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Urban Area Classification From Satilite Images Using Convolution Neural Network

Atkuri Vinay, Challa Srikanth, Burla Devi Vara Prasad,
Dodda Hemanth Reddy, Dr. P. Siddaiah
Seshadri Rao Gudlavalleru Engineering College, Gudlavalleru, India

Abstract
This project presents the design and implementation Accurate urban and environmental Land Use/Land Cover (LULC) classification from satellite imagery is essential for sustainable urban planning, environmental monitoring, and resource management. This study presents a high-precision land cover classification framework based on deep image segmentation using a U-Net convolutional neural network architecture. The proposed system processes RGB satellite images resized to a uniform resolution of 256 × 256 pixels to ensure computational efficiency and spatial consistency. Ground truth segmentation masks are converted from RGB format into categorical class labels representing five major land cover types: Urban, Water, Forest, Agriculture, and Road. To enhance model generalization and robustness, extensive data augmentation techniques, including rotation, flipping, and scaling, are applied during training. The core segmentation model employs a four-stage encoder–decoder U-Net architecture that enables hierarchical extraction of spatial and textural features through successive convolution and pooling operations, followed by symmetric upsampling and skip connections for precise boundary localization. This design effectively captures both global contextual information and fine-grained structural details in complex urban and environmental scenes. Experimental results demonstrate that the proposed Deep U-Net–based segmentation approach achieves high classification accuracy and clear class separability across diverse land cover categories. The framework provides a reliable and scalable solution for automated urban and environmental LULC mapping, supporting data-driven decision-making in geospatial analysis, smart city development, and environmental conservation applications.

Keywords: *Land Use/Land Cover (LULC) Classification, Satellite Image Segmentation, Deep Learning, U-Net Architecture, Urban and Environmental Mapping*

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I. Introduction

Accurate extraction of Land Use/Land Cover (LULC) information from satellite imagery plays a vital role in understanding urban growth patterns, monitoring environmental changes, and enabling sustainable resource management. With the rapid expansion of urban areas and increasing pressure on natural ecosystems, traditional manual and pixel-based classification techniques often struggle to handle the high spatial complexity and spectral variability present in modern high-resolution satellite data. In this context, deep learning–based image segmentation has emerged as a powerful alternative, offering superior capability in learning discriminative spatial and contextual features directly from data.

This study proposes an automated and high-precision LULC classification framework based on a U-Net convolutional neural network architecture. The system processes RGB satellite images standardized to a resolution of 256 × 256 pixels, ensuring spatial consistency and computational efficiency. Ground truth segmentation masks are transformed into categorical labels representing five dominant land cover classes: Urban, Water, Forest, Agriculture, and Road. To improve robustness and generalization across diverse landscapes, comprehensive data augmentation strategies are incorporated during training.

The adopted U-Net architecture follows a four-stage encoder–decoder design with skip connections, enabling effective fusion of low-level spatial details and high-level semantic information. This architectural advantage allows accurate delineation of complex boundaries and heterogeneous land cover regions. Experimental evaluation confirms that the proposed approach achieves high classification accuracy and reliable class separability, making it suitable for large-scale urban and environmental monitoring, smart city planning, and geospatial decision-support systems.

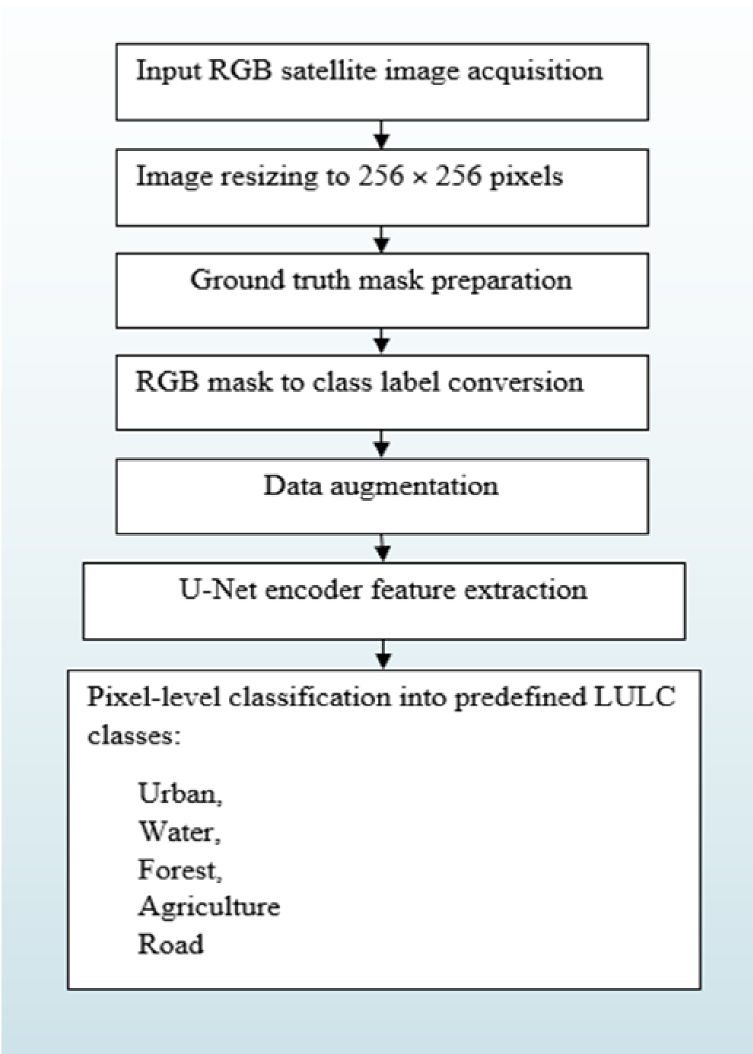
II. Methods

Existing Methods:

A commonly used existing method for Land Use/Land Cover (LULC) classification is traditional pixel-based image classification using machine learning algorithms such as Support Vector Machine (SVM) or Random Forest. In this method, each pixel in a satellite image is classified independently based on its spectral values. Hand-crafted features such as color intensity, texture, or statistical measures are extracted from the image. These features are then given to a classifier, which assigns a land cover class (such as urban, water, or vegetation) to each pixel. This approach does not consider spatial relationships between neighboring pixels and mainly depends on manually designed features.

Proposed Method:

The proposed methodology uses deep learning–based image segmentation to classify urban and environmental Land Use/Land Cover (LULC) from satellite images. First, RGB satellite images are collected and resized to a standard size of 256 × 256 pixels to maintain uniformity and reduce computational complexity. The corresponding ground truth segmentation masks are converted from RGB color values into categorical labels representing five land cover classes: Urban, Water, Forest, Agriculture, and Road. Next, data augmentation techniques such as rotation, horizontal and vertical flipping, and scaling are applied to the training dataset. This step increases data diversity and helps the model learn robust features, reducing overfitting. The augmented images are then fed into a four-stage U-Net architecture. The U-Net model consists of an encoder that extracts important spatial and texture features using convolution and pooling layers, and a decoder that reconstructs detailed segmentation maps using upsampling layers. Skip connections between encoder and decoder layers preserve fine details and improve boundary accuracy. During training, the model learns to map input images to pixel-level class labels. Finally, the trained model predicts accurate LULC maps for new satellite images, providing precise and reliable land cover classification results.



III. Implementation Flow Diagram

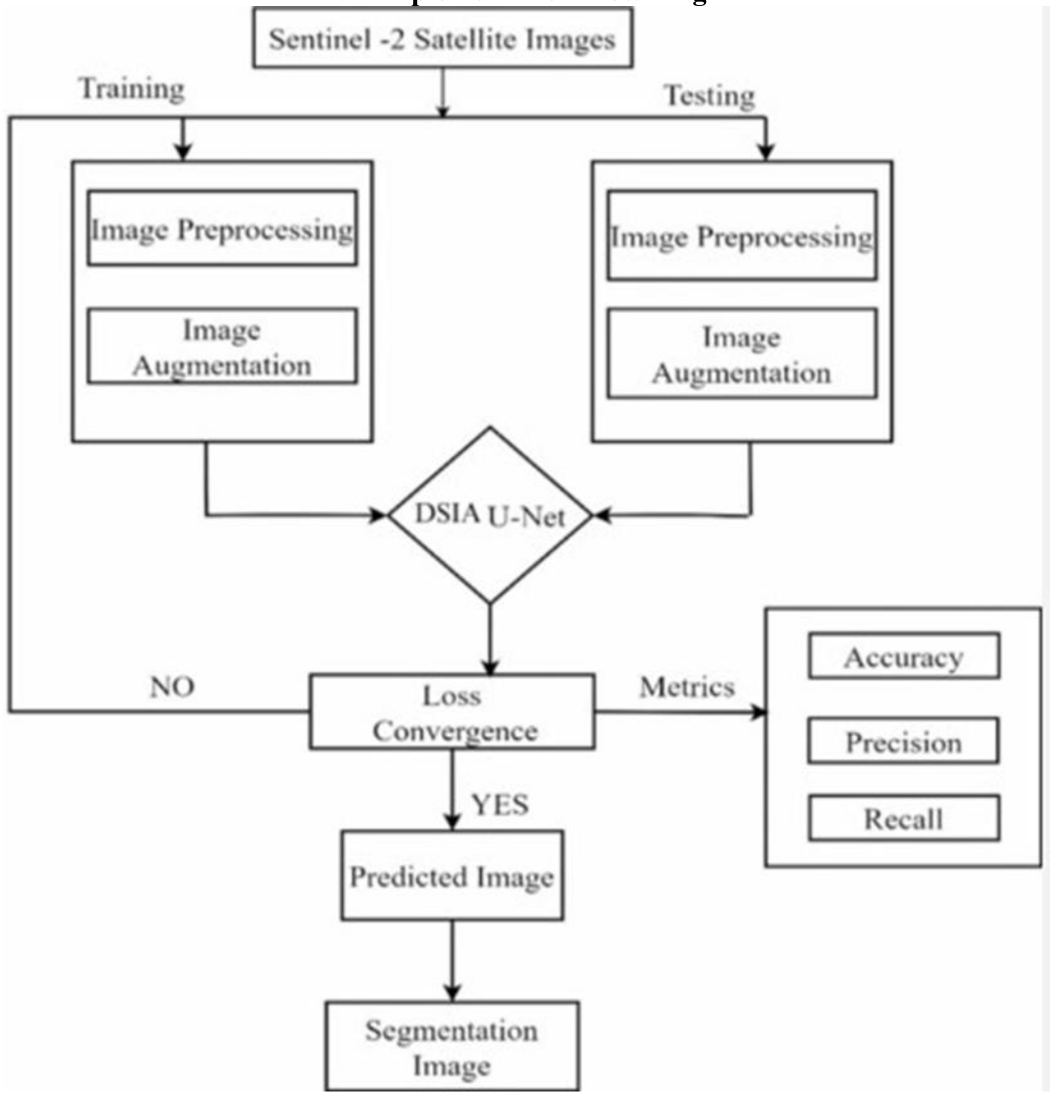


Fig: Proposed Block Diagram

IV. Software/Hardware details

Software: Matlab R2020a or above
Hardware:
Operating Systems:
- Windows 10
- Windows 7 Service Pack 1
- Windows Server 2019
- Windows Server 2016

Processors:
Minimum: Any Intel or AMD x86-64 processor
Recommended: Any Intel or AMD x86-64 processor with four logical cores and AVX2 instruction set support

Disk:
Minimum: 2.9 GB of HDD space for MATLAB only, 5-8 GB for a typical installation
Recommended: An SSD is recommended A full installation of all MathWorks products may take up to 29 GB of disk space

RAM:
Minimum: 4 GB
Recommended: 8 GB

V. Simulation Results

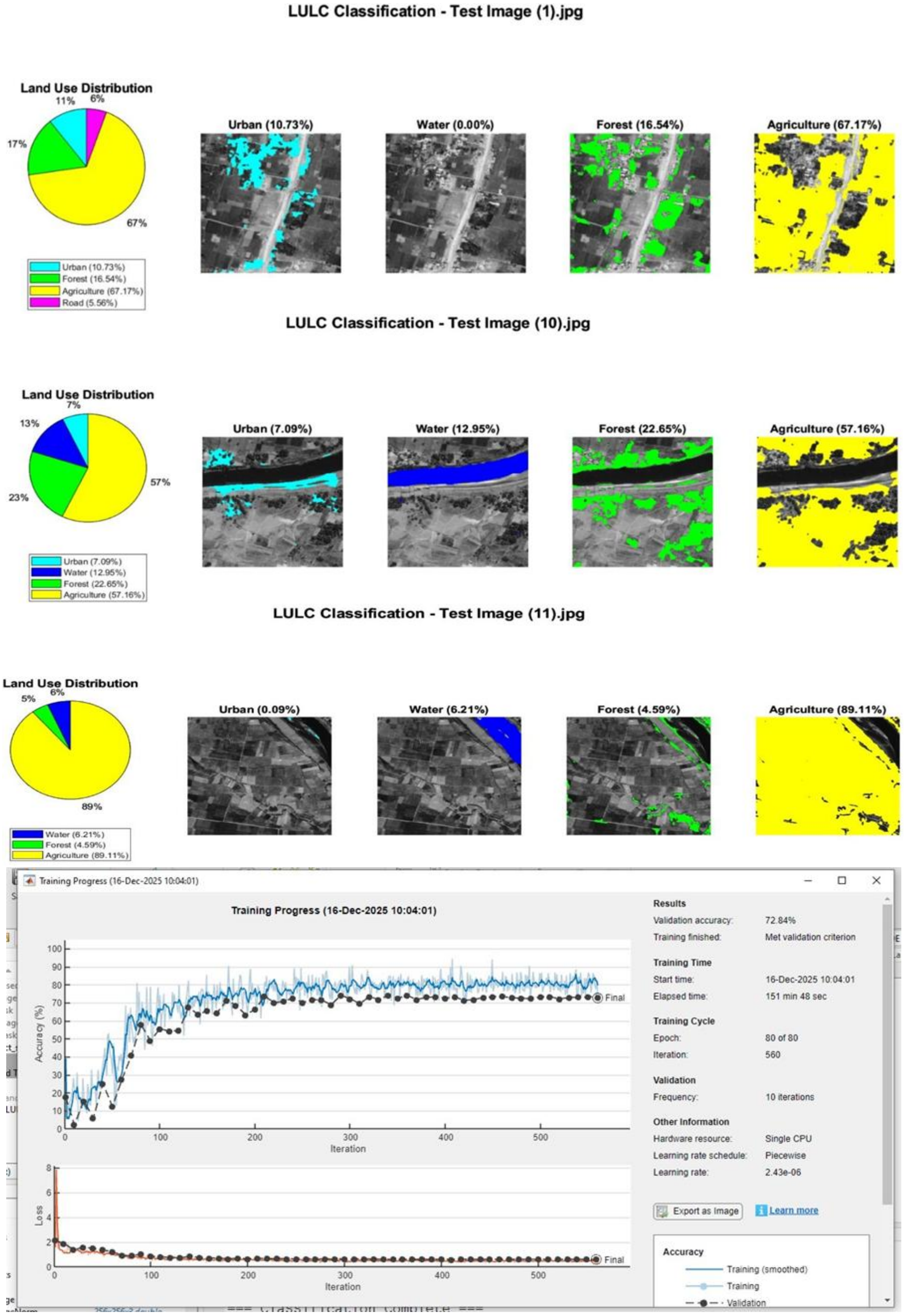
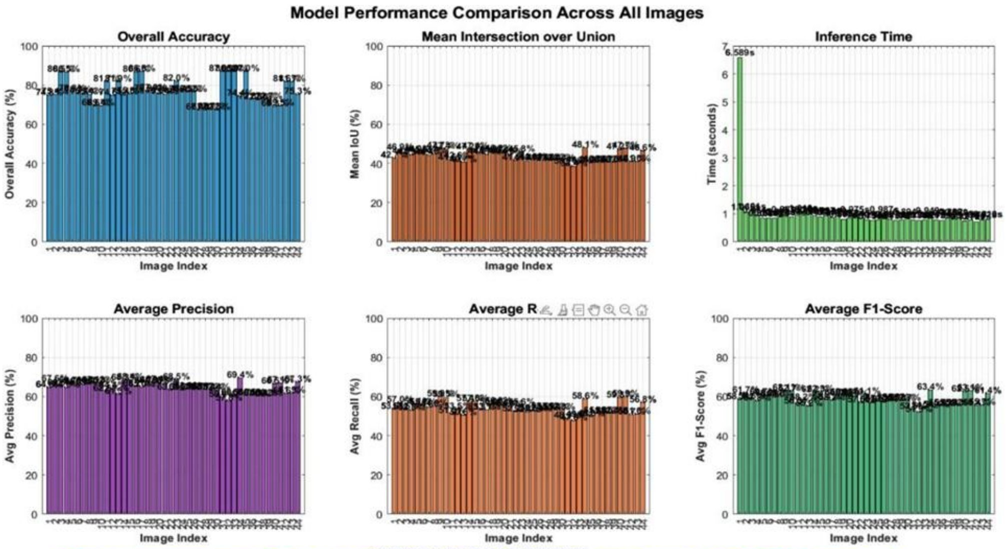
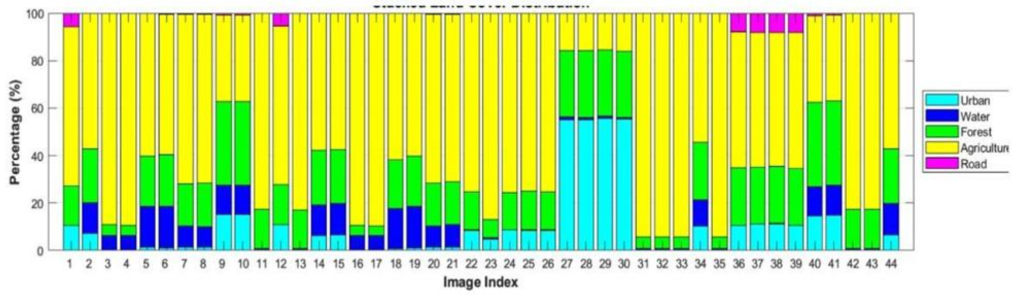
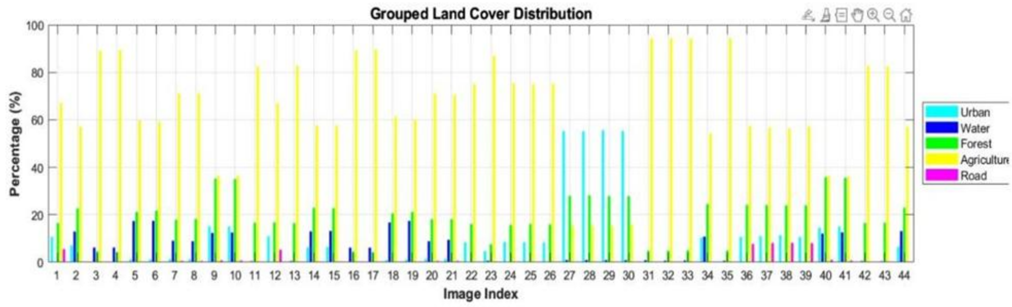


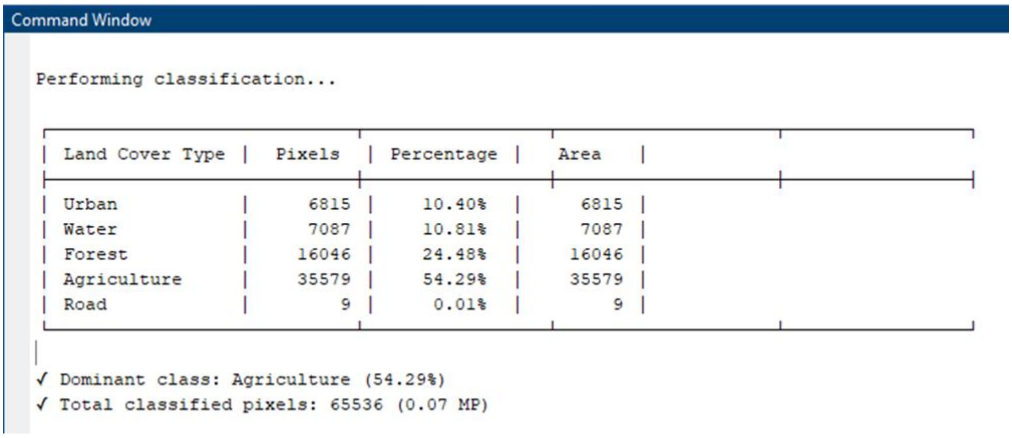
Fig 4.1: Perfomence Parameters


Model Performance Comparison Across All Images
Overall Accuracy
Overall Accuracy (%)
Image Index
Mean Intersection over Union
Mean IoU (%)
Image Index
Inference Time
Time (seconds)
6.589s
Image Index
Average Precision
Avg Precision (%)
Image Index
Average R
Avg Recall (%)
Image Index
Average F1-Score
Avg F1-Score (%)
Image Index


Percentage (%)
Image Index
Urban
Water
Forest
Agriculture
Road


Grouped Land Cover Distribution
Percentage (%)
Image Index
Urban
Water
Forest
Agriculture
Road


Model Performance Analysis & Accuracy Metrics
Confusion Matrix
True Class
Predicted Class
Urban
Water
Forest
Agriculture
Road
Per-Class Metrics
Precision
Recall
F1-Score
Percentage (%)
Intersection over Union (IoU)
IoU (%)
41.9%
25.2%
45.3%
70.0%
31.1%
Overall Performance Metrics
Overall Accuracy (OA): 74.76%
Mean IoU (mIoU): 42.70%
Mean Precision: 64.47%
Mean Recall: 53.55%
Mean F1-Score: 58.30%
Average Confidence: 81.26%
Inference Time: 1.710 sec
Processing Speed: 0.6 FPS
Per-Class Performance Details
Class Precision Recall F1-Score IoU
Urban 67.40% 52.50% 59.02% 41.87%
Water 47.50% 35.00% 40.30% 25.24%
Forest 70.06% 56.16% 62.34% 45.29%
Agriculture 82.36% 82.36% 82.36% 70.01%
Road 55.02% 41.74% 47.47% 31.12%
Prediction Confidence per Class
Confidence (%)
70.9%
50.0%
73.7%
86.7%
57.9%


Command Window

Performing classification...

Land Cover Type	Pixels	Percentage	Area
Urban	6815	10.40%	6815
Water	7087	10.81%	7087
Forest	16046	24.48%	16046
Agriculture	35579	54.29%	35579
Road	9	0.01%	9

✓ Dominant class: Agriculture (54.29%)
✓ Total classified pixels: 65536 (0.07 MP)

VI. Conclusion

This study demonstrates the effectiveness of deep learning–based semantic segmentation for accurate urban and environmental Land Use/Land Cover (LULC) classification using satellite imagery. By adopting a U-Net convolutional neural network architecture, the proposed framework successfully captures both high-level contextual information and fine-grained spatial details required for precise land cover mapping. Standardizing RGB satellite images to a resolution of 256 × 256 pixels ensures computational efficiency while maintaining spatial consistency across the dataset. The conversion of ground truth masks into categorical class labels representing Urban, Water, Forest, Agriculture, and Road enables reliable supervised learning and clear class discrimination. The incorporation of extensive data augmentation strategies significantly improves model robustness and generalization, allowing the system to handle variations in scale, orientation, and spatial patterns commonly observed in real-world satellite images. The four-stage encoder–decoder structure with skip connections proves particularly effective in preserving boundary information and accurately delineating complex urban features such as roads and built-up regions. Experimental results confirm that the proposed Deep U-Net framework achieves high classification accuracy and strong class separability across diverse land cover categories. Overall, the developed approach offers a scalable and automated solution for LULC mapping, making it well suited for large-scale geospatial applications. The framework can effectively support urban planning, environmental monitoring, smart city initiatives, and sustainable resource management by providing reliable, data-driven insights from satellite imagery.

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