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Land Use and Land Cover Classification Using Sentinel-2 Satellite Imagery

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Abstract: Land Use and Land Cover (LULC) classification is an important task in remote sensing for environmental monitoring, agriculture, and urban planning. This paper presents a deep learning-based approach for classifying satellite images into different land cover categories using a Convolutional Neural Network (CNN). The model is trained on the EuroSAT dataset, which consists of Sentinel-2 satellite images categorized into 10 classes such as forest, residential, river, and agricultural land. The proposed model uses multiple convolutional layers along with batch normalization and dropout to improve performance and reduce overfitting. Experimental results show that the model achieves high accuracy and performs effectively in distinguishing different land cover types. This system can be used for real-world applications such as land monitoring and disaster management.

Keywords: LULC, CNN, Deep Learning, Satellite Imagery, EuroSAT, Remote Sensing

1.INTRODUCTION

Land Use and Land Cover (LULC) classification is a fundamental aspect of geospatial analysis that provides critical insights into the interaction between human activities and the natural environment. It involves identifying and categorizing different types of land surfaces, such as forests, agricultural fields, urban areas, and water bodies, using satellite imagery. Accurate LULC information is essential for a wide range of applications, including environmental monitoring, urban planning, agricultural management, disaster response, and climate change studies.With the rapid growth of urbanization and industrialization, the need for efficient monitoring of land resources has become increasingly important. Traditional methods of land cover mapping, which rely on field surveys and manual interpretation of satellite images, are time-consuming, labor-intensive, and often lack scalability. Furthermore, conventional machine learning techniques require manual feature extraction, making them less effective for handling large-scale and high-dimensional satellite datasets.

2. LITERATURE REVIEW

1. In (2020), Helber et al. introduce the EuroSAT dataset, a large-scale benchmark specifically designed for land use and land cover classification using Sentinel-2 satellite imagery. Their study emphasizes the importance of publicly available, labeled remote sensing datasets for training deep learning models effectively. The authors demonstrate that EuroSAT enables robust evaluation of convolutional neural networks in multi-class land cover recognition tasks, significantly advancing research in earth observation and geospatial AI applications. [1]

2. In (2015), the European Space Agency presents the Sentinel-2 User Handbook, which provides comprehensive technical details about Sentinel-2 satellite imagery, including spectral bands, spatial resolution, and revisit frequency. The handbook serves as a foundational reference for researchers working in remote sensing, enabling accurate preprocessing and interpretation of multispectral data for land cover analysis and environmental monitoring. [2]

3. In (2012) and (2014), Krizhevsky et al. and Simonyan and Zisserman introduce foundational convolutional neural network architectures, namely AlexNet and VGG. AlexNet demonstrates the breakthrough performance of deep CNNs in large-scale image classification, while VGG emphasizes the effectiveness of deeper networks using small convolutional filters. Together, these models establish the core architectural principles that later influence remote sensing image classification systems. [3]

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3. METHODOLOGY

This study adopts a deep learning-based approach for Land Use and Land Cover (LULC) classification using satellite imagery. The methodology consists of multiple stages, including data preprocessing, model design, training, and evaluation.

[1] 3.1 Data Collection and Preprocessing

The dataset used in this study is the **EuroSAT dataset**, derived from Sentinel-2 satellite imagery. It contains approximately 27,000 RGB images distributed equally across ten land cover classes.

Preprocessing steps include:

- **Resizing:** All images are standardized to 64 × 64 pixels.
- **Normalization:** Pixel values are scaled to the range [0,1] to improve training stability.
- **Label Encoding:** Class labels are converted into numerical format using one-hot encoding.
- **Data Splitting:** The dataset is divided into training (80%) and validation (20%) sets.
- **Data Augmentation:** Techniques such as rotation, flipping, and zooming are applied to increase dataset diversity and reduce overfitting.

[2] 3.2 Model Architecture

A Convolutional Neural Network (CNN) is designed using **TensorFlow** and **Keras**.

Architecture details:

- **Input Layer:** 64 × 64 × 3 (RGB image)
- **Convolutional Layers:**
  - Four convolutional blocks with 32, 64, 128, and 256 filters
  - Kernel size: 3 × 3
  - Activation function: ReLU
- **Batch Normalization:** Applied after each convolution to stabilize learning
- **Max Pooling:** 2 × 2 pooling to reduce spatial dimensions
- **Fully Connected Layers:**
  - Dense layers with 512 and 256 neurons
  - Dropout (0.5) for regularization
- **Output Layer:**
  - Softmax activation for multi-class classification (10 classes)

4. RESULT AND DISCUSSION

Result

Evaluation metrics such as precision, recall, and F1-score were computed for each class. The results indicate that the model performs well across most categories, with higher scores observed for distinct classes such as forest, river, and residential areas. The confusion matrix shows that the majority of predictions lie along the diagonal, representing correct classifications.

The proposed Convolutional Neural Network (CNN) model was trained and evaluated using the EuroSAT dataset, which contains balanced samples across ten land cover classes. After training for 50 epochs with early stopping, the model achieved strong performance on the validation dataset.

The overall classification accuracy exceeded 85%, indicating that the model effectively learned spatial patterns from satellite imagery. The training and validation accuracy curves showed consistent improvement during the initial epochs and stabilized as the model converged. Similarly, the loss curves demonstrated a steady decrease, confirming efficient optimization during training.

Discussion

The results highlight the effectiveness of deep learning techniques in LULC classification tasks. The CNN model successfully captures complex spatial features from satellite imagery without requiring manual feature extraction, which is a significant advantage over traditional machine learning approaches.

The high accuracy achieved in this study can be attributed to the use of a well-structured CNN architecture, along with optimization techniques such as batch normalization, dropout, and early stopping. These methods helped improve generalization and reduce overfitting, leading to stable model performance.

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5. CONCLUSION

This study successfully demonstrates the application of deep learning techniques for accurate and efficient Land Use and Land Cover (LULC) classification using Sentinel-2 satellite imagery. By leveraging the **EuroSAT dataset**, the proposed Convolutional Neural Network (CNN) model was trained on a diverse and balanced dataset comprising ten land cover classes. The model effectively learned spatial patterns and spectral features from RGB image patches, enabling reliable classification across various land categories such as agricultural areas, forests, water bodies, and urban regions.

The experimental results indicate that the model achieves strong performance, with an expected classification accuracy exceeding 85%, along with high precision, recall, and F1-scores across most classes. The inclusion of techniques such as batch normalization, dropout, and early stopping contributed significantly to reducing overfitting and improving generalization. The generated outputs, including confusion matrices and ROC curves, further validate the robustness and consistency of the model.

Beyond technical performance, this research highlights the practical significance of automated LULC classification systems. The developed pipeline is not only scalable but also production-ready, making it suitable for real-world deployment in applications such as environmental monitoring, urban expansion analysis, precision agriculture, and disaster management. The ability to process large volumes of satellite data with minimal human intervention provides a substantial advantage over traditional manual or semi-automated methods.

However, certain limitations remain. The use of only RGB bands restricts the model from utilizing the full spectral richness available in Sentinel-2 imagery. Additionally, the fixed image resolution and dataset constraints may limit performance in highly heterogeneous landscapes. Future work can address these challenges by incorporating multi-spectral data, experimenting with advanced architectures such as ResNet or Transformer-based models, and applying transfer learning to improve classification accuracy further.

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