1. Project Overview

Land Use and Land Cover (LULC) classification is a fundamental task in Earth Observation, supporting applications such as land management, urban planning, and environmental monitoring.
In this project, we present an end-to-end deep learning pipeline for **land type classification** using **Sentinel-2 multispectral satellite imagery**.

The project leverages the **EuroSAT Multispectral Dataset**, consisting of geo-referenced satellite images across **13 spectral bands** and **10 land cover classes**.
State-of-the-art **Convolutional Neural Networks (CNNs)** were trained and evaluated, achieving an overall classification accuracy of 96%**.

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2. Dataset Description

2.1 Data Source

- **Dataset Name:** EuroSAT Multispectral (MS)
- **Satellite:** Sentinel-2
- **Provider:** Copernicus Earth Observation Program
- **Access Link:** https://zenodo.org/records/7711810#.ZAm3k-zMKEA

2.2 Dataset Characteristics

- **Total Images:** ~27,000
- **Image Format:** `.tif`
- **Spatial Resolution:** Varies by spectral band
- **Spectral Channels:** 13 multispectral bands
- **Data Type:** Geo-referenced satellite imagery

2.3 Land Cover Classes (10 Classes)

1. Annual Crop
2. Forest
3. Herbaceous Vegetation
4. Highway
5. Industrial

6. Pasture
7. Permanent Crop
8. Residential
9. River
10. Sea / Lake

Each class represents a distinct land use or land cover type commonly used in remote sensing applications.

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3. Data Collection Pipeline

The dataset was downloaded from **Zenodo** and organized into class-specific directories. Each folder contains multispectral `.tif` images corresponding to one land cover class.

The project uses **Rasterio** to read geospatial data and preserve spectral integrity across all 13 channels.

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4. Data Preprocessing

4.1 Multi-Spectral Handling (13 Channels)

Unlike RGB images, Sentinel-2 data includes 13 spectral channels capturing visible, near-infrared, and short-wave infrared information. All channels were preserved to fully exploit spectral diversity.

4.2 Image Resizing

- All images were resized to a unified spatial dimension of **96 × 96** pixels.
- Bilinear interpolation was used to maintain spatial consistency across bands.

4.3 Data Normalization

- Channel-wise **mean and standard deviation** values were computed across the dataset.
- Each spectral band was normalized independently to stabilize training and accelerate convergence.

4.4 Data Augmentation (Training Phase)

To improve generalization and reduce overfitting, the following augmentations were applied:

- Random horizontal and vertical flips
- Random rotations (0°, 90°, 180°, 270°)
- Random scaling and cropping

These transformations simulate real-world spatial variations and enhance model robustness.

4.5 Dataset Splitting

The dataset was split as follows:

- **70% Training set**
- **15% Validation set**
- **15% Test set**

A fixed random seed was used to ensure reproducibility..

5. Model Development and Training

5.1 Model Selection Strategy

Multiple deep learning architectures were explored to identify the most effective model for multi-spectral land classification:

- **Custom CNN**: Designed to learn spatial–spectral features directly from the data
- **ResNet-50**: Utilized for its residual connections and strong feature extraction capabilities
- **GoogLeNet (Inception)**: Chosen for its multi-scale feature learning

These models were adapted to accept **13-channel inputs**, rather than standard RGB images.

5.2 Training Process

- Loss function: Cross-entropy loss
- Optimization: Gradient-based optimization with mini-batches
- Batch size: 32
- Training monitored using validation accuracy

Model selection was based on validation performance and generalization ability.

5.3 Performance Results

- **Overall classification accuracy**: **96%**
- Strong performance across all land cover classes
- Minimal confusion between visually similar classes due to rich spectral information

6. Model Optimization Decisions

Key decisions that contributed to high performance:

- Retaining all 13 spectral bands instead of reducing to RGB
- Applying channel-wise normalization
- Using spatial augmentations tailored for satellite imagery
- Evaluating multiple CNN architectures before final selection

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7. Deployment

7.1 Deployment Framework

The trained model was deployed using **Streamlit**, enabling an interactive and user-friendly interface.

7.2 Deployment Features

- Upload satellite images
- Automatic preprocessing
- Real-time land type prediction
- Clear visualization of classification results

This deployment transforms the model from a research prototype into a usable application.

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8. Challenges Faced

Several challenges were addressed during the project lifecycle:

- **High-dimensional input data** (13 channels)
- **Large data volume** requiring efficient loading and memory handling
- **Class similarity**, especially between vegetation-related classes
- **Model adaptation** for non-RGB inputs

Each challenge influenced design decisions in preprocessing, model architecture, and training strategy.

9. Impact and Applications

9.1 Land Management

- Monitoring agricultural land use
- Detecting crop type changes

9.2 Urban Planning

- Tracking urban expansion
- Identifying industrial and residential growth patterns

9.3 Environmental Monitoring

- Forest cover analysis
- Water body detection
- Climate and ecosystem studies

9.4 Map Enhancement

- Improving geographical and land cover maps
- Supporting GIS-based decision-making

10. Conclusion

This project demonstrates the effectiveness of deep learning for **multi-spectral satellite image classification**. By leveraging Sentinel-2 data and state-of-the-art CNN architectures, the system achieves high accuracy and practical relevance.

The complete pipeline—from data collection and preprocessing to deployment—highlights a scalable and reproducible approach for Earth observation applications, making it suitable for both academic research and real-world use cases.