restricts widespread vegetation monitoring, necessitating the development of methods that can effectively utilize freely available Google Earth data for ecological studies.
- Current classification techniques struggle to accurately identify mixed vegetation patterns, highlighting the need for robust deep learning approaches that can handle variations in both image quality and land cover complexity.

Introduction

- In the era of rapid environmental change and urban expansion, the ability to accurately monitor and classify vegetation is more critical than ever.
- Geospatial analysis has become an essential tool for understanding and managing land resources.
- This project aims to automate vegetation classification from Google Earth images using deep learning to enhance precision and detect subtle variations in vegetation cover, advancing geospatial analysis.

Objectives

- **Develop a Robust Classification Model:** Build a deep learning model capable of accurately categorizing vegetation, even across different zoom levels and mixed land cover types.
- **Enhance Geospatial Analysis:** Automate classification processes to improve efficiency and reduce the need for manual interpretation, enabling scalable monitoring.
- **Support Environmental Monitoring:** Provide a tool for tracking vegetation coverage, aiding in ecological, urban, and agricultural assessments.
- **Optimize for Real-World Application:** Fine-tune the model to handle varying resolutions and contexts for applicability in real-world geospatial analysis scenarios.

Literature Review: Geospatial Analysis Techniques

Table: Geospatial Analysis Techniques

Key Findings
• **Traditional vs. Advanced Techniques**: Evolution from traditional geospatial methods to deep learning techniques such as CNNs for feature extraction in land use and land cover (LULC) classification. • **Transfer Learning**: Highlighted as effective for improving model accuracy when datasets are limited, enabling better generalization across geospatial tasks.

Literature Review: Challenges in Dataset Quality and Labeling

Table: Challenges in Dataset Quality and Labeling

Key Findings
• **Dataset Limitations**: Lack of sufficient labeled data hinders model accuracy. Solutions include data augmentation and semi-supervised learning, though effectiveness varies with dataset quality. • **Resolution and Zoom Level Variations**: Studies show model performance declines with varying image resolutions and zoom levels, identifying a gap in robustness for real-world applications with non-uniform images.

Literature Review: Modeling Strategies for LULC Classification

Table: Modeling Strategies for LULC Classification

Key Findings
• **Deep Learning Models**: CNNs U-Net architectures are used, with U-Net's encoder-decoder structure allowing for precise pixel-wise segmentation, beneficial in dense urban and mixed land areas. • **GIS Data Integration**: Integrating GIS data with deep learning models enhances accuracy by adding spatial context, which is essential for detailed geospatial mapping. • **Real-Time Solutions**: Developing models for real-time land classification faces challenges when adapting from controlled test environments to real-world settings.

Research Gap

- **Custom Dataset Exploration:** There is a notable lack of research applying deep learning models to custom datasets, especially those sourced from platforms like Google Earth.
- **Handling Image Variability:** Existing studies often assume consistent image resolutions, neglecting the impact of varying zoom levels and image quality on model performance.
- **Image Scale Management:** Existing models struggle to manage changes in image scale, affecting vegetation classification accuracy.
- **Real-World Testing:** Many deep learning models are often tested in controlled settings, overlooking their adaptability to real-world scenarios where satellite imagery can significantly differ in content and quality,

Methodology

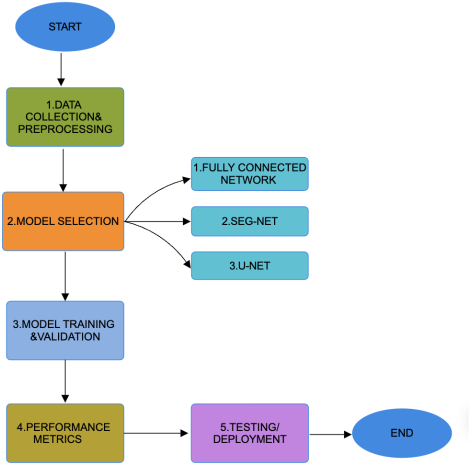


Figure: Flowchart of Methodology

Data Collection and Preprocessing

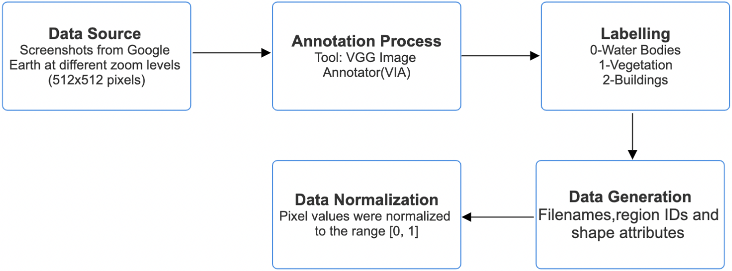


Figure: Flowchart of Data Collection

Data Collection and Preprocessing

- **Annotation Process:** Manual labeling using VGG Image Annotator (VIA), categorizing land features into three classes: Waterbodies (0), Vegetation (1), and Buildings (2).
- **CSV Compilation:** Created a unified dataset with filenames, region IDs, and shape attributes across different zoom levels for detailed analysis.
- **Normalization and Preprocessing:** Normalized pixel values to [0, 1] to ensure consistent input for the neural network.

	Name
1	Vegetation

Implementation (U-Net)

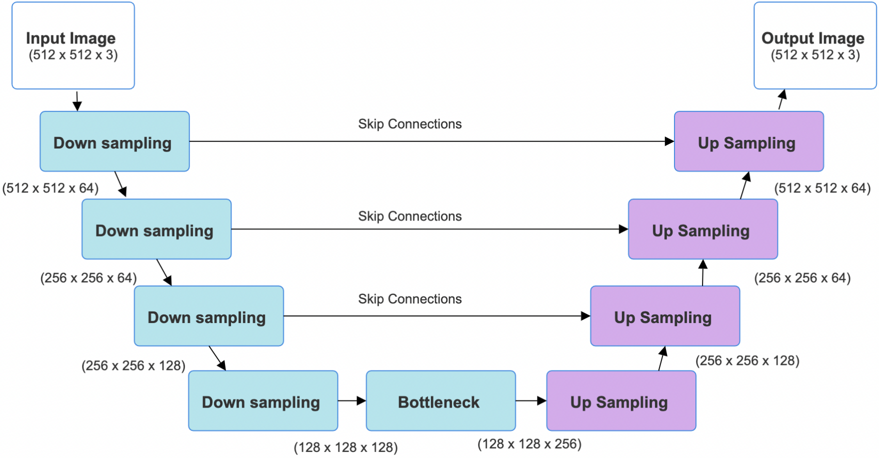


Figure: Flowchart of U-Net Methodology

Implementation of U-Net

- It consists of an encoder-decoder structure with skip connections, allowing it to capture both low-level and high-level features efficiently.
- The encoder extracts features from the input image, while the decoder reconstructs the output segmentation map, and the skip connections help retain spatial information lost during downsampling.
- It has proven to perform well even with relatively small datasets, making it a popular choice for image segmentation tasks.
- It can handle complex pixel-level predictions, which is critical when distinguishing between closely related features.

Implementation (SegNet)

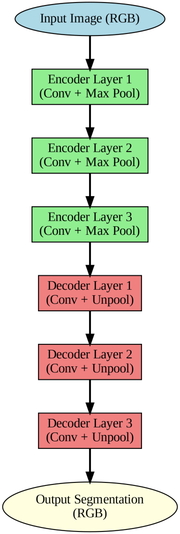


Figure: Flowchart of Seg-Net Methodology

Implementation of Segnet

- SegNet is a deep learning model designed for precise per-pixel image labeling, ideal for detailed segmentation tasks.
- It employs an encoder-decoder architecture where it uses an encoder to downsample and a decoder to upscale images, classifying each pixel effectively.
- SegNet's pixel-level accuracy enables accurate classification of fine-grained land cover features in satellite and aerial imagery.
- SegNet is more memory and computationally efficient compared to other segmentation models, as it only stores max-pooling indices during encoding.

Implementation (FCN)

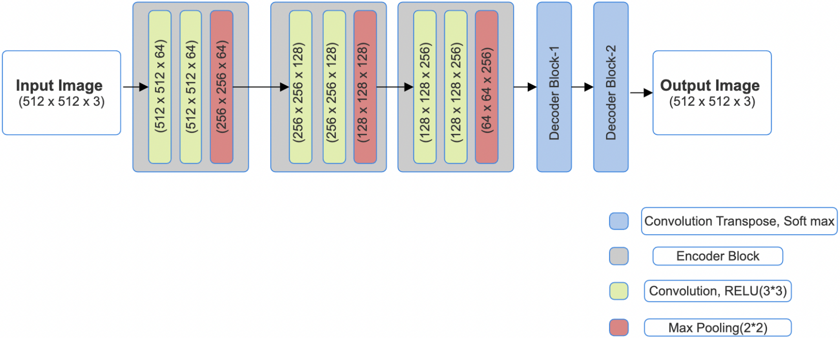
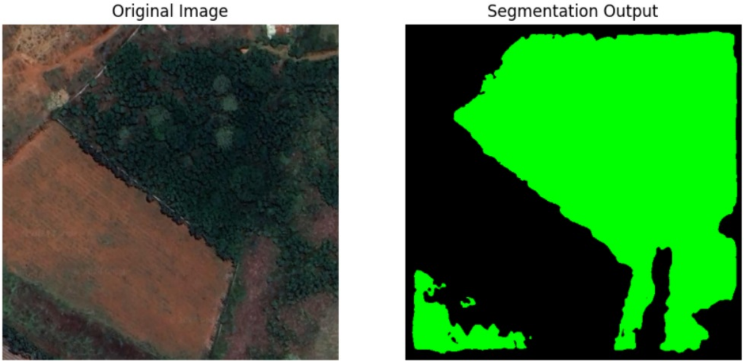


Figure: Flowchart of FCN Methodology

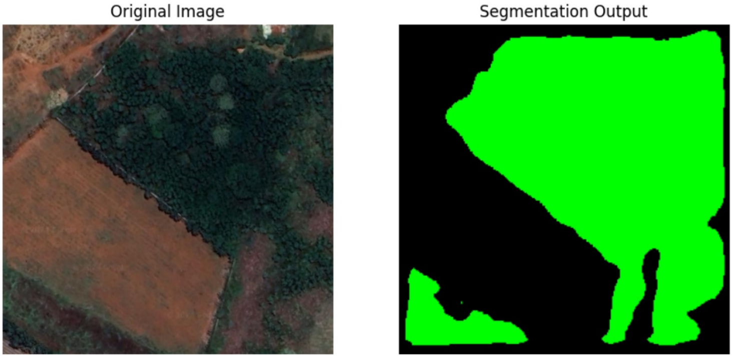
Implementation of FCN

- Unlike traditional CNNs, FCNs replace fully connected layers with convolutional layers, enabling per-pixel label predictions which is essential for tasks like semantic segmentation.
- Maintain spatial dimensions to identify distinct regions across an image, ideal for semantic segmentation.
- Well-suited for segmenting features like water bodies, vegetation, and buildings in satellite imagery.
- Its architecture allows for efficient, detailed segmentation, helping to separate and label multiple classes accurately in satellite or aerial imagery.

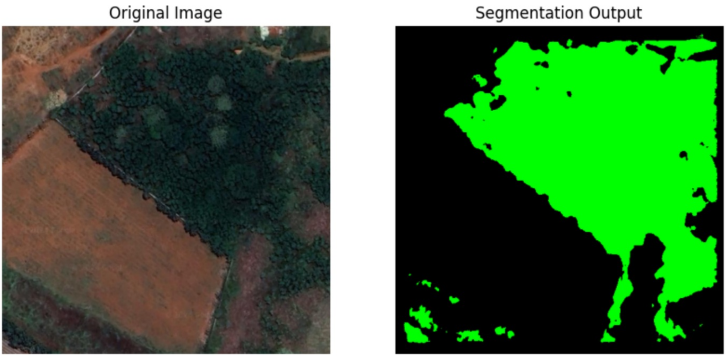
Results of U-Net



Results of Segnet



Results of FCN



Comparison of Performance Metrics

Metric	Score (U-Net)	Score (SegNet)	Score (FCN)
IoU (Jaccard Score)	0.550744	0.290616	0.587516
Dice Coefficient	0.606393	0.402930	0.612930
Pixel Accuracy	0.632974	0.604537	0.659437
F1 Score	0.595393	0.402930	0.602930

Table: Performance Metrics Comparison of U-Net,SegNet,FCN

Challenges and Limitations

- Handling Varied Zoom Levels: The images were taken at different zoom levels, making it difficult to maintain uniformity in segmentation.
- Class Imbalance: There is an imbalance in the number of samples for waterbodies, vegetation, and buildings, affecting model training.
- Time-Consuming Manual Annotation: Annotating each image manually using the VGG Image Annotator was labor-intensive, especially for large datasets.

Conclusion

- This project demonstrated the successful use of deep learning models, specifically Fully Convolutional Networks (FCN) and U-Net, for classifying land features from Google Earth images.
- By using Google Earth images instead of traditional satellite data, we improved accessibility to high-resolution geospatial analysis, which broadens the applicability of such methods for research and practical use.
- Our approach addressed common issues in traditional land classification, such as varying image resolutions and mixed land cover types, by leveraging multi-zoom images and enhancing feature details.
- This framework highlights the scalability of deep learning for geospatial tasks, with future opportunities to integrate multispectral data and optimize model architectures for real-time applications in larger regions.

Future Work

- Developing a Web or Mobile Application: Build a user-friendly application where users can input latitude and longitude coordinates, allowing the app to capture screenshots from Google Earth automatically, process the image, and provide classified segmentation.
- User Interaction: Upload existing images and receive land feature classification.
- Potential Users: Urban planners, environmental researchers, and GIS professionals.

References

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