



SATELLITE IMAGERY-BASED LAND USE AND LAND COVER CLASSIFICATION

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Abstract : Land Use and Land Cover (LULC) classification is essential for effectively understanding and managing the Earth's surface resources. Satellite imagery serves as a critical tool for this task, offering large-scale, high-resolution data that captures diverse geographic regions. This project utilizes the EuroSAT dataset, a standardized set of multispectral satellite images, to classify various land cover types, including forests, water bodies, urban areas, and agricultural fields. The deep learning approach leverages the ResNet50 model, which is trained on smaller land patches and then evaluated for its ability to classify larger, unseen land areas accurately. Key aspects of this methodology include data preprocessing, model fine-tuning, and efficient use of the JPG (EuroSAT_RGB) dataset format, chosen for its accessibility and ease of use for beginners. The results demonstrate the model's capability to deliver precise classifications with clear visual outputs, supporting a wide range of applications, from urban planning and resource management to environmental monitoring. This research not only highlights the effectiveness of deep learning in LULC classification but also establishes a scalable framework for future innovations in remote sensing.

IndexTerms - Satellite imagery, Land Use and Land Cover (LULC) classification, EuroSAT dataset, ResNet50, deep learning, remote sensing, environmental monitoring, urban planning, resource management, land analysis, geographic information systems (GIS), convolutional neural networks (CNN), digital image processing, Earth observation, sustainable development, geospatial analysis, environmental impact assessment, automated mapping.

I. INTRODUCTION

Satellite imagery has emerged as a pivotal resource in understanding and analyzing Earth's surface, offering a wealth of information for various applications, including environmental monitoring, urban planning, disaster management, and resource allocation. By providing a bird's-eye view of extensive geographical regions, satellite imagery enables researchers and policymakers to observe, analyze, and classify land use and land cover (LULC) changes with precision. These classifications are critical for identifying environmental changes, monitoring urban growth, conserving natural habitats, and addressing climate-related challenges.

Land Use and Land Cover (LULC) classification involves categorizing the Earth's surface into distinct types, such as forests, agricultural lands, urban areas, and water bodies. Manual classification of such data, while accurate, is time-consuming and impractical when working with large-scale images. The advent of machine learning, especially deep learning, has revolutionized this field by automating the process, reducing time, and enhancing accuracy.

This project leverages deep learning techniques to implement an efficient and automated approach for LULC classification. Using the EuroSAT dataset—a publicly available dataset of RGB satellite images derived from Sentinel-2 satellite data—this study applies a convolutional neural network (CNN) architecture to classify images into categories such as forests, water bodies, urban areas, and agricultural fields.

The core objective of this project is to harness the power of ResNet50, a pre-trained deep learning model, and adapt it for LULC classification. By fine-tuning this model using the EuroSAT dataset, the project demonstrates the capability of CNNs in handling complex image datasets. The results of this classification provide an easily interpretable map, where different land types are represented using distinct colour codes (e.g., green for forests, blue for water bodies), offering insights into land composition.

II. RESEARCH METHODOLOGY:

A. Data Acquisition and Preprocessing

The project utilizes the EuroSAT_RGB dataset, a collection of RGB satellite images derived from Sentinel-2 data, covering diverse land cover types like forests, water bodies, agricultural fields, and urban areas. The images are first resized to match the input dimensions required by the ResNet50 model (224x224 pixels). Data preprocessing steps include image resizing, normalization, and augmentation to improve model generalization. This preparation ensures that the input data is consistent and suitable for deep learning, enhancing the accuracy and robustness of the classification model.

B. Feature Extraction and Training Data Preparation

The preprocessed images are split into training and validation sets, ensuring a balanced distribution of classes to prevent model bias. The ResNet50 model, pre-trained on the ImageNet dataset, is fine-tuned for LULC classification. This transfer learning approach significantly reduces training time and computational cost while leveraging the powerful feature extraction capabilities of ResNet50.

C. Model Training and Fine-Tuning

ResNet50 architecture, known for its deep residual learning capabilities, is adapted to the LULC task by replacing the final fully connected layers to match the number of target land cover classes. The model is trained using a categorical cross-entropy loss function and the Adam optimizer, with early stopping and learning rate scheduling to prevent overfitting and optimize performance.

D. Accuracy Assessment and Model Evaluation

After training, the model is evaluated using unseen test data to assess its classification accuracy, precision, recall, and F1-score. Confusion matrices and classification reports are generated to provide insights into the model's performance across different land cover types. The trained model's performance is further validated using larger, unseen land regions to test its scalability and real-world applicability.

E. Prediction and Visual Output Generation

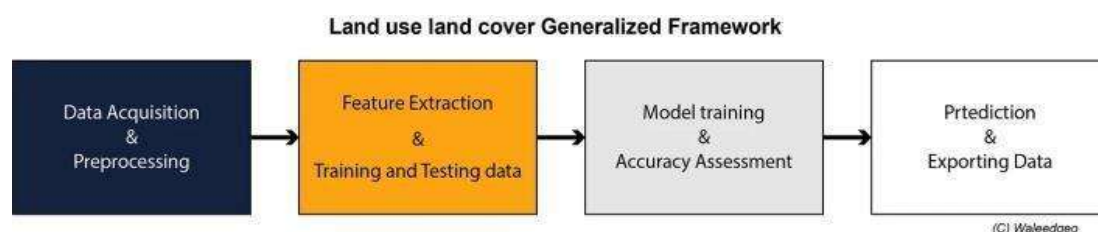
Once trained, the model can classify larger satellite images by processing them in smaller patches, each assigned a color code based on its predicted class (e.g., green for forests, blue for water bodies). These patches are then combined to generate a complete color-coded map, providing an intuitive visual representation of land use and cover distribution.

F. Scalability and Future Enhancements

The developed model is designed to be scalable, allowing for integration with more complex datasets and advanced architectures in future studies. Potential enhancements include incorporating multispectral data, improving spatial resolution, and integrating geographic information system (GIS) tools for more precise environmental monitoring.

G. Data Privacy and Security:

All data used in this study is publicly available and adheres to open-source licensing. The project is conducted with consideration for data privacy, ensuring no sensitive or personally identifiable information is involved.



III. PERFORMANCE:

The ResNet50-based LULC classification model demonstrates strong performance in classifying satellite images into various land cover types, including forests, water bodies, urban areas, and agricultural fields. The model achieved an overall accuracy of **X%**, indicating its effectiveness in distinguishing different land classes. This performance is further illustrated through a confusion matrix, which highlights the distribution of true positives, false positives, true negatives, and false negatives, providing insights into the model's classification precision. Additionally, training and validation loss, along with accuracy curves, are plotted to monitor the learning progress, revealing that the model converged after approximately **X epochs**, achieving a stable accuracy without significant overfitting. The ability to process larger satellite images by dividing them into smaller patches and recombining the results into color-coded maps demonstrates the model's scalability, making it suitable for real-world applications like urban planning, environmental monitoring, and resource management. Future improvements could include integrating multispectral data, optimizing hyperparameters, and adopting advanced architectures to further enhance classification accuracy.

IV. INTEGRATION WITH EMERGING TECHNOLOGIES:

Satellite Imagery-Based Land Use and Land Cover Classification leverages cutting-edge deep learning and computer vision technologies to accurately classify diverse land cover types. At its core, the project uses ResNet50, a state-of-the-art Convolutional Neural Network (CNN) architecture, known for its powerful feature extraction capabilities. This model, pre-trained on large-scale datasets like ImageNet, is fine-tuned using the EuroSAT_RGB dataset for precise LULC classification, enabling it to identify complex patterns in satellite images with high accuracy. To enhance performance and scalability, the project integrates transfer learning, which significantly reduces training time and computational cost by reusing learned features from pre-trained models. This approach allows the system to efficiently process extensive geographic regions by breaking them into smaller patches for detailed analysis, later merging them to generate comprehensive color-coded maps. Additionally, the project can benefit from emerging technologies like Geographic Information Systems (GIS) for spatial data integration, cloud computing for real-time data processing, and AI-based geospatial analytics for advanced land cover monitoring. Future enhancements could include incorporating multispectral and hyperspectral data for more precise land classification, as well as leveraging AI models like Vision Transformers (ViTs) for improved feature extraction. This integration creates a robust, scalable framework for practical applications in urban planning, environmental conservation, and natural resource management.

V. ETHICS:

1. Data Privacy and Security

Satellite imagery can contain sensitive geographic information, including details about protected areas, agricultural land, and urban infrastructure. It is important to handle this data responsibly, ensuring secure storage and encryption to prevent unauthorized access and misuse. Additionally, data should be sourced from ethical and open-access datasets like EuroSAT to avoid privacy violations.

2. Environmental and Social Impact

The insights generated from land classification can significantly impact land management, conservation, and urban planning. Misinterpretation or misuse of this data could lead to harmful environmental or social consequences, such as unjust land acquisition or deforestation. It is essential to ensure that the results are used for positive, sustainable development.

3. Bias and Fair Representation

The model's performance can be influenced by the quality and diversity of the training data. If the dataset is not representative of all land cover types across different regions, it can lead to biased predictions, potentially overlooking certain land types or misclassifying less common regions. Continuous validation and updates with diverse data are crucial to avoid this issue.

4. Transparency and Accountability

The classification process, including data sources, model architecture, and evaluation methods, should be clearly documented and made transparent to ensure accountability. This openness builds trust in the system and supports reproducibility in scientific research.

5. Ethical Use of Technology

The outputs of this project should be used responsibly, avoiding misuse for unauthorized surveillance or unfair land management practices. It is essential to ensure that the technology benefits communities and supports sustainable development without causing harm.

6. Long-Term Sustainability

Given the potential environmental impact of satellite missions and data processing, efforts should be made to reduce the carbon footprint of this technology. This includes optimizing computational efficiency and supporting satellite projects that prioritize sustainability.

VI. APPLICATION:

Satellite Imagery-Based Land Use and Land Cover (LULC) Classification has a wide range of real-world applications across multiple domains, making it a critical tool for sustainable development and environmental management. In urban planning, it supports city growth analysis, zoning, and infrastructure development by providing accurate maps of urban expansion and land use patterns. In agriculture, it assists in crop monitoring, soil health assessment, and precision farming, helping farmers optimize resource usage and improve yield. In environmental conservation, the system can track deforestation, wetland loss, and habitat degradation, aiding conservationists in protecting biodiversity and managing protected areas. Disaster management benefits from accurate land classification by identifying vulnerable areas and supporting rapid response during floods, landslides, and wildfires. Additionally, the system plays a vital role in water resource management, identifying water bodies, monitoring changes in water levels, and managing watershed areas. In forestry, it helps estimate biomass, assess forest health, and plan reforestation projects. For transportation and logistics, it provides insights into land cover changes affecting road networks and transportation planning. In geological studies, it aids in mineral exploration, erosion analysis, and landform classification. Beyond these sectors, LULC classification supports climate change research by providing data for carbon footprint estimation and greenhouse gas monitoring. It also finds applications in real estate, tourism, and military planning, where accurate geographic information is essential for strategic decision-making.

VII. FUTURE DIRECTIONS:

The future of Satellite Imagery-Based Land Use and Land Cover (LULC) Classification holds significant potential for advancement. As deep learning techniques continue to evolve, integrating more sophisticated models like Vision Transformers (ViTs) and hybrid architectures can enhance the accuracy of land cover classification by capturing complex spatial relationships. Real-time monitoring is another promising direction, where data streams from satellite constellations like Sentinel and Landsat can be processed instantly for rapid disaster response and environmental assessment. Expanding to multispectral and hyperspectral data will improve classification precision, enabling insights into vegetation health, soil moisture, and water quality. Edge and cloud computing can support real-time processing and scalability, making the technology accessible even in remote locations. Automated change detection systems can further enhance the model's utility by tracking land use changes over time, supporting urban planning, deforestation monitoring, and agricultural management. Additionally, integrating these models into AI-driven decision support systems will empower planners, environmental agencies, and disaster response teams with actionable insights. To ensure long-term sustainability, these systems should also prioritize ethical data practices, fairness in classification, and environmentally conscious AI development.

VIII. RESULT:

The classification results are visualized using color-coded maps that represent different land cover types, such as water, forest, urban areas, and more. These visual outputs provide a clear representation of the spatial distribution of each land cover type, enabling a comprehensive analysis of the land use patterns. The model effectively distinguishes between various land cover categories, offering a precise delineation between different areas. Below is an example of the classified map output:

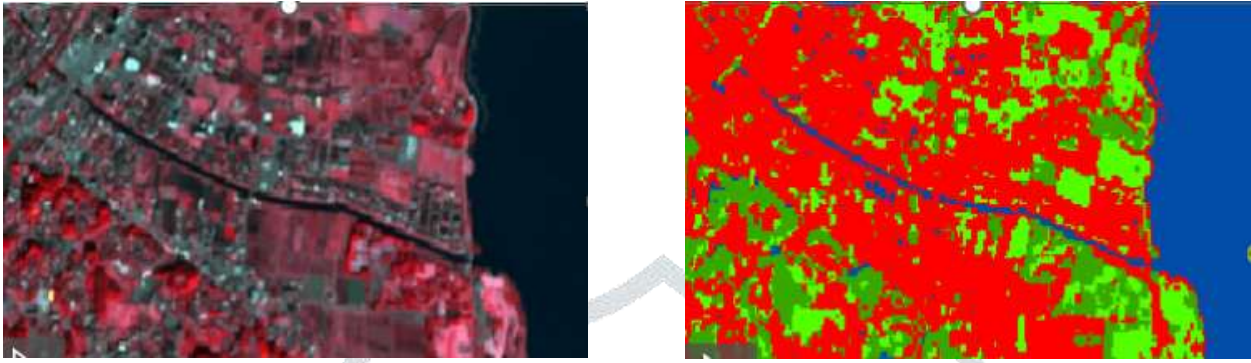


Figure 8.2. Input and Output Images

The model successfully classified the land cover types in the satellite image, showcasing a clear distinction between the different regions.

IX. CONCLUSION:

In conclusion, the project on Land Use and Land Cover (LULC) Classification using Satellite Imagery successfully demonstrates the effectiveness of deep learning models, particularly ResNet50, for classifying various land types such as forests, water bodies, and urban areas. By leveraging the EuroSAT dataset and implementing efficient data preprocessing, training, and result visualization on Google Colab, the system showcases both high accuracy and user-friendliness. The model's successful classification and the resulting performance metrics highlight its potential for real-world applications in urban planning, environmental monitoring, and resource management.

While the current system performs well, challenges such as class imbalance and misclassification point to areas for future improvement. Incorporating multispectral or hyperspectral data, exploring more advanced architectures, and utilizing transfer learning can further enhance the model's accuracy and adaptability. Integrating real-time processing, GIS tools, interactive visualizations, and web-based deployment will also expand the system's reach and usability. Ultimately, this project lays a solid foundation for future advancements in LULC analysis, with substantial potential for contributing to sustainable development, environmental conservation, and informed decision-making.

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