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Satellite Image to Map Conversion and Land Cover Analysis Using Deep Learning

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Abstract: The automated interpretation of satellite imagery is a significant challenge in the field of remote sensing and computer vision. This paper presents a deep learning-based approach for translating raw satellite images into simplified, map-style representations and analyzing land cover types. Using a conditional Generative Adversarial Network (Pix2Pix), the model learns the mapping between paired satellite and map images, producing visually coherent outputs that preserve key geographical structures. Further, a post-processing module performs land cover classification into land, water, and vegetation categories. The system is deployed with a user-friendly interface using Streamlit, enabling real-time image processing and visualization. The results demonstrate high visual accuracy and practical usability, indicating strong potential for applications in urban planning, environmental analysis, and geospatial intelligence.

I. INTRODUCTION

With the growing availability of high-resolution satellite imagery from sources like Google Earth, NASA, and Sentinel satellites, there is a need for intelligent systems that can interpret this data without human intervention. Manual extraction of map information is time-consuming and often error-prone. This research addresses the need for automation by introducing a model that not only converts satellite images to map views but also identifies and quantifies land cover types.

The significance of this work lies in its dual functionality: image-to-map conversion and land classification. The former is achieved using the Pix2Pix GAN model, which has been widely adopted for tasks involving image translation. The latter uses simple but effective pixel-level analysis to compute the percentage of terrain types. Unlike many existing tools that only offer one of these capabilities, this integrated system is designed to be modular, accessible, and adaptable.

1. Satellite Image 2. Generated Image 3. Feature Detection 4. Land Cover Analysis

II. PROBLEM DEFINITION

Converting satellite images into meaningful maps is a non-trivial problem due to variations in scale, lighting, weather conditions, and terrain. Traditional image processing methods fall short in handling such variability. Moreover, manually segmenting land cover classes from satellite images requires domain knowledge and extensive human effort. This research aims to automate the entire workflow—from raw satellite input to visually interpretable maps and quantitative land cover metrics.

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III. OBJECTIVES

- Develop a deep learning model for satellite-to-map image translation.
- Implement a module for land cover classification and percentage calculation.
- Design an interactive web interface for real-time user interaction.
- Evaluate system accuracy through visual inspection and user feedback.

IV. RELATED WORK

Several researchers have explored the use of GANs for geospatial applications. Isola et al. introduced Pix2Pix for paired image translation tasks such as maps to aerial photos. In another study, Zhang et al. explored the use of CycleGAN and Pix2Pix for satellite-to-map conversion, concluding that Pix2Pix performed better for paired datasets. In land cover analysis, traditional methods rely on classification algorithms like Random Forest or Support Vector Machines, often applied to multispectral imagery. However, these techniques lack the visual appeal and ease of integration that GANs offer.

V. METHODOLOGY

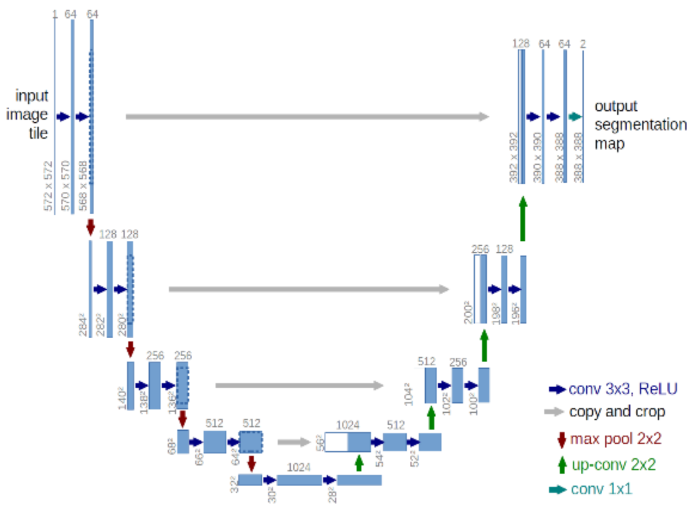
5.1 Data Collection and Preprocessing

A dataset of paired satellite and map images was collected from OpenStreetMap and Google Maps. Images were resized to 256×256 pixels and normalized to match the input requirements of the model. Data augmentation techniques such as flipping and rotation were applied to improve generalization.

5.2 Model Training: Pix2Pix GAN

The Pix2Pix architecture consists of:

- Generator (U-Net): Extracts spatial features from the input image and reconstructs the map image.
- Discriminator (PatchGAN): Evaluates image patches to distinguish real from generated outputs.



U-Net Architecture

$L_{total}(G,D)=L_{cGAN}(G,D)+\lambda\cdot L_{L1}(G)$

Where:

- $L_{cGAN}(G,D)$ = Conditional GAN loss:

$E_x[\log D(x,y)]+E_x[\log(1-D(x,G(x))$

- $L_{L1}(G)$= L1 Loss between real and generated map:

$$E_{x,y}[\|y-G(x)\|_1]$$

- G = Generator
- D = Discriminator
- x = input satellite image
- y = real map image
- λ = weighting factor (usually set to 100)

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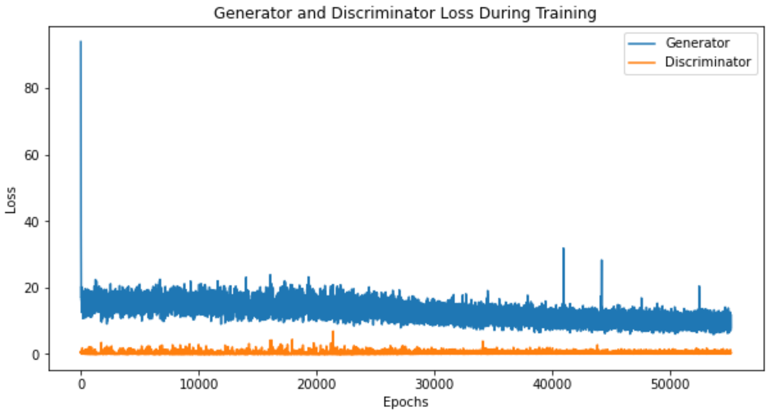

Generator and Discriminator Loss
During Training

5.3 Land Cover Analysis
Once a map image is generated, it is passed to a classification module that segments the image into three categories using color thresholding techniques. The pixel count of each class is computed to derive percentage values.

5.4 User Interface (Streamlit)
The application is deployed using Streamlit. Users can upload satellite images, process them, and view the results—converted maps and land cover statistics—in real time through a clean and interactive dashboard.

VI. IMPLEMENTATION DETAILS

- Programming Language: Python 3.10
- Libraries Used: PyTorch, OpenCV, NumPy, Streamlit
- Model Input: Satellite images (256×256, RGB)
- Output: Map-style images and percentage breakdown of land cover
- System Requirements: 8 GB RAM, CUDA-enabled GPU recommended

VII. TESTING AND EVALUATION

7.1 Unit Testing
All modules—upload, preprocessing, GAN inference, analysis—were tested independently to validate their outputs.

7.2 Integration Testing
The complete pipeline was tested for consistent data flow and response time.

7.3 User Testing
Several users from academic and non-technical backgrounds tested the app and provided feedback on usability and clarity. All users could successfully upload images and interpret results without guidance.

VIII. RESULTS

The Pix2Pix model produced map outputs that closely resembled the ground truth. The land cover analysis module was able to segment and compute the distribution of terrain types with reasonable accuracy. On average, the system processed and displayed results in under 10 seconds per image. The user interface contributed to a smooth and engaging experience.

8.1 Model Training Progress
To illustrate the model's improvement over time, Figure 1 shows a side-by-side comparison of the generator output at the beginning (1st epoch) and after extended training (800th epoch). The early output appears blurry and lacks structure, while the later output demonstrates improved spatial detail and visual accuracy, resembling a map closely aligned with the ground truth.

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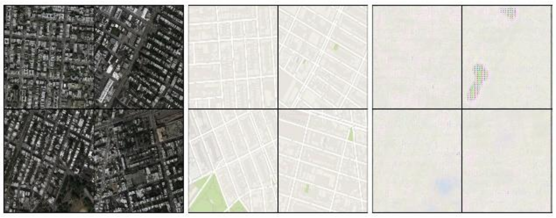
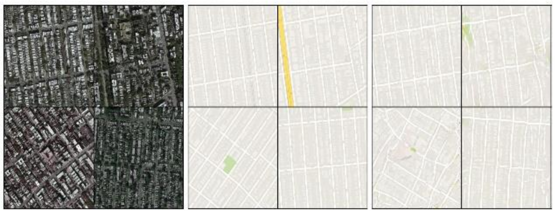


After 1 Epoch



After 800 Epoch

IX. FUTURE ENHANCEMENTS

- Extend land classification to include roads, buildings, and barren regions.
- Incorporate semantic segmentation models for improved accuracy.
- Export map and analysis outputs in GIS-compatible formats.
- Integrate real-time satellite APIs or drone imagery for live processing.

X. CONCLUSION

This project successfully combines generative modeling with basic image analysis to automate satellite-to-map conversion and land cover interpretation. The system demonstrates the capability of GANs in preserving spatial context while providing usable outputs for non-expert users. Its simplicity and efficiency make it adaptable for diverse real-world applications.

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