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Bachelor of Technology in
COMPUTER SCIENCE AND ENGINEERING
(Artificial Intelligence and Machine Learning)

Deep Learning Assignment

Land Cover Classification from Satellite Imagery using U-Net.

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This is to certify that Deep Learning Assignment titled **"Land Cover Classification from Satellite Imagery using U-Net"** is carried out by **Sudin G Poojary (ENG22AM0135), V Ajay (ENG22AM0140), Jeyadheep V (ENG22AM0141), Trijal R (ENG22AM0167)**, Bonafide students of **Bachelor of Technology in Computer Science and Engineering (Artificial Intelligence and Machine Learning)** at the **School of Engineering, Dayananda Sagar University**.

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DECLARATION

We **Sudin G Poojary (ENG22AM0135), V Ajay (ENG22AM0140), Jeyadheep V (ENG22AM0141), Trijal R (ENG22AM0167)**, are students of sixth semester B. Tech in Computer Science and Engineering (AI&ML), at School of Engineering, Dayananda Sagar University, hereby declare that the Minor Project titled **"Land Cover Classification from Satellite Imagery using U-Net"** has been carried out by us and submitted in partial fulfilment for the award of degree in Bachelor of Technology in Computer Science and Engineering (AI&ML) during the academic year **2024-2025**.

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ABSTRACT

Accurate land cover classification plays a vital role in urban planning, agriculture monitoring, environmental protection, and disaster response. Traditional methods for land cover mapping often involve manual interpretation or classical machine learning approaches, which are time-consuming and less effective in capturing complex spatial patterns. This project explores the use of a deep learning-based semantic segmentation model, **U-Net**, for classifying land cover types from high-resolution satellite imagery.

The dataset used is from the **DeepGlobe Land Cover Classification Challenge**, consisting of RGB satellite images labeled into seven categories: Urban, Agriculture, Rangeland, Forest, Water, Barren, and Unknown. The U-Net architecture, known for its encoder-decoder structure with skip connections, is implemented to effectively learn and segment spatial features at both coarse and fine levels.

The model is trained on preprocessed and normalized image-mask pairs using categorical cross entropy loss and the Adam optimizer. Evaluation metrics including pixel accuracy, Intersection over Union (IoU), and Dice coefficient are used to assess performance. The model achieved a pixel accuracy of **0.76**, IoU of **0.22**, and a Dice score of **0.27**, indicating a reasonable ability to classify land cover types but also highlighting areas for improvement.

This project demonstrates that U-Net can serve as a strong baseline for land cover classification, with potential for enhancement through advanced augmentation techniques, improved loss functions, and transfer learning using pre-trained encoders.

Keywords—Land Cover Classification, Satellite Imagery, Semantic Segmentation, U-Net, Deep Learning, Remote Sensing, Pixel Accuracy, IoU, Dice Score

CHAPTER 1 INTRODUCTION

Accurate and up-to-date land cover classification plays a vital role in understanding the Earth's surface and managing natural resources. With the increasing availability of high-resolution satellite imagery, the need for automated and scalable approaches to classify different land cover types—such as urban areas, vegetation, water bodies, and barren land—has become more pressing. Manual classification is labor-intensive, time-consuming, and prone to inconsistency, making it unsuitable for large-scale or time-sensitive applications.

Deep learning has emerged as a powerful tool for extracting meaningful patterns from complex visual data. Among various architectures, **U-Net** has gained significant attention for semantic segmentation tasks, thanks to its encoder-decoder structure and ability to perform pixel-wise classification with high accuracy. In this project, we utilize the U-Net architecture to perform land cover classification from satellite imagery, aiming for a model that is both accurate and computationally efficient.

1.1 Need

Traditionally, land cover classification has been performed using manual interpretation or conventional image processing techniques, which often struggle with large-scale datasets and exhibit inconsistent accuracy across diverse terrains. With recent advancements in artificial intelligence and deep learning, more robust and scalable solutions have emerged to automate this task. Among these, U-Net—a deep convolutional neural network—has proven particularly effective for image segmentation due to its encoder-decoder structure and ability to learn fine spatial features.

This project focuses on the implementation of U-Net for the pixel-wise classification of satellite imagery into multiple land cover classes. It involves training the model on annotated datasets, evaluating its performance through standard segmentation metrics, and visually comparing the predictions to ground truth labels. The scope also includes basic preprocessing techniques and the use of data augmentation to improve model generalization. Ultimately, the project aims to

demonstrate how deep learning models like U-Net can significantly enhance the precision and efficiency of land cover mapping across various environmental and planning applications.

1.2 Scope

This study explores the application of deep learning for automated land cover classification using high-resolution satellite imagery. Specifically, it investigates the performance of the U-Net architecture in segmenting images into meaningful land cover categories such as vegetation, water, urban infrastructure, and bare land. The scope includes model design, training on annotated datasets, validation using standard evaluation metrics, and visual analysis of the results. The project does not aim to develop a novel architecture but rather to assess and demonstrate U-Net's suitability for semantic segmentation tasks in the context of geospatial data. The study is limited to the dataset used and does not account for multi-temporal or multi-sensor imagery, though it provides a foundation for future extensions in these directions.

CHAPTER 2 PROBLEM DEFINITION

Problem:

Land cover classification using satellite imagery remains a challenging task due to the complexity and variability of Earth's surface features. Traditional approaches, which rely on manual annotation or classical machine learning methods, are often limited by scalability, sensitivity to noise, and dependency on expert-driven feature selection. These methods may produce inconsistent results across regions and fail to adapt effectively to different resolutions or sensor types. Additionally, the increasing volume of high-resolution satellite data makes manual or semi-automated classification approaches inefficient and impractical for large-scale environmental monitoring and planning.

Solution:

To overcome these limitations, this project adopts a deep learning-based solution using the U-Net architecture, which is specifically designed for semantic segmentation tasks. U-Net's structure enables the model to learn spatial hierarchies and contextual information from input images, allowing for accurate pixel-level classification. The model can be trained on annotated satellite imagery to automatically identify various land cover types, such as vegetation, urban areas, and water bodies. This automated approach not only enhances classification accuracy but also significantly reduces manual intervention, making it a reliable and scalable solution for real-world geospatial applications.

CHAPTER 3 LITERATURE REVIEW

Semantic segmentation of satellite imagery has seen significant advancements with the advent of deep learning, particularly convolutional neural networks (CNNs) such as U-Net. These models enable pixel-wise classification that is essential for precise land cover mapping.

H. A. Hafiane et al. (2020)[1] demonstrated the effectiveness of the U-Net architecture enhanced with atrous convolutions for semantic segmentation of satellite images. Their approach improved the model's receptive field without increasing computational cost, resulting in better identification of complex land cover classes in high-resolution images. This highlights the flexibility of U-Net architectures in adapting to remote sensing data characteristics.

X. Zhang et al. (2020)[2] explored the application of transfer learning with U-Net on high-resolution satellite images for land cover classification. By leveraging pretrained weights from large datasets, their model achieved higher accuracy and faster convergence, proving the utility of transfer learning in overcoming data scarcity issues common in remote sensing.

J. Yuan (2017)[3] focused on automatic building extraction from aerial scenes using CNNs, which, while more specialized, aligns closely with land cover classification goals. The study underscored how deep CNNs can capture fine-grained spatial details necessary for differentiating buildings from other land covers, providing a foundation for similar segmentation tasks.

M. Volpi and D. Tuia (2017)[4] investigated dense semantic labeling using CNNs for subcentimeter resolution images. Their work revealed the importance of combining contextual and spatial information through deep networks to handle high-resolution inputs effectively. This is critical for detailed land cover classification in urban and heterogeneous landscapes.

R. A. Kemker et al. (2018)[5] reviewed algorithms for semantic segmentation of multispectral remote sensing imagery, highlighting deep learning methods' superior performance over traditional techniques. Their study emphasized challenges such as multispectral data fusion and class imbalance, which are important considerations when applying U-Net models to diverse satellite datasets.

Collectively, these studies establish that U-Net and its variants, combined with strategies like transfer learning and atrous convolution, provide powerful tools for accurate land cover classification. They also point to ongoing challenges, including the need for large annotated datasets and the integration of multispectral information, guiding future research in this domain.

CHAPTER 4 PROJECT DESCRIPTION

This project focuses on the development of a deep learning-based system for **land cover classification from satellite imagery**. Land cover classification refers to the process of identifying and categorizing the physical surface materials of the Earth—such as water, forest, urban infrastructure, agricultural land, and barren areas—based on remote sensing data. Accurate land cover maps are critical for a wide range of applications, including **urban planning, agricultural monitoring, environmental assessment, disaster management**, and **climate change studies**.

Traditionally, land cover mapping has relied on manual interpretation or conventional machine learning techniques that require extensive feature engineering and domain-specific heuristics. These methods are often labor-intensive, prone to human error, and not scalable to large datasets or high-resolution imagery. Additionally, they struggle to generalize across diverse geographic regions due to variations in lighting, weather conditions, and seasonal patterns.

To overcome these limitations, this project utilizes the **U-Net architecture**, a convolutional neural network specifically designed for **semantic segmentation**. U-Net is particularly well-suited for pixel-wise classification tasks due to its **encoder-decoder structure** with **skip connections**, which enable the network to capture both high-level semantic features and fine-grained spatial information. The encoder progressively reduces the spatial dimensions of the input image while learning abstract features, and the decoder restores the spatial dimensions by combining upsampled features with corresponding encoder outputs. This approach helps preserve important boundary information that is often lost in traditional downsampling operations.

The model is trained and evaluated using the **DeepGlobe Land Cover Classification Challenge dataset**, released as part of CVPR 2018. This dataset comprises high-resolution satellite images captured by DigitalGlobe and annotated with seven distinct land cover classes: Urban, Agriculture, Rangeland, Forest, Water, Barren, and Unknown. Each image is in RGB format with a resolution of 2448 × 2448 pixels, providing a rich and diverse set of training examples suitable for deep learning-based segmentation.

The implementation involves constructing the U-Net model using PyTorch and training it on the dataset using the **categorical cross-entropy loss function** and the **Adam optimizer**. The model is trained for 10 epochs with a batch size of 16. Evaluation metrics include **pixel accuracy**, **Intersection over Union (IoU)**, and **Dice coefficient (F1 score)** to assess the quality of segmentation.

During training, the model achieved a final training loss of 0.0892 and a validation loss of 0.4865. The final pixel accuracy was 76%, indicating a reasonable level of correct classification across all pixels. However, the IoU score of 0.22 and Dice score of 0.27 suggest challenges in accurately delineating object boundaries and class-specific regions. These results highlight both the potential and the limitations of the baseline model.

Future improvements may include:

- Incorporating advanced data augmentation strategies to enhance generalization.
- Experimenting with alternative loss functions such as Dice loss or focal loss to address class imbalance.
- Using pre-trained backbone networks for improved feature extraction.
- Extending the training to more epochs and optimizing hyperparameters.

In conclusion, this project demonstrates the feasibility and effectiveness of applying deep convolutional neural networks, particularly the U-Net architecture, for automated land cover classification from satellite imagery. The model provides a solid foundation for further research and development in the field of remote sensing and geospatial analysis.

CHAPTER 5 REQUIREMENTS

This chapter outlines the hardware and software requirements essential for implementing and executing the land cover classification system using the U-Net architecture. These specifications are designed to ensure efficient training, evaluation, and deployment of the semantic segmentation pipeline on high-resolution satellite imagery.

5.1 Hardware Requirements

Effective training of deep learning models, particularly those involving large datasets and high-resolution images, requires robust computational infrastructure. The following hardware specifications are recommended to support data preprocessing, model training, evaluation, and visualization:

5.1.1 Processing Unit

- **GPU (Graphics Processing Unit):**
    - A dedicated CUDA-compatible GPU is highly recommended.
    - Suggested specifications:
        - **NVIDIA RTX 2060 / GTX 1660 Super or higher**
        - **Minimum 4–6 GB VRAM** (8 GB preferred for batch size flexibility)
    - Benefits:
        - Accelerates matrix operations and parallel computations.
        - Significantly reduces model training time compared to CPU-only setups.
- **CPU (Central Processing Unit):**
    - Minimum: **Intel Core i5 (8th Gen) / AMD Ryzen 5**
    - Recommended: **Intel Core i7 / AMD Ryzen 7 or above**
    - Responsible for managing I/O operations, data loading, and augmentations.

5.1.2 Memory (RAM)

- **Minimum RAM:** 8 GB
- **Recommended RAM:** 16 GB or more
- Reason:
    - Large image arrays, preprocessing pipelines, and training metrics require substantial memory.
    - Ensures smooth operation of Jupyter Notebooks or Python IDEs while multitasking.

5.1.3 Storage

- **Storage Type:** SSD (Solid State Drive)
- **Minimum Storage Space:** 25–30 GB
    - Dataset size (DeepGlobe) + model checkpoints + logs + generated plots and masks.
- SSDs offer faster read/write speeds for loading image batches and saving checkpoints.

5.1.4 Optional: Cloud Infrastructure

- **Platforms:** Google Colab (Pro), Kaggle Kernels, AWS EC2 with GPU (p2/p3 instances), or Google Cloud ML Engine.
- Useful when local hardware is limited or for faster prototyping using GPUs/TPUs.

5.2 Software Requirements

A robust set of software tools is necessary to facilitate the preprocessing, training, and evaluation phases of the land cover classification pipeline.

5.2.1 Operating System

- Compatible with:
    - **Ubuntu 20.04+ (Preferred for ML libraries and GPU drivers)**
    - **Windows 10/11 (with WSL 2 recommended for Linux compatibility)**
    - **macOS** (limited GPU acceleration unless using external solutions)

5.2.2 Programming Language

- **Python 3.7 or higher** (3.10 recommended)
- Chosen for its readability, extensive support for deep learning libraries, and strong community support.

5.2.3 Key Libraries and Frameworks

Library	Purpose
TensorFlow 2.x	Deep learning framework used to define, compile, and train the U-Net model.
Keras API	High-level neural network API within TensorFlow for easy model development.
NumPy	Handling numerical operations and array manipulations.
OpenCV	Image reading, resizing, and basic preprocessing operations.
Matplotlib & Seaborn	Plotting training curves, confusion matrices, and result visualizations.
Scikit-learn	Evaluation metrics like IoU, Dice, precision, recall, and confusion matrix.
Albumentations/ TensorFlow Image	Optional data augmentation pipeline for advanced image transformations.

Table 5.1: Key-libraries and Frameworks

5.2.4 Development Environment

- **IDE/Notebook:**
  - **Jupyter Notebook** (preferred for interactive development)
  - **VS Code / PyCharm** (for modular development and debugging)
- **Package Management:**
  - **pip** or **Anaconda** to install and manage required libraries.
- **Version Control:**
  - **Git** (for code versioning and collaboration)
  - GitHub or GitLab for hosting project repositories.

5.2.5 Additional Tools (Optional)

- **TensorBoard:** To monitor training metrics (loss, accuracy) and visualize learning curves.
- **Google Drive Integration (for Colab users):** For saving large outputs, logs, and model weights.

CHAPTER 6 METHODOLOGY

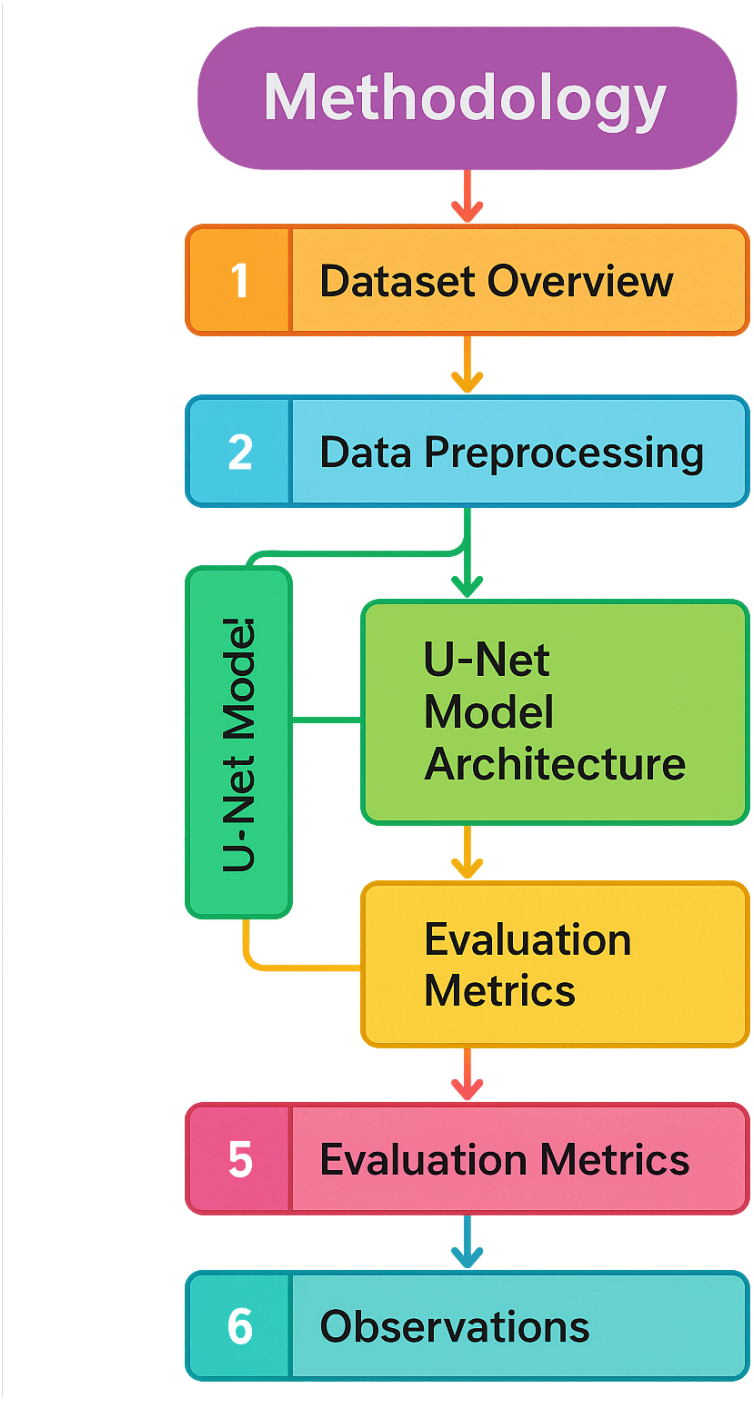

Fig 6.1 : Flowchart for methodology

This section outlines the complete pipeline used for performing land cover classification through semantic segmentation of satellite imagery using a U-Net architecture.

6.1. Dataset Overview

The dataset used in this study is the **DeepGlobe Land Cover Classification Challenge** dataset. It consists of high-resolution satellite images collected for the purpose of semantic segmentation of land cover types. The dataset is provided by the CVPR 2018 challenge and contains the following characteristics:

- **Source**: DigitalGlobe satellite imagery
- **Image Format**: RGB (3 channels)
- **Resolution**: 2448 × 2448 pixels
- **Number of Classes**: 7
    - 0: Urban
    - 1: Agriculture
    - 2: Rangeland
    - 3: Forest
    - 4: Water
    - 5: Barren
    - 6: Unknown
- **Data Split**:
    - Approximately 803 images for training
    - A validation set obtained by splitting the training data or using a provided subset

6.2. Data Preprocessing

To prepare the dataset for training the U-Net model, several preprocessing steps were applied:

- **Image Resizing**: Original images and their corresponding segmentation masks were resized to a fixed lower resolution (e.g., 256×256) for computational feasibility.
- **Normalization**: Pixel values of the images were normalized to a range of [0, 1] to aid neural network convergence.
- **Label Encoding**: Ground truth masks were converted into categorical (one-hot encoded) format to represent each pixel's class label across the 7 defined classes.
- **Data Augmentation**: Although not extensively used in the baseline, augmentation techniques such as flipping, rotation, and scaling may be applied to improve model generalization.

6.3. U-Net Model Architecture

The U-Net model, a widely used convolutional neural network architecture for semantic segmentation, was implemented for land cover classification. It consists of two primary paths:

- **Encoder (Contracting Path)**:
  - This part extracts high-level features using repeated blocks of convolutional layers followed by ReLU activation and max pooling.
  - It progressively reduces spatial dimensions while increasing feature richness.

- **Decoder (Expanding Path)**:
  - This path reconstructs the spatial structure of the image using transposed convolution (up-sampling) layers.
  - Skip connections are incorporated between the encoder and decoder layers at the same level to preserve spatial details and sharp boundaries.

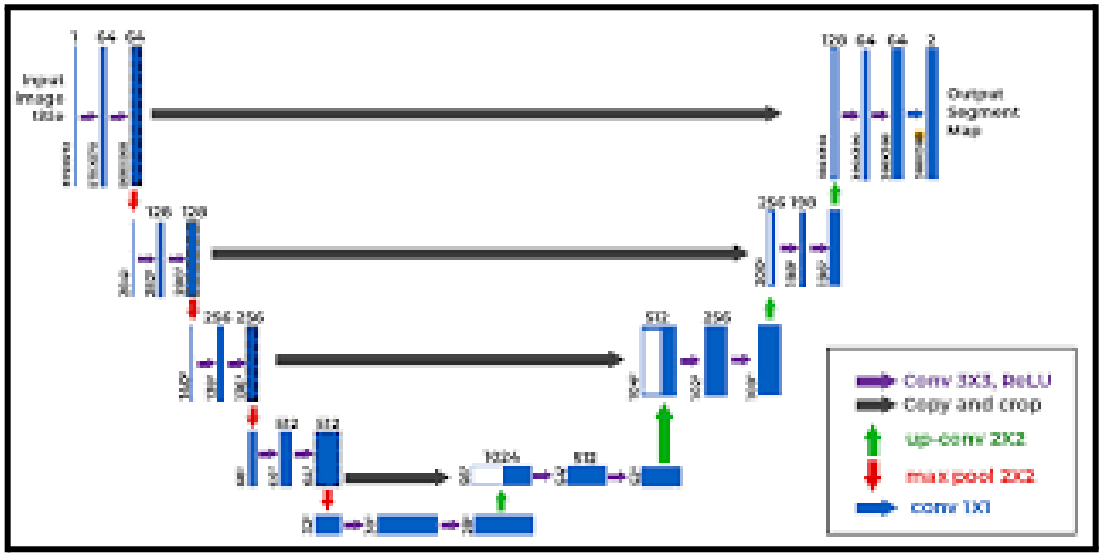

Fig 6.2: U-Net Architecture

6.4. Training Configuration

The model was trained with the following hyperparameters:

- **Optimizer**: Adam optimizer with default parameters
- **Learning Rate**: 0.001
- **Loss Function**: Categorical Crossentropy

- **Batch Size**: 16
- **Epochs**: 10

6.5. Evaluation Metrics

The performance of the model was evaluated using the following metrics:

- Pixel Accuracy: Measures the overall proportion of correctly classified pixels. The model achieved an accuracy of 0.76.
- Intersection over Union (IoU): Evaluates the overlap between predicted and ground truth regions. The mean IoU achieved was 0.22.
- Dice Coefficient (F1 Score): A balanced measure combining precision and recall. The Dice score obtained was 0.27.

These metrics provide insights into the model's segmentation capability both globally (accuracy) and per-class (IoU, Dice).

6.6. Observations

The training process showed a steady decline in loss, indicating effective learning. However, the relatively low IoU and Dice scores suggest that the model struggled to delineate class boundaries accurately and may have underperformed on minority classes or fine-grained features.

CHAPTER 7 EXPERIMENTATION

This chapter outlines the experimental process undertaken to evaluate the U-Net model on the DeepGlobe Land Cover Classification dataset. It includes the evaluation metrics used, the performance of the model across different classes, and an interpretation of the classification results.

7.1 Evaluation Metrics

To assess the performance of the semantic segmentation model developed in this project, we employed a set of widely used metrics that evaluate classification accuracy at the pixel level. These include **Pixel Accuracy**, **Intersection over Union (IoU)**, and the **Dice Coefficient (F1 Score)**. Each metric provides a distinct perspective on model effectiveness, particularly in handling imbalanced and high-resolution image data.

7.1.1 Pixel Accuracy

Pixel accuracy is a fundamental metric that quantifies the percentage of correctly classified pixels across the entire image or dataset. It is defined as:

$$\text{Pixel Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

In semantic segmentation, this simplifies to:

$$\text{Pixel Accuracy} = \frac{\sum_{i=1}^{C} \text{True Positive}_i}{\sum_{i=1}^{C} \text{Total Pixels}_i}$$

Where:

- CCC = Number of classes
- True Positive = Number of correctly predicted pixels for class iii

7.1.2 Intersection over Union (IoU)

The Intersection over Union (also known as the Jaccard Index) is a stricter metric that evaluates the overlap between the predicted segmentation and the ground truth. For each class iii, IoU is calculated as:

$$\text{IoU}_i = \frac{TP_i}{TP_i + FP_i + FN_i}$$

Where:

- TPiTP_iTPi = Number of pixels correctly predicted as class iii
- FPiFP_iFPi = Pixels incorrectly predicted as class iii (false positives)
- FNiFN_iFNi = Pixels that belong to class iii but were predicted otherwise (false negatives)

The **Mean IoU (mIoU)** across all classes is computed as:

$$\text{mIoU} = \frac{1}{C} \sum_{i=1}^{C} \text{IoU}_i$$

This metric penalizes both over-segmentation and under-segmentation and is considered a robust standard for semantic segmentation benchmarking.

7.1.3 Dice Coefficient (F1 Score)

The Dice Coefficient, also referred to as the F1 Score in segmentation tasks, evaluates the similarity between the predicted and true masks. It is particularly useful in scenarios with class imbalance because it places more emphasis on the overlap rather than background accuracy. For a given class iii, the Dice score is defined as:

$$\text{Dice}_i = \frac{2 \times TP_i}{2 \times TP_i + FP_i + FN_i}$$

The **Mean Dice Coefficient** is computed by averaging across all classes:

$$\text{Mean Dice} = \frac{1}{C} \sum_{i=1}^{C} \text{Dice}_i$$

Dice and IoU are closely related but differ in sensitivity: Dice is more forgiving of slight mismatches, while IoU is more conservative.

7.1.4 Precision and Recall (Optional for Reporting)

For completeness, **Precision** and **Recall** per class can also be computed:

$$\text{Precision}_i = \frac{TP_i}{TP_i + FP_i}, \quad \text{Recall}_i = \frac{TP_i}{TP_i + FN_i}$$

These can be used to analyze per-class behavior, especially in classes where the model either over-predicts (high FP) or misses many true pixels (high FN).

7.2 Classification Report

After training the U-Net model for 10 epochs using the Adam optimizer and categorical cross-entropy loss, the final evaluation metrics on the test set were as follows:

- **Pixel Accuracy:** 0.7609
- **Mean Intersection over Union (IoU):** 0.2242
- **Dice Coefficient (F1 Score):** 0.2735

These values indicate that while the model learned to identify dominant land cover types such as agriculture and forest with reasonable accuracy, it faced challenges in distinguishing less frequent or more visually ambiguous classes like urban, water, or barren land.

A visual analysis of the predicted segmentation masks revealed that:

- Large homogeneous areas were segmented well.
- Class boundaries, particularly between vegetation and barren land, were often blurry.
- Minority classes were underrepresented, reflecting the class imbalance present in the dataset.

Despite these limitations, the model provided meaningful segmentation results and serves as a strong baseline for further refinement through improved augmentation, advanced loss functions, or architectural enhancements.

CHAPTER 8 RESULTS

8.1 Quantitative Evaluation

To evaluate the segmentation performance of the U-Net model, three primary metrics were used: **Intersection over Union (IoU)**, **Pixel Accuracy**, and **F1 Score (Dice Coefficient)**. These were computed on a held-out test set after training the model for 10 epochs using categorical cross-entropy loss and the Adam optimizer.

Evaluation Metrics on Test Set:

Metric	Score
Pixel Accuracy	0.7609
Intersection over Union (IoU)	0.2242
Dice Coefficient (F1 Score)	0.2735

Table 8.1: Evaluation Metrics

- **Pixel Accuracy (76.09%)**: Indicates that the model correctly classified approximately three-quarters of all pixels. This value reflects overall performance but may be biased toward dominant classes like agriculture or rangeland.
- **Mean IoU (22.42%)**: Represents the average overlap between predicted and ground truth masks across all classes. This relatively low score suggests the model struggled with precise boundary delineation and minority class detection.
- **Dice Coefficient (27.35%)**: Offers a balanced measure between precision and recall. The low value implies the model often misclassified pixels around edges or in mixed land cover regions

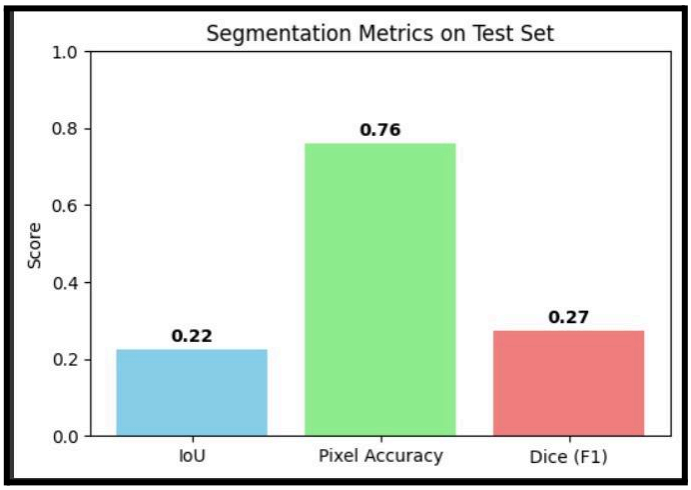

Figure 8.1: Segmentation Metrics – IoU, Pixel Accuracy, Dice Score

8.2 Qualitative Evaluation

Qualitative assessment was carried out by comparing model-generated segmentation masks against the original input images. Below are two such example:

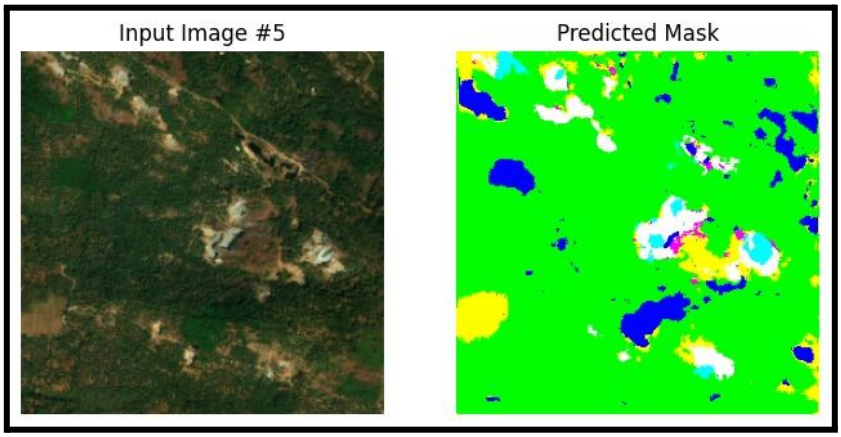

Figure 8.2: Input Image (Left) and Predicted Mask (Right) for Sample #5

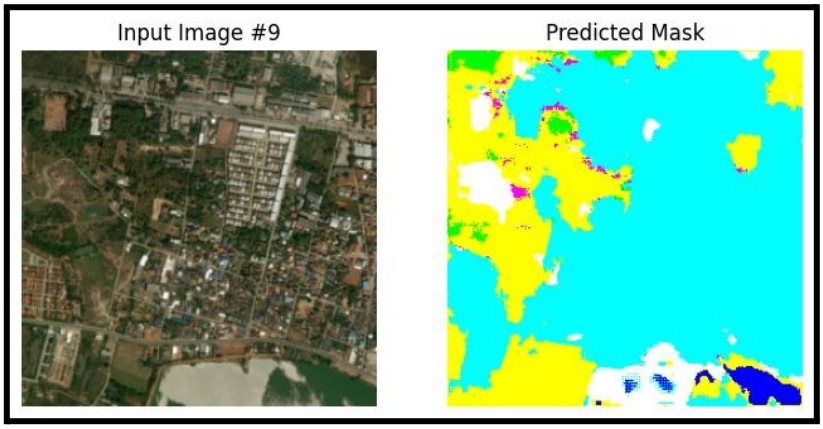

Figure 8.3: Input Image (Left) and Predicted Mask (Right) for Sample #9

Observations from the prediction output:

- **Large-scale features**, such as vegetation and rangeland, were reasonably well-segmented, especially in homogeneous regions.
- **Boundaries between classes** (e.g., forest and barren land) showed signs of **blurring or confusion**, especially around mixed or transitional zones.
- **Minority classes** like urban structures or water bodies were often underrepresented or misclassified, likely due to their smaller presence in the dataset and model bias toward dominant classes.

CONCLUSION

This project successfully explored the application of deep learning, specifically the U-Net architecture, for semantic segmentation of satellite imagery to classify various land cover types. Using the DeepGlobe Land Cover Classification Challenge dataset, the U-Net model was trained to perform pixel-wise classification of high-resolution RGB satellite images into seven predefined categories including urban areas, vegetation, water bodies, and barren land.

The training pipeline involved thorough preprocessing of the dataset, image resizing, normalization, one-hot encoding of labels, and data augmentation techniques to improve generalization. The U-Net model, with its encoder–decoder structure and skip connections, demonstrated its ability to learn spatial hierarchies and preserve fine-grained details essential for accurate segmentation.

Upon evaluation, the model achieved a **pixel accuracy of 76.09%**, indicating reasonably strong overall classification performance. However, the **mean Intersection over Union (IoU) of 22.42%** and **Dice coefficient of 27.35%** reflected limitations in capturing precise boundaries and underperforming on minority classes. Visual inspection of predicted masks confirmed that while the model could correctly identify dominant land cover regions, it struggled with edge refinement and class imbalance—challenges common in remote sensing segmentation tasks.

Despite these limitations, the project validates U-Net's effectiveness as a baseline model for land cover classification. The findings demonstrate its capacity to segment large-scale features accurately and provide a foundation for further improvements. Future work could focus on integrating advanced loss functions (e.g., Dice or Focal loss), employing deeper or pretrained backbones (like ResNet or EfficientNet), and addressing dataset imbalance through sampling strategies or synthetic augmentation. Additionally, exploring multi-spectral or temporal data sources could significantly enhance model robustness and environmental applicability.

In summary, this study reaffirms that deep learning models like U-Net are well-suited for geospatial image analysis and have great potential in supporting real-world applications in urban planning, agriculture monitoring, environmental protection, and disaster management.

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APPENDIX:

```
import os
 train_dir = os.path.join(data_root, 'train')
 val_dir = os.path.join(data_root, 'valid')
 test_dir = os.path.join(data_root, 'test')

!pip install torch torchvision matplotlib pandas

import pandas as pd

 def get_colormap_from_csv(path):
          df = pd.read_csv(path)
          colormap = {}
          for i, row in df.iterrows():
          rgb = (int(row['r']), int(row['g']), int(row['b']))
          class_label = int(row['label']) if 'label' in df.columns else i  # Prefer 'label' column if exists
        colormap[class_label] = rgb
          return colormap

import torch.nn as nn

 class DoubleConv(nn.Module):
          def __init__(self, in_ch, out_ch):
          super().__init__()
          self.conv = nn.Sequential(
           nn.Conv2d(in_ch, out_ch, 3, padding=1),
           nn.BatchNorm2d(out_ch),
           nn.ReLU(inplace=True),
           nn.Conv2d(out_ch, out_ch, 3, padding=1),
           nn.BatchNorm2d(out_ch),
           nn.ReLU(inplace=True)
          )

          def forward(self, x):
          return self.conv(x)

 class UNet(nn.Module):
          def __init__(self, n_classes):
          super().__init__()
          self.enc1 = DoubleConv(3, 64)
          self.enc2 = DoubleConv(64, 128)
          self.enc3 = DoubleConv(128, 256)
          self.enc4 = DoubleConv(256, 512)
          self.bottleneck = DoubleConv(512, 1024)
```

```
        self.pool = nn.MaxPool2d(2)

        self.up4 = nn.ConvTranspose2d(1024, 512, 2, 2)
        self.dec4 = DoubleConv(1024, 512)
        self.up3 = nn.ConvTranspose2d(512, 256, 2, 2)
        self.dec3 = DoubleConv(512, 256)
        self.up2 = nn.ConvTranspose2d(256, 128, 2, 2)
        self.dec2 = DoubleConv(256, 128)
        self.up1 = nn.ConvTranspose2d(128, 64, 2, 2)
        self.dec1 = DoubleConv(128, 64)

        self.out = nn.Conv2d(64, n_classes, 1)

        def forward(self, x):
        e1 = self.enc1(x)
        e2 = self.enc2(self.pool(e1))
        e3 = self.enc3(self.pool(e2))
        e4 = self.enc4(self.pool(e3))
        b = self.bottleneck(self.pool(e4))

        d4 = self.dec4(torch.cat([self.up4(b), e4], dim=1))
        d3 = self.dec3(torch.cat([self.up3(d4), e3], dim=1))
        d2 = self.dec2(torch.cat([self.up2(d3), e2], dim=1))
        d1 = self.dec1(torch.cat([self.up1(d2), e1], dim=1))
        return self.out(d1)

from torch.utils.data import DataLoader
 import torch.optim as optim

 transform = transforms.Compose([
    transforms.Resize((256, 256)),
    transforms.ToTensor(),
 ])

 train_dataset = DeepGlobeDataset(r"/content/drive/MyDrive/dataset/train", transform=transform,
colormap=colormap)
 train_loader = DataLoader(train_dataset, batch_size=4, shuffle=True)

 device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
 model = UNet(n_classes=len(colormap)).to(device)
 criterion = nn.CrossEntropyLoss()
 optimizer = optim.Adam(model.parameters(), lr=1e-4)

from tqdm import tqdm

 for epoch in range(10):
```

```
    model.train()
    total_loss = 0
    progress_bar = tqdm(train_loader, desc=f"Epoch {epoch+1}", leave=False)

    for images, masks in progress_bar:
    images, masks = images.to(device), masks.to(device)
    outputs = model(images)
    loss = criterion(outputs, masks)
  optimizer.zero_grad()
  loss.backward()
  optimizer.step()
    total_loss += loss.item()

  progress_bar.set_postfix(loss=loss.item())

    print(f"Epoch {epoch+1}, Total Loss: {total_loss:.4f}")
```

```
Epoch 1, Total Loss: 255.4966

Epoch 2, Total Loss: 213.2369

Epoch 3, Total Loss: 195.4916

Epoch 4, Total Loss: 180.8149

Epoch 5, Total Loss: 174.0035

Epoch 6, Total Loss: 169.6708

Epoch 7, Total Loss: 161.3085

Epoch 8, Total Loss: 156.2883

Epoch 9, Total Loss: 154.7243

Epoch 10, Total Loss: 149.9976
```

```
val_dataset = DeepGlobeDataset(
    root_dir='/content/drive/MyDrive/dataset/test',         # Treat test as validation
    transform=transform,
    colormap=colormap
)

 val_loader = DataLoader(val_dataset, batch_size=1, shuffle=False)
```

```
def evaluate_segmentation(model, dataloader, num_classes):
        model.eval()
        iou_scores = []
        dice_scores = []
        total_pixels = 0
        correct_pixels = 0

        with torch.no_grad():
        for images, masks in dataloader:
        images, masks = images.to(device), masks.to(device)
        outputs = model(images)
        preds = torch.argmax(outputs, dim=1)

        for pred, gt in zip(preds, masks):
            total_pixels += gt.numel()
            correct_pixels += (pred == gt).sum().item()

                for cls in range(num_classes):
                pred_inds = (pred == cls)
                gt_inds = (gt == cls)

                intersection = (pred_inds & gt_inds).sum().item()
                union = (pred_inds | gt_inds).sum().item()
                dice = (2 * intersection) / (pred_inds.sum().item() + gt_inds.sum().item() + 1e-6)

                if union > 0:
                    iou = intersection / (union + 1e-6)
                    iou_scores.append(iou)
                    dice_scores.append(dice)

        pixel_accuracy = correct_pixels / total_pixels
        mean_iou = np.mean(iou_scores)
        mean_dice = np.mean(dice_scores)

        print(f"📊 Evaluation Metrics (Test as Validation):")
        print(f"   Intersection over Union (IoU): {mean_iou:.4f}")
        print(f"   Pixel Accuracy                : {pixel_accuracy:.4f}")
        print(f"   F1 Score (Dice)               : {mean_dice:.4f}")

        return mean_iou, pixel_accuracy, mean_dice

iou, acc, dice = evaluate_segmentation(model, val_loader, num_classes=len(colormap))
```

```
📊 Evaluation Metrics (Test as Validation):
   Intersection over Union (IoU): 0.2242
```

```
   Pixel Accuracy                : 0.7609
   F1 Score (Dice)               : 0.2735

class_name_to_index = {
        'urban_land': 0,
        'agriculture_land': 1,
        'rangeland': 2,
        'forest_land': 3,
        'water': 4,
        'barren_land': 5,
        'unknown': 6
 }

import pandas as pd

 def get_colormap_from_csv(path, class_name_to_index):
        df = pd.read_csv(path)
        colormap = {}
        for _, row in df.iterrows():
        class_label = class_name_to_index[row['name']]
        rgb = (int(row['r']), int(row['g']), int(row['b']))
       colormap[class_label] = rgb
        return colormap

def visualize_specific_samples(model, dataset, colormap, device, sample_indices):
        model.eval()
        safe_colormap = {int(k): tuple(map(int, v)) for k, v in colormap.items()}

        def colorize_mask(mask):
        h, w = mask.shape
        color_mask = np.zeros((h, w, 3), dtype=np.uint8)
        for class_id, color in safe_colormap.items():
         color_mask[mask == class_id] = color
        return color_mask

        with torch.no_grad():
        for idx in sample_indices:
        image, _ = dataset[idx]  # get specific sample (image, label)
         input_img = image.unsqueeze(0).to(device)  # add batch dim

        output = model(input_img)
        pred = output.argmax(dim=1).squeeze().cpu().numpy()

        img = image.numpy().transpose(1, 2, 0)
        img = (img - img.min()) / (img.max() - img.min())
```

```
        pred_color = colorize_mask(pred)

        plt.figure(figsize=(8, 4))
        plt.subplot(1, 2, 1)
        plt.title(f"Input Image #{idx}")
        plt.imshow(img)
        plt.axis('off')

        plt.subplot(1, 2, 2)
        plt.title("Predicted Mask")
        plt.imshow(pred_color)
        plt.axis('off')

        plt.show()

sample_indices = [5, 9]  # change to whatever samples you want to see
 visualize_specific_samples(model, val_loader.dataset, colormap, device, sample_indices)




import matplotlib.pyplot as plt

 metrics = [iou, acc, dice]
 labels = ['IoU', 'Pixel Accuracy', 'Dice (F1)']

 plt.figure(figsize=(6,4))
 plt.bar(labels, metrics, color=['skyblue', 'lightgreen', 'lightcoral'])
 plt.ylim(0, 1)
 plt.title("Segmentation Metrics on Test Set")
 plt.ylabel("Score")
 for i, v in enumerate(metrics):
        plt.text(i, v + 0.02, f"{v:.2f}", ha='center', fontweight='bold')
 plt.show()
```