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Land Use Land Cover-Based Intelligent System for Urban and Environmental Applications

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Abstract—**Rapid urban growth and environmental damage have greatly increased the need for effective and easy-to-use land monitoring systems. This paper presents a web-based platform for Land Use and Land Cover (LULC) analysis that combines satellite remote sensing, geospatial data processing, and deep learning methods. The system allows users to define an Area of Interest (AOI), create LULC maps using the Dynamic World V1 dataset, and conduct multi-year comparisons along with detailed change detection. To improve analytical capabilities, a U-Net-based deep learning model is used to forecast future land changes by learning spatial patterns from historical data. The system produces probability-based heatmaps that highlight areas with a higher chance of urban growth. It also provides automated analytical insights and report generation, helping users better un-derstand complex geospatial information. The results show that the proposed system effectively identifies urban expansion and environmental changes while offering a user-friendly interface for analysis. By combining powerful computational methods with straightforward visualization, the platform aids decision-making in urban planning, environmental monitoring, and sustainable land management.**

Index Terms—**Land Use Land Cover (LULC), Satellite Remote Sensing, Multi-Temporal Analysis, Deep Learning, U-Net Architecture, Pixel-Level Change Detection, Urban Growth Prediction**

I. INTRODUCTION

Land Use and Land Cover (LULC) analysis is one of the vital areas that helps in understanding the usage of land and its variations over time. Land use refers to activities such as agriculture, development of infrastructure, and industrialization, whereas land cover refers to the physical features on the Earth's surface.

With urbanization occurring rapidly, there is an increase in converting natural features to built-up areas, resulting in deforestation and environmental imbalance. Conventional techniques for performing Land Use and Land Cover analysis are based on manual interpretation of features on the Earth's surface. However, with the advent of satellite images and artificial intelligence techniques, there is now scope for performing this analysis in a more efficient and automated manner.

Although there is now scope for performing Land Use and Land Cover analysis in an automated manner, there is still less focus on integrated features such as multi-year analysis and prediction. To overcome this problem and to create an efficient system for Land Use and Land Cover analysis, this paper proposes an intelligent web-based system.

II. RELATED WORKS

Recent advancements in satellite remote sensing and deep learning have greatly improved the accuracy and efficiency of Land Use and Land Cover (LULC) classification. Many studies have looked at using convolutional neural networks (CNNs) to extract important spatial features from multispectral satellite images. For instance, Balarabe and Jordanov [1] demonstrated that deep CNN models can achieve high classification accuracy, especially when using data augmentation techniques to manage variations among land cover classes.

To tackle the challenge of processing large satellite images, tile-based methods have become more popular. Pallavi et al. [2] introduced a technique that divides large Sentinel-2 images into smaller patches, which makes computation more efficient and manageable. Their findings showed that ResNet50 outperformed other models, achieving an accuracy of about 98.47%, demonstrating how strong deep residual networks are for LULC classification tasks.

Besides classification models, semantic segmentation techniques have gained traction for their ability to analyze data at the pixel level. Sathyanarayanan et al. [3] created a multiclass framework using a modified SegNet architecture for LULC classification with multispectral data. Their method achieved a weighted accuracy of roughly 84%, showing how effective encoder-decoder models are in capturing both spatial and spec-tral features. Similarly, Cecili et al. [4] compared various CNN architectures like VGG16, DenseNet121, and ResNet50. They found that using multi-temporal data improves classification performance compared to single-date images.

Additionally, review studies such as Vali et al. [5] underline the growing role of deep learning in analyzing hyperspectral and multispectral satellite data. Their work shows that models like U-Net are particularly good for semantic segmentation, as they can keep fine spatial details while learning larger contextual patterns. However, they also mention challenges like the limited availability of labeled datasets, differences across regions, and similarities among land cover classes. These factors can impact model performance.

Despite these advancements, most current methods focus only on classification tasks and lack a complete analytical framework. Many features, such as multi-temporal analysis, pixel-level change detection, and future prediction, are of-ten absent. Moreover, many existing tools require skills in Geographic Information Systems (GIS), making them less accessible for users without a technical background.

These limitations point to the need for a user-friendly system that combines LULC mapping, temporal analysis, change detection, and predictive modeling in one place. The proposed system aims to fill these gaps by integrating satellite data processing, deep learning predictions, and easy visualization, enabling better and more accessible land monitoring.

III. PROPOSED WORK

The proposed system is designed as a web-based intelligent platform that integrates satellite remote sensing, geospatial analysis, and deep learning to provide a comprehensive so-lution for Land Use and Land Cover (LULC) analysis. The primary objective of the system is to simplify complex geospa-tial operations while offering advanced analytical capabilities such as multi-year comparison, change detection, and future prediction within a unified interface.

The system is structured into multiple functional modules that work together to deliver end-to-end LULC analysis. Initially, users interact with the platform through an intuitive interface where they can define an Area of Interest (AOI) using an interactive map. Based on the selected region and time period, the system retrieves relevant LULC data from the Dynamic World V1 dataset and generates corresponding land cover maps.

To support temporal analysis, the system includes a multi-year comparison module that enables users to visualize and compare LULC maps across different time periods. This allows for the identification of long-term trends such as urban expansion, vegetation loss, and land transformation patterns. In addition, a pixel-level change detection module is incorporated to provide a more detailed analysis of land cover transitions. This module identifies specific changes between classes, such as the conversion of vegetation into built-up areas, and quantifies these transformations through area-based metrics.

A key feature of the proposed system is its predictive capability, which is achieved using a U-Net-based deep learning model. The model is trained on temporally paired LULC datasets to learn spatial patterns of land transformation. Based on this learning, the system generates probability-based heatmaps that indicate regions with a higher likelihood of future urban growth. This predictive insight enhances the system’s ability to support proactive planning and decision-making.

Furthermore, the system incorporates automated analytical insights and report generation features to improve usability. By summarizing complex geospatial data into interpretable information, the platform reduces the need for specialized expertise in Geographic Information Systems (GIS). Overall, the proposed system provides a scalable and user-friendly solution that combines data retrieval, analysis, and prediction within a single integrated framework.

IV. METHODOLOGY

The proposed methodology integrates satellite-based data analysis with deep learning techniques to perform comprehensive Land Use and Land Cover (LULC) analysis and prediction. The workflow is designed as a multi-stage pipeline consisting of data acquisition, preprocessing, multi-temporal analysis, change detection, and predictive modeling, ensuring a structured and scalable approach to land monitoring.

The process begins with user interaction through a web-based interface, where an Area of Interest (AOI) is defined using an interactive map. This spatial input serves as the primary boundary for all subsequent analysis. Based on the selected AOI and user-defined time range, LULC data is retrieved from the Dynamic World V1 dataset, which is derived from Sentinel-2 satellite imagery. The dataset provides near real-time, high-resolution land cover classifications across multiple temporal instances, making it suitable for longitudinal analysis.

Once the data is retrieved, a preprocessing stage is per-formed to ensure consistency and accuracy. This includes spatial clipping of the satellite data to match the AOI, temporal filtering to extract relevant years, and alignment of multi-temporal datasets to maintain uniform spatial resolution and coordinate systems. These steps are essential to enable accurate comparison across different time periods.

Following preprocessing, LULC maps are generated for each selected year. These maps represent various land cover classes such as built-up areas, vegetation, water bodies, and barren land. The system supports multi-temporal analysis by enabling simultaneous visualization of LULC maps from different years, allowing users to observe long-term trends and patterns in land transformation.

To provide a more detailed understanding of land changes, pixel-level change detection is performed. This involves com-paring corresponding pixels across different time periods to identify transitions between land cover classes. For instance, changes such as vegetation converting into built-up areas are detected and quantified. A transition matrix is generated to represent these changes, providing a structured view of class-wise transformations. Additionally, area-based metrics are computed to measure the extent of urban expansion, deforestation, and other significant changes.

For predictive analysis, a deep learning-based approach is adopted using a U-Net architecture. The model is trained on temporally paired LULC datasets, where each pair represents land cover changes between two time periods. This enables the model to learn spatial patterns and trends associated with land transformation. The encoder component of the U-Net extracts hierarchical spatial features, while the decoder reconstructs high-resolution output maps, allowing precise localization of predicted changes.

After training, the model is used to predict future land cover scenarios. The output is generated in the form of probability maps, which are visualized as heatmaps indicating areas with a higher likelihood of future urban growth. These predictions provide valuable insights into potential development zones and help support proactive planning and decision-making.

In addition to analytical processing, the system integrates automated insight generation and reporting functionalities. The results of change detection and prediction are summarized into interpretable formats, enabling users to understand complex geospatial patterns without requiring advanced technical expertise.

Overall, the proposed methodology combines multi-temporal satellite data analysis, pixel-level change detection, and deep learning-based prediction within a unified frame-work, ensuring accurate, efficient, and user-friendly LULC analysis.

V. RESULTS AND DISCUSSION

The proposed system was implemented and evaluated using multi-temporal satellite data to assess its effectiveness in performing Land Use and Land Cover (LULC) analysis, change detection, and future prediction. The Dynamic World V1 dataset was utilized to generate LULC maps for different time periods, and the trained U-Net model was used to predict future land transformation patterns.

A. LULC Map Generation and Visual Analysis

The system successfully generated year-wise LULC maps for the selected Area of Interest (AOI). These maps provide a clear representation of land cover classes such as built-up areas, vegetation, water bodies, and barren land.

Visual comparison of LULC maps across different years indicates a noticeable increase in built-up regions, while vegetation areas show a gradual decline. This trend reflects ongoing urban expansion and highlights the impact of land conversion over time.

B. Multi-temporal Analysis and Area Statistics

To quantitatively analyze land cover changes, area-based statistics were computed for each class across multiple years. The results indicate a significant increase in built-up area over time, accompanied by a reduction in vegetation cover.

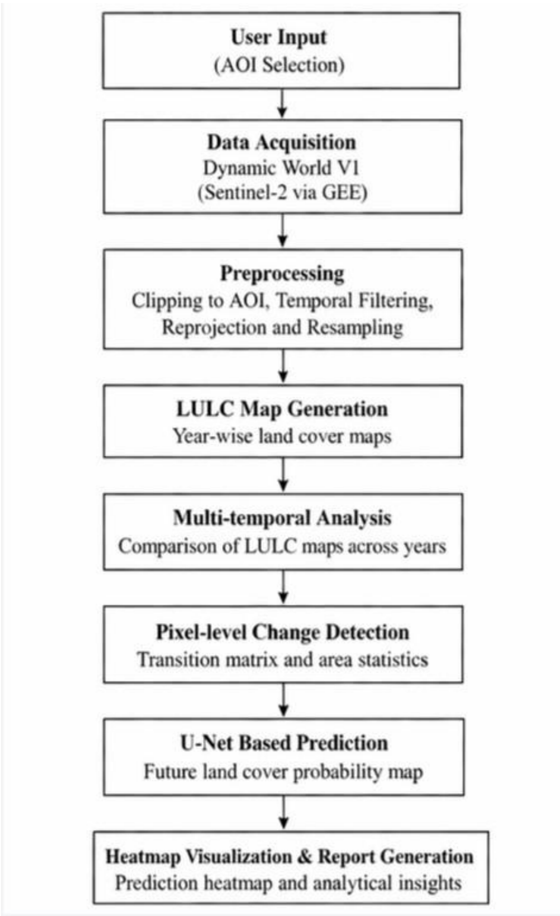

Fig. 1. Workflow of proposed LULC analysis and prediction system.

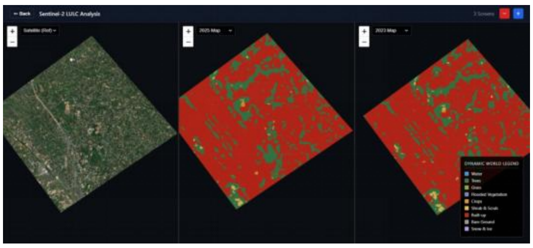

Fig. 2. LULC maps for different years.

This trend confirms the presence of continuous urban growth within the study region. The use of multi-temporal data enables a clearer understanding of long-term land transformation patterns and supports data-driven environmental assessment.

C. Pixel-level Change Detection

Pixel-level change detection was performed by comparing LULC maps across different time periods. This analysis identifies specific land cover transitions at a fine spatial resolution. The results show that a considerable portion of land has transitioned from vegetation to built-up areas, indicating urban expansion. Minor transitions between other classes were also observed. The transition matrix provides a structured representation of these changes, enabling detailed analysis of land cover dynamics.

D. Future LULC Prediction Using U-Net

The U-Net-based model was trained using temporally paired LULC datasets to learn spatial patterns of land transformation. The model successfully generated probability-based predictions of future land cover changes.

The predicted heatmaps highlight regions with a higher likelihood of urban development. High-probability zones are primarily concentrated around existing urban areas and along major development corridors, suggesting potential directions of future expansion.

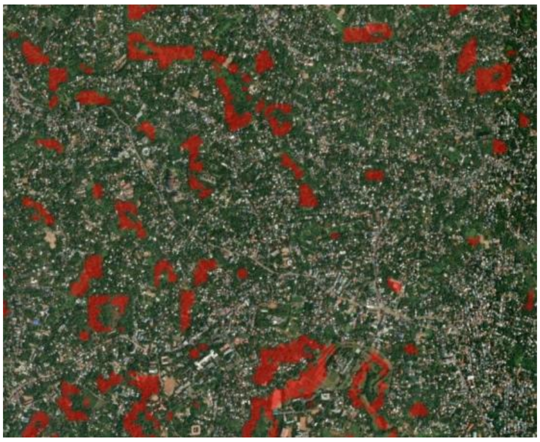

Fig. 3. Predicted heatmap for future urban growth.

E. Discussion

The results demonstrate that the proposed system effectively integrates satellite data analysis and deep learning to perform comprehensive LULC analysis. The combination of multi-temporal analysis, pixel-level change detection, and predictive modeling provides both descriptive and predictive insights into land transformation.

The system not only identifies past and present land changes but also offers a forward-looking perspective through prediction. This makes it a valuable tool for urban planners, environ-mental analysts, and decision-makers involved in sustainable land management.

VI. CONCLUSION

This paper presented a web-based intelligent system for Land Use and Land Cover (LULC) analysis that integrates satellite remote sensing, geospatial analysis, and deep learning techniques. The system enables users to generate LULC maps, perform multi-temporal analysis, and detect land cover changes at a pixel level, providing a comprehensive under-standing of land transformation patterns.

The incorporation of a U-Net-based model allows the system to predict future land use changes and generate probability-based heatmaps, offering valuable insights into potential urban growth areas. The results demonstrate that the proposed approach effectively identifies urban expansion trends and environmental changes while maintaining a user-friendly interface.

By combining data analysis, visualization, and prediction within a single platform, the system addresses the limitations of existing tools and supports informed decision-making in urban planning and environmental monitoring. Future work can focus on improving model accuracy, incorporating additional datasets, and enhancing scalability for large-scale applications.

REFERENCES

[1] G. Cecili, P. De Fioravante, P. Dichicco, L. Congedo, M. Marchetti, and M. Munafo`, ”Land Cover Mapping with Convolutional Neural Networks Using Sentinel-2 Images: Case Study of Rome,” *Land*, vol. 12, no. 4, p. 879, 2023.

[2] D. Sathyanarayanan, D. V. Anudeep, C. A. K. Das, S. Bhanadarkar, U. D., R. Hebbar, and K. G. Raj, ”A Multiclass Deep Learning Approach for LULC Classification of Multispectral Satellite Images,” in *2020 IEEE India Geoscience and Remote Sensing Symposium (InGARSS)*, pp. 102–105, 2020.

[3] A. Vali, S. Comai, and M. Matteucci, ”Deep Learning for Land Use and Land Cover Classification Based on Hyperspectral and Multispectral Earth Observation Data: A Review,” *Remote Sensing*, vol. 12, no. 15, p. 2495, 2020.

[4] P. M. and T. T. K., ”A Tile-Based Approach for the LULC Classification of Sentinel Image Using Deep Learning Techniques,” in *2022 Interna-tional Conference for Advancement in Technology (ICONAT)*, 2022.

[5] A. T. Balarabe and I. Jordanov, ”LULC Image Classification with Convolutional Neural Network,” in *IGARSS 2021 IEEE International Geoscience and Remote Sensing Symposium*, pp. 5985–5988, 2021.

[6] P. Helber, B. Bischke, A. Dengel, and D. Borth, ”EuroSAT: A Novel Dataset and Deep Learning Benchmark for Land Use and Land Cover Classification,” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 12, no. 7, pp. 2217–2226, 2019.

[7] O. Ronneberger, P. Fischer, and T. Brox, ”U-Net: Convolutional Net-works for Biomedical Image Segmentation,” in *Proc. MICCAI*, pp. 234–241, 2015.

[8] K. He, X. Zhang, S. Ren, and J. Sun, ”Deep Residual Learning for Image Recognition,” in *Proc. IEEE CVPR*, pp. 770–778, 2016.

[9] A. Krizhevsky, I. Sutskever, and G. E. Hinton, ”ImageNet Classification with Deep Convolutional Neural Networks,” in *Advances in Neural Information Processing Systems*, vol. 25, 2012.

[10] K. Simonyan and A. Zisserman, ”Very Deep Convolutional Networks for Large-Scale Image Recognition,” arXiv preprint arXiv:1409.1556, 2014.

[11] M. Mahdianpari, B. Salehi, M. Rezaee, F. Mohammadimanesh, and Y. Zhang, ”Very Deep Convolutional Neural Networks for Complex Land Cover Mapping Using Multispectral Remote Sensing Imagery,” *Remote Sensing*, vol. 10, no. 7, p. 1119, 2018.

[12] N. Kussul, M. Lavreniuk, S. Skakun, and A. Shelestov, ”Deep Learning Classification of Land Cover and Crop Types Using Remote Sensing Data,” *IEEE Geoscience and Remote Sensing Letters*, vol. 14, no. 5, pp. 778–782,

2017.
[13] G. J. Scott, M. R. England, W. A. Starms, R. A. Marcum, and C. H. Davis, ”Training Deep Convolutional Neural Networks for Land-Cover Classification of High-Resolution Imagery,” *IEEE Geoscience and Remote Sensing Letters*, vol. 14, no. 4, pp. 549–553, 2017.