# Classifying Land Use and Land Cover for Sustainable Urban Planning and Ecosystem Conservation

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*Abstract -* **Accurate classification of Land Use and Land Cover (LULC) is fundamental to understanding the spatial distribution of natural and anthropogenic features on the Earth's surface. It provides essential insights for urban planning, agricultural development, environmental monitoring, and resource management. The rapid pace of urbanization—particularly in developing regions—has amplified the demand for timely and precise LULC data. Traditional methods, such as manual interpretation and field surveys, are increasingly inadequate due to limitations in scalability, efficiency, and consistency. This study proposes an automated LULC classification approach that leverages deep learning and remote sensing technologies. Utilizing the ResNet50 deep convolutional neural network and the EuroSAT dataset comprising multispectral satellite imagery, the model is trained to classify land cover types such as urban areas, vegetation, water bodies, agricultural zones, and barren land. The classification process involves tiling satellite images into smaller segments, enabling fine-grained spatial pattern detection and high-resolution mapping. The resulting LULC maps visualize land cover categories with color-coded tiles, facilitating rapid and accurate assessments. This approach demonstrates notable improvements in classification speed, accuracy, and consistency, making it suitable for regular environmental monitoring. By integrating artificial intelligence with satellite imagery, the proposed system offers a scalable solution for informed decision-making in land management, sustainability planning, and urban development. As remote sensing data becomes increasingly accessible and frequent, deep learning-based LULC classification systems will play a pivotal role in addressing contemporary environmental and urban challenges.**

*Keywords:* Land Use and Land Cover (LULC), deep learning, ResNet50, remote sensing, EuroSAT, satellite imagery, spatial analysis, environmental monitoring, urban planning.

## I. INTRODUCTION

Land Use and Land Cover (LULC) mapping is an important component of understanding how land use changes and how land is used in a given area. LULC mapping is critical for sustainable urban planning, environmental surveillance, and resource management. Satellite imagery and deep learning are employed in this project to map various land covers like vegetation, water, and built-up land. By integrating the EuroSAT dataset, Google Earth Engine, and a ResNet50 model, the system delivers visual insights into land distribution. The aim is to facilitate smart city development and ecosystem conservation using data-driven decision-making and understandable LULC maps.

### 1.1 Background

A key step in comprehending how land is being used and how it varies as a result of both natural and man-made processes is the classification of land use and land cover, or LULC. While land cover refers to the physical surface (e.g., vegetation, water, built-up areas), land use refers to how humans use the land (e.g., agriculture, urban development). For efficient planning in industries like agriculture, forestry, urban development, water management, and disaster response, accurate LULC data is essential. Reliable, current information is becoming more and more necessary to support environmental conservation and sustainable development initiatives as cities expand and land use patterns change quickly.

Field surveys and manual interpretation of satellite or aerial photos were the mainstays of LULC mapping in the past. These techniques are labor-intensive, time-consuming, and challenging to scale over wide geographic areas or frequent time intervals, even though they produced accurate results at smaller scales. The growing land-use changes brought on by urban sprawl, deforestation, and industrial expansion have highlighted the shortcomings of manual

mapping. Automated classification techniques utilizing remote sensing technologies have been developed to address this. Frequent, wide-coverage satellite imagery from remote sensing makes it possible to efficiently identify and classify different types of land cover with little assistance from humans when machine learning and deep learning techniques are applied.

The field of LULC classification has made significant strides in recent years thanks to deep learning, especially Convolutional Neural Networks (CNNs). By learning intricate spatial features from satellite imagery, these models can increase accuracy and decrease the need for manually created features. In order to categorize different types of land cover from multispectral satellite images, a ResNet50 CNN model is trained using the EuroSAT dataset. After breaking down satellite images into smaller tiles, the model classifies each tile as either water, vegetation, urban, or barren land.

This method facilitates extensive, automated LULC monitoring and enables high-resolution mapping. Future studies and applications in urban planning, ecosystem assessment, and climate impact studies are made possible by the outputs produced by this system. The project shows a scalable, effective, and precise way to monitor land use and land cover in dynamic and varied environments by fusing deep learning models with remote sensing data.

**1.2 Objectives**

To automate Land Use and Land Cover classification using satellite imagery and deep learning. To generate high-resolution, tile-based LULC maps for selected regions. To integrate administrative boundaries for flexible, location-specific analysis. To provide interactive visualizations for easy interpretation of classified land cover data.

## II. LITERATURE REVIEW

Li and Zhang proposed a land use and land cover (LULC) [1] classification approach using ResNet-50 combined with transfer learning on satellite imagery. Their method significantly improved classification accuracy by leveraging deep pre-trained models. The study highlighted the importance of using deeper convolutional networks for complex spatial pattern recognition. They achieved robust performance across multiple satellite datasets with minimal manual feature extraction. This work demonstrates the efficiency of transfer learning in remote sensing applications In [2]Liu and Yang explored land use classification using deep convolutional neural networks (CNNs) with high-resolution remote sensing data. Their model effectively captured fine-grained spatial features, outperforming traditional machine learning classifiers. They emphasized the role of deep layers in learning hierarchical spatial representations. The study also evaluated the effect of different network architectures on classification performance. It confirmed the suitability of deep CNNs for urban planning and land resource management.[3] Ranjan and Kumar introduced a multi-source deep learning framework for urban land use classification. The model integrated data from various remote sensing sources to enhance accuracy and generalizability. They demonstrated the value of combining multispectral, spatial, and temporal features for land use analysis. Their approach improved classification in complex urban environments, where single-source data often fails. This work supports the growing trend of data fusion in geospatial deep learning research trained on actual farmer questions. It is multilingual and weather-enabled but only accepts text input at present, without multimodal capabilities such as voice or image input. A multimodal approach was investigated in [7],[16] where a chatbot employs CNN-based image processing to detect plant diseases and is hosted on the Heroku cloud. The system has a feedback loop for ongoing improvement, but needs internet access and compatible hardware, thus being less suitable for remote field deployment.

In [8], a prototype AI rover for farm monitoring was constructed utilizing an ESP32 camera and CNN models with real-time notifications using the Blynk platform. While promising, it is still a prototype and has no proof of efficacy on massive farms.Lastly, an extensive survey in [9] surveyed several AI-powered agriculture technologies such as drone technology, computer vision, and IoT. It mentioned case studies such as the Hands-Free Hectare and weed detection technology. Nonetheless, it also emphasized ongoing challenges such as cost, unavailability of datasets, digital illiteracy, and privacy issues that hinder intensive adoption.

Taken together, these studies demonstrate the advances and gaps in leveraging AI and IoT for smart agriculture. As prototypes and pilot tools become more advanced, their deployment in real-world settings needs to overcome infrastructural, educational, and economic barriers. Future research should prioritize inclusivity, field-level useability, and localized development to make a greater impact.

## III. METHODOLOGY

The project adopts a systematic approach to categorize Land Use and Land Cover from satellite images and deep learning. To train a ResNet50 convolutional neural network, the EuroSAT dataset of labeled Sentinel-2 satellite images was initially employed. The model learns to identify different land cover classes including water, vegetation, and urban infrastructure. Google Earth Engine (GEE) was utilized to

retrieve recent satellite imagery for various places in India. These images were pre-processed and segmented into tiles like the training data. The trained ResNet50 model was then utilized to predict the class of each tile. A Streamlit-based web interface was created to enable users to choose a location and see its LULC map. The system further computes the percentage of significant land types and contrasts them with optimum urban values to ascertain if a region is environmentally balanced. The end-to-end process enables sustainable planning via precise LULC visualization.
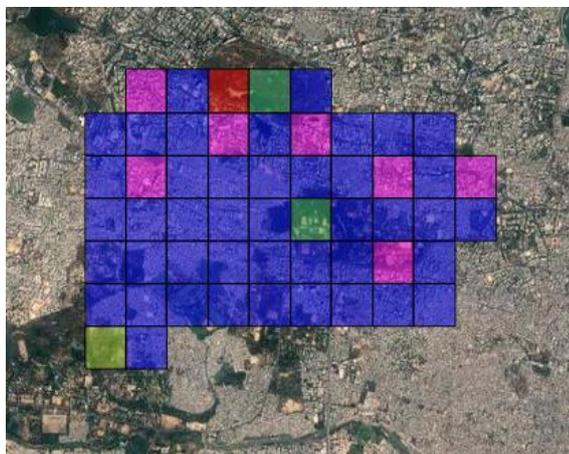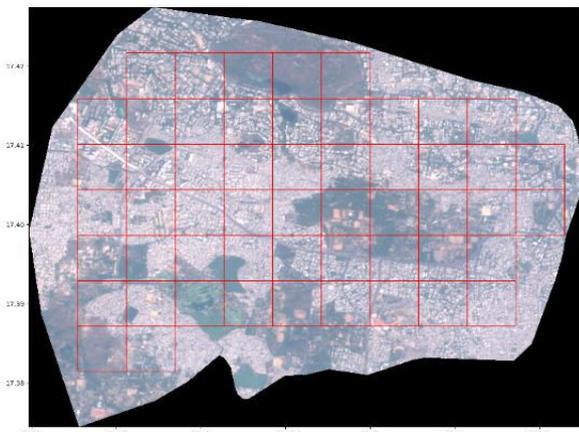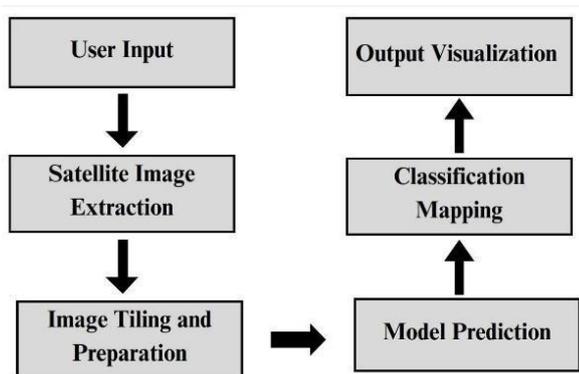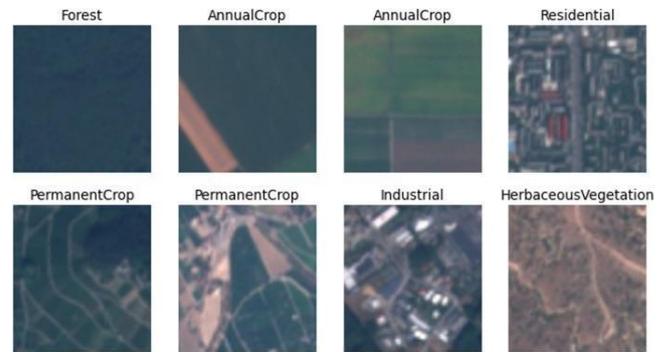






## IV. RESULTS

The Land Use and Land Cover classification model attained a high accuracy of around 95–96% with the ResNet50 architecture trained on the EuroSAT dataset. The system was able to classify different land cover classes like water bodies, vegetation, barren land, and built-up areas from Sentinel-2 satellite images. The web interface enabled users to enter or choose specific locations and display color-coded LULC maps along with class-wise percentage breakdowns. These results corresponded to the desired ground conditions in the majority of instances, confirming the performance of the model. The system further computed whether the area is environmentally preserved according to ideal urban land composition values.

| Metric | Value (%) |
|---|---|
| Accuracy | 95.00 |
| Precision | 93.40 |

## V. DISCUSSIONS

The LULC classification initiative showcases the competency of deep learning in interpreting satellite imagery. High accuracy was experienced by the ResNet50 model in classifying land cover areas such as vegetation, water bodies, and cities. Such categorizations can enable sustainable planning as they assist governing bodies in keeping track of patterns of land utilization and identifying ecological imbalances quickly.

Future research can emphasize the use of multi-temporal satellite imagery to monitor temporal changes, employ higher-resolution imagery for increased detail, and include more class categories for greater specificity. Adding climatic and demographic information could provide greater insight, and employing state-of-the-art models such as transformers might continue to enhance classification accuracy in various environments.

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