MACHINE LEARNING FRAMEWORK FOR AUTOMATED DETECTION OF ILLEGAL LAND ENCROACHMENT USING MULTI-TEMPORAL SATELLITE IMAGERY

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Abstract -- Illegal land encroachment has become a critical issue affecting urban planning, environmental sustainability, and government land protection. Manual monitoring techniques are slow, expensive, and often ineffective for large geographic regions. This project proposes an intelligent machine learning framework that automatically detects illegal land encroachment using multi-temporal satellite imagery. The system utilizes deep learning-based semantic segmentation to classify land cover types and applies temporal change detection to identify newly constructed built-up areas. These changes are further validated using GIS-based government land records to determine legality. An Attention U-Net architecture is employed to enhance segmentation accuracy by focusing on relevant spatial features. The framework also incorporates a risk scoring mechanism to prioritize encroachment cases. The proposed system provides an automated, scalable, and transparent solution for digital land governance. It supports smart city initiatives and sustainable urban development strategies.

I. INTRODUCTION

Rapid urbanization and population growth have significantly increased unauthorized construction activities across urban and semi-urban regions. Illegal land encroachment on government land, forest areas, and water bodies creates serious environmental and administrative challenges. Traditional monitoring methods depend on physical inspections and manual surveys, which are inefficient and resource-intensive. With advancements in satellite imaging technologies provided by organizations such as NASA and European Space Agency, large-scale land observation has become more accessible. Recent developments in deep learning, especially convolutional neural networks, have enabled precise land cover classification from satellite images. However, most existing systems lack integration with legal land ownership data for automated governance decisions. This project bridges that gap by combining machine learning, temporal analysis, and GIS verification into a unified framework. The proposed approach enhances efficiency, reduces human intervention, and ensures data-driven decision-making. It represents a significant step toward intelligent land management systems.

II. BACKGROUND AND MOTIVATION

A. Overview

The project focuses on building a computational framework that combines satellite image processing, deep learning, and GIS analytics to detect illegal land encroachment automatically.The system processes multi-temporal satellite images (T1 and T2), applies semantic segmentation to classify land types such as built-up, vegetation, water, and open land, and detects newly emerged structures. These changes are cross-verified with official land ownership shapefiles.An Attention U-Net model improves segmentation accuracy by focusing on spatially important features. A change detection module compares classified outputs over time to identify new construction.

B. Importance of the Project

Illegal encroachment leads to:

- Environmental degradation
- Flood risks due to water-body encroachment
- Loss of public property
- Urban planning inefficiencies

The proposed framework offers:

- Automated surveillance
- Early detection capability
- Reduced manual inspection costs
- Objective and data-driven governance

C. Motivation for This Research

Urban expansion and population growth increase land pressure. Monitoring large geographic areas manually is impractical.

Key motivations include:

- Need for automated monitoring systems
- Advances in deep learning segmentation models
- Availability of open satellite datasets
- Requirement for governance transparency
- Smart city and digital governance initiatives

III. SYSTEM ARCHITECTURE AND METHODOLOGY

A. Data Collection

Satellite imagery is obtained from:

- USGS (Landsat)
- European Space Agency (Sentinel-2)

Multi-temporal images (T1 and T2) are preprocessed and resized to 256×256 pixels

B. Semantic Segmentation Using Attention U-Net

The segmentation model consists of:

- Encoder – Feature extraction
- Attention Gates – Focus on relevant spatial features
- Decoder – Reconstruction to original resolution

Output classes:

- Built-up
- Vegetation
- Water
- Open land

Loss Function:

Loss = CrossEntropy + Dice Loss

Performance Metric:

IoU = Intersection / Union

C. Temporal Change Detection

Change detection is performed using:

Change(x,y) = 1 if
Class_T2(x,y) = Built-up AND
Class_T1(x,y) ≠ Built-up

This identifies newly constructed areas.

D. GIS-Based Encroachment Verification

Detected changes are converted into polygons and overlaid with government land shapefiles.

If overlap exists:
→ Mark as Illegal Encroachment

E. Risk Scoring Module

Risk Score =
Encroached Area × Land Type Weight × Growth Speed

Risk categories:

- Low Risk
- Moderate Risk
- High Risk

This assists administrative authorities in prioritization.

IV.PROPOSED MODEL

The core component of the framework is the Attention U-Net deep learning model, which performs semantic segmentation of satellite imagery. The model architecture consists of an encoder-decoder structure designed to extract hierarchical spatial features and reconstruct high-resolution segmentation maps. The encoder section includes multiple convolutional layers followed by rectified linear unit activation functions and max-pooling operations. These layers progressively reduce spatial dimensions while increasing feature depth, enabling the extraction of complex patterns such as building edges and land textures.

A key enhancement over the traditional U-Net model is the integration of attention gates. These attention mechanisms selectively emphasize relevant spatial regions while suppressing background noise. In satellite imagery, small-scale constructions can be difficult to detect due to complex backgrounds. The attention gates enable the model to focus specifically on built-up regions, thereby improving detection of small encroachments. The model is trained using a hybrid loss function combining Cross-Entropy Loss and Dice Loss to balance pixel-wise classification accuracy and overlap-based similarity.

After segmentation, the temporal change detection model compares classified outputs from T1 and T2 images. The algorithm identifies pixels classified as built-up in T2 but not in T1, representing newly constructed areas. These detected regions are further processed to remove noise using morphological filtering techniques. The resulting change mask is converted into geospatial polygons compatible with GIS systems. The model is optimized using GPU acceleration to enable efficient processing of large satellite datasets. By combining deep learning segmentation with logical temporal comparison, the proposed model ensures accurate identification of encroachment while minimizing false positives. The architecture is designed to be scalable and adaptable to future transformer-based segmentation models or real-time satellite feeds.

V. ROLES AND APPLICATION

The intelligent land encroachment detection framework plays a significant role in modern digital governance and environmental management systems. Rapid urban expansion has increased the need for automated monitoring solutions capable of covering vast geographical regions. The proposed system enables government authorities to detect unauthorized constructions at early stages, reducing long-term infrastructural and ecological damage. By leveraging multi-temporal satellite imagery, the framework provides continuous monitoring without the need for constant physical inspections. This reduces operational costs and increases efficiency in land administration departments.

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The system also contributes to transparency in governance by providing data-driven evidence for legal action. It can be integrated into centralized dashboards where administrators can visualize encroachment hotspots, generate automated reports, and track historical land-use changes. In disaster-prone regions, monitoring encroachment near water bodies and drainage systems can help reduce flood risks. The framework supports smart city initiatives by combining artificial intelligence, remote sensing, and geospatial analytics into a unified platform. Furthermore, the system can be expanded to include drone-based imagery, blockchain-secured land records, and real-time satellite streaming for enhanced monitoring. Overall, the proposed solution demonstrates how advanced machine learning technologies can strengthen public administration, environmental sustainability, and urban governance in the digital era.

VI.INNOVATIVE INTEGRATIONS

The proposed Intelligent Machine Learning Framework integrates multiple advanced technologies into a unified automated land governance system. Unlike traditional land monitoring systems that operate independently using either satellite classification or manual GIS inspection, this framework strategically combines deep learning, multi-temporal analysis, geospatial verification, and risk-based prioritization into a single intelligent pipeline. The innovation lies in the seamless interaction between artificial intelligence models and governance data systems, transforming raw satellite imagery into legally actionable insights.

One of the major innovations is the integration of multi-temporal satellite imagery from organizations such as NASA and European Space Agency with attention-based deep learning segmentation models. Instead of analyzing a single snapshot of land use, the system compares images across different time intervals to detect new construction activities. This temporal intelligence enables proactive monitoring rather than reactive investigation.

Another important integration is the conversion of deep learning outputs into GIS-compatible spatial polygons. The segmented built-up regions are transformed into vector layers and automatically overlaid with government cadastral maps. This creates a direct bridge between AI-based detection and legal land ownership records. The framework therefore goes beyond simple land-cover classification and provides governance-level verification

The inclusion of a dynamic risk scoring model further strengthens the system. After detecting illegal overlap, the system evaluates severity based on land sensitivity, encroached area size, and expansion rate. This integration allows authorities to prioritize high-risk cases such as encroachment near water bodies or forest reserves.

Key Innovative Integrations

- • Integration of multi-temporal satellite imagery for time-based encroachment detection
- • Attention U-Net based semantic segmentation for precise built-up area extraction
- • Pixel-to-polygon conversion for GIS compatibility
- • Automated overlay with cadastral land ownership shapefiles
- • Temporal change detection logic to identify newly constructed structures
- • Morphological filtering to reduce seasonal and noise-based false positives
- • Risk scoring mechanism based on land sensitivity and encroachment size
- • Cloud-based scalable processing architecture
- Dashboard-based real-time visualization for authorities
- Modular architecture enabling future integration with blockchain and drone imagery

VII.CHALLENGES

Developing an intelligent machine learning framework for automated detection of illegal land encroachment using multi-temporal satellite imagery involves several technical, computational, and governance-related challenges. One of the primary challenges is the availability and quality of satellite imagery. Satellite images often contain cloud cover, atmospheric distortion, and seasonal variations that affect visual clarity and classification accuracy. Differences in lighting conditions and image resolution between two time periods can introduce inconsistencies during temporal comparison. Preprocessing techniques such as normalization and cloud masking help reduce noise, but complete elimination of environmental variability remains difficult.

Another major challenge lies in acquiring accurate and up-to-date land ownership shapefiles. Government cadastral maps may not always be digitized or synchronized with satellite data timelines. Inconsistent coordinate reference systems between satellite images and GIS shapefiles can lead to spatial misalignment during overlay analysis. Even minor georeferencing errors can produce incorrect encroachment detection results. Therefore, precise geospatial alignment and coordinate transformation are critical yet technically demanding tasks.

VIII.FUTURE WORK

Although the proposed intelligent framework demonstrates effective detection of illegal land encroachment using multi-temporal satellite imagery, several enhancements can be incorporated in future developments to improve scalability, accuracy, and real-time applicability. One major direction for future work involves integrating advanced transformer-based segmentation models to replace or complement the existing Attention U-Net architecture. Vision Transformer models have shown superior capability in capturing long-range spatial dependencies, which can improve segmentation performance in complex urban environments.

Another potential enhancement is the incorporation of higher-resolution satellite imagery and commercial remote sensing data sources. While current datasets from agencies such as USGS and European Space Agency provide reliable coverage, integrating sub-meter resolution imagery could significantly improve detection of small-scale encroachments. Additionally, combining satellite imagery with drone-based aerial data can offer more localized and precise monitoring in sensitive regions.

IX. CONCLUSION

This project presents an intelligent machine learning framework for automated detection of illegal land encroachment using multi-temporal satellite imagery. By integrating Attention U-Net-based segmentation, temporal change detection, and GIS-based legal verification, the system provides a comprehensive and scalable monitoring solution. The framework addresses limitations of traditional land monitoring approaches by enabling automated and data-driven analysis. It enhances governance transparency and supports sustainable urban planning strategies. The proposed model demonstrates strong potential for real-world deployment in smart city and environmental monitoring initiatives. Future improvements may include real-time satellite data integration and advanced transformer-based segmentation models. Overall, the system represents a significant advancement in applying artificial intelligence to public land management. It offers a practical and efficient approach to combating illegal land encroachment

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