Semantic Segmentation for Land Cover using Bhuvan Satellite Images

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Introduction

- Land cover, defined as the assemblage of biotic and abiotic components on the Earth’s surface, is one of the most crucial properties of the Earth system

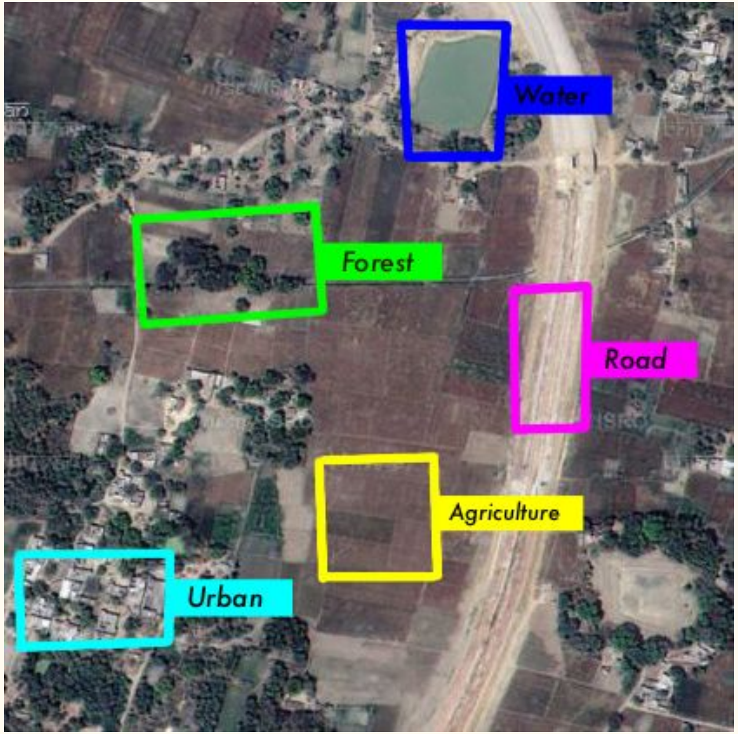
- Land cover includes grass, water bodies, forests, trees, lakes, agricultural land, open waters, wetlands, barren areas and crop lands.

- Land cover classification is the process of identifying and categorizing different types of land cover in a specific geographic area using remote sensing data.

- Land cover classification has many practical applications, including monitoring land use changes, assessing environmental impacts, and planning land management activities.

Problem Statement

Performing semantic segmentation for land cover classification using Bhuvan satellite images of **India** with the help of the VGG U-Net model.



Objective

- To develop a robust semantic segmentation model using the VGG U-Net architecture for accurate land cover classification in Bhuvan satellite images.

- To evaluate the accuracy of the land cover classification model using statistical metrics such as Intersection over Union (IoU), Dice coefficient (F1-Score), pixel accuracy, and loss.

- To overcome the problem of poor spectral reflectance properties of satellite imagery and limited dataset size, which can limit the generalizability of the models.

Methodology

Dataset Collection:

Study Area - *Varanasi, a city located in the north India in the state of Uttar Pradesh, with coordinates ranging from 25.3-25.5° N, 83-83.2° E.*

Programme – *Bhuvan Indian Geo Platform by ISRO.*

Image – *Satellite/Sensor Image type.*
Created a satellite image dataset of the region of Varanasi.
A set of manually generated masks were created for each image in dataset.
Performed data augmentation to increase the size of the dataset.

Methodology

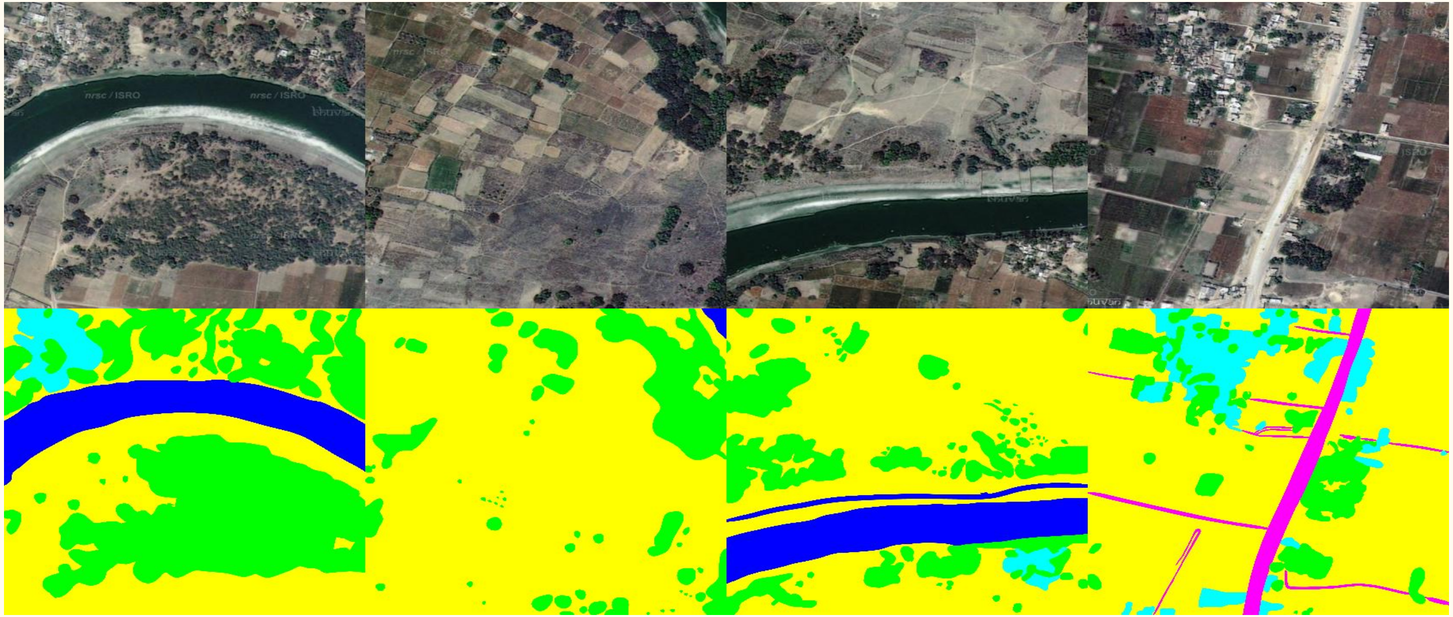
Preprocessing:

- After collecting the data, we resized the original images

- Employed data augmentation techniques, including rotation, flipping, and scaling.

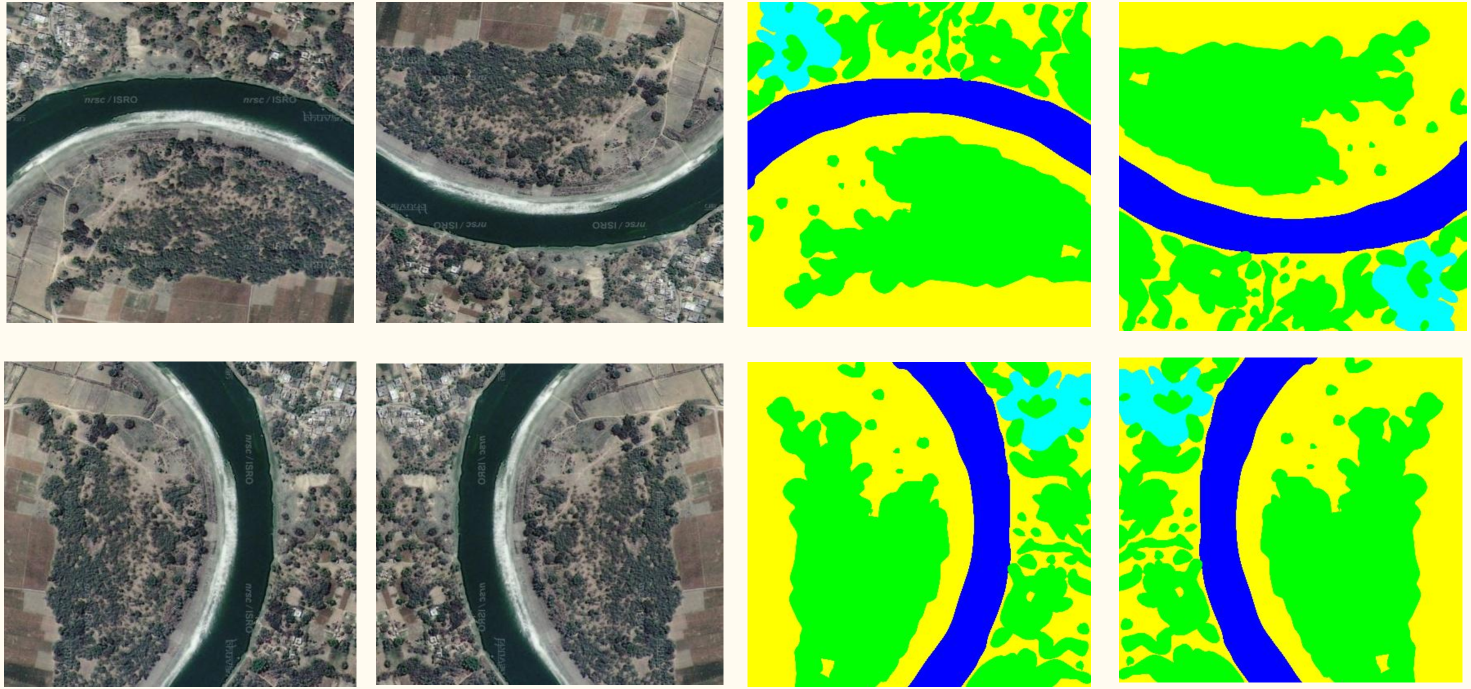
Methodology

Satellite Images and their corresponding Mask. - In order to train the land cover classification model, we generated a set of masks manually for each image in the dataset.



Methodology

Data Augmentation



Methodology

Training and Evaluation:

- We divided the dataset into a training set and a test set, using an 80:20 ratio.
- We trained the VGG U-Net model using the augmented training set.
- The training process involved feeding the Bhuvan satellite images and their corresponding masks into the model, optimizing the model parameters, which in turn predicts the land cover map.

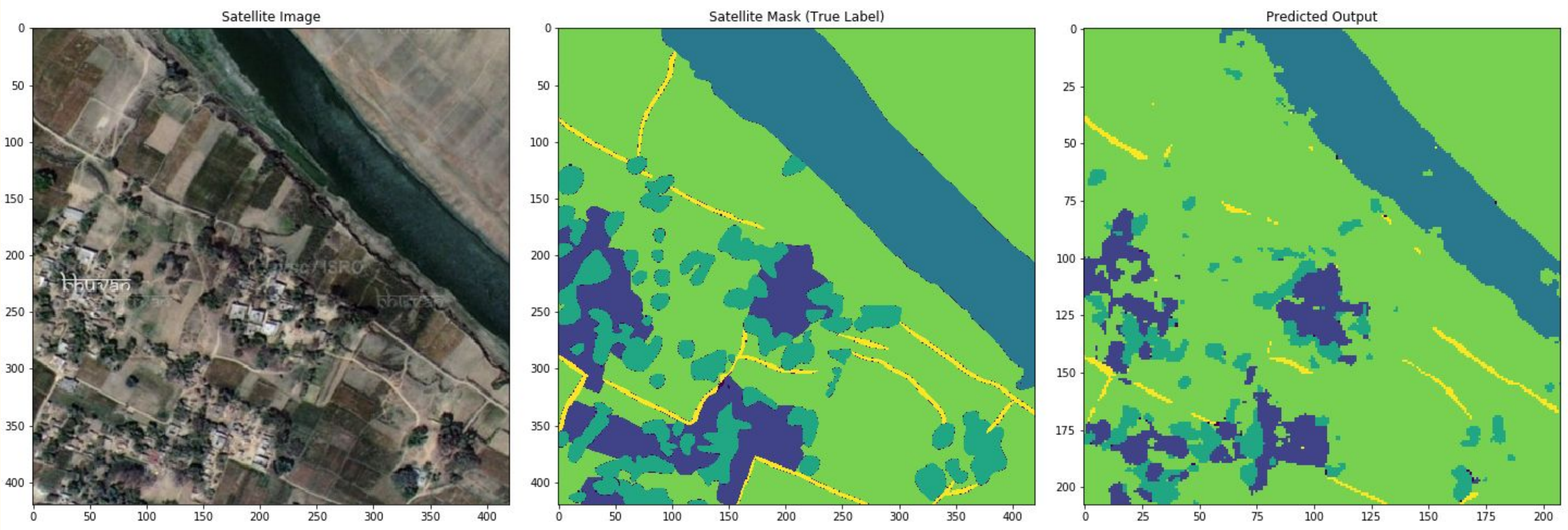
Proposed Solution

Semantic segmentation is a deep learning algorithm that associates a label or category with every pixel in an image. It is used to recognize a collection of pixels that form distinct categories.

VGG U-Net model:

- The VGG U-Net model is based on the popular VGG16 architecture, which was originally designed for image classification tasks.
- It consists of an encoder-decoder structure, where the encoder extracts high-level features from the input image, and the decoder reconstructs the segmentation map.
- One key feature of VGG U-Net is skip connections that retain low-level and high-level features, preserving fine details and contextual information, enhancing segmentation accuracy.

Results



Satellite Image
Satellite Mask (True Label)
Predicted Output

Performance Metrics

1. IoU: It also known as the Jaccard index, calculates the overlap between the predicted and ground truth masks.
   $$IoU = TP/(TP + FN + TN)$$

2. Dice Coefficient: The Dice coefficient quantifies the agreement between the two masks, emphasizing the common regions while penalizing false positives and false negatives.
   $$Dice = 2 \times TP/(2 \times TP + FN + TN)$$

3. Classification Report: The classification report provides a detailed summary of performance metrics including precision, recall, F1-score, and support (number of occurrences) for each class.

Results

The performance metrics at epoch 10 show comparatively lower scores for the "Road" and "Urban" classes.

Insufficient examples or exposure to these classes could impact accurate classification.

To improve IoU and Dice coefficient, training the model on a larger dataset with more instances of these classes is recommended.

Classes	IoU	Dice Coefficient
Urban	0.425	0.597
Water	0.785	0.879
Forest	0.601	0.751
Agriculture	0.864	0.927
Road	0.215	0.354

Table: Performance Metrics for Different Land Cover Classes at Epoch 10

Results

Epoch 10 achieves the highest performance with a Dice coefficient of 0.70, outperforming other epochs in the VGG U-Net model evaluation.

High pixel accuracy in epoch 15 does not guarantee superior segmentation ability.

Epochs	Mean IoU	Mean Dice Coefficient	Pixel Accuracy
5	0.56	0.68	0.88
10	0.58	0.70	0.88
15	0.56	0.68	0.89
20	0.57	0.69	0.88
30	0.56	0.68	0.88

Table: VGG U-Net Model: Performance Metrics for Different Epochs

Conclusion

- Bhuvan satellite Images and its corresponding mask are given to the VGG U-net machine learning model, which in turn is predicting the land cover map.
- Our model achieves a training accuracy of 96.63%, test accuracy of 88% with dice coefficient of 0.70.
- The results demonstrate the potential of the VGG U-net model for semantic segmentation of satellite images and highlight the importance of developing accurate and efficient algorithms for classification of land cover using remote sensing data.

References

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Thank you